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Evaluation of the utility efficiency of subway stations based on spatial information from public social media

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ABSTRACT

Subway systems are important for urban transport, and effective subway systems should meet the travel needs of urban transport users. A critical feature of a subway system is the location choice of subway stations. These locations should maximize the utility value of subway stations for residents, thus contributing to ease of accessibility and level of mobility. Traditionally, the utility evaluation of subway systems has been based on static and unilateral information. This study describes the utility efficiency of subway stations in Central Chongqing, China, by assessing the balance between the supplied train services and the travel needs of the population. The information used in this study was taken from public social media; therefore, the decision-making process was bilateral, with the public voting for a subway station with “their feet”. Spatial analysis, including methods of hot spot analysis, buffer zone analysis and spatial stratified heterogeneity analysis, were used to test this process. The results indicated that spatial inequality of utility efficiency of subway stations still exists; however, the extent of the spatial inequality was dependent on the size of the walking catchment area and their location, be it within the city center or in more remote areas.

1. Introduction

Mega infrastructure projects are making significant contributions to social and economic development (Pagliara & Papa, 2011). There has been considerable investment in infrastructure projects worldwide in recent years (Zayed, Amer, & Pan, 2008). The construction of subway systems as part of urban mega infrastructure projects is one example of urban development investment that yields significant benefits and improves both social and economic levels for urban populations.

Planning is one of the early phases in an urban subway system. A unique feature of subway system planning is that it requires public support as these systems provide an important means of daily commuting throughout major cities worldwide (Shen, Wu, & Zhang, 2010). However, problems relating to subway systems, such as long waiting times and long walking distances, due to unreasonable planning, have been identified (Yu, Yang, & Li, 2012).

There are two types of public transport designs: supply-oriented and demand-oriented (Guy & Marvin, 1996). Although the development of subway systems can be supply-oriented and generate its own environment, most are demand-oriented and planned in well-developed areas, where a fixed public service radius has developed. People living and working in these areas need only find the nearest subway station for their travel needs, and the relationship between people and their destination is predefined.

This paper argues that subway system planning should focus on serving people by providing a convenient means of transporting them to their desired urban location, thereby achieving the maximum value. Therefore, consideration of the spatial relations between subway stations and urban services needs to be included in the core planning stages (Xu, Ding, Zhou, & Li, 2015). As the subway system is associated with people's life and work, its efficiency plays an important role in promoting urban development and reducing social problems. Allport (1990) confirmed that evaluating the value of subway projects can be of great assistance in optimizing the planning of a subway line and station; therefore, analysis of utility deviations are required and future improvement in locating subway stations should be based on the results.

Although several subway projects have been implemented or are currently under construction in China, their efficiency has not matched

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expectations (Yue, Zhang, & Liu, 2016). In recent years, attempts have been made to estimate the value of existing infrastructure projects. Shen, Jiao, He, and Li (2015) presented a utility efficiency evaluation index model to demonstrate the utility performance of metro infrastructure projects. This model provides a novel means of evaluating the efficiency of subway projects in different cities in China; however, it lacks quantitatively down-scaled evaluations based on real projects, particularly from a spatial perspective, such as a comparison between urban and rural areas (Wang, Liu, Li, & Li, 2016b; Yeh, Yang, & Xu, 2017).

Utility-cost analysis is the evaluation of different alternatives based on the ratio between their cost and utility (Levin & McEwan, 2000). The term "utility" refers to the degree of one alternative satisfying a criterion or attribute (Girginer & Kaygisiz, 2013). The utility-cost ratio is the comparison between the cost of an alternative and its utility score, and the lowest ratio indicates the best utility value (Levin & McEwan, 2000).

As there are few quantitative studies that evaluate subway systems by analyzing their utility-cost value, the aim of this study is to evaluate the utility efficiency of subway stations based on their spatial location and relationship to popular urban services, using information from public social media. The optimal subway station location should be in an area with the highest utility efficiency, be it within the city center or in more remote areas.

2. Data and methodology

2.1. The integrated framework

This study developed a utility evaluation model to describe subway station utility value. This utility efficiency evaluation model determined the subway station utility efficiency using four steps: local cluster analysis, utility-cost analysis, buffer analysis and spatial stratified heterogeneity (SSH). The local cluster analysis was the fundamental measurement of the spatial layout of urban services. The utility-cost value of the subway station provided information regarding train service and the public's travel needs. The third measurement assessed the spatial relations between subway stations and urban services. Additionally, SSH quantified the spatial inequality of utility efficiency. The data required by this model was collected from public social media.

The evaluation model was followed by a case study to test its effectiveness. Central Chongqing was selected as the study area due to its large spatial scale and the large investment in subway system planning and construction in the last 15 years. An effective subway system layout plan should maximize the utility efficiency of stations from different walking catchment distances in the city center to remote areas. This analysis was a practical application of the utility evaluation model and the resulting subway station utility value provided a guideline for evaluating the rationality of the Central Chongqing subway system. The results from this study could also support the development of future subway station locations.

2.2. Study area

The selected study area was Central Chongqing, China, which incorporates nine districts: Yuzhong, Dadukou, Jiangbei, Nan'an, Shapingba, Jiulongpo, Beibei, Yubei and Ba'nan. It covers 5472.68 km^2 and had a total population of 8.348 million in 2015 (Chongqing Municipal Bureau of Statistics, 2016).

