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Spatiotemporal pattern evolution and influencing factors of population spatial distribution in Changsha-Zhuzhou-Xiangtan urban agglomeration, China

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ABSTRACT

Population, as a fundamental element in urban development, often reflects a city's economic development pattern through its spatial distribution and dynamic changes. Studying population spatial distribution is pivotal for bolstering the economic activity capacity in urban agglomerations and guiding regional economic health. Using the Changsha-Zhuzhou-Xiangtan urban agglomeration as a case study, this paper analyzes its overall spatial structure and the spatiotemporal evolution of population at the district and county levels. This analysis utilizes population density, population redistribution index, and population geographic concentration as key indices. Additionally, a spatial econometric model is constructed to assess the impact of economic, social, and environmental factors on population spatial patterns. Findings reveal several key points: (1) Furong District serves as the primary central area, boasting a population geographic concentration of 25.1% in 2021. Tianxin District, Kaifu District, Yuhua District, Shifeng District, Yuelu District, and Hetang District constitute the secondary central areas, while Yutang District, Tianyuan District, Lusong District, Yuhu District, Wangcheng District, and Changsha County form the tertiary level areas. (2) Population density within the Changsha-Zhuzhou-Xiangtan urban agglomeration gradually decreases from Furong District outward. The first central area and sub-central areas experience increasing population density, highlighting a polarization trend in the population distribution. (3) The overall Moran's index for the spatial distribution of population in the Changsha-Zhuzhou-Xiangtan urban agglomeration is significantly positive, indicating a strong spatial autocorrelation and a deepening spatial agglomeration of population distribution. (4) Per capita disposable income, financial expenditure, and education level positively influence the geographical concentration of population in the urban agglomeration, while GDP per capita, road area per capita, and environmental quality exert a negative impact. Notably, the most influential factors shaping population spatial distribution are GDP per capita, disposable income per capita, and air quality.

KEYWORDS

Spatiotemporal pattern evolution; Influencing factors; population spatial distribution; Changsha-Zhuzhou-Xiangtan urban agglomeration

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1. Introduction

In China, urban agglomerations serve as the primary mechanism for advancing new urbanization. High-quality urban agglomerations exhibit a distinct demographic-industrial division of labor, well-established transportation networks, and a regional development pattern indicative of sustainability. Over the past 40 years of reform and opening-up, China has witnessed the formation of urban agglomerations in various forms and sizes. As the fundamental component and crucial determinant of high-quality development within urban agglomerations, a balanced and rational spatial population pattern is vital for fostering the coordinated development of the economy, society, and the ecological environment. The spatial distribution of population elements serves as a pivotal entry point for optimizing the development pattern of urban agglomerations. However, with the rapid progress of urbanization, unbalanced development within urban agglomerations has intensified. Urban challenges, such as traffic congestion and environmental pollution, have become prominent due to high population density. The inadequate radiation capacity of the central city and the saturation of land usage in core metropolitan districts further exacerbate these issues.

The current research literature on the evolution of population spatial patterns spans various spatial scales, encompassing regions, cities, and counties. Notably, disparities in population distribution and economic development among counties within Chinese cities have grown, leading to overlapping distribution characteristics in economically developed and densely populated counties. Simultaneously, urban-rural population structures in cities and counties exhibit notable differentiation, a trend gradually diminishing (Zhao et al., 2020; Wu et al., 2016). Scholars investigating the spatial distribution characteristics of urban populations have employed diverse methodologies, including the urban primacy index, population distribution structure index, and spatial autocorrelation model (Wang et al., 2022; Li and Song, 2020; Tong et al., 2018; Ma, 2012). Additionally, foreign researchers such as Moran (1948), Cliff (1973), and Getis (1992) have explored the spatial evolution pattern of populations using spatial statistical methods, highlighting spatial correlation in the geographical distribution of regional populations.

To efficiently advance the optimization of population spatial patterns, an examination of influencing factors is imperative. Existing literature predominantly explores these factors within three dimensions: natural, economic, and social. The natural geographic environment serves as the fundamental material condition for human survival, life, and production. Fang et al. (2012) categorized natural environmental factors into climate, topography, and water systems based on ecological population carrying capacity. Their study delves into the reciprocal influence of these natural factors on the evolution of population spatial patterns. Various studies indicate the significance of river, topographic, and climatic factors in influencing population distribution (Wang et al., 2014; Ma et al., 2018). Regarding economic factors, substantial research has explored the impact of industrial structure on population spatial patterns. For instance, Ge et al. (2023) observed that, within 14 poverty pockets, the development of secondary and tertiary industries primarily attracts population inflow, while the low value-added nature of the primary industry stands out as a key factor contributing to population outflow. Simultaneously, the influence of industrial structure, including its derived employment structure, on the population's spatial pattern in provinces or urban agglomerations is evident (Zhang, 2019; Ju, 2019; Wu et al., 2020).

Additionally, scholars have examined economic factors such as total factor productivity, urbanization and industrialization levels, price indexes, and income levels, investigating their impact on population distribution patterns in cities or regions (Lu and Sun, 2014; Jordan Rappaport, 2017; Ma et al., 2018; Zeng et al., 2018). The role of public services in residential choices is noteworthy; higher levels of urban public services attract mobile populations and enhance the population aggregation capacity of cities (Liu et al., 2022; Sheng and Yang, 2021; Xia and Lu, 2015). Urban public services often serve as indicators of administrative levels, and research suggests that cities functioning as administrative centers in a region, especially those with higher administrative levels, exhibit distinct advantages in infrastructure construction, land utilization, and public service allocation. This has led to a growing and intensified trend of population clustering around provincial and prefectural administrative centers (Chen et al., 2017; Liu and Zhuo, 2022). Nevertheless, Liu Tao et al. (2022) propose that the primacy enhancement effect driven by administrative force diminishes over the province's developmental stages. Beyond administrative influence, critical factors shaping the spatial distribution of population in cities, urban agglomerations, and regions include the two-child policy, educational resources, and urban transportation (Wang et al., 2016; Huang, 2006; Chen, 2022).

