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Research article

The impact of population agglomeration on ecological resilience: Evidence from China

Qingsheng Zhu[1,2], Changwen Xie[1] and Jia-Bao Liu[3,*]

[1] School of Economics and Management, Anhui Jianzhu University, Hefei 230601, China
[2] Anhui Institute of Urban-Rural Green Development and Urban Renewal, Anhui Jianzhu University, Hefei 230601, China
[3] School of Mathematics and Physics, Anhui Jianzhu University, Hefei 230601, China

* **Correspondence:** Email: liujiabaoad@163.com.

Abstract: Due to climate change and human activities, ecological and environmental issues have become increasingly prominent and it is crucial to deeply study the coordinated development between human activities and the ecological environment. Combining panel data from 31 provinces in China spanning from 2011 to 2020, we employed a fixed-effects model, a threshold regression model, and a spatial Durbin model to empirically examine the intricate impacts of population agglomeration on ecological resilience. Our findings indicate that population agglomeration can have an impact on ecological resilience and this impact depends on the combined effects of agglomeration and crowding effects. Also, the impact of population agglomeration on ecological resilience exhibits typical dual-threshold traits due to differences in population size. Furthermore, population agglomeration not only directly impacts the ecological resilience of the local area, but also indirectly affects the ecological resilience of surrounding areas. In conclusion, we have found that population agglomeration does not absolutely impede the development of ecological resilience. On the contrary, to a certain extent, reasonable population agglomeration can even facilitate the progress of ecological resilience.

Keywords: population agglomeration; ecological resilience; entropy method; threshold regression model; spatial Durbin model

1. Introduction

In recent years, the issues of environment and sustainable development have garnered fervent attention from scholars [1,2]. Urban ecological resilience, as one of the important attributes of the urban ecological system, is an important guarantee for cities to cope with external environmental pressures and ensure the sustainable development of the urban ecological system. However, as one of the core driving forces of urbanization, population agglomeration may have complex and far-reaching effects on urban ecological resilience, thereby affecting sustainable urban development. Therefore, delving into the impact of population agglomeration on urban ecological resilience contributes to a better understanding of the intricate effects of population agglomeration on the ecological environment and provides a theoretical foundation for achieving sustainable development goals.

In 1973, ecologist Holling [3] introduced the concept of resilience to the field of ecology, which refers to the ability of a system to absorb disturbances and maintain itself in the face of external shocks. Brand considers ecological resilience as the ability of an ecosystem to resist disturbances and still maintain a specific state [4]. Folke considers ecological Folke argues that ecological resilience is the ability to absorb disturbances and adapt, learn and self-organize to achieve a harmonious development of human and environmental systems [5]. Regarding the measurement of ecological resilience, scholars have currently been measuring it by constructing an evaluation index system. Duo et al. construct an ecological resilience index system from three dimensions: resistance, adaptability and vitality [6]. Shi et al. construct an ecological resilience index system from two dimensions: sensitivity and adaptability of urban ecosystems [7]. Zhao et al. used the DPSIR framework to construct an indicator system for ecological resilience [8].

Population agglomeration is the phenomenon whereby a population gathers in an area or a specific location. Over the years, the relationship between population agglomeration and the environment has garnered fervent attention from scholars. It has been shown that population agglomeration has significant effects on carbon emissions [9–11], $PM_{2.5}$ emissions [12–14] and haze pollution [15,16]. As an important factor driving the urbanization process, population agglomeration has already significantly impacted regional economic development and the ecological environment in many ways [17]. Some scholars argue that population agglomeration has a negative impact on the environment [18–20]. With the increase in population and intensification of urbanization, resource consumption and environmental pollution also increase. Additionally, population agglomeration leads to significant waste and wastewater emissions, putting pressure on water resources and soil quality. On the other hand, some scholars believe that population agglomeration has positive effects on the environment [21–23]. They argue that population agglomeration can promote efficient resource utilization and foster innovative development, thus reducing pollutant emissions.

In summary, the existing literature mainly focuses on the impact of population agglomeration on the environment from the perspective of pollutant emissions, lacking a study of this impact from the perspective of ecological resilience. Therefore, building upon the groundwork of previous research, we first established an index system for ecological resilience using panel data from 31 provinces in China spanning 2011 to 2020. Second, we employed a fixed effects model to study the fundamental relationship between population agglomeration and ecological resilience. Subsequently, we examined whether the effect of population agglomeration on ecological resilience exhibits non-linear traits due to differences in population size. Lastly, we explored the spatial spillover effects of population agglomeration on ecological resilience. Aiming to provide a fresh perspective on the intricate impact of population agglomeration on the environment and offering valuable decision-making insights for achieving regional sustainable development.

