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RESEARCH ARTICLE

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Fine-scale intra- and inter-city commercial store site recommendations using knowledge transfer

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Abstract

The rapid development of urban retail companies brings new opportunities to the Chinese economy. Due to the spatiotemporal heterogeneity of different cities, selecting a business location in a new area has become a challenge. The application of multi-source geospatial data makes it possible to describe human activities and urban functional zones at fine scale. We propose a knowledge transfer-based model named KTSR to support citywide business location selections at the land-parcel scale. This framework can optimize customer scores and study the pattern of business location selection for chain brands. First, we extract the features of each urban land parcel and study the similarities between them. Then, singular value decomposition was used to build a knowledge-transfer model of similar urban land parcels between different cities. The results show that: (1) compared with the actual scores, the estimated deviation of the proposed model decreased by more than 50%, and the Pearson correlation coefficient reached 0.84 or higher; (2) the decomposed features were good at quantifying and describing high-level commercial operation information, which has a strong relationship with urban functional structures. In general, our method can work for selecting business locations and estimating sale volumes and user evaluations.

1 | INTRODUCTION

With the rapid development of the national economy and local market demands, Chinese internet companies have started to change their traditional single-service mode as online content providers to a multi-service mode as online-to-offline (O2O) life service/goods providers (Ellison & Ellison, 2006; Ma & Bureau, 2017; Singh, Bansal, & Kaur, 2012). Such a new retail pattern exists mainly in the form of a company that has both an online presence and physical retail locations. According to marketing theory, the location of offline retail stores has great impact on not only their profit, but also their future development (Roig-Tierno, Baviera-PuigJuan, Buitrago-Vera, & Mas Verdúet, 2013). Choosing an optimal location for a physical retail store, especially in a complex urban context, is thus an important topic in both O2O practices and GIS algorithm studies.

Traditional commercial site selections rely mainly on field surveys to conduct assessments of customers' needs in target areas (Chang & Lin, 2015; Hong & Zhang, 2011; Yıldırım & Önder, 2014; Zhou, Wang, & Liu, 2005). These methods require many human and material resources, as well as being difficult to fit to the rapidly changing markets and dynamic developments of cities (Shakhsi-Niaei, Torabi, & Iranmanesh, 2011). In the field of GIS, gravity models (Pearson, 2007; Yu, Zhang, & Yang, 2014), linear regression (Qu, Yu, Tian, & Guo, 2015; Yu et al., 2014), and decision trees (Karamshuk, Noulas, Scellato, Nicosia, & Mascolo, 2013) have commonly been used to determine site selection suitability based on multiple datasets, such as passenger traffic volume, sales and road network data.

Based on the heterogeneous multi-source geospatial data produced by massive activities within cities, the fusion of multi-source data can effectively address the bias problem generated from a single data source (Liu et al., 2015, 2017; Yao et al., 2017), and the study of location selection for stores has gradually shifted to be multi-source data-driven (Eravci, Bulut, Etemoglu, & Ferhatosmanoğlu, 2016; Jensen, 2006; Karamshuk et al., 2013). Previous studies were conducted basically with abundant tagged stores data (Eravci et al., 2016; Jensen, 2006; Qu et al., 2015); however, the main issue encountered in site selection for stores currently is the so-called "cold-start" problem, which requires decision-makers to conduct site-selecting action in a new city without any prior knowledge (Bobadilla, Ortega, Hernando, & Bernal, 2012).

To tackle the abovementioned problems, some studies suggest that collaborative filtering can be used to build a site-selection model for a target business, as it can learn knowledge from other cities or similar stores (Lian et al., 2015; Zafarani, Abbasi, & Liu, 2014; Zheng, Cao, Zheng, Xie, & Yang, 2010). The general idea of collaborative filtering is making automatic predictions (filtering) about the interests of a user by collecting preference information from many users (collaborating), mostly seen in the commercial recommendation field. Nevertheless, there are huge gaps for inter-city site selection, including gaps in social economies, human activity patterns and geographical conditions (Kotthaus & Grimmond, 2014; Shwartz, Shirley, & Kark, 2008; Zhou, Pickett, & Cadenasso, 2016; Zhou, Yang, & Lu, 2013). Considering the uneven distribution of socioeconomic conditions across geographical space, traditional machine-learning methods cannot be adopted directly when transferring knowledge across different cities and different sectors (Cuo, Li, Zheng, Wang, & Yu, 2018; Zheng et al., 2010). In such cases, transfer learning can be a feasible solution, using existing knowledge to solve problems in different but related fields, especially when little or no sample data is available in the target area (Pan & Yang, 2010).

Based on the abovementioned ideas of knowledge transfer and collaborative filtering, Cuo et al. (2018) proposed the CityTransfer model. CityTransfer uses a twofold knowledge-transfer framework to conduct site-selection recommendations. On the one hand, knowledge for a specific business in the source city is transferred to the target city; on the other hand, local features of the target city are also learned to improve the traditional collaborative filtering for site selection. Compared with empirical methods, CityTransfer achieved the highest accuracy with a grid resolution of 500 m. However, for actual site-selection applications, site-selection evaluations conducted at planned land-parcel scale would be more practical and reasonable, especially in an urban context (Jiang & Yao, 2010; Zheng, Capra, Wolfson, & Yang, 2014).

Also, in megacities, there is substantial heterogeneity of crowd activities between different planned land parcels, especially in China. To our knowledge, in addition to the expansion of their own urban areas, the formation and expansion of large cities in China relies mainly on the merger or annexation of several smaller cities (Bai, Shi, & Liu, 2014; Chen, Chang, Karacsonyi, & Zhang, 2014; Ma, 2005). Due to the differences in residents' behavioral activities and natural geographical attributes in different regions, spatial heterogeneity of geographical phenomena will occur in different regions of the big cities, especially in China's megacities (Beijing, Shanghai, Guangzhou and Shenzhen) (Fang, Song, & Zhang, 2005; Feng, Wu, & Logan, 2008; Li, Peng, Yanxu, & Yi'na, 2017). Thus, knowledge transfer across different urban regions should involve further investigations (Zhou et al., 2016).

Aimed at commercial store site recommendations for intra- and inter-city cases at the land-parcel scale, this study proposes a collaborative filter-based knowledge-transfer framework named KTSR (Knowledge Transfer-based Site Recommendation). We chose two megacities in the southern part of China as the study area, and utilized the customer ratings of three major Chinese hotel chains as the criteria for location suitability. Based on the comparison between the obtained estimation and the actual scores, the accuracy of the proposed fine-scale site-selection model is evaluated.

The remainder of the article is organized as follows. Section 2 briefly introduces the case study area and the multi-source datasets. Section 3 describes the KTSR model and comparative experiments in detail. In Section 4, we present the experimental parameters and experimental results, and analyze the significance of the model parameters. Section 5 discusses the findings of the research in detail, summarizes the innovations, and explores the potential shortcomings of this study. Finally, we give conclusions and future work in Section 6.

