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Spatial spill-over effects of air pollution on aortality in Gansu Province, China

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Abstract

Introduction and Objective. Currently, air pollution remains a significant factor affecting health. The aim of the study is to explore the spatial distribution characteristics of air pollutants in Gansu Province, China, as well as the direct effects and spatial spill-over effects of air pollutants on mortality rates in various regions of the province.

Materials and Method. Panel data was collected from 2015–2022 (excluding 2020) and employed a panel spatial autoregressive model with fixed effects for both time and space, using three types of spatial weight matrices to explore the spatial impacts of air pollution on mortality rates among residents.

Results. It was found that the mortality rate and degree of air pollution across various areas of Gansu were not randomly distributed, but showed obvious correlations and spatial aggregation characteristics. The median air quality index value significantly influenced the mortality rate of residents, and air pollution showed a spatial spill-over effect on the mortality rate. Mortality rates of the permanent population in a specific area were influenced not only by local air pollution but also by air pollution in neighbouring or economically-related areas. Numerical values of the direct and spatial spill-over effect of air pollution were calculated.

Conclusions. It was concluded that air pollution significantly impacts the mortality rate among Gansu's permanent residents through spatial spill-over effects. Collaborative efforts by governments across different regions are essential to mitigate the detrimental health effects of air pollution.

Key words

mortality, air quality index, spatial econometrics analysis

INTRODUCTION

China's economy has sustained ongoing growth, leading to enhancements in urban healthcare and elevating the living standards of its residents. However, this development has brought about the issue of environmental air pollution. Research indicates that, among secondary risk factors, air pollution is the fourth leading cause of death globally for both men and women [1]. China is a major industrial country, but the advancement of industry has brought with it the issue of air pollution, which markedly impacts the health of the local residents [2]. According to the Air Quality Index (AQI) standards[a] of China, the domestic AQI is used as a metric to assess the degree of air pollution in a specific region. The AQI is a dimensionless scale that provides an overview of levels of air quality[b]; it reflects worsening air quality conditions and escalating risks to human health. The main pollutants evaluated using the AQI are particulate matter (PM10), inhalable particles (PM2.5), sulfur dioxide, nitrogen dioxide, ozone (O3), and carbon monoxide. Taking the air quality of 14 regions in Gansu during 2022 as an example, 10 regions had an AQI above 100 for more than 30 days within a year, with the most severe region having an AQI above 100 for 77 days. It is therefore evident that air pollution in some areas of Gansu is still very serious, and studying the impact of air pollution on mortality in Gansu holds significant practical relevance.

Studies submitted to Biomedical Journals indicate that air pollutants can trigger a variety of health conditions, including respiratory diseases [3], cardiovascular [4] and cardiopulmonary diseases [5], brain damage [6], lung cancer [6], and mental disorders [5]. These pollutants can also disrupt the immune system [7] and are closely associated with increased mortality rates [8]. Although research has directly or indirectly proven the impact of air pollutants on health, due to differences in baseline and data characteristics, results regarding the impact of different pollutants on health are not consistent. In addition, due to varying development stages across different areas of Gansu, the degree of air pollution also varies considerably across various areas. For example, in 2022, Wuwei City had an AQI greater than 100 for 77 days, whereas Longnan City had only 6 days with an AQI greater than 100. Significantly, as some air pollutants exhibit spatial spillover effects [9], it is essential to consider both spatial correlation and spatial lag effects when analyzing the influence of air pollution on mortality rates.

Current research mainly considers the effects of exposure to the main pollutant (PM2.5) on health and the health

a. National Environmental Protection Standards of the People's Republic of China (Technical Regulation on Ambient Air Quality Index [on trial]).

b. AQI is divided into six levels: 0–50: excellent, 51–100: good, 101–150: mild pollution, 151–200: moderate pollution, 201–300: high pollution, and greater than 300: severe pollution.

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burden [10], but ignores the fact that when PM2.5 is not the main pollutant – other air pollutants also have a substantial impact on health. Taking Lanzhou, the capital of Gansu, as an example, in 2022, Lanzhou had 67 days with an AQI greater than 100, of which 11 days were primarily owing to PM2.5, and 33 days were primarily owing to O3. Therefore, the impact of air pollutants other than PM2.5 on human health in the Gansu region cannot be ignored.

OBJECTIVE

The aim of the current study was to thoroughly assess the overall effects of air pollutants by employing the median AQI values in order to examine their influence on mortality rates of the population. Also taken into consideration were population density, the number of elderly people, hospital resources, *per capita* gross domestic product (GDP), and industrial structure, to control the impact of extraneous confounding variables on the mortality rate. Panel data were utilized spanning 2015 – 2022 (2020 excluded) from 14 cities in Gansu to investigate both the direct and spatial spillover impacts of air pollutants on mortality rates, and to calculate the effect values. The results obtained will provide a reference for local governments to formulate pollution control plans.

MATERIALS AND METHOD

Study area and data. Gansu, situated in China's western region, has an average altitude of 2,158 m and a dry and arid climate with little rainfall. The presence of deserts within the province and in the adjacent regions of Xinjiang, Qinghai, Ningxia, Inner Mongolia and Shaanxi, has resulted in severe particulate matter pollution in Gansu. In addition, the presence of factories and mining areas within and around Gansu, coupled with a heavy traffic burden within the province, has resulted in Gansu facing increased levels of pollutants such as SO_2 and O_3. The main pollutants in Gansu Province are not solely particulate matter, multiple pollutants also need to be considered when studying air pollution in the region. Gansu Province, which is severely affected by air pollution, was therefore selected for study using the AQI to measure the comprehensive impact of air pollutants.

The study examines the spatial impact of air pollution on mortality rates by selecting 14 regions within Gansu, China, for analysis covering the period from 2015–2022. Owing to the main data for 2020 not being published, that year was excluded from the study. The 14 regions comprise all the municipal administrative units in Gansu Province. The AQI data (China National Environment) and the area data [12] for each region used in this study were sourced from archival records. Additional indicators, including population data, number of hospitals, and GDP data, were also collected from the Gansu Development Yearbook [13].

