Postprint: Prediction of Accessibility of Park Green Spaces for the Elderly in Xining City Based on Mobile Phone Location Data

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Abstract

Predicting and analyzing the accessibility of park green space resources for the elderly is of great significance for improving the quality of life of older adults and effectively addressing the challenges posed by China's aging society. To make the distribution of urban park green spaces more "age-friendly," this study identifies and predicts the spatial distribution of the elderly population based on mobile phone location data with age identifier information from Xining City, and employs the Gaussian two-step floating catchment area method to investigate and forecast elderly park green space accessibility. The results indicate that: (1) The elderly population will increase significantly from 2018 to 2028, with the change in the number of elderly people exhibiting a ring-shaped distribution pattern characterized by lower values in the central urban area and outer suburbs, and higher values in the inner suburbs. (2) Over the 10-year period, the overall spatial distribution pattern of elderly park green space accessibility has not changed significantly, but the accessibility level has generally declined. (3) The relative change in elderly park green space accessibility from 2018 to 2028 is substantial; under 30-minute walking and public transit conditions, approximately 87% of spatial units experienced a reduction in park green space accessibility of more than 70%. The research findings address the gap in urban elderly park green space accessibility studies at high spatial resolution and provide recommendations for future urban park green space planning oriented toward the development needs of population aging.

Full Text

Prediction of the Accessibility of Parks and Green Spaces for the Elderly in Xining City Based on Mobile Phone Location Data

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Abstract

Predicting and analyzing the accessibility of park green space resources for the elderly is of great significance for improving their quality of life and effectively addressing the challenges posed by China's aging society. To make the distribution of urban park green spaces more "elderly-friendly," this study identifies and predicts the spatial distribution of the elderly population based on mobile phone location data with age identification information in Xining City, and employs the Gaussian-based two-step floating catchment area (G2SFCA) method to study and predict the accessibility of park green spaces for the elderly. The results show that: (1) Between 2018 and 2028, the number of elderly people increased significantly, and the variation in elderly population exhibited a circular distribution pattern with lower increases in the central urban area and outer suburbs, and higher increases in the inner suburbs. (2) During 2018–2028, the overall spatial distribution pattern of accessibility to park green spaces for the elderly did not change significantly, but the overall accessibility level declined. Under the condition of walking for 15 min, the population covered by relatively high and high grades of accessibility decreased from 17.58% to 6.70%. Moreover, under the condition of public transportation for 30 min, the population covered by relatively high and high grades of accessibility decreased from 26.41% to 9.28%. (3) The relative change in accessibility of park green spaces for the elderly from 2018 to 2028 was substantial; under 30-minute walking and public transport conditions, approximately 87% of spatial units experienced a reduction in accessibility of park green spaces by more than 70%. The research findings supplement the deficiency in studies on urban elderly park green space accessibility at high spatial precision and provide recommendations for future urban park green space planning oriented toward the needs of aging develop-

ment.

Keywords: the elderly; park green space; mobile phone data; accessibility; Gaussian-based two-step floating catchment area method; Xining City

1 Introduction

Population aging is a significant challenge facing human society in the 21st century. According to reports from the National Health Commission, the population aged 60 and above in China will exceed 400 million around 2035, entering a stage of severe aging. The elderly are gradually becoming a major component of urban life. The 20th National Congress of the Communist Party of China emphasized the need to "implement a national strategy to actively respond to population aging." Ensuring and optimizing the accessibility of public service resources for the elderly is an important part of meeting their aspirations for a better life.

Accessibility refers to the ease of traveling from one point to another in space[], reflecting residents' opportunities to access public service resources through transportation. It is a commonly used measurement indicator for evaluating the service level of public facilities. Main measurement methods include the gravity model[], network analysis[], nearest neighbor method[], and two-step floating catchment area (2SFCA) method[]. Among them, the 2SFCA method, proposed by Radke[], can effectively consider both supply scale and demand allocation, and has been used for accessibility evaluation and optimization of various public service facilities.

As an important component of urban green open space, urban park green spaces are crucial venues for outdoor leisure activities for the elderly, helping to meet their physiological and psychological needs. Predicting and rationally allocating urban park green spaces to make them more "elderly-friendly" is an important approach to improving the quality of life for older adults.