2. Theory and research hypotheses

Given the intricate impact of population agglomeration on the environment, we have reason to believe that its influence on ecological resilience is equally intricate. This necessitates a comprehensive analysis from various perspectives. On one hand, population agglomeration brings about increased transportation, industrial activities and human endeavors, resulting in various environmental pollution issues such as air pollution, traffic congestion and water scarcity [18,19]. These environmental problems can reduce the ecological resilience of cities. At the same time, population agglomeration increases the demand for urban resources including water, food and energy. This leads to pressures on resource supply, affecting the ecological balance and sustainability of cities. Additionally, population agglomeration often necessitates the expansion of urban infrastructure and increased land use for construction, which can potentially disrupt urban ecosystems and diminish urban ecological resilience.

On the other hand, the agglomeration of population brings about economies of scale that are beneficial in reducing overall pollution emissions [24,25]. With the increase in population, cities can more efficiently utilize resources and energy, reducing pollution emissions per unit of output through centralized supply and distribution networks. This kind of economies of scale contributes to improving environmental quality and enhancing urban ecological resilience. At the same time, higher population density can also promote the development of new production and consumption models such as public transportation and the sharing economy, thereby achieving maximized resource utilization and conservation. Additionally, the increase in population density can facilitate the upgrading of industrial structures [26]. With the upgrading and transformation of industries, traditional high-polluting and energy-intensive sectors gradually decrease, making way for more environmentally friendly and sustainable industries. This transformation of industrial structure reduces pollution intensity and improves the ecological environment [27,28], enhancing urban ecological resilience. Therefore, the impact of population agglomeration on ecological resilience has both negative and positive effects. Based on this, we propose Hypothesis 1.

Hypothesis 1: Population agglomeration can have an impact on ecological resilience and this impact depends on the combined effects of agglomeration and crowding effects.

Some scholars have found a non-linear relationship between urban population agglomeration and pollution emissions [29,30]. In small-scale cities, population growth often leads to environmental issues like air pollution and water scarcity, typically resulting in negative ecological impacts. That is to say, the ecological environment experiences mounting pressure with the growth of the population. In such scenarios, the congregation of people can potentially impede the advancement of urban ecological resilience. However, in large-scale cities, as urban planning and environmental consciousness strengthen, it will prompt people to strive for the improvement of the urban environment, reducing pollution emissions and thus alleviating the negative impact of population growth on the ecosystem. In this situation, population agglomeration may promote the development of urban ecological resilience. Based on this, we propose Hypothesis 2.

Hypothesis 2: The impact of population agglomeration on ecological resilience exhibits non-linear traits due to differences in population size.

When populations concentrate within a given region, the benefits and externalities they generate tend to spread to the surrounding areas, consequently influencing the development and economic outcomes of those neighboring regions. These spillover effects can encompass a wide range of aspects including economic, social and environmental factors. Some research indicates that population agglomeration has spatial spillover effects on the economic resilience and haze pollution in the surrounding areas [31,32]. This suggests that population agglomeration can influence the economy and ecological environment of the neighboring regions to a certain extent. Therefore, we have reason to believe that population agglomeration also has spatial spillover effects on the ecological resilience of the surrounding areas. Based on this, we propose Hypothesis 3.

Hypothesis 3: Due to spatial spillover effects, population agglomeration not only directly affects the ecological resilience of the local area but also indirectly influences the ecological resilience of the surrounding areas.

3. Variables, models and data

3.1. Variables description

3.1.1. Explained variable

The explained variable of this paper is ecological resilience (*Er*). Based on the existing literature references [33,34], we have developed an ecological resilience index system, as shown in Table 1.

Table 1. Ecological resilience index system.

Primary indicator	Secondary indicators	Unit	Nature of indicator
Ecological resilience	Per capita park green space area.	m^2/person	+
	Green coverage rate in built-up areas.	%	+
	Local government expenditure on environmental protection.	100 million yuan	+
	Comprehensive utilization of general industrial solid waste.	10,000 tons	+
	Urban sewage treatment rate.	%	+
	Rate of harmless treatment of household waste.	%	+
	SO_2 emissions per square kilometer.	tons/km^2	–
	Per capita daily domestic water consumption.	liters	–
	Proportion of built-up area to area.	%	–

Note: The symbol "+" indicates a positive indicator and "–" indicates a negative indicator.

We have calculated the level of ecological resilience using the entropy method with the specific calculations outlined in Eqs (1)–(4).

The data were first normalized according to the nature of the indicators.

