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The analysis and delimitation of Central Business District using network kernel density estimation

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ABSTRACT

Central Business District (CBD) is the core area of urban planning and decision management. The cartographic definition and representation of CBD is of great significance in studying the urban development and its functions. In order to facilitate these processes, the Kernel Density Estimation (KDE) is a very efficient tool as it considers the decay impact of services and allows the enrichment of the information from a very simple input scatter plot to a smooth output density surface. However, most existing methods of density analysis consider geographic events in a homogeneous and isotropic space under Euclidean space representation. Considering the case that the physical movement in the urban environment is usually constrained by a street network, we propose a different method for the delimitation of CBD with network configurations. First, starting from the locations of central activities, a concentration index is presented to visualize the functional urban environment by means of a density surface, which is refined with network distances rather than Euclidean ones. Then considering the specialties of network distance computation problem, an efficient way supported by flow extension simulation is proposed. Taking Shenzhen and Guangzhou, two quite developed cities in China as two case studies, we demonstrate the easy implementation and practicability of our method in delineating CBD.

1. Introduction

The fast economic growth and rapid urbanization presents a challenge to the limited urban public resources in China. Specifically they encourage a shift in the concentration of urban functions from the monocentric structure to the polycentric structure, which tends to produce a more complex urban environment (Wang and Li, 2002). According to the *Shenzhen Statistic Yearbook of 2010* of our case-study city, the construction acreage of the well-developed region, the Shenzhen Special Economic Zone increased by 64% from 1990 to 2000 but by only about 8% from 2000 to 2010. The city's outskirts became the main areas of city spreading in last decade. As a developing country with a very large population, the change in central urban landscape and functions is critical for promoting sustainable progress in China, since the Central Business District is considered as the economic and social nerve center of the city (Murphy and Vance, 1954; Alonso, 1964; Haggett, 2000).

Highlighting functional areas within cities, such as the CBD or other areas characterized by different kinds of human activities, is an important issue for urban planning field and has drawn the attention of policymakers and scholars (Comedia, 1991; Wang and Li, 2002; Montello et al., 2003). However, many of them require the people to complete complicated and time consuming surveys, and it has proven to be deficient in the management of these emerging urban spaces, such as Shanghai, Guangzhou and Shenzhen. Alternatively the geographical information system-based (GIS) technique, such as the density analysis, acts as an effective means to support the cartographic definition and representation of CBD in a complex urban environment.

The determination of urban CBD has to consider the distribution of different facilities. So the facility distribution characteristics including distribution hot-spot, density and trends, plays an important role in CBD analysis. Previous researches in urban geography have discussed the availability of density surface in the visualization of the urban functional distribution and acknowledged a well-known density analysis method, namely the kernel density estimator in this field. In the era of geographical big data, the increasing availability of crowd-source data and VGI (volunteered geographic information) data (e.g., OpenStreetMap) makes this

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method an attractive approach to detect the main distribution properties from large volume data (Thurstain-Goodwin and Unwin, 2000; Okabe et al., 2006; Borruso and Porceddu, 2009). As an efficient spatial statistics tool in spatial density evaluation, the kernel density estimation is superior to other fundamental methods (e.g., Quadrat analysis) in certain classes of application, because it considers the decay impact of services based on the Tobler's *First Law of Geography* (Tobler, 1979; Silverman, 1986; Bailey and Gatrell, 1995). However the application of KDE needs to concern the effect of density distribution under different spaces, especially to consider the distance meaning. Note that most KDE methods assume that the real world is abstracted as an infinitely homogeneous and isotropic space, and use a certain type of kernel estimator with the distance measured by the Euclidean ones. Miller (1994) pointed out that this is probably ill-suited, since many human activities are constrained only to the network portion of the planar space, the so-called network space. Yamada and Thill (2004, 2007) conclude that the planar method tends to overestimate clustering tendency of network phenomenon. It is the network distance rather than Euclidean distance that impacts on the analyses related to social and economic phenomena in urban space (Lu and Chen, 2007; Steenberghen et al., 2010; Okabe and Sugihara, 2012).

Aiming at the question above, this paper provides an applicable approach within network space to facilitate the recognition and delineation of CBD using statistical aggregation of socio-economic point data. Its main contribution lies in the refining of the density surfaces that is restricted by transportation network. Namely, the proposed method uses the new network KDE (KDE based on network distance) instead of a traditional planar KDE (KDE based on Euclidean distance) to transform activity data from point 'object' into continuous surfaces of spatial densities. The estimated density can be considered as an indicator of 'Urban Centredness Index', which supports to delineate CBD by the derivation of key isoline model. As secondary objective, the paper also investigates an efficient network KDE algorithm supported by the stream flowing simulation. The basic idea is that supposes the stream flowing along certain linear channels until arriving at the boundary of 'sphere of influence' or at the end of route. In such process, the network is firstly tessellated into a set of 1-D quadrats to aggregate density value of point activities. Then the assumed streams would spread from each focused quadrat to neighbor quadrats based on the network topology. The quadrats which streams go through can be weighted according to the number of steps to them. Compared to the previous algorithms (Xie and Yan, 2008; Okabe et al., 2009), the proposed method avoids lots of repeat computation in searching shortest path in a graph, and also has the advantages of simple operation and easy calculation. By conducting a kriging interpolation on the resultant 1-D quadrat dataset with density attribute, it is possible to produce a 2-D centredness surface enabling the possibility of generating index isolines.

The remainder of the paper is organized as follows. Section 2 discusses the related development of CBD analysis. Section 3 presents the extension of centredness surface computed from the Euclidean space to the network space and proposes a novel algorithm to implement network KDE based on the stream flowing idea. In Section 4, study areas and experiments in Shenzhen and Guangzhou city are presented. Section 5 discusses the experiment results. Section 6 concludes with future works.

2. Related work

According to the survey of Central Business District from Yan et al. (2000), the literature in the urban study field has suggested that CBD is a common phenomenon that can significantly control the urban renewal and evolution. From a theoretical perspective, this important phenomenon involves the aggregation process of human activities in urban space; then how to quantitatively evaluate such process using spatial statistical techniques becomes the key to CBD delimitation.

2.1. Theoretical aspect: CBD delineation in urban study

The CBD, described as the 'heart of the city' by Murphy and Vance (1954), is located in the central part of a city, together with particular central activities, such as banks, offices, hotels, cinemas and theatres. Because of CBD's central role in urban development and human life, there are many empirical evaluations and observations in urban studies trying to narrow the center of business and identify it (Thurstain-Goodwin and Unwin, 2000; Borruso and Porceddu, 2009; Hollenstein and Purves, 2010). These works generally implement both qualitative and quantitative indexes, with the former being mainly based on individual choices and the latter mainly used in quantitative and distributive analysis.

Classical study in urban geography defines the CBD by mapping land zones that contained the highest concentration of central activities and high land values. Several similar approaches are recently presented with computing indices of central business activity (Thurstain-Goodwin and Unwin, 2000; Borruso and Porceddu, 2009). They are specifically focused on the development of point pattern analysis, starting from data concerning social-economic activities georeferenced at address-point level. Specialized techniques using statistical methods are adopted to attribute the concentration of activities to area units as urban districts and to derive their density. In such sense the core of the city is highlighted in terms of dominance of the economic activities located there. In the era of big geo-data, the crowding-source data and the uploaded VGI data make the urban facility POI (Point of Interest) easily be collected, and also facilitate the urban spatial analysis, such as CBD detection (Hollenstein and Purves, 2010; Elwood et al., 2012; Sun et al., 2013).

Despite the need of new information on CBD, few studies in China have looked at this issue of studying urban development and its functions with spatial statistic methods. As one of the most classic studies in China, Yan et al. (2000) pays attention to the delimitation of CBDs in Guangzhou, a city of South China, in terms of documents, statistical data and on-the-spot investigation. The result reveals that the traditional CBD is dominated by retail activities but the new developing CBDs by professional, finance and insurance, and information consultation. For many cities in China, 'old' urban functions have changed and transformed since the 1980', when the policy of reform and opening to the outside world is implemented (Wang and Li, 2002; Jia et al., 2008). Especially as China's first special economic zone, Shenzhen practices market economy earlier and gains more experience characterized by new urban development mechanism. The city administrative department reports that the location of Business District in Shenzhen is transforming from a single central location to more decentralized ones (UPLRCSM, 2010). In order to analyze an urban environment like Shenzhen or Guangzhou that is constantly changing, we propose a method for automatic delineation of CBD through point pattern analysis of central activities.

2.2. Technological aspect: density estimation supported CBD analysis

This paper explores the vaguely defined phenomena of CBD using officially collected activities data, which is reduced to a simple point in GIS environment. Such type of point dataset contains inherent spatial information for locating places as well as statistical data about other social-economic attributes. After the density of points is computed for area units through density estimation, it is then used as the attribute for representing centredness index which can be visualized through a continuous surface. The statistical analysis conducted on the surface, therefore, makes it possible to evaluate formally the borderline of CBD with high density values. CBD analysis can provide references for city developing and land-use planning.

Through the technologies of spatial smoothing and spatial interpolation, each location in space could estimate a density value to represent the local distribution intensity of activities (Jones, 1990; Bailey and Gatrell, 1995). Conventionally, three methods are widely used in spatial density analysis, namely Quadrat analysis, Voronoi-based analysis and KDE method. Quadrat analysis drapes a grid of equal-sized and homogeneous cells (i.e. quadrats) over the study area and counts the number of event points falling in each cell to simplify the spatial distribution. Voronoi-based method also needs to divide the study region into sub-regions corresponding to the partitioning cells in Voronoi construction (Gold, 1992; Ai et al., 2015). By computing the Voronoi polygons of a point set, the region of influence of each activity can be achieved and the reciprocal of sub-regional area can be computed as the density value of the Voronoi sub-region (Yan and Weibel, 2008).

However the former two methods have disadvantages of: (1) the restriction that the defined geographic grid cells must keep appropriate size, often results in loss of spatial detail within each quadrat, and that is also the problem facing the Voronoi-based analysis and (2) the nature of geographical continuity across the quadrat (or Voronoi cell) boundary is not remained as the methods do not consider the distribution in the neighborhood of grid cell. The KDE has been suggested as an alternative to overcome the above limitations. KDE provides an estimate of the intensity in each point of the grid by means of 'moving three-dimensional functions that weight events within its sphere of influence according to their distance from the point at which the intensity is being estimated' (Bailey and Gatrell, 1995; Gatrell et al., 1996). With the weight function, the estimated intensity in a cell is related to the distributions in neighbor cells. As shown in Fig. 1, it can be observed that the intensity variation generated by a kernel estimator is much smoother than that obtained from a fixed grid of square cells or Voronoi cells. Compared to the other two methods, the advantage of KDE lies in that it allows estimation of the density at any location in the study region (O'Sullivan and Unwin, 2010).

