Environmental Health

RESEARCH

Temporal and Spatial Effects of Extreme Drought Events on Human Epidemics over Ancient China in 1784–1787 CE

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Abstract

Extreme drought events can impact human health, notably triggering epidemics that impose significant global health and economic burdens. Understanding these effects and developing response strategies is crucial. However, there is limited epidemiological evidence on how climate change influenced ancient epidemics before large-scale urbanization and frequent population movements. In this study, we utilized the Reconstructed East Asian Climate Historical Encoded Series (REACHES) climate database and the self-constructed ancient Chinese epidemics database to examine extreme drought events in ancient China from 1784–1787 CE. We analyzed factors like grain prices, population density, and socioeconomic conditions to explore the temporal and spatial mechanism and influence the degree of extreme drought events on epidemics outbreaks. The results show that there is a clear positive link between drought and the spread of epidemics, with a notable one-year lag effect of drought. Drought impacts epidemics directly and indirectly through locust plague, famine, crop failure, and social turmoil, with famine being the most crucial factor. Official disaster management can mitigate epidemics. This study intuitively shows the relationship between extreme drought events and epidemics in ancient China and offering insights into the climate change-epidemic relationship. Placing the conclusions of this paper in a broader context has global implications, providing historical experience for polycrisis and modern challenges.

Keywords Extreme drought events, Human epidemics, Historical climate restoration, Socioeconomic factors, Ancient China

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Introduction

Climate change, characterized by global warming, has become one of the greatest threats to mankind in the twenty-first century [1, 2]. Among all kinds of extreme weather events, drought is widely regarded as the most costly, complex, and destructive phenomenon [3]. The Lancet Countdown 2023 report showed that the global land area affected by extreme drought increased from 18% in 1951–60 to 47% in 2013–22, and the number of people with moderate or severe food insecurity increased by 127 million, putting millions of people at risk of malnutrition and potentially irreversible health effects [4]. Luo Bin found that drought may not only increase the risk of respiratory diseases in children and adolescents [5], but also have a significant interaction with air pollutants, increasing the number of outpatient visits for children with upper respiratory tract infections [6]. The increase in the incidence of epidemics, especially the transmission and development of vector-borne diseases, such as dengue fever, malaria, chikungunya fever, West Nile virus, and other diseases are also health risks related to drought and how to reduce the health risks related to drought has become the research focus of countries all over the world [7].

The impact of climate change on human health has become complex and diverse in the context of modern urbanization and frequent population dynamics [8]. Consequently, several scholars have delved into the correlation between climate change and the prevalence of epidemics during historical periods, aiming to elucidate the nexus between climate change and human health under conditions characterized by simpler socioeconomic structures and reduced population mobility [9, 10]. However, many of these studies have focused on the century-long timescale, potentially overlooking the interannual dynamics between drought evolution and epidemics. Individual studies on the restoration of historical extreme weather events can provide a "microscopic" focus on the impact processes of disasters over short-term time scales. For example, Zhang De'er restored the extreme rain and waterlogging event that occurred in eastern China in 1755 CE [11]. Hao Zhixin made a historical reconstruction of the facts, effects and climatic background of the drought that occurred in North China from 1876 to 1878 CE [12]. This research method is conducive to better grasping the occurrence patterns of natural disasters and providing a reference for future disaster prevention and mitigation work [13, 14].

Between 2000 and 2023, more than 1.6 billion people worldwide were affected by drought. Among them, South Asia and sub-Saharan Africa are the regions most vulnerable to extreme weather, with more than 1.1 billion people affected by drought. This staggering figure highlights the widespread and severe nature of drought as a global challenge [15]. Under the influence of long-term drought in these areas, agricultural food production, water supply and sanitation conditions have been destroyed, resulting in widespread social conflicts, unrest and displacement, as well as serious epidemics. The cholera outbreak in Ethiopia in 2017 was accompanied by severe famine against the backdrop of drought, and an estimated 5.6 million Ethiopians needed emergency food aid [16]. During the same period, cholera has been reported to spread continuously in Somalia. Conflict, mass population displacement caused by drought, and social turmoil have exacerbated the cholera epidemic in Somalia. By the end of 2022, an estimated 3.86 million people across Somalia have been internally displaced [17]. The restoration of historical events will strengthen the connection between historical experience and modern challenges, and point out the direction of key interventions. Especially in the recent context of multi-system crises such as the epidemic, climate change, and the Russia-Ukraine war, the concept of 'polycrisis' has been proposed. A crisis is defined as a sudden (non-linear) event or series of events that severely impair the human in a relatively short period of time [18]. 'polycrisis' refer to causal crises in multiple global systems, and their interactions significantly weaken human development prospects [19]. Combined with typical historical events, we will deepen our understanding of 'polycrisis' and the relationship between ecological and social pressures from the perspective of historical variables.

There was a typical extreme drought event during a relatively warm climate period (1784–1787 CE) in the Qianlong period of the Qing Dynasty. Previous studies only focused on the evolution of this drought, and did not deeply explore the outbreak of associated epidemics, nor did they quantify the impact of population, economic, and social factors on it [20]. This study reconstructs the historical event spanning from 1784 to 1787 CE and scrutinizes the impact of the ensuing drought on the emergence of epidemics. It incorporates an analysis of population, economic, and social factors into the discourse, with the aim of offering valuable insights for the disaster management and mitigation of current climate change-induced epidemics against the backdrop of global warming. By examining the past, we can glean lessons that inform our present and future strategies.

Materials and data

Drought data

The drought data utilized in this study is sourced from the REACHES (Reconstructed East Asian Climate Historical Encoded Series) [21]. This comprehensive database is founded on the "*Compendium of Meteorological*

Records of China in the Last 3000 Years" edited by Zhang De'er. It digitizes, categorizes, and encodes historical documents to reconstruct historical climate data. Referring to previous studies, we retrieved drought-related records in corresponding time periods, including meteorological drought (main and subcategory codes 3001 and 3002) and hydrological drought (main and subcategory codes 3011–3051) [22]. Given that the primary source did not provide a quantification of the severity of disaster events, we employed data from the *"Yearly Charts of Dryness/Wetness in China for the Last 500-Year Period"* [23] to quantify the degree of drought. Spatial interpolation techniques were implemented in ArcGIS Pro 3.0 to generate national raster data, facilitating the extraction of quantified arid land values.

Epidemics data

The epidemics data comes from the *"Compilation of Infectious Disease Records in China for 3000 Years"* edited by Gong Shengsheng [24]. This book focuses on epidemics, extensively collects historical documents (including 25 official histories, more than 5,700 local chronicles, more than 400 anthologies, more than 300 kinds of newspapers and magazines, etc.), and is carefully researched and arranged. It was compiled by a team of Chinese historical geographers for more than 20 years, providing records of major epidemics in China for nearly 2,700 years from 674 BCE to 1949 CE. It is the richest, most comprehensive, and most credible data set of epidemics in the existing historical period of China. In this study, the relevant contents of the book are classified, extracted, and entered into the database, and then the locations are standardized according to the modern county-level administrative regions as the basic geographical units. Finally, semantic recognition was used to evaluate the severity of epidemics. The specific evaluation methods are provided in Section S1 (Supplementary Materials).

Grain prices data

Grain prices is an important intermediate hub of food production and consumption, which can be used to measure the stable state of society and embody the impact of climate change on the social and economic system [25]. The grain prices data of the Qing Dynasty comes from the " Qing Dynasty Grain Prices Database" established by Wang Yeh-chien [26, 27]. Based on the grain prices in 1783 (one year before the drought occurred), this study uses the multiple of the subsequent year compared with 1783 as an index to study. Specific grain prices data processing methods are provided in Section S2 (Supplementary Materials).

Population data

Disasters caused by climate change are also affected by population factors. In the past, spatial methods under long time series or century-year time scales were mostly used for research [28]. Therefore, this study includes population data to show the impact of population factors in the drought-epidemics disease chain at interannual time scales. Population data mainly comes from *"Chinese Population History Volume 5"* compiled by Cao Shuji [29]. This book reconstructs the population of sub-prefectures in five key years: 1776, 1820, 1851, 1880, and 1910. In accordance with the population growth rates of each prefecture, this study estimates the population figures for sub-prefectures during the study period. These estimates are then divided by the respective administrative areas to derive population density, which is subsequently adopted as an analytical index.