Positive indicators:

$$y_{ij} = \frac{x_{ij} - \min\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right)}{\max\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right) - \min\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right)}. \tag{1}$$

Negative indicators:

$$y_{ij} = \frac{\max\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right) - x_{ij}}{\max\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right) - \min\left(x_{1j}, x_{2j}, \cdots, x_{nj}\right)}, \left(i = 1, 2, \cdots, n, \quad j = 1, 2, \cdots, m\right). \tag{2}$$

Then, we calculate the indicator entropy value:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} \left\{ \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}} \ln \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}} \right\}. \tag{3}$$

The final calculation of the overall score is

$$U_i = \sum_{j=1}^{m} \left\{ \frac{1-e_j}{\sum_{j=1}^{m} \left(1-e_j\right)} \times y_{ij} \right\}. \tag{4}$$

3.1.2. Explanatory variable

The explanatory variable of this paper is population agglomeration (*Pop*). Following existing literature [35,36], we represent this using population density.

3.1.3. Threshold variable

The threshold variable of this paper is population size (*Res*). We denote the population size by the year-end resident population of the region.

3.1.4. Control variables

Based on the existing literature [32], our selection of control variables includes market size (*Mark*) measured by total retail sales of social consumer goods, technological investment (*Tec*) measured by the proportion of expenditure on science and technology in public fiscal expenditure, education investment (*Edu*) measured by the proportion of educational expenditure in public fiscal expenditure, industrial structure (*Ind*) represented by the proportion of the tertiary industry in GDP, infrastructure level (*Road*) indicated by the per capita urban road area.

3.2. Models construction

Mathematical and statistical models are widely used for a number of phenomena in society [37–42]. To test the three hypotheses proposed in Section 2, we constructed the following three models. We first constructed a fixed-effects model to investigate the basic relationship between population agglomeration and ecological resilience. Second, we constructed a threshold regression model to verify whether the effect of population agglomeration on ecological resilience exhibits non-linear traits due to differences in population size. Finally, we constructed a spatial Durbin model to explore the spatial spillover effects of population agglomeration on ecological resilience in the surrounding areas.

3.2.1. Benchmark model

We have constructed the following benchmark model to empirically study the impact of population agglomeration on ecological resilience:

$$Er_{i,t} = \alpha_0 + \alpha_1 Pop_{i,t} + \beta Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \ , \tag{5}$$

where $Er_{i,t}$ denotes the ecological resilience of province i in year t. $Pop_{i,t}$ denotes the population agglomeration of province i in year t. $Z_{i,t}$ denotes a set of control variables. α_0 is a constant term, α_1 and β are the regression coefficients of the variables. μ_i stands for the individual effect, δ_t stands for the time effect and $\varepsilon_{i,t}$ is an error term.

3.2.2. Threshold regression model

Given the complex impact of population agglomeration on ecological resilience and in order to verify whether the effect of population agglomeration on ecological resilience exhibits non-linear traits due to differences in population size, we have constructed the following threshold regression model, drawing upon the research by Hansen [43]:

$$Er_{i,t} = \alpha_0 + \alpha_1 Pop_{i,t} \times I\left(Res_{i,t} \le \lambda\right) + \alpha_2 Pop_{i,t} \times I\left(Res_{i,t} > \lambda\right) + \beta Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \ , \tag{6}$$

where $Res_{i,t}$ denotes the population size of province i in year t, λ is the threshold value and $I(\cdot)$ is the indicator function $I = 1$ when the condition is satisfied. Otherwise $I = 0$. The equation is a single-threshold regression model and the type of threshold regression model is selected according to the results of the threshold effect test.

3.2.3. Spatial Durbin model

To analyze whether population agglomeration has an impact on the ecological resilience of surrounding areas, we have constructed the following spatial Durbin model:

$$Er_{i,t} = \alpha_0 + \rho W Er_{i,t} + \alpha_1 Pop_{i,t} + \eta_1 W Pop_{i,t} + \beta Z_{i,t} + \eta_2 W Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \ , \tag{7}$$

where ρ is the spatial autoregressive coefficient, η_1, and η_2 are the spatial lag term coefficients and W is the spatial weight matrix. Referring to the existing literature [44,45], we employ the adjacency matrix (W_1) and the inverse distance matrix (W_2). The expressions for both are as follows:

$$W_{1,ij} = \begin{cases} 1, & i \text{ and } j \text{ are adjacent} \ , \\ 0, & i \text{ and } j \text{ are not adjacent} \ , \end{cases} \tag{8}$$

$$W_{2,ij} = \begin{cases} 1/d_{ij} \ , & i \ne j \ , \\ 0 \ , & i = j \ , \end{cases} \tag{9}$$

where d_{ij} is the geographical distance calculated from the latitude and longitude of regions i and j.

3.3. Data sources and description

All data are sourced from the National Bureau of Statistics of China, China Statistical Yearbook and China Environmental Statistical Yearbook. Some of the missing data values were filled in using interpolation. The descriptive statistics of each variable are shown in Table 2.

Table 2. Descriptive statistics of variables.

