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Characteristics and Influencing Factors of Population Migration under Different Population Agglomeration Patterns—A Case Study of Urban Agglomeration in China

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Abstract: China's urban agglomerations (UAs) are striving to build a new development pattern oriented towards the new era and new stage, and the population distribution is facing new problems of synergy with the layout of labor factor productivity and regional coordinated development. Therefore, this study couples UAs with population distribution, using data from three population censuses and nighttime light data in 2000, 2010, and 2020, to measure the population agglomeration patterns of Chinese UAs using population agglomeration indicators and to explore the influencing factors and spatial stratification heterogeneity characteristics by constructing an econometric model. The results show that: (1) the population agglomeration patterns of Chinese UAs can be classified into four major categories: weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs, and China's UAs are in a low-level stage dominated by weakly polycentric UAs at present. (2) In terms of influencing factors, 15 indicators, such as economic development and social conditions, are important factors affecting the population agglomeration patterns of the four UAs, but their effects vary greatly due to specific patterns. (3) For specific agglomeration models, the total passenger volume has always been the strongest positive influencing factor for weakly polycentric UAs; the industry location entropy index, scale of fiscal expenditure, and total passenger volume in municipal districts are relatively strong positive effects to weakly monocentric UAs, the per capita GDP and urbanization rate are relatively strong positive effects to strongly monocentric UAs, and the urbanization rate is always the strongest positive effect to strongly polycentric UAs. The refined analysis of population migration in Chinese UAs in this study enriches the theoretical results related to population migration in Chinese UAs to a certain extent and provides a feasible basis for the development of new development patterns in Chinese UAs and the formulation of regional population policies in the new stage. Meanwhile, this study divided the polycentric attributes of different UAs, which provide a reference for the theoretical development of polycentric spatial structure of UAs.

Keywords: population agglomeration degree; population agglomeration pattern; geographic detector model; urban agglomeration; China

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1. Introduction

As an important region in the world with a high concentration of population, the share of population in urban agglomerations (UAs) has increased from 46.69% in 2000 to 56.15% in 2020 [1] and is expected to reach 68% by 2050 and 85% by 2100 [2]. In addition, the population of the world's top 100 UAs has increased by about 36%, with an average annual growth of about 6.6 million people [3]. The idea of UAs first originated from the concept of "town clusters" proposed by E. Howard (UK) [4], and then Gottmann (France) proposed the concept of "megalopolis" when he analyzed the dense distribution of cities along the northeastern coast of the United States [5]. There are other concepts similar to UAs in Western academia, such as "Desakota" [6] and "Global City Region" [7,8]. Meanwhile, in Chinese academia, Yao Shimou first systematically proposed the concept of UAs [9], and, although scholars have also proposed similar concepts, such as "extended metropolitan regions" [10] and "metropolitan regions" [11], most of the current Chinese geographers use the term "urban agglomeration (UA)" in their studies [12,13]. In China, with the development of the economy, UAs have become important places with the highest concentration and most frequent flow of the Chinese population, so the agglomeration pattern presented by UAs is unique.

Population mobility is usually a process of pursuing individual interests, which makes factors such as economic opportunities, geographical proximity, and environmental conditions in the inflow location important factors influencing population mobility [14]. With the further enhancement of the development imbalance between regions and the gradual relaxation of the household registration system, the dynamism of population mobility in China is increasing [15]. This dynamism is also reflected in relevant studies on population mobility. Not only have some scholars used census data or statistical data, radiation model, social network analysis, and other methods to analyze the population mobility characteristics from a macro perspective [16] but some scholars have also used mobile positioning data and location big data to explore the population mobility characteristics in short time periods [17], while others have used data from mobile population surveys and sampling questionnaires to analyze the population mobility characteristics from a microscopic perspective [18]. Under the influence of factors such as natural environment, economic development, and social conditions, a large number of population movements will have a profound impact on the spatial structure of a region, especially UAs [19]. In terms of studies on the spatial structure of UAs, some scholars have studied the spatial structure and morphology of UAs in terms of the evolution process of the spatial structure of UAs [20]. Some scholars also believe that the formation and development of the spatial structure of UAs is the process of continuous agglomeration of various production factors [21]. The polycentric structure, as an important form of spatial structure of UAs, has gradually attracted the attention of scholars [22]. Some scholars have conducted in-depth exploration on the polycentric spatial structure of UAs using diversified big data [23,24] and believe that the polycentric spatial structure of UAs is conducive to promoting green economic growth [25], and enhancing the economic performance of UAs [26]. However, some scholars believe that the polycentricity of UAs may have certain negative effects [27,28], and the economic benefits generated by UAs in different development stages often show significant differences [29].

Scholars have focused more on the study of polycentric spatial structure at the urban scale [30,31]. There are often several central regions within Chinese cities based on population grid data [32]. The polycentric spatial structure is conducive to promoting the sustainable development of some mega-cities [33]. In terms of the study on polycentric spatial structure and economic performance, some studies suggest that the adjacent agglomerations formed by small-scale cities in a morphological polycentric spatial structure are unable to generate a synergy effect, nor do they have a significant impact on the economic development of central cities [34]. Additionally, the agglomeration of factors such as population and industry in small-scale cities can, to some extent, reduce the negative externalities [35]. However, some scholars believe that polycentric spatial structure may weaken the effect of urban economic growth poles [36], and the efficiency of factor flow decreases due to the increase in commuting distance and transportation costs [37]. In contrast, a monocentric spatial structure with good accessibility can more easily promote economic growth [38], and, therefore, some scholars believe that monocentric spatial structure may be more beneficial to economic performance. In addition, research has also found that a polycentric spatial structure can reduce the intensity of the urban heat island [39], produce a significant pollution reduction effect by affecting the region's PM2.5 [40], and also reduce industrial enterprise pollution emissions by enhancing the mobility of factors [41].

Scholars have gradually explored the demographic characteristics presented by the spatial structure of UAs due to the in-depth exploration on the polycentric spatial structure [42]. The essence of the urban agglomeration model is to analyze the spatial distribution pattern of population and its evolution trend within the UAs from the perspective of population, and the data used are gradually expanded from the census and statistical data to the dynamic monitoring data of floating population and location big data, and the methods adopted are gradually changed from the statistical methods to the social network analysis methods. It was found that the population distribution in the Tokyo metropolitan area gradually changed from "isolated agglomeration" to "contiguous spreading" [43]. The spatial distribution of the population in the northeastern urban agglomerations of the United States tends to change from unipolar to multipolar, and the spatial structure of the population is both aggregated and dispersed [44]. The distribution structure of employees in the 356 metropolitan areas of the United States indicates that the spatial structure can be divided into three main types: monocentric, polycentric, and decentralized distribution, with the polycentric type located mainly in large cities [45]. The urban areas in central Scotland show polycentric characteristics in terms of morphology [46].

When analyzing the population agglomeration characteristics for regional or national UAs, more Chinese scholars mainly analyze them from a single or several UAs, such as the Yangtze River Delta urban agglomeration (YRD) [47,48] and the Middle Reaches of Yangtze River urban agglomeration (MYZ) [49,50]. The central cities of the YRD urban agglomeration show a tendency of agglomeration and clustering, while the peripheral cities show a tendency of dispersed deviation [51]. The Central Plains urban agglomeration (CPL) evolved from a core growth weak core traction in the early age to the current polycentric grid-based spatial development pattern [52]. The MYZ urban agglomeration has an obvious core–edge trend, showing a "pyramid" structure [53]. In addition, some scholars have analyzed the population agglomeration pattern of Chinese UAs as a whole [54]. It was found that, since the 1980s, most Chinese UAs have formed a polycentric spatial structure [55]. Additionally, based on two indices, the Gini index and the urban primary degree, Chinese UAs can be classified into four categories: strongly monocentric, weakly monocentric, polycentric, and weakly central [56]. The eastern coastal UAs in China exhibit a high degree of polycentricity, while the UAs in the western region generally lack polycentricity [57]. Further, UAs at higher levels of development are mainly located in the eastern coastal regions of China, forming a certain population hierarchy [13]. The UAs of China show an obvious polycentric trend, and different attributes, such as economic level, population size, and transport infrastructure, play a significant positive role in shaping the polycentric nature of UAs [58].

At the same time, with the increase in scholars' study on the population agglomeration patterns in UAs, there has been a gradual increase in the number of studies on the influencing factors of population agglomeration to UAs, which involve the natural environment, economic development, and social conditions [59,60]. It was found that the natural environment is a fundamental factor influencing population distribution and mobility; i.e., changes in the natural environment can enhance population mobility and thus affect the spatial agglomeration pattern of the regional population [61]. Economic development factors, on the other hand, are facilitating factors that influence population agglomeration and spatial distribution, and economic factors can enhance the attractiveness of a population by providing advantages such as higher income levels and more employment opportunities to the population, thus promoting spatial mobility and agglomeration [16,62]. Meanwhile, social conditions factors are guiding factors; social factors such as employment opportunities, expected income levels, and technology drive population spatial agglomeration through their attractiveness to the population [61,63]. In short, UAs attract many populations through a higher degree of opening to the outside world, stronger level of economic development, better-quality public services, and stronger agglomeration scale benefits [64,65]. For UAs in China, economic factors, whose influence is more important than policy factors, are the main factors for higher population mobility within UAs [66].

For example, for the Beijing–Tianjin–Hebei urban agglomeration (BTH), on the one hand, human capital accumulation, industrial structure characteristics, and public service levels are important factors for long-term population mobility [67]; on the other hand, work and business are still the main factors for short-term population mobility [68].

