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Research article

Spatiotemporal distribution and lag effect of extreme temperature exposure on mortality of residents in Jiangsu, China

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ABSTRACT

Background: With the ever-increasing occurrence of extreme weather events as a result of global climate change, the impact of extreme temperatures on human health has become a critical area of concern. Specifically, it is imperative to investigate the impact of extreme weather conditions on the health of residents.
Methods: In this study, we analyze the daily death data from 13 prefecture-level cities in Jiangsu Province from January 2014 to September 2022, using the distributed lag nonlinear model (DLNM) to comprehensively account for factors such as relative humidity, atmospheric pressure, air pollutants, and other factors to evaluate the lag and cumulative effects of extreme low temperature and high temperature on the death of residents across different age groups. Additionally, we utilize the Geographical Detector to analyze the effects of various meteorological and environmental factors on the distribution of resident death in Jiangsu Province. This provides valuable insights that can guide health authorities in decision-making and in the protection of residents.
Results: The experimental results indicate that both extreme low and high temperatures increase the mortality of residents. We observe that the impact of extreme low temperatures has a delayed effect, peaking after 3–5 days and lasting up to 11–21 days. In contrast, the impact of extreme high temperature is greatest on the first day, and lasts only 2–4 days.
Conclusion: Both extreme high and low temperatures increase the mortality of residents, with the former being more transient and stronger and the latter being more persistent and slower. Furthermore, residents over 75 years of age are more vulnerable to the effects of extreme temperatures. Finally, we note that the spatial distribution of resident deaths is most closely associated consistent with the spatial distribution of daily mean temperature, and there is significant spatial heterogeneity in deaths among residents in Jiangsu Province.

1. Introduction

Global climate change has resulted in more frequent and severe extreme weather events, posing serious threats to human life and health. Climate change is affecting human health in many ways, with a significant increase in the frequency and intensity of extreme

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weather events (e.g., heatwaves, storms and floods), leading to deaths and illnesses that greatly affect public health. This is especially true for vulnerable populations that are sensitive to the environmental climate, such as women, children, poor communities, the elderly and patients with underlying diseases. Extreme temperatures affect the health of the population not only in terms of temperature-induced related illnesses, but also in terms of deaths of inhabitants through the triggering or aggravation of diseases they themselves suffer from. Studies have shown that heat-related deaths increased by four times from 1990 to 2019 [1]. Moreover, elderly people aged 65 and above are more vulnerable to death from extreme temperatures than other age groups, as high or low temperatures can worsen their existing health conditions and cause fatalities [2–4].

The Global Burden of Disease Study has identified non-optimal temperatures as one of the major risk factors for global mortality [5]. A globally based study suggests that 9.4 % of deaths are caused by extreme low and high temperatures [6]. Studies in the United States, Europe, Latin America, India and other parts of the globe have also shown that extreme temperatures have a significant impact

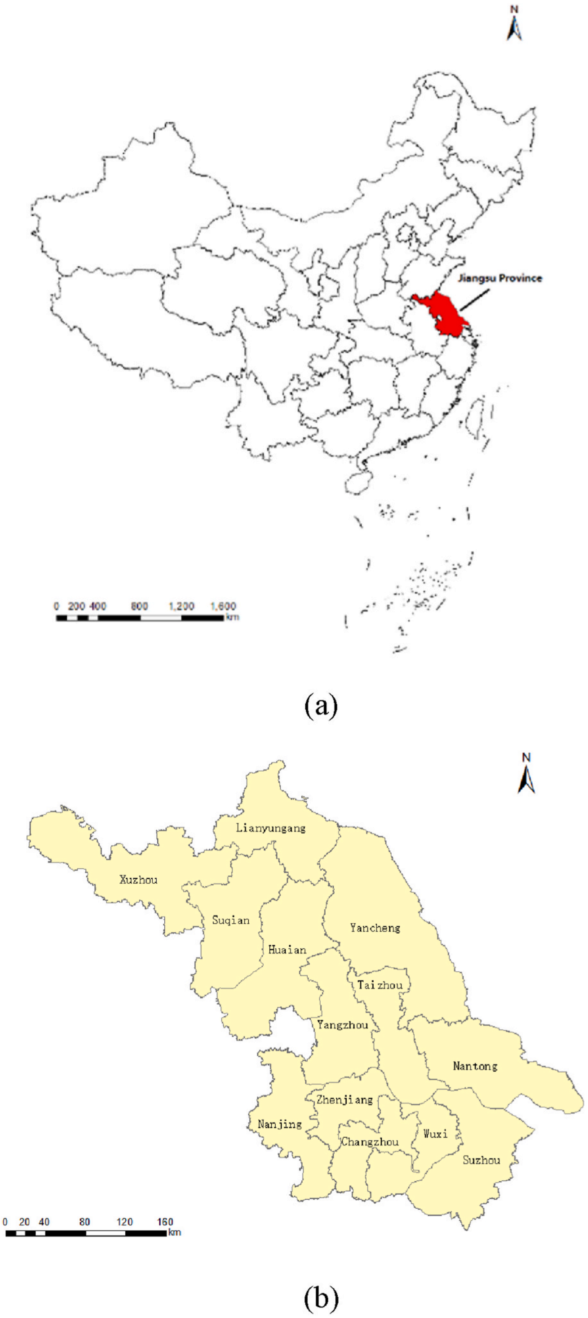


Fig. 1. Geographic Location Map of Jiangsu Province and 13 prefecture level cities.

on mortality, with extreme low and high temperatures leading to varying increases in mortality [7–11]. In China, extreme weather occurs frequently and lasts for a long time, especially extreme high temperatures, which can cause fatal harm to the elderly fragile population in terms of morbidity rates of chronic diseases, medication adherence rates, as well as physiological and behavioral response disorders [12–15]. For regions with dense populations and relatively high economic levels, the public health hazards and economic losses caused by extreme temperatures are even greater. Situated within the Yangtze River Delta economic zone, China's Jiangsu Province boasts a robust economy and substantial urbanization. As one of the provinces with the highest level of overall development in China, it holds a crucial position in the country's social progress. Nevertheless, with a sizable resident population, particularly a significant elderly demographic, the province faces heightened vulnerability to extreme temperatures. Therefore, accurately estimating the impact of extreme temperatures on human health risks in Jiangsu Province is essential to address the health threats arising from the climate crisis and evaluate the health benefits of tackling climate change. Previous studies have predominantly focused on individual cities, limiting the ability to capture the broader relationship between public health and temperature extremes on a larger scale. Moreover, most research has concentrated on assessing the health effects of high-temperature heatwaves, with less emphasis placed on the consequences of extreme low temperatures.

To address the issues mentioned above, this paper uses the distributed lag nonlinear model (DLNM) based on data from 13 cities in Jiangsu Province and incorporates various meteorological and environmental factors to quantitatively describe the temperature-death relationships for residents in 13 cities and age groups, and to assess the health risks associated with extreme temperatures in different cities for residents of different age groups. We also use the geographical detectors to analyze the impact of various environmental factors on the distribution of deaths among residents in Jiangsu Province, which provides a basis and theoretical support for public health departments to evaluate the protection of key populations in order to minimize the harm caused by extreme temperatures to residents.