The evolution of population spatial patterns in urban agglomerations constitutes a prolonged process of adjustment and optimization. Investigating the patterns and influencing factors aligns with macro objectives emphasizing the "upgrading of city quality and promoting regional coordinated development." Additionally, it aids in identifying fundamental patterns of spatial evolution over time and facilitates reasonable predictions of future development trends. Current research predominantly adopts a macro perspective, focusing on the optimization of population spatial distribution primarily at the provincial and municipal levels. Most studies on the influencing factors of population spatial distribution tend to investigate the impact of individual factors, with fewer comprehensive analyses across multiple dimensions like nature and family. Limitations in research methodology and modeling assumptions contribute to discrepancies between findings and objective facts. Most existing literature on population spatial patterns and influencing factors relies on traditional econometric analysis methods. Few studies employ ESDA (exploratory spatial data analysis) and spatial econometric modeling. Therefore, at the spatial scale of districts and counties, this study synthesizes existing research experiences, and employs a combined approach of normative analysis and empirical analysis to systematically investigate the evolution of population spatial patterns and their influencing factors in the Changsha-Zhuzhou-Xiangtan urban agglomeration. Furthermore, the study proposes strategic recommendations for optimizing the population spatial distribution within the urban agglomeration.

2. Material and methods

2.1. Case

The Changsha-Zhuzhou-Xiangtan urban agglomeration consists of three cities and 23 districts and counties. It was designated a national pilot area for comprehensive supporting reforms in constructing a two-oriented society in 2007. Subsequently, the agglomeration's four-level structure evolved to include provincial central cities, regional sub-centers, key towns, and general towns. The Changsha-Zhuzhou-Xiangtan region, situated at the national level, is strategically positioned within the city circle in the middle reaches of the Yangtze River. It serves as a vital nexus at the convergence point of the Yangtze River Economic Belt and the Beijing-Guangzhou Economic Belt, bordered by the Pan-Pearl River Delta Economic Zone to the south and the Middle Reach of the Yellow River Comprehensive Economic Zone to the north. Given its role as a pivotal link between China's major economic belts, optimizing the spatial distribution of population and fostering coordination among the three cities emerge as paramount objectives for advancing the Changsha-Zhuzhou-Xiangtan urban agglomeration.

The Changsha-Zhuzhou-Xiangtan region, characterized by a high degree of openness and robust innovation capacity, functions as an economic growth pole in Hunan Province, with a dynamic flow of production factors. Figure 1 illustrates a continuous increase in the permanent resident population within the Changsha-Zhuzhou-Xiangtan urban agglomeration, growing from 12.4 million in 2001 to 16.8 million in 2021. Analyzing the urban-rural structure, the urban population escalates from 5.14 million in 2001 to 13.08 million in 2021, while the rural population declines from 7.26 million in 2001 to 3.75 million in 2021. Continued rural-urban migration has resulted in a reversal in the urban and rural resident population sizes of the Changsha-Zhuzhou-Xiangtan urban agglomeration since 2007. Concurrent with the urbanization of the rural population, the average urbanization rate in the Changsha-Zhuzhou-Xiangtan urban agglomeration has significantly risen over the past decade, reaching 73.45% in 2021, up from 40.45% in 2001. This rate surpasses both the 2021 national average and is slightly lower than that of the Yangtze River Delta (YRD) and Pearl River Delta (PRD) urban agglomerations, at 73.8% and 87.5%, respectively. It is evident that, in comparison with major city clusters in the eastern region, the Changsha-Zhuzhou-Xiangtan urban agglomeration still grapples with challenges such as a small population size and a relatively low level of urbanization. These issues may undermine the driving force for the sustainable development of the Changsha-Zhuzhou-Xiangtan urban agglomeration.

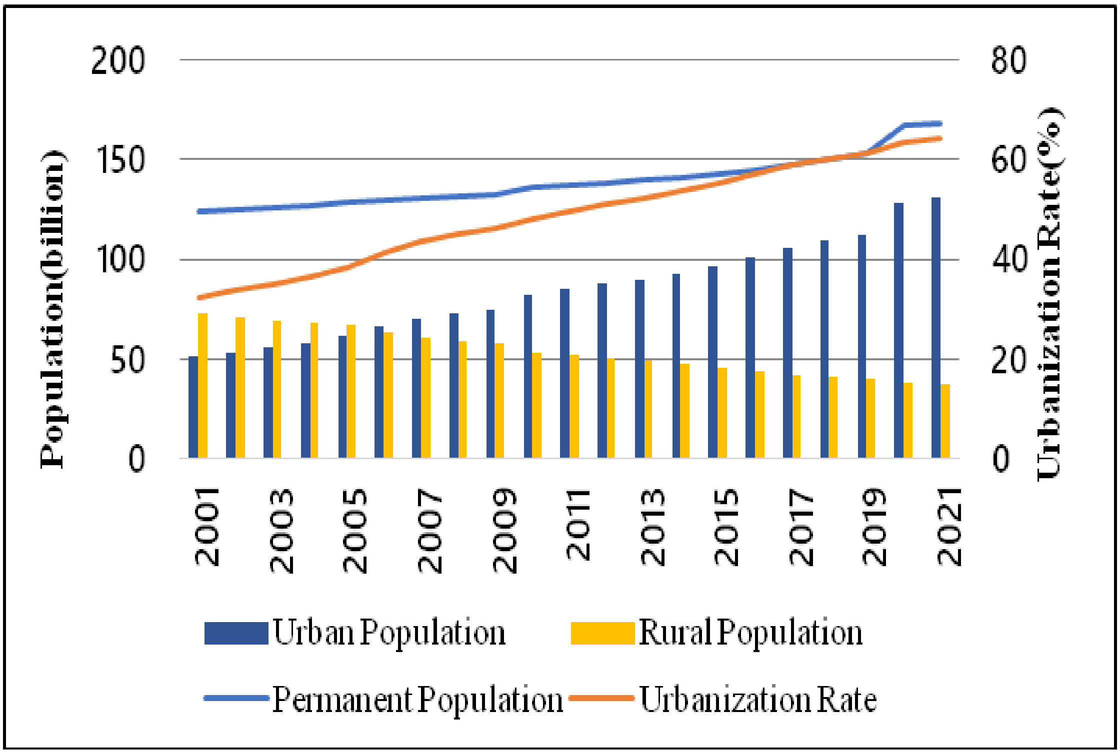

Figure 1. Resident population and urbanization rate of Changsha-Zhuzhou-Xiangtan urban agglomeration.