Statistical analysis. Numerous studies currently explore the effects of air pollutants on health, measuring the health burden using various dependent variables, with most using the number of outpatient visits or number of hospitalizations [14]. In addition, to avoid the biased results caused by the above-mentioned variables [15], some studies have used

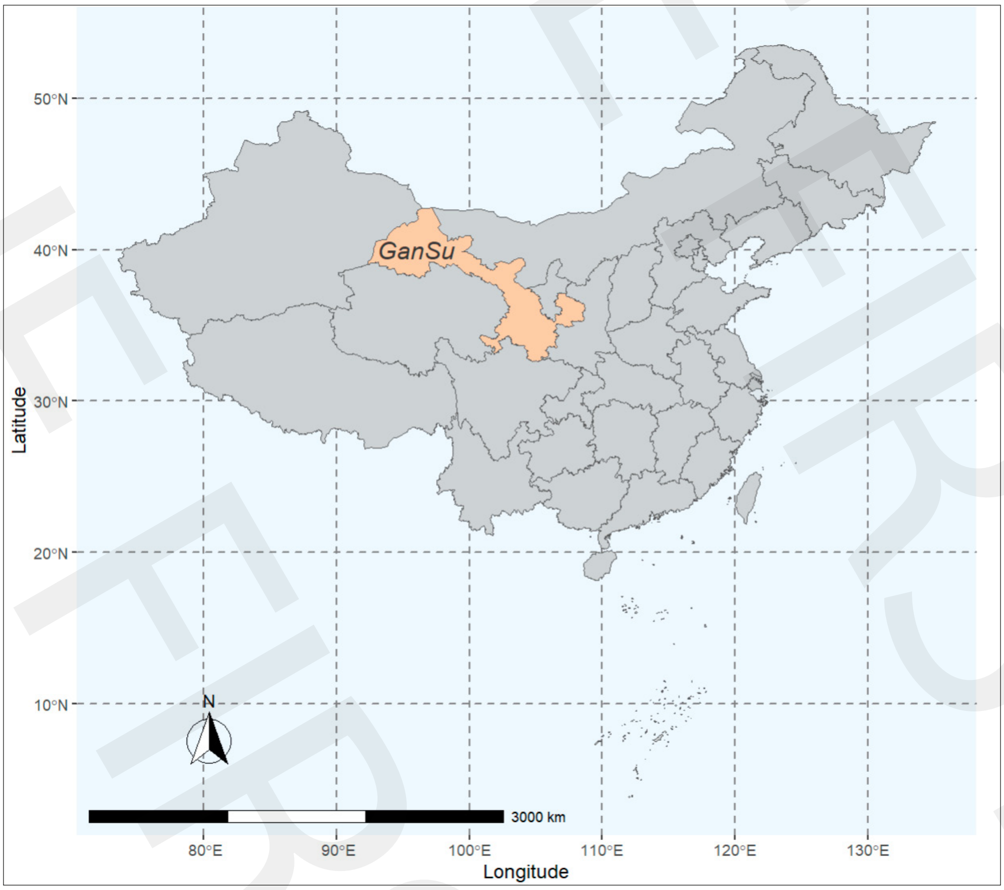

Figure 1. Location of Gansu

outpatient costs, the number of outpatient visits, and the number of hospitalizations as measurement standards for the health burden [16]. Furthermore, research has confirmed that air pollution affects mortality [8]. This study used mortality as the dependent variable to examine the impact of air pollution on residents' mortality. The AQI is reported by taking the highest value [17] derived from multiple pollutants. To avoid ignoring the impact of other air pollutants on health when PM2.5 is not the main pollutant, as well as the impact of high values in special situations on the accuracy of the research, this study employs the median AQI value within a year (AQI_med) to represent the air pollution level in a particular region within 1 year. According to the actual situation, many factors affect residents' health, with air pollution being just one of these factors.

Referring to existing research [10, 16, 18], in this study, the following control variables were used: population density (year-end density of the permanent population, measured in individuals/km^2), *per capita* hospital resource quantity (year-end ratio of hospitals to the permanent population, measured in units/10,000 people), *per capita* GDP (pgdp, *per capita* GDP, measured in 10,000 RMB/person), and industrial structure (ratio of the GDP from secondary industry to that of tertiary industry).

Research additionally shows that some common respiratory diseases have a considerable impact on human life, and the mortality rate among elderly people is relatively high [19]. A large elderly population will lead to the inclusion of natural deaths in the total number of deaths; therefore, in this study, additionally selected was the percentage of residents aged over 65 within the total population of the region (year-end ratio of the population aged 65 years and above to the permanent population, measured in percentage [%]) as a control variable. Research shows that for some diseases, inhalable particulate matter (PM2.5) is the main influencing factor [4]. Thus, in the current study, the median value of PM2.5 within 1 year (PM2.5_med) and the median value of PM10 within 1 year (PM10_med) were selected as replacement independent variables in the robustness test.

Spatial autocorrelation test. To thoroughly investigate the spatial spillover effects of atmospheric pollutants on mortality rates, the study employed both global and local indices of spatial correlation during the exploratory analysis phase. These indices were assessed using Moran's index (Moran's I), which is employed to ascertain the spatial correlation. The formulas for calculating these indices are as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(y_i - \bar{y}\right)\left(y_i - \bar{y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i, S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \quad (1)$$

$$I_i = \frac{\left(y_i - \bar{y}\right)}{S^2}\sum_{j \neq i} w_{ij}\left(y_j - \bar{y}\right), \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i, S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \quad (2)$$

where n represents the total number of spatial units, w_{ij} denotes the spatial weight, and y_i corresponds to the observed value in the ith region.

The global Moran's I statistic spans from –1 to 1. A value greater than 0 indicates positive spatial autocorrelation within the dataset. Additionally, as this value approaches 1, the observed positive spatial autocorrelation intensifies. Conversely, a value below 0 implies negative spatial autocorrelation, where values nearing –1 reflect an increasingly strong negative spatial autocorrelation.

The local indicator of spatial association (LISA) is a spatial decomposition of the global spatial correlation detection index. The LISA metric effectively captures the correlation traits of each spatial unit with its adjacent counterparts, and facilitates the identification of 'cluster areas' – zones of either high or low aggregation. Additionally, it aids in pinpointing 'hotspot areas', which are regions exhibiting values distinctly divergent from those of their neighboring units.

