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Changes in spatiotemporal pattern and network characteristics in population migration of China's cities before and after COVID-19

Yaming Zhang[1,2], Xiaoyu Guo [1,2 ✉], Yanyuan Su[1], Yaya Hamadou Koura H[3], Na Wang[1,2] & Wenjie Song[1,2]

Population mobility is a key component in promoting the re-agglomeration and dissemination of social and economic factors. Based on Spring Festival data from 2019 to 2023 on Baidu Migration Big Data, this paper analyses the spatiotemporal patterns and structural characteristics of population mobility in cities across China through spatiotemporal statistics and social network analysis and investigates the evolution patterns of Chinese population migration behavior under the influence of COVID-19 epidemic during Spring Festival. The results of the study show that: (1) There are significant temporal and spatial differences in the impact of COVID-19 on population migration, with much stronger shocks on the cities of middle migration scale; (2) Population migration in Chinese cities is robust, and the impact of COVID-19 on population movement and community evolution is mainly manifested in short-term effects, with essentially no residual effects; (3) Between 2020 and 2023, a total of 119 cities experience a transfer of communities (32.25%), of which 69 cities transfer once, 20 cities transfer twice, and 30 cities transfer three times. In addition, it is found that the closeness of urban links based on population movements remains subject to geospatial effects, and the boundaries of "communities" coincide very closely with provincial borders. The results of this study have important theoretical and practical implications for a deeper understanding of the long-term impact of major public health events on changes in the geographical characteristics of population distribution and the structure of population mobility networks.

[1] School of Economics and Management, Yanshan University, 066004 Qinhuangdao, China. [2] Development of Center for Internet Plus and Industry, Yanshan University, 066004 Qinhuangdao, China. [3] School of Foreign Languages, Yanshan University, 066004 Qinhuangdao, China. ✉email: xy@stumail.ysu.edu.cn

Introduction

Population mobility is considered to be a spatial reallocation of factors of production, and it has been witnessed as an essential driver of population redistribution and human settlement patterns (Rees et al., 2017). Movement patterns are primarily driven by socioeconomic factors such as wage imbalance, differences in welfare and living conditions, and globalization in modern times (Barbosa et al., 2018). The economic activities (Cao et al., 2023), social norms (Luo et al., 2020), energy consumption (Qi et al., 2021), and disease transmission (Merrill et al., 2021; Wei and Wang, 2020) of human society are all impacted by population movement. Understanding human mobility and how it manifests across spatiotemporal scales has important significance (Liu and Yan, 2020; Salvati et al., 2019), and many related types of research have been conducted, such as the study of population mobility spatial patterns (Zhang et al., 2020) and the prediction of population flow (Iwata et al., 2019). Attention has also been paid to the risk of pandemic outbreaks in megacities as a result of population mobility (Shi et al., 2020).

Research on population mobility in the past has been conducted primarily based on static data, such as census data or statistical yearbooks, which are unable to dynamically capture the spatial patterns of rapid mobility and urban development in real time and thus cannot directly and accurately reflect the directions of population flow. The development of global positioning systems (GPS), location-based services (LBS), and other technologies has provided technical support for the observation of spatial and temporal characteristics of large-scale population behaviors. Certain recent studies have analyzed human mobility by using spatiotemporal labeled data with individual granularity (including mobile phone call data, social network check-in data, etc.), such as the global variation in human mobility (Kraemer et al., 2020), human mobility characteristics during typical flow periods like the Spring Festival (Pan and Lai, 2019). Big data on population movements has been used in epidemiological investigations since before the COVID-19 outbreak, and its use has increased since then. These studies can be divided broadly into three categories.

The first category is the study of the correlation between epidemic cases and population movements. Complex human movement patterns influenced by a variety of economic, health, social, and environmental factors affect the spread of infectious illnesses (Merrill et al., 2021). Appropriate restrictions on population movement have proven to be effective in containing the spread of the epidemic (de Oliveira et al., 2021; Guo et al., 2022). Transmission significantly decreased with the initial reduction in mobility in 73% of the 52 countries analyzed (Nouvellet et al., 2021). To examine the spatiotemporal association between population mobility and the COVID-19 outbreak, mobile phone-based datasets are used to track particular changes in population mobility (Dai et al., 2021; Jeffrey et al., 2020).

The second category is using population movement data to predict pandemic infection trends. Integrating intercity travel data with classical infectious disease models enables the prediction of the arrival time of peak numbers of infections in individual cities (Zhan et al., 2020; Zhan et al., 2020). In addition to characterizing the dynamics of disease transmission in closed populations, cross-regional and global epidemic transmission dynamics can also be predicted by models such as Network Analysis (So et al., 2021) and Transfer Graph Neural Networks (Panagopoulos et al., 2021). Furthermore, transmission patterns derived from general human movement models can improve forecasts of epidemics' spatiotemporal transmission patterns in places where local mobility data is unavailable (Kraemer et al., 2019).

The third category is the analysis of the impact of epidemics on population movements. There are regional differences in population mobility and resilience under the influence of epidemics (Galeazzi et al., 2021), for example, between countries with different political ideologies (Hill et al., 2021) and between cities in the same country (Tong et al., 2020). COVID-19 has limited many people's capacity for mobility and raised the associated expenses (Jolivet et al., 2023). In China, although some scholars found no significant difference in the geographical distribution of the outflow population in Wuhan during 2020 Spring Festival compared to the same period in previous years (Xu et al., 2020a, 2020b), the pattern of population mobility during COVID-19 has in fact produced new changes compared with the SARS epidemic period, such as the changing geography of migration, the diversification of jobs taken by migrants, the rapid growth of tourism and business trips, and the longer distance taken by people for a family reunion (Shi et al., 2020).

An important strand of the third category was concerned with the reasons behind the changes that lead to population movements. Changes in mobility levels are partly the result of private decisions made by people in response to health threats posed by epidemics, and partly the result of a wide range of policies and regulations adopted by governments to restrict mobility (Gupta et al., 2020; Yan et al., 2021). Stay-at-home (SAH) mandates have dramatically reduced mobility outside the home, with an estimated 2.5 percentage points increase in the amount of time people spend at home in the United States after SAH mandates came into effect (Abouk and Heydari, 2021), but compliance with social distancing policies was lower among men and young adults (Park et al., 2020). Meanwhile, travel preferences during the pandemic are significantly associated with factors such as social responsibility, fear of infection, perceived risk and travel anxiety (Chen et al., 2022; Li et al., 2022), and social distancing behavior began even before the implementation of government stay-at-home dates (Abdalla et al., 2021; Lee et al., 2020).

Extensive research has been conducted for the first and second categories, while for the third category, most of the studies based on the real-time impact of the epidemic on the economy and society are still focused on the impact of the outbreak period, and there are few studies on the delayed effect and long-term impact. The resilience of population migration, the recovery of the city's economy, and even the appropriateness of epidemic prevention measures can all be learned by researching the long-term impacts of the epidemic on population migrations. Studying the long-term effects of the epidemic on population movements not only provides insights into the robustness of population migration but also into the recovery of the city's economy and even the appropriateness of the stringency of measures to restrict population movements.

As the first country in the world to adopt strict restrictions on population movement, China has achieved remarkable results in preventing and controlling the epidemic (Cheng et al., 2020), but sluggish population movement has also slowed economic development to some extent. Thus, this study attempts to answer two questions: (1) What are the long-term effects of the outbreak on large-scale population movements in China? How well have cities recovered in terms of the scale of population migration and the scale of population return? (2) How did the population flow network and city network status in China change before and after the epidemic? Based on Baidu migration big data, this article (1) constructs the Population Migration Scale Index (PMSI) to analyze the changes in the spatiotemporal characteristics of human mobility in Chinese cities, (2) constructs the index of the recovery of population return scale ($PRSI_{re}$) to reveals the urban resumption of work and production after the festival, and (3) assesses the changes of city network status compacted by COVID-19 applying social network analysis.

Data and methods

Data pre-processing

Data sources. Baidu Migration Big Data was launched in 2014 during the Spring Festival, which defines and mines migrating people by identifying the spatial and temporal displacement of a large number of LBS service users and determines the migration characteristics of people between regions, which has been gradually applied to research in geography (Jiang et al., 2022; Yang et al., 2022) and sociology (Zhu et al., 2023; Huang et al., 2021). After the outbreak of COVID-19, Baidu Migration Big Data has been used in a large number of epidemic surveillance (Tian et al., 2021; Zhou, 2022). Baidu Migration Big Data provides indices of migration scale (including an in-migration scale index and an out-migration scale index) recorded in days for 369 cities[1] in China and the percentage of in-migration from a particular city to the total in-migration from that city for each city's in-migration sources. The migration data reflects the active level of migration in cities and the network of population movements between cities. The migration scale index reflects the size of a city's in-migration or out-migration populations and allows for cross-city comparisons. Of its real-time updating and large sample size, migration data is more flexible than the census, a sample survey of 1% of the population, and a sample survey of 1 per 1000 population changes. Therefore, we use the Baidu Migration Platform (http://qianxi.baidu.com) as the data source in this investigation.

The spatiotemporal scale of the data. Spring Festival travel rush is a massive phenomenon of high transport pressure that occurs in China around the Lunar New Year for a total of around 40 days It has a completely different scale and characteristics as compared to daily population movement (Hu, 2019). As a major social phenomenon unique to China, the Spring Festival travel rush has become an important perspective to study the migration of floating populations (Gao et al., 2021a, 2021b). Observing the movement of people during the Chinese New Year provides insight into the cognitive, cultural, economic, and lifestyle habits of the population in China's social development.

Therefore, the period chosen for this paper is the fifteen days before and the 25 days after the Chinese New Year, totaling 40 days. To reveal the long-term impact of major emergencies such as epidemics on population migration patterns between Chinese cities and the structure of urban networks, this paper uses 369 cities in China as the research target and obtains population migration data for each of the 369 cities for 40 days over 5 years (from 2019 to 2023) through Baidu Migration Platform.