Existing studies mostly focus on the analysis of population agglomeration patterns of single or several UAs while less on the analysis of population agglomeration patterns of UAs and their evolutionary characteristics from a demographic perspective [52,69]. Additionally, in the process of classifying the types of UAs, although some studies have classified national UAs from demographic data [55] and judged the types of individual UAs from nighttime light data (NTL) and diversity data [70], relatively few studies have been conducted on the correlation between the two. Moreover, in the process of analyzing the factors influencing population agglomeration, existing studies have focused more on the influence of a certain factor on urban population agglomeration and less on the spatial heterogeneity characteristics of the influencing factors, which is not comprehensive [71]. Compared with existing studies, this study does not simply analyze the population migration characteristics under the large scale of Chinese UAs but classifies the types of population agglomeration patterns based on the differentiated characteristics of different UAs and summarizes the general laws of their evolution, which makes this study more in line with the reality of population migration in Chinese UAs. Additionally, based on different population agglomeration patterns, this study analyzes the population migration characteristics of different UAs and their influencing factors, and the findings conclude feasible Chinese experiences for population migration in UAs.

This study aims to investigate the following questions: first, what is the basis for classifying the population agglomeration patterns of UAs in China? Second, from 2000 to 2020, what are the characteristics and evolution rules of population migration in different agglomeration patterns of UAs in China? Third, what are the possible factors influencing the population agglomeration patterns of different UAs, and what are the main differences among them? Compared with existing studies, this study mainly conducts new analysis and discussion on theories, study methods, and data. Firstly, by exploring the internal population flow and agglomeration characteristics of different population agglomeration attributes in UAs, the study to some extent enriches the theoretical and practical achievements of population migration in UAs and the polycentric spatial structure of UAs. Secondly, by using two dimensions, population agglomeration degree and population primacy degree, to divide the population agglomeration pattern of UAs, this study makes the results of population migration in large-scale UAs in China more credible. Finally, by using the geographical detector model, the spatially stratified heterogeneous characteristics of the influencing factors are obtained. This study hopes to provide a reference for the development of new urbanization in Chinese UAs and the formulation of regional population policies.

2. Materials and Methods

The research framework contains three main sections. The first part reveals the characteristics of population agglomeration in China's UAs from the aspects of population agglomeration degree, population primacy degree, and net migration rate. The second part first obtains the classification of population agglomeration patterns of UAs and classifies China's 19 UAs into 4 categories: weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs. Secondly, this study provides an analysis of the population migration characteristics presented by different urban agglomeration patterns. Then, this study comprehensively considers the influencing factors of population agglomeration from the factors of both economic development and social conditions and uses the geographical detector model to obtain the spatial stratified heterogeneity characteristics of influencing factors. The third part summarizes the evolution law of population agglomeration patterns in China's UAs based on population data and compares and evaluates the types of UAs obtained from NTL data. The working flowchart is as follows (Figure 1).

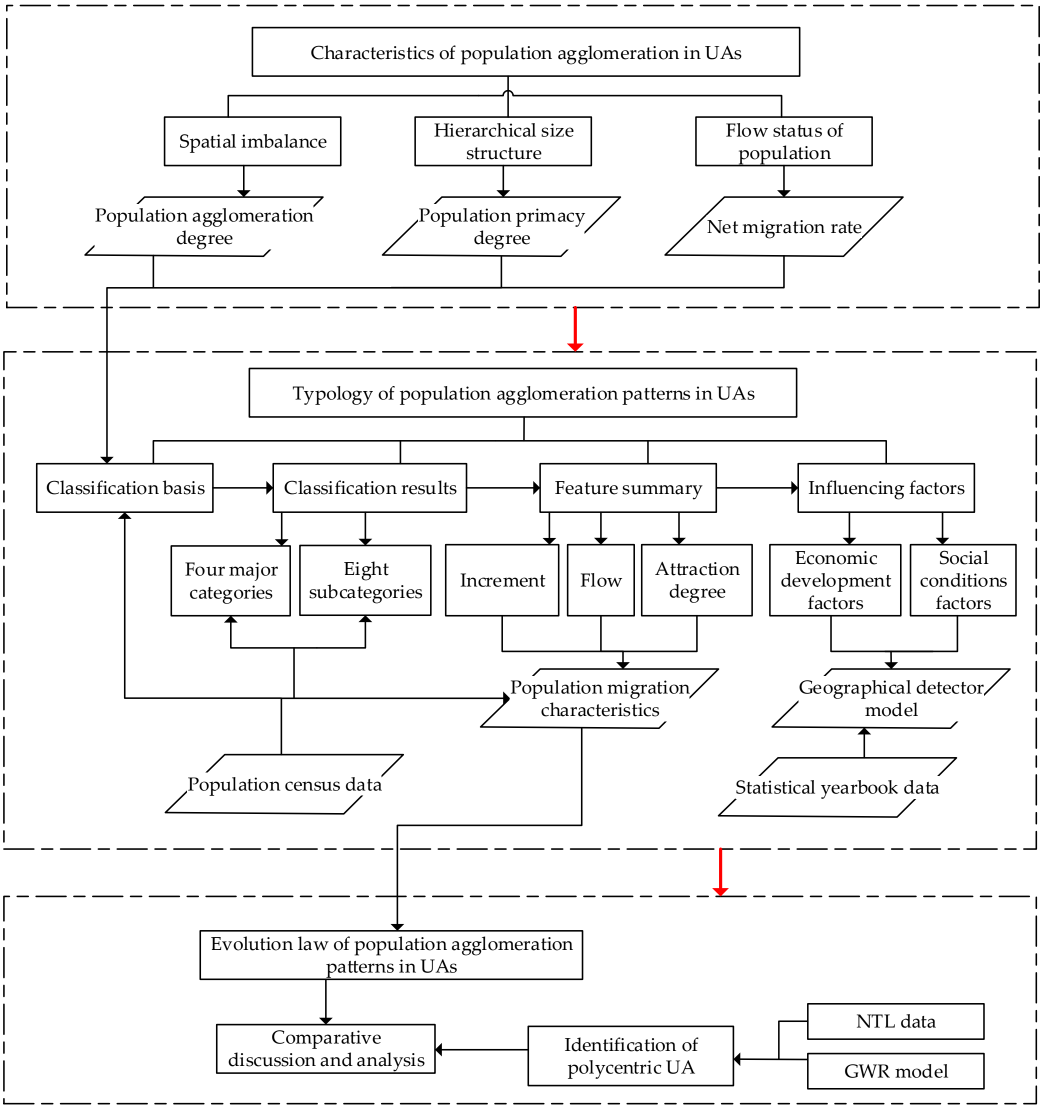

Figure 1. Working Flowchart.

2.1. Study Area

The scope of the 19 UAs in China is mainly derived from the thirteenth five-year plan (from 2016 to 2020) [72]. In 2020, the number of cities involved in the 19 UAs is 257, accounting for about 40% of the total number of cities in China; their GDP, on the other hand, accounts for about 85% of the total GDP of all Chinese cities [73]. The population agglomeration degree of 19 UAs has increased from 2.57 in 2000 to 2.70 in 2020, and the total number of permanent residents increased from 901.95 million to 1069.88 million; meanwhile, the net migration rate of the population in UAs has also increased from 2.68% in 2000 to 5.50% in 2020, which indicates that the UAs are important places with large populations, rapid growth, and net population inflow in China. The UAs, with their strong economic development strength, have stronger attraction to the population than outside UAs. From 2000 to 2020, the YRD, PRD, and 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 [74,75]. Additionally, according to the development level of the 19 UAs in China in 2010, they can be classified into four development types, namely Low level, Low-middle level, Upper-middle level, and High level UAs [13] (Figure 2).

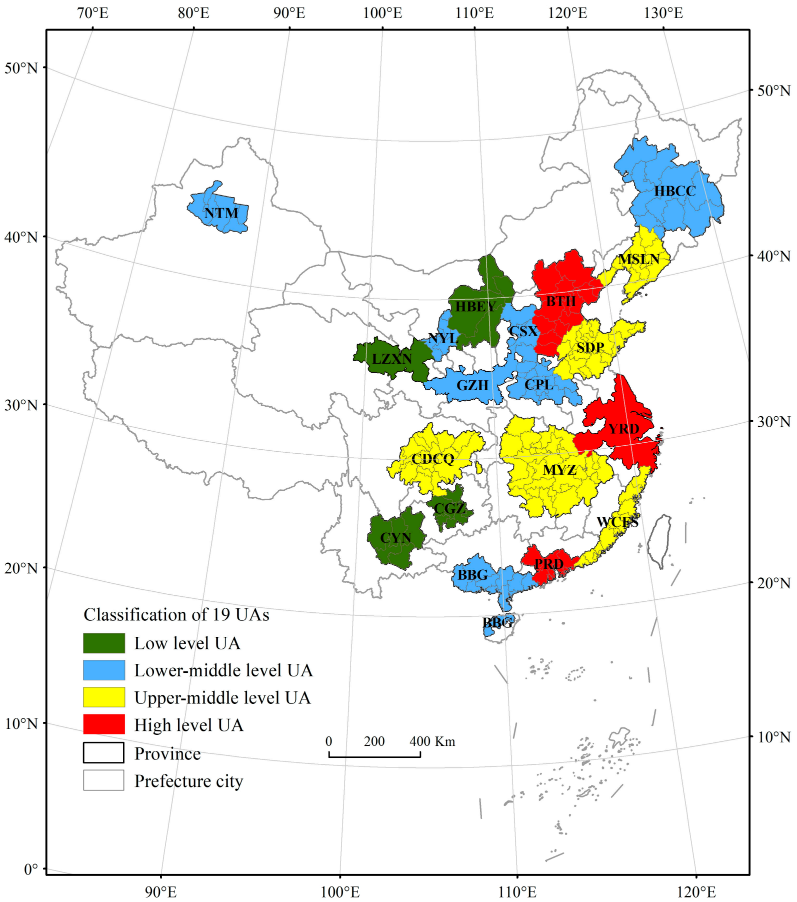

Figure 2. Spatial Scope of 19 UAs in China. Note: original source is from the Standard Map Service website (http://bzdt.ch.mnr.gov.cn/, accessed on 25 September 2021), Number: GS (2019) 1699.