Other data

In REACHES, we retrieved famine (main category code 35), locust plague (main and subcategory code 3201), and crops (main category code 33) for the corresponding time period. Social turmoil was a major category item with main category code 71, selected as the most relevant sub-category items for this study included migration/displacement (sub-code 03), combat/war (sub-code 05), poverty (sub-code 09), death/serious injury (sub-code 10), human trafficking (sub-code 12) and abandoned settlements (sub-code 16). Finally, the government's disaster management (main and subcategory code 7101) is included as an official relief factor.

Methods

Kernel density estimation

Kernel density estimation is a widely used spatial smoothing method, which is especially beneficial to presenting the spatial distribution trend of discrete points [30]. A report used this method to describe the overall temporal and spatial distribution characteristics of natural disasters in Qing Dynasty, especially the distribution and migration of disaster-prone areas [31]. Using the kernel density analysis method in ArcGIS Pro 3.0 software, the kernel density values of disaster severity are divided into five grades from low to high by the natural break point classification method, and the spatial distribution is described (Section S3 in Supplementary Materials).

Standard deviation ellipse

The standard deviation ellipse is an important tool to effectively explore the spatial characteristics of point elements. It can be used to determine the distribution center, main distribution direction, and evolution trend of point elements, and reveal the overall spatial distribution characteristics of geographical elements and their spatio-temporal evolution process [32]. A Study have used this method to explore the spatial characteristics of human cases of influenza A (H7N9) in China in 2013–2014: concentration trend, dispersion, and directional trend [33]. Operation of standard deviation ellipse with ArcGIS Pro 3.0 (Section S4 in Supplementary Materials).

Spatial autocorrelation

Univariate spatial autocorrelation is mainly used to explore the overall distribution of research objects and can analyze whether disasters themselves are aggregated in space (Section S5 in Supplementary Materials) [34]. Bivariate spatial autocorrelation can be used to explore the degree of correlation between two hazards (Section S6 in Supplementary Materials) [35]. An article analyzes the spatial aggregation of dengue incidence in Brazil by univariate spatial autocorrelation, and analyze the relationship between dengue incidence and Ae. aegypti ovitrap positivity index by bivariate spatial autocorrelation [36]. The value range of Moran's I index is [−1, 1], greater than 0 indicates a positive correlation, and the larger the value, the greater the spatial correlation; Less than 0 indicates a negative correlation, and the smaller the value, the greater the spatial difference; Equal to 0 means that it presents a random distribution. The two-sided test showed that $P < 0.05$ indicated that the difference was statistically significant. Spatial autocorrelation analyses were all done in GeoDa 1.22. 02 [37].

Social network analysis

Social network analysis is a statistical method widely used in sociology to explore how different agents relate to each other to determine their unique network types [38]. A report have used this method to explore the relationship between one variable and other variables in the drought data set of Qing Dynasty [22]. In this study, we use the pairwise method to calculate the relationship between variables, based on county-level administrative units. If drought, locust plague, and famine occur simultaneously in a certain year in a county, then drought and locust plague, drought and famine, locust plague and famine constitute each event separately. The network was constructed using Gephi 0.1 software.

Path analysis

Path analysis takes the linear relationship between variables as the basic assumption and is used to study the potential direct and indirect causal relationships between variables. There is a study exploring the dependent climate drivers of human epidemics in ancient China through path analysis [39]. In the path analysis, the model is tested using the covariance matrix as input and the parameters are estimated using the generalized least squares estimation method [40]. In this study, we think that the model fitting is acceptable when the model fitting index GFI > 0.9 and RMR < 0.05 [41, 42]. The statistics were completed with AMOS 24.0, and drawing with R 4.3.2. Not just the number of occurrences, but the severity is also a crucial factor. From the drought and epidemics data included in the analysis, we combined the frequency and severity, taking the county level as the smallest unit to collect the average severity.

Geographical detector

The geographical detector can not only quantify the explanatory power of a single influencing factor X but also quantify the explanatory power of the interaction of different factors on the dependent variable Y, which can reflect the geographic phenomenon more comprehensively than the traditional method [43]. A Study have examined the effects of socio-economic and eco-environmental factors on tuberculosis incidence in Guangzhou, China through geographical detector [44]. The explanatory power is expressed by the *q*-value measure, and the value ranges from 0 to 1. The larger the value, the stronger the explanatory power of the independent variable X to the attribute Y. The interaction of the two factors (Xs) is quantified by the geographical detector. The research of Wang Jinfeng elaborated on the principle and formula of geographic detectors [43]. The software can be downloaded from www.geodetector.cn. Explanatory power and interaction applications using R 4.3.2 to complete the drawing.

Results

Nuclear density analysis of drought and epidemics

The spatial distribution patterns of drought and epidemics across the nation were delineated using kernel density analysis. Given that the subsequent discussion frequently references the names of Chinese provinces, which may be perplexing for readers not well-versed in Chinese geography, a simplified map has been included for reference. This map is based on the 2018 edition of the China Digital Map Database from the State Bureau of Surveying and Mapping and illustrates the locations of the provinces mentioned in this article. It is important to clarify that this map is not intended to represent the full territorial extent of China as recognized officially (Fig. 1).

An extreme drought event that initially emerged north of the Yangtze River, subsequently expanding to encompass the middle and lower reaches of the Yangtze River and South China (Fig. 2a). The overall pattern exhibited a progression of dispersion, concentration, and subsequent dispersion. The year 1785 marked a

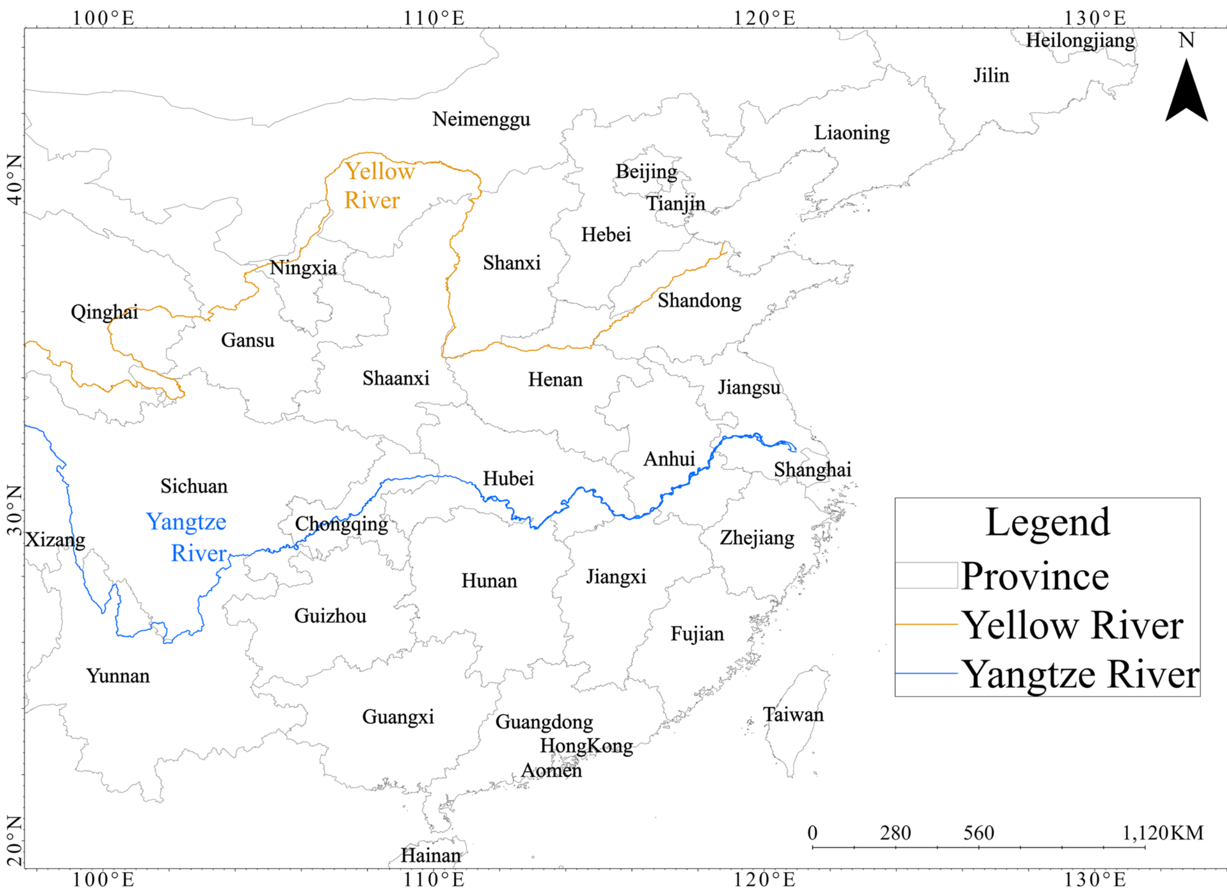

Fig. 1 Provincial boundaries of Chinese provinces relevant to this study

period of intense drought development (Fig. 2b). In 1786, the drought's geographical focus began to shift, with areas in East China, including Shandong and Jiangsu, as well as regions south of the Yangtze River such as Jiangxi, Hubei, Hunan, Fujian, Guangdong, and Guangxi, experiencing drought conditions (Fig. 2c). By 1787, the drought had mitigated, resulting in scattered occurrences (Fig. 2d).

