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Research Article

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Is there an equality in the spatial distribution of urban vitality: A case study of Wuhan in China

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Abstract: Urban vitality is a spatial phenomenon and a public service. Previous studies often did not measure the fairness of the accessibility of urban vitality. This research analyzed the spatial distribution of urban vitality in Wuhan as a case study area using big data from multiple sources. The study used the two-step floating catchment area method (2SFCA) to measure the accessibility level of each residential district to the vibrant zones (VZs). Furthermore, the inequality in the level of accessibility of residential areas with different housing prices was assessed on the basis of the Gini coefficient. The main conclusions are as follows: (1) the Gini coefficient of reaching the accessibility level of high-grade VZs is 0.426, and the corresponding sub-high-grade Gini coefficient is 0.274. This shows that the inequality in accessibility of different residential areas is more obvious as the level of vitality is higher and (2) residential areas with high housing prices have greater accessibility than those areas with low housing prices. It was also noticed that the level of accessibility and fairness in vitality is generally higher in central urban areas than in suburban areas. The Gini coefficient of high-grade vitality is generally higher than that of sub-high-grade. The results of this study provide a reference for researching the accessibility level of urban vitality, which considers the needs of population, and can also provide guidelines in urban planning regarding the allocation of services and resources.

Keywords: urban vitality, spatial accessibility, 2SFCA, Gini, Wuhan

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1 Introduction

Diverse and vibrant urban spaces are receiving increased attention in modern urban planning [1,2]. Space is the carrier of human activities, and its attractiveness and capacity for human activities are key factors in determining the quality and degree of urban vitality. Because of different degrees of human aggregation and activities, there is a spatial differentiation of the vitality distribution in the city [3]. Some areas have lively street and dazzling shops where residents can enjoy the benefits of urban vitality, while other areas can lack activities for nearby residents and they have increased commuting costs to reach vibrant shopping and working. This difference could be interpreted from the dimension of supply and demand. On one hand, the convenience of reaching vibrant areas is different (supply), while, on the other hand, the number of people served by each vibrant area is also different (demand). However, one of the main gaps in the urban vitality research is that the service levels of vibrant spaces are often not considered from the perspective of supply and demand. In particular, the difference between the urban rich and the urban poor, which is reflected in housing prices, is ignored. Therefore, the analysis of differences in the spatial distribution of accessibility to high-vitality areas and its relationship with communities with different social and economic status will better assist urban planning and promote social equality and justice.

1.1 Vitality definition and evaluation

It is generally accepted that urban vitality is characterized by adequate population agglomeration and diverse urban activities [4–6]. Starting with the observation of urban street life, the study of Jacobs noticed that the diversity of urban life is a necessary condition for vitality, with the intertwined processes of human activities and living places that form the diversity of the city [1]. Montgomery et al. recognized activity, transactions, and diversity as the constituent elements of urban vitality [7]. Dougal et al. defined urban vitality as a measure of the spillover effects generated by interactions between urban residents [8]. Furthermore, Wu et al. believe that urban vitality is generated by residents' activities and their interactions with spatial units [9]. Accordingly, it can be stated that the urban environment provides a place for people's activities, carries urban life, and provides a container for urban vitality, while people are there to create urban vitality. Some subsequent scholars also expressed their personal opinions on the definition of urban vitality [6,10,11]. However, sufficient spatial attention [4,6,12], diverse commercial activities, and population agglomeration [11,13–15] are the most common features in describing urban vitality. Summarizing the definitions of previous scholars, urban vitality is defined in this paper as a spatial phenomenon of rich and diverse urban life and activities generated by population agglomeration.

In the past, qualitative rather than quantitative measurements of urban vitality have been more dominant because of difficulties in obtaining relevant data for urban vitality studies [4,16]. Nevertheless, there are several quantitative studies based on traditional urban statistics, such as community population and road mileage [4], yet it has not been applicable for accessing the level of urban vitality on a microscale. The development of information and communication technologies and the increasing availability of multi-sourced geographical big data have provided new opportunities for urban research capable of depicting details of urban vitality and accurately quantifying spatial relationships between residents and cities [13]. For example, location-based data, such as the density of Weibo check-in, and the number of point of interest (POI), have become a proxy for evaluating urban vitality [4,17]. The measurement of urban vitality can be based on a single data index, such as small catering businesses [10], call detailed records [18], position-based data [15], Wi-Fi data [19],transport mobility data [20], population density [13], land use mix [13,16], and check-in density [16]. However, a single indicator can reflect only one feature of urban vitality. For example, cell phone signal density can reflect the degree of agglomeration of people, but it cannot indicate whether urban activities are abundant. Although a multi-dimensional index formed by a combination of multiple single-type indices can compensate for the lack of single-type indices (see ref. [4–6,20]), there is still controversy over the choice of index types. Therefore, to comprehensively evaluate the spatial vitality from multi-dimensional features, a detailed index selection is required.

