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Urban Agglomerations in China: Characteristics and Influencing Factors of Population Agglomeration

CAO Yongwang, ZHANG Rongrong, ZHANG Dahao, ZHOU Chunshan

(*School of Geography and Planning*, *Sun Yat-sen University*, *Guangzhou* 510006, *China*)

Abstract: Urban agglomeration (UA) is an advanced spatial economic form formed and developed in the process of rapid industrialization and urbanization, and an important carrier of urbanization and economic development. The economy has developed rapidly in the recent decades of China, and the UAs have also developed rapidly. However, as a large population country, the population distribution and changes of UAs in China has unique characteristics. Using the fifth, sixth and seventh population census data, spatial auto-correlation and spatial econometric models, we analyzed the spatial-temporal evolution characteristics and influencing factors of population agglomeration in China's UAs. Results revealed that: 1) from 2000 to 2020, the population gradually converged into UAs, and the characteristics of population agglomeration in different development degree of UAs differ. The higher the development degree of UA, the higher the population agglomeration degree. Besides, UAs are the main area with the most significant population agglomeration degree, and the spatial autocorrelation show that the cities with similar degree tend to be concentrated in space. The urban population gathering in UAs has a certain positive spillover effect on population size of neighboring cities. 2) Economic development and social conditions factors are important factors affecting population agglomeration degree in UAs. The main factors of population gather into UAs are similar with the outside UAs, but the positive promotion of urbanization rate and proportion of tertiary industry in GDP on population agglomeration of UAs in China are enhancing from 2000 to 2020. Meanwhile, the other factors, such as high-quality public services, good urban living environment conditions, high-quality medical and educational resources, are also important factors to promote urban population gather into UAs. This study provides a basis for formulating the development planning of UAs in China, and enriches the relevant theoretical research of population evolution and influencing factors of UAs.

Keywords: urban agglomerations (UAs); population agglomeration; influencing factors; spatial econometric models; China

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1 Introduction

Urban agglomeration (UA) generally refers to urban aggregates with spatial order, with core cities as nodes and peripheral towns as strong functional links. The idea of UA originated from the concept of 'town cluster' proposed by British urban scholar Ebenezer Howard in his book published in 1898, in which he advocated a new planning model with a focal city and other garden towns lying on the peripheries (Ebenezer, 1898). The spatial pattern of a core city with several surrounding towns was the embryo of UA. In his study 'megalopolis or the urbanization of the northeastern seaboard' published in 1957, French geographer Jean Gottmann proposed the concept of the 'Megalopolis'. In this, the term Megalopolis was used to describe the functional cities densely

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Corresponding author: ZHOU Chunshan. E-mail: zhoucs@mail.sysu.edu.cn

distributed along the northeastern coast of the United States (Gottmann, 1957). McGee proposed the concept of ‘Desakota’ to examine urban and rural areas in southern and southeastern Asia (McGee, 2008). Other similar concepts also have been introduced, such as ‘Global City Region’ (Scott, 2001). In addition, with the rapid development of China’s cities, the idea of Gottman’s Megalopolis was introduced by Chinese scholars to study the country’s UAs (Zhou, 1988; Chan and Yao, 1999). Yao et al. (1998) first proposed the concept of UA systematically, defined as a relatively complete urban aggregation with one or two large cities as the core, and compact internal relationships between different cities of specific geographical range. Zhou (1988) defined ‘extended metropolitan regions’ as a huge urban-rural integration area with several major cities as the core and maintaining strong interaction and close socio-economic ties with the surrounding areas. At present, Chinese geographers usually use the term ‘Urban Agglomeration’ in research, and have conducted many studies of UAs focusing on the spatial scope definition (Liang, 2009), formation and development (Xu et al., 2016), spatial structure (Liu et al., 2020; He et al., 2021) and evolution process (Fang and Yu, 2017; Fu and Zhang, 2020).

China has a large population and is a region with rapid development of UAs. The population distribution and changes of UAs are unique. In recent years, UAs in China have gradually developed into an important place with the most developed economy, the highest population concentration and frequent mobility. In 2020, the 19 UAs comprised 257 cities, accounting for about 40% of the total number of cities in China. The total GDP of UAs accounts for 85.13% of China’s GDP (Department of Urban Society and Economic Statistics National Bureau of Statistics of China, 2022). In addition, the proportion of permanent population of UAs has increased from 72.59% in 2000 to 75.89% in 2020, and the proportion of registered population has also increased from 71.11% to 71.55% in the same period (Population Census Office Under the State Council and Department of Population, Social, Science and Technology Statistics National Rureau of Siatistics of China, 2002). It is estimated that 80% of permanent population will be distributed in 19 UAs by 2030 based on the average annual population growth rate from 2010 to 2020 (Office of the Leading Group of the State Council for the Seventh National Population Census, 2022). Therefore, UAs are reshaping the spatial pattern of population agglomeration in China.

The research on the spatial-temporal characteristics and influencing factors of population distribution in foreign UAs gradually increase. The population distribution maintains strong trend of population concentration of the Tokyo Metropolitan Area, and the trend of population agglomeration in the core area is still strengthening (Chen et al., 2020). The population proportion of core area of the northeastern UAs in the United States has experienced the trend of rising first and then falling, and the population spatial distribution has witnessed the trend from single core to multipolar (Yin and Shi, 2016). The population growth of UAs in Cracow agglomeration and the Upper Silesian conurbation was generally large by analyzing the changing characteristics of urban population density in southern Poland (Jażdżewska, 2017). The refoundation of the mean city-population size index was used to measure the development of UAs in Arriaga region (Lemelin et al., 2016). The population of UAs in the world have been predicted, and the population scale and proportion of UAs will continue to expand in the future (Chen et al., 2022). Besides, as one of larger population countries in the world, the spatial-temporal of population distribution in China is also an important aspect of research.

The research on the aforementioned spatial pattern can be traced back to 1935, when Hu Huanyong first discovered the abrupt change line of population density in the Southeast and Northwest, and defined this as ‘Hu Huanyong’s line’ (Hu Line) (Hu, 1935). Chen argued that the population pattern revealed by the Hu Line will not change fundamentally over a long period of time due to the impact of comprehensive natural and geographical environment (Chen et al., 2016). In addition, with the prominence of the importance of UAs in shaping population patterns, the research on analyzing population agglomeration characteristics and high-quality development in China from the perspective of UAs has gradually increased (Zhang et al., 2022). Among these, some scholars have analyzed the population characteristics of a single UA. The population concentration trend of the Changsha-Zhuzhou-Xiangtan UA is obvious, and Changsha, as the core city, has an important impact on population concentration (He et al., 2019). The population aggregation trend dominated by some cities in the Yangtze River Delta has not changed, and the population concentration has shown a steady growth trend (Yan et al., 2020). Furthermore, some scholars have also conducted an overall analysis of the population characteristics of UAs in China. The spatiotemporal evolution characteristics of China's population was analyzed from the perspective of UAs, and UAs with a higher level of development are found to be mainly located in the eastern coastal areas, which have strong population attraction and gradually form a certain hierarchical structure (Zhang et al., 2018). In China, UAs are the regions with the strongest population mobility, and that within a province is the main feature of population mobility in UAs (Zhou et al., 2021).

