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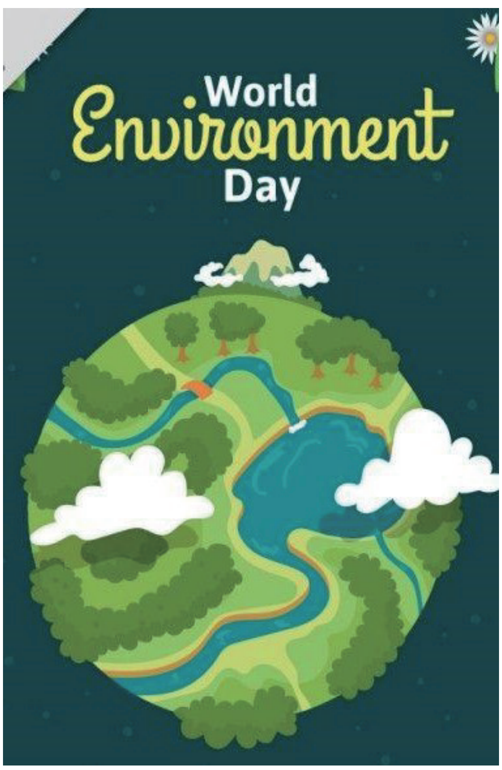

WORLD ENVIRONMENT DAY ISSUE

Foreword

Preplanned Studies

ISSN 2096-7071

This week's issue was organized by Guest Editor Haidong Kan.

Foreword

Climate Change, Weather Conditions, and Population Health

There is near unanimous consensus that the global climate is warming and most of the warming is attributable to human activities. The world economic expansion has largely been driven by fossil fuels, leading to increasing emissions of greenhouse gases (GHGs). The world's average temperature has risen at a rate of 0.07 ℃ per decade since 1880 and nearly triple that rate since the 1990s. In addition to heat waves and cold spell, climate change may lead to a wide range of extreme weather conditions, including drought, floods, typhoons, windstorms, and landslides. Exposure to non-optimal temperatures and extreme weather conditions has been associated with a range of adverse health outcomes, including excess mortality and morbidity from various causes, and changes in the ecology of infectious diseases. For example, in China, 14.3% of non-accidental mortality during 2013–2015 may be related to non-optimal temperatures, with 11.6% and 2.7% explainable by exposure to cold and heat, respectively (*1*). The recent global burden of diseases study (GBD 2019) shows that non-optimal temperatures are among the ten leading causes of death worldwide (*2*). A projection study showed that under high-emission scenarios, the negative health impacts of climate change would disproportionately affect warmer and poorer regions of the world (*3*). Climate change can also affect climate-sensitive infectious diseases carried by animal hosts or vectors, including malaria, dengue fever, schistosomiasis, Japanese encephalitis, and *Angiostrongylus cantonensis*.

In this special issue, we invited colleagues from Sun Yat-Sen University, China CDC, Peking University, and Shanghai Meteorology Bureau to report their latest findings on climate change, weather conditions, and population health. Qi and coworkers examined the associations between ambient temperature and years of life lost from stroke in 93 Chinese cities (*4*). Zhang et al. assessed the regional distribution of health vulnerability to extreme heat in China (*5*). Using a modelling approach, Huang et al. estimated the $PM_{2.5}$-related health impacts from climate change and air pollution emission control in China (*6*). Finally, Ye et al. evaluated the impact of a health forecasting service on outpatient visits for chronic obstructive pulmonary disease patients in Shanghai (*7*).

In short, the findings from this special issue further confirmed that climate change and extreme weather conditions have posed substantial health risks for population health in China as well as other parts of the world. Future research will need to improve characterization of climate-health relationships, to develop effective and adaptive strategies to help reduce the health risks of climate change, and to promote healthy lifestyles in line with the reduction of greenhouse gas emissions. Finally, GHG emissions need to be controlled. China aims to reach carbon emissions peak before 2030 and achieve carbon neutrality before 2060. Consideration of the health impact of climate change and extreme weather conditions can help decision-makers with appropriate urgency.

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Preplanned Studies

Association Between Ambient Temperature and Years of Life Lost from Stroke — 30 PLADs, China, 2013–2016

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Summary

What is already known about this topic?

Previous studies have mainly focused on the relationship between temperature and mortality from stroke, but analysis on the effects on years of life lost (YLL) is limited.

What is added by this report?

YLLs were used as the health outcome, and cold and hot weather were found to be significantly associated with an increase in YLLs from stroke and for different groups, with a stronger effect found to be associated with low temperature.

What are the implications for public health practice?

These findings could help identify vulnerable regions and populations that have a more serious temperature-related burden and to guide the practical and effective measures for stroke control from a YLL perspective.

Although numerous studies suggested non-optimal temperatures may lead to increased stroke mortality, the evidence concerning the effect of ambient temperature on years of life lost (YLLs) due to stroke is still scarce (*1*). Data on daily mortality, years of life lost, meteorological factors, and air pollution from 93 cities within 30 provincial-level administrative divisions (PLADs) between 2013 and 2016 was collected. We applied a two-stage analytic strategy to assess the association between temperature and YLLs. We used a distributed lag non-linear model (DLNM) with a Gaussian link to evaluate the city-specific association between ambient temperature and YLLs from stroke, and then we applied a multivariate meta-analysis to obtain the pooled effects at regional and national levels. Inverse "J" shaped associations between temperature and YLLs from stroke were found. At the national level, we observed 19.77 (95% CI: 11.16, 28.40), 15.34 (95% CI: 7.77, 22.91), 5.47 (95% CI: 2.57, 8.37), and 2.99 (95% CI: 0.49, 5.49) of YLLs were associated with the effects of extreme cold, mild cold, extreme heat, and mild heat relative to the optimum temperature, respectively. In addition, 10.91% (95% CI: 5.67%, 16.15%) of YLLs could be attributed to non-optimum temperatures, and for each deceased person, a national-averaged 1.39 YLLs (95% CI: 0.72, 2.06) were caused by non-optimum temperature. This study suggested both cold and hot weather would lead to significant life lost for stroke patients and regional adaptation policies and interventions should be considered.

We initially obtained the mortality and YLL data for 100 representative cities from the China Cause of Death Reporting System (CDRS) between January 1, 2013 and December 31, 2016. After checking the daily mortality and YLLs distribution in each city, we finally selected 93 cities as our study sites. Based on the climate types and administrative regions (*2*), the study sites were divided into seven regions (Supplementary Figure S1 available in http://weekly.chinacdc.cn/): north, northeast, northwest, east, central, south, and southwest. And according to initial diagnosis coded by 10th International Classification of Diseases (ICD-10), stroke was extracted from the system (I60-I64).

We obtained daily mean temperature (°C) and relative humidity (%) of the selected cities from China Meteorological Data Sharing Service System (http://data.cma.cn/). Also, daily concentrations of fine particulate matter with an aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) was collected from the National Real-time Publishing Platform for Air Quality (http://106.37.208.233:20035).

We conducted a two-stage analysis to assess the associations between ambient temperature and YLL of stroke. At the first stage, we estimated city-specific temperature-YLL associations. Since the daily YLL obeys a normal distribution (*3*), we used a DLNM with a Gaussian link to evaluate the nonlinear and delayed effects of ambient temperature on YLLs due to stroke. To capture the nonlinear relationship between temperature and YLLs, we fitted the exposure-response relationship through a natural cubic B-spline function with three placed knots at 10th, 75th, and 90th percentiles of city-specific temperature distribution. A B-spline with three knots at equally-spaced log scales was applied for the space of lags, with a maximum set of 21 days in according with previous studies (*4*). Some confounding factors, including relative humidity, $PM_{2.5}$, day of the week, public holidays, and long-term trend and seasonality were also controlled in the model. At the second stage, we obtained the regional and national effects within 21 lags between temperature and YLLs by using the best linear unbiased prediction (BLUP) approach. The minimum YLL temperature (MYLLT) corresponds to the minimum risk of YLL across the temperature range, based on the overall temperature-risk curve. On this basis, we further calculated the effects of extreme cold, mild cold, extreme heat, and mild heat on YLL risk and the attributable YLL fraction and attributable life expectancy loss per death. The detailed methods concerning the attributable burden analyses and sensitivity analyses were provided in the Supplementary Material (available in weekly.chinacdc.cn). We used R (Version 3.3.2, R Foundation for Statistical Computing, Vienna, Austria) to conduct all the analyses, "dlnm" package was used to fit DLNM model, and "mvmeta" package was used to conduct meta-analysis. *P*<0.05 (two-tailed) was considered statistically significant.

A total of 1,317,503 deaths due to stroke with 16,793,014 years of life lost were recorded in the 93 cities from January 1, 2013 to December 31, 2016. In Table 1, we observed that the daily death and YLL from stroke varied across study regions, with highest daily deaths and YLL in the northeast. The lowest daily stroke death counts and YLLs were found in the northwest, corresponding to 7 deaths and 97.7 years, respectively. In addition, the daily average temperature

TABLE 1. Summary statistics for daily deaths, years of life lost from stroke and ambient temperature in in seven regions of China, 2013–2016.

Variables	Northwest	North	Northeast	East	Central	Southwest	South	Nationwide
Daily YLL of stroke								
Mean	97.7	158	218	153	145	172	114	155
SD	111	122	160	128	117	230	75	143
Minimum	2.9	2.9	2.4	2.9	2.4	2.4	2.9	2.4
25th percentile	22.4	62.9	108	58.6	71.5	46.8	55	59.1
Median	50.9	119	168	213	121	92.1	102	116
75th percentile	129	230	277	121	184	150	160	202
Maximum	697	736	1,070	1,180	1,530	1,490	540	1,530
Daily mortality of stroke								
Mean	7	14	15	14	12	13.6	9	12
SD	8	11	11	11	9	18.9	6	11
Minimum	1	1	1	1	1	1	1	1
25th percentile	2	5	8	5	6	4	4	5
Median	4	10	12	10	10	7	8	9
75th percentile	9	19	19	19	14	11	13	16
Maximum	91	95	70	95	112	136	37	136
Daily temperature (°C)								
Mean	11.5	12.4	8.6	16.2	17.3	16.9	22.0	15.0
SD	10.7	11.2	13.2	9.4	8.8	7.2	6.6	10.6
Minimum	−22.4	−23.9	−26.4	−20.4	−9.5	−8.1	1.7	−26.4
25th percentile	2.9	2.3	2.5	8.4	9.8	11.7	16.8	7.6
Median	12.7	14	10.4	17.5	18.4	17.5	23.8	16.8
75th percentile	20.3	22.3	20.6	24.0	24.6	22.2	27.5	23.5
Maximum	35.1	33.4	30.8	36.5	35.8	36.2	33.5	36.5

Abbreviations: YLL=years of life lost; SD=standard deviation.

ranged from 8.6 °C in the northeast to 22.0 °C in the south.

We observed the optimum temperature that caused the lowest YLL risk ranged from 16.7 °C in central region to 28.7 °C in the south region in Table 2. In general, the estimated effects of cold weather were stronger than that of high temperature. Specifically, extremely cold weather was significantly associated with YLLs due to stroke, with the strongest magnitude of effects in the northeast, corresponding to 53.73 (95% CI: 8.91, 98.55) years of life lost relative to the reference temperature.

Figure 1 show the BLUP on exposure-response curves of the cumulative effects of temperature on YLLs from stroke at the national level in China, 2013–2016. We observed an inverse "J" shaped association, with increasing YLLs for moving up and down from the minimum YLL temperature. Furthermore, we found consistent curves stratified by sex, regions, and subtypes of stroke (Supplementary Figures S2–S4 available in http://weekly.chinacdc.cn/), particularly in the terms of the general shape.

In attribution burden analysis (Supplementary Table S1 available in http://weekly.chinacdc.cn/), we observed that at the national level, the total fraction of YLLs by non-optimum temperature was 10.91% (95% CI: 5.67, 16.15), in which cold temperature (10.84%, 95% CI: 5.69, 15.99) accounted for a significantly higher contribution. The national-pooled life expectancy loss per death due to non-optimum temperature was 1.39 years (95% CI: 0.72, 2.06), with a significantly higher contribution of cold weather (1.38, 95% CI: 0.72, 2.04) than that of hot weather (0.01, 95% CI: −0.00, 0.02). The life expectancy loss caused by cold temperature was higher than that of hot temperature in all the regions, and the highest estimate occurred in the north region (2.19, 95% CI: 0.31, 4.07).

DISCUSSION

Our present study explored the associations between ambient temperature and daily YLL due to stroke in 93 Chinese cities. We found cold and hot weather were significantly associated with an increase in years of life lost from stroke and for different groups, with stronger effects in low temperature. The present study could provide ample evidence to planning and policy-making in stroke control and climate governance.

A large body of epidemiological studies have documented the link between temperature and mortality due to stroke and its subtypes, however the relevant research about association of temperature with YLL from stroke within China was still scarce. Previous studies have provided similar findings, applying the YLL as the outcome measurement. Luan et al. reported

TABLE 2. Estimated cumulative effects ($lag_{0\text{-}21}$) on YLL under different patterns of temperature relative to the YLL at the reference temperature.