2.2. Data Sources

The sources of demographic data, economy, vector layer, NTL, and other data are shown in Table 1. Among them, the economic data are selected from the China City Statistical Yearbook in 2001, 2011, and in 2021; the main reason for such selection is because they reflect the economic development of the previous year, which is more consistent with the years of the fifth, sixth, and seventh census data. In addition, the administrative divisions used in the vector layers uniformly use the 2010 division results.

Table 1. Data Sources.

Type	Data Sources	Accessed Date	Acquisition Websites
Demographic Data	Tabulation on the Population Census of the People's Republic of China by County(2000, 2010, 2020)	15 September 2021	http://www.stats.gov.cn/ (accessed on 25 September 2021) [74,75]
Economic Data	China City Statistical Yearbook (2001, 2011, 2021)	1 September 2021	https://data.cnki.net/yearBook/ (accessed on 25 September 2021) [73]
Vector Layer	Resource and Environmental Data Center	25 September 2021	http://www.resdc.cn/ (accessed on 25 September 2021)
NTL Data	The National Center for Environmental Information (NCEI) of National Oceanic and Atmospheric Administration (NOAA) (2000, 2010, 2020)	5 September 2021	https://eogdata.mines.edu/products/vnl/ (accessed on 25 September 2021)

2.3. Index System

The spatial agglomeration and flow of population is a dynamic process, and its influencing factors often involve natural environment, economic development, social conditions, and policies. The natural environment, a fundamental factor, mainly affects the flow and spatial agglomeration of population through geographical location, altitude, temperature, precipitation, and other factors [59]. Many scholars have explored the correlation between natural environmental factors and population distribution and flow through qualitative analysis, and research showed that the impact of natural environmental factors is gradually declining [61]. In addition, economic development factors and social condition factors, as important pulling forces for population spatial agglomeration and flow, have increasingly increased their impact on population [16].

As the main factor influencing population migration, the spatial migration of population is mainly for economic development factors, such as access to higher wages, more employment opportunities, higher economic status, etc. [76,77]. Economic differences between regions drive population movement and concentration from less developed regions to economically developed regions, mainly because, first, cities with higher levels of economic development tend to offer higher labor compensation, more employment opportunities, etc. Second, the higher the degree of regional economic development, the greater the demand for various factors, such as capital, technology, and personnel, which facilitates the free flow of various factor resources and thus creates a stronger attraction for the population [78,79]. Third, the optimization and upgrading of industrial structure also attracts the cross-regional mobility of labor by providing more jobs, which makes the population of the region change [80]. Fourth, a convenient transportation system can bring closer the intensity of connections among cities, as well as the intra-city movement of various factors, thus reducing production and commuting costs, which in turn has an important impact on the spatial agglomeration of population in the region [81,82]. In addition, as the scale of financial expenditures that cities can provide increases, the level of public service capacity spent on public services also increases, which is conducive to enhancing the attractiveness of people with different needs, such as schooling and medical care [83], and the ability to provide higher quality public services, higher levels of openness, and a good living environment are likely to be attractive to the population [84,85]. The cities with high urbanization rates also attract a large inflow of population and increase the level of population agglomeration through policy preferences and other measures [86]. Compared with existing studies, this study mainly focuses on economic development and social condition factors (Table 2).

Table 2. Influencing Factor Index System.

Factors	Name of Indicator (Abbreviation)	Representational Meaning	References
economic development factors	per capita GDP (PerGDP)	reflecting the regional economic development degree	[62,85]
	Proportion of tertiary industry in GDP (Ind)	reflecting the urban industrial modernization level	[67,76]
	Investment scale of fixed assets (Fai)	reflecting the urban economic development vitality	[78]
	Total passenger volume (Tpv)	reflecting the convenience of personal mobility ability of other cities outside the city	[65,82]
	Total freight volume (Tfv)	reflecting the convenience of goods mobility ability of other cities outside the city	[82]
	Total passenger volume in municipal districts (Tpvmd)	reflecting the convenience of personal mobility ability within the city	[81]
	Industry location entropy index (Ilei)	reflecting the urban employment structure	[13]
	Growth index of enterprise structure above Designated Size (Gies)	reflecting the economic development vitality of urban industrial subjects	[13]
social conditions factors	Scale of fiscal expenditure (Exp)	reflecting the ability to provide urban public services and infrastructure	[82]
	Average wage of on-the-job employees (Wag)	reflecting the urban average wage level	[63,66]
	Teacher–student ratio in primary and secondary schools (Edu)	reflecting the ability to provide education resources	[80,85]
	Number of beds in welfare institutions per ten thousand people (Wel)	reflecting the ability to provide medical service	[67,82]
	Standard rate of industrial wastewater treatment (Iwt)	reflecting the urban production environment conditions	[82]
	Greening coverage rate of built-up area (Gcr)	reflecting the urban living environment conditions	[84,85]
	Urbanization rate (Urb)	reflecting the population migration degree to city	[76,86]

2.4. Study Methods

2.4.1. Measuring of Population Agglomeration Patterns in UAs

(1) Net Migration Rate

The net migration rate of the population can clearly reflect the inflow or outflow status of the population in the region and thus identify the net inflow population area or net outflow population area [87]. The calculation formula is provided in Equation (1).

$$NM = (P_{permanent} - P_{registered})/P_{permanent} \times 100\% \tag{1}$$

where NM is the net migration rate of population, $P_{permanent}$ is the permanent population, and $P_{registered}$ is the registered population. When NM value is positive, it indicates that the population is flowing into the area, forming a net inflow population area; conversely, it forms a net outflow population area.

(2) Population Agglomeration Degree

Population agglomeration degree refers to the ratio of regional population density to the population density of China in the current year, which can clearly reflect the degree of population agglomeration of a region relative to the population of China [88]. The calculation formula is provided in Equation (2).

$$JJD_i = \frac{(P_i/P_n) \times 100\%}{(A_i/A_n) \times 100\%} = \frac{P_i/A_i}{P_n/A_n} \tag{2}$$

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

(3) Population Primacy Degree

Population primacy degree is the degree of variability between primary city and secondary city, which can clearly reflect the hierarchical size structure of population distribution [89,90]. The calculation formula is provided in Equation (3).

$$Q = \frac{P_1}{P_2} \tag{3}$$

where Q is the population primacy degree, P_1 and P_2 are the population size of the primary city and the secondary city, respectively.

2.4.2. Measuring of Factors Influencing Population Agglomeration Degree in UAs

(1) Linear regression model

This study selects the population agglomeration degree (JJD) of the city as the dependent variable and 15 indicators to be tested as independent variables and constructs linear regression model to explore the factors that affect the population agglomeration degree of UAs. The population primacy degree reflects the hierarchical size structure of population distribution and the population gap characteristics between the first city and the second city, which is not as significant as the population agglomeration degree index on characterizing the significance of population agglomeration. The calculation formula is provided in Equation (4).

$$\begin{aligned} JJD = \beta + \beta_1\, perGDP + \beta_2\, ind + \beta_3\, fai + \beta_4\, tpv + \beta_5\, tfv + \beta_6\, tpvmd + \beta_7\, ilei + \beta_8\, gies + \beta_9\, exp + \beta_{10}\, wag + \beta_{11}\, edu \\ + \beta_{12}\, wel + \beta_{13}\, iwt + \beta_{14}\, gcr + \beta_{15}\, urb + \xi \end{aligned} \tag{4}$$

where β, β_1, β_2, ... , β_{15} are parameters to be estimated, JJD is the population agglomeration degree. The meaning of indicators to be tested is shown in Table 2. ξ is a random disturbance term obeying normal distribution. Subsequently, this study takes the indicators that significantly affect JJD as independent variables of the geographical detector model and further explores the spatial stratification heterogeneity characteristics of the influencing factors.

(2) Geographical detector model

The geographical detector model was initially used to explore the geographical relationship between disease causes and disease distribution and was used to explore the spatial heterogeneity of the effects of influencing factors by using the advantages in spatial regression [91,92]. This study uses geographical detector model to explore the spatial stratification heterogeneity characteristics of influencing factors in UAs. Specifically, the population agglomeration degree is dependent variable and 15 variables that have a significant impact on JJD in the linear regression model are selected as independent variables. The calculation formula is provided in Equation (5).

$$q = 1 - \frac{1}{N\sigma^2}\sum_{m=1}^{L} N_m \sigma_m^2 \tag{5}$$

where q is the explanatory power of regional geographic environmental factors, $m = 1, 2, \ldots, L$ is the number of categories, N_m and N are the number of layer m and the number of cells in the whole region, respectively, σ^2 is the variance of the indicator. Further, values range from 0 to 1, and larger q values indicate stronger explanatory power of spatial heterogeneity.

3. Results

3.1. Typology of Population Agglomeration Patterns in UAs

3.1.1. Evolution Characteristics of Population Agglomeration in UAs

The change in population agglomeration degree reflects that China's population is more concentrated in UAs with higher levels of economic development. Overall, population agglomeration degree shows a positive correlation with the development degree of UAs; that is, the higher the development degree of UAs, the more attractive they are to the population and the higher the population agglomeration degree. From 2000 to 2020, the share of permanent population in Low level, Low-middle level, Upper-middle level, and High level UAs evolves from 4.31%, 16.45%, 31.33%, and 20.49% in 2000 to 4.61%, 16.18%, 30.03%, and 25.07% in 2020, respectively, with the High level UAs increase of 4.58%, which indicates that the attractiveness of such UAs to the population is increasing. In addition, from 2000 to 2020, only the total permanent population of the Harbin–Changchun urban agglomeration (HBCC) decreases by −3.66 million, while the other 18 UAs show an increase in the total permanent population, with the Pearl River Delta (PRD) and the YRD urban agglomerations ranking the top two, with an increase of 2.08% and 1.92% of the share of the permanent population, respectively (Figure 3).

