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The Association between Compound Hot Extremes and Mortality Risk in Shandong Province, China: A Time-Series Analysis

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Abstract: Background: The occurrence of compound hot extreme (CHE) events in China is increasingly frequent. This study aimed to investigate the association between CHEs and all-cause mortality in Shandong Province and to estimate the attributable excess deaths. Methods: We collected daily data on weather, air pollution, and all-cause mortality at the subdistrict level in Shandong Province from 2013 to 2018. A CHE was defined as both daily maximum and minimum temperatures being higher than their historical 90th percentiles during 2013–2018 hot seasons. A case time-series analysis with a distributed lagged non-linear model was applied to analyze the subdistrict-specific association between different hot extremes and mortality risk, which were then pooled at the province level using meta-analysis. Results: Hot nights (RR = 1.44, 95%CI: 1.35–1.53) and CHEs (RR = 1.77, 95%CI: 1.64–1.90) were significantly associated with an increased mortality risk. CHEs had a greater effect for females (RR = 1.99, 95%CI: 1.81–2.19) and the elderly (>74 years) (RR = 2.14, 95%CI: 1.93–2.38) than their counterparts, respectively. Cardiovascular and respiratory deaths were more susceptible to CHEs than other deaths. Each year, 4888 (95%CI: 4133–5811) excess deaths in Shandong Province were attributable to CHEs, accounting for 2.60% (95%CI: 2.20–3.10%) of all-cause deaths and equating to 50 (95%CI: 42–58) deaths per 1,000,000 residents. The CHE-related mortality burden varied across subdistricts, with the highest occurring in the southeastern area and the lowest occurring in the northeastern and southwestern regions. Conclusion: CHEs and hot nights were substantially associated with excess deaths in Shandong Province, especially for females, the elderly, and residents living in the southeastern area. Our findings may facilitate the development of a heat alert warning system and preventive measures for vulnerable populations.

Keywords: compound hot extreme; mortality risk; excess death

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1. Introduction

Global warming is an unprecedented challenge for humanity today and in the coming decades. The Sixth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC AR6) states that the average temperature of the Earth's surface increased by 1.09 °C between 2011 and 2020 compared to that in the pre-industrial period (1850–1900), which is projected to increase by another 4.8 °C in 2100 without adequate mitigation strategies [1]. In the context of global warming, hot extremes, both in terms of frequency and intensity, are on the rise on a global scale, with the increase in daily minimum temperatures outpacing the increase in daily maximum temperatures in recent decades [2–6]. This trend poses significant risks and challenges to human beings and the environment.

Daytime and nighttime persistent hot extremes, which are commonly referred to as compound hot extremes (CHEs), can be especially detrimental to human health [7,8]. These events subject individuals to prolonged periods of high temperatures during the day and night, leading to heat stress and hindered recovery. Hot extremes in summer pose serious health risks to individuals, especially occurring day and night and continuously over 24 h [9,10]. Previous studies have primarily applied the mean daily temperature as an indicator to investigate the adverse effects of extreme temperature events. However, this approach has its limitation in capturing the distinct effects of daytime and nighttime temperatures separately [11,12]. In addition, some studies have only examined the individual health effects of either hot days or hot nights, without considering the combined effects of both types of hot extremes [13,14]. For example, a commonly used metric for studying the effects of high temperatures is heat waves (HW). Although there is no universal definition, it is generally defined based on the number of consecutive days that the maximum daily temperature exceeds a certain threshold [15,16]. Daily maximum temperatures generally capture only the effects of daytime high temperatures. Accompanied by global warming, the frequency, intensity, and duration of CHEs are projected to increase in the coming future [17], and the urban heat island effect may exacerbate this progress [18]. It is therefore necessary to explore the disease burden associated with CHE for a better development of adaptation strategies against climate change and CHEs.

As one of the largest countries in the world in terms of population and land area, China shows a warming pace that is significantly higher than the global average between 1951 and 2021, making it one of the most vulnerable nations to climate change [19]. Among the provinces in China, Shandong Province is particularly threatened by climate change and extreme heat events [20,21]. The province has a large population, rapid aging trends, and a unique geographical location, which make it an ideal representative for evaluating the impacts of CHEs in China [22]. The frequency of high-temperature events and the long duration of the hot season in Shandong Province, coupled with the large population of the province, have led to the widespread exposure of Shandong residents to high temperatures. In addition, Shandong Province has a varied topography, dominated by plains and hills, with mountainous outcrops in the south-central part of the province and the coastal areas in the east. Factors such as the distance to the sea and elevation may contribute to differences in the effects of high-temperature exposure.

In the current study, we used subdistrict-scale data in Shandong Province to explore the association between CHEs and population mortality. Then, we calculated the excess mortality burden due to CHEs by comparing it with normal days. Our study aimed to quantify the risk of mortality related to CHEs and to assess the attributable deaths across the subdistricts. The findings were expected to contribute to the development of specific regional public health strategies for mitigating the adverse effects of hot extremes.