2 | STUDY AREA AND DATA

The study area includes two metropolitan cities, namely Guangzhou and Shenzhen (Figure 1). Due to rapid urbanization, Guangzhou and Shenzhen have become two leading economic centers in the Pearl River Delta, which is the most important economic zone in southern China. As the capital of Guangdong Province, Guangzhou is typically characterized as a top-down development mode with strong government intervention, while Shenzhen is characterized as a bottom-up development mode with a less powerful government and enjoys considerable autonomy in economic affairs, given it's "Special Economic Zone" status (Ng & Tang, 1999). Figure 1 shows the administrative regions and planned land parcels of Guangzhou and Shenzhen, with their built-up urban areas. A total of 15,716

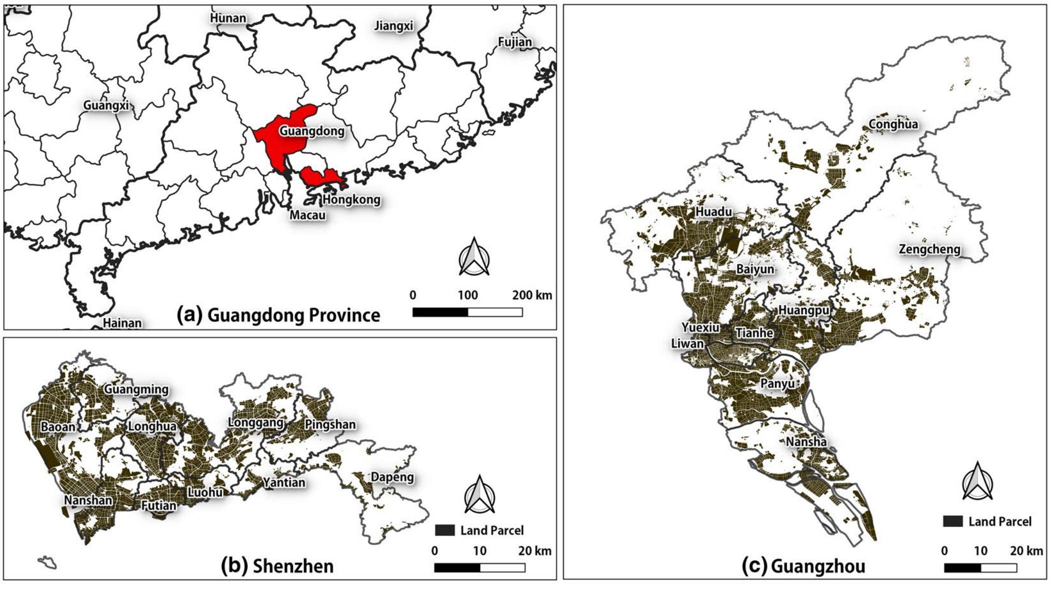

FIGURE 1 Case study areas

and 6,913 planned land parcels are delineated in Guangzhou (Figure 1b) and Shenzhen (Figure 1c), respectively, which are decided and published by the Guangdong Urban and Rural Planning and Design Institute.

Although Guangzhou and Shenzhen both lie along the Pearl River Delta and have experienced rapid urbanization, their economic development and residential activity modes are completely different (Sui & Zeng, 2001). As one of the earliest trading ports in China, Guangzhou still relies on traditional industry and international trade (Fan, 2001; Lin, Li, & Yang, 2011); as the youngest metropolis in China, Shenzhen is famous for its high-tech innovations and advanced producer services (Wang, Lin, & Li, 2010).

Dianping.com is the largest Chinese O2O local life service platform, with a built-in consumer review system for locally found products and services. Dianping.com scores each store in a range from 0 to 10 points: the higher the score, the greater the user's recommendation. The user rating data from Dianping.com is often used to recommend shops to users (Fang, Xu, Shamim Hossain, & Muhammad, 2016), and to evaluate the popularity of shops in a certain area (Zhai et al., 2015). Online reviews have been proven to show great potential in commercial site recommendation in the new retail era (Xiang, Du, Ma, & Fan, 2017; Zheng, Du, Ma, & Fan, 2017). More specifically, the rating data can reflect user preferences and business performance both qualitatively and quantitatively, thus affecting management decisions like site selection (Li et al., 2018; Xie, Zhang, & Zhang, 2014). Moreover, the previous study has demonstrated that such user rating score data can reflect commercial site-selection suitability, which can be applied well to optimal retail store placement in China (Zhang, Chen, & Chen, 2017). In this study, we designed a web crawler to fetch the locations of the top three largest hotel chains (7-Days Inn, Home Inn, and Hanting Inn) and their customer rating scores from Dianping.com (Figure 2).

Social media data, including points of interest (POIs) from Baidu.com, real-time Tencent user densities (RTUD) from QQ.com, road networks from OpenStreetMap (OSM), and house price data from Fang.com, are used to extract commercial and geographical features for site recommendations in the study area. Baidu POIs have 20

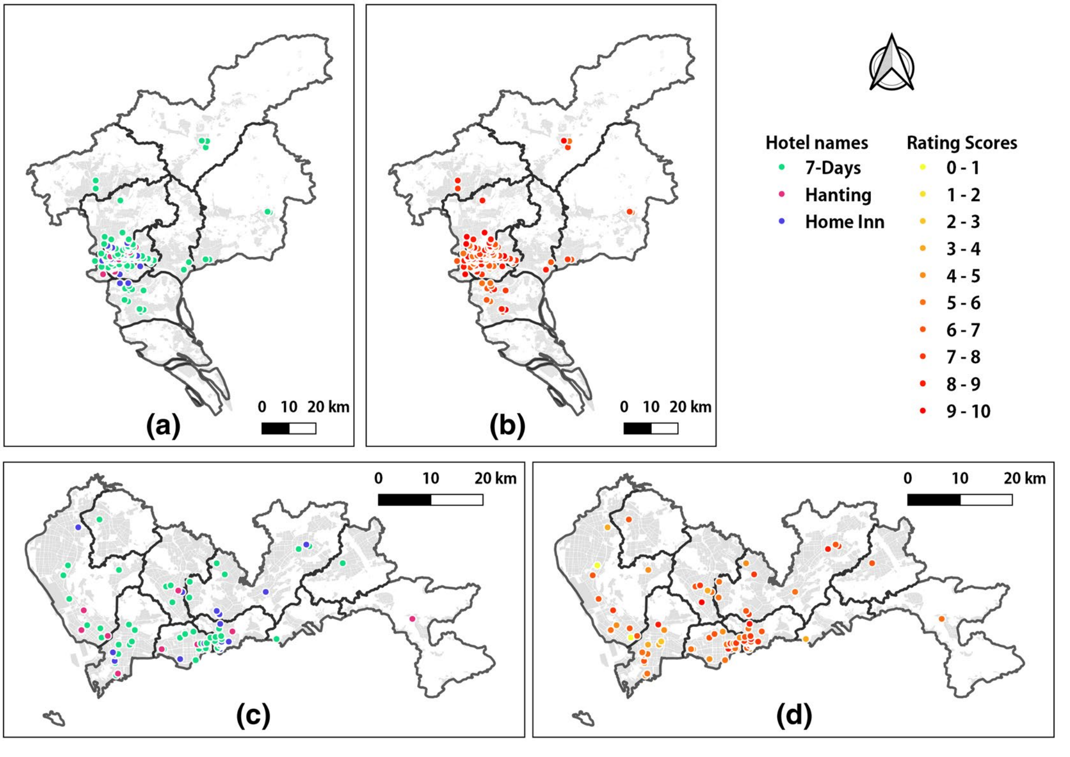

FIGURE 2 Distribution of three chain hotel brands (7-Days Inn, Home Inn, and Hanting Inn) and their user rating scores obtained from Dianping.com, which is the largest website that provides O2O services in China

categories (Table 1), including life services, residential communities, hotels, etc. Previous studies have proved that Baidu POIs can reflect urban functional structures effectively in China (Rodrigues, Pereira, & Oliveira Alves, 2012; Yao et al., 2016). The road network data obtained from OSM in this study are shown later in Figure 4; these data can reflect the traffic suitability of urban areas. In this study, we calculate the density of the road network using autocorrelated kernel density estimation (Terrell & Scott, 1992); we also take the distances to main roads (including highways, first and second-class roads) into consideration.