The general form of a kernel density estimator is expressed as:

$$f(s) = \sum_{i=1}^{n} \frac{1}{h^2} K\left(\frac{s - c_i}{h}\right) \tag{1}$$

where $f(s)$ is the estimated density value at location s, n is the total number of event point under concern, h is the search bandwidth (e.g., for a circular kernel it is the radius of the circle), $s - c_i$ is the distance between event point c_i and location s, and K is a weight function (called kernel function) characterizing how the contribution of point c_i varies as a function of $s - c_i$. In fitting with Tobler's *First Law of Geography*, each local weighted process in KDE actually is estimated with events whose influence decays with distance, distances that are commonly defined as straight line or Euclidean (Fig. 1b).

KDE requires two parameters, namely, the bandwidth h and the kernel function K. While it is reported that the choice of the kernel function has little influence on the results, the selection of bandwidth is more important (Silverman, 1986; Bailey and Gatrell, 1995; Schabenberger and Gotway, 2005). Thus all the planar KDEs in our experiments would adopt a Quartic kernel function (Eq. (2)) which is one of the most commonly used functions. The bandwidth can significantly affect the statistical results by controlling the smoothness of the estimated density—basically the larger the bandwidth, the smoother is the resultant density distribution. A bandwidth that is too large leads to too many generalizations, and a bandwidth that is too small over-emphasizes local variation. Therefore a well-chosen bandwidth should vary according to the densities of points and the spatial scale of research.

$$K\left(\frac{s - c}{h}\right) = \frac{3}{4}\left(1 - \frac{(s - c)^2}{h^2}\right) \tag{2}$$

3. Method

The purpose of our method is to delimitate the CBD of city on network-constrained centredness surface. Through representing the intensity of central activities and constraining the density estimation, CBD can be delineated with both accuracy and efficiency.

3.1. Network kernel density estimation

Given a homogeneous space, the traditional planar KDE superimposes a bell-shaped weighted function over any location with isotropic property. This function is easy to implement but difficult to reflect the actual distribution of urban phenomenon, because human activities within urban areas are naturally constrained by the layout of the street network. In this respect, to precisely model urban environment, a specific KDE variant based on network distance (i.e. network KDE) is more appropriate for calculating density of central activities, which is taken as the statistical indicator of urban centredness in our study.

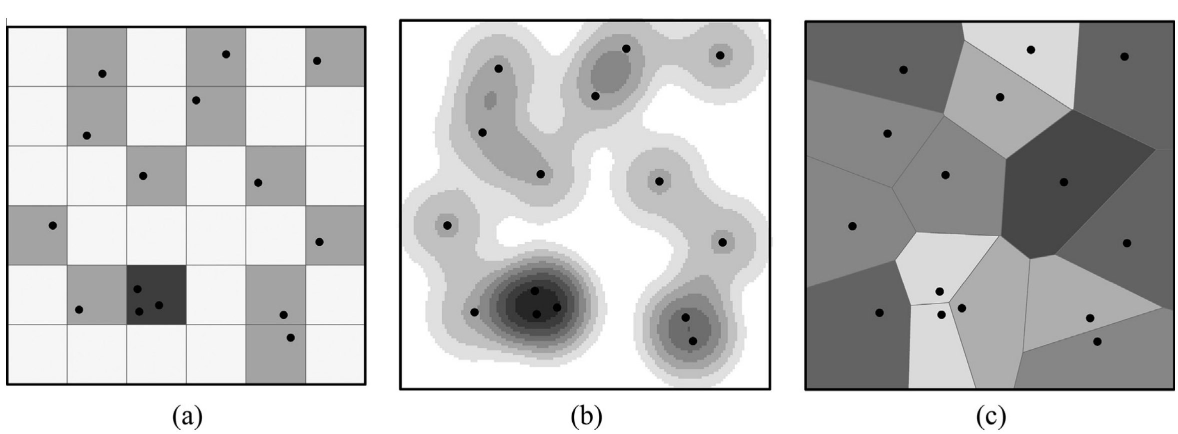

Fig. 1. Illustration of three common methods for density estimation in planar space. (a) Quadrat analysis; (b) kernel density estimation; and (c) Voronoi-based analysis.

A network KDE is an extension of the standard 2-D KDE, while it still preserves the principle of near events more related than distant events and uses the same form (Eq. (1)) of kernel estimator for the density estimation (Tobler, 1979). Based on the literature (Okabe et al., 2009; O'Sullivan and Unwin, 2010), the choice of kernel function in network KDE is also less important than the choice of search bandwidth. Hence this paper only tests the Quartic function in implementing network KDE.

As the configuration of the network is usually irregular, implementing network KDE is not as straightforward as it is in the case of the planar KDE. This paper presents a linear referencing method, a method which first projects the facility POI onto network segments by nearest distance search, and thereby calculates the network distance from the projected location to its neighbor locations on the network in terms of shortest-path distance. In such process, the density value is computed by a breadth-first search and assigned to a certain type of linear quadrat which results from the division of original street network. For details of the definition of linear quadrat, see Shiode (2008). The linear quadrats with activities geocoded are called source quadrats. For each source quadrat, the network kernel density values are computed for the quadrat and its neighbors. For a quadrat falling within the search bandwidth of multiple source quadrats, its density is the cumulative value of the densities computed from all relevant source quadrats.

The changes of distance concept in KDE would affect the outcome of density estimation, such as the search window constructed as the 'sphere of influence' of event, and the computed density value representing the centredness index. To illustrate such effects more clearly, consider a sample spatial data set, which is shown in Fig. 2 with circle denotes activity location, square denotes sample location and solid lines represent the network edges. It can be noted that the planar KDE tends to overestimate clustering tendency of network-constrained point process with five locations falling within the search bandwidth in the case of planar method, where three in the case of network method. For details of the computational implementation of network KDE, see Section 3.2.

The linear referencing method would generate a set of basic linear units (i.e. 1-D quadrats) with density values. And that means, only the locations of street network are attributed with a density value, while the places apart from network is not considered yet. Note that the referents of CBD are aimed to be delineated on a 2-D centredness surface covering the whole study region. The existence of many zero entries in Euclidean plane and the irregular arrangement of network would make it much difficult to select the continuous core regions from density cells. Thus in order to transform 1-D density quadrats into a high-dimensional surface, kriging interpolation method could be utilized. Kriging is an effective means for the entire grid cells, including 2-D cells without stable sample data (Cressie, 1993). Traditional kriging, such as simple kriging and ordinary kriging, can obtain good results only for homogeneous data. However, according to previous studies (Murphy and Vance, 1954; Thurstain-Goodwin and Unwin, 2000), central activities data have explicit spatial heterogeneity, as they are influenced by region and exhibit spatial aggregation in local regions, so simple kriging and ordinary kriging cannot capture their complexity. Therefore, in this study we adopt local universal kriging with a linear semivariogram model. The linear semivariogram model is a widely used approach for parameter estimation, such as nugget, sill and range (Cressie, 1993). To perform interpolation processing, we choose ESRI's *ArcGIS* software which provides robust implementation of semivariogram modeling with a specific linear function. For details on this function, refer to ESRI (2011).

Although we start with discontinuous point located data with a large proportion of zero entries, the result of surface is further enriched by estimating local density values to every point in the space. This surface is able to be visualized using conventional surface display techniques. Especially many GIS software (e.g. ArcGIS) are recently developed, making the color-thematic representation of regional units easily realized. By a simple observation, the 'peaks' of the density surface could enable the clear identification of urban centers.

3.2. Algorithm

Previous implements on network kernel density estimation have so far been done, but due to the computational complexity of the shortest-path distance calculating, these methods all tend to be very time consuming, especially for large datasets (Flahaut et al., 2003; Xie and Yan, 2008; Okabe et al., 2009). This section introduces a new algorithm supported by an operator of *1-D expansion*. The idea is inspired by the natural phenomenon that water flow extends along certain linear channels until arrives at the boundary of bandwidth or at the end of route. To simulate this process, street network shall be firstly represented by a set of linear

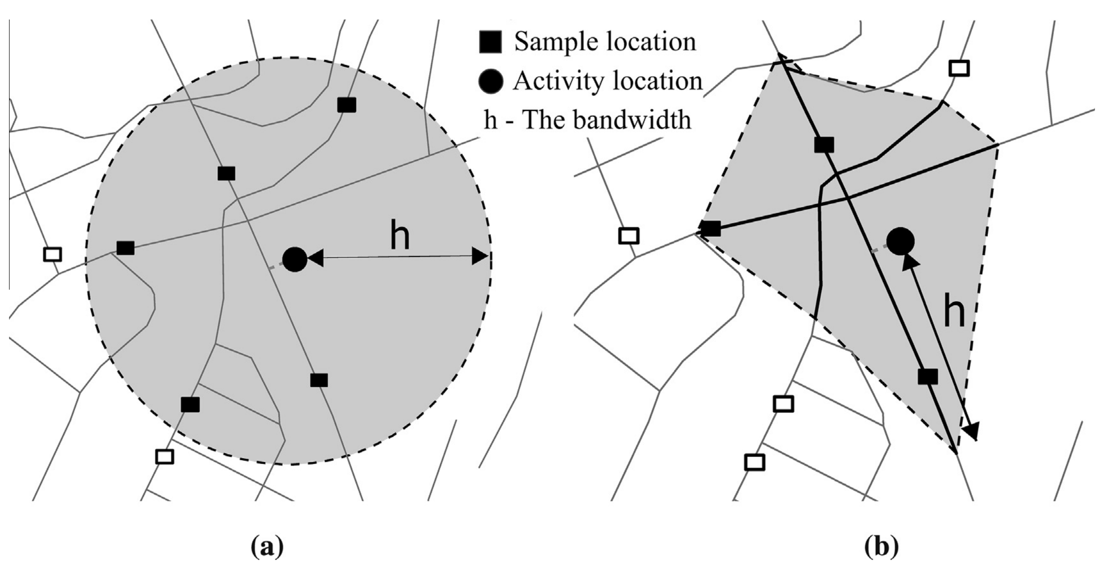

Fig. 2. An illustration of (a) the planar KDE versus (b) the network KDE over the same data.

basic spatial units, which is termed as network-based quadrat (or *NQ* for short) by Shiode (2008). Such 1-D quadrat is equal-length and occupies a linear shape following the irregular configuration of networks. As shown in Fig. 3a, two neighboring street intersections are connected by a street segment, and each segment consists of a finite sequence of 1-D quadrat (i.e. *NQ*). Similar to cells in 2-D grid, *NQ* is treated as a homogeneous unit and the internal variation is not considered. *1-D sequential expansion* operator can be performed on the network tessellation with each step moves outward one step. After doing that, the network distance could be measured in terms of steps of *expansion*. The algorithm has the advantage that the time consuming GIS tasks (e.g. iterative comparisons for neighbor nodes' weight in a graph) are avoided, and replaced with a linear time operation. Actually the *expansion* operator is an extension of the dilation operator developed in mathematical morphology (Heijmans and Ronse, 1990), where the structuring element is restricted to the network topology.

