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RESEARCH

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A new approach to estimate the heat thresholds at the county level in China

Qian Yin[1*], Jinfeng Wang[1,2], Jiayi Zhou[1] and Zhoupeng Ren[1]

Abstract

Background High temperature beyond the comfort threshold is the main hazard to cause heat-related mortality. However, existing methods of defining the heat thresholds are usually based on case studies in data-rich regions and rarely considers the acclimatization.

Methods Based on the temperature–mortality relationship observed in 36 locations covering all six major climate zones in China, we found that the relative risk (RR) of heat-related mortality and the annual frequency of temperature (AFT) have a power function relationship (adjusted $R^2 = 0.74$)), and the association is independent to the variation of the temperature across the territory. Furthermore, the association is slightly changed when the GDP/capita, proportion of elderly population and latitude are adjusted. According to this association, we proposed a new method to choose the heat threshold at finer resolution using only AFT. As the temperature frequency is easy to calculate, this method can be promoted to any geographical location without mortality data.

Results According to the relationship between AFT and RR, using the daily time series of temperature at 2405 observation stations in China, we estimated and mapped the distribution of heat thresholds at the county level across China. We find that when the AFT is just 1 day per year, the corresponding RR is approximately 1.4 (95% CI, 1.2-1.8). As the AFT increases to 5 days per year, the RR decreases to about 1.2 (95% CI, 1.1–1.3). When the AFT reached 10 days per year, the RR further decreased to about 1.05 (95% CI, 1.0–1.1).

Conclusions This study advances the understanding on the driver of human beings' adaptation to high temperature. It also contributes significantly to the research on heat-related mortality in the context of global climate change.

Keywords Annual temperature frequency, Heat wave, Heat threshold, Adaptation, Variable risk, Spatial heterogeneity

Introduction

For centuries, the impact of ambient temperature on human health has been a public health concern. Historically, the health impact due to heat exposure has attracted more attention. Globally, an increasing frequency and intensity of heat waves has been observed since the 1950s [4]. In epidemiological studies, use of the term 'heat' implies that it is a day of unusually high temperature-related heat stress, which results in temporary modifications in lifestyle and which may have adverse health consequences for the affected population. Heat exposure may exacerbate the adverse health effects of heat-related stress. For example, extreme heat has been associated with increased hospitalizations for respiratory and renal diseases in 114 U.S. cities [11]. In 15 Chinese cities, extreme temperatures were significantly associated with cardiovascular mortality, especially in older adults [32]. In 43 U.S. communities, research has found

*Correspondence:
Qian Yin
yinq@lreis.ac.cn
[1] State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Nature Resources Research, Chinese Academy of Sciences, A11, Datun Road, Chaoyang District, Beijing, China
[2] University of Chinese Academy of Sciences, Shijingshan District, A19, Yuquan Road, Beijing, China

that heat wave timing in the season might lead to different nonaccidental mortality risks,heat waves earlier during the summer had higher mortality risks than later heat waves [1]. In these studies, the choose of heat threshold value is the core problem in the study of the adverse health effects of heat-related stress.

How can we scientifically choose heat thresholds that account for region-specific adaptation capacities and localized climatic conditions? In terms of research methods, previous studies have presented many methods to choose the heat threshold value [3, 5, 27, 36]. They have generally followed two approaches: 1) exceedance of fixed absolute values (e.g. 35 °C) or relative values (e.g. 95th vs. 97.5th percentile of temperature); 2) deviation from normal. Such as exceedance of the daily mean value by a fixed standard deviation and exceedance of the daily mean by an absolute fixed amount. The estimated effects of heat exposure on mortality rates increase as the amount of exceedance increases. For example, according to a comparison of the associations between different heat definitions and cause-specific mortality in Nanjing, China, Chen et al. found that different heat definitions had considerably different impacts on cardiovascular, respiratory, stroke and ischemic heart disease mortality [5]. Although these studies presented various definitions of heat, the selection of above thresholds is based on the statistical relations of case data, without further discussion of the physical meaning. Moreover, the physiological adaptation of organisms to the environment can reduce the impact of high temperature on health. This factor was not considered. Thus, it is still unclear whether a common mechanism drives the adverse effects of high temperatures?