The RTUD records the locations of smartphone users who are using Tencent applications and are able to reflect the characteristics of urban residents' behavior in megacities, since over 93% of residents in Guangzhou and Shenzhen use Tencent location-based services (Chen et al., 2017; Yao et al., 2017; Yuan, Zheng, & Xie, 2012). The spatial resolution of the RTUD data is 25 m, and covers a temporal range from May to June 2016, as shown in Figure 3. Besides, house prices are an important commercial factor for merchants to target potential customers and find suitable store locations. This study obtained house price data in Guangzhou and Shenzhen via a web crawler, which yielded a house price distribution in urban areas using ordinary kriging interpolation (Kuntz & Helbich, 2014).

3 | METHODOLOGY

The flowchart of the proposed method is illustrated in Figure 4. We attempt to mine the operation characteristic information of the intra- and inter-cities to recommend sites for the location selection of chain stores. The procedure can be divided into three parts, including feature extraction, knowledge transfer, and comparing the results with several traditional models to reveal the advantages and disadvantages of the proposed knowledge transfer-based model.

TABLE 1 Feature list of spatial variables

Feature source	Dimensionality	Details
Baidu POIs	20	Density of each type: administrative landmark (ADL); government (GOV); corporation (COR); clinical facility (CLF); education (EDU); life services (LIF); location annotation (LOC); entertainment (ENT); catering (CAT); traffic facility (TRA); shopping (SHP); residential community (RSC); financial industry (FII); road (ROD); automobile service (AMS); hotel (HOT); business building (BUB); scenic spot (SCE); green space (GRE); natural mountains (MOU)
	1	Entropy of POI categories at the land-parcel level
Tencent RTUD	24	Average density of active users from 0:00 to 24:00 during working days
	24	Average density of active users from 0:00 to 24:00 during other days
OSM roads	1	Road density
	1	Distance to main roads
Fang.com	1	Average house price (by ordinary kriging interpolation)
Basic geographical data	2	Area and perimeter of land parcel
	1	Distance to bus stations
	1	Distance to subway stations

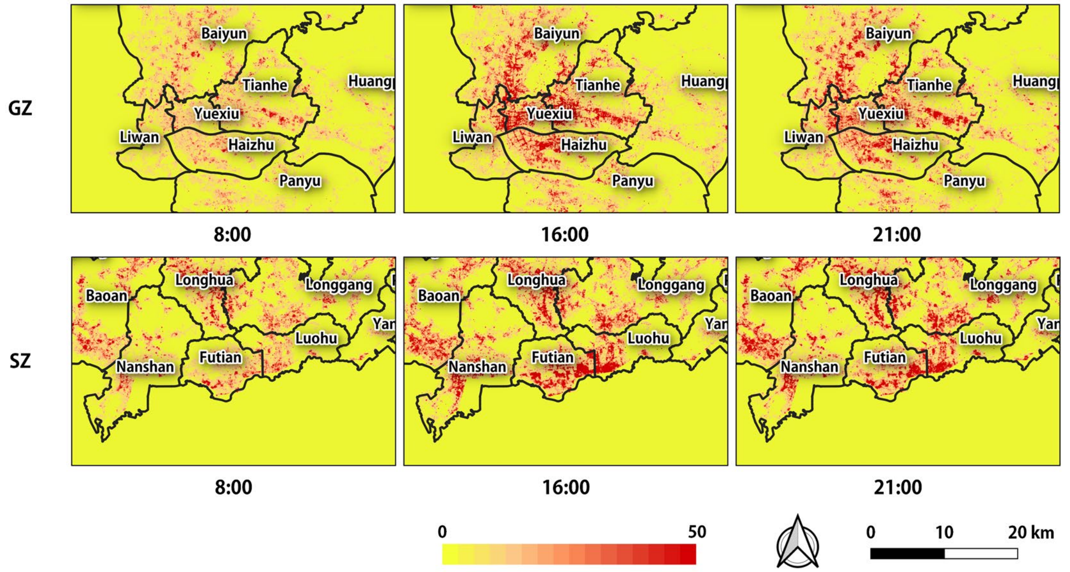

FIGURE 3 Distribution of RTUD in the main urban areas of Guangzhou (GZ) and Shenzhen (SZ) at three different times

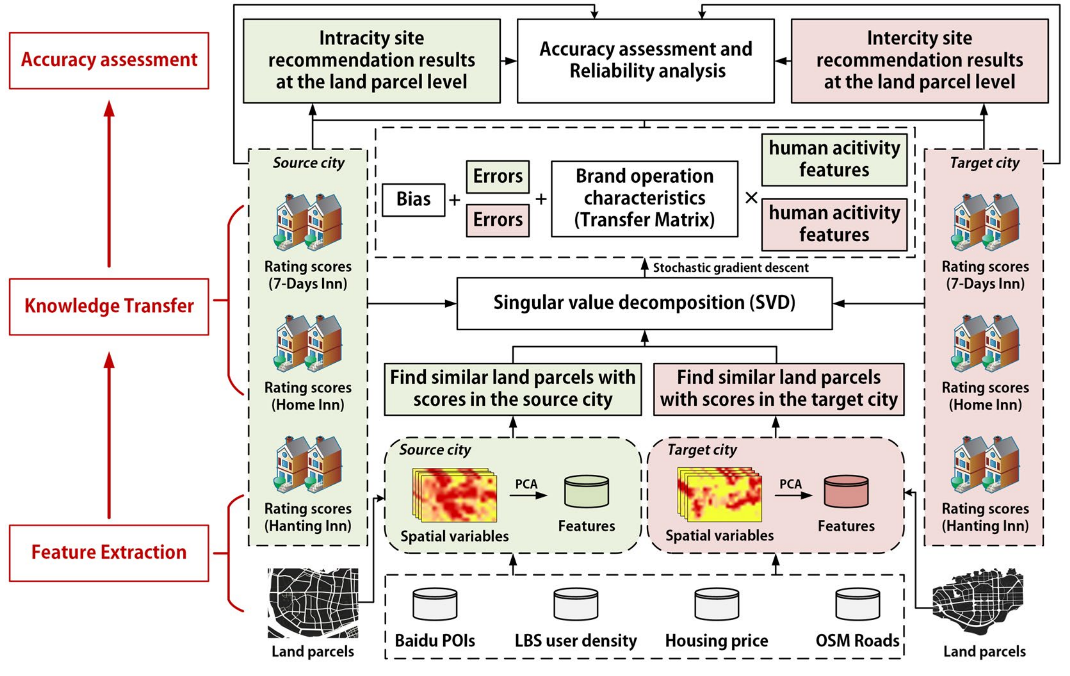

FIGURE 4 Flowchart of intra- and inter-city commercial store site recommendations via knowledge transfer using multi-source geospatial big data

3.1 | Feature extraction and dimensionality reduction

As illustrated in Table 1, several geographical and commercial features are extracted from multi-source geospatial data, including POIs, Tencent user density, house prices, road network density, etc. We obtained 658,718 recorded POIs with 20 categories in the study area. For each land parcel j, we counted the number of each POI category; based on this, the entropy of the POI was extracted to characterize the functional diversity (Li, Xing, Xia, & Huang, 2016; Liao, Xiao, & Huan-Zhang, 2007). As shown in Table 1, the geographical and commercial features of each land parcel can be represented by a 75-dimensional vector. To solve the problem of excessive dimensions and sparse features, this study adopts principal component analysis (PCA) to reduce the feature dimensions.