For the network tessellation structure, we record the state of *NQ* as *occupied* or *unoccupied*, according to whether the *NQ* is processed by the flow *expansion* from current generator. For our computational method, two types of *NQ* sets are used: the set of current active expanding quadrats (i.e. *active-NQs*), the set of next unoccupied quadrats (i.e. *next-NQs*). The first set, *active-NQs*, consists of quadrats which act as an active head in stream flowing and relate to the neighbor of unoccupied *NQs*. The second set, *next-NQs*, consists of quadrats adjacent to the active *NQ* that is under consideration at the current stage of processing. Furthermore, we define three attributes to record *NQ's* density related information: (1) the *flow-source* storing the ID of the source *NQ* which the flow comes from; (2) the *steps-length* storing the number of steps of *expansion* (i.e. network distance) from source *NQ*; (3) the *density-value* storing the density value dependent on the *steps-length* and the chosen kernel function.

The basic algorithm is presented as follows:

(1) Divide the street network into a set of basic linear units (*NQs*) of a defined network length *l*. The intersection point of two adjacent *NQs* is called *NQN*. Street intersections are always *NQNs*.
(2) Create a *NQ*-based linear reference system by establishing the network topological relationship between *NQs*, as well as between *NQs* and *NQNs*.
(3) Define a search bandwidth *h*, measured with the number of steps of *flow expansion*. The bandwidth can also be transformed to the shortest-path distance by using the product of *h* and *NQ*'s length *l*.
(4) Project activity POIs onto *NQs* (acting as the source of stream flow), by nearest distance search. Those *NQs* with one or more POIs assigned to them are identified as *source NQs*.
(5) Initiate the numeric attribute *steps-length* of each *NQ* as ∞ (infinity) and the attribute *density-value* as 0.
(6) Initiate set *active-NQs*. For each source *NQ*, push it into *active-NQs*, and assign its attribute *steps-length* as 0, and record its attribute *flow-source* the activity ID.
(7) For each element in *active-NQs*, calculate its density by repeating the *expansion* operation (steps *a–f*) until the *active-NQs* is null (see Fig. 3):
    a. For current element *q* generate its next neighboring *NQs* on the basis of the network topology, and store them in a temporary set *next-NQs*.
    b. Record the number of steps of *expansion* at the current stage of processing, and assign it to *next-NQs* as their attribute *steps-length*.
    c. Transform the attribute *flow-source* of element *q* to *next-NQs*.
    d. Remove *NQ* from *next-NQs* if its *steps-length* is larger than the bandwidth *h*.
    e. For *next-NQs* calculate their density from *flow-source* by using the attribute *steps-length* and the chosen kernel function (i.e. Eq. (1)), and add it to the attribute *density-value* of *next-NQs*.
    f. Remove element *q* out of *active-NQs* and push *next-NQs* into *active-NQs*.
(8) Divide the studied region into a regular 2-D grid. For each grid cell, calculate its density value by utilizing a local universal kriging as discussed in the previous section.

Two types of spatial partition are included in the implement, namely, *steps* (1)–(7): dividing the network into 1-D basic units to aggregate the density of activity POIs along the street network; *step* (8): dividing the planar space into 2-D grid to represent the intensity of activities in the whole urban space. The first process which also is the innovation point of this algorithm solves the problem of long time spent on network analysis mainly in the following components. First is to divide the road network into basic linear units. The time complexity for the component is $O(n)$, where n is the number of road segments. Second is to progressively perform *NQ* expansion to estimate the kernel density on the linear reference system. Assume the number of activity POIs is m. The time complexity for this component is dominant by $O(m)$. Hence the total time complexity is $O(m + n)$. As a comparison, the traditional vector-based algorithms under graph theory will take a very long time to compare all nodes whose shortest path to the start node is unknown. Taking a typical research for example, the network KDE algorithm developed by Okabe et al. (2009) have a computational complexity with $O(mn + k \log k)$, where k is the number of intersection. It can be noticed that the flow expansion algorithm is more efficient since $m + n < mn + k \log k$ for $m, n > 2$ and, in the practice m and n are large numbers. Like the planar KDE method, the second process (*step* (8)) in our algorithm still uses a 2-D grid of plane as the final unit of aggregating density and visualization. The finer the grid cell is, the more local variations of the space the result can present.

4. Experiments

4.1. Experiment data

The research has been carried on considering two developed cities, Shenzhen and Guangzhou, in Southeastern coastal region of China, adjacent to Hong Kong. Both of the cities belong to the representative cases in China where urban functions and urban structures have significantly changed in the past years.

The two cities studied both act as the central cities in southern China, while they are two apparently different cities. First, Guangzhou is a city with a long history, functioning as the political, economic and cultural center of the whole province. However, Shenzhen is a new immigrant city, gaining its development in recent years due to the government's supportive policies. Presently the manufacturing of Guangzhou has been expanding, but its tertiary industry tends to be in recession (Ye and Wang, 2004). As a comparison, economic diversity has become the main trend of development in Shenzhen. The advantage of the new city lies in its high-tech industries and finance (Wang and Li, 2002). Actually together the cities, Guangzhou and Shenzhen, represent two typical urban forms in China, i.e. developed cities based on the traditional basic industry and the new cities gathering many regional and international business activities. The research of CBD analysis on the two cities thus is of universal significance, and could be broadened to other ones in China.

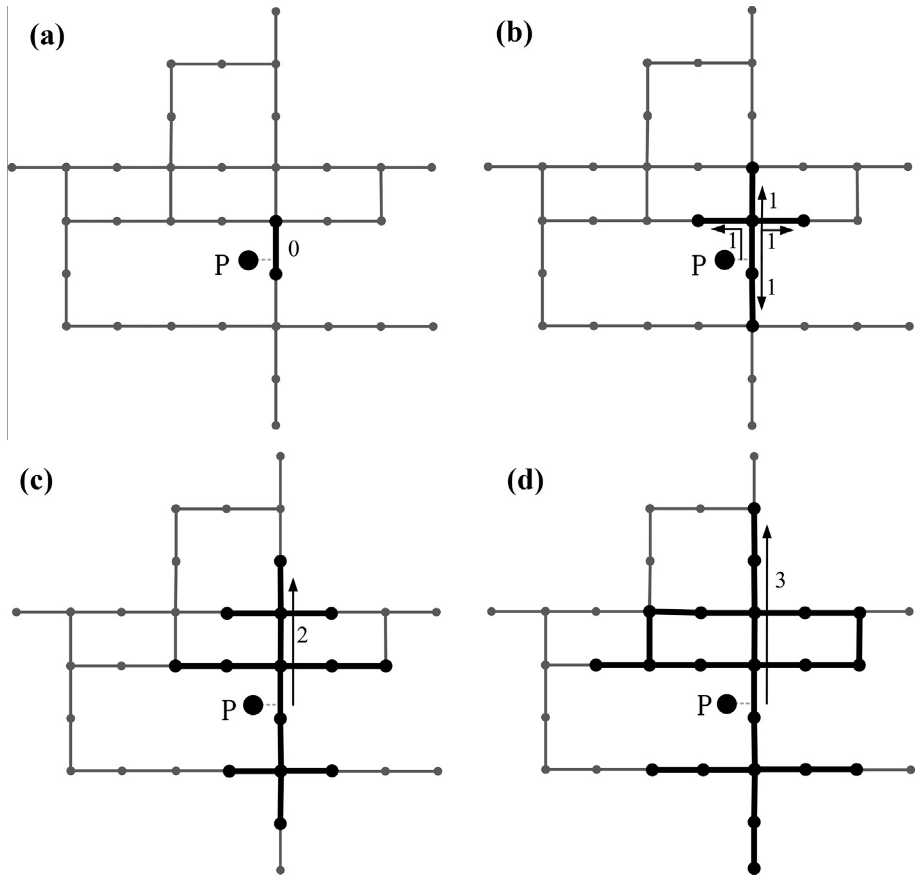

Fig. 3. 1-D sequential *expansion* operation supported by the stream flowing simulation. (a) Example of a tessellated network with activity *P*; (b) flow's original state through one step *expansion*; (c) flow's intermediate state through two step *expansion*; and (d) flow's completion state through three step *expansion*, i.e. the operation would be stopped when the number of steps from the source *NQ* to the *next-NQs* is larger than the search bandwidth *h* (*h* = 3 *NQs*).

Two experiments were carried out in this paper, including the first experiment for the Shenzhen city and the second experiment for the Guangzhou city. Since the algorithm steps are the same in our cases, the first experiment will be presented as the main example. The first experiment data include a real transportation network system in a southern portion of the city, with activity POI data for 2013 (Fig. 4). The study region is the most advanced region of Shenzhen, located in the city's Economic Development Zone. The activity dataset is provided by the Geomatics Center of Shenzhen.

In order to identify locations of CBD, the experiment chose different types of activity POIs which are the most likely to be located in urban centers. Categories were selected among those available in our spatial dataset and we tried to follow previous research on central functions (i.e., Murphy and Vance, 1954). The detail of activity POIs is listed in Table 1. A total of activities 11,213 are analyzed in the case study, grouped in six main categories. In the past, CBD was studied as the areas where high value activities take place and we take these activities as "central". Central functions have the particular ability to organize an urban space according to people's needs and the most used activities in CBD analysis include jewelers, fashion retail and financial activities (Murphy and Vance, 1954; Haggett, 2000; Yan et al., 2000). Murphy and Vance (1954) classically defined the CBD by delineating land zones that contained the highest concentration of tertiary activities, referring mainly to specialized retail activities. Nowadays, with the development of cities and increase of resource pressures, the choice of central activities should consider the changes of urban structure and functions. Specifically, the up-to-date characteristics of CBD in China's cities are that: covering numerous leisure activities for evening times, more than working daily activities; compulsorily covering government sectors (e.g. local bodies, regional offices) (Yan et al., 2000; Wang and Li, 2002; Jia et al., 2008). Therefore as presented in Table 1, those providing the highest quality of services in our case study include not only retail activities, but also the administrative, professional and leisure ones.