1.2 Review of accessibility and inequality

Urban vitality can be measured on different scales using new data and technologies. However, we cannot directly observe the level of urban vitality "radiation" enjoyed by residents living in different locations in the city, i.e., the vitality accessibility. The vitality accessibility is first defined as the convenience of reaching vibrant zones (VZs). VZs can be understood as a clustering of high vitality points. There are numerous studies on the topic of accessibility and majority of them are based on the application of the geographic information system methods for measuring accessibility. Three main methods are generally used to estimate accessibility: (1) the nearest-neighbor analysis model that uses Euclidean distance or network distance to the nearest facility to measure accessibility [21,22]; (2) the gravity-based models that measure the attractiveness of each facility in a sub-area and add these attractions to obtain the reachability value for the facility in the sub-area [23]; and (3) the floating catchment area (FCA) model based on supply point and demand point [24–26]. It takes the critical value of the defined travel distance limit as the search radius (i.e., the distance threshold). For example, a mobile search was conducted twice to compare the number of resources or facilities accessible to residents within a critical value. The higher the value, the better the accessibility. The first method assumes that residents will choose to go to the nearest facility, yet residents actually have more choices. Although gravity-based models consider the possibility of residents' multi-choice, it does not consider the supply–demand relationship between green space and population. FCA considers supply (vitality), demand (residents), and their interactions. However, the traditional methods are mainly based on the buffer zone of the Euclidean distance or the road network distance when setting the search range, while less consideration is given to the actual commuting conditions of the road. Housing conditions and real estate values can change because of inequality of public services around housing [23,27]. High-income families have the freedom to choose the type of housing and are more likely to choose to live in areas with high-quality public services. In contrast, groups with lower socioeconomic status are forced to gather in inconvenient areas and are often deprived of the opportunity to approach the urban vitality center, leading to unfair phenomenon because residents of different socioeconomic status will enjoy different urban vitality. The inequality in urban residents' enjoyment of urban vitality is mainly reflected in their different accessibility to VZs, i.e., possibilities for people to participate in various activities, which is an important index on the fairness of social resources. To measure the accessibility fairness, it is necessary to compare the differences in the accessibility of resources/facilities among the residents with different socioeconomic characteristics.

1.3 Current research gap and research questions

In the current literature, we can easily find studies on the evaluation of vitality, as well as measures of the accessibility levels to a certain infrastructure (e.g., park or hospital). However, according to the authors' knowledge, none of the studies focused on the accessibility of VZs, let alone considered the inequality of access to VZs among people with different socioeconomic status. VZ, as a type of clustering of high vitality points, analyzes its accessibility and is a supplement to the previous studies that considers only the convenience of facilities. Meanwhile, measuring the inequality of accessibility of people with different social and economic levels will provide a reference for planning and promoting urban equity in the future. To compensate for the limitations noticed in previous studies (e.g., the spatial distribution of urban vitality was not accessed from a supply and demand perspective, and the distance threshold of the search area of the FCA model did not consider the actual traffic cost), this research focused on two research issues: (1) What is the distribution in accessibility of VZs for urban residents from the perspective of the balance between supply and demand? Moreover, does it show a significant difference with the results of the evaluation of urban vitality space? and (2) Is there inequality in people's accessibility to vitality spaces in different residential areas because of different housing prices? Wuhan, a city in central China, was selected as the research area in this paper. The Yangtze River and the Han River divide Wuhan into three areas: Hankou, Hanyang, and Wuchang (see Figure 2). Consequently, several urban vitality centers are formed and this provides a basis for researching the accessibility level of VZs by considering the needs of the local population. The results of this study can potentially have an important impact on the local government decision-making in the process of allocating services and resources in the city.

2 Methodology

To answer the above-mentioned two research questions, this paper first collects multi-source geographic big data to evaluate urban vitality of the study area. Research units are often at street/block scale [10,20], patch scale [13], or overall urban scale [4]. In this paper, a 1 km grid is used as the evaluation unit of urban vitality and is combined with population density data obtained at a 1 km resolution from Landscan. The Jenks natural breaks (JNBs) are used to classify and display the high and low levels of urban vitality distribution. JNB is a frequently used statistical method for grading and classifying according to the law of numerical statistical distribution. Generally, an odd number of classes is used to reflect the gradual transition from low to high values. We decided to divide the vitality into five levels, because three levels represent only a few categories, while more than five levels are too scattered. This paper uses the two-step FCA method (2SFCA) to analyze the accessibility level of urban vitality areas by taking into account supply and demand perspective. In this study, we consider high-level and sub-high-level VZs as suppliers, while residents are on the demand side. Finally, we measured the difference in accessibility of different urban income groups with Gini and discussed whether there are significant differences based on income inequality. The flow chart of the method is shown in Figure 1.

2.1 Urban vitality evaluation

Good urban functions and sufficient human activities are generally considered to be the basics of urban vitality [5]. GPS data can help to understand the distribution of urban population, their activities, movements, and needs. Urban functions consist of facilities/entities with associated activities. Urban POI refers to a geographic facility or entity that is closely related to people's life, including real estate, shopping, traffic facilities, finance, hotel, scenic spots, life services, recreation and entertainment, healthcare, food and delights, and incorporated business. POI provides spatial and attribute information about facilities/entities, such as name, address, and coordinates. In addition, the density of POIs can reflect the abundance of urban facilities [13] that enable the flow of material, population, traffic, and information generated by urban political, economic, and cultural activities. People check-in at different places in the city can reflect the impact of the geographical environment on human activities [28]. The study found that places with more

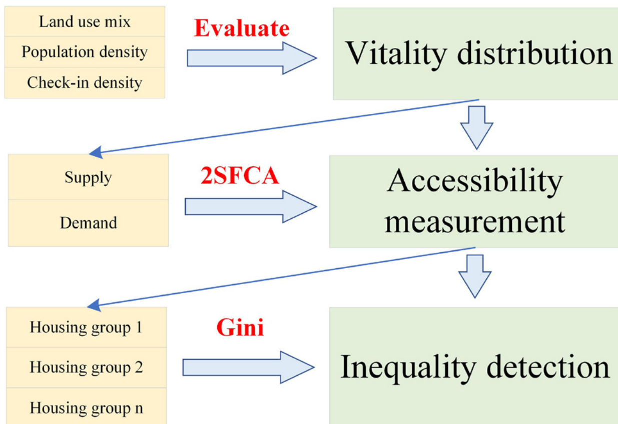

Figure 1: Flow chart of methodology.

