

# Spatio-Temporal Distribution and Network Characteristics of Epidemic Disasters in Provinces Along the Middle and Upper Reaches of the Yellow River During the Qing Dynasty

Haili Zhao, Yamei Yao <sup>a,\*</sup>

College of Geography and Environmental Science, Northwest Normal University, Lanzhou 730000, China.

<sup>a</sup>yaoyamei0902@163.com

## Abstract

As a top-tier disaster within the disaster chain network, epidemics have profoundly influenced human civilization while simultaneously driving societal development and progress. Understanding the spatiotemporal distribution patterns and chain-network characteristics of historical epidemics offers critical insights for developing modern infectious disease prevention and control strategies. By applying polynomial curve fitting, wavelet analysis, spatial autocorrelation, and network analysis to provinces along the middle and upper reaches of the Yellow River, this study identified the following findings: (1) During the Qing Dynasty, epidemic frequency in the middle and upper Yellow River region showed a stepwise upward trend, with early epidemics being predominantly minor or small-scale and later ones mainly moderate, major, or catastrophic; (2) epidemic incidence peaked during summer and autumn; (3) the overall epidemic trend displayed an alternating “up-down-up-down” pattern, with a dominant periodicity of approximately 68 years; (4) epidemics generally exhibited an “east-heavy, west-light” spatial distribution pattern; and (5) natural disasters acted as the primary drivers of epidemic outbreaks, whereas large-scale mortality represented both a key environmental condition for epidemic incubation and a direct social outcome of such events.

## Keywords

Epidemics; Qing Dynasty; Provinces in the Middle and Upper Reaches of the Yellow River Basin; Spatiotemporal Distribution; Network Characteristics.

## 1. Introduction

Epidemic disasters—large-scale outbreaks of acute and highly contagious infectious diseases—are essentially biological disasters but are closely linked to environmental change and human activity <sup>[1][2]</sup>. Weak infectious disease prevention and control continue to threaten human survival and sustainable development. In the context of global environmental change and intensified human–land interaction, disease transmission patterns and pathogen dynamics have undergone profound transformations.

The Sendai Framework for Disaster Risk Reduction (2015–2030) outlines a comprehensive approach emphasizing three key tasks: assessing and governing disaster risks, increasing investment and scientific management, and strengthening preparedness and response capacity <sup>[3]</sup>. Yet, practical challenges such as inadequate funding, weak interdepartmental coordination, and insufficient professional capacity persist <sup>[4]</sup>. Strengthening global cooperation, improving early-warning and emergency-response systems, and advancing interdisciplinary research on epidemic occurrence and prevention remain imperative. Historical epidemic studies provide valuable lessons for modern epidemic risk management.

Current research on historical epidemics primarily examines their spatiotemporal distribution and environmental contexts, focusing on: (1) specific diseases <sup>[5]-[6]</sup> or comprehensive epidemic patterns within given historical periods <sup>[7]-[7]</sup>; (2) multiple dynasties, with the Ming, Qing, and Republican periods receiving greater attention due to richer documentation <sup>[9]-[14]</sup>; (3) analyses at national <sup>[1]</sup>, provincial <sup>[15]</sup>, or densely populated regional scales <sup>[16]</sup>; (4) methodological reliance on descriptive statistics for temporal patterns <sup>[17]</sup> and spatial interpolation or standard deviation ellipses for spatial patterns <sup>[18]</sup>; and (5) environmental determinants encompassing pathogens, susceptible populations, and environmental conditions <sup>[19]</sup>.

Building on this, biological studies examine pathogen characteristics <sup>[20]</sup>, epidemiology focuses on infected population traits <sup>[21],[21]</sup>, and geography explores the combined effects of natural and socioeconomic factors <sup>[22]</sup>. Debate continues over their relative primacy: Pei Qing et al. <sup>[13]</sup> proposed a framework of “climate change — socioeconomic transformation — epidemic occurrence,” while Tang Daixing et al. <sup>[23]</sup> emphasized human-induced environmental modification as a trigger for cross-regional and persistent epidemics.

Despite these advances, few studies analyze epidemic patterns across river-basin provinces. Epidemic disasters, as apex biological events in the disaster-chain network, are influenced by multiple interacting drivers and pathways, yet their structural and network characteristics remain underexplored.

The middle and upper Yellow River Basin form a transitional zone with pronounced environmental heterogeneity and shifting agro-pastoral boundaries. The Qing Dynasty coincided with the “Ming–Qing Cosmic Period,” a distinctive climatic stage, while the region’s ecological fragility heightened its sensitivity to climate and human disturbances. This study examines epidemic disasters across eight provinces—Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi, and Henan—covering 99 prefecture-level and 821 county-level units. Using polynomial fitting and wavelet analysis, temporal patterns are identified; spatial autocorrelation methods reveal spatial clustering; and a knowledge-based network model clarifies key nodes and transmission pathways within the epidemic disaster chain. The findings aim to inform modern strategies for epidemic prevention and disaster mitigation.

## 2. Data Sources and Research Methods

### 2.1. Epidemic Disaster Data Sources and Quantitative Indicators

A total of 1,316 epidemic disaster records from provinces in the middle and upper reaches of the Yellow River Basin during the Qing Dynasty were obtained from the Compilation of Historical Materials on Epidemic Disasters in China over Three Millennia (Qing Dynasty volume) <sup>[24]</sup>. Following the methodological framework proposed by Gong Shengsheng et al. <sup>[1],[25],[26]</sup>, this study employs a comprehensive set of indicators to characterize epidemic disasters, including epidemic sequence, season, year count, frequency, number of affected counties, spatial extent, depth, density, severity, and composite epidemic indices.

The epidemic disaster index is expressed in three forms: ① Epidemic Disaster Years Index ( $I_{ey}$ ): The number of epidemic disaster years within a consecutive five-year period, reflecting the long-term evolution of epidemic frequency. ② Epidemic Disaster Counties Index ( $I_{ec}$ ) or Epidemic Area Index ( $I_{es}$ ): The cumulative number of affected counties or total epidemic area within all epidemic years during a five-year period, indicating long-term changes in the spatial extent of epidemics. ③ Epidemic Severity Index ( $I_{el}$ ): The cumulative severity level of epidemics within a five-year period, representing long-term variations in epidemic intensity <sup>[1]</sup>. To quantify the severity of epidemics, historical data were categorized into five levels of epidemic severity based on the number of affected counties, reported fatalities, and mortality rates. Classification was performed using the natural breakpoint (Jenks) method, ensuring objective differentiation between severity categories (Table 1).

Table 2 Standard for classification of Epidemic disasters in the Yellow River Basin during the Qing dynasties

Qualitative Description	Minor Epidemic	Small Epidemic	Moderate Epidemic	Large Epidemic	Major Epidemic
Number of Affected Counties	1~2	3~4	5~10	11~17	21~89
Number of Deaths from the Epidemic	<8000	8000~11000	11001~31000	31001~105000	>105000
Epidemic Mortality Rate (%)	<10	10~34	35~49	50~70	>70

## 2.2. Methods

### 2.2.1. Data Processing Methods

(1) Because the administrative boundaries of the middle and upper Yellow River Basin changed frequently during the Qing Dynasty, this study adopts modern Chinese administrative divisions as the analytical framework. To avoid ambiguity caused by historical place-name variations, all toponyms were standardized and converted to their current equivalents before data analysis.