Furthermore, the research on influencing factors of population agglomeration has gradually become focused, and existing research has mainly been carried out from the aspects of natural environment, economic development and social conditions (Ma and He, 2021). The natural environment factors are basic factors affecting the spatial distribution pattern of the population (Liu et al., 2019). The change of natural environment will increase population mobility, affecting the regional population spatial agglomeration (Borderon et al., 2019; Hoffmann et al., 2020). The spatial imbalance of economic development is also an important factor affecting population spatial distribution (Alperovich, 1992). Economic scale and development level play an absorbing role in China's population distribution (Qi et al., 2021). Scientific and technological progress helps to improve human living conditions and affects population distribution (Glaeser and Resseger, 2010). The difference between income levels and employment opportunities will lead to population migration, and population will tend to gather in cities with high income levels and more employment opportunities (Liu and Shen, 2014). Furthermore, with the increase of population mobility in UAs, the analysis of influencing factors of population agglomeration in UAs has gradually become a hot topic. In general, existing studies focus on analysis of influencing factors of a single UA, and there is a relative lack of overall analysis of influencing factors of 19 UAs in China. Meanwhile, most studies of factors affecting population agglomeration in UAs are mainly from the viewpoint of natural environment and economic development factors, but relatively few consider that of the social conditions. UAs attract population mainly through modern industrial structure, higher production efficiency, and higher degree of opening (Ye et al., 2019). The urban population growth and total trade have negative correlation of UAs in Sub-Saharan African by using panel fixed effect model (Asogwa et al., 2020). UAs can reduce various costs in the process of factor flow through perfect infrastructure and convenient transportation networks, and enhance their attractiveness to promote population agglomeration (Zhang et al., 2020). The development of high-speed rail can promote the short-term population flow of the Yangtze River Delta UA, but it will also have a negative impact on long-term population migration (Wang et al., 2019). The industry, population, and space elements of the Pearl River Delta UA have a short-term mutual promotion effect, but it is difficult to form a long-term and stable mutual promotion mechanism (Liu and Tian, 2018).

Overall, existing studies focus more on population characteristics from a single UA, while there is relatively less research on UA of country and region as a system. This study considers 19 UAs in China as a whole, analyzes the spatial-temporal evolution characteristics and influencing factors of population agglomeration in UAs, and focuses on demographic characteristics in 2000–2010 and 2010–2020. Thus, this study mainly explores: 1) what are the spatial-temporal evolution characteristics of population agglomeration of UAs in China from 2000 to 2020? Are there similarities and differences in the population agglomeration characteristics of different development degree of UAs? 2) what are the main factors affecting China's population agglomeration in UAs? What is the main difference of factors affecting population agglomeration into UAs and outside UAs? Compared with the existing studies, this study conducts new analysis in the field of research perspectives of UAs, and spatial econometric models, which enrich the theoretical achievements of population distribution change and provide reference for the formulation of regional policies.

2 Materials and Methods

2.1 Study area

A total of 19 urban agglomerations (UAs), which were mentioned in the outline of the 13th Five-year Plan (2016–2020), were selected as the research object (Fang et al., 2016). The prefecture-level city is usually basic administrative unit in China, but since UAs may only include some districts and counties of such cities, this study delimits the scope of UAs in strict accordance with the names of districts and counties included in each UA, which can ensure the accuracy of population calculation results (Fig. 1). It should be noted that due to the limited access of data, the national data does not consider Hong Kong, Macao, Taiwan of China and the South China Sea Islands. In addition, according to the development degree of UAs in 2010, the 19 UAs are divided into four types: Low, Lower-middle, Upper-middle, and High level (Zhang et al., 2018).

2.2 Data sources

The population data are mainly extracted from population censuses by county (2000, 2010, and 2020) (http://www.stats.gov.cn/). The economic data are mainly derived from the *China City Statistical Yearbook* 2001, 2011, and 2021 (https://data.cnki.net/yearBook/) that reflect the economic development in 2000, 2010 and 2020 respectively, which is consistent with the time of population situation in the fifth, sixth and seventh population censuses data. The vector data of prefecture-level city boundary was provided by the Resource and Environment Data Centre (http://www.resdc.cn/). Owing to the large changes in administrative divisions, to maintain the data consistency, only the administrative divisions of 2010 are adopted for further analysis.

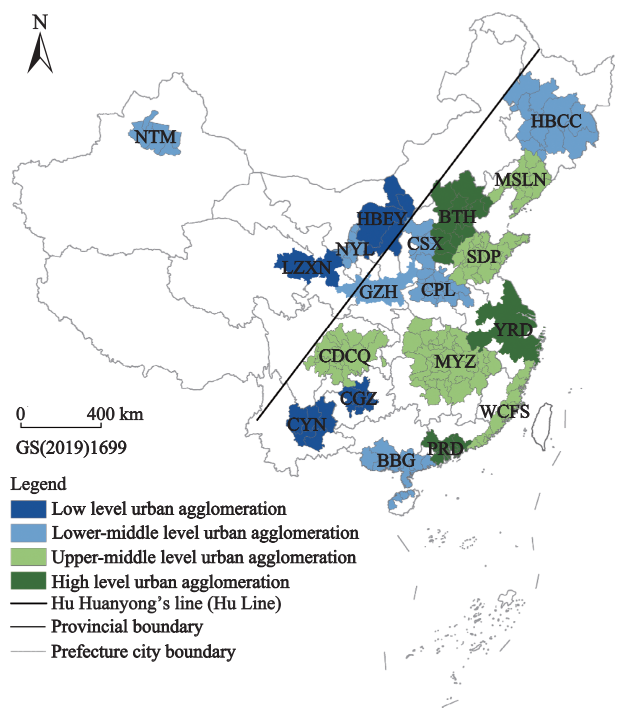

Fig. 1 Location of urban agglomeration (UA), China. CGZ, central Guizhou; HBEY, Hohhot-Baotou-Ordos-Yulin; LZXN, Lanzhou-Xining; CYN, Central Yunnan; NYI, Ningxia Yellow River; BBG, Beibu Gulf; HBCC, Harbin-Changchun; CSX, Central Shanxi; CPL, Central Plains; GZH, Guanzhong; NTM, Northern Tianshan Mountains; CDCQ, Chengdu-Chongqing; MYZ, Middle Reaches of Yangtze River; MSLN, Mid-southern Liaoning; WCFS, West Bank of the Taiwan Strait; SDP, Shandong Peninsula; BTH, Beijing-Tianjin-Hebei; YRD, Yangtze River Delta; PRD, Pearl River Delta

2.3 Methods and empirical models

2.3.1 Methods

(1) Population agglomeration degree

As a ratio of regional to national population density in the same year, population agglomeration degree mainly reflects the concentration degree of regional population relative to national population, and clearly reflects the difference between local and national average levels (Liu et al., 2010). The equation for population agglomeration degree is as follows:

$$JJD_i = \frac{(P_i/P_n)\times 100\%}{(A_i/A_n)\times 100\%} = \frac{P_i/A_i}{P_n/A_n} \tag{1}$$

where JJD_i is population agglomeration degree of area i, P_i and A_i are population number and land area of area i, respectively, and P_n and A_n are population number and land area in China.