2.2. Model specification

In accordance with the first law of geography, asserting that all things are related, with closer proximity indicating stronger relationships, spatial data for econometric analyses is generated by incorporating location information (or mutual distance) into the original cross-section or panel data. This approach comprehensively considers spatial effects, encompassing spatial dependence and spatial heterogeneity. The paper initiates by examining spatial correlation between explanatory and explained variables using a spatial autocorrelation test. Subsequently, the consideration of a spatial lag model or spatial error model is explored, followed by the estimation of the maximum likelihood estimator (MLE) for the spatial panel model and the execution of the Hausman test. The general spatial panel model is presented below.

$$y_{it} = \tau y_{i,t-1} + \rho w' y_t + x_{it}{}' \beta + d_i{}' X_t \delta + u_i + \gamma_t + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \lambda m_i{}' \varepsilon_t + v_{it} \tag{2}$$

Where, W_i is row i of the spatial weight matrix W, $W_{i,j}$ is the (i,j) element of the spatial weight matrix W. $y_{i,t-1}$A is the first order lag of the explanatory variable y_{it}.$d_i X_i \delta$denotes the spatial lag of the explanatory variables. d_i is row i of the corresponding spatial weight matrix D. u_i is the individual effect for region i,γ_t is the time effect, and m_i is row i of the spatial weight matrix M of the perturbation term.

If $\lambda = 0$, it is a Spatial Durbin Model (SDM). If $\lambda = 0$and $\delta = 0$, then it is a Spatial Autoregressive Model (SAR), i.e., a spatial autoregressive model with a spatial autoregressive error term. If $\tau = 0$ and $\delta = 0$, then it is a Spatial Autocorrelation Mode (SAC). If $\tau = \rho = 0$ and $\delta = 0$, then it is a spatial error model (SEM).

2.3. Variables and data

The chosen explanatory variable is population geographic concentration, which not only signifies the spatial arrangement of the population within an area but also represents the area's proportion within the entire region. Drawing upon geo-economics and demographic economics theories, along with findings from both domestic and international literature, this paper aligns these insights with the distinctive features of the population's spatial structure in the Changsha-Zhuzhou-Xiangtan urban agglomeration. The selected indicators for use as explanatory variables are derived from this synthesis.

This paper's explanatory variables encompass economic development, social development, and environmental conditions. The economic development dimension includes per capita GDP, per capita disposable income, the proportion of the secondary industry in GDP, and employment rate. The social development dimension incorporates variables such as housing price level, teacher-student ratio, and local financial expenditures. Additionally, the environmental conditions dimension is represented by the air quality index. This study utilizes panel data spanning 2011 to 2021 from 23 districts and counties within the Changsha-Zhuzhou-Xiangtan urban agglomeration for spatial econometric analysis, employing ArcGIS and Stata. The sample data primarily originates from sources such as the Hunan Statistical Yearbook, National Economic and Social Development Statistical Bulletin of Districts and Counties, China Regional Economic Statistical Yearbook, and Census data.

3. Results

3.1. Spatial distribution characteristics of population

3.1.1. Population Distribution in Changsha-Zhuzhou-Xiangtan urban agglomeration

This section examines the population distribution characteristics of the Changsha-Zhuzhou-Xiangtan urban agglomeration, employing district and county population density as a metric (refer to figure 2). The population density map reveals a notable imbalance in population distribution, indicating a concentrated population in the central and northern regions, with sparser distribution in the eastern, western, and southwestern areas.

In 2021, the districts of Furong, Tianxin, and Kaifu exhibit the highest population densities, registering 15,068, 6,081, and 4,521 people/km^2, respectively. Furong stands out as the sole district in the Changsha-Zhuzhou-Xiangtan urban agglomeration with a population density exceeding 10,000 people/km^2. Conversely, Yanling County reports the lowest population density at 78 people/km^2, representing the sole area in the agglomeration with a density below 100 people/km^2. As the urbanization level of the Changsha-Zhuzhou-Xiangtan urban agglomeration has significantly risen in recent years, there is an increasingly pronounced trend of population distribution polarization. Population concentration is notably growing in the capital city of Changsha, particularly in its downtown area. Changsha's advantageous geographical location, abundant employment opportunities, and robust infrastructure have attracted a substantial influx of enterprises and residents. In contrast, the cities of Zhuzhou and Xiangtan, integral parts of the core area of the agglomeration, along with the peripheral areas of Changsha, have experienced a continual decline in population densities, resulting in a relatively weaker population agglomeration effect.

