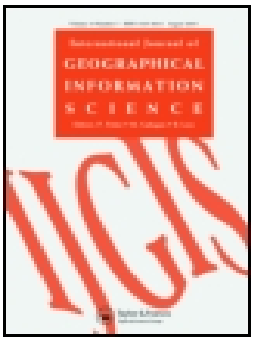

International Journal of Geographical Information Science

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tgis20

Delineating urban job-housing patterns at a parcel scale with street view imagery

Yao Yao, Jiaqi Zhang, Chen Qian, Yu Wang, Shuliang Ren, Zehao Yuan & Qingfeng Guan

INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE
https://doi.org/10.1080/13658816.2021.1895170

RESEARCH ARTICLE

Delineating urban job-housing patterns at a parcel scale with street view imagery

Yao Yao [a,b], Jiaqi Zhang [a], Chen Qian [c], Yu Wang [a], Shuliang Ren [a], Zehao Yuan [d] and Qingfeng Guan [a]

[a]School of Geography and Information Engineering, China University of Geosciences(Wuhan), Wuhan, Hubei Province, China; [b]Alibaba Group, Hangzhou, Zhejiang Province, China; [c]School of Engineering and Applied Science, University of Virginia, Charlottesville, Virginia, USA; [d]State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, Hubei Province, China

ABSTRACT
Empirical data are limited to decipher where people live and work in large cities; however, neighborhood information, such as street view image, is rich and abundant. We construct a ResNet-50-based social detection model to explore the potential relationship between street view images and job-housing attributes. The method extracts street view images of a neighborhood in all eight directions to predict land parcels' job-housing attributes and uses an entropy index to measure the degree of job-housing mixture in Shenzhen as an example. The social-detection model performs well with a low RMSE (0.1094) in identifying job-housing patterns. The eight-direction neighborhood method shows the best support for sufficient neighborhood information from street view images (RMSE = 0.1135) compared with other neighborhood methods. This study demonstrates the feasibility of using street-view images and deep learning to characterize job-housing attributes consistent with findings from urban studies with socioeconomic data; for example, the research finding concurs that Shenzhen has many high job-housing mixtures with very few areas designated for jobs or residences. The proposed method, when applied regularly, can help monitor spatial dynamics of urban job-housing patterns to inform city planning and development.

ARTICLE HISTORY
Received 6 October 2020
Accepted 21 February 2021

KEYWORDS
Urban spatial structure; job-housing; street view images; deep learning; socioeconomic characteristics

1. Introduction

The spatial distribution pattern of job and housing (job-housing) is an indispensable component in studying urban spatial composition (Wang and Murie 2000). Since the reform of China's housing system, many residents have preferred to rent or buy newly built commercial housing (Wang and Murie 1999, Wu 2004), causing increased separation of working and living and unbalanced job-housing spatial relations (Ta *et al*. 2017).

The separation of working and living is conducive to finance and manufacturing (Lucas and Rossi-Hansberg 2002). However, this separation also leads to long commutes, traffic congestion, and increased environmental burdens (Van Acker and Witlox 2011, Zhao *et al*. 2011). The increasingly severe traffic and environmental concerns need to be addressed

CONTACT Qingfeng Guan guanqf@cug.edu.cn

urgently. Therefore, it is crucial to study urban job-housing patterns for optimizing urban spatial structures.

Some scholars have studied spatial job-housing patterns based on census or survey data (Zhou *et al*. 2014b, Li and Liu 2016, Zhou *et al*. 2017). For example, Zhou *et al*. (2014b) used data from a travel survey to analyze the job-housing balance and commuting efficiency in Xi'an city. Li and Liu (2016) investigated the commute and job-housing balance of people with and without household registration in Guangzhou city. However, these studies' spatial scale is limited by the basic units of the census or survey, making it challenging to reflect the urban job-housing spatial distribution details. Furthermore, data collection requires substantial manual labor and a long update cycle. The accuracy of these studies is also limited by data characteristics and cannot be further enhanced.

With the popularity of location-based services (LBS), spatiotemporal data that can characterize people's location and trajectory are emerging. These data provide an opportunity to identify human behavior patterns, which helps describe and understand the structure of urban job-housing from a 'bottom-up' perspective (social perception) (Ahas and Mark 2005, Zheng 2015). Urban smart cards (Zhou and Long 2014, Long and Thill 2015, Huang *et al*. 2018), floating car trajectories (Mao *et al*. 2016, Shao *et al*. 2018), and mobile phone data (Zhang *et al*. 2017, Yang *et al*. 2018, Zhou *et al*. 2018) are widely used in the study of urban job-housing patterns. For example, Zhang *et al*. (2017) analyzed job-housing patterns by identifying people's locations through cellphone data. Long and Thill (2015) coupled smart bus cards and household travel survey data to explore urban job-housing patterns. These studies have improved spatial resolution and enhanced the understanding of dynamic changes in job-housing patterns. However, LBS data have data bias and are challenging to obtain. Additionally, most of these studies focus mainly on human behaviors and activities, which would only allow for the qualitative identification of job-housing locations from a 'bottom-up' perspective.

The building environment can provide static attributes of locations and reveal urban functions (Ye *et al*. 2020). Based on deep learning, Yao *et al*. (2020) extracted the socioeconomic characteristics of job-housing patterns from high-resolution remote sensing images. They obtained mixed urban job-housing patterns by merging building environments from a 'top-down' perspective. This finding demonstrates that two different observations ('bottom-up' and 'top-down') effectively represent urban socioeconomic characteristics (Yao *et al*. 2020). Remote sensing images only reflect the environment from the top-down perspective.

In contrast, street view images can describe every corner of the city from a human perspective and capture more granular information about the building environment (Hu *et al*. 2020, Zhang *et al*. 2019, Zhou *et al*. 2014a). Moreover, compared with LBS spatiotemporal data, street view images are publicly available and easy to access and use. Many scholars have attempted to explore the socioeconomic characteristics and urban spatial structures based on street view images, such as measuring the type of urban land use (Cao *et al*. 2018), estimating environmental quality (Liu *et al*. 2017a), exploring the perception of urban environment sentiment (Naik *et al*. 2014, Li *et al*. 2015, Zhang *et al*. 2018), analyzing the movement patterns of people (Zhang *et al*. 2019), predicting house prices (Law *et al*. 2019), and discovering urban functions (Kang *et al*. 2018, Ye *et al*. 2020).

The above studies show that the building environment reflected by street view images can reveal urban socioeconomic characteristics. The building environment reflected in street view images can also characterize buildings' functions to indicate the working and living attributes (Kang *et al*. 2018). However, no studies have attempted to explore the association between street view images and job-housing attributes due to a lack of data and valid models. This study aims to address the following questions: Can street view images represent potential job-housing attributes? Do street view images of different land parcels reflect the job-housing attributes from the perspective of 'outside-in'? Finally, how do we effectively assess the job-housing attributes within a land parcel based on street view images?

This study introduces a social detection ResNet-50 model to predict job-housing attributes at the land parcel scale based on street view images and anonymous user location data extracted from mobile phone applications. Then, the job-housing patterns at the parcel scale in Shenzhen city are simulated using street view images. Finally, this study quantitatively measures each land parcel's mixing degree and analyzes the urban job-housing spatial distribution.

2. Study area and data

The study area is Shenzhen city (Figure 1(a)). Shenzhen is the most developed city in South China, with a resident population of 13,348,800. The downtown areas of Shenzhen include Futian District, Luohu District, Yantian District, Nanshan District, Bao'an District, Longgang District, Longhua District, Pingshan District, Guangming District, and Dapeng District. The land-use planning parcel is the basic unit of urban cadaster management in China (Wu 2013). There are a total of 6,913 land parcels in Shenzhen (Figure 1(b)) with an average size of approximately 0.11 square kilometers (https://pnr.sz.gov.cn/).