2. Materials and method

2.1. Study area

Jiangsu is located on the eastern coast of mainland China (Fig. 1(a)), covering a total area of 107,200 square kilometers, and stretching from 116°18′-121°57′ E and 30°45-35°20′ N. The region spans from north to south and belongs to the East Asian monsoon climate zone. The Huai River and Main Irrigation Channel of North Jiangsu demarcate the boundary, with the area north of the Huai River characterized by a warm temperate humid and semi-humid monsoon climate; while the area south of the Huai River has a subtropical humid monsoon climate. The study area encompasses 13 prefecture-level cities in Jiangsu Province namely Xuzhou, Lianyungang, Suqian, Huai'an, Yancheng, Nanjing, Yangzhou, Taizhou, Zhenjiang, Nantong, Changzhou, Wuxi, and Suzhou (Fig. 1 (b)). Jiangsu has a total population of is 84,748,000, with 16.8 % of the population aged over 65 years. The region has entered the stage of deep aging [16].

2.2. Pollutant and meteorological data

The study mainly requires four types of data, including meteorological data, air pollution data, population death data, and administrative map data. The death data were obtained from Health Information Platform of Jiangsu Province, which provides daily death data for 13 cities in Jiangsu Province from January 1, 2014 to September 30, 2022, categorized by age group (under 65, 65–75, and over 75). The pollutant data used in this study were acquired from the real-time national urban air quality release platform of the China National Environmental Monitoring Centre (http://www.cnemc.cn/). The platform provides daily data on $PM_{2.5}$, SO_2, NO_2, and O_3 for the 13 cities. The meteorological data for the same period were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation global atmospheric reanalysis (ERA5), including mean temperature, dew point temperature, atmospheric pressure, and other related variables. The daily data of daily mean temperature, atmospheric pressure, relative humidity, and other parameters for the 13 meteorological stations were obtained by calculation and interpolation. The administrative zone map data were obtained from the Yangtze River Delta Science Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://geodata.nnu.edu.cn/).

2.3. Statistical analysis

The non-linear curves are commonly observed in the temperature-death exposure-response relationship, and they often exhibit U-, V- or J-shaped distributions, and significant lagged effects [17]. To investigate the effects of lagged exposures on the risk of residential death, we utilized the DLNM to assess the relationship between temperature and death. Specifically, we evaluated the impact of temperature on both the regular exposure-response relationship and the additional lagged response relationship for residents. Daily resident death is characterized by a low probability of occurrence and follows the Poisson distribution. To overcome the problem of overdispersion, we used a quasi-Poisson model as the connecting function to analyze the influence of temperature on resident death. The model incorporates various factors, including relative humidity, air pollutants, long-term trends, weekly effects, and atmospheric pressure [18–20].

To analyze the spatial distribution differences of resident deaths in Jiangsu Province, we used a geographic detector to analyze the impact of meteorological factors and air pollutants on the distribution of resident deaths. The geographical detector, as a spatial analysis method, does not require assumptions and restrictions on the number of resident deaths and environmental impact factors

[21]. Through the concept of the power of determinant (PD), it includes four detectors: factor detector, risk detector, interaction detector, and ecological detector, to explore the impact of influencing factors on the spatial distribution of resident deaths from multiple perspectives. One major advantage of the geographic detector compared to other classical regression models is that it can handle both quantitative and qualitative data without restrictions on the number of categories.

The principle of minimizing the QAIC minimum was applied in this study to determine the degree of freedom for time, which was set to 7/year, representing one day in a week, and controlling for seasonal and long-term trends [22–25]. The maximum lag days of the crossbasis matrix were set to 21 days, covering the period of extreme low and high temperatures on the population, while the degrees of freedom for relative humidity, atmospheric pressure, SO_2, NO_2, $PM_{2.5}$, and O_3 were set to 3. The median daily mean temperature was used as the reference temperature for the model, and P2.5 and P97.5 of the daily mean temperature were used as extreme low and high temperatures to assess the effect of cold and heat on death [26,27].

The 'dlnm' package in R(version:4.2.1) was utilized for data processing and statistical analysis. The DLNM was constructed using this package, and a two-sided P-value <0.05 was set as the level of statistical significance. The geographic detector is implemented through the Excel- GeoDetector software.

Table 1

Meteorological factor, air pollutant concentration and daily death in 13 cities of Jiangsu Province from January 2014 to September 2022.

Regions	Temperature(°C)					Atmospheric Pressure (hPa)			Relative Humidity (%)		
	$\bar{x}\pm s$	Min	Max	$P_{2.5}$	$P_{97.5}$	$\bar{x}\pm s$	Min	Max	$\bar{x}\pm s$	Min	Max
Xuzhou	15.9 ± 9.7	−10.2	32.9	−0.9	30.5	1011.1 ± 9.7	985.9	1038.0	67.7 ± 15.0	22.9	98.7
Lianyungang	15.5 ± 9.5	−10.5	33.0	−0.8	30.0	1015.5 ± 9.7	984.6	1041.1	69.6 ± 14.6	24.5	97.7
Suqian	15.9 ± 9.6	−10.6	33.1	−0.7	30.5	1014.1 ± 9.7	986.1	1040.6	71.1 ± 13.5	26.9	99.4
Huai'an	16.1 ± 9.3	−9.1	33.7	−0.3	30.7	1015.8 ± 9.6	986.0	1041.8	71.4 ± 13.4	25.9	99.5
Yancheng	16.0 ± 9.1	−9.1	33.3	0.0	30.4	1016.6 ± 9.5	986.1	1041.6	72.1 ± 13.5	26.7	98.1
Nanjing	17.1 ± 9.0	−6.9	35.2	1.3	31.4	1015.3 ± 9.4	988.0	1040.7	74.2 ± 12.4	34.9	99.9
Yangzhou	16.7 ± 9.0	−7.4	34.4	0.9	31.0	1014.4 ± 9.5	986.8	1040.1	73.6 ± 12.7	30.8	99.2
Taizhou	16.6 ± 9.0	−7.8	34.6	0.7	30.9	1015.8 ± 9.5	987.2	1041.2	73.1 ± 13.0	28.6	99.6
Zhenjiang	16.8 ± 9.0	−7.2	34.6	1.1	31.2	1014.3 ± 9.4	986.9	1039.9	74.3 ± 12.4	32.7	99.4
Nantong	17.0 ± 8.8	−7.2	35.4	1.9	31.3	1016.1 ± 9.3	988.8	1040.4	75.5 ± 11.6	32.1	98.2
Changzhou	17.3 ± 9.0	−6.6	35.3	1.5	31.7	1015.9 ± 9.4	988.3	1041.4	74.7 ± 12.0	36.4	100
Wuxi	17.5 ± 8.9	−6.3	35.4	1.9	31.9	1015.2 ± 9.3	987.7	1040.1	74.4 ± 11.7	35.1	99.6
Suzhou	17.7 ± 8.8	−5.9	35.3	2.4	31.8	1015.3 ± 9.2	986.2	1040.0	74.9 ± 11.4	36.7	98.4