The change in the degree of population primacy reflects the increasing unevenness of population distribution in most UAs in China. This is not only related to the total existing population and the average annual growth rate of population in cities of different size classes within UAs but is also related to the increase in the number of population in the primary city due to the change in the administrative division of cities; it is related to the fact that some provinces are promoting the development strategy of provincial capital cities one after another as well so as to attract a large population. From 2000 to 2020, among the nineteen UAs, the population primacy degree of twelve UAs shows an increasing trend, and six UAs show a decreasing trend. Additionally, in the three time periods from 2000 to 2010, from 2010 to 2020, and from 2000 to 2020, the population primacy degree of eight UAs, mostly belonging to the less developed UAs (the Beibu Gulf (BBG), Central Yunnan (CYN), Guanzhong Plain (GZH), Central Shanxi (CSX), Lanzhou–Xining (LZXN), Ningxia Yellow River (NYL), Northern Tianshan Mountains (NTM), and BTH urban agglomeration), continues to increase, while the population primacy degree of four UAs, mostly belonging to the more developed UAs (Chengdu–Chongqing (CDCQ), Hohhot–Baotou–Ordos–Yulin

(HBEY), Shandong Peninsula (SDP), and PRD urban agglomeration), continues to decrease (Figure 3).

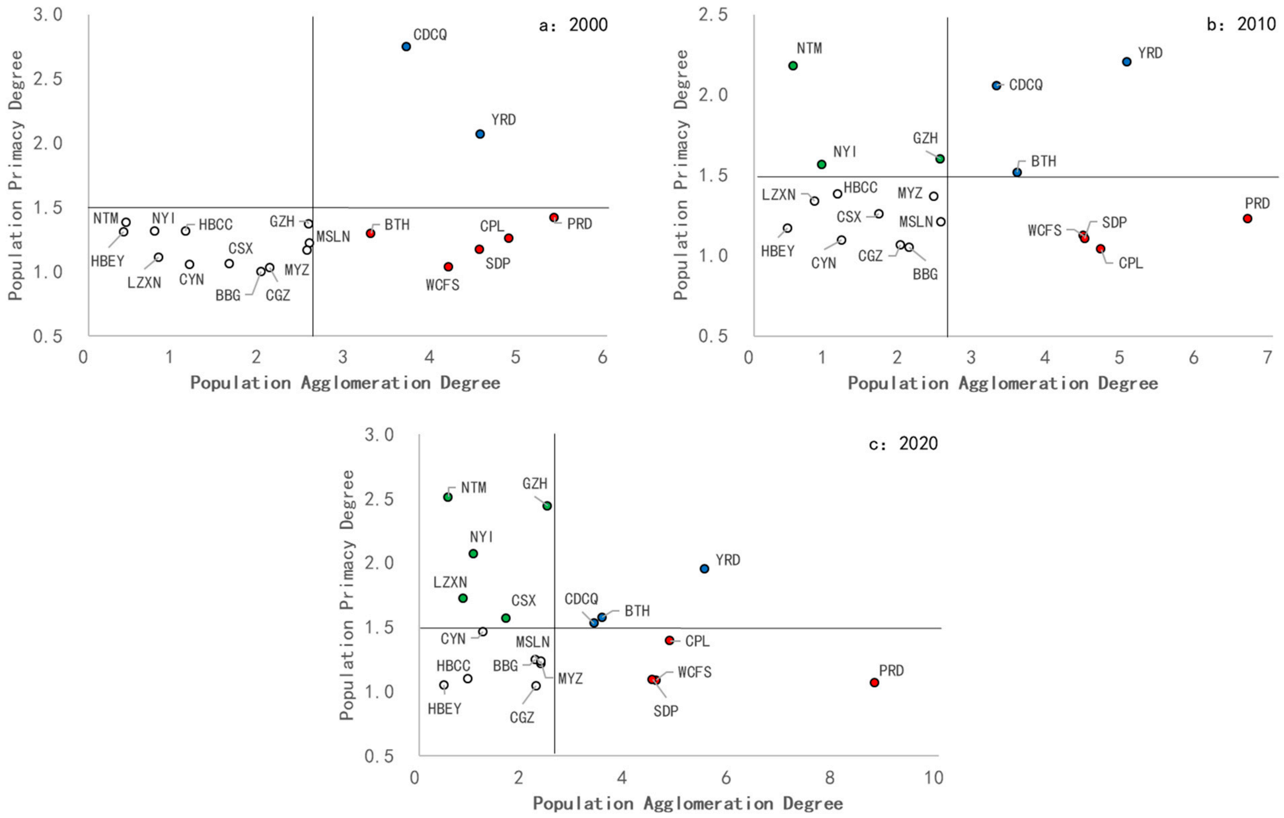

Figure 3. Evolution Characteristics of Population Agglomeration Degree and Population Primacy Degree of UAs in China from 2000 to 2020 ((**a**): 2000; (**b**): 2010; (**c**): 2020).

3.1.2. Classification Results of Population Agglomeration Patterns in Different UAs

The classification of population agglomeration pattern of UAs is mainly achieved by the two indices, namely population agglomeration degree and population primacy degree. On the one hand, UAs can be classified into strong population agglomeration and weak population agglomeration according to the level of population agglomeration degree. On the other hand, UAs can be classified into monocentric and polycentric according to the level of population primacy degree, and then can be further classified into four major categories, weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs (Figure 4), among which weakly polycentric UAs means that the UAs have both a low population agglomeration and a low population primacy, while weakly monocentric UAs means the UAs have low population agglomeration but high population primacy. Strongly monocentric UAs means that the UAs have both a high population agglomeration and a high population primacy, while strongly polycentric UAs means that the UAs have a high population agglomeration but a low population primacy. From 2000 to 2020, the population agglomeration degree of 19 UAs in China mainly ranges from 1 to 3, while the population primacy degree mainly ranges from 1 to 2. Therefore, this study extracts 2.6 and 1.5 as the boundary values of population agglomeration degree and population primacy degree, respectively, to determine the types of population agglomeration patterns of UAs.

The four major categories of urban agglomeration patterns are then continued to be divided into eight subcategories based on the net population inflow or outflow status presented by the UAs as a whole, mainly using the CorelDRAW software to present the schematic diagram of population migration (Figure 5).

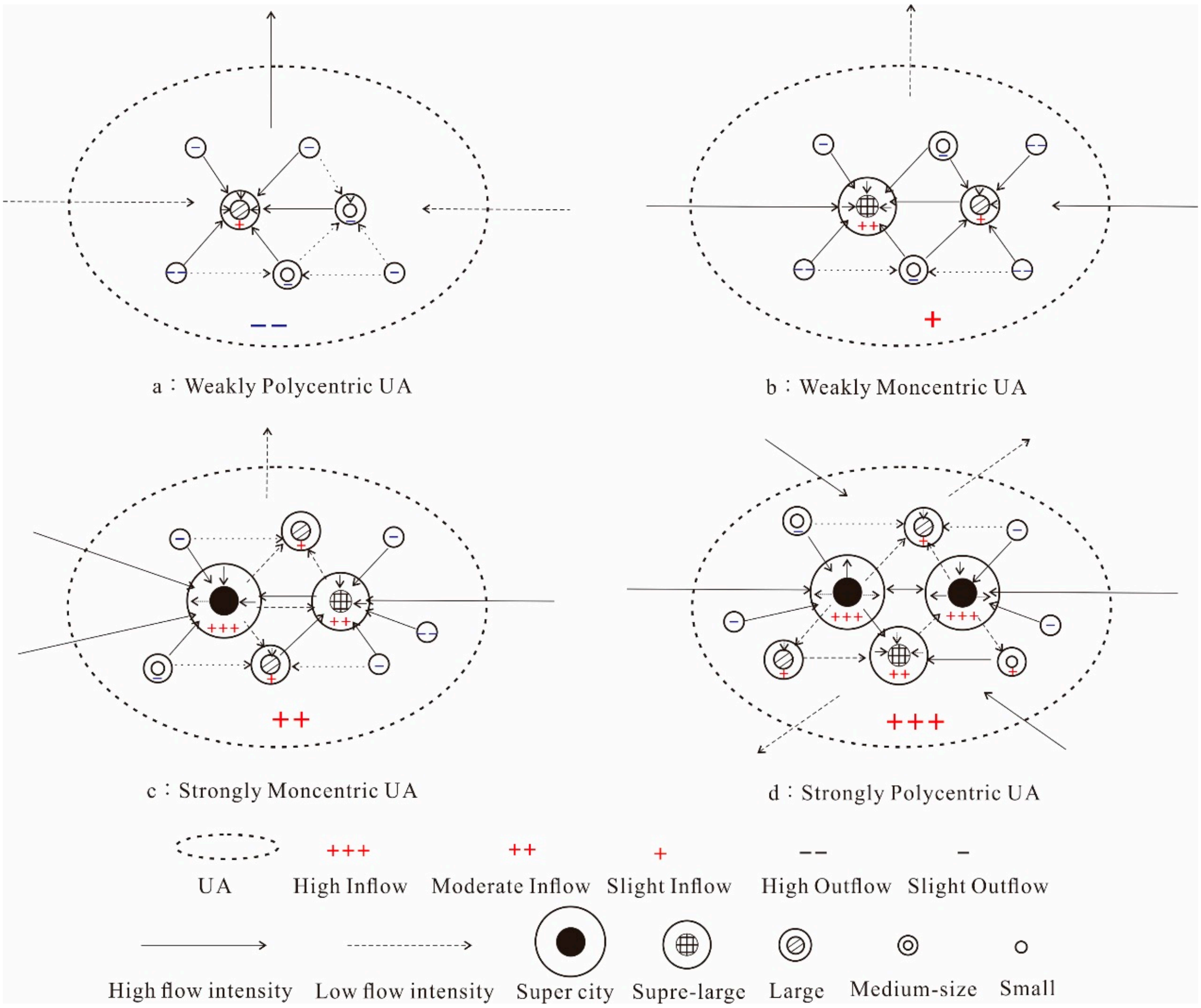

Figure 4. Four Major Categories of Population Agglomeration Patterns in Chinese UAs. Note: cities are divided into five levels based on their permanent resident population, including Super city, Super-large city, Large city, Medium-sized city, and Small cities. "+" is used to represent population inflow state, and, the more "+" signs there are, the greater the degree of population inflow. "−" represents population outflow state, and, the more "−" signs there are, the more severe the degree of population outflow. Arrows represent the direction and intensity of population mobility, with solid lines indicating a higher flow intensity and dotted lines indicating a lower flow intensity.

