# Visualizing spatiotemporal patterns of city service demand through a space-time exploratory approach

**Abstract**

City service demand fluctuates across space and time. Although various data, such as 311 hotline data and social media data, have been used to explore the spatiotemporal patterns of city services, data uncertainty and the uneven distribution of service demand are oversimplified to some extent and thus could result in bias. To overcome these shortcomings, top-down collected city service data that fully cover urban areas are used as an emerging data source in this paper. A visual analytical approach that employs a 3D model based on a space-time cube combined with the Mann-Kendall algorithm is developed and applied in Xicheng District, Beijing, China. The results show that in comparison to other methods, the emerging data and visualization method have more power to explain city services in terms of overall trends and micro-scale details. For instance, city service cases demonstrate a significant downward trend. Meanwhile, the distribution of hot/cold spots is found to be related to the built environment and population density. For example, high-incidence cases are located in some communities that are the key governance areas, indicating a demand to increase the staffing of grid administrators. The findings of this work can potentially benefit other cities in China and worldwide.

**Key words:** City management, space-time cube, spatiotemporal pattern, city service data

## 1. Introduction

According to the 2018 Revision of World Urbanization Prospects, almost 55% of the world's population lives in cities, and this proportion is expected to reach 68% by 2050 (United Nations, 2018). However, this will inevitably result in negative impacts, such as environmental pollution, traffic congestion and issues for public health and safety, that will affect limited city resources in urban areas. With the wide adoption of information communication technology (ICT), smart city strategies are expected to collect citizen feedbacks and complaints, monitor urban infrastructure states, and provide knowledge for improving the quality of urban life (Chong et al., 2018). In particular, geospatial big data related to city management have attracted attention from the academic and industrial sectors (Yang et al., 2020).

The process of determining the spatiotemporal pattern behind geospatial big data to improve city services has been a popular research area. For city service data sources, hotlines, such as 311 in many American cities (Ghodousi et al., 2019; Xu et al., 2017), and social media data (Chae et al., 2012) are widely used. The 311 hotline data contain citizen complaints with semantic descriptions for place and detailed information, which provides the chance to explore estimation methods and predictive models of neighborhoods, ethnic issues, and governmental policy making (C. Kontokosta et al., 2017; Minkoff, 2016; O'Brien, 2016; Xu et al., 2017). Social media data, such as Twitter, Facebook, and Flickr, have been widely used to study urban natural disasters, such as earthquakes, tsunamis, and floods (Han & Wang, 2019; Theja Bhavaraju et al., 2019), social activities, and public perception (Hu et al., 2020).

Many studies have been conducted to identify patterns, explore factors and predict citizen demands and human mobility. Traditional spatial methods, such as heat map, clusters and statistics, have been used to visualize citizen requests and complaints (Hubert et al., 2017). Four machine learning models, i.e., Naive Bayes, K-Nearest Neighbor, Random Forest and AdaBoost models, have been engaged to evaluate and predict the citizen engagement pattern via tweet data (Siyam et al., 2020). Moreover, a response predicting model has been applied to New York City 311 service requests with a sparse Gaussian conditional random field model (DeFazio et al., 2018). The gradient boosting regression and random forest models have been used to profile and predict the 311 service data (Zha & Veloso, 2014).

Although many studies have been conducted on the analysis of city service demand, there are some drawbacks. First, new emerging data sources should be utilized to discover more insightful patterns. In existing works, the most widely used data sources have been 311 service-request data (Hagen et al., 2019) and social media data (Ghodousi et al., 2019; Wang et al., 2017), which are almost subjectively reported by users and belong to voluntary geographic information (VGI) data (Elwood et al., 2012). These datasets may be sparse and missing spatial and temporal information. Quality and accuracy are other issues arising from unprofessional data collection (Granell & Ostermann, 2016). Second, the existing literature has explored statistical and machine learning methods to profile and predict the city service event, although the spatiotemporal visualization approach has rarely been used for city service demand. Owing to the complex scientific feature of cities, mathematical methods, such as statistical methods, might be weaker than interactive visualization methods in discovering deep insight in city services. Spatiotemporal visualization technology is an efficient and lightweight method that has been widely used in many research fields, such as criminology (Nakaya & Yano, 2010) and urban transport (Kang et al., 2018). This technology can provide comprehensive and valuable information from data sources and predict patterns in citizen requirements and mobility, which will help the government understand urban issues and allocate resources efficiently (Hagen et al., 2019). Although many analysis methods, e.g., kernel density (Ye et al., 2015) and k-means clustering (Hagen et al., 2019), have been widely used to study urban issues, they often focus on two-dimensional visualization instead of three-dimensional techniques. To explore time variations, three-dimensional methods, such as space-time cubes, provide an opportunity to address this shortcoming (Andrienko et al., 2010).

To address the abovementioned gaps in data sources and holistic spatiotemporal visualization methods, we used a new city service data source to study city service demand in Beijing, China. The contributions of this paper can be summarized as follows:

(1) The new city service data are introduced and validated to study city service demand. The data are mainly obtained through the daily work of the "city grid inspector" in the grid-based inspection and management mechanism, which has high accuracy and even distribution for city service demand research. Details about the data are introduced in Section 3.

(2) The second contribution of our work is that a spatiotemporal visualization approach based on the space-time cube model was proposed to identify and analyze the city service demand pattern. A case study in Beijing was carried out that demonstrated the usability of the new data source and the ability to support decision-making for urban management.

The remainder of this article is organized as follows: Section 2 introduces related literature on city service issues and visual analysis methods. In Section 3, we introduce the data and methods used in this article. The experimental results of this paper are described in detail in Section 4 and analyzed based on the feasibility and mining results. Section 5 discusses the results. Section 6 summarizes our work.

## 2. Related work

This work focuses on newly emerging citizen service data and spatiotemporal pattern analysis methods. A thorough investigation of existing data and methods will be important to this work. Therefore, this section reviews the research data and spatiotemporal visualization analysis method to provide background information.