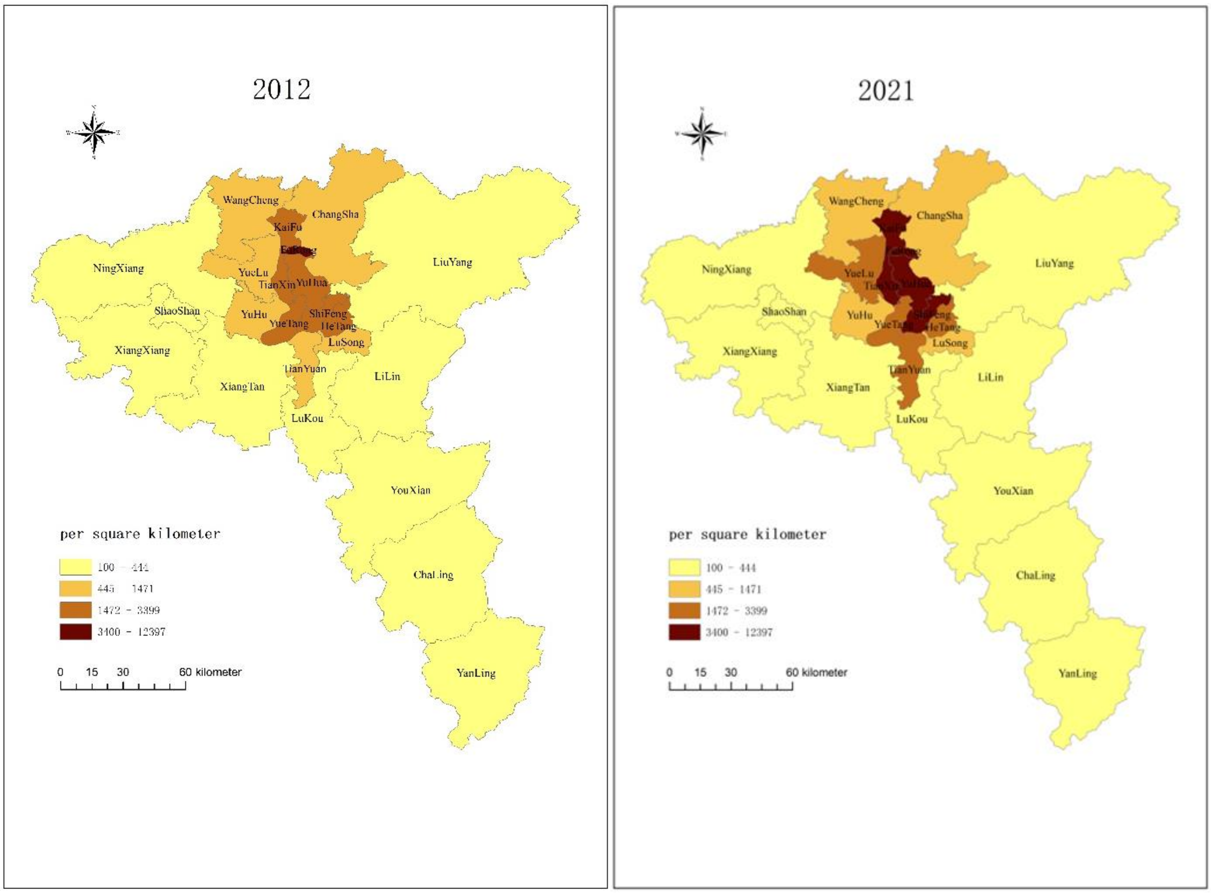

Figure 2. Population density map of Changsha-Zhuzhou-Xiangtan urban agglomeration.

Beyond population density, the population geographic concentration index is commonly employed to gauge the geographic concentration degree within a specified area, providing insights into the dispersal characteristics of population distribution in a given region. Its calculation is represented by the equation.

$$GPR_{it} = \frac{POP_{it}/ARE_{it}}{\sum_{i=1}^{n} POP_{it}/\sum_{i=1}^{n} ARE_{it}} \tag{3}$$

The population geographic concentration index (GPR) is denoted by the equation where i and t represent area and time, respectively. GPR quantifies the geographic concentration of the population within a specified area. POP represents the number of permanent residents in the area, while ARE signifies the land area of the same region.

Table 1 demonstrates that the geographic concentration of population within each district and county of the Changsha-Zhuzhou-Xiangtan urban agglomeration exceeds 1 in the central urban areas of Changsha, Zhuzhou, and Xiangtan, displaying an upward trend. Conversely, surrounding districts and counties predominantly exhibit population geographic concentrations below 1, indicative of a decreasing trend. This highlights a high degree of population concentration in the three urban centers and a distinct trend of concentration from the periphery towards the central city. Furthermore, Furong District in Changsha, Shifeng District in Zhuzhou, and Yutang District in Xiangtan exhibit notably higher geographic concentrations of population compared to other districts and counties within the urban agglomeration. This observation implies a distinct mono-core structure in the Changsha-Zhuzhou-Xiangtan urban agglomeration, where the central urban area consistently holds advantages in terms of employment opportunities, infrastructure, and public services. Consequently, the central urban area exerts a greater allure on the population, leading to a continuous migration of residents from surrounding districts and counties toward the central urban hub.

Table 1. Geographic concentration of population in districts and counties.

	GPR_{2012}	GPR_{2015}	GPR_{2018}	GPR_{2021}
Furong	25.111	24.928	25.661	25.086
Tianxin	6.885	8.320	8.848	10.124
Yuelu	2.980	2.943	3.014	4.765
Kaifu	6.246	6.336	6.588	7.527
Yuhua	4.921	5.316	5.667	6.951
Wangcheng	1.136	1.191	1.303	1.636
Changsha County	1.152	1.025	1.155	1.327
Ningxiang	0.827	0.836	0.866	0.727
Liuyang	0.520	0.513	0.486	0.475
Hetang	4.446	4.280	3.847	4.017
Lusong	2.726	2.712	2.511	2.332
Shifeng	6.565	7.081	7.540	6.154
Tianyuan	1.750	1.755	1.886	2.457
lukou	0.557	0.551	0.536	0.409
You County	0.531	0.522	0.468	0.394
Chaling	0.469	0.462	0.442	0.325
Yanling	0.202	0.198	0.187	0.130
Liling	0.900	0.892	0.836	0.680
Yuhu	2.681	2.605	2.495	2.283
Yuetang	4.506	4.464	4.326	3.916
Xiangtan County	0.802	0.790	0.758	0.610
Xiangxiang	0.811	0.802	0.769	0.610
Shaoshan	0.756	0.777	0.763	0.697

3.1.2. Population Mobility in Changsha-Zhuzhou-Xiangtan urban agglomeration

Given the dynamic nature of population distribution influenced by various factors, the resultant evolution is broadly termed population redistribution. The population redistribution index serves as a valuable metric to gauge the intensity of regional population migration. This study employs said index to characterize the population mobility within the Changsha-Zhuzhou-Xiangtan urban agglomeration. The calculation of the population redistribution index (denoted as R) is detailed in the following equation.

$$R = \frac{1}{2}\sum_{i=1}^{n}\left|y_{i,t} - y_{i,t-m}\right| \tag{4}$$

where n is the geographical number of enumerated administrative districts, $y_{i,t}$ and $y_{i,t-m}$ are the share of the population of the district in the total population at time t and the share of the district in the total population at time $t-m$ (m years ago), respectively.