check-ins are more likely to attract people willing to commute, and these activities will increase the concentration of population and commerce, and will enhance the vitality of the city [13]. Different types of POIs can promote mixing of functions in an area, and mixed land use can stimulate urban vitality, both of which have been recognized by academia and urban planning practices. A high degree of land function mixing can promote the flow of people at different time points [1,3] and generate increased social interaction, diversified consumption, and improved economic and social benefits. We selected POI density (POID), land function mix (MIX), and Weibo check-in density as proxy for urban vitality. Different elements included in each indicator are shown in Table 1.

The equations for the abovementioned indices are as follows:

$$\mathrm{MIX} = -\sum_{n=1}^{h} (r_n \times \ln r_n), \tag{1}$$

$$\mathrm{CIQ} = \frac{N_{\mathrm{tag}}}{S}, \tag{2}$$

$$\mathrm{POID} = \frac{N_{\mathrm{poi}}}{S}, \tag{3}$$

where MIX represents the mixed degree of land use, r_n represents the proportion of the number of the n-th POI type, h represents the total number of POI types, N_{poi} represents the total number of POIs in the patch, and N_{tag} represents the total number of Weibo check-ins and commented times in the patch. S represents the area of each study unit, and here $S = 1\,\mathrm{km}^2$. It should be noted that the number of elements involved in each indicator is determined by urban areas within each grid.

To eliminate the influence of dimension, MIX, POID, and CIQ were standardized to the range from 0 to 100, and the urban vitality of each patch was evaluated according to Formula 6 using a straightforward method to evaluate urban vibrancy that avoids subjective settings for the weight of each dimension [4,14], where EV represents the urban vitality:

$$\mathrm{EV} = \mathrm{MIX} \times \mathrm{POID} \times \mathrm{CIQ}. \tag{4}$$

2.2 Accessibility measurement

The 2SFCA method can consider the level of accessibility from a supply and demand perspective. In this study, the supply of urban vitality comes from each VZ that can be divided into different levels by applying different threshold values. The source of demand comes from the urban residential area. In this regard, there are two specific steps for supply and demand:

(1) For each supply source j, search all demand points (k) within j search radius (d_O), and calculate the supply-demand ratio R_j as follows:

$$R_j = \frac{S_j}{\sum_{k\in\{t_{kj}\le t_0\}} \mathrm{G}(c_{kj}, c_0) P_k}, \tag{5}$$

where P_k is the total number of households in ($c_{kj} \le t_0$) community k within the spatial scope of VZ j; t_{kj} is the actual travel time from community k to the center of VZ j; S_j is the area of VZ j; and $\mathrm{G}(c_{kj},c_0)$ is the weight equation

Table 1: Elements included in the urban vitality indicators

Indicator	Element	Proxy of urban vitality
MIX	Residential community (extract from real estate), shopping, bus station and metro station (extract from traffic facilities), catering, and incorporated business	Agglomeration of function
CID	Weibo check-in location (point)	Spatial attraction
POID	Real estate services, shopping, traffic facilities, finance, hotel, scenic spots, life services, recreation and entertainment, healthcare, food and delights, and incorporated business	Concentration of facility distribution

considering the blocking effect of travel expenses. In general, the distance weight is calculated by Gauss equation.

(2) For each demand point i, search all supply points within the search radius (t_0) of i, and sum all supply–demand ratios R_j to obtain the accessibility AF_i of point i.

$$\mathrm{AF}_i = \sum_{l\in\{t_{il}\le t_0\}} \mathrm{G}(c_{il}, c_0)R_l. \tag{6}$$

In the traditional 2SFCA method, the above search radius generally applies the traditional Euclidian distance or the road network distance without considering the actual traffic conditions during different commuting times. In this study, "distance" was replaced by the shortest real commuting time. In general, the desire to reach the active area decreases with increasing commuting expenses. Therefore, we improved the distance attenuation function defined by Gauss and changed the distance to the actual time cost. The calculation formula for this is as follows:

$$\mathrm{G}(c_{kj}, c_0) = \begin{cases} e^{-\left(\frac{1}{2}\right)\times\left(\frac{c_{kj}}{c_0}\right)^2} - e^{-\left(\frac{1}{2}\right)}, & \text{if } c_{kj} \le 0, \\ 0, & \text{if } c_{kj} > 0 \end{cases} \tag{7}$$

where c_0 is the time threshold and c_{kj} is the time cost of driving a car.

2.3 Inequality detection

In this paper, the measure of inequality includes two dimensions: (i) inequality of vitality accessibility as a whole and (ii) inequality of vitality accessibility of communities with different incomes. The statistical unit of household as an original measure of the income gap is mapped to the community unit, and the level of household income is mapped to the level of vitality accessibility. Afterward, the accessibility level of urban vitality of the community was divided into five groups from low to high, and the proportion of households and accessibility in each group was counted by the Gini coefficient according to the following formula:

$$\mathrm{GC} = 1 + \sum Y_iP_i - 2\sum\left(\sum P_i\right)' Y_i, \tag{8}$$

where GC stands for Gini coefficient, Y_i represents the proportion of vitality accessibility level in group i to the total vitality accessibility, P_i represents the proportion of households in the group i to total households, and $(\sum P_i)'$ represents the percentage of cumulative number of households from group 1 to group i in total households.