### 2.1. Related work on city service demand

City service demand data are defined as the interactive information between citizens and the government. The government provides infrastructure and services for people and inspects their usability and operation. Otherwise, when citizens have demands or complaints, they can express their concerns and demands that can be discovered by analyzing the city service data. The wide use of ICT technologies has led to the exponential growth of city service data and information in smart cities (Chatfield & Reddick, 2018). Cities such as New York, Singapore, and Chicago have employed city service data to innovate urban governance and intelligence by reducing governance costs and improving governance efficiency. The 311 and similar hotline data are the main format of city service data.

City service data are sparse, heterogeneous spatiotemporal data. The content of city service data includes spatial and temporal information, which is helpful for improving urban management. Detailed information, including geographic location, time, and problem descriptions and self-experiences, is recorded. The 311 dataset for Chicago contains 12 report categories, including abandoned vehicles, graffiti removal, alley lights out, and garbage carts (Xu et al., 2017). Citizens can actively express their concerns and complaints about streets, infrastructure and others by a variety of channels, including text messages, web pages, and mobile apps. However, owing to active and volunteer reports by citizens, the data exist in only certain places, which leads to sparse and heterogeneous data distributions.

Data quality and data application analysis are two popular research issues. To understand the city service data categories and distribution, the citizen participant degree has been investigated to help refine policies to encourage citizen participation in e-government (X. Gao, 2018). To detect the relationship between the quality of life of citizens and social-economic and demographic factors, the distribution of 311 data points in Miami has been validated (Hagen et al., 2019). Optimized resource allocation and social-economic competition have been examined to improve the quality of life (Wang et al., 2017; Xu et al., 2017). Although many studies have been performed, these analyses and prediction models may be limited by data quality, i.e., lack of data or uneven data distribution. A previous study compared 311 data and social media data (Twitter) in five cities (Chicago, New York, Philadelphia, San Francisco, and Kansas City, Missouri) (X. Gao, 2018) and demonstrated that the amount of city service data does not reflect the severity of the complaints owing to the uneven distribution (Xu et al., 2017). As noted in other VGI data, data quality and distribution are more sensitive to socio-economic factors, such as education level, ethnic differences, and religion (Kitchin, 2014; Lu & Johnson, 2016).

In summary, there are problems with data sources. The existing data are often collected in a bottom-up manner. Due to the influence of citizens' experience, culture, emotions, etc., data uncertainty and deviations exist. As a result, citizen complaints may be ignored or be difficult to mine. Therefore, to avoid data shortcomings, this article focuses on the actively top-down collected data in urban management. City service data represent the occurrence of city management events, which are collected by professional inspectors within a spatial grid of approximately 100 square meters. The data record contains location and time information for each case. Given the changes in space and time within the data, the spatiotemporal patterns of urban management and city service demand are well understood. Therefore, this paper uses the space-time visualization method to discover the spatiotemporal patterns and uses the spatiotemporal statistical analysis method to explore the spatial-temporal hot spot distribution of city service demand.

**2.2. Spatiotemporal visualization analysis methods**

Visualization, statistics and prediction models are widely used analysis methods for spatiotemporal data (Offenhuber, 2015; Rimaityte et al., 2012; Xu et al., 2017). However, few studies have explored spatial patterns and time trends as a holistic approach. In particular, the multiple dimensions and heterogeneity of city data increase the difficulty of developing a new visualization approach.

Mapping and spatiotemporal analysis are the most widely used spatiotemporal visualizing methods. They are widely used in the fields of ecology (Krishnan et al., 2019), environmental health (Fan et al., 2020) and emergency management (C. E. Kontokosta & Malik, 2018). For the urban management domain, distribution patterns and hot spots are both common applications in criminal patterns (Ajayakumar & Shook, 2020), public facilities (Shi et al., 2020), and rainfall monitoring (Jing et al., 2016). In terms of the mapping method, flow maps are commonly used to visualize trajectory data and user contact data (Ni et al., 2017). For the spatial analysis method, density-based and spatial cluster methods have been examined. The kernel density is commonly used to estimate smoothed social media intensity surfaces for mapping spatiotemporal patterns of social media events (Y. Gao et al., 2018). The seasonality of tourism has been determined using the kernel density estimation (KDE) method (Jing et al., 2020). The spatiotemporal clustering method can be used to identify dynamic trends and space-time patterns. These methods are powerful in describing two-dimensional data (i.e., x-y coordinates). However, these methods are weak in terms of holistically visualizing space-time data with multiple dimensions.

A space-time cube model can provide cubic visualizations of spatiotemporal data. The space-time cube can not only visualize the spatiotemporal clustering pattern but also display the statistical results in three dimensions and analyze the statistical significance of these hot spots. The dynamic phenomena can be aggregated by estimating the space-time density as a volume in the three-dimensional space-time model (Andrienko et al., 2010). This model was first proposed by Hägerstrand (1989) and has been widely used in many fields, such as epidemiology (Zhao et al., 2019) and urban transportation (Kang et al., 2018). Kang et al. constructed a traffic accident spatiotemporal cube model with Seoul traffic accident data, integrating emerging hot spot analysis and spatiotemporal KDE analysis to visualize the spatiotemporal characteristics of traffic accidents involving the elderly (Kang et al., 2018). This model can help develop preventive measures to reduce such traffic accidents. Krishnan et al. used the space-time cube method to analyze the overall change trend in wheat crop cultivation data over time and used a spatiotemporal statistical model to evaluate the relationship (Krishnan et al., 2019). In the context of tourism management, Jing et al. used the spatiotemporal cube model to develop a spatiotemporal dynamic model of Beijing inbound tourists under fine-grained conditions with Flickr, thus providing a scientific basis for relevant departments to formulate inbound tourism policies (Jing et al., 2020). In the public health field, Huang et al. used a combination of a space-time cube and space-time scan statistics to analyze the pathogenesis of hand-foot-mouth disease in Guangdong Province (Huang et al., 2015).