A higher R value indicates increased dynamism in regional population distribution. Generally, the population redistribution index correlates with the regional economy. Lower economic levels correspond to relatively stagnant population distribution, resulting in smaller R values. The Changsha-Zhuzhou-Xiangtan region, as the growth pole of Hunan Province, exhibits representative local population flow dynamics. These dynamics are directly influenced by the economic radiation and its impact on neighboring cities. Consequently, this study focuses on a three-year period (m=3), comparing the population redistribution index (R) at four stages in Changsha-Zhuzhou-Xiangtan urban agglomeration: 2012, 2015, 2018, and 2021.

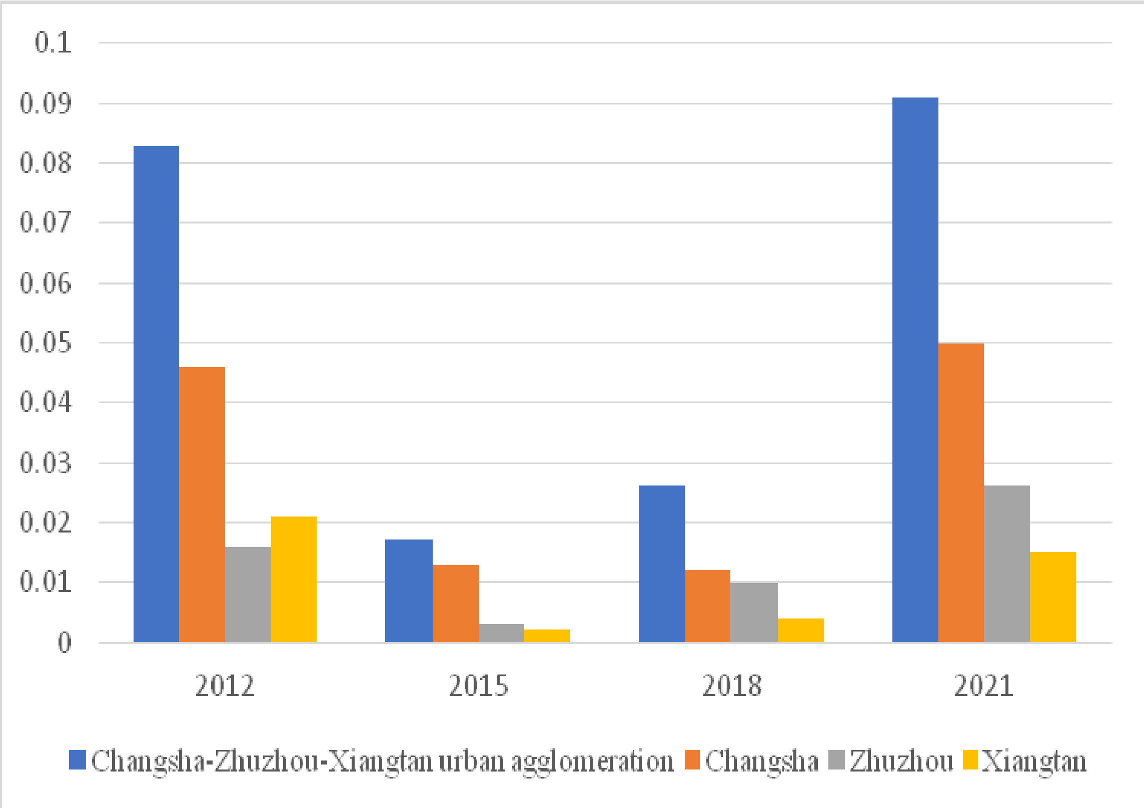

Figure 3. Population redistribution index.

The population redistribution activity in the Changsha-Zhuzhou-Xiangtan urban agglomeration has consistently increased since 2015, reflecting a growing trend in population mobility. Notably, the population redistribution index experienced pronounced growth from 2018 to 2021. This trend is closely associated with the objectives outlined in the "13th Five-Year Plan for Population Development in Hunan Province," emphasizing the guidance of orderly population movement and the implementation of a generally relaxed and differentially guided urban settlement policy. In recent years, the relaxation of the household registration system, advancements in transportation infrastructure, and diverse information channels have increased accessibility to employment, housing, education, and transportation information for residents in the Changsha-Zhuzhou-Xiangtan urban agglomeration. This heightened convenience has led residents to exhibit a greater willingness to relocate according to their individual needs, seeking more fulfilling employment, improved living conditions, and higher-quality education.

At the city level, population redistribution activities in Changsha City, Zhuzhou City, and Xiangtan City exhibit a declining trend followed by an increase, with a notable surge observed between 2018 and 2021. Despite these variations, Changsha City's population movement constitutes over 50% of the total activity within the Changsha-Zhuzhou-Xiangtan urban agglomeration, indicating economic development disparities and unbalanced spatial population distribution among the three cities.

3.2. Autocorrelation analysis of spatial patterns of population

"Spatial autocorrelation" denotes the tendency for geographically proximate regions to exhibit similar variable values. Positive spatial autocorrelation occurs when high values cluster with high values and low values cluster with low values. Conversely, "negative spatial autocorrelation" arises when low values are adjacent to high values. The absence of spatial autocorrelation occurs when high values are randomly juxtaposed with low values. Moran's index (Moran's I) and Getis-Ord index (G) serve as tests for spatial autocorrelation. Moran's index assesses the overall spatial clustering of the entire sequence, offering insights into the similarity of attribute values among spatially adjacent or neighboring regional units.

The statistical outcomes of the comprehensive Moran index indicate a persistent positive trend in the spatial distribution of the population within the Changsha-Zhuzhou-Xiangtan urban agglomeration. There is an observable pattern of a brief decline followed by a sustained increase. This pattern signifies a substantial spatial autocorrelation in the population distribution, where areas with higher population concentration are in proximity to other high-concentration areas, and similarly for lower-population concentration areas. Furthermore, there is a discernible upward trend in the spatial autocorrelation of population distribution within the Changsha-Zhuzhou-Xiangtan urban agglomeration. Regions characterized by high population concentration draw population inflows, while areas with low population concentration experience gradual population outflows.