This study's most crucial dataset is anonymous user location data provided by one of the largest Internet companies in China. The location information is acquired from anonymous users granted permission to collect global positioning system (GPS) data while using LBS (Yao *et al*. 2020). The user penetration rate in Shenzhen for this application is more than 95%. This dataset contains approximately 480,000 random anonymous users' location information within three months (2018.3.1–2018.5.30) in 3,003 communities of Shenzhen (distributed throughout the study area). The main working and living areas are estimated based on human activities with a buffer zone set to 300 meters in width (Wan and Lin 2013, 2016). Three types of job-housing attributes, namely, only working (OW), only living (OL), and both working and living (WL), together with the location information, are obtained. The sum of OW, OL, and WL residents within each parcel is not equal to 1 in the original data, as some users do not use the GPS function when using an application. We transform the original dataset to make the sum equal to 1, and Table 1 shows the transformed dataset.

The street view images from Tencent Street View in 2018 are another important dataset used in this paper. Tencent Street View has already covered over 400 cities in China with relatively high-quality and low-bias data in urban environments (Kang *et al*. 2020). Many studies based on Tencent Street View image data have already proved its effectiveness (Dong *et al*. 2018, Wang *et al*. 2019a). The pitch angle

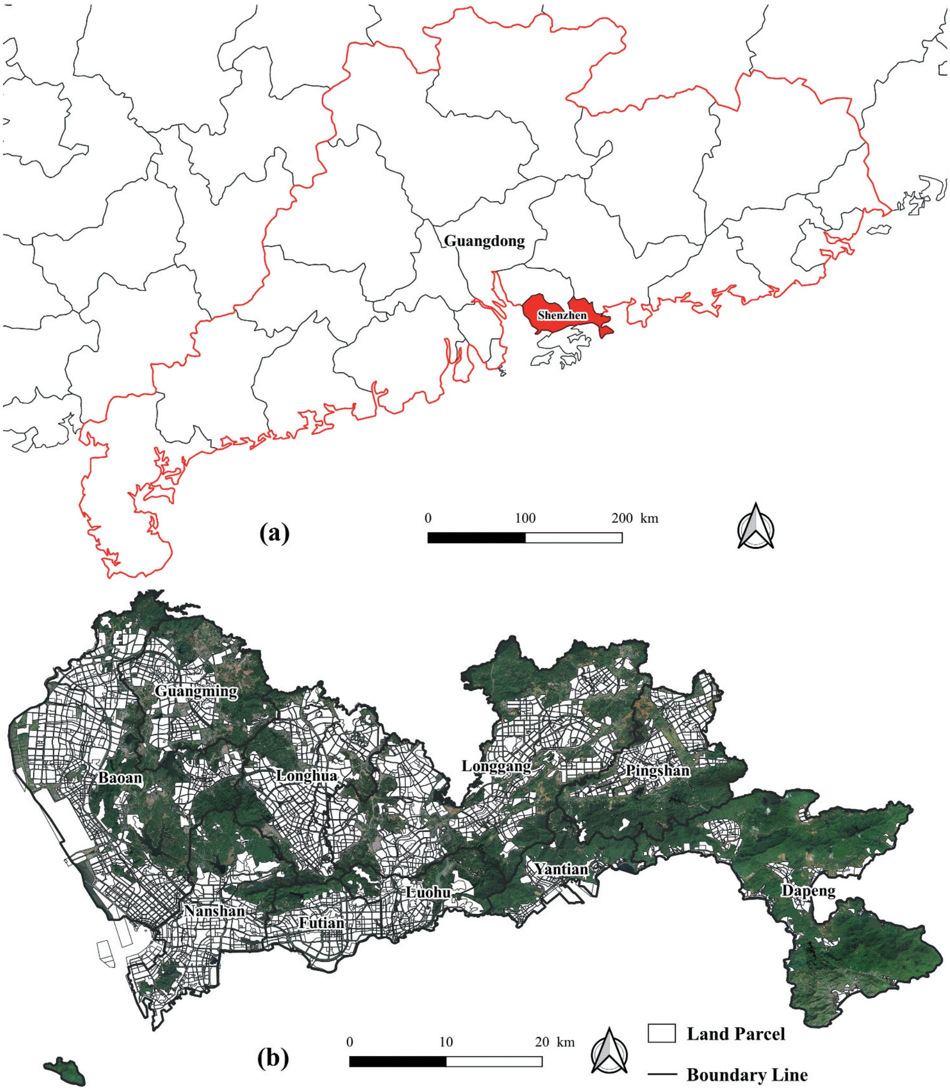

Figure 1. Case study area: (b) Shenzhen, located in (a) Guangdong Province.

Table 1. The anonymous user dataset, including geographic location information and three different types of job-housing attribute percentages. OW: only working, OL: only living, and WL: working and living.

Name of Community	Latitude	Longitude	WL	OL	OW
Haiguan Residential Area	22.5814	114.1202	0.0754	0.8718	0.0528
Lily Star City	22.5983	114.1211	0.3131	0.4611	0.2258
Telford Plaza (Bowery Road)	22.5954	114.1072	0.0271	0.9600	0.0129
City Construction Group Residential Area	22.5811	114.1387	0.1370	0.8065	0.0565
...	...	...	...	...	...
Nanling Garden	22.6021	114.1416	0.1264	0.8456	0.0280

indicates the lens's angle concerning the horizontal reference line from which the image was taken. This study sets the pitch angle of street view images to 0° to ensure that the field of view is approximately equal to a normal human's visual field (Liang *et al*. 2017). Street view images collect location information in association with anonymous user data. As shown in Figure 2, we obtain four shots with the heading directions of 0°, 90°, 180°, and 270° at the location of anonymous user data. This method is used to simulate the perspective of a person standing at the corresponding site. Four street view images were obtained for each community's user data and a total of 11,440 street view images were acquired.

Meanwhile, the street view images are labeled with job-housing attributes based on anonymous user information. Each community's user data corresponds to 4 street view images with the corresponding OW, OL, and WL attribute values assigned to them, respectively. Table 2 shows the datasets' distribution and statistical information within the study area (including the three job-housing attributes after transformation and the street view image data).

It has been shown that FCN (Fully Convolutional Network) models can predict the semantic features of each pixel in an image and obtain segmentation results for various scene elements in an image (e.g. buildings, vehicles, roads) (Long *et al*. 2015). To avoid the effect on the results due to large occlusions such as vegetation and vehicles in the images, we segmented this valid street image dataset using the

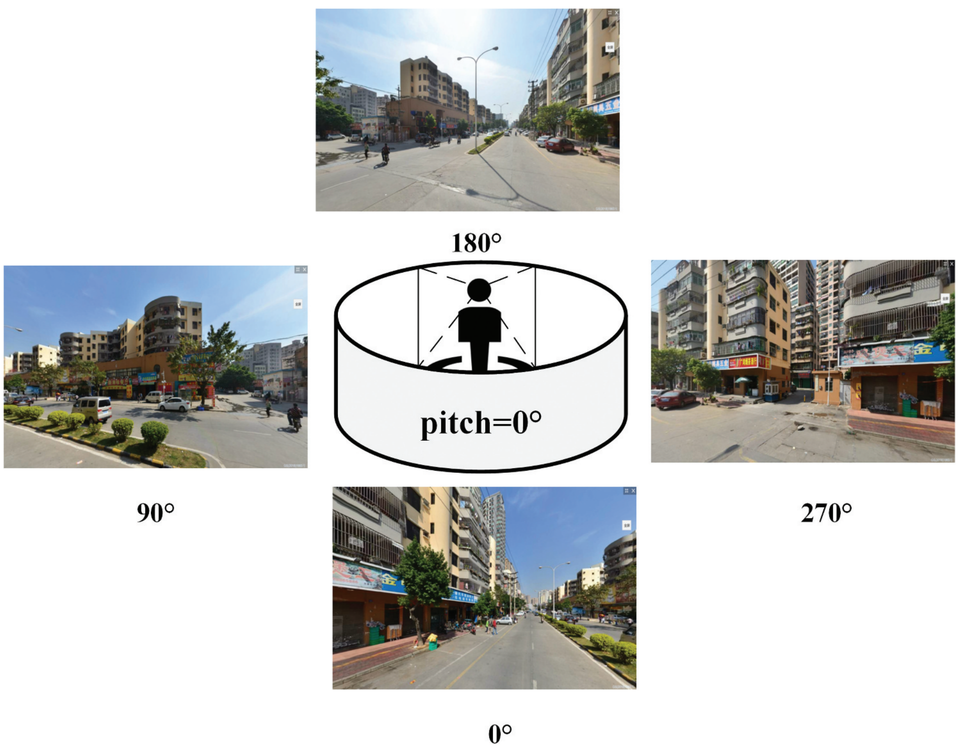

Figure 2. An example of acquiring street view images in a specific location, where the pitch angle of street view is 0° and heading angles of 0°, 90°, 180°, and 270°.