A positive local Moran's I index represents a region where a high value is surrounded by high values, or a region where a low value is surrounded by low values. A negative local Moran's I index represents a region where a high value is surrounded by low values, or a region where a low value is surrounded by high values.

The incorporation of spatial weighting matrices is essential to depict inter-regional relationships in conducting spatial econometric analysis. To methodically examine the spatial correlation attributes across various regions in Gansu, the current study utilized the spatial adjacency matrix W1, the spatial distance matrix W2, and the spatial economy matrix W3. The elements of W1 were defined as follows:

$$w_{ij} = \begin{cases} 1, i \neq j \\ 0, i = j \end{cases} \quad i, j = 1, 2, \cdots, n.$$

The aim was to strengthen the robustness of the analytical outcomes and investigate whether the spatial spill-over effect will be affected by the distance between 2 regions, that is, as spatial proximity increases, the spatial effect intensifies; conversely, as distance expands, the spatial effect diminishes. A spatial distance matrix was constructed. W2 is defined in the following manner:

$$w_{ij} = \begin{cases} 1/d_{ij}, i \neq j \\ 0, \quad i = j \end{cases} \quad i, j = 1, 2, \cdots, n$$

where d_{ij} is the distance between the geographic centres of region i and region j.

The spatial adjacency matrix and spatial distance matrix only reflect the impact of geographic proximity. To improve the reliability of the analytical outcomes and to explore whether economic variables influence the spatial spill-over effect between 2 regions, a spatial weight matrix was used to predicate economic distance, designated as W3 [20]. The element setting form is as follows:

$$w_{ij} = \begin{cases} \dfrac{X_j}{\sum_{k \in J_i} X_k}, i \text{ and } j \text{ have a shared border.} \\ 0, \ i \text{ and } j \text{ do not have a shared border or } i = j \end{cases}.$$

where X_j represents the economic variable chosen to form the spatial weight matrix; in the presented study, *per capita* GDP (pgdp) is used. J_i is the set of all spatial units that share a common boundary with spatial unit i.

Spatial econometric model. A spatial econometric model was used to assess the influence of atmospheric pollutants on mortality rates of residents in Gansu, and calculates the direct effects and spatial spillover effects. Three panel data models were adopted: the Traditional Linear Regression Model (TLRM), Spatial Autoregressive Model (SAR), and the Spatial Error Model (SEM) [21], to test spatial effects. Building on the traditional panel model, the SAR incorporates a spatial lag term of the dependent variable, while the SEM introduces a spatial lag effect of the error term. After these modifications, we developed the following three models:

TLRM:

$$\begin{gathered} Y_{it} = \alpha + \beta_1 AQI\_med_{it} + \beta_2 \text{pop\_den}_{it} + \beta_3 \text{hos\_res}_{it} \\ + \beta_4 pgdp_{it} + \beta_5 ind\_str_{it} + \beta_6 old_{it} + u_{it} \\ u_{it} = \mu_i + \gamma_t + \varepsilon_{it}; \varepsilon_{it} \sim IID\left(0, \sigma_\varepsilon^2\right); i = 1, \cdots, N; t = 1, \cdots, T; \end{gathered} \tag{3}$$

SAR:

$$\begin{gathered} y_{it} = \alpha + \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 AQI\_med_{it} + \beta_2 \text{pop\_den}_{it} + \beta_3 \text{hos\_res}_{it} \\ + \beta_4 pgdp_{it} + \beta_5 ind\_str_{it} + \beta_6 old_{it} + \mu_i + \varepsilon_{it} \\ \varepsilon_{it} \sim IID\left(0, \sigma_\varepsilon^2\right); i = 1, \cdots, N; t = 1, \cdots, T; \end{gathered} \tag{4}$$

SEM:

$$\begin{gathered} y_{it} = \alpha + \beta_1 AQI\_med_{it} + \beta_2 \text{pop\_den}_{it} + \beta_3 \text{hos\_res}_{it} + \beta_4 pgdp_{it} \\ + \beta_5 ind\_str_{it} + \beta_6 old_{it} + \mu_i + \rho \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \\ \varepsilon_{it} \sim IID\left(0, \sigma_\varepsilon^2\right); i = 1, \cdots, N; t = 1, \cdots, T; \end{gathered} \tag{5}$$

where:
- Y is the dependent variable (mortality);
- AQI_med is the core independent variable;
- pop_den, hos_res, pgdp, ind_str, and old are control variables;
- X denotes the afore-mentioned primary independent variables and control variables;
- x_{it} represents the vector of observed values of K explanatory variables for the *ith* individual at time *t*;
- W is the spatial weight matrix;
- w_{ij} is the element of the *ith* row and *jth* column of the spatial weight matrix W;
- α is a scalar representing the intercept term;
- β represents the coefficient of the impact of the independent variables on the dependent variable;
- λ represents the spatial autoregressive coefficient;
- ρ represents the spatial error coefficient;
- ε_{it} is a normally distributed random error vector;
- *i* represents regions;
- *t* represents year.

By combining spatial dependence and individual effect forms, the model of spatial panel data is categorized into 4 distinct types [21]. When the sample must infer population properties through specific individual properties, the random effects model was chosen; when regression analysis is limited to some specific individuals, the fixed effects model was chosen (Zhao, Fang, and Wu 2014). In the current study, the spatial econometric model applies to all cities and states in Gansu; consequently, the fixed effects model was selected for this analysis.

Model test. Anselin extended the Lagrange multiplier tests (i.e., LM-lag and LM-err) in the cross-sectional model to the panel data model. Additionally, Elhorst provided the robust spatial error LM test (RLM-lag) and robust spatial error LM test (RLM-error), which should be applied judiciously [21]. The above methods were used to test the selection of SAR and SEM models. Since this test is influenced by the fixed effects within the model, it is essential to first ascertain the suitable model form based on the outcomes of the non-spatial fixed effect model. Subsequently, the LM test for spatial interaction effects should be implemented [21]. Additionally, this test is specifically effective for distinguishing between the SAR and the SEM. When both LM-lag and LM-error tests yield significant results, it is necessary to proceed with the robust LM-lag and LM-error tests. If these tests are also significant, other spatial models need to be considered [22].