Methods

Evaluation indicators of urban resilience. The recovery of the scale of population migration is constructed to measure the relative resilience of urban (Tong et al., 2020). To analyze the long-term impact of COVID-19 on the population activity in China, this research mainly calculates the daily population migration scale index (PMSI) and population return scale index (PRSI) for 40 days during the Spring Festival travel rush from 2020 to 2023, comparing them with the data on the same period in 2019. Our purpose is to describe the resumption of social production and life under the influence of the epidemic via two main indicators: recovery of population migration scale ($PMSI_{re}$), and recovery of the population return scale ($PRSI_{re}$). The calculation of each index is as follows.

① Population migration scale index:

$$PMSI_{i,t} = PMSI_{i,t}^{in} + PMSI_{i,t}^{out} \qquad (1)$$

where $PMSI_{i,t}$ denotes the population migration scale index for city i at time t, $PMSI_{i,t}^{in}$ is the population in-migration scale index, and $PMSI_{i,t}^{out}$ is the population out-migration scale index. PMSI can measure of how active a city is in terms of population migration while allowing for cross-sectional comparisons between cities. The higher the PMSI value, the more active the city is in terms of population migration.

② Recovery of population migration scale:

$$PMSI_{i,t}^{re} = PMSI_{i,t}/PMSI_{i,t'} \qquad (2)$$

where $PMSI_{i,t}^{re}$ denotes the recovery of the scale of population migration for city i at time t, $PMSI_{i,t'}$ is the population migration scale index for city i at time t of the historical period (i.e., 2019). $PMSI_{i,t}^{re} > 1$ means that the city's PMSI for that year is higher than that for the same period in the lunar calendar, and vice versa. The higher the $PMSI_{i,t}^{re}$ value, the better the recovery in the activity of the city's population movement in that year.

③ Recovery of population return scale:

$$PRSI_{i,t} = PMSI_{i,t}^{in} - PMSI_{i,t}^{out} \qquad (3)$$

$$PRSI_{i,t}^{re} = PRSI_{i,t}/PRSI_{i,t'} \qquad (4)$$

where $PRSI_{i,t}$ denotes the population return scale index for city i at time t, $PRSI_{i,t}^{re}$ is the recovery of the scale of population return for city i at time t, $PRSI_{i,t'}$ is the population return scale indexes for 2019 of city i. PRSI is the difference between a city's population in-migration scale index and the population out-migration scale index - net population inflow (Xu et al., 2020a, 2020b). PRSI reflects the scale of a city's return population after Chinese New Year, with PRSI > 0 representing population inflow and PRSI < 0 representing population outflow. The return of population reflects the resumption of work and production in a city, where the closer the population return is to the historical level of the same period, i.e., the higher the $PRSI_{re}$ value, the better the resumption of work and production.

Social network analysis. Using the social network analysis, we establish a 369 × 369 inter-urban population migration matrix, in which taking PM (Population Migration) between cities is the weight (Xiang and Wang, 2020). The calculation of PM is as follows.

$$PM_{ij} = \sum_{t}^{n} PR_{ij,t} \times PMSI_{i,t}^{in} \times 1000 \qquad (5)$$

Where PM_{ij} is the index of spatial connection of population migration between city i and city j, $PR_{ij,t}$ is the percentage of the number of population moving into city i from city j to the total population moving into city i at time t. As the PM values are used to measure the relative strength of population mobility linkages between cities, the multiplier value of 1000 only enhances the ease of research and calculation and has no other substantive significance.

In this article, we use five network indicators, including Degree, Weighted Degree, Density, Clustering Coefficient, and Characteristic Path Length to quantitatively analyze the network structure characteristics of the population mobility network in Chinese cities for four years. These five indicators are widely used in the analysis of population migration networks (Gou et al., 2020; Wu and Liu, 2022), and the formulae of the indicators have been described in detail in relevant papers, so we will not repeat them in this paper.

The degree is able to measure the frequency of interactive population flows between cities and the radiation and attractiveness of the node cities, and the weighted degree can be used to
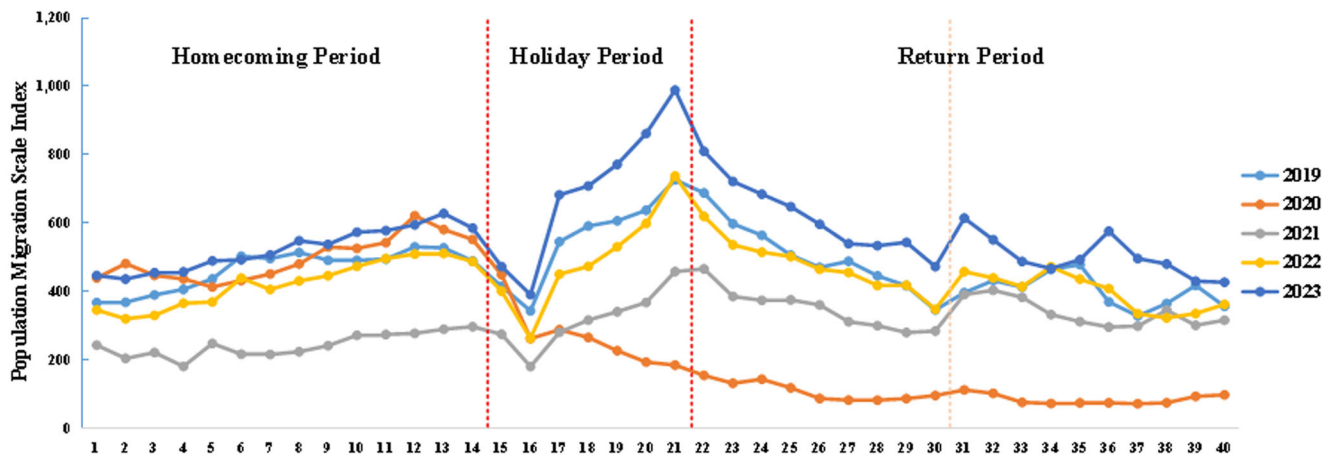
Fig. 1 Time series characteristics of the population migration scale in China. This figure shows the population migration scale index (PMSI) for China during the Spring Festival from 2019 to 2023, and displays the 40 days of the Spring Festival in three phases: Homecoming Period, Holiday Period and Return Period.

indicate the total population flows between cities. The density is a measurement used for determining the closeness of the links between the network nodes. The more links between members, the greater the density of that network, and the greater the density of the overall network, the greater the influence it is likely to have on the attitudes and behavior of the actors within it. The average degree in the network is equal to the degree divided by the number of nodes, and other metrics can be averaged in the same way. The average clustering coefficient reflects the aggregation degree of the network, and the average path length reflects the efficiency of element flow between nodes.

Results and analyses
Changes in population migration scale
Temporal analysis of the population migration scale. Under the influence of traditional festival culture and customs, a large floating population flows from work cities to their home cities before the Spring Festival, forming the "migration back home". After the Spring Festival, people return from their home cities to their work cities, forming the "migration back to the workplace". According to the data provided by the Baidu Migration Platform, plotting the change curve of the Chinese population migration scale index from January 7th to February 15th, 2023, and the same period of the historical lunar calendar (Fig. 1), it can be seen that the population movement scale during the Spring Festival period has obvious stage differences characteristics. Based on the temporal fluctuation pattern of the population movement scale and the realistic holidays, the Spring Festival period can be divided into three stages: Homecoming Period, Holiday Period, and Return Period.

(1) Homecoming period: A large number of migrant workers begin to return to their hometowns, and the scale of population movement across the country gradually increases. Before the Spring Festival in 2020, the population's disdain and the health sector's underestimation for the severity of the COVID-19 virus led to a short delay in the impact of the outbreak on population movement, and the scale of population migration in 2020 was basically the same as that in 2019. However, COVID-19 had an enormous effect on the magnitude of population migration in 2021, resulting in a sharp decline in the PMSI and a 47.77% drop in China's average daily PMSI compared to 2019. The PMSI curve was also noticeably flat and devoid of any notable peaks. The magnitude of population migration

started to recover in 2022 and continued to increase in 2023 instead of decreasing due to a large increase in COVID-19-infected persons. The PMSI curve significantly correlated to the index curve in 2019, and the average daily PMSI was even 12.67% higher than in the historical period.

(2) Holiday period: Historically, the PMSI tends to fall to its lowest level on the first day of the Lunar New Year when most people have already returned home, and then rises sharply and peaks due to travel and other activities. However, as can be seen in Fig. 1, the PMSI changes dramatically in 2020 compared to the same period in the past, with PMSI decreasing rather than increasing during this period, and continuing to fall throughout the holiday period. This suggests that intercity population movements were largely stagnant at this time. As stronger traffic control regulations were still being introduced and the public was currently aware of the seriousness of the epidemic, the perceived risk has led to a significant reduction in traveling activities, resulting in a downturn in population movement activities. After the full transport liberalization in 2023, the scale of population movement across the country continued to increase, with the PMSI peaking on January 27th and exceeding the historical PMSI for the same period by 36.19%. China's average daily PMSI for the period was 26.20% higher than the historical PMSI for the same period. It can be seen that the impact of the COVID-19 epidemic on China's population migration has turned from negative to positive, reflecting the resilience and elasticity of Chinese society.

(3) Return period: Cities started to resume work and production during the return period, and the PMSI gradually returned to the daily state from a high level and was stable after the Lantern Festival (the pink dividing line in Fig. 1). However, the PMSI for the return period in 2020 hovered at a low level, and China's daily average PMSI is 78.78% lower than in 2019. This indicates that the resumption of work and production across the country after the holidays has been greatly affected by COVID-19. The PMSI for 2021 has already shown some rebound from the previous year. It is worth noting that there is a significant difference in the average daily PMSI before and after the Lantern Festival, with China's average daily PMSI falling by 30.71% in the nine days before the Lantern Festival compared to the same period in history, while the gap between China's average daily PMSI and the same period in history narrowed to

16.02% in the 10 days after the Lantern Festival. The official abolition of all epidemic restrictions in Sweden, the United Kingdom, and other countries in 2022 has shaken the Chinese people's belief in the prevention of epidemics. This, along with the economic downturn brought on by the ongoing prolonged pandemic prevention, has also led to more and more people insisting on the fight against the epidemic at the same time more active resumption of work and production. By 2022 and 2023, the scale of migration has largely recovered.