Table 2. Statistics of anonymous user data attributes and street view images in the study area.

District	WL	OL	OW	Number of Street View Images
Futian District	0.0973	0.7016	0.0187	1901
Luohu District	0.0534	0.6176	0.0374	1475
Yantian District	0.1254	0.6578	0.0195	170
Nanshan District	0.0547	0.7814	0.0096	1798
Bao'an District	0.6525	0.7508	0.0047	2056
Longgang District	0.2340	0.3446	0.1687	2072
Longhua District	0.0455	0.7292	0.0100	1384
Pingshan District	0.0220	0.7884	0.0023	208
Guangming District	0.1348	0.6585	0.0299	287
Dapeng District	0.0798	0.7643	0.0076	89

FCN-8s model employed by Yao *et al*. (2019), which was trained under the ADE-20k dataset published by MIT. This FCN-8s element segmentation model has been commonly used to segment street view images and has been widely applied in various fields such as public health (Wang *et al*. 2019b) and emotion perception (Yao *et al*. 2019). Table 3 shows each element's proportion in the street view image dataset, such as buildings, roads, vehicles, etc. Street view images are captured by map service providers using street view vehicles. These street-view collection vehicles are generally high (2 m), which can avoid vehicle occlusion to some extent.

This paper also adopts a flat view (pitch angle of 0) when acquiring street view images. From the segmentation results, we can find that the proportion of building environment elements (including buildings, roads, etc.) is 0.7855, while the proportion of elements that potentially cause occlusion to the environment (such as vehicles, vegetation, etc.) is only 0.0786. This result indicates that the street view dataset is valid.

3. Methodology

Figure 3 shows the workflow of the study, which the following steps can summarize: (1) Associating an anonymous user dataset with street view images and labeling each image with WL, OL, and OW values based on location; (2) building a ResNet-50-based social detection (SD) model to explore the relationship between street view images and three job-housing attributes; (3) obtaining street view images at sample locations to predict job-housing attributes on planning land parcels and presenting the spatial distribution of job-housing attributes in Shenzhen; and (4) evaluating the mixed pattern of different land parcels in Shenzhen and analyzing the characteristics of the job-housing spatial distribution.

Table 3. The statistics results of street view image element segmentation.

Category	Element	Proportion
Building Environment	Buildings, roads, etc	0.7855
Occlusion	Vehicles, vegetation, etc	0.0786
Others	Humans, water bodies, etc	0.1359

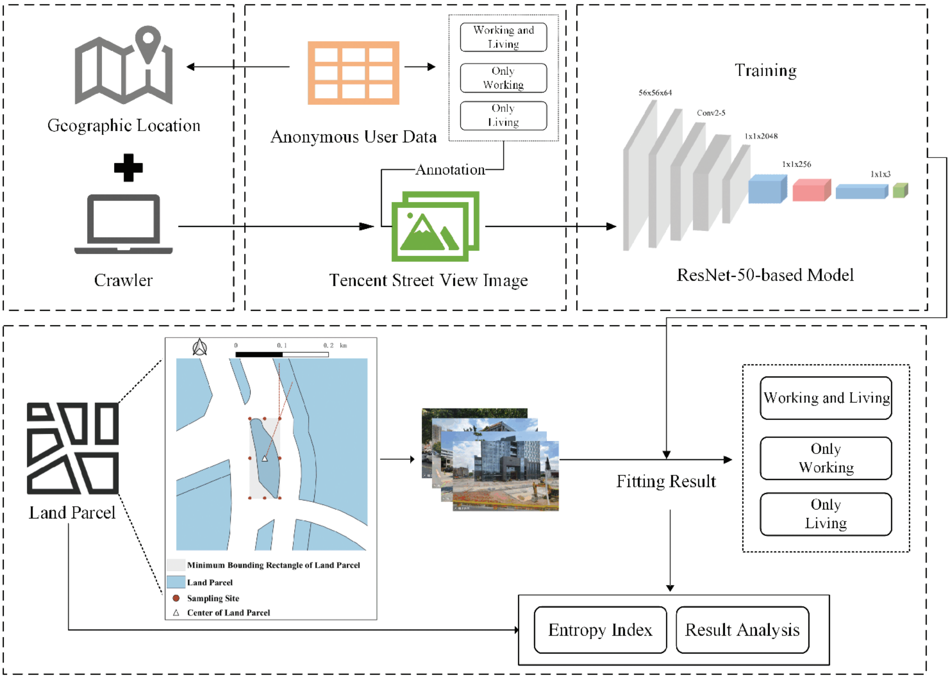

Figure 3. The workflow of job-housing analysis using ResNet-50-based social detection model.

3.1. Job-housing pattern delineation via street view images based on deep learning

3.1.1. ResNet-50-based SD model

Convolutional neural networks (CNNs) are a class of classic deep neural networks. Many CNNs models have emerged since 2012, such as AlexNet (Krizhevsky *et al.* 2012), VGGNet (Simonyan and Zisserman 2014), and GoogLeNet (Szegedy *et al.* 2015). In the network structure of traditional CNNs, the problems of vanishing gradients and gradient explosion often occur as the network layer deepens. ResNet, proposed by He *et al.* (2016), solves this problem by adding identity mapping in the network.

ResNet-50 is an easy-to-optimize, less computationally burdensome deep residual network consisting of 49 convolutional layers and one fully-connected layer. The model proposed in this paper uses the feature extraction part of ResNet-50. We have added batch normalization to the last fully connected layer to speed up the model's convergence. Batch normalization internally saves the exponential moving average of the mean and variance of each batch of data read during the training process, allowing the adaptive standardization of feature data even if the mean and variance change over time during training (Ioffe and Szegedy 2015). Dropout is employed to avoid overfitting (Hinton *et al.* 2012). To simultaneously mine the relationships between the street view images and the three types of job-housing attributes, SoftMax, responsible for the multiclassification task, is replaced with a 3-dimensional fully connected layer. Then, we use the sigmoid activation function to map the results between 0 and 1. Generally, deep learning models with sigmoid activation functions use cross-entropy as the loss function, but such models' primary purpose is the classification (Druzhkov and Kustikova 2016, Xin and Wang 2019). Traditional regression models generally use L2 loss as a loss function (Yang *et al*. 2019). While the model proposed in this paper uses the SmoothL1Loss function, it can reduce the model's sensitivity to outliers and anomalies, making the model converge more smoothly (Girshick 2015).

Figure 4 shows the structure of the model (ResNet-50-based SD model). The topological features are extracted by inputting a street view image to obtain the scores of three types of job-housing attributes.

3.1.2. Prediction of job-housing attributes at the land parcel scale

To obtain multi azimuth and comprehensive information for each land parcel, we sample and extract street view images from the parcel to predict its job-housing attribute. The method is as follows: For each land parcel, based on the latitude and longitude, the eight-direction neighborhood of the least bounded rectangle is formed as the sampling site. We calculate the azimuthal angle between the sampling site location and the parcel center to ensure that sufficient scene information of land parcels could be obtained. The heading angle of the street view image at this location is then calculated and determined following Ye *et al*. (2019) study. Because the street view images of some sampling locations are not fully covered, the nearest location within a radius of 20 meters is used to replace sampling locations without street view images.

Figure 5 shows the sampling sites for a land parcel and the corresponding street view images, where α is an example of the heading angle of the street view image at the sampling site.

For each land parcel, the corresponding street view images are input into the trained model, and the job-housing attributes at the land parcel scale are obtained.