Chongqing Subway is also known as Chongqing Rail Transit. Its first line commenced operation on June 18, 2005, and was the first subway in the Western region of China. Until December 30, 2015, there were four operating lines (numbered 1, 2, 3 and 6), with 120 stations and 202 km of operating distance, covering all nine districts (Fig. 1). Central Chongqing is a typical polycentric urban structure divided into 28 groups, 19 of which are serviced by the subway system.

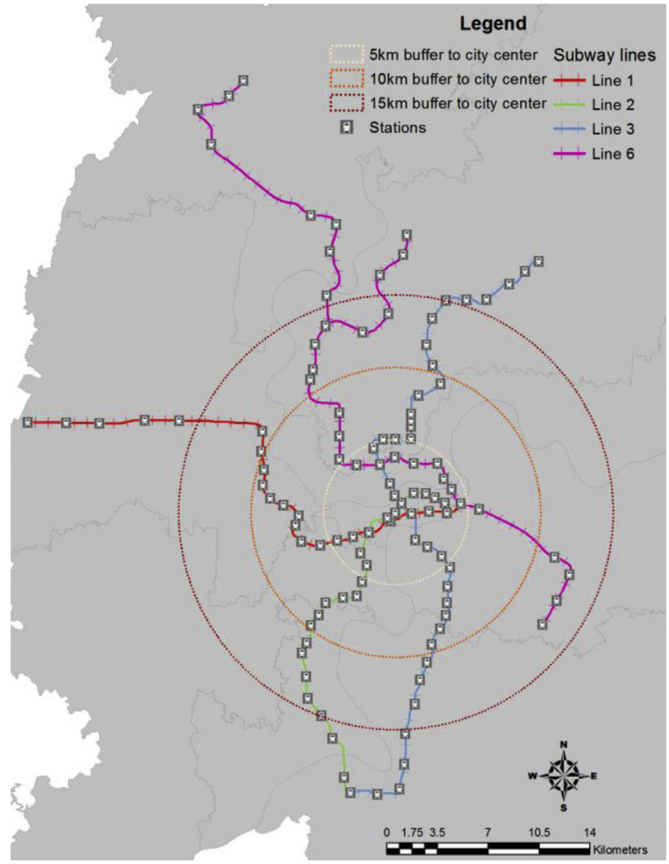

Fig. 1. Distribution of subway lines, subway stations and three buffer ring zones in Chongqing.

The transport connections between these 28 groups were one of the priorities in designing the Chongqing subway system. In addition, construction costs, such as minimizing demolition cost and facilitating construction site layout, was another factor that was taken into account. However, the passengers' needs, particularly accessibility from urban services, were rarely discussed or evaluated in previous studies.

2.3. Data description

2.3.1. Subway and administrative boundaries

Spatial data on administrative boundaries and associated features were obtained from publicly accessible open-resource data released by Chongqing Geographic Information Center. Data relating to subway station locations and the subway line path were obtained from the Chongqing Municipal and Rural Construction Committee Office in November 2015.

2.3.2. Web-captured information

One of the largest network media websites in China is "dianping.com", which publishes crowd-sourced reviews about local business performance. Information available on this website includes business name, business type, customer scoring and reviews, and geographic location linked to an online map.

Points of Interest (POI) spatial clustering is based on user-based collaborative filtering to derive residents' preferences (Ye, Yin, Lee, & Lee, 2011). Geospatial points representing local businesses (27,208) in Central Chongqing were collected in November 2015, using the sources listed above. Each data unit was a POI data point containing four information categories: business name, category (including educational, medical, entertainment, shopping and food), spatial coordinates and customer feedback (including usage frequency and evaluation). The

