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ARTICLE

Dynamic Assessment of Spatiotemporal Population Distribution Based on Mobile Phone Data: A Case Study in Xining City, China

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Abstract

High-resolution, dynamic assessments of the spatiotemporal distributions of populations are critical for urban planning and disaster management. Mobile phone big data have real-time collection, wide coverage, and high resolution advantages and can thus be used to characterize human activities and population distributions at fine spatiotemporal scales. Based on six days of mobile phone user-location signal (MPLS) data, we assessed the dynamic spatiotemporal distribution of the population of Xining City, Qinghai Province, China. The results show that strong temporal regularity exists in the daily activities of local residents. The spatiotemporal distribution of the local population showed a significant downtown-suburban attenuation pattern. Factors such as land use types, holidays, and seasons significantly affect the spatiotemporal patterns of the local population. By combining other spatiotemporal trajectory data, high-resolution and dynamic real-time population distribution evaluations based on mobile phone location signals could be better developed and improved for use in urban management and disaster assessment research.

Keywords China · High-resolution mobile phone data · Spatiotemporal population distribution · Urban management · Xining City

1 Introduction

Population exposure to disasters is one of the most important issues of disaster risk management and can cause serious casualties during times of disaster (UNISDR 2015). With the rapid development of urbanization and the accelerating pace of urban life, the spatial activities and movements of the population also have characteristics of highly dynamic temporal changes and spatial differences. Understanding urban population development dynamics at fine temporal and spatial scales can provide an important scientific basis for exploring the laws that govern urban residents' activities to optimize the allocation of public resources and allow the formulation of public safety emergency plans.

Because urban population distribution has the dual uncertainties of scope and time, it is difficult to accurately analyze the spatial distribution of a population. In traditional population density monitoring methods, the main data types involved include census data (Huang et al. 2021), land use data (Zhang 2012), urban area data (Ding et al. 2014), data representing the number of residential units (Yang et al. 2006), and remote sensing images (Wu et al. 2005; Feng 2010; Li et al. 2013), among others. Some scholars have begun to pay attention to the study of population distribution with high spatial resolution based on census data and satellite imagery (Tiecke et al. 2017; Huang et al. 2021). However, the evaluation results have been mostly static in the urban population distribution (Dong et al. 2016). But population distributions vary widely throughout the course of a day, especially in densely populated urban areas, due to human activities (Wei et al. 2022).

The advent of the era of big data has provided the opportunity to dynamically evaluate temporal and spatial population distributions. With the rapid development and

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popularization of sensor networks, mobile positioning, wireless communication, and mobile Internet technologies, obtaining massive individual-level, high-accuracy spatiotemporal data has become a reality (Zheng et al. 2012; Li et al. 2014; Liu et al. 2014; Lu et al. 2014; Yue et al. 2014). Various individual-level spatiotemporal data types, such as volunteer positioning data (Shen and Chai 2013), floating car positioning data (Tang et al. 2015), mobile phone positioning and communication data (Ahas et al. 2015), social network check-in data (Hawelka et al. 2014; Cai et al. 2017; García-Palomares et al. 2018), and bus smart card data (Long et al. 2012), are emerging. These location-based data effectively record spatiotemporal distribution and behavioral information at the individual scale and are important data sources for conducting fine-scale human mobility research (Chen, Song et al. 2018).

Mobile signalling data can represent the real-time distribution of an urban population and have optimal characteristics such as strong timelines and wide coverage. The large sample size of individual-level spatiotemporal mobile location information provided by mobile phone data has introduced unprecedented possibilities for research in geography, urban planning, and other disciplines that require the use of spatial location data (González et al. 2008; Liu et al. 2011; Guo et al. 2014). Researchers have conducted many important studies in the fields of urban spatial structures (Reades et al. 2009; Calabrese et al. 2011), built-up environment evaluations (Wang et al. 2015), job-housing relationships (Kung et al. 2014; Leng et al. 2015; Niu and Ding 2015), transportation and commuting behaviors (Ahas et al. 2010; Yuan et al. 2012; Csáji et al. 2013), activity patterns (Song et al. 2010; Calabrese et al. 2013; Wang 2014), and so on. In the population spatial distribution field, researchers have used mobile phone data to conduct studies regarding population spatial behaviors and flows and on the identification of densely populated areas (Vieira et al. 2010; Deville et al. 2014; Gao 2014). The correlation between mobile phone location records and the spatiotemporal characteristics of human activities has been revealed in many studies (Cao et al. 2017; Li, Chen et al. 2017; Xie et al. 2020). A general conclusion of these studies is that it is more appropriate and reliable to use mobile phone data than previously used data types to evaluate the spatial distribution of a population.

China is a country that is experiencing rapid urbanization. By 2020, the urbanization rate in China reached 63.89%. The actual floating population reached 370 million.[1] Rapid urbanization has also accelerated the population flow in the nation. It is thus necessary to determine the activity patterns of local populations throughout the daily cycle to account

for fine-scale spatiotemporal variabilities. However, currently available population data are often collected only at the administrative unit level in China, and this scale is too coarse to analyze the spatial variations of interest. Census data also have low temporal resolutions that cannot reflect the spatial distribution variations that occur over the course of a single day (Feng 2010; Ding et al. 2014). Compared to conventional static data sources such as population census data, mobile phone data are representative indicators with a much finer spatiotemporal scale that can show the actual dynamic activities of urban dwellers. With the popularity of mobile big data in recent years, some researchers have begun to try to use mobile phone data to evaluate the spatiotemporal distribution of population in China. Kang et al. (2012), for example, estimated an urban population distribution by using mobile phone call data based on the service area of base stations in Harbin, China. Yang et al. (2017) used mobile phone base station data to estimate the temporal and spatial residence distribution of the urban population in Shenzhen City, China. Zhong et al. (2017) and Li, Chen et al. (2017) used mobile phone data to analyze the spatial agglomeration and temporal population movement characteristics in Shanghai. Through constructing a parametric model and nonparametric model, Chen, Wu et al. (2018) assessed the spatial distribution of urban population in near real time using mobile phone call data. Chen et al. (2019) assessed the high-precision spatial and temporal distribution of population using mobile phone data in Tianjin City, China. However, these studies usually used mobile phone call location data, which actually reflect the location of the base station used for mobile phone calls, not the specific location of the population (Kang et al. 2012; Yang et al. 2017). At the same time, the mobile phone call location data also have the characteristics of irregular sparse sampling in the time dimension (Yin et al. 2017). Thus, the assessment results of population distribution based on mobile phone call location data usually have a deviation from the actual distribution of population (Barabási 2005; Candia et al. 2008; Zhao et al. 2016). In recent years, with the development of information push technology and the widespread popularity of application programs such as WeChat, Weibo, and Qunar, it is possible to obtain mobile phone user actual location information. Through the anonymization and group processing of personal information, on the premise of protecting personal privacy, the mobile phone data based on the users' location can more accurately reflect the real-time distribution of the population (Li, Huang et al. 2017; Chen, Song et al. 2018; Xia et al. 2020). However, at present, the study on population spatiotemporal distribution based on the mobile phone user-location signal (MPLS) data is relatively limited, and it is urgent to strengthen the empirical application research.

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[1] http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/qgrkpcgb/202106/t20210628_1818826.html.