The remaining paper is organized as follows. Section 2 describes the study site, data, and methods used in this paper. Section 3 reveals the effect of CHE on the risk of mortality in the population, along with subgroup analysis results, and explores the excess mortality burden attributed to CHEs. Finally, the discussion and conclusion are, respectively, in Sections 4 and 5.

2. Methods

2.1. Study Site

This study was conducted in Shandong, which is a coastal province located in eastern China. It covers a land area of approximately 155,800 square kilometers and is divided into 1822 subdistricts. The province has a warm temperate monsoon climate, characterized by four distinct seasons throughout the year. As of the end of 2022, Shandong had a permanent population of 101.62 million, making it the second-largest province in China in terms of population. More meteorological, geographic, and demographic information about Shandong Province can be found in Supplementary Table S1 and Supplementary Figures S1–S3.

2.2. Data Collection

Daily mortality data were collected from the cause of mortality surveillance system of the Shandong Provincial Center for Disease Control and Prevention during 2013–2018. The recorded data include information such as date of death, gender, age, education, address, date of death, and cause of death. The causes of death were coded using the International Classification of Diseases, 10th Revision (ICD-10), which were grouped into cardiovascular disease (I00-I99), respiratory disease (J00-J98), accidental death (S00-T98), and other non-accidental deaths (all other encodings). We further categorized the causes of death based on our previous studies [21].

Daily meteorological data, including daily mean temperature, daily maximum temperature (Tmax), daily minimum temperature (Tmin), and relative humidity (RH) during 2013–2018, were collected from the China Meteorological Data Network (http://data.cma.cn/; accessed on 15 December 2022). The China National Environmental Monitoring Center collected daily pollutant data during the same period (http://www.cnemc.cn/; accessed on 23 December 2022). Meteorological and pollutant information was matched to the subdistrict where the individual's home address was located. The population data were from LandScan Global (http://landscan.ornl.gov/; accessed on 3 May 2023), developed by Oak Ridge National Laboratory (ORNL).

2.3. Definition of CHEs

According to previous studies [7,23], the hot day and hot night were defined when the daily Tmax and Tmin were higher than their historical 90th percentiles on the specific calendar day of summer (from June 1 to September 30) during 2013–2018, respectively. The daily-based 90th percentile was determined by the sequence which was first to extract 15-day samples surrounding this day (i.e., present-day and 7 days before and after that day), followed by the data in the same date of all study periods (15 days *6 years, 90 days). Moreover, these daily-based percentiles take into account the intra-seasonal variation and therefore performed better than the seasonal-fixed threshold in defining hot extremes at different stages of summer [23]. Considering that heat tolerance and adaptation vary across different phases of summer, regions, and ethnic groups [24,25], day-based and site-specific percentiles may be better thresholds for defining hot days and hot nights when estimating their effects on the mortality risks. Consequently, these data were integrated and ranked, and three types of hot summertime extremes were defined for each subdistrict: (1) a CHE: a hot night and a hot day occur continuously throughout the day; (2) an independent hot day: a hot day without a preceding hot night; (3) an independent hot night: a hot night without a following hot day. Finally, the day when Tmax and Tmin were less than the 90th percentile for a specific calendar day was defined as normal.

2.4. Statistical Analysis

We used a two-stage study design. In the first stage, we performed a case time series (CTS) analysis [26] to model the subdistrict-specific association within each district through a conditional Poisson regression. The CTS design was developed recently to analyze the short-term risks associated with time-varying exposures, which can analyze risks and outcomes on smaller geographic units while reporting more precise risks at a higher geographic level [27]. We used the distributed lag non-linear model (DLNM) to assess the association between hot extremes and mortality [28]. Our initial analysis defined the maximum lag period as 14 days to capture the delayed effect. We used specifically natural cubic splines of a day of the year with three degrees of freedom and an interaction with the year indicator to model differential seasonal effects from 2013 to 2018. The potential confounding effect of RH was adjusted for using a natural cubic spline with three degrees of freedom. A categorical variable was entered into the model to adjust for the day of the week. The RR values and 95%CI were used to express the cumulative relative risk of each hot extreme compared to a normal day.

Further, in the second stage, we applied a multivariate random-effects meta-regression to pool the subdistrict-specific exposure–response association. We conducted subgroup analysis by gender, age group (<65, 65–74 and ≥75 years), and the cause of death to identify vulnerable subgroups. Finally, according to the method proposed earlier [29], we used excess deaths (*ED*) to describe the additional burden of the disease due to CHEs compared to normal days as follows:

$$ER_i = RR_i - 1$$

$$ED_i = Death \times ER_i \times D_i$$

$$YED_i = ED_i \div N$$

where i refers to types of hot extreme events, and RR_i refers to the relative risk of death due to the different hot extremes. The $Death$ is the average daily deaths on normal days, the D_i is the duration of the hot extreme event, and the N refers to the years of our study (6 years). The YED_i is the average annual excess deaths. In addition, we also calculated the ratio between excess deaths and all-cause deaths (i.e., the excess death ratio) and the excess deaths per 1,000,000 residents.