Regarding the assessment of inequality between different income levels, differences in housing prices can represent the income of residents to a certain level. Therefore, the average price of a house in the community obtained through an online real estate trading platform was taken as the proxy of residents' income. Based on the distribution of housing prices in the study area, five groups of communities with different housing price (≥20,001, 15,001–20,000, 12,001–15,000, 10,001–12,000, and ≤10,000 Yuan/m^2) were used to indicate different income levels. The community with an average house price of less than 10,000 Yuan/m^2 was taken as the reference group, and the four dummy variables, i.e., [0,0,0,1], [0,0,1,0], [0,1,0,0], and [1,0,0,0], represented the other four experimental groups, respectively. A regression model was applied to evaluate differences in the accessibility of urban vitality in the community.

3 Study area and data

Wuhan, the largest city in central China, is located from 113° 41′ to 115° 05′ E and from 29° 58′ to 31° 22′ N. The city connects nine provinces and is also known as "River City" with numerous lakes and rivers and the largest amount of freshwater per capita in the world. The Yangtze River and the Han River, as its largest tributary, divide Wuhan into three parts (Wuchang, Hankou, and Hanyang) that face each other across the river (Figure 1). By 2018, Wuhan's gross domestic product (GDP) was 1.48 trillion Yuan (about $220 billion), ranking the city on the eighth place in terms of GDP in the Chinese mainland. The city has jurisdiction over seven central districts and six suburban districts. This paper focuses only on the seven central districts. The built-up area of the city is about 1,217 km^2, with a total population of 11.08 million and an urbanization rate of 80.2%. Wuhan is a vibrant city and is ranked at the forefront of the first-tier cities in China. The city is also an important science and education center that gathers numerous universities and has the largest number of college students in the world (about 1.3 million).

To measure the vitality of urban areas, we first define urban areas as the built-ups in the national land-use/cover database of China produced by the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences, in which, built-ups were defined by impervious surface as interpreted by remote sensing images [29,30]. The comprehensive

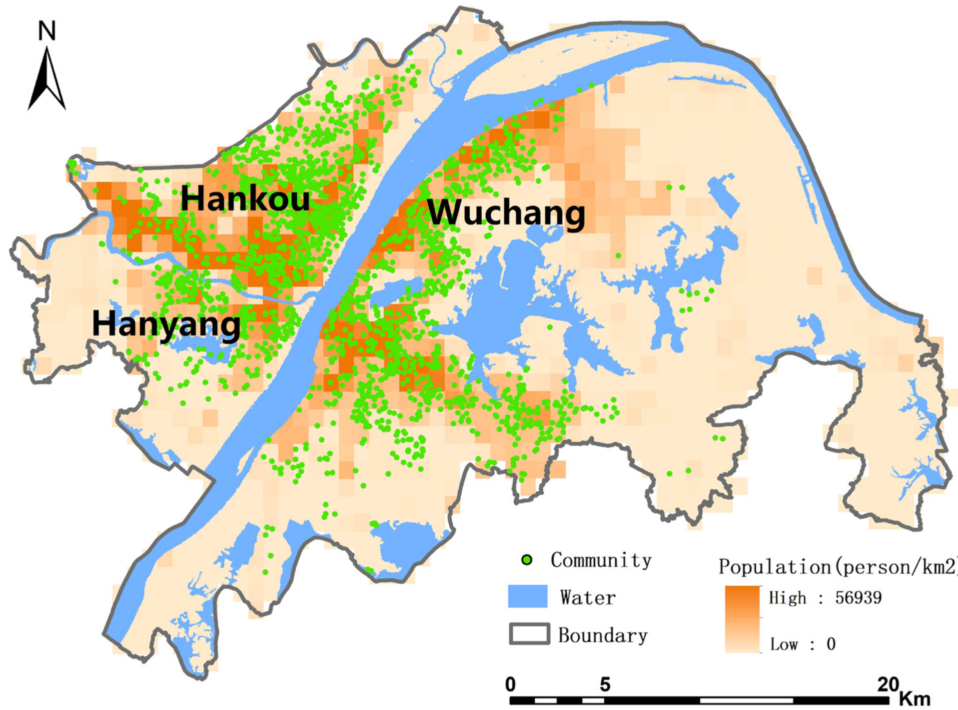

Figure 2: Study area and the distribution of communities and population.

evaluation of data accuracy exceeds 90% and is considered as one of the most reliable sources of land use data in China [29,31]. The analysis of urban vitality is based on the open multi-source geographic big data that is captured by applying the web crawler technology to obtain POI data from Baidu Map (https://map.baidu.com), Weibo check-in data of the China's largest social platform, i.e., Sina Weibo (https://weibo.com/), and a location-based food evaluation platform, i.e., Dianping data (http://www.dianping.com/). LandScan of population spatial distribution at 1 km resolution was downloaded from the Oak Ridge National Laboratory (USA) (available at: http://web.ornl.gov/sci/landscan/) (Figure 2). Community data were obtained from Anjuke (available at: https://wuhan.anjuke.com/sale/?from=navigation) and Fangtianxia (available at: https://wuhan.esf.fang.com/), which are two leading online real estate trading platforms in China. The obtained attributes include the latitude and longitude of the community, the total number of households, and the average house price. Complete information was collected for 2,115 communities (Figure 2). The shortest commuting time between two points in the urban grid was automatically recorded and stored using a Python-based program through the application program interface provided by AMap (the largest navigation website in China). The capture time represents the average commuting time at 8 AM, 12:00 PM, 5 PM and 8 PM on July 2019. We have also collected a geographic national base map, a vector map of the administrative division of the study area, major rivers/lakes, trunk roads, the spatial location of the government residence, etc. as auxiliary data. All spatial data were checked and verified before use.