Variables	Overall YLL	OT (°C)	Extreme cold * (years, 95% CI)	Mild cold * (years, 95% CI)	Mild heat * (years, 95% CI)	Extreme heat * (years, 95% CI)
Overall region	16,793,014.0	25.6	19.77 (11.16, 28.40)	15.34 (7.77, 22.91)	2.99 (0.49, 5.49)	5.47 (2.57, 8.37)
Northeast	3,562,080.8	23.2	53.73 (8.91, 98.55)	30.15 (−5.48, 65.77)	23.96 (4.88, 43.04)	21.16 (0.45, 41.88)
Northwest	979,861.7	17.0	12.51 (−22.04, 47.05)	14.57 (−18.83, 47.97)	1.13 (−17.55, 19.80)	10.53 (−5.84, 26.90)
North	1,573,462.6	24.9	41.67 (3.70, 79.64)	46.61 (7.83, 85.39)	11.95 (−4.68, 28.)	11.39 (−0.07, 22.85)
Central	2,380,406.4	16.7	22.28 (−16.52, 61.07)	15.58 (−17.04, 48.20)	0.01 (−0.56, 0.59)	17.09 (−2.79, 36.97)
East	5,413,438.8	25.2	21.80 (8.38, 35.23)	7.38 (−5.65, 20.41)	1.69 (−3.35, 6.72)	18.90 (9.89, 27.90)
Southwest	1,786,702.7	27.7	54.18 (9.90, 29.19)	16.54 (7.86, 25.21)	3.34 (0.01, 6.68)	4.41 (2.31, 6.51)
South	1,097,060.8	28.7	84.98 (22.29, 147.68)	32.24 (−1.88, 66.37)	3.99 (−11.59, 19.57)	2.24 (−8.18, 12.66)
Subtype						
Hemorrhagic stroke	9,852,444.0	28.2	11.62 (4.51, 18.73)	10.53 (4.08, 16.97)	3.13 (0.13, 6.12)	0.36 (−0.60, 1.32)
Ischemic stroke	6,028,666.0	22.4	7.55 (3.50, 11.60)	4.63 (1.18, 8.08)	0.03 (−0.20, 0.25)	6.33 (3.64, 9.01)
Sex						
Male	10,033,788.0	26.0	13.05 (6.87, 19.24)	10.57 (5.32, 15.81)	2.09 (−0.02, 4.21)	2.43 (0.71, 4.17)
Female	6,759,226.0	25.1	5.53 (0.92, 10.15)	4.19 (0.04, 8.34)	0.84 (−0.53, 2.21)	2.45 (0.76, 4.13)

Abbreviations: YLL=years of life lost; OT=optimum temperature. The reference temperature was set at the temperature with lowest YLL.

* Extreme cold, mild cold, extreme hot, and mild hot temperature were defined as 2.5th, 25th, 97.5th and 75th percentile of temperature distribution, respectively, compared with the reference temperature (minimum YLL temperature).

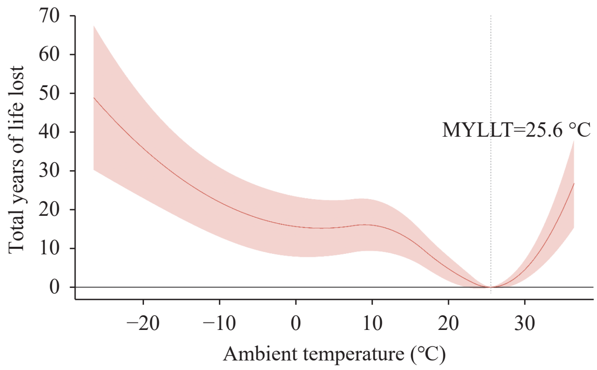

FIGURE 1. Exposure-response curve of the cumulative effects of temperature on years of life lost from stroke at the national level in China (93 cities), 2013–2016.
Abbreviation: MYLLT=The minimum years of life lost temperature.

that both cold and hot temperature were significantly associated with increasing YLL of cardiovascular diseases in which the effects of low temperature took such a large share (*5*). A recent study conducted in three largest English cities found that there was an increased risk in YLL with the increment and decline of the temperature from the thresholds (*6*).

The non-linear relationships between temperature and YLLs from stroke that emphasized the adverse health effects of both low and high temperatures were found in present study. Furthermore, there was biologically plausible evidence for these associations. The effects induced by cold temperature were in association to increasing the level of inflammatory response, and oxidative stress in brain and variation of the blood pressure and autonomic nervous system (*7–8*). In addition, high outdoor temperature was associated with increasing cardiac output and heart rates, dehydration, hypotension, and vasodilatation, which would lead to microvascular thrombosis in brain and elevate the mortality of stroke (*9*). In addition, compared with the heat exposure, the effects from low temperatures on stroke tended to be stronger, which might be explained by the variation in autonomic nervous system and thermogenesis, and fluctuation in blood pressure in cold days (*7*).

We also found that the temperature-related effects could variy across geographical regions. For example, in south region, where the mean temperatures reached 8.4 °C or below (2.5th percentile of the temperature distribution in south region), we observed the strongest YLL (84.98, 95% CI: 22.29, 147.68) for extreme cold temperature, while in northwest region the corresponding number declined to be nonsignificant (12.51, 95% CI: –22.04, 47.05). The observed differences in the estimated effects of temperature across regions might be explained by the discrepancy in climate condition, population susceptibility, and socioeconomic status (*10*). In addition, central heating capacity might be another important region-level characteristic to explain the observed differences across different regions.

We further assess the attributable fraction of YLLs and life expectancy loss per death relative to the reference temperature at the regional and national level. The attributable burden analysis reported that the effects of non-optimum temperature constituted 10.91% of YLLs due to stroke and 1.39 years potential gain in life expectancy per death would achieve by attaining the optimum temperature rom the national perspective. As stroke was the leading cause of death with remarkably high prevalence in China, our study would provide guiding and fundamental advice to improve existing preventive strategies for stroke and reduce the ambient temperature-related burden.

This study was subject to at least some limitations. First, we used monitoring temperature data as the real exposure for the population due to the unavailability of the individual exposure, which may cause exposure misclassification. Second, this study was an ecological study in essence without adjustment for the unmeasurable individual-level covariates. Third, due to mortality data unavailability, the included cities were mainly distributed in the east and central regions but fewer in the northwest, which could lead to a low representativeness of the data and uncertainty to draw a nationwide conclusion. Finally, the coding errors and misclassification may inevitably occur in the nationwide registry-based YLL data, though this process was under strict quality control.

In summary, this nationwide analysis elaborated non-linear associations between ambient temperature and YLLs from stroke in China, with evident adverse health effects due to both cold and hot temperatures. Reducing exposure to ambient non-optimum temperature could lead to a substantial benefit in life expectancy. Our findings could help identify the vulnerable regions and populations that bore more serious temperature-related burdens and to guide the practical and effective measures for stroke control.

Conflicts of Interest: No conflicts of interest.

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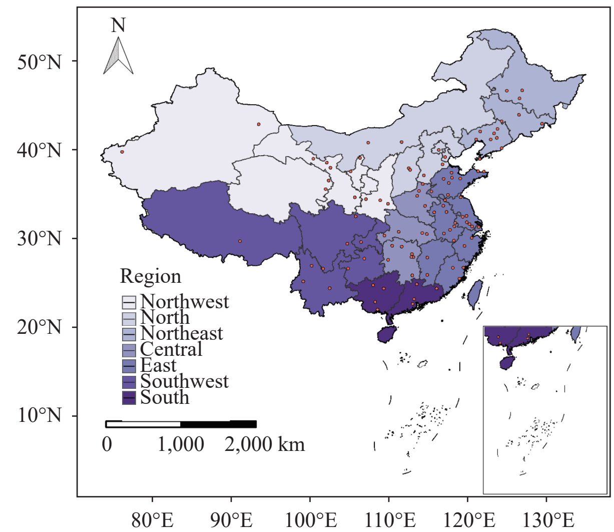
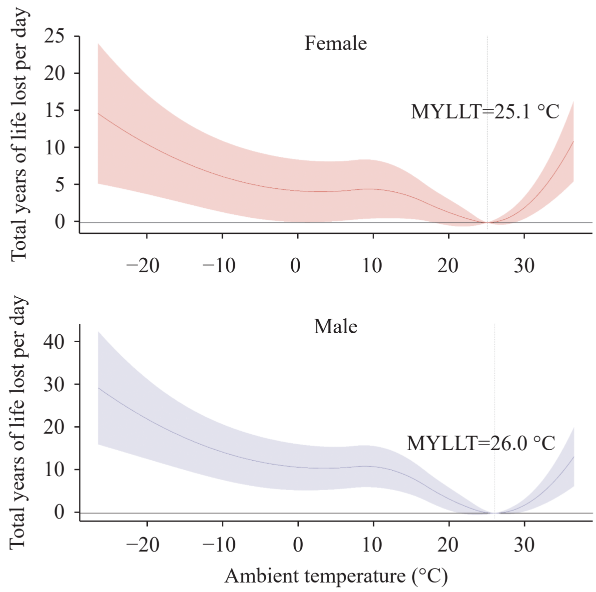
Supplemental Material

Statistical Model

We used the best linear unbiased prediction (BLUP) to pool the regional- and national- overall cumulative associations. This method allows cities with small numbers of deaths to borrow information from larger populations sharing similar characteristics, which could provide more accurate estimates (*1*). To account for the effect modifications of climatological, demographic and socioeconomic factors, we included latitude and longitude, urbanization rates, population, gross domestic product (GDP), average temperature, and temperature range of each city into the BLUP estimations. Cochran Q test and I^2 statistic was reported to represent the residual heterogeneity (Supplementary Table S2).



SUPPLEMENTARY FIGURE S1. The spatial distribution of 93 study cities from 30 provincial-level administrative divisions in China used to explore the associations between ambient temperature and years of life lost due to stroke.

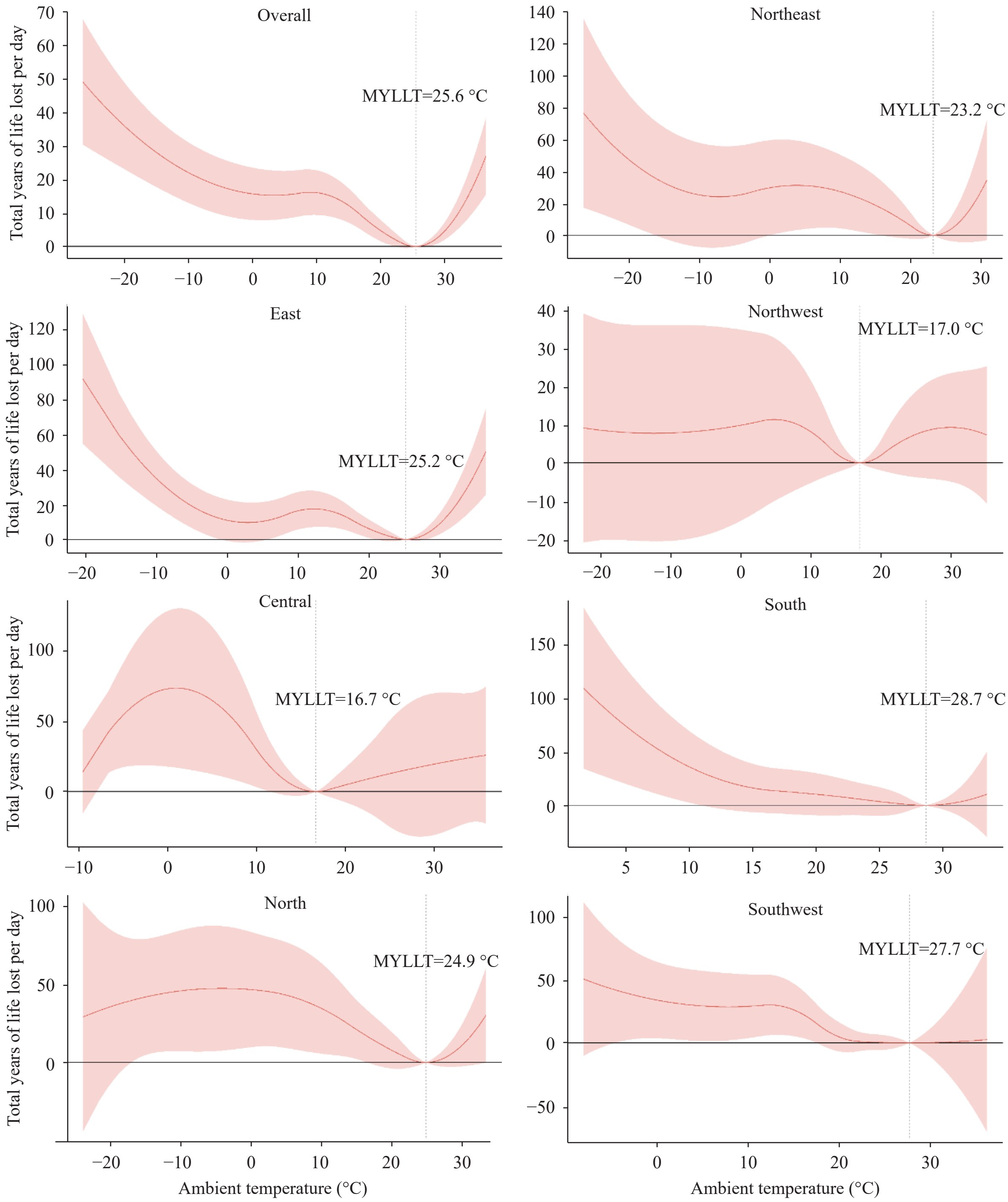


SUPPLEMENTARY FIGURE S2. The associations between ambient temperature and years of life lost due to mortality from stroke by sex in China, 2013–2016.
Abbreviation: MYLLT=The minimum years of life lost temperature.