Although many visualization and space-time cube models have been widely used, an integrated visualization approach for the new city service demand data to identify and visualize spatiotemporal patterns should be designed and developed. In our work, we proposed a holistic visualization approach based on the space-time cube model to unfold city service demand patterns and temporal trends. The space-time cube model was used to organize the visualization data and methods for multidimensional data. Trend analysis methods were employed to detect spatial and temporal patterns in city service data. Finally, the theoretical results and a case study analysis were conducted to identify the spatiotemporal pattern.

## 3. Data and methodology

### 3.1. Study area and data preprocessing

1) Study area

The study area is Xicheng District of Beijing, China. There are seven communities in Xicheng District, including Changanjie, Yuetan, Shichahai, Zhanlanli, Xinjiekou, Jinrongjie and Desheng. Xicheng District is not only the core functional area of the capital but also the political and cultural center. It is also an important area that reflects the national image and international communication. Its core geographical location and political role necessitate that it have higher requirements and criteria in terms of urban planning and management. Furthermore, it is necessary to study the spatiotemporal pattern in urban infrastructure operation status, i.e., city services.

2) Data sources and preprocessing

The data sources used in this paper were collected by government "grid inspectors" who have been professionally trained. The study area was divided into spatial units (grids) of approximately 100 square meters, and each inspector was assigned several grids to perform regular patrol. The data collection flow included inspection, problem determination, information collection and uploading. These data were obtained through the daily work of city grid inspectors. During inspection patrols, once a city service event was found, the inspector determined whether it was a city service event according to technological specification issued by the government and their experience. Then, the grid inspector collected information by taking spot pictures through mobile devices, completing an information form, and uploading it to the city management service database by specified software or mobile APP. Thus, a record in a database was generated as city service data. The city service data include public infrastructure and citizen complaints, such as the loss of urban public facilities, garbage clustering, and illegal buildings. The new data collection is a top-down approach that involves the use of government-assigned inspectors to actively discover city service events instead of passive notifications from citizen hotlines. Therefore, this collection mechanism not only collects city service data in a timely and seamless manner but also changes the data collection method from passive to active.

The city service data types can be divided into two categories: component case and event case. The former involves infrastructure with fixed positions, such as municipal administration, transportation and gardens. The latter refers to the events or phenomena that cause the destruction of urban facilities or the environment due to human factors or natural disasters, thus requiring maintenance by the urban management department. The case type is subdivided into Level-1 class and Level-2 class (Table 1). The master-slave relationship is existed between two classes. The specific classification criteria are shown in Table 1.

Table 1. Three-level classification of case types

| Case type | Level-1 class | Level-2 class |
|---|---|---|
| Parts | public utilities | street lights, manhole cover |

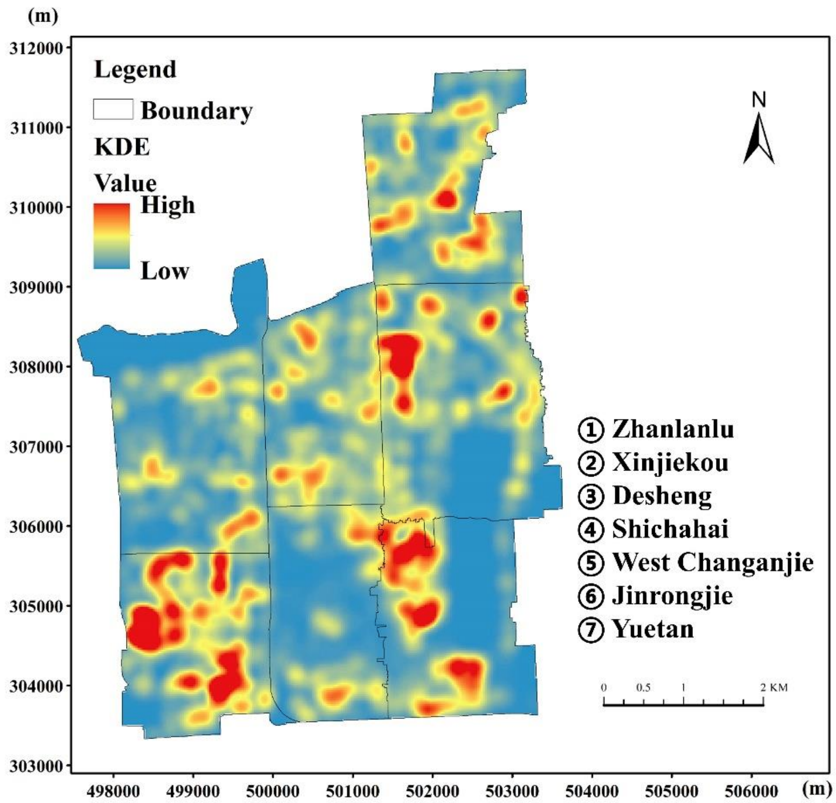
| | | |
|---|---|---|
| | the traffic | parking lots, traffic lights, |
| | cityscape environment | public toilets, advertising plaques |
| | landscaping | green space, sculpture |
| | housing land | bulletin board |
| | other facilities | water ancillary facilities |
| | expansion parts | wall billboards, construction guardrails |
| | cityscape environment | exposure to garbage, dirty roads |
| | advertisement | illegal advertising, damaged advertising signs |
| Events | construction management | construction occupation, dust on construction site |
| | emergencies | road surface collapse, road water accumulation, etc. |
| | street order | illegal parking |
| | extended event | illegal taxi operation |

For the city service data, each record was used to provide basic information about the requested case, such as the case number, case type, case location, geographical coordinates of the case, the community where the case occurred, and the time when the case was reported. The specific field types are shown in Table 2.