3.1.3. Performance assessment

In econometrics, socioeconomics, and other related fields, R^2 or Adjusted R^2 is not generally used as an evaluation indicator (Moksony 1990), Pearson R and root means

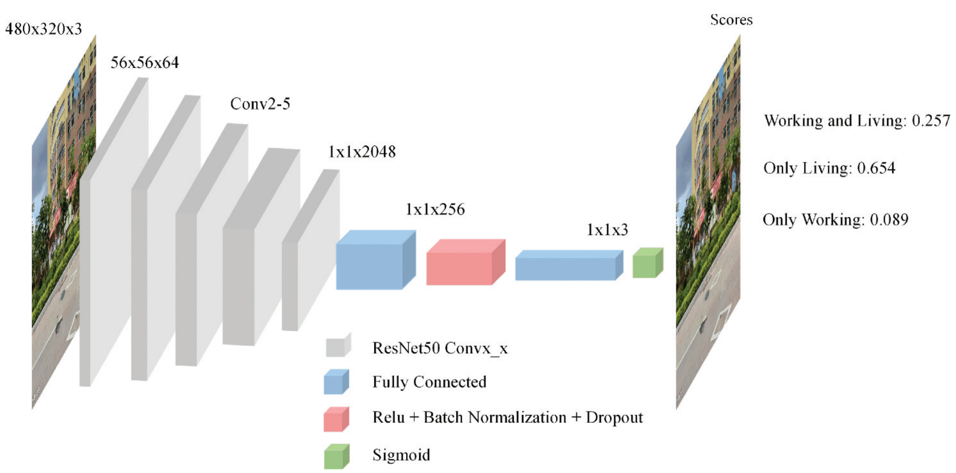

Figure 4. The proposed ResNet-50-based SD model structure, which can obtain the perception score of three types of job-housing attributes by inputting a street view image.

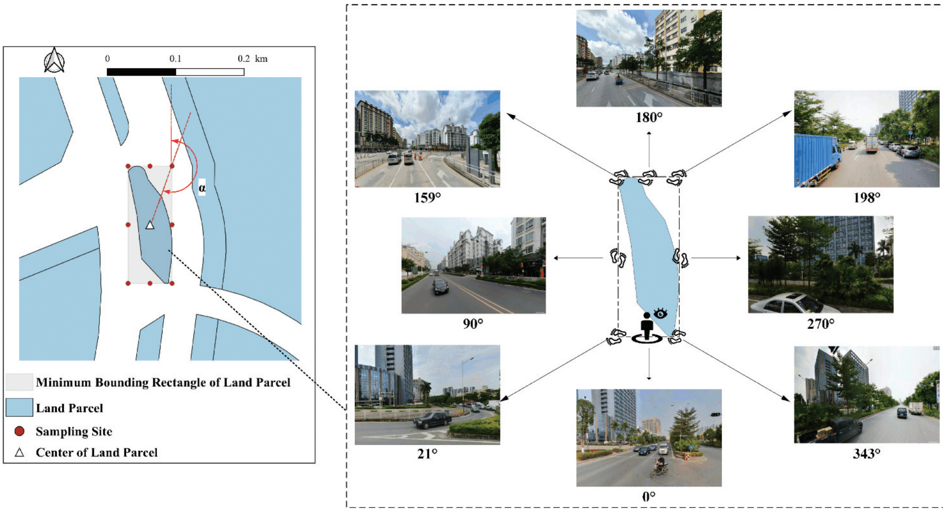

Figure 5. An example of sampling sites of a land parcel and its surrounding street view images.

square error (RMSE) are considered as valid evaluation indicators (Günay *et al.* 2016). Therefore, in this paper, RMSE and mean absolute error (MAE) are employed to reflect the model's performance. Pearson R is employed to measure the correlation between the actual and predicted values of the model. The formulas are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}\left|(y_i - \hat{y}_i)\right| \tag{2}$$

where y_i and $\hat{y}_i$ are the actual and predicted values of the job-housing attribute for the i_{th} street view image, respectively, and m is the total number of samples.

The planning land parcels that contain the raw data samples are identified for evaluation. The average of the parcel's true values is used as the actual value, and the average of the fitting values within the parcel is used as the predicted value. We present the spatial distribution of RMSE to show the model's performance at the land parcel scale.

3.2. Analysis of the job-housing mixed degree

The entropy index (EI) (Turner *et al.* 2001, Plexida *et al.* 2014) describes the mixing degree of job-housing spatial pattern quantitatively. The entropy index EI_j of the j_{th} land parcel is calculated by Equation (3):

$$EI_j = -\frac{\sum_{i=1}^{n} p_{ij} \times \ln p_{ij}}{\ln n} \tag{3}$$

where p_{ij} represents the i_{th} job-housing attribute in the j_{th} parcel, and n is the total number of job-housing attributes in the j_{th} parcel. The value of n in this paper is 3. EI takes a value between 0 and 1.

4. Results

4.1. Performance evaluation and error assessment

4.1.1. Fitting performance of the ResNet-50-based SD model

A total of 11,440 street view images and their corresponding three types of job-housing attributes were obtained based on the anonymous user dataset's geographic locations. This dataset was randomly divided into two parts: 80% was used as the training dataset, and 20% was used as the testing dataset. Table 4 shows the results of the performance evaluation on the testing dataset.

The Pearson R between the model's predicted and actual values for the three types of job-housing attributes is 0.6275, 0.6885, and 0.4914, respectively, indicating its plausibility. The fitting model's overall performance suggests that this model can effectively explore the relationship between street view images and job-housing attributes without extracting intermediate features. The fitting results show that the RMSE of OL is higher than that of WL and OW. On the one hand, among the three types of job-housing attributes, the proportion of OL attributes is higher than the remaining two attributes, which may also cause higher errors; on the other hand, buildings with a single function are more comfortable to identify, but some office buildings and office areas are similar to residential communities in appearance and will cause confusions. These two reasons make the deviation of identifying the proportion of OL attributes larger than WL and OW attributes.

The actual and predicted values of the job-housing attributes for 1,079 planning land parcels were obtained based on the anonymous user data and the fitting model. Figure 6 shows the RMSE spatial distribution of planning land parcels and the three typical regions.

The fitting model yielded good overall results regarding the planning land parcels, with only a few regions had large errors. Three typical regions were selected for further validation. Figure 6(a) represents typical urban villages near Hongli village and Huaxin village in Futian District. The RMSE result is 0.371, which is much higher than the overall error value. It is difficult for street view images to reflect urban villages' internal job-housing attributes due to the dilapidated surrounding environment and complex internal functions (Hao *et al.* 2012). Figure 6(b) is a typical university area with a high percentage of greenery, which can easily overshadow buildings and lead to large errors. Figure 6(c) is located near Huafu Industrial Park in Longhua District, a typical working and living area with a concentration of industrial parks and supporting residential areas. The low RMSE (0.036) shows that the fitting model predicts well on traditional working and living areas.

Table 4. The performance assessment results of the ResNet-50-based SD model.

Performance Evaluation Index	RMSE	MAE
WL	0.0982	0.0740
OL	0.1533	0.1108
OW	0.0766	0.0416
Average	0.1094	0.0755