Currently, China's UAs are in a low-level stage dominated by weakly polycentric UAs. Overall, the evolution of population agglomeration patterns of UAs at different time points from 2000 to 2020 indicates that the number of UAs with different population agglomeration patterns in China is gradually equalized. Specifically, from 2000 to 2010, there are four UAs whose population agglomeration patterns change, among which the GZH, NYL, and NTM urban agglomerations change from weakly polycentric to weakly monocentric while the BTH urban agglomeration changes from strongly polycentric to strongly monocentric. Meanwhile, from 2010 to 2020, there are only two UAs whose population agglomeration patterns change, of which both LZXN and CSX urban agglomerations change from weakly polycentric to weakly monocentric. The main reason for such results is the increasing attractiveness of the primary city to the population, which leads to the enlargement of the population primary degree. Therefore, this study uniformly analyzes the population migration characteristics presented by the population agglomeration patterns of UAs according to the results of the agglomeration pattern classification in 2020 (Table 3).

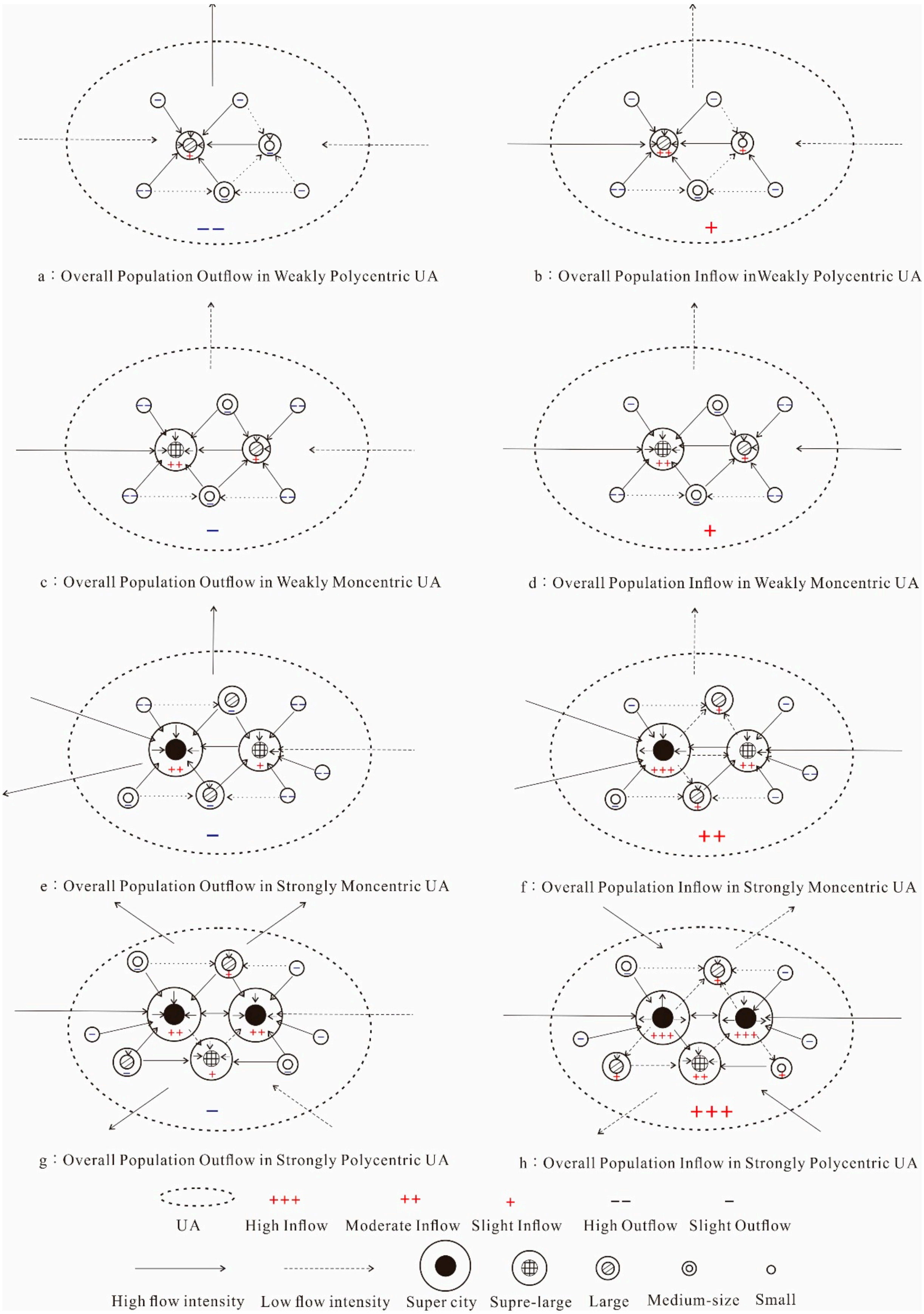

Figure 5. Population Migration of Different Urban Agglomeration Patterns in China.

Table 3. Classification Results of Population Agglomeration Patterns of UAs in China from 2000 to 2020.

Type	Name		
	2000	**2010**	**2020**
Weakly Polycentric UAs	CYN, BBG, MYZ, CGZ, HBCC, GZH, NYI, HBEY, CSX, MSLN, NTM, LZXN (n = 12)	CYN, BBG, MYZ, CGZ, HBCC, HBEY, CSX, MSLN, LZXN (n = 9)	CYN, BBG, MYZ, CGZ, HBCC, HBEY, MSLN (n = 7)
Weakly Moncentric UAs		NTM, GZH, NYI (n = 3)	LZXN, NTM, GZH, NYI, CSX (n = 5)
Strongly Moncentric UAs	CDCQ, YRD (n = 2)	CDCQ, YRD, BTH (n = 3)	CDCQ, YRD, BTH (n = 3)
Strongly Polycentric UAs	WCFS, SDP, CPL, PRD, BTH (n = 5)	WCFS, SDP, CPL, PRD (n = 4)	WCFS, SDP, CPL, PRD (n = 4)

3.2. Population Migration Characteristics of UAs with Different Population Agglomeration Types

3.2.1. Population Migration Characteristics of Weakly Polycentric UAs

Generally speaking, such UAs have a low degree of population agglomeration, a small total population, and a low degree of population primacy. The main manifestations are as follows: first, intra-provincial in-migrants are the major part of the inflow population, while the inter-provincial in-migrants are small and concentrated in the municipal districts of central cities. Second, although the natural population growth rate is at a high level, UAs are less attractive to the population. Additionally, the central cities have a high inflow of population in their municipal districts, while the surrounding districts and counties have a high outflow of population (Table 4). Such UAs can be divided into two subcategories.

Table 4. Population Migration Characteristics of Population Agglomeration Patterns in UAs.

Characteristics	Weakly Polycentric UAs	Weakly Moncentric UAs	Strongly Moncentric UAs	Strongly Polycentric UAs
Population agglomeration degree	low	lower	higher	high
Total population	small	larger	large	large
Population primacy degree	low	higher	high	lower
Population increment	The population increment of central cities is larger while the polarization effect is weaker	The primary city is experiencing more population growth and the polarization effect is increasing	The population growth of the central cities is large, and the polarization effect is more prominent	Large incremental growth in central cities, narrowing the gap with the primary city and increasing the trickle-down effect
Total in-migrant population	low	lower	higher	higher
Population attraction degree	weaker	weaker, but improving	stronger	strong
Population outflow	The inflow of population is large in the municipal districts of central cities, while the outflow of population is large in the surrounding counties.	The inflow of population in the municipal district of the central city is large, the inflow of population in the municipal district of the general city is small, and the majority of the county area shows a large outflow of population.	Both the municipal districts of the central cities and the surrounding counties show a large inflow of population; the municipal districts of the general cities show a large inflow of population, while the surrounding counties mostly show a large outflow of population	The central cities have high population inflows in their municipal districts and surrounding counties have lower population outflows
Natural population growth rate	high	higher	lower	lower

One subcategory is the UAs in an overall state of population outflow, which is manifested by a high net emigration rate of population. First, the incremental permanent population in the central cities is higher while the incremental population in other cities is lower and the polarization effect is weaker. Second, the population is mainly concentrated in the core cities, with natural population growth being the main reason for the increase in the total population of UAs. Therefore, districts and counties with high population outflow and high population inflow are the main types. This type is applicable to the BBG, Central Guizhou (CGZ), and MYZ urban agglomerations (Figure 5a).

The other subcategory is the UAs in an overall state of population inflow, which is manifested by a low net in-migration rate of population. First, there is a significant increase in permanent population in the central cities and a stronger increase in other cities, as well as cities with negative population growth, and a polarization effect is formed. Second, the population flows mainly to the central cities, as well as to the municipal districts of other cities. Additionally, the population increase in UAs is mainly influenced by the higher natural population growth rate, as well as the higher population inflow within the UAs, while most of the districts and counties continue to have population outflow. This type is applicable to the HBEY, HBCC, CYN, and Mid-southern Liaoning (MSLN) urban agglomerations (Figure 5b).