Spatial differentiation characteristics of the population migration scale. The 369 cities were divided into seven groups using PMSI values and Natural Breaks (Jenks) offered by ArcGIS 10.5, as illustrated in Fig. 2. According to internal relationships, data is naturally grouped using Natural Breaks, which maximizes the distance between groups and optimizes similarity values within groups to maximize classification objectivity.

China can be divided into eight human geographic regions, namely Northeast China, North China, East China, Central China, South China, Northwest China, Southwest China, and Qinghai-Tibet (Fang et al., 2017), and the scopes of the administrative divisions for each human geography region are given in Appendix 1. According to Fig. 2, the impact of COVID-19 on the scale of population migration varies significantly by region. Due to their isolation and underdeveloped economic activities, several cities have very low ($0 \leq PMSI \leq 1$) or low ($1 \leq PMSI \leq 2$) scales of population movement chronically. COVID-19 has had little effect on these cities' average daily PMSI, which is below 2 from 2019 to 2023. Cities in Northeast, Northwest, Qinghai-Tibet, South China (Hainan, Taiwan, Hong Kong, and Macao), and Southwest China (Yunnan Province) are primarily home to these less active population migratory cities. There is also a subset of megacities with PMSI values above 9 from 2019 to 2023, like Shanghai, Guangzhou, Shenzhen, Dongguan, and Chengdu, where the extent of population mobility is less affected by COVID-19.

The rank of the average daily PMSI for the majority of cities has recovered to or is higher than historical contemporaneous levels in 2023 based on the seven levels of the Natural Breaks(Jenks), as can be seen by comparing Fig. 2a, e, even though the average daily PMSI for Chinese cities under the influence of COVID-19 fluctuates to varying degrees. Only three cities—Hong Kong, Macao, and Jiamusi City—saw their average daily PMSI rank drop. This demonstrates once more how resilient the urban population movement is in China. In 2023 compared to 2019, 28.46% of cities exhibited an improvement in each city's average daily PMSI ranking. After the conclusion of epidemic prevention and control, these cities likewise showed a large increase in population mobility activity, indicating that the impact of COVID-19 on urban population migration activity did not have a significant aftereffect. Cities with a rising rank of the average daily PMSI are mainly located in five regions: Southwest China, North China, East China, Central China, and South China, especially in Southwest China. The majority of these cities are dispersed among various locations and do not compose sizable contiguous territories.

Figure 3 displays the analysis results of the population migration scale recovery in each city. As can be seen in Fig. 3a, all of the cities' population migration recovery in 2020 is comparatively weak, and COVID-19 has had a significant short-term impact on migration in China. According to Fig. 3b, the population migration scale recovery index in Chinese cities in 2021 has a general spatial pattern that is "low in the northeast and high in the southwest." In terms of population migration scale, Qinghai-Tibet was the first to start recovering, with a

comparatively high degree of recovery, whereas Northeast China's recovery was relatively subpar, with most cities having a recovery index of less than 60%.

The scale of population migration has largely recovered (average daily $PMSI_{re} \geq 100\%$) in 2022 in two regions, one in the eastern coastal region (including Shandong, Anhui, Hubei, Jiangxi, and Fujian) and the other in the western region (including Xinjiang, Gansu, Ningxia, Tibet, Qinghai, and Guizhou). According to Figs. 3d, 95.12% of the cities have mostly reached their pre-recession levels average daily ($PMSI_{re} \geq 100\%$), and 59.26% of these cities have a daily average population migration scale recovery index that is greater than 120%. In 2023, only 18 cities—mostly in Northeast China—will still not have reached their pre-recession levels.

The Cluster and Outlier Analysis of the $PMSI_{re}$ is shown in Fig. 4. $PMSI_{re} PMSI_{re} PMSI_{re} PMSI_{re}$ In 2020, Hong Kong is Low-High Outlier, indicating that the majority of the nearby cities have fully recovered. Changde is classified as High-Low Outlier, making it the area's most resilient city.

In terms of spatial clustering, the High-High Cluster in 2020 forms two major plates, one plate is mainly distributed in Qinghai-Tibet (including Tibet, Qinghai, and part of Xinjiang), and the other plate is mainly distributed in South China (including Guangdong and part of Hunan). In addition, Dalian and Chaoyang cities in Liaoning Province also recovered to a high degree and are High-High Cluster. From Fig. 4b–d, it can be seen that the High-High Cluster is mainly scattered in Qinghai-Tibet from 2021 to 2023, and the high-high clustering characteristics of some cities in Guangdong and Hunan largely disappear. This suggests that COVID-19 has a weaker impact on population movement in regions that are more remote and less accessible and that the scale of population movement in these regions can recover earlier.

Low–Low Cluster forms two major segments in 2020, located in Central China (Henan Province, Hubei Province, Jincheng City, and Shangluo City) and East China (Zhejiang Province, Huangshan City, Jingdezhen City, and Jiujiang City) respectively. The change in Low–Low Cluster from 2021 to 2023 shows two features. One is the disappearance of the low–low-clustering characteristics of cities in the Central China and East China region, and the other is the persistence of low–low clustering characteristics in Northeast China. In the context of the COVID-19 epidemic, as Wuhan City was the first city to discover the epidemic and for a short period was mistakenly believed to be the origin of the world's COVID-19 virus, the COVID-19 epidemic had a strong impact on the neighboring region centered on Wuhan in 2020, bringing economic activities and social functioning in the city to a standstill and resulting in poor population mobility in the region. However, as the epidemic is brought under control, the truth about "viral stigmatization" is revealed, and economic activity is resumed, the population migration scale for most cities in Central China, centered on Wuhan, has largely recovered to their historical contemporaneous levels in 2022, indicating that the negative impact of COVID-19 on population migration in the relevant cities has gradually disappeared, with no significant residual effects. In Northeast China, there have been repeated outbreaks of the COVID-19 epidemic from 2020 to 2022, which has had a relatively large impact on the social activities of the population and has accelerated the outflow of people from Northeast China to some extent. This phenomenon suggests that there has been a sustained and permanent change in the scale of population migration in the concerned cities.

Changes in population return scale

Recovery of the scale of population return on the provincial level. During the Spring Festival, the net population flow in Chinese
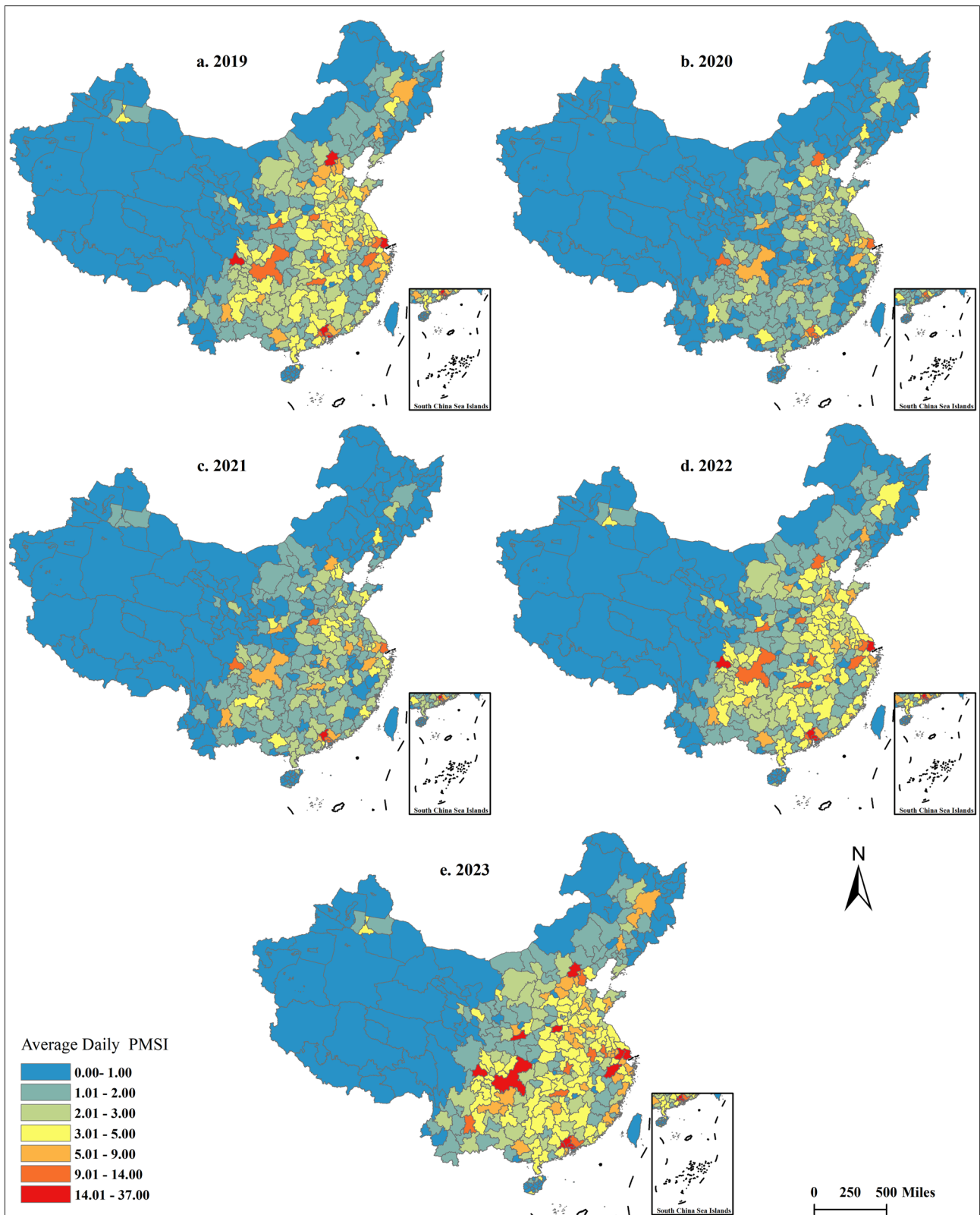
Fig. 2 Chinese cities' average daily population migration scale index, 2019–2023. This figure shows the 40-day average daily migration scale index (PMSI) for 369 cities in China from 2019 to 2023, where panels (**a**–**e**) show the details from 2019 to 2023, respectively.