Previous studies have applied this method to research on the allocation of public resources such as healthcare and park green spaces. However, early versions of the 2SFCA method did not consider distance decay factors, limiting their practical applicability. Subsequently, researchers introduced a Gaussian function to measure distance decay effects, proposing the Gaussian-based two-step floating catchment area (G2SFCA) method, which enhances the rationality of accessibility calculations and has been widely applied in accessibility evaluation of urban public service facilities, including park green spaces, elderly care facilities, and medical facilities.

As global population aging deepens, scholars have begun to focus on differences in park green space accessibility among different age groups. Studies show that compared with younger groups, elderly groups have reduced activity levels and fewer opportunities to access green space resources. Some scholars have used mobile phone data to obtain the spatial distribution of elderly populations and their willingness to enter parks, exploring the impact of socioeconomic status on elderly park green space accessibility. Other research has taken Hanover, Germany as a case study, focusing on differences between the elderly and other age groups in accessing urban green spaces. Scholars have also studied park green space accessibility for elderly groups in mountainous cities and old urban residential areas, finding unreasonable and inequitable phenomena in both spatial distribution and resource matching of park green spaces.

Census data and WorldPop are important sources of population distribution data in existing research. Publicly available census data have relatively low spatial precision, long update cycles, and lack age structure information at finer spatial scales (such as county-level divisions). WorldPop data, which relies heavily on census data, also suffers from time lags in updates and credibility limitations dependent on the quality of geographic environmental attribute data. These two types of data are insufficient to support precise analysis and applications targeting specific populations. With the rapid development of information and communication technologies, high spatial precision population location sensing capabilities have significantly improved. Large-scale population location sensing data, represented by mobile phone location data, have been widely applied in analyzing human mobility characteristics. Currently, domestic and foreign scholars mainly use mobile phone data for research on population activity pattern identification, urban commuting characteristics analysis, and resident travel behavior modeling. Some scholars have used mobile phone data for urban park green space accessibility analysis, but research on elderly park green space service needs remains limited due to the lack of age information. Furthermore, existing studies have focused primarily on past or current urban park green space accessibility, lacking assessment of future urban park green space service levels.

Therefore, this study identifies and predicts the spatial distribution of the elderly population based on mobile phone location data with age identification information, and employs the Gaussian-based two-step floating catchment area method to study and predict the accessibility of park green spaces for the elderly. The relevant methods and conclusions can address the needs of aging development and provide methodological support and decision-making assistance for optimizing urban park green space planning.

2 Study Area and Data

2.1 Study Area

This study takes the main urban districts of Xining City as the research area (Fig. 1). Xining City, the capital of Qinghai Province, is located in the eastern part of Qinghai Province, in the valley basin of the middle Huangshui River. It is an important central city in Northwest China. Constrained by topographical factors, the built-up area of Xining's main urban districts exhibits an east-west "cross-shaped" radial strip spatial structure. By 2018, Xining had an urban population of 1.71×10^{6} and a main urban district area of approximately 360 km^2. According to the Qinghai Provincial Civil Affairs Information Network, in 2018, Xining had an elderly population aged 60 and above of 3.89×10^{5}, accounting for 16.5% of the total population and 23.3% of Qinghai Province's elderly population, making it the earliest city in the province to enter an aging society and the region with the highest degree of aging.

2.2 Data Sources and Processing

Mobile phone location data. The mobile phone location data used in this study were obtained from a mobile network operator, covering the spatial scope of Xining's main urban districts. The dataset includes 3.8×10^{5} users, accounting for 22.2% of Xining's urban permanent population. The data span 10 working days and 4 rest days, with an average of approximately 4.3×10^{7} records per day and an average temporal sampling interval of 29 minutes, which can relatively completely record users' daily location information. Each record contains basic information such as user ID, location, and time, as well as non-sensitive attribute label information including age group and gender. Therefore, this dataset can effectively reflect the daily activity location information of the relevant population and has good representativeness for urban resident activity analysis. Based on the mobile phone data, this study identified nearly 1.5×10^{4} base stations, with an average distance of 191.26 m between base stations. The density distribution of base stations is shown in Fig. 2.