2.5. Sensitivity Analysis

To verify the robustness of the model, we conducted the following sensitivity analysis: (1) Changing maximum lags between 12, 13, and 15 days; (2) alternating the degrees of freedom of time from three to five; (3) adding the $PM_{2.5}$ or O_3 data in the same period to check the stability of the model; (4) changing the degrees of freedom of relative humidity from three to four or removing it from the model to test the stability of our model.

The statistical analysis was performed using R software (version 4.2.2), using the "dlnm" and "mvmeta" packages to conduct DLNM and multivariate meta-analysis.

3. Results

During the study period, 1,125,907 deaths were recorded in all subdistricts of Shandong Province (Table 1). From 2013 to 2018, 6.11% of days could be classified as independent hot days, 5.95% could be classified as independent hot nights, and 3.44% could be classified as CHEs (Supplementary Table S2).

Figure 1 illustrates that the adverse effects on mortality last for three days during hot days and for 13 days during hot nights. CHEs had the strongest death risk compared to independent hot days or hot nights in lag 0–4 days. Compared to normal days, independent hot nights (RR: 1.44, 95%CI: 1.35–1.53) and CHE (RR: 1.77, 95%CI: 1.64–1.90) were significantly associated with an increased mortality risk, while no significant association was found for independent hot days (Table 2).

Subgroup analysis revealed that the association between CHEs and mortality was stronger for females (RR: 1.99, 95%CI: 1.81–2.19) than for males (RR: 1.59, 95%CI: 1.46–1.73) and stronger for the elderly population (RR for those aged 65–74 years: 1.59, 95%CI: 1.39–1.82; RR for those aged ≥75 years: 2.14, 95%CI: 1.93–2.38) than for the subgroup aged <65 years (RR: 1.32, 95%CI: 1.19–1.48). The effects of hot extremes on mortality varied across different disease types, as indicated by the overall and the lag structures observed (Supplementary Figures S4–S8). For example, cardiovascular deaths (RR: 2.30, 95%CI: 2.08–2.55) and respiratory diseases (RR: 2.04, 95%CI: 1.71–2.43) were more vulnerable than other death causes.

Table 1. Descriptive statistics on the number of daily deaths from June to September 2013–2018 in each subdistrict of Shandong Province, China.

Variables	Mean	Median	Sum	Proportion (%)	*p* Value
Total	0.85	0.85	1,125,907	100.00	
Gender					
Male	0.49	0	649,409	57.68	<0.001
Female	0.36	0	476,498	42.32	
Age (year)					
0–	0.24	0	318,782	28.31	
65–	0.19	0	247,244	21.96	<0.001
≥75	0.42	0	559,881	49.73	
Educational level					
Junior high school and below	0.75	0	996,012	88.46	
Technical secondary school, high school degree, or above	0.04	0	63,193	5.61	0.003
Lack of academic qualifications	0.05	0	66,706	5.92	
Type of Disease					
Cardiovascular diseases	0.42	0	549,110	48.77	
Respiratory diseases	0.06	0	79,030	7.02	
Tumor	0.24	0	324,537	28.82	<0.001
Other non-accidental deaths	0.07	0	88,595	7.87	
Accidental death	0.07	0	84,489	7.50	

Note: (1) "Mean" is calculated as the average of the number of deaths per day for each variable, "Median" is the median number of deaths per day, "Sum" is the total number of deaths per day during the study period, and "Proportion" is the sum of the daily number of deaths in the study period for each variable as a proportion of all deaths in the study period. (2) There was no subdistrict scale information in Qingdao City and the two districts of Dezhou, so they were not included in calculating the mean and median value of mortality on the subdistrict level.

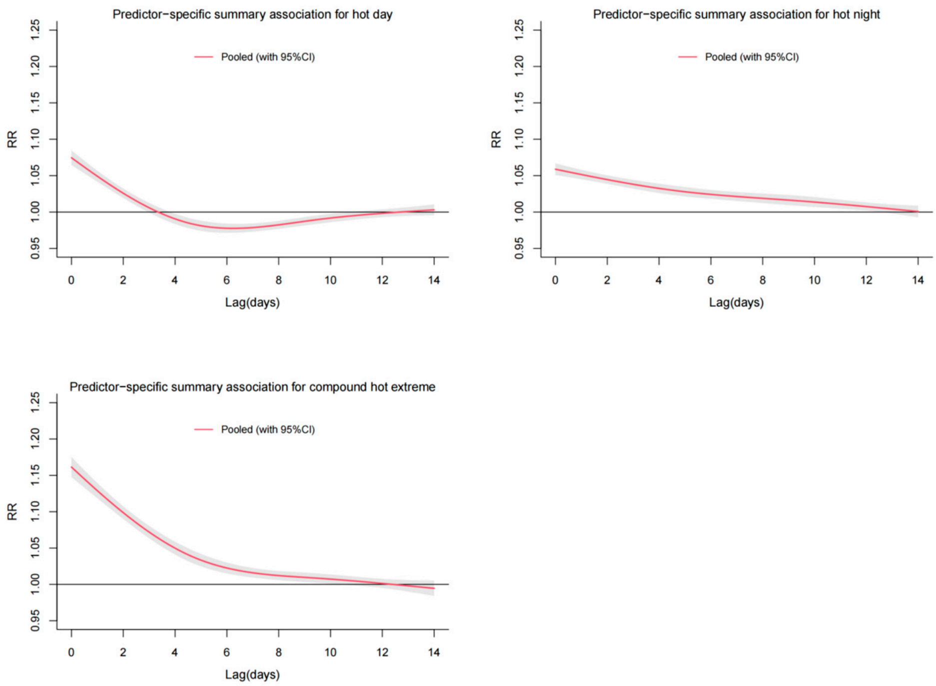

Figure 1. Overall lag structure in effects of hot extremes on daily mortality in Shandong Province, 2013–2018. RRs represent the relative risk of death due to the different hot extremes compared to non-hot days, and the 95%CI values are reported as grey areas. The horizontal line means RR = 1.