Regions	O_3(μg/m3)			$PM_{2.5}$(μg/m3)			NO_2(μg/m3)			SO_2(μg/m3)		
	$\bar{x}\pm s$	Min	Max	$\bar{x}\pm s$	Min	Max	$\bar{x}\pm s$	Min	Max	$\bar{x}\pm s$	Min	Max
Xuzhou	65.6 ± 33.3	5.8	190.3	57.6 ± 39.1	3.2	293.0	37.2 ± 16.5	7.0	121.5	21.3 ± 16.7	3.9	131.5
Lianyungang	74.0 ± 32.0	1.4	201.2	45.3 ± 34.9	2.9	301.0	29.8 ± 15.2	3.9	115.0	17.2 ± 14.2	2.0	125.0
Suqian	71.0 ± 33.0	5.3	185.5	51.2 ± 35.0	4.3	271.0	29.3 ± 15.4	2.9	134.0	13.6 ± 11.5	1.8	112.0
Huai'an	72.2 ± 31.3	5.0	203.5	49.3 ± 34.8	5.1	370.0	26.1 ± 14.0	2.0	96.5	13.7 ± 10.4	2.8	86.4
Yancheng	77.8 ± 27.3	9.9	171.1	40.9 ± 31.6	3.0	220.8	23.9 ± 13.5	2.8	99.8	10.8 ± 8.4	1.4	72.9
Nanjing	66.5 ± 31.0	5.8	181.9	44.1 ± 32.2	4.7	297.0	41.5 ± 19.0	5.5	130.0	13.0 ± 9.3	3.0	79.0
Yangzhou	69.4 ± 30.1	4.4	178.1	47.0 ± 32.1	3.6	255.0	31.1 ± 17.9	1.8	127.0	16.7 ± 14.4	1.4	99.0
Taizhou	69.7 ± 27.1	3.6	171.8	49.0 ± 32.6	5.4	240.4	27.7 ± 16.3	3.0	114.3	14.5 ± 11.7	2.1	98.2
Zhenjiang	66.8 ± 30.0	3.1	175.9	49.6 ± 32.0	4.2	263.0	36.5 ± 17.4	4.2	137.8	14.6 ± 10.9	2.2	104.2
Nantong	71.9 ± 26.3	6.0	178.8	42.1 ± 29.6	3.8	240.0	32.7 ± 19.5	2.1	119.9	17.2 ± 13.7	2.0	131.4
Changzhou	66.3 ± 30.8	4.0	178.9	48.9 ± 31.6	5.8	264.6	40.9 ± 17.8	6.5	147.7	17.6 ± 12.6	4.0	96.9
Wuxi	65.3 ± 31.4	3.1	189.0	44.9 ± 29.3	4.3	235.2	39.7 ± 18.1	5.4	131.0	14.3 ± 10.4	3.0	88.0
Suzhou	64.2 ± 29.8	3.8	184.3	43.2 ± 29.5	3.3	232.0	43.2 ± 20.5	3.2	155.8	12.0 ± 9.2	2.0	64.8

Regions	0-64 (y)				65-74 (y)				≥75(y)			
	$\bar{x}\pm s$	Min	Max	%	$\bar{x}\pm s$	Min	Max	%	$\bar{x}\pm s$	Min	Max	%
Xuzhou	40.4 ± 9.9	7	91	24.17	35.0 ± 9.0	6	78	20.91	91.9 ± 27.6	20	244	54.92
Lianyungang	20.0 ± 6.0	3	51	26.05	15.9 ± 5.7	1	41	20.72	40.8 ± 14.3	8	124	53.22
Suqian	21.1 ± 5.8	4	46	23.34	18.0 ± 5.3	2	41	19.85	51.4 ± 15.8	11	139	56.81
Huai'an	21.5 ± 5.4	6	48	23.94	19.6 ± 5.3	6	44	21.80	48.7 ± 14.3	14	126	54.26
Yancheng	35.3 ± 7.8	12	80	22.80	34.1 ± 8.3	12	84	22.08	85.2 ± 25.3	26	275	55.12
Nanjing	25.3 ± 5.4	9	57	21.47	23.6 ± 5.7	8	55	20.03	69.0 ± 14.8	32	135	58.51
Yangzhou	18.6 ± 4.9	4	55	19.04	23.0 ± 6.4	5	66	23.58	56.0 ± 16.9	14	240	57.37
Taizhou	18.7 ± 5.3	4	48	18.76	22.0 ± 6.9	4	57	22.01	59.2 ± 20.7	16	230	59.24
Zhenjiang	12.4 ± 3.7	2	29	21.13	13.6 ± 4.1	2	29	23.19	32.5 ± 8.5	11	77	55.68
Nantong	33.5 ± 7.1	12	72	17.76	36.6 ± 8.2	11	70	19.38	118.6 ± 32.1	44	294	62.86
Changzhou	16.0 ± 4.5	3	35	21.64	15.6 ± 5.0	1	35	21.03	42.5 ± 12.4	13	85	57.33
Wuxi	20.8 ± 5.3	6	58	20.99	20.5 ± 6.1	4	40	20.67	57.7 ± 16.0	16	125	58.33
Suzhou	29.3 ± 5.9	12	64	20.47	26.6 ± 6.4	9	58	18.56	87.3 ± 21.3	41	190	60.97

3. Results

3.1. Descriptive analysis

From January 1, 2014 to September 30, 2022, the daily average number of resident deaths in Jiangsu Province was 1457, with an average daily number of deaths of deaths of 312, 303 and 840 for individuals under 65, 65–75 and over 75 years old, respectively. Among all age groups, the minimum number of deaths occurred in Zhenjiang, while the maximum number of deaths for individuals under 65 years old was observed in Xuzhou, and for those between 65 and 75 years old, as well as over 75 years old, it was found in Nantong. Table 1 shows a summary of the daily deaths, daily mean temperature, relative humidity, atmospheric pressure, $PM_{2.5}$, NO_2, SO_2 and O_3 levels in 13 cities in Jiangsu Province over the same period. The P2.5 and P97.5 of the daily mean temperature were used as extreme low and high temperatures respectively to evaluate the impact of cold and heat effects on death. The extreme low temperature ranged from −0.9 °C to 2.4 °C, with the lowest recorded in Xuzhou and the highest Suzhou. The extreme high temperature varied from 30.0 °C to 31.9 °C, with the lowest observed in Lianyungang and the highest in Wuxi. The standard deviation of daily deaths was higher for individuals over 75 years old than for other age groups, indicating that daily deaths among this group are unstable and vary widely from day to day.

The total number of resident deaths and number of resident deaths over 75 years of age in 13 cities exhibited a clear temporal pattern (Fig. 2(a–n)). Deaths among residents aged 65–75 do not exhibit a clear temporal trend. In contrast, resident deaths among individuals under 65 years were unaffected by temperature fluctuations. These findings suggest that temperature primarily affects the elderly population, particularly those over 75 years of age. Indeed, resident deaths among individuals over 75 years displayed seasonal variations that corresponded with temperature changes. Overall, lower temperatures during winter months (January–February) were associated with higher and more prolonged total mortality rates. The effects of low temperatures on residents were gradual and sustained. Conversely, higher temperatures during summer months (June–July) were associated with lower total mortality rates. However, it can be seen from the figures that the summer months in 2016, 2017 and 2022 revealed spikes in single-day death that exceeded those observed during winter months. This suggests that extreme heat has a more potent impact than low temperature.