SUPPLEMENTARY TABLE S1. The fractions of years of life lost and life expectancy loss caused by hot, cold and overall temperature across the seven regions.

Region	Attributable fraction (%, 95% CI)			Attributable life expectancy loss (years, 95% CI)		
	Hot	Cold	Non-optimum	Hot	Cold	Non-optimum
North	0.10 (−0.14, 0.35)	16.85 (2.36, 31.35)*	16.96 (2.21, 31.70)*	0.01 (−0.02, 0.05)	2.19 (0.31, 4.07)*	2.20 (0.29, 4.11)*
Northeast	0.16 (−0.16, 0.47)	8.59 (−0.70, 17.87)	8.75 (−0.85, 18.34)	0.02 (−0.02, 0.07)	1.26 (−0.10, 2.61)	1.28 (−0.12, 2.68)
Northwest	1.72 (−1.07, 4.50)	5.79 (−8.56, 20.14)	7.51 (−9.63, 24.64)	0.24 (−0.15, 0.62)	0.80 (−1.18, 2.77)	1.03 (−1.32, 3.38)
East	0.55 (0.15, 0.94)*	4.88 (0.35, 9.40)*	5.42 (0.50, 10.35)*	0.06 (0.02, 0.11)*	0.56 (0.04, 1.08)*	0.62 (0.06, 1.19)*
Central	2.40 (−8.21, 13.02)	8.30 (−2.51, 19.12)	10.71 (−10.72, 32.14)	0.31 (−1.07, 1.69)	1.08 (−0.33, 2.48)	1.39 (−1.39, 4.17)
South	0.07 (−0.37, 0.50)	8.68 (−4.60, 21.97)	8.75 (−4.97, 22.47)	0.01 (−0.05, 0.06)	1.08 (−0.57, 2.73)	1.09 (−0.62, 2.79)
Southwest	9.36×10^{-5} ($-2.89\times^{10-3}$, 3.08×10^{-3})	12.91 (1.10, 24.71)*	12.91 (1.10, 24.71)*	1.19×10^{-5} (-3.69×10^{-4}, 3.92×10^{-4})	1.64 (0.14, 3.15)*	1.64 (0.14, 3.15)*
Nationwide	0.07 (−0.02, 0.16)	10.84 (5.69, 15.99)*	10.91 (5.67, 16.15)*	1.47×10^{-2} (3.60×10^{-3}, 2.58×10^{-2})	1.38 (0.72, 2.04)*	1.39 (0.72, 2.06)*

* The estimated value is statistically significant.



SUPPLEMENTARY FIGURE S3. The associations between ambient temperature and years of life lost due to mortality from stroke by regions in China, 2013–2016.
Abbreviations: MYLLT=The minimum years of life lost temperature.

Estimating the Attributable Number and Fraction of YLLs

Based on the overall cumulative temperature-YLL curve, we divided daily mean temperature into components related to low and high temperatures separated by MYLLT. The coefficients corresponding to each unfavorable temperature were then extracted for the following analyses. The calculation formula for a specific region was shown as below:

SUPPLEMENTARY TABLE S2. I^2 statistic and Cochran Q test from different multivariate random-effects meta-regression models.

Model	Predictor	Test for predictor	Q test	I^2 (%)
Intercept-only	–	<0.00	904.79	46.90
Single predictor				
	Average temperature	<0.01	889.71	46.60
	Temperature range	<0.01	891.63	46.70
	GDP	<0.01	858.59	44.70
	Urbanization rate	<0.01	888.13	46.50
	Latitude	<0.01	892.71	46.80
	Longitude	<0.01	874.32	45.70
Full model	–	<0.01	767.27	42.00

Abbreviation: GDP=gross domestic product.

$$AY = \sum_{(i=1)}^{j} (Temp_i - MYT) \times coef_i$$
$$AF = AY / TotalYLLs$$

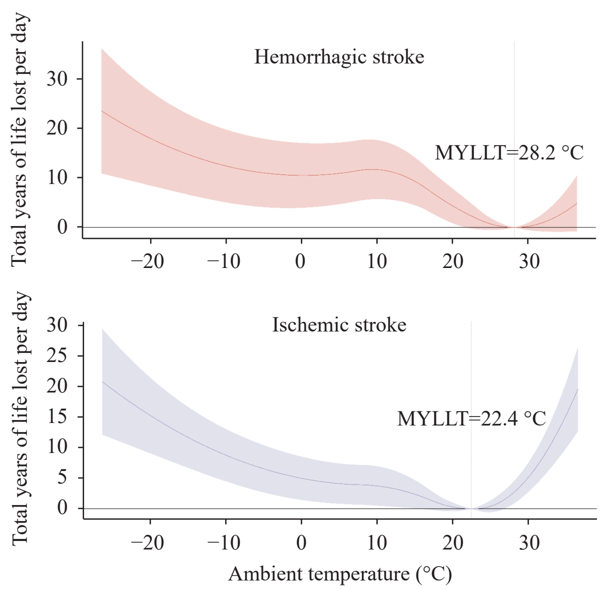
where j represents the sequence of non-optimum temperature days; $Temp_i$ refers to the value of unfavorable temperatures on day i; MYLLT represents the temperature corresponding to minimum YLL risk; $coef_i$ represents exposure-response coefficient at specific temperature; AY and AF represents the YLLs and fraction attributable to non-optimum temperatures, respectively; Total YLLs represents the sum of the daily YLLs during the study period.

Calculating the Attributable Loss of Life Expectancy

To assess how many years of life expectancy lost to each of the deceased person due to unfavorable temperatures, we further calculated the attributable life expectancy loss in a specific region, by adopting the following formula:

Attributable life loss = AY / Total deaths

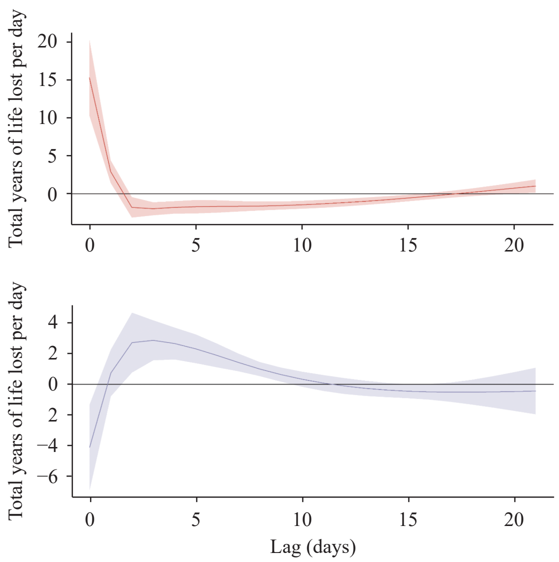
where AY represents the attributable YLLs, total deaths represent the sum of daily death count during the study period.



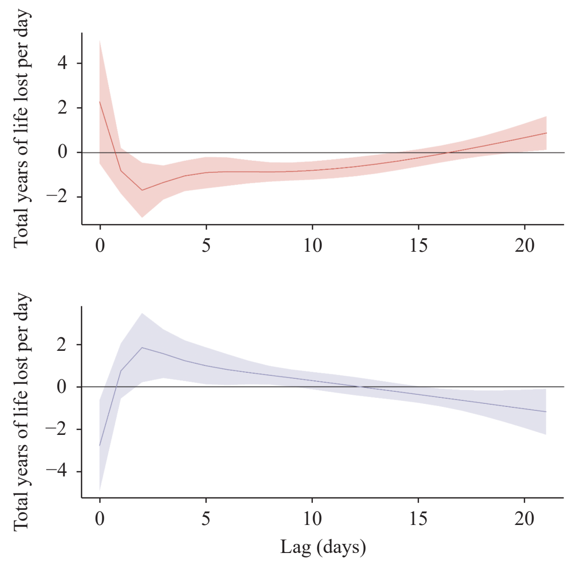
SUPPLEMENTARY FIGURE S4. The associations between ambient temperature and years of life lost due to mortality from hemorrhagic stroke and ischemic stroke in China, 2013–2016.
Abbreviation: MYLLT=The minimum years of life lost temperature.

Lag Effects of Temperature on YLLs from Stroke

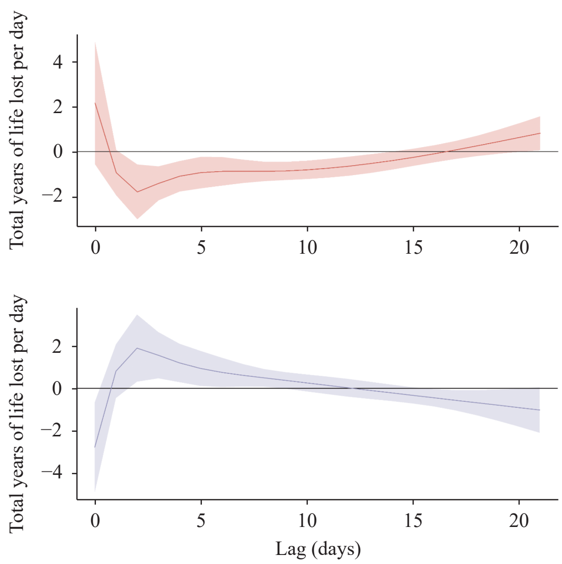
Supplementary Figure S5 depict the pooled delayed associations within 21 days between cold and heat weather and YLL due to stroke. We defined the 2.5th and 97.5th percentile of the daily average temperature to represent cold and hot days. We observed that cold weather was associated with longer-lasting effects on YLL than heat weather and the YLL risk could last for 10 days with a highest effect on lag 3 day. For hot temperatures, there was the strongest YLL risk on the current day and the effects decreased rapidly to zero until lag 2 day, which followed by an obvious mortality displacement. In addition, we observed the similar patterns for lag-response curves of the heat and cold temperature, stratified by subtypes of stroke (Supplementary Figures S6, S7).



SUPPLEMENTARY FIGURE S5. Lag-response curves of effects of extreme heat and extreme cold temperature on years of life lost due to stroke on the days of death (lag=0) and up to 21 days prior to death.
The red and blue sections represent extreme heat and extreme cold temperature, respectively.



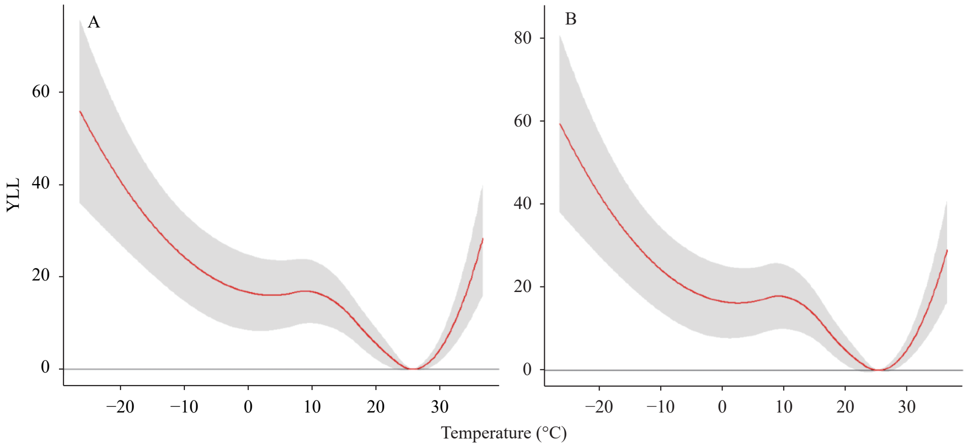
SUPPLEMENTARY FIGURE S6. Lag-response curves of effects of extreme heat and extreme cold temperature on years of life lost due to hemorrhagic stroke on the days of death (lag=0) and up to 21 days prior to death.
The red and blue sections represent extreme heat and extreme cold temperature, respectively.