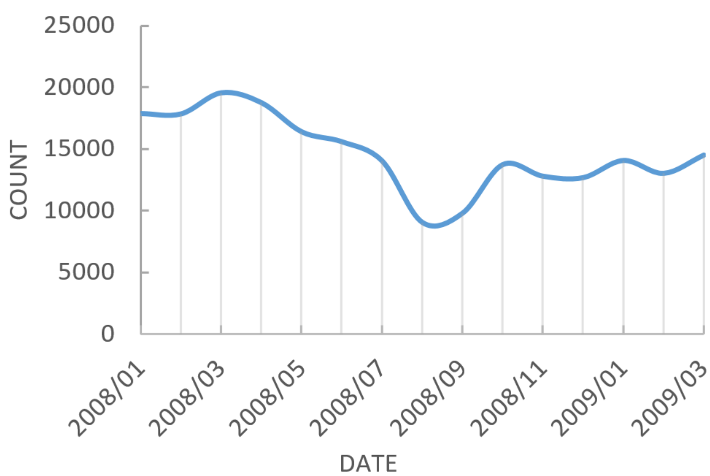
Table 2. Data attributes and types

| Name | Type | Description |
|---|---|---|
| InstanceID | Int | Unique ID for city service data |
| CaseType | Int | Case contains two major types of events and parts |
| Level-1 | Int | Each type contains multiple categories |
| Level-2 | Int | Each category contains multiple subcategories |
| STName | Text | Street where the case occurred |
| CommName | Text | Community where the case occurred |
| CaseAddress | Text | Location of the case |
| CoordX | Float | X coordinate of the location where the case occurred |
| CoordY | Float | Y coordinate of the location where the case occurred |
| RegisterTime | Date | Time when the inspector reported the case |

In the process of data collection, various problems will inevitably exist, such as duplicate cases, errors, and missing attribute values. To ensure the accuracy and validity of the spatial data, some data preprocessing work was performed. The work involved primarily reviewing repeated values, error values and outlier data to fill in missing data. This study selected all case type data from January 2008 to March 2009 as the data source. After preprocessing, 219,644 records were selected. Kernel density analysis of the cases was performed to determine the spatial distribution of events. The result is shown in Fig. 1(a). The monthly time variation in the number of city service events is shown in Fig. 1(b).




(a)




(b)

Figure 1. Spatial and statistical distribution of cases: (a) kernel density analysis of seven communities and (b) temporal variation on a monthly basis

### 3.2. Methodology

This section mainly introduces the methods used in this article. There were three steps involved. First, the space-time cube of the city service data was created, and the case locations in the two-dimensional plane were mapped into the cube to show the distribution in space and time. Second, the Mann-Kendall trend test method was employed to analyze the changing trend in the time series. Finally, emerging hot spot analysis with the Getis-Ord *Gi** hotspot statistical method was used to explore the classification of the hot spots from the city service data and assess the temporal and spatial evolution of these hot spots.

1) Space-time cube model for multiple dimensional visualization

The space-time cube is used to create a cube containing spatial and temporal data for a specified data set requiring further space-time pattern mining (Langran, 1989). A spatiotemporal cube tool was created to obtain the time-stamped point characteristics of case data; then, these points were aggregated into a spatiotemporal bin in Network Common Data Form (NetCDF) format to store space-time cubes for city service data. Based on the newly created space-time cube, time-series analysis and spatiotemporal hot spot analysis were performed. Then, visualization was achieved with two-dimensional maps or three-dimensional scenes. The created data structure can be thought of as a cube composed of space-time bins. In this case, a two-dimensional axis is used to represent the real-world space of plane positions, and a one-dimensional time axis is used to represent the change in plane positions over time. The space-time cube model uses the geometric features of the temporal dimension to vividly represent the processes of city services over time.

Bins in the same spatial location share the same ID, which denotes a time series. Bins with the same time step interval have the same time ID, which is composed of a time slice. The count value in each bin represents the number of city service data that fall into a certain location and time range. In the three-dimensional scene, the rows represent the number of cases at different locations within a specified time, and the columns represent the time series of a particular spatial location.

In our research, the STC model was used to aggregate city service data into spatiotemporal bins with time series, which denote the spatiotemporal trends. The time interval and spatial interval parameters are the key to evaluating the trend. Studies have shown that aggregating data points with smaller time steps and spatial distances can detect cold spots and hot spots in more detail (Kang et al., 2018). In our work, several parameter experiments with different distance intervals (100 m, 160 m and 250 m) and time intervals (1 week, 2 weeks, 3 weeks and 1 month) were tested. The parameters of 160 m and 1 month had better results.

2) Mann-Kendall trend analysis for time variations

In our work, the Mann-Kendall trend test, which has been widely used in the analysis of temperature data, climate data, and river discharge data, was conducted to detect time variations in the temporal data. The Mann-Kendall trend test is a nonparametric test that is suitable for all distributions and insensitive to sample distributions. The null hypothesis is that data set samples are independent and consistent in distribution; that is, the data have a tendency to increase or decrease monotonically. The following formulas come from an existing study (Hamed, 2009). The Mann-Kendall test statistic was calculated according to the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \qquad (1)$$

$$a_{ij} = sgn(x_j - x_i) = sgn(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \qquad (2)$$

The statistic $S$ follows a normal distribution, where mean value of $S$ is $E(S) = 0$, and the variance is

$$\mathrm{Var}(S) = \frac{n(n-1)(2n+5)-\sum_{j=1}^{m}(t_j-1)(2t_j+5)}{18} \quad (3)$$

where $m$ is the number of groups with the same observation value, $t_j$ is the observation value of each group, and the standardized test statistic is as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & S < 0 \end{cases} \quad (4)$$

The normalized $z$ result is the $z$-score, which is calculated by formula 4. When $z$ is greater than 0, the time series of the case shows an upward trend, and the larger the value is, the more obvious the upward trend is. In contrast, when $z$ is less than 0, the time series of the case shows a downward trend. The smaller the value is, the more obvious the downward trend is. When the value of $z$ is close to 0, the time series of the case does not have any trend characteristics.

3) Emerging hot spot analysis for spatiotemporal patterns

In our work, emerging hot spot analysis was used to detect the spatiotemporal pattern in city service data. First, the Getis-Ord *Gi** hotspot statistical method was used to estimate spatial statistics by setting neighborhood distance and time step parameters. Then, the Mann-Kendall trend test was used to perform a spatiotemporal hot spot analysis of the city service data. The result is hot and/or cold patterns that are classified by the $z$-scores and $p$-values generated for each location containing data (Hamed, 2009). The total patterns included 17 classes: 8 hot spot patterns, 8 cold spot patterns, and no significant spatiotemporal patterns. The classification and definitions of the patterns are shown in Table 3. Owing to the similarity and correspondence between hot spots and cold spots, their definitions are summarized in Table 3 (Cheng et al., 2018).