(2) Annual average growth rate of permanent population

Population flow and migration lead to urban expansion or shrinkage; thus, cities are defined as expanding (or shrinking) cities according to the state of increasing (or decreasing) population over time, and are divided according to the annual average growth rate of permanent population (Haase et al., 2014). The equation for annual average growth rate of permanent population is as follows:

$$S_n = \left[\left(P_{\mathrm{end}}/P_{\mathrm{beg}}\right)^{1/n} - 1\right]\times 100\% \tag{2}$$

where S is annual average growth rate of permanent population, P_{end} and P_{beg} are population at the end and start of the study period respectively, and n is the study duration. S represents the increase (or decrease) of urban population when the value is positive (or negative). In addition, S_1 and S_2 are used to represent the regional annual average growth rate of permanent population of each unit in 2000–2010 and 2010–2020, respectively. The cities are divided into four types according to annual average growth rate of permanent population in stage S_1 and S_2: cities with continuous population expansion ($S_1 > 0$, $S_2 > 0$), with population expansion turning into reduction ($S_1 > 0$, $S_2 < 0$), with population shrinkage to expansion ($S_1 < 0$, $S_2 > 0$), and with continuous population shrinking ($S_1 < 0$, $S_2 < 0$) (Qi et al., 2019).

(3) Spatial autocorrelation

The spatial autocorrelation, is the correlation between observed variable value due to the spatial proximity of observation points. To quantitatively measure the distribution state and concentration degree of urban population agglomeration degree in China, the global spatial autocorrelation index (Moran's I) is introduced (Cliff and Ord, 1981). The equation for Moran's I is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (3)$$

Additionally, when further exploring local autocorrelation between cities, Local Spatial Autocorrelation Analysis (LISA) is used to describe the similarity between cities and neighboring cities (Anselin, 1995). The equation for LISA is as follows:

$$I_i = \frac{n(x_i - \overline{x})\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (4)$$

where n is number of cities, x_i and x_j are the population agglomeration degree of cities i and j, and W_{ij} is spatial weight matrix of each city. Based on the characteristics of population agglomeration of cities and neighboring cities, the cities are divided into four types according to the LISA index, where High (H) represents that the population agglomeration value is higher than the average value and Low (L) represents that the population agglomeration value is lower than the average value. Specifically, the type of High-High (H-H) means high population agglomeration of cities is surrounded by high neighboring cities, the type of High-Low (H-L) means high population agglomeration of cities is surrounded by low neighboring cities, the type of Low-High (L-H) means low population agglomeration of cities is surrounded by high neighboring cities, and the type of Low-Low (L-L) means low population agglomeration of cities is surrounded by low neighboring cities.

(4) Spatial econometric model

Spatial econometric models, which incorporate spatial effects into spatial regression models, mainly include the spatial lag model (SLM) and spatial error model (SEM) (Wang et al., 2018). Specifically, the spatial interaction of SLM is reflected by the spatial lag term of the explained variable, which means the population agglomeration degree of the city is affected by that of neighboring cities. SLM is used to discuss whether urban population agglomeration has a spillover effect within UAs. The equation for SLM is as follow:

$$Y = \rho W_y Y + \beta X + \varepsilon \quad (5)$$

where Y is the interpreted variable, X is the $n \times k$ exogenous explanatory variable matrix, ρ is the regression coefficient of the spatial lag term of the explained variable, W_y is the spatial weight matrix of the explained variable, $W_y Y$ is the spatial lag term of the explained variable, β is the coefficient of the explanatory variable, and ε is the random error term vector.

In addition, the spatial interaction of SEM is reflected by the spatial error term, which means the population agglomeration degree of the city is affected by some ignored variables (error terms) in the model. SEM is used to discusses the impact of spatial spillover caused by the error of explained variables in the neighboring cities. The equation for SEM is as follows:

$$Y = \beta X + \varepsilon$$

$$\varepsilon = \lambda W_{\varepsilon\varepsilon} + \mu \quad (6)$$

where Y is the interpreted variable, X is the $n \times k$ exogenous explanatory variable matrix, β is the coefficient of the explanatory variable, ε is a random error term vector, λ is the regression coefficient of the spatial error term, W_ε is the spatial weight matrix of the error term, $W_{\varepsilon\varepsilon}$ is the spatial error term, and μ is the random error vector of normal distribution.

2.3.2 Variable selection

The reasons of population migration and spatial agglomeration are mainly to increase income level and improve economic status according to the new migration economics theory (He et al., 2016). The economic factors are the main reasons that affect population migration according to the classical migration theory, and the purpose of population migration is to obtain higher wages, higher job opportunities and so on (Hunt, 1993). Regional economic theory believes that the strengthening of economic and social links between cities of UAs can realize the economic benefits of agglomeration, which motivate the population elements gradually gather into the UAs (Zhou et al., 2021). The urban population agglomeration degree of UAs is affected by many factors, which have been proved in previous studies (Liu et al., 2007). The regional economic differences can lead to population agglomeration to economically developed regions, thus accelerating population emigration from economically underdeveloped regions (Guan et al., 2018). By increasing the average wage level, cities with high levels of economic development have greater attraction for the population, and promote the population to gather in economically developed areas (He et al., 2016; Liu et al., 2017). Moreover, the regions with high wage income, developed non-agricultural industries, and more employment opportunities are more attractive to floating population(s), which can enhance the urban population agglomeration degree (Cao et al., 2018). For the industrial factors such as development level of the tertiary industry, the optimization and upgrading of industrial structure can provide more job opportunities to attract many external populations, and can promote the cross-regional flow of labor, which may lead to changes in regional population patterns (Fu and Gabriel, 2012).

For the public service factors such as medical facilities, education level, and transportation convenience, with the increase of coverage and availability of urban infrastructure, the mobility of various elements between and within cities has been accelerated, which has an important impact on the spatial migration of population. Meanwhile, with the increase in fiscal expenditure on public service facilities such as medical and education, the ability to provide public services continues to strengthen in cities, which have strong attraction to the floating population with need for school and medical treatment, and increases the willingness of the external population to settle (Bereitschaft and Cammack, 2015). Furthermore, the degree of environmental pollution, quality of human settlements and urbanization rate also have an important impact on population spatial agglomeration. Specifically, a good human settlements environment can improve happiness with urban life, and form a population attraction, which improves the level of population agglomeration degree. Conversely, high environmental pollution intensity can drive populations to move out of existing cities, and form a repulsive force, which reduces the level of population agglomeration degree (Cui et al., 2019; Liang et al., 2021). With the development of the economy and the improvement of people's living standards, the impact of urban comfort factors on population migration is gradually increasing (Buch et al., 2014; Grave, 1976). Thus, this study selects eight economic development factors and seven social condition factors as explanatory variables for in-depth analysis (Table 1).