In terms of research scopes, many researchers have conducted the studies on the mortality burden due to high temperatures in many areas. Research on a large study area, such as a national scale, usually only considered the temperature distribution and ignored effects on health [21, 24, 33]. While some studies that provided definitions of the heat threshold were based on temperature–mortality associations in specific regions, these studies typically rely on case studies conducted in data-rich areas, leaving significant limitations in heat threshold research for numerous data-scarce regions [7, 13, 14, 37]. Consequently, large-scale, high-resolution analyses (e.g., national-scale studies with county-level or finer spatial resolutions) remain virtually unexplored. Temperature varies considerably across regions. Importantly, climate change is now widely recognised as a global threat to human health in the 21 st century [30]. Global mean temperatures are expected to increase as much as 3.2 °C by the end of this century if modelled pathways consistent with the continuation of policies implemented by the end of 2020 [19]. This rise, in turn, is expected to increase the frequency and intensity of heat waves around the world, with a larger relative effect on in developing regions [18, 26, 28]. In the context of global warming, a more meaningful method to choose the heat threshold is applicable to different regions has important practical implications for investigating the relationship between temperature and mortality as well as calculating the mortality burden due to exposure.

To fill the above research gap, in this study, we analysed the risk of heat-related mortality in 36 typical cities covering all six major climate zones in China and proposed a new method to estimate nationwide heat thresholds at finer resolution without the need for mortality data.

Materials and methods

Materials

The research period for the 36 cities in the present study spanned from 1996 to 2021, covering all the six of eight major climatic zones, (including middle temperate zone, warm temperate zone, north subtropical zone, middle subtropical zone, south subtropical zone and marginal tropical zone, excluding frigid temperate zone and the Tibetan Plateau area). Figure 1 and Table 1 respectively show the locations and descriptive data on annual mean temperature in the 36 Chinese cities. The annual mean temperature ranged from 5.1 °C in Harbin to 24.2 °C in Haikou.

Proportion population being elderly (≥ 65 years of age) data for these 36 cities were obtained from the Sixth National Census (http://www.stats.gov.cn/sj/pcsj). GDP/capita data for 36 cities was obtained from China Statistical Yearbook 2010 (http://www.stats.gov.cn/sj/ndsj).

The daily mean temperature of 2405 locations in China (Fig. 2) were obtained from the China Meteorological Administration (http://data.cma.cn).

Statistical analysis

We searched Web of Science, PubMed, Scopus and EMBASE for articles published in English from 2000 to 2023 with the study region in China using the terms temperature or heat, and death or mortality. To ensure the results are comparable, we focused on studies using the distributed lag non-linear model (DLNM). A total of 42 papers investigated the relationships between daily temperature and human mortality counts for non-external causes using the DLNM method. Excluding the literature from the repeated study areas, four papers [6, 9, 23, 31] of which are chosen. These studies involved 36 typical cities covering all six major climate zones.

From above four prior publications, we collected the U-shaped curves of the daily mean temperature and the relative risk (RR) of heat-related mortality fitted by