Park green space data. Through the Baidu Maps open platform, we collected location, entrance, and area data for park green spaces in Xining City in 2018, identifying a total of 72 park green spaces in the study area.

Data preprocessing. To reduce the impact of invalid and abnormal data on the analysis results, this study preprocessed the mobile phone location data, mainly including: (1) deletion of null values; (2) deletion of duplicate values; (3) deletion of typical erroneous values, where typical erroneous values refer to records with anomalies in longitude and latitude, user ID, time, etc.

2.3 Research Methods

Based on mobile phone location data, this study identifies the home locations of elderly and potentially elderly individuals, constructs a linear regression model to predict the spatial distribution of the elderly population as demand information, uses park green space data collected through the Baidu Maps open platform as supply information, and then calculates the time cost from demand points to supply points. The Gaussian-based two-step floating catchment area method is employed to calculate the accessibility of park green spaces for the elderly in 2018 and to predict the accessibility for 2028. The technical flowchart is shown in Fig. 3 [Figure 3: see original paper].

2.3.1 Home Location Identification This study identifies users' home locations based on mobile phone location data from 10 working days and 4 rest days. First, positions where users stayed for more than 2.5$×10^{4}$ seconds between 00:00–06:00 each day were identified as candidate home locations. Then, among the candidate home locations, if the same user was identified at identical locations, that location was designated as the user's home location; otherwise, the centroid of different candidate home locations was calculated, and the location point closest to the centroid was selected as the user's home location. Ultimately, home locations for 3.5$×10^{5}$ users were identified. Second, among users whose home locations could be identified, those aged 60 and above were screened and identified as elderly, and those aged 50–59 were identified as potentially elderly. To test the representativeness of elderly mobile phone users, this study conducted a consistency test between the number of elderly mobile phone users and WorldPop elderly population data at the 500 m$×500mgridscale, findingaSpearmancorrelationcoefficientof0.75(p < 0.001).Additionally, thisstudycomparedthenumberofelderlymobilephoneuserswithsixthcensusdata.Afterrem
0.05)forallstreetsexceptthosewithobviouslyabnormalpopulationdatainPengjiazhaiTownandYunjiakouTown
elderly people use feature phones, accounting for 53.0% of the elderly population, while 38.6% use smartphones, with a cumulative percentage exceeding 90%. This indicates that with the development of mobile communication technology, mobile phones (including both smartphones and feature phones) have a relatively high penetration rate among the elderly, and mobile phone location data have certain representativeness in assessing elderly home locations.

2.3.2 Elderly Population Prediction Due to the lack of valid elderly migration data within the forecast period, this study assumes that residential locations do not change with age. Therefore, the number of elderly people in a local area can be predicted through the following logic: the number of elderly people in the forecast year equals the number of elderly people in the previous year, minus the number of deceased elderly, plus the net number of newly added elderly. The calculation formula is as follows:

$$P_{m+1} = P_m - \eta_m + \mu_m$$

Where: P_{m+1} is the elderly population in year m+1; P_m is the elderly population in year m; η_m is the number of deceased elderly in year m; μ_m is the net number of newly added elderly from year m to $m + 1$.

η_m is calculated based on the elderly population base and its mortality rate in the current year. Considering that elderly mortality is higher than total population mortality, this study uses a correction coefficient to adjust the total population mortality rate to obtain the elderly mortality rate. The specific formula is as follows:

$$\eta_m = s_m \times \alpha \times P_m$$

Where: s_m is the total population mortality rate in year m; α is the elderly mortality rate correction coefficient.

s_m is estimated based on historical mortality rates obtained from Xining City's statistical bulletins from 2011–2021. This study uses a linear regression model to predict the total population mortality rate for a given year in Xining City. The specific formula is as follows:

$$s_m = a \times m + b$$

Where: a and b are coefficients to be estimated. This study calculates them using the least squares principle based on historical mortality rates.