Fig. 1 Location of the study area—Xining City, Qinghai Province—and mobile phone user-location signal (MPLS) sites
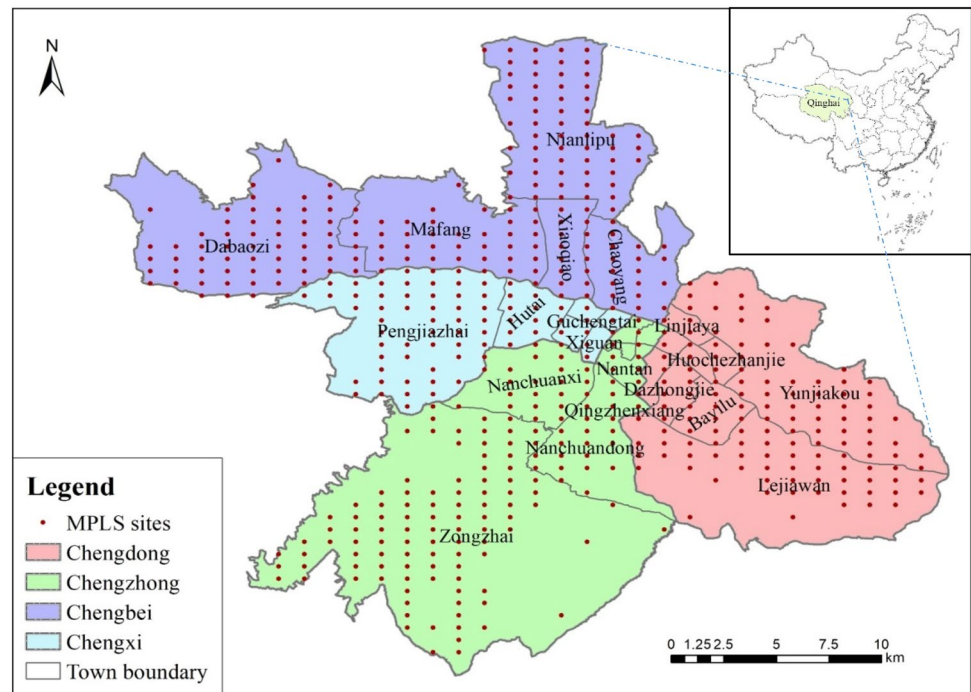
In view of the gap identified, taking Xining City, Qinghai Province, China, as an example, we conducted a real-time assessment of the spatiotemporal distribution of local population based on the hourly MPLS big data at a fine scale. Xining is not only a disaster-prone area, but also a rapidly urbanized area. The study on the spatiotemporal distribution of population at a fine scale is of great significance to both local disaster management and urban planning. However, at present, there is a lack of research on local high-resolution population spatiotemporal dynamic changes. Census data are still the basic data for most studies, which makes it difficult to accurately evaluate the real-time distribution and spatiotemporal evolution of population. Thus, the main objectives of this study were: (1) to analyze the characteristics of the daily activities of local residents based on the hourly MPLS data; (2) to distinguish the differences in population activity characteristics in areas of different urban land use types; (3) to determine the spatiotemporal distribution pattern of local population and identify the main factors that influence this pattern; and (4) to provide some suggestions for population-level spatiotemporal dynamic evaluations based on MPLS data.

2 Study Area

The study was conducted in Xining City, Qinghai Province, China. Xining is located in the northeastern region of the Qinghai-Tibet Plateau and in eastern Qinghai Province (Fig. 1). It is the capital city of Qinghai Province. The city

has an average elevation of 2261 m. The terrain is high in the southwest and low in the northeast, showing an east-west gradient. The city has a semiarid continental plateau climate, with an annual average sunshine duration of 2510.1 hours, an annual average temperature of 5.5 °C, and an annual average precipitation total of 500 mm.[2] Xining is also a natural hazard-related disaster-prone area. Earthquakes, floods, landslides, droughts, snowstorms, and other disasters occur from time to time.

Xining City includes five districts (Chengdong, Chengzhong, Chengbei, Chengxi, and Huangzhong Distircts) and two counties (Datong County and Huangyuan County), with a total area of 7660 km². The regional gross domestic product (GDP) was approximately RMB 154.88 billion yuan (USD 22.16 billion) in 2021.[3] By 2021, the permanent resident population of the city had reached 2.47 million.[4] It is a typical immigrant city with multiethnic gatherings and multiple religions. Among the ethnicities present, Hui, Tibetan, and Tu are the main ethnic minority groups in the region. Xining is the only central city on the Qinghai-Tibet Plateau with a population of more than one million and is one of the large high-elevation cities in the world. Among the local population, urban population accounted for 79.33%

of the permanent resident population. The urbanization rate of the resident population increased from 63.70% in 2010 to 79.33% in 2021, with an average annual increase of 1.42%.[5] Additionally, based on the statistics, the penetration rate of mobile phones in Qinghai Province reached 132.35 units/100 people, more than 1 mobile phone per person in 2019 (XBS 2020). Due to the limitation of data acquisition, this study mainly focused on the four core urban districts of Xining City—Chengdong District, Chengzhong District, Chengbei District, and Chengxi District (Fig. 1).

3 Data and Methods

In order to analyze the pattern of population activity, mobile phone signal data and land use data were used in this study. To further analyze the temporal and spatial distribution characteristics of local population, the kernel density analysis and the spatial autocorrelation analysis methods were employed.

3.1 Mobile Phone Signal Data

The MPLS data used in this study were obtained from a leading third-party mobile push service provider, the cooperative companies of which include first-line mainstream applications (APPs), such as WeChat, Weibo, and Qunar. This push service technology covers billions of terminals and hundreds of thousands of access applications, and the numbers of monitored daily users and concurrent online users are nearly one billion and more than hundreds of millions, respectively. Using the message push service, mobile phone user location information (in latitude and longitude coordinates) can be recorded at a 1-min updating frequency, thus providing dense time series population movement dynamics from the hourly to daily, weekly, and monthly temporal scales. Therefore, the MPLS data could be used as an indicator to characterize human activities and population distribution information at a fine spatiotemporal scale (Chen, Song, et al. 2018).

After the data had been collected, cleaned, and deduplicated, the original MPLS data were recorded by summing the real-time locations of active mobile phone users using a 6-bit geohash format with longitude and latitude geodetic coordinates. One 6-bit geohash unit corresponds to a 0.72 km^2 rectangular area that contains a certain number of MPLS, and represents the number of people using mobile phones in that area (see Fig. 1). To reflect the impacts of different factors on population activities, we selected six days of hourly MPLS data for analysis, including data collected on a summertime Monday (2 July 2018) and Saturday (7 July 2018), a wintertime Monday (2 December 2018) and Saturday (8 December 2018), the National Day Golden Week holiday (1 October 2018), and the Chinese New Year (Spring Festival) holiday (16 February 2018). All data were collected in 2018 for Xining City. All the information regarding users' identities and privacies were removed from the MPLS dataset. The intensity of human activities was estimated from these MPLS records. Larger MPLS records would indicate a higher human activity intensity.