4 Results

4.1 Vitality evaluation, accessibility, and Gini value

The evaluation value of urban vitality for each 1 km grid is obtained in the study area. The spatial distribution of the five grades of urban vitality, based on the natural breakpoint method, can be seen in Figure 3. It can be noticed that the distribution of the high-grade VZ is limited, but it directly reflects the distribution of the five major business districts in Wuhan (marked in Figure 3), which account for only 1.70% of the total study area. These areas are characterized by frequent business activities and a dense flow of personnel, which makes them a convenient area for life and recreation. The sub-high-grade VZ has a wider spatial distribution (9.87% of the study area) with various activities that promote urban vitality, in addition to commercial activities. The Gini

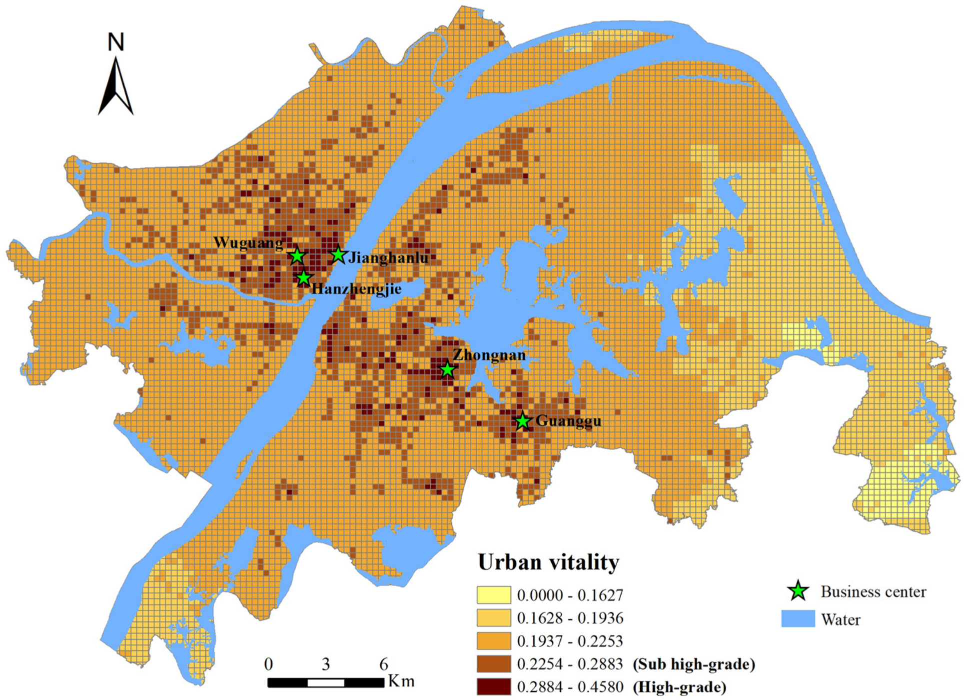

Figure 3: Spatial distribution of urban vitality in Wuhan.

coefficient of vitality distribution is only 0.076, which indicates equality distribution of urban vitality supply in the districts. However, this result can easily lead to a misunderstanding that the urban vitality distribution is balanced. This result confirmed our initial concern that the uneven distribution of urban vitality could be concealed from a supply perspective alone. However, if both supply and demand are considered, then equality will be disrupted. Figure 4 shows the spatial distribution of accessibility level for different communities to enjoy the high-grade and sub-high-grade levels of urban vitality. It can be noticed that the locations of high dynamic agglomeration and high accessibility do not match, i.e., high accessibility is mainly distributed in the south. This is a deviation from our usual understanding, i.e., from Figures 2 and 3, we can see that there are population clusters and high vitality distribution in Hankou (see Hankou's location in Figure 1). We imagined it might have high accessibility as well, but the results differ from our assumptions. It is precisely because of the large population that there is a higher demand, and if the supply is insufficient, then the accessibility will be low. The high accessibility in the south means that although supply may not be as high as in the north, the actual accessibility level will be higher because the population in need of services is significantly lower than in the north. We noticed that regardless of the level of vitality being investigated, the most significant feature is the neighborhood near the Optical Valley (see circle in Figure 4) as a high-accessibility cluster. The Optical Valley is the main development area in Wuhan, and it is also the area with the most concentrated optoelectronic industry and scientific research in the world. In addition, the Optical Valley is the most popular business district for the local population. These characteristics ensure that the residents of this area can comfortably enjoy a variety of urban services. By measuring accessibility levels from the perspective of supply and demand, we noticed that the Gini coefficient for the high-grade VZ for the whole district is 0.426, which exceeds the warning threshold of 0.40. This indicates a significant inequality in the enjoyment of VZ by residents with different incomes. As for the sub-high-grade of VZ, the corresponding Gini coefficient is 0.274, which indicates that the accessibility of VZ is relatively fair in different districts. We can therefore conclude that the unreasonable spatial distribution of the high-grade urban vitality areas is the main reason for the inequality in accessibility of VZ in Wuhan.