Table 2. The relative risk of mortality associated with hot extremes over 0–14 days lag-stratified by gender, age group, and the cause of death.

Group	Relative Risk (95%CI)		
	Hot Day	**Hot Night**	**Compound Hot Extreme**
Total	1.012 (0.948, 1.080)	1.439 (1.351, 1.533) *	1.765 (1.636, 1.904) *
Gender			
Male	0.971 (0.899, 1.050)	1.341 (1.253, 1.436) *	1.586 (1.455, 1.728) *
Female	1.050 (0.963, 1.145)	1.601 (1.463, 1.753) *	1.993 (1.814, 2.190) *
Age (year)			
0–	0.946 (0.859, 1.042)	1.266 (1.159, 1.383) *	1.323 (1.186, 1.475) *
65–	0.926 (0.829, 1.035)	1.313 (1.193, 1.445) *	1.589 (1.389, 1.819) *
≥75	1.057 (0.971, 1.151)	1.625 (1.487, 1.776) *	2.142 (1.932, 2.375) *
Type of Disease			
Cardiovascular diseases	1.062 (0.972, 1.162)	1.640 (1.502, 1.791) *	2.303 (2.077, 2.554) *
Respiratory diseases	0.854 (0.716, 1.020)	1.614 (1.377, 1.892) *	2.037 (1.708, 2.430) *
Tumors	0.899 (0.822, 0.983)	1.083 (0.995, 1.178)	1.053 (0.941, 1.180)
Other non-accidental deaths	0.987 (0.837, 1.164)	1.420 (1.225, 1.647) *	1.772 (1.491, 2.106) *
Accidental death	0.959 (0.813, 1.130)	1.500 (1.285, 1.752) *	1.518 (1.245, 1.850) *

Note: * Statistically significant results at $p < 0.05$.

The total excess deaths ratio associated with three different types of hot events was 5.47% (95%CI: 4.55–6.16%) in Shandong Province (Table 3); it was 2.69% (95%CI: 2.14–3.25%) for independent hot nights, 2.60% (95%CI: 2.20–3.10%) for CHEs, and 0.18% (95%CI: −0.51–1.41%) for independent hot days, respectively. In total, there were 10,270 (95%CI: 8543–11,565) excess deaths related to extreme heat events in Shandong Province per year (105 deaths per 1,000,000 residents), consisting of 4888 (95%CI: 4133–5811) CHEs-related deaths (52 deaths per 1,000,000 residents), 5041 (95%CI: 4010–6072) deaths associated with independent hot nights (50 deaths per 1,000,000 residents), and 341 (95%CI: −331–902) deaths associated with independent hot days (3 deaths per 1,000,000 residents).

The burden of excess deaths varied in different geographical patterns across Shandong Province (Figures 2 and 3). The graphical results are consistent with Table 2, with CHE and hot nights resulting in a much higher excess mortality burden than hot days. For hot nights, the burden was higher in the west-central parts of the province compared to the eastern coastal areas, especially in some subdistricts in Liaocheng and Tai'an. By contrast, the CHE-related burden was higher in the north-central, south-central, and northeastern coastal regions, especially in some subdistricts in Zibo, Binzhou, and Rizhao. For example, the CHE-related excess deaths ratio ranged from 0.83% (95%CI: −0.03–1.97%) to 8.68% (95%CI: 5.03–13.80%) across all subdistricts, equating up to 22 (95%CI: 13–35) excess death cases and up to 347 (95%CI: 233–503) excess death cases per 1,000,000 residents per year.

The sensitivity analysis suggested that the main results were reliable when we changed the maximum lag from 12 to 15 days, the degrees of freedom of time from three to five, the degrees of freedom for relative humidity from three to four, or removed it, or additionally added the $PM_{2.5}$ or O_3 into the model (Supplementary Table S3).

Table 3. Annual excess deaths, excess deaths ratio, and deaths per 1,000,000 residents per year attributable to extreme hot events in cities of Shandong Province, 2013–2018.