3.2. Lagged effects of extreme temperatures on resident mortality

Fig. 3(a–n) illustrates the relationship between the daily mean temperature, the number of lag days and the mortality risk across 13 cities and Jiangsu Province. The three-dimensional graph reveals a ‘U’ shaped distribution between daily mean temperature and mortality risk. High temperature was associated with the greatest mortality risk on the first day, but this risk rapidly declined within

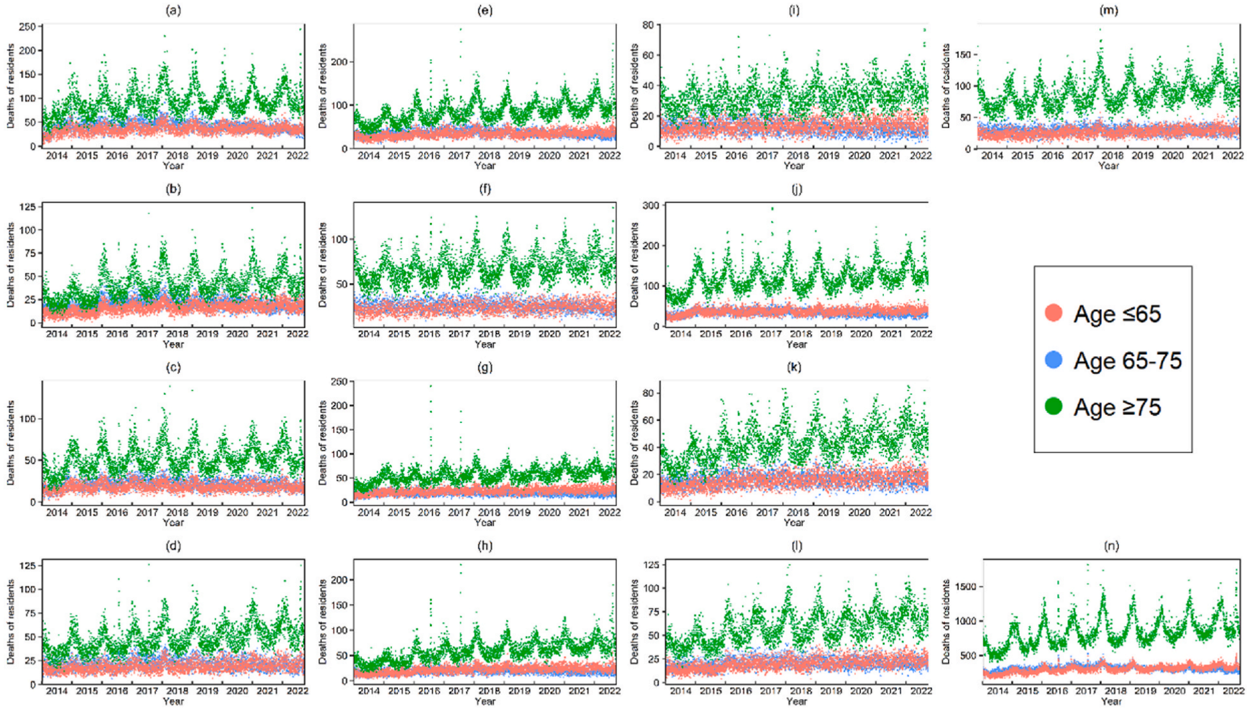


Fig. 2. Change of death toll in 13 cities of Jiangsu Province from January 2014 to September 2022.
Note:(a) Xuzhou, (b) Lianyungang, (c) Suqian, (d) Huai'an, (e) Yancheng, (f) Nanjing, (g) Yangzhou, (h) Taizhou, (i) Zhenjiang, (j) Nantong, (k) Changzhou, (l) Wuxi, (m) Suzhou, (n) Jiangsu Province.

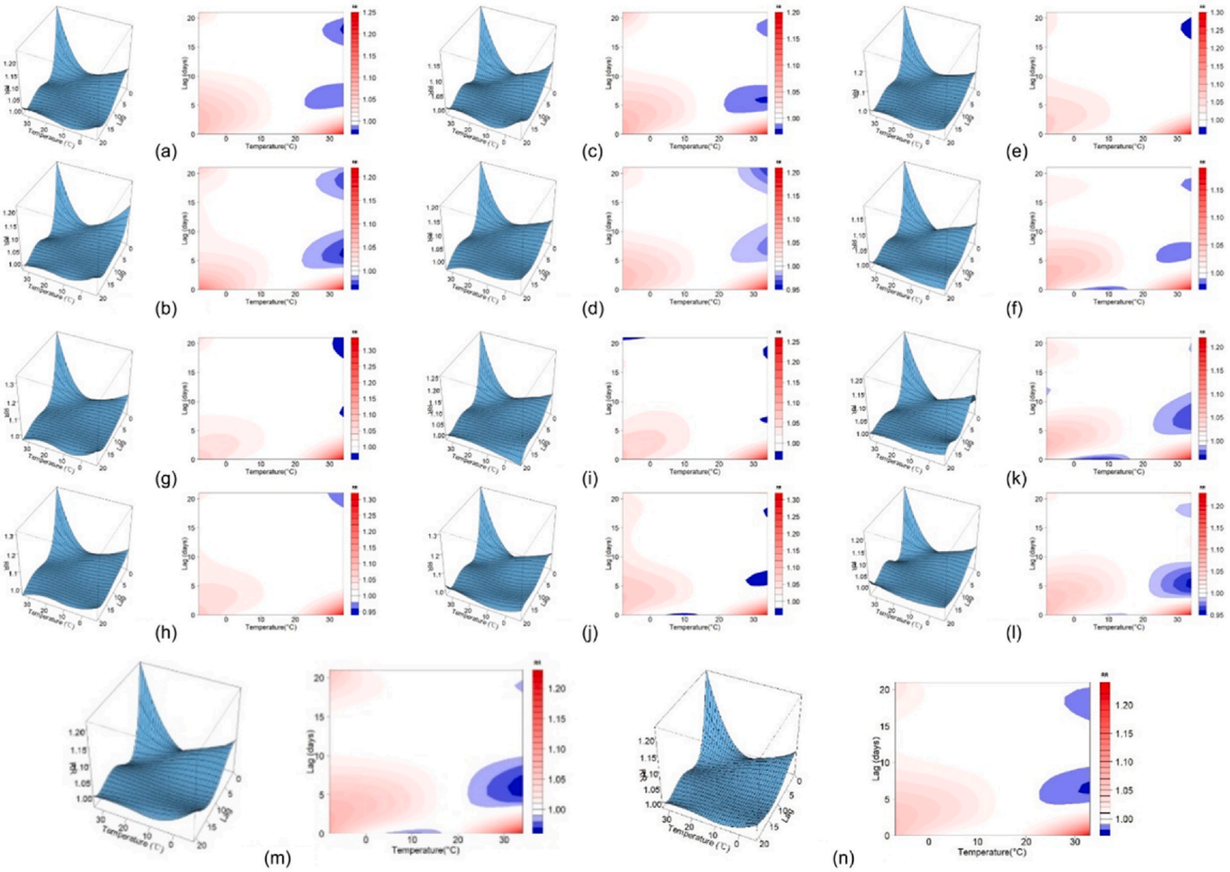


Fig. 3. Association Chart of daily average temperature, lagging days and resident death risk.
Note:(a) Xuzhou, (b) Lianyungang, (c) Suqian, (d) Huai'an, (e) Yancheng, (f) Nanjing, (g) Yangzhou, (h) Taizhou, (i) Zhenjiang, (j) Nantong, (k) Changzhou, (l) Wuxi, (m) Suzhou, (n) Jiangsu province.