Depending on application settings and data involved, both the network segments and the 2-D plane could be divided into basic units of different sizes. The size of unit can affect the continuous of the density surface- Basically, the finer the grid cell is, the more local variations of the space the result can present. But finer character would lead to more computational burdens, which is undesirable in the real-world applications emphasizing the practicality of the method. Therefore, to make such a trade-off between accuracy and efficiency, we have considered the data used in the applications. In our first case, the minimum parameter of search bandwidths is 300 m, and the maximum length of the side of our study region is about 15,800 m. By taking into consideration of these elements and through several experiments, we finally adopted the 10-m grid cell and 10-m *NQ* which are able to provide enough details so our CBD analysis can follow. The total numbers of grid cells and *NQs* are 1,083,923 and 104,023, respectively.

In addition, our research selects the main districts of the Guangzhou city as the second study area (Fig. 5). The total number of central activity POIs is 16,898 and the network contains 5996 segments. Compared to Shenzhen city, Guangzhou also is a developing city but the spatial density of the network segments is relatively low. Our experiment divides the city's network into a set of 10-m *NQs* and the resultant density value is attributed to a 10-m

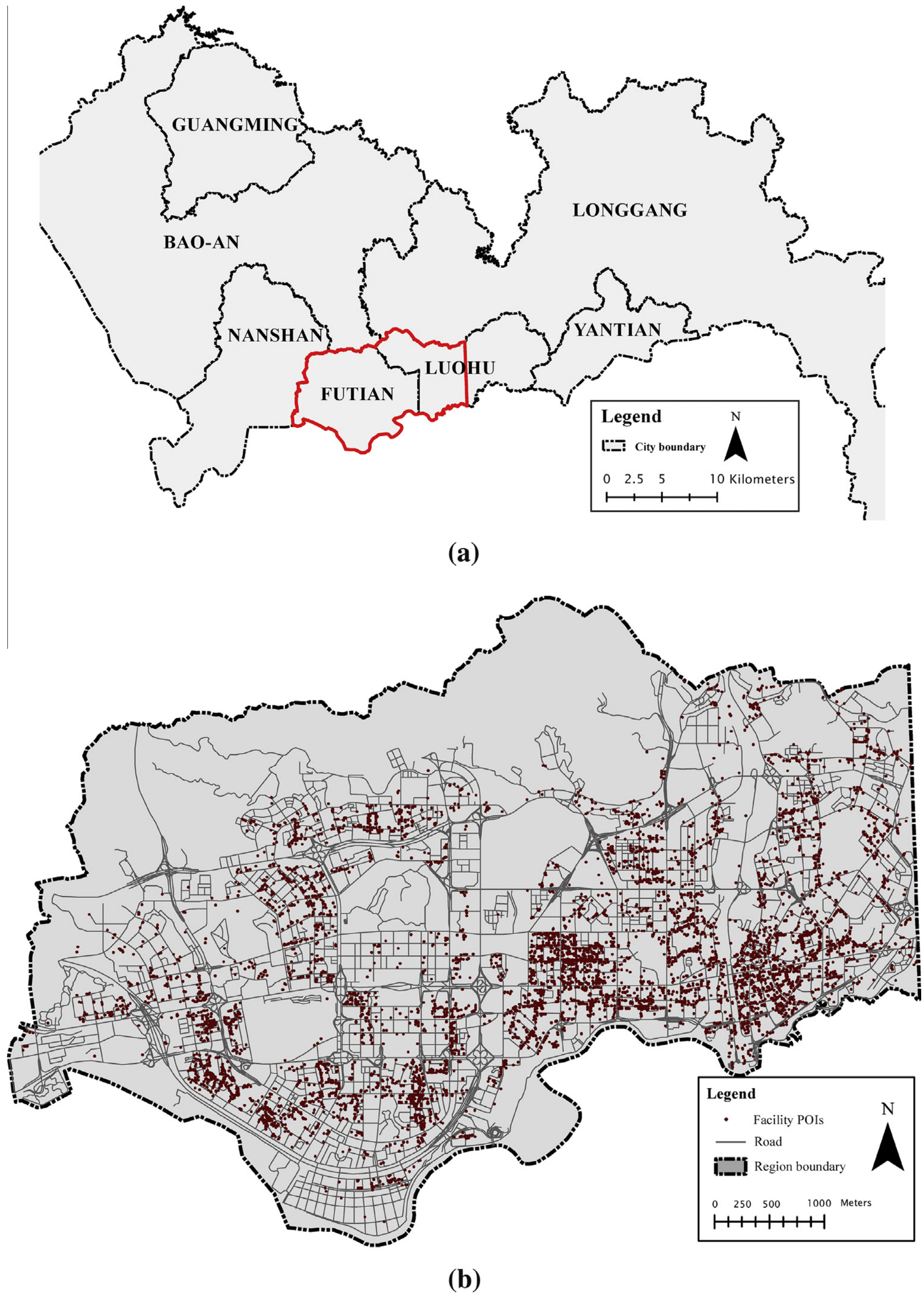

Fig. 4. The Shenzhen city and the study region: (a) the position of the study region (red box), (b) the distribution of central activity POIs and street network in the study area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

grid. For Guangzhou city, other relevant parameters in density estimation are the same as the ones in the Shenzhen's case.

4.2. Experiment settings

The proposed algorithm is implemented in C++. We experiment the applicability of the algorithm by conducting a series of tests, utilizing different bandwidths for network KDE and planar KDE. The impacts of search bandwidth are examined at local and large spatial extents. Total three search bandwidths are used, including 300, 600, and 1200 m. In view of the literature, many other researches on urban areas also adopted the parameter of 300 m (Thurstain-Goodwin and Unwin, 2000; Borruso and Porceddu, 2009). They suggested that such distance is suitable for urban analysis because of the fact that people are reluctant to walk more than 200–300 m in an urban center. However, these methods are all based on Euclidean distance. At present, there are few rules for bandwidth selection on network KDE and many studies determine the parameter through a trial and error process (Borruso, 2008; Okabe et al., 2009). Therefore, the optimal one varies according to the characters of data and application requirements. For example, the previous works by Borruso (2008) and Okabe et al. (2009) choose, respectively, 125-m bandwidth and 200-m bandwidth for density estimation, both of which are not applicable to our case.

Table 1
Urban central activities in the special economic zone, the southern part of Shenzhen.

ID	Category	Sub-category	Number of sub-categories	Total number of activities
1	Financial activities	ATMs and banks, security firms, investment firms, insurance companies	4	4454
2	Professionals	Commercial and financial consultants	1	280
3	Arts and culture	Art galleries, exhibition centers, museums, concerts, cinemas	5	468
4	Retail	Supermarket, jewelers, fashion, antiques	4	793
5	Public activities	Local bodies, regional offices, chambers of commerce, convention centers, reporter stations	5	358
6	Leisure	Hotels, bars & café, pubs, restaurants, internet café	5	4860
	Total		24	11,213

The reason is that our study region has a larger spatial extent and those small bandwidths could cause a too 'spiky' pattern of the phenomenon. Therefore, to better reflect the underlying distribution of human activities on a network, larger search bandwidths are additionally used in our case, i.e. 600 and 1200 m.

To obtain parameters (i.e. nugget, sill and range) in kriging interpolation method, we adopt the linear semivariogram, a conventional approach for parameter estimation. Table 2 shows the results of estimation for the three search bandwidths (i.e. 300 m, 600 m, 1200 m) adopted in network KDE. As the density values attributed to network-based quadrats would be different at the three bandwidths, the parameter estimation also shows different results.

5. Results and discussion

5.1. Comparison of planar KDE and network KDE

After mapping the cells with density attribute to a 3D surface, Fig. 6 shows the overall spatial pattern of density values estimated by a standard planar KDE and the new network KDE. In these

Table 2
The result of kriging parameter estimation for network kernel density calculation using different bandwidths (linear semivariogram model).

Kriging parameter	Search bandwidth		
	300 m	600 m	1200 m
Nugget	0	0	0
Sill	107.3	277.0	739.0
Range	3868.4	3699.3	4048.2

figures, the difference between the new algorithm and a planar KDE is compared by observing three figure groups, including the group containing Fig. 6a and b, the group containing Fig. 6c and d, and the group containing Fig. 6e and f. By a simple visual comparison, both KDE based maps in each group present a general density distribution of human activities with similar patterns. However, some details of the density patterns of planar KDE and network KDE are rather different, mainly reflected in the nearby regions of road intersections. The high density values by the planar KDE homogeneously extend in all directions from each POI cluster, while that by the network KDE hinges around the network segments. For all defined bandwidths, it is observed that the density surfaces generated by planar KDE are always more smoothed than that by network KDE. Besides, as the maps indicate, the planar method is likely to overestimate the concentration of activities in comparison to the network method. For example, the density value with 600-m bandwidth can reach as high as over 1030.4 (activities per km^2) based on Euclidean distance, however, that value is only about 68.0 (activities per km) based on network distance.