Table 3. Classification of hot and cold spot trends

| Trend category | Definition |
|---|---|
| Consecutive hot spots (or cold spots) | Current hot spots (or cold spots) that were previously and continuously statistically significant. |
| Diminishing hot spots (or cold spots) | 90% of this location is a statistically significant hot spot (or cold spot). In addition, the intensity of the larger number of clusters in each month increased overall, and the increase was statistically significant. |
| Persistent hot spots (or cold spots) | This location already contains 90% of statistically significant hot spots (or cold spots), and there is no clear trend indicating that the clustering strength has changed over time. |
| Diminishing hot spots (or cold spots) | This location already has a statistically significant hot spot (or cold spot) at 90% of the time intervals. In addition, the intensity of clustering in each time step decreased. |
| Sporadic hot spots (or cold spots) | This location exhibited intermittent hot spots (or cold spots). |

At most, 90% of the time interval was already a statistically significant hot spot (or cold spot), and each month was not a statistically significant cold spot (or hot spot).

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The Getis-Ord *Gi** statistical information uses the concept of space-time proximity; the formulas are shown as follows (Songchitruksa & Zeng, 2010).

Based on the hot spot analysis, the Mann-Kendall trend test was used to evaluate the hot spot and cold spot trends. According to the trend *z*-score and *p*-value generated for each location containing data and the hotspot *z*-score and *p*-value of each bin, the emerging hot spot analysis tool classified the location of each research area. This method has two kinds of results, both of which can reflect the spatiotemporal trend over the whole spatiotemporal range. One result is a two-dimensional space for display, and the other is a three-dimensional visualization with a space-time cube. The above 17 different trend classifications were displayed in the form of a two-dimensional map; then, the visualization results of the above two-dimensional hot spot were displayed in a three-dimensional space through the space-time cube.

## 4. Results

### *4.1. Space-time cube visualization*

This work was done in ArcGIS Pro 2.1 software. The space-time cubes were created by setting 1 month as the time interval and 160 m as the spatial interval. In total, there were 219,647 points aggregated into 1,908 grids over 15 time step intervals (Fig. 2). Among the 1,908 grids, 1,187 of them (62.2%) contained at least one city service data point for at least one month. Combined with the 15 monthly intervals, 17,805 space-time bins were generated, and 14,839 of them (83.3%) had at least one city service data point. Fig. 2 shows the spatiotemporal pattern and trend in city service data. The different colors denote the level of points falling into a bin. The darker a bin is, the more cases the month has. In addition, this visualization is interactive for users; that is, users can zoom in/out and rotate in 3D. When a user moves the mouse over a grid at a time interval position (from 1 to 15), the property information of the cases will be shown.

The visualization shows the cube data and visually represents trends in space and time. The spatiotemporal distribution of city services is shown in Fig. 2. The z-score calculated according to formula (4) is -2.28, corresponding to a p-value of 0.02 and indicating a statistically significant downward trend (95% confidence) in the amount of city service data over time.

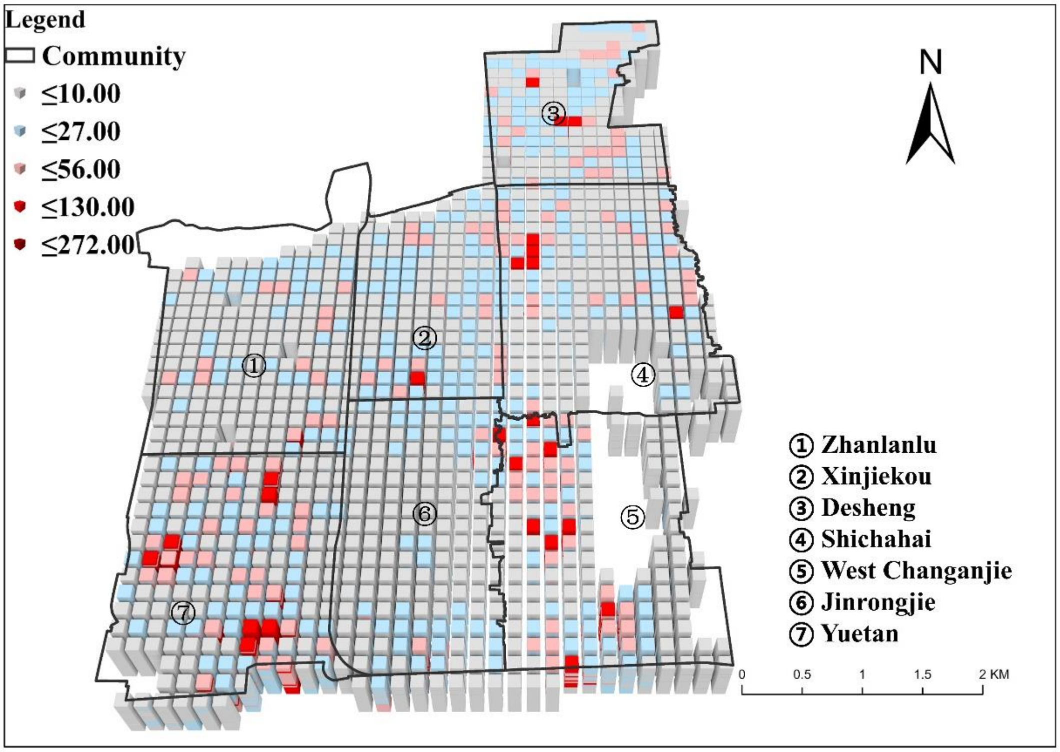


Figure 2. Space-time cube visualization

### *4.2. Spatiotemporal pattern in city service data*

The emerging hot spot method and Mann-Kendall algorithm were integrated to identify and visualize the spatiotemporal patterns. Getis-Ord *Gi** hotspot statistical analysis was performed on the city service data. The corresponding *z*-score and *p*-value were determined for each bin. Then, the Mann-Kendall trend test method was used to statistically analyze the random scores for each grid. The trends and their *z*-scores, *p*-values, and confidence levels are shown in Table 4.

