Years of life lost and life expectancy attributable to ambient temperature: a time series study in 93 Chinese cities

Siqi Ai 1,*, Jinlei Qi 2,*, Jiangmei Liu 2, Lijun Wang 2, Peng Yin 2, Ruiyun Li 3,4, Chongjian Wang 2, Hualiang Lin 1,*, and Maigeng Zhou 2, *

1 Department of Epidemiology, School of Public Health, Sun Yat-sen University, Guangzhou 510080, People’s Republic of China
2 National Center for Chronic and Noncommunicable Disease Control and Prevention, Chinese Center for Disease Control and Prevention, Beijing 100050, People’s Republic of China
3 Centre for Ecological and Evolutionary Synthesis, Department of Biosciences, University of Oslo, N-0316 Oslo, Norway
4 MRC Centre for Global Infectious Disease Analysis, Department of Infectious Disease Epidemiology, School of Public Health, Faculty of Medicine, Imperial College London, London W2 1PG, United Kingdom
5 Department of Epidemiology and Biostatistics, College of Public Health, Zhengzhou University, Zhengzhou, Henan, People’s Republic of China
6 Contributed equally to this work.

* Authors to whom any correspondence should be addressed.

E-mail: linhualiang@mail.sysu.edu.cn and zhoumaigeng@ncncd.chinacdc.cn

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Abstract

Although increasing evidence has reported that unfavorable temperature may lead to increased premature mortality, a systematic assessment is lacking on the impact of ambient temperature on years of life lost (YLL) and life expectancy in China. Daily data on mortality, YLL, meteorological factors and air pollution were obtained from 93 Chinese cities during 2013–2016. A two-stage analytic approach was applied for statistical analysis. At the first stage, a distributed lag non-linear model with a Gaussian link was used to estimate the city-specific association between ambient temperature and YLLs. At the second stage, a meta-analysis was used to obtain the effect estimates at regional and national levels. We further estimated the corresponding YLLs and average life expectancy loss per deceased person attributable to the non-optimum temperature exposures based on the established associations. We observed ‘U’ or ‘J’ shaped associations between daily temperature and YLL. The heat effect appeared on the current day and lasted for only a few days, while the cold effect appeared a few days later and lasted for longer. In general, 6.90% (95% confidence interval (CI): 4.62%, 9.18%) of YLLs could be attributed to non-optimum temperatures at the national level, with differences across different regions, ranging from 5.36% (95% CI: −3.36%, 6.89%) in east region to 9.09% (95% CI: −5.55%, 23.73%) in northwest region. For each deceased person, we estimated that non-optimum temperature could cause a national-averaged 1.02 years (95% CI: 0.68, 1.36) of life loss, with a significantly higher effect due to cold exposure (0.89, 95% CI: 0.59, 1.19) than that of hot exposure (0.13, 95% CI: 0.09, 0.16). This national study provides evidence that both cold and hot weather might result in significant YLL and lower life expectancy. Regional adaptive policies and interventions should be considered to reduce the mortality burden associated with the non-optimum temperature exposures.

List of abbreviations

| Abbreviation | Description |
|--------------|-------------|
| YLL          | Years of life lost |
| DLNM         | Distributed lag non-linear model |
| RR           | Relative risk |
| CI           | Confidence interval |
| AF           | Attributable fraction |
| MYT          | Minimum YLL temperature |
| CDRS         | China Cause of Death Reporting System |

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1. Introduction

It has been estimated that the global average temperature will rise by 2.6 °C–4.8 °C before the end of this century, accompanied by its regional amplification effect and other adverse effects (Watts et al 2015). The warming could affect the natural ecosystem and social system closely related to human health, thus bringing great disease burden (Ebi et al 2017, Cai et al 2020). It has been a research hotspot to clarify the relationship between ambient temperature and various health outcomes in recent years (Lam et al 2018, Zhao et al 2019a, 2019b).

Increasing epidemiological evidence has shown that unfavorable ambient temperatures were associated with a rising risk of morbidity and premature mortality (Tian et al 2018, Wondmagegn et al 2019). For example, Chen et al evaluated the impact of ambient temperature on non-accidental mortality in 272 Chinese cities, they found that the relative risk (RR) of total mortality was 1.68 (95% confidence interval (CI): 1.57, 1.81) for extreme high temperature exposures and 1.16 (95% CI: 1.12, 1.21) for extreme high temperature exposures, and 14.33% of total deaths could be attributable to non-optimum temperatures (Chen et al 2018).