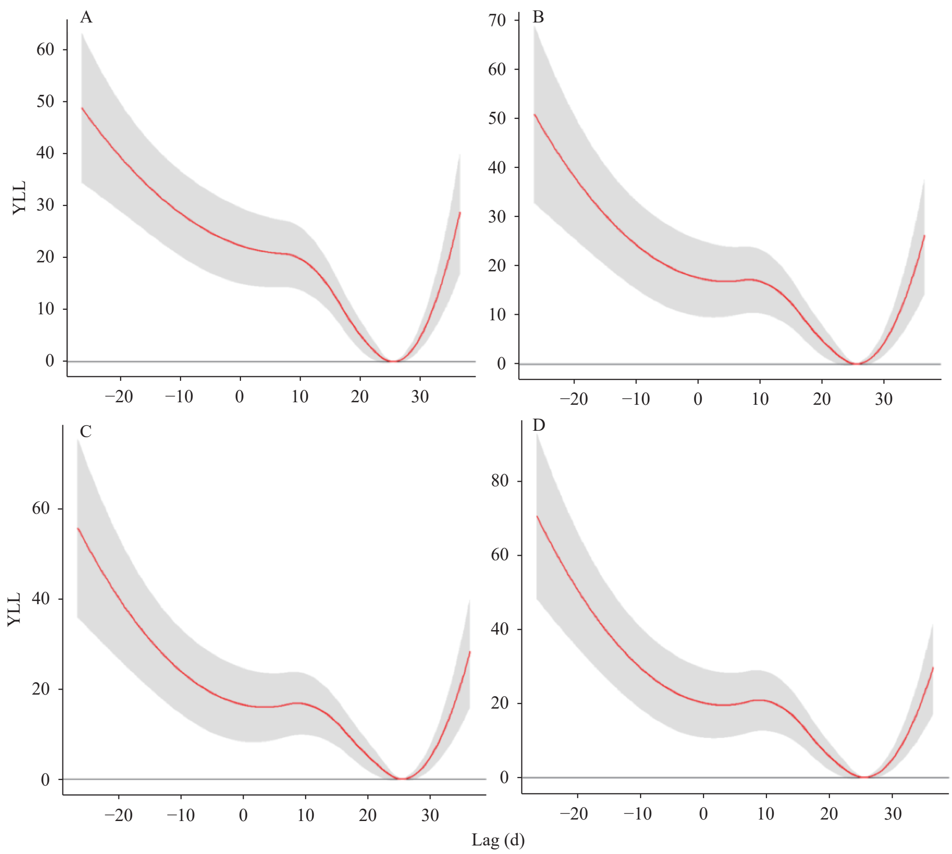
SUPPLEMENTARY FIGURE S7. Lag-response curves of effects of extreme heat and extreme cold temperature on years of life lost due to ischemic stroke on the days of death (lag=0) and up to 21 days prior to death.
The red and blue sections represent extreme heat and extreme cold temperature, respectively.

Sensitivity Analyses

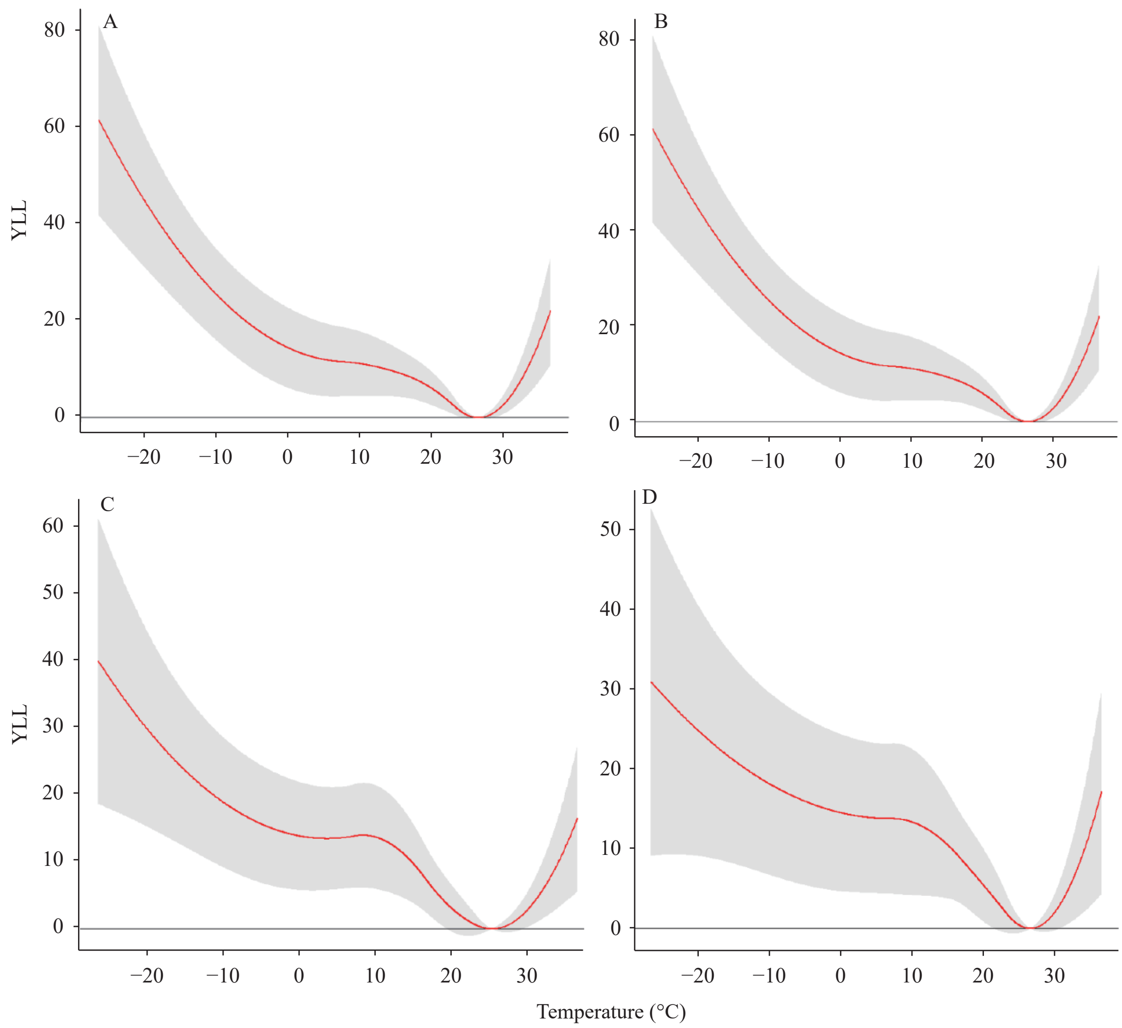
To evaluate the robustness of the main model, we conducted the following sensitivity analyses by: (1) controlling for the confounding effects of other air pollutants by adding the concentrations of O_3, SO_2, and NO_2; (2) alternating maximum lags at 15 d, 18 d, 21 d, and 24 d; (3) alternating the df of time term from 6 to 9. And we obtained the robust findings from the sensitivity analyses. (Supplementary Figures S8, S9 and S10).



SUPPLEMENTARY FIGURE S8. The national-pooled cumulative temperature-years of life lost (estimates and 95% confidence intervals), with and without the adjustment of O_3, SO_2, and NO_2. A, B represents not added and added the above pollutants, respectively. Abbreviations: YLL=years of life lost.



SUPPLEMENTARY FIGURE S9. The national-pooled cumulative temperature-years of life lost (estimates and 95% confidence intervals), by changing maximum lags. A, B, C, and D represents 15 d, 18 d, 21 d, and 24 d, respectively. Abbreviation: YLL=years of life lost.



SUPPLEMENTARY FIGURE S10. The national-pooled cumulative temperature-years of life lost (estimates and 95% confidence intervals), by changing degree of freedom (df) of time term. A, B, C, and D represents the df set to 6, 7, 8, and 9, respectively. Abbreviations: YLL=years of life lost.

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Preplanned Studies

Assessment of Regional Health Vulnerability to Extreme Heat — China, 2019

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Summary

What is already known on this topic?

The health risk caused by high-temperatures depends on the interaction between high temperature exposure and the sensitivity and adaptability of the affected populations.

What is added by this report?

A comprehensive assessment model was established by principal component analysis using the data of 19 cities, 15 provincial-level administrative divisions and used to identify regional characteristics and major influencing factors of health vulnerability to extreme heat in China.

What are the implications for public health practice?

The results of the health vulnerability assessment could effectively identify the regions highly vulnerable to extreme heat in China and provide scientific evidence for the development of adaptive measures and resource allocation plans.

With global warming, the impacts of extremely high temperatures on health have been gradually increasing. Due to the differences in population adaptability, socioeconomic development levels, geographical locations, and climatic conditions, health impacts of extremely heat vary across regions. This study intends to construct an evaluation index system, to evaluate the regional health vulnerability to extreme heat, and to identify the major influencing factors of health vulnerability in China. First, a comprehensive assessment model for health vulnerability to extreme heat was established by principal component analysis with the data from 19 representative cities from a national project, which were distributed in different climatic zones (Supplementary Figure S1 available in http://weekly.chinacdc.cn/), and the results were verified by using the proportion of deaths on extreme heat days in the summer. Then, the extreme heat-health vulnerability index of 31 provincial-level administrative divisions (PLADs) in 2019 were calculated using the established comprehensive assessment model. It was found that regions with high vulnerability were mainly located in the western and central China. The major influencing factors of health vulnerability to extreme heat included indicators of healthcare levels, living environment indicators, socioeconomic level indicators, and air quality. This study could effectively identify areas highly vulnerable to extreme heat in China and provide scientific evidence for the development of adaptive measures and resource allocation plans.

Data on air pollutants (e.g., $PM_{2.5}$, NO_2), meteorological factors (e.g., temperature, precipitation), demographics, and socioeconomic conditions were collected from the China Environment Statistical Yearbook, China Meteorological Administration, China Statistical Yearbook, China Urban Statistical Yearbook, China Health Statistics Yearbook, relevant statistical bulletin, and provincial statistical yearbooks. Data in the 19 representative cities, 15 PLADs were collected from 2014 to 2018 and data in the 31 PLADs were collected in 2019. The mortality data from 2014 to 2018 were obtained from China's Cause of Death Reporting System with assistance by local CDCs. In this study, the 95th percentiles of the temperature range were selected as extreme heat temperatures.

The assessment of health vulnerability to extreme heat was conducted in a three-stage analysis. First, the evaluation indicators for health vulnerability to extreme heat were selected in three dimensions including exposure, sensitivity, and adaptability through literature review, correlation analysis, and principal component analysis (PCA). Second, a comprehensive assessment model of health vulnerability to extreme heat was established by a PCA method using data from 19 representative cities in 15 PLADs in which the death data were collected. The value of health vulnerability index of extreme heat was calculated by the following function: vulnerability index = exposure index score + sensitivity index score - adaptability index score. The results of the vulnerability assessment were verified by correlation analysis between the vulnerability index and the proportion of deaths on extreme heat days. Finally, the extreme heat-health vulnerability indexes of 31 PLADs in 2019 were calculated with the same model in 19 representative cities, 15 PLADs. All analyses were performed using R statistical software (version 4.0.2; The R Foundation for Statistical Computing, Vienna, Austria).

A total of 20 indicators in 3 dimensions were selected for assessment of health vulnerability to extreme heat, including 6 exposure indicators, 7 sensitivity indicators, and 7 adaptability indicators (Table 1). PCA extracted 4 principal components that had a cumulative variance contribution rate of 77% (Table 2). The first principal component mainly represented healthcare indicators including the elderly dependency ratio, maternal mortality rate, perinatal mortality rate, morbidity rate of infectious diseases, etc. The second principal component mainly represented living environment factors including the proportion of households with five or more persons, air temperature, etc. The third principal component represented socioeconomic indicators such as the percentage of people living alone, air temperature, per capita gross domestic product (GDP), and electricity demand. The fourth principal component represented air quality conditions that mainly included concentration of $PM_{2.5}$ and NO_2.

The correlation coefficient between the vulnerability index and the proportion of deaths on hot days in summer in 19 representative cities was 0.518

TABLE 1. The selected evaluation indicators of exposure, sensitivity and adaptability for vulnerability assessment.

Dimension	Indicators	Function relationship
Exposure	Annual average temperature (℃)	+
	Daily maximum temperature≥P_{95}* days	+
	Frequency of heat waves*	+
	Annual average relative humidity (%)	+
	$PM_{2.5}$ (μg/m^3)	+
	NO_2 (mg/m^3)	+
Sensitivity	Elderly dependency ratio (%)*	+
	Poverty population ratio (%)	+
	Living alone (%)	+
	Proportion of households with 5 or more persons* (%)	+
	Maternal mortality rate* (1/100,000)	+
	Perinatal mortality rate* (‰)	+
	Morbidity rate of infectious diseases* (1/100,000)	+
Adaptability	Per capita GDP* (RMB)	–
	Per capita medical care* (RMB)	–
	Green coverage rate of built district* (%)	–
	Air conditioning quantity*	–
	Electricity demand* (100,00/kWh)	–
	Daily water consumption* (L)	–
	Volume of precipitation*	–

* P_{95} is the 95th percentile of the daily maximum temperature; Frequency of heat waves is frequency for 3 consecutive days ≥P_{95} of daily maximum temperature; Elderly dependency ratio is the ratio of the elderly population aged 65 and over to the working-age population aged 15-64; Poverty population ratio is minimum Living Allowances and over to the Total population at year end; Proportion of households with 5 or more persons is the ratio of households with 5 or more persons to the total number of households; Maternal mortality rate is the number of maternal deaths per 100,000 maternal; Perinatal mortality rate is the number of neonatal deaths from 28 weeks of gestation or ≥ 1,000 grams of birth to 7 days after delivery; Morbidity rate of infectious diseases is the number of cases of Class A and B infectious diseases per 100 thousand population in the reference year; Per capita GDP is per capita gross domestic product, the ratio of the GDP by a region to the permanent population; Per capita medical care expenditure is the expenditure on drugs, supplies and services of medical and health care; Green coverage rate of built district is the percentage of green coverage in urban built-up areas to built-up areas; Air conditioning quantity is per 100 households air conditioning quantity; Electricity demand is annual total electricity consumption in urban households; Life-water quantity is the average Daily water consumption per person; Volume of precipitation is the annual precipitation is the summation of 12 months precipitation of a year.