Table 4. Classification of Mann-Kendall trend analysis results

| *z*-score | *p*-value | Confidence | Trend |
|---|---|---|---|
| < -2.58 | < 0.01 | 99% | Down |
| -2.58 ~- 1.96 | 0.01 ~ 0.05 | 95% | Down |
| -1.96 ~- 1.65 | 0.05 ~ 0.1 | 90% | Down |
| -1.65 ~ 1.65 | > 0.1 | - | No trend |
| 1.65 ~ 1.96 | 0.05 ~ 0.1 | 90% | Up |
| 1.96 ~ 2.58 | 0.01 ~ 0.05 | 95% | Up |
| > 2.58 | < 0.01 | 99% | Up |

For the overall trend validation, the *z*-score was -2.28, and the corresponding *p*-value was 0.02. This result shows that the city service data for the entire study area had a statistically significant decreasing trend (95% confidence) over time. Using fine-granularity analysis, the hot spots and cold spots were analyzed. The result shows that the total number of hot and cold spots was 549 of 1,187, including 210 hot spots and 339 cold spots. Table 5 shows the hot and cold spot results.

Table 5. Space-time cube hot and cold spot detection results

| Category | Hot Spot | Cold Spot |
|---|---|---|
| New | 0 | 1 |
| Consecutive | 11 | 197 |
| Intensifying | 0 | 78 |
| Persistent | 43 | 29 |
| Diminishing | 58 | 0 |
| Sporadic | 98 | 32 |
| Oscillating | 0 | 1 |
| History | 0 | 1 |
| No pattern | 0 | 0 |

The results show that there were different types of statistically significant cold spots and hot spots. The distribution and statistical results of the emerging hot spots are shown in Fig. 3. The grids in the warm orange colors denote the spatiotemporal hot spots, and those in the cold blue colors represent the spatiotemporal cold spots.

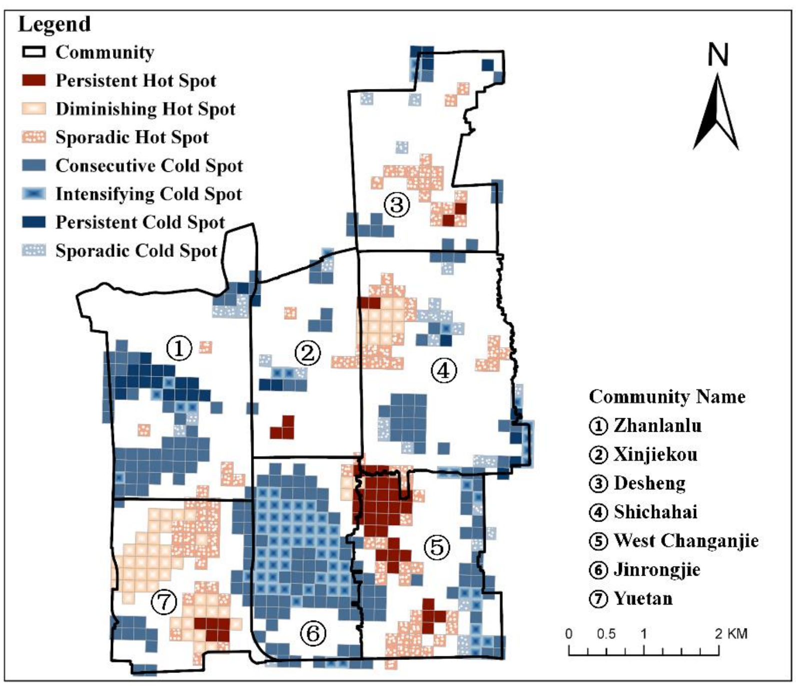


Figure 3. Emerging hot and cold spot analysis

For the time variation of patterns, a comparative figure (Figure 4) and two difference maps were created. Three key time periods (Jan. 2008, Jul. 2008 and Jan. 2009) were selected for comparison by the city service number. The difference map derived from the difference of city demand number of two time periods. All the bins in three time periods were categorized into ten levels from 1 to 9 according to the city services event number. One difference map (Fig. 5a) denotes the minus operation between Jan. 2008 and Jul. 2008. The another one (Fig. 5b) represents the difference from Jul. 2008 to Jan. 2009.