However, previous studies mainly considered the daily morbidity or mortality as the health outcome, which ignored the differences in ages of death (Huang et al 2012a). Compared with the deaths among the young people, if most temperature-related deaths occurred in elderly people who had a shorter life expectancy, there would be less public health significance in estimating the temperature-related mortality burden (Jiao et al 2019). So a few recent studies further proposed years of life lost (YLL) as a new indicator to reflect premature mortality effects of unfavorable temperature exposures (Huang et al 2018, Zeng et al 2018). For instance, one study in Guangzhou found that the hot effect occurred immediately, while the cold effect delayed and lasted for 14 d, with different increments of YLL due to non-accidental, cardiovascular and respiratory mortality (Yang et al 2015). A multi-city study in Hubei province, China suggested that both low and high temperatures were associated with increased YLL, heat effect (1 °C increase from 75th to 99th percentile of temperature range) on lag 0–2 d and cold effect (1 °C drop from 25th to 1st percentile of temperature range) on lag 0–21 d may increase YLL due to non-accidental deaths by 1.91% (95% CI: 0.83%, 3%) and 5.09% (2.79%, 7.40%), respectively (Zhang et al 2018).

Given the widely reported associations between non-optimum temperature exposure and premature mortality, as well as increased YLLs, it was reasonable to hypothesize that unfavorable temperature exposure could reduce the life expectancy. However, the evidence on this association has been largely scarce.

We thus conducted this study in 93 Chinese cities with the objectives: (a) to assess the association between daily temperature and YLL; (b) to estimate the AF of YLL associated with non-optimum temperature exposures; and (c) to calculate the average effects of non-optimum temperature exposures on life expectancy loss per deceased person. We conducted this analysis at both regional and national level, findings from this study will provide new scientific evidence on the health impacts of ambient temperature and developing regional adaptive policies and interventions.

2. Methods

2.1. Daily mortality and YLL

We obtained the death data for 100 representative cities from the China Cause of Death Reporting System (CDRS) between 18 January 2013 and 31 December 2016. After checking the daily average deaths and YLLs in these cities, we excluded seven cities, and finally selected 93 cities as our study sites. The number of daily deaths in those excluded cities was either too small (<5 per day) to ensure the accuracy and power of statistical analysis (Bhaskaran et al 2013), or there was a large fluctuation (such as abnormal increase or decrease) on YLL in a continuous period of time. The CDRS is a combination of the new disease surveillance points (DSPs) system, which was made up of the old DSP system of the Chinese Center for Disease Control and Prevention (CDC) and the vital registration system of the Chinese Ministry of Health since 2013, the expanded non-DSP registration system at provincial and county level, and the in-hospital death reports (Zeng et al 2020). Based on the internet reporting mechanism established and operated by China CDC, the CDRS covers the entire population of each county or district in principle, and reports more than 7.5 million deaths in real time each year. If a death event occurs in any county, whether the deceased is a local (who has lived in the county for more than 6 months) or non-local resident, the basic demographic characteristics, residential address, place of death and cause of death information should be reported to the system (Liu et al 2016, Yang et al 2020). Since the data source of the CDRS comes from three independent collection channels, there is almost no duplication. In addition, the death data of the system is verified regularly and compared with the data of the Ministry of Public Security and the Ministry of Civil Affairs of China, so the data quality can be guaranteed (Zeng et al 2020). Non-accidental mortality was coded as A00-R99, according to primary diagnosis coded by...
ICD-10 (International Classification of Diseases, 10th revision).

According to administrative units, geographical and climatic characteristics (Luan et al 2018), we divided the study areas into seven regions (figure 1), namely north, northeast, northwest, east, central, south and southwest. There are five climate types in seven regions. The characteristics of temperate monsoon climate (northeast, northwest, central and east region) are that winter is cold and dry, summer is hot and rainy; subtropical monsoon climate (south and southwest region) is characterized by high temperature and rainy summer, and mild temperature and rainy winter; temperate continental climate (north region) mainly presents hot and humid summer, and cold and dry winter; the tropical monsoon climate (south region) is characterized by high temperature throughout the year with the annual average temperature above 22 °C, and the coldest winter temperature is generally above 16 °C; plateau mountain climate (southwest region) generally accompanied by high terrain and cold temperature throughout the year.