3.2.2. Population Migration Characteristics of Weakly Monocentric UAs

Generally speaking, such UAs have a low degree of population agglomeration and an increase in total population. The main manifestations are, first, the gap between the primary city and the secondary city is gradually widening, and the polarization effect is increasing. Second, although the population increase in central cities is more obvious and the amount of inter-provincial in-migration has slightly increased, it is still concentrated in the municipal districts of central cities. Third, although the attractiveness of UAs to the population is still weak, it has improved. Fourth, the natural population growth rate has increased, with higher natural population growth being the main reason for the increase in the total population of UAs. Additionally, the central city has a large inflow of population in its municipal district, the general city has a slight inflow of population in its municipal district, while the county mostly shows a large outflow of population (Table 4). Such UAs can be divided into two subcategories.

One subcategory is the UAs in an overall state of population outflow, which is manifested by a low net emigration rate but an increasing net emigration of the population. Intra-provincial in-migration is an important mainstay of in-migration in UAs, with high population outflow from districts and counties as the main type. It applies to the GZH urban agglomeration (Figure 5c).

The other subcategory is the UAs in an overall state of population inflow, which shows a predominant net in-migration of population. Districts and counties with high population inflow and high population outflow are the main types of such UAs. The intra-provincial in-migration is the important mainstay of in-migration in UAs, while the population inflow rate is low, which applies to NYL, CSX, and LZXN urban agglomerations. The more special one is the NTM urban agglomeration; the inter-provincial in-migration population is an important mainstay of the in-migration population of the UAs, with a high population inflow rate (Figure 5d).

3.2.3. Population Migration Characteristics of Strongly Monocentric UAs

Generally speaking, such UAs have a high and continuously increasing population agglomeration degree, and the population scale further increases. The main manifestations are, first, the gap between the primary city and the secondary city is greater, and the polarization effect is more pronounced. Second, central cities are still the regions with the most obvious increase in permanent population, and, although the scale of inter-provincial in-migration has further increased, it is still concentrated in central cities. Third, although the attractiveness of UAs to the population has further increased, the natural population growth rate is at a low level, and districts and counties with negative natural population growth rates have started to appear (Table 4). Such UAs can be divided into two subcategories.

One subcategory is the UAs in an overall state of population outflow, the main manifestations of which are as follows: first, the central city has a large inflow of population in its municipal district, the general city has a slight inflow of population in its municipal district, while the county mostly shows a large outflow of population. Additionally, intra-provincial in-migration is an important mainstay of in-migration in UAs. Therefore, districts and counties with high population outflow are the main types, such as the CDCQ urban agglomeration (Figure 5e).

The other subcategory is the UAs in an overall state of population inflow, the main manifestations of which are as follows: first, both the municipal districts of the central cities and the surrounding counties exhibit significant population inflows. The general city has a large inflow of population in its municipal district, while the county mostly shows a large outflow of population. Second, inter-provincial in-migration is gradually becoming an important part of in-migration in UAs. Therefore, districts and counties with high population inflow are the main types of such UAs. Meanwhile, it is noteworthy that the municipal districts of the central cities show a trend of population migration to the surrounding districts and counties, and the trickle-down effect of the central cities is increasing, such as the BTH and YRD urban agglomerations (Figure 5f).

3.2.4. Population Migration Characteristics of Strongly Polycentric UAs

Generally speaking, such UAs have a high degree of population agglomeration with a large total population. The main manifestations are, first, several central cities are formed within the UAs, and the gap with the primary city is gradually narrowing, and the degree of population primacy is low. Second, although the UAs are more attractive to the population, the natural population growth rate is at a low level (Table 4). Such UAs can be divided into two subcategories.

One subcategory is the UAs in an overall state of population outflow. The main manifestations are, first, intra-provincial in-migration is an important part of the in-migration of UAs. Second, with the increasing polarization effect of central cities, the municipal districts of central cities have high population inflow, while the surrounding districts and counties have population outflow, and, the farther away from the municipal districts, the higher the degree of population outflow. Therefore, districts and counties with high population outflow and central cities with weak trickle-down effect are the main types, such as the CPL urban agglomeration (Figure 5g).

The other subcategory Is the UAs In an overall state of population Inflow. First, the population of the central city flows from the municipal districts to the surrounding districts and counties. Second, while the polarization effect of the central city is enhanced, its trickle-down effect is also enhanced, and all other cities within the UAs show an increase in permanent population. Thus, the intra-provincial in-migration is still the mainstay of the in-migration population in UAs, and the districts and counties with high population outflow and high population inflow are the main types, but, overall, the population inflow rate is still low, such as the West Bank of the Taiwan Strait (WCFS) and SDP urban agglomerations. A special case is the PRD urban agglomeration, where inter-provincial in-migration is an important mainstay of in-migration and is relatively scattered in all cities of the UAs. Districts and counties with high population inflow are the main types, with high population inflow rate on the whole (Figure 5h).

The study finds that the evolution of population agglomeration patterns In Chinese UAs has distinctive periodic and regional characteristics. By analyzing the population agglomeration patterns of 19 UAs in 2000, 2010, and 2020, these UAs are considered to proceed through the evolution patterns of weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs (Figure 4). It should be noted that, for the three main types of weakly monocentric, strongly monocentric, and strongly polycentric UAs, the type that presents an overall positive net migration rate of the population of the UAs is the main form in its subcategories. Additionally, by comparing the population characteristics of different UAs at the same point in time and the population characteristics of the same UAs at different points in time, this study finds that the four patterns have different characteristics. First, the population of the weakly polycentric UAs is characterized by “agglomeration in outflow”, with a high degree of population outflow. Second, weakly monocentric UAs show "absolute concentration", with an overall population inflow, but the inflow is concentrated in the central cities, while many cities lose population. Third, strongly monocentric UAs show "relative concentration", with an overall increase in population inflow but still with more population in the central cities. Finally, strongly polycentric UAs show a "relatively decentralized" characteristic, with a higher overall population inflow and a higher population inflow to other cities besides the central cities, and the trickle-down effect of the central cities to other cities is also increasing.

3.3. Analysis on the Influencing Factors of Population Migration in UAs of Different Population Agglomeration Types

Firstly, the linear regression model shows that there is no collinearity among the 15 indicators to be tested, and they all significantly affect the population agglomeration degree at the level of 5% (Table 5).

Table 5. Linear Regression Model Results of Population Agglomeration Degree of UAs (from 2000 to 2020).

Indicators	Coefficient (t Statistic)			VIF		
	2000	2010	2020	2000	2010	2020
PerGDP	0.213 (1.301)	−0.465 *** (−2.623)	0.106 (0.555)	7.92	7.71	5.02
Ind	0.394 (1.505)	0.083 (0.354)	1.734 *** (4.710)	2.38	2.44	2.33
Fai	−0.281 *** (−2.807)	−0.012 (−0.091)	−0.269 ** (−2.441)	5.16	7.11	5.49
Tpv	0.098 (1.276)	0.255 *** (3.390)	0.056 (0.937)	2.48	3.19	2.11
Tfv	−0.055 (−0.617)	−0.053 (−0.655)	0.006 (0.085)	3.42	2.83	2.38
Tpvmd	0.001 (0.025)	0.003 (0.073)	0.043 (0.645)	3.96	3.31	4.69
Ilei	0.232 ** (2.600)	0.183 *** (2.828)	0.406 *** (5.391)	5.24	3.54	4.47
Gies	0.192 * (1.937)	0.456 *** (4.396)	0.409 *** (4.167)	8.68	6.92	5.36
Exp	0.190 ** (2.156)	−0.437 *** (−2.702)	−0.344 ** (−2.248)	5.56	9.16	8.27
Wag	0.124 (0.478)	0.415 (1.385)	−0.108 (−0.310)	3.39	3.39	3.1
Edu	−0.548 ** (−2.513)	−0.828 *** (−3.230)	−0.802 ** (−2.580)	2.76	1.47	1.44
Wel	−0.589 *** (−3.150)	−0.482 ** (−2.562)	−0.602 *** (−2.745)	3.16	1.86	1.89
Iwt	0.146 * (1.738)	0.078 (0.591)	−0.056 (−0.103)	1.23	1.31	1.12
Gcr	0.035 (0.360)	−0.066 (−0.619)	0.246 (0.536)	1.5	1.28	1.5
Urb	−0.001 (−0.005)	1.077 *** (3.710)	0.398 (1.022)	5.24	5.54	4.05

Note: *, **, and *** represent significance level at 10%, 5%, and 1%, respectively. VIF value is used to test the collinearity of variables.

Secondly, the geographical detector model shows that the explanatory power of spatial stratified heterogeneity (q statistics) of various influencing factors on population agglomeration degree is strong (Table 6). The results are as follows:

(1) For the weakly polycentric UAs, only two influencing factors have weakened explanatory power, namely the growth index of enterprise structure above designated size (*Gies*) and the greening coverage rate of built-up area (*Gcr*). From 2000 to 2020, the explanatory power of total passenger volume (*Tpv*) on the spatial distribution of population agglomeration has always been the strongest, with the explanatory power of 2000, 2010, and 2020 being 0.223, 0.200, and 0.233, respectively, and passing the significance test at the 5% level. For cities in weak polycentric UAs, the inner cities tend to have relatively lower levels of economic development, weaker polarization effects of the central cities, and relatively limited attractiveness to the population, while high total passenger volume means a more convenient transportation network and stronger population mobility, which is conducive to enhancing the cities' attractiveness to population agglomeration.

(2) For the weakly monocentric UAs, although there are two influential factors with weakened explanatory power, namely average wage of on-the-job employees (*Wag*) and the standard rate of industrial wastewater treatment (*Iwt*), the explanatory power of industry location entropy index (*Ilei*), scale of fiscal expenditure (*Exp*), and total

passenger volume in municipal districts (*Tpvmd*) on the spatial distribution of population agglomeration are always relatively strong from 2000 to 2020, among which the explanatory power of *Ilei* is 0.434, 0.501, and 0.554 in 2000, 2010, and 2020, respectively, and passes the significance test at the 5% level. The explanatory power of *Tpvmd* is 0.333, 0.479, and 0.596 in 2000, 2010, and 2020, respectively, and passes the significance test at the 5% level. Meanwhile, the explanatory power of *Exp* is 0.485 and 0.586 in 2010 and 2020, respectively, and passes the significance test at the 5% level. For cities in weakly monocentric UAs, their ability to provide more alternative employment opportunities and better-quality public services will attract more mobile people to work and live in the city and enjoy the various services it offers. At the same time, closer intra-city transportation links not only indicate greater population mobility but also contribute to lower commuting costs and higher levels of population agglomeration.