(2) Knowledge elements—the smallest units of knowledge—form the basis of knowledge management [27]. Following the general knowledge-element framework, this study represents epidemic disasters through meta-event and object models.

The meta-event model describes attributes such as time, location, cause, and consequence, while the object model defines each object's properties, carrying capacity, and degree of impact. After an initial meta-event occurs, it interacts with surrounding objects: the event damages and alters them, while the affected objects influence the event's progression. When an object reaches a critical state, it triggers a secondary event, forming a chain reaction [27].

This chain-reaction model abstracts the epidemic process through the relationships between meta-events and objects, supporting the construction of a network structure of epidemic transmission in the middle and upper Yellow River Basin during the Qing Dynasty for complex-network analysis.

As an example, the Compilation of Historical Materials on Epidemic Disasters in China over Three Millennia (Qing Dynasty Volume) records the 1877 epidemic in Jiangzhou (modern Xinjiang County): "In the third year of the Guangxu reign (1877), a devastating famine struck. Starvation reached such extremes that acts of cannibalism occurred, and even close relatives turned against one another. The bodies of the famished lay scattered across the wilderness, filling ravines and pits; half the villagers perished, and as many as six or seven in ten people lost their lives. At that time, the market price of rice and wheat soared to three taels and six qian of silver per dou. By April and May, even corn had vanished from the markets, and grass seeds and pū roots sold for over one tael of silver per dou. In the autumn, a widespread plague erupted once again, compounding the region's suffering."

This entry forms the knowledge-element dictionary for the epidemic of that year:

{“ID”: “1”,

“Time”: “1877”,

“Historical Place Name”: “Jiangzhou”,

“Modern Place Name”: “Xinjiang County”,

“Specific Disease”: “”,

“Cause”: “a devastating famine struck. Starvation reached such extremes that acts of cannibalism occurred, and even close relatives turned against one another. The bodies of the famished lay scattered across the wilderness”,

“Season”: “Autumn”,

“Month”: “”,

“Death Toll”: “”,

“Mortality Rate”: “60%”,

“Impact”: “the market price of rice and wheat soared to three taels and six qian of silver per dou. By April and May, even corn had vanished from the markets, and grass seeds and pū roots sold for over one tael of silver per dou.”,

“Duration”: “”,

“Crisis Response”: “”,

“Source”: “Compilation of Historical Materials from Three Millennia of China (Qing Dynasty Volume)”).

The meanings of each node in the epidemic disaster-chain network are summarized as follows (Table 3).

Table 4 The meaning (or event) of nodes in the disaster chain network

Node Name	Meaning (or event)	Node Name	Meaning (or event)
A1	Drought	C2	Bountiful harvests (abundant wheat crops, high grain yields)
A2	Flooding	C3	Famine
A3	Hailstorm	C4	Piles of corpses
A4	Smog (or dust storm)	C5	War, banditry
A5	Heatwave	C6	Low grain prices hurting farmers
A6	Earthquake	C7	Population displacement (fleeing famine, military movements, etc.)
A7	Cold weather (such as heavy snowfall)	C8	Dysfunctional human-animal relationships
A8	Locust plague	C9	(Beyond locust plagues, e.g., invasive species infestations)
B1	Mass deaths (or mass flight) of the population	D1	Number of people infected with epidemics
B2	Abandoned farmland	D2	Livestock epidemic figures
B3	Decreased grain production	E1	Social instability (such as selling children)
B4	Rising grain prices	E2	Government funding shortages
B5	Mass deaths of livestock (or poultry, etc.)	E3	Commercial downturn
C1	Unreasonable diets (such as eating grass roots, marmots, etc.)	E4	Transportation disruptions

Epidemic disaster nodes are categorized into five types—A, B, C, D, and E—according to their roles within the epidemic disaster chain network. Category A nodes represent the origins of epidemic spread, typically arising from natural factors, especially natural disasters. For instance, an epidemic triggered by drought is denoted as node A1. These nodes initiate epidemic processes and influence subsequent nodes, but are not themselves caused by other factors. Category B nodes act as intermediary mediators, indirectly promoting epidemic development. They serve both as outcomes of preceding events and as drivers of subsequent processes. Category C nodes are mainly related to socioeconomic conditions and are influenced

by the 13 nodes from A1 to B5. Category D nodes denote the epidemic events themselves. This study focuses exclusively on human epidemics, excluding animal diseases, which are considered only as possible triggers. Category E nodes mark the endpoints of the epidemic chain, reflecting the social and environmental impacts of epidemics. Unlike Category B nodes, which possess dual attributes as both sources and receivers of disasters, Category E nodes act solely as recipients, no longer affecting other nodes.

Although natural disasters may lead to issues such as social unrest or fiscal strain, these links were excluded from the network model to maintain analytical clarity and focus [2].

### 2.2.2. Time-Series Analysis Methods

Polynomial curve fitting was used to analyze the temporal trends in epidemic frequency and severity across provinces in the middle and upper reaches of the Yellow River Basin during the Qing Dynasty [28], identifying long-term variations and key inflection points. Wavelet analysis was then applied to detect intrinsic periodicity within the time series. By decomposing data across multiple temporal scales, this method uncovers latent cycles, clarifies system evolution, and qualitatively indicates potential future trends [29].

### 2.2.3. Spatial Feature Analysis Methods

The global Moran's I index was calculated to assess the spatial clustering of epidemic frequency and severity [30], determining whether epidemic occurrences were spatially aggregated or randomly distributed. The Getis-Ord  $G^*_i$  statistic was further applied to identify significant spatial hotspots and coldspots, revealing the spatial heterogeneity and regional differentiation of epidemic distribution [31].

### 2.2.4. Statistical Characteristics of Networks

To assess the structural characteristics and node significance within the epidemic disaster chain network, several network metrics were employed. Degree and degree centrality represent a node's direct connections and relative influence, while closeness and betweenness centrality describe its efficiency in transmitting effects and its role as an intermediary bridge. Connectivity reflects the network's overall integrity. At the global level, the average clustering coefficient and network density were used to evaluate the network's cohesion and compactness [32].

## 3. Spatiotemporal Distribution Characteristics of Epidemic Disasters in Provinces Along the Middle and Upper Reaches of the Yellow River Basin During the Qing Dynasty

### 3.1. Temporal Distribution Characteristics

#### 3.1.1. Characteristics of Dynastic Changes

During the Qing Dynasty, epidemic frequency and severity in provinces along the middle and upper reaches of the Yellow River generally showed an upward trend. Over 268 years, 199 years experienced epidemics, yielding an overall frequency of 74.25%, or roughly one epidemic every 1.5 years. By reign, epidemic frequencies were as follows: Shunzhi (66.67%), Kangxi (67.21%), Yongzheng (61.54%), Qianlong (63.33%), Jiaqing (68.00%), and Daoguang (73.33%). Epidemics peaked during the Xianfeng, Tongzhi, Guangxu, and Xuantong reigns, when outbreaks occurred annually (Figure 1a). Except for a slight decline under Yongzheng, epidemic frequency exhibited a steady, stepwise increase across successive reigns [2].