Variables	Obs	Mean	Std. Dev.	Min	Max
Er	310	0.349	0.107	0.143	0.714
Pop	310	0.285	0.115	0.052	0.582
Res	310	4.462	2.892	0.309	12.624
Mark	310	0.982	0.841	0.024	4.295
Tec	310	0.020	0.015	0.003	0.068
Edu	310	0.162	0.027	0.099	0.222
Ind	310	0.473	0.097	0.297	0.839
Road	310	15.901	4.768	4.040	26.780

As can be seen from Table 2, the minimum value of ecological resilience is 0.143 and the maximum value is 0.714, indicating that the level of ecological resilience varies widely among regions. Further empirical analysis is necessary.

4. Empirical results

4.1. Benchmark regression

We used Stata 17 software for the empirical analysis. The Pearson correlation coefficients and VIF values of the independent variables are shown in Table 3.

Table 3. Pearson correlation coefficients and VIF values of the independent variables.

Variables	*Pop*	*Mark*	*Tec*	*Edu*	*Ind*	*Road*	VIF
Pop	1.0000						1.15
Mark	-0.0395	1.0000					2.19
Tec	-0.0886	0.6221	1.0000				2.66
Edu	0.1397	0.4161	0.1598	1.0000			1.54
Ind	-0.1251	0.1885	0.5554	-0.3000	1.0000		1.89
Road	-0.2496	0.1919	-0.1546	0.1851	-0.2431	1.0000	1.34

From Table 3, it can be seen that the Pearson correlation coefficients between variables are less than 0.7 and the VIF values of each variable are less than five, indicating that there is no serious problem of multicollinearity among the variables. Based on Eq (5), we obtained the benchmark regression results, as shown in Table 4.

According to Table 4, it is found that the impact of population agglomeration on ecological resilience is significantly negative at the 1% level. This indicates that overall, population agglomeration has a significant inhibitory effect on ecological resilience. In terms of control variables, the impact of market size on ecological resilience is significantly positive at a level of 1%. This is because the larger the market size, the greater the economies of scale it brings. These economies of scale have positive effects on ecological resilience in two aspects. First, the growth of economies of scale means an enhanced ability of urban ecosystems to withstand external shocks. When the market size expands, the infrastructure and resource utilization efficiency in cities often improve. For example, in large cities more resources can be concentrated and shared such as shared transportation, energy and water resources, which reduces waste and improves resource efficiency. Second, economies of scale enable businesses to access more resources and technological support, thereby enhancing production efficiency. This increased benefit helps improve resource utilization efficiency, reduce resource waste and environmental pollution and ultimately enhance urban ecological resilience. Technological investment is positively correlated with ecological resilience. First, technological investment contributes to the development of more advanced environmental protection technologies such as emission reduction, clean energy and circular economy technologies, among others. These technologies can diminish adverse impacts on ecosystems and enhance their resilience. Second, technological investment can improve environmental monitoring and early warning systems, enhancing the ability to monitor and anticipate environmental pollution and ecological damage. Increased investment in education might potentially draw populations from neighboring areas to cluster within the local area. This could exacerbate urbanization and crowding effect in the area, thereby impeding the enhancement of ecological resilience.

Table 4. Benchmark regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Pop	-0.206***	-0.219***	-0.224***	-0.227***	-0.223***	-0.219***
	(-3.599)	(-4.822)	(-5.152)	(-5.113)	(-5.295)	(-5.518)
Mark		0.045***	0.035***	0.035***	0.034***	0.034***
		(3.253)	(2.974)	(3.098)	(3.015)	(3.022)
Tec			0.954	1.063*	1.044*	1.026*
			(1.531)	(1.878)	(1.902)	(1.826)
Edu				-0.351*	-0.393*	-0.412*
				(-1.788)	(-1.959)	(-1.976)
Ind					-0.080	-0.082
					(-1.066)	(-1.087)
Road						0.001
						(0.494)
Constant	0.356***	0.332***	0.323***	0.379***	0.418***	0.413***
	(20.338)	(19.851)	(18.602)	(9.906)	(7.282)	(7.600)
Individual effect	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES
N	310	310	310	310	310	310
R^2	0.672	0.734	0.741	0.747	0.749	0.749

Note: robust t-statistics in parentheses, * indicates p < 0.1, ** indicates p < 0.05, *** indicates p < 0.01, and the same in the following table.

4.2. Robustness tests

4.2.1. The explanatory variable is lagged by one period

Acknowledging the potential time lag in population agglomeration changes, we lagged the explanatory variable by one period (*L.Pop*). The regression results are presented in column (1) of Table 5. The regression coefficient of population agglomeration on ecological resilience is still significantly negative, consistent with the conclusions drawn in Section 4.1.

4.2.2. Winsorizing the sample

Considering that there may be individual outliers in the sample, we winsorized the sample at the 1% and 99% levels before regression, as presented in column (2) of Table 5. The results are still significantly negative at the 1% level, indicating that the model is robust.