cities generally shows an "S" shaped reverse interaction pattern (Lai and Pan, 2020). The net daily population inflow for each city was negative or positive, respectively, before the festival, while the positive and negative characteristics reversed after the festival. As

can be seen from the change in the provincial population return scale index (Fig. 5), PRSI reverses its positive and negative values roughly between February 4th and February 10th, particularly the 7th and the 8th of February. This distinctive feature indicates that
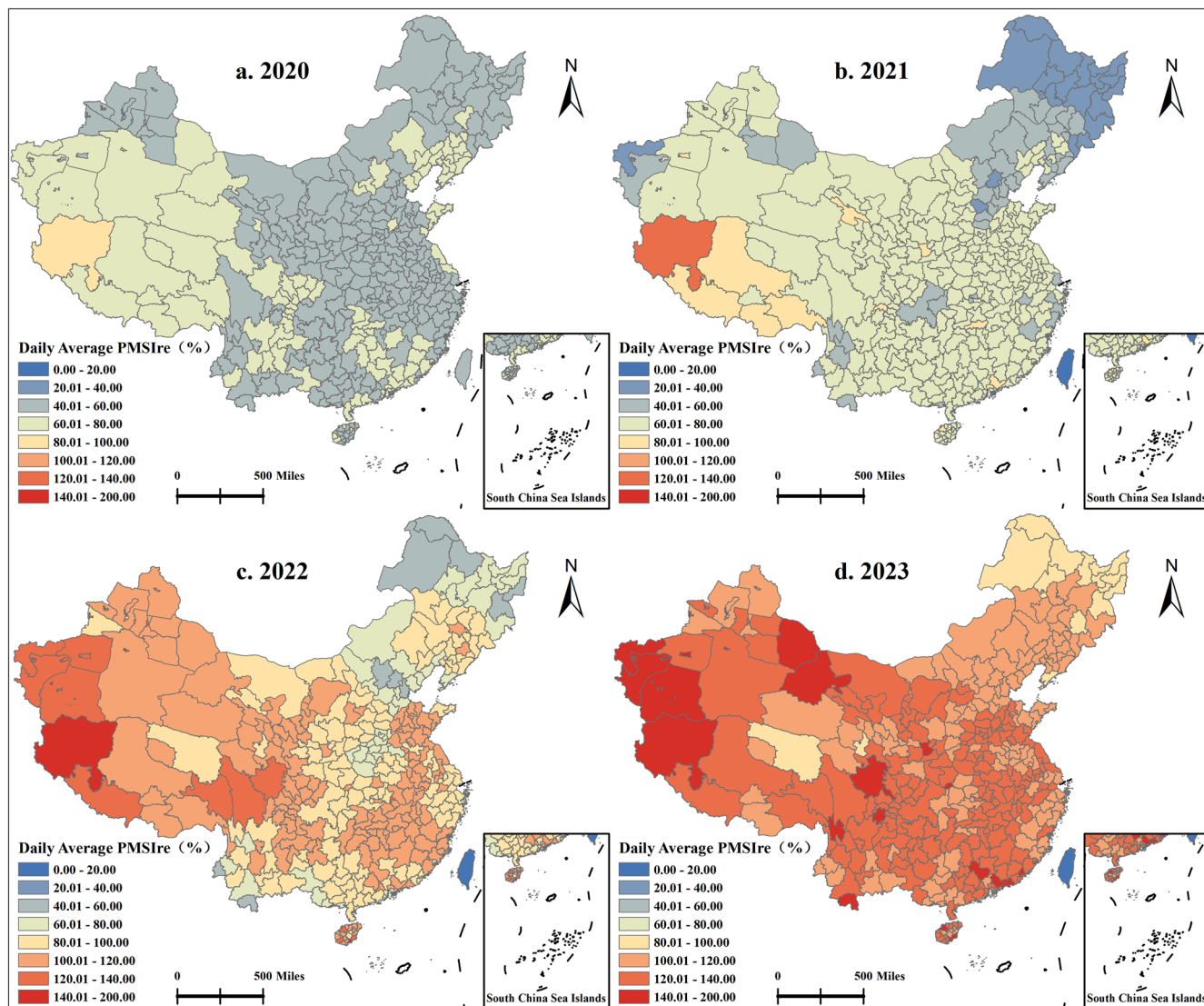
Fig. 3 Spatial characteristics of average daily population migration scale recovery index in China. This figure shows the recovery of the daily average population migration scale index (daily average $PMSI_{re}$) for 369 cities in China from 2020 to 2023, where panel (**a**) shows daily average $PMSI_{re}$ in 2020. Similarly panels (**b**–**d**) show the details from 2021 to 2023, respectively.

there is a clear "return-to-work flow" after Spring Festival, with labor-exporting provinces experiencing a large outflow of people and labor-absorbing provinces experiencing a large inflow of people after the festival. The change in the population return scale after the festival somewhat reflects the extent to which cities have resumed work and production.

The Natural Breaks method provided by ArcGIS 10.1 is used to classify the 34 provincial administrations (hereinafter referred to as "Province") into seven categories based on the average daily population return scale index for the return period (February 11th to March 1st) in 2019, which can be classified as a high inflow (H_in), moderate inflow (M_in), low inflow (L_in), relative equilibrium (E), high outflow (H_out), moderate outflow (M_out), low outflow (L_out) 7 classifications. Using the breakpoint value of the average daily PRSI for 2019 as the baseline breakpoint value, the population return scale from 2020 to 2023 was divided.

At the provincial level, the impact of COVID-19 on the scale of population return is mainly focused on short-term effects, which are more influenced by short-term epidemic prevention and control policies such as traffic control. Strict prevention policies significantly dampened labor returns between provinces after the

Spring Festival in 2020, the number of provinces with High Inflow, Moderate Inflow, and High Outflow were all zero that year, and the scale of return flows was in relative balance across the 21 provinces(over 50%), with fewer movements across provinces. The reduction in the movement of people between provinces will have a very significant impact on the resumption of work and production after the holidays, especially for the typically labor-importing provinces (e.g., Zhejiang, Guangdong, etc.); the economic recovery of labor-exporting provinces (e.g., Henan, Anhui, Hunan, etc.) will likewise be affected as workers will not be able to return to work on time and earn an income.

The majority of provinces have largely recovered the scale of population return in 2023, with the number of inflowing cities remaining consistent with 2019, but with a significant decrease in low and high-outflowing provinces and an increase in moderate-outflowing provinces. Some provinces experienced significant changes in the average daily net outflow scale, suggesting a shift in the size of cross-provincial workers in these provinces, reflecting sideways shifts in provincial employment opportunities. Specifically, three provinces—Hunan, Sichuan, and Shanxi—experienced a decrease in the scale of net population outflows,
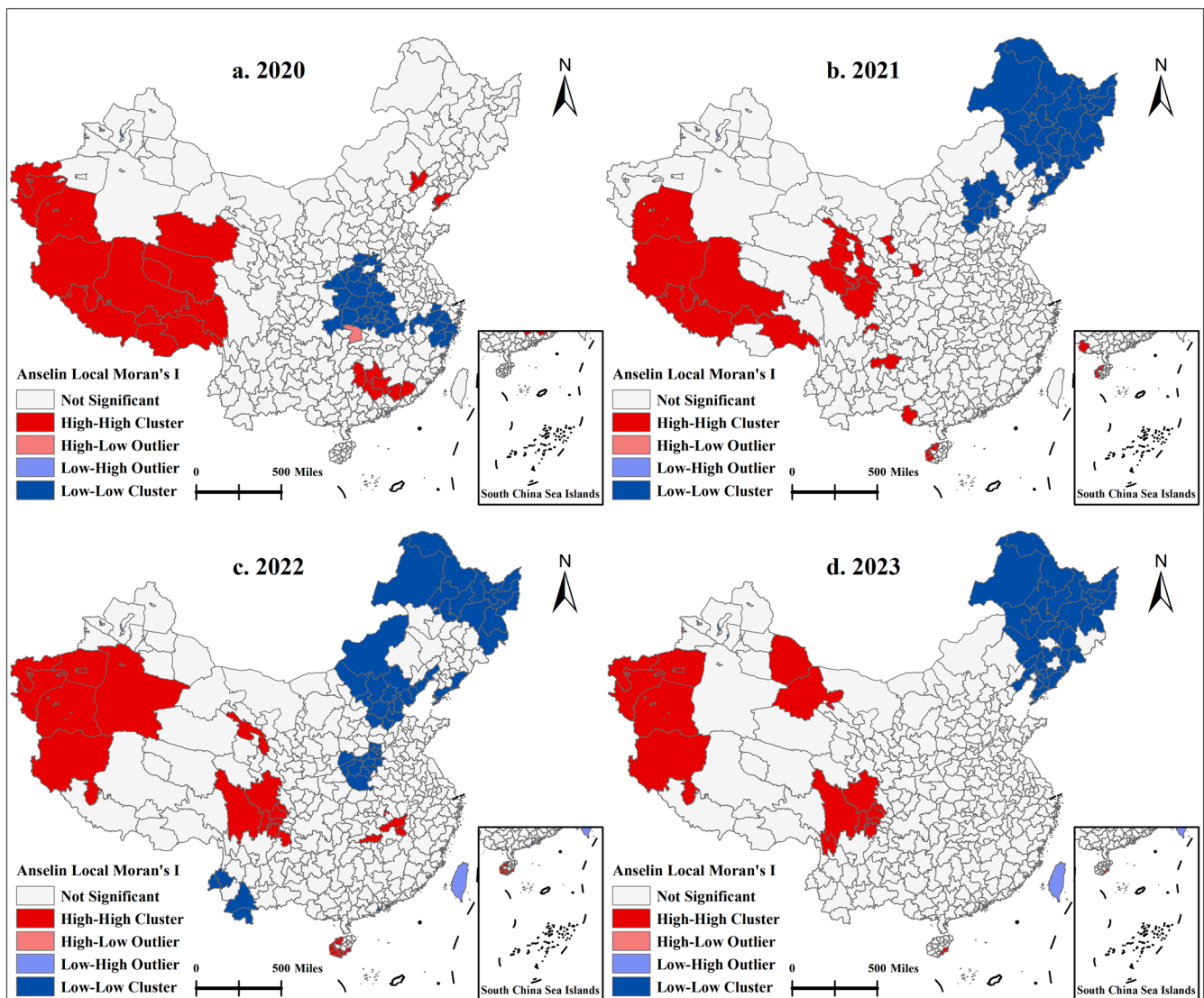
Fig. 4 Cluster and outlier analysis of PMSI$_{re}$. Spatial clustering analysis of the average daily population migration scale recovery index (PMSI$_{re}$) for 369 cities, where high–high clusters denote high average daily PMSI$_{re}$ for themselves and corresponding high average daily PMSI$_{re}$ for neighbouring regions; high–low outliers denote high daily PMSI$_{re}$ for themselves and low daily PMSI for neighbouring regions. Panels (**a**–**d**) show the details from 2020 to 2023, respectively.

while three provinces—Hebei, Guizhou, and Yunnan—experienced an increase in the scale of net population outflows.