3.2 Land Use Data

Land use is an important manifestation of human activities in terrestrial space. Land use types reflect the functional attributes of urban spaces. Different land use types attract urban populations to gather or disperse (Qi et al. 2013; Shi 2019). The land use data used in this study were derived from the Chinese urban land use database established by Gong et al. (2019). It is the first set of object-oriented, high-resolution urban land use maps produced at the plot scale in China by combining remote sensing and multisource big data sources. The land use classifications in the Chinese urban land use database comprise 5 first-class land use categories and 12 second-class categories (for the detailed classification information, please refer to the work of Gong et al. (2019)). The land use types of Xining City include 4 first-class land use categories (residential, commercial, industrial, and public management and service) and 9 second-class categories. Among the first-class categories, commercial lands include 2 second-class categories (business office and commercial service); and public management and service lands include 5 second-class categories (administrative office, educational, medical, sport and cultural, and park and greenspace) (Fig. 2). Since the mobile phone data obtained do not cover the 2 second-class categories of administrative office and sport and cultural land use, the following analysis on population activities of different land use types focused on the 7 second-class categories, namely, residential, business office, commercial service, industrial, educational, medical, and park and greenspace.

3.3 Hourly Population Activity Assessment

Although the MPLS data do not represent actual population sizes, they have been proven to be a reasonable indicator for use in delineating spatiotemporal population distribution patterns (Chen, Wu et al. 2018). Mobile phone location data reflect changes caused by the movements of people. These changes can be regarded as stable and regular during working hours when people are mostly concentrated in working areas. In contrast, during nonworking hours, people are

Fig. 2 Land use types (second-class categories) in Xining City, Qinghai Province *Source* Gong et al. (2019)
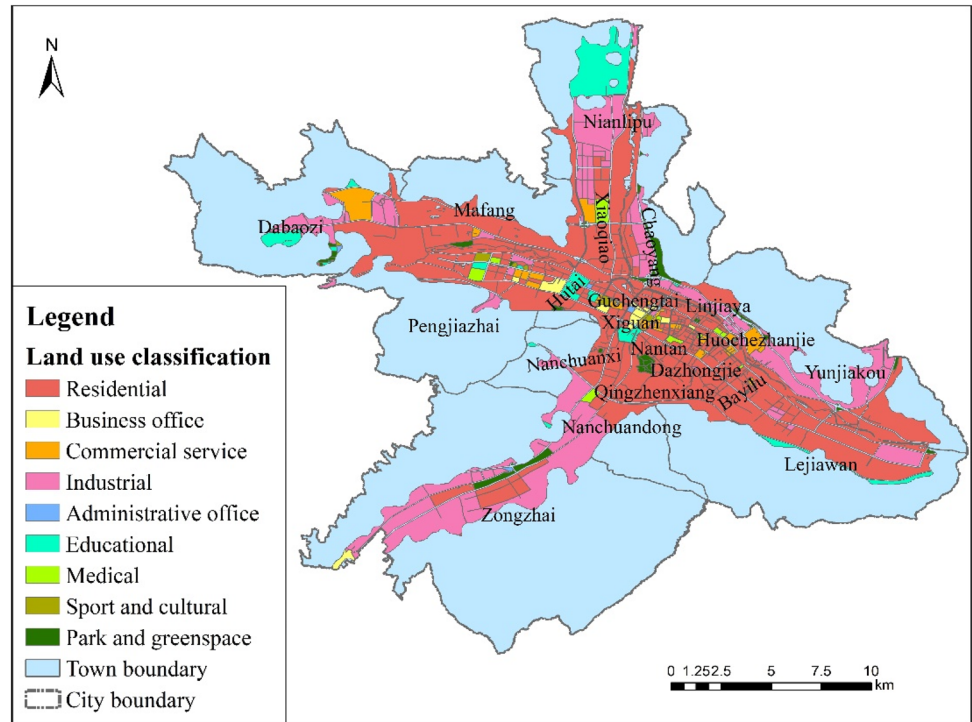
mostly concentrated in nonworking areas such as residential areas and restaurant areas. To understand the daily activity patterns of local residents, we selected six days of hourly MPLS records to simulate the general daily activities of people in this study. Specifically, we first obtained an arithmetic average of the number of MPLSs in each evaluation unit at the same time point, t, to obtain the average regional MPLS value. Then, the hourly population flow over 24 hours each day—which represents the general daily activities of people—was analyzed to evaluate the population activity patterns under the influence of different times of the day, seasons, holidays, and other factors. The temporal regularity of population activities could be evaluated according to the following formula:

$$RMPLS_t = \frac{1}{n} \sum_{i=1}^{n} MPLS_{ti}$$

where $RMPLS_t$ represents the average amount of regional mobile phone signals at time t; $MPLS_{ti}$ is the number of mobile phone signals in evaluation unit i at time t; and n represents the total number of evaluation units in the region.

3.4 Differential Analysis of Population Activities for Different Land Use Types

Different land use types promote the automatic agglomeration or dispersion of urban populations due to differences in the purposes of various human activities. Thus, the spatial distribution of the urban population should present different characteristics for different land use types. It is critical for us to further understand the spatiotemporal activity patterns of regional populations and learn more about the mechanisms of relevant population dynamics. We first obtained population activities data by conducting a spatial overlay analysis of the MPLS and land use type data. Then we analyzed the patterns of hourly population activities through statistical analyses performed for different land uses in a day.

3.5 Spatiotemporal Characteristic Analysis of Population Distribution

In general, the population distribution per unit area is regular but not uniform. To analyze the population density distribution characteristics, we employed kernel density analysis to evaluate the spatiotemporal distribution of the local population in the study area. A kernel density analysis was used to calculate a magnitude-per-unit area from point or polyline features by applying a kernel function to fit a smoothly tapered surface to each point or polyline. Then, the discrete point set was transformed into a smooth density change map to reveal the spatial distribution pattern. The kernel density was calculated using the equation:

$$F(u) = \sum_{i=1}^{n} \frac{w}{d^2} \left(\frac{u - c_i}{d} \right)$$

where $F(u)$ is the kernel density calculation function at the spatial position u; d is the distance attenuation threshold; n is the number of elements whose distance from position

Fig. 3 Daily changes in hourly population activities in Xining City, Qinghai Province, on six days in 2018
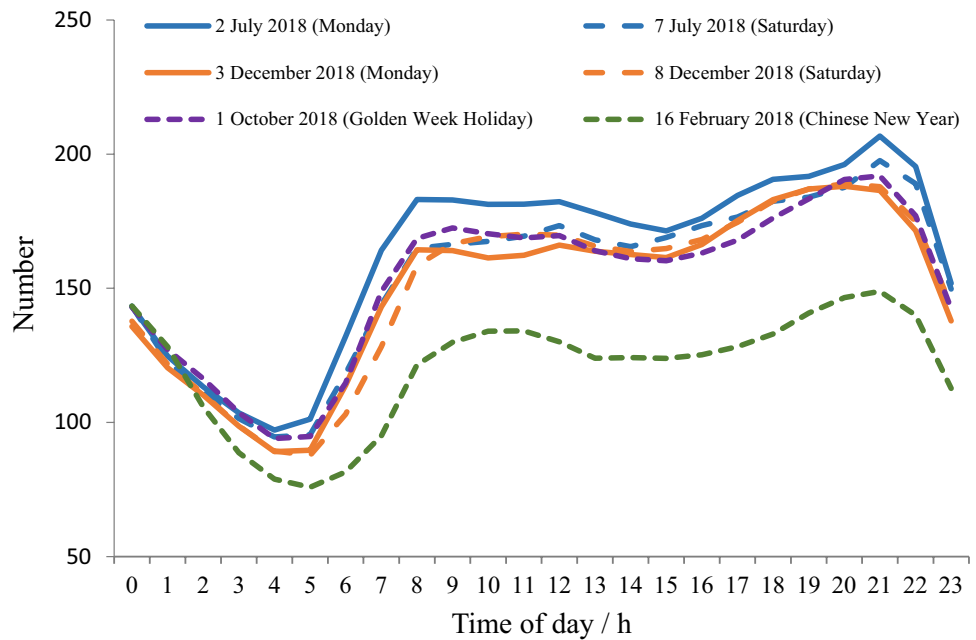
u is less than or equal to *d*; *w* represents the spatial weight function; and c_i is the core element *i*.