2.3.3 Models

Taking the urban population agglomeration degree as the dependent variable and other factors as independent variables, the spatial econometric model is used to analyze the spatial spillover effect caused by population agglomeration. The model is constructed as follows:

$$\begin{aligned} JJD = {} & \beta + \beta_1 PerGDP + \beta_2 Ind + \beta_3 Fai + \beta_4 Tpv + \beta_5 Tfv + \\ & \beta_6 Tpvmd + \beta_7 Ilei + \beta_8 Gies + \beta_9 Exp + \beta_{10} Wag + \\ & \beta_{11} Edu + \beta_{12} Wel + \beta_{13} Iwt + \beta_{14} Gcr + \beta_{15} Urb + \xi \end{aligned} \tag{7}$$

where β, β_1, β_2, ..., β_{15} is the parameter to be evaluated, *JJD* represents population agglomeration degree, ξ is a random interference term subject to normal distribution, the definitions of *PerGDP*, *Ind*, *Fai*, *Tpv*, *Tfv*, *Tpvmd*, *Ilei*, *Gies*, *Exp*, *Wag*, *Edu*, *Wel*, *Iwt*, *Gcr*, and *Urb* are listed in Table 1.

3 Results

3.1 Change characteristics of permanent population of UAs

The UAs, with its strong economic development strength, have relatively stronger attraction to the population than outside UAs, and are the major region with large permanent population growth in China from 2000 to 2020. Specifically, the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Beijing-Tianjin-Hebei (BTH) UAs have higher permanent population growth with a growth scale of 43.44 million, 35.07 million, and 20.27 million, respectively, accounting for 58.82% of the total growth scale of UAs in the same period. The Harbin-Changchun (HBCC) UA is the only one with a permanent population negative increase with –3.66 mil-

Table 1 Description of variables and system of influencing factors

Factors	Indicator (abbreviation)	Representational meaning
Economic development factors	Per capita GDP (*PerGDP*)	Reflects the regional economic development degree
	Proportion of tertiary industry in GDP (*Ind*)	Reflects the urban industrial modernization level
	Investment scale of fixed assets (*Fai*)	Reflects the urban economic development vitality
	Total passenger volume (*Tpv*)	Reflects the convenience of personal mobility ability of other cities outside the city
	Total freight volume (*Tfv*)	Reflects the convenience of goods mobility ability of other cities outside the city
	Total passenger volume in municipal districts (*Tpvmd*)	Reflects the convenience of personal mobility ability within the city
	Industry location entropy index (*Ilei*)	Reflects the urban employment structure
	Growth index of enterprise structure above Designated Size (*Gies*)	Reflects the economic development vitality of urban industrial subjects
Social condition factors	Scale of fiscal expenditure (*Exp*)	Reflects the ability to provide urban public services and infrastructure
	Average wage of on-the-job employees (*Wag*)	Reflects the urban average wage level
	Teacher student ratio in primary and secondary schools (*Edu*)	Reflects the ability to provide education resources
	Number of beds in welfare institutions per ten thousand people (*Wel*)	Reflects the ability to provide medical service
	Standard rate of industrial wastewater treatment (*Iwt*)	Reflects the urban production environment conditions
	Greening coverage rate of built-up area (*Gcr*)	Reflects the urban living environment conditions
	Urbanization rate (*Urb*)	Reflects the population migration degree to city

lion. In addition, although the average annual growth rate of permanent population inside and outside UAs has shown a slow declining trend, the population gap inside and outside UAs has been further widened due to the large scale of original accumulated permanent population in UAs. In general, from 2000 to 2020, the main type of cities was those with continuous population expansion with 153 cities (44.61%), indicating the permanent population of most cities has increased continuously. On the other hand, the proportion of cities with continuous population shrinkage is 17.49% with 60 cities, reflecting that the permanent population of several cities has continually declined.

The population change of UAs have obvious stage characteristics from the perspective of dividing the period from 2000 to 2020 into two different stages (i.e., 2000–2010 and 2010–2020). Specifically, from 2000 to 2010, the proportions of expanding and shrinking cities were 71.72% and 28.28%, respectively, and the cities with significant population increase are mainly located in the YRD, PRD, Beijing Tianjin, Qinghai Tibet, and other regions. In this period, the permanent population increment inside and outside UAs was 84.88 million and 5.32 million, respectively. The permanent population increment inside UAs was 15.97 times that outside UAs, reflecting the fact that the gap inside and outside UAs was large. The Chengdu-Chongqing (CDCQ) UA was the only UA with negative population growth during this period, with a permanent population increment of –3.3 million (Fig. 2a). In addition, from 2010 to 2020, the number of expanding and shrinking cities was 189 and 152 with proportions of 55.43% and 44.57%, respectively, and the cities with significant population increase are still mainly located in the YRD, PRD, and other regions. In this period, the permanent population increment inside and outside UAs was 83.04 million and –6.07 million, respectively. The permanent population increment inside UAs was 13.68 times that outside UAs, indicating that permanent population further converged into UAs in China. The HBCC and Mid-southern Liaoning (MSLN) UAs were the only two UAs with negative population growth during this period with the permanent population increment of –6.28 million and –0.81 million, respectively (Fig. 2b). Compared with the previous stage, the number of shrinking cities has increased significantly from 2010 to 2020, and the population mobility has also increased.

3.2 Spatial-temporal evolution characteristics of population agglomeration degree of UAs

From 2000 to 2020, the permanent population gradually gather to economically developed UAs in the eastern