Recovery of the scale of population return on the urban level. The 369 cities are once more separated into seven groups using the Natural Breaks provided by ArcGIS 10.1 based on the average daily PRSI during the return period in 2019. Figure 6 shows the classification results for 2020–2023 using the breakpoint value of the average daily PRSI for 2019 as the baseline breakpoint value.

As can be seen in Fig. 6, inflowing cities are scattered and dotted, while outflowing cities have a patchy distribution. The outflowing cities are distributed around the inflowing cities to form urban agglomerations, and the inflowing cities with well-developed economic activities and transport networks often being the center of the agglomerations. The Hu Huanyong Line is the boundary, with the cities to the east of the line experiencing greater population movements, while the cities to the west of the line experience more stagnant population movements, with most of the cities being balanced. Using the Hu Huanyong Line as a boundary, the cities to the east of the line are more dynamic in

terms of population movement, while those to the west of the line are relatively inactive, and most of the cities are classified as relative equilibrium (E).

Figure 6b demonstrates the short-term impact of COVID-19 on the scale of population return following the festival. In 2020, post-holiday movement of people throughout the city was significantly constrained, causing a significant disruption to businesses resuming work and production. In contrast, from 2021 to 2023, the PRSI of cities steadily improves, and the impact of COVID-19 on the population return scale gradually decreases. Figure 7 illustrates the changes in the classification of population return scale and transfer paths of China's cities from 2019 to 2023.

In 2023, 91.87% of cities whose classification based on the scale of population return is consistent with 2019 with just 30 cities suffering a shift (see Appendix 2). Specifically, two types of changes in the classification of the population return scale to Chinese cities after COVID-19 emerge, one in which the scale of the population return decreases and the outflow from the city increases, and the other in which the scale of the population
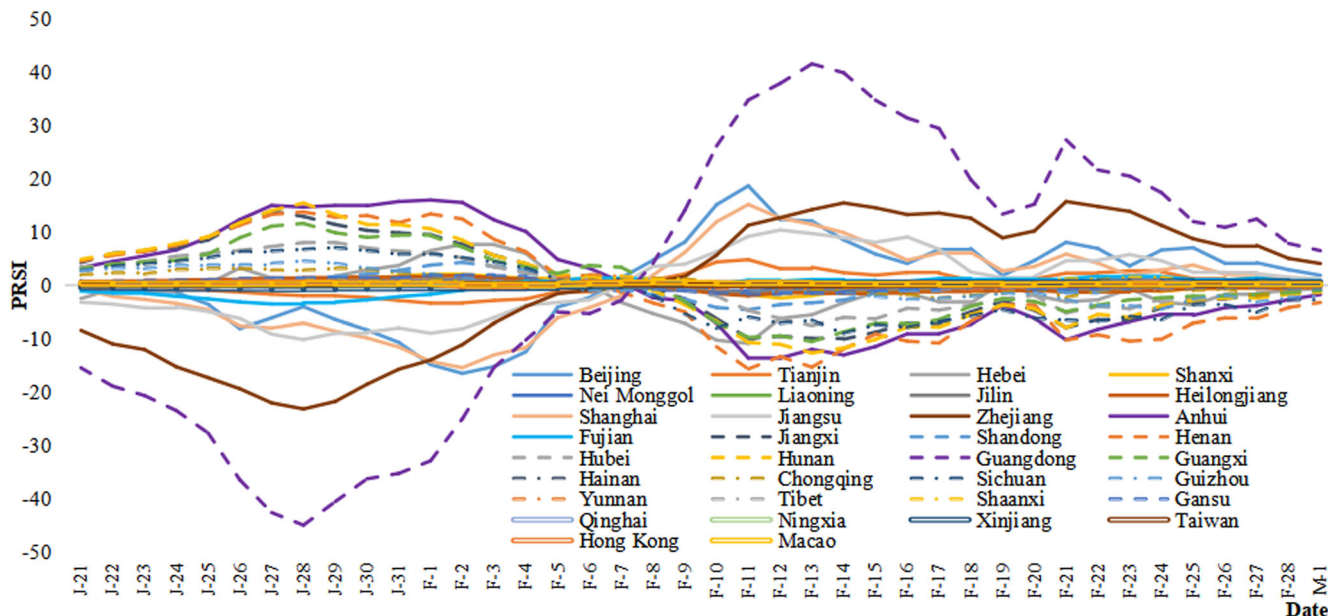
Fig. 5 Provincial curve of population return scale in 2019. This figure shows the time evolution of the population return scale index (PRSI) from 21 January to 1 March 2019 for 34 provincial administrative regions in China.

Table 1 Basic characteristics of the population mobility network.					
	Average degree	**Average weighted degree**	**Density**	**Average clustering coefficient**	**Average path length**
2020	246.065	2,742,986.888	0.670	0.712	1.3261639939846042
2021	224.645	3,143,430.166	0.610	0.644	1.3843301916290705
2022	215.089	4,573,874.481	0.584	0.623	1.4130447730081446
2023	203.967	5,875,478.138	0.554	0.597	1.4472015008710413

return increases and the inflow to the city increases. In addition, a notable change in the scale of population return is the increase in relative equilibrium cities, such as Dalian, Harbin, Urumqi, Wuhu, and 15 others in total. Population mobility equilibrium means that the population can move freely between cities and there is no unidirectional binding force in cities that hinders mobility. Population migration, including intercity migration and rural-urban migration, is driven mainly by economic factors, and the reduction in intercity population flows indicates, to some extent, a reduction in economic differences between the cities with labor mobility.

The closer the urban net population inflow in the short term after the Spring Festival is to the historical level of the same period, the better the urban resumption of work and production (Gao et al., 2021a, 2021b). The recovery in the scale of population return to the country's cities is generally characterized by a "west to east and south to north" trend as can be seen from Fig. 8. Northwest China and Qinghai-Tibet regions are the first to recover, with some cities (Tibetan Autonomous Prefecture of Garzê, Lhasa, Kashi Prefecture, etc) recovering to historical levels(daily average $PRSI_{re} \geq 100\%$) in 2021. By 2023, the daily average $PRSI_{re}$ has already reached 80% or more in 78.92% of cities across the country, and the daily average $PRSI_{re}$ has already exceeded historical levels in 52.57% of these cities, indicating a good resumption of work and production.

Changes in city network and Analysis of community evolution
Network topological features. As depicted in the above sections, the scale of population mobility and population return recovery were significantly impacted by COVID-19 epidemic. Population

mobility of a city reflects the status of this city in the city network, and to further evaluate the changes in the status and structure of Chinese urban network before and after COVID-19 is discussed. The population mobility network Average Degree, Average Weighted Degree, Density, Average Clustering Coefficient, and Average Path Length of 369 cities in China are calculated from 2020 to 2023. The population mobility networks for 40 days in each of the four years were synthesized into four static networks, with the relevant network base characteristics listed in Table 1. From the perspective of the whole network, three indicators (Average Degree, Density, and Average Clustering Coefficient) have been decreasing, while Average Weighted Degree and Average Path Length have been increasing year by year during this period.