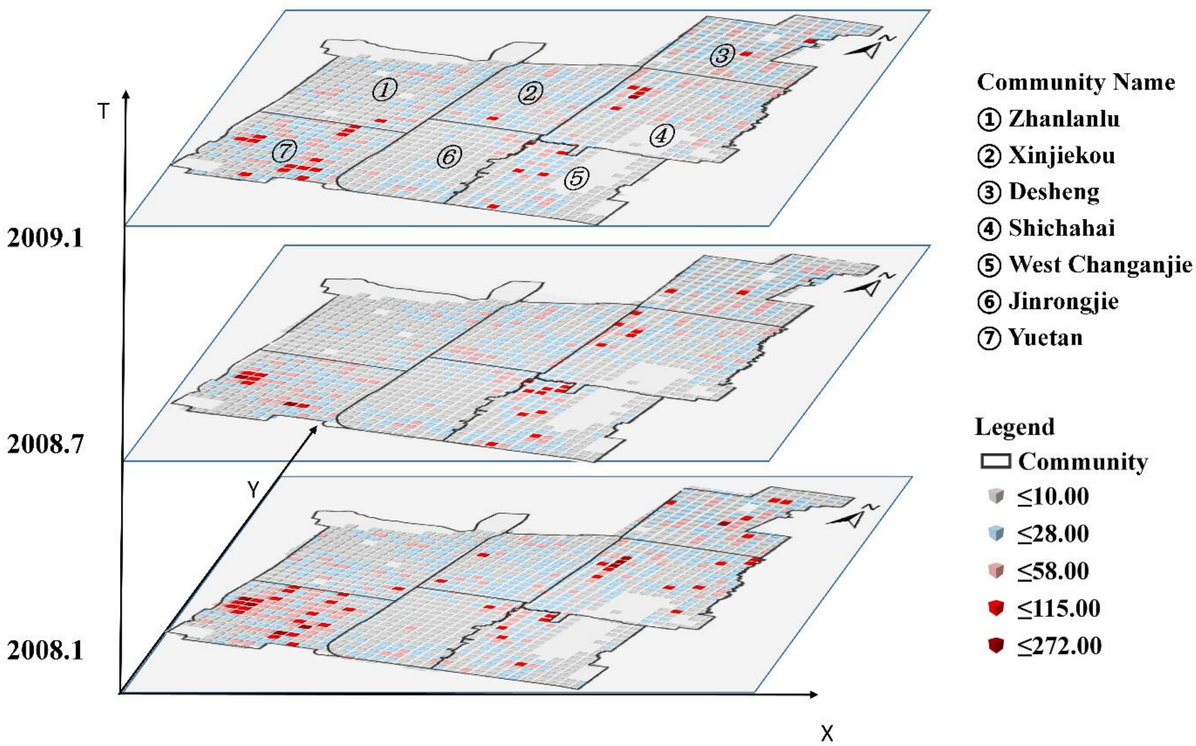


Figure 4. Time variation of space-time bins

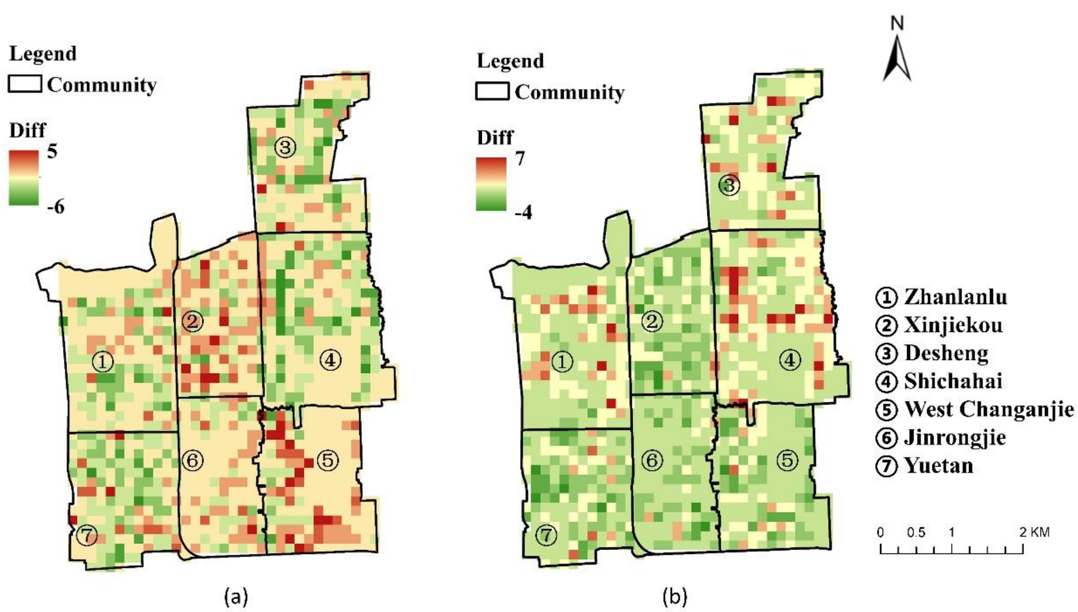

Figure 5. The difference map between key time periods. (a) from Jan. 2008 to Jul. 2008, (b) from Jul. 2008 to Jan. 2009

## 5. Discussion

### *5.1. Spatiotemporal pattern of hot/cold spots*

The hot spot types shown in Fig. 3 consist primarily of diminishing, persistent, and sporadic hot spots. There were approximately 43 diminishing hot spots in the Yuetan community (Fig. 3). This means that at least 90% of the time intervals (13 months) were statistically significant and changed significantly over time. According to the field investigation, this was an old community with many old buildings and government departments. The persistent hot spots were mainly concentrated in the West Changanjie community area. This category includes statistically significant hot spots at least 90% of the time but no significant change over time. For this region, the amount of city service data remained at a high level, and there was no decreasing tendency. There were 98 sporadic hot spots in the central Desheng community and northeastern Yuetan and West Changanjie communities. These areas were characterized by hot spots fluctuating over time. Locations with sporadic hot spots occurred in less than 90% of the time intervals containing hot spots, and none of the time intervals included statistically significant hot spots. For both areas, the potential for a case increase still exists. For those persistent and sporadic hot spots areas, they denote the urge city services demand that means the more policies should be enhanced. For the central Desheng community and northeastern Yuetan and West Changanjie communities, there are many famous tourism attractions in these areas, which represents more populations and stores. Therefore, the measurement for tourism management and urban management should be considered to lower the rate of citizen complaints.

Table 5 shows that four types of cold spots, consecutive, intensifying, persistent and sporadic, make up a majority of the cold spots. The spatial distribution indicated that these cold spots occurred mainly in the southern part of the study area. The persistent and sporadic cold spots had discrete geographical distributions. Parts of the Shichahai community were classified as sporadic cold spots (Fig. 3). Compared with other communities, in this community, there is a large area lake with sparse population and minimal traffic, meanwhile, there isn't comprehensive shopping malls. Therefore, the lower citizen complaints and sporadic cold spots are the correspond result. Most of the consecutively occurring cold spots were located south of the Zhanlanlu community and on the edge of the center of the Jinrongjie community. This result means that in the last month (March 2019), approximately 90% of the time intervals for these locations had statistically significant cold spots. In contrast, the intensifying cold spots occurred primarily within the Jinrongjie community. The number of points in each bin increased over time in those areas, and statistically significant cold spots accounted for at least 90% of the time intervals.