RESULTS

Descriptive statistics.

Table 1. Descriptive statistics

Variable	Obs	Mean	S.D.	Min	Median	Max
mortality	98	6.883	1.4930	3.98	6.80	10.55
AQI_med	98	63.460	8.9832	35	64	80
PM2.5_med	98	26.730	6.6616	10	26	42
PM10_med	98	64.540	15.5430	29	62	104
pop_den	98	133.710	89.5313	5.54	83.68	337.48
hos_res	98	0.262	0.1247	0.0657	0.2674	0.6717
pgdp	98	4.441	3.0141	1.099	3.271	12.016
ind_str	98	0.688	0.5465	0.2004	0.5060	3.1123
old	98	10.753	1.8363	7.40	10.45	15.09

Table 1 presents the descriptive statistics of the panel data during the study period (2015 – 2022, excluding 2020). The minimum value of AQI_med is 35 (Gannan, 2021), and the maximum value is 80 (Lanzhou, 2016; Lanzhou, 2017). The minimum mortality rate is 3.98‰ (Jiayuguan, 2016), and the maximum – 10.55‰ (Wuwei, 2022).

Description of spatial distribution of the AQI and mortality rates in Gansu.

Figure 2 shows the spatial distribution of AQI_med values (Figure 2a1, a2, a3) and mortality rates (Fig. 2b1, b2, b3) for all selected areas within Gansu Province in 2015, 2018, and 2022. These specific years and the most recent year (2022) were chose for analysis due to the revisions of the law[c] in 2015 and 2018. Figure 2a1, a2, a3 shows that the high-value regions of AQI_med are mainly divided into 2 parts: 1) concentrated in Lanzhou City and the neighbouring cities of Baiyin and Wuwei; the other part is Jiuquan City. Figure 2b1, b2, b3 shows that the high values of mortality are predominantly localized in the southern cities of Gansu. A notable characteristic of this Figure is that the extent of air pollution in Gansu Province exhibits clear spatial clustering tendencies, meaning that regions experiencing the highest levels of air pollution are grouped closely together, as are those with the minimal levels of pollution. Similar to air pollution, mortality rates of the permanent population also have certain clustering characteristics.

Spatial autocorrelation analysis of AQI and mortality rates in Gansu.

Table 2 presents the global Moran's index for mortality rate and AQI_med under different spatial weight matrices.

c. Air Pollution Prevention and Control Law of the People's Republic of China

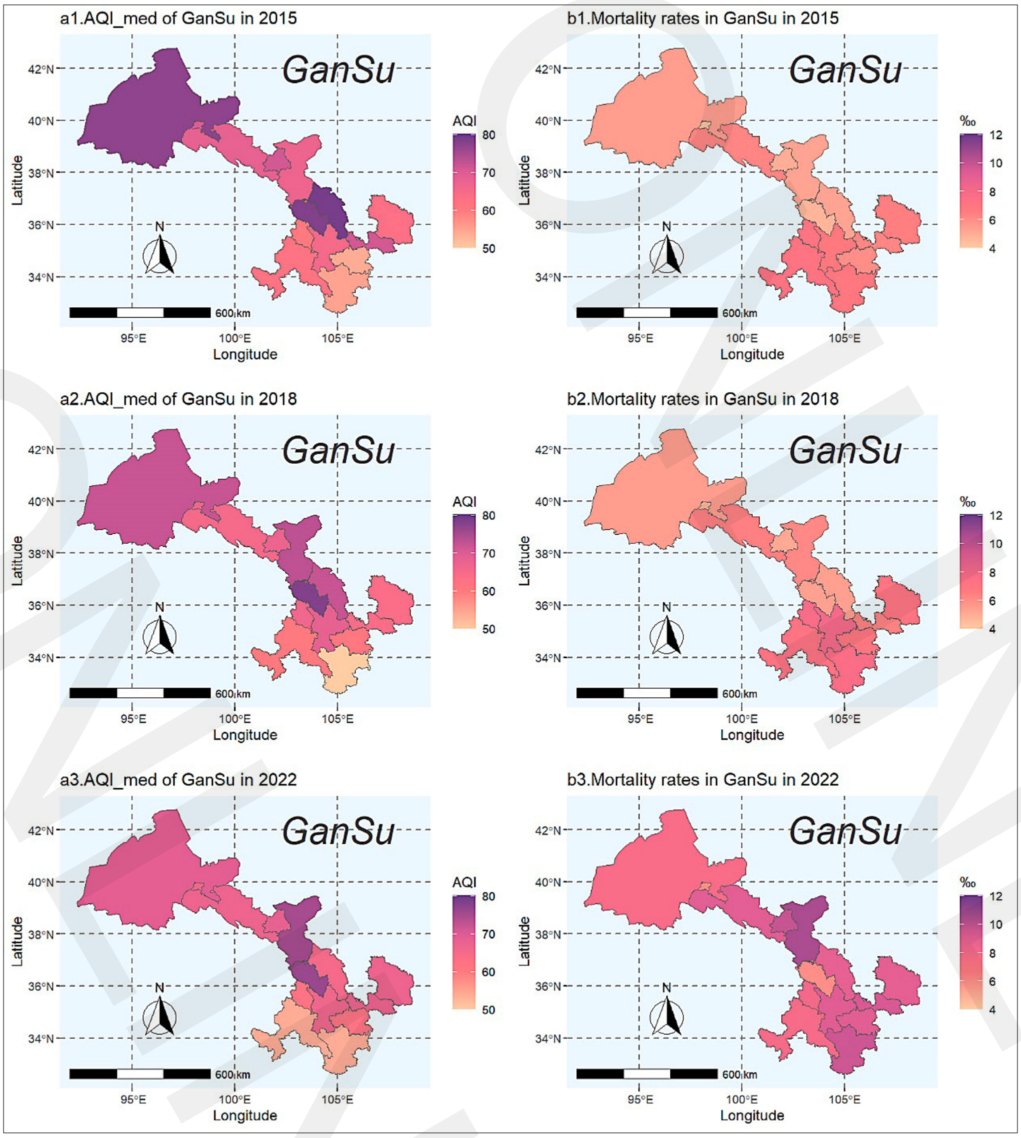

Figure 2. Spatial distribution of core variables in 2015, 2018, and 2022

Table 2. Global Moran's I values of mortality rate and AQI_med (2015–2022, except 2020)