3.2 | Knowledge transfer-based location selection

By mining the associated knowledge between user rating scores and multi-source geospatial data, the proposed KTSR model can transfer the knowledge to regions without scoring information at the land-parcel level. To quantify and transfer the knowledge from different areas for calculating the suitability of site selection, land parcels with similar properties (e.g. socioeconomic conditions, human activities) were first chosen by quantifying their similarities for both intra- and inter-city cases. For land parcels in the source city and target city, the Pearson correlation coefficient is used to characterize their similarities (Pearson, 1969; Zafarani et al., 2014).

When the intra-city transfer process is carried out (i.e. learning location selection knowledge in the case that the source and target city is the same) for the land parcel $LP_i^{(s)}$, the top γ land parcels would be picked according to their Pearson correlation coefficient values in descending order (except $LP_i^{(s)}$ itself) in the same city. When the inter-city transfer is performed, as location selection knowledge from one city to the other needs to be localized, we pick land parcels both in the source city and in the target city when $LP_j^{(t)}$ does not contain any valid rating score for any hotel. For simplicity, we denote the set of selected land parcels as $\Delta = \{LP_1, LP_2, \dots, LP_\gamma\}$.

This study aims to make full use of the characteristics of enterprises and land-parcel features to recommend location selections. We use $\boldsymbol{s}$ and $\boldsymbol{p}$ matrices to represent the characteristics of the stores and the features of the land parcels, respectively, where $\boldsymbol{s}_i$ represents the characteristics of store i and $\boldsymbol{p}_j$ represents the feature vector of land parcel j. Similar to singular value decomposition (SVD), $\boldsymbol{s}_i$ and $\boldsymbol{p}_j^T$ are multiplied to get a preliminary rating score. For the selected source-city land parcels Δ, we decompose the rating matrices $\boldsymbol{Y}^{(s)}$ and $\boldsymbol{Y}^{(t)}$ into $\boldsymbol{s}$ and $\boldsymbol{p}$, respectively, with SVD-based collaborative filtering (Konstan et al., 1997), where $\boldsymbol{s}_i$ and $\boldsymbol{p}_j$ are used to predict the score of store i in land parcel j.

Due to the difference in the rating standards of different cities and different stores, we introduce the bias parameter $\boldsymbol{BS}_i$ for store i and $\boldsymbol{BP}_j$ for land parcel j to adjust the prediction scores. Since chain corporations generally have a fixed market position and location preferences, $\boldsymbol{BS}_i$ and $\boldsymbol{s}_i$ are generally unchanged between different cities; hence, we can transfer enterprise knowledge from the source city to the target city. However, the features of the land parcels between different cities are generally dissimilar (Wei, Zheng, & Yang, 2016). Therefore, we introduce $\boldsymbol{BP}_j^{(s)}$ and $\boldsymbol{BP}_j^{(t)}$ as the biases of land parcel j in the source city and the target city, respectively.

Based on this, we predict the scores $\hat{y}_{ij}^{(s)}$ and $\hat{y}_{ij}^{(t)}$ of hotel i in land parcel j in the source city s and the target city t with Equations (1) and (2):

$$\hat{y}_{ij}^{(s)} = \boldsymbol{BS}_i + \boldsymbol{BP}_j^{(s)} + \boldsymbol{s}_i \boldsymbol{p}_j^{(s)T} \tag{1}$$

$$\hat{y}_{ij}^{(t)} = \boldsymbol{BS}_i + \boldsymbol{BP}_j^{(t)} + \boldsymbol{s}_i \boldsymbol{p}_j^{(t)T} \tag{2}$$

Therefore, the loss function is constructed based on the predicted score and the real score, as shown in Equation (3):

$$J = \sum_{y_{ij}^{(s)} \in \boldsymbol{Y}^{(s)}} \left(\hat{y}_{ij}^{(s)} - y_{ij}^{(s)} \right)^2 + \lambda \sum_{y_{ij}^{(t)} \in \boldsymbol{Y}^{(t)}} \left(\hat{y}_{ij}^{(t)} - y_{ij}^{(t)} \right)^2 \tag{3}$$

Here, J is the loss function and λ is a fine-tuning parameter that is no less than 0.

To avoid overfitting, we introduced the L2 regularization term as shown in Equation (4):

$$R=\sum_{i=1}^{c} BS_i^2+\sum_{i=1}^{m} BP_i^{(s)2}+\sum_{i=1}^{n} BP_i^{(t)2}+\sum_{i=1}^{n} ||s_i||^2 \tag{4}$$

where c denotes the number of hotels, m the number of validation land parcels in the source city, and n the number of validation land parcels in the target city. For the intra-city analysis case, n would be set to 0 since the source and the target city are the same. By combining loss function J and the regularization term R, we can finally obtain the optimization target ζ, as shown in Equation (5):

$$\zeta = J + \mu R \tag{5}$$

Here, μ is a parameter which controls the importance of the regularization term, adjusting the penalty for generalization purposes. In this study, a stochastic gradient descent (SGD) method is used to minimize the loss function. Specifically, for each iteration, a land parcel in Δ is selected randomly during the SGD process, and the loss function ζ is calculated. The initial values of bias (***BS*** and ***BP***) at the beginning of the iteration are set to 0. The standard R^2, root-mean-square error (RMSE), and Pearson correlation coefficient (Pearson R) are applied to quantify the accuracy between the actual and the estimated rating scores.

3.3 | Comparison with traditional location models

After extracting the geographical and commercial features of each land parcel, we design inter- and intra-city site-recommendation models based on three different machine-learning methods, namely proposed knowledge transfer (KT), linear regression (LR) (Qu et al., 2015; Yu et al., 2014), and random forest (RF), to demonstrate the effectiveness of our proposed KT model. LR is a classical model addressing the site-selection problem, and RF is a multi-decision tree ensemble model which is good at solving high-dimensional nonlinear regression problems and can avoid overfitting problems effectively (Biau, 2012; Breiman, 2001). The RF algorithm carries out splits based on bagging instead of trying to balance features (Palczewska, Palczewski, Robinson, & Neaguet, 2014), which indicates that the RF-based fitting model is capable of solving the correlation problem of high-dimensional spatial variables in geographical applications (Liu et al., 2017; Yao et al., 2017).

3.4 | Detecting the relationship between operating characteristics and urban land-use patterns

After obtaining the transfer matrix ***s*** of each land parcel, we can characterize the operating characteristics of different chain hotels. In this study, the number of rows in ***s*** equals the number of hotel chain brands, and the number of columns equals the dimensions of the features after performing PCA reduction: 3 and 30, respectively.

k-Means clustering with a cosine distance is adopted for the operating characteristics of Hanting Inn for each land parcel, using the silhouette index to estimate the optimal clustering level (Campello & Hruschka, 2006; Chen, Li, Liu, & Ai, 2014). The numerical range of the silhouette index is between − 1 and 1. The closer the index is to 1, the better the clustering effect. In this study, the best clustering results are selected and compared with the enrichment factors of the POIs (Chen et al., 2017). The enrichment factor of a POI class greater than 1 signified that the proportion of the POI in that cluster was higher than that of the entire study area, and the corresponding land parcel was more functional (Verburg, de Nijs, van Eck, Visser, & de Jong, 2004).