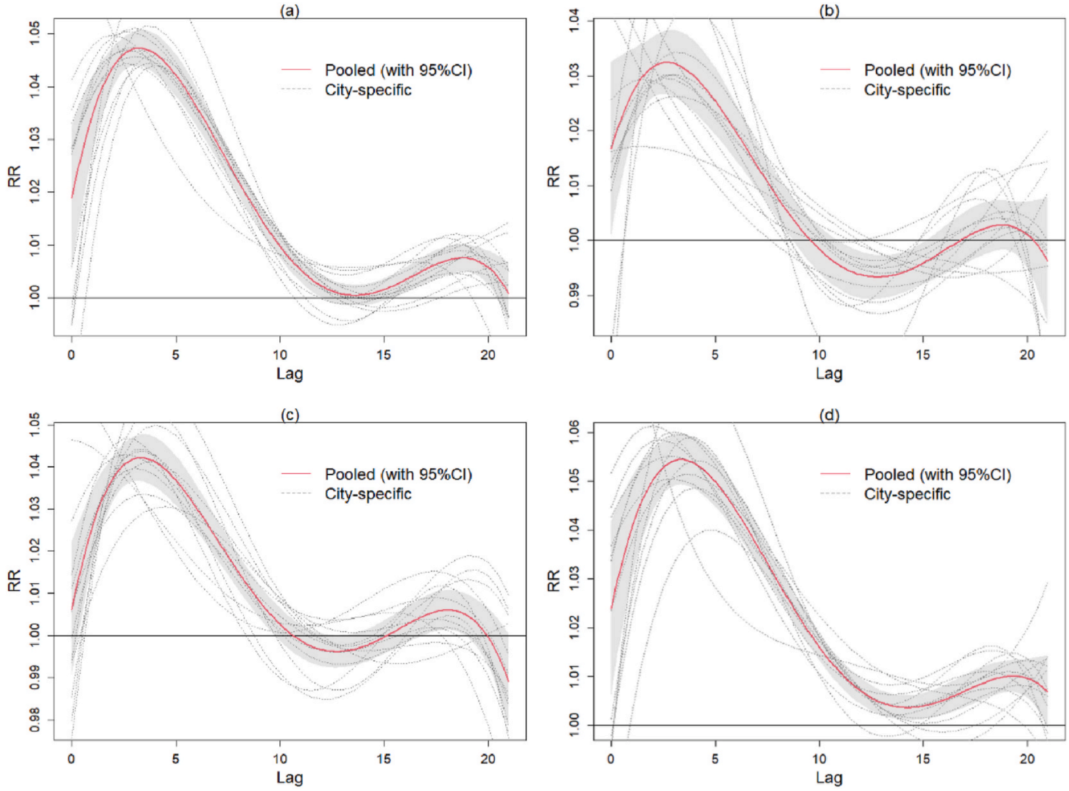
2–4 days. In contrast, the effects of low temperatures were more enduring, persisting for more than 10 days.

Fig. 4-1(a-d) and Fig. 4-2(a-d) illustrate the lagged effects of extreme high and low temperatures on death among different age groups in 13 cities within Jiangsu Province. For the entirety of Jiangsu Province, mortality risk across all age groups reaches its zenith on the first day of extreme heat. This is succeeded by a swift reduction, with a sustained impact lasting approximately five days. In the context of individual cities, with the exception of individuals under the age of 65 in Lianyungang and Suqian, the highest mortality risk due to extreme high temperatures is encountered on the very first day across all cities and age cohorts. This risk rapidly declined thereafter, with slightly different but shorter lag times. Suzhou and Wuxi had the shortest duration of high temperature effects at 2 days for all age groups, while Yancheng, Yangzhou and Taizhou had the longest duration at up to 4 days. Across all cities, individuals over 65 years old were affected by extreme heat for the longest duration. In contrast, individuals under 65 years and those aged 65–75 years were affected for approximately the same duration.

The impact of extreme low temperatures typically peaked after 3–5 days before gradually declining. The duration of the effects ranged from 11 to 21 days depending on the extreme low temperature value. Individuals over 75 years old experienced significantly longer durations of low temperature effects compared to other age groups. The highest relative risk values for extreme high temperatures were considerably higher than those for extreme low temperatures. This indicates that the effects of extreme high temperatures are more potent than those of extreme low temperatures.

3.3. Accumulated risk analysis of the impact of extreme temperatures on resident mortality

Table 2 shows the cumulative relative risk(CRR) values for the impact of extreme temperatures on death across 13 cities in Jiangsu Province. It can be seen from the table that in Jiangsu Province, the impact of extreme low temperatures on each age group is greater than that of extreme high temperatures, and the older the age, the greater the harm from extreme temperatures. Among these cities, Changzhou had the lowest CRR for the effects of extreme low temperatures (CRR = 1.29, 95 % CI: 1.16–1.44), while Suqian had the highest temperatures (CRR = 1.55, 95 % CI: 1.37–1.75). The lowest CRR for extreme low temperatures was observed among individuals under 65 years of age in Taizhou (CRR = 1.06, 95 % CI: 0.85–1.32), while the highest CRR was observed among individuals



Figs. 4–1. Lagging effect of extreme low temperature ($P_{2.5}$) on death of residents of all ages in 13cities (reference temperature: median).

over 75 years old in Lianyungang city (CRR = 1.76, 95 % CI: 1.48–2.08).

Across all 13 cities, individuals the over 75 years had higher CRR values than other age groups. Except for Xuzhou, Huai'an, Changzhou and Zhenjiang, individuals aged 65–75 years had higher CRR values than those under 65 years in the remaining nine cities. These findings indicate that the elderly population is more susceptible to the effects of extreme low temperatures.

Analyzing the broader perspective encompassing the entirety of Jiangsu Province, the cumulative relative risk value regarding the influence of extreme temperatures highlights the most significant value among individuals aged 75 and above. In contrast, the lowest value is observed within the age group under 65. Remarkably, with the cumulative relative risk value of the impact of extreme low temperatures being higher than that of extreme high temperatures for the same age group.