5.2. Impacts of search bandwidth on density pattern

Search bandwidth is most important in structuring the density pattern in network KDE. As shown in our study region (Fig. 6), the density surface gets smoother with increasing bandwidth (300, 600, and 1200 m, respectively), similar to the case in planar KDE. The density pattern is quite bumpy with a 300-m bandwidth, whereas the density values are almost invariant with a 1200-m bandwidth. As the bandwidth increases from 300 m to 1200 m, the local 'hot spots' continue toward integration with their neighbors, and a larger cluster appears in the southeast area. These observations demonstrate that a narrower bandwidth (300 m) could

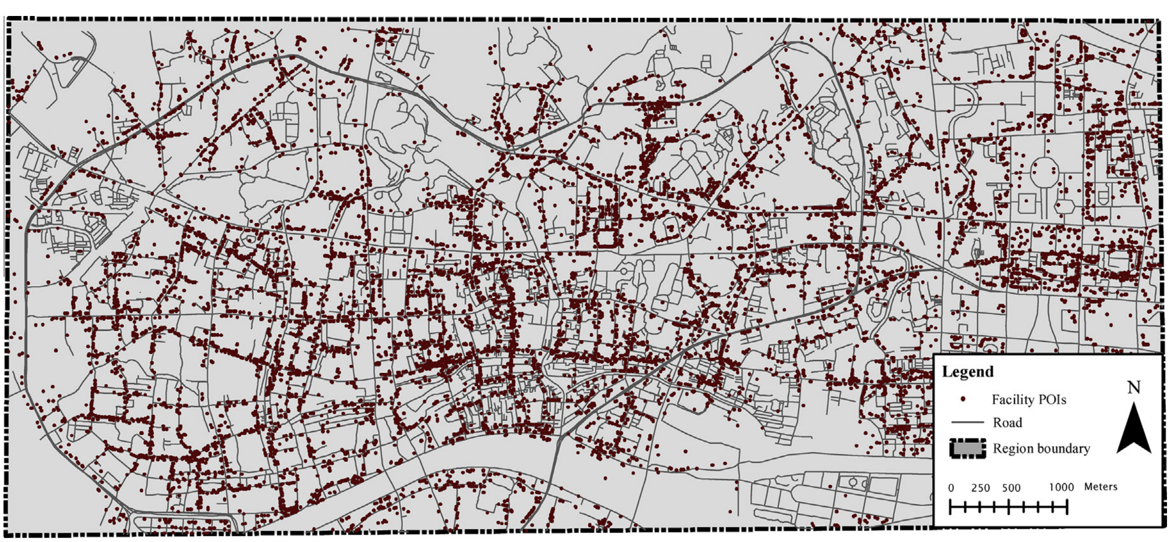

Fig. 5. The distribution of central activity POIs and street network in Guangzhou city, southern China.

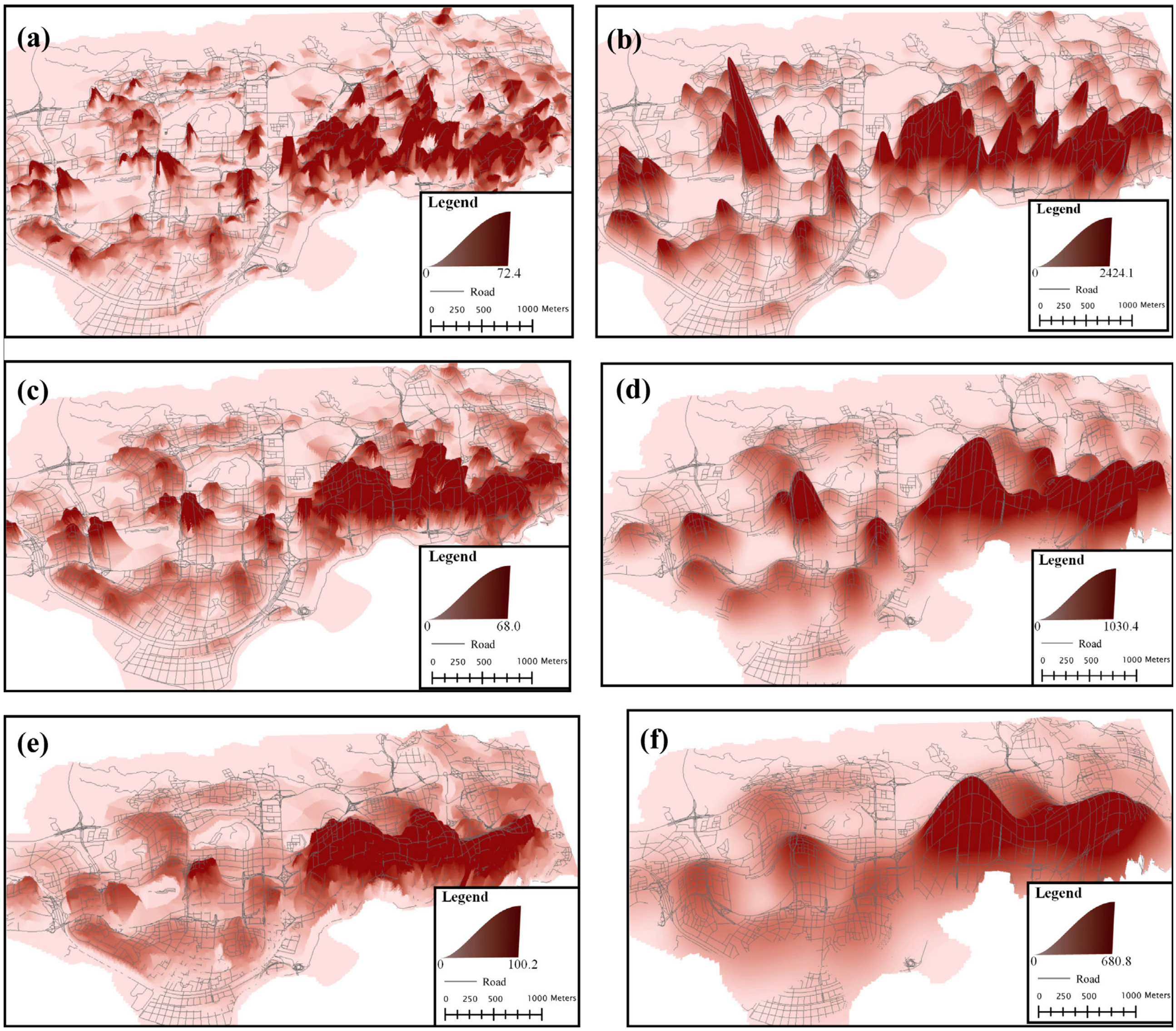

Fig. 6. The centredness surfaces in the study area produced by the network KDE and the planar KDE with a Quartic kernel and different bandwidths: (a) result by network KDE with 300 m bandwidth, (b) result by planar KDE with 300 m bandwidth, (c) result by network KDE with 600 m bandwidth, (d) result by planar KDE with 600 m bandwidth, (e) result by network KDE with 1200 m bandwidth, and (f) result by planar KDE with 1200 m bandwidth.

make concentration of activities much more obvious at smaller spatial scales, whereas a wider bandwidth (1200 m) produces patterns suitable for presenting ‘hot spots’ at large scales.

5.3. Delimitation of CBD

Analysis of peaks on density surfaces provides a means of delimiting the geographical extent of CBD by generating a centredness statistics. To facilitate the representation of core characteristics, contour maps as shown in Fig. 7 were generated from the density attribute of each cell. These map observations show that, the contours delineated on denser cells have a higher concentration of central activities, which are mainly located in the northeastern and western areas of the study region. These regions present a relevant ‘peak’ of the density surface compared to the rest of the city. Note that although some common hot regions enclosed by contours can be identified by the planar KDE method and the network KDE method, the contours in Fig. 7b, d and f present smooth and round wave shape while that in Fig. 7a, c and e are rather jagged and linked closely with the network structure. Through comparing these figures at different bandwidths we can also notice such variation was increasingly reduced as the search bandwidth increase. Since a wider bandwidth expands the candidate borderline of the CBD, it is possible to evaluate formally the centredness index of locations adapt to different levels’ needs, for example, a general CBD area for an over-all city planning, and a local center area for precise facility location problems.

Besides, by observing Fig. 7, there are more similarities in shape between the planar KDE of 300-m bandwidth and the network KDE of 600-m bandwidth. In the future, a new criterion attempts to be adopted using the planar KDE results when estimating the most suitable search bandwidth in a network-constrained environment. From the literature, few rules exist for the bandwidth parameter determination concerning network KDE, and often repetitive and also time-consuming evaluation experiments are required to be conducted to compare the ‘candidate’ parameters. If the related criterion is established based on the planar KDE, the practical cost from bandwidth determination experiment would be largely reduced, as the Euclidean distance calculating is much easier than the network distance calculating.