Our analysis reveals a correlation between the occurrence of extreme drought events in China from 1784 to 1787 CE and the emergence of severe epidemics in the corresponding affected regions. In 1784, the epidemics were predominantly concentrated in the Jiangsu area (Fig. 3a). As the drought escalated, sporadic outbreaks of epidemics began to appear in the middle and lower reaches of the Yangtze River in 1785 (Fig. 3b). The year 1786 marked a period of widespread epidemic breakouts, with high prevalence observed in both the middle and lower reaches of the Yangtze River and the Yellow River regions (Fig. 3c). By 1787, the incidence of epidemics had diminished, with sporadic occurrences mainly limited to southwestern China (Fig. 3d).

Standard deviation ellipse analysis of drought and epidemics

The standard deviation elliptic analysis delineates the distribution center of gravity, migration trajectory, and evolutionary tendencies of both drought and epidemics events. The annual standard deviation ellipses for drought and epidemics are detailed in the Supplementary Materials (Figures. S1 and S2 online). Figure 4 illustrates the migratory pattern of the gravity centers for these events. We have also provided specific gravity center coordinates and detailed positioning (Table S2 online). The overall trend of this drought event was a southward progression. It began in the lower reaches of the Yellow River in 1784, migrated to the lower reaches of the Yangtze River in 1785, and then shifted to the southwest in the middle and lower reaches of the Yangtze River over the subsequent two years. The epicenter of the epidemics was notably concentrated in the lower reaches of the Yangtze River until 1787, at which point it moved to Hunan, located in the middle reaches of the Yangtze River.

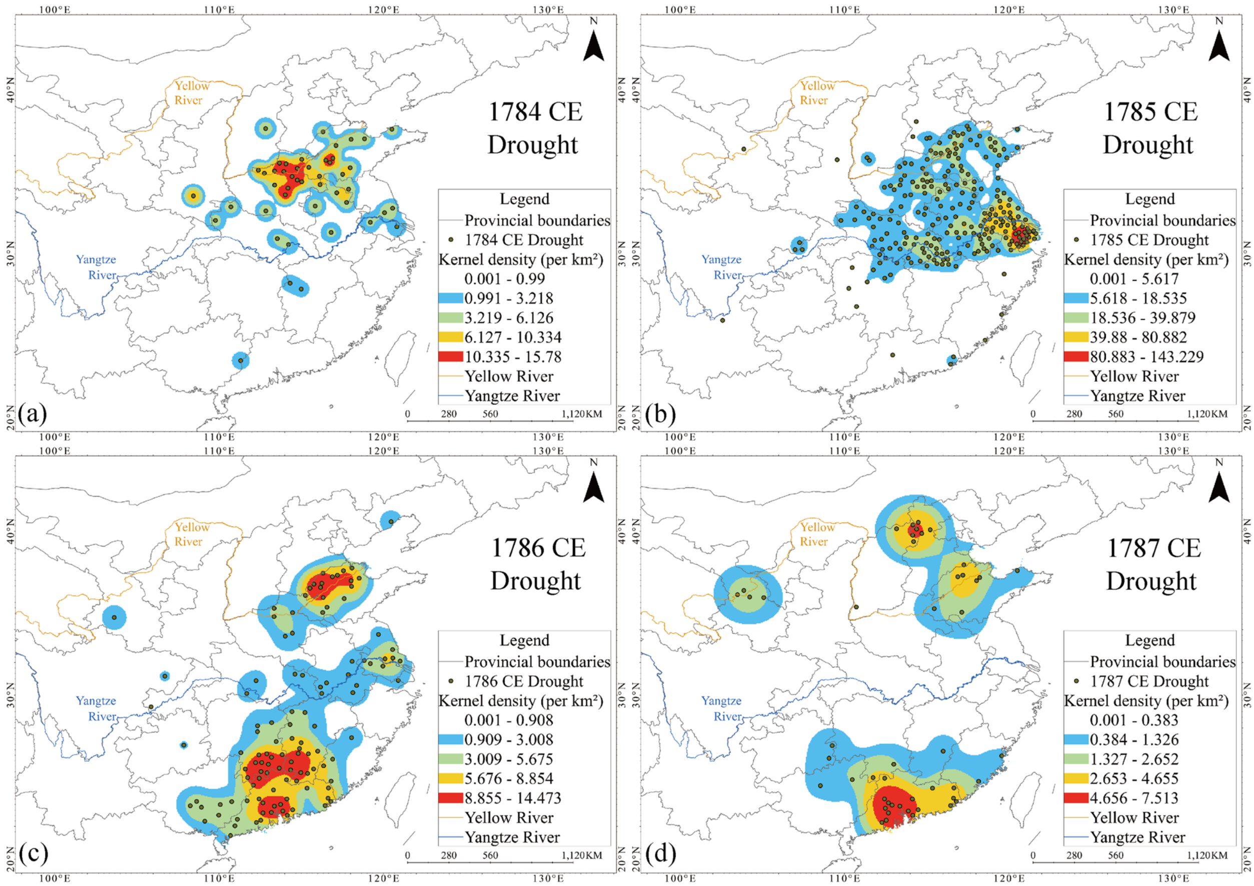

Fig. 2 Analysis of nuclear density in 1784–1787 CE drought. **a** 1784 CE drought. **b** 1785 CE drought. **c** 1786 CE drought. **d** 1787 CE drought. Brown dots indicate the place where drought occurred, and white, blue, green, yellow, and red respectively represent levels 1–5 of nuclear density values from low to high

Spatial autocorrelation

Univariate spatial autocorrelation can explore the spatial aggregation of drought and epidemics themselves, while bivariate spatial autocorrelation can explore the epidemics correlation between drought and epidemics (Fig. 5 and Figure. S3). In the univariate spatial autocorrelation, it can be seen that except in 1787, the epidemics did not show spatial correlation because they were too sporadic and scattered, the Moran index of drought and epidemics in other years was greater than 0, and the occurrence and development of both showed the characteristics of spatial aggregation. Moreover, the Moran index of epidemics from 1784 to 1786 was higher than that of drought every year, indicating that epidemics have stronger spatial aggregation characteristics than drought. In bivariate spatial autocorrelation analysis, the Moran index of drought and epidemics in the same year, one year lag, two years lag and three years lag (for example, the drought in 1784 corresponds to the epidemics in 1785) is calculated respectively. It can be seen that there is a positive correlation between drought and epidemics in the same year and one year lag and two years lag. In the three years lag analysis, although the drought in 1785 and the 1788 epidemics were negatively correlated, it was actually caused by the drought in 1785 as an upward period, and the epidemics in 1788 has subsided. It has a most significant impact on epidemics with one year lag. (The bivariate Moran's index for the same year of the 1785 drought and epidemics disease is 0.15, while the bivariate Moran's index for the 1785 drought and the 1786 epidemics disease is 0.25 with a one-year lag. The largest Moran's index in two years lag is 0.12 and that is 0.05 in three years lag.)