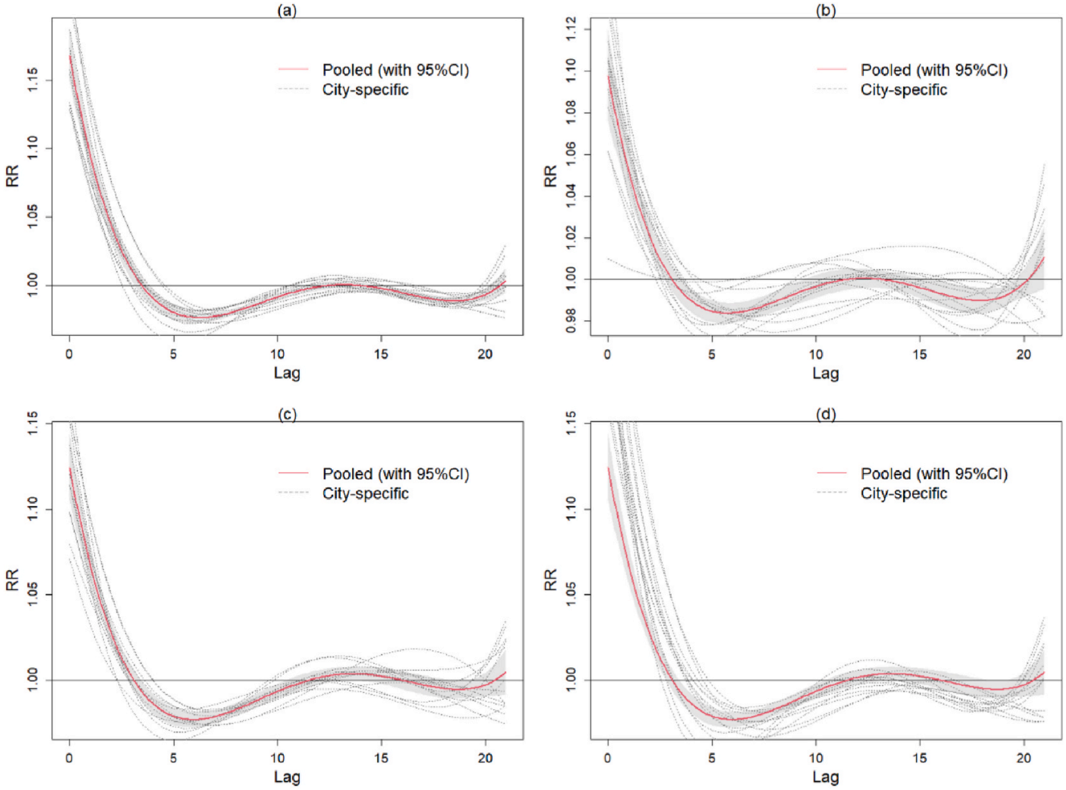
3.4. *Sensitivity analysis*

To verify the stability of the model, the following sensitivity tests were conducted: 1. We only added air pollutants to the model one by one. 2. The relative humidity, atmospheric pressure, and degrees of freedom of air pollutants (4 or 5) were altered. As shown in Table 3, compared to the base model, the changes in the above parameters did not have a significant impact on the model results, indicating that the model exhibits a certain level of stability.

3.5. *The impact of environmental factors on the distribution of resident death*

A geographical detector was employed to analyze the influence of daily mean temperature, relative humidity, atmospheric pressure, SO_2, NO_2, $PM_{2.5}$ and O_3 on the resident death distribution. Geographical detectors are a set of statistical methods designed to detect spatial heterogeneity and reveal its driving forces. These methods include factor detector, risk detector, interaction detector and ecological detector.

In this study, factor detectors were utilized to detect spatial heterogeneity in resident death and to determine the extent to which various factors contributed to the spatial heterogeneity [28,29]. Table 4 shows the explanatory power of each factor in detecting the effect on resident death. It can be seen that the daily mean temperature exhibited the strongest explanatory power, followed by atmospheric pressure, while O_3 and $PM_{2.5}$ had the weakest explanatory power. This indicates that the spatial distribution of resident death is most closely aligned with the spatial distribution of daily mean air temperature, while pollutant factors such as O_3 and $PM_{2.5}$ have minimal influence on the spatial distribution of resident death. Table 5 shows the impact of mean daily temperature on the number of deaths in Jiangsu Province. The relationship between temperature and mortality risk shows a "U" shape, with a risk of death



Figs. 4–2. Lagging effect of extreme high temperature ($P_{97.5}$) on death of residents of all ages in 13cities(reference temperature: median)
Note:(a) All residents, (b) Residents under 65, (c) Residents aged 65–75, (d) Residents over 75.

at 195.17 when the daily mean temperature exceeds 35 °C, 150.55 when it falls below −5 °C, and the lowest risk of death at 103.46 when it ranges between 15 and 22 °C.

The interaction detector was employed to determine the interaction between various meteorological and pollutant factors. It was used to compare the explanatory power of the two factors acting together on resident death versus acting alone and to analyze whether the interaction tended to be stronger or weaker [30,31]. Table 6 shows an assessment of the impact of the interaction between meteorological and pollutant factors on resident death. The combination of each factor with others increased their effect on resident mortality, with the largest interaction occurring between daily mean temperature and SO_2 at 0.069 and the smallest interaction between O_3 and $PM_{2.5}$ at 0.009. The combination of different factors significantly elevated the risk of resident mortality.

The risk detector was utilized to detect whether there was significant variability in resident death between cities [32]. Table 7 compares the differences in residential mortality risk among 13 cities and reveals that, except for Suqian and Huai'an, the remaining cities exhibited heterogeneity in terms of residential mortality risk. This heterogeneity is attributed to differences in meteorological and pollutant factors between the cities, particularly in daily mean temperature. The spatial heterogeneity in death distribution in Jiangsu is due to the variability of meteorological and pollutant conditions between cities, given the country's large geographical area.

4. Discussion

In this study, we utilized the DLNM to analyze the relationship between temperature and death among residents of 13 prefecture-level cities in Jiangsu Province across different age groups. The daily mean temperature served as the primary variable for the model. Additionally, we employed the geographical detector to investigate the effects of various meteorological and pollutant factors such as daily mean temperature, relative humidity, atmospheric pressure, NO_2, SO_2, $PM_{2.5}$ and O_3 on the distribution of resident death of Jiangsu Province.

The results revealed a non-linear relationship between daily mean temperature and death across all age groups. The effects of extreme low temperatures were slower, with a peak after 3–5 days, and lasting longer, typically 11–21 days or more. In contrast, the effects of extreme high temperatures were more rapid, typically peaking on the first day, but the duration of the high temperature effects was shorter, typically only lasting 2–4 days. In addition, in overall terms, extreme low temperatures have a greater impact on mortality in the resident population than do extreme high temperatures. These findings are consistent with previous studies [33,34]. Jiangsu Province is geographically located in the East Asian monsoon climate zone and has a generally warm and humid climate. Due to the province's higher overall economic level and urbanization rate more widespread use of cooling equipment such as air

Table 2

Cumulative relative risk value of the impact of extreme temperature on resident death in 13 cities of Jiangsu Province.