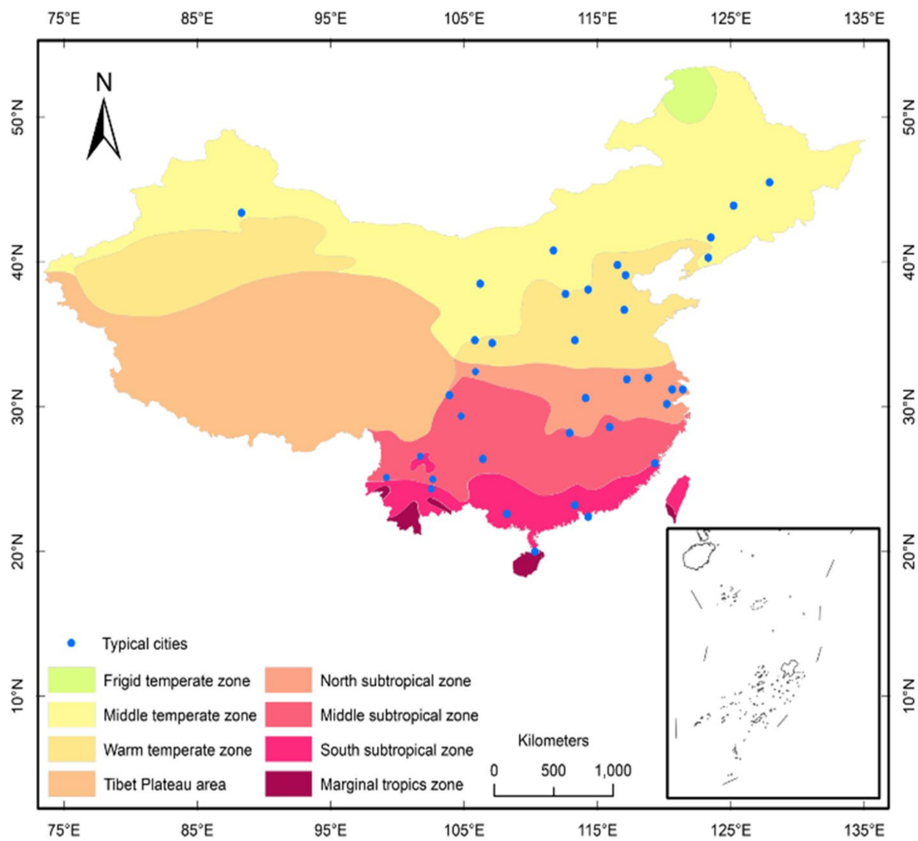

Fig. 1 Locations of 36 cities in different climate zones

DLNM in 36 typical cities from 1996 to 2021 covering all six major climate zones and different demographic, socioeconomic, and infrastructural characteristics in China. Based on the U-shaped curves relationship, we observed a significant power function relationship between the RR and the AFT. We verified this relationship and proposed a new method for choosing the heat threshold value using only the AFT.

(1) Theoretical modeling: the relationship between RR and AFT

Step 1: From prior publications [6, 9, 23, 31], extracting the corresponding RR and temperature frequency for each temperature bin (1 °C width) in each U-shaped curves and temperature histogram from the lowest point of the curve (where the temperature is equal to minimum mortality temperature, MMT) to the highest daily temperature in 36 cities. In this study, we used GetData software (http://getdata-graph-digitizer.com/) to achieve this step.

Step 2: The above temperature frequency was divided by the study period (years) to obtain the annual average frequency. This was the AFT.

Based on these two steps, we obtained a data array (Daily mean temperature, AFT, RR) for 36 cities during their respective study periods.

Step 3: We randomly selected 2/3 of the cities (n = 24) to use as the training set, while using the remaining 1/3 (n = 12) as the testing set. For the training data, we utilized a multiple non-linear regression (MNLR) to investigate the associations between the RR and the four independent variables in Table 2.

The model is defined below (Eq. (1)):

$$y = \alpha + \sum_{i=1}^{4} \beta_i f_i(x_i) \tag{1}$$

where y is the corresponding RR, α is the intercept. x_1, ... x_4 are the independent variables in Table 1, β_1, ... β_4 are the regression coefficients, and f_1, ... f_4 are the regression functions.

(2) Practical implementation: a new method for choosing heat thresholds

Table 1 Descriptive data of 36 Chinese cities

Locations (Province)	(Longitude, Latitude)	Study period	Annual mean temperature (°C)	Climate Zones
Harbin (Heilongjiang)	(127.9°, 45.6°)	2008–2013	5.1	1
Changchun (Jilin)	(125.2°, 43.9°)	2008–2013	5.9	1
Urumqi (Xinjiang)	(88.3°, 43.4°)	2006–2007	8.5	1
Shenyang (Liaoning)	(123.5°, 41.7°)	2005–2008	6.4	1
Hohhot (Inner Mongolia)	(111.7°, 40.8°)	2008–2013	7.6	1
Anshan (Liaoning)	(123.3°, 40.3°)	2004–2006	10.7	1
Beijing (Beijing)	(116.5°, 39.8°)	2007–2008	10.5	2
Tianjin (Tianjin)	(117.1°, 39.1°)	2005–2008	11.8	2
Yinchuan (Ningxia)	(106.2°, 38.5°)	2008–2013	10.3	1
Shijiazhuang (Hebei)	(114.3°, 38.1°)	2008–2013	14.2	2
Taiyuan (Shanxi)	(112.6°, 37.8°)	2004–2008	10.1	2
Jinan (Shandong)	(117°, 36.7°)	2008–2013	14.5	2
Lanzhou (Gansu)	(105.8°, 34.6°)	2004–2008	10.4	1
Zhengzhou (Henan)	(113.3°, 34.6°)	2008–2013	15.6	2
Xi'an (Shaanxi)	(107.1°, 34.4°)	2004–2008	11.3	2
Guangyuan (Sichuan)	(105.9°, 32.4°)	2016–2021	16.3	4
Chengdu (Sichuan)	(103.9°, 30.8°)	2008–2013	16.8	3
Panzhihua (Sichuan)	(101.7°, 26.6°)	2016–2021	21.6	3
Zigong (Sichuan)	(104.8°, 29.4°)	2016–2021	18.9	4
Nanjing (Jiangsu)	(118.8°, 32°)	2008–2013	16.3	3
Suzhou (Jiangsu)	(120.6°, 31.2°)	2005–2008	15.6	3
Hefei (Anhui)	(117.2°, 31.9°)	2008–2013	16.6	3
Shanghai (Shanghai)	(121.4°, 31.2°)	2008–2012	17.4	3
Wuhan (Hubei)	(114.1°, 30.6°)	2003–2005	16.4	3
Hangzhou (Zhejiang)	(120.2°, 30.2°)	2002–2004	18.5	3
Nanchang (Jiangxi)	(115.9°, 28.6°)	2008–2013	18.6	4
Changsha (Hunan)	(112.9°, 28.2°)	2008–2013	18.3	4
Guiyang (Guizhou)	(106.4°, 26.4°)	2008–2013	14.4	4
Fuzhou (Fujian)	(119.3°, 26.1°)	2004–2006	19.8	4
Baoshan (Yunnan)	(99.2°, 25.1°)	2014–2020	16.8	4
Kunming (Yunnan)	(102.7°, 25°)	2014–2020	16	4
Yuxi (Yunnan)	(102.6°, 24.3°)	2014–2020	16.7	3
Guangzhou (Guangdong)	(113.3°, 23.2°)	2007–2008	21.2	5
Nanning (Jiangxi)	(108.2°, 22.6°)	2008–2013	21.5	5
Hong kong	(114.3°, 22.4°)	1996–2002	23.5	5
Haikou (Hainan)	(110.3°, 19.7°)	2008–2013	24.2	6