The elderly and potentially elderly mortality rate correction coefficients α and β are calculated based on national age- and gender-specific mortality conditions from the China Population and Employment Statistical Yearbook for the period 2011–2021, and their average values are ultimately taken. The calculation formulas are as follows:

$$\alpha = \frac{\sum_{i=60}^{100} p_i^d}{\sum_{i=60}^{100} p_i} \bigg/ \frac{p^d}{p}$$

$$\beta = \frac{\sum_{i=50}^{59} p_i^d}{\sum_{i=50}^{59} p_i} \bigg/ \frac{p^d}{p}$$

Where: p_i^d is the number of deaths at age i; p_i is the population at age i; p^d is the total number of deaths; p is the total population.

2.3.3 Time Cost Calculation To account for urban road connectivity, traffic capacity, and the efficiency of different transportation modes, this study uses the Baidu Maps open platform to obtain travel times from demand points to supply points during off-peak hours under different transportation modes as the time cost. Specifically, under walking and public transportation modes, travel times from grid centroids to park green spaces were obtained during weekday 10:00–16:00 and rest day 18:00–22:00 periods. Compared with traditional calculations based on road network data, this method can comprehensively consider road hierarchy, congestion conditions, traffic signals, and other actual road conditions, providing more accurate evaluation results.

2.3.4 Park Green Space Accessibility Calculation This study divides the research area into 500 m$\times$500 m grids as analysis units and employs the Gaussian-based two-step floating catchment area method[] to calculate park green space accessibility.

Step 1: Calculate the supply-demand ratio. First, obtain the supply location and scale of park green space services. This study uses park area to measure service supply scale and designates each park entrance location as supply point j. If a park green space has no retrievable entrance, its centroid is used as the supply point; if a park has multiple entrances, the entrance with the shortest travel time from demand points to the park green space is selected as the supply point. Then, assign a time service threshold d to supply point j and search for all demand points within the supply range (i.e., grid centroids k) to calculate the supply-demand ratio R_j for each supply point j. The calculation formula is:

$$R_j = \frac{S_j}{\sum_{k|d_{kj}\leq d} D_k \times G(d_{kj}, d)}$$

Where: R_j is the supply-demand ratio of supply point j; S_j is the service scale of supply point j; d_{kj} is the time cost between grid centroid k and supply point j; d is the set time threshold; D_k is the demand of consumers (i.e., $d_{kj} \leq d$) within the search area, using elderly population numbers; $G(d_{kj}, d)$ is the Gaussian function, calculated as:

$$G(d_{kj}, d) = \begin{cases} \frac{e^{-1/2\times(d_{kj}/d)^2} - e^{-1/2}}{1-e^{-1/2}} & \text{if } d_{kj} \leq d \\ 0 & \text{if } d_{kj} > d \end{cases}$$

Step 2: Calculate accessibility. For each demand point i, search for all supply points j within the time threshold d. For the supply-demand ratio R_j of each supply point falling within the spatial interaction domain, assign weights using the Gaussian function and sum these weighted R_j values to calculate the accessibility A_i for demand point i. A larger A_i indicates better accessibility. The calculation formula is:

$$A_i = \sum_{j|d_{ij}\leq d} R_j \times G(d_{ij}, d)$$

Where: d_{ij} is the time cost from demand point i to supply point j.

3 Results and Analysis

3.1 Elderly Population Prediction

Using 2018 as the base period, this study predicts the distribution of the elderly population from 2018 to 2028. The number and density of elderly people in Xining's main urban districts from 2018 to 2028 show a spatial distribution pattern of high in the center and low around the periphery, with over 60% of elderly people distributed in the central urban area and inner suburbs.

The change in elderly population numbers from 2018 to 2028 is positive and exhibits a circular change characteristic (Fig. 4 [Figure 4: see original paper]), with relatively small increases in the central urban area and outer suburbs, and larger increases in the inner suburbs. The main reasons are: in the central urban area, the population structure is balanced across all age groups, including the elderly, resulting in stable growth. In the outer suburbs, the population structure shows a concentration of labor force in the urban area, with fewer potential aging populations, thus resulting in relatively smaller increases. In the inner suburbs, dominated by the working-age population, the elderly population base is low but the potential elderly population is large, making it the main area for elderly population growth.