4 | RESULTS

4.1 | Implementation and results

As illustrated in Table 2, we estimate the customer rating scores of 7-Days Inn, Home Inn, and Hanting Inn in each land parcel for both intra-city (Shenzhen → Shenzhen, Guangzhou → Guangzhou) and inter-city (Shenzhen → Guangzhou, Guangzhou → Shenzhen) scenarios. Previous studies have suggested that a site-selection recommendation model may be constructed with a combination of data from the source city and land-parcel data from the target city (Pan & Yang, 2009; Wang, Chen, & Huang, 2015). Thus, GZ&SZ2SZ represents the regression model (LR and RF) that uses data from Guangzhou and half of that from Shenzhen to estimate the chain hotel scores for each land parcel in Shenzhen.

During the construction of the intra-urban transfer model KT and regression models LR and RF, the score data of each chain hotel are divided equally into training and testing data. Also, in the proposed KTSR model, the source city is set to Guangzhou and the target city is Shenzhen. The input of each hotel in the target city in the KTSR model is equal to the combination of all the hotel rating data in the source city (Guangzhou) and that of the

TABLE 2 Average estimation accuracy of customer rating scores by different models

	Hotel name	R^2	Pearson *R*	RMSE
KT-based models				
KT_GZ2GZ	7-Days Inn	0.629	0.779	1.592
	Home Inn	0.669	0.806	1.402
	Hanting Inn	0.674	0.835	1.375
KT_GZ2SZ	7-Days Inn	0.852	0.946	1.152
	Home Inn	0.795	0.898	1.532
	Hanting Inn	0.685	0.840	1.600
LR-based models				
LR_GZ2GZ	7-Days Inn	0.171	0.470	2.944
	Home Inn	0.237	0.444	2.886
	Hanting Inn	0.265	0.655	1.953
LR_GZ2SZ	7-Days Inn	0.004	−0.078	6.167
	Home Inn	0.045	0.192	6.606
	Hanting Inn	0.011	−0.183	8.186
LR_GZ&SZ2SZ	7-Days Inn	0.002	0.224	3.681
	Home Inn	0.003	−0.105	3.859
	Hanting Inn	0.090	0.005	3.525
RF-based models				
RF_GZ2GZ	7-Days Inn	0.841	0.975	1.409
	Home Inn	0.824	0.972	1.367
	Hanting Inn	0.834	0.973	1.002
RF_GZ2SZ	7-Days Inn	0.002	0.160	3.610
	Home Inn	0.005	0.115	3.222
	Hanting Inn	0.019	−0.037	2.970
RF_GZ&SZ2SZ	7-Days Inn	0.052	0.170	3.441
	Home Inn	0.001	0.233	2.911
	Hanting Inn	0.000	−0.073	3.350

other two hotels in the target city (Shenzhen). Specifically, the number of decision trees in the RF algorithm is set to 80, and the out-of-bag rate is equal to 0.5. In the KTSR model, the learning rate (α) has been set to 0.001, and the ranges of the similar land-patch number γ and penalty rate μ are set to [0, 20] and [0.0, 1.0], respectively. The KTSR model is adjusted in steps of $\Delta\gamma = 1$ and $\Delta\mu = 0.1$, and we calculate the average estimated accuracy of the model under all combinations of similar land-patch numbers (γ) and penalty rates (μ).

Table 2 demonstrates the average accuracy of the estimated customer rating scores via different models. The model with the highest estimation accuracy is the RF-based Guangzhou intra-city and Shenzhen intra-city regression model ($R^2 > 0.8$, RMSE < 1.5), while the accuracy of the LR-based model is rather low, which illustrates two issues: first, the geographical and commercial features selected in this study are effective for the site recommendation; second, even by reducing the dimensionality with the PCA, these features are still strongly correlated. Linear regression is not able to reveal the correlation problem in high-dimensional features, which results in low estimation accuracy. As the best machine learning-based regression model, RF can address well the strong correlation problem of high-dimensional variables (Fernández-Delgado, Cernadas, Barro, & Amorim, 2014). Also, the accuracy of the proposed KTSR model ($R^2 > 0.6$, RMSE < 1.6) is slightly lower than that of the RF-based regression model, which reveals that the KTSR is effective for intra-city site-selection modeling, and its accuracy approaches that of the nonlinear regression model.

As for the cross-city (GZ2SZ) user rating estimation results, the proposed KTSR model obtains the highest estimation accuracy ($R^2 > 0.6$, RMSE < 1.6). We can observe that the accuracies of the LR and RF-based inter-city regression models are both very low ($R^2 < 0.05$, RMSE > 3.0). Even if the data of the target city are added to the model, such as LR_GZ&SZ2SZ and TF_GZ&SZ2SZ, a robust regression model cannot be obtained. The main reason is that there are huge differences in geographic features and consumer preferences among different cities. If the site-selection model does not take into account the differences in residential behavior characteristics and urban function patterns that exist between cities, then simply applying the socioeconomic model of the source city to address the spatially related issues of the target city cannot obtain a reasonable result. The proposed KT-based inter-city site-selection model maps the common business model of the source and target cities at the land-parcel scale into mathematical space vectors. By multiplying space vectors with socioeconomic features of the land parcel, accurate customer rating score estimations are obtained, providing a reliable reference for the location selection.

Figures 5 and 6 display the estimated customer rating scores of 7-Days Inn, Home Inn, and Hanting Inn via the KTSR model at the land-parcel level in Guangzhou and Shenzhen. Overall, the KTSR model assigns a different user evaluation score to each land parcel, which provides a reference for site selection. Some very interesting phenomena can be found in the details.

1. Areas where people or tourists are more concentrated, such as colleges and universities [Figure 5 (#2) and Figure 6 (#1)] and well-known tourist attractions [Figure 5 (#1) and Figure 6 (#2)], are basically the most ideal sites for all chain hotels, reflecting the common preference for chain hotel site selecting.
2. The site selection of chain hotels also needs to consider economic factors, such as house prices, fully. Figure 5 (#5) shows that higher site-selection suitability appears in the center of Panyu District, where house prices are relatively low. Figure 6 (#3) shows poor site-selection suitability in the center of Shenzhen, which has extremely high house prices (>80,000 RMB yuan/m^2). Although passenger flow for Shenzhen's center is relatively high, the site-selection suitability stays relatively low compared to other regions.
3. The estimated result shows that site-selection decision-making is affected greatly by the enterprise's business model and its target customer group. From Figures 5 and 6, we can see that the suitability of Hanting Inn in the city village [Figure 5 (#4)] is lower than that of the others, while its suitability value near the park [Figure 6 (#5)] is higher. Based on the description from official websites, Hanting Inn is more inclined to run its business in areas where traffic is convenient and security is guaranteed, which explains its estimated suitability distribution with respect to city village and park.