In 2020, the overall network has the highest average degree value, indicating a relatively high degree of direct correlation between various nodes in the urban network. It also has the highest density and average clustering coefficient, indicating that the network is more likely to have an impact on its members and that the members are more closely related to each other than the urban network in other years. Changes in the density and clustering coefficients of the overall network are closely related to changes in the average degree, where a high average degree means an increase in the number of connections between any two nodes in the network, and an increase in the number of connections in the network as a whole is reflected in the higher density. This explains the significant decrease in population mobility in 2020 in terms of the PMSI, while the degree of connectivity between nodes in the urban network is high. The average path length of the network represents the average value of the distance between
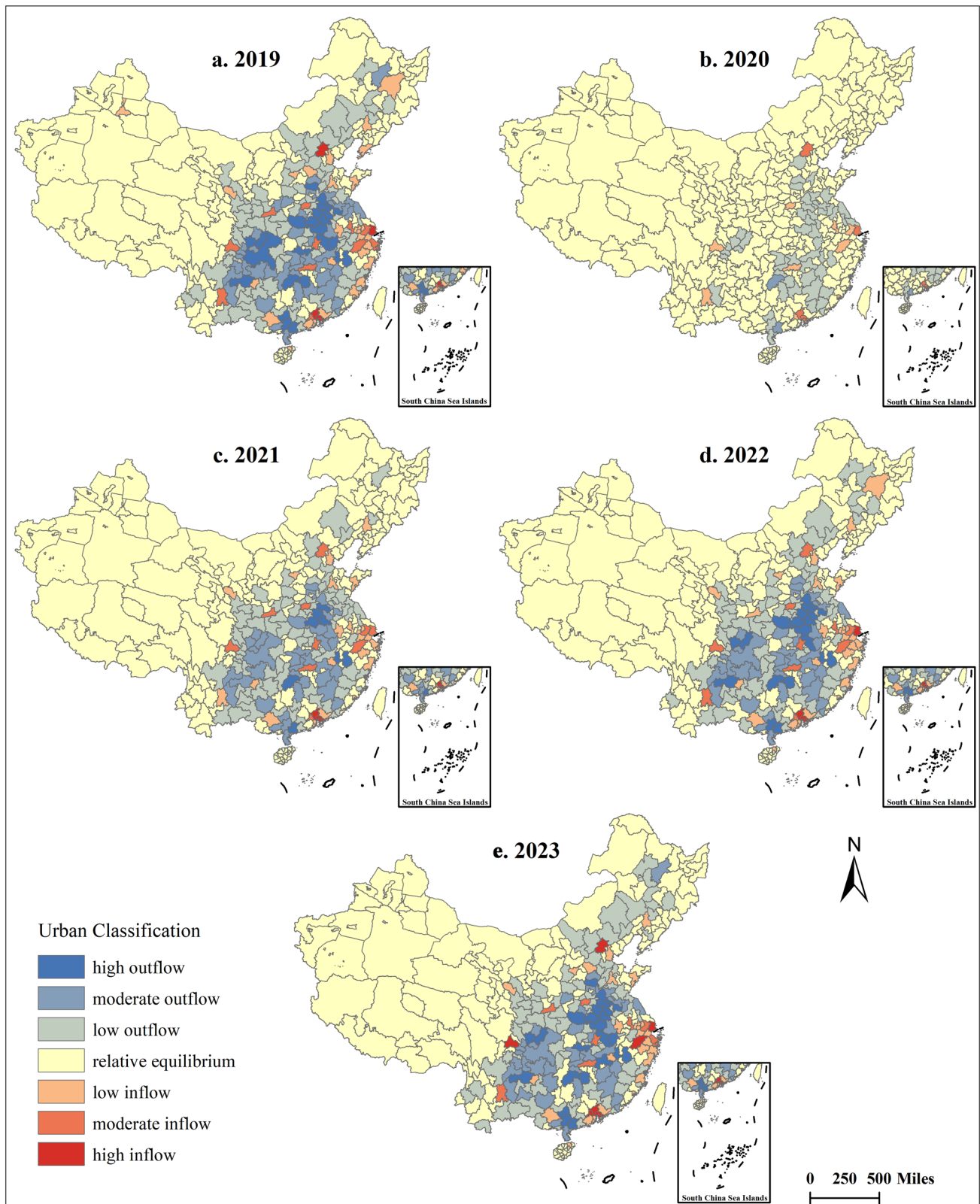
Fig. 6 Classification of Chinese cities based on average daily PRSI. a The classification of Chinese cities in 2019, and 369 cities are separated into seven groups using the Natural Breaks provided by ArcGIS 10.1 based on the average daily PRSI during the return period. Using the 2019 average daily PRSI breakpoint values as the baseline breakpoint values, cities are classified based on the average daily PRSI for the return period of that year, where panels (**b–e**) show the results of the city classification for 2020–2023, respectively.
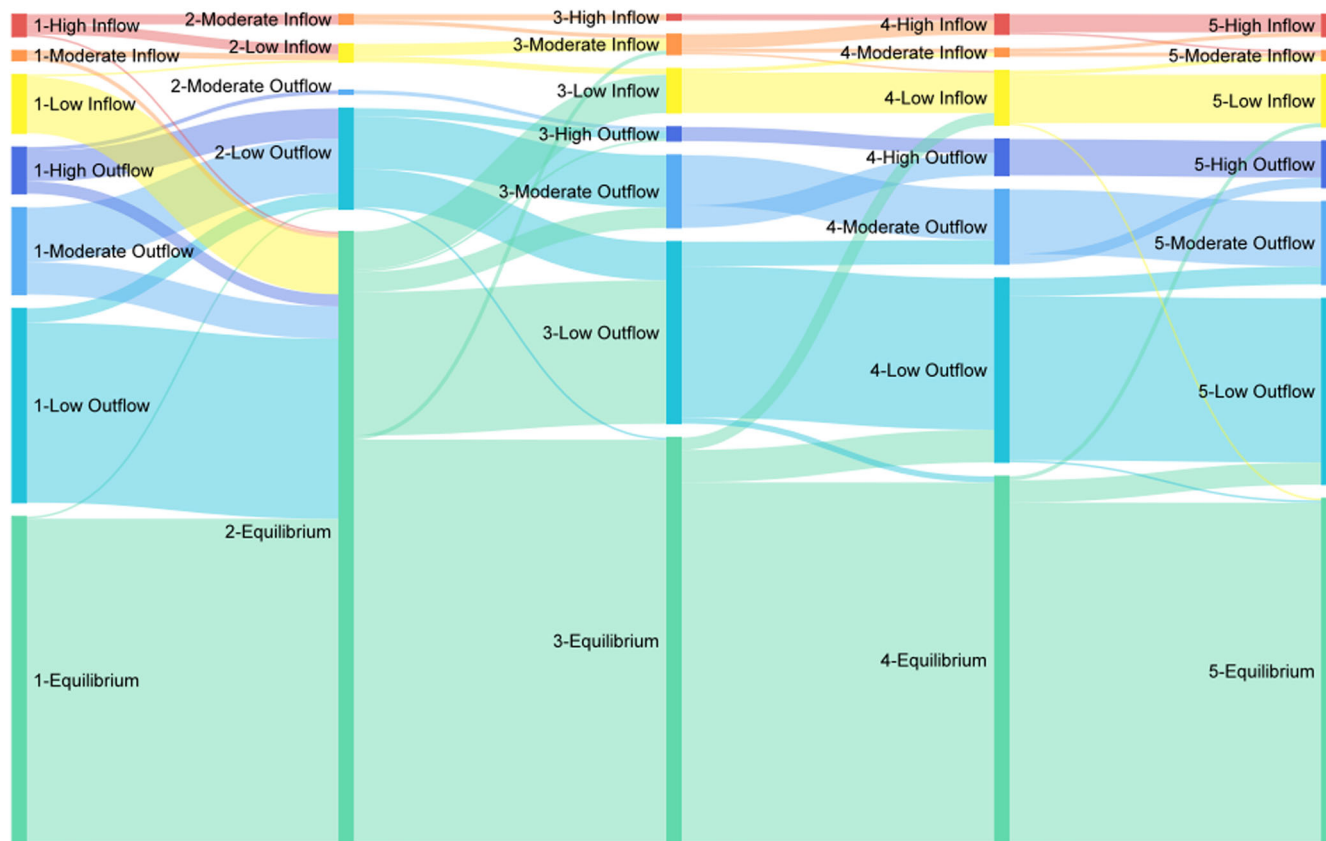
Fig. 7 Sankey diagram of average daily PRSI of urban classifications. The width of the extended branches in the Sankey diagram corresponds to how many cities are included in the category, visualizing the change in city types from 2019 to 2023 based on the daily average PRSI. "1-" to "5-" in the figure corresponding to the 4 years from 2019 to 2023, respectively.

any two nodes in the network, and when there is no connected path between two nodes, the distance between these two nodes is infinite, which leads to the average path length of the entire network being infinite.

The trend changes in all four metrics, Average Degree, Density, Average Clustering Coefficient, and Average Path Length, all reflect one thing: an increase in direct connectivity in the 2020 urban network. In reality, after the sudden outbreak of COVID-19 in 2020, people in China and around the world were under "death threat", and the unknown and fear of the virus greatly reduced people's willingness to travel. However, it was the traditional Chinese New Year holiday, and the Chinese government had not issued any mandatory restrictions on the movement of people at the beginning of the outbreak, so people still had a chance to "go back to their hometowns to celebrate the New Year" in spite of their fear. With the ambivalence of both fear and chance, people choosing to travel will opt for direct rather than cross-city transfers in order to reduce the risk of virus exposure. With the introduction of strict anti-epidemic policies—such as nucleic acid test reports and itinerary codes, tighter restrictions on inter-municipal mobility of the population. Thus, passengers traveling across cities by public transport such as trains do not stop and get off at the city they are traveling through, but choose to arrive directly at the destination city, while the number of people choosing to travel by private transport has also increased considerably.

A network is said to be small-world if most of its nodes are reachable by any other points via few associations, and the presence of a small-world effect is generally determined by a combination of Clustering Coefficients and Average Shortest Paths. If the average clustering coefficient of a network is

significantly higher than that of a random network generated by the same number of nodes, and the average shortest path of the network is close to that of a random network, then this network is considered to have small-world properties (Zhu et al., 2013). The average clustering coefficient for the urban network in 2023 is 0.597, and the average path length is 1.447, indicating that it has a more pronounced small-world character compared to 2020.

Analysis of community evolution. Due to the clustering nature of the network, and the distinct community characteristics of urban networks during the Chinese Spring Festival (Herrera-Yaguee et al., 2015; Jia et al., 2021), Gephi's Modularity function can be used to classify cities into communities. Gephi was used to modularize the urban network, where PM values were used as weights and the resolution was set to 1.0 (1.0 is the standard resolution; the lower the resolution, the more communities; the higher the resolution, the fewer communities). "Modularity" is the categorization of nodes according to the connectivity of the graph, where nodes of the same type are added to a field and represented by the same number. Modularity can be used in sociology for community discovery. Typically, Modularity > 0.44 indicates that the network has reached a certain level of modularity, and the results for the Chinese urban network for 2020 to 2023 are 0.628, 0.690, 0.679, and 0.662, respectively.