The ranking pattern of elderly population numbers by street changed somewhat from 2018 to 2028 but remained relatively stable overall (Fig. 5 [Figure 5: see original paper]). Yunjiakou Town, Mafang Street, Bayi Road Street, Pengjiazhai Town, and Xiaoqiao Avenue Street were the top five areas in terms of elderly population numbers in 2018, and they remained in the top five in 2028. Among them, Pengjiazhai Town rose from fourth to second, with an increase in elderly population, while Bayi Road Street and Mafang Street each dropped one rank. Additionally, Dabaizi Town showed a significant rise in ranking. Further analysis reveals that the proportion of elderly population in inner and outer suburbs generally increased, while that in the city center decreased.

3.2 Current Accessibility of Park Green Spaces for the Elderly

To compare accessibility changes under different conditions, based on public transport 30-minute accessibility values, the classification results were divided into six accessibility levels (no supply, low, relatively low, medium, relatively high, and high) using the geometric interval method. This classification serves as the benchmark for expressing and comparing analysis results under other threshold parameters (Figs. 6–9 [Figure 6: see original paper][Figure 7: see original paper][Figure 8: see original paper][Figure 9: see original paper]).

Under walking mode, the accessibility of park green spaces for the elderly is generally low and exhibits a clustered spatial distribution pattern. Taking walking 15 minutes as an example, spatial units with medium or higher accessibility account for 9.06%, covering 35.64% of the elderly population. Areas with high accessibility are mainly distributed in Nanchuan Industrial Park, Yunjiakou Town, Nantan Street, Pengjiazhai Town, and Nianlipu Town (Fig. 7 [Figure 7: see original paper]). When the time threshold is 30 minutes, overall accessibility improves, but 23.73% of the population still cannot access park green space services, and the spatial distribution pattern of accessibility levels does not change significantly.

Under public transport mode, the accessibility of park green spaces for the elderly exhibits an overall "cross-shaped" strip distribution pattern, consistent with Xining's spatial structure. Comparing with Fig. 6 [Figure 6: see original paper] shows that park green space accessibility under the 15-minute public transport condition is significantly lower than that under the 15-minute walking condition. As the time threshold increases, accessibility results change more significantly. Under the 30-minute public transport condition, 19.42% of spatial units can access park green space services, covering 73.44% of the elderly population, with high accessibility areas mainly distributed in Nanchuan Industrial Park and Pengjiazhai Town. As the time threshold further increases, areas with high accessibility shift noticeably. For example, under 30-minute public transport, high accessibility areas are mainly distributed in the Biotechnology Industrial Park, Nianlipu Town, and Yunjiakou Town. To reduce travel time for elderly people to park green spaces, consideration could be given to adding park facilities or expanding existing park green spaces in these areas. According to the results, there are significant differences in accessibility outcomes under different time threshold conditions, which is consistent with Zhai Shiyan et al.'s finding that "when distance and time thresholds are set differently, accessibility results vary significantly." Therefore, when making application decisions based on the results, parameter selection should be based on specific objectives to avoid resource waste.

3.3 Prediction and Change Analysis of Accessibility

Assuming that current road construction and park green space resources remain unchanged, this study predicts that the overall spatial distribution pattern of accessibility to park green spaces for the elderly under walking and public transport modes in 2028 will not change significantly, but the accessibility level will generally decline (Figs. 10–13 [Figure 10: see original paper][Figure 11: see original paper][Figure 12: see original paper][Figure 13: see original paper]).

Under the 15-minute walking condition, the population covered by relatively high and high accessibility levels decreased from 17.58% to 6.70%. When the time threshold is 30 minutes, the population covered by relatively high and high accessibility levels decreased from 26.41% to 9.28%, and high accessibility clusters such as northern Nianlipu Town, Pengjiazhai Town, and Nantan Street disappeared completely.

Under walking mode, the relative change in accessibility of park green spaces for the elderly from 2018 to 2028 is substantial (Fig. 11 [Figure 11: see original paper]). Taking 30-minute walking as an example and considering only areas with supply, 87% of spatial units experienced a reduction in park green space accessibility of more than 70%. The most significant reductions occurred in Pengjiazhai Town and Yunjiakou Town, which is consistent with changes in elderly population—areas with greater increases in elderly population experience faster accessibility decline. Although the accessibility reduction in Pengjiazhai Town and Yunjiakou Town is significant, their accessibility remains at relatively high levels, indicating that park green space facilities in these areas are well planned. Bayi Road Street and Nanchuan East Road Street also experienced significant accessibility reductions, with accessibility at relatively low levels. For these areas, early countermeasures should be prepared, with greater attention paid to elderly needs for park green spaces.