4.2.3. Instrumental variable method

In light of potential endogeneity issues in the model, we use the product of the one-period lagged population agglomeration and the national population density as an instrumental variable and proceed with estimation using the 2SLS method. The results in column (3) of Table 5 indicate that even after accounting for the endogeneity of the model, the impact of population agglomeration on ecological resilience remains significantly negative at the 1% level. Simultaneously, the LM statistic and the Wald F statistic significantly reject the null hypotheses of insufficient instrumental variable identification and weak instrumental variable respectively, indicating that the selection of the instrumental variable is reasonable.

Table 5. Robustness test results.

Variables	The explanatory variable is lagged by one period (1)	Winsorizing the sample (2)	Instrumental variable method (3)
L.Pop	-0.131***		
	(-2.902)		
Pop		-0.210***	-0.203***
		(-4.940)	(-2.692)
Control variables	YES	YES	YES
Constant	0.401***	0.408***	0.409***
	(6.920)	(7.869)	(5.132)
Kleibergen-Paap rk LM statistic			9.451
			[0.002]
Kleibergen-Paap rk Wald F statistic			59.487
			{16.38}
Individual effect	YES	YES	YES
Time effect	YES	YES	YES
N	279	310	279
R^2	0.691	0.737	0.965

Note: Value in [ ] is the p-value and value in { } is the critical value at the 10% level of the Stock-Yogo weak identification test.

4.3. Heterogeneity test

4.3.1. Regional heterogeneity

Given the variances in economic development, industrial structure and environmental protection among different regions, this could result in regional heterogeneity in the impact of population agglomeration on ecological resilience. Therefore, in accordance with Chinese regional planning standards, we have divided the 31 provinces into three areas: East, Central and West for regression analysis. The results can be found in Table 6.

Table 6. Results of the regional heterogeneity test.

Variables	Eastern region	Central region	Western region
Pop	-0.116	-0.134*	-0.310***
	(-1.087)	(-1.909)	(-10.553)
Control variables	YES	YES	YES
Constant	0.134	0.602***	0.397***
	(0.654)	(8.725)	(7.445)
Individual effect	YES	YES	YES
Time effect	YES	YES	YES
N	120	90	100
R^2	0.965	0.971	0.949

According to the regression results in Table 6, population agglomeration does not have a significant inhibitory effect on ecological resilience in the eastern region. This is because the eastern region has a higher level of economic development and possesses a well-established infrastructure and resource allocation capability, which can to some extent mitigate the impact of population agglomeration on the ecological environment. Furthermore, the relatively advanced economic structure in the eastern region also implies that people are more likely to adopt environmental protection measures and technological innovations to reduce damage to the ecological environment. In contrast, the western region lags behind economically, with insufficient infrastructure and resource allocation. This could result in significant ecological impacts from population agglomeration. Additionally, the western region may face issues such as water scarcity and environmental pollution, all of which can exert substantial inhibitory effects on the ecological resilience. Therefore, the inhibitory effect of population agglomeration on the ecological resilience of the western region is most pronounced.

4.3.2. Temporal heterogeneity

Since the State Council of China formulated several environmental conservation policies in 2016, the environmental protection system has gradually improved, which may cause temporal heterogeneity in the impact of population agglomeration on ecological resilience. Therefore, we have divided the samples into two time periods for regression analysis. The results can be found in Table 7.

Table 7. Results of the temporal heterogeneity test.

Variables	Year ≤2016	Year >2016
Pop	-0.250***	0.015
	(-7.255)	(0.208)
Control variables	YES	YES
Constant	0.423***	0.607***
	(4.905)	(6.441)
Individual effect	YES	YES
Time effect	YES	YES
N	186	124
R^2	0.979	0.983

From Table 7, it can be observed that the inhibitory effect of population agglomeration on ecological resilience is not significant after 2016 and the regression coefficient has also decreased significantly. This indicates that with the gradual standardization and improvement of environmental protection system, the inhibitory effect of population agglomeration on ecological resilience is gradually diminishing.

4.3.3. Regional-temporal heterogeneity

To gain a more nuanced understanding of the changes in the influence of population agglomeration on ecological resilience around the year 2016 across different regions, we have conducted temporal heterogeneity analyses for each area separately. See Table 8 for regression results.

Table 8. Results of the regional-temporal heterogeneity test.