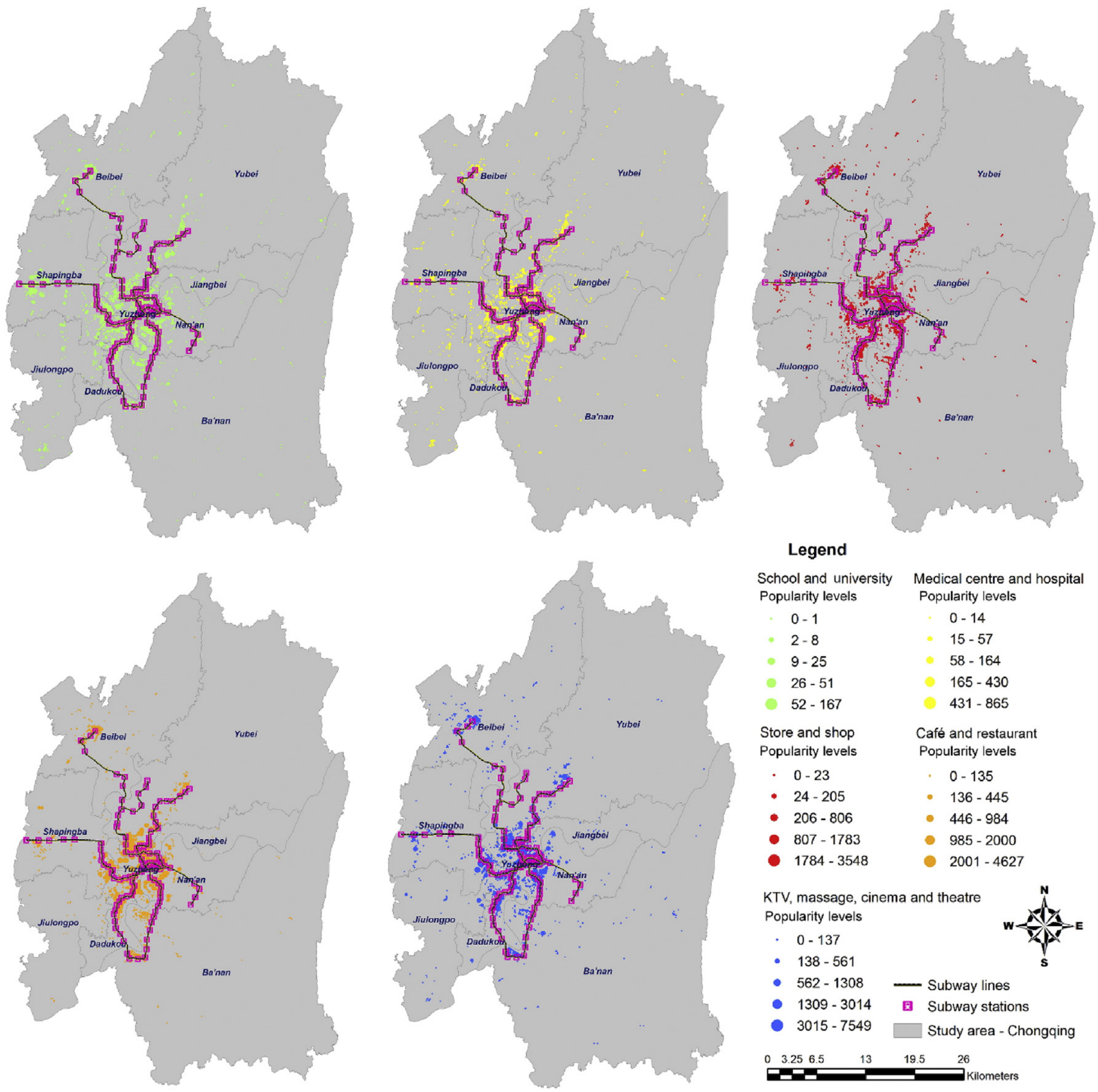

Fig. 2. Spatial distribution of urban and subway services in Central Chongqing.

evaluation was defined by five classes: excellent, very good, average, poor and terrible. To objectively reflect the distribution of popular urban services, services with poor and terrible evaluation outcomes were excluded from the analysis.

In this study, a number of comments were used as an additional indicator to quantify the popularity of an urban service, which partially reflected the visiting rate (Fig. 2). The natural breaks classification method was used to determine the optimized arrangement of values into different classes. This approach minimized the variation within each class and maximized the variation among the classes (Jenks, 1967).

2.4. Cluster analysis of urban services

The measure of the popularity of an urban service can be viewed as a geographic problem. The First Law of Geography states: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This suggests that popular urban services are likely to cluster. The clusters show locations of high demand and ideal locations for public transport development (Hu., 2003).

Global spatial autocorrelation identifies clusters located across the study area, while local spatial autocorrelation maps local clusters (hot or cold spots). As most events and features are non-stationary or structurally unstable over space, the latter provides a more appropriate approach for understanding local patterns (Anselin, 1995). Local urban service hot spots can provide a more objective guide where public transport developments are needed.

However, few previous studies have reported quantitative evaluations of the relationship between popular destinations and subway station accessibility. The limited data resources and traditional methods, such as questionnaire surveys and sampling methods, have not accurately revealed the popularity of urban services over a large study area, e.g. a city or country. Information collection across a large spatial region necessitates support from the public, which can be facilitated using social media.

Cluster analysis is often used to identify statistically significant hot and cold spots. Studying the spatial relationship between features or events, identified clusters present an assessment of their spatial heterogeneity and areas of focus. Furthermore, cluster analysis can provide insight as to the causes of a hot or cold spot.

There are two different methods for spatial cluster analysis. The first is pattern analysis, which determines whether spatial clustering exists in a given area (global spatial autocorrelation). The second is cluster mapping, which provides more information than the pattern analysis by localizing the clusters (local spatial autocorrelation), resulting in a visual representation (Fotheringham, 2009). This study used cluster mapping to identity urban services hot and cold spots.

Commonly used cluster mapping methods include the generalized additive model (Hastie & Tibshirani, 1987), Getis-Ord Gi* (Getis & Ord, 1992), kernel intensity function (Kelsall & Diggle, 1995), Anselin local Moran's I (Anselin, 1995) and spatial scan statistical methods (Fritz, Schuurman, Robertson, & Lear, 2013). The Anselin local Moran's I is the only method that can detect spatial heterogeneity from a geostatic perspective, as it is a local indicator of spatial association. Chongqing is a typical polycentric urban structure, and therefore global spatial association analysis can ignore the spatial variation of urban characteristics. The Anselin local Moran's I method was used in this study to provide a greater insight into the planning and selection of the locations for subway station, and is defined by (Anselin, 1995):

$$I_i = (x_i - \overline{X}/S_i^2) \sum_{j=1, j \neq i}^{n} \omega_{i,j}(x_i - \overline{X}) \tag{1}$$

in which x_i is the popularity of an urban service, i and j indicate attractions at two different locations, n is the total number of urban services, $\overline{X}$ is the mean of the popularity (the number of comments), and $\omega_{i,j}$ is the spatial weighting between two different locations i and j. The weighting can be determined by many different spatial relationship functions, such as inverse distance and contiguity edges. In this study, where attractions are point data and the walkable catchment distance is fixed, the fixed distance band was chosen to calculate the weighting between two urban services. This resulted in neighboring destinations within the walkable catchment distance were weighted ‘1’, i.e. they exert influence, while any destinations outside this distance received a weighting of ‘0’.