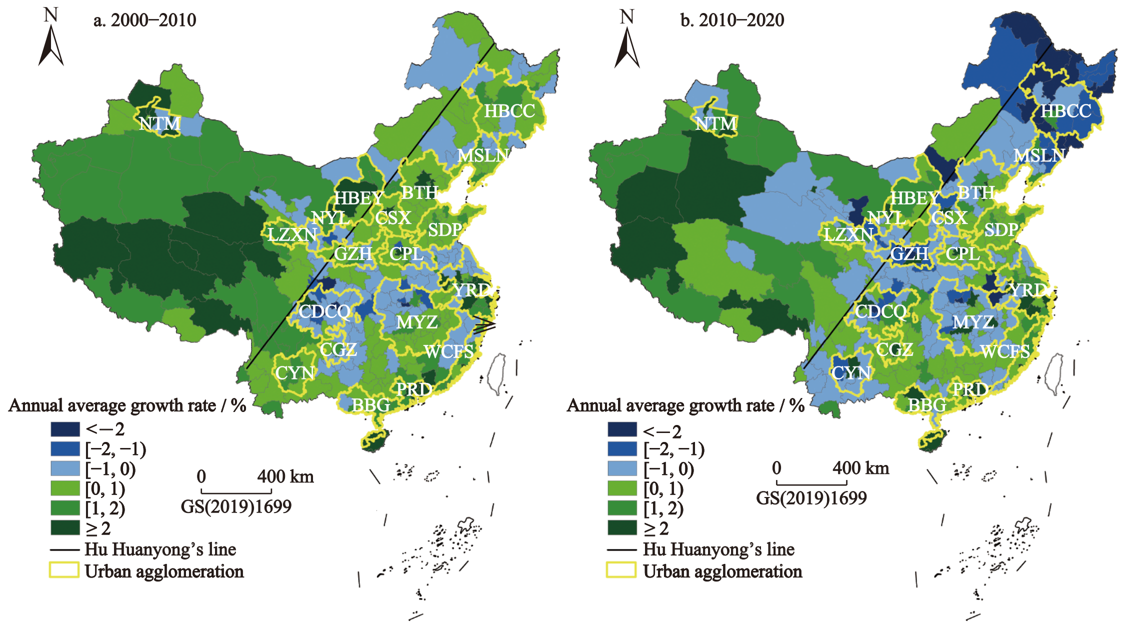

Fig. 2 Spatial distribution pattern of annual average growth rate of permanent population in China from 2000 to 2020 (a): 2000–2010; (b): 2010–2020. The abbreviation of the UA is the same as Fig. 1

and central region of China. The UAs with higher population agglomeration degree than the national average was mainly located in the southeast of Hu Line in China, and the population growth is mainly affected by UAs (Fig. 3). Specifically, the population agglomeration degree inside and outside UAs have changed from 2.57 and 0.38 in 2000 to 2.70 and 0.34 in 2020, respectively. During the study period, Guanzhong (GZH), MSLN, and Middle Reaches of Yangtze River (MYZ) UAs exhibited a declining trend of population agglomeration degree and are considered continuous shrinking UAs. Beibu Gulf (BBG), Central Yunnan (CYN), West Bank of the Taiwan Strait (WCFS), Hohhot-Baotou-Ordos-Yulin (HBEY), Lanzhou-Xining (LZXN), Ningxia Yellow River (NYL), Northern Tianshan Mountains (NTM), BTH, YRD, and PRD UAs displayed an increased trend of population agglomeration degree and are considered continuous expansion UAs. UAs, a major region with higher level of economic development and stronger economic vitality in China, attract more population to continuously gather in UAs by using their own higher economic level, stronger degree of openness, stronger agglomeration effects, and high-quality public services.

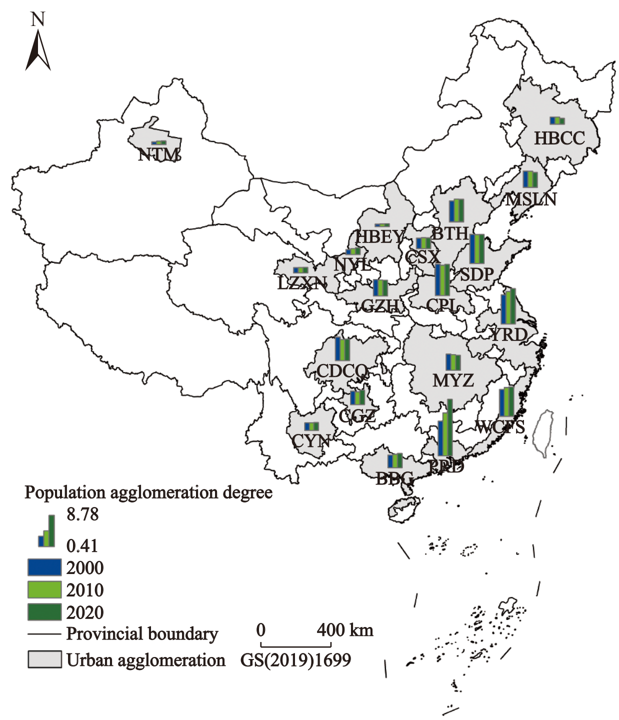

Fig. 3 Characteristics of population agglomeration degree of Urban agglomerations in China from 2000 to 2020. The abbreviation of the UA is the same as Fig. 1

The development levels of UAs show a positive correlation with population agglomeration degree, and the population attraction to High level UAs is constantly increasing. From 2000 to 2020, the proportion of permanent population in Low, Lower-middle, Upper-middle, and High level UAs has evolved from 4.31%, 16.45%, 31.33%, and 20.49% in 2000 to 4.61%, 16.18%, 30.03% and 25.07% in 2020, with corresponding growth rates of 0.30%, –0.27%, –1.30%, and 4.58%, respectively. Specifically, HBCC, Central Plains (CPL), GZH, CDCQ, MYZ, MSLN, and Shandong Peninsula (SDP) UAs have exhibited a decrease in the proportion of permanent population, belonging to the Lower-middle and Upper-middle level UAs. Meanwhile, the proportion of permanent population has increased in twelve UAs, including four Low level, three High level, four Lower-middle, and one Upper-middle level UA. Specifically, the PRD and YRD UAs exhibit a higher increase in the proportion of population with 2.08% and 1.92%, respectively, while the growth rate in the proportion of population in Low level UAs is generally small. From 2000 to 2020, the development degree of 19 UAs in China has increased to varying degrees, but high level UAs are still mainly located in the YRD, PRD, and BTH UAs along the eastern coast of China. These UAs use their own advantages to continuously attract large numbers of population, becoming the main UAs with high population agglomeration degree in China. This trend of population change also reflects that an increasing proportion of the population are willing to gather into UAs with high level of economic development (Table 2).

3.3 Spatial autocorrelation analysis of population agglomeration degree of UAs

The spatial agglomeration characteristics of urban population agglomeration degree is analyzed using Moran's *I* index. Results indicate that the UAs are the main areas with the most significant population agglomeration degree in China. The Moran's *I* index of population agglomeration degree in 2000, 2010, and 2020 are 0.366, 0.329, and 0.281, respectively, and the corresponding Z statistical values are 27.381, 25.140, and 22.154, respectively. The *Z* value in three years is greater than 2.58, and the *P* value in three years is 0.000, indicating that urban population agglomeration degree has a positive spatial autocorrelation, and cities with a similar degree tend to be concentrated in space overall. It should be noted that the positive spatial autocorrelation of urban population agglomeration degree has gradually weakened from 2000 to 2020.

