



Climate change and epidemics in Chinese history: A multi-scalar analysis



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ABSTRACT

This study seeks to provide further insight regarding the relationship of climate-epidemics in Chinese history through a multi-scalar analysis. Based on 5961 epidemic incidents in China during 1370–1909 CE we applied Ordinary Least Square regression and panel data regression to verify the climate-epidemic nexus over a range of spatial scales (country, macro region, and province). Results show that epidemic outbreaks were negatively correlated with the temperature in historical China at various geographic levels, while a stark reduction in the correlational strength was observed at lower geographic levels. Furthermore, cooling drove up epidemic outbreaks in northern and central China, where population pressure reached a clear threshold for amplifying the vulnerability of epidemic outbreaks to climate change. Our findings help to illustrate the modifiable areal unit and the uncertain geographic context problems in climate-epidemics research. Researchers need to consider the scale effect in the course of statistical analyses, which are currently predominantly conducted on a national/single scale; and also the importance of how the study area is delineated, an issue which is rarely discussed in the climate-epidemics literature. Future research may leverage our results and provide a cross-analysis with those derived from spatial analysis.

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1. Introduction

Climate change and its linkages to epidemics has long been a key interest among researchers (Jones et al., 2008; Kiska, 2000; Patz and Lindsay, 1999; Wu et al., 2016). Temperature fluctuations may favour the proliferation of vectors and pathogens by providing a more agreeable environment for organisms to reproduce in water bodies and food, as well as reducing the extrinsic incubation period of pathogens (Wu et al., 2016). Certain temperature ranges are favourable to spread of certain pathogens, and may have increased the spread of potential epidemics (Gerba, 1999; Kuhn et al., 2005).

Increasing evidence has linked the spread of infectious disease with famines, starvation, migration and other forms of socio-economic disruptions in history, which were exacerbated by climatic fluctuations (Lee, 2014; Lee and Zhang, 2010, 2013;

McMichael, 2012; Pei et al., 2015b; Zhang et al., 2011a; Zhang et al., 2011b). Dunstan (1975) spearheaded Chinese historical epidemiological studies by offering comprehensive analysis on major Late Ming epidemics. Other illustrative evidence from Chinese imperial archives revealed a 35–40% greater risk of epidemics under cooler climates in comparison to warmer periods (McMichael, 2012). Zhang et al. (2011a) explored the causal linkages between climate change and societal crisis in historical Europe, and identified migration and nutritional status as the direct triggers of plagues in Europe. They found that climate change was the underlying factor contributing to the surge of epidemics. Pei et al. (2015b) took a macro-analytical approach to examine the underlying interactions behind climate, epidemic outbreaks and population in historical China, and suggested economic downturn as a major mediator between climate change and disease outbreak. They illustrated the fundamental role of climate change in dampening food supply, leading to socio-economic downturn and ultimately causing epidemics. The Chinese economy was almost entirely weighted on the agricultural sector by the twentieth-

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century, exacerbating the impact of climate on the economy (Perkins, 1969). Changes in temperature and precipitation have long been regarded as crucial factors in the quality of arable land and bio-productivity, especially in the pre-industrial era when countries did not benefit from technological advances in food production and medical technologies (Clark, 2009; Pei et al., 2015b). As modern technologies still fail to completely neutralize the climatic impacts in contemporary societies (Hidore et al., 2009; Lobell et al., 2007), the agro-economy in historical China was seemingly much more vulnerable to climate change.

Despite having an established mechanisms of climate change and epidemics in historical societies, relevant studies focusing on historical China remain scarce. This is in part due to the lack of long-term and reliable datasets (Patz et al., 2005; Pei et al., 2015b). Moreover, studies that have looked at these issues have tended to focus only on a single, macro scale. Watson (1978) argued that scale is a “geographic variable” almost as sacred as distance’ (p. 36), and that ‘macro and micro scale studies do not complement each other for a host of philosophical, methodological and substantive reasons’ (p. 36). For China, where geographic types range from tropical zones in the south to arid and snowy regions in the north (Kottek et al., 2006), macro-scale analyses cannot explain every epidemic pattern in different climatic settings. On the other hand, micro-scale analysis can reveal the details obscured behind the aggregated data. But, it cannot be used to provide a comprehensive overview of the entire climate system. The process underlying the scale effect is currently poorly understood. A change in scale can impart drastic changes on subsequent correlational directions and explanatory power of the associative regression models (Fotheringham and Wong, 1991). There is, understandably, wide acknowledgment that in order to create knowledge that is comprehensive with regard to the context, correlation and the mechanics of a phenomenon there is great need for studies that cover multiple scales (Sayre, 2005). This study, therefore, attempts to provide further insight regarding the climate-epidemics relationship in historical China through a multi-scalar analysis.

2. Methodology and data

2.1. Study area and study period

Our study is focused on China during the Ming (1368–1644 CE) and Qing (1644–1911 CE) Dynasties. The study period is set as 1370–1909 CE, in order to align with the decadal resolution of the temperature datasets. This may help avoid any incongruity between the data, enhancing the accuracy of our statistical analysis.

Given that the territorial holdings of China have varied over the course of history, to ensure data consistency, the political boundary of the current Chinese polity was adopted as our area of interest. The provinces were delineated as per the current administration division system (Fig. 1).

2.2. Climate data

The temperature reconstruction by Yang et al. (2002) was adopted in this study. The temperature series is in decadal resolution, and was developed based on reliable proxy temperature data across China. While datasets from other sources have also been considered (Ge et al., 2013), Yang et al., (2002) data is regarded as one of the more representative and accurate datasets available. Validity and comparability of our results are further reinforced by the extensive use of the data in other studies on climate-human interactions in historical China (Lee, 2014; Lee and Zhang, 2013; Pei et al., 2016a).