In order to calculate the YLLs of the deceased, we first obtained the Chinese national life table between 2013 and 2016 from WHO’s website (www.who.int/gho/countries/chn/country_profiles/en/). The life expectancy table shows the expectation years of life at a specific age and sex (table S1 (available online at stacks.iop.org/ERL/16/064015/mmedia)). We firstly calculated the YLL for each death through matching age and gender to the life table, then summing the YLL for all deaths on the same day to generate the daily YLL, and finally forming the YLL time series data (Guo et al 2013). For example, there were only two male deaths (aged 16 and 75 years) occurring on 1 January 2016 in a certain city. By matching with the life table, the corresponding YLLs of the two persons were 60.9 and 8.8 years, respectively. Therefore, the total YLL on 1 January 2016 in the city was 69.7 years. The R code for calculating the YLL was available in supplemental materials. After obtaining the YLL time series dataset, we linked this dataset to the corresponding daily meteorological factors and air pollution data for the subsequent analyzes.

This study was based on a project to examine the short-term health effects of air pollution on Chinese populations, which has been approved by the Ethics Review Committee of the Institute of Environmental
Health and Related Product Safety, CDC. Since all data were analyzed at an aggregated level, individual consent was not required.

2.2. Meteorological factors and air pollution data
Meteorological data, including daily mean temperature (°C) and relative humidity (%), were obtained from China Meteorological Data Sharing Service System (http://data.cma.cn/), which can provide weather data to the public. The mean daily temperature and relative humidity were calculated from central monitor stations.

We also extracted daily concentrations of air pollution, including fine particulate matter with an aerodynamic diameter \( \leq 2.5 \ \mu m \) (PM\(_{2.5}\)) and ozone (O\(_3\)) from the National Real-time Publishing Platform for Air Quality (http://106.37.208.233:20035). The platform is managed by the China’s Ministry of Environmental Protection and releases the real-time concentrations of air pollutants in the city where the monitoring sites are located. The 24 h averaged concentrations of PM\(_{2.5}\) and maximum 8 h averaged concentrations of O\(_3\) were first calculated in each monitoring site, and then averaged from all sites within a city.

2.3. Statistical analysis
2.3.1. Evaluating temperature-YLL association
A two-stage analytical approach was applied in this study. At the first stage, we examined the temperature-YLL associations in each city. As the daily YLL follows a normal distribution (figure S1), we applied a distributed lag non-linear model (DLNM) with a Gaussian link to assess the non-linear and delayed effects of ambient temperature on YLL. To account for the non-linear and delayed effects of temperature, a cross-basis function of temperature was established through a quadratic B-spline with 5 degree of freedom (df) for the temperature-YLL relationship and a natural cubic spline with 4 df at equally-spaced log values for the space of lags, with maximum lag of 21 d (Gasparrini and Armstrong 2013). Some potential confounding factors were also adjusted in the model. Specifically, day of the week and public holidays were adjusted using dummy variables. A natural cubic B-spline of temporal trend with 7 df/ per year was considered to control for the long-term trend and seasonality (Bhaskaran et al 2013, Zhang et al 2020). A natural cubic spline function of daily relative humidity with 3 df, and the linear term of PM\(_{2.5}\) and O\(_3\) were also included for other confounding effects.

The minimum YLL temperature (MYT) corresponds to the minimum YLL across the temperature range, which was identified based on the overall exposure-response relationship curves between temperature and YLL. Briefly, we used the univariate meta-analysis to generate the regional and national temperature-YLL curve, then set the temperature corresponding to the minimum cumulative effect as MYT. We referred to this value as the optimum temperature, and used it as the reference for calculating the exposure-response relationship and attributable burdens. We also estimated the lag patterns in YLL risks associated with extreme low temperature (2.5th percentile) and extreme high temperature (97.5th percentile).