Table 2 Permanent population at different levels of UAs from 2000 to 2020

Development level	Urban agglomeration	Level	Total permanent population / 10^6 person			Population agglomeration degree		
			2000	2010	2020	2000	2010	2020
Low level	CGZ	4.53	15.24	15.67	18.68	2.09	1.98	2.24
	HBEY	4.91	9.16	10.81	11.93	0.41	0.45	0.47
	LZXN	5.06	10.60	11.56	12.48	0.81	0.82	0.84
	CYN	5.25	18.60	20.25	21.95	1.17	1.19	1.22
Lower-middle level	NYL	5.43	4.10	5.07	6.06	0.76	0.93	1.05
	BBG	5.44	34.75	39.37	44.01	1.99	2.10	2.22
	HBCC	5.53	46.31	48.92	42.65	1.13	1.13	0.93
	CSX	5.63	14.51	16.11	16.76	1.63	1.69	1.66
	CPL	5.64	64.75	66.55	72.32	4.87	4.68	4.82
	GZH	6.07	35.43	37.69	39.25	2.54	2.52	2.49
	NTM	6.15	4.53	6.10	7.01	0.43	0.53	0.58
Upper-middle level	CDCQ	6.26	93.51	90.21	97.65	3.68	3.28	3.37
	MYZ	6.75	120.78	124.65	126.52	2.53	2.42	2.33
	MSLN	6.80	36.74	38.88	38.07	2.56	2.52	2.34
	WCFS	7.09	48.34	55.19	59.61	4.17	4.45	4.56
	SDP	7.27	89.97	95.79	101.53	4.52	4.47	4.49
High level	BTH	9.19	90.10	104.41	110.37	3.27	3.55	3.56
	YRD	10.57	121.64	143.49	165.09	4.53	5.04	5.49
	PRD	11.31	42.88	56.13	77.95	5.39	6.66	8.77

Note: the abbreviation of the UA is the same as Fig. 1

The local spatial autocorrelation of urban population agglomeration is analyzed based on the LISA index. Results reveal that the H-H areas were mainly distributed in the CPL, SDP, YRD, and PRD UAs in 2000, H-L areas located in the NTM UA, L-H areas mainly distributed outside UAs near the PRD and WCFS, L-L areas concentrated in northwest and southwest regions (Fig. 4a). In 2010, the number of agglomeration areas decreased and their distribution became more dispersed. Specifically, H-H areas are still mainly distributed in the CPL, SDP, YRD, and PRD UAs except with slightly smaller scope, L-H areas are mainly distributed outside UAs near the PRD and WCFS, L-L areas are mainly distributed outside the UA near the LZXN, and there are no significant H-L areas (Fig. 4b). In 2020, the number of agglomeration areas decreased continuously. Specifically, H-H areas are mainly located in the YRD and PRD UAs, and distributed in the core areas of the SDP, CPL, and BTH UAs, L-H areas are still mainly distributed outside the UA near the PRD, H-L areas are loc-

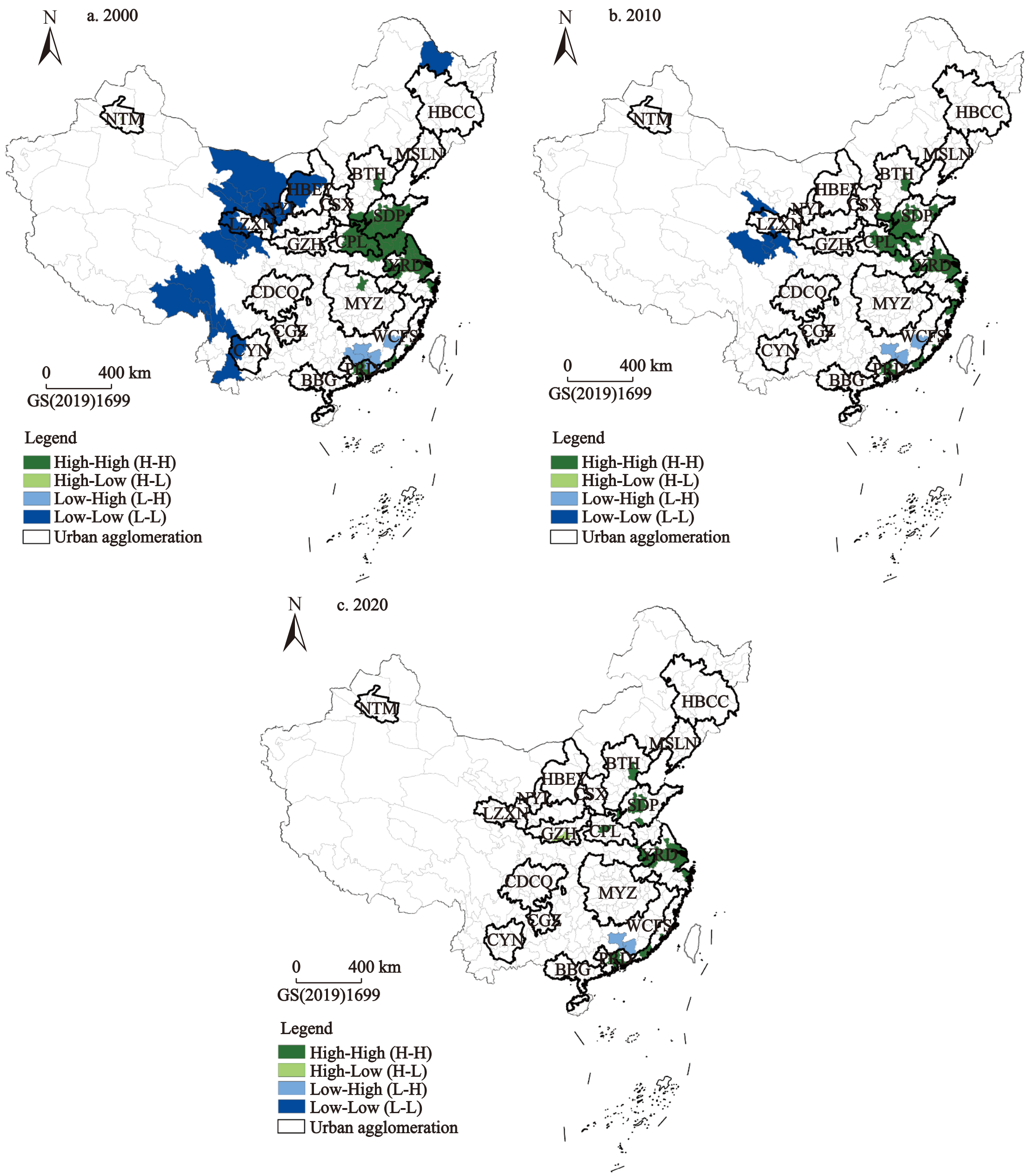

Fig. 4 Spatial distribution pattern of Local Spatial Autocorrelation Index (LISA) of permanent population agglomeration degree of China in 2000, 2010 and 2020. The abbreviation of the UA is the same as Fig. 1

ated in the GZH UA, and there are no significant L-L areas (Fig. 4c).