Climate zones: 1: Middle temperate zone; 2: Warm temperate zone; 3: North subtropical zone; 4: Middle subtropical zone; 5: South subtropical zone; 6: Marginal tropical zone

Step 1: Based on the daily mean temperature time series during the study period in each city, round all daily mean temperature values to integer values (or draw the temperature histogram with a 1 °C bin width), then calculate the annual average frequency of each daily mean temperature during the study period at each station, that is, the AFT. With this step, we obtain the array (Daily mean temperature, AFT).

Step 2: Based on the relationship of Eq. 1, plus the AFT and other influencing factors at each station in Table 2, calculating the corresponding RR of each AFT. In this step, we obtain the array (AFT, RR).

Step 3: Correlate the results of step 1 and step 2, we can draw the Temperature ~ RR curve.

Step 4: We have the flexibility to choose the heat thresholds according to the tolerability (RR) at each station. The calculation process is as follows:

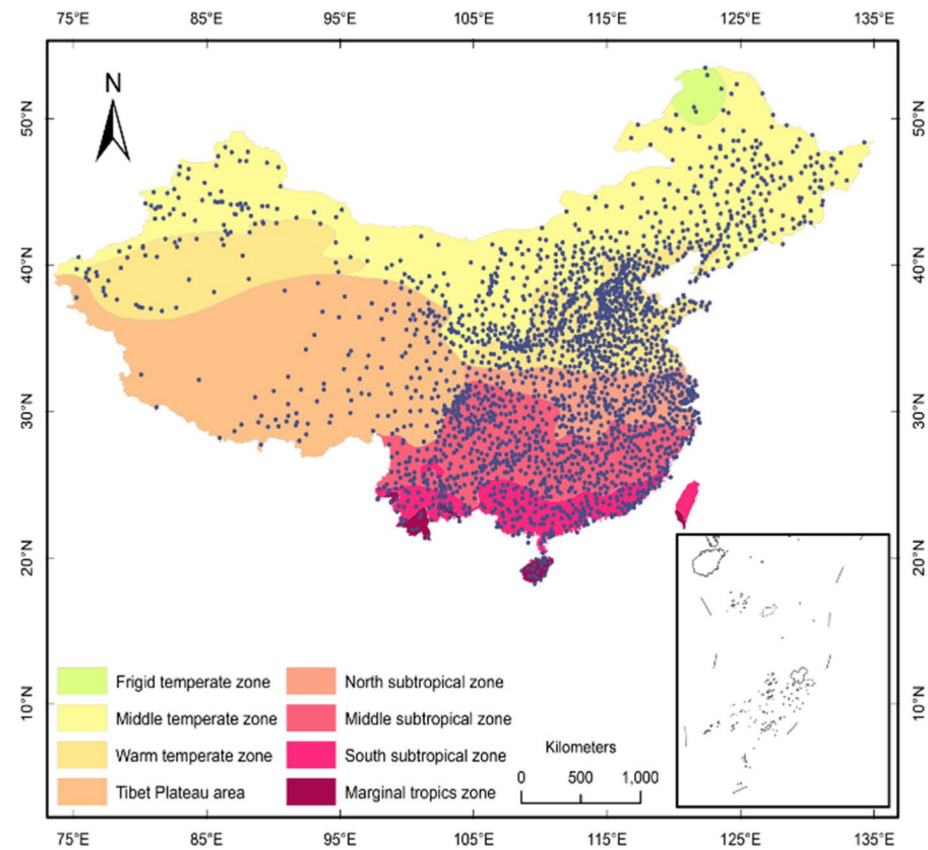

Fig. 2 Locations of 2405 meteorological observation stations in China

Table 2 Independent variables considered in the statistical analysis (the dependent variable is y)