$$S_i^2 = \sum_{j=1, j \neq i}^{n} (x_i - \overline{X})^2/n - 1 \tag{2}$$

The p-value significance indictor was derived from the z_{I_i} score, which was defined as:

$$z_{I_i} = I_i - E[I_i]/\sqrt{V[I_i]} \tag{3}$$

where,

$$E[I_i] = -\sum_{j=1, j \neq i}^{n} \omega_{i,j}/n - 1 \tag{4}$$

$$V[I_i] = E[I_i^2] - E[I_i]^2 \tag{5}$$

The significance values and confidence level enabled the hot and cold spots to be identified.

2.5. Utility-cost analysis

Utility-cost analysis is the evaluation of different alternatives based on the ratio between their cost and utility (Levin & McEwan, 2000). The term “utility” refers to the degree of one alternative satisfying a criterion or attribute (Girginer & Kaygisiz, 2013). The utility-cost ratio is the comparison between the cost of an alternative and its utility score, and the lowest ratio indicates the best utility value (Levin & McEwan, 2000).

In this study, utility represents a standardized number of weighted services that can be covered by the catchment area of a subway station, and the cost function is a standardized number of the capacity each station can support. Utility-cost value is the ratio between the two:

$$UC_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} w_j S_j / CC_i \tag{6}$$

where UC_i is the utility-cost value of station i, R_j is the ratio between weighted (w_j) service S_j and carrying capacity supplied at station i within the catchment d_0. Both the total number of weighted services and the carrying capacity at each station were normalized between 0 and 1. Therefore, the utility-cost value of each station was only a comparison between the stations in Chongqing.

One of the advantages of utility-cost analysis is its capacity to value individual preferences and different outcomes (Girginer & Kaygisiz, 2013). However, due to the limited sample size used in traditional analysis, the results from utility-cost analysis is difficult to reproduce. This study addresses this by including all evaluators (services) in Chongqing.

2.6. Spatial stratified heterogeneity (SSH)

In order to further investigate the spatial pattern of the utility-cost value of subway stations in Chongqing, Geodetector (Wang, Zhang, & Fu, 2016a, 2010) developed to model the SSH. SSH compares spatial variations between and within different strata (zones), indicated by the geographical detector q-statistic:

$$\mathrm{q}(Y|h) = 1 - {}^{1}\!/_{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \tag{7}$$

where N and σ^2 are the total number of stations and the variation of utility-cost value Y in Chongqing, respectively. L stands for the total number of strata. N_h and σ_h^2 present the number of stations and the variation of utility-cost value within each strata (zone).

q-statistic measures the spatial distribution pattern of utility value of the stations in Chongqing. To further understand the difference of utility values between different strata (zones), e.g. different distances from city center, a t-test was used:

$$t_{\overline{y}_{h=1} - \overline{y}_{h=2}} = (\overline{Y}_{h=1} - \overline{Y}_{h=2}) \Big/ \left[{}^{Var(\overline{Y}_{h=1})}\!/_{n_{h=1}} + {}^{Var(\overline{Y}_{h=2})}\!/_{n_{h=2}} \right]^{1/2} \tag{8}$$

where $\overline{Y}_h$ represents the mean of the utility-cost values within strata h, n_h is the total number of stations within strata h, and Var stands for the variance.

3. Results and discussion

3.1. Spatial distribution of popular urban services

Spatial statistic-based cluster analysis was used to determine the popularity of urban services in Central Chongqing using five different categories: educational, medical services, shopping, food and entertainment. Fig. 3 presents the results, which indicated that all urban services had a degree of spatial association. Both local autocorrelations (hot spots or clusters with high values, arising from popular destinations surrounded by popular destinations in this study) and spatial heterogeneity (a high number of outliers arising from popular destinations surrounded by unpopular destinations) were identified in this study. In Fig. 3, only statistically significant hot spots and high value outliers ($p < 0.05$) are presented. The former can be interpreted as mature urban services with high public transport demand, while the latter can be considered as developing urban services with the potential to become a future high public transport demand areas.

Fig. 3 shows a larger total number of mature popular urban services compared to developing popular urban services, likely to be located in central Chongqing. Furthermore, the mature popular urban services were densely distributed, while the distribution of developing urban services was sparse and more likely to be found in remote areas.

The most significant concentration of popular mature urban services was for food services (Fig. 3d), followed by entertainment services (Fig. 3e). The least number of hot spots were shopping services (Fig. 3c). Popular mature urban educational services in remote areas were only found in a University town (Fig. 3a), where there was less development of medical and shopping services compared to food and entertainment services.