3.4 Influencing factors of population agglomeration degree of UAs

3.4.1 Model selection on influencing factors of population agglomeration degree

The collinear relationship between different influencing factors and urban population agglomeration degree is tested via Pearson correlation analysis using SPSS software. Results indicate that the significance level of each variable is mostly below 0.01 from 2000 to 2020, which means each variable passes the significance level test. The VIF value corresponding to each variable does not exceed 10, indicating that there is no collinearity problem between each variable in the equation. A total of three regression models, namely non-spatial linear (ordinary least squares (OLS)), SLM, and SEM models, are applied to explore the correlation between different factors and population agglomeration degree of UAs, which enables us to select the best model. According to the test criteria of the models (Le Gallo and Chasco, 2015), the SEM model has the highest R^2 from 2000 to 2020, with the largest log likelihood function value (log L), and the smallest Akaike information criterion (AIC) and Schwartz criterion (SC), indicating that the SEM model has the best fitting effect and more accurate regression results (Table 3).

3.4.2 Influencing factors of urban population agglomeration degree of UAs by using SEM model

The influencing factors of urban population agglomeration degree of UAs in China are analyzed using the SEM model (Table 4). Results indicated that from the perspective of urban spatial interaction, the spatial error term (λ) first rises and declines from 0.588 in 2000, 0.647 in 2010, to 0.459 in 2020. In addition, the spatial error term (λ) passed the 1% level test, indicating that cities have significant positive spatial autocorrelation, and urban population agglomeration has a positive spillover effect in the adjacent geographical space. Without considering other factors, when the population agglomeration degree of neighboring cities increases by 1%, the positive impact caused by the error term drops from 0.588% in 2000 to 0.459% in 2020. This may be due to the connection between the core cities of UAs and neighboring cities are gradually deepened with the strengthened economic connection, coordinated industry development, and improved traffic network system, which is conducive to promoting the coordinated development of UAs and enhancing its economic development. In addition, with the continuous strengthening of economic connection, the population within UAs have evolved from centripetal agglomeration of core cities in early stage to centrifugal diffusion from core cities to surrounding cities in sequent stage. The population agglomeration degree in different cities of UAs show enhanced trend with the mobility of population is increasing, and the spatial distribution pattern of the population has changed.

From 2000 to 2020, the positive promotion effects of *Ind*, *Gies*, *Tpv*, *Ilei*, and *Urb* on the urban population agglomeration degree exhibit an upward trend, while the negative promotion effects of *Fai*, *Tfv*, *Edu*, and *Wel* display a downward trend. It should be noted that only *Exp* displayed a positive effect in 2000, *PerGDP*, *Tpvmd* and *Gcr* showed negative effects in 2010, and *Wag* and *Iwt* exhibited a negative effect in 2020.

Specifically, the regression coefficients of *Ilei* were

Table 3 Comparison of statistical results of OLS, SLM and SEM

Statistical test	OLS			SLM			SEM		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
R^2	0.494	0.571	0.629	0.605	0.655	0.671	0.633	0.709	0.691
log L	–162.624	–153.740	–160.335	–142.839	–135.722	–150.286	–141.127	–128.030	–148.156
AIC	357.248	339.480	352.669	319.678	305.445	334.571	314.255	288.060	328.312
SC	410.101	392.412	405.602	375.834	361.685	390.812	367.108	340.992	381.244
Breusch-Pagan	45.018***	55.713***	37.787***	57.736***	53.391***	34.579***	94.466***	61.542***	41.136***

Notes: *** represent significance level at 1%, respectively. log L, AIC, and SC were used to test goodness of fit of model, and the fitting effect will better when the AIC and SC values are smaller. Breusch-Pagan were used to test heteroscedasticity. Ordinary least squares (OLS), spatial lag model (SLM), spatial error model (SEM)

Table 4 Regression analysis results of the SEM (2000 to 2020)

Indicator	2000		2010		2020	
	Coefficient	*Z* value	Coefficient	*Z* value	Coefficient	*Z* value
Spatial error term (λ)	0.588***	9.676	0.647***	11.668	0.459***	6.312
_cons	–2.354***	–1.070	–5.332	–2.630	–5.809	–1.582
PerGDP	0.080	0.573	–0.277*	–1.842	0.060	0.326
Ind	0.199	0.943	0.413**	2.078	1.648***	4.891
Fai	–0.139	–1.630	–0.031	–0.309	–0.186*	–1.695
Tpv	0.056	0.795	0.200***	2.947	0.054	1.014
Tfv	–0.021	–0.276	–0.171**	–2.431	–0.027	–0.415
Tpvmd	0.026	0.655	–0.008	–0.198	0.013	0.214
Ilei	0.196***	2.654	0.139**	2.527	0.286 ***	4.131
Gies	0.025	0.283	0.279***	2.985	0.364***	3.683
Exp	0.105	1.402	–0.233*	–1.748	–0.242*	–1.669
Wag	0.221	0.935	0.522**	1.968	–0.051	–0.148
Edu	–0.212	–1.053	–0.649**	–2.507	–0.588*	–1.875
Wel	–0.818***	–4.625	–0.695***	–3.690	–0.558***	–2.836
Iwt	0.028	0.423	0.124	1.156	–0.248	–0.507
Gcr	0.053	0.642	–0.152*	–1.867	0.230	0.574
Urb	0.540***	2.694	1.351***	5.369	0.873**	2.351

Notes: *, **, and *** represent significance level at 10%, 5%, and 1%, respectively. The abbreviation of the indicator is the same as Table 1

0.196 and 0.286 in 2000 and 2020, respectively, with significance test at the 1% level. The regression coefficient was 0.139 in 2010, with significance test at the 5% level, indicating *Ilei* has a significant positive effect on urban population agglomeration degree. This may because the cities with high *Ilei* tend to have better employment structure, meaning they can provide more types of jobs, meet the employment choices of different groups of people, and attract more people to gather in cities.

The regression coefficients of *Urb* were 0.540 and 1.351 in 2000 and 2010, respectively, with significance test at the 1% level, while the regression coefficient was 0.873 in 2020, with significance test at the 5% level, indicating *Urb* has a significant positive effect on urban population agglomeration degree. This may be because it was easier for cities with high *Urb* to attract people to enter and gradually settle using its advantages of higher economic development level, which can improve the population agglomeration degree.

The regression coefficient of *Ind* was 1.648 in 2020, with significance test at the 1% level, while it was 0.413 in 2010 with significance test at the 5% level, indicating *Ind* has a significant positive effect on urban population agglomeration degree. This may be because the cities with high *Ind* tend to have a higher level of urban industrial modernization, and provide more job opportunities to attract labor to enter cities, which can increase the population agglomeration degree.

The regression coefficients of *Gies* were 0.279 and 0.364 in 2010 and 2020, respectively, with significance test at the 1% level, indicating *Gies* has a significant positive effect on urban population agglomeration degree. This may be because the cities with high *Gies* tend to have higher development vitality of industrial entities, and can meet the needs of labor force for different jobs, thereby attracting population agglomeration.

The regression coefficients of *Wel* were –0.818, –0.695, and –0.558, in 2000, 2010 and 2020, respectively, with significance test at the 1% level, indicating *Wel* has a significant negative effect on urban population agglomeration degree. This may be because the cities with larger population size tend to have more medical resources and beds in welfare institutions. However, compared with larger permanent population, the number of beds in welfare institutions per ten thousand people will be lower. In addition, the cities with higher scale can provide a high level of medical services, and attract people to enter large cities for medical treatment even when facing medical resources shortage, which can also enhance population agglomeration degree to a certain extent.