District	Excess Deaths (95%CI)			Excess Death Ratio (95%CI)			Excess Deaths per 1,000,000 Residents (95%CI)		
	Hot Day	Hot Night	Compound Hot Extreme	Hot Day	Hot Night	Compound Hot Extreme	Hot Day	Hot Night	Compound Hot Extreme
Shandong Province	341 (−331, 902)	5041 (4010, 6072) *	4888 (4133, 5811) *	0.18% (−0.51%, 1.41%)	2.69% (2.14%, 3.25%) *	2.60% (2.20%, 3.10%) *	3 (−3, 8)	52 (40, 62) *	50 (42, 58) *
Jinan	−54 (−227, 144)	780 (422, 1234) *	373 (167, 616) *	−0.36% (−1.51%, 0.96%)	5.18% (2.80%, 8.20%) *	2.48% (1.11%, 4.10%) *	−7 (−27, 17)	93 (50, 147) *	45 (20, 73) *
Zibo	95 (−19, 226)	163 (40, 321) *	555 (279, 937) *	1.11% (−0.22%, 2.64%)	1.91% (0.46%, 3.74%) *	6.48% (3.26%, 10.94%) *	20 (−3, 50)	35 (8, 70) *	120 (60, 203) *
Zaozhuang	115 (−17, 290)	−28 (−124, 95)	172 (3, 452) *	1.57% (−0.23%, 3.96%)	−0.38% (−1.70%, 1.30%)	2.35% (0.04%, 6.17%) *	30 (−5, 75)	−7 (−32, 25)	45 (0, 117) *
Dongying	−39 (−89, 27)	−7 (−66, 77)	69 (−17, 224)	−1.12% (−2.58%, 0.79%)	−0.21% (−1.92%, 2.23%)	2.01% (−0.49%, 6.50%)	−18 (−42, 13)	−3 (−32, 37)	33 (−8, 107)
Yantai	−78 (−215, 107)	21 (−13, 211)	405 (244, 578) *	−0.48% (−1.32%, 0.66%)	0.13% (−0.08%, 1.30%)	2.50% (1.50%, 3.56%) *	−12 (−30, 15)	3 (−2, 30)	57 (33, 80) *
Weifang	22 (−131, 203)	319 (119, 555) *	238 (104, 397) *	0.12% (−0.75%, 1.16%)	1.82% (0.68%, 3.18%) *	1.36% (0.59%, 2.27%) *	2 (−13, 22)	33 (13, 60) *	25 (12, 42) *
Jining	109 (−89, 351)	899 (583, 1288) *	226 (68, 431) *	0.72% (−0.58%, 2.31%)	5.91% (3.83%, 8.47%) *	1.48% (0.45%, 2.83%) *	13 (−10, 42)	108 (70, 155) *	27 (8, 52) *
Taian	189 (37, 383) *	951 (685, 1288) *	142 (−6, 336)	1.58% (0.30%, 3.19%) *	7.92% (5.71%, 10.74%) *	1.18% (−0.05%, 2.80%)	33 (7, 68) *	168 (122, 228) *	25 (−2, 60)
Weihai	−14 (−115, 103)	147 (21, 339) *	158 (69, 287) *	−0.22% (−1.83%, 1.65%)	2.34% (0.33%, 5.41%) *	2.51% (1.10%, 4.58%) *	−5 (−40, 35)	52 (7, 117) *	55 (23, 100) *
Rizhao	−54 (−115, 36)	100 (−4, 238)	357 (207, 568) *	−1.04% (−2.20%, 0.70%)	1.92% (−0.08%, 4.57%)	6.86% (3.97%, 10.91%) *	−18 (−40, 12)	33 (−2, 82)	122 (70, 193) *
Linyi	−84 (−285, 176)	549 (320, 839) *	580 (305, 963) *	−0.44% (−1.51%, 0.93%)	2.90% (1.69%, 4.44%) *	3.07% (1.61%, 5.09%) *	−8 (−28, 17)	53 (32, 82) *	57 (30, 93) *
Dezhou	−23 (−242, 291)	220 (10, 505) *	441 (188, 793) *	−0.21% (−2.26%, 2.72%)	2.05% (0.09%, 4.70%) *	4.11% (1.75%, 7.39%) *	−3 (−42, 50)	38 (2, 87) *	77 (32, 137) *
Liaocheng	272 (−13, 679)	476 (227, 765) *	190 (−38, 600)	2.33% (−0.11%, 5.82%)	4.09% (1.94%, 6.56%) *	1.63% (−0.32%, 5.15%)	45 (−2, 112)	78 (38, 127) *	32 (−7, 100)
Binzhou	−1 (−12, 12)	107 (−34, 323)	373 (223, 566) *	−0.01% (−0.16%, 0.17%)	1.47% (−0.46%, 4.43%)	5.12% (3.06%, 7.76%) *	0 (−3, 3)	28 (−8, 83)	97 (58, 147) *
Heze	−41 (−375, 515)	274 (64, 544) *	396 (151, 696) *	−0.23% (−2.08%, 2.85%)	1.52% (0.35%, 3.01%) *	2.19% (0.83%, 3.86%) *	−5 (−43, 60)	32 (7, 63) *	47 (17, 80) *
Qingdao	−73 (−202, 80)	71 (−67, 233)	214 (101, 357) *	−0.51% (−1.42%, 0.56%)	0.50% (−0.47%, 1.63%)	1.50% (0.71%, 2.50%) *	−8 (−23, 8)	8 (−7, 27)	23 (12, 40) *

Note: * Statistically significant results at $p < 0.05$.