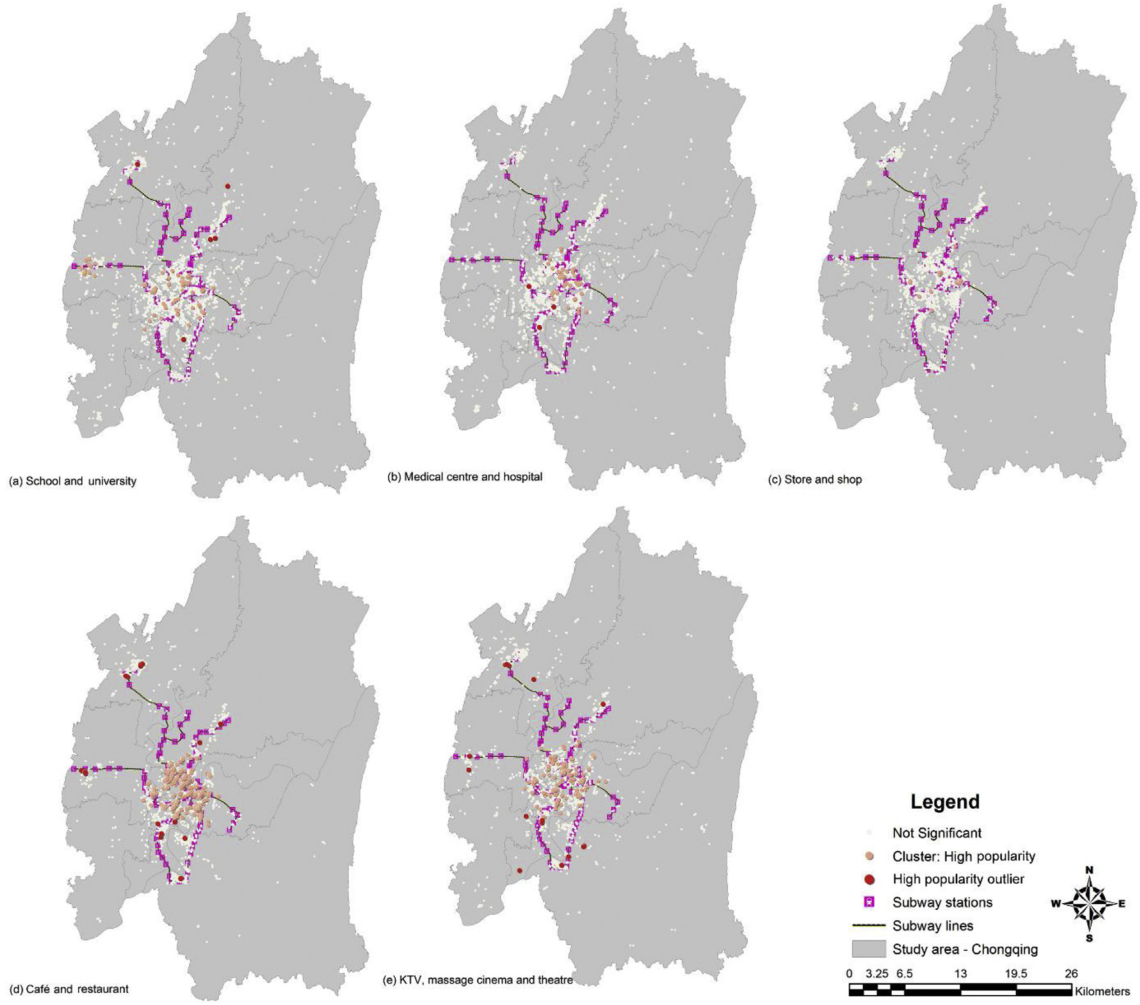

Fig. 3. Hot spot analysis for urban services.

Analysis of the distribution of urban services provides an insight into mismatch between subway stations and urban services. Traditional subway station planning is based on the populations commuting behavior and little consideration is given to the need for urban services. Therefore, subway stations are mostly located in residential and commercial centers, and the distribution of recreational facilities are not sufficiently considered as an influencing factor for subway station planning.

As part of urban renewal, subway system construction as the main transportation infrastructure improvement should match the function and scale of the new urban project. For example, in urban planning, new commercial outlets often attract large numbers of recreational facilities, normally located on city outskirts due to lower land prices. These areas are not easily covered by subway systems. Therefore, it is necessary to further analyze the spatial distribution of the utility-cost values of subway stations with different distances to the city center.

3.2. Comparison of the utility-cost values of subway stations

Further investigation into the connection between subway stations and popular urban services to analyze the utility-cost value of subway stations in Chongqing was performed. The average walking speed is 72 m per minute (Fitzpatrick, Brewer, & Turner, 2006), and 1.5–2.5 km has been widely accepted as the “maximum walkable distance” to services (Frie, Syku, & Zhou, 2012; Grauel & Chambers, 2014), whilst the ideal distance for walkability is 400 m–800 m (Knaap, Song, & Nedovic-Budic, 2007; Macedo & Haddad, 2016). Four different catchments (360 m, 720 m, 1440 m and 2160 m) were used in this study, representing walking times of 5 min, 10 min, 20 min and 30 min, respectively. Furthermore, to better understand the spatial inequality of utility-cost value of subway stations, the city was divided into four areas: inner area, outer area, remote area and very remote area, based on the distance to city center, 0–5 km, 5–10 km, 10–15 km and > 15 km, respectively (Fig. 1).