Social network analysis

To explore the statistical characteristics of the relationship between one variable and other variables in this extreme drought event, we conducted a social network analysis (Fig. 6 and Figure S4). Through the social network analysis, it can be seen that in the same year, lag 1 year, lag 2 years analysis, drought is closely related to crop failure and famine, followed by epidemics and official management. This makes it even more clear that this

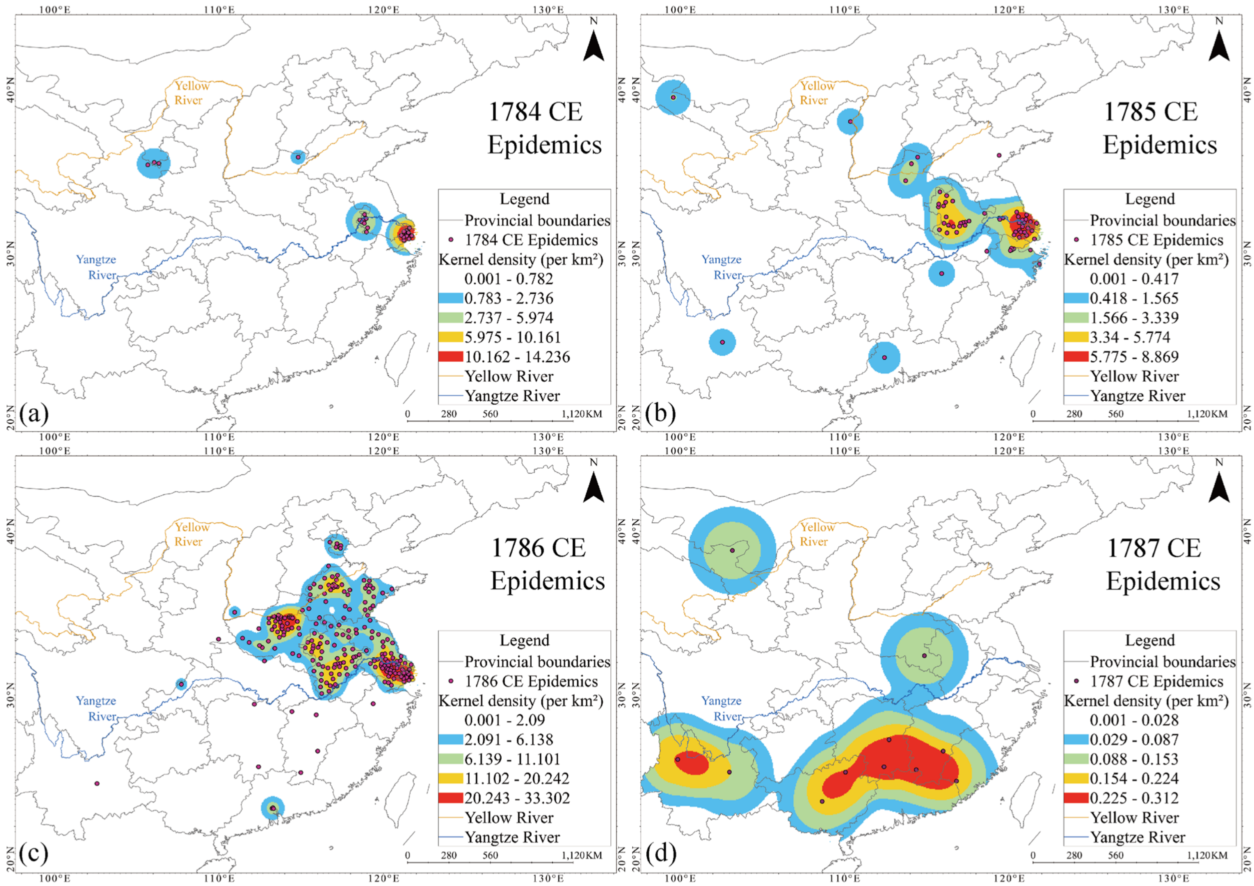

Fig. 3 Nuclear density analysis of 1784–1787 CE epidemics. **a** 1784 CE epidemics. **b** 1785 CE epidemics. **c** 1786 CE epidemics. **d** 1787 CE epidemics. The purple dots indicate the place where the epidemics occurred, and white, blue, green, yellow, and red respectively represent levels 1–5 of nuclear density values from low to high

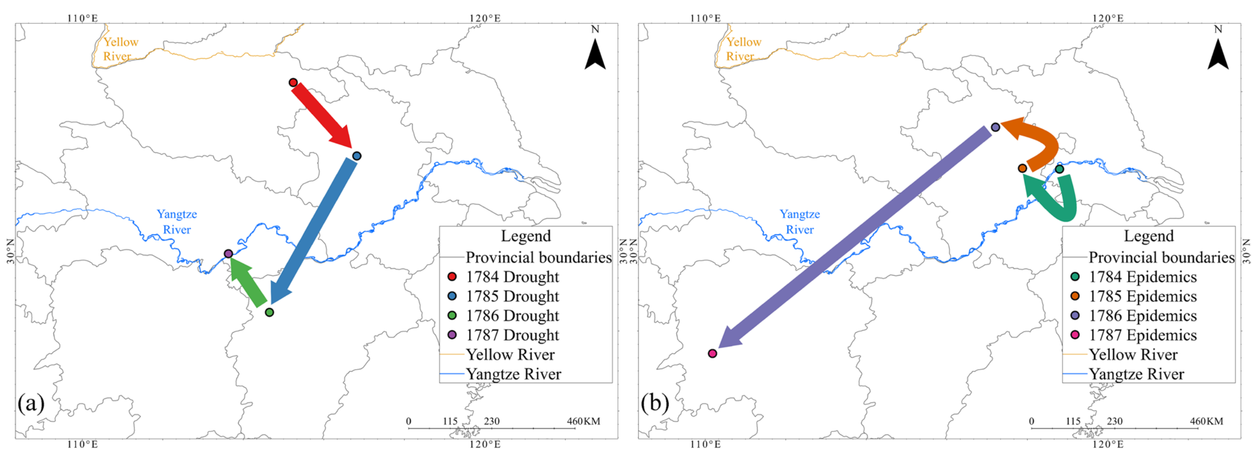

Fig. 4 Process of shifting center of gravity of drought and epidemics

drought is accompanied by severe epidemics. In the three years lag analysis, official disaster management replaced epidemics and became the factor most closely related to drought, crop failure and famine. Like spatial correlation analysis, this was caused by the few remaining epidemics in 1788. This further suggests that the epidemics quickly subsided with the intervention of official disaster management. This drought event (1784–1787 CE) From

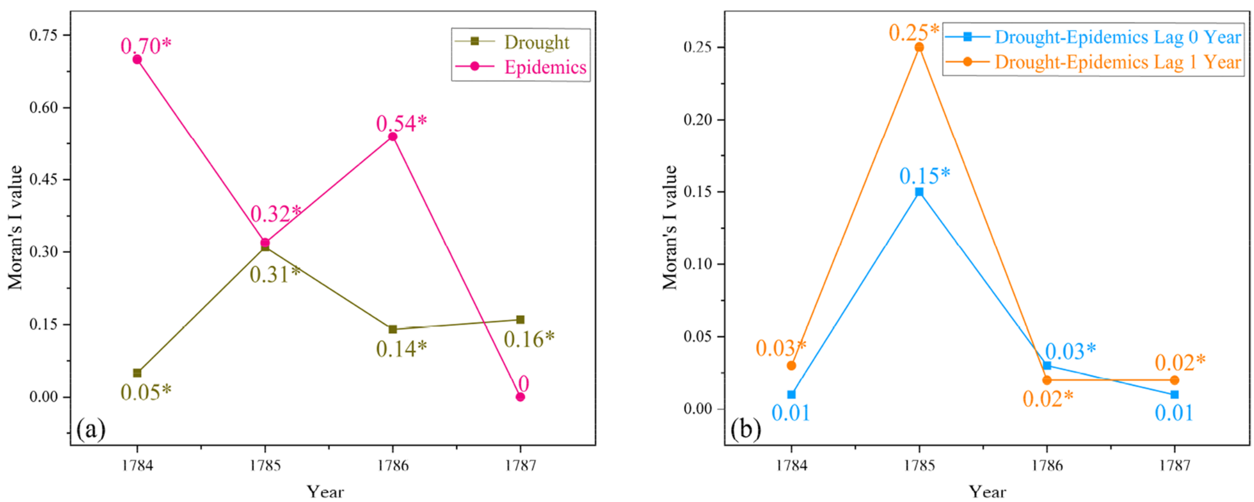

Fig. 5 Moran Index Line Chart. **a** Univariate spatial autocorrelation Moran index, brown represents drought, purple represents epidemics. **b** Bivariate spatial autocorrelation Moran index, blue represents drought-epidemics in the same year, and orange represents drought-epidemics lag by 1 year. *: $P < 0.05$