Variables	Eastern region		Central region		Western region	
	Year ≤2016	Year >2016	Year ≤2016	Year >2016	Year ≤2016	Year >2016
Pop	-0.290	0.484**	-0.168*	0.166	-0.330***	-0.134
	(-1.471)	(2.734)	(-1.820)	(0.984)	(-10.799)	(-1.609)
Control variables	YES	YES	YES	YES	YES	YES
Constant	0.774***	0.165	0.451***	0.602**	0.355***	0.418***
	(3.623)	(0.506)	(4.849)	(2.219)	(6.678)	(3.189)
Individual effect	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES
N	72	48	54	36	60	40
R^2	0.980	0.989	0.982	0.978	0.973	0.972

Table 8 reveals that, when statistical significance is disregarded, population agglomeration manifests an initial suppressive, then promotive effect on the ecological resilience in the eastern and central regions. While population agglomeration has consistently shown a suppressive effect on the ecological resilience in the western regions, there has been a significant reduction in both the regression coefficient and significance. This suggests that the suppressive impact of population agglomeration on the ecological resilience in the western regions is also weakening. The above results indicate that the gradual standardization and improvement of the environmental protection system can rationalize the population agglomeration. Rational population agglomeration will make the benefits from agglomeration economy far outweigh the costs from the crowding effect, thus contributing to the development of ecological resilience. In conclusion, when the economic benefits brought about by population agglomeration are less than the costs incurred by crowding effect, population agglomeration will have a significant inhibitory impact on ecological resilience. However, when the economic benefits from population agglomeration outweigh the costs of crowding effect, population agglomeration will exhibit a significant promoting effect on ecological resilience. Hypothesis 1, proposed in Section 2, is tested.

5. Threshold effect analysis

5.1. Test of threshold effect

Given that population size may influence the correlation between population agglomeration and ecological resilience, we have constructed a threshold regression model to investigate the impact of population agglomeration on ecological resilience under various population size scenarios. The results of the threshold effect test are shown in Table 9, Figures 1–3. The results indicate that when population size is considered as a threshold variable, the influence of population agglomeration on ecological resilience presents a dual-threshold effect, with threshold values at 7.323 and 9.941, respectively.

Table 9. Results of the threshold effect test.

Number of thresholds	F-value	P-value	Threshold value	95% confidence interval	Number of Bootstrap
Single	57.57***	0.000	7.323	[7.288, 7.360]	500
Dual	37.25***	0.002	9.941	[9.901, 9.973]	500
Triple	8.60	0.762			500

Note: Because the triple threshold did not pass the significance test, the threshold values and confidence intervals are not shown.

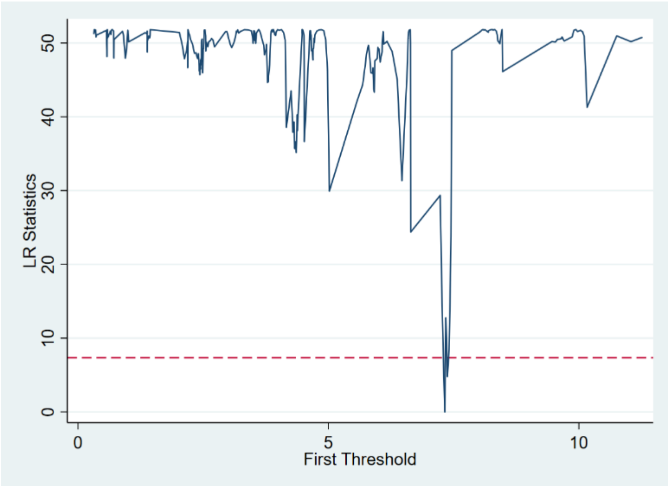

Figure 1. LR plot of the first threshold value.

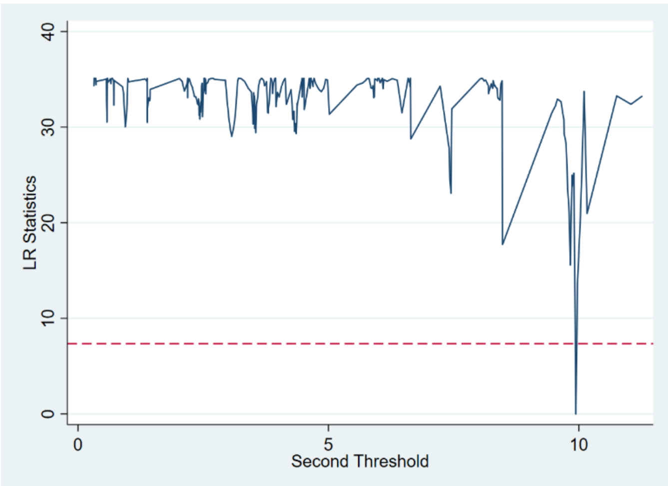

Figure 2. LR plot of the second threshold value.