The meta-analysis employed at the second stage was used to combine the city-specific temperature-YLL associations to regional and national pooled estimates. This method could synthesize the multi-parameterized non-linear associations from two-stage hierarchical analyzes, and has been widely used in multi-site studies (Chen et al 2014, Yin et al 2017). \( I^2 \) statistics and Cochran Q tests were reported to show the heterogeneity across the cities.

2.3.2. Estimating the attributable YLLs and AF
Considering the non-linear association between temperature and YLL, we separated the total temperature to components related to high temperatures and low temperatures by MYT. Then we extracted the coefficient separately for cold and hot effects corresponding to each unfavorable temperature from the fitted models for the subsequent analyzes.

We then estimated the attributable YLLs due to hot and cold temperatures in each city. The formula for the calculation can be specified as:

\[
\text{Attributable YLLs} = \sum_{k=1}^{n} (\text{Temp}_k - \text{MYT}) \beta_k
\]

where \( n \) refers to the number of days of non-optimum temperatures in a certain city; \( \text{Temp}_k \) represents the value of non-optimum temperatures on a certain day \( k \); MYT represents the temperature corresponding to the minimum YLL risk from the pooled association; \( \beta_k \) represents the coefficient value corresponding to specific non-optimum temperatures, based on the non-linear associations curve; Total YLLs represents the sum of daily YLL during the study period in a certain city.

2.3.3. Calculating the attributable life expectancy loss
Based on the estimated attributable YLLs in the previous steps, we further estimated the averaged life expectancy loss attributable to hot, cold and non-optimum temperatures for each death, using the following formula:

\[
\text{Attributable life expectancy loss} = \frac{\text{Attributable YLLs}}{\text{Total deaths}}
\]

where the total deaths refers to the sum of daily death count during the study period in each city.
In order to account for the potential effect modifications of demographic, geographical and socioeconomic factors, we included average temperature, temperature range, annual gross domestic product per capita, population, urbanization rates, and latitude and longitude of each city as meta-predictors in the multivariate meta-regression analysis to pool city-specific AF and attributable life expectancy loss per deceased person due to cold, hot and non-optimum temperatures at the regional and national level. We tested the residual heterogeneity through Cochran Q test and \( I^2 \) statistic.

### 2.4. Sensitivity analysis
To test model fit and evaluate the robustness of results in the main model, we conducted model checking and a series of sensitivity analyses by: (a) performing the residual and residual partial autocorrelation plot (PACF) of the fitted model; (b) controlling for the confounding effects of air pollution by using 3 d moving average of PM\(_{2.5}\) and O\(_3\) concentrations instead of current day’s concentrations; (c) alternating maximum lags to 14, 18, 21 and 24 d; (d) changing the df of current day’s concentrations; (e) altering maximum lags to 14, 18, 21 and 24 d; (f) changing the df of current day’s concentrations; (g) using different lag structures; (h) using different lag structures; (i) using different lag structures; (j) changing the df of current day’s concentrations; (k) using different lag structures; (l) using different lag structures; (m) using different lag structures; (n) using different lag structures; (o) using different lag structures; (p) using different lag structures; (q) using different lag structures; (r) using different lag structures; (s) using different lag structures; (t) using different lag structures; (u) using different lag structures; (v) using different lag structures; (w) using different lag structures; (x) using different lag structures; (y) using different lag structures; (z) using different lag structures.

We used R software (version 3.3.2, R Foundation for Statistical Computing) to perform all the analyses, with ‘dlm’ package to fit DLNM model and ‘metafor’ to perform the meta-analysis. For all statistical tests, \( P < 0.05 \) (two-tailed) was considered statistically significant.

### 3. Results

#### 3.1. Descriptive statistics
Table 1 displays the descriptive summary of the daily mean temperature and YLL in cities between 2013 and 2016. The daily mean temperature ranged from 8.14\(^\circ\)C to 21.86 \(^\circ\)C in the seven regions. For daily mean YLL, the maximum value appeared in north region (13819.51 years), while the minimum value appeared in northwest region (390.54 years). The overall daily mean temperature and YLL was 15.50 \(^\circ\)C and 1055.38 years, respectively.

SD, Min and Max represent the standard deviation, minimum and maximum value of daily mean temperature range, respectively. City count represents the number of study sites in each region.