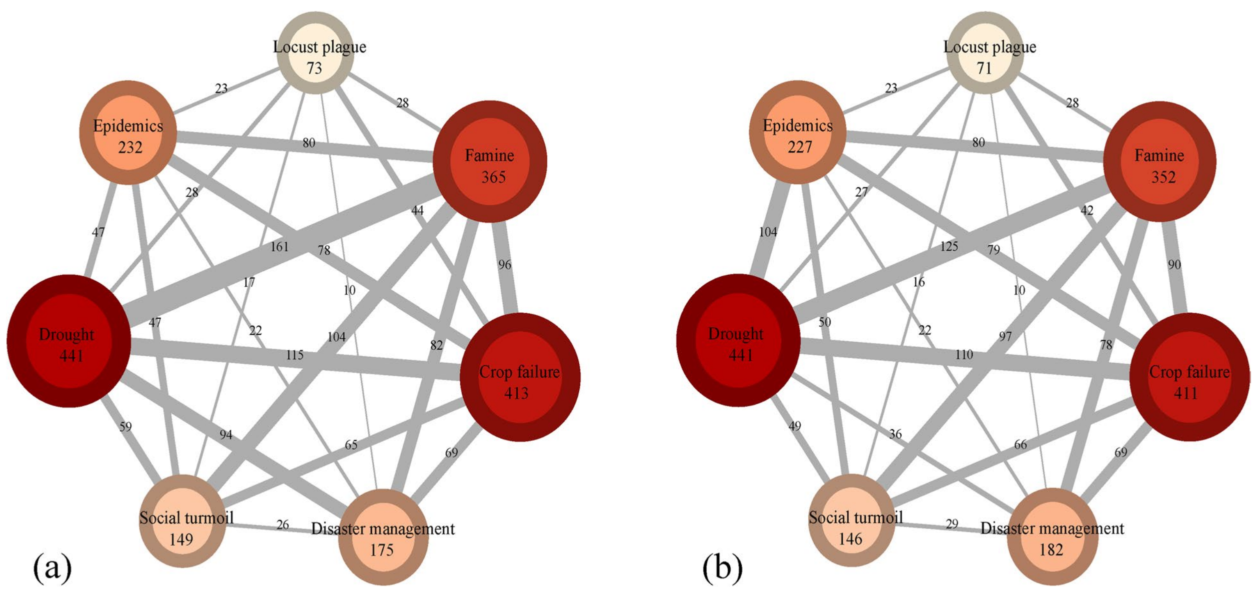

Fig. 6 Social network analysis diagram. **a** Drought and epidemics are in the same year. **b** Drought-epidemics lag by 1 year. The size and color of the circle represent the number of occurrences of events. The larger the circle, the darker the color, the more times, the thickness of the line represents the number of co-occurrences, and the thicker the line, the more times

the forty-ninth year of Qianlong to the fifty-second year of Qianlong. During this period, China's politics was relatively stable [22]. Social turmoil and official relief coexisted, so epidemics quickly subsided after a rapid outbreak.

Path analysis

Through path analysis, we can identify the pathways by which various variables affect the epidemics. We constructed a path analysis model for the same year of drought infectious disease (Fig. 7a), the one-year lag of drought (Fig. 7b), the two-year lag of drought (Figure. S5a) and the three-year lag of drought (Figure. S5b). The model includes factors such as drought, locust plague, famine, crop failure, official relief, social unrest, and epidemics, especially grain prices indicators because grain prices indicators truly reflect the socio-economic and agricultural situation at that time. The effect values of the

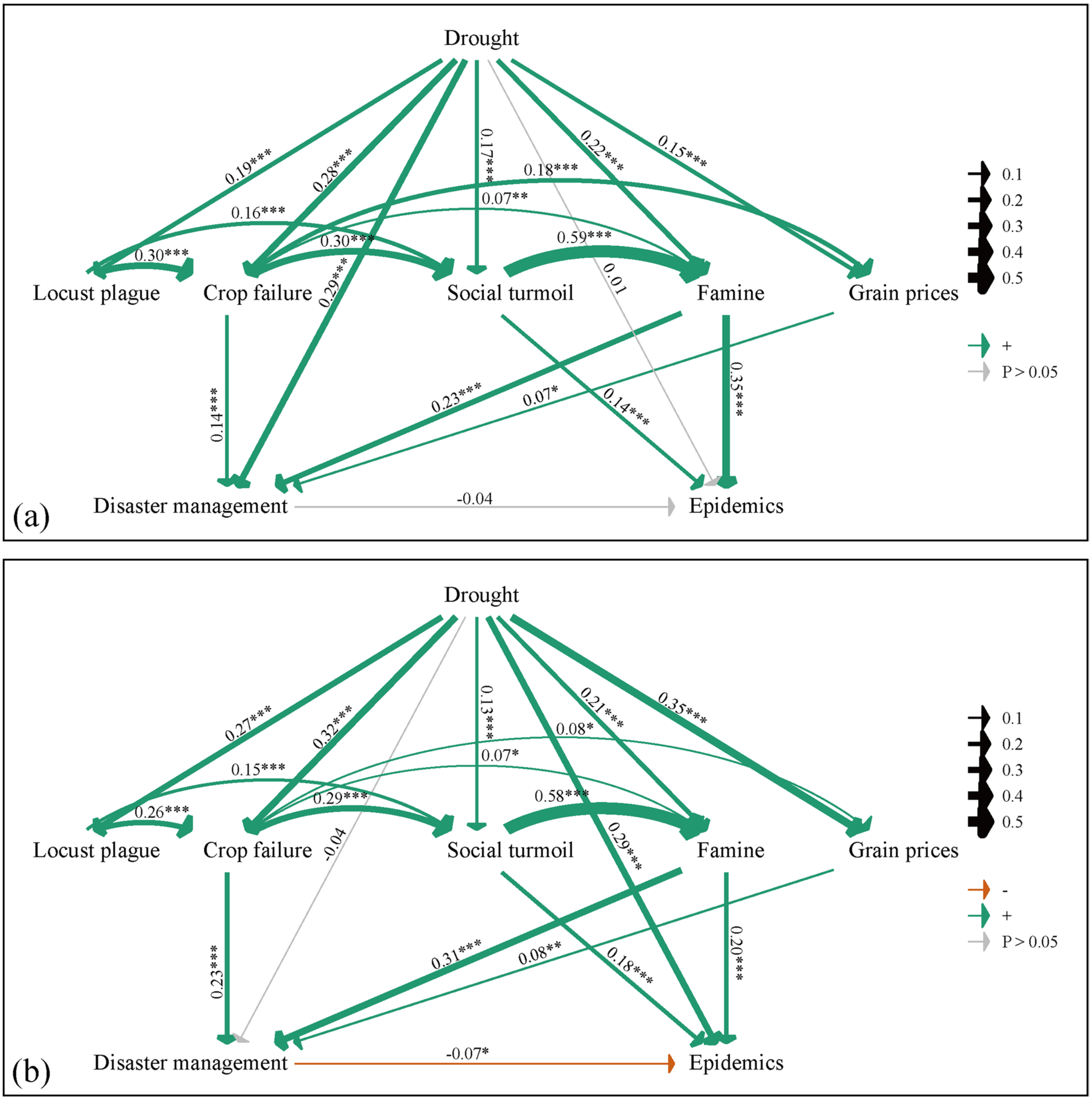

Fig. 7 Path analysis diagram. **a** Drought and epidemics are in the same year. **b** Drought and epidemics are in one-year lag. The arrows in the figure indicate causality, the green arrows indicate that the normalized path coefficient is positive, the orange arrows indicate that the normalized path coefficient is negative, all of which passed the 95% significance test, and the gray arrows indicate that they failed the significance test. The thickness of the arrow represents the size of the standardized path coefficient, and the black number is the value of the standardized path coefficient, *: $P<0.05$; **: $P<0.01$; ***: $P<0.001$

same year and one-year lag are shown in the Fig. 8. The goodness of fit of the model and effect values of two-year lag and three-year lag of drought are shown in the Supplementary Materials (Table S3 online, Figure S6). It can be seen that the drought has no direct effect on the epidemics in the same year, two-year lag and three-year lag ($P>0.05$) but has an indirect effect through other factors. In the model with a delay of 1 year, it can be found that drought has a significant direct effect on the epidemics ($\beta=0.29$, $P<0.001$). In the same year, one-year lag and two-year lag models, famine directly promoted the epidemics, and it was the key link in the epidemics caused by drought ($\beta=0.35$, $P<0.001$ in the same year; $\beta=0.20$, $P<0.001$ in the one-year lag; $\beta=0.25$, $P<0.001$ in the