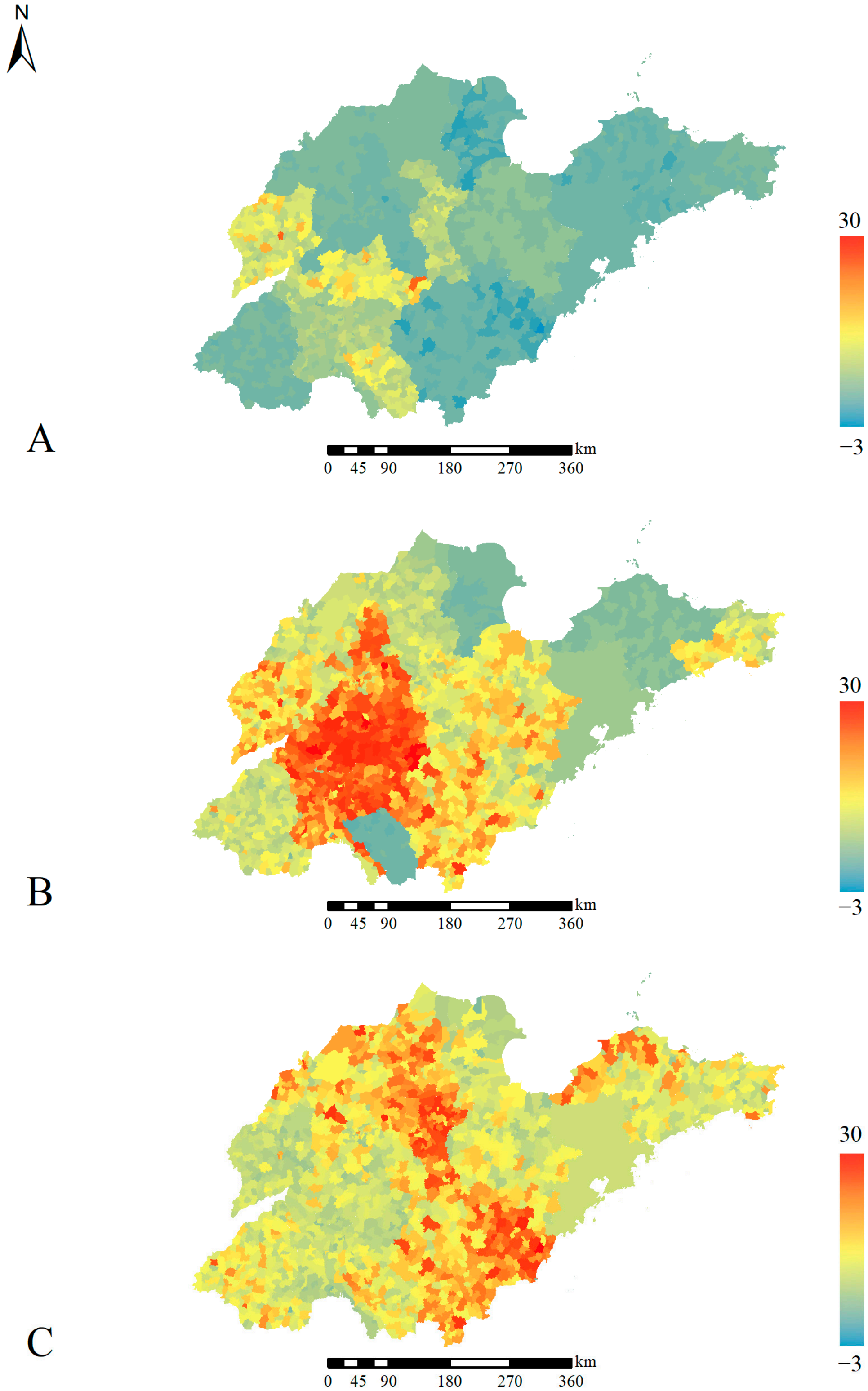

Figure 2. The spatial distribution of average annual excess deaths (deaths/year) of mortality attributable to hot days (**A**), hot nights (**B**), and CHE (**C**) over 0–14 days lag in Shandong Province, 2013–2018.