#### 3.2. The temperature-YLL associations
Figure 2 shows the city-specific and pooled cumulative temperature-YLL associations across regions and nationwide. These curves are approximately ‘U’ or ‘J’ shaped, with significantly elevated risk for extreme temperature. Figure S2 illustrates that the YLL risk of extreme cold temperature appeared to be significant and strongest on lag 3 d, then gradually reduced to null. As a contrast, the risk of extreme hot temperature appeared instantly on the current day, then decreased sharply to estimate below 0. Table 2 shows the MYT and estimates of YLL associated with non-optimum temperatures. The MYT percentile varied by regions between 2.90th and 72.10th percentile, with the temperature ranging from \(-8.80\) \(^\circ\)C (northwest) to 24.10 \(^\circ\)C (south). Among them, the MYTs in the northern regions were significantly lower than that in the central and southern regions. The national MYT was 22.20 \(^\circ\)C, corresponding to the 74.90th percentile of temperature distribution. Extreme low temperature showed a strong effect in south and southwest region, with an estimate of 273.28 (95% CI: 2309.63, 274.96 (95% CI: 134.45, 415.47), respectively. While extreme high temperature had a significant effect in east region (150.37, 95% CI: 276.66, 338.10, 2301.92, respectively). We used R software (version 3.3.2, R Foundation for Statistical Computing) to perform all the analyses, with ‘dlm’ package to fit DLNM model and ‘metafor’ to perform the meta-analysis. For all statistical tests, \( P < 0.05 \) (two-tailed) was considered statistically significant.

#### 3.3. AF for YLLs
Table 3 presents the estimated AFs of YLL due to hot, cold and overall non-optimum temperatures in each region and nationwide. Overall, the total fraction of YLL due to overall non-optimum temperature exposures was 6.90% (95% CI: 4.62%, 9.18%), in...
Figure 2. Overall cumulative temperature-YLL associations from first-stage estimates by regions. Gray dotted curves represent city-specific temperature-YLL associations. Red curves represent the pooled temperature-YLL associations with 95% CIs (light blue). All curves referred to the minimum YLL temperature of pooled estimates.

which the contribution of cold temperature (6.05%, 95% CI: 4.03%, 8.08%) was significantly higher than that of hot temperature (0.85%, 95% CI: 0.60%, 1.10%).

We observed regional heterogeneity across the seven regions. In most of the regions, the fraction caused by cold was remarkably higher than that of hot, with the highest estimate in northeast (6.72%, 95% CI: 4.72%, 8.72%).
Table 2. Estimates of daily YLL associated with non-optimum temperatures by regions.

| Region   | Percentile | MYT   | Extreme low (95% CI) | Extreme high (95% CI) |
|----------|------------|-------|----------------------|-----------------------|
| North    | 67.30      | 19.80 | 32.04 (−99.59, 163.68) | 34.80 (−40.51, 110.11) |
| Northeast| 16.40      | −7.30 | 134.62 (33.69, 235.53) | 124.59 (30.63, 218.52) |
| Northwest| 2.90       | −8.80 | 0.39 (−3.36, 4.14)    | 113.41 (10.01, 216.81) |
| East     | 72.10      | 23.60 | 138.13 (49.72, 248.54) | 108.54 (35.14, 181.93) |
| Central  | 57.80      | 20.50 | 168.65 (−0.37, 337.67) | 110.56 (49.64, 171.49) |
| South    | 51.90      | 24.10 | 273.28 (49.72, 496.84) | 65.38 (−18.30, 149.06) |
| Southwest| 66.70      | 20    | 157.89 (103.46, 212.31)| 112.40 (82.87, 141.93) |

*The estimated value is statistically significant. Percentile represents minimum YLL centile of temperature distributions. MYT represents minimum YLL temperature of pooled associations.