Variable	Description
x_1	AFT
x_2	GDP per capita
x_3	Proportion of elderly population (≥ 65 years of age)
x_4	Latitude
y	The relative risk (RR) of heat-related mortality

$$RR \overset{\text{Step 2}}{\rightarrow} AFT \overset{Step1}{\rightarrow} \textit{the heat threshold value}$$

Results

Relationship between RR and AFT

We used a multiple nonlinear regression (MNLR) to investigate the associations between RR and four independent variables in the training set (n = 24). After analyzing the scatter plot distribution of these variables, we found that AFT and RR are significantly negatively correlated and have a power function relationship (Model 1). The formula is as follows (Equation (2)):

$$RR = 1.348 * AFT^{-0.094} \tag{2}$$

Figure 3 shows a scatter plot of all the AFTs and the corresponding RRs in 24 cities (training data set) and the power function relation between them. The adjusted R^2 is 0. 74. The Geodetector q statistic [29] reports that the AFT explains the 71% (p < 0.001) spatially stratified heterogeneity of the RR. Different-colored dots represent distinct climatic zones. There was no significant difference in the results among different climatic zones.

On the basis of Model 1, we added another 3 variables to get Model 2. The results are shown in Table 3.

We found that if we use only the AFT (x_1) as a predictor (Model 1), the predictive ability is as good as that of Model 2 (the adjusted R^2 is both equal to 0.74). The coefficients of Model2 are shown in Supplementary Table 1. Based on the data in Supplementary Table 1, it appears that the association between the RR and AFT slightly change when we adjust the GDP/capita, proportion of

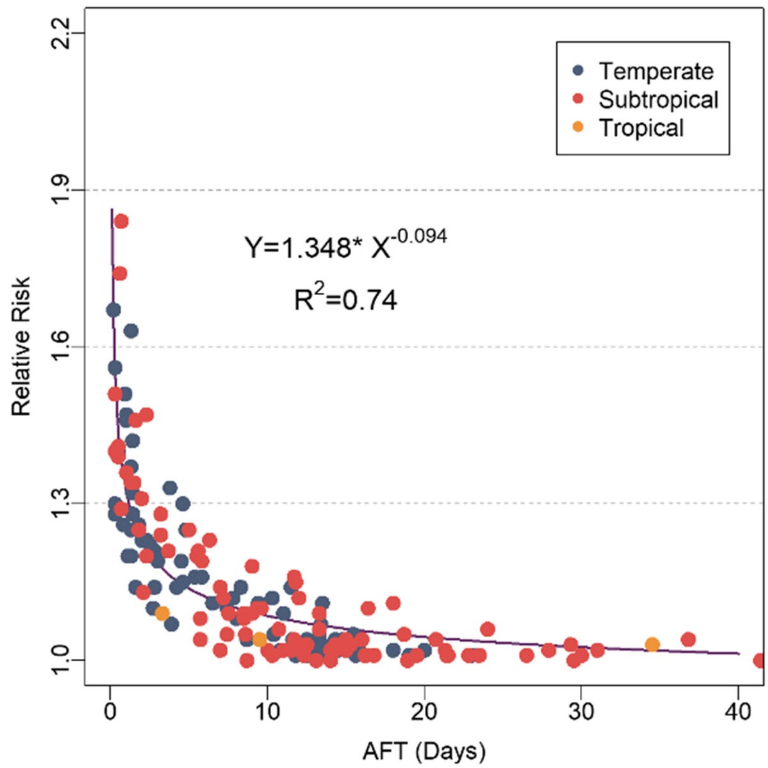

Fig. 3 Non-linear association between AFT and the corresponding RR in the training dataset

Table 3 The models and multiple regression results

Name	Model formula	Adjusted R^2	AIC
Model 1	$RR \sim f_1(AFT)$	0.74	− 362
Model 2	$RR \sim f_1(AFT) + f_2(Latitude) + f_3(GDP/capita) + f_4$(Proportion of elderly population)	0.74	− 361

AIC Akaike information criterion

f_1 is a power function, $f_2, \ldots f_4$ are all linear functions

elderly population and latitude. Therefore, as a simple model for practical use, we recommend using Model 1 to predict the RR.

Predictor: prediction of RR based on AFT

Based on the above relationship between AFT and RR (Fig. 3), we estimated the RR for the testing dataset (n= 12). The relationship between the estimated and observed RRs for them is shown in Fig. 4.

From Fig. 4, we can see that the observed and estimated RR match well. The regression line almost passes through the origin, with a slope of 1 and R^2 of 0.74 ($p <$ 0.001). The results showed that Model 1 performed well for the estimation of RR.