Fig. 4 shows the variation of utility-cost of different stations under different scenarios. Within 10-min walking distance, the utility-cost value of stations in remote and very remote areas were close to zero. This situation only changes when the walking time becomes greater than 10 min, where Line 2 had the largest utility values. Stations on Line 2 had the best spatial equality performance, except those in the very remote area. In contrast, Line 3 had a high utility-cost value in the inner city only. The overall utility-cost value of Lines 1 and 6 increased as the walking catchment became larger in inner and outer areas. Overall, there was a decreasing trend in utility-cost value from the inner area to very remote area within a 10-min walking catchment; however, if people preferred to walk for longer distances, the difference of utility-cost values became unclear, particularly between the inner and outer areas of Chongqing.

Shapingba and Yangjiaping stations in the outer area consistently had high utility-cost values within 20 min of the catchment area. Nanping station's high performance only existed within 10 min walking distance. In contrast, utility-cost values of Xiejiawan, Sigongli and Daxuecheng (University town) were higher than the other stations on Line 3 in the inner area, Line 3 in the outer area and Line 1 in the very

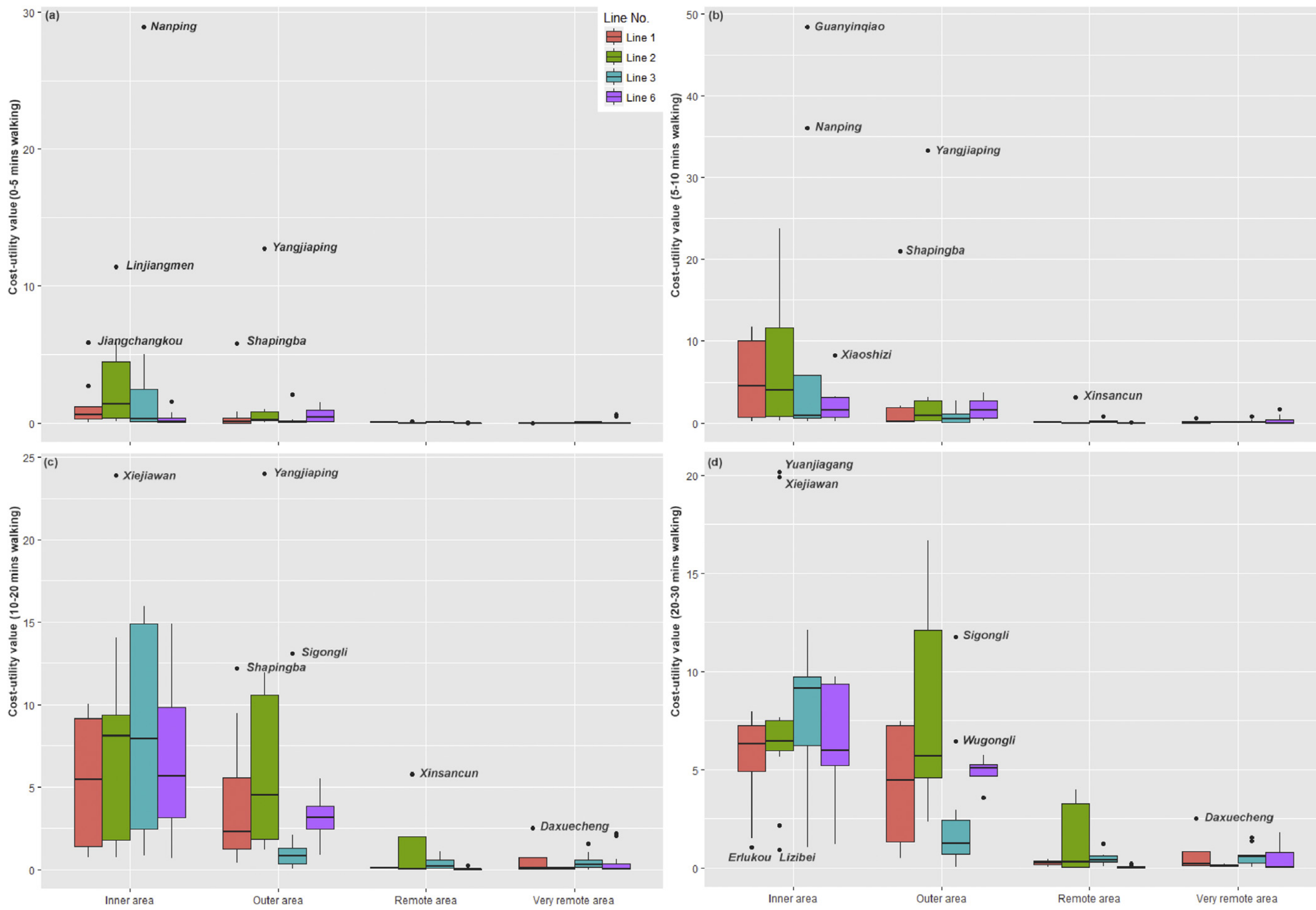

Fig. 4. Statistical summary of stations' utility-cost values separated by different lines, different remoteness and walking times: (a) 0–5 mins, (b) 5–10 mins, (c) 10–20 mins and (d) 20–30 mins.

remote area, respectively. Notably, in the scenario 20- to 30-min walking catchment, Erlukou and Lizibei had low utility-cost values, compared to the other stations on Lines 1 and 2, respectively.