Year	Mortality			AQI_med		
	W1	W2	W3	W1	W2	W3
2015	0.2889**	0.2856**	0.3797**	0.2675**	0.2806**	0.3033**
2016	0.2344*	0.2391*	0.3059**	0.1508	0.1472	0.0607
2017	0.2875**	0.2977**	0.3262**	0.2003*	0.1982*	0.2592**
2018	0.3416**	0.3552**	0.3707**	0.3414***	0.3404**	0.4348***
2019	0.3448**	0.3578**	0.3800**	0.2878**	0.2175*	0.3624**
2021	0.1027	0.1873	0.0768	0.4612***	0.4177***	0.5620***
2022	0.1076	0.1923*	0.0835	0.3747***	0.3012**	0.4914***

Levels of statistical significance:*** at 1%; ** at 5%, and * at 10%.
Moran's I values for additional variables are omitted

For AQI_med, under the W1 condition, the global Moran's I in 2017 was significantly positive at the 10% level, and the global Moran's I in 2015 and 2019 was significantly positive at the 5% level; the global Moran's I in 2018, 2021, and 2022 was significantly positive at the 1% level.

Under the W2 condition, the global Moran's I in 2017 and 2019 was significantly positive at the 10% level, and the global Moran's I in 2015, 2018, and 2022 was significantly positive at the 5% level; the global Moran's I in 2021 was significantly positive at the 1% level.

Under the W3 condition, the global Moran's I in 2015, 2017, and 2019 was significantly positive at the 5% level; the global Moran's I in 2018, 2021, and 2022 was significantly positive at the 1% level.

For mortality rates, under the W1 condition, the global Moran's I for 2016 demonstrated significant positivity at the 10% significance level, while the global Moran's I between 2015 – 2019 showed significant positivity at the 5% level. In the W2 condition, the global Moran's I value for both 2016 and 2022 were notably positive at the 10% level, and from 2015 – 2019, they remained significantly positive at the 5% level. For the W3 condition, the global Moran's I covering the period from 2015 – 2019 was significantly positive at the 5% level.

These findings suggest that the distributions of the mortality rate and AQI_med in different regions of Gansu were not random; instead, they demonstrated clear spatial correlation and spatial clustering tendencies throughout the duration of the study. Consequently, when analyzing the impact of air pollution on mortality rates in Gansu it is imperative to account for spatial correlation; neglecting this factor could lead to biased findings.

Figure 3 shows the significant local spatial autocorrelation levels of mortality rate and AQI_med in all regions in 2018, based on W1, W2, and W3, as well as the significant correlation characteristics of spatial individuals with their neighboUrs (considering both Z-score and P-value; only the P-value is marked in the Figure). The Figure demonstrates that regions with significant local Moran's I primarily exhibit 3 types of clustering: high-high (H-H), where both the observed value of the local variable and its weighted average among neighbors exceed the overall average; low-low (L-L), where both the observed and the neighboUring weighted averages fall below the overall average; and high-low (H-L), where the observed value exceeds the average but the weighted average among neighboUrs does not. Notably, no low-high (L-H) clusters are present where the observed value is below the average, yet the neighbouring weighted average surpasses it.

Figures 3a1, a2, and a3 show that for the AQI_med in 2018, the findings from the 3 spatial weight matrices display a general consistency. Wuwei, Baiyin and Lanzhou in the central part of Gansu Province are H-H value areas, and the cities of Tianshui and Longnan in the southern part of Gansu Province are L-L value areas. Figure 3b1, b2, b3 shows that for mortality in 2018, the findings from the 3 spatial weight matrices display a general consistency. The city of Wuwei is an L-L value area; the city of Zhangye is an H-L value area; and the cities of Tianshui, Longnan, and Gannan in the southern part of Gansu Province, are H-H value areas. These findings largely align with prior conclusions. Additionally, it has been observed that varying spatial weight matrices exert an influence on the local Moran's I.

Spatial econometrics analysis. Table 3 shows the LM test for spatial interaction effects. Considering the test results and the consistency of model usage, it was decided to use the panel spatial autoregressive model with time–space fixed effects.

In the current study, the annual median AQI_med was used primarily as the independent variable to examine the spatial spill-over effects of air pollution on residents' mortality rates. To mitigate selection bias in the independent variables, PM2.5_med and PM10_med, two types of inhalable