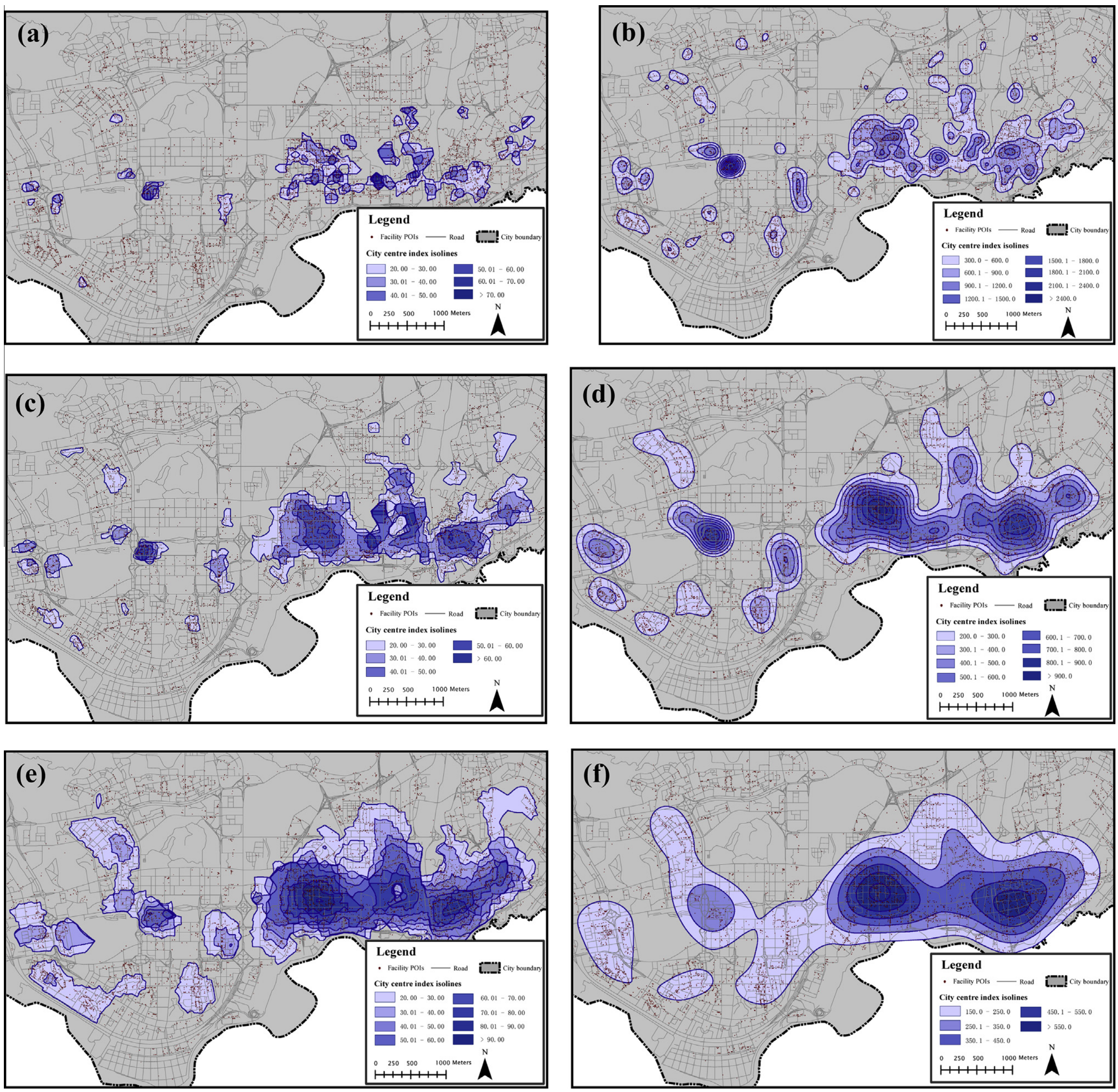

Fig. 7. Isolines of city centredness index in Shenzhen produced by the network KDE and the planar KDE with different bandwidths: (a) result by network KDE with 300 m bandwidth, (b) result by planar KDE with 300 m bandwidth, (c) result by network KDE with 600 m bandwidth, (d) result by planar KDE with 600 m bandwidth, (e) result by network KDE with 1200 m bandwidth, and (f) result by planar KDE with 1200 m bandwidth.

From Fig. 7, the essential fuzziness of the CBD is captured by generating regularly spaced isolines in a wide range of density values. In order to delineate the true urban 'core' we further examine the tail values of the density function using positive standard deviation values. Fig. 8 shows the thematic classification of the network density surface using isolines of standard deviations of 1, 2 and 3, respectively, with the search bandwidth 600 m. The observation indicates that the more internal isolines have a higher concentration of central activities, which can be confirmed by the density pattern shown in Fig. 6c. From that point the enclosed area by a higher value could better express the city's functional core, though a smaller area would be generated. Besides, according to the literature on delimitating CBD, a value of three standard deviations is often suggested (Chainey et al., 2002; Borruso and Porceddu, 2009). This value, however, is not directly applicable in an urban area of dimensions as Shenzhen. We used a specified value of two standard deviations (Fig. 9), which was chosen after several simulations and considered as one of the most suitable for our case.

The simple data scatter plot (Fig. 4) presents that the alignment of many activities along the main roads and its parallel streets. The shape and extensions of the final computed CBDs (Fig. 9) also conform well to this network-constrained pattern, specifically along the *Shen Sth Avenue*. When search bandwidth is set to 300 m or 600 m, the central functions are concentrated in two circumscribed areas of the city, presenting a polycentric structure. However, the CBD delineated at 1200-m bandwidth is reduced to a monocentric structure as the density surface would be largely generalized at wider search bandwidths. Actually the polycentric characteristics above were also identified from the related literatures (Wang

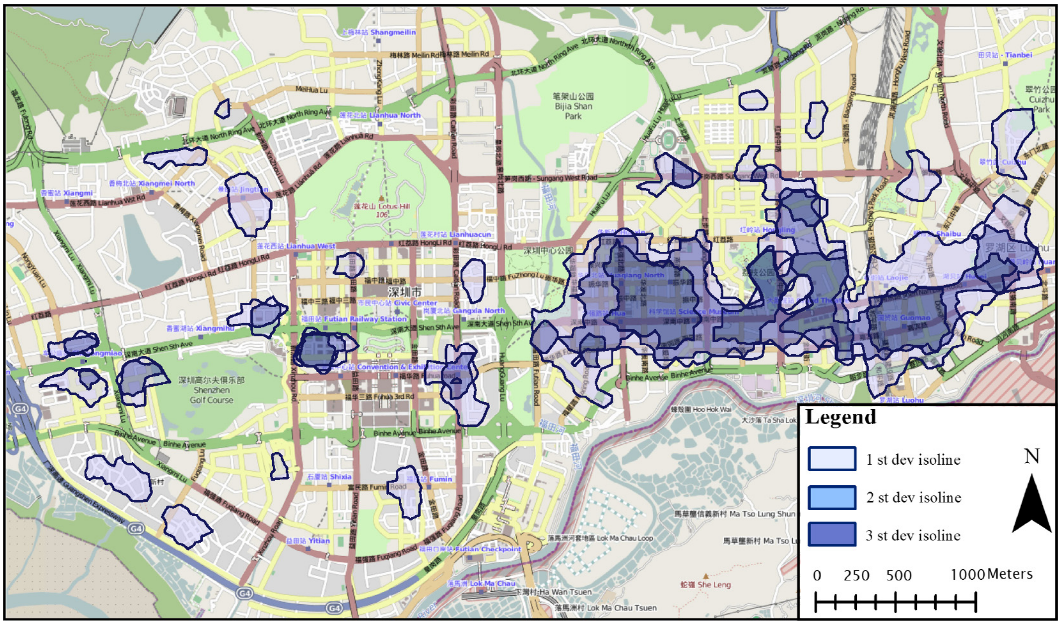

Fig. 8. 'Candidates' for delimitating CBD area in Shenzhen produced by isolines of standard deviation values of 1, 2 and 3. A network Quartic kernel and a 600-m bandwidth are used. Background mapping © OpenStreetMap.

and Li, 2002) and from the inputs of the government groups that supported the work (UPLRCSM, 2010, 2011). According to the Comprehensive Plan of Shenzhen City (2010–2020), Shenzhen's functional core will be mainly located in two regions, the traditional Luohu's Shangbu center and the new Futian center (see yellow[1] polygons in Fig. 9a). Luohu's Shangbu CBD becomes the economic hotspot in the city since the 1980s, the early stage of the reform and opening policy in China. Nowadays, with the westward shift of the urban economic weight and the limitation of available space in Luohu, Shenzhen's center has been gradually transformed to Futian CBD, which can be better revealed by the maps at narrower search bandwidths (300 and 600 m). Given present trends, the urban development and its functions evolve as its original planning.

5.4. Summary statistics

Table 3 shows the number of activities in the CBD areas accordingly (Fig. 9). More activity POIs are located within the areas delineated by using network KDE than that by using planar KDE, except for 300-m bandwidth. It is also worth noting that if compared to the planar KDE, a higher density values expressed as the number of activities per square kilometer are obtained within the computed CBD areas using network KDE. For example with a bandwidth 600 m, planar method delimitates an area of 6.345 km^2 containing 4506 activity POIs, where the density value is 710.165 activities/km^2. On the other hand, a larger area of 6.361 km^2 but containing 4714 activities is delimitated by the network method, and thus the density value in that area reaches 741.078 activities/km^2. The statistical result here suggests that, the delineated CBD based on network KDE gives better sense of locations of the 'functional core' in the city.

5.5. Evaluation

To testify the effectiveness of our network KDE-based method, we further collect the standard land price of Shenzhen's commercial land in 2013, based on the land-use condition and the land-use right (UPLRCSM, 2013). The detailed data has been released by China's government, Urban Planning Land and Resources Commission of Shenzhen Municipality, regarding 250-m quadrat as a basic statistical unit. Fig. 10a shows the spatial distribution of land price within the study region and Table 4 presents the relevant statistics.

As suggested by geographers, highest land value is one of the most dominant features of Central Business District (Murphy and Vance, 1954; Haggett, 2000; Yan et al., 2000). The CBD area has very limited land resources, while undertaking the major responsibility in city's society and economy development. That commercial and retail activities gathering in the limited space makes the land price in CBD standing out beyond the land zones else. Actually, most on the China's urban study choose to analysis CBD using land price statistics, especially in the cities like Shenzhen, Guangzhou which are growing rapidly in recent years (Yan et al., 2000; Wang and Li, 2002). Therefore, we consider the high-land-price region as the object of the comparative study. As with the KDE-based method, the comparative area consists of land-price quadrats of standard deviation values of 2 (Fig. 10b).

To evaluate the delimitating results quantitatively, we compare the results obtained by the KDE-based methods (Fig. 9) and those from land-price statistics (Fig. 10b), and two evaluation indicators (i.e. *Precision* and *Average_price*) are calculated as follows:

$$Precision = \frac{Area_{Identical}}{Area_{KDE}} \times 100\%$$

$$Average\_price = \frac{\sum_{i=1}^{k}(Area_i \times Price_i)}{Area_{KDE}} \times 100\% \qquad (3)$$

where $Area_{KDE}$ is the area of the CBD delineated by the network KDE method or by the planar KDE method, $Area_{Identical}$ is the area of the identical CBD region between KDE-based result and land-price-based result, and the value of $Area_{Identical}$ can be computed by using overlap analysis tool in GIS software, $Area_i$ is the area of the ith quadrat from a k-element quadrat set spatially covered by the KDE-based CBD, $Price_i$ is the corresponding land-price value of $Area_i$.

Specifically, the indicator *Precision* is used to determine the area ratio of KDE-based CBD spatially located within the land-price-

[1] For interpretation of color in Fig. 9, the reader is referred to the web version of this article.