The precipitation data for this study was obtained from Zhang

et al. (2015), based on historical data of droughts or floods, weather diaries, rainfall data, lake variations and the occurrence of dust storms. The adopted precipitation index with the annual resolution could well present the past wet-dry patterns of the whole of China at the national scale.

2.3. Population data

We retrieved historical population size data within the current political boundaries of China from Lu and Teng’s (2006) Chinese provincial population dataset published in *Examination of Historical Chinese Population in Various Provinces and Districts*. As Lu and Teng (2006) give estimates of Chinese population size at irregular time intervals, the common logarithm of the data points was taken, linearly interpolated and then anti-logged back to create an annual time-series. This method avoids distortions of the population growth rate in data interpolation, which has been applied in our previous studies (Lee et al., 2008, 2009). The population data were then divided by the area of associated geographic units to obtain population density figures.

2.4. Epidemics data

Our epidemics data were obtained and aggregated from three large, independently derived datasets, namely (1) *Collection of Meteorological Records in China over the Past Three Thousands Years* (Zhang, 2004), (2) *Historical Records of Infectious Diseases in China* (Li, 2004), and (3) *Epidemic Records in Historical China* (Zhang, 2007). The three datasets are tabulated from official dynastic histories and local chronicles. Each record in the datasets was supplemented by the year of onset (in calendar year), the location of outbreak (in current place names), and quotes from historical literature providing details about the epidemics as well as the original data sources.

In this study, we focused on human endemics and epidemics which were contagious and could potentially spread to a huge population through food, breathing, or human contact within a relatively short period of time. Those diseases are often recorded as *yi* or *yili* (pestilence) in historical documents. In order to organize the data into a relevant database, we followed a three step procedure. First, the records which contain the word *yi* or *yili* in each of the three datasets were selected. Then, the chosen records in the three datasets were cross-checked among themselves, and duplicated records were removed. Finally, epidemics were counted according to the number of counties affected by epidemics in a year, which could better capture the spatial influence and geographic coverage of epidemics (Lee et al., 2016b). The number of counties in China is presented in detail in Web Appendix Table A1. A total count of 5961 epidemic incidents was identified during the study period. Although there exist other epidemics datasets (Chen, 1986; Sun, 2004) that have been employed by other scholars in examining the climate-epidemics relationship in Chinese history, those datasets do not provide information about the exact location of epidemic outbreaks and/or the original data source of each record, and were therefore not applicable to this study.

Historical China adopted a vastly different medical and recording system compared to the West because modern epidemiology and medical technologies were only introduced to China in the late 19th century. Historical literatures only gave rather vague descriptions about the diseases with little traceability concerning the nature, magnitude, root cause, time length, and so on. Due to the limitation to the data source, we hereby assume that all epidemic records (*yi* or *yili*) in the literature are ‘major epidemics’.



Fig. 1. Map of the study area. The political boundary of the current Chinese polity was adopted as our area of interest. The provinces were delineated as per the current administration division system, while the macro regions were delineated as per Chinese traditions (see Lee et al., 2008, 2009).

2.5. Aggregation/disaggregation of data

As the temperature data are in decadal resolution, to ensure compatibility between the temperature series and other records, all of the data were aggregated into decadal analytical units prior to statistical analysis. Epidemics and population data were aggregated according to different geographical levels (i.e., country, macro region, and province, see Fig. 1). Our data were analysed on three spatial scales. First, epidemic records from all provinces in China were summed into a national aggregate, and a national-level analysis was conducted to offer a holistic assessment of the climate-epidemic phenomena on a macro scale. Second, at the regional level, the country-wide epidemics data were decoupled to four regional panels according to Lee et al. (2008, 2009). The approach was largely based on Chinese traditions, by which the provinces were zoned into four major regions with respect to their geographical locations (see Web Appendix Table A2). Third, at the provincial level, the country-wide epidemics data were further decoupled to 32 provincial panels (including Beijing, Tianjin, Shanghai, and Chongqing municipalities). The country, regions, and provinces were delineated according to current administrative boundaries. As the epidemic and population datasets are compiled on a provincial level, such a delineation method may offer a clear-cut classification of provinces.

2.6. Statistical analysis

At the country-wide level, Ordinary Least Square (OLS)

regression was run. At the regional and provincial scales, panel data regression was run. The significance level was set at $p < 0.05$.

Panel data allows for repeated observations of the same subjects over a period of time (Frees, 2004). Panel data analysis is a well-established method to reveal dynamic relationships and patterns of one or more phenomenon over time, and is commonly used in various fields of social and natural sciences (Frees, 2004). There are two approaches for quantifying heterogeneity among subjects in panel data regression. One way is to treat it as an unknown constant that is to be estimated (the estimator), which is known as the fixed-effects model. Another approach is to assume the estimator as a random variable from an unknown population, which is known as the random-effects model (Hsiao, 2003). The question of which model can achieve a higher efficiency depends on the panel data's match with the models' assumptions and specifications, which was assessed by the Hausman test (see section 3.5).

3. Statistical modelling of epidemics outbreak

The independent variables for epidemics outbreaks were chosen according to the following principles:

3.1. Climate and epidemics

Epidemics and famines have been consistently linked in historical records. The decrease in agricultural yields brought by cooling, along with an increase in the frequency of famines, often leads to a general decline in nutrition (Dunstan, 1975). Apart from

the deficiency diseases and the various gastro-enteric disorders, chronic undernourishment increases the body's susceptibility to infections. Hence, endemic diseases of varying degrees of severity can have increased virulence and rampancy among the population, resulting in even higher mortality rates (Dunstan, 1975; McMichael, 2012). Climate-induced agricultural shrinkage can also trigger economic hardship, social instability and, consequently, mass migration, which increases the frequency of interactions among different groups of the population – and the probability of contracting contagious diseases (Galloway, 1986; Zhang et al., 2011a).

We overlaid the climate records with the count of epidemics (Fig. 2). The aberrant peaks of epidemics (in 1580s CE, 1640s, 1820s, and 1860s) are coincident with the fall in temperature, the drop in precipitation, or the combination thereof. Additionally, the last three spikes of epidemics are also matched with Manchurian Invasion, Hakka Migration, and Taiping Rebellion – the historical events associated with mass migration (Pei et al., 2016a). This indicates the necessity of including temperature and precipitation as independent variables for epidemic outbreaks.

3.2. Population density and epidemics

Cooling resulted in human catastrophes only if the population system had already pushed against its Malthusian constraints (Lee, 2014; Lee and Zhang, 2010, 2013; Stenseth and Voje, 2009; Turchin and Nefedov, 2009). Empirical studies show that during population decline, when population pressure within societies had been reduced, the effect of deteriorating climate on Malthusian checks was weakened (Lee and Zhang, 2010; Lee et al., 2015). Therefore, population density is proposed to be an important factor in mediating the climate-epidemics relationship.

We plotted the count of epidemic outbreaks against population density in the Ming and Qing Dynasties, respectively. The population density data were log transformed to stabilize their variances (Durbin et al., 2002). A strong positive association between the two variables was revealed in the two periods (Fig. 3). Therefore, log population density was included as another independent variable to account for mean shifts in epidemics and the change in the climate-epidemics relationship over time.

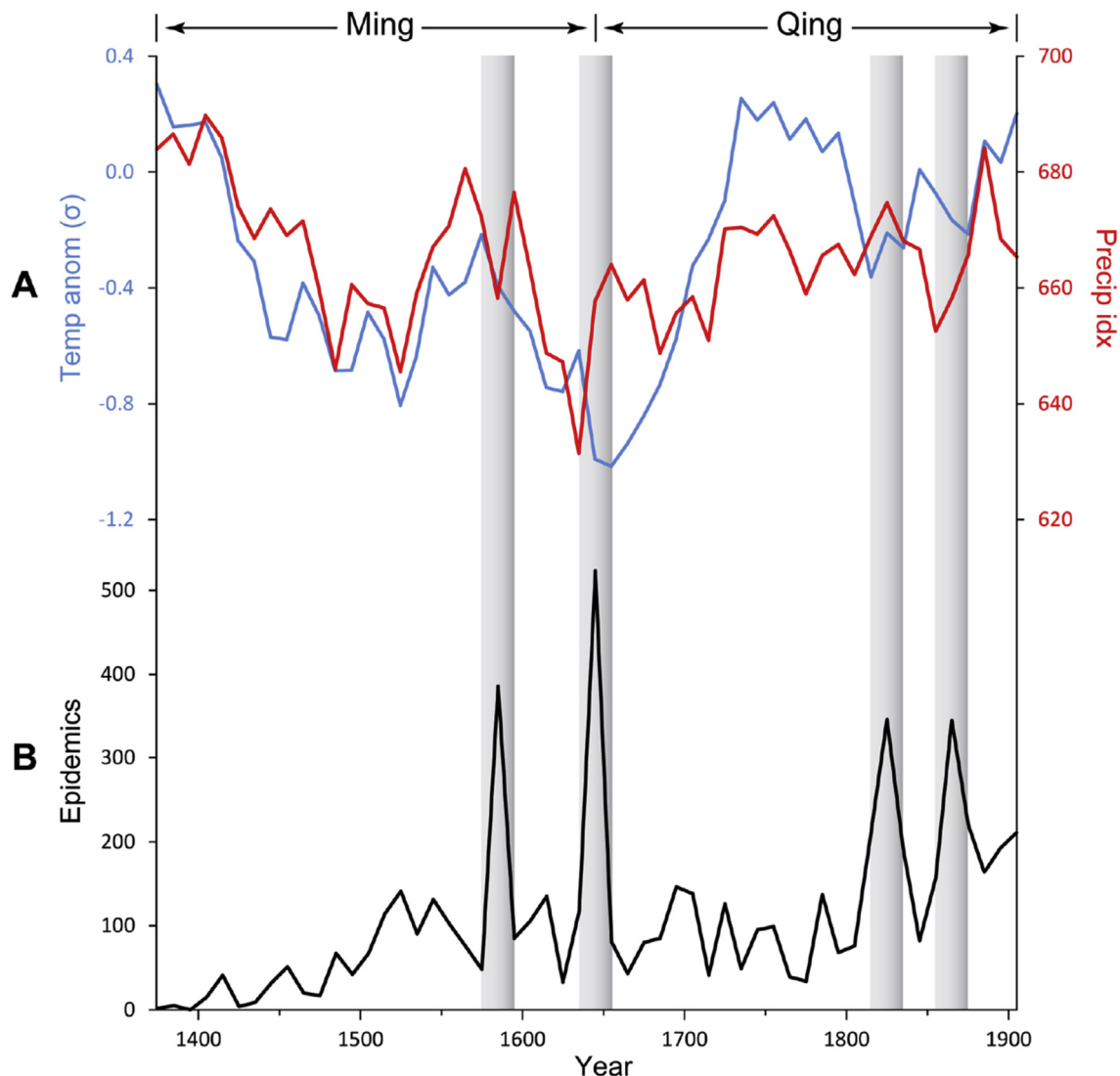


Fig. 2. Climate change and epidemics in the whole of China, 1370–1909 CE. (A) Temperature anomaly ($^{\circ}\text{C}$) (blue line) and precipitation index (red line), and (B) count of epidemics incidents. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

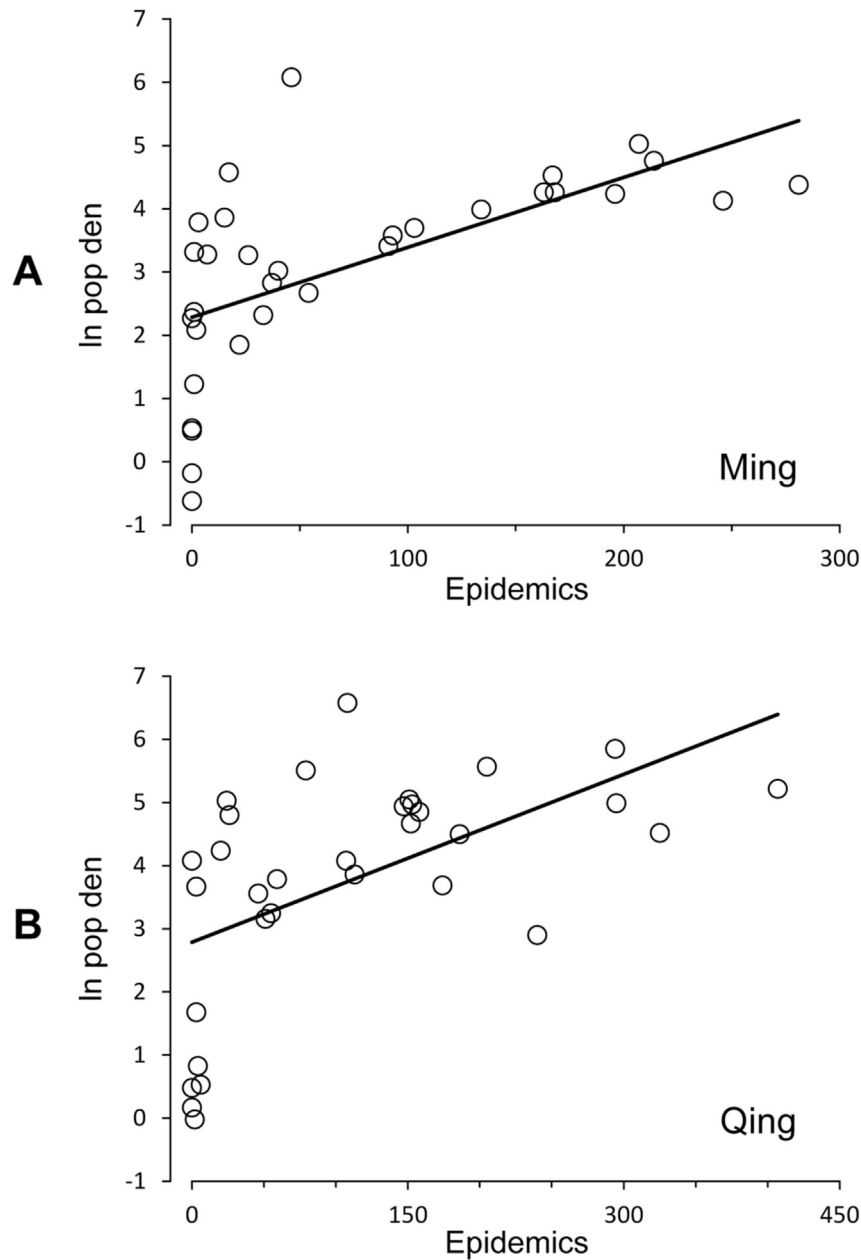


Fig. 3. Scatter plots of population density (natural log) and epidemics at the country level in historical China. (A) Ming Dynasty, and (B) Qing Dynasty.

3.3. Auto-correlated errors

A recent epidemic outbreak may trigger the outbreak of a new epidemic outbreak (Pei et al., 2015b). This phenomenon may result in auto-correlated errors in statistical analysis. Hence, the inclusion of an auto-regressive term in our regression models is necessary (Hamilton, 1994). We employed autocorrelation function (ACF) and the partial autocorrelation function (PACF) to examine the degree of autocorrelation of our epidemics records (Harvey, 1993). Given that our epidemics data is in decadal resolution, the auto-regressive term was defined as the number of epidemics in the previous decade ($t-10$). As shown in the ACF and PACF plots and auto-regressive (AR) modelling, epidemics exhibit weak but positively significant correlation with the first lag ($P < 0.05$) (Web Appendix Fig. A1 and Tables A3–A7). We had an AR (1) process, in which the number of epidemics in the previous time step ($epidemics_{t-10}$) was

included in our regression model to control for the auto-correlated errors. Its validity could be confirmed by the ACF and PACF plots of our AR (1) model's residuals, in which no significant correlation is found (Web Appendix Fig. A2).

3.4. Control variables

The link from climate to Malthusian checks can be summarized as: deteriorating climate causes poor harvest, followed by economic hardship, and eventually wars, famines and epidemics (Pei et al., 2015b; Zhang et al., 2011a). However, when we examined the climate-epidemics nexus, we did not control for the effect of agricultural production and food price on epidemics, as those factors themselves are affected by climate variation (Pei and Zhang, 2014; Pei et al., 2016b, 2015a, 2013). Their inclusion as control variables may (1) incorrectly absorb the signal contained in our

concerned climate variable; and (2) result in a biased estimate because populations differ in unobserved ways and become artificially correlated with climate (Hsiang et al., 2013). On the other hand, the upward trend in the epidemics curve was observed (Fig. 2), which may be attributable to the increasing coverage of the data sources over the study period. Therefore, we included calendar year (*year*) as a control variable to account for mean shifts in epidemics over time.

3.5. Procedures

We ran four regression models in sequence, and the variables mentioned in Sections 3.1–3.4 are in different combinations in each of the models. First, we regressed our decadal epidemics time series on log population density (*ln pop density*) as a base model to capture the influence of population on epidemic outbreaks. Second, we added the two climatic factors (*temperature* and *precipitation*) as independent variables into the base model to see whether climatic factors could result in a significant increase of epidemic outbreaks when the effect of population density on epidemics was controlled. Third, based on the second model, we added the number of epidemic outbreaks in the previous time step (*epidemics_{t-10}*) as an explanatory variable to control for auto-correlated errors. Finally, based on the third model, we added calendar year (*year*) as an additional control variable to control the mean shifts in epidemics over time.

We also decoupled our epidemics time series to region and province panel data to replicate our regression analysis. Subject to the results of Hausman test ($p < 0.01$), the null hypothesis that the unique errors of those time-invariant characteristics are not correlated with other individual characteristics in our panel data was rejected. Hence, the fixed-effects model was adopted for our panel data regression analysis, with estimated standard errors clustered by the associated spatial units.

Three sensitivity tests were conducted to further verify our statistical results. First, collinearity statistics were run to check for any multicollinearity problems in our regression model. Second, as the time trend of the epidemics data may be non-linear, we also replaced our time trend variable (*year*) with its squared (*year*²) and cubic (*year*³) terms to check whether our statistical findings were still valid (Galloway, 1986). Third, epidemics may be clustered at certain locations. Such spatial clustering of data may induce bias in the associated statistical results (O'Loughlin et al., 2012). Therefore, we included the variable '*spatial lag*' in our regression model to control for the spatial auto-correlation of epidemics data at the provincial level. Spatial lag measures the spatial dependency to previous nearby epidemics at a certain unit (Buhaug and Rød, 2006; Yue et al., 2016). Here the spatial lag of epidemics was defined as whether the epidemics in a particular province were correlated with the epidemics in its adjacent provinces (with shared boundary) in previous decades. For instance, the value 3 denotes the existence of epidemics in three of its adjacent provinces in previous decades. Then, the value was divided by the total number of adjacent provinces to have it range between 0 and 1 (Yue et al., 2016).

Variables that were significant to epidemic outbreaks at the country level were included in our multi-scalar analysis (Lee et al., 2016a). Caution is needed when interpreting these results. Though the abovementioned variables were entered into our regression models, the interpretation should remain focused on the effect of climate change on epidemics, with the influence of population density, the auto-correlated errors and the time trends of epidemics data as controls.

4. Results

When the whole of China was taken as a spatial aggregate, population density was positively correlated with the count of epidemics (Table 1). When the effect of population density on epidemics was controlled we still detected a significant increase in epidemic outbreaks associated with lower temperature values ($P < 0.01$). On the other hand, no statistically significant influence of precipitation upon epidemic outbreaks were found ($P > 0.05$). When we included the number of epidemic outbreaks in the previous time step (*epidemics_{t-10}*) as an explanatory variable, the temperature effect on epidemic outbreaks still remained statistically significant ($P < 0.01$). This indicates that our results were not driven by any autoregressive disturbances.

Collinearity statistics were run to check for any multicollinearity problems in our regression model. No problem was found (Web Appendix Table A8). When the calendar year (*year*) was also included in our regression model, the temperature effect on epidemic outbreaks was still statistically significant ($P < 0.01$). This implies that our results were not driven by the time trend embedded in the epidemics time series. At the regional level, for every one standard deviation decrease of temperature, an increase of 162 epidemic outbreaks would be expected.

We proceeded to decouple our epidemics time series to region and province panel data to replicate our regression analysis. When regions and provinces were taken as spatial analytical units, population density was positively correlated with epidemics ($P < 0.01$), while temperature was negatively correlated with epidemics ($P < 0.01$) (Tables 2 and 3). The above results still applied when the auto-correlated errors and the time trend of epidemics data were controlled, which is largely consistent with the national-scale analysis as presented in Table 1. At the regional level, for every one standard deviation decrease of temperature, an increase of 34 epidemic outbreaks would be expected. At the provincial level, for every one standard deviation decrease of temperature, an increase of 3.4 epidemic outbreaks would be expected.

While the results remain statistically significant, stark differences could be found in the correlational strength at various spatial scales, as demonstrated by the decrease in the beta value of temperature. For instance, the beta value of temperature reached -0.565 at the national scale (Table 1), but was damped to -0.309 at the regional scale (Table 2), and a rather humble -0.161 at the provincial scale (Table 3).

To see whether the relationship we observed is driven by particular regions within China, we ran panel data regression analysis for each of the macro regions individually. Our results show that the temperature effect is statistically significant only for northern China ($P < 0.01$) and central China ($P < 0.001$) (Table 4). This suggests that the overall country-wide temperature-epidemics relationship is mainly attributable to the temperature-epidemics association in these two regions. In addition, according to the beta value of temperature (Table 4), the negative temperature-epidemics association is stronger in central China than in northern China.

To cater for the possible non-linear time trend of the epidemics data, we re-ran all of our regression analysis, with our time trend variable (*year*) replaced by its squared (*year*²) and cubic (*year*³) terms. All of the temperature-epidemics correlations shown in Tables 1–4 still remained statistically significant (Web Appendix Tables A9–A15). To address the spatial auto-correlation of epidemics data at the provincial level, we included the variable *spatial lag* in our regression model. The statistical relationship between temperature and epidemics was basically unaffected, as the beta value of temperature only changed from -0.161 (Table 3) to -0.155 (Web Appendix Tables A16).

Table 1

Estimates of the effect of climate change and population pressure on epidemic outbreaks in China at the country level.

	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value
Constant	−168.968 (76.474)		0.032	−779.696 (921.137)		0.403	−982.273 (1018.077)		0.339	−1591.166 (1183.746)		0.185
In pop density	216.644 (58.670)	0.456	0.001	308.779 (63.397)	0.650	0.000	344.889 (84.351)	0.721	0.000	234.429 (138.306)	0.490	0.097
Temperature				−131.621 (46.158)	−0.467	0.006	−153.046 (56.495)	−0.534	0.009	−162.034 (57.186)	−0.565	0.007
Precipitation				0.677 (1.323)	−0.076	0.611	0.916 (1.439)	0.102	0.528	1.559 (1.574)	0.173	0.327
Epidemics t_{-10}							−0.070 (0.148)	−0.070	0.639	−0.123 (0.157)	−0.124	0.437
Year										0.199 (0.197)	0.298	0.319
Observation	54			54			53			53		
R-squared	0.208			0.353			0.347			0.361		
Adj R-squared	0.193			0.314			0.292			0.292		
F-statistics	13.64			9.07			6.37			5.30		
P-value	0.001			0.000			0.000			0.001		

Notes. The dependent variable is the count of epidemic outbreak incidents in China in 1370–1909 CE. All of the data are in decadal units. Coefficients and beta are reported, with standard errors in brackets.

Table 2

Estimates of the effect of climate change and population pressure on epidemic outbreaks in China at the macro-regional level.

	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value
Constant	−47.442 (16.787)		0.005	−205.137 (171.516)		0.233	−186.851 (179.674)		0.300	−267.518 (200.072)		0.183
In pop density	61.407 (10.809)	0.863	0.000	82.979 (11.902)	1.167	0.000	82.788 (13.973)	1.159	0.000	67.443 (21.790)	0.944	0.002
Temperature				−32.306 (8.420)	−0.300	0.000	−32.534 (9.365)	−0.295	0.001	−34.038 (9.511)	−0.309	0.000
Precipitation				0.174 (0.245)	0.051	0.478	0.145 (0.255)	0.042	0.569	0.234 (0.273)	0.068	0.392
Epidemics t_{-10}							0.026 (0.071)	0.025	0.718	0.012 (0.072)	0.012	0.871
Year										0.027 (0.030)	0.107	0.360
Observation	216			216			212			212		
Fixed-effects	Yes			Yes			Yes			Yes		
Hausman test	P < 0.01			P < 0.01			P < 0.01			P < 0.01		
R-squared	0.294			0.356			0.354			0.356		
Adj R-squared	0.281			0.337			0.331			0.331		
F-statistics	22.00			19.22			15.93			14.04		
P-value	0.000			0.000			0.000			0.000		

Notes. The dependent variable is the count of epidemic outbreak incidents in China in 1370–1909 CE. All of the data are in decadal units. Coefficients and beta are reported, with standard errors in brackets. The fixed-effects indicate the inclusion of indicator variables for the identity of various macro-regions in China.

Table 3

Estimates of the effect of climate change and population pressure on epidemic outbreaks in China at the provincial level.

	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value
Constant	−6.496 (1.545)		0.000	−12.168 (12.318)		0.323	−5.125 (12.493)		0.682	−32.067 (13.915)		0.021
In pop density	6.289 (0.681)	0.507	0.000	7.735 (0.740)	0.623	0.000	7.006 (0.793)	0.561	0.000	4.103 (1.038)	0.328	0.000
Temperature				−2.994 (0.589)	−0.143	0.000	−2.589 (0.615)	−0.121	0.000	−3.445 (0.644)	−0.161	0.000
Precipitation				0.003 (0.018)	0.005	0.857	−0.006 (0.018)	−0.009	0.737	0.025 (0.019)	0.036	0.199
Epidemics t_{-10}							0.099 (0.025)	0.098	0.000	0.078 (0.025)	0.077	0.002
Year										0.007 (0.002)	0.145	0.000
Observation	1728			1728			1696			1696		
Fixed-effects	Yes			Yes			Yes			Yes		
Hausman test	P < 0.01			P < 0.01			P < 0.01			P < 0.01		
R-squared	0.240			0.258			0.266			0.274		
Adj R-squared	0.226			0.243			0.250			0.258		
F-statistics	16.75			17.32			17.14			17.36		
P-value	0.000			0.000			0.000			0.000		

Notes. The dependent variable is the count of epidemic outbreak incidents in China in 1370–1909 CE. All of the data are in decadal units. Coefficients and beta are reported, with standard errors in brackets. The fixed-effects indicate the inclusion of indicator variables for the identity of various provinces in China.

5. Discussion

5.1. Climate change and epidemic outbreaks

Our results are generally coherent with existing literature, that temperature is negatively correlated with epidemic incidents (Lee, 2014; Lee and Zhang, 2010, 2013; McMichael, 2012; Pei et al., 2015b; Zhang et al., 2011a; Zhang et al., 2011b). Cooling tends to precede changes in epidemics (Fig. 2), which supports the notion that climate change, be it the ultimate cause or direct trigger, acts as a driver of historical epidemics. Pei et al. (2015b) and Zhang et al.

(2011a) proposed the underlying mechanism behind such phenomenon (cf. Introduction). A recent empirical study evidences that temperature has a greater influence than precipitation on the agrarian economy of the late imperial China, as the economy was sustained by rice production and was vulnerable to temperature change (Pei et al., 2016b).

Economic downturn brought by deteriorating climate has often been associated with deterioration in public health conditions. For instance, unaffordable food prices, along with the lack of social buffer, could have led to widespread malnutrition. Debilitated people may consume 'famine foods' (unripe grain, grass, or roots) to

Table 4

Estimates of the effect of climate change and population pressure on epidemic outbreaks among different macro regions in China.

	Northern			Central			Southern			Marginal		
	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value	Coefficient (SE)	Beta	P-value
Constant	−42.080 (34.935)		0.229	−77.476 (33.219)		0.020	−28.555 (16.200)		0.079	0.636 (5.784)		0.913
ln pop density	6.517 (2.284)	0.312	0.004	4.025 (2.705)	0.211	0.138	1.200 (1.499)	0.078	0.424	0.963 (0.503)	0.290	0.056
Temperature	−5.250 (1.603)	−0.179	0.001	−7.652 (1.596)	−0.349	0.000	−1.051 (0.750)	−0.076	0.162	0.006 (0.264)	0.002	0.982
Precipitation	0.016 (0.048)	0.017	0.744	0.082 (0.046)	0.119	0.072	0.023 (0.022)	0.052	0.305	−0.002 (0.008)	−0.015	0.830
Epidemics _{t-10}	0.062 (0.046)	0.061	0.176	−0.075 (0.054)	−0.075	0.163	0.318 (0.046)	0.307	0.000	−0.024 (0.057)	−0.023	0.681
Year	0.011 (0.004)	0.160	0.004	0.011 (0.005)	0.221	0.015	0.007 (0.002)	0.219	0.005	0.001 (0.001)	0.072	0.312
Observation	530			371			477			318		
Fixed-effects	Yes			Yes			Yes			Yes		
Hausman test	P < 0.01			P < 0.01			P < 0.01			P < 0.01		
R-squared	0.271			0.161			0.338			0.195		
Adj R-squared	0.251			0.136			0.320			0.169		
F-statistics	13.69			6.27			18.20			7.42		
P-value	0.000			0.000			0.000			0.000		

Notes. The dependent variable is the count of epidemics outbreak incidents in China in 1370–1909 CE. All of the data are in decadal units. Coefficients and beta are reported, with standard errors in brackets. The fixed-effects indicate the inclusion of indicator variables for the identity of various provinces in China.

suppress hunger. This can cause diarrhea and/or vomiting, which results in a further weakening of the body (Murton, 2000). This could in turn have led to the widespread occurrence of diseases across the village. Economic downturn could also lead to the poor provision of healthcare and hygiene systems, which promotes the occurrence of large-scale epidemics (Folland et al., 2007).

In unison, the economic hardship and social instability brought by climate-induced (cooling in particular) agricultural shrinkage triggered more frequent mass migration, which elevated epidemics by increasing the frequency of interaction among different population groups. This increases the probability of contracting virulent diseases in human population. Also, migration has the effect of spreading diseases to areas not directly affected by famines or harvest failure (Galloway, 1986; Zhang et al., 2011a).

The overall country-wide temperature-epidemics relationship is primarily attributable to the temperature-epidemics association in northern China and central China, particularly in central China. This concurs with the findings in previous climate-war (Zhang et al., 2005, 2006, 2007b) and climate-population studies (Lee et al., 2008, 2009) in ancient China, in which the catastrophic socio-political and demographic effect of cooling was observed. This may be related to the regional geographic context in central China. The economic and cultural centres of China were once in the Yellow River Delta (northern China). Since the beginning of the North Song dynasty (960 CE), the centres shifted to the fertile land of the Yangtze River Delta (central China), as the northern wheat and pastoral regions could not support a more dense population (Zhang et al., 2006). Since that time, the population density in central China remained the highest among various regions in China throughout the past millennium (Lee et al., 2008, 2009). The region's vulnerability of epidemic outbreaks was amplified by existing pressure on the agricultural resource base, which can be substantiated with the exact match of the ranks of population density (Fig. 4) and the beta value of temperature (Table 4) among the four macro regions in China (i.e., higher population density is associated with larger beta value of temperature). Also, the climate-epidemics relationship in central China might have been reinforced by the war-epidemics connection, as warfare became more frequent in central China in a cold climate (Zhang et al., 2006).

5.2. Scaling the climate-epidemics nexus

Significant temperature-epidemics correlations were reported for all geographic scales (Tables 1–3). While the correlation remains statistically significant at all geographic scales, a stark

reduction in the correlational strength towards lower geographic levels was observed, suggesting that the phenomenon is scale-dependent. The results were in accord with existing literature on correlational studies, showing that coefficient sizes could be strongly influenced by aggregation levels (Glaeser et al., 2003). This phenomenon leads us to the modifiable areal unit problem. As demonstrated in previous literature (Amrhein, 1995), the correlation is affected by scale due to the change in the number of areal observations, as in this case, the change from 54 observations at the country level to 1728 at the provincial level.

The reasons behind the amplification of correlational strength up the aggregation level remain unclear based on the available results. One could argue that climate change (and consequently the economic downturn) tends to occur on a large geographic scale, and an aggregated national level analysis may better capture the effects of a macro environmental phenomenon (Pei et al., 2016b). Alternatively, the effect could be attributed to the 'aggregation problem', where statistical results are prone to errors and biases due to loss of locational information further up the aggregate level (Clark and Avery, 1976; Goodchild, 1979). As smaller areal units are aggregated, the original values of these small scale units are recorded and replaced by a new, representative value. Variances and extreme values within the original data are smoothed out during the data transformation. Hence, the correlational results will tend to be inflated further up the spatial scale. Clark and Avery (1976) argued that it is the resulting change in covariance between the dependent and independent variables at different aggregation levels that influence the correlation coefficients. Higher aggregation levels tend to create groups with higher within-subject heterogeneity, and lower between-group heterogeneity, which ultimately leads to a decrease in potential spatial autocorrelation and a fast decrease in covariation in relation to the increased data consolidation.

In this study, we attempted to disaggregate the climate-epidemics nexus in historical China by using regional and provincial level data. Subject to the dearth of high spatial resolution historical data, further data disaggregation may not be an option. Similar to the case of climate-conflict nexus (Lee et al., 2016a), it remains questionable to assign the potential causes of an epidemic incident to conditions within extremely sub-divided spatial units, since many factors located beyond that spatial unit may affect the likelihood of epidemic outbreaks in a region.