TABLE 2. Factor loadings for extreme heat vulnerability for the four retained varimax-rotated based on data from 19 representative cities, 15 PLADs in China from 2014 to 2018.

Item	Principal component 1	Principal component 2	Principal component 3	Principal component 4
Frequency of heat waves	−0.24	0.70	−0.21	0.23
Annual average temperature (℃)	−0.35	**0.80**	0.29	0.17
Annual average relative humidity (%)	−0.28	0.76	−0.01	−0.29
$PM_{2.5}$ (μg/m^3)	−0.15	−0.11	−0.20	**0.90**
NO_2 (mg/m^3)	0.08	−0.12	0.18	**0.88**
Daily maximum temperature≥P_{95}^* days	0.17	0.49	0.04	−0.02
Elderly dependency ratio (%)	**−0.82**	0.02	−0.25	0.31
Poverty population ratio (%)	0.13	−0.35	−0.47	−0.66
living alone (%)	−0.07	0.08	0.85	−0.21
Proportion of households with 5 or more persons (%)	0.23	**0.81**	−0.09	0.09
Maternal mortality rate (1/100,000)	**0.89**	−0.17	−0.28	0.07
Perinatal mortality rate (‰)	**0.91**	−0.07	−0.21	0.05
Morbidity rate of infectious diseases (1/100,000)	**0.90**	0.09	−0.06	−0.01
Per capita GDP (CNY)	−0.21	0.11	**0.83**	0.08
Per capita medical care expenditure (CNY)	0.39	−0.56	0.37	0.17
Green coverage rate of built district (%)	−0.04	0.50	0.45	0.42
Air conditioning quantity	−0.62	0.50	0.45	0.25
Electricity demand (100,00 / kWh)	−0.05	−0.04	**0.84**	0.26
Daily water consumption (L)	0.06	0.77	0.36	−0.10
Volume of precipitation	−0.31	0.78	0.36	−0.20

* P_{95} is the 95th percentile of the daily maximum temperature; Bold font is the greater correlation between the evaluation index and the principal component

(P=0.023). We used the same method to evaluate health vulnerability to extreme heat in 31 PLADs (Supplementary Table S1 available in http://weekly.chinacdc.cn/). Results showed that higher vulnerability regions were located in the western and central China (Figure 1). The four highest vulnerability regions were the Tibet (Xizang) Autonomous Region (0.182), Qinghai Province (0.112), Tianjin Municipality (0.076), and Xinjiang Uyghur Autonomous Region (0.075).

DISCUSSION

In this study, an extreme heat-health vulnerability assessment model that included 20 factors in 3 dimensions was created using data from 19 representative cities, and the health vulnerability to extreme heat in 31 PLADs in China was assessed according to the health vulnerability assessment model. It was found that heat vulnerability varied across regions, with generally higher scores of vulnerability in the western and central China, which could be possibly explained by relative lower adaptability in such areas. Healthcare and living environment factors were important influencing factors of regional vulnerability. Regions with poorer healthcare capacities and higher $PM_{2.5}$ or NO_2 concentration tended to have higher extreme heat vulnerability. The findings could provide scientific evidence for local authorities to improve the local adaptability and decrease the health vulnerability to extreme heat.

The distribution of healthcare resources in China demonstrated some inequalities (*1*). The medical and healthcare levels in the western region had relatively lower standards (*2*), where health services were insufficient and access to health information was also limited. In this scenario, people in those regions might be at higher risk when exposed to extreme heat events. For example, western regions of Tibet, Qinghai, and Xinjiang, which had relatively poorer healthcare, had high vulnerability even with their relative mild and temperate climates. Therefore, great efforts should be taken to improve the healthcare conditions in those areas to elevate capability of response to extreme heat

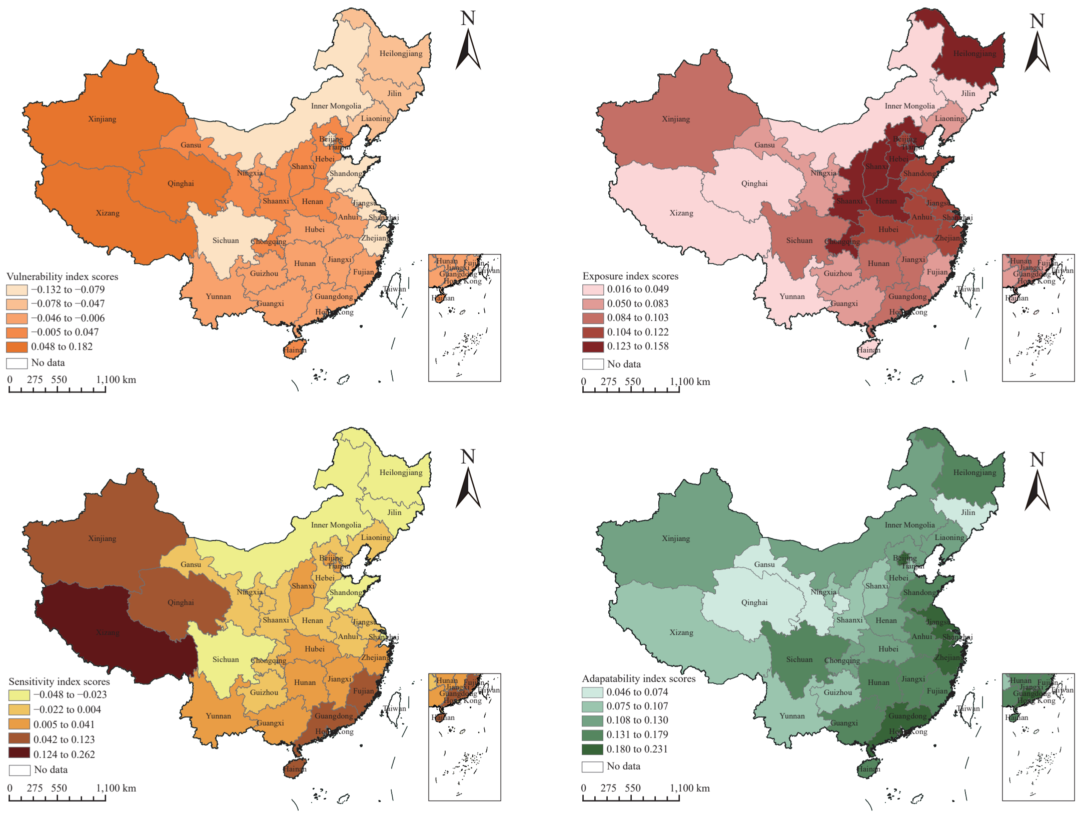

FIGURE 1. National map of extreme heat vulnerability, exposure, sensitivity and adaptability index scores in 31 provincial-level administrative divisions in China, 2019.

Air quality also presented national spatial variability. The annual $PM_{2.5}$ and NO_2 levels in northern China were higher than those in southern China (*3*). In recent years, air pollution had caused more than 1 million deaths per year in China (*4*). Furthermore, a previous study had shown that air pollution could increase the health risks of exposure to heat (*5*). Therefore, regions with higher concentrations of air pollutants tended to have higher extreme heat vulnerability in the central regions, such as Hebei and Shanxi. With rapid urbanization and development of transport infrastructure, it is also important to improve air quality to reduce extreme high temperature vulnerability.

In addition, it was found that eastern PLADs such as Shandong, Jiangsu, and Zhejiang were at low health vulnerability even with usually higher temperatures in summer. This might be due to the higher levels of the per capita GDP, which is highly correlated to the level of local medical services (*6*). In contrast, due to imbalances, western and central regions had lower economic development (*7*), resulting in potentially lower adaptive capacity.

This study was subject to two limitations. First, we excluded some important indicators that were unavailable, such as proportion of population with chronic diseases and high-temperature warnings, which may induce some bias. Second, the lack of provincial health outcome indicators in this study made it impossible to verify the provincial assessment results of health vulnerability to extreme heat. In future studies, we should add a more precise index and optimize the model with more data.

In conclusion, the results of this study showed to some extent that the vulnerability index could reflect comprehensive health effects of extreme heat. Identification of regional health vulnerability to extreme heat can help guide public health authorities to appropriately allocate resources to the more vulnerable regions. A comprehensive adaptation plan should also be developed by local governments to improve local adaptive capacities.

Conflicts of interest: No conflict of interest.

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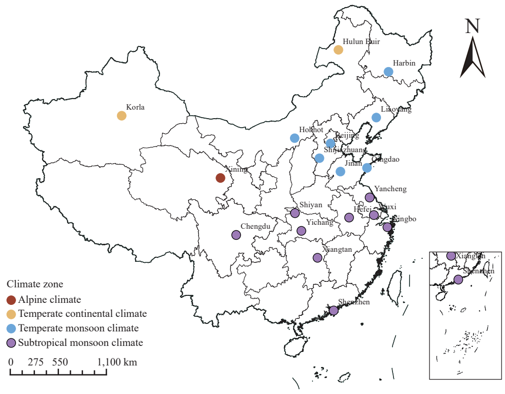

SUPPLEMENTARY FIGURE S1. Location, climate of 19 cities, 15 provincial-level administrative divisionsin China

SUPPLEMENTARY TABLE S1. The analysis results of exposure, sensitivity, adaptability score for the 31 provincial-level administrative divisions in 2019.

Item	Exposure index score	Sensitivity index score	Adaptability index score	Vulnerability index score	Vulnerability ranking
Tibet	0.016	0.262	0.096	0.182	1
Qinghai	0.034	0.123	0.046	0.112	2
Tianjin	0.157	0.015	0.096	0.076	3
Xinjiang	0.091	0.096	0.112	0.075	4
Shanxi	0.133	0.021	0.107	0.047	5
Shaanxi	0.139	0.001	0.104	0.036	6
Henan	0.154	0.004	0.123	0.035	7
Chongqing	0.158	−0.006	0.128	0.024	8
Gansu	0.068	−0.005	0.049	0.014	9
Hebei	0.148	−0.017	0.127	0.004	10
Hainan	0.037	0.109	0.142	0.004	11
Hunan	0.103	0.031	0.141	−0.006	12
Hubei	0.109	0.006	0.130	−0.015	13
Guangdong	0.089	0.121	0.230	−0.020	14
Guangxi	0.075	0.041	0.143	−0.028	15
Auhui	0.122	−0.011	0.140	−0.029	16
Ningxia	0.083	−0.014	0.100	−0.031	17
Fujian	0.073	0.075	0.179	−0.032	18
Yunnan	0.036	0.020	0.088	−0.032	19
Guizhou	0.063	−0.006	0.090	−0.033	20
Jiangxi	0.097	0.008	0.142	−0.036	21
Liaoning	0.080	−0.004	0.122	−0.047	22
Heilongjiang	0.135	−0.023	0.161	−0.049	23
Shanghai	0.135	−0.023	0.161	−0.049	24
Jilin	0.049	−0.026	0.074	−0.051	25
Zhejiang	0.112	0.007	0.198	−0.079	26
Shandong	0.111	−0.030	0.163	−0.082	27
Inner Mongolia	0.048	−0.023	0.114	−0.090	28
Sichuan	0.097	−0.048	0.146	−0.097	29
Beijing	0.118	0.012	0.231	−0.100	30
Jiangsu	0.112	−0.013	0.231	−0.132	31

Preplanned Studies

The Impact of a Health Forecasting Service on the Visits and Costs in Outpatient and Emergency Departments for COPD Patients — Shanghai Municipality, China, October 2019–April 2020

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Summary

What is already known on this topic?

The morbidity and mortality of chronic obstructive pulmonary disease (COPD) is associated with adverse weather and air pollution. However, COPD patients are not able to be alerted in advance of high risk environments.

What is added by this report?

This prospective controlled trial conducted in Pudong New Area of Shanghai from October 2019 to April 2020 provided evidence of COPD risk forecasting service on the reductions in visits and costs of COPD patients in outpatient and emergency departments in China for the first time.

What are the implications for public health practice?

This study suggests that COPD risk forecasting service could be integrated into existing COPD management in public health to improve the health and economic outcomes.

Chronic obstructive pulmonary disease (COPD) is a public health challenge in China because of its high prevalence, related disability and mortality, and heavy economic burden (*1–3*). COPD morbidity and mortality is associated with adverse weather and air pollution (*4–7*). However, it is difficult for both COPD patients and medical staff to be alerted in advance of high-risk periods with existing tools. The Shanghai Meteorological Service (SMS) has developed a health forecasting service for COPD patients based on the weather and air quality forecasts. A prospective controlled trial was conducted in Pudong New Area of Shanghai from October 2019 to April 2020 to examine whether such a forecasting service being available to COPD patients and their general practitioners (GPs) could reduce visits and costs in outpatient and emergency departments (OPED) for COPD. In this study, 1,349 patients in each group were analyzed after balancing the control and intervention groups by using the propensity score matching (PSM) method. Compared with the control group, there was a 17.6% reduction in the proportion of OPED patients and a 13.9% reduction in the OPED visits in the service group. The results of this study suggest that COPD risk forecasting service could be a novel method of COPD management in public health to improve health and economic outcomes.