Regions	Age group	Cumulative Relative Risk (CRR，95%CI)	
		Extreme low temperature (P2.5)	Extreme high temperature (P97.5)
Xuzhou	All	1.51(1.34–1.71)	1.13(1.02–1.25))
	Under 65	1.31(1.11–1.55)	1.00(0.87–1.15)
	65–75	1.26(1.05–1.50)	1.07(0.92–1.24)
	Over 75	1.70(1.48–1.96)	1.23(1.08–1.38)
Lianyungang	All	1.54(1.35–1.76)	0.99(0.88–1.11)
	Under 65	1.25(1.00–1.56)	1.08(0.91–1.30)
	65–75	1.39(1.09–1.76)	0.84(0.69–1.02)
	Over 75	1.76(1.48–2.08)	1.02(0.88–1.18)
Suqian	All	1.55(1.37–1.75)	1.11(1.00–1.24)
	Under 65	1.36(1.10–1.67)	1.11(0.94–1.31)
	65–75	1.51(1.21–1.88)	0.98(0.81–1.17)
	Over 75	1.63(1.40–1.89)	1.18(1.04–1.34)
Huai'an	All	1.43(1.28–1.60)	1.03(0.95–1.13)
	Under 65	1.18(0.97–1.45)	0.96(0.82–1.12)
	65–75	1.17(0.95–1.45)	1.12(0.95–1.32)
	Over 75	1.67(1.44–1.92)	1.04(0.92–1.17)
Yancheng	All	1.48(1.34–1.64)	1.23(1.14–1.34)
	Under 65	1.20(1.02–1.42)	1.15(1.02–1.31)
	65–75	1.36(1.15–1.61)	1.07(0.94–1.21)
	Over 75	1.65(1.45–1.87)	1.36(1.22–1.50)
Nanjing	All	1.40(1.28–1.53)	1.17(1.09–1.26)
	Under 65	1.19(1.00–1.41)	1.02(0.89–1.17)
	65–75	1.20(1.00–1.44)	1.26(1.09–1.46)
	Over 75	1.55(1.39–1.73)	1.21(1.10–1.32)
Yangzhou	All	1.46(1.30–1.64)	1.29(1.18–1.42)
	Under 65	1.13(0.92–1.40)	1.11(0.94–1.30)
	65–75	1.25(1.03–1.51)	1.20(1.03–1.39)
	Over 75	1.67(1.44–1.93)	1.40(1.25–1.58)
Taizhou	All	1.45(1.29–1.63)	1.35(1.23–1.48)
	Under 65	1.06(0.85–1.32)	1.06(0.90–1.25)
	65–75	1.22(1.00–1.49)	1.22(1.05–1.43)
	Over 75	1.68(1.45–1.93)	1.52(1.36–1.71)
Zhenjiang	All	1.47(1.30–1.66)	1.14(1.03–1.26)
	Under 65	1.29(1.01–1.66)	1.14(0.94–1.38)
	65–75	1.25(0.99–1.58)	0.98(0.81–1.18)
	Over 75	1.64(1.40–1.93)	1.22(1.07–1.39)
Nantong	All	1.52(1.39–1.66)	1.31(1.21–1.40)
	Under 65	1.13(0.97–1.33)	1.12(1.00–1.27)
	65–75	1.24(1.07–1.45)	1.26(1.12–1.42)
	Over 75	1.73(1.55–1.93)	1.39(1.27–1.51)
Changzhou	All	1.29(1.16–1.44)	1.11(1.01–1.21)
	Under 65	1.18(0.94–1.47)	1.09(0.92–1.29)
	65–75	1.15(0.92–1.44)	1.15(0.97–1.37)
	Over 75	1.40(1.21–1.60)	1.10(0.98–1.23)
Wuxi	All	1.42(1.29–1.57)	1.08(0.99–1.17)
	Under 65	1.20(0.99–1.46)	1.13(0.97–1.32)
	65–75	1.21(0.99–1.47)	1.03(0.88–1.20)
	Over 75	1.59(1.40–1.79)	1.07(0.97–1.19)
Suzhou	All	1.42(1.30–1.55)	1.11(1.03–1.19)
	Under 65	1.10(0.93–1.30)	0.98(0.87–1.12)
	65–75	1.40(1.18–1.67)	1.05(0.92–1.21)
	Over 75	1.53(1.37–1.71)	1.18(1.08–1.29)
Jiangsu Province	All	1.43(1.34–1.52)	1.18(1.12–1.24)
	Under 65	1.18(1.10–1.26)	1.08(1.03–1.14)
	65–75	1.26(1.17–1.36)	1.11(1.05–1.18)
	Over 75	1.59(1.48–1.72)	1.25(1.18–1.33)

The city that exhibited the lowest CRR value for the impact of extreme high temperatures was Lianyungang (CRR = 0.99, 95 % CI: 0.88–1.11). In contrast, Taizhou had the highest CRR value (CRR = 1.35, 95 % CI: 1.23–1.48). Among age groups, individuals aged 65–75 in Lianyungang had the lowest CRR value for extreme high temperatures (CRR = 0.84, 95 % CI: 0.69–1.02), while those aged over 75 in Taizhou had the highest CRR value (CRR = 1.52, 95 % CI: 1.36–1.71).

conditioners, residents have a certain degree of adaptability to high temperatures [35,36]. The greater impact of extreme low temperatures may be attributed to the fact that the maximum risk level for the impact of low temperatures tends to arrive a few days later and its duration is longer. Residents tend to pay attention to keeping warm only on the day of the low temperature, and not enough during the impact period after the low temperature has passed. This finding also reminds residents that protection against low temperatures should last for 10 days or more.

Table 3
Sensitivity analysis of the impact of extreme temperatures on residential mortality in Jiangsu Province.

Age group	CRR,95%CI						
	Model	Air pollution				Adjustment of df	
		Only PM2.5	Only NO2	Only SO2	Only O3	4	5
Extreme low temperature (P2.5)							
All	1.43(1.34–1.52)	1.42(1.33–1.52)	1.43 (1.35–1.53)	1.43(1.35–1.53)	1.47 (1.38–1.56)	1.43 (1.34–1.53)	1.43 (1.35–1.53)
Under 65	1.18(1.10–1.26)	1.18(1.11–1.26)	1.18 (1.1–1.26)	1.18(1.11–1.26)	1.2 (1.12–1.28)	1.18 (1.10–1.26)	1.18 (1.11–1.26)
65–75	1.26(1.17–1.36)	1.25(1.16–1.35)	1.27 (1.18–1.36)	1.26(1.17–1.36)	1.29 (1.2–1.38)	1.25 (1.17–1.36)	1.26 (1.17–1.36)
Over 75	1.59(1.48–1.72)	1.57(1.46–1.69)	1.6 (1.48–1.72)	1.6 (1.48–1.72)	1.64 (1.53–1.77)	1.6 (1.48–1.72)	1.62 (1.49–1.72)
Extreme high temperature (P97.5)							
All	1.18(1.12–1.24)	1.2 (1.15–1.26)	1.21 (1.15–1.27)	1.2 (1.14–1.26)	1.17 (1.11–1.23)	1.16 (1.11–1.24)	1.18 (1.12–1.24)
Under 65	1.08(1.03–1.14)	1.08(1.03–1.13)	1.09 (1.03–1.14)	1.08(1.02–1.13)	1.07 (1.01–1.12)	1.09 (1.03–1.15)	1.08 (1.02–1.14)
65–75	1.11(1.05–1.18)	1.13 (1.07–1.2)	1.13 (1.07–1.2)	1.13 (1.07–1.2)	1.11 (1.05–1.17)	1.11 (1.04–1.17)	1.11 (1.04–1.17)
Over 75	1.25(1.18–1.33)	1.29(1.21–1.37)	1.29 (1.21–1.37)	1.28(1.21–1.36)	1.24 (1.17–1.32)	1.25 (1.17–1.33)	1.24 (1.17–1.32)

Table 4
Explanatory power of meteorological and pollutant factors on death in Jiangsu Province.