The kernel density method considers the distance attenuation effect of a point on its surrounding position, and the resulting values gradually decrease as the central radiation distance increases (Yu and Ai 2015). We adopted the statistical MPLS data to represent the population at each 6-bit geohash point (see Fig. 1). When using the population data for kernel density analyses, the sampling point can be regarded as the highest value on the local surface. Farther away from the sampling point, the surface value gradually decreases. When the distance is beyond the search radius, the surface value is zero. Thus, this method has obvious advantages when simulating population densities due to the clustering characteristics of population distributions (Li, Chen et al. 2017; Sun 2020). Since each 6-bit geohash grid represents a rectangular area of 0.72 km², a search radius of 1 km was selected and the resolution of the output cell size was set to 30 m.

3.6 Population Spatial Autocorrelation Analysis

We used the spatial autocorrelation analysis method to further analyze the spatial population distribution differences in the study area. Specifically, we first used high/low clustering analysis (Getis-Ord General G), a method that can measure the degree of clustering of either high or low values, to evaluate the overall concentration of the regional population. Then, the difference in the regional population density distribution was analyzed by using the cluster and outlier analysis method (Anselin Local Moran's I). Given a set of weighted features (including the neighborhood relationships

among points), Anselin Local Moran's Index analysis can be used to identify statistically significant hotspots (densely populated areas), cold spots (sparsely populated areas), and spatial outliers (transition zone points) where the population density changes. This method can thus be used to assess the staggered distribution of densely populated areas and sparsely populated areas (Sun 2020).

4 Results

An individual's daily activities are always composed of habitual behaviors and exhibit overall regularity. However, due to differences in the purpose of various activities, the patterns of population activities of different land use types also differ. Due to human mobility, spatiotemporal patterns of population distribution change continuously over time.

4.1 Daily Population Activities

Figure 3 shows the hourly MPLS number changes in Xining City throughout the 24 hours in a day. On the whole, two peak periods can be observed in local residents' activities on weekdays (2 July and 3 December 2018). One peak occurred at approximately 8–9 a.m., and the other at approximately 9 p.m. After 10 p.m., population activities began to decrease significantly until reaching their lowest value at approximately 4–5 a.m. the following day. On weekend days (7 July and 8 December 2018), population activities also showed two peaks, at 11–12 a.m. and at approximately 9 p.m. Although the patterns of population activities on holidays (1 October and 16 February 2018) are generally

consistent with those observed on weekdays, including the two activity peaks, the occurrence time of the first peak is delayed on holidays. This peak appeared at approximately 9–10 a.m. on the National Day Golden Week holiday and at approximately 10–11 a.m. on the day of the Spring Festival holiday. The activities of the regional residents on the day of the latter holiday were much lower than the daily activities at the same time on the other five days (Fig. 3).

4.2 Population Activities of Different Land Use Types

Due to differences in the purposes of various activities, the patterns of population activities of different land use types also differ. Figure 4 shows the different characteristics of regional population activities in various land use type areas in Xining City. Population activities in areas with different types of land use have some similar characteristics. For example, on the whole, all population activities gradually decrease after 10 p.m., reaching the lowest point at 4–5 a.m. the following day, and starting from 6 a.m., the population activity begins to increase gradually.

However, there are also significant differences in the characteristics of population activities among various land use types. First, the population activities observed in commercial lands (including commercial service and business office lands) changed significantly throughout the day, exhibiting more substantial variation than the other land use types. Commercial lands are the areas with the most active population. Second, the population activity pattern of residential lands differed from that in commercial land areas. In residential areas, population activities began to rise at approximately 6 a.m. and reached the first active peak at approximately 8–9 a.m. They gradually decreased until approximately 3 p.m. and then began to rise again until approximately 9 p.m., at which time the second active peak occurred; and finally, the population activities gradually decreased again to the lowest value at 4–5 a.m. the following day. The population activities in residential lands showed roughly the opposite trend compared to the one observed in commercial lands from 9 a.m. to 6 p.m.

Figure 4 also shows that the patterns of daily population activities in various land use type areas on working days are basically similar to those on weekend days. However, holidays impact population activities in various land use types to varying degrees. For example, little difference was observed between the population activity characteristics recorded during the National Day Golden Week holiday (1 October 2018) and those on other days. However, during the Spring Festival holiday (16 February 2018), the population activities in various land use type areas decreased significantly compared to the usual trends.

## 4.3 Spatiotemporal Pattern of Population Distribution

Figure 5 shows the spatiotemporal changes observed in population activities in the study area throughout the day. According to the general regularity of local population activities shown in Fig. 3, the spatial distributions of the population at 9 a.m., 12 noon, and 9 p.m. were chosen to reflect the spatiotemporal changes in population activities in Xining. From the regional distribution perspective, the densely populated areas (over 3000) are mainly distributed in the central streets or towns of Xining City (see Fig. 1 for location):

- Chengxi District: Shengli Street, Guchengtai Street, Xinghai Street, Xiguan Street, and the northeast of Pengjiazhai Town;
- Chengzhong District: Cangmen Street, Yinma Street, Renmin Street, and Lirang Street;
- Chengdong District: Qingzhenxiang Street, Dongguan Street, Zhoujiaquan Street, Dazhong Street, and Bayi Street; and
- Chengbei District: the southern part of Xiaoqiao Street.

These densely populated areas not only have a large amount of residential land, but also have concentrated commercial, educational, and medical lands. Therefore, there is a considerable number of population activities in these areas no matter in the daytime or nighttime. The population movement intensities in these areas were much higher than those in other areas (Fig. 5). In view of temporal changes, whether it was a weekday or a weekend day, relatively high activity occurred in the period from 9 a.m. to 9 p.m. each day with regard to regional activities, and residential activities were found to be mainly located in the core areas of the city center, in Chengxi, Chengzhong, and Chengdong Districts.

Holidays have a significant impact on regional population activities, especially traditional Chinese holidays such as the Spring Festival. Figures 3 and 5 show that the local population activities on the Spring Festival holiday (16 February 2018) were significantly lower than the usual activities. The scope of densely populated areas was also significantly smaller during this holiday than in normal times. However, there were also differences in the impacts of holidays on population activities. For example, the population activities observed during the National Day Golden Week holiday (1 October 2018) did not change significantly compared with the activities observed in normal times. Additionally, the wintertime population activities (on 3 and 8 December 2018) were lower than the summertime activities (on 2 and 7 July 2018) at the same time of day, and the scale of densely populated areas was also smaller in winter than in summer (Fig. 5).