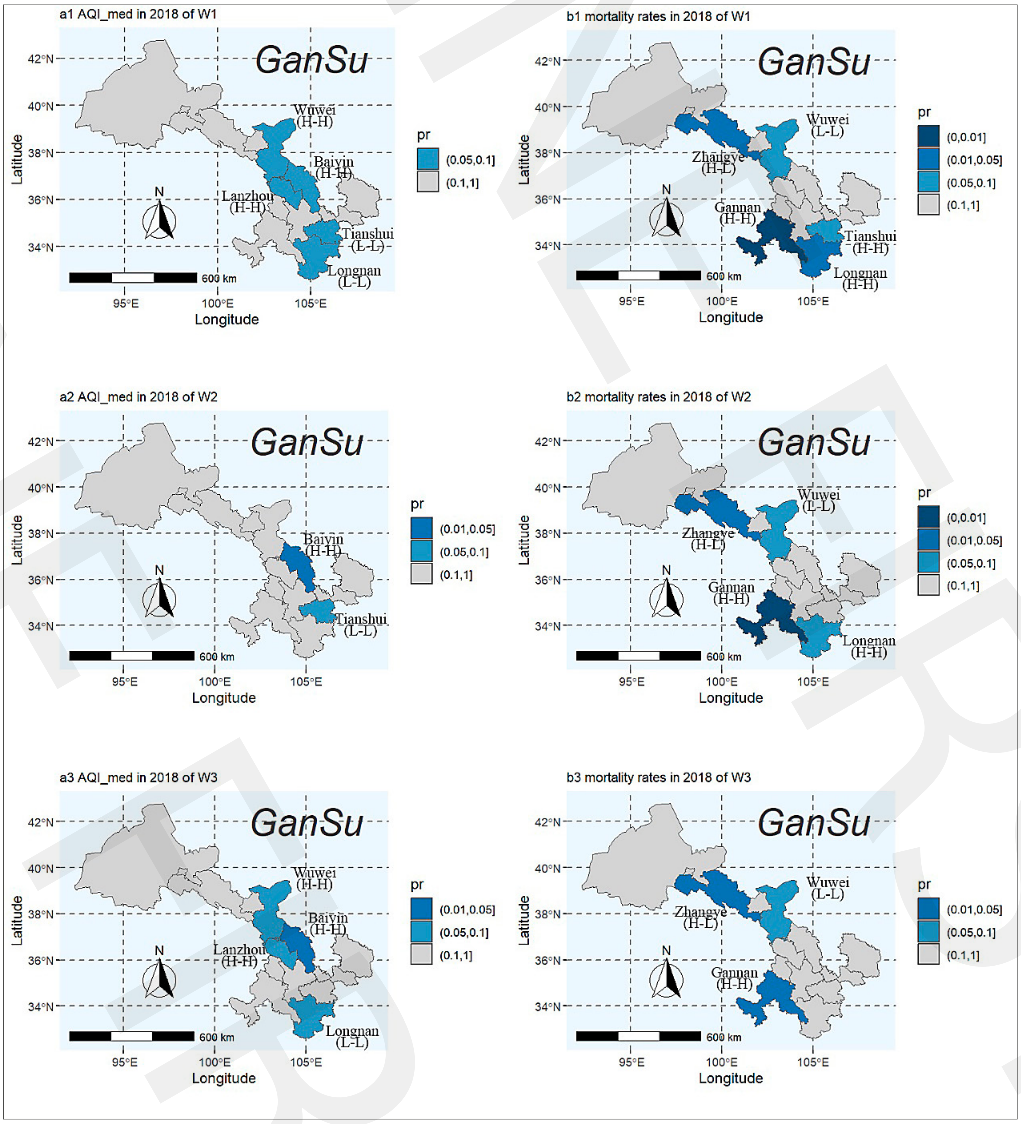

Figure 3. Spatial distribution of core variables W1, W2, and W3 for 2018: significance levels in local Moran's I analysis of AQI_med and mortality rates

Table 3. Results of the Lagrange multiplier test

Spatial Weight Matrix	Test Type	Mixed regression	Space fixed	Time fixed	Time-space fixed
W1	LM-lag	16.264 (0.000)	35.18 (0.000)	3.3525 (0.067)	4.9506 (0.026)
	LM-error	9.5228 (0.002)	24.497 (0.012)	3.272 (0.070)	0.34605 (0.556)
	RLM-lag	7.7679 (0.005)	10.684 (0.001)	0.2242 (0.636)	9.398 (0.002)
	RLM-error	1.0271 (0.311)	0.0014 (0.970)	0.14362 (0.705)	4.7934 (0.029)
W2	LM-lag	17.366 (0.000)	37.382 (0.000)	6.110 (0.013)	7.354 (0.026)
	LM-error	11.977 (0.000)	30.033 (0.000)	6.752 (0.009)	1.826 (0.177)
	RLM-lag	5.641 (0.018)	7.643 (0.006)	0.154 (0.695)	7.736 (0.005)
	RLM-error	0.252 (0.616)	0.294 (0.588)	0.796 (0.372)	2.208 (0.137)
W3	LM-lag	13.896 (0.001)	28.512 (0.000)	3.873 (0.049)	3.500 (0.061)
	LM-error	10.436 (0.001)	27.612 (0.012)	4.154 (0.042)	0.381 (0.537)
	RLM-lag	3.472 (0.062)	2.816 (0.093)	0.162 (0.688)	4.908 (0.027)
	RLM-error	0.012 (0.912)	1.916 (0.166)	0.443 (0.506)	1.790 (0.181)

Number within parentheses represents the P-value

particulate matter, were selected as substitutes for AQI_med to ensure the robustness of the experiment. The model employed a panel spatial autoregressive model with time-space fixed effects, and robustness checks were conducted under W1, W2 and W3. The spatial econometric results are presented in Table 4, indicating that the coefficients for AQI_med, PM2.5_med, and PM10_med were all significantly positive at the 1% significance level. Additionally, the panel spatial autoregressive coefficient (lambda) was significantly positive at the 5% significance level.

Due to the distinctive nature of spatial econometric models, direct identification of spatial spillover effects is not straightforward. Table 5 presents the analysis in which the direct, spillover was quantified, as well as the cumulative impacts of AQI_med on mortality rates. The direct and total effects of AQI_med were both statistically significant at the 1% level, while the spill-over effect was significant at the 5% level. Specifically, the direct effect of AQI_med was 0.0512, and the spillover effect was 0.0238. The total effect was 0.0750, with spill-over accounting for 31.73% of this total. This indicates that a 1% rise in AQI_med in a local area and its neighbouring regions leads to mortality increases of 5.12% and 2.38%, respectively. In summary, air pollution in the Gansu region elevates mortality rates both locally and in neighbouring cities – a significant effect that warrants attention. Under the W2 and W3 spatial weight matrices, the direct and total effects from the panel spatial autoregressive model with time-space fixed effects were significant at the 1% level, while the spillover effect was significant at the 5% level. Specifically, under W2, the direct effect of AQI_med was 0.0485, the spill-over effect was 0.0249, and the total effect – 0.0735, with spillover contributing 33.88% of the total impact. This implies that a 1% increase in AQI_med in a local area and its surroundings leads to mortality increases of 4.85% and 2.49%, respectively. Under W3, the direct effect of AQI_med was 0.0514, the spillover effect – 0.0149, and the total effect – 0.0663, with spill-over representing 22.47% of the total impact. This indicates that a 1% rise in AQI_med in a local area and its surrounding regions corresponds to mortality increases of 5.14% and 1.49%, respectively. This

Table 4. Results of the SAR robustness tests (replacing the spatial weight matrix and variables)