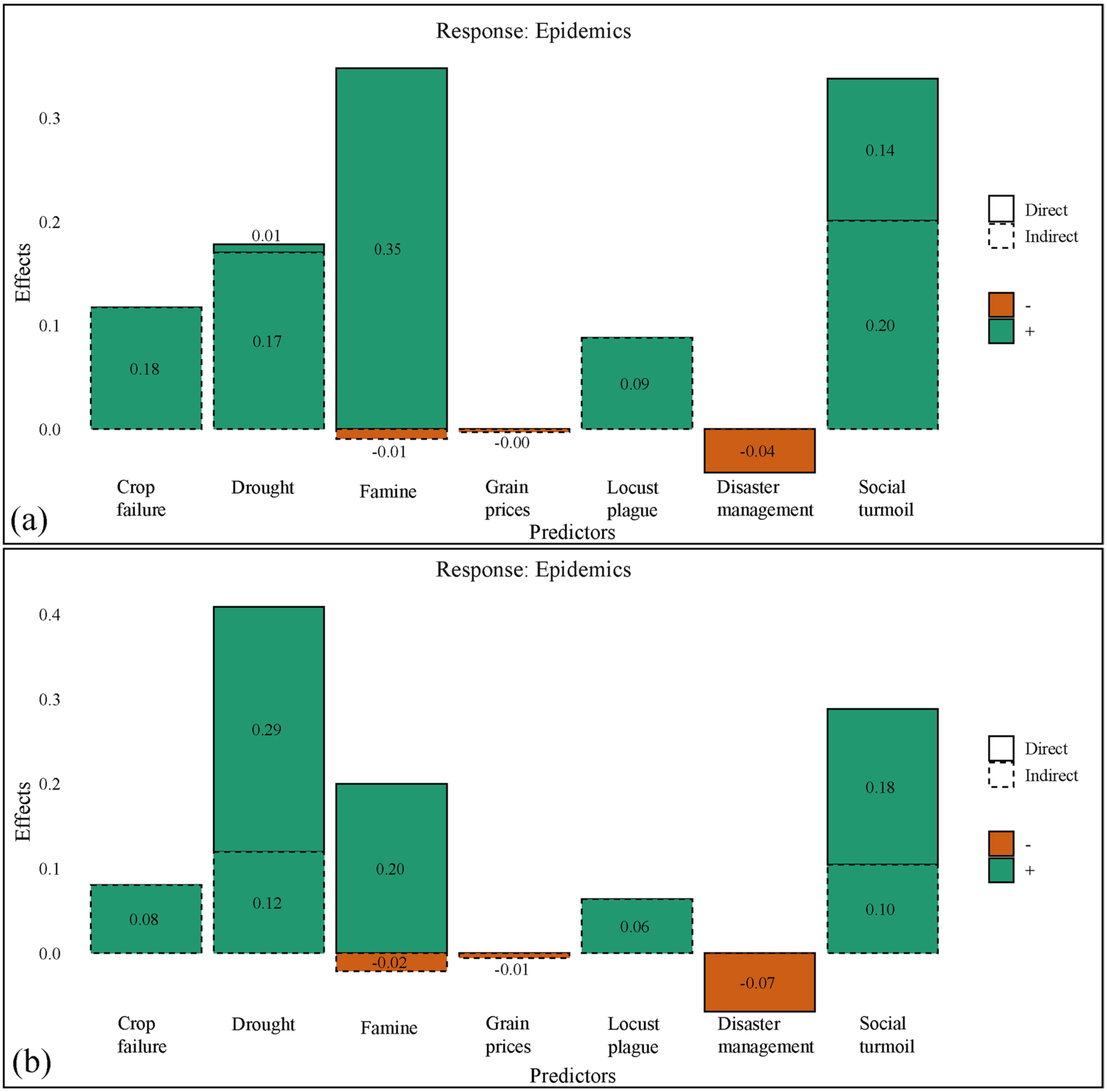

Fig. 8 Path analysis effect diagram. **a** Drought and epidemics are in the same year. **b** Drought epidemics lag 1 year. The solid line of the box indicates the direct effect, the dashed line indicates the indirect effect, the green indicates the positive direct effect value, and the orange indicates the negative indirect effect value. The black number indicates the effect value

two-year lag). Social turmoil was another important factor, contributing to the prevalence of epidemics ($\beta=0.14$, $P<0.001$ in the same year; $\beta=0.18$, $P<0.001$ in the one-year lag; $\beta=0.28$, $P<0.001$ in the two-year lag; $\beta=0.19$, $P<0.001$ in the three-year lag). Drought and crop failure will lead to an increase in grain prices, which directly or indirectly promotes the government's disaster management, disaster relief, tax exemption, and other measures (the same year: drought-disaster management $\beta=0.29$, $P<0.001$, crop failure-disaster management $\beta=0.14$, $P<0.001$, grain prices-disaster management $\beta=0.07$, $P<0.05$; Lag 1 year: crop failure-disaster management $\beta=0.23$, $P<0.001$, grain prices-disaster management $\beta=0.08$, $P<0.05$; Lag 2 year: crop failure-disaster management $\beta=0.23$, $P<0.001$; Lag 3 year: drought-disaster management $\beta=0.12$, $P<0.001$, crop failure-disaster management $\beta=0.26$, $P<0.001$). In the three-year lag, drought has a negative relationship with famine and grain prices (drought-famine $\beta = -0.08$, $P < 0.001$; drought-grain prices $\beta = -0.12$, $P < 0.001$), it may be that famine was quickly eliminated under disaster management, and grain were oversupplied under the vigorous intervention of the government. The background that Qing Dynasty government attached great importance to the grain prices reporting policy, officials could judge the disaster status of residents through the rise and fall of grain prices and decide whether to carry out effective disaster relief [45]. Government disaster management has a suppressive effect on the epidemics in the one-year lag model ($\beta = -0.07$, $P < 0.05$), but it is not significant in others. This may be caused by the continuous disaster relief policies of the Qing government, or the political delay may lead to the backwardness of policies and measures in time [46]. In conclusion, we find that active and effective official disaster relief actions can suppress the outbreak of epidemics caused by extreme drought events.

Inspired by the concept of 'polycrisis' and non-linear, feedback-laden connection between ecological and social pressures being experienced today, we do flipping analysis in this section, especially about social turmoil and disaster management (Figure. S7-S14). We used these two factors as response variables instead of epidemics. In the analysis, locust plague ($\beta = 0.07$, $P < 0.01$ in the same year; $\beta = 0.08$, $P < 0.01$ in the one-year lag; $\beta = 0.06$, $P < 0.05$ in the two-year lag), crop failure ($\beta = 0.14$, $P < 0.001$ in the same year; $\beta = 0.14$, $P < 0.001$ in the one-year lag; $\beta = 0.13$, $P < 0.05$ in the two-year lag), famine ($\beta = 0.60$, $P < 0.001$ in the same year; $\beta = 0.58$, $P < 0.001$ in the one-year lag; $\beta = 0.56$, $P < 0.001$ in the two-year lag; $\beta = 0.47$, $P < 0.001$ in the three-year lag) and epidemics ($\beta = 0.11$, $P < 0.001$ in the one-year lag; $\beta = 0.12$, $P < 0.001$ in the two-year lag; $\beta = 0.14$, $P < 0.001$ in the three-year lag) promoted the occurrence of social turmoil. There is no difference between the increase of grain prices and social turmoil, which may be related to the active food security policy of Qing Dynasty at that time. It is interesting that the drought and social turmoil has a negative relationship in the model with one year lag ($\beta = -0.08$, $P < 0.001$). Perhaps the government's attention is focused on arid areas, which made social turmoil has been reduced. In another analysis, crop failure ($\beta = 0.16$, $P < 0.001$ in the same year; $\beta = 0.25$, $P < 0.001$ in the one-year lag; $\beta = 0.22$, $P < 0.001$ in the two-year lag; $\beta = 0.26$, $P < 0.001$ in the three-year lag), drought ($\beta = 0.28$, $P < 0.001$ in the same year; $\beta = 0.12$, $P < 0.001$ in the three-year lag), famine ($\beta = 0.25$, $P < 0.001$ in the same year; $\beta = 0.34$, $P < 0.001$ in the one-year lag; $\beta = 0.39$, $P < 0.001$ in the two-year lag; $\beta = 0.33$, $P < 0.001$ in the three-year lag) and grain prices ($\beta = 0.08$, $P < 0.01$ in the same year; $\beta = 0.09$, $P < 0.001$ in the one-year lag) promoted the occurrence disaster management. Epidemics and disaster management show obvious negative relationship ($\beta = -0.07$, $P < 0.05$ in the same year; $\beta = -0.10$, $P < 0.01$ in the one-year lag; $\beta = -0.12$, $P < 0.001$ in the two-year lag). The results show that active and effective official management actions are essential.