Fig. 4 Population activity characteristics in different land use type areas in Xining City, Qinghai Province, on six days in 2018
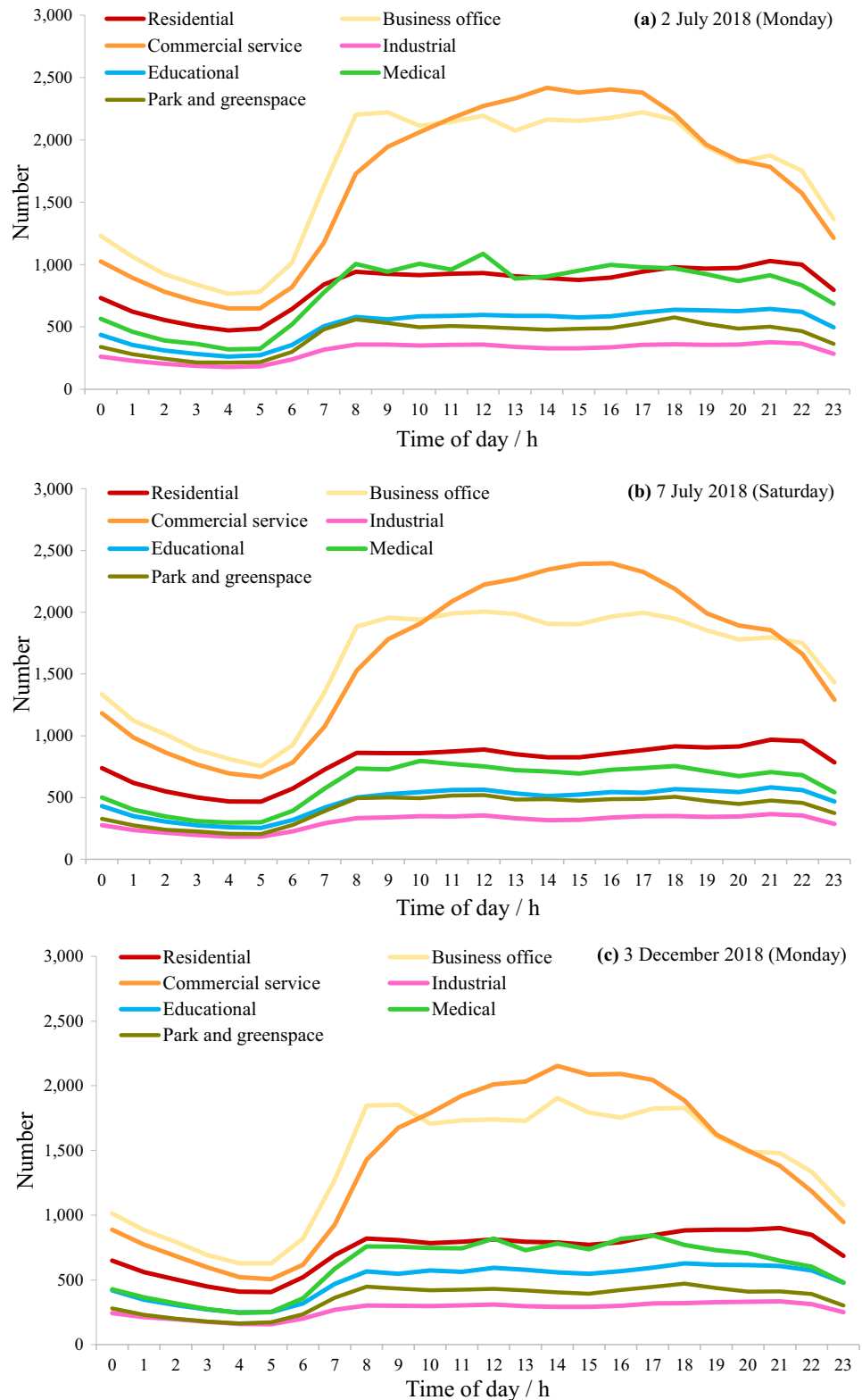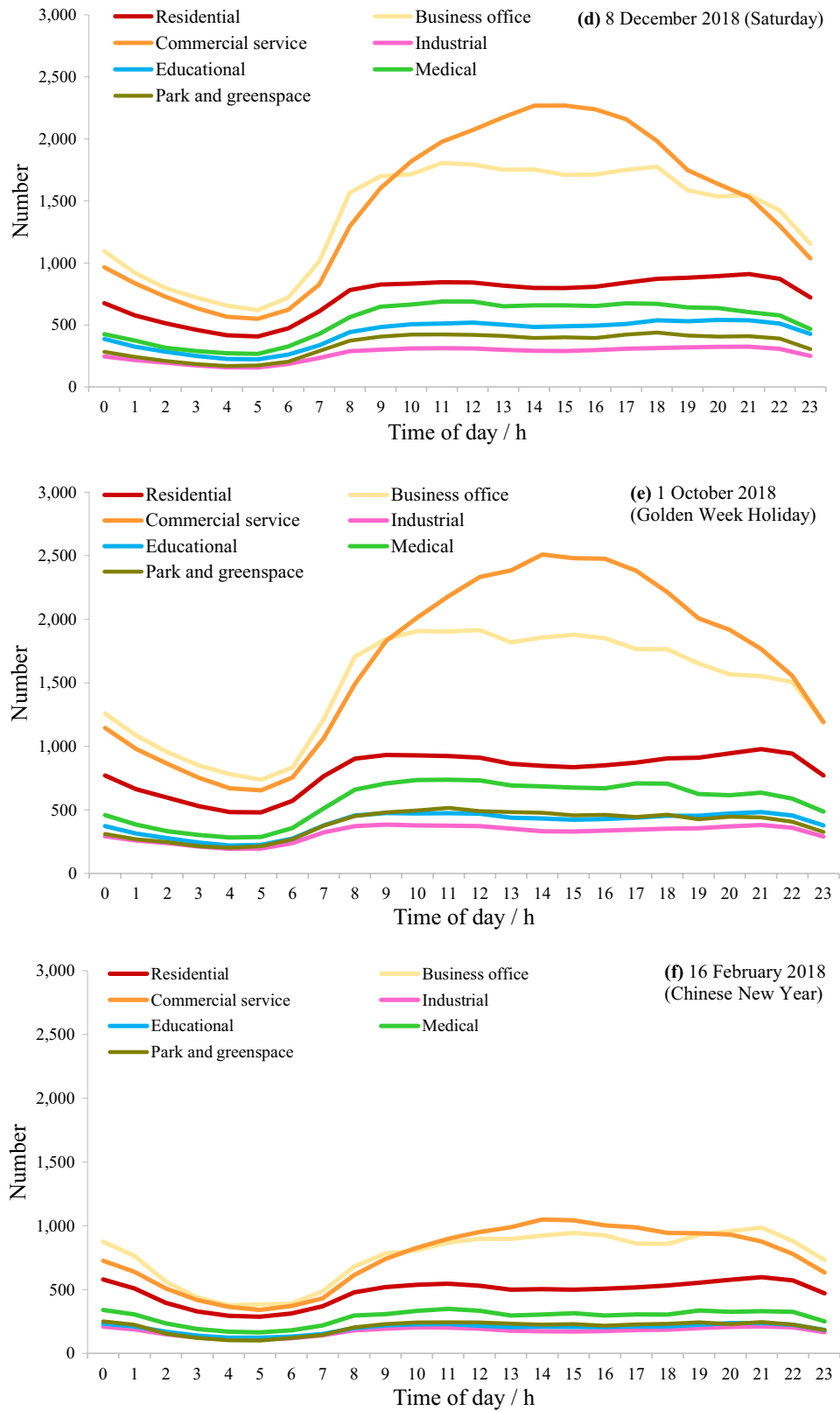