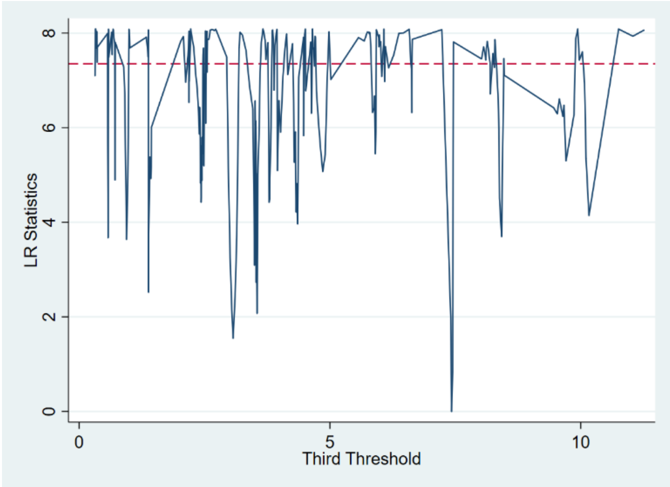

Figure 3. LR plot of the third threshold value.

5.2. Regression analysis of threshold effects

Based on the results from Table 9, we expanded Eq (6) into a dual-threshold regression model and the regression results can be found in Table 10.

Table 10. Threshold effect regression results.

Variables	*Res* ≤ 7.323	7.323 < *Res* ≤ 9.941	*Res* > 9.941
Pop	-0.254***	0.030	0.444***
	(-7.097)	(0.813)	(5.836)
Control variables	YES	YES	YES
Constant	0.420***	0.420***	0.420***
	(8.651)	(8.651)	(8.651)
Individual effect	YES	YES	YES
Time effect	YES	YES	YES
N	310	310	310
R^2	0.813	0.813	0.813

As can be seen from Table 10, the differences in population size can lead to significant variations in the impact of population agglomeration on ecological resilience. When the population size lies below the low threshold value of 7.323, population agglomeration shows a significant inhibitory effect on ecological resilience. When the population size lies between the threshold value of 7.323 and 9.941, the impact of population agglomeration on ecological resilience is not significant. When the population size crosses the high threshold value of 9.941, population agglomeration has a significant promoting effect on ecological resilience. This is because when the population size reaches a high level, the benefits brought by economic agglomeration far outweigh the costs incurred by the crowding effect. Thus, the inhibitory effect of population agglomeration on ecological resilience is changed to a facilitating effect on ecological resilience. The above findings suggest that in areas with different levels of population size, the effect of population agglomeration on the ecological resilience can vary. For some regions with particularly large population sizes, population agglomeration can even be advantageous for the development of ecological resilience. Hypothesis 2, proposed in Section 2, is tested.

6. Spatial effect analysis

6.1. Spatial autocorrelation test

The fundamental premise of using spatial econometric models is that there exists spatial autocorrelation in ecological resilience. Drawing on the existing literature [46–48], we conducted a spatial autocorrelation test on the ecological resilience of the 31 provinces in China using the global Moran's index. The results are presented in Table 11. The relevant equations can be found in (8)–(11).

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{10}$$

$$s^2 = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}{n} \tag{11}$$

where W_{ij} is the spatial weight matrix.

Table 11. Spatial autocorrelation test.

Year	*Er*			
	W_1		W_2	
	Moran's *I*	z-value	Moran's *I*	z-value
2011	0.205**	2.027	0.041**	2.220
2012	0.249***	2.385	0.049***	2.426
2013	0.254***	2.430	0.048***	2.404
2014	0.254***	2.435	0.057***	2.690
2015	0.227**	2.224	0.055***	2.640
2016	0.170**	1.757	0.039**	2.192
2017	0.215**	2.135	0.052***	2.584
2018	0.157*	1.628	0.034**	2.035
2019	0.141*	1.480	0.040**	2.202
2020	0.177**	1.798	0.043**	2.291

From Table 11, it can be observed that under both the adjacency matrix and inverse distance matrix, the Moran's index of ecological resilience for the 31 provinces in China was consistently significant and positive from 2011 to 2020. This indicates a positive spatial autocorrelation among the ecological resilience of each province, suggesting that provinces with high ecological resilience tend to cluster together, while provinces with low ecological resilience also tend to cluster together.

6.2. Identification and testing of spatial econometric models

Spatial econometric models are typically classified into SAR, SEM and SDM. To assess which model is more suitable for this study, we first conducted an LM test. Only the Robust LM_lag under the adjacency matrix did not pass the significance test. Next, we employed LR and Wald tests, both of which passed the 1% significance level under the two matrix types. This indicates that SDM will not degrade into SAR or SEM. The test results are presented in Table 12.

Table 12. Identification and testing of spatial econometric models.

Test	W_1		W_2	
	Chi[2]	P-value	Chi[2]	P-value
LM_error	50.855***	0.000	31.493***	0.000
Robust LM_error	16.509***	0.000	2.842*	0.092
LM_lag	35.101***	0.000	34.756***	0.000
Robust LM_lag	0.755	0.385	6.104**	0.013
LR test for SAR	27.12***	0.000	38.14***	0.000
LR test for SEM	37.45***	0.000	51.80***	0.000
Wald test for SAR	27.36***	0.000	39.58***	0.000
Wald test for SEM	39.98***	0.000	54.09***	0.000

6.3. Spatial Durbin model regression analysis

According to the test results in Table 12, we employed the spatial Durbin model (SDM). The SDM regression results, obtained from Eqs (7)–(9), are presented in Table 13.