Table 3. The estimated fractions of YLLs attributable to hot, cold and non-optimum temperature across the seven regions.

| Region   | Total YLLs | AF (%, 95% CI) | Hot          | Cold         | Non-optimum  |
|----------|------------|----------------|--------------|--------------|--------------|
| North    | 13 551 596 | 0.37 (−0.10, 0.85) | 5.96 (−1.56, 13.47) | 6.33 (−1.67, 14.32) |
| Northeast| 22 775 504 | 0.57 (0.14, 1.00)* | 6.72 (1.90, 11.53) | 7.29 (2.04, 12.53)* |
| Northwest| 7392 124  | 9.09 (−5.54, 23.73) | 0.00 (−0.01, 0.02) | 9.09 (−5.55, 23.73) |
| East     | 48 432 308 | 4.25 (2.18, 6.31)* | 1.12 (0.37, 1.87) | 7.29 (2.04, 12.53)* |
| Central  | 24 359 786 | 1.59 (−0.37, 3.54) | 3.92 (−0.39, 8.24) | 5.51 (−0.76, 11.78) |
| South    | 11 132 402 | 0.92 (−0.23, 2.08) | 5.09 (−1.09, 11.27) | 6.01 (−1.33, 13.35) |
| Southwest| 14 067 601 | 3.00 (−2.63, 8.62) | 5.89 (3.16, 8.61)  | 8.88 (0.53, 17.24)* |
| Nationwide| 129 779 235 | 0.85 (0.60, 1.10)* | 6.05 (4.03, 8.08)* | 6.90 (4.62, 9.18)* |

*The estimated value is statistically significant.

Table 4. The life expectancy loss attributable to hot, cold and non-optimum temperature across the seven regions.

| Region   | Total deaths | Hot         | Cold         | Non-optimum  |
|----------|--------------|-------------|--------------|--------------|
| North    | 951 402      | 0.05 (−0.01, 0.12) | 0.85 (−0.22, 1.92) | 0.90 (−0.24, 2.04) |
| Northeast| 1458 015     | 0.09 (0.02, 0.16)* | 1.05 (0.30, 1.80)* | 1.14 (0.32, 1.96)* |
| Northwest| 436 030      | 1.54 (−0.94, 4.02) | 0.00 (−0.00, 0.00) | 1.54 (−0.94, 4.03) |
| East     | 3496 905     | 0.59 (0.30, 0.87)* | 0.15 (0.05, 0.26)* | 0.74 (0.35, 1.13)* |
| Central  | 1590 342     | 0.24 (−0.06, 0.54) | 0.60 (−0.06, 1.26) | 0.84 (−0.12, 1.80) |
| South    | 700 348      | 0.15 (−0.04, 0.33) | 0.81 (−0.17, 1.79) | 0.96 (−0.21, 2.12) |
| Southwest| 893 860      | 0.47 (−0.42, 1.36) | 0.93 (0.50, 1.36)  | 1.41 (0.08, 2.73)* |
| Nationwide| 8785 528     | 0.13 (0.09, 0.16)* | 0.89 (0.59, 1.19)  | 1.02 (0.68, 1.36)* |

*The estimated value is statistically significant.

95% CI: 1.90%, 11.53%), while in northwest and east regions, the fraction attributable to hot was responsible for most of the burden, with the highest fraction in northwest (9.09%, 95% CI: −5.54%, 23.73%).

3.4. Attributable life expectancy loss per death
The estimated attributable life expectancy loss per death caused by hot, cold and total temperatures were shown in table 4. The national pooled life expectancy loss per death attributable to non-optimum temperature was 1.02 years (95% CI: 0.68, 1.36), with a significantly higher cold contribution (0.89, 95% CI: 0.59, 1.19) than that of hot (0.13, 95% CI: 0.09, 0.16). The life expectancy loss attributable to cold temperature was higher than that of hot temperature in most of the regions, with the highest estimation in southwest (0.93, 95% CI: 0.50, 1.36), while the attributable life expectancy loss caused by hot temperature accounted much in northwest and east region, with the highest estimation in northwest (1.54, 95% CI: −0.94, 4.02).

There was no statistical significance in the effect value for non-optimum temperature in north, northwest, central, and south region.

3.5. The results of multivariate meta-regression analyses
Results from our multivariate meta-regression suggest that all the single predictors would significantly modify the YLLs burden attributable to non-optimum temperatures, with urbanization rate...
accounting for a much higher proportion (75.90%) of heterogeneity than do longitude (75.80%) or temperature range (74.40%). The residual heterogeneity decreased after all the single factors included as meta-predictors, with an $I^2$ of 70.50% (table S3).