4.4 Population Spatial Distribution Differences

The spatial distribution of population changes continuously over time due to the effects of many factors, such as land use types, the time of day, holidays, and so on. In order to analyze the differences in the spatial distribution of population, high/low clustering analysis (Getis-Ord General G) and cluster and outlier analysis (Anselin Local Moran's I)

Fig. 4 (continued)

(d) 8 December 2018 (Saturday)

(e) 1 October 2018 (Golden Week Holiday)

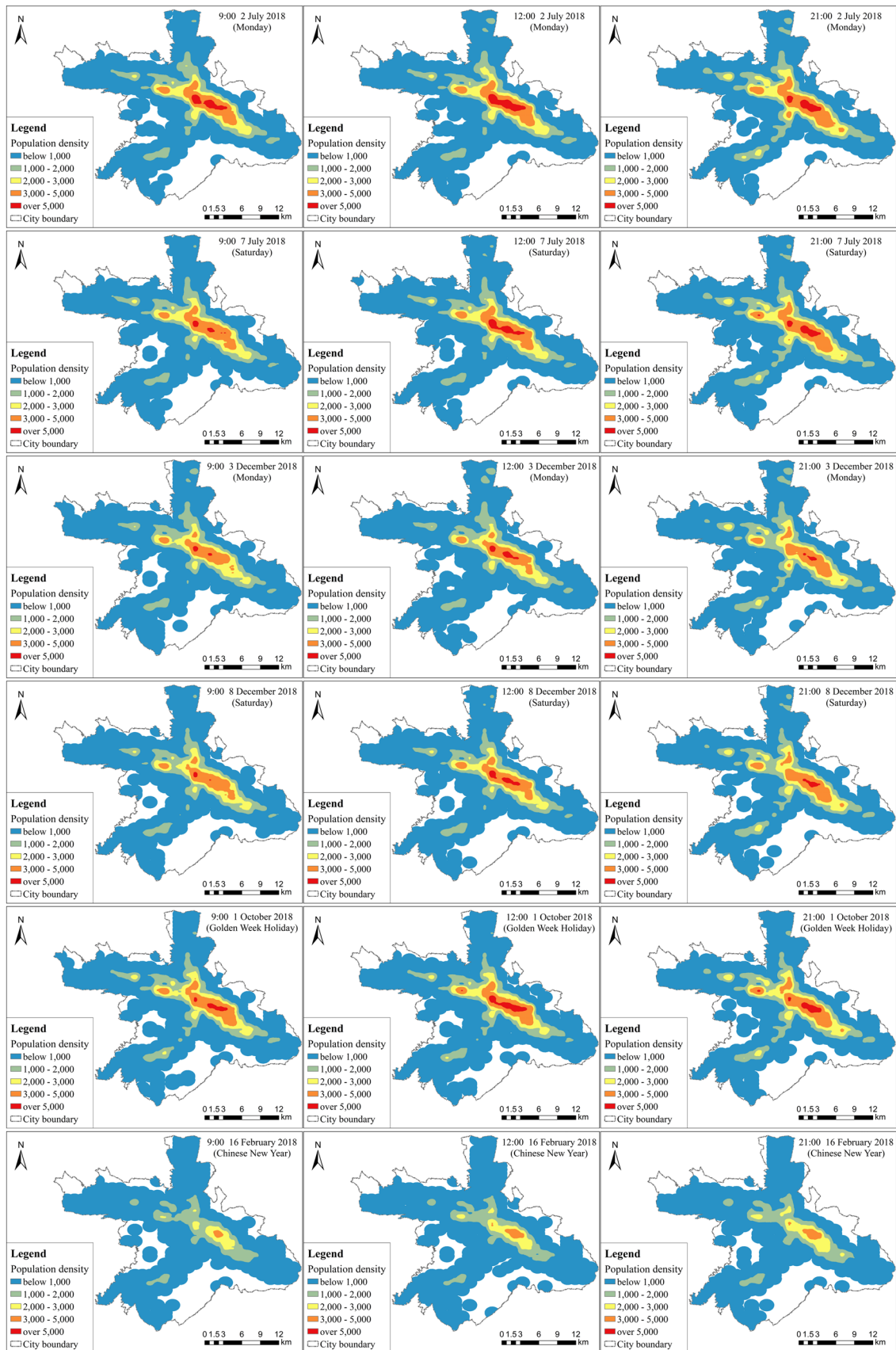(f) 16 February 2018 (Chinese New Year)

Fig. 5 Spatiotemporal changes of population distribution in Xining City, Qinghai Province, on six days in 2018

were employed to evaluate the overall concentration of the regional population and the differences in the regional population density distribution, respectively.

4.4.1 Concentrations of the Overall Population Distribution

High/low clustering analysis (Getis-Ord General G) can be used to evaluate the overall concentration degree of a regional population. A higher (lower) z score indicates a stronger (weaker) clustering intensity. A z score near zero indicates no apparent clustering within the study area. A positive z score indicates high-value clustering. A negative z score indicates low-value clustering. The analysis results obtained for the 2249 MPLS points in Xining City show that the average z score value of the local MPLS was over 20, indicating that the population distribution in the city was highly aggregated. The clustering intensity in Xining is thus very strong.

4.4.2 Differences in the Regional Population Distribution

Due to human mobility, population distributions change continuously over time. To further distinguish the differences in the population spatial distribution at different times throughout the day, we used the Anselin Local Moran's Index to analyze the hourly population distribution in Xining City. Anselin Local Moran's I analysis can identify statistically significant densely populated points, sparsely populated points, and transition zone points where the population density changes (at a 95% confidence level). Figure 6 shows the cluster and outlier analysis results obtained for the population distribution in Xining. We use the results at two representative time stages on three days as examples. In the figure, the MPLS density of sampling points is divided into five categories: nonsignificant points, high-high clusters, low-high outliers, high-low outliers, and low-low clusters. Among these categories, high-high clusters represent areas with high population densities, which is basically consistent with the distribution of densely populated areas shown in Fig. 5.

The low-low clusters represent areas with low population densities; these areas were mainly located in suburban areas, such as Dabaozi Town, Pengjiazhai Town, Zongzhai Town, and Nianlipu Town (see Fig. 1).