Fig. 5 provides a spatially continuous view of the utility-cost value distribution in the city. As indicated by the confidence intervals (grey area), the variation in stations' utility-cost values become smaller when people chose to walk longer distances, especially for Lines 1 and 6. Compared to the other 3 lines, Line 3 had the most consistent utility-cost value across the city, particularly within 10-min walking catchment.

With the exception of Line 3, the first peak utility-cost value of the other 3 lines occurred at approximately 5 km from the city center, and a strong fluctuation with clear spatial pattern of utility-cost values across the city was identified, which is not common in monocentric cities. Generally, the lowest utility-cost value was found at approximately 15 km from the city center for all lines and all four walking catchment scenarios, which indicates the need for attention by urban planners.

3.3. Spatial inequality of utility-cost values

There are many dimensions of inequality, and unequal access to opportunities is one of the most important (Haddad & Barufi, 2017; Hu, Fan, & Sun, 2017; You, 2016). Recently, Moreno-Monroy, Lovelace, and Ramos (2018) and Dadashpoor and Rostami (2017) described the concept of urban inequality as it relates to accessibility and mobility; however, there are no studies that evaluate the spatial inequality of utility-cost values.

Spatial analysis has been widely applied to assess spatial patterns and even urban inequality (Gutiérrez & Delclòs, 2016; Macedo & Haddad, 2016; Martínez, Pfeffer, & Baud, 2016). Traditional spatial analysis methods address the spatial distribution of utility-cost values of subway stations in cities, which is often uneven; however, variations in spatial patterns within and between different zones cannot be quantified by these methods. In this study, Geodetector (q-statistic value) provided a new perspective in understanding spatial inequality by assessing the SSH over the space.

Generally, the q-statistic value [0–1] indicates how the zoning contributes to the spatial heterogeneity of a phenomenon. In this study, the q-statistic value addressed whether there was a significant difference between utility-cost values from the different zones of Chongqing (inner area, outer area, remote area and very remote area). If this difference was dominantly greater than the difference within each of the zones, the q-statistic value was 1. If the distribution of the utility-cost values was even and dispersed across each zone, the q-statistic value was 0.

Table 1 presents data suggesting no clear distribution pattern of utility-cost values for Lines 1 and 2, and no clear pattern for each individual line when the catchment was less than a 5 min walk. Overall, Line 6 had more spatial unbalance of utility-cost values compared to Line 3. The spatial inequality of utility-cost value becomes significant when the walking catchment becomes larger, for both Lines 3 and 6. The combination of all four lines can reduce the effect of spatial inequality of utility-cost, particularly for the 10-min walk catchment area; however, the spatial unbalance of utility-cost becomes significant as the walking catchment increases.