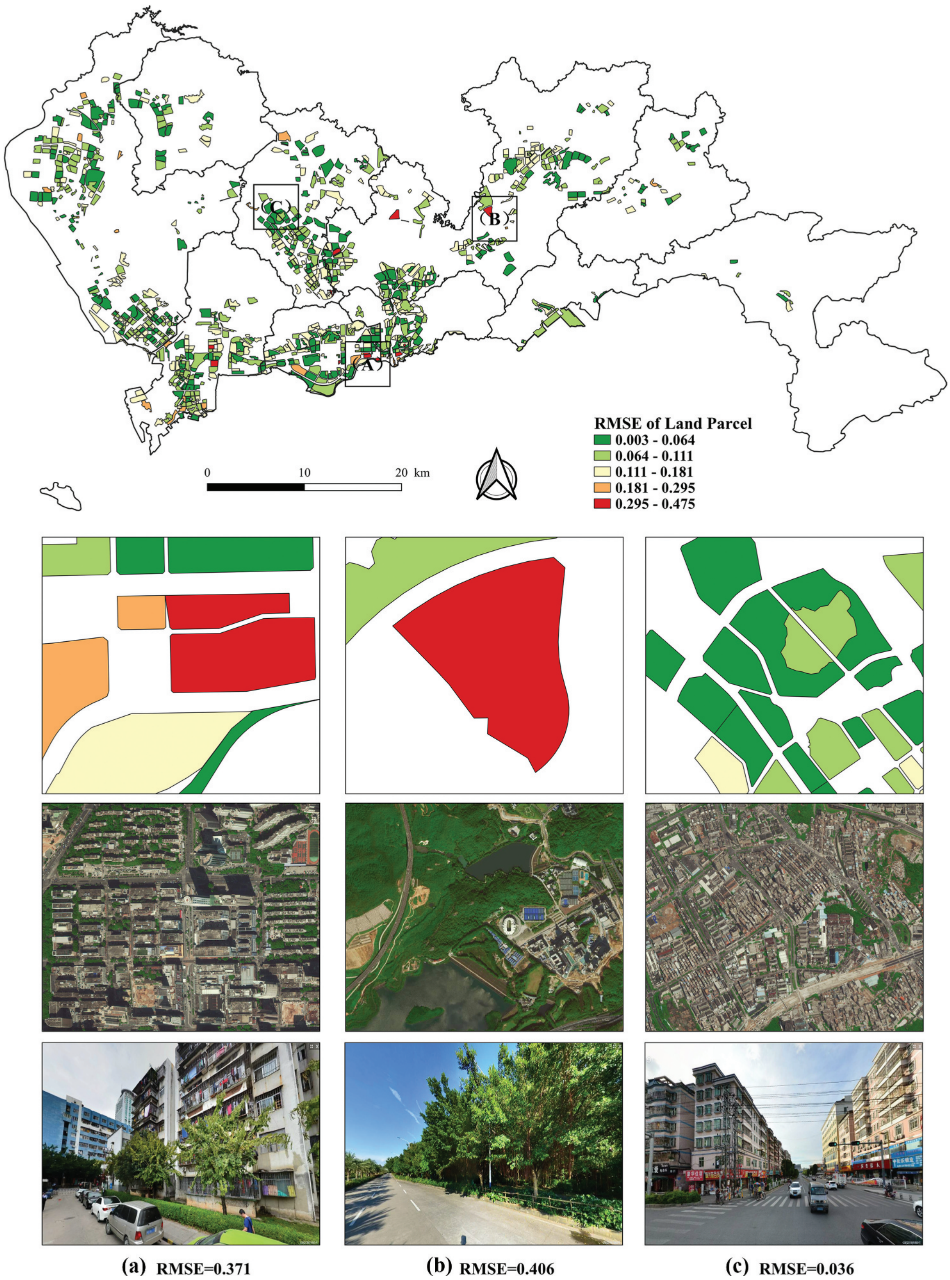

Figure 6. RMSE spatial distribution of the proposed model: (a) Hongli village and Huaxin village, Futian district; (b) Shenzhen MSU-BIT university, Longgang district; (c) Huafu industrial park, Longhua district.

4.1.2. Comparison among different prediction methods of land parcels

We conducted two sets of comparative experiments with a random one-direction neighborhood method and a four-direction neighborhood method. These experiments are compared with the method used in this paper, named the eight-direction neighborhood method. Table 5 shows a comparison of the three prediction methods' performance according to land parcels' actual values.

The eight-direction neighborhood method achieved the best overall results related to the urban complexity (Rapoport and Hawkes 1970, Salat *et al*. 2010). Urban land parcels often have mixed functions with the process of urbanization (Tu *et al*. 2017, Zhang et al 2021). A mixed pattern of land parcel functions is difficult to reflect using only one street view image. The eight-direction neighborhood method allows us to better extract and describe land parcels' job-housing attributes from the human perspective.

4.1.3. Comparison with 'top-down' perspective

Based on deep learning models, Yao *et al*. (2020) explore urban socioeconomic characteristics from remote sensing images and conducted experiments in Wuhan, China. The results show that it is practical to extract socioeconomic factors based on remote sensing images. We conducted a similar investigation in the study area based on remote sensing images. Table 6 shows the results.

As shown in Tables 4–Tables 6, compared to the 'top-down' model, the model based on street view images achieves better performance. Figure 7 shows the spatial distribution of errors for the 'top-down' model based on remote sensing images. To further examine the consistency and difference between the two models, the same three case study areas in Figure 6 are selected for analysis.

The two models are consistent in identifying urban socioeconomic characteristics, especially in job-housing attributes. Consistent with Figure 6(a,b) the two regions of Figure 7(a,b) also exhibit large RMSE errors. The reason is that street view images, and remote sensing images represent the building environments from different perspectives. Both models have a large error in reflecting urban job-housing attributes in urban villages and abundant vegetation cover areas. However, the 'top-down' model based on remote sensing images have relatively higher errors due to image quality issues, such as missing information (Ng *et al*. 2017) and inaccurate image information caused by building shadows (Liu *et al*. 2020). The spectral and spatial heterogeneity is also a challenge in urban remote

Table 5. Performance comparison among different prediction methods of land parcels.

RMSE	1-Direction	4-Direction	8-Direction
WL	0.0714	0.0919	0.0921
OL	0.6451	0.1632	0.1590
OW	0.7544	0.0882	0.0894
Average	0.4903	0.1144	0.1135

Table 6. The performance assessment results using remote sensing images.

Performance Evaluation Index	RMSE	MAE
WL	0.4577	0.2762
OL	0.3686	0.2607
OW	0.0631	0.0354
Average	0.2965	0.1908

Figure 7. RMSE spatial distribution of the 'top-down' perspective mode: (a) Hongli village and Huaxin village, Futian district; (b) Shenzhen MSU-BIT university, Longgang district; (c) Huafu industrial park, Longhua district.

sensing (Gong *et al.* 2020). Street view images achieve better results in reflecting job-housing attributes than remote sensing images because of the ability to reflect the building environment more comprehensively from the human perspective (Kang *et al.* 2020).

4.2. Job-housing mixed pattern delineation

4.2.1. Spatial distribution of the job-housing pattern

Based on the fitting model and the prediction method, a total of 40,070 street view images of 6,100 land parcels were obtained. The spatial distributions of all three types of job-housing attributes at the planning parcel scale in Shenzhen, China, are shown in Figure 8, where the red, green and blue bands represent WL, OL and, OW, respectively.

Land parcels with OL attribute account for more areas in Shenzhen than other attributes, scattered and mostly around land parcels with OW attribute. Each administrative district has a specific concentration of OW attributes. The gradual weakening of OW attribute and gradual strengthening of OL attribute along the work concentration area's periphery are consistent with previous studies (Yang *et al*. 2018, Yuxuan and Nan 2020). Shenzhen's primary industry is the electronic information manufacturing industry, which develops rapidly with emerging large industrial parks for information technology, high-end equipment manufacturing, and biomedicine.

Simultaneously, as a national economical center, Shenzhen's financial industry is slowly growing into its strategic leading industry. Large industrial parks generally provide living spaces for workers, and finance companies are located in busy downtown areas for daily commuters' convenience. These industries provide a large number of jobs for Shenzhen residents. Areas that emphasize OW attributes, such as shopping malls and exhibition halls, are not dominant in Shenzhen. As a result, WL attribute predominates in the parcels with working attributes, while OW attribute encompasses a relatively small proportion.

4.2.2. Relationship between street view images and the job-housing pattern

As shown in Figure 9, several street view images of typical communities were selected for each type of job-housing attribute to verify the reliability. Figure 9(a) has a higher percentage of WL areas, typical industrial parks with internal staff housing, or commercial and residential office buildings. Therefore, there is a certain mix of working and living and a higher percentage of WL. Figure 9(b) is a typical OL-dominated community, with OL ratios all above 0.8. Although there are some neighborhood shops, living is still the primary function. Figure 9(c) is a typical workplace, including integrated markets, exhibition halls, and industrial areas. In contrast to Figure 9(a), the industrial areas in Figure 9(c) are purely industrial clusters and do not have functional commercial areas or employee dormitories to meet employee living needs.