Figures 7 and 8 demonstrate the estimated error during the SVD process when obtaining rating scores in each land parcel. Except for a few regions, the estimated RMSE for the land parcels in the study area is within 2.0. In

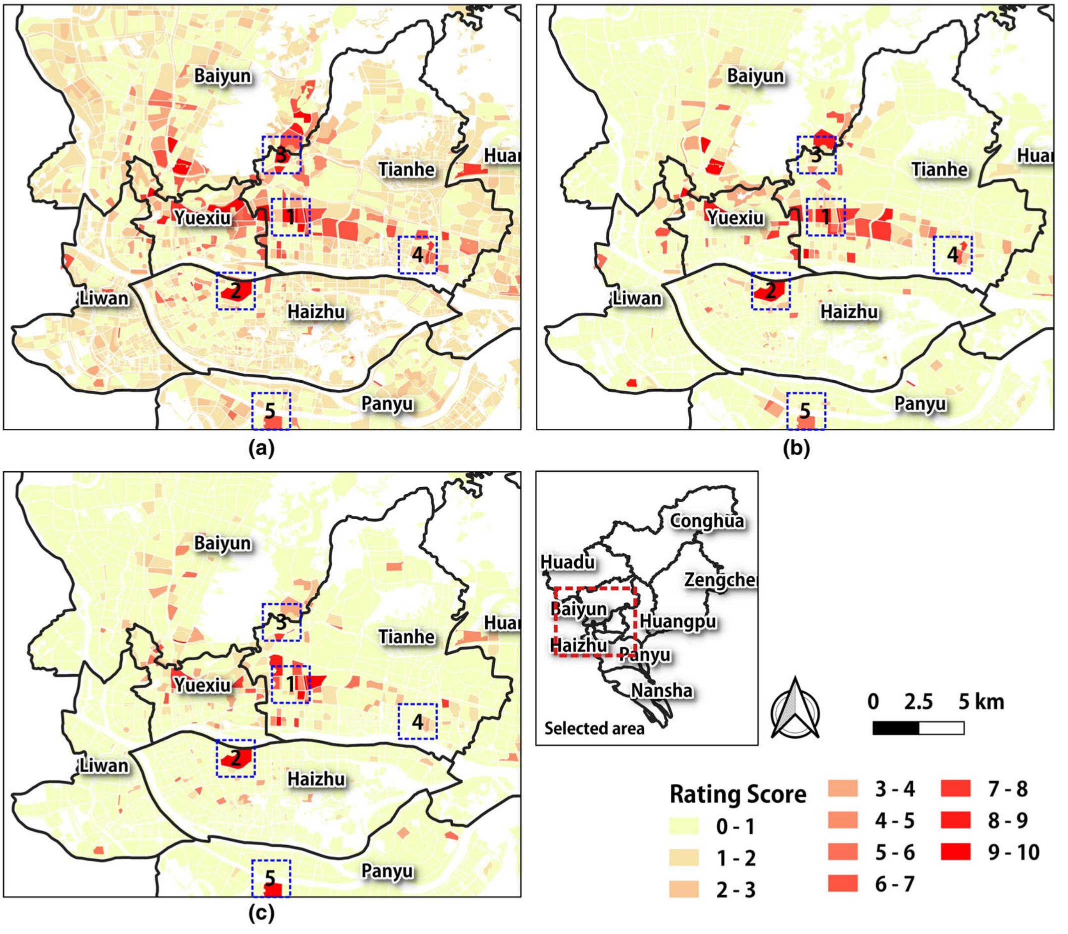

FIGURE 5 Estimated user rating scores for (a) 7-Days Inn, (b) Home Inn, and (c) Hanting Inn at the land-parcel scale in the main urban areas of Guangzhou. Among them, area (#1) is the sports center of Guangzhou, (#2) is Sun Yat-sen University, (#3) is Wanda Plaza near the Guangzhou railway station, (#4) is an urban village named Chebei, and (#5) is the downtown center of the Panyu District

GZ–GZ intra-city transfer cases, the land parcel of Baiyun Airport has an RMSE value over 5.0. As Baiyun Airport is the only airport in Guangzhou, such a result is reasonable since no similar functional plots could be found for site-selection references in this case. Besides, it is worth noting that the RMSE of Nanshan District's coastal area reached 2.0–2.5. On the one hand, this is because of the lack of chain hotel rating data; on the other hand, as an inland city, Guangzhou lacks land parcels with similar functional structures and crowd activity characteristics.

4.2 | The relationship between the transfer matrix and urban land use

In this study, we chose the operating characteristics of Hanting Inn for clustering as an example. The best clustering results (silhouette value = 0.780) divided the land parcels into five categories. Figure 9 and Table 3 show the clustering results and enhancement factors of various POIs in land parcels, respectively.

The results indicate that the chain hotels correlate strongly with brand operating characteristics and urban functional structures. From Table 3, Classes 1 and 5 are mainly composed of government agencies, educational facilities, and residential communities. The land functions of Class 2 are mainly green spaces and scenic areas; areas

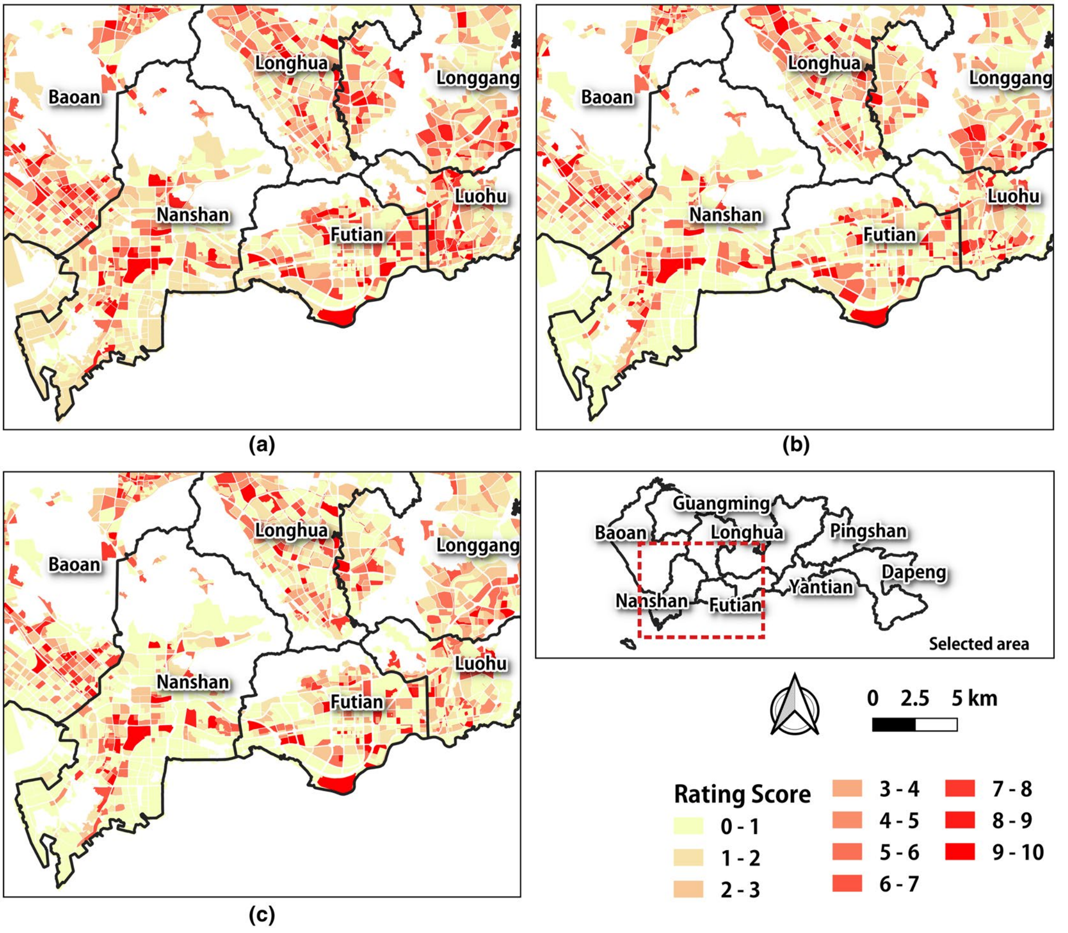

FIGURE 6 Estimated user rating scores for (a) 7-Days Inn, (b) Home Inn, and (c) Hanting Inn at the land-parcel scale in the main urban areas of Shenzhen. Among them, area (#1) is Shenzhen University, (#2) is a mangrove ecotourism area near the beach, (#3) is the citizen center of Futian District, (#4) is the Meilin shopping center, and (#5) is the flower expo park

with high crowd mobility, such as airports and amusement parks, are also in this category. The crowd activities within the land parcel marked as Class 3 are relatively sparse; by comparing with RS images, we characterize this category with construction sites and factories.