3.6. Results of sensitivity analyzes

A plot of residuals (figure S3–left) shows a band of points with no particular pattern evenly distributed over time, suggesting long-term patterns have been adequately controlled for. PACF plot of the deviance residual (figure S3–right) displays that there was no remaining autocorrelation in the deviance residuals. Model estimates changed little after the inclusion of moving average of air pollution (figure S4), the alternations of df (figure S5) and the maximum lags (figure S6), which illustrates a proper parameter setting.

4. Discussion

We conducted this nationwide study to assess the association between ambient temperature and YLL due to all-cause mortality, and to estimate the attributable YLL and life expectancy loss per deceased person associated with non-optimum temperature exposures in China. We used YLL as an outcome to reflect the weight of death at different ages and therefore conveyed a more accurate estimation and informative meaning in the impact of premature death caused by adverse weather conditions (Steenland and Armstrong 2006, Zhang et al 2018).

The ‘U’ or ‘J’ shaped temperature-YLL associations in the seven regions and nationwide indicated that both low and high temperatures may contribute to the increased YLLs, which was consistent with previous studies (Huang et al 2012b, Zhang et al 2018). The physiological mechanism of death related to adverse temperature is not fully clear, and is considered to be different in regards to different causes of death. In general, high temperature has a great influence on the circulatory system, which could lead to the death of cardiovascular and cerebrovascular diseases by increasing cardiac output, blood viscosity and coagulation, weakening vasoconstriction and cerebral perfusion pressure (Wang et al 2017). Cold weather could trigger a range of involuntary responses, including skeletal muscle tremors, peripheral vascular contractions, sympathetic excitation, and increased blood pressure and heart rate, thus leading to coronary ischemia and even myocardial infarction (Egondi et al 2015). The effects of cold temperature on the respiratory system may be related to inflammatory pathways or pathophysiological responses, such as constriction of blood vessels in the respiratory mucosa and suppression of immune responses (Huang and Barnett 2014). The health effects of cold temperature may be more complicated in the actual situation (Ebi and Mills 2013, Huang and Barnett 2014, Kinney et al 2015): the direct effects of cold weather, the incidence rate of heart and lung diseases in winter, the incidence of infectious diseases, the poor heating facilities and the lack of medical facilities may lead to increased seasonal deaths. Researches on seasonal, multiple diseases and various socio-economic factors are warranted in future studies.

The observed lag patterns of temperature extremes on YLL were in line with previous studies (Yang et al 2015, Liu et al 2019): the effects of extreme low temperature appeared on lag 3 d and lasted for 6 or 7 d, whereas the effects of extreme high temperature appeared instantly and persisted only 2 or 3 d, followed by mortality displacement on the subsequent days (Chen et al 2018). This finding has some important implications for public health response. For example, in hot weather, the medical service department should arrange plenty ambulance resources and hospitalization facilities in advance, while in cold weather, the service time should be extended.

We observed varying optimum temperatures across different regions, with distinctive low temperature (ranging from −8.80 °C to 19.80 °C) in northern region and high temperature (ranging from 20 °C to 24.10 °C) in southern region, which was consistent with the study of Luan et al (2018), which found the regional minimum mortality temperature increased with the reduced latitude, indicating the government should make health policies and conduct interventions based on local conditions, considering adaptation and vulnerability of local residents to climate (Guo et al 2014, Luan et al 2018).