Geographical detector

We use geographical detectors to quantify the explanatory power of various influencing factors on epidemics outbreaks (Figure. S15-18). Making geo-detector statistics, it can be found that population density is an important factor affecting the epidemics in the whole drought event from 1784 to 1787, showing varying degrees of explanatory power. At the beginning of the drought in 1784, population density was an important factor affecting epidemics. With the increasing intensity of drought, drought became the dominant factor in 1785. In 1786, the explanatory power of drought for epidemics was not as good as that of grain prices, population density, famine, social unrest, crop failure, and other factors. The reason was due to the lag of the effects of drought mentioned above. Under the influence of drought, these factors directly or indirectly play a role in the epidemics, which is also reflected in the path analysis. In the study of one-year lag data, our view is further verified. Drought, grain prices, famine, population density, social unrest, and crop failure dominate the explanation of epidemics. In addition, it can be seen from the two models that after any two factors are combined in any pair, the explanatory power of epidemics increases (double-factor increase or nonlinear enhancement), which further suggests that extreme drought events have an impact on epidemics. The outbreak is a compound event that combines multiple factors.

Discussion and conclusion

The Qing Dynasty (1644–1911 CE) is the nearest ancient Chinese dynasty. It is not only a historical period of frequent natural disasters but also an era of abundant historical documents. The massive disaster information preserved in official archives, local chronicles, and private documents has always been the key object of scholars' collation and research [31]. Therefore, different from previous studies, this study includes various variables such as grain prices, population density, and socio-economy, and applies multiple research methods to quantitatively demonstrate the response of epidemics disease outbreaks to extreme drought events during historical dynasties.

As a study of typical historical events, the majority of conclusions in this paper are corroborated by ancient textual records. Regarding the drought-famine-epidemics disaster chain, the Funing County Annals document: "Following the drought, rice prices surged catastrophically. A severe famine ensued in spring, marked by instances of cannibalism, followed by a major epidemic in summer." (《阜宁县志》: "旱后米腾贵, 春大饥, 人相食, 夏大疫。") The Dantu County Annals similarly record: "Drought preceded pestilence, with calamities compounding each other." (《丹徒县志》: "先旱后疫, 荒疫相因。") The Anyi County Annals describe: "Southern Shanxi experienced extreme drought, particularly severe in Anyi. The profound drought precipitated widespread famine, which in turn triggered disease outbreaks." (《安邑县志》: "晋南大旱, 安邑为甚, 大旱引发大饥, 大饥诱发疾疫。") Historical records of governmental disaster management demonstrate systematic responses. The Qing Shi Gao·Gaozong Ji records: "In May, relief provisions were distributed across sixteen prefectures in Jiangsu (including Tongshan) and forty counties in Shandong (including Lingxian) affected by drought." (《清史稿·高宗纪》: "五月, 赈江苏铜山等十六州县、山东陵县等四十州县旱灾。") The Anhui Provincial Chronicles document an imperial edict from December: "Multiple provinces including Henan, Shandong, Jiangsu, Anhui, and Hubei suffered extensive spring–summer drought this year. Through successive decrees, we have implemented differentiated tax remissions and relief distributions to ensure sustenance for affected populations, thereby preventing displacement." (《安徽通志》: "十二月奉上谕: 本年河南、山东、江苏、安徽、湖北等省春夏之间雨泽缺少, 被旱处所较多, 业经节次降旨, 分别蠲赈各该处灾黎糊口有资, 自不致复虞失所。") The Dongtai County Annals provide detailed quantification: "Dongtai County endured severe drought with complete crop failure. From March until the 13th day of the following February, precipitation ceased entirely—the salt transport river desiccated and wells depleted. Concurrent locust infestations exacerbated food scarcity, with rice prices escalating to ten taels per shi and wheat to five taels per shi. Authorities implemented emergency measures including relief grain distribution, tax exemptions, and suspension of salt stove levies." (《东台县志》: "东台县大旱, 无麦禾。自三月至次年二月十三日方雨, 运盐河竭, 井涸。蝗。米石价十两, 麦石价五两, 民饥。赈粜, 蠲免民赋灶折。") Many ancient historical records (such as rich records and huge numbers of county chronicles) reflect the small-scale situation in their respective regions. Thanks to the summary and digitization of rich books and information, this paper can use modern scientific methods to make quantitative analysis from the national macro level to further prove the conclusion of qualitative analysis and discover new viewpoints.

Through the analysis of extreme drought events from 1784 to 1787 CE, we found that the increase of drought can directly or indirectly promote the outbreak of epidemics. Modern studies have also found that the prevalence of cholera increased everywhere during drought [47]. It is also reported that drought was the main factor in the development of the typhus epidemic in Mexico between 1655 and 1918. Historical documents describe large numbers of refugees gathering in towns for relief during droughts, and crowded crowds created the necessary conditions for the spread of typhus [48]. This epidemics disease incident is in line with the basic law of Chinese historical epidemic disasters, that is, the outbreak of epidemics is roughly related to the high population density pattern [49]. This is different from the research results on long-term scales (population density is negatively correlated with human epidemics events) [39], which further shows the necessity of researching different temporal and spatial scales. The difference is that we quantitatively analyzed that this drought has an obvious lag effect on the epidemics. This has not been explicitly stated in previous studies, perhaps because of different study time scales [22, 48, 50]. Our conclusions are of global significance. India experienced a mega drought triggered by El Nino in 1876–1878 [51]. Accompanying famine is the most critical intermediary factor, causing pandemics of malaria, smallpox, cholera, dysentery and other infectious diseases, which are responsible for most deaths [52]. We found that an obvious feature of the recovery study of this drought-famine-epidemics event in India is the lag of infectious diseases, which is similar to the characteristics of the Qianlong drought. 1877, not 1876, was the concentrated outbreak of infectious diseases. Many severe diarrhea patients were observed in relief camps in Madras in early 1877. The total number of smallpox-related deaths increased significantly in 1877 and remained high in 1878. The total number of deaths also reached its peak in 1877 [52].

In addition, this study also found that famine is the key factor that drought has an indirect impact on the epidemics. Previous studies have also proved that famine can force people to emigrate, and at the same time, the deterioration of personal health due to malnutrition promotes the spread of epidemics [53]. Famine can also lead to wars and population movements, which indirectly lead to the spread of epidemics [54]. Other studies on Chinese history also show that drought, famine, and epidemic diseases are the most closely related influencing factors [55]. The results of this study show that the disaster chain of drought-famine-epidemics is clearly defined under different temporal and spatial scales and historical periods.

Of course, we also found that this accompanying epidemics disease subsided rapidly, which may be related to the official relief actions that suppressed the epidemics. The smooth circulation of disaster information is the key to the smooth operation of disaster relief system [56]. From 1736 CE in the Qing Dynasty, a complete grain prices reporting system was gradually formed: the main grain prices at the county level were compiled into a list in a standardized format and transmitted to the central government layer by layer [57]. This study intuitively shows the relationship between climate change, grain prices, and epidemics in historical periods. The conclusion shows that the rise in grain prices provides important information for the government to respond to climate change, prompts the government to increase relief actions, and indirectly suppresses the epidemics. This is consistent with the historical fact: the emperor needs to know the grain prices in all parts of the country, especially in famine-stricken areas, to take timely measures to maintain social stability [45]. In addition, Emperor Qianlong attached great importance to local officials' disaster reports, and set up a strict supervision and punishment system, such as sending central officials to supervise the disaster relief and establishing a performance evaluation mechanism [58]. Local officials will go to the affected areas to verify the number of deaths, property losses, field disasters [59]. In the face of disasters, the specific management measures of the government include grain transportation, tax-free loans, immigration control, etc. These measures can effectively help people cope with famines and epidemics caused by extreme weather events.