The structure of Chinese urban network communities from 2020 to 2023 is shown in Fig. 9. The community detection based on intercity population movements provides a more refined delineation of urban agglomerations, and the results of this delineation are to some extent coupled with the traditional geographical delineation of the eight human geography regions. Figure 10 shows in detail the membership changes and transfer
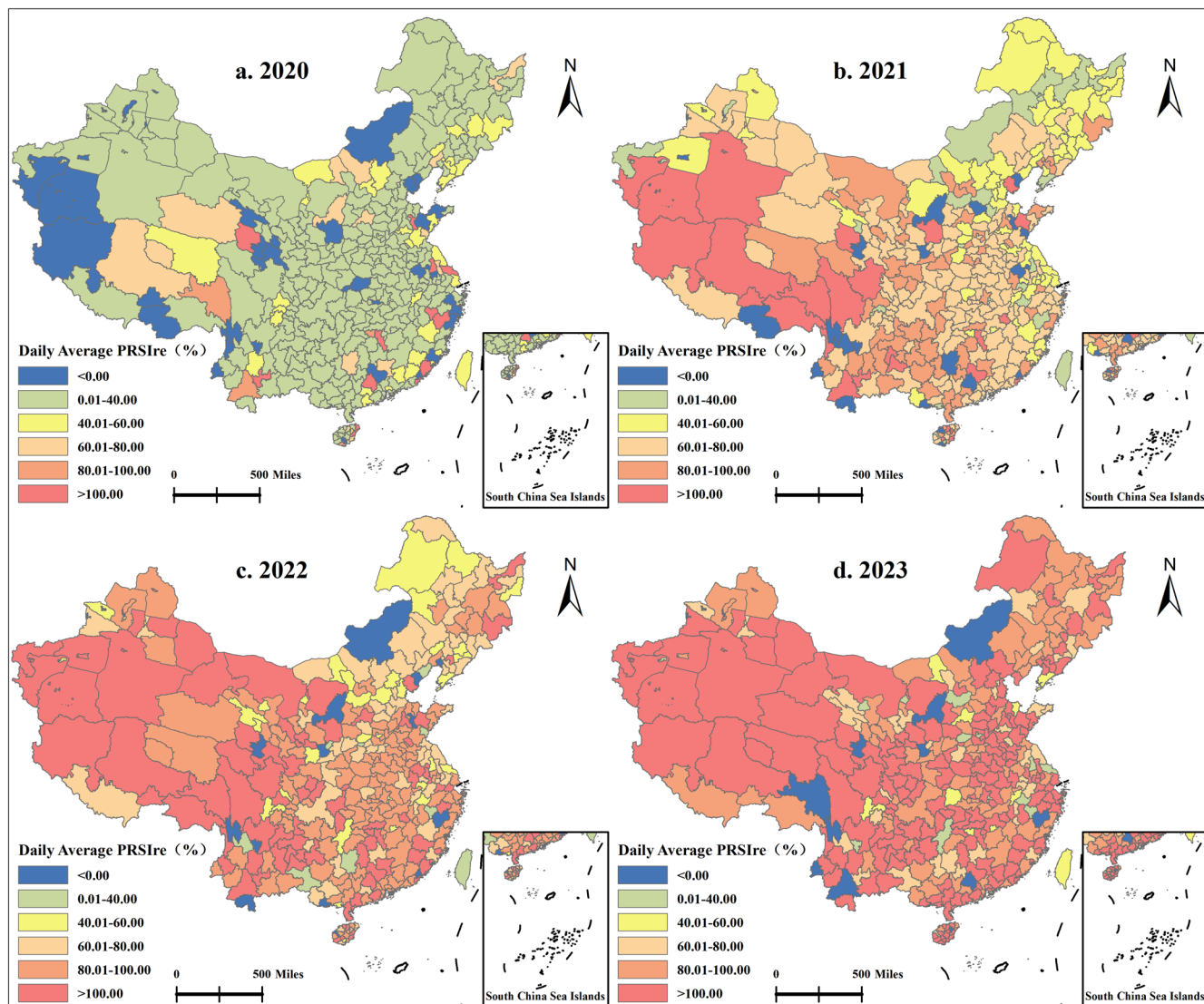
Fig. 8 Spatial characteristics of average daily population return scale recovery index in China. This figure shows the recovery of the daily average population return scale index (daily average PRSI$_{re}$) for 369 cities in China from 2020 to 2023, where panel (**a**) shows daily average PRSI in 2020. Similarly panels (**b**–**d**) show the details from 2021 to 2023, respectively.

paths between Chinese urban communities in the four phases from 2020 to 2023. The evolution of the community structure is mainly characterized by the following features.

(1) Five communities (Northeast China Community, Xinjiang Community, Henan Community, Taiwan Community, and Hainan Community) are very stable, with no city breakaways or accessions over the four years. The main areas of change in community structure were concentrated in the southern regions (south of the Qinling-Huaihe line). There are two reasons for this phenomenon: the first is that the southern region was the first to experience a large outbreak in the early stages of the epidemic and was more significantly affected by the epidemic, and the second is that the southern region is more developed in terms of socioeconomic and transport conditions, and is more densely populated and mobile than the northern region.

(2) Compared to 2020, the urban agglomerations have changed significantly in 2021, with 88 cities having shifted communities. Most of the cities in Hunan and Yunnan provinces are separated from their original communities and form

relatively independent provincial communities——Hunan Community and Yunnan Community. Some cities previously part of the North China Community, such as Datong, Jincheng Jinzhong, and so on, and Chamdo City, formerly belonging to the Southwest China Community, joined the QT and Northwest China Community. The change in the community structure of the city network in East China is even more pronounced: the Fujian Community has expanded further and the Jiangsu Community has contracted, with 14 cities in Zhejiang Province (Hangzhou, Huzhou, Jiaxing, etc.) and Jiangxi Province (Jingdezhen, Shangrao, Yingtan) moving from the Jiangsu Community into the Fujian Community. In addition, Ganzhou City and Ji'an City, which were previously part of the South China Community, have also joined the Fujian community.

(3) The vast majority of urban agglomerations in 2022 remain the same as in 2021, with only a few cities shifting communities. The Hunan Community disappears, and all cities previously affiliated with the Hunan Community join the South China Community. The urban cohesion of the
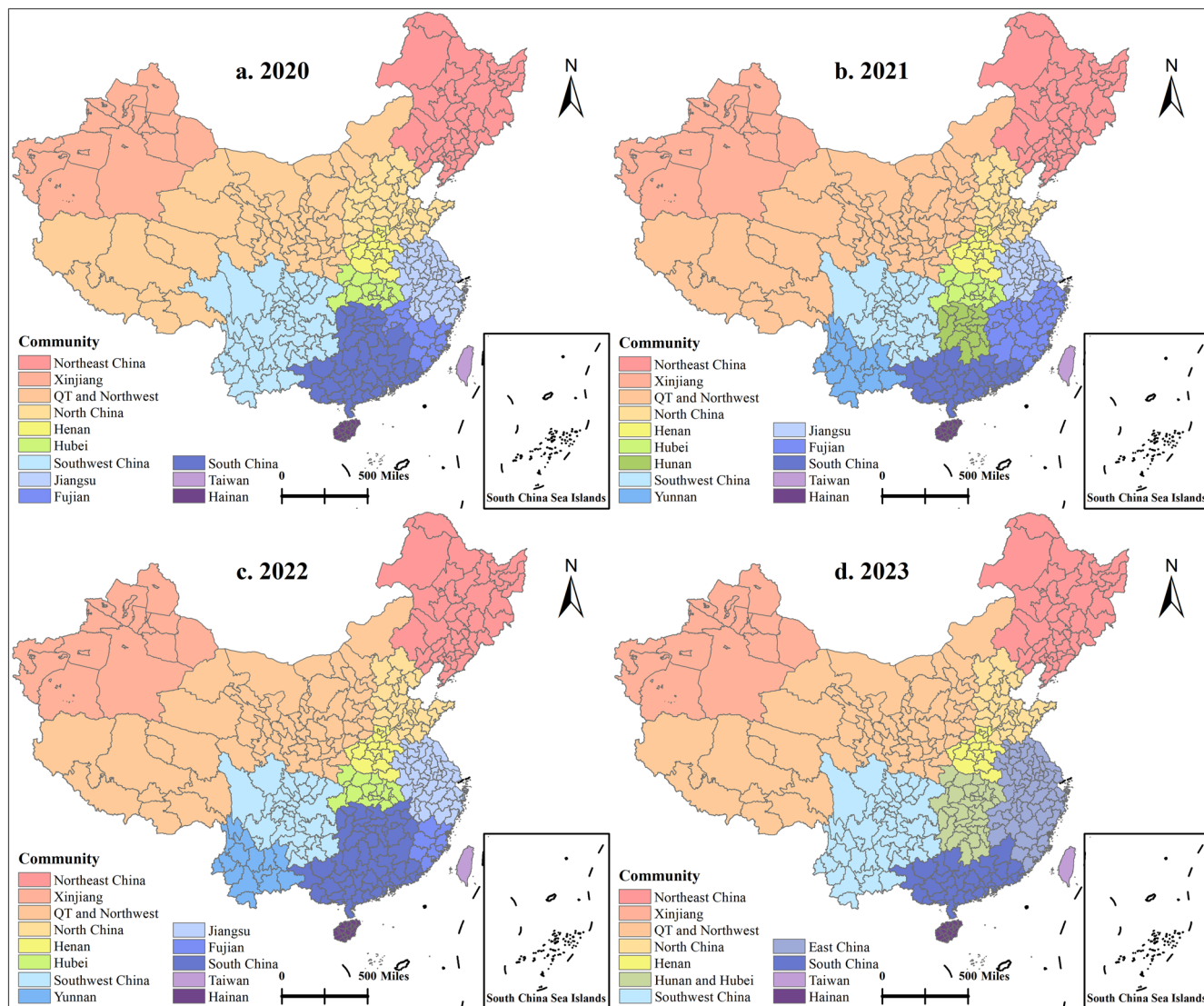
Fig. 9 Evolution of city network community structure in China. This figure shows in detail the changes in urban communities from 2020 to 2023, as well as the changes in member relationships between communities.

Fujian community has weakened, with a large number of cities breaking away, some of them (Nanchang, Xinyu, and other 6 cities) being absorbed by the South China Community and others (Hangzhou, Huzhou, and other 12 cities) by the Jiangsu community. It can be seen that the urban agglomeration consisting of 14 cities, including Hangzhou, Jingdezhen, and so on, has a strong cohesiveness of its own, but at the same time, it can be easily influenced by other urban agglomerations around it, so the cluster jumps repeatedly across between the Jiangsu Community and Fujian Community.

(4) Following the full liberalization of China's epidemic policy, the structure of urban communities changed considerably during the Spring Festival of 2023. The closeness of the Jiangsu Community and the Fujian Community increased, while six cities in the South China Community broke away from their original community, and cities of these three sources together formed a new community of greater scope, the East China Community. The South China Community has become less attractive to the cities of Hunan Province, and the Hubei Community, which formed as a result of the epidemic, has also increased its links with cities outside the

province. The closeness between the cities of Hunan and Hubei provinces has grown considerably, and all the cities of the two provinces plus Pingxiang City have formed a new community, the Hunan and Hubei Community.