(3) For the strongly monocentric UAs, although there are three influencing factors with weaker explanatory power, namely per capita GDP (*PerGDP*), teacher–student ratio in primary and secondary schools (*Edu*), and the number of beds in welfare institutions per ten thousand people (*Wel*), overall, the explanatory power of *PerGDP* and urbanization rate (*Urb*) on the spatial distribution of population agglomeration is still stronger from 2000 to 2020, with explanatory power evolving from 0.424 and 0.346 in 2000 and 0.494 and 0.420 in 2010 to 0.417 and 0.518 in 2020 and passing the significance test at the 1% level. For cities in strongly monocentric UAs, higher GDP per capita means higher level of economic development, higher demand for labor and population, and relatively higher level of labor wages that can be provided to meet the consumption needs of the population in the city, which can easily attract the population. Meanwhile, cities with higher urbanization rates also usually have higher levels of economic development, which is more attractive to the population and more conducive to generating scale agglomeration effects and increasing population agglomeration.

(4) For the strongly polycentric UAs, there is a weakening of the explanatory power of the five influencing factors of *Tpv*, *Gies*, *Wag*, *Edu*, and *Wel*. Meanwhile, the explanatory power of *Urb* on the spatial distribution of population agglomeration is always the strongest from 2000 to 2020, with the explanatory power being 0.470, 0.547, and 0.593, respectively, and passing the significance test at the 1% level. This type of UAs tends to have multiple central cities with closer inter-city ties, making it easier for the population to disperse to the various levels of cities within the UAs, which also allows for greater mobility and thus higher population agglomeration.

Table 6. Detection Results of Factors Influencing the Spatial Stratified Heterogeneity of the Population Patterns of the Four UAs (from 2000 to 2020).

Indicators	Weakly Polycentric UAs			Weakly Moncentric UAs			Strongly Moncentric UAs			Strongly Polycentric UAs		
	2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
PerGDP	0.051	0.006	0.136 *	0.050	0.200	0.299	0.424 ***	0.494 ***	0.417 ***	0.167	0.182	0.179
Ind	0.022	0.019	0.054	0.239	0.351	0.302	0.048	0.229 **	0.133	0.208 *	0.267 **	0.293 **
Fai	0.010	0.018	0.016	0.050	0.578 ***	0.539 **	0.178 *	0.308 ***	0.336 ***	0.068	0.069	0.091
Tpv	0.223 ***	0.200 **	0.233 ***	0.230	0.270	0.301	0.129	0.305 ***	0.236 **	0.176	0.249 **	0.167
Tfv	0.045	0.029	0.060	0.306	0.242	0.476 **	0.138	0.287 ***	0.289 ***	0.026	0.068	0.215 *
Tpvmd	0.076	0.129 *	0.119	0.333 *	0.479 **	0.596 ***	0.249 **	0.219 **	0.269 **	0.228 **	0.195 *	0.470 ***
Ilei	0.102	0.199 **	0.213 ***	0.434	0.501 **	0.554 ***	0.199 *	0.313 ***	0.367 ***	0.105	0.099	0.352 ***
Gies	0.141 *	0.054	0.030	0.167	0.464 **	0.419 *	0.238 **	0.323 ***	0.345 ***	0.177	0.187 *	0.060
Exp	0.085	0.013	0.099	0.284	0.485 **	0.586 ***	0.316 ***	0.234 **	0.378 ***	0.247 **	0.171	0.290 **
Wag	0.012	0.011	0.083	0.313	0.010	0.178	0.308 ***	0.475 ***	0.446 ***	0.297 **	0.186 *	0.151
Edu	0.058	0.122 *	0.160 **	0.082	0.060	0.124	0.182 *	0.148	0.108	0.113	0.177	0.108
Wel	0.048	0.078	0.049	0.134	0.159	0.210	0.225 **	0.047	0.046	0.194 *	0.033	0.117
Iwt	0.062	0.052	0.094	0.140	0.255	0.123	0.087	0.152	0.127	0.012	0.069	0.066
Gcr	0.199 **	0.100	0.166 **	0.272	0.277	0.287	0.038	0.162	0.193 *	0.025	0.134	0.026
Urb	0.075	0.037	0.079	0.199	0.174	0.461 ***	0.346 ***	0.420 ***	0.518 ***	0.470 ***	0.547 ***	0.593 ***

Note: *, **, and *** represent significance level at 10%, 5%, and 1%, respectively.

4. Discussion

4.1. Comparative Study

In analyzing the population mobility and agglomeration characteristics of UAs, it has been found that the population mobility of the five major UAs with high levels of economic development in China shows a spatial pattern of both agglomeration and diffusion, while the trend of population agglomeration to the central cities remains unchanged [93]. Specifically, the spatial distribution of population in the YRD urban agglomerations shows a clear "central-edge" structure [48]. The trend of population agglomeration in the Changsha–Zhuzhou–Xiangtan urban agglomeration is obvious [50]. The Wuhan metropolitan area shows the characteristics of "strong central city-edge city" [49]. The population of the Beijing metropolitan area is gradually dispersed to the periphery, and the trend of polycentric spatial structure is strengthened [69]. In analyzing the population agglomeration patterns of 19 UAs in China from 2000 to 2020, this study finds strong similarities with existing studies; i.e., although most UAs show a trend of increasing population agglomeration, the unevenness of their population spatial distribution is gradually increasing, especially for the less developed UAs, because the population primacy degree is increasing as their central cities develop vigorously and gradually pull away from the population size of other classes of cities. The difference in this study is that some of the UAs with a higher degree of development show not only a centripetal concentration of population in the central city but also a diffusion of population from the central city to the outside. The increased mobility of the population in UAs refers not only to more frequent population movements within UAs but also to closer linkages between UAs and UAs, resulting in greater variation in the state and degree of mobility within UAs. Such changing characteristics further enrich the types of population agglomeration patterns in Chinese UAs, which need to be studied in depth.

In analyzing the classification and the evolution patterns of population agglomeration patterns in UAs, studies have been conducted both from data such as population census data, statistical data, or data from dynamic monitoring surveys of mobile populations [45,55] and from the Gini index, centrality index, and urban agglomeration development [54,56]. In this study, when population agglomeration degree and population primacy degree are used to classify the population agglomeration patterns of UAs, certain similarities with existing studies are found; i.e., strong polycentric UAs are mainly located in UAs with higher development and higher population mobility, while weak polycentric UAs are mainly located in UAs with lower development and lower population mobility. The difference is that, because of the large number of UAs in China, their different locations, and different degrees of economic development, their population agglomeration and flow dynamics also differ greatly, so the process of classifying the population agglomeration patterns of UAs needs to be more refined. Therefore, based on the four categories of urban agglomeration patterns, this study continues to classify eight subcategories according to the net inflow or outflow of population in the UAs as a whole, which can, to a certain extent, more accurately classify the types of urban agglomeration patterns in Chinese UAs. At the same time, this study also classifies urban agglomeration types by nighttime lighting data, which further supports the scientificity of this study's classification.

While analyzing the influencing factors of population agglomeration in UAs, more studies have been conducted from a certain factor, such as the degree of economic development, transportation convenience, public service supply, and air quality in terms of natural environment, economic development, and social conditions, which are not comprehensive enough in the analysis process [82,94]. In this study, on the other hand, 15 indicators are selected to explore the influencing factors of population agglomeration in UAs from the factors of both economic development and social conditions, and the spatially stratified heterogeneity characteristics of the influencing factors are analyzed by geographic detector model. Similar to existing studies, economic development factors and social conditions factors are important factors influencing population mobility and distribution. Cities with higher levels of economic development, more employment opportunities, higher labor compensation, and stronger public service supply capabilities are more attractive to the population and have higher levels of population agglomeration. This study differs from other studies in that the population agglomeration degrees of cities in different urban agglomeration patterns have different influencing factors. For weakly polycentric UAs, the convenient transportation network helps the flow of various factors, and the total passenger volume has a stronger contribution to their population agglomeration, while, for UAs with stronger population agglomeration, the contribution of urbanization rate is more obvious.

4.2. Additional Analysis from Other Perspectives

In this study, different types of population agglomeration in Chinese UAs are classified into weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric based on the evolutionary law of population agglomeration, but the results of different types of UAs centers are difficult to be verified due to the strong spatial correlation between population agglomeration and economic agglomeration in urban agglomeration space. Therefore, in order to supplement the classification results of population agglomeration patterns in UAs, Suomi National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite NTL data of 2000, 2010, and 2020 are used to identify the economic agglomeration centers of UAs and to compare the similarities and differences between population agglomeration and economic agglomeration centers [31,70]. The results are shown in Figure 6. It can be found that only three UAs, BBG, GZH, and HBEY, evolve from monocentric UAs in 2000 to polycentric UAs in 2020, with multiple central regions forming within them. The other 16 types of UAs are the ones where only the area of the central area has been expanded, while the others remain unchanged. Overall, polycentric UAs are the main type, with the number of 10 in 2000 increasing to 13 in 2020. As for the six UAs of HBCC, WCFS, MSLN, SDP, MYZ, and CPL, they are identified by the NTL data to exist in multiple central regions, belonging to polycentric UAs, and the population agglomeration model of the UAs also identifies that its primary city has a small population gap with its secondary city, and there exist two or more large cities with populations that belong to polycentric UAs. The identification results of both are in perfect agreement. Overall, the economic agglomeration polycenter identified by NTL data is basically similar to the results of this study's classification, which supports the scientificity of this study's UAs type based on the population agglomeration model.