The low-high outliers indicate low population density areas surrounded by high population density areas. These areas represent transitional areas from high population densities to low densities. Figure 6 shows that differences in the distribution of low-high outliers were found among different times during the day. Moreover, the differences between the distributions of low-high outliers at the same time on working days and weekend days were also obvious. In general, the distribution ranges and change extents of the population

densities in these transitional zones on working days were stronger than those on weekend days. Furthermore, low-high outliers were all located around areas with high population densities on the whole. In contrast to low-high outliers, the high-low outliers indicate areas with high population densities surrounded by areas with low population densities. These areas represent transitional areas from low population densities to high densities, and this category was relatively rare in the city, with instances mainly located in suburban areas. For the Chinese New Year, the high-low outliers showed a significant increase in Dabaozi Town (see Fig. 1 for location).

5 Discussion

Behavioral geography holds that an individual's daily activities are always composed of habitual behaviors such as going to work, going home, and shopping. Temporary or accidental behaviors are the secondary component (Chai and Shen 2008). Daily activity behaviors are a mixture of choices and restrictions. By analyzing the temporal trajectory of residents' activities, the temporal characteristics and regularity of residents' daily travel can be summarized to synthesize more abstract travel modes of residents (Chai et al. 2008).

5.1 Regional Population Activity Pattern

Residents first choose their travel activities according to their own needs associated with life and work. In addition, residents' choices are influenced by external environmental factors, especially social and cultural factors. Although the purposes and durations of daily travel activities associated with different groups are different, they exhibit overall regularity (Zhang et al. 2010). Our study showed that the daily population movement pattern exhibited strong temporal regularity during the day, especially on weekdays. Low population activities were generally observed approximately between 4:00 and 5:00 in the morning each day, while the peak values appeared at 08:00–09:00 in the morning and at 21:00 in the evening each day. The trends of residential and work activities showed a concave-convex phenomenon over the 24 hours in a day. These findings are consistent with those of similar studies conducted in China (Chen et al. 2019; Shi 2019; Hu et al. 2020).

The various travel activities of urban residents are basically carried out around urban buildings, for work-, shopping-, and school-related activities. During travel, residents living in an area may leave that area, while residents living outside the area may enter into the area. These movements mainly depend on the service function (land use types) provided by the area or on the use of various buildings in the area. When an area mainly contains residential lands, a large
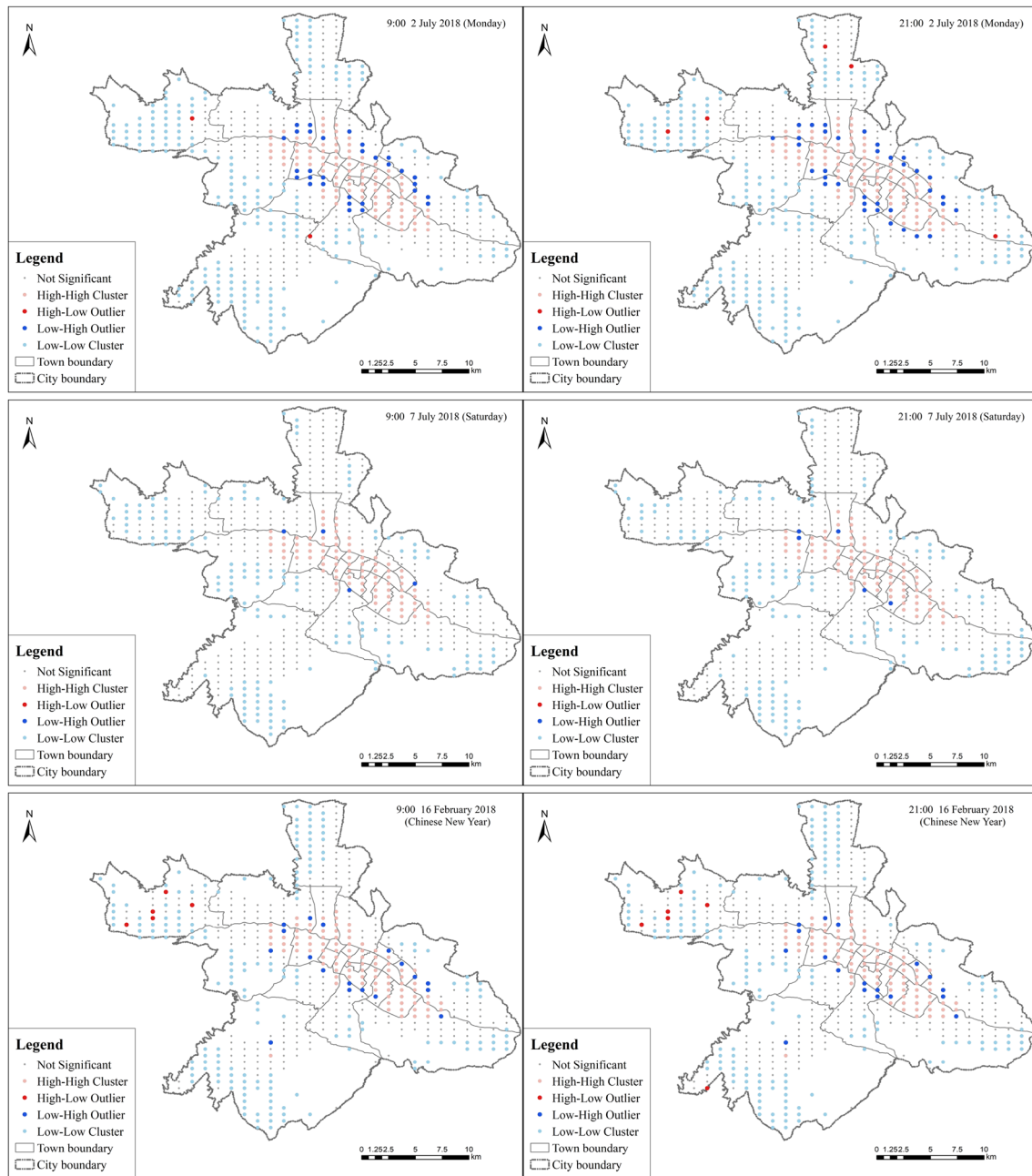
Fig. 6 Cluster and outlier analysis results of the population distribution in Xining City, Qinghai Province, on three days in 2018

number of commuting trips will leave the area, while return-ing trips will enter the area. If an area mainly contains com-mercial buildings, the population movements will be in the opposite direction (Wei et al. 2022). In our study, we found that the population activities in residential lands showed roughly the opposite trend compared to the one observed in commercial lands from 9 a.m. to 6 p.m. This finding has also been confirmed in previous studies (Cao et al. 2017). In addition, we found that the trend of population activities

within other nonresidential lands such as educational and medical lands is similar to that of residential lands during some parts of the day. However, this similarity reflects dif-ferent activity patterns between them. For example, after 10:00 p.m., although the number of MPLS in residential lands also showed a downward trend, this decline reflects the deactivation of mobile signalling (such as shutdown, hibernation, and so on), not the movement of population. However, in nonresidential lands, the decline of the MPLS

number after 10:00 p.m. means that people leave these areas and the number of mobile phone users decreases, reflecting the movement of the population. Thus, the pattern of population activities in other nonresidential lands such as educational and medical areas is actually different from that in residential lands.