4.2 Inequality in vitality accessibility for different income levels

Table 2 presents the inequality measurements between communities with different income levels. The results show that for the high-grade VZ with the increase in

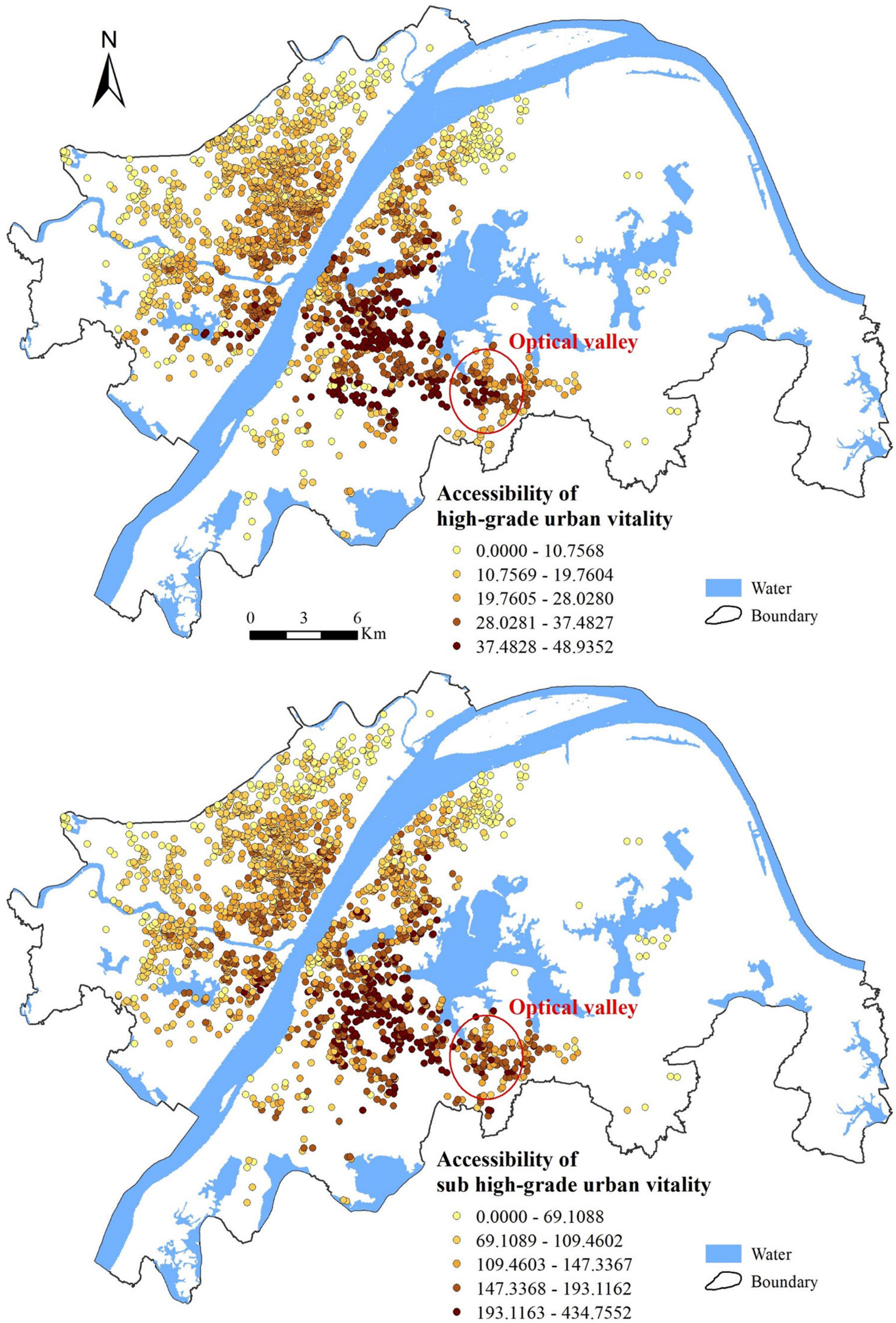

Figure 4: Spatial distribution of accessibility levels for different communities to enjoy the high-grade level and sub-high-grade level of urban vitality.

the level of housing prices in the community, the coefficient is increasing and has a significant positive value. This suggests that people with higher incomes are more likely to enjoy the high-quality and vibrant urban areas than people with lower income. For communities with different income, it is more difficult to reach the sub-high-grade vitality area, and it was further noticed that with increasing housing prices comes a coefficient that does not show a monotonic increasing trend. For example, the coefficient value (20.78) of the third group

Table 2: A comparison of equity among communities with different levels of housing prices

Ref: ≤10,000 Yuan	High-grade	Sub-high-grade
10,001–12,000	5.77***	21.07***
12,001–15,000	6.23***	20.78***
15,001–20,000	6.68***	26.22***
≥20,001	8.52***	31.59***

*** means significant at 99% level.

of communities (12,001–15,000) is smaller than the coefficient value of the second group of communities (10,001–12,000). We noticed that with the increase in the housing price level in the community, the average number of households in the community is also increasing. The average number of households in the third group increased by 70.63% compared to the second group (from 606 households to 1,034 households), which is far more than the other two groups. For example, the number of communities in the second group increased compared to the first group (598 vs 606), the fourth group increased compared to the third group (1,034 vs 1,389), and the fifth group increased compared to the fourth group (1,389 vs 1,491). As a result, an excessive increase in demand may reduce the accessibility level so that the accessibility level of communities of the third group is lower than that of the second group communities. This result also shows that the imbalance in reaching the sub-high-grade urban vitality areas observed between communities with different income levels is not so obvious.