Regarding epidemic severity (Figure 2b), minor epidemics were most common (36.68%), followed by moderate ones (26.13%), while major (5.53%) and catastrophic epidemics (8.04%) were relatively rare. Catastrophic epidemics occurred in all reigns except Shunzhi, Xianfeng, and Xuantong, with the Tongzhi period recording the highest proportion (30.77%). Large-scale

epidemics appeared in all but the Shunzhi, Yongzheng, Qianlong, and Jiaqing reigns, again peaking under Tongzhi (38.46%). Minor epidemics prevailed during most reigns—especially Qianlong (55.26%)—but were absent during Tongzhi, Guangxu, and Xuantong. Moderate epidemics were most frequent in the Xuantong reign (66.67%) and least in Jiaqing (27.27%). In summary, epidemics in the early Qing period were predominantly minor and small-scale, gradually evolving into moderate, large, and catastrophic outbreaks during the late Qing era [2].

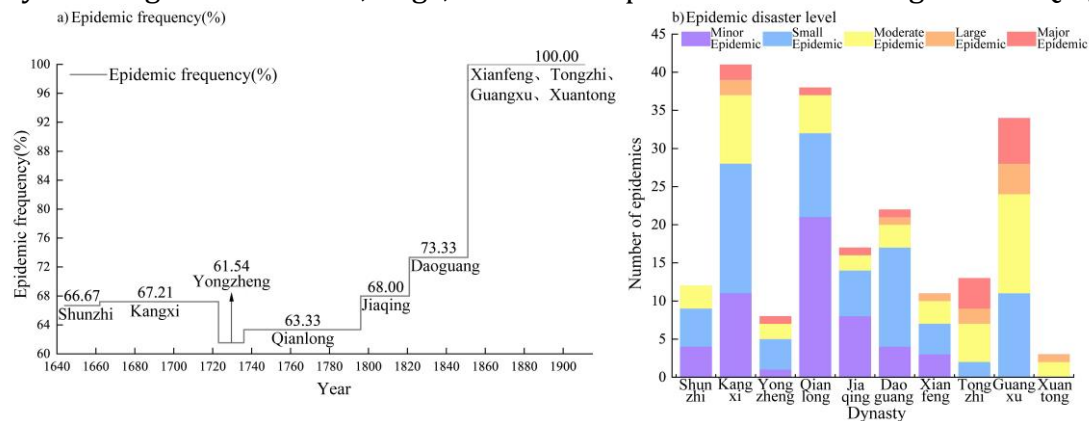


Fig.3 Epidemic frequency and epidemic grade in the middle and upper reaches of the Yellow River Basin in Qing Dynasty

### 3.1.2. Seasonal Variation Characteristics

Epidemic disasters in the middle and upper reaches of the Yellow River during the Qing Dynasty mainly occurred in summer and autumn. Over 268 years, 294 epidemic seasons were recorded, with a seasonal incidence of 27.43%: spring 70 (23.81%), summer 101 (34.35%), autumn 85 (28.91%), and winter 38 (12.93%). Epidemics thus peaked in summer, followed by autumn, and were least frequent in winter (Figure 4) [2].

This pattern reflects three key factors. First, hot and humid summer–autumn conditions favored the spread of pathogens such as *Vibrio cholerae* and *Plasmodium* spp. Second, natural disasters like floods and famines, common in these seasons, created favorable environments for outbreaks. Third, plague epidemics showed strong seasonality—14 of the documented cases (63.64%) occurred in summer and autumn. Overall, epidemic activity in the Qing Dynasty was closely tied to seasonal climate and concurrent natural hazards.

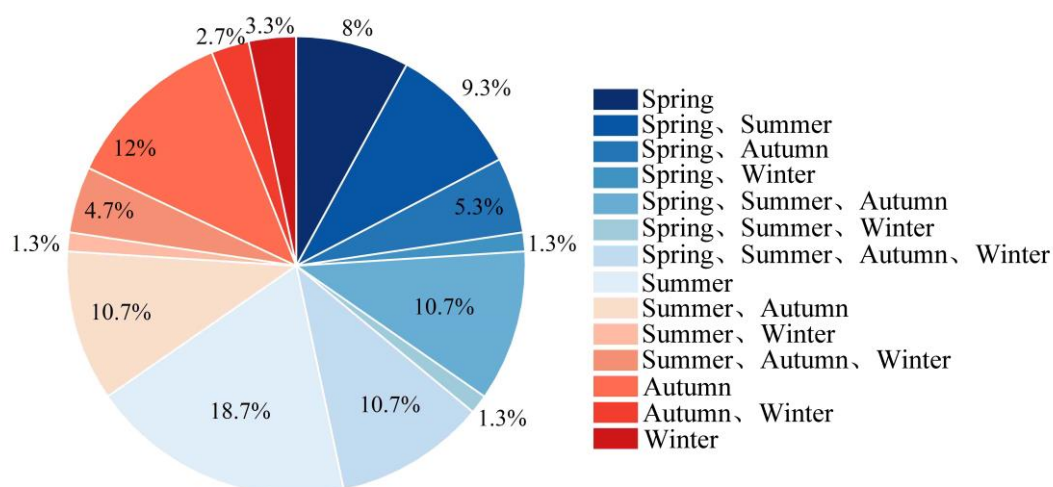


Fig.5 Seasonal distribution characteristics of epidemic disasters in the middle and upper reaches of the Yellow River Basin in Qing Dynasty

### 3.1.3. Characteristics of Trend Changes

The epidemic disaster year index ( $I_{ey}$ ), epidemic disaster county index ( $I_{ec}$ ), and epidemic disaster severity index ( $I_{el}$ ) for provinces in the middle and upper reaches of the Yellow River basin during the Qing Dynasty, after applying a 20-year moving average, all exhibit fluctuating upward trends in their curve patterns. Linear fitting results also indicate a long-term growth trajectory (Figure 6). Specifically,  $I_{ey}$  exhibited a relatively gradual increase, rising from 1.5 epidemics per year in the early period to 1 epidemic per year in the late period.  $I_{ec}$  showed the most pronounced upward trend ( $k=0.1628$ ), surging from 16.6 counties per year to 54.7 counties per year—the largest increase among the three index series. The average value of  $I_{el}$  also increased, climbing from 7 in the early period to 16 in the late period. Polynomial curve fitting results indicate that fourth-order polynomials best fit the  $I_{ey}$  and  $I_{el}$  indicators, while fifth-order polynomials suit  $I_{ec}$ . All three fitted curves exhibit a cyclical pattern of “rise-fall-rise-fall.” Integrating the trends of these three indices, the epidemic process in this region during the Qing Dynasty can be divided into four developmental stages:

Phase I: 1644–1694 (Shunzhi reign and early-to-mid Kangxi reign). During this period,  $I_{ey}$ ,  $I_{ec}$ , and  $I_{el}$  all exhibited fluctuating upward trends. Specifically, the mean value of  $I_{ey}$  indicates that epidemics occur at a rate of 3.3 per 5 years. The average number of affected counties per year was 5.7, with the widest-spread outbreak occurring in 1692, affecting 55 counties. The average  $I_{ec}$  was 16.6. Although the highest epidemic severity level recorded was “extreme,” the average severity level was 2.1. The average  $I_{el}$  value was 7, indicating that the overall disaster severity generally fell between ‘minor’ and “moderate” epidemics. Historical records indicate that some epidemic disaster entries from this period contain limited information. Regarding causative factors, meteorological disasters—particularly droughts—were the primary triggers. Droughts caused significant grain yield reductions and widespread famine, creating conditions conducive to the emergence and spread of epidemics [2].