This study was designed as a prospective intervention study with two groups: the service group (patients receiving COPD risk forecasting service; also known as the intervention group) and the control group (patients not receiving the COPD risk forecasting service). According to previous studies, every 1 °C increase of daily mean temperature was associated with a 7.0% decrease (95% CI: 4.9, 9.0) in the risk of COPD hospitalization in Beijing (*8*) and a 3.0% decrease (95% CI: 2.0, 4.0) in COPD symptoms in Shanghai (*4*). The proportion of COPD patients receiving outpatient treatment, the primary dichotomous endpoint, was usually around 50% (*3*). Assuming that rate ratio of OPED visit for the service group was 0.85 compared with the control group, a total of 1,854 subjects (927 for each group) were required to detect a difference between the two groups at a 90% power with a two-sided significance level of 0.05.

COPD patients in Pudong New Area of Shanghai Municipality were selected as the local CDC had an established routine COPD management system with thousands of clinically diagnosed COPD patients registered to community health service centers. Patients consenting to participate were required to provide following information at baseline: age, sex, number of acute exacerbations of COPD (AECOPD) within the last year. Furthermore, patients selected to receive the COPD risk forecasting service were also asked to provide contact details.

Overall, there were three methods the COPD risk forecast service was provided: 1) a specially designed platform for WeChat displaying daily updated forecast information and chat groups including patients, GPs, CDC staff, and SMS staff; 2) mobile phone text messages; and 3) automated phone calls. Except for the WeChat platform, COPD risk forecast was provided regularly 2 to 3 times per week and before adverse weather events. Patients were sent an information pack that described how future weather could affect COPD and detailed advice on self-management of COPD, such as keeping warm, reducing exposure to cold temperature or air pollution, appropriate exercise, and so on. They were also advised to contact their GP if necessarily. At the end of study, adherence of patients in the service group was self-reported in questionnaire according to whether they adjusted their behavior when they were alerted in high-risk period. Their satisfaction with the forecasting service was also evaluated with answers of satisfied, moderate, or dissatisfied.

In both the service and control groups, patients had died from other diseases during the study period (October 2019–April 2020) and those less than 40 years old were also excluded. As the baseline characteristics of the service and control group were unbalanced (Table 1), the PSM method was used to balance variables and reducing the bias between the control and service groups. The method has been used with increasing frequency in observational studies and clinical trials (*9*), which attempts to adjust post hoc for recognized unbalanced factors at baseline to approximate a randomized data to analyze. Logistic regression was used to calculate the propensity score of each patient. Then the 1∶1 case-control matching was conducted according to the principle of neighboring matching with caliper value of 0.01. The matching variables were the patients' age, gender, and the AECOPD counts within the last year. The service group was also divided into the WeChat group, the text group, the call group, and the mixed group (the group of patients receiving COPD risk forecast in two or more methods). After matching, monthly COPD-related OPED visits and costs of each group during the study period were collected from the information center of Pudong New Area Health Commission. All the COPD-related OPED visits were defined according to clinical diagnosis (J40, J42–J44). OPED costs for COPD were also divided into costs for registration, medication, examination, etc.

A generalized estimation equation (GEE) was used to examine the effects of COPD risk forecasting service on OPED visits and costs for COPD. Monthly visits and costs were used as dependent variables. As the number of OPED visits was approximately Poisson distributed, the Poisson distribution was used in the analysis. OPED visits were also treated into dichotomous variable (yes or no). Patients' age, gender, and AECOPD counts within the last year were adjusted as covariates in the GEE model. All statistical analyses were conducted with R version 4.0.2 (R Development Core Team, Auckland, Nz). The geepack package was used to conduct GEE. The significance level was set at 0.05 (two-tailed).

A total of 4,880 COPD patients participated in this study. After some patients were excluded, 2,204 patients were included in the service group, and 1,631 patients were in the control group (Table 1). Before using PSM, baseline conditions of the two groups were unbalanced. In the service group, the age and proportion of patients having AECOPD in the last year were both smaller than those of the control group. After PSM, 1,349 patients in the service group were

TABLE 1. Characteristics of COPD patients in groups of receiving or not receiving the COPD risk forecast service before and after propensity score matching in Pudong New Area, Shanghai Municipality from October 2019 to April 2020.

Characteristics	Before PSM			After PSM		
	Patients not receiving service (n=1,631)	Patients receiving service (n=2,204)	*P* value	Patients not receiving service (n=1,349)	Patients receiving service (n=1,349)	*P* value
Age, years	71.7±10.3	67.9±9.3	<0.001	69.3±9.1	69.5±9.0	0.522
Male,N (%)	932 (57.1)	1303 (59.1)	0.232	761 (56.4)	774 (57.4)	0.641
AECOPD counts within the last year, N (%)			<0.001			0.010
0	1,307 (80.1)	1,431 (64.9)		1,060 (78.6)	1,002 (74.3)	
1	172 (10.6)	451 (20.5)		143 (10.6)	224 (16.6)	
≥2	152 (9.3)	322 (14.6)		146 (10.8)	123 (9.1)	

Abbreviations: PSM=propensity score matching; COPD=chronic obstructive pulmonary disease; AECOPD=acute exacerbation of COPD.

successfully matched with 1,349 controls. Patients in the control and service group were balanced in age and gender. Compared with the control group, the proportion of patients having AECOPD in the last year increased by 4.3% in the service group, whereas the proportion of patients having more than one time of AECOPD decreased by 1.7%, as shown in Table 1. After a 6-month forecasting service, 85.8% of patients in the service group reported good compliance with advice in the forecasting service. There were 88.7%, 79.6%, and 90.0% of patients satisfied with the service provided by WeChat, text, and call, respectively.

There were 545 COPD patients in the service group that visited OPED at least once for COPD for a total of 1,986 person-times during the study period, while 502 patients in the control group visited for a total of 2,031 person-times. Figure 1 showed the proportion of COPD patients visiting COPD-related OPED in the service and control groups in Pudong New Area, Shanghai, from October 2019 to April 2020. In the service group, 18.1% of patients visited OPED in December 2019, and 12.3% visited OPED in April 2020. Showing a similar time trend in the control group, there were 19.1% and 13.3% of patients visiting OPED in December 2019 and April 2020, respectively. The proportion of patients visiting COPD-related OPED in the service group was consistently lower than that in the control group from December 2019. The monthly person-times of OPED visits also peaked in December 2019 and gradually declined in the following months. In the service group, patients visited OPED for 244 times in December 2019 and 166 times in April 2020. In the control group, the figures were 258 times and 180 times, respectively.

The results of the GEE models in evaluating the effects of COPD risk forecasting service on the proportion of COPD patients visiting OPED and person-times of OPED visits in Pudong New Area of Shanghai from October 2019 to April 2020 were shown in Table 2. When the proportion of patients was analyzed, the relative risk (RR) for patients receiving service relative to those not receiving it was 0.824 (95% CI: 0.686, 0.990), i.e., a 17.6% reduction with a wide 95% CI of 1.0% reduction to 31.4% reduction. When the person-times of OPED visits were used, the corresponding RR was 0.861 (95% CI: 0.744, 0.995), which meant that receiving such service had effect of reducing OPED visits by 13.9%. The RRs for patients receiving service via WeChat, text, or call were mainly less than 1 with wide CIs across 1, suggested less OPED visits although the effects were not significant for patients receiving the service only through a single method. When two or more service methods were used, there was a significant effect of reduction in person-times of OPED visits with a RR of 0.755 (95% CI: 0.597, 0.955).

The total OPED costs of these 2,698 patients were 1.34 million RMB during the study period, in which medicine accounted for 82.9%. The total OPED costs and medicine costs per patient due to COPD were 495.1 RMB and 410.9 RMB, respectively, during the study period. Table 2 also showed the effect of COPD risk forecasting service on the OPED costs for COPD using GEE. In general, patients receiving the COPD risk forecast service seemed to have lower total

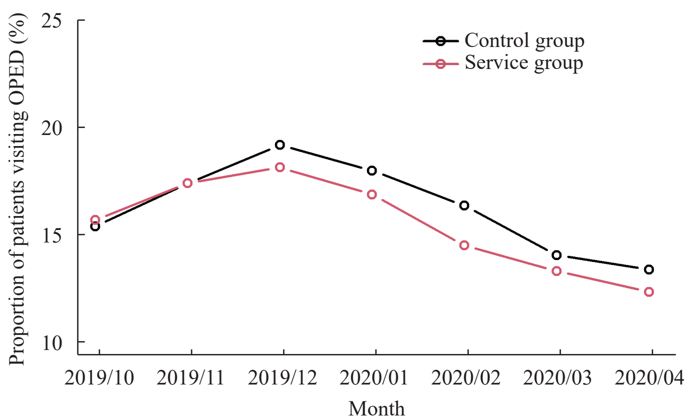

FIGURE 1. The monthly proportion of COPD patients visiting outpatient and emergency departments for COPD in the service group (1,349 patients) and the control group (1,349 patients) in Pudong New Area, Shanghai Municipality from October 2019 to April 2020.

Abbreviation: OPED=outpatient and emergency departments.

TABLE 2. Effects of the COPD risk forecasting service on the visits and costs of outpatient and emergency departments for COPD in Pudong New Area, Shanghai Municipality from October 2019 to April 2020.

Groups	N	Patients visiting OPED		Person-times of OPED visits		OPED costs, RMB		Medicine costs, RMB	
		Persons (%)	RR (95% CI)	Times	RR (95% CI)	Mean	β (95% CI)	Mean	β (95% CI)
Control	1,349	502 (37.2)	Ref	2,031	Ref	511.7	Ref	422.6	Ref
Service	1,349	545 (40.4)	0.824 (0.686, 0.990)*	1,986	0.861 (0.744, 0.995)*	478.4	−11.194 (−24.579, 2.191)	399.1	−9.522 (−21.285, 2.241)
WeChat	204	73 (35.8)	0.945 (0.659, 1.354)	273	1.012 (0.768, 1.335)	455.8	−0.797 (−28.194, 26.600)	394.1	1.727 (−22.287, 25.741)
Text	619	258 (41.7)	0.855 (0.683, 1.071)	919	0.913 (0.764, 1.093)	505.6	−5.389 (−23.368, 12.590)	420.9	−5.120 (−20.985, 10.744)
Call	169	75 (44.4)	0.747 (0.502, 1.112)	294	0.759 (0.532, 1.084)	464.3	−25.900 (−50.865, -0.935)*	370.0	−24.895 (−44.945, −4.845)*
Mixed	357	139 (38.9)	0.756 (0.558, 1.025)	500	0.755 (0.597, 0.955)*	450.9	−20.258 (−39.644, -0.872)*	378.1	−16.172 (−33.425, 1.081)

Abbreviations: OPED=outpatient and emergency departments; Ref=reference group;RR= Relative risk.
* P<0.05.

spending on OPED services and medication than those not receiving the service, although these results were not significant. The cost-reducing effects varied by way of providing the forecasting service, with significantly stronger effects in the call group and mixed group. For example, patients receiving the service via calls and in two or more methods had a decline of 25.90 RMB (95% CI: 0.87, 50.94) and 20.26 RMB (95% CI: 0.87, 39.64), respectively, per patient in OPED costs relative to those not receiving service.

DISCUSSION

This study evaluated the impact of environment-based health forecasting service, a new method of COPD management for the first time in China. Patients receiving the forecasting service had less visits and costs in outpatient and emergency departments due to COPD than those not receiving it between October 2019 and April 2020. It seemed that better effects could be reached by providing services via automated calls or in multiple methods than via WeChat or text messages.

In this study, compared with the control group, there was a 17.6% reduction in the proportion of OPED patients and a 13.9% reduction in the OPED visits in the service group. The effects were similar with those reported in UK (*10–11*), where a COPD forecasting service appeared to reduce the frequency of COPD exacerbation by 18.8% and the severity of exacerbation, but the effects did not reach statistical significance perhaps due to their smaller number of participants (only 79 patients) and lower exacerbation rates. Our study had 2,698 COPD patients participating in and using OPED visits instead of AECOPD hospitalization to enlarge outcome rates.

We used several methods to provide COPD risk forecasting service to patients. However, patients receiving the service via phone calls appeared to have less OPED visits and costs than those receiving the service via WeChat and text. It may be due to different accessibility of these methods. In this study, more than 80% of patients in the call group answered frequently whereas only around 60% of patients registered in the specific WeChat platform. As the most popular social network in China, WeChat has been widely used in chronic disease management (*12*). However, WeChat may be not easy for older patients to use because their education levels, income levels, and physical conditions tend to make app use more challenging. Mobile phone text message is a traditional method to send weather forecast and disease-related information to patients. The use of text messages can be also affected by its higher barrier to engagement (due to being purely text) and the patients' education level, although there was great uncertainty of the proportion of COPD patients in the text group successfully receiving the forecasting service.