Under public transport mode, the accessibility of park green spaces for the elderly in 2028 changes significantly with increasing time thresholds (Figs. 12–13 [Figure 12: see original paper][Figure 13: see original paper]). Under the 15-minute public transport condition, both the number of spatial units and population covered by accessibility are relatively small. When the time threshold is 30 minutes, the coverage of park green space accessibility expands significantly, showing a "cross-shaped" strip distribution, though most outer suburbs still cannot access park green space services. From 2018 to 2028, the overall accessibility of park green spaces for the elderly shows a declining trend, with more significant reductions in the western and southwestern parts of the study area. Under the 30-minute public transport condition, the population covered by relatively high and high accessibility levels decreased from 26.41% to 9.28%. Considering only areas with supply, 87% of spatial units experienced a reduction in park green space accessibility of more than 70%. Areas with relatively large accessibility changes are mainly distributed in Pengjiazhai Town and Yunjiakou Town. Under both 30-minute public transport and walking conditions, the accessibility reduction in the city center is smaller than in the suburbs, and accessibility in the western part of the study area decreased significantly.

3.4 Recommendations for Urban Park Green Space Resource Allocation

Based on the analysis results, the following recommendations are proposed: (1) Decision-makers should clearly identify target populations and have a clear positioning. The accessibility of park green spaces for the elderly under walking and public transport modes varies greatly with different time threshold selections. When different time thresholds are selected, the population covered by medium and above accessibility levels can change by more than 20%. Therefore, when making application decisions based on the results, specific public facility service objectives and scenarios should be clearly defined to avoid potential resource waste due to improper parameter selection.

(2) From the resource supply perspective, for central urban areas and inner suburbs with dense park distributions, service supply capacity of park green spaces can be improved by adding park entrances and exits, increasing park carrying capacity (such as adding elderly exercise equipment and introducing refined management models), and building "pocket parks." This measure can effectively improve park green space accessibility for more than 60% of the elderly population. For outer suburbs with fewer park green space supplies, consideration should be given to increasing park green space supply through new construction or expansion to alleviate insufficient park green space resource supply.

(3) From the travel optimization perspective, rational road layout planning,

improvement of the urban road network system, and addition of bus stops and fast walking paths at main park green space entrances and exits can also promote greater enjoyment of park green space services among the elderly. (4) When planning the layout of elderly care facilities, comprehensive consideration can be given to diverting the elderly population by intensively deploying public service facilities in certain areas (such as building elderly care towns and elderly-themed parks) to alleviate the contradiction between demand for elderly care public service facilities and overall urban development needs.

4 Conclusion

This study proposes a method for forecasting future demand for elderly park green space accessibility using mobile phone location data with age identification information. The method analyzes the current status and future demand of elderly park green space accessibility by constructing a population prediction model and integrating the Gaussian-based two-step floating catchment area method. Data from Xining's main urban districts validate the feasibility of the method, and the following conclusions are drawn:

(1) Between 2018 and 2028, the number of elderly people increased significantly, and the variation in elderly population exhibited a circular pattern with lower increases in the central urban area and outer suburbs and higher increases in the inner suburbs.

(2) During 2018–2028, the overall spatial distribution pattern did not change significantly, but the accessibility level of park green spaces for the elderly generally declined. Under the 15-minute condition, the population covered by relatively high and high accessibility levels decreased from 17.58% to 6.70%. Under the 30-minute condition, the population covered by relatively high and high accessibility levels decreased from 26.41% to 9.28%, with more significant accessibility reductions in the western part of the study area.

(3) The relative change in accessibility of park green spaces for the elderly from 2018 to 2028 was substantial. Under 30-minute walking and public transport conditions, approximately 87% of spatial units experienced accessibility reductions of more than 70%, with accessibility reductions in suburbs being greater than in the city center.

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Note: Figure translations are in progress. See original paper for figures.