Choose heat thresholds based on the flexible risk of heat-related mortality

From Fig. 3, we find that when the annual average frequency of a temperature (AFT) is as low as 1 day per year, the corresponding RR is approximately 1.4 (95% CI, 1.2–1.8), representing a 40% increase in the RR of heat-related mortality. Whereas when the AFT increased to 5 days per year, the RR decreased to approximately 1.2 (95% CI, 1.1–1.3). When the AFT reached 10 days per year, the RR further decreased to about 1.05 (95% CI, 1.0–1.1). Based on this finding, we propose a new method to choose the heat threshold according to temperature occurrence frequency. Clearly, RR level of heat-related mortality could be flexible to choose according to the different needs in different regions. For example, for higher-level warnings, we can choose a lower AFT.

The heat distribution of China

Using the daily mean temperature of 2405 locations in China, we calculated and mapped the distribution of heat thresholds at the county level in China from 2019 to 2021 (Fig. 5). The thresholds vary considerably on a national scale in China. They tend to decrease from low latitudes to high latitudes. The highest thresholds mainly appear in the mid- to high-latitude regions and the arid desert region of the northwest, with the highest value reaching

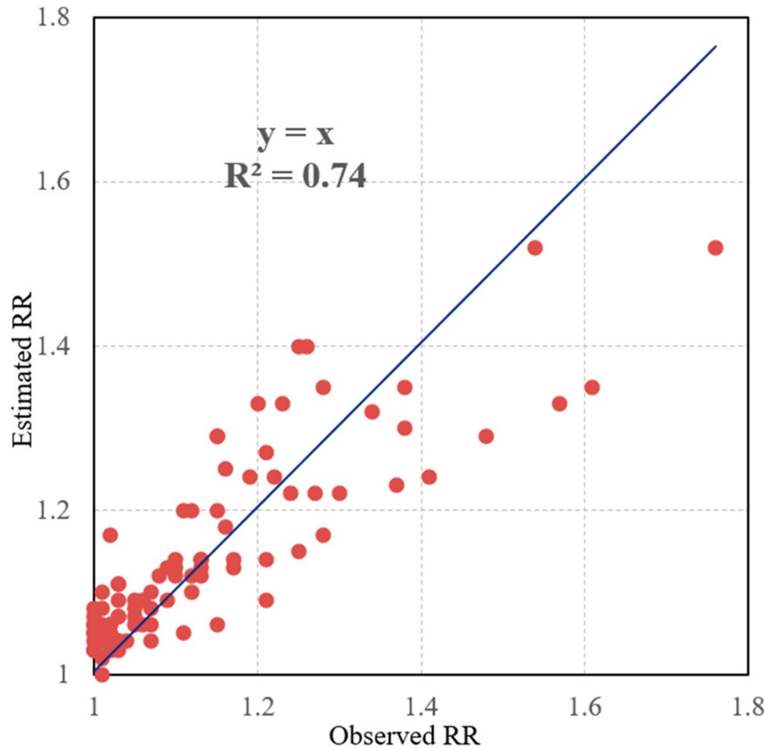

Fig. 4 Relationship between the estimated and observed RRs for the testing dataset

35 °C, while the lowest thresholds reach as low as 11 °C in Tibetan Plateau area. These thresholds at each location represent a 10% increase in the RR of heat-related mortality when compared with the MMT. Thus, a heat warning can be issued when the temperature reaches these thresholds. Actually, RR level of heat-related mortality could be flexible to choose according to the different needs in different regions.

Discussion

Although there have been numerous methods to choose the heat threshold and then issue heat warning in the last decades, these methods have some limitations. First, the existing heat thresholds were usually developed based on case studies conducted in data-rich regions [7, 13, 14, 17, 37], meaning that their applicability in data-scare areas, which are usually less developed, is uncertain. Second, the selection of heat thresholds is based on statistical associations without explicit physical meaning, and the physiological adaptations of organisms to the environment are not considered.

Our study fills the gaps. First, we find that although temperature varies considerably across the planet, the RR of heat-related mortality is significantly negatively correlated with the annual frequency of temperature. Thus, practitioners can use the identified association to easily determine the temperature threshold and RR without the need for mortality data but the AFT (Fig. 3). The analysis of data from 36 locations covering all six major climate zones and in populations with different demographic, socioeconomic, and infrastructural characteristics in China provides evidence for this. Frequency can reflect the adaptation of humans to temperature. Humans adapt to climate in several ways, such as physiological, behavioural and technological adaptations [12, 20, 25]. Our previous research found that the local most frequent temperature (MFT) is the temperature that humans are most commonly exposed to and, therefore, physiologically acclimatised to [35]. Accordingly, the MFT is a good indicator of fitting the minimum mortality temperature (MMT) [35]. Based on this theory, we infer that if a temperature occurs with a very low frequency, people will not adapt to it as well as they do to the MFT because of the short adaptation time, meaning that the less frequent temperature would pose a greater risk to humans. This theory is confirmed by the data presented in Fig. 3. For example, if the frequency of a daily mean temperature (e.g. as 35 °C) is very low in a given study area (i.e. only two days per year), then 35 °C would be a high-risk temperature. In addition to this, similar to the previous research [35], wherein the association between MFT and MMT is not affected by socioeconomic conditions, the