Moran's indices effectively discern similarities and differences in neighboring data, revealing the degree of similarity in attribute values and their spatial distribution patterns. While proficient in describing overall spatial autocorrelation, Moran's indices lack the capability to identify distinct spatial aggregation patterns, such as "hot spots" or "cold spots," and cannot discern their overarching trends. Hot spot regions are characterized by the clustering of high values, whereas cold spot regions involve the clustering of low values. Both hot spot and cold spot regions demonstrate positive autocorrelation under the first two indices, necessitating the introduction of the Getis-Ord index G.

$$G(d) = \frac{\sum\sum w_{ij}(d) x_i x_j}{\sum\sum x_i x_j} \tag{5}$$

In the formula, $w_{ij}(d)$ represents a non-standardized symmetric spatial weight matrix. Larger values in $w_{ij}(d)$ indicate high-value agglomeration in the observations, while smaller values signify low-value agglomeration. Figure 4 illustrates the cold hotspot analysis, revealing that from 2012 to 2021, population agglomeration hotspots and sub-hotspots in the Changsha-Zhuzhou-Xiangtan urban agglomeration are concentrated in the central and northern regions. In contrast, cold spot and sub-cold spot areas are prevalent in the eastern, western, and southeastern parts of the region. The analysis aligns with hot and cold spot principles, highlighting a high degree of autocorrelation in the population distribution of the urban agglomeration.

The tables and figures above reveal that both spatial autocorrelation indicators decisively reject the initial hypothesis of "no spatial autocorrelation," affirming the existence of spatial autocorrelation. This implies that regions with higher population concentration exhibit spatial proximity, and conversely, regions with lower concentration also spatially coalesce. Consequently, the Changsha-Zhuzhou-Xiangtan urban agglomeration displays a discernible spatial correlation structure with a cluster effect. The partial spatial autocorrelation index aligns with the overall spatial autocorrelation test results in certain areas, providing robust evidence against the hypothesis of "no spatial autocorrelation." The degree of rejection displays a temporal pattern of decrease followed by an increase, signaling a progressive augmentation of spatial dependence in the population concentration within the Changsha-Zhuzhou-Xiangtan urban agglomeration.

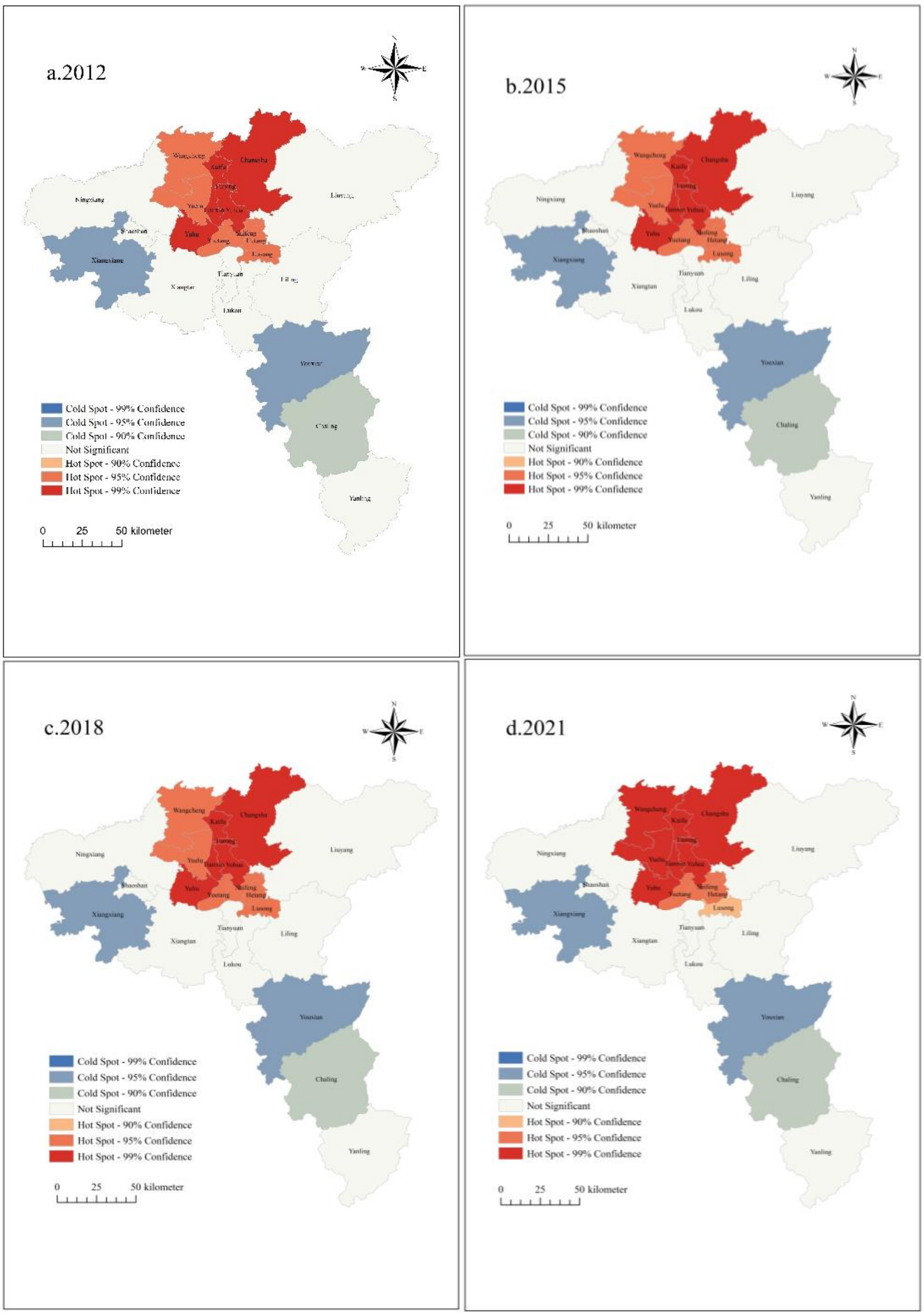

Figure 4. Cold-hot spot analysis of population distribution.