4.3. Spatial distribution of mixed job-housing patterns

Figure 10 shows the distribution of the EI at the planning parcel scale in Shenzhen. The center of each district has a higher mixed degree of job-housing than the periphery. Furthermore, as China's first special economic zone, Shenzhen has been developed to build polycentric urban development structures (Tang *et al*. 2018). Therefore, few areas in Shenzhen present a single job-housing attribute. The government's strict control is a useful guide for optimizing urban spatial structure, making the urban function compact and homogeneous (Deng *et al*. 2018). Shenzhen's urbanization process has promoted mixed land uses (Ren *et al*. 2020). Besides, spatial autocorrelation analysis was introduced to the EI, yielding a global Moran's I of 0.4390, corresponding to a p-value < 0.001 and a z-score of 16.6514. A p-value of less than 0.01 indicates statistical significance. The z-score is greater than the corresponding critical value of 2.58, meaning that the EI at the

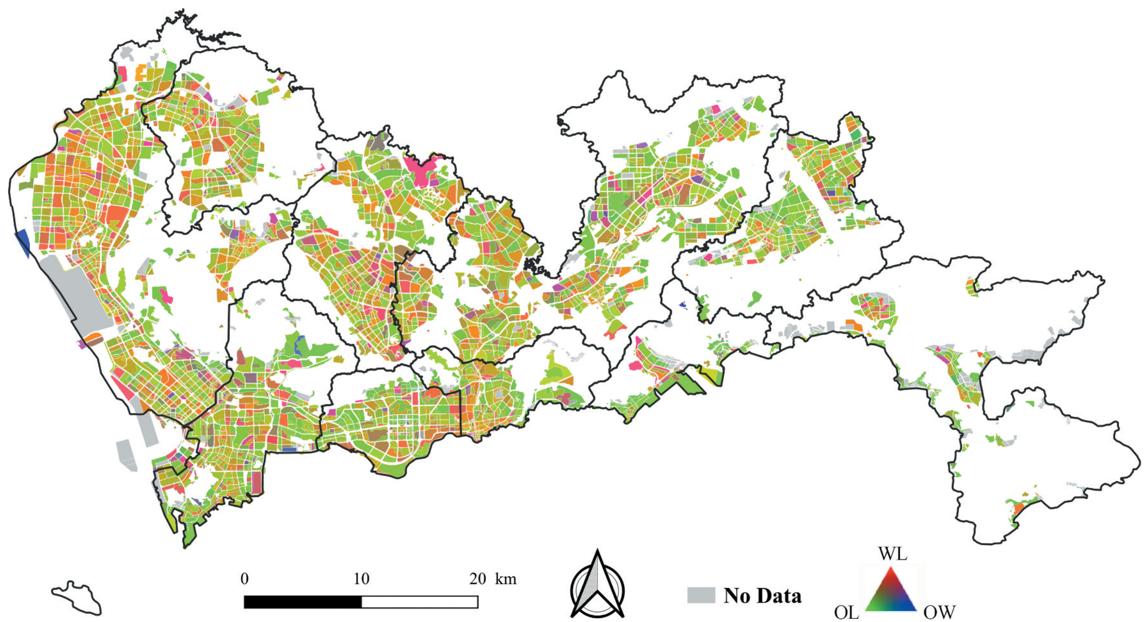

Figure 8. Spatial distribution of the job-housing patterns in Shenzhen, where the red, green and blue bands represent WL, OL and OW, respectively.

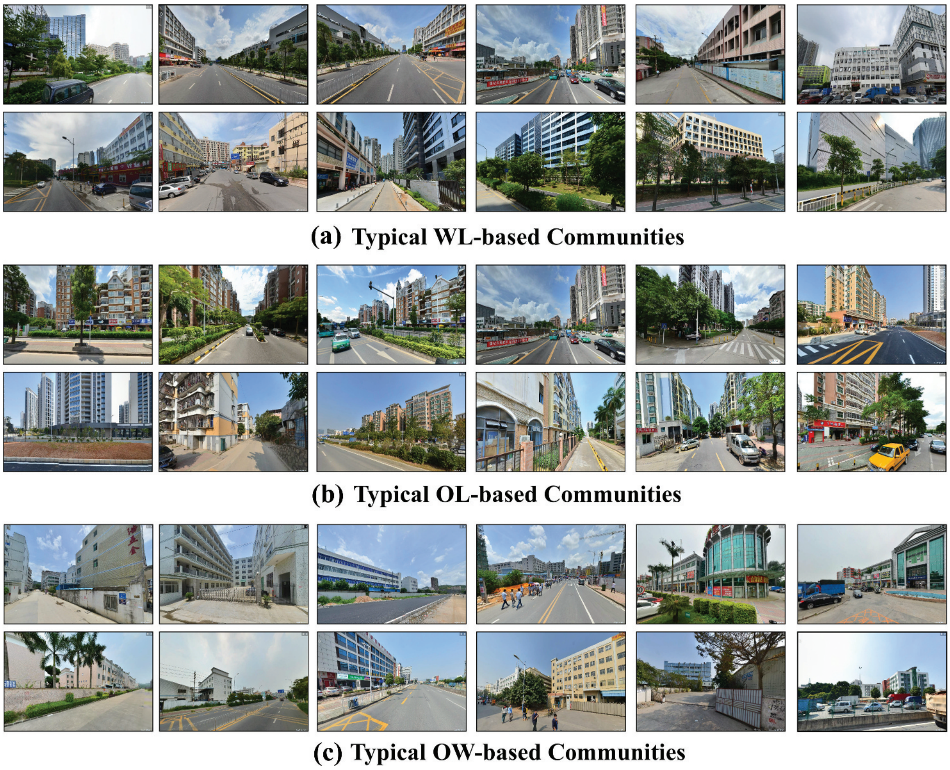

Figure 9. The typical areas of three 'job-housing' patterns in Shenzhen: (a) typical WL-based communities, (b) typical OL-based communities, and (c) typical OW-based communities.

scale of Shenzhen's planning parcels shows clustering and positive spatial correlation. Most of the land parcels with high mixed entropy are surrounded by high mixed entropy areas, consistent with the analysis of clustered working areas in Shenzhen.

We selected a specific mixed area in Bao'an District to analyze the mixed job-housing patterns in Shenzhen, which contains independent working and living places. The Huifu Office Building and Tongfu Industrial Park in Figure 10(a2,a3) serve the working function. The Yukang Hua Ting residential community in Figure 10(a1) serves the living function. Both working and living functions can be reflected in this typical mixed-function parcel, matching EI results (0.7068). The above analysis shows that the proposed model can effectively and reasonably explore the relationship between the street environment and job-housing attributes at the land parcel scale, quantifying the mixed urban patterns.

5. Discussion

Lack of proper models and data has affected the effectiveness of the studies on analyzing the spatial distribution of urban job-housing patterns from human activities. Existing studies' spatial scales are relatively coarse and cannot reflect the job-housing pattern at a land parcel scale. This study employed ResNet-50, which can reveal the urban job-housing patterns through human vision using the eight-