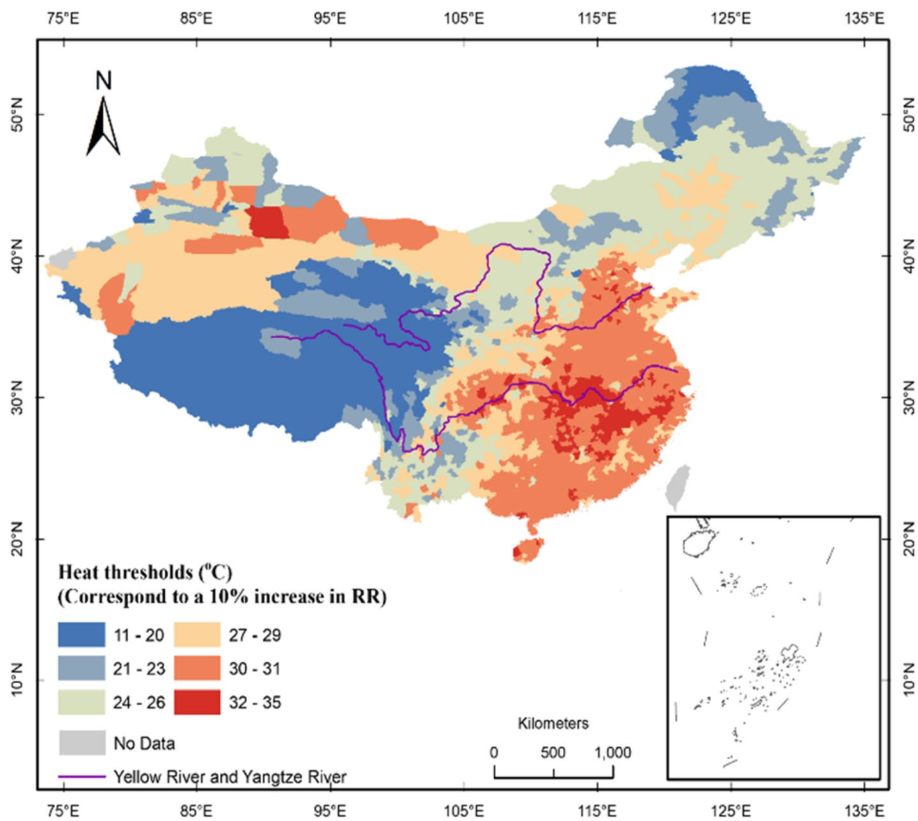

Fig. 5 Distributions of heat thresholds at the county level in China from 2019-2021

association between AFT and RR is also slightly changed when the GDP/capita, proportion of elderly population and latitude are controlled (Table 3). Although we believe that socioeconomic conditions can affect human adaptation to local temperature. According to this relationship between AFT and the corresponding RR, in this study, we propose a new method to choose heat threshold based on temperature occurrence frequency. For example, we could choose the heat threshold as the temperature at which the RR of heat-related mortality reaches 10%. Through analysis, we find that the AFT corresponding to this RR is approximately eight days per year in China. Moreover, the RR level can be flexibly selected and calculated according to the tolerability and resources available to handle the risk in different regions. Compared with the fixed temperature (e.g. 35 °C), the method based on frequency takes into account the differences of temperature distributions in different regions. Compared with the relative temperature (e.g. 97.5th percentile of temperature), our method can also calculate the number of days of a heat more accurately.