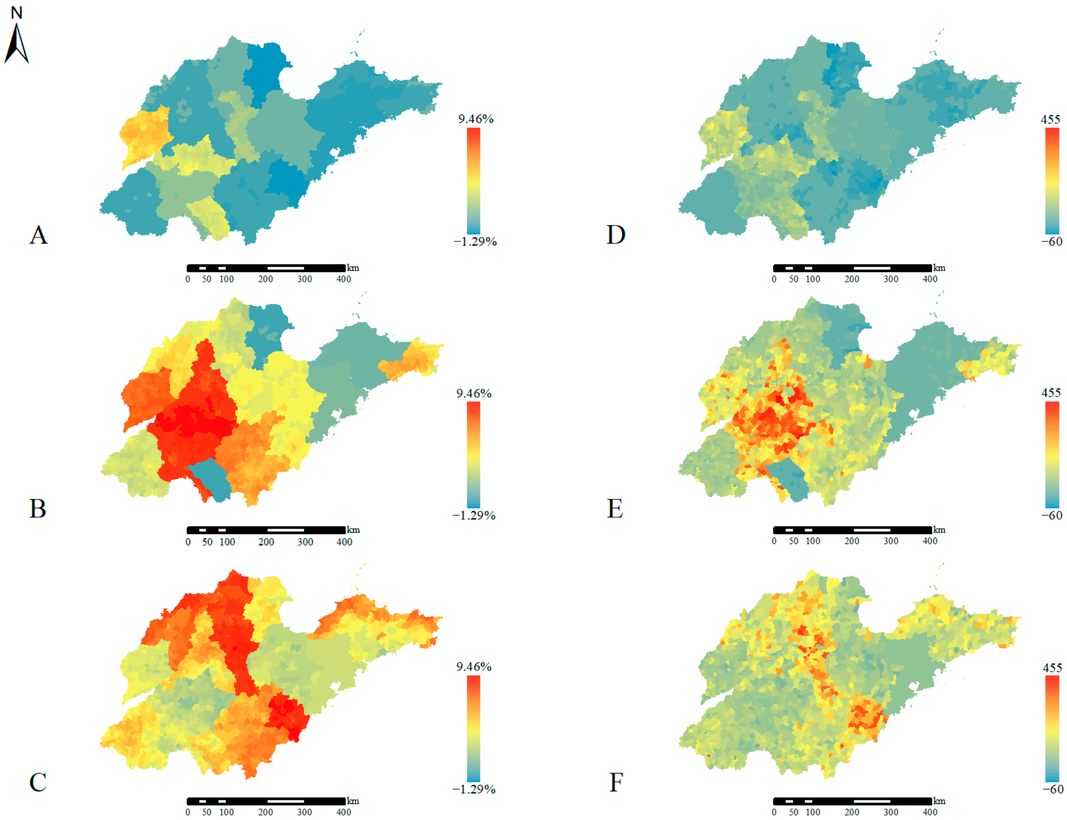

Figure 3. The spatial distribution of the excess deaths ratio of mortality attributable to hot days (**A**), hot nights (**B**), and compound hot extreme (**C**) and excess deaths per 1,000,000 residents of mortality attributable to hot days (**D**), hot nights (**E**), and CHE (**F**) over 0–14 days lag per year in Shandong Province, 2013–2018.

4. Discussion

Our study investigated the relationship between CHEs and mortality in Shandong Province, China from 2013 to 2018. Hot nights and CHEs were substantially associated with an increased risk of mortality, while the adverse effect of hot days was insignificant. Furthermore, we identified significant geographical differences in the cumulative effects of hot extremes, highlighting the need for localized approaches to public health interventions and policies.

In the context of a warming climate, previous studies have shown that human exposure to CHEs is expected to be four to eight times greater by the end of the century than in 2010 [23,30]. Exposure to hot extremes can lead to heat stress symptoms such as exhaustion and heat stroke. When the body temperature rises to 40 °C or higher, it can rapidly damage vital organs like the brain, heart, and kidneys and may even result in death if not promptly treated [31]. The prolonged heat stress experienced during CHEs can further worsen this situation, exacerbating the risk of mortality. In a multi-site study in China [8], the duration of the effect of hot nights and hot days was close to three days, while the lag time of the effect of hot nights in our study was even longer. A multi-center study in East Asia reinforces these findings by suggesting that high nighttime temperatures can significantly increase the risk of mortality [32]. Moreover, the frequency and intensity of high nighttime temperatures are projected to rise significantly with future warming, which will consequently exacerbate the burden of heat-related diseases. Consequently, it may be related to sleep deprivation and sleep disturbance due to increased nighttime temperatures [33]. Decreased sleep quality not only increases the risk of hypertension, heart disease, diabetes, and stroke but also increases the likelihood of accidents [34,35].

We observed that women and elderly individuals were more susceptible to the effects of hot extreme events compared to men and young people. The findings were consistent with previous studies [36,37]. The higher vulnerability of women to high temperatures can be attributed to differences in their physiological makeup, particularly in terms of heat stress capacity. Women have weaker vasodilatation and contraction, as well as weaker thermoregulation, which puts them at a higher risk of dying in high temperatures compared to men [38]. Moreover, the aging population faces an increased susceptibility to hot extremes due to the gradual decline in various physiological functions. The diastolic and contractile capacities of blood vessels in the elderly decline, as does their ability to thermoregulate and cope with high temperatures [36]. As a result, relevant authorities are recommended to focus on finding ways to enhance the adaptability of elderly individuals to hot extreme events, particularly considering the aging demographic.

In line with previous studies [39–41], we also found a strong sensitivity of cardiovascular and respiratory diseases to temperature. Although the mechanisms of the increased mortality risk of respiratory diseases caused by high temperatures are unclear, previous studies have suggested that acute exacerbations of respiratory disease may be associated with airway inflammation and cardiovascular comorbidities that may be triggered by heat exposure [42,43]. Additionally, exposure to high temperatures can increase platelet and red blood cell counts and plasma cholesterol levels, leading to arterial thrombosis, which may also explain part of our findings [44,45]. Some studies suggest that heat waves may also increase the risk of traffic accidents and trauma [46]. Similarly, the study found that hot nights increase the risk of accidental death, while CHEs actually decrease the risk. This observation aligns with a report from Adelaide, which mentioned a reduction in traffic accidents and injuries during more extreme temperatures, likely due to the preference of most individuals to stay indoors during extreme heat [47].