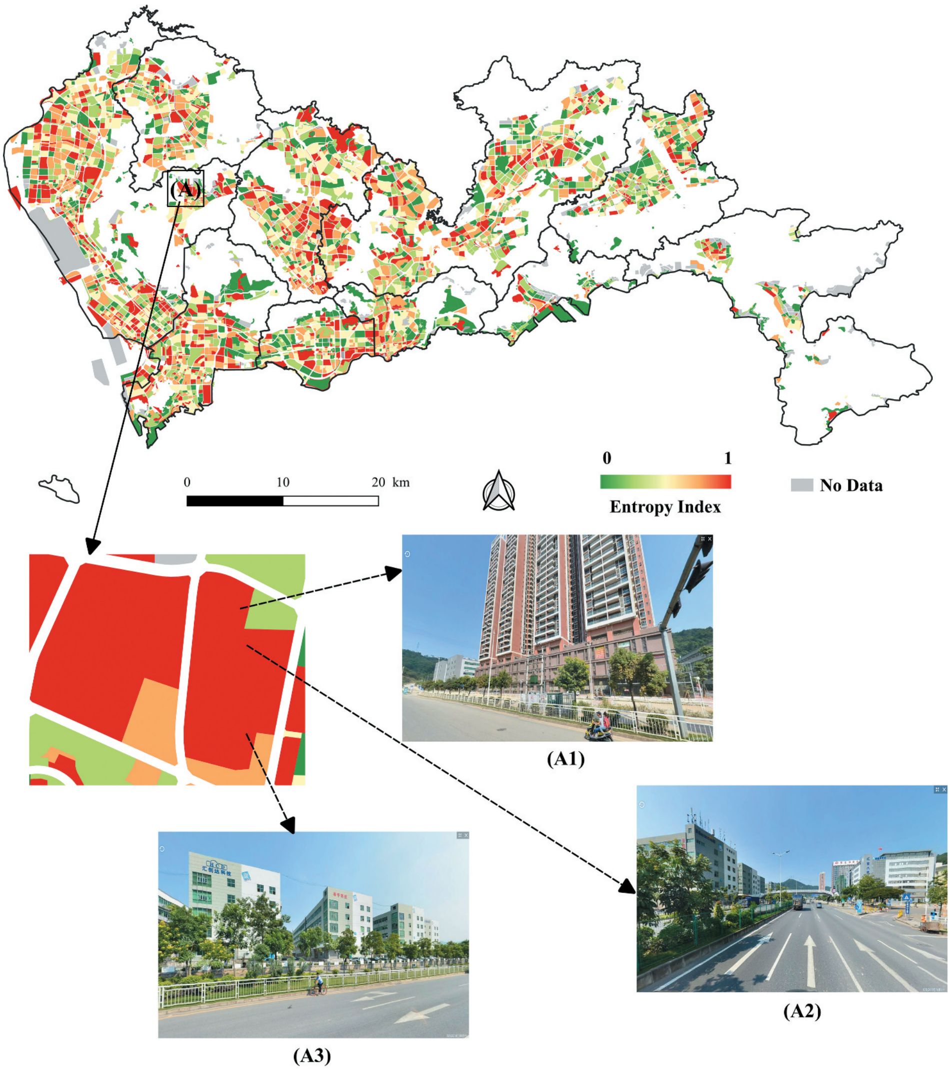

Figure 10. The mixed job-housing distributions results in Shenzhen: (a) Aiqun road, Bao'an district (WL = 0.1746, OL = 0.7210; OW = 0.1044, EI = 0.7068), including (a1) Yukang Hua Ting residential community, (a2) Huifu Building, (a3) Tongfu industrial park.

direction neighborhood prediction method for land parcels. The environment's topological features are extracted by inputting street view images around the land parcel, and the proportions of the three job-housing attributes are fitted. The ResNet-50-based social detection model performs well through the SmoothL1Loss function (RMSE = 0.1094, MAE = 0.0755). Besides, the eight-direction neighborhood prediction method best supports obtaining sufficient information from street view images (RMSE = 0.1135) compared to other neighborhood prediction methods. The street view images around a parcel provide data to describe the parcel's characteristics and eliminate the one-sidedness of a single or random street view.

The experiments were conducted in Shenzhen, and findings revealed that the prediction errors are more considerable in urban villages and universities due to the complexity of their functions and compositions. In schools and some areas with a high proportion of greenery, vegetation can easily block the environment and obstruct the street view images from reflecting internal job-housing attributes. The spatial structure of the mixed job-housing pattern in Shenzhen shows a multi-center layout. Work-gathering areas are typically distributed around the center with a significant mix of job-housing attributes. Additionally, few regions in Shenzhen present a single job-housing attribute, and the urban structure is compact and homogeneous, indicating positive development progress led by the Shenzhen municipal government.

This study revealed that street view images' semantic features could be mined and used to assess socioeconomic characteristics like job-housing attributes. We found that POI data (Yao *et al*. 2017), remote sensing imagery (Yao *et al*. 2020), and street view imagery effectively identified the socioeconomic characteristics of potential job-housing attributes within the land parcels. This suggests that different modes of observation, namely, 'bottom-up' (Yu 2016), 'top-down' (Liu *et al*. 2017a), and 'outside-in,' are consistent in identifying and analyzing urban socioeconomic characteristics. Furthermore, although both street view and remote sensing images can reflect the building environment, the 'outside-in' model based on street view is better than the 'top-down' model based on remote sensing images. The end-to-end multioutput social detection model proposed in this paper can mine the correlations between street scenes and socioeconomic characteristics like job-housing attributes. This social detection model can also be applied to economic conditions, consumption levels, and various other socioeconomic characteristics.

In recent years, China has been actively promoting 'City Health Check' projects to monitor urban socioeconomic characteristics, mainly in questionnaires or on-site surveys (Roberts 2013, Carmona 2019). This study proposes a time-saving and non-laborious method to achieve the same goal. The easily accessible street view images can provide urban planners with fast and feasible solutions for understanding urban socioeconomic characteristics, such as job-housing balance estimation. This study can help urban planners understand the effects of government regulations on urban development and construction.

However, there are still some limitations in this study. Some street view images are not available at some locations. The street view images used in this paper (collected since 2018) are collected by map service providers and cannot be updated in real-time. Although Shenzhen's urban development is changing mainly by expanding to the outside (Fei and Zhao 2019), street view changes are still occurring within its city from 2018 to the present. Therefore, future studies would focus on acquiring time-series street view image data through video collection, which could improve the dataset's comprehensiveness and real-time performance. Referred to previous studies (Lu 2019, Wang *et al*. 2019b and 2019c), this study collected the street view image dataset by using 0°, 90°, 180°, and 270° to achieve full coverage of the viewpoint around the land parcel. Whether the roads' varying orientation will potentially affect the street view coverage is an issue to be further considered. Future studies would focus on obtaining topological features from street networks (Ye *et al*. 2019) and discussing the influence of road orientation on street view coverage as an optimization direction.

urthermore, the proposed model only focuses on a single street view image and only provides preliminary evidence of the correlations between street view images and job-housing attributes. Future studies should consider utilizing multiple street views as input to refine the models and improve performance. Besides, this paper only conducted experiments in Shenzhen, China. However, spatial heterogeneity exists among different cities (Deng *et al*. 2020). Combining this paper's methods and knowledge transfer method on large-scale datasets is a question to be considered in future research. Besides, semantic segmentation of street view images (Yao *et al*. 2019) could be performed in the future to study the elements of street view images that have a strong influence on the relationship between job-housing attributes, making the results interpretable. Finally, this study only examines the job-housing attributes but does not address other socioeconomic characteristics. The potential correlation between street view images and other complex socioeconomic factors can be considered in the future by using the multioutput social detection model.

6. Conclusion

A ResNet-50-based social detection model was built to explore the relationship between the street view images and the job-housing attributes in this study. The proposed method was validated in Shenzhen city with a low RMSE (0.1094). Besides, we find that Shenzhen city's functional structure is compact with few areas exhibiting a single attribute, indicating that governmental planning is a useful guide for optimizing urban spatial structures. Further development should focus on promoting urban villages' transformation to optimize polycentric urban development structures. This study established that the potential job-housing attributes can be obtained from the street view images' building environment through deep learning techniques. The surrounding street views can effectively and reasonably reflect the internal job-housing characteristics from the 'outside-in' perspective, which is consistent with the 'bottom-up' and 'top-down' modes in analyzing urban socioeconomic characteristics. In comparison, we found that this street-view image-based model performs better than the remote-sensing-image-based model, especially in reflecting job-housing attributes. This study provides an effective and convenient method to reflect the mixed urban job-housing spatial distribution pattern and provides a new perspective for monitoring urban socioeconomic characteristics. Our study could help urban planners better understand the urban job-housing patterns at the land parcel scale, providing references for 'City Health Check' and urban planning.

Acknowledgments

Thanks to the editor and three anonymous reviewers for their careful work and detailed suggestions. We are also grateful to Starbucks, located on the first floor of the New Development International Center Building in Optics Valley, Wuhan, for providing a place to work and discuss the study and the patience of its staff.

Data availability statement

The data and codes that support the findings of the present study are available on Figshare at https://doi.org/10.6084/m9.figshare.12960212.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Key Research and Development Program of China [2019YFB2102903], the National Natural Science Foundation of China [41801306, 41671408].

Notes on contributors

Yao Yao is currently an Associate Professor in the School of Geography and Information Engineering at China University of Geosciences (Wuhan). His research focuses on geospatial big data mining and urban computing.

Jiaqi Zhang is a master candidate in the School of Geography and Information Engineering at China University of Geosciences (Wuhan). Her research focuses on street-view analysis, spatial analysis and urban computing.