4.3 Inequality in vitality accessibility in different spatial ranges

To further verify whether the vitality accessibility has spatial characteristics, we defined 18 buffer rings (with a 1 km resolution) from the center, which is represented by the location of the Wuhan municipal government. Furthermore, we defined four areas that are divided by four traffic loops. Afterward, the average accessibility and Gini coefficients for the sub-high-grade level and the high-grade level VZ of each buffer ring and four inner areas were calculated (Figure 5). It can be noticed that the equality of vitality accessibility increases from the innermost to the outermost ring, while the average level of accessibility decreases. For a high-grade VZ, the average level of accessibility is 4.95 times higher in the first ring than in the fourth ring, while the corresponding gap is 2.90 times higher for the sub-high-grade level. The accessibility of buffer ring did not show a trend of gradual increase or decrease. The highest (26.83) and lowest (15.25) accessibility of the high-grade VZ occurred in the 15 km ring and 13 km ring, respectively. The corresponding values of the sub-high-grade appear in the 17 km ring (144.49) and 18 km ring (100.87). It can be seen that the gap between the highest and the lowest in the buffer ring is much smaller than the corresponding gap in the road ring. Gini coefficient of the high-level vitality is generally higher than that of the secondary high-level, indicating that the high-level inequality is more obvious. In particular, the inequality in vitality accessibility gradually increased from 2 to 10 km from the city center, while the accessibility inequality increased within 13–17 km. The correlation analysis between the vitality accessibility and Gini coefficient of the rings obtained the correlation coefficient value of −0.594 (significant at the 99% level), indicating that higher accessibility is associated with lower equality.

5 Discussion

5.1 Comparison with non-real commuting distance

Real commuting costs are used instead of the traditional Euclidian distance or network distance in this study. Euclidian distance uses the straight-line distance of a simple two-point connection, neglecting the actual structure of the traffic network. Although the network distance may be closer to the real path, it does not consider the actual situation of the commuting capacity. Accordingly, none of the above-mentioned approaches can accurately reflect the true cost of commuting. According to statistics, the Gini coefficients of the Euclidian distance and network distance are, respectively, 0.322 and 0.387 for the high-grade vitality area, while the Gini coefficients are, respectively, 0.245 and 0.281 for the sub-high-grade level vitality region. Regardless of the levels of VZs, the Gini coefficient obtained by the straight-line distance method is lower than that obtained by considering the real commuting costs. This suggests that the straight-line distance method decreases the real gap between different income communities that enjoy urban vitality because they inflate the real traffic situation near the low-income neighborhoods. For example, a low-income community may have a short straight-line distance to a nearby mall