4 Discussion

4.1 Innovation and significance

Existing studies have focused more on the analysis of demographic characteristics of a single UA, making it easy to ignore the universality and regional characteristics of population development of UAs. Research showed that the population distribution of the Tokyo metropolitan area shows a 'continuous expansion' trend (Chen et al., 2020), and the population spatial distribution of the northeastern UAs in the United States shows a multipolar feature (Yin and Shi, 2016; Amir and Shima, 2017). Compared with the research on population characteristics of UAs abroad, China not only focuses on analyzing the population characteristics of economically developed UAs such as the YRD, BTH and et.al, but also focuses on the population characteristics of UAs with relatively low levels of economic development (Sun et al, 2012; He et al, 2019). This study analyzed the characteristics of population agglomeration by taking UAs as whole, and discussed the relationship between UAs to country and region, which provide a new perspective for the study of population agglomeration of country and region. This study established that the total population of UAs in China presents a similar spatial distribution pattern to the Hu Line from the perspective of UAs, and permanent population gradually gather to the economically developed UAs in the eastern and central regions of China (Yin et al., 2023). The UA with higher development level has more attractive to population, and exhibit higher population agglomeration degree. However, the main difference is that annual average population growth rate of most UAs on the southeast side of the Hu Line has slowed, while that of UAs on the northwest side has significantly increased. The population increase in the area southeast of the Hu Line of China is mainly affected by UAs. This may be related to increasing policy support for economic development in the central and western regions of China, which has accelerated economic development and enhanced attractiveness to the population. It may also be related to population backflow in the process of population flow in China in recent years. With more people willing to return to their hometown or provincial capital cities in the central and western regions to settle and live, the population gathering capacity of these core cities are constantly strengthened (Yu et al., 2017; Liu et al., 2021). In addition, although the population scale of most UAs continued to expand from 2010 to 2020, that of the HBCC and MSLN UAs was significantly reduced, which may be related to large population loss of shrinking cities in Northeast China (Meng and Long, 2022; Su and Zhang, 2010). In recent years, due to the low natural population growth rate, coupled with the slow economic development level and weak attraction to external population, the scale of new permanent population in the northeastern China has gradually decreased, leading to the negative population growth in the HBCC and MSLN UAs from 2010 to 2020 (Ma et al., 2021; Sun and Wang, 2021). This study is conducive to analyzing the characteristics of population changes on both sides of the Hu Line caused by the rapid development of UAs in the new development stage to some extent, as well as its impact on the spatial distribution pattern of China's population.

In addition, existing studies have focused more on certain factors such as traffic conditions and industrial development to analyze factors affecting population agglomeration (Zeng et al., 2019), while lacked comprehensive analysis of factors and spatial spillover effect of the influencing factors. The natural environment factors have relatively limited impact on population growth in China (Shi et al., 2023), while the economic factors and comfort factors on population spatial flow and agglomeration is constantly increasing, and become an important factor affecting the changes in regional population spatial pattern (Liu et al., 2022). A total of 15 indicators including economic development and social conditions factors was selected to comprehensively analyze the factors affecting population agglomeration of UAs from multiple dimensions, and the spatial econometric model was used to further explore whether the population agglomeration of UAs causes spatial spillover effects and the extent of spillover effects. *Urb* and *Ind* are found to play a strong role in promoting population agglomeration degree, and more people will be attracted to cities of UAs by improving these, which can promote the level of urban population agglomeration degree. With the gradual advancement of new urbanization, relaxed urban settlement policy and various preferential policies conducive to the citizenization of external population can reduce various hidden costs in the process of population mobility and migration, and strengthen the ability of the population agglomeration effect of core cities. Furthermore, it may also be related to the fact that the optimization and upgrading of industrial structure provides more employment opportunities, and drives the development of relevant industries, which is conducive to attracting many people to gather in cities of UAs.

4.2 Policy implications

Against the background of development of new urbanization, this study puts forward the following suggestions: 1) Improving the spatial coverage of public service facilities, increasing the number of basic public service items enjoyed by non-registered permanent residents in inflow places, and promoting the full coverage of urban basic public services, the permanent population in UAs can fully enjoy the high-quality public services, medical resources, and education, and the quality of urbanization of agricultural transfer population can be improved. 2) Promoting the development of UAs by classification, will improve the population and economic carrying capacity of UAs, and can create new power source and growth pole for high-quality development of UAs. 3) Making use of different type of capital in economic development and utilizing the advantages of capital, technology, and other factors will improve the level of urban industrial modernization.

4.3 Limitations and future research

This study mainly analyzes spatial-temporal evolution characteristics and influencing factors of UAs using cross-sectional data of the fifth, sixth, and seventh population censuses, focusing more on long-term and dynamic analysis of population spatial characteristics. However, it lacks the application of big data such as Tencent location, mobile signaling, and so on, and fails to integrate the concept of population flow, which needs to be further deepened in the future.

5 Conclusions

Based on data of the fifth, sixth, and seventh population censuses, this study uses spatial econometric models as main methods to analyze spatial-temporal evolution characteristics of population agglomeration of UAs in China, and explore factors affecting such population agglomeration. The main conclusions are as follows:

(1) From 2000 to 2020, the population gradually converged into UAs in China. The higher the development level of UA, the higher the population agglomeration degree. Although UAs are the main regions with large permanent population growth, and population scale of most UAs continues to increase, the HBCC and MSLN UAs exhibit a population reduction trend from 2010 to 2020. In addition, the cities with similar population agglomeration degree tend to be concentrated in space, but the positive spatial autocorrelation of urban population agglomeration degree in China has gradually weakened from 2000 to 2020. The urban population agglomeration has a positive spillover effect on the adjacent geographical space. Without considering other factors, when the population agglomeration degree of neighboring cities increases by 1%, the positive impact caused by the error term is 0.459% in 2020.

(2) From the perspective of factors affecting population agglomeration and spatial distribution of UAs in China, the economic development factors have gradually become the promoting factors, and the social conditions factors have become the guiding factors. In addition, the main factors to population gather into UAs are similar with the outside UAs, while the factors of *Urb* and *Ind* are important to promote population gather into UAs in this study, and the promotion of *Urb* and *Ind* of UAs in China are enhancing. Besides, the urban comfort factors, such as high-quality public services, good urban living environment conditions, high-quality medical and educational resources, are also important factors to promote urban population gather into UAs.

This study has analyzed the population distribution and influencing factors of UAs in China from the perspective of UAs by using the latest data of the seventh population census, which provide a basis for formulating the development planning of UAs. In addition, the influencing factors of UAs in China have both similarities and differences with the outside UAs, which the promotion of *Urb* and *Ind* on population gather into UAs are enhancing, and the urban comfort factor has also gradually enhanced the role of promoting population agglomeration.

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