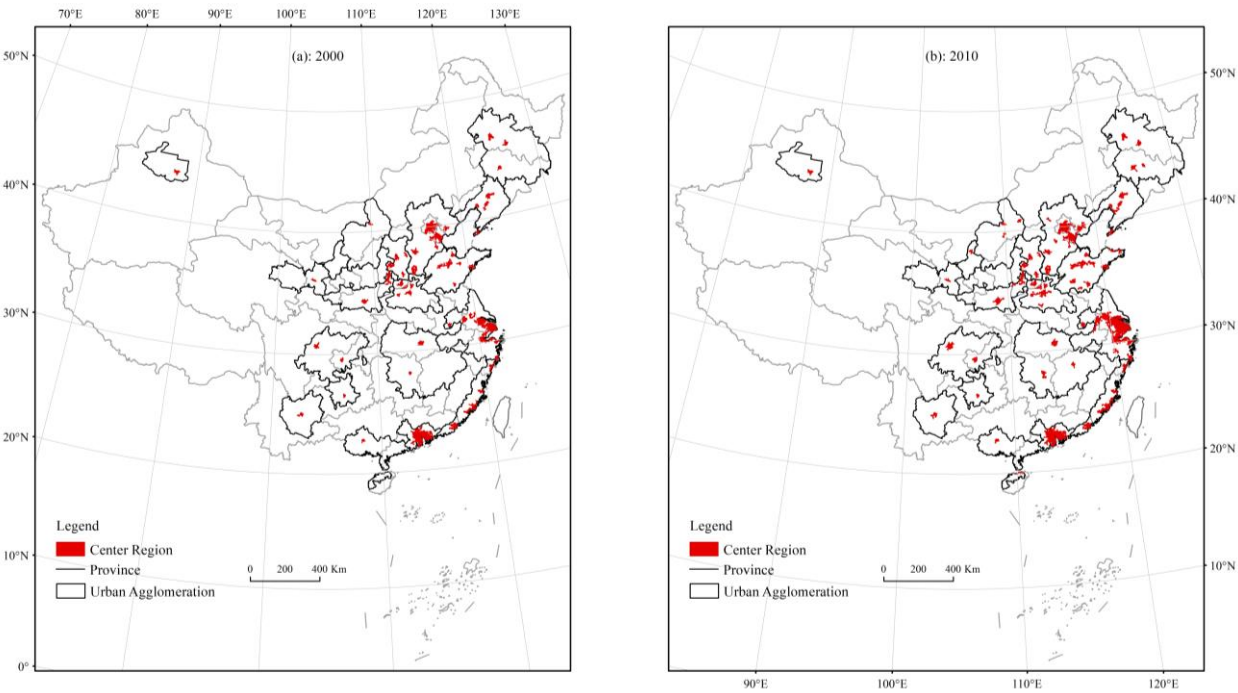

Figure 6. *Cont.*

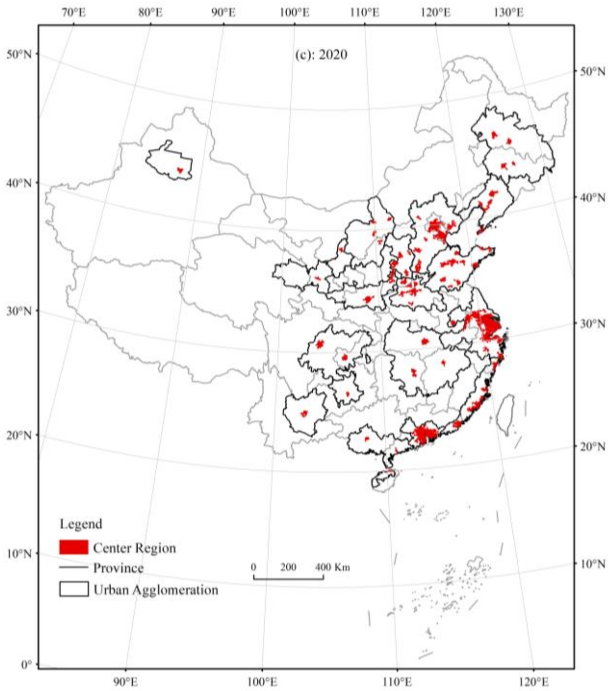

Figure 6. Range of UAs Centers Identified by NTL Data ((**a**): 2000; (**b**): 2010; (**c**): 2020).

4.3. Implications of the Study

In theory, by analyzing the population migration characteristics presented by 19 UAs, it is found that the population agglomeration patterns of Chinese UAs go through the evolution patterns of weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs. Meanwhile, this study finds that the evolution of population agglomeration patterns of UAs has distinctive stage and regional characteristics; that is, the population of the weakly polycentric UAs is characterized by "agglomeration in outflow", weakly monocentric UAs show "absolute concentration", while the strongly monocentric UAs show "relative concentration", and strongly polycentric UAs show a "relatively decentralized" characteristic. In conclusion, this study provides a more in-depth exploration of the characteristics of population mobility and agglomeration within UAs, enriching the theoretical and practical results of population migration and polycentric UAs research based on the existing studies [66].

In methods, by using population data, this study classifies the population agglomeration patterns into four major categories, namely weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs, by using two indices, namely population agglomeration degree and population primacy degree, which has not been carried out in previous studies. Meanwhile, there are obvious differences in the population agglomeration patterns of different UAs because of the large number of UAs in China, their different locations, and different degrees of economic development. Therefore, based on the four categories of urban agglomeration patterns, this study continues to classify eight subcategories according to the net inflow or outflow of population in the UAs as a whole, which can, to a certain extent, more accurately classify the types of urban agglomeration patterns in Chinese UAs. Such processes have not been carried out in previous studies.

In conclusion, the spatially stratified heterogeneous characteristics of the influencing factors of population agglomeration are obtained in this study using the geographic detector model. The study shows that economic development factors and social condition factors are important factors influencing population mobility and distribution, and that different urban agglomeration patterns have differential influencing factors on urban population agglomeration. For weakly polycentric UAs, their relatively low level of economic development results in limited attractiveness to the population, while a convenient transportation network facilitates the free mobility of population factors and helps increase the population agglomeration degree. For weakly monocentric UAs, due to their relatively limited level of economic development, more job opportunities and more quality public services are important to attract population. For strongly monocentric UAs and strongly polycentric UAs, based on their higher level of economic development, the establishment of closer economic and social ties and the realization of a higher urbanization rate are more likely to exert a scale agglomeration effect, which in turn enhances the attractiveness of the population to increase the degree of population agglomeration.

4.4. Study Deficiencies and Prospects

This study analyzes the evolution characteristics and influencing factors of the population agglomeration patterns of UAs using three cross-sectional datasets from the fifth, sixth, and seventh censuses and statistical yearbook data, focusing on the population perspective to explore the population agglomeration patterns of UAs, with more emphasis on long time and dynamic analysis. In addition, although the UAs types in 2000, 2010, and 2020 are identified by NTL data and are compared with the population agglomeration patterns of UAs identified by demographic data, which, to a certain extent, supports the scientificity of demographic data classification, population migration is actually a real-time and dynamic process, which means the characteristics and patterns of population migration in China's UAs revealed in this study are partial to a certain extent, and subsequent refined analyses are needed to combine with big data on UAs migration and other data, and it is also necessary to explore the differential impacts of population migration in different types of UAs on the development of UAs. Further, considering the complexity of UAs in China, the population evolution characteristics of different UAs in the long term can be analyzed for a single or a few UAs. Meanwhile, the population mobility characteristics of different UAs in the short term can also be analyzed by using new data, such as location data, and then compare and analyze with the population mobility characteristics presented in the long term of UAs. We can also continue to explore the influencing factors of population agglomeration from different factors, such as natural environment, economic development, social conditions, etc., which can provide a reference for the formulation of population policies in different UAs.

5. Conclusions

Using the data of China's fifth, sixth, and seventh population censuses, statistical yearbooks, NTL data, and other data, this study discusses and analyzes the characteristics of population migration, evolution rules, and influencing factors of population agglomeration patterns in UAs in China by combining with the methods of geographic detector model, population agglomeration degree, population primacy degree, and net migration rate. The main conclusions obtained are as follows:

(1) UAs are the main areas with high population agglomeration in China. The more developed UAs are, the more attractive they are to the population, and the higher their population agglomeration degree and net migration rates would be. The attraction of UAs to population leads to an increase in the unevenness of population distribution in China, as well as the unevenness degree of population distribution within UAs with different levels of development in China.

(2) The population agglomeration patterns of Chinese UAs can be divided into four major categories, namely weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs, and will undergo the evolution pattern of weakly polycentric, weakly monocentric, strongly monocentric, and strongly polycentric UAs. From 2000 to 2020, China's UAs are in a low-level stage dominated by weakly polycentric UAs. Additionally, it is also found that the types of UAs obtained by NTL data are generally consistent with the population agglomeration patterns of UAs derived from population data in this study.

(3) From the perspective of factors influencing population agglomeration in UAs, the factors influencing population agglomeration patterns in different UAs are quite different. The explanatory power of total passenger volume to weakly polycentric UAs is always the strongest, the explanatory power of industrial location entropy index, scale of fiscal expenditure, and total passenger volume of municipal district is relatively strong for weakly monocentric UAs, while the explanatory power of per capita GDP and urbanization rate is relatively strong for strongly monocentric UAs, with the urbanization rate always being the strongest explanatory power for strongly polycentric UAs.

This study analyzes the evolutionary characteristics and influencing factors of population agglomeration patterns of UAs in China from the scale of UAs, and the findings provide a basis for formulating UAs development plans in China. In the process of analyzing the influencing factors of population agglomeration patterns, the study finds that the contribution of urbanization rate is more obvious for UAs with stronger population agglomeration, and its contribution has been increasing.

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