Table 2 presents the results from the *t*-test and further illustrates the

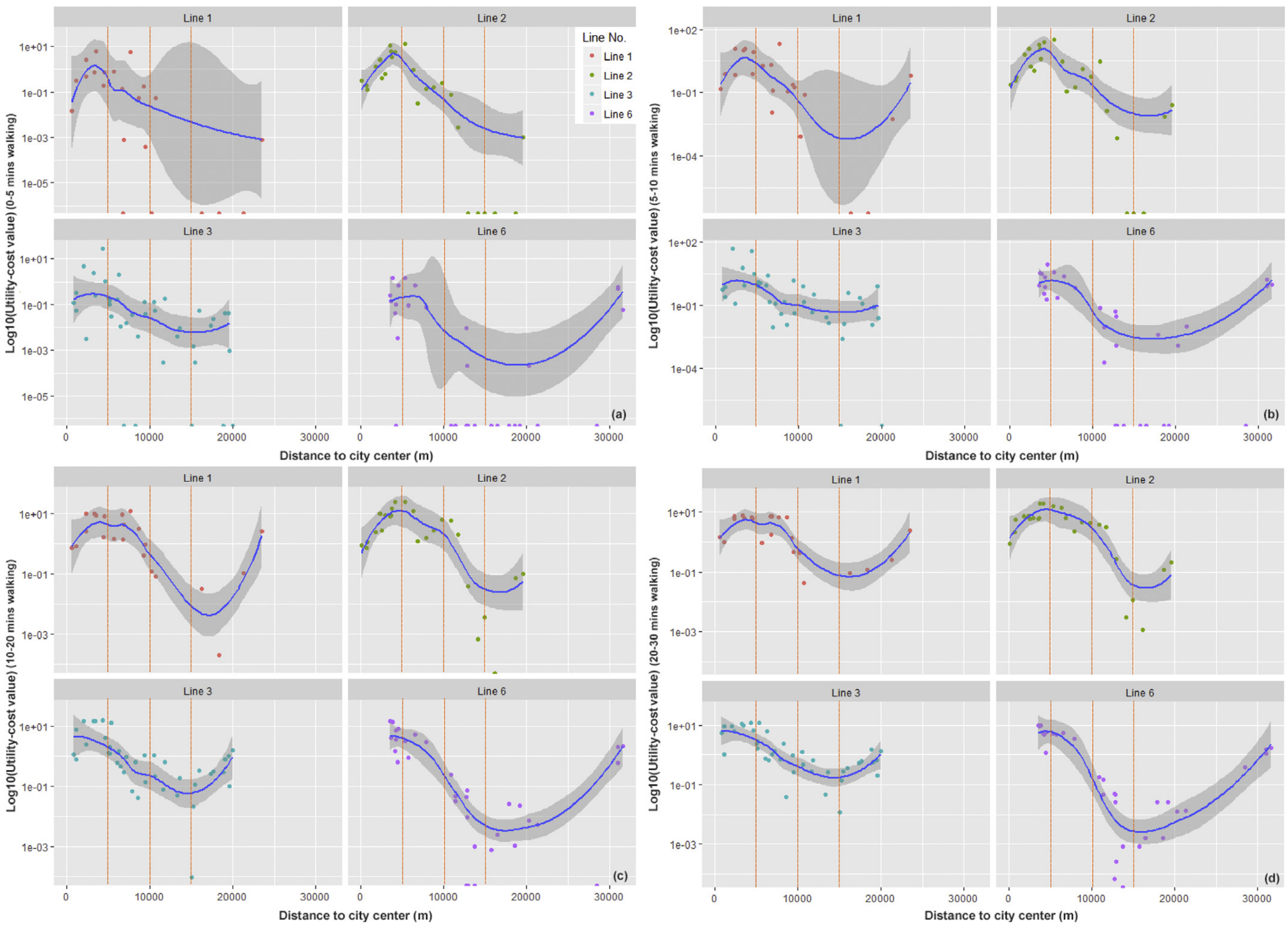

Fig. 5. Utility-cost values of different stations against distance to city center with 0.95 confidence interval under four different walking catchment scenarios: (a) 0–5 mins, (b) 5–10 mins, (c) 10–20 mins and (d) 20–30 mins.

Table 1
Spatial stratified heterogeneity (SSH) level of different lines by different walking catchments.

	0–5 mins	5–10 mins	10–20 mins	20–30 mins
Line 1	n.s.	n.s.	n.s.	n.s.
Line 2	n.s.	n.s.	n.s.	n.s.
Line 3	n.s.	n.s.	0.45**	0.59**
Line 6	n.s.	0.34*	0.53**	0.79**
All lines	0.09*	0.14**	0.31**	0.45**

*indicates result was significant at 0.05 level; ** indicates result was significant at 0.01 level; n.s. means not significant.

Table 2
Difference of utility-cost values of all subway stations in different areas of the city.

	0–5 mins	5–10 mins	10–20 mins	20–30 mins
inner area-outer area	N	N	Y	Y
inner area-remote area	Y	Y	Y	Y
inner area-very remote area	Y	Y	Y	Y
outer area-remote area	N	N	Y	Y
outer area-very remote area	N	N	Y	Y
remote area-very remote area	N	N	N	N

spatial inequality of utility-cost values for all lines between different zones. A walking time of 10 min is the threshold separating two different spatial inequality patterns of utility-cost values. Within a 10-min walk two unbalances come from the inner area-remote area and inner area-very remote area. However, greater than 10-min walking times across all areas had significantly different utility values, with the exception of remote area-very remote area. The results in Table 2 further explain the q-statistic value by indicating the contributors to the spatial inequality of utility-cost values of the stations in Chongqing.

4. Conclusion and research perspectives

This study describes the utility-cost value of subway stations in Central Chongqing using three measures: local cluster analysis, utility-cost analysis and SSH analysis. Although Chongqing is considered as a polycentric urban structure, its rapid development in urban services and public transport system are still concentrated in the city center; however, this did not result in the city center having higher utility-cost values. This study confirms a predictable unbalance between the utility efficiency of subway stations in the city center and rural areas. It also confirms that subway stations in the city center overall have better accessibility to urban services than those in rural areas. The threshold distance for lowest utility-cost value was determined to be approximately 15 km from the city center.

Furthermore, this study found that the utility efficiency of the subway station was related to its location and its walking time catchment. Within a 10-min walk, stations in the remote (10–15 km) and very remote (> 15 km) were close to zero. The utility efficiency of stations in remote and very remote areas would only improve if the population chose to walk longer than 10 min to reach a station or if complementary services were added to the system such as feeder lines or park-and-ride.

Similarly, the utility efficiency of each individual station was determined by their distance to the city center and how far people would be prepared to walk. For example, Shapingba and Yangjiaping had consistently high utility-cost values within a 20-min walking catchment only. Extremely low utility efficiency was found for stations on Line 1 and Line 2, which was not common when the walking catchment was below 20 min.

In this study, the SSH method provided a new approach in understanding spatial inequality by accessing the SSH over the space. There were no clear spatial patterns for the utility-cost value of the stations on Lines 1 and 2. The combination of all four lines reduced the effect of spatial inequality of utility-cost, particularly in the 10-min walking catchment areas. A walking distance of 10 min was determined as the threshold for the two different spatial inequality patterns of utility-cost values for all the stations in Chongqing. Generally, a large walking catchment results in significant spatial inequality between different zones in Chongqing, with the exception of remote and very remote areas.

There were a number of limitations to this study, including origin accessibility to subway stations, commuter trips, population distribution, environmental factors and other potential influencing factors, which were not included here but offer opportunities for further research. Additionally, long-term time-series analysis could be included in future studies to determine the relationship between people and popular urban services from a supply-oriented perspective.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.habitatint.2018.07.006.

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