3.3. Analysis of factors influencing spatial patterns of population

3.3.1 Baseline regression and quantile regression estimates

The benchmark and quantile regression results demonstrate that per capita disposable income, financial expenditure, and education level exert a notably positive influence on the geographical concentration of the population. Specifically, a 1% rise in per capita disposable income corresponds to a 1.43% increase in the spatial concentration of the population. Likewise, a 1% increase in fiscal expenditure is associated with a 0.178% rise in the spatial concentration of the population, and a 1% increase in education level results in a 0.623% increase in geographic population concentration. Specifically, the positive impact of education level on population concentration is evident solely at the 10th percentile of spatial concentration. Conversely, an inhibitory effect is observed at the 25th, 50th, 75th, and 90th percentiles of education level. GDP per capita, road area per capita, and environmental quality exert a notable negative influence on population geographic concentration. Specifically, a 1% increase in GDP per capita corresponds to a 1.057% decrease in population concentration. This suggests that the rise in GDP per capita within the Changsha-Zhuzhou-Xiangtan urban agglomeration does not result in population concentration; instead, it induces population dispersion. This phenomenon may arise from the sizable population base and a regional GDP growth rate that lags behind the regional population growth rate, leading to a counter-directional shift in population geographic concentration due to GDP per capita; a 1% increase in road area per capita results in a 0.432% reduction in population spatial concentration. However, road area per capita exhibits a positive influence on population geographic concentration when it is at the 10th percentile. This occurs because, at low population geographic concentration levels, an augmented road area per capita indicates improved transportation accessibility, attracting population inflow and consequently increasing population geographic concentration.

Table 2. Baseline regression and quantile regression.

	(1) OLS	(2) 10point	(3) 25point	(4) 50point	(5) 75point	(6) 90point
gdp	-1.057***	1.726***	2.387***	3.617***	4.120*	14.555***
	(0.262)	(0.245)	(0.484)	(0.784)	(2.467)	(3.310)
income	1.430***	-0.809**	-0.887	-1.801	1.454	-7.908
	(0.280)	(0.387)	(0.764)	(1.236)	(3.890)	(5.219)
price	0.127	0.085	0.610	1.254	-1.101	-1.106
	(0.169)	(0.308)	(0.608)	(0.983)	(3.094)	(4.151)
industry	0.260	-3.250***	-4.078***	-7.201***	-12.411***	-22.013***
	(0.503)	(0.463)	(0.913)	(1.478)	(4.652)	(6.241)
traffic	-0.432***	0.219	-0.576	-0.982	-1.990	-1.295
	(0.114)	(0.202)	(0.399)	(0.646)	(2.032)	(2.727)
fiscal	0.178***	0.039	-0.111	-0.052	-0.474	-1.378
	(0.066)	(0.079)	(0.157)	(0.254)	(0.798)	(1.071)
education	0.623**	0.136	-0.546	-0.628	-2.772	-6.830
	(0.254)	(0.355)	(0.700)	(1.133)	(3.565)	(4.783)
environment	-0.933***	-4.254***	-4.863***	-4.518**	-5.712	-8.676
	(0.339)	(0.626)	(1.236)	(2.001)	(6.296)	(8.447)
_cons	-0.974	-6.896***	-12.659***	-20.095***	-25.975	-25.486
	(3.158)	(2.080)	(4.105)	(6.644)	(20.904)	(28.045)
N	184	184	184	184	184	184

*Note: *** P<0.01, ** P<0.05, * P<0.1; t-statistics in parentheses (the same below).*

3.3.2 Estimation and discussion of spatial effects

When considering the Lagrange Multiplier (Lag) test and the Lagrange Multiplier (Error) test, opt for the model associated with the statistically significant result if only one of them exhibits significance. In cases where both tests yield significance, select the more statistically significant model by comparing the significance levels and integrating the robust estimates, namely Robust LM (Lag) and Robust LM (Error). In this context, "Lag" denotes spatial lag, and "Error" denotes spatial error. Referring to Table 3, where two spatial errors reject the original hypothesis, the spatial error model is chosen.

Table 3. LM test results.

Inspection Indicators	Coefficient	P-value
Lagrange multiplier (error)	11.300	0.001
Robust LM(error)	20.307	0.000
Lagrange multiplier (lag)	0.717	0.040
Robust LM (lag)	9.723	0.000

The Spatial model is constructed as follows.

$$GPR_{it} = \beta_{1\mathrm{i}}GDP_{it} + \beta_{2i}INCOME_{it} + \beta_{3i}PRICE + \beta_{4\mathrm{i}}INDUSTRY_{it} + \beta_{5i}TRAFFIC_{it}u_i + \beta_{6i}FISCAL_{it} + \beta_{7i}EDUCATION + \beta_{8i}ENVIRONMENT + u_i + \gamma_t + \varepsilon_{it} \tag{6}$$

$$\varepsilon_{it} = \lambda m_i{}' \varepsilon_t + v_{it} \tag{7}$$

Where i denotes the districts, counties, and proxy cities under the jurisdiction of Changsha-Zhuzhou-Xiangtan urban agglomeration, and t denotes the year. u_i signifies the individual effect of region i, γ_t is the time effect, while m_i is row i of the spatial weight matrix M of the disturbance term, and ε_{it} is the error term, reflecting errors introduced by individual and cross-sectional influencing factors. The other symbolic variables retain their aforementioned meanings.

Table 4 reveals that the sign and significance of coefficients in the mixed ordinary least squares (OLS) estimation align with those in both random and fixed effects models. Specifically, under fixed effects, 1 percentage point increase in GDP per capita, road area per capita, and air quality corresponds to a decrease in population geographic concentration by 1.671, 0.414, and 0.893 percentage points, respectively. Additionally, 1 percentage point increase in disposable income per capita and fiscal expenditure leads to an increase in population geographic concentration by 1.462 and 0.162 percentage points, respectively. In the random effects model, 1 percentage point increase in GDP per capita, road area per capita, and air quality results in a decrease of 1.109, 0.424, and 0.915 percentage points, respectively, in the geographic concentration of the population. Conversely, 1 percentage point increase in disposable income per capita and fiscal expenditures leads to an increase of 1.462 and 0.169 percentage points, respectively, in population geographic concentration. The observed discrepancy between spatial measurements and the expected coefficients' signs can be attributed to various factors. In older urban areas and regions with well-developed transportation networks, road area approaches saturation levels, causing a decline in road area per capita with increasing population—a trend mirrored in GDP per capita.