Chen Qian is a Ph.D. candidate in the School of Engineering and Applied Science at the University of Virginia. His research focuses on data mining and geographical information science.

Yu Wang is an undergraduate student in the School of Geography and Information Engineering at China University of Geosciences (Wuhan). His major is software engineering.

Shuliang Ren is a master candidate in the School of Geography and Information Engineering at China University of Geosciences (Wuhan). His research focuses on data mining and social computing.

Zehao Yuan is a Ph.D. candidate in the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing at Wuhan University. His research focuses on trajectory data mining and spatial analysis.

Qingfeng Guan is a Professor in the School of Geography and Information Engineering at China University of Geosciences (Wuhan). His research focuses on high-performance spatial intelligent computing and urban modeling.

ORCID

Yao Yao http://orcid.org/0000-0002-2830-0377
Chen Qian http://orcid.org/0000-0002-4028-4752
Qingfeng Guan http://orcid.org/0000-0002-7392-3709

References

Ahas, R. and Mark, U.L., 2005. Location based services—new challenges for planning and public administration? *Futures*, 37 (6), 547–561. doi:10.1016/j.futures.2004.10.012.

Cao, R., *et al*., 2018. Integrating aerial and street view images for urban land use classification. *Remote Sensing*, 10 (10), 1553. doi:10.3390/rs10101553.

Carmona, M., 2019. Place value: place quality and its impact on health, social, economic and environmental outcomes. *Journal of Urban Design*, 24 (1), 1–48. doi:10.1080/13574809.2018.1472523.

Deng, X., et al., 2018. Internal differentiation within the rural migrant population from the sustainable urban development perspective: Evidence from China. *Sustainability*,*10*(12), 4839.

Deng, Y., *et al*., 2020. Geographical transformations of urban sprawl: exploring the spatial heterogeneity across cities in China 1992–2015. *Cities*, 105, 102415. doi:10.1016/j.cities.2019.102415.

Dong, R., *et al*., 2018. How green are the streets within the sixth ring road of Beijing? An analysis based on tencent street view pictures and the green view index. *International Journal of Environmental Research and Public Health*, 15 (7), 1367. doi:10.3390/ijerph15071367.

Druzhkov, P.N. and Kustikova, V.D., 2016. A survey of deep learning methods and software tools for image classification and object detection. *Pattern Recognition and Image Analysis*, 26 (1), 9–15. doi:10.1134/S1054661816010065.

Fei, W. and Zhao, S., 2019. Urban land expansion in China's six megacities from 1978 to 2015. *Science of the Total Environment*, 664, 60–71. doi:10.1016/j.scitotenv.2019.02.008.

Girshick, R., 2015. Fast R-CNN. *In*: *Proceedings of the IEEE International Conference on Computer Vision*, 1440–1448. Hawaii, United States.

Gong, J., *et al*., 2020. Advances in urban information extraction from high-resolution remote sensing imagery. *Science China Earth Sciences*, 2020, 1–13.

Günay, M. E. (2016). Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey. *Energy Policy*,*90*, 92–101.

Hao, P., *et al*., 2012. The land-use diversity in urban villages in Shenzhen. *Environment and Planning A*, 44 (11), 2742–2764. doi:10.1068/a44696.

He, K., *et al*., 2016. Deep residual learning for image recognition. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778. Las Vegas, United States.

Hinton, G.E., *et al*., 2012. *Improving neural networks by preventing co-adaptation of feature detectors*, arXiv preprint arXiv:1207.0580.

Hu, C., *et al*., 2020. Classification and mapping of urban Canyon geometry using Google street view images and deep multitask learning. *Building and Environment*, 167, 106421–106424. doi:10.1016/j.buildenv.2019.106424.

Huang, J., *et al*., 2018. Tracking job and housing dynamics with smartcard data. *Proceedings of the National Academy of Sciences*, 115 (50), 12710–12715. doi:10.1073/pnas.1815928115.

Ioffe, S. and Szegedy, C., 2015. *Batch normalization: accelerating deep network training by reducing internal covariate shift*, arXiv preprint arXiv:1502.03167.

Kang, J., *et al*., 2018. Building instance classification using street view images. *ISPRS Journal of Photogrammetry and Remote Sensing*, 145, 44–59. doi:10.1016/j.isprsjprs.2018.02.006.

Kang, Y., *et al*., 2020. A review of urban physical environment sensing using street view imagery in public health studies. *Annals of GIS*, 26 (3), 261–275. doi:10.1080/19475683.2020.1791954.

Krizhevsky, A., Sutskever, I., and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. *In*: *Advances in neural information processing systems*, 1097–1105.

Law, S., *et al*., 2019. Take a look around: using street view and satellite images to estimate house prices. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10 (5), 1–19. doi:10.1145/3342240.

Li, S. and Liu, Y., 2016. The jobs-housing relationship and commuting in Guangzhou, China: Hukou and dual structure. *Journal of Transport Geography*, 54, 286–294. doi:10.1016/j.jtrangeo.2016.06.014

Li, X., Zhang, C., and Li, W., 2015. Does the visibility of greenery increase perceived safety in urban areas? Evidence from the place Pulse 1.0 dataset. *ISPRS International Journal of Geo-Information*, 4 (3), 1166–1183. doi:10.3390/ijgi4031166.

Liang, C., *et al*., 2017. Use of tencent street view imagery for visual perception of streets. *ISPRS International Journal of Geo-Information*, 6 (9), 265–284. doi:10.3390/ijgi6090265.

Liu, L., *et al*., 2017a. A machine learning-based method for the large-scale evaluation of the qualities of the urban environment. *Computers, Environment and Urban Systems*, 65, 113–125. doi:10.1016/j.compenvurbsys.2017.06.003.

Liu, X., *et al*., 2017b. Classifying urban land use by integrating remote sensing and social media data. *International Journal of Geographical Information Science*, 31 (8), 1675–1696. doi:10.1080/13658816.2017.1324976.

Liu, Y., *et al*., 2020. Object-oriented detection of building shadow in TripleSat-2 remote sensing imagery. *Journal of Applied Remote Sensing*, 14 (3), 036508. doi:10.1117/1.JRS.14.036508.

Long, J., *et al*., 2015. Fully convolutional networks for semantic segmentation. *In*: *Proceedings of the IEEE conference on computer vision and pattern recognition*, 3431–3440. Boston, United States.

Long, Y. and Thill, J., 2015. Combining smart card data and household travel survey to analyze jobs-housing relationships in Beijing. *Computers, Environment and Urban Systems*, 53, 19–35. doi:10.1016/j.compenvurbsys.2015.02.005

Lu, Y., 2019. Using Google street view to investigate the association between street greenery and physical activity. *Landscape and Urban Planning*, 191, 103435. doi:10.1016/j.landurbplan.2018.08.029

Lucas, R.E. and Rossi-Hansberg, E., 2002. On the internal structure of cities. *Econometrica*, 70 (4), 1445–1476. doi:10.1111/1468-0262.00338.

Mao, F., Ji, M., and Liu, T., 2016. Mining spatiotemporal patterns of urban dwellers from taxi trajectory data. *Frontiers of Earth Science*, 10 (2), 205–221. doi:10.1007/s11707-015-0525-4.

Moksony, F. (1990). *Ecological analysis of suicide,problems and prospects*. Current Concepts in Suicide.

Naik, N., *et al*., 2014. Streetscore-predicting the perceived safety of one million streetscapes. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 779–785. Columbus, United States.

Ng, M.K.P., *et al*., 2017. An adaptive weighted tensor completion method for the recovery of remote sensing images with missing data. *IEEE Transactions on Geoscience and Remote Sensing*, 55 (6), 3367–3381. doi:10.1109/TGRS.2017.2670021.

Plexida, S.G., *et al*., 2014. Selecting landscape metrics as indicators of spatial heterogeneity—a comparison among Greek landscapes. *International Journal of Applied Earth Observation and Geoinformation*, 26, 26–35. doi:10.1016/j.jag.2013.05.001.

Rapoport, A. and Hawkes, R., 1970. The perception of urban complexity. *Journal of the American Institute of Planners*, 36 