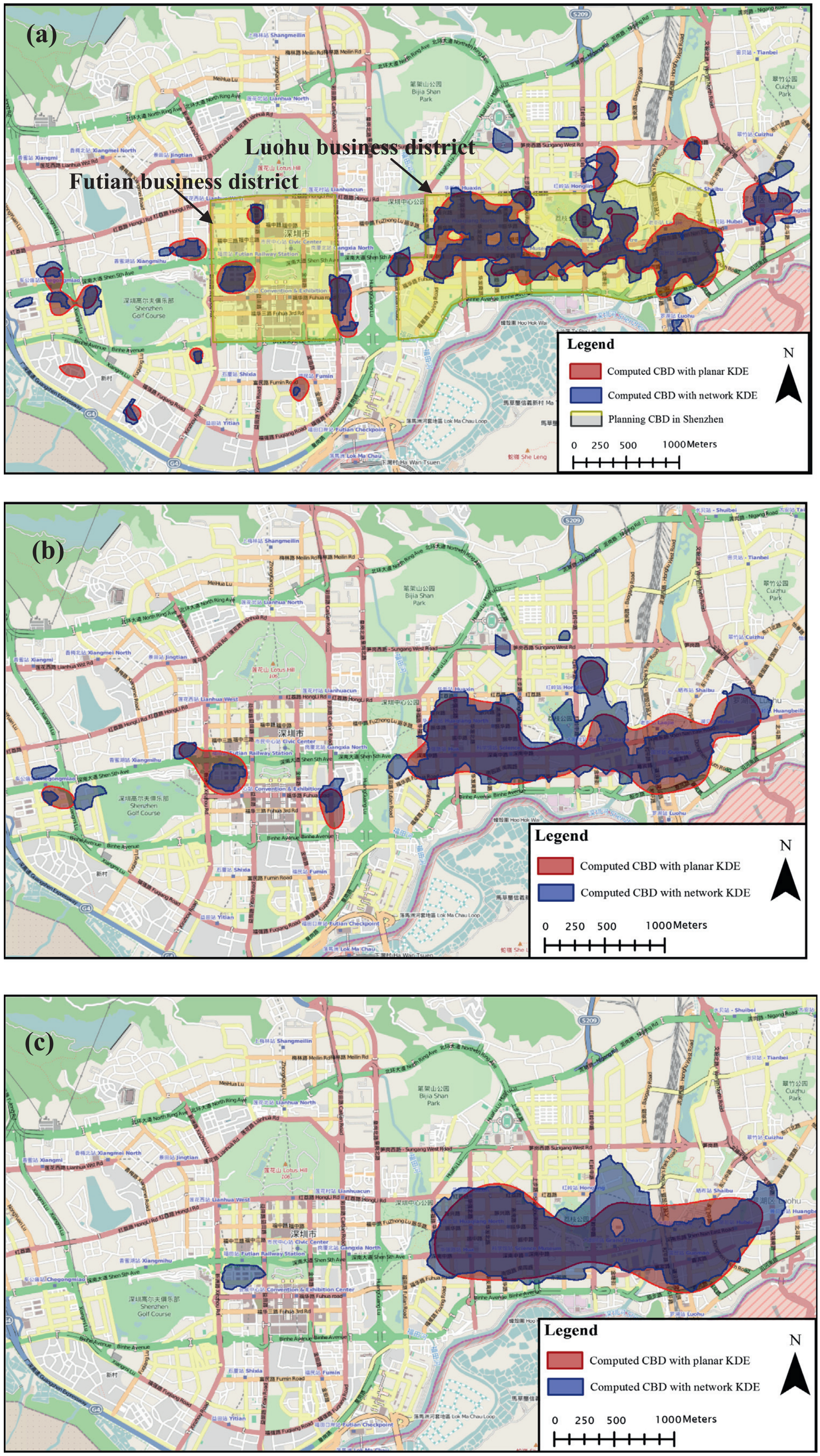

Fig. 9. CBD area in Shenzhen computed by the 2 standard deviations isolines of the planar and network density functions: (a) result with 300-m bandwidth, (b) result with 600-m bandwidth, and (c) result with 1200-m bandwidth. Background mapping © OpenStreetMap.

Table 3
The distribution of central activities in regions of 2 standard deviations using different KDE functions.

Region	Central activities		Area (km^2)		Count density (activities/km^2)	
	Planar KDE	Network KDE	Planar KDE	Network KDE	Planar KDE	Network KDE
Study area	11,213	11,213	111.302	111.302	100.744	100.744
2 *st. dev* isoline with 300 m bandwidth	5384	5171	5.932	5.479	907.620	943.785
2 *st. dev* isoline with 600 m bandwidth	4506	4714	6.345	6.361	710.165	741.078
2 *st. dev* isoline with 1200 m bandwidth	3686	4324	6.584	6.873	559.842	629.128

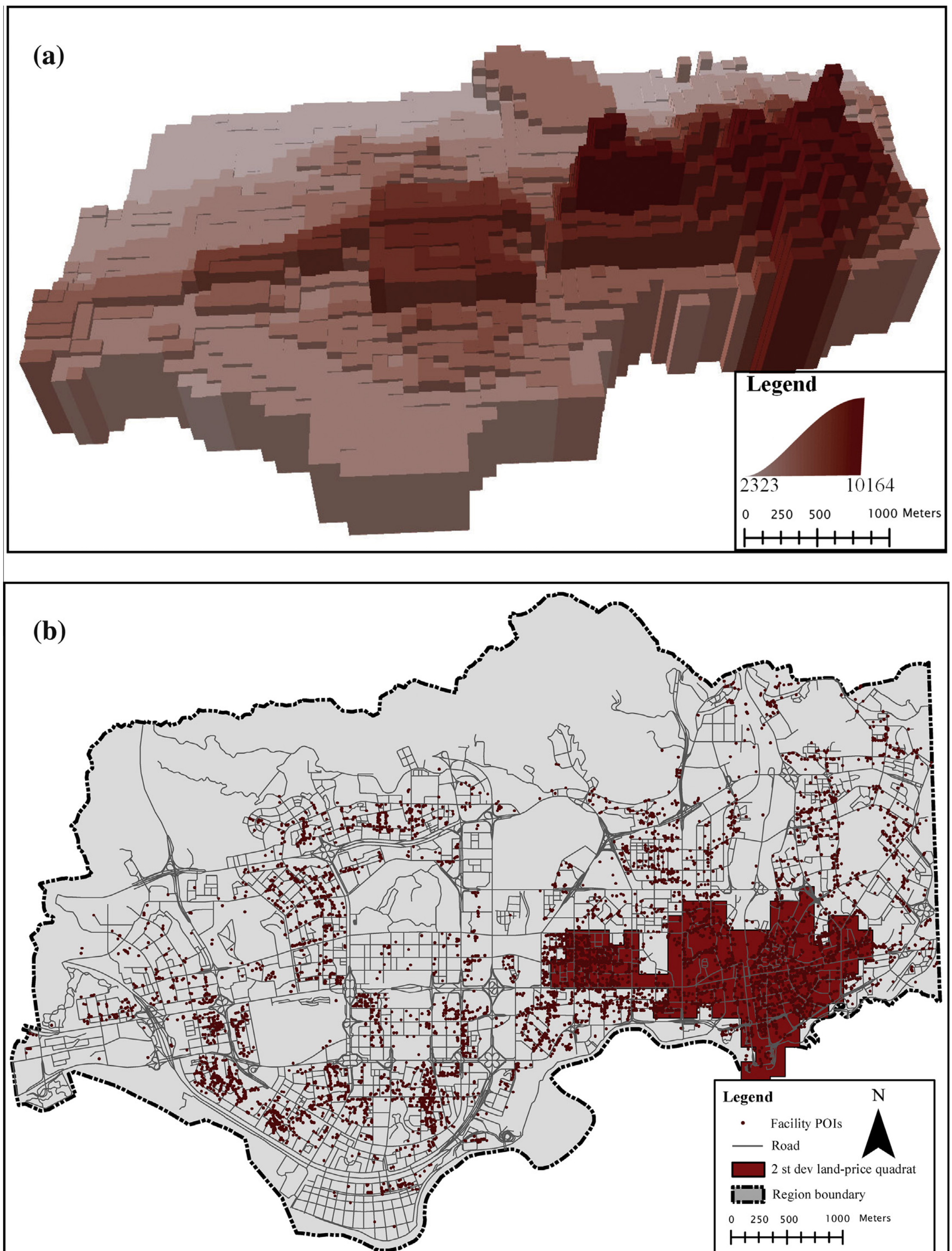

Fig. 10. Standard land price of Shenzhen's commercial land in 2013: (a) data quadrats with land price value and (b) central area in Shenzhen produced by quadrats of standard deviation values of 2.

Table 4
Standard land price of Shenzhen's commercial land in 2013.

Statistics of land price	Number of basic statistical units	Minimum value (RMB/m^2)	Maximum value (RMB/m^2)	Mean value (RMB/m^2)	Standard deviations
	1826	2323	10,164	4242	1458

based CBD, and *Average_price* is further calculated to illustrate the centrality strength of KDE-based CBD in terms of average land price. The evaluation result of Fig. 9 is presented in Table 5. We can find that the *Precision* of network-constrained result reach 59.2%, 66.7% and 74.1% at the three search bandwidths, and all the indicators are larger than the corresponding ones from planar-based result, i.e. 57.3%, 66.4%, and 73.4%. Such evaluation with *Precision* illustrates that the proposed method achieves more central space.

Table 5
The evaluation of the network constrained method and the planar method in terms of *Precision* and *Average_price* measures (Shenzhen city).

Statistics	2 *st. dev* isoline with 300 m bandwidth		2 *st. dev* isoline with 600 m bandwidth		2 *st. dev* isoline with 1200 m bandwidth	
	Planar KDE	Network KDE	Planar KDE	Network KDE	Planar KDE	Network KDE
2 *st. dev* central area based on commercial land price (km^2)	6.624	6.624	6.624	6.624	6.624	6.624
CBD area using KDE method (km^2)	5.932	5.479	6.345	6.361	6.584	6.873
Identical CBD area between land-price-based region and KDE-based region (km^2)	3.401	3.244	4.212	4.240	4.833	5.095
Precision (%)	57.3	59.2	66.4	66.7	73.4	74.1
Average_price (RMB/m^2)	8246	8463	8201	8498	8232	8575