The grain reserve system plays a fundamental role in the construction of the entire government management system. Grain mobilization and national storage ensure the grain supply in the disaster-stricken areas and effectively respond to famine, a key intermediary factor [60]. Qianlong in the Qing Dynasty and before, there were significantly better than The perfect grain storage system in other periods, It has a huge amount of grain reserves [61, 62]. When there is no disaster, the government buys grain storage. When grain prices are low in bumper years, the government sells it at a reduced price to reduce the occurrence of famine. Grain transportation is the main means of macro-control by the central government. In the Qing Dynasty, the scale of grain transfer was very large, with the coordination and support of various states and counties in the province, and the nationwide inter-provincial transportation [46]. Especially for inter-provincial food transportation, such a large-scale food transportation makes it possible to quickly alleviate the impact of disasters and accompanying famines at the national level, and has high social resilience. It is worth noting that the storage system and grain adjustment measures all declined with the decline of national strength in the late Qing Dynasty, making the resilience weakened and the vulnerability deepened. Drought, famine and associated epidemics often lead to widespread population movements. This vicious circle will lead to further epidemics. The Qing government controlled immigration. For the victims who have not left the affected areas, the government has set up special officials to dissuade the people from staying in their hometown and waiting for relief. For the refugees who have fled their families from the disaster-stricken areas, the government has two measures: adopting the poor and sending the refugees to their homes [46]. In traditional unified countries, when the national capacity declines, the material and institutional guarantees are insufficient, and the effect of government disaster management is also greatly reduced [63]. The average annual population associated with extreme climate in the late Qing Dynasty was ten times that in the prosperous period of Kangxi and Qianlong [55]. In the history of Qing Dynasty in China, this incident is in sharp contrast with the Guangxu drought that occurred in 1876–1879. The Guangxu drought was a typical drought event that affected many provinces and cities, accompanied by serious social unrest, famine and infectious diseases [64]. Due to the Taiping Heavenly Kingdom Movement from 1851 to 1864 and the two Opium Wars, the Qing government had fiscal crisis, weakening the social resilience [65]. Compared with the large number of official relief in Qianlong period, this official relief only accounts for a small number. The water transportation system and storage system also exist in name only. A large amount of farmland has been converted to opium planting, and grain production has dropped sharply, resulting in a shortage of grain savings, leaving granaries around the world with no food available for disaster relief [66]. The emperor's control over local officials weakened, and officials corrupted, sold the remaining grain storage, and took bribes. At the same time, neglect of duty and ineffective disaster relief have caused aggravation of social turmoil [64]. Therefore, unlike the rapid decline of infectious diseases described in this paper, the drought in Guangxu caused unprecedented social unrest, accompanied by severe epidemics of infectious diseases that lasted for many years, resulting in a large number of deaths [67].

From this drought in Qianlong, the connection between this historical period and modern challenges can be further strengthened. Without corresponding government policies, such as food allocation, improvement of medical conditions, extreme weather events (such as drought) may continue to aggravate the cholera epidemic in the Horn of Africa [68]. In Somalia, in 2011, there was a complex drought-famine-epidemics disease event. Drought was the starting factor (some affected areas had the lowest rainfall in 50 years). The rapid rise in domestic and global food prices in Somalia has been secondary to severe famine. The armed conflict caused by the lack of an effective central government has aggravated social unrest in the region. Militias and warlords severely restrict the relief of humanitarian agencies while diverting food aid [69]. Severe drought and famine, intensified civil war, and mass exodus of Somali refugees to crowded refugee camps located in Ethiopia and Kenya eventually triggered widespread epidemics of severe measles, a highly contagious viral disease [70]. Studies on the relationship between drought occurrence and mortality also highlight the importance of early warning systems and timely intervention, especially early warning systems to enhance resilience are essential to reduce mortality. In regions where such systems are strong, data show that mortality rates tend to be lower even when the number of drought events is high [15]. This is very similar to Emperor Qianlong's emphasis on disaster reporting, early warning through a sound grain prices reporting mechanism, timely adjustment and intervention in disasters. The storage and allocation of food, in particular, is essential to mitigate the short-term effects of extreme disasters and in the context of population growth, decline in cultivated land and commercialization and globalization of food production [71]. Of course, the most important thing is to reduce conflicts, establish a stable central government, and improve the comprehensive strength of the country to cope with extreme weather events such as famines and epidemics caused by disasters.

Based on the simpler socio-economic structure, through the flip analysis of social turmoil and disaster management, the understanding of 'polycrisis' and the relationship between ecological and social pressures is deepened from the perspective of historical variables. Extreme drought events break the threshold of ecological and social systems, trigger nonlinear mutations, and produce serious consequences such as famine outbreaks and epidemics of infectious diseases. This typical event can be further explained by domino effects. As a climate crisis, extreme drought can not only directly lead to human health crisis (epidemics), but also be transmitted across systems through biological crisis and agricultural crisis, leading to food crisis, famine, social turmoil, and then causing epidemics. The stress, triggering events generated by a crisis can form a feedback loop, and more commonly in two or more systems is an escalating crisis, which is difined as inter-systemic feedbacks. Guangxu drought is a suitable example. Especially during extreme climate events, if there is a war conflict, the risk of natural disasters will be further amplified, impacting social stability and human health (such as Somalia in 2011).

To sum up, this study has three advantages compared with previous studies. Firstly, this study provides a comprehensive understanding of the impact of extreme drought on epidemics outbreaks during the Qing Dynasty by integrating various historical variables. Secondly, it captures the immediate and lagged effects of drought on epidemics through a short-term interannual analysis, complementing research that examines longer time scales. Lastly, the study employs quantitative methods on rich historical data, allowing for a precise exploration of the relationship between socio-economic factors and the drought-epidemics chain across different periods.

The present study also has several limitations. First of all, population density data is calculated based on the growth rate, which cannot fully show the true situation of the population, especially the lack of population mobility data, which may affect the discovery of the true relationship between population and epidemics. Secondly, the geographical scale is different. The data scale of drought and epidemics is county, and the data scale of population and grain prices is prefecture. Although we have unified the scale of administrative regions in statistics, the accuracy lost in this process may have an impact on our conclusion. Finally, because this study is the recovery of historical extreme weather events, it will still be affected by the missing historical records, and can only be infinitely close to the historical truth.

Different from previous studies of historical climate events, this study uses the recovery study of a single extreme climate event to observe the relationship between drought and epidemics on a short-term interannual time scale. In this study, it is found that there is a significant correlation between drought and the spatial distribution of epidemics. In this 1784–1787 CE drought event, the effect of drought lag of one year is obvious. Drought has a direct or indirect impact on the outbreak of epidemics. It will indirectly lead to the occurrence of epidemics through locust plague, famine, crop failure, and social turmoil. Among them, famine is the most critical link. The government's official relief actions can curb the epidemics. The government of the Qing Dynasty paid special attention to food security, and a sound grain prices reporting mechanism could provide early warning for relief, which cut off the chain of epidemics transmission to some extent. Population density is also an important factor affecting the occurrence of ancient epidemics. This study innovatively incorporates grain prices, population density, and socioeconomic factors into the analysis to explore the impact of extreme weather events on epidemics disease outbreaks before high urbanization, and provides reference and ideas for the study of the relationship model between climate change and epidemics disease epidemics and offer historical experience for polycrisis and modern challenges.

Supplementary Information

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Supplementary Material 1.

Authors' contributions

X.H.: Software, Formal analysis, Visualization, Writing -original draft. Z.S.: Conceptualization, Project administration, Funding acquisition, Investigation, Writing-Reviewing and Editing. J.H.: Supervision, Funding acquisition, Writing -review editing. J.X.: Data curation, Methodology, Software. S.Z.: Writing -review editing. Y.Z.: Writing -review editing. Z.T.: Writing-review editing. L.H.: Investigation. Y.H.: Software.All authors reviewed the manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

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