Phase II: 1695–1780 (Late Kangxi, Yongzheng, and Early-Mid Qianlong Eras). During this phase,  $I_{ey}$ ,  $I_{ec}$ , and  $I_{el}$  all exhibited fluctuating yet gradually declining trends. Specific data shows: The average number of affected counties per year was 3.7, a decrease of 2 compared to the first phase. The highest number of affected counties occurred in 1728, reaching 34, corresponding to an average  $I_{ec}$  of 13.1, a decrease of 3.5 from the first phase. Although major epidemics still occurred during this period, the overall average epidemic severity level was 1.9, and the average  $I_{el}$  was 6, indicating disaster levels ranging from minor to small epidemics. This era coincided with the Kangxi-Qianlong Golden Age and a period of warming climate. Combined with favorable socioeconomic conditions, the frequency of epidemic outbreaks notably decreased compared to the first phase. Regarding causative factors, drought remained the primary driver of epidemics, though famine resulting from meteorological disasters eased relative to earlier periods.

Phase III: 1781–1890 (Late Qianlong Era, Early Guangxu Era). During this period,  $I_{ey}$ ,  $I_{ec}$ , and  $I_{el}$  all exhibited fluctuating growth trends. Specifically, the average  $I_{ey}$  reached 4.0a, an increase of 0.9a/5a compared to the second phase. The number of epidemic-affected counties rose to 7.6 per year, representing an average annual increase of 4 affected counties over the second phase. The widest-spread disaster occurred in 1878, affecting 89 counties, corresponding to an average  $I_{ec}$  of 30.6—an increase of 17.5 compared to the second phase. Although the highest epidemic severity level could still reach catastrophic proportions, the overall average severity level was 2.4, with an average  $I_{el}$  of 10. The severity ranged between minor and moderate epidemics, significantly higher than the previous two phases. This period saw a cooling climate and frequent meteorological disasters, leading to reduced crop yields. Following the Opium War, China endured relentless warfare. The Qing government, beset by internal turmoil and external threats, imposed increased local taxes to repay indemnities, exacerbating famine and

further raising epidemic occurrence rates. Under the combined impacts of climate anomalies and famine, epidemic outbreaks were particularly frequent in provinces along the middle and upper reaches of the Yellow River.

Phase IV: 1891–1911 (Late Guangxu and Xuantong Eras). Polynomial curve fitting for  $I_{ey}$ ,  $I_{ec}$ , and  $I_{el}$  showed a slight downward trend, yet all three indices remained at elevated levels, exceeding the average values of Phase III. Specifically, the mean value of  $I_{ey}$  was 5a, an increase of 1a/5a compared to the previous period. The average number of counties affected annually was 11.1, an increase of 3.5 compared to the third stage. The mean value of  $I_{ec}$  was 54.7, an increase of 24.1 compared to the third stage. The highest epidemic disaster level remained “catastrophic,” with an average disaster level of 3.2 and an average  $I_{el}$  of 16, indicating predominantly moderate epidemics. Beyond meteorological disasters and famines continuing to trigger epidemics, population mobility emerged as a significant factor expanding the scope of epidemic disasters. Reforms such as the Westernization Movement and the Hundred Days' Reform facilitated the introduction of Western public health concepts and medical technologies, which to some extent curbed the rise in mortality and shortened the duration of epidemics. Although cholera and smallpox incidence rates remained high in provinces along the middle and upper reaches of the Yellow River, the recovery of temperatures compared to the previous phase led to a significant reduction in the frequency of famine-induced epidemics.

#### 3.1.4. Periodic Variation Characteristics

The real part of the Morlet wavelet coefficients reflects fluctuations in the epidemic disaster series across multiple time scales, with alternating positive and negative values indicating variations in epidemic intensity [33][34]. In the wavelet spectrum (Figure 7), red and blue denote positive and negative values respectively, while zero indicates abrupt transitions. Epidemic disasters in the middle and upper Yellow River basin during the Qing Dynasty show periodicities of approximately 10, 16, 22, 39, 68, and 128 years. The 68-year cycle, dominant throughout 1644–1911, features slower transitions in the early Qing and faster ones in the late Qing. The 128-year cycle emerged around the nineteenth century, while shorter cycles (10–39 years) occurred during different phases from the seventeenth to nineteenth centuries [2]. Notably, the 68-year principal cycle approximates multiples of the 11-year solar activity cycle, suggesting that solar variability may have periodically influenced epidemic frequency and intensity through associated climatic fluctuations [1].

#### 3.2. Spatial Distribution Characteristics

Using the natural breakpoint method to classify epidemic years into five categories (Figure 5a), epidemic disasters in the middle and upper reaches of the Yellow River basin during the Qing Dynasty showed an overall pattern of being dense in the east and sparse in the west. A total of 632 counties experienced epidemics, with a prevalence rate of 76.98% and a density of 1.89 per  $10^4 \text{ km}^2$ . The cumulative number of epidemic-affected counties reached 3,058, yielding an epidemic thickness of 3.72 layers.

Major epidemic centers included Minqin and Jingyuan (Gansu), Yangcheng (Shanxi), Huaiyang, Xixia, and Neixiang (Henan), and Mizhi (Shaanxi), with Minqin and Huaiyang recording the longest durations (21 years each). Henan and Shanxi exhibited the highest epidemic frequencies, while Qinghai showed the lowest. These spatial disparities were strongly linked to topography and population, as elevation influenced settlement density and thus epidemic exposure.

The global Moran's  $I$  (0.29) passed the significance test, indicating positive spatial autocorrelation—epidemics tended to cluster geographically, spreading more easily among neighboring counties. Hotspot analysis (Figure 5b) identified clusters in eastern Gansu, southern Ningxia, central-southern Shanxi, and most of Shaanxi and Henan, while coldspots

were concentrated in central-eastern Inner Mongolia and northern Ningxia, and in eastern-central Qinghai and peripheral Sichuan [2].