The monthly COPD-related OPED patients and visits were both found to peak in December 2019 and declined in the following months. This is possibly caused by there being more COPD morbidity in the cold season than in the warm season. Also, the coronavirus disease 2019 (COVID-19) pandemic occurred in the last 3 months of this study, which might have reduced the OPED visits for COPD to some extent. In a cross-sectional survey in Beijing (*13*), compared with that before the COVID-19 epidemic, fewer COPD patients maintained their pharmacological treatment. It was reported that only 15.6% of COPD patients who experienced respiratory symptoms aggravation sought medical care in hospital as 55.5% were concerned about cross-infection of COVID-19 in the hospital and the remaining 28.8% took more medication by themselves.

This study was subject to some limitations. Patients were not randomly allocated in the control and service groups. However, the PSM method had been adopted to control for selection bias to achieve the goal of balancing. In addition, some potential risk factors (the severity of COPD, respiratory infection, socioeconomic status, and smoking) associated with outpatient visit for COPD might have been missed in the baseline investigation. Moreover, the unexpected emergence of COVID-19 in the late period of the study period changed both patients' and hospitals' practice and resulted in trends such as less hospital visits and better self-management, which thus reduced some OPED visits in both groups during the late period and may limit the effects of the forecasting service.

Despite these limitations, the evaluation shows an association between the delivery of COPD risk forecasting service and the reduction of visits and costs of COPD patients in outpatient and emergency departments. The effectiveness of the service depends on the methods of patients receiving it. More longitudinal research with random allocation of patients and more influencing factors considered on the effectiveness of forecasting service is warranted.

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Preplanned Studies

A Modelling Study on $PM_{2.5}$-Related Health Impacts from Climate Change and Air Pollution Emission Control — China, 2010s and 2040s

Jing Huang[1]; Heng Tian[2]; Jiawei Wang[1]; Teng Yang[1]; Yiran Peng[3]; Shaowei Wu[4]; Tzung-May Fu[5]; Guoxing Li[1,#]

Summary

What is already known about this topic?

Climate change and air pollution are two important environmental issues in China. It is important to investigate particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$)-related health impacts from climate change and air pollution emission control.

What is added by this report?

Deaths and years of life lost related to $PM_{2.5}$ would increase in climate change scenario, although emission control would outweigh the influence of climate change.

What are the implications for public health practice?

More targeted actions should be taken to meet challenges of exacerbated $PM_{2.5}$ pollutions and its health impacts related to climate change in the future.

Climate change and air pollution are two important environmental issues in China. The study aimed to model different scenarios to assess the health impacts related to ambient particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$) from climate change and air pollution emission control in China. A regional meteorology-climate model was used to simulate the ambient $PM_{2.5}$ concentrations in China in the 2010s and the 2040s under different scenarios (climate change scenario, air pollution emission control scenario, and climate change and emission control scenario). Furthermore, changes in mortality and years of life lost (YLLs), an indicator which considers life expectancy at death, were adopted to estimate $PM_{2.5}$-related health impacts. The concentrations of $PM_{2.5}$ were estimated to slightly increase in climate change scenario but decrease in emission control scenario in 2040s. $PM_{2.5}$-related health impacts would increase in climate change scenario in the 2040s, although emission control would outweigh the influence of climate change. The findings suggest that more targets actions should be taken to confront challenges of exacerbated $PM_{2.5}$ pollutions and its health impacts attributable to climate change in the future.

As the biggest global health threat of the 21st century, tacking climate change could be the greatest global health opportunity (*1–2*). There are multiple linkages connecting climate change and air quality, and climate change is expected to degrade air quality (*3*). Considering $PM_{2.5}$ is one of the leading contributors to global disease burden (*4*), it is of great importance to predict future ambient $PM_{2.5}$ concentrations and its related health impacts by considering both the near-term changes in climate conditions and the changes in anthropogenic pollutant emissions in China on interdecadal timescales. Nevertheless, evidence investigating the health impacts attributable to ambient $PM_{2.5}$ from both climate change and air pollution emission control under different scenarios in China is still lacking.

In order to assess the combined effects of interdecadal climate change and anthropogenic emission reductions on ambient $PM_{2.5}$, the Flexible Global Ocean-Atmosphere-Land System Model, Grid-point Version 2 (FGOALS-g2) decadal climate prediction and a Multi-Resolution Emission Inventory for China (MEIC) were used to drive a Weather Research Forecast Model Coupled with Chemistry (WRF-Chem) model to simulate the ambient $PM_{2.5}$ concentrations in China during the 2010s and the 2040s in the national level and different districts under the Representative Concentration Pathway 4.5 (RCP4.5) scenario. The WRF-Chem model is a flexible and efficient atmospheric simulation model, the chemical module of this model mainly includes the emission, transport, photolysis, gaseous chemical reaction, deposition, aerosol dynamics, and chemical processes of air pollutants. It was used to simulate $PM_{2.5}$ concentrations in the 2010s, which were set as baseline; and $PM_{2.5}$ concentrations with only climate change and emission control, respectively, and under both scenarios in the 2040s in this study (*5*).

The burden attributable to $PM_{2.5}$ under the scenarios above for ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lung cancer was estimated using the integrated exposure–response functions (IER) for each cause of death, which have been used in a Global Burden of Disease study (*6*) and are based on studies of ambient air pollution, household air pollution, and second-hand smoke exposure and active smoking (*7*). Data of the annual average population size were collected from the China Statistical Yearbook, and the city-level proportions of different age groups were obtained from the 2010 census. Yearly mortality data in the mainland of China were obtained from the national death surveillance data, which originated from China CDC. The age-specific and cause-specific mortality rates were estimated based on the death surveillance points, and the proportions of cause-specific mortality in different districts and age groups were collected from the China Death Surveillance Data set. The deaths and YLLs attributable to ambient $PM_{2.5}$ were then calculated by applying the year-specific, location-specific, and age-specific population-attributable fractions to the number of deaths and YLLs (*8*). Monte Carlo simulations were used to calculate the 95% confidence interval of death burden of $PM_{2.5}$. Because the data used in the study were collected without any individual identifiers, the study was exempted from the Institutional Review Board of Peking University Health Science Center in Beijing.

The national $PM_{2.5}$ concentrations in the 2010s and the changes of its predicted concentrations under different scenarios in the 2040s in China are presented in Figure 1. Climate change scenarios increased the $PM_{2.5}$ concentrations in most regions, while emission control scenarios would decrease the $PM_{2.5}$ concentrations at the national level. With the impact of both climate change and emission control, the

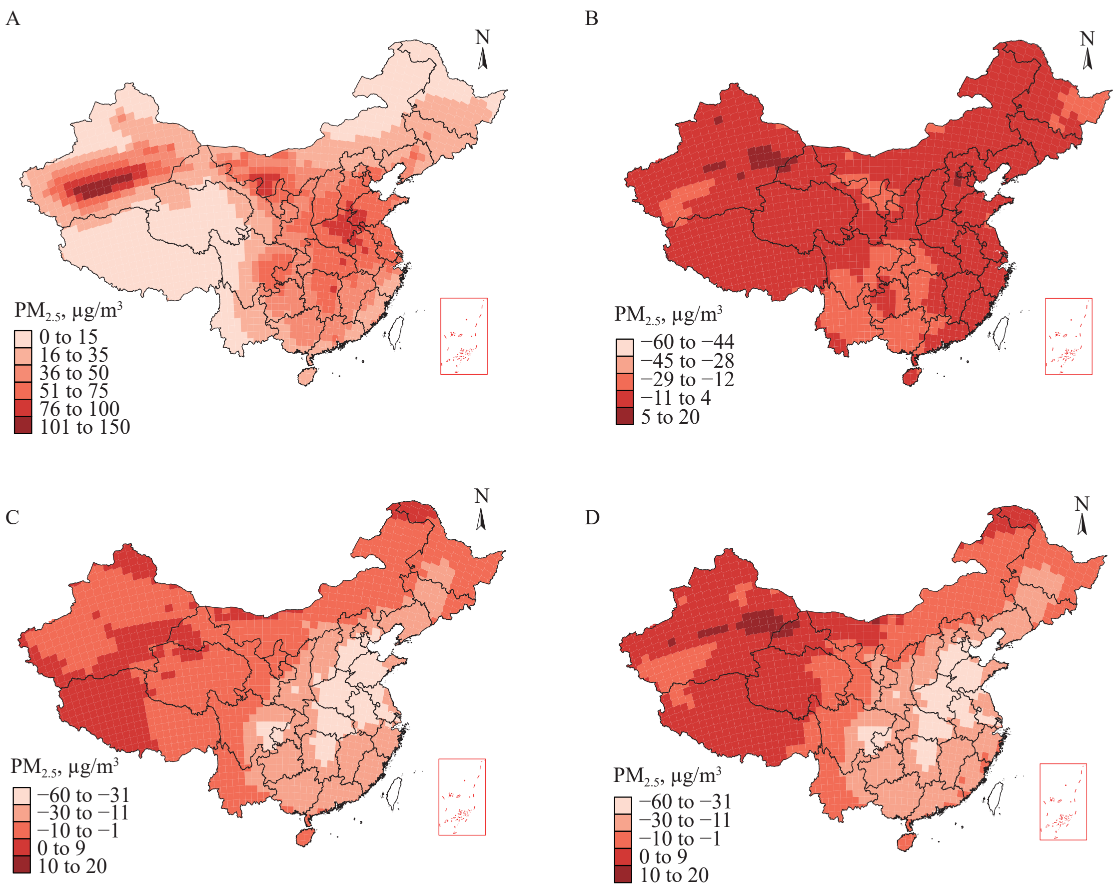

FIGURE 1. Baseline $PM_{2.5}$ concentration in the 2010s and the changes of its predicted concentrations under different scenarios in the 2040s in China. (A) Baseline $PM_{2.5}$ concentrations in the 2010s; (B) Changes of $PM_{2.5}$ concentrations under climate change scenario in the 2040s; (C) Changes of $PM_{2.5}$ concentrations under emission control scenario in the 2040s; (D) Changes of $PM_{2.5}$ concentrations under both climate change and emission control scenarios in the 2040s.

$PM_{2.5}$ concentrations at the national level would decrease from 28.05 μg/m^3 in the 2010s to 18.75 μg/m^3 in the 2040s, with a reduction percentage of 33.16%.

Climate change scenario under RCP4.5 would aggravate the health impacts of $PM_{2.5}$ pollutions on death and YLLs, while the emission control scenario would alleviate the health influence of $PM_{2.5}$ from the 2010s to the 2040s in the national level. The attributable number of deaths related to ambient $PM_{2.5}$ pollutions was estimated to be 1,278,734 in the national level in the 2010s, which comprised of 371,939, 610,694, 177,455, and 118,646 cases from IHD, stroke, COPD, and lung cancer, respectively. In the 2040s, the estimate would increase by 0.96% under the climate change scenario, while it would decrease by 32.20% under the emission control scenario. Considering both the impact of both climate change and emission control, there were an estimated 385,004 fewer deaths, with a reduction percentage of 30.11%. The corresponding YLL would increase by 0.85% under the climate change scenario, while it would decrease by 31.06% under the emission control scenario. The attributable YLLs would decrease from 16,328,977 in the 2010s to 11,577,480 in the 2040s considering both scenarios. There would be 4,751,497 fewer YLL at the national level, with a reduction percentage of 29.10%. The largest reduction number is stroke among the four major diseases (Figure 2).

Table 1 showed the prediction of deaths and YLLs from main types of diseases associated with ambient $PM_{2.5}$ pollutions in different districts of China in the 2040s. Generally, the attributable deaths and YLLs from major diseases would increase in most of the districts in the climate change scenario, with the largest increasing percentage in the east region. While considering both climate change and emission control scenarios, the attributable deaths and YLLs would decrease in the 2040s compared with the 2010s, with the largest percentage change in the Northeast.