Variables	TIME-SPACE FIXED PANEL SAR MODEL								
	W1			W2			W3		
AQI_med	0.0491*** (0.0118)			0.0459*** (0.0115)			0.0502*** (0.0120)		
PM2.5_med		0.0303*** (0.0117)			0.0281*** (0.0113)			0.3152*** (0.0119)	
PM10_med			0.0193*** (0.0067)			0.0170*** (0.0066)			0.0203*** (0.0068)
pop_den	-0.0078 (0.0063)	-0.0086 (0.0068)	-0.0043 (0.0066)	-0.0088 (0.0062)	-0.0098 (0.0066)	-0.0055 (0.0064)	-0.0072 (0.0066)	-0.0080 (0.0071)	-0038 (0.0068)
hos_res	-0.1581 (0.7992)	0.3053 (0.8268)	0.0212 (0.8347)	-0.3432 (0.7781)	0.1035 (0.8001)	-0.1433 (0.8133)	-0.3145 (0.8166)	0.1625 (0.8433)	-1389 (0.8495)
pgdp	0.1655*** (0.0436)	0.1405*** (0.0453)	0.1457*** (0.0451)	0.1532*** (0.0426)	0.1284*** (0.0117)	0.1341*** (0.0440)	0.1746*** (0.0446)	0.1490*** (0.0462)	0.1539*** (0.0459)
ind_str	0.0015 (0.2488)	-0.0538 (0.2647)	0.0041 (0.2600)	-0.0018 (0.2438)	-0.0477 (0.2578)	0.0073 (0.2550)	0.0208 (0.2549)	-0.0780 (0.2707)	0.0203 (0.0068)
old	0.4137*** (0.0821)	0.4152*** (0.0886)	0.4467*** (0.0847)	0.3840*** (0.0808)	0.3786*** (0.0866)	0.4164*** (0.0834)	0.4466*** (0.0860)	0.4473*** (0.0851)	0.4756*** (0.0882)
lambda	0.3453*** (0.0833)	0.3271*** (0.0068)	0.3361*** (0.0908)	0.3749*** (0.0836)	0.3746*** (0.0851)	0.3683*** (0.0860)	0.3453*** (0.0833)	0.2245** (0.0876)	0.2408*** (0.0864)
Log-Likelihood	-31.5426	-36.2611	-35.5600	-29.8609	-34.2538	-33.9927	-32.9462	-37.5559	-36.7322
R^2	0.9515	0.9464	0.9472	0.9537	0.9494	0.9496	0.9492	0.9440	0.9451
Obs	98	98	98	98	98	98	98	98	98

Levels of statistical significance: *** at 1%; ** at 5%; * at 10%. The figures in parentheses indicate standard errors

Table 5. Effects and coefficients of the spatial autoregressive model SAR

Variable	Spatial weight matrix	Values	Direct Effects	Spatial Spillover	Total
AQI_med	W1	Impact measures or Estimat	0.0512*** (0.0124)	0.0238** (0.0116)	0.0750*** (0.0216)
		z-values	4.1371	2.1544	3.5452
	W2	Impact measures or Estimat	0.0485*** (0.0122)	0.0249** (0.0116)	0.0735*** (0.0214)
		z-values	4.018	2.2942	3.5004
	W3	Impact measures or Estimat	0.0514*** (0.0124)	0.0149** (0.0079)	0.0663*** (0.0178)
		z-values	4.1794	1.9742	3.7702

further corroborates the conclusion that severe air pollution in Gansu, accounting for spatial factors, increases mortality rates and has a notable spillover effect. Additionally, the results vary somewhat depending on the spatial weight matrices used.

DISCUSSION

A study on the impact of air pollution on health and the economy in India provides evidence that air pollution significantly increases the risk of mortality. This research examined the effects and trends of PM2.5, ozone, and household air pollution on mortality, distinguishing between indoor and outdoor exposure scenarios [23]. Compared to the study on Indian, the current research employed the AQI as the core variable, considering a wider spectrum of air pollutants, thereby offering a more comprehensive and accurate representation of the overall impact of air pollution. Although the study in India provides a detailed distinction between indoor and outdoor pollution exposure, which enhances the precision of analysis, its assessment of outdoor pollution is limited to PM2.5 and ozone, without fully accounting for the effects of other pollutants. Additionally, while the study highlights the spatial heterogeneity of air pollution, it does not employ spatial statistical methods to examine the spatial correlation and clustering effects of pollution.

Previous research in China has shown that PM2.5 concentrations exhibit significant spatial clustering. Regions with the highest PM2.5 pollution tend to cluster together, as do those with minimal pollution [10]. This finding broadly aligns with the results of the current study. By examining air pollution across 14 regions in Gansu Province, it was found that severe pollution is mainly concentrated in the central part of the province, with Lanzhou experiencing the highest levels of air pollution. One major distinction is that existing studies on air pollution in China primarily focus on the economically-developed eastern regions, such as Beijing-Tianjin-Hebei (Jing-Jin-Ji), the Yangtze River Delta, and the Pearl River Delta, whereas the current study centres on Gansu Province. Additionally, the study examines the spatial distribution of AQI, whereas previous studies primarily concentrated on PM2.5, which may result in differences in findings. The authors hypothesize that this is due to the combined influence of multiple factors, leading to the most severe air pollution in Lanzhou, which has the largest population density. In addition, the terrain of Lanzhou comprises a narrow and long valley area, and it is difficult for public transportation to develop, such as rail transit, meaning that Lanzhou has enormous traffic pressure. Heavy vehicle emissions make the local air pollution in Lanzhou the most severe in Gansu. However, the mortality rate in Lanzhou and its surrounding cities, which also have the most severe pollution, is not the highest. This is because Lanzhou and its surrounding cities have sufficient medical resources, and residents can receive timely treatment when necessary. In contrast, the less-developed southern regions of Gansu exhibit relatively high mortality rates.