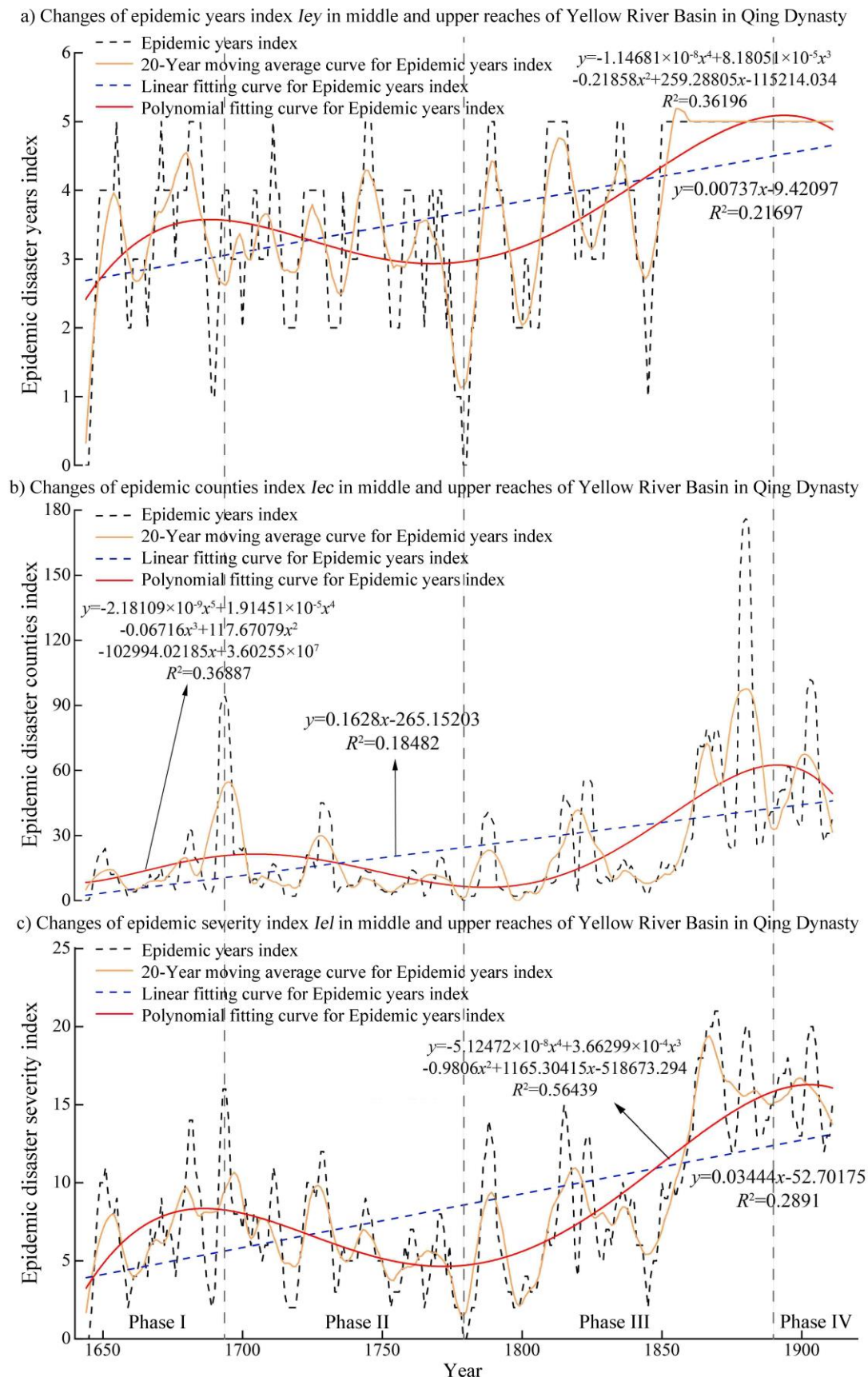


Fig.8 Changes of epidemic index in middle and upper reaches of Yellow River Basin in Qing Dynasty

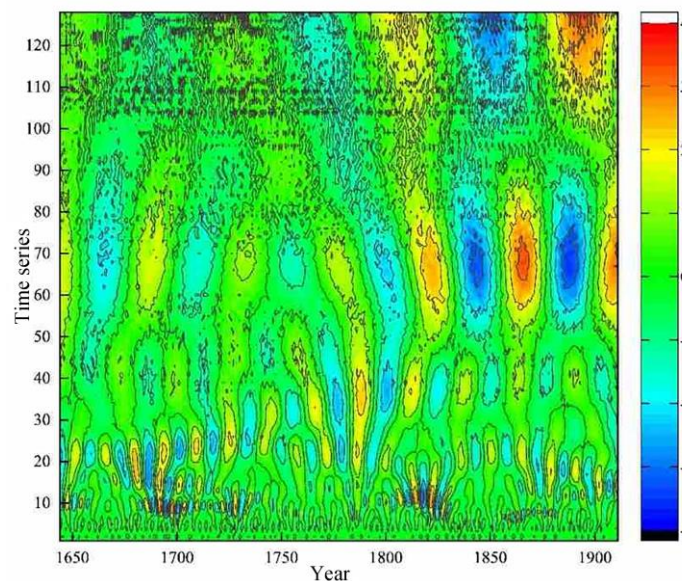


Fig.9 Wavelet analysis of epidemic disasters in the middle and upper reaches of the Yellow River Basin in Qing Dynasty

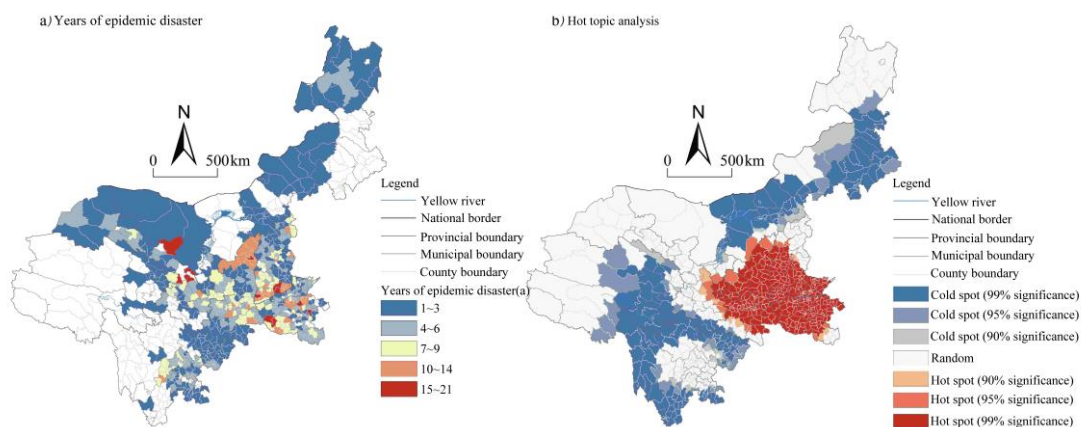


Fig.10 Distribution characteristics of epidemic disasters at county level in the middle and upper reaches of the Yellow River Basin in Qing Dynasty

Note: This map was created using the standard map with review number GS(2020)4619 downloaded from the National Administration of Surveying, Mapping and Geoinformation's Standard Map Service website. The base map has not been modified.

#### 4. Epidemic Disaster Chain Network Characteristics in Provinces Along the Middle and Upper Reaches of the Yellow River Basin During the Qing Dynasty

Using a knowledge-based model to systematically organize and extract key information from historical epidemic disaster records, a schematic diagram of the epidemic disaster chain network for the middle and upper reaches of the Yellow River basin during the Qing Dynasty was constructed (Figure 11) [35].