Table 13. Spatial Durbin model regression results.

Variables	W_1			W_2		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Pop	-0.179***	0.176**	-0.004	-0.180***	0.435***	0.255
	(-4.112)	(2.297)	(-0.034)	(-3.692)	(2.701)	(1.528)
Control variables	YES	YES	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES
N	310	310	310	310	310	310
R^2	0.431	0.431	0.431	0.398	0.398	0.398
Log-L	791.513	791.513	791.513	798.595	798.595	798.595

Table 13 shows that, under both spatial weight matrices, the direct effect of population agglomeration on ecological resilience is significantly negative at the 1% level, while the indirect effects are significantly positive at the 5% and 1% levels, respectively. This indicates that, population agglomeration has a significant inhibiting effect on the ecological resilience level in the local area, while it has a significant promoting effect on the ecological resilience level in the surrounding areas. This is because the siphoning effect generated by population agglomeration will attract the population from the surrounding areas to flow into the local area, which reduces the population agglomeration level in the surrounding areas and promotes the improvement of the ecological resilience level in the surrounding areas. The reason why the total effect is not significant may be due to the offsetting effects of the positive and negative effects. Therefore, population agglomeration not only has a direct impact on the ecological resilience of the local area but also exerts an indirect influence on the ecological resilience of surrounding areas. Hypothesis 3, proposed in Section 2, is tested.

7. Conclusions and suggestions

7.1. Conclusions

We have empirically investigated the impact of population agglomeration on ecological resilience and the threshold effect of population size in it by combining panel data from 31 Chinese provinces from 2011 to 2020. We have derived the following four conclusions: First, overall, population agglomeration significantly inhibits the improvement of ecological resilience. This conclusion still holds after robustness testing of the model. Second, with increased investment in environmental protection in China since 2016, the gradual standardization and improvement of the environmental protection system have led to a progressive weakening of the inhibitory effect that population agglomeration has on ecological resilience. Especially in the economically developed eastern regions, the inhibitory effect of population agglomeration on ecological resilience gradually transforms into a promoting effect. Third, the impact of population agglomeration on ecological resilience exhibits typical dual-threshold traits due to differences in population size. As the population size crosses the first and second threshold values, the inhibitory effect of population agglomeration on ecological resilience gradually transforms into a promoting effect. Fourth, while population agglomeration has a significant inhibitory effect on the ecological resilience level of the local area, it has a significant promoting effect on the ecological resilience level of the surrounding areas. Therefore, we can observe that the impact of population agglomeration on ecological resilience is complex. Population agglomeration does not absolutely impede the development of ecological resilience. On the contrary, to a certain extent, reasonable population agglomeration can even facilitate the progress of ecological resilience. Compared to existing research, we have empirically studied the impact of population agglomeration on the environment from the perspective of ecological resilience. Our aim is to provide fresh insights and understanding while offering policy foundations for achieving sustainable development goals.

7.2. Suggestions

With the above findings, we propose the following suggestions:

1) Efforts should be made to fully leverage the scale benefits and positive externalities of population agglomeration and guide population agglomeration to promote the development of ecological resilience. Considering the variations in resource endowments, location conditions and industrial structures across different regions, the government should strategically plan and guide population agglomeration in accordance with local circumstances. This approach will bolster ecological resilience and achieve more efficient economic development. In addition, the government can increase support for talent introduction, provide more preferential policies and welfare benefits to attract more outstanding talents to the local area. This can not only promote local economic development, but also raise the level of knowledge and technology in the city, further promote the modernization process of the city and provide strong support for the development of the local economy and ecological environment.

2) Increase investment in technology and actively develop green energy technologies. The government should increase investment in technology, encourage enterprises and universities to actively develop and apply green energy technologies. At the same time, the government can also issue relevant policies to encourage enterprises to increase investment in green technology, promote the development of green industries and promote the transformation and upgrading of urban industries. These measures can improve the ecological adaptability and disaster response capacity of the city as well as the environmental quality and ecological resilience.

3) Accelerate the construction of an ecological civilization community and achieve regional ecological and economic coordinated development. The government should strengthen cooperation and communication with surrounding areas, jointly promote ecological environmental protection and sustainable development. The government should also strengthen the formulation and implementation of ecological environmental protection policies, ensure that the public can actively participate in

ecological environmental protection and promote the green development of the city. These measures can strengthen the coordinated development of regional ecological economy, improve the ecological resilience and sustainable development capabilities of the city and achieve the long-term development and prosperity of the city.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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