5.2 Influencing Factors of the Regional Population Spatiotemporal Distribution

Many factors influence the spatiotemporal distributions of regional populations, including land use types, the time of day, holidays, population structure, and building functions (Freire and Aubrecht 2012; Wei et al. 2017). Urban land use types reflect the functional attributes of urban spaces. Different human behaviors correspond to different urban functional areas. Our study showed that in general, regardless of whether it was daytime or nighttime, the urban population density showed a significant downtown-suburban attenuation pattern from the center of the city to its periphery in space. The densely populated areas are mainly located in the core urban area of Xining City. Large sections of urban residential lands, as well as prosperous trade and logistics markets—including public management and service lands such as finance, catering, hotels, transportation, medical treatment, and tourism—predominate in these areas and determine the population activities and high population mobility density. These findings are consistent with previously established modern urban development patterns in China (Kuang and Du 2011; Gu 2012).

Holidays have an important impact on regional population activities, especially traditional Chinese holidays. Previous studies have shown that on weekends or holidays, people mainly stay at home during both the day and the night, except to travel (Qi et al. 2013). Our study found that the intensity and scope of local population activities during the Spring Festival holiday were significantly lower than those in a typical day. However, we also found differences in the impacts of holidays on population activities. For example, the population activities during the National Day Golden Week holiday did not change significantly compared with those observed in normal times. This may have been related to the nature of the holiday and residents' habits. The Spring Festival is the most important holiday for returning home and visiting relatives and friends in China. At this time, some people who live and work in urban areas generally return to the suburbs or to their rural hometowns, and this could cause a decline in urban population activities. The National Day Golden Week in China is a holiday meant to encourage people to travel. Tourism-based cities such as Xining thus do not experience reduced population activities. In contrast, the population mobility in this city may be more active on this holiday than usual.

In addition, seasonal factors seem to have a certain impact on the intensity of population activities. Although the range of population activities exhibited no significant changes at concurrent times between summer and winter, the activity intensity of the local population was significantly higher in summer (July) than in winter (December). This might have been mainly affected by climate factors such as temperature. Xining is known as the "summer capital" of China. The average summertime temperature in the city ranges from 17 °C–19 °C, and the climate is pleasant, thus enhancing the willingness of people to engage in outdoor activities, in addition to regular daily travel. In winter, the local temperatures are relatively cold (with an average winter temperature of – 6 °C), and the daily sunshine duration is short, potentially causing the relative decrease observed in the activities of local residents, although regular daily travel does not change. Due to the limitation of data access, we only compared the population activities of two days each in July and December. The representativeness of the sample size with respect to the seasons needs further discussion. However, given the regularity of daily activities of the regional population, the findings of this study are in line with basic expectations.

5.3 Implications

High-resolution and dynamic assessments of spatiotemporal population distributions are critical for urban planning, urban management, disaster risk assessments, and post-disaster emergency rescues (Li et al. 2013; Li et al. 2019; Wei et al. 2022). Mobile phone big data have the advantages of being real-time, dynamic, and high-resolution. These data can be used to track the activities and behavioral characteristics of groups to improve our understanding of human daily activities and enhance the accuracy of population spatiotemporal dynamic distribution assessments. The results of this study also confirmed the superiority of MPLS data in evaluating population activity patterns and the spatiotemporal population distribution. In particular, through clustering and outlier analyses considering the neighborhood relationships among points, these data can be used to discern high-population density areas distributed in different times and spaces and the key transition points where population density changes to provide direction for the differentiated determination of population spatiotemporal distributions. Density maps, hotspots distribution, or mobile landscapes can be easily generated from mobile phone data, which are a useful tool for understanding urban rhythms and structure. The static population distribution or land uses are not informative for depicting this progress. The MPLS data provide a more objective indicator for assessing the actual use of urban space.

The MPLS data can also be applied to uncover attractions and accessibility of different urban spaces, even to explore the interaction between transportation and the built environment. For example, in Xining City, the population density showed a significant downtown-suburban attenuation pattern. The distribution of MPLS data was more concentrated in the downtown area during the daytime than the distribution at 21:00 when people usually stay in their homes and travel less. In addition, the areas with high-low outliers were located in the suburbs, which means that the population activities in these areas are highly active, and they are population gathering places and key areas for urban planning or disaster risk management. We thus can go a step further in understanding urban traffic while considering the path-choosing strategies, or geographical constraints. Optimal commuting allocation implies an excellent urban configuration and traffic condition (Kang et al. 2012).

Through the refined assessment of the spatiotemporal distribution of population exposure, the MPLS data can provide a more objective and accurate reference basis for local disaster risk management. In traditional studies, the risk assessment based on static and administrative data such as census data cannot consider the diurnal flow of population, which usually results in errors and low spatial resolution. The MPLS data indicate the actual locations of mobile phone users. It is possible to achieve a refined assessment of the spatiotemporal changes of population exposure to disaster based on the MPLS data, thus improving the accuracy of disaster risk assessment and response efficiency. Although MPLS data do not represent actual population sizes, previous studies have confirmed the high correlation between mobile phone data and population distribution and the feasibility of using these data in population distribution evaluation applications (Cao et al. 2017; Li, Huang et al. 2017; Chen, Song et al. 2018; Chen, Wu et al. 2018; Xie et al. 2020). In the future, with the popularization of smartphones and the development of big data utilization and mining technologies, MPLS big data-based studies on population dynamics and the application of these data in disaster research and other fields will be further improved. In addition, by combining other spatiotemporal trajectory data, such as volunteer positioning data, floating car positioning data, social network check-in data, and bus smart card data, high-resolution and dynamic real-time population distribution evaluation technologies will be better developed for application in urban management and disaster assessment research.

With the increase in demand for MPLS data with high spatial-temporal resolution, even anonymous MPLS data have a risk of privacy leakage that cannot be ignored (Yin et al. 2015). Therefore, establishing a secure mobile phone data use mechanism to protect user privacy is the foundation for better development and application of MPLS data.

6 Conclusion

In this study, we conducted a dynamic real-time assessment of the daily spatiotemporal population distribution in Xining City, China, based on six days of MPLS data. By analyzing the characteristics of the daily activities of local residents, we determined the spatiotemporal distribution patterns associated with group activities. The results show that the daily activities of local residents exhibited strong temporal regularity each day. In general, two peaks and one trough were observed in the daily activities of the analyzed population. The specific population activity characteristics differed among various land use types. The population activity trends observed in residential lands were the opposite of those identified for commercial lands, showing a concave-convex phenomenon in the daytime. The spatiotemporal distribution of the local population showed a significant downtown-suburban attenuation pattern. Factors such as land use types, holidays, and seasons all affected the population spatiotemporal patterns.

The study revealed the regularities and differences in the spatial and temporal distributions of group activities in an urban space. Compared to traditional census data and other methods, the methodology utilized has the advantages of a large sample size, wide coverage, real-time, and a dynamic assessment. Although the short-term sampled data have a short repeatable period, which may result in some errors in the spatiotemporal constraint recognition results, these data are critical for analyzing the travel activities of residents in the city and in assisting urban planning and disaster management.

In the future, with the further popularization of mobile phones and the development of big data mining technologies, population dynamics research based on MPLS big data and its applications in disaster and other fields will be further improved. However, privacy protection must be the foundation of the MPLS data application and development in the future. Establishing a set of scientific mobile phone data use and protection mechanisms is fundamental for the application of MPLS data in local urban planning and disaster risk management.

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