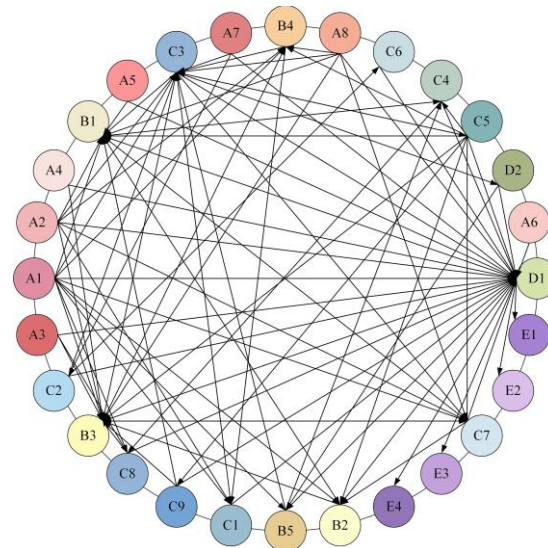


Fig.12 Epidemic chain network of provinces in the middle and upper reaches of the Yellow River Basin in Qing Dynasty

#### 4.1. Node Importance Analysis in the Epidemic Disaster Chain Network

As shown in Table 5, D1—Number of Infected Individuals is the most influential node in the epidemic disaster chain network, with a degree centrality of 0.963. It is followed by C3—Hunger and B3—Crop Yield Decline (both 0.519), indicating their strong direct linkages with other nodes during epidemic spread. Among natural disasters (A1–A8), A1—Drought ranks highest (0.370), serving as the key natural trigger.

Regarding closeness centrality, aside from D1, B3—Crop Yield Decline (0.530) and B1—Mass Mortality (0.516) show high values, implying their capacity to rapidly activate multiple components of the epidemic chain. Betweenness centrality identifies C3—Hunger (0.173) as the main intermediary node connecting different processes and facilitating epidemic transitions.

Connectivity analysis shows that A1—Drought and C5—War/Banditry have the highest coefficients (0.393), reflecting their extensive linkages. Notably, drought events can trigger cascading effects across ten subsequent nodes, confirming their role as critical initiating factors. Based on the entropy weight method, the most significant node overall is still D1—Number of Infected Individuals (0.134). In the social-environmental subsystem (C1–C8), C3—Hunger (0.081) and C5—War/Banditry (0.059) are most important; in the socioeconomic subsystem (B1–B5), B3—Crop Yield Decline (0.076) and B1—Mass Mortality (0.051) act as key precursors. Among natural disasters, A1—Drought (0.035) remains the dominant external trigger.

Overall, epidemic prevention should prioritize food security, hunger alleviation, and socioeconomic stability to disrupt key transmission pathways within the epidemic disaster network.

Table 6 The importance of each node in the disaster chain network

Node Name	Degree Centrality	Closeness Centrality	Betweenness Centrality	Connectivity	Importance	Node Name	Degree Centrality	Closeness Centrality	Betweenness Centrality	Connectivity	Importance
A1	0.370	0	0	0.393	0.035	C2	0.074	0	0	0.107	0.008
A2	0.259	0	0	0.286	0.025	C3	0.519	0.426	0.173	0.250	0.081
A3	0.111	0	0	0.143	0.011	C4	0.185	0.377	0.013	0.071	0.031
A4	0.074	0	0	0.107	0.008	C5	0.407	0.288	0.068	0.393	0.059
A5	0.074	0	0	0.107	0.008	C6	0.074	0.037	0	0.071	0.008
A6	0.037	0	0	0.071	0.005	C7	0.333	0.408	0.014	0.143	0.043
A7	0.111	0	0	0.143	0.011	C8	0.222	0.236	0.002	0.143	0.023
A8	0.222	0	0	0.250	0.021	C9	0.148	0.223	0	0.143	0.134
B1	0.407	0.516	0.019	0.107	0.051	D1	0.963	0.676	0.286	0.321	0.023

B2	0.222	0.456	0.017	0.071	0.037	D2	0.111	0.292	0.002	0.107	0.021
B3	0.519	0.530	0.138	0.143	0.076	E1	0.037	0.403	0	0.036	0.021
B4	0.259	0.384	0.010	0.107	0.036	E2	0.037	0.403	0	0.036	0.021
B5	0.185	0.408	0.045	0.107	0.038	E3	0.037	0.403	0	0.036	0.021
C1	0.185	0.311	0.005	0.071	0.027	E4	0.037	0.403	0	0.036	0.023

#### 4.2. Overall Network Characteristics of the Epidemic Disaster Chain Network

The average shortest path in the epidemic disaster network is 1.29, with an average clustering coefficient of 0.3. Analysis indicates that while the average distance between nodes in the network is relatively short, the clustering coefficient value is not high, failing to meet the characteristics of a “small-world” network. This suggests that the occurrence of nodes within the epidemic disaster network does not exhibit a pronounced clustering distribution trend, meaning they do not tend to “group together.” Additionally, the network density of 0.11 is also relatively low, indicating that connections between nodes in the epidemic disaster network are not tightly knit [2].

Systematic research on the nodes and overall structure of the epidemic disaster network reveals that the formation of epidemic disasters in this region stems from the combined effects of two major factors: disaster-causing agents and disaster-prone environments. After an epidemic disaster occurs, the disaster-bearing entities bear the impact of the disaster. The interaction among these three types of elements collectively drives the expansion of the epidemic disaster's scope, the escalation of its severity level, and the prolongation of its duration.

Disaster-causing factors served as the initial drivers of epidemic disasters, categorized into natural and human-induced types. Natural disasters in the middle and upper reaches of the Yellow River during the Qing Dynasty included meteorological disasters (most commonly drought, followed by floods, hailstorms, wind-blown dust storms, cold waves, and extreme heat), geological disasters (primarily earthquakes), and biological disasters (mainly locust plagues). Natural disaster factors (e.g., floods, droughts, earthquakes) disrupt critical infrastructure (water supply/sewage, housing, transportation/communications) and alter environmental ecosystems (standing water/water pollution, vector breeding, rodent invasions). This increases population exposure and susceptibility (crowding, poor ventilation, displacement, malnutrition, interrupted immunization), amplifying fecal-oral, vector-borne, and droplet/airborne transmission. Airborne, and zoonotic transmission routes, leading to sporadic or clustered cases. Whether this escalates into an epidemic disaster depends on the government's disaster management capacity and the timeliness of public health responses. Prompt action can contain the outbreak, while delays amplify it through social feedback loops like panic, migration, and delayed medical care. Man-made disasters primarily encompass warfare, banditry, and environmental pollution. Warfare and banditry disrupt social order and may lead to the accumulation of human and animal carcasses. Improper disposal can easily cause harm through indirect pathways such as water contamination and vector proliferation, compounding or intensifying the hazards of natural disaster factors. A disaster-prone environment constitutes the natural-human context that facilitates the formation and expansion of disasters. On one hand, various disaster factors cause farmland abandonment and reduced yields, driving up grain prices and triggering famines. Even in bumper harvest years, low grain prices can harm farmers, leading to income loss, malnutrition, population migration, and overcrowding—all providing fertile ground for disease transmission. On the other hand, the unregulated disposal of large numbers of dead humans and animals can increase pollution and provide habitats for vectors, expanding both the number and geographic reach of susceptible populations. The affected entities are the targets of disaster factors. The most direct victims of epidemics are human illness and death, with spillover effects including property and resource depletion and societal instability: social unrest, such as the sale of wives and children;

fiscal constraints and shortages of grain and military provisions; commercial decline and shop closures; and disrupted or halted transportation.