(5) Overall, the structure of urban agglomeration in northern regions is more stable, while the structure of urban agglomeration in the southern regions is less stable with large changes. At the same time, the closeness of cities based on population movements remains subject to geospatial effects, and the boundaries of 'communities' coincide very closely with provincial borders, reflecting the administrative characteristics of the Strong links of cities within the province. There are some exceptions, such as Pingxiang in Jiangxi Province, which are more dependent on the surrounding cities due to their weak urban attractiveness and special geographical location (at the border of provinces). These cities are more influenced by the attractiveness of the surrounding cities, jumping from one community to another. In addition, the independence and stability of city linkages within Henan Province are strong, with cities within Henan Province consistently and steadily forming a provincial community (Henan Community) from
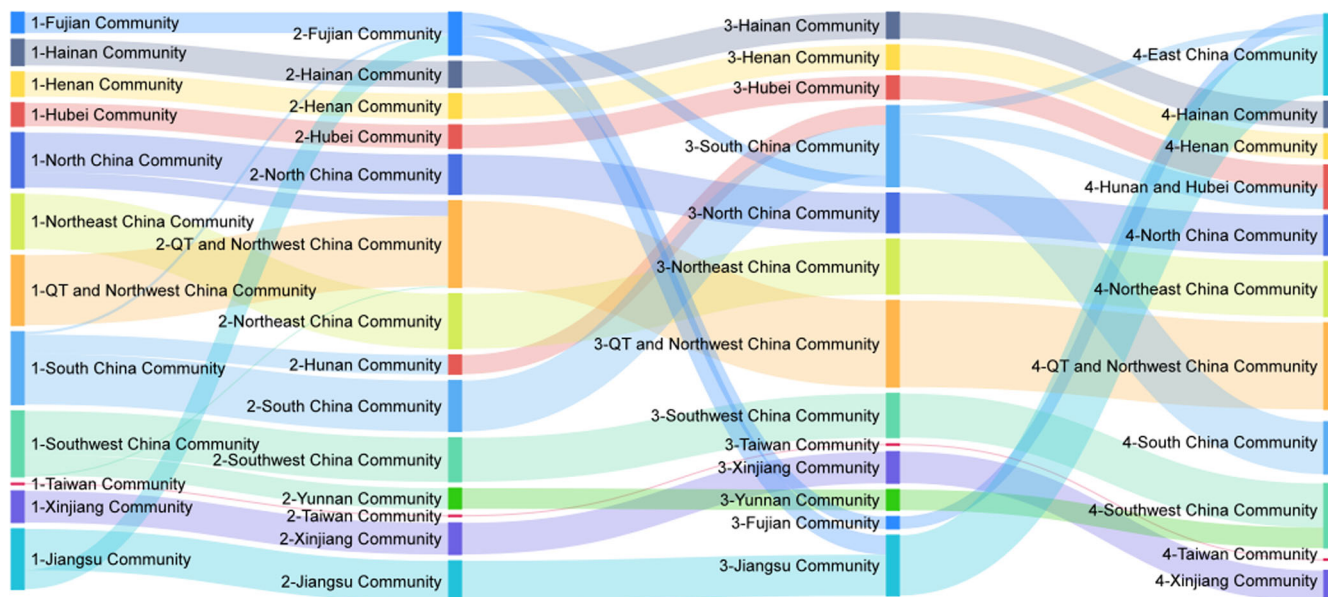
Fig. 10 Sankey diagram of urban communities based on population mobility network. The width of the extension branches in the Sankey diagram corresponds to the number of cities contained in that community. "1-" to "4-" in the figure corresponding to the 4 years from 2020 to 2023, respectively.

2020 to 2023, although the exact reasons for this remain to be further explored.

Discussion

In early 2020, the sudden outbreak of COVID-19 broke the closed loop of the seasonal movement of people during the Spring Festival, causing large numbers of people to be unable to return to their places of residence or work as planned due to the requirements for quarantine and prevention of epidemics, leading to an even more severe "labor shortage" than before in many cities in China. According to the National Bureau of Statistics, during the 25-day period after the Spring Festival, a total of 333 million passengers were sent by railways, highways, waterways and civil aviation across the country, less than 30% of the number before the festival (January 10th to 24th). Undoubtedly, the inability of a large number of people to return to work on time has become one of the key factors restricting the timely resumption of work by enterprises, while the shrinkage of production and business activities by enterprises has further led to a reduction in labor demand, and the job market has suffered a heavy blow. Compared to agriculture and manufacturing, the service sector requires a higher concentration of people. As a result, the service sector was the most directly and severely affected during the epidemic in China, with industries such as sports and entertainment, tourism, catering, and accommodation, almost ceasing to operate at one time.

The long-term impact of the epidemic on the labor force market is more worrisome than the short-term effects. COVID-19 not only leads to a contraction of the total labor market, but also reduces the matching efficiency of employment, which can lead to an increase in the natural rate of unemployment in the medium to long term. The United States labor market is facing low unemployment and very high vacancy rates, suggesting that its labor market is overheating and that the natural unemployment rate has risen. It has increased by about 1.3 percentage points from its pre-COVID level (Olivier et al., 2022). The critical situation on the labor force market has exacerbated inequalities (Soares and Berg, 2022), especially gender inequalities (Dang and Cuong, 2021; Dias et al., 2020). The epidemic has made working

from home the only option for the majority of people to continue working and minimize the risk of exposure to the virus. Young, unskilled, and temporary workers are least likely to be able to work from home and most susceptible to the labor market shocks caused by COVID-19 (Sanchez et al., 2021).

The changes in China's internal migration activities after the outbreak of COVID-19 have both similarities and differences compared with other countries, especially developed countries. Firstly, although the magnitude of the reduction in migration rates varies across countries due to differences in size and type of population mobility, most countries, such as Australia (Perales and Bernard, 2023), Spain (González–Leonardo and Rowe, 2022), and Japan (Fielding and Ishikawa, 2021), experienced significant reductions in the size of domestic migration during the early days of the pandemic. Secondly, these paper reveal that COVID-19 generated shock waves leading to temporary changes in the patterns of population movement in China, but it has not significantly reshaped the prevalent structures in the national pattern of population movement. This phenomenon has also been found in developed countries, such as Great Britain (Rowe et al., 2023). Finally, the boundaries of urban "communities" coincide very closely with provincial borders in China, which is relatively rare in developed countries. An important reason for this unique phenomenon is the cultural context of family and clan in Chinese society, which places a greater emphasis on the role of the family, whereas re-urbanization in developed countries has been documented as "the destabilization and dissolution of traditional family structures". A country's internal migration is caused by disparities in economic development and demographics between different classes of cities in its particular social context, and different patterns of internal migration indicate different national characteristics. Thus, the study of China is an important complement to internal migration research universally, providing a case of developing country and different cultural context.

This study still has certain limitations and uncertainties, despite its contributions and ramifications. (1) Baidu migration data comes from all software that chooses to use Baidu's Location Based Services API service, so the smart device users on which the mobility measure is based cannot include all populations, such as older people who do not use smart devices or people in remote

areas. (2) The 2019 migration data may not have accurately reflected the regular state of China's population movement prior to COVID-19 epidemic due to the anomalies that may have been caused by new policies enacted by individual cities in 2019 on attracting non-local populations to those cities. (3) More attention has been placed on what kind of change has occurred in population migration of Chinese cities before and after COVID-19, without much digging into the reasons behind that change. In future research, the causes of changes in migratory activity can be further explored by building mathematical models to analyze the impact of a wider range of variables on migration, such as traffic conditions, settlement policies, economic development and other relevant contextual factors specific to each city.

Conclusion

This thesis focuses on exploring the long-term impact of the epidemic on intercity population migration activities and whether intercity migration resumed after the end of the epidemic. By using Baidu Migration Big Data to construct a population mobility network, we explore the evolutionary patterns and spatial mechanisms of population mobility and urban networks in Chinese cities under the impact of the epidemic by comparing the population migration situation for five years before and after COVID-19.

The results of the study show that: (1) The impact of the epidemic on population migration in Chinese cities is mainly focused on the short-term impact, while the long-term impact is weak, and the after-effects are basically absent. Urban population patterns can largely revert to their original patterns when the epidemic subsides or disappears, but this does not mean that the impact on population movements and urban associations immediately disappears. (2) There are clear regional differences in the extent of the impact and the resilience of migration, and the order of recovery in the scale of population return in the country's cities is "west to east, south to north". (3) In terms of the evolution of community structure, the overall structure of urban agglomerations in the northern regions is more stable, while the structure of urban associations in the southern regions is less stable and varies considerably.

In addition, there are some obvious changes before and after the epidemic: Firstly, the spatial clustering results based on the average daily PMSI show that Northeast China has been showing a low–low clustering after the outbreak (starting in 2021), indicating a relatively low degree of population migration scale recovery within the region. Secondly, based on the average daily PRSI, the number of cities with relatively balanced net population inflow increased from 164 to 173 after the end of the epidemic. Thirdly, the Average Degree was high but the Average Weighted Degree was low in the urban network during the pandemic (2020) compared to the non-epidemic period, meaning that despite the reduced scale of migration, there are more direct connections between urban networks.

The analysis in this paper has practical implications for population movement and epidemic control, helping the government and other authorities to understand the resilience of population movements in cities and to reflect on the adequacy of policies to control population movements in major public health emergencies, as well as to understand the impact of public health emergencies on population movement patterns and population agglomeration effects. In addition, the results of this study suggest that spatiotemporal big data has good potential for evaluating the impact of major public health emergencies.

Data availability

The datasets generated during and/or analyzed during the current study are available in the Figshare repository, https://doi.org/10.6084/m9.figshare.24116424.

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Note

1 Four municipalities directly under the central government, 2 special administrative regions, 293 prefecture-level cities, 7 prefectures, 30 autonomous prefectures, 3 leagues, 29 county-level administrative units directly managed by the province (Excluding Huyanghe and Xixing of Xinjiang Uygur Autonomous Region), and Taiwan Province.

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Author contributions

Conceptualization, XG and YZ; data curation, XG and NW; formal analysis, XG and YZ; methodology, XG; validation, YZ and YS; investigation, YZ and WS; software, XG and NW; writing-original draft preparation, XG; writing-review and editing, YZ, XG, KYH, and WS; visualization, XG and YS; supervision, YZ; project administration, YZ; funding acquisition, YZ.

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Correspondence and requests for materials should be addressed to Xiaoyu Guo.

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