Many mountain and scenic POIs are found within Class 4, which indicates that this class mainly contains parks and leisure areas inside the city. From these results, the regional functions of the city affect the business model and economic behavior of the same hotel brand. These results confirm the socioeconomic hypothesis that the business model and behavior of the hotel derive from the internal economic activities of the city, and their quantifications can reflect the internal functional structure of the city effectively (Myint, 2008; Zhou, Lin, & Yan, 2008).

5 | DISCUSSION

How to select site locations to obtain maximum commercial profit has always been a hot topic of interest to both GIS academia and business. This study aims to tackle the spatial heterogeneity problem for intra- and inter-city

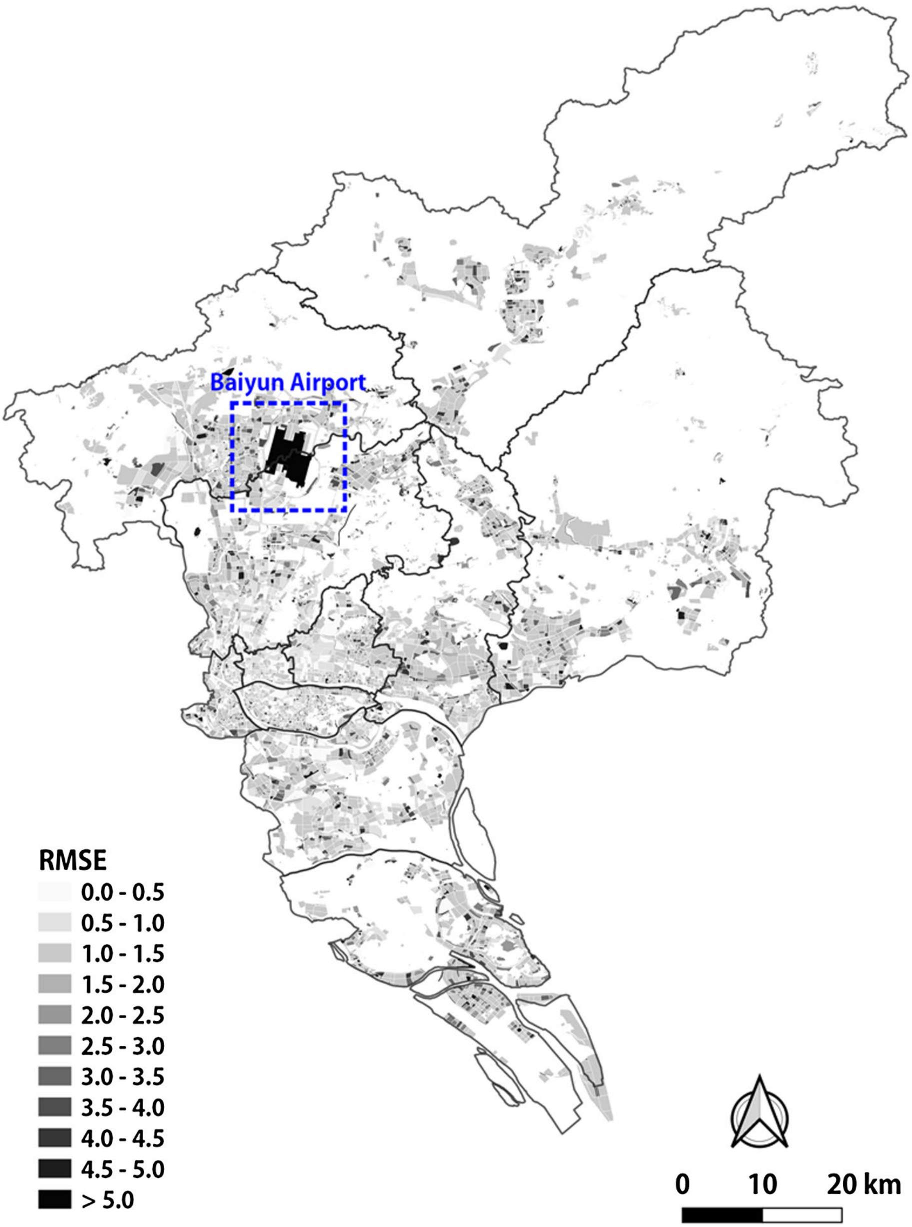

FIGURE 7 Estimated error distribution of user rating scores at the land-parcel scale in Guangzhou

commercial site recommendations at the land-parcel level. Based on the idea of knowledge transfer, the proposed KTSR model carried out the transmission of intra- and inter-city brand operation characteristics successfully, and obtained high-accuracy site-selection suitability results in Guangzhou and Shenzhen for three chain hotel brands (R^2 > 0.6, RMSE < 1.6).

As an intra-city site-recommendation model, the KTSR model can achieve the accuracy of the nonlinear regression model (RF-based fitting model). As an inter-city location model, by introducing the idea of knowledge transfer, the model can obtain much higher accuracy than traditional location-recommendation models, with R^2 increasing from 0.01 to over 0.65, which illustrates that the conventional regression models lack consideration of

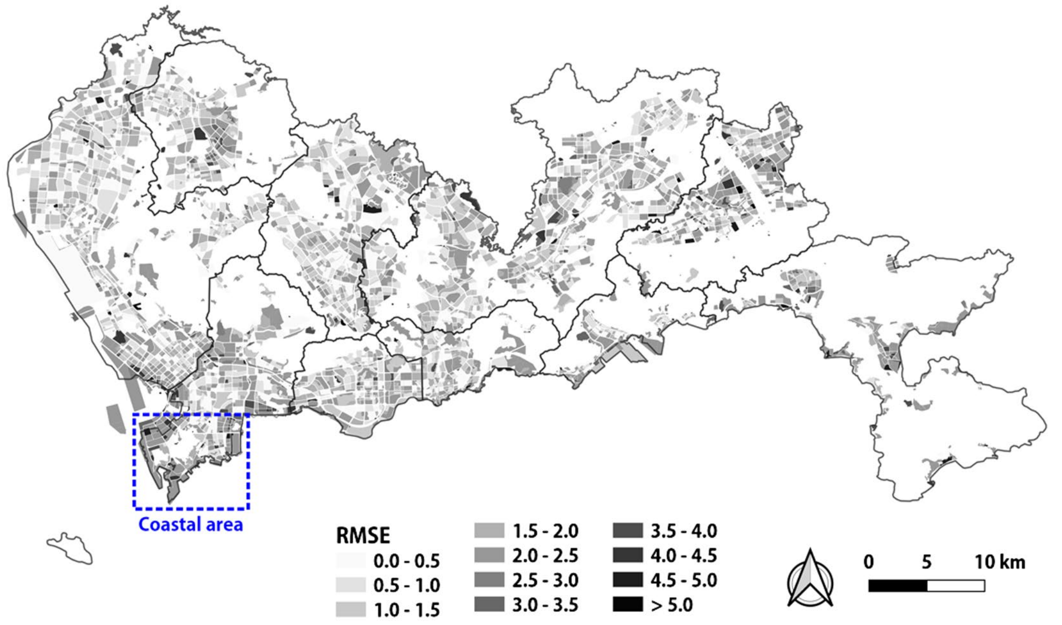

FIGURE 8 Estimated error distribution of user rating scores at the land-parcel scale in Shenzhen