The main results of our study were the estimated attributable burden of YLL. We found few studies on temperature-related mortality burden of YLL in China, with quite different estimates between cities and for different causes of death (Luan et al 2017, 2019, Xu et al 2019). For example, one study in a northern Chinese city showed a fraction of 10.88% (95% CI: −0.38%, 20.09%) and 1.23% (95% CI: 0.26%, 2.08%) on YLL of total death could be attributed to cold and heat effect, respectively (Xu et al 2019). Another study in 31 Chinese provincial capitals suggested a range of AFs to cold effect between 8.19% (95% CI: −8.52%, 19.38%) and 28.98% (95% CI: −64.78%, 67.59%), while the fractions to hot effect varied from 0.02% (95% CI: −0.13%, 0.05%) to 5.73% (95% CI: 0.31%, 10.22%) (Luan et al 2018). Compared with our study, these studies were only conducted at the city level or confined to a specific disease, which limited the generalization of the findings across the nation. In this study, we found that non-optimum temperature could contribute an overall fraction of 6.90% (95% CI: 4.62%, 9.18%) in total YLL in China, with a remarkably higher contribution from cold effect (6.05%, 95% CI: 4.03%, 8.08%) than hot effect (0.85%, 95% CI: 0.60%, 1.10%), indicating similar predominant contributions of cold effect with
previous studies using mortality as outcome indicator (Chen et al 2018). We further assessed the life expectancy loss per deceased person in regards to hot, cold and total temperatures. We believe that this indicator is more of public health significance and policy guidance, which is embodied in two aspects: first, its calculation combines the concepts of YLL with the corresponding attributable numbers, thereby could provide important policy implications on the potential benefits after an intervention (Steenland and Armstrong 2006). Second, by taking the total number of deaths into account, it provides a novel and intuitive perspective to reflect the health effects of climate change.

Our findings suggested that non-optimum temperature may cause a national-averaged 1.02 years (95% CI: 0.68, 1.36) of life loss per person, with 0.89 years (95% CI: 0.59, 1.19) due to low temperature and 0.13 years (95% CI: 0.09, 0.16) by high temperature. Although the number was small, we should not ignore the public health significance behind the small numbers: with the increase of China’s aging population, even if the risk changes slightly, it may cause a large economic burden on public health resources, and the age, gender and regional characteristics of disease burden should be considered into the future healthcare expenditure plan (Watts et al 2015, Zhao et al 2020). Just as what the 2015 Lancet Commission advocated on dealing with global climate change, our study provided ‘accurate quantification of the avoided burden of disease’ (Watts et al 2015), which may be of guiding significance to better understand the regional differentiation rule of risks due to climate change, so as to achieve targeted policy formulation and intervention implementation.

This study had several major strengths. First of all, our dataset came from CDRS, which have good internal consistency, and through strict inclusion and exclusion criteria, diagnosis plot and sensitivity analysis, the authenticity and reliability of the results could be guaranteed. Second, this study provided a comprehensive analysis of the relationship between temperature and YLL at different regional and national levels in China, the findings could lay a foundation for further understanding of the regional differentiation law of temperature-mortality risks. Third, different from some studies calculating the total regional burden by directly adding the city-specific effect value (Gasparrini et al 2015, Chen et al 2018), here we used multivariate meta-analysis to derive the regional estimate, which could avoid the case that when the effect value of a city has a wide CI, the overall effect of this region would become null. Fourth, this study may provide new ideas regarding the attributable burden and intervention strategy to cope with climate change in China.

Some limitations should be noted: First, as an ecological study, we cannot eliminate the ecological fallacy caused by the unmeasurable individual-level variables. Second, the temperature data were from fixed monitoring stations rather than real exposure of individuals, thus may result in exposure misclassification. Third, due to the unavailability of life table related to the characteristics of vulnerable groups (e.g. the elderly, infirm, and socially isolated), we cannot make a more accurate assessment of YLL for vulnerable groups. Fourth, some individual-level confounders (e.g. low-income, living alone, living without air conditioning) were not available due to the limitation of the data, which may provide important information for exploring the causes of regional risk variation and identifying vulnerable populations. Fifth, since we can only obtain YLLs data of the dead, only the average life expectancy loss of the dead could be calculated, which cannot reflect the average life expectancy loss of the total population. This nationwide study reveals that non-optimum temperature exposure may lead to increased YLL and lower life expectancy, in which low temperatures contribute a significantly higher burden than that of high temperatures.

Data availability statement

The data generated and/or analyzed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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Author’s contributions

H L and M Z was responsible for design of the study. S A contributed to the data analysis and draft writing, J Q contributed to the interpretation of findings. J L, L W and P Y contributed to data curation and project administration. R L and C W contributed to the revision of the article.

Conflict of interest

The authors declare that they have no competing interests.

Ethics approval and consent to participate

Not applicable
Consent for publication

Not applicable

Availability of data and materials

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ORCID iDs

Siqi Ai  https://orcid.org/0000-0002-2268-463X
Hualiang Lin  https://orcid.org/0000-0002-3643-9408

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