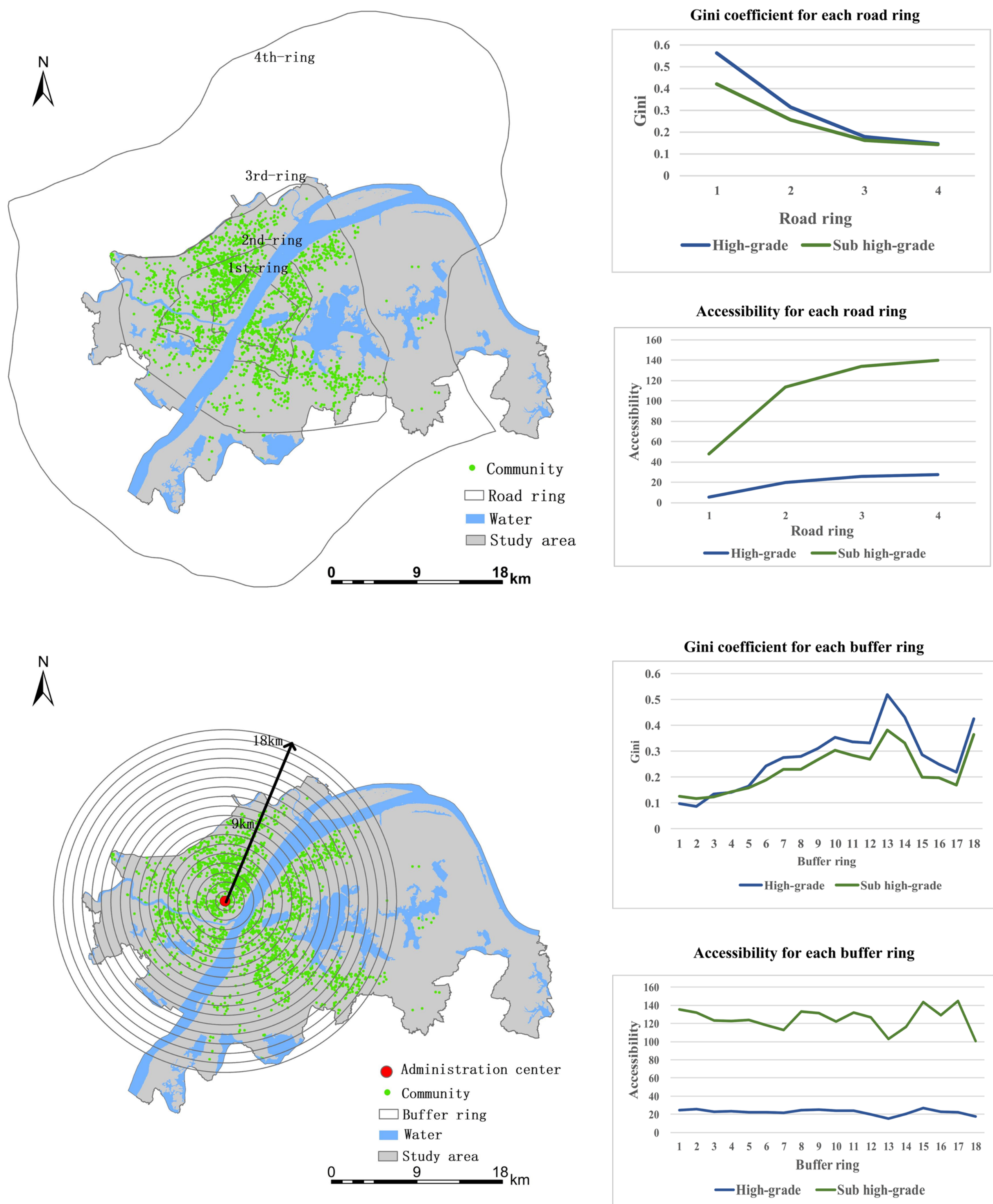

Figure 5: Accessibility and Gini coefficients for the sub-high-grade level and the high-grade level vitality of buffer rings and four inner areas.

and the associated evaluation of the accessibility would show good results, but the actual cost of commuting may be relatively high because of the lack of convenient travel facilities. The situation gets more complex when the network distance method is used in which the Gini coefficient for the high-level vitality area is smaller than that calculated by the real commuting cost. Nevertheless, Gini is higher at the lower level, which indicates that the former hides the urban vitality equality gap, while the latter widens the gap. This is because the network distance method generally starts with choosing the shortest route and does not consider the actual commuting costs caused by morning and evening commuting peaks, speed limits, road grades, etc. which can lead to a difference in the real accessibility situation.

5.2 Possible policy recommendations to promote equality of urban vitality accessibility

Equality of urban vitality accessibility is limited by multiple factors such as demand and households in the community, regional distribution of supply and vitality, and spatial cost between them. The policy proposal could be to connect vitality areas with the low-accessibility communities by building transportation facilities, such as subways and buses. Furthermore, the number of households in the community can be modified and new vitality areas can be built to enhance equality. It is feasible to plan and build new vitality areas, such as large shopping malls, schools, and other facilities. However, it is not feasible to force the families in the community to move out or move in. Accordingly, the starting point of our policy is to promote the voluntary relocation of the community residents and to develop plans for the construction of new vitality areas. It is possible to identify areas with a high spatial concentration of population and low accessibility by overlapping the map of spatial clusters of households in the community with the map of the spatial clusters of the accessibility level. A total of 46 grids with a high population concentration (i.e., high demand) and low supply were identified and recognized as priority areas for the construction of schools and shopping malls. For example, the development of shopping malls can greatly increase the effect of population concentration, can promote a variety of urban activities, and significantly enhance urban vitality. In China, a family with children can only choose schools near their community. Therefore, the construction of schools, especially high-quality schools, can attract many families to move to the community near schools, thus contributing to the population mobility. Furthermore, the basic principle, i.e., the ratio of the average number of households per unit area to the average accessibility, can be used to plan shopping malls and schools in a chronological order. This suggests that with a higher ratio comes higher planning urgency. Based on this principle, we divided the above-mentioned 46 grids into "urgent planning," "priority planning," and "moderate planning" by applying the natural breakpoint method. These divisions can provide a reference in decision-making and can suggest time priorities in urban planning.

6 Conclusions

Accessibility is a popular spatial index in urban geography research that can indicate justice in resource allocation. Justice means that everyone has equal access to adequate resources, services, and healthcare. Urbanization in most Chinese cities has a common characteristic of rapid urban expansion and poor quality, and urban planners and designers generally underestimate the importance of urban vitality [10] and often do not consider equality of space and society. This research identified a pattern of spatial distribution of urban vitality in Wuhan based on multi-source big data. It considered the community as a unit and also considered the dual dimensions of supply and demand to measure the level of accessibility of the VZ reached by the residents of each community. This approach is based on the Gini coefficient that is necessary to estimate whether there is inequality in the accessibility of different income groups to reach the VZ. Important conclusions from this study are as follows:

(1) Approximately 1.70% of the total investigated area is a high-grade vitality space, with a corresponding proportion of 9.87% at a sub-high-grade level. The Gini coefficient of the high-grade level of urban vitality has a value of 0.426, while the corresponding Gini coefficient at the sub-high-grade level is 0.274. Thus, it means that the higher the level of vitality, the more obvious is the inequality of accessibility of different communities;
(2) Comparing the accessibility of different housing price groups, it was observed that high-priced communities have higher accessibility than low-priced communities. The vitality accessibility inequality level of central urban communities is generally higher than suburban communities, and the associated Gini coefficient of high-grade vitality is generally higher than sub-high-grade level, indicating that the inequality of the high-grade is more obvious.

The above conclusions are obtained based on the classification of spatial vitality distribution by the JNB.

In fact, these conclusions are also applicable to other classification methods. For example, after sorting vitality value from small to large, it is divided into five categories according to equal number (each category has the same number of samples) or equal interval of value; then the Gini coefficients of vitality accessibility in the high-grade and sub-high-grade category were 0.401 vs 0.393 and 0.375 vs 0.298, respectively, and at the same time, high-income groups are more likely to access areas with higher vitality. This paper revealed that the inequality of urban vitality accessibility in different income groups is a universal phenomenon, but it has not yet been proposed how to alleviate this unjust planning program. In future research, the authors want to realize the explicit configuration of space in shopping malls, schools, and other facilities with the aim of promoting spatial justice. This can be achieved through a spatial optimization allocation model (e.g., a spatialized genetic algorithm) that can assist the urban planning decision-making process to enhance the justice of the accessibility of vitality space.

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