DISCUSSION

In this study, the ambient $PM_{2.5}$ in the 2010s and the 2040s in China was simulated. The changes of $PM_{2.5}$ under the scenarios of climate change, emission control, and both climate change and emission control in the 2040s were evaluated. Furthermore, the deaths and YLLs attributable to $PM_{2.5}$ were also assessed. Climate change would aggravate $PM_{2.5}$ pollution and cause adverse health effects, while emission control would reduce $PM_{2.5}$ concentration and alleviate adverse health effects of $PM_{2.5}$ to some degree. The health benefits would be noticeable under the scenario of climate change with emission control. The results were similar to a modelling study conducted in Great Britain which assessed the public health impacts of the air quality changes arising from climate change interventions and indicated that mitigation policies have the potential to generate dramatic improvements in public health through the improvement in air quality (*9*). The findings suggest that emission control may mitigate $PM_{2.5}$-related impacts attributable to climate change and may inform policymaking

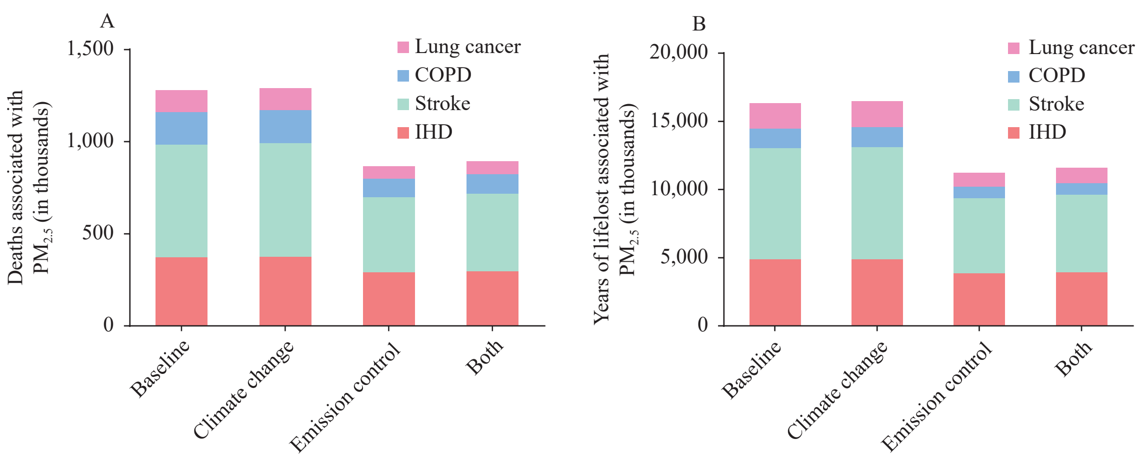

FIGURE 2. Deaths and years of life lost from main types of diseases associated with ambient $PM_{2.5}$ pollution in the national level in the 2010s (baseline) and different scenarios in the 2040s. (A) Deaths associated with $PM_{2.5}$ (in thousands). (B) Years of life lost associated with $PM_{2.5}$ (in thousands).
Abbreviations: COPD=chronic obstructive pulmonary disease; IHD=ischemic heart disease.

TABLE 1. Deaths and years of life lost from main types of diseases associated with ambient $PM_{2.5}$ pollution in different districts in the 2010s and in different scenarios in the 2040s in China.

	Disease	Region	Baseline (2010s)	Emission control (2040s)	Climate change (2040s)	Both scenarios (2040s)
Deaths	Lung cancer	Central	38,961(37,072−40,985)	21,519(20,212−22,825)	39,130(37,309−40,992)	22,109(20,752−23,487)
		East	27,963(25,783−30,140)	16,408(14,688−18,013)	29,371(27,182−31,550)	17,854(16,009−19,647)
		North	26,498(24,619−28,218)	14,537(13,202−15,761)	27,741(25,959−29,476)	16,217(14,873−17,596)
		Northeast	7,446(6,727−8,254)	3,410(2,917−3,866)	7,570(6,724−8,372)	3,325(2,819−3,817)
		Northwest	5,211(4,757−5,652)	3,886(3,509−4,274)	5,283(4,863−5,744)	3,976(3,616−4,353)
		South	12,568(11,544−13,715)	7,352(6,629−8,055)	12,349(11,302−13,432)	7,017(6,294−7,750)
		Subtotal	118,646 (114,756−122,448)	67,112(64,362−69,925)	121,444 (117,581−125,190)	70,498 (67,662−73,192)
	COPD	Central	64,204(61,198−67,190)	35,962(33,880−38,073)	63,973(60,818−67,072)	36,224(34,063−38,449)
		East	36,447(33,740−39,034)	21,779(19,727−23,965)	38,210(35,595−41,120)	23,597(21,496−25,654)
		North	31,488(29,716−33,292)	17,800(16,458−19,084)	32,920(31,243−34,905)	19,710(18,206−21,074)
		Northeast	8,258(7,454−9,026)	3,964(3,460−4,499)	8,393(7,586−9,228)	3,869(3,354−4,396)
		Northwest	11,841(10,900−12,783)	8,919(8,180−9,672)	12,004(11,063−12,987)	9,117(8,342−9,864)
		South	25,217(23,769−26,741)	14,720(13,658−15,827)	24,395(22,823−25,911)	13,894(12,733−14,934)
		Subtotal	177,455(172,588−182,322)	103,144(99,239−106,638)	179,895(175,040−185,082)	106,411(102,670−110,041)
	Stroke	Central	211,289(207,855−214,510)	143,301(140,430−145,945)	211,024(207,658−214,034)	145,453(142,741−148,320)
		East	134,204(130,650−137,631)	94,621(91,183−97,837)	137,556(133,848−141,212)	101,686(98,280−105,428)
		North	114,137(111,590−116,745)	77,724(75,660−80,055)	116,413(113,937−118,848)	85,351(83,266−87,702)
		Northeast	40,158(38,860−41,346)	17,860(17,105−18,580)	40,436(39,159−41,638)	17,379(16,647−18,099)
		Northwest	33,097(32,288−33,905)	26,975(26,238−27,812)	33,454(32,670−34,341)	27,579(26,891−28,303)
		South	77,808(75,814−79,792)	46,743(45,324−48,253)	75,754(73,877−77,502)	44,132(42,768−45,573)
		Subtotal	610,694 (604,864−616,772)	407,224(401,877−412,712)	614,637(608,880−620,705)	421,580(416,769−426,887)
	IHD	Central	122,087(120,667−123,605)	94,903(93,821−95,959)	122,239(120,806−123,808)	96,030(94,922−97,213)
		East	86,372(84,339−88,472)	68,678(67,149−70,229)	88,168(86,186−90,257)	71,379(69,693−73,016)
		North	73,129(71,754−74,462)	56,570(55,614−57,606)	74,447(73,095−75,727)	59,453(58,444−60,418)
		Northeast	28,545(27,984−29,102)	19,549(19,127−19,945)	28,684(28,096−29,275)	19,166(18,780−19,593)
		Northwest	15,877(15,599−16,138)	13,954(13,732−14,182)	16,029(15,778−16,306)	14,209(13,986−14,415)
		South	45,929(44,978−46,852)	35,896(35,282−36,514)	45,404(44,460−46,285)	35,005(34,323−35,639)
		Subtotal	371,939(368,700−375,355)	289,550(287,271−291,731)	374,971(371,754−378,145)	295,242(292,987−297,421)

TABLE 1. (Continued)

	Disease	Region	Baseline (2010s)	Emission control (2040s)	Climate change (2040s)	Both scenarios (2040s)
Years of life lost	Lung cancer	Central	618,254(586,213−649,797)	341,506(319,484−362,722)	621,022(591,164−650,132)	351,005(330,626−373,382)
		East	418,525(382,735−449,965)	245,493(220,072−271,775)	439,634(403,395−473,071)	267,137(241,539−292,445)
		North	420,444(392,967−449,296)	231,199(213,427−249,338)	440,286(411,122−469,785)	257,814(238,033−278,906)
		Northeast	122,896(109,279−136,079)	55,989(48,557−63,878)	124,838(112,378−138,037)	54,451(46,232−62,246)
		Northwest	92,129(83,979−100,523)	68,858(62,224−75,353)	93,412(85,682−102,071)	70,491(64,039−76,854)
		South	195,933(180,046−211,995)	113,982(101,729−125,447)	192,213(176,544−209,435)	108,683(97,777−121,219)
		Subtotal	1,868,180(1,812,549−1,923,629)	1,057,027(1,016,384−1,099,968)	1,911,405(1,853,155−1,968,896)	1,109,581(1,066,029−1,153,705)
	COPD	Central	533,842(508,080−559,411)	298,877(280,884−317,152)	531,693(506,880−555,737)	300,812(283,007−319,205)
		East	264,192(245,779−282,745)	157,595(143,103−171,801)	276,908(258,560−294,864)	170,783(156,431−185,607)
		North	249,773(235,613−264,032)	142,174(132,390−151,925)	261,227(247,682−275,951)	157,236(146,015−168,021)
		Northeast	68,880(62,685−75,530)	32,767(28,474−36,638)	69,885(63,360−76,504)	31,828(27,951−35,856)
		Northwest	115,897(10,6659−125,847)	87,489(80,382−94,952)	117,461(109,153−126,100)	89,434(82,145−96,694)
		South	201,664(190,662−214,335)	116,153(107,836−124,542)	194,344(182,096−205,559)	109,339(101,195−117,871)
		Subtotal	1,434,247(1,396,645−1,473,934)	835,055 (807,109− 862,422)	1,451,518(1,415,206−1,490,994)	859,433 (831,918−888,195)
	Stroke	Central	2,897,759(2,862,356−2,933,572)	1,989,408(1,957,755−2,023,614)	2,894,476(2,857,322−2,928,761)	2,019,695(1,985,656−2,052,569)
		East	1,635,016(1,604,390−1,666,452)	1,166,149(1,135,143−1,192,614)	1,674,562(1,642,650−1,705,592)	1,249,500(1,219,969−1,277,281)
		North	1,512,628(1,488,675−1,536,426)	1,044,102(1,022,670−1,066,083)	1,542,562(1,520,764−1,565,874)	1,141,362(1,118,516−1,164,129)
		Northeast	576,933(562,761−591,702)	264,880(255,562−273,217)	580,051(566,909−594,491)	256,258(247,343−264,957)
		Northwest	524,131(512,919−534,952)	430,440(419,469−440,682)	529,729(517,994−540,703)	440,257(430,930−450,217)
		South	1,024,580(1,006,117−1,041,922)	626,070(613,184−638,980)	995,327(977,612−1,013,550)	591,710(579,543−604,362)
		Subtotal	8,171,047(8,112,361−8,227,274)	5,521,049(5,469,542− 5,570,697)	8,216,707(8,153,930−8,275,064)	5,698,783(5,647,037− 5,751,956)
	IHD	Central	1,615,329(1,601,388−1,629,674)	1,278,244(1,268,105−1,289,128)	1,616,886(1,602,627−1,630,338)	1,291,823(1,280,616−1,303,193)
		East	1,014,773(1,000,467−1,028,710)	820,795(810,026−831,461)	1,034,273(1,020,591−1,048,177)	850,757(839,236−862,970)
		North	951,341(940,914−961,546)	750,993(743,038−759,030)	967,379(955,759−978,445)	786,134(778,072−794,507)
		Northeast	402,678(397,267−408,094)	280,576(276,317−285,381)	404,150(398,385−409,863)	274,587(269,975−278,978)
		Northwest	264,156(260,580−267,665)	234,337(231,380−237,418)	266,697(263,514−269,950)	238,737(235,792−241,603)
		South	607,226(600,696−614,201)	479,783(474,860−485,079)	599,035(592,333−605,730)	467,646(462,523−472,811)
		Subtotal	4,855,503(4,830,782−4,879,767)	3,844,728(3,825,368−3,862,978)	4,888,419(4,862,291−4,914,803)	3,909,683(3,889,792− 3,930,251)

Note: The number in parentheses indicates the 95% confidence interval of the mean death number or years of life lost. Both scenarios indicate considering both climate change and emission control scenarios.

Abbreviations: COPD=chronic obstructive pulmonary disease; IHD=ischemic heart disease.

decisions of emission control to confront climate change.

$PM_{2.5}$ concentrations show an increasing trend with climate change in this study. Climate change is expected to degrade air quality by changing air pollution meteorology, precipitation, and other removal processes and by triggering some amplifying responses in atmospheric chemistry and in anthropogenic and natural sources, which would shape distributions and extreme episodes of particulate matter (*3*). Following higher $PM_{2.5}$ concentrations triggered by climate change, the attributable deaths and YLLs related to $PM_{2.5}$ would increase in most districts. The largest increasing percentage would be in the east region considering high increment in $PM_{2.5}$ concentrations in this region under climate change scenario. Making policies to rival climate change considering the severe health effects and the burden of diseases caused by it is of vital importance. In this modelling study, the measure of emission control could counteract the health impacts attributable to $PM_{2.5}$ generated by climate change due to reduction of $PM_{2.5}$ concentrations. Among the main types of diseases, stroke had the most noticeable health benefits. The evidence emphasizes the necessity of evaluating the effects of mitigation policies such as emission control on health impacts triggered by climate change, which could verify the effectiveness and evaluate the benefits of the policies and, in turn, inform policymaking decisions.

For different districts, the health benefits of avoiding attributable deaths and YLLs from main types of diseases associated with ambient $PM_{2.5}$ pollution varied. The deaths and YLLs from main types of diseases experienced the largest decreasing percentage in the Northeast region under both the climate change and emission control scenarios, which may result from the large reduction percentage of $PM_{2.5}$ concentration in this region.

This study was the first to estimate the health impacts related to ambient $PM_{2.5}$ from both climate change and air pollution emission control under different scenarios in China, and it provided evidence for policymaking related to climate change and emission control. However, the study was subject to some limitations. First, the emission control scenario was designed based on RCP4.5, which only stands for a moderate level of greenhouse gas emissions. Second, accounting for some factors, such as population structure, would affect the climate-related health burden in the future (*10*), and assuming that the $PM_{2.5}$-mortality association, mortality rate, and population structure were constant at the 2010s levels might lead to some deviations. Further exploration should be performed if data are available.

In summary, the findings suggest the ambient $PM_{2.5}$-related health benefits from air pollution emission control outweighed the influence of climate change. The health impacts of $PM_{2.5}$ related to climate change should be prioritized in the future.

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