### 4.3. Contemporary Implications

Overall, a systematic analysis of the spatio-temporal patterns and disaster chain networks of epidemics in the middle and upper reaches of the Yellow River basin during the Qing Dynasty not only deepens our understanding of historical epidemic evolution but also offers valuable insights for contemporary public health prevention and control. Historical evidence indicates that epidemic disasters typically arise from the interplay of multiple factors rather than a single trigger, exhibiting distinct networked characteristics in their formation mechanisms. Climate fluctuations lead to environmental stress, population movements extend transmission pathways, while wars and famines exacerbate social vulnerability. These factors persist in contemporary forms and are further amplified by globalization and climate change. Therefore, distilling patterns from historical disaster networks offers the following insights for modern infectious disease control: First, establish regional joint prevention and control mechanisms to strengthen cross-provincial information sharing and risk warning capabilities. Second, enhance dynamic monitoring of climate anomaly zones, ecologically fragile areas, and population mobility hotspots by building a spatiotemporal risk identification system based on multi-source data. Third, prioritize social governance and public resource provision to mitigate the amplifying effect of social vulnerability on epidemic spread. Fourth, strengthen key controls in underdeveloped regions, transitional zones, and transportation hubs to enhance the overall resilience of the system. A comprehensive risk governance system must integrate the coordinated regulatory capabilities of natural-social systems to address potential future public health emergencies. This represents the ultimate objective and practical value of studying historical epidemics in this paper.

## 5. Discussion and Conclusions

### 5.1. Discussion

This study focuses on provinces in the middle and upper reaches of the Yellow River basin. It first analyzes the spatiotemporal distribution characteristics of epidemic disasters, concluding that epidemic patterns exhibit distinct trends, cyclical variations, and spatial configurations across different spatial scales or temporal phases. Second, it examines the commonalities of epidemic outbreaks from the perspective of epidemic chain networks. The findings indicate that the formation mechanism of epidemics in the mid-to-upper reaches provinces during the Qing Dynasty aligns with both the theoretical framework of “climate change-socioeconomic transformation-epidemic occurrence” [13] and the explanatory model proposed by Tang Xing et al. [23] of “human activity intensification-natural environment evolution-epidemic occurrence,” though the former represents the primary disaster pathway. Although the epidemic chain network cannot directly reveal precise mathematical correlations between epidemics and geographical factors like climate, its construction still uncovers underlying mechanisms that correlation analysis struggles to capture. Analysis reveals a bidirectional influence between population and epidemics: on one hand, epidemics cause mass illness or death; on the other, issues like corpse accumulation and famine triggered by mortality create conditions for epidemic proliferation and spread, forming a self-reinforcing disaster cycle. It is worth noting that some epidemics in the middle and upper reaches of the Yellow River basin occurred after bumper harvests. For instance, in 1760, Zhuanglang County experienced “a year of great abundance, yet epidemics raged fiercely, claiming numerous lives,” and in 1878, Changyuan County saw “a bountiful autumn harvest, yet epidemics spread widely, causing many deaths” [24]. Limited by the comprehensiveness of historical records and the constraints of medical knowledge at the time, it remains challenging to analyze the underlying mechanisms of this

disaster pathway. Further research is needed to explore and unravel these connections. This study has certain limitations that should be addressed in future investigations: First, a more precise analysis of the spatial distribution of epidemic disasters should be conducted, taking into account the actual administrative divisions of the historical period. Second, network dynamics models could be introduced to quantify the energy transmission mechanisms within ancient epidemic disaster chains. Furthermore, while this empirical study provides observational evidence on epidemic characteristics and influencing factors, the theoretical framework for studying “epidemic disasters” from a historical geography perspective remains nascent. Core concepts and analytical paradigms require further refinement and deepening.

From a broader perspective, this study's analysis of epidemic chain network structures in the middle and upper reaches of the Yellow River basin during the Qing Dynasty aims to provide historical reference points for understanding epidemic evolution mechanisms within “nature-society composite systems.” Epidemic chain networks reveal the coupled relationships among factors such as climate change, ecological environments, population mobility, and social governance—coupling that remains a core driver of infectious disease transmission in contemporary times. Integrating historical patterns into modern public health research helps identify regional vulnerabilities, critical nodes, and triggering factors, thereby facilitating the development of comprehensive, cross-regional, and cross-sectoral governance frameworks. Consequently, this examination of historical epidemics not only advances academic understanding but also provides crucial knowledge support for strengthening the ecological security barrier in the Yellow River basin, enhancing public health resilience in Northwest China, and improving the national infectious disease prevention and control system—demonstrating clear practical implications.

## 5.2. Conclusions

Based on a comprehensive analysis of epidemic frequency, spatial distribution, and causative mechanisms, this study systematically reveals the overall patterns and formation pathways of epidemic outbreaks in the provinces of the middle and upper reaches of the Yellow River basin during the Qing Dynasty. Findings indicate that, with the exception of the Yongzheng reign, epidemic frequency exhibited an overall upward trend throughout the Qing Dynasty, evolving from predominantly minor and small-scale outbreaks in the early period to moderate, major, and even catastrophic epidemics. Seasonally, epidemics predominantly occurred during summer and autumn, following a cyclical pattern of “rise-fall-rise-fall” with a primary cycle of approximately 68 years. Spatially, epidemics exhibited significant positive clustering. High-frequency hotspots were concentrated in Henan, Shanxi, Shaanxi, and Gansu—regions with dense populations and transportation networks—while cold spots with lower epidemic incidence were found in Inner Mongolia and Qinghai, characterized by harsh natural conditions and sparse populations. At the level of driving mechanisms, this study constructed a disaster chain network to reveal the complex multi-factor coupling process among disaster-causing factors, disaster-bearing entities, and disaster-prone environments. Drought emerged as the most critical natural trigger, while hunger proved the most influential socioeconomic factor. Mass mortality, serving both as a direct consequence of epidemics and a key environmental condition fostering their persistence and recurrence, reflects the self-reinforcing dynamics within the disaster chain.

## Contributions

Haili Zhao: Visualization, Validation, Funding acquisition, Methodology.

Yamei Yao: Writing, Visualization, Software, Methodology, Formal analysis, Conceptualization.

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## Ethical Approval

This study did not involve human participants or animal subjects, and therefore ethical approval was not required.