Previous studies have shown a high degree of geographic heterogeneity in the health effects of unsuitable temperatures [48,49]. Our study also found that the number of excess deaths caused by CHEs varied widely among subdistricts in Shandong Province. Considering that the number of excess deaths is influenced by the size of the population, we also calculated the excess death ratio and excess death rate (per 1,000,000 residents). The excess death rate and ratio due to the CHEs were higher in the north-central, south-central, and northeastern coasts. In contrast, the southwestern and southeastern coastal areas had lower excess deaths rates and ratios associated with CHEs. We also found that the number of excess deaths attributable to hot days and hot nights may differ considerably from the excess mortality attributable to CHE in the same area. This may be due to the geographic location, topography, and meteorological factors, and the occurrence of hot days and hot nights in a given area may or may not be synchronized. If hot days and hot nights are frequently synchronized, there will be a higher frequency of CHE.

This study has several strengths. First, in contrast to other city-level ecological studies, our study used subdistrict-scale meteorological information, improving the exposure variable measurements' accuracy. Second, we used a case time series design as an alternative to the case-crossover design [26], which allows for the time series modeling of multiple subdistrict-specific deaths with hot extreme events within each district and county, even though each subdistrict is characterized by no more than one or a few deaths per day and no deaths on most days. Third, to our knowledge, this is the first study to simultaneously assess the mortality risk and excess mortality related to CHE in China. We acknowledge the following limitations of our study. First, we calculated excess deaths caused by hot extremes at the city level, which may result in excessive variation between adjacent subdistricts located in different cities. Second, as an ecological study, even with the use of more precise meteorological data, it is still not possible to accurately estimate individual exposure levels. Third, we cannot rule out the impact of short-term localized special events, such as hot air masses and foehn events. Fourth, residents may have different thermal sensitivities in different time periods of the summer months; however, we did not carry out analyses for the early and late periods of the thermal period. The variability between the early and late thermal seasons should be taken into account in future studies.

5. Conclusions

In conclusion, our study found that the mortality risk related to CHEs is higher than that of independent hot days and independent hot nights. However, the excess mortality burden due to independent hot nights is higher than that of CHEs, and the dangers of independent hot nights should not be underestimated. Furthermore, susceptibility varies among subgroups, with cardiovascular and respiratory diseases being more sensitive to CHEs than other diseases. Understanding the compounding effects of various climate-related factors on human health can draw the public's attention to high-temperature events and motivate people to take precautions to avoid heat in hot weather. Given the warming climate and aging population, these findings could inform early warning measures and health policy development and help mitigate the impact of extreme heat on population health.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos14121710/s1, Table S1: Monthly averages of mean temperature, relative humidity, wind speed, and sunshine duration for the top ten most densely populated subdistricts of Shandong Province; Table S2: Distribution of deaths during different types of hot extremes; Table S3: Sensitivity analysis of mortality risk associated with compound hot extremes by changing lag days, df of time, the relative humidity and adding $PM_{2.5}$ or O_3; Figure S1: Distribution of average daily temperatures in summer in Shandong Province from 2013–2018. The red dotted line in the figure shows the average temperature from 2005 to 2020 (24.11 °C); Figure S2: Population density distribution map of Shandong Province. The unit of population density is population/square kilometer. Population density data with a spatial resolution of ap-proximately 1 km were obtained from WorldPop (https://www.worldpop.org/; accessed on 15 September 2023); Figure S3: Elevation map of Shandong Province. Elevation data with a spatial resolution of ap-proximately 1 km were obtained from SRTM (http://srtm.csi.cgiar.org; accessed on 15 September 2023); Figure S4: Overall lag structure in effects of hot extremes on daily mortality from cardiovascular diseases in Shandong Province, 2013–2018; Figure S5. Overall lag structure in effects of hot extremes on daily mortality from respiratory dis-eases in Shandong Province, 2013–2018; Figure S6. Overall lag structure in effects of hot extremes on daily mortality from tumor in Shan-dong Province, 2013–2018; Figure S7. Overall lag structure in effects of hot extremes on daily mortality from other non-accidental deaths in Shandong Province, 2013–2018; Figure S8. Overall lag structure in effects of hot extremes on daily mortality from accidental deaths in Shandong Province, 2013–2018.

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Abbreviations

CHE(s)	Compound hot extreme(s)
IPCC	Intergovernmental Panel on Climate Change
AR6	The Sixth Assessment Report
HW	Heat waves
ICD-10	International Classification of Diseases, 10th Revision
Tmax	Daily maximum temperature
Tmin	Daily minimum temperature
RH	Relative humidity
ORNL	Oak Ridge National Laboratory
CTS	Case time series
DLNM	Distributed lag non-linear model
ED	Excess deaths

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