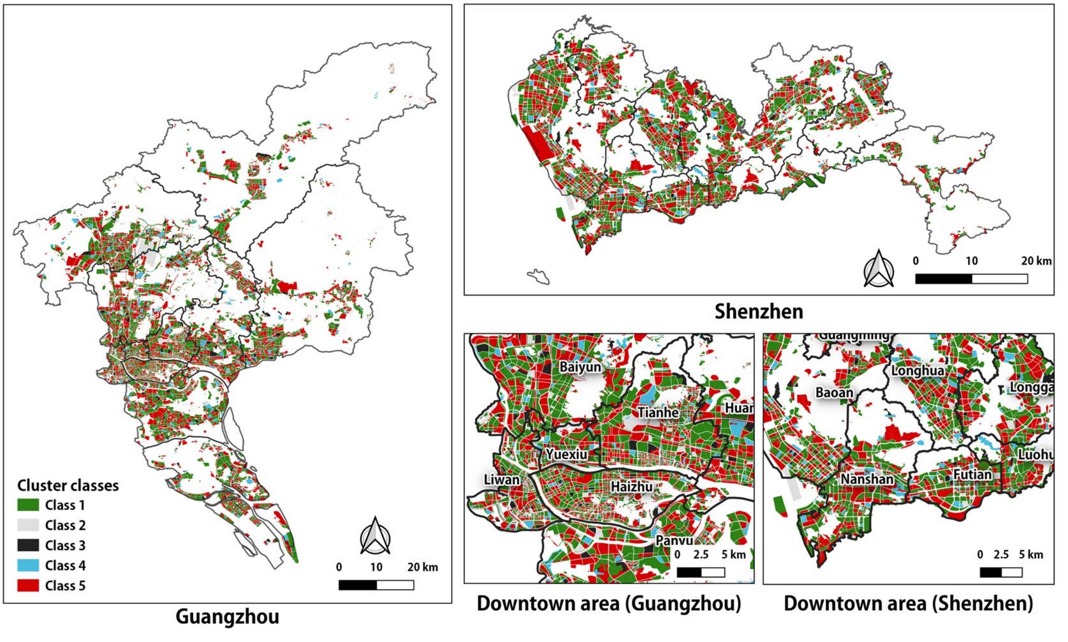

FIGURE 9 Land parcel-scale clustering results of the brand operating features

the spatial heterogeneity issues between cities. The proposed KTSR model can extract the transfer information effectively for site selection, and the deviation calculated in the model expresses the spatial heterogeneity between cities.

TABLE 3 Enrichment factors of POIs in different clustering classes

Class	ADL	GOV	COR	CLF	EDU	LIF	LOC	ENT	CAT	TRA	SHP	RSC	FII	ROD	AMS	HOT	BUB	SCE	GRE	MOU
1	0.983	2.989	0.985	0.986	0.988	1.806	0.927	1.010	1.008	1.015	1.010	1.995	1.398	1.016	1.021	1.021	1.038	0.855	0.354	0.757
2	1.006	0.933	0.950	1.093	1.023	0.692	1.546	0.962	1.063	0.951	1.029	0.899	1.067	1.094	1.093	2.019	0.713	2.357	3.444	0.794
3	1.121	1.005	0.951	1.007	0.740	0.535	1.369	0.997	1.092	0.970	0.998	0.963	0.634	1.133	1.000	0.679	0.869	0.637	0.000	0.368
4	0.973	0.806	1.081	0.997	0.830	0.602	1.087	0.931	1.009	0.904	1.030	0.906	0.966	0.955	0.933	1.059	0.790	2.340	0.000	3.075
5	1.013	1.039	1.017	1.004	4.029	1.690	0.965	1.004	0.970	1.008	0.979	2.039	1.006	0.961	0.973	0.997	1.041	0.874	1.327	1.382

Types of POI: ADL, administrative landmark; GOV, government; COR, corporation; CLF, clinical facility; EDU, education; LIF, life services; LOC, location annotation; ENT, entertainment; CAT, catering; TRA, traffic facility; SHP, shopping; RSC, residential community; FII, financial industry; ROD, road; AMS, automobile service; HOT, hotel; BUB, business building; SCE, scenic spot; GRE, green space; MOU, natural mountains.

From the perspective of urban geography, on the one hand, the site-selection suitability results (Figure 6) obtained with the proposed KTSR model reflect well the commonality and brand positioning of different brand chain hotels in different cities. The results also reflect the balance between population activity densities and urban house prices. The extent of the impact of these on site selection, however, has not been quantified, which is a topic worthy of further exploration. On the other hand, the results demonstrate that the brand operating characteristics of each chain hotel have a strong correlation with urban land-use patterns, which was not discovered by previous research (Cuo et al., 2018). These results (Figure 9 and Table 3) quantify the characteristics of internal social and economic activities in the city and provide a quantitative research method for the analysis of an urban business and economy model in future studies.

There are still several limitations to this study. We aim to verify the effectiveness of the KTSR model for intra- and inter-city site selection and select several feature sets that can reflect geographical and commercial characteristics. Although our results have demonstrated the effectiveness of this feature set, business activities are far more complex, and many factors need to be taken into consideration. In the actual operation of shop-location selection, local planning policies, store visibility (e.g. on the street or in shopping malls), and other factors are also vital. This study provides a site-selection recommendation method. In future work, we will introduce and quantify the factors mentioned earlier based on the results of this research to provide a more accurate location selection plan. Besides, how to quantify the impact of various spatial factors on the suitability of shop site selection is of great practical interest. We will introduce global sensitivity analysis (Homma & Saltelli, 1996; Sudret, 2008) for space-driven factor analysis of site-selection suitability, to provide more accurate and reliable reference recommendations for businesses.

Cities are complex systems, and vast differences exist among the functional structures, social economics, and crowd activities of different cities (Yao et al., 2017). For example, during the process of intra- and inter-city transfer with the KTSR model, abnormal plots would be derived due to the lack of prior knowledge (e.g. Baiyun Airport in Guangzhou and the coastal area of Shenzhen). To solve this problem, collecting data from multiple cities to form a site-selection database will be necessary. By building a multi-city KTSR model, we can obtain more accurate target site selections for the target city. With sufficient data, the method proposed in this study can not only estimate the scores of chain brand hotels, but also predict the customer flows and sales of locations where shops will be located.

6 | CONCLUSIONS

Differences in physical geography and human economic attributes among cities and regions lead to spatial heterogeneities within and between megacities. These spatial heterogeneities can lead to inaccuracies in the results of traditional location-selection models based on regression algorithms. Aimed at this problem, the proposed KTSR model considers and explores: (a) the spatial heterogeneity between cities or regions; and (b) the brand characteristics of chain stores, for knowledge transfer. With user rating scores as the fitting target, the proposed KTSR model outperforms the traditional location-recommendation models. The study also found that there is a connection between the brand identity matrix of chain stores and urban land use, which is a meaningful result and can be used as a basis for understanding the correlation between urban commercial and functional structures.

In future research, we will consider the following aspects: (a) adding more local factors to optimize the KTSR model; (b) analyzing the correlation between the site suitability of various shops and the spatial variables, and finding the corresponding driving factors; and (c) considering more diverse urban land-use patterns, and building a location–shop–sales dataset with real sales data to train the KTSR model used in real-world applications. In summary, in a new retail era, the KTSR model can help internet companies promote their O2O services by recommending precise offline store locations, as well as building feasible commercial appraisal models for their offline business.

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