Secondly, to our knowledge, for the first time, we give a quantitative estimation of heat threshold at the fine resolution (county level) and large scale (a national scale) on the base of the RR of heat-related mortality. Previous studies are usually based on case studies conducted in data-rich regions [7, 13, 14, 37]. They did not estimate the heat thresholds for every region within a country because of the unavailability of mortality data. As the temperature frequency is easy to calculate, we can therefore estimate the heat thresholds in any geographical location without mortality data. We find that, as expected, heat thresholds are higher in hot areas than in cold areas. The heat thresholds we calculated for different regions of China are consistent with those reported in existing literature. By analyzing meteorological and mortality data from 66 disease surveillance sites (population> 200,000) across China, Lin et al., proposed absolute heatwave thresholds for seven regions as follows: 21.6 °C (Northeast), 23.7 °C (North China), 24.3 °C (Northwest), 25.7 °C (East China), 28.0 °C (Central China), 25.3 °C (Southwest), and 30.4 °C (South China) [22]. By investigating the impact of extreme high temperature on mortality in five Chinese cities, Gao et al., defined heat waves of Beijing, Tianjin, Nanjing, Shanghai and Changsha with daily mean temperatures exceeding 30.2 °C, 29.5 °C, 32.9 °C, 32.3 °C and 34.5 °C respectively [8]. Furthermore, interestingly, our results suggested that the number of high-risk heat days is more in cold areas than in hot areas, especially in northeast China, which has the lowest temperature percentile of the threshold. Thus, a heat warning can be issued when the temperature reaches this threshold.

Lastly, in the context of global warming, on the one hand, the distribution of temperature and the frequency of extreme weather events may change in the future [2, 3, 16]. On the other hand, the impact of heat changes over time [7]. The existing prediction of an increase in heat-related mortality and a decrease in cold-related mortality may be questionable when based on an unchanged threshold [10, 15]. Using changing thresholds and days of heat may provide more precise predictions on the mortality burden due to high temperatures.

Different climate regions have different climate characteristics and temperature distributions, which may lead to different health effects. For three main climate zones (tropical, subtropical, and temperate region), we compared the associations between the AFT and RR. The results showed that in these three climate regions, their relationships are similar, and the AFT is a good predictor of RR for them (Fig. 3).

Our findings hold several policy implications. Firstly, it is essential to developing a national early warning system at the county level or higher resolution (e.g., 0.5° grid), utilizing the"temperature frequency-mortality risk"model proposed in this research. This system could implement a three-tier warning framework (e.g., red: ≤3 days/year; orange: 4–10 days/year; yellow: >10 days/year). The AFT methodology serves as a robust solution to mitigate data scarcity challenges. Secondly, we propose implementing a cyclical update mechanism for AFT thresholds every 3–5 years through integrating IPCC climate model projections. These updates should account for regional temperature distribution changes and variations in extreme weather frequency. This will provide a scientific basis for future health burden assessments. Third, we recommend adding these measures via amendments to the *National Climate Change Adaptation Strategy 2035* public health action plan, ensuring operational synergy with existing meteorological disaster management frameworks.

This study has some limitations. First, similar to all large-scale analyses, data were not available for every climate zone. The 36 cities we chose did not cover the Tibetan Plateau area and the frigid temperate zone. Nonetheless, these two missing regions have very small resident populations and account for less than 1% of the total population of China. Our research results could still provide a reference for the vast majority of populations in China. Second, in addition to the variables considered in Table 1, the use of air conditioning and medical conditions may also affect human's vulnerability to high temperature, but due to the data validity, these two factors were not included in the statistical analysis. Third, the selection of heat threshold in our study does not consider the duration of high temperature. Previous many studies have analysed the heat-related excess mortality under different heatwave definitions by combining thresholds at the 90th, 92.5th, 95th, or 97.5th percentiles of year-round daily mean temperatures and durations of >2, 3, or 4 consecutive days. However the results of these studies in different regions are not completely consistent [13, 14, 34, 38], although most of them have shown that high temperatures and long durations were associated with higher risk than heatwaves with low temperatures and short durations. This is an interesting topic that we plan to focus on in our upcoming research.

Conclusions

Heat exposure is the important determinant of the heat-related mortality. In this study, by analysing the risk of heat-related mortality in 36 locations covering all six major climate zones in China, we find that the mortality risk of high temperature is significantly negatively related to the annual frequency of high temperature. According to this association, we propose a new method to choose heat threshold based on the temperature occurrence frequency. Then, using the daily time series of temperature at 2405 observation stations, we map the distribution of heat thresholds at the county level in China.

This study will contribute significantly to the research on urban climate in the context of global climate change. Our research advances the understanding on the driver of human beings' adaptation to high temperature and urban climate.

Abbreviations

RR	Relative risk
AFT	The annual frequency of temperature
DLNM	Distributed lag non-linear model
MMT	Minimum mortality temperature
MFT	Most frequent temperature

Supplementary Information

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Supplementary Material 1.

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Not applicable.

Authors' contributions
Q, Y and JF, W conceived of and designed the study.Q, Y and ZP, R carried out the computations and wrote the manuscript. All the authors contributed to the final version of this paper.

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no role in determining the study design, data collection or analysis methods employed, in our decision to publish or in preparing the paper.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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