## References

- [1] Gong S S, Li Z M, Xie H C, et al. Spatiotemporal characteristics and influencing factors of the epidemic disasters for the past 3000 years in China, *Acta Geographica Sinica*, Vol. 76 (2021) No.8, p.1976-1996. (In Chinese)
- [2] Li J L. Spatial-temporal distribution and social impact of epidemic disasters in the middle and upper reaches of the Yellow River Basin in Qing Dynasty. Northwest Normal University, 2023. (In Chinese)
- [3] United Nations International Strategy for Disaster Reduction. Sendai framework for disaster risk reduction 2015—2030. United Nations, 2015. UN Documents, documents-dds-ny.un.org/doc/UNDOC/GEN/N15/167/16/PDF/N1516716.pdf?OpenElement. Accessed 23 Nov. 2022.
- [4] Cutter Susan L, Ismail-Zadeh Alik, Alcántara-Ayala Irasema et al. Global risks: Pool knowledge to stem losses from disasters, Vol. 522 (2015), p.277-79.
- [5] Shan L, Frequency of Cholera Pandemic in China based on Local Gazetter: Discussion around the significance of modern history about the first Cholera Pandemic, *Journal of Chinese Historical Geography*, Vol. 32 (2017) No.1, p.146-158. (In Chinese)
- [6] Li Z M, Spatial-temporal characteristics, danger simulation and boundary detection of cholera in the late Qing Dynasty (1816-1911), *Geographical Research*, Vol. 39 (2020) No.1, p.129-139. (In Chinese)
- [7] Lee Harry F, Fei Jie, Chan Christopher Y S et al. Climate change and epidemics in Chinese history: A multi-scalar analysis, *Social Science & Medicine*, Vol. 174 (2017) p. 53-63.
- [8] Jiang W H. The plague in Nanzhili during the Late Ming Dynasty: Environmental fragility and social salvation under the background of "Great Changes", *Agricultural Archaeology*, (2022) No.1, p.172-180. (In Chinese)
- [9] Wang F C. Epidemics, battles against epidemics and space narrative in Southern China during the Han Dynasty, *Journal of Shenzhen University(Humanities & Social Sciences)*, Vol. 37 (2020) No.4, p.5-13. (In Chinese)
- [10] He M F, Bu F X. Epidemic peak and climate change during the Wei, Jin, Northern and Southern Dynasties, *Agricultural Archaeology*, (2021) No.3, p.150-156. (In Chinese)
- [11] Gong S S. Research on geography of epidemic disasters in the Sui, Tang, and Five Dynasties, *Jinan History*, (2004) No.3, p.32-51. (In Chinese)
- [12] Wang X W, Gong S S, Li Z M, et al. Relationship between the spatial pattern of epidemic disasters and environment in China from 960 to 1368, *Journal of Arid Land Resources and Environment*, Vol.35 (2021), No.1, p.70-75. (In Chinese)
- [13] Pei Qing, David D Z, Guodong Li, et al. Epidemics in Ming and Qing China: Impacts of changes of climate and economic well-being, *Social Science & Medicine*, Vol.136 (2015), p.73-80.
- [14] Li B C. A study on the human and domestic animal epidemics in Gansu province during the Republic of China, *Gansu Social Sciences*, (2020) No.5, p.214-221. (In Chinese)
- [15] Wang Z L. Urban disease disaster and social response in Hubei Province during the Republic of China, *Hubei Social Sciences*, (2020) No.1, p.114-122. (In Chinese)
- [16] Gong S S, Shi G N, Li Z M. A geographic study of epidemic disasters in the Jiangnan area in China (1912-1949), *The Chinese Historical Geography*, Vol.40 (2020) No.1, p.18-30. (In Chinese)

- [17] Liu J, Yin S Y. Spatiotemporal distribution of significant epidemic disaster and its relation to climate change during historical period in China, *Journal of Natural Disasters*, Vol.25 (2016) No.1, p.137-146. (In Chinese)
- [18] Zhao Y L, Yin S Y, Liu J, et al. Temporal and spatial distribution and disaster chain of epidemics that caused massive death in Ming and Qing dynasties, *Journal of Arid Land Resources and Environment*, Vol.35 (2021) No.2, P.73-80. (In Chinese)
- [19] Jean Maguire van Seventer, Natasha S Hochberg. *Principles of Infectious Diseases: Transmission, Diagnosis, Prevention, and Control*, International Encyclopedia of Public Health (Second Edition). (2017), p.22-39.
- [20] Zhang W X, Yin X Y, Liu H, et al. Experimental study of T-2 toxin-induced myocardial injury in rats, *Chinese Journal of Endemiology*, Vol.20 (2001) No.1, p.29-30. (In Chinese)
- [21] Wang S Q, Shang Z H, Wang J H. 20-Year review and analysis of Keshan disease surveillance in Liaoning Province, *Chinese Journal of Endemiology*, Vol.37 (2018) No.3, p.239-242. (In Chinese)
- [22] Li Z M. Influence of geographical environment on spatial distribution pattern of epidemic disasters in Qing dynasty, *Journal of Arid Land Resources and Environment*, Vol.34 (2020) No.10, p.78-86. (In Chinese)
- [23] Tang D X, Zhou Q Q. Social formation and humanistic review of plague ecological field, *Gansu Social Sciences*, (2020) No.6, p.48-55. (In Chinese)
- [24] Gong S S. *Annals of Epidemics in China over the Past 3000 Year*. Qilu Press, (2019). (In Chinese)
- [25] Gong S S. Changes of the temporal-spatial distribution of epidemic disasters in 770BC-AD1911 China, *Acta Geographica Sinica*, (2003) No.6, p.870-878. (In Chinese)
- [26] Li Z M. A Geographic Study of Epidemic Disasters During Qianlong's Reign (1736—1795) in Qing Dynasty, *The Chinese Historical Geography*, Vol.42 (2022) No.1, p.104-115. (In Chinese)
- [27] WANG N, LU G C, CHAO K. Reasoning Method of Emergency Chain Reaction Path Based on Knowledge Element, *Systems Engineering*, Vol.34 (2016) No.5, p.121-128. (In Chinese)
- [28] Yu W K, Wu P D, Zhang H N, et al. Offshore towed-streamer seismic positioning based on polynomial curve fitting, *Acta Geodaetica et Cartographica Sinica*, Vol.51 (2022) No.5, p.772-780. (In Chinese)
- [29] Wang Z Y, Liu Z G, Deng Z W, et al. Phase extraction of non-stationary interference signal in frequency scanning interferometry using complex shifted Morlet wavelets, *Optics Communications*, Vol.420 (2018) p.26-33.
- [30] Zhu L, Li Y N, Hu J, et al. Multi-scale characteristics and influencing mechanism of spatial pattern on research and practice bases in China, *Arid Land Geography*, Vol.46 (2023) No.4, p.625-635. (In Chinese)
- [31] Xie J, Wang S J, Dou W K, et al. The spatio-temporal characteristics and evolution law of Chinese ski resorts from 1989 to 2019, *Scientia Geographica Sinica*, Vol.42 (2022) No.6, p.1064-1072. (In Chinese)
- [32] Ren H K, Wei W, Wang K H. Structural evolution of tourism flow network in Ningxia under the influence of COVID-19, *Arid Land Geography*, Vol.46 (2023) No.2, p.316-324. (In Chinese)
- [33] Zhang T, Chen Z Y, Zeng Y X, et al. Spatio-temporal patterns and influencing mechanisms of cholera epidemics in Hubei province from 1850 to 1949, *Acta Geographica Sinica*, Vol.79 (2024) No.7, p.1661-1681. (In Chinese)
- [34] Yang S L, Wang H R, Yin S X. Analysis of temporal and spatial evolution characteristics of precipitation in Fujian province in recent 60 years, *Water Resources Planning and Design*, (2023) No.9, p.47-52. (In Chinese)
- [35] Wen B, Zhang R X, Qui J N, et al. Research on construction of the knowledge element model on the emergency management, *Mathematics in Practice and Theory*. Vol.43 (2013) No.17, p.89-97. (In Chinese)