The spatiotemporal pattern of hot/cold spots can be demonstrated using time variations. There key time periods as milestone were selected to show the time variations. The comparison in the number of city service events was shown in Fig. 4. The colors denote different numbers of city service events. For example, tt can be seen that the red bins decreased in the Yuetan community, which means the same spatiotemporal pattern in Fig. 3, 43 diminishing hot spots existed. The pattern said the city demands in this area have been decreasing. According to the government policy reports, during the 2008, many measurements were carried out to improve urban built environment, which is helpful to reduce the city service events. In order to clarify the time variation, two difference map were generated by the three key time periods as shown in Fig.5. These figures were derived from pixel minus operation of corresponding pixels in two time periods. For an instance, in Yuetan community, the decrease tendency (in green pixel) is shown from the Jan. 2008 to Jul. 2008 in Fig.

5(a). Meanwhile, the change is more clear during Jul. 2008 to Jan. 2009 in Fig. 5(b). There are also significant changes in other communities like Xinjiekou, Shichahai and West Changanjie communities.

### *5.2. Data usability of city service data for spatiotemporal patterns*

Social media, 311 hotline data and other VGI data are used to collect city data or citizen data for urban management. However, they are collected through bottom-up collection methods, likely resulting in low accuracy and uneven spatial and temporal distribution bias. These bias may owing to the economic income, internet use, social class and ethnic relations(Cavallo et al., 2014; Lu & Johnson, 2016). In contrast, a top-down city service data collection method was introduced and carried out by professional city inspectors in this study. This method assigns one professional inspector for each 10,000 square meters area to patrol and collect city service event information (Chen, 2006). These data included detailed spatial and temporal properties about city service events. Therefore, the city service data in our study have a wide range of data coverage, high accuracy and even distribution, which can avoid data uncertainties and uneven spatiotemporal distributions from social media and 311 hotline data. Inspiring from literature (Xu et al., 2017), a quantitative experiment was conducted between 311 Sanitation complaints data of Chicago city and our city services data. We downloaded the data from the Chicago official website (https://www.chicago.gov/city/en/dataset/sanitation_code_violations.html) covering date from Jan. 2011 to Dec. 2018. For the Chicago 660.1 square kilometers, the maximum monthly event is 2718, and the average number is 1588. For the data intensity, our study area covering 31.66 square kilometers, the average monthly number of city service events is about 15,000. Therefore, the data intensity ensures powerful and usability of the new data source for identifying patterns.

The results showed that the new emerging city service data had higher explanatory power and finer granularity than those of other data. By presetting time and spatial intervals, multiscale spatiotemporal patterns can be generated. In our study, hot spots were mostly distributed in the western Changanjie community, Yuetan community, and western area of Shichahai. Cold spots were focused in the Zhanlanli community, Xinjiekou community and Jinrongjie community. Based on validation through a field investigation and experience, the Yuetan community had many administrative divisions and a large population compared with those in other communities, which resulted in more issues with vehicle parking and piled garbage on the roadside. Owing to the well-known business land use type east of the western Changanjie community, including Xidan Commercial Street, the National Theater, etc., a higher population may result in more city service data, such as piled garbage, graffiti, and illegal advertising, which can affect the landscape of the city. The results were consistent with the existing experiential conditions in the study area. Therefore, in comparison with other data, city service data have more potential to explain urban management events.

The new emerging city service data also suffered some limitations. Although we employed high-density patrols of city inspectors, city service data are always aligned with the road network and are constrained by the inspector's patrol path. Thus, these data lack information regarding city service events inside a community. Moreover, the data cover the working time of inspectors instead of the full time of day. Therefore, in our future work, we plan to incorporate hotline data and social media data to enrich the city service data to further improve its performance.

### *5.3. Multidimensional spatiotemporal visualization method*

The map-based two-dimensional visualization method is widely used. However, it is weak in terms of using space-time coupled analysis to determine spatiotemporal patterns, particularly for multidimensional data. Although big data analysis and data-mining methods have been widely used in cities (Li et al., 2016), many of these studies have employed loosely integrated models.

The space-time cube model supports visualizing spatiotemporal patterns in a three-dimensional space with multidimensional data and powerful visual perception. It supports high customization by setting time and spatial interval parameters. The cubic scene visualization increases the multidimensional information for city service demand. Therefore, it can determine the monthly spatiotemporal pattern of city service data with fine granularity in arbitrary locations by mapping (as shown in Fig. 2). Compared with other visual analysis methods, the space-time cube method can reflect more detailed information and the spatiotemporal development and change pattern of events. Two visualization methods, mapping (Fig. 3) and cubic scenes (Fig. 2), were proposed in this study to visualize the spatiotemporal pattern at an overview level and in more detail. Two-dimensional maps can show the overall change trends over an entire research time range. The space-time cube supports the flexible customization by presetting parameters, i.e., the time step and spatial distance interval. It is helpful to achieve fine-grained visualizations and observe the refined space-time distribution patterns of hot spots and cold spots.

## 6. Conclusion

A comprehensive and thorough understanding of spatiotemporal patterns and dynamics of city service demand is essential for urban planning, management, and decision-making. Although there are many existing studies aimed at exploring the spatiotemporal patterns of city services, due to the lack of accurate data sources and emerging methods, the exploration and analysis of spatiotemporal models still face challenges. To address these challenges, we adopted a method that uses top-down city service data instead of bottom-up report data and novel spatiotemporal analysis methods to obtain holistic and fine-grained insights into the spatiotemporal pattern of city services. This article utilized the space-time cube model to store spatiotemporal data and identify and visualize spatiotemporal patterns. Finally, combined with the spatiotemporal statistical analysis method, the distribution of hot spots was verified, and the high-incidence areas and time periods of hot spots were explored. From our case study, two conclusions are drawn: (1) the parameters of the space-time cube can provide significant spatiotemporal pattern changes and (2) the hot spots are mostly distributed in the western Changanjie community, Yuetan community, and western area of Shichahai. The cold spots were focused in the Zhanlanli community, Xinjiekou community and Jinrongjie.

However, our method still has room for improvement in future research, such as by (1) classifying cases and exploring the spatial and temporal distribution characteristics of various case types and (2) verifying the correlation among city service data and the social geography environment and built environment. Future work may reveal deeper insights into the pattern of the spatiotemporal distributions of city service demand data.

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