Table 4. Fixed effects and Random effects results.

	(1) RE	(2) FE	(3) OLS
gdp	-1.109**	-1.167**	-1.057***
	(0.469)	(0.478)	(0.262)
income	1.444**	1.462**	1.430***
	(0.584)	(0.584)	(0.280)
price	0.124	0.129	0.127
	(0.160)	(0.163)	(0.169)
industry	0.280	0.330	0.260
	(0.865)	(0.871)	(0.503)
traffic	-0.424**	-0.414**	-0.432***
	(0.166)	(0.164)	(0.114)
fiscal	0.169*	0.162*	0.178***
	(0.098)	(0.097)	(0.066)
education	0.595	0.576	0.623**
	(0.367)	(0.366)	(0.254)
environment	-0.915***	-0.893***	-0.933***
	(0.338)	(0.338)	(0.339)
_cons	-0.434		-0.974
	(4.287)		(3.158)
N	184	184	184
Spatial lambda	-0.026 (0.180)	-0.026 (0.183)	

4. Conclusion and policy implications

This study integrates the Moran index, population redistribution index, and the Getis-Ord statistical model, employing quantile regression estimation and spatial effect estimation, to investigate the spatial patterns of population in the Changsha-Zhuzhou-Xiangtan urban agglomeration and its influencing factors at the district and county spatial scale. The subsequent conclusions are as follows.

Firstly, employing population geographic concentration as the criterion, Furong District emerges as the primary central area, recording a population geographic concentration of 25.1 in 2021. Tianxin District, Kaifu District, Yuhua District, Shifeng District, Yuelu District, and Hetang District constitute the sub-central areas, while Yutang, Tianyuan, Lusong, Yuhu, Wangcheng District, and Changsha County are categorized as tertiary areas. Additionally, the population density of the Changsha-Zhuzhou-Xiangtan urban agglomeration progressively diminishes outward from Furong District, with both the first central area and sub-center areas experiencing continuous increases in population density. This accentuates the discernible trend toward population distribution polarization in the Changsha-Zhuzhou-Xiangtan urban agglomeration. Secondly, from 2011 to 2021, the overall Moran index of the spatial population distribution in the Changsha-Zhuzhou-Xiangtan urban agglomeration exhibits a consistently significant positive trend, indicating a robust spatial autocorrelation in population distribution. This suggests a progressive intensification of spatial agglomeration within the urban agglomeration. Following its inclusion in the National Eleventh Five-Year Plan in 2005, the Changsha-Zhuzhou-Xiangtan urban agglomeration, guided by diversification policies, has actively pursued the establishment of a two-oriented society. This initiative involves enhancing regional communication, fostering cooperation, improving urban transportation networks, optimizing industrial structures, and creating favorable employment, living, and business environments. Consequently, the spatial population agglomeration in the Changsha-Zhuzhou-Xiangtan urban agglomeration has experienced notable growth in recent years. Thirdly, whether employing fixed or random effects, per capita disposable income, financial expenditure, and education level exhibit a significant positive impact on population geographic concentration within the Changsha-Zhuzhou-Xiangtan urban agglomeration. Conversely, GDP per capita, road area per capita, and environmental quality exert a notable negative influence on population geographic concentration in the same region. Notably, the three foremost factors influencing population geographic concentration are GDP per capita, disposable income per capita, and air quality. Guided by economic development policies, the division of labor within the Changsha-Zhuzhou-Xiangtan urban agglomeration has become more distinct and rational, contributing to an overall improvement in economic development levels. This, in turn, attracts population inflows from neighboring cities. Consequently, economic factors remain the primary determinants influencing population distribution in the Changsha-Zhuzhou-Xiangtan urban agglomeration.

In light of the aforementioned analysis and findings, the paper offers the following recommendations. Firstly, aligning with the characteristics of population distribution and migration, precise positioning of areas and demographic groups is advised to foster the evolution of the spatial population pattern. In regions characterized by high population density, exemplified by Furong District, Tianxin District, and Kaifu District, it is imperative to not only support local pillar industries and establish a distinctive development model but also to proactively mitigate "urban diseases" stemming from population agglomeration. Simultaneously, efforts should focus on expediting the establishment of a central city marked by a substantial population, advanced technology, robust service functions, and well-developed infrastructure. Conversely, in regions with low population density, such as Yiling County and Chaling County, addressing labor shortages and insufficient infrastructure resulting from population outflows is the primary concern. Initiatives should aim at fostering alternative factor-intensive industries. The government should facilitate the expansion of infrastructure and public services from the central city to its surrounding areas, enhancing the population-carrying capacity in these regions.

Secondly, give full play to geographical proximity and strengthen regional cooperation. As indicated by the

Moran Index, the spatial agglomeration of the population within the Changsha-Zhuzhou-Xiangtan urban agglomeration is progressively intensifying, leading to an expanding economic hinterland. Strengthening population agglomeration capabilities and optimizing the spatial alignment of population and industrial development are integral to expediting the establishment of a balanced population development trend. In considering positive impacts, attention must be given to two key aspects. On the one hand, regional communication and cooperation should align with local resource endowments to mitigate negative effects arising from misalignment and overexploitation. On the other hand, the emphasis should be on cultivating a sustainable development model that fosters self-renewal rather than relying on negative paradigms.

Lastly, there is a need to underscore a comprehensive development concept while concentrating on emerging developmental factors. Spatial econometric analysis reveals a substantial influence of economic, social, and environmental factors on the spatial distribution of the population in the Changsha-Zhuzhou-Xiangtan urban agglomeration. This underscores the imperative for the urban agglomeration to embrace a comprehensive development paradigm that integrates economic, political, cultural, social, and ecological dimensions. It must not only champion high-quality economic development to establish itself as a pivotal national growth hub but also prioritize considerations such as social security and the ecological environment. Moreover, there is a need to advance the new urbanization strategy with a central focus on human-centric approaches.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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