	Temperature	Atmospheric pressure	Relative humidity	NO_2	SO_2	O_3	$PM_{2.5}$
q statistic	0.053	0.036	0.004	0.010	0.006	0.003	0.003
p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5
Daily death risk of residents stratified by daily mean temperature in Jiangsu Province.

Temperature group	<-5 °C	−5~5 °C	5~15 °C	15~22 °C	22~35 °C	>35 °C
Risk of death	150.55	131.84	119.34	103.46	103.75	195.17

Table 6
Explanatory power of interaction between meteorological and pollutant factors on death in Jiangsu Province.

	NO_2	SO_2	$PM_{2.5}$	O_3	Mean Temperature	Atmospheric Pressure	Relative Humidity
NO_2	0.010						
SO_2	0.030	0.006					
$PM_{2.5}$	0.012	0.020	0.003				
O_3	0.012	0.010	0.009	0.003			
Mean Temperature	0.058	0.069	0.059	0.053	0.053		
Atmospheric Pressure	0.043	0.052	0.041	0.037	0.056	0.036	
Relative Humidity	0.014	0.014	0.008	0.009	0.055	0.039	0.004

The three cities most affected by extreme low temperatures were Suqian, Lianyungang and Nantong. The extreme low temperatures ($P_{2.5}$) in Lianyungang and Suqian were −0.8 °C and −0.7 °C respectively, the second and third lowest in Jiangsu Province. In contrast, the extreme minimum temperature in Nantong is 1.9 °C, the second highest in Jiangsu Province. The main reason for being greatly affected by extreme low temperatures is likely due to its relatively high proportion of elderly population. Nantong ranks first in Jiangsu Province with 22.67 % of its total population over the age of 65 [5].The three cities most affected by extreme high temperatures are Taizhou, Nantong, and Yangzhou. These cities rank among the top three in Jiangsu Province in terms of aging population, although their extreme high temperatures ($P_{97.5}$) fall within the middle range. The results indicate that the impact of extreme temperatures on the elderly population (especially those over 75) is significant. The elderly population is more vulnerable to extreme temperatures due to several factors. Firstly, their ability to regulate body temperature deteriorates with age, reducing their capacity to adapt to and withstand extreme temperatures. Secondly, the elderly often suffers from pre-existing cardiovascular and respiratory diseases, which can be exacerbated by extreme temperatures, increasing the risk of mortality [37–39].

According to the analysis of geographical detector, daily mean temperature has the greatest impact on the distribution of resident death in Jiangsu Province, with a q-value of 0.053. This is consistent with previous research indicating that temperature plays a crucial role in determining human health outcomes [40–42]. This is because extreme temperatures can significantly affect the body's metabolism, cardiovascular system, nervous system, and more. These impacts can lead to the development of various illnesses, ultimately increasing the mortality rate [43,44]. Although air pollutants such as O_3 and $PM_{2.5}$ have minimal individual impact, with a q-value of only 0.003, their combined impact should not be ignored. Furthermore, the interaction detector indicates that the effect of multi-factor interactions is much greater than the effect of individual factors, especially SO_2, which alone has a q-value of 0.006, when interacting with daily mean temperature, the q-value increases to 0.069, indicating a significant increase in the risk of resident deaths

Table 7

Difference of death risk among residents in 13 cities.

Region	Xuzhou	Lianyungang	Suqian	Huai'an	Yancheng	Nanjing	Yangzhou	Taizhou	Zhenjiang	Nantong	Changzhou	Wuxi	Suzhou
Xuzhou	N												
Lianyungang	Y	N											
Suqian	Y	Y	N										
Huai'an	Y	Y	N	N									
Yancheng	Y	Y	Y	Y	N								
Nanjing	Y	Y	Y	Y	Y	N							
Yangzhou	Y	Y	Y	Y	Y	Y	N						
Taizhou	Y	Y	Y	Y	Y	Y	Y	N					
Zhenjiang	Y	Y	Y	Y	Y	Y	Y	Y	N				
Nantong	Y	Y	Y	Y	Y	Y	Y	Y	Y	N			
Changzhou	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N		
Wuxi	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	
Suzhou	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N

with notable spatial heterogeneity.

5. Conclusions

In summary, both extreme low and high temperatures are associated with an increased risk of mortality for residents. The effects of extreme low temperatures occur with a delay and can last up to 11–21 days. Therefore, effective protection measures are required to ensure sustained protection against extreme low temperatures. In contrast, the impact of extreme high temperatures peaks on the first day but lasts for a shorter period of 2–4 days. in the case of extreme high temperatures, protection measures must be implemented quickly.

With 16.8 % of its population over the age of 65, Jiangsu Province has entered a profoundly aging society. Extreme temperatures have a significant impact on the elderly population, which requires increased protection measures, particularly regarding the importance of warming measures during low temperatures. Additionally, the spatial distribution of deaths in Jiangsu Province is closely associated with the spatial distribution of average daily temperatures. Therefore, local areas should implement effective protective measures according to the variation of local daily mean temperature to reduce the risk of mortality.

However, it is important to recognize the limitations of this study. First, the death data lacked gender disaggregation to analyze differences in the impact of extreme temperatures on male and female deaths. Secondly, because annual population data for all age groups in the 13 cities of Jiangsu Province was not available, we had to rely on the number of deaths rather than mortality rates as the study data. Additionally, due to data constraints, we were only able to access mortality data encompassing all causes of death, rather than data specific to non-accidental deaths, resulting in potentially less precise experimental outcomes. In addition, various other factors (e.g., the level of economic development, the construction of medical facilities, and the living habits of residents) may also have an impact on the experimental results. In the future, it is necessary to consider and incorporate more relevant factors for further research.

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Data availability statement

The population death data were collected from the Universal Health Information Platform of Jiangsu Province. The meteorological data for the same period were collected from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation global atmospheric reanalysis (ERA5). The administrative zone map data were obtained from the Yangtze River Delta Science Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://geodata.nnu.edu.cn/data/datadetails.html?dataguid=38785244005601&docid=1001).

CRediT authorship contribution statement

Xu Yang: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Junshu Wang:** Writing – review & editing, Validation, Supervision, Methodology, Data curation, Conceptualization. **Guoming Zhang:** Writing – review & editing, Supervision, Resources, Methodology. **Zhaoyuan Yu:** Writing – review & editing, Validation, Supervision, Funding acquisition.

Declaration of competing interest

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