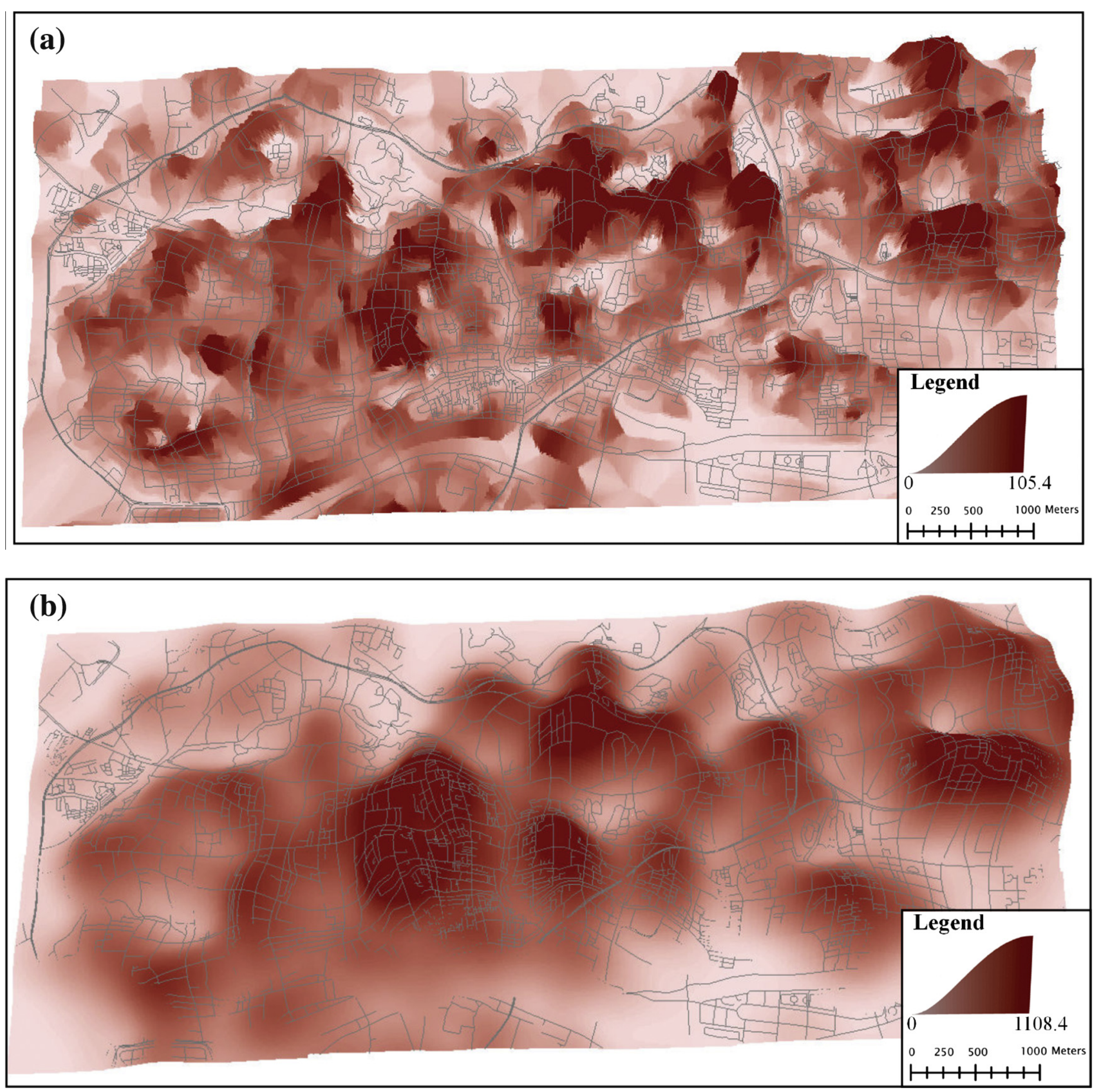

Fig. 11. The centredness surfaces in Guangzhou produced by the network KDE and the planar KDE with a Quartic kernel and 600-m bandwidth: (a) result by network KDE and (b) result by planar KDE.

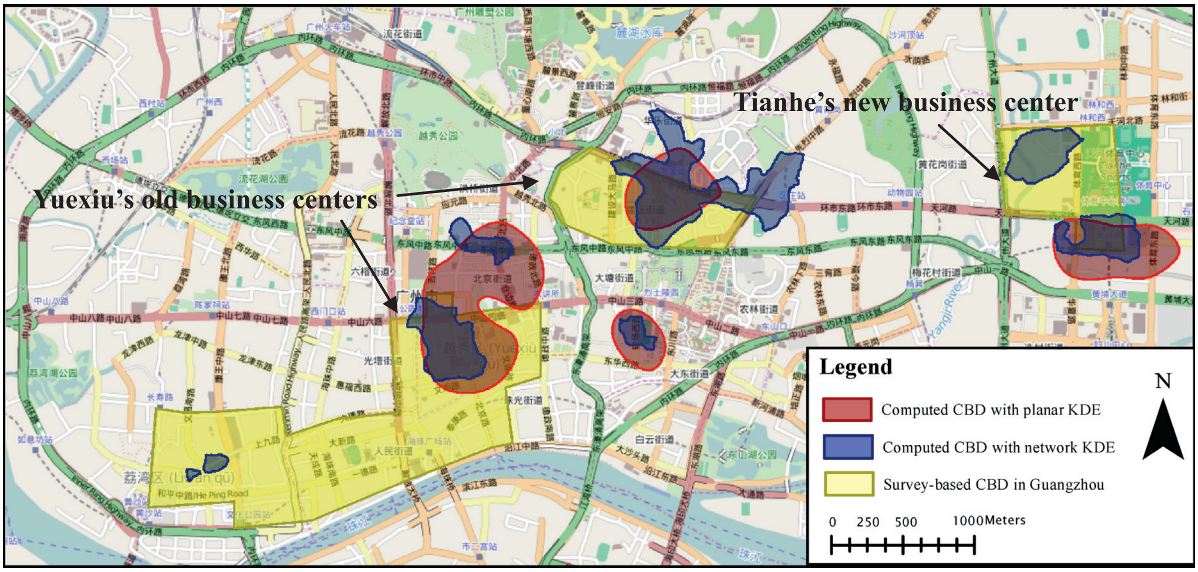

Fig. 12. CBD area in Guangzhou computed by the 2 standard deviations isolines of the planar and network density functions (600-m bandwidth). Background mapping © OpenStreetMap.

Table 6
The evaluation of the network constrained method and the planar method (Guangzhou city).

Method	Total area (km^2)	Identical area (km^2)	*Precision′* (%)
Survey-based method by Yan et al. (2000)	6.573	6.573	100
Planar KDE	2.547	1.073	42.1
Network KDE	1.991	1.112	55.9

In addition, as the corresponding land price of different land quadrat is different, another important indicator (i.e. *Average_price*) is also calculated. As shown in Table 5, all the average land prices in network-constrained CBDs are higher than those in planar-based CBDs. From this perspective, our approach is more effective and reasonable than the planar KDE method.

5.6. Case study of Guangzhou, southern China

In this section, we verify the feasibility of the proposed method using a different city in China, i.e. Guangzhou. Like Shenzhen city, Guangzhou has maintained a rapid economic development since the late 1970s. This brings significant changes in the urban structure and urban form. Presently, the central functions in the city of Guangzhou have extended from one single core to some districts around the traditional core (Yan et al., 2000).

Fig. 11 presents the intensity distributions of central activities by computing the density value for each spatial unit. It can be noted that though the study region is changed, there also are different observations from the centredness surfaces generated by the network method and the planar method, i.e. the planar KDE produces a rather smooth surface while that by the network KDE is bound to the network structure. Then, in order to verify the feasibility of the proposed method, the final CBDs are computed by generating isolines of standard deviations of 2. As shown in Fig. 12, the spatial distribution of the central functions expands outside the western old core area of the city (i.e. Yuexiu's business centers), and tended to eastern district, which is Tianhe's business center. This is due to the society and economy development since the years of the reform and opening in China.

The effectiveness of the proposed method can be illustrated via the reference research of Guangzhou CBD (Yan, 1999; Yan et al., 2000). In those studies, the reference CBD is investigated from the field survey on the basic land value and the spatial location of central activities (e.g. retail, enterprise offices, finance and insurance, and information consultant). Fig. 12 shows the detailed reference CBDs (yellow polygons). Based on the result, we next compare the network method and the planar method by calculating one evaluation indicator (i.e. *Precision′*) as follows:

$$Precision' = \frac{Area'_{Identical}}{Area_{KDE}} \times 100\% \tag{4}$$

where $Area_{KDE}$ is the area of the CBD delineated by the network method or by the planar method, $Area'_{Identical}$ is the area of the identical CBD region between the computed CBD and the survey-based CBD.

Table 6 presents the evaluation result. We can find that if compared to the network method, the planar method achieves a larger space for CBD (i.e. 2.547 km^2), but statistics show that it is further from the classic research by Yan et al. (2000), i.e. the identical region from the survey-based CBD is 1.073 km^2, less than that of the network method. Through the calculating of the evaluation indicator (i.e. *Precision′*), we present that the proposed method is feasible for different cities.

6. Conclusions

Defining and delineating the Central Business District as it is characterized by human activities plays an important role in applications of urban planning, commercial site selection and advertisement recommendation. In such applications, area-based methods of urban analysis (e.g. kernel density estimation) are widely adopted to generate continuous surface with its density attribute indicating 'central'. However, most of these methods simply consider the urban space as a homogeneous space with the neighbor distances calculated as Euclidean straight-line distance. The transit in an urban environment actually is constrained by transportation network, especially for the urban-centric activities. In such sense this study has developed a method to analysis CBD with network configuration considered. Specifically with a chosen set of 'central' human activities georeferenced as point events in space, network analysis was utilized to refine the surface of centredness by replacing traditional planar KDE with network KDE.

Considering that the shortest-path distance computation is a much complex operation in practical applications, we also proposed a new network KDE algorithm with a linear time complexity. The use of network tessellation structure and flow *expansion* operator leads to a more efficient implementation of the algorithm. This method is particularly suitable for the cases involving the use of wide search bandwidth or large dataset, as the time consuming GIS task (i.e. comparing for weights of nodes in a graph) is avoided.

We evaluate the proposed approach with Shenzhen, Guangzhou street networks and the related activity datasets of 2013 statistics. It is observed that a narrower bandwidth highlights more local effects, while a wider bandwidth makes a general trend much more obvious over the study region. Results of evaluation research show that compared to the planar-based method the computed CBDs based on network KDE gives better sense of locations of the 'functional core' at the chosen spatial scales.

Our proposed method emphasizes the structural constraints of street network on density analysis. Essentially, the effect of network structure is closely associated with the network density in urban space. When the streets are very crowded, the network structure becomes less evident and approximating a straight line distance. In this regard, the network-constrained method can be considered as most suitable for developing cities such as Guangzhou and Shenzhen. And in the future, we are planning to test this idea using different developing cities (e.g. Changsha in China), and also developed cities (e.g. Tokyo in Japan).

With increasing availability of activity data, our proposed approach to delineate CBD will attract additional research attention. The ubiquitous use of GPS-enabled devices makes it easy and convenient to track a person's trajectory, or activity location, over time.

Since main categories of activities were also organized in subcategories, the further works of our study will calibrate the CBD model by assigning both qualitative and quantitative weights for the different sub-categories before the density analysis of urban centredness. Besides, since traffic congestions change over time, it would be interesting to discover dynamic functional patterns on a time-dependent network.

Acknowledgements

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