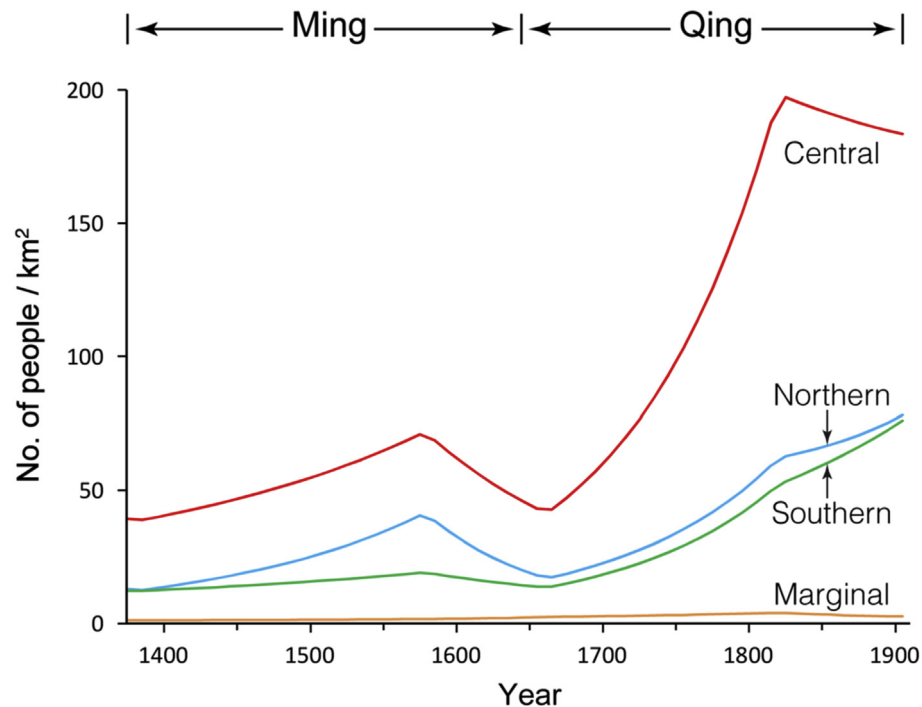


Fig. 4. Population density in various macro regions in China, 1370–1909 CE.

5.3. Contextualizing the climate-epidemics nexus

Climate change did not uniformly drive up epidemic outbreaks among the sub-regions within China (Table 4). Indeed, the vulnerability of epidemic outbreaks to climate change is determined by the synergistic work of climate-induced agricultural shrinkage and population growth (Lee, 2014; Lee and Zhang, 2010, 2013). In regions where population pressure and agricultural dependence on climate were higher, the influence of climate change on human societies was stronger and more apparent (Zhang et al., 2007a, 2011a). This highlights the problem of uncertain geographic context (Kwan, 2012). The problem originates from the neglect of the true geographic context of the climate-epidemics nexus. In the case of the climate-epidemics nexus in historical China, once a location reached a certain threshold of population this seemed to amplify the likelihood of an epidemic outbreak. That is, climate change may only yield significant impact on epidemics if a certain population threshold has been exceeded.

The uncertain geographic context problem indicates that the manner in which the study area is delimited also matters in climate-epidemics research. If our study area was delimited to northern and central China, where the population density was much higher than that in marginal and southern China, we could obtain rather strong climate-epidemics correlation. However, if the study area was delimited to marginal and southern China, where the population density was much lower, the climate-epidemics relationship could be found insignificant (Fig. 4; Table 4). Although the delineation of study area had a significant effect on estimating the climate-epidemic link, we do not have any definite answer about whether or not marginal and southern China should have been excluded from this study. Perhaps this issue should be explored further in future work.

5.4. Knowledge contributions and limitations of this study

McMichael (2012) illustrates the population health vulnerability

to climatic changes spanning multi-century to single-year duration. His work provides deep insights into climatic impacts on human health and survival over a range of temporal scales. In this study, we make a pioneering attempt to focus on the climate-epidemics nexus over a range of spatial scales, with country, regional, and provincial data employed for statistical analysis. In comparison to a previous study that is based on 244 recorded epidemic events during the Ming and Qing Dynasties in China (Pei et al., 2015b), this study utilizes on a much larger sample size (i.e., 5961 epidemics incidents). We focused on multi-scalar analysis, rather than simply taking the whole of China as single a spatial aggregate. We proved that epidemics outbreaks at various geographic levels in historical China could be attributable to temperature change. Also, we found that cooling mainly drove up epidemic outbreaks in northern and central China. Our findings supplement the existing literature about the climate-epidemics relationship in historical China. More broadly, this study also helps to illustrate the modifiable areal unit and the uncertain geographic context problems in climate-epidemics research, which are the two fundamental methodological problems in the examination of area-based attributes on individual behaviours or outcomes (Kwan, 2012).

This study is however limited by the resolution of the data source. While the epidemic and population records could offer a spatial resolution at the provincial level, our temperature and precipitation data were constrained to a nationally-aggregated level. As discussed with the modifiable areal unit problem, the deviation in spatial resolution implies that the highly aggregated climate data would most likely exhibit a lower variance than epidemic datasets at the regional or provincial level. The mixed use of multi-resolution data may thus create bias toward national-scale analysis, at which the data tend to exhibit more comparable properties (e.g., low variance, identical spatial resolution, and so on) (Gotway and Young, 2002). The averaged data may omit temperature and precipitation variation across regions which may potentially undermine the significance of results down the aggregation hierarchy. Unfortunately, the problem could not be solved, as

paleo-climate reconstructions of high spatial resolution covering the entire China are not available at the moment.

6. Conclusions

Our study has provided strong support for the climate-epidemics link in imperial China, alongside spatial scales and geographic context. Researchers need to consider the scale effect during panel data analysis, which are currently predominantly conducted on a national/single scale. Researchers are also reminded about the importance of how a study area is delineated, which is rarely discussed in the climate-epidemics literature. Future research may leverage our results and provide a cross-analysis with those derived from spatial analysis. This may promote further understanding on panel data application in a spatial context, and offer more insight on the spatial correlation between climate change and epidemics outbreak in Chinese history.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.socscimed.2016.12.020>.

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