A study conducted in China on the impact of PM2.5 on the burden on public health provides evidence suggesting that air pollution not only directly affects public health, but also influences health outcomes through spatial spill-over effects. Moreover, the health impact of PM2.5 exhibits both spatial and temporal lag effects [16]. The afore-mentioned study examined the health effects of PM2.5 from both temporal and spatial perspectives. However, as with most studies, it focused on a single air pollutant. This approach may lead to an over-estimation of impact of PM2.5 on health, while potentially underestimating the actual effects of other pollutants. The study additionally analyzed multiple regions across the country, while research on the impact of air pollution on health across different prefecture-level cities within the same province has been relatively scarce. By analyzing the correlation between air pollution levels and mortality rates across prefecture-level cities in Gansu Province, the results were found to be largely consistent with existing research [8], specifically, that air pollution in Gansu Province is positively correlated with mortality rates. The findings of the current study contribute to the body of research on the health impacts of air pollution in the Gansu Province in northwestern China. Furthermore, the study also reveals that air pollution in Gansu not only increases the mortality rate among local residents, but also affects mortality rates in adjacent cities, suggesting spill-over effects on health outcomes. It is hypothesize that this phenomenon can be attributed to the rise in air pollution levels, as measured by AQI, in a given region, which in turn contributes to an increase in pollution levels in neighbouring areas, ultimately manifesting as a spatial spill-over effect.

The presented study investigated the differences in direct effects, spatial spill-over effects, and total effects of air pollution on mortality under different spatial weight matrices (W1, W2, and W3), while simultaneously conducting robustness tests. Research shows that the impact of air pollution on mortality rates of residents is not exactly the same under different spatial weight matrices [16]. The current findings indicate that the direct and spatial impacts of air pollution exposure on mortality are influenced by both geographic and regional economic characteristics, aligning with the results mentioned in previous research. Using spatial weight matrices W1, W2, and W3, the direct impacts of air pollution on mortality were observed to be 0.0512 (W1), 0.0485 (W2), and 0.0514 (W3), and the values of spatial lag effects were 0.0238 (W1), 0.0249 (W2), and 0.0149 (W3).

Comparing the data, it was found that the spatial spill-over effect between 2 locations with a close geographic relationship was significantly greater than that between 2 locations with close economic relationships; also, the spatial spillover effect of air pollution on mortality rates was stronger when the geographic relationship was close. The closer the geographic distance, the easier it is for air pollutants to cause spatial lag effects on nearby cities, that is, the increase in local air pollution levels will increase the air pollution levels of adjacent cities, thereby affecting the mortality rate in adjacent cities.

The main advantage of the presented study is that calculations were conducted based simply on PM2.5 or a single pollutant, but calculations were conducted based on the specificity of the AQI calculation method. Using the median AQI as the core independent variable, the effect was examined of air pollution on mortality with different pollutants as the main pollutants, considering the combined impact of multiple pollutants, and avoiding neglect of the impact of other pollutants on mortality when PM2.5 is not the main pollutant. In addition, the main influencing factors were controlled, including the number of elderly people, population density, *per capita* GDP, and *per capita* hospital resources. Based on W1, W2, and W3, using the panel spatial autoregressive model with time-space fixed effects, a quantitative analysis was conducted to determine the direct influence of air pollution on mortality rates in the area, as well as its spatial spill-over effect on neighbouring areas.

Limitations of the study. The authors acknowledge that the study has some shortcomings of research. The absence of extensive data precluded the possibility of conducting a longitudinal panel data analysis. Moreover, specific data for cities surrounding Gansu were unobtainable, and disparate statistical standards used in the yearbooks of these cities compared to Gansu, introduced bias into the results. This bias hinders the ability to accurately assess the impact of air pollution on the mortality rates in Gansu and its neighbouring cities.

CONCLUSIONS

The primary findings can be summarized as follows.

1) Within Gansu Province, the distribution of mortality rates and air pollution across various regions exhibits significant spatial correlations and clustering tendencies. A discernible positive spatial correlation exists between air pollution levels and mortality rates among the permanent population.
2) Air pollution significantly negatively affects the health of residents in Gansu. When air pollution becomes severe, the mortality rate among permanent residents is increased. Air pollution exhibits a spatial spill-over effect on the mortality rate, that is, the air pollution in a particular region of Gansu will not only increase the mortality rate of local residents, but will also increase the mortality rate of residents in adjacent cities. This is an impact that cannot be ignored.
3) The spatial spill-over effect between 2 locations with close geographic relationships is significantly greater than that between 2 locations with close economic relationships, and the spatial spill-over effect of air pollution on mortality rates will be stronger when the geographic relationship is close.

The findings examining the relationship between AQI and mortality rates should be considered when formulating air pollution control policies. During the study period, Lanzhou was consistently one of the cities with the most severe air pollution. As the economy and technology advance, it is important to address the air pollution associated with these developments. Data from the Traffic Police Detachment of the Lanzhou Municipal Public Security Bureau reveal that by the end of June 2023, the motor vehicle count in Lanzhou had escalated to 1,277,284, of which merely 2.96% were comprised of new energy vehicles. The government should formulate corresponding policies to encourage citizens to switch to renewable energy vehicles or use public transportation.

Furthermore, owing to the findings, regions should strengthen cooperation, share pollution control information technology, jointly control air pollution, strengthen enterprise control, and severely punish or close enterprises that are heavy polluters and that do not comply with the regulations. High-pollution enterprises should undergo technological transformation and reduce pollutants produced during their production processes. Simply moving heavily polluting factories from urban areas to the suburbs cannot solve the problem at its root because air pollution in cities where these factories are located will be aggravated, which affects not only local residents but also the residents in surrounding cities. To improve the quality of life and ensure the well-being of local residents, local governments in various regions must implement measures to control air pollution.

Abbreviations

- AQI – Air Quality Index;
- PM10 – Particulate Matter;
- PM2.5 – Inhalable particles
- GDP – Gross Domestic Product
- LISA – Local Indicator of Spatial Association
- TLRM – Traditional Linear Regression Model
- SAR – Spatial Autoregressive Model
- SEM – Spatial Error Model
- LM – Lagrange Multiplier tests
- H-H – both the observed value of the local variable and its weighted average among neighbours exceed the overall average
- L-L – both the observed and the neighboring weighted averages fall below the overall average
- H-L – the observed value exceeds the average, but the weighted average among neighbours does not
- L-H – the observed value falls below the average, but the weighted average among neighbours does not

Statements & Declarations

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Data Availability. The datasets analysed during the study are available at: http://www.cnemc.cn/ and http://tjj.gansu.gov.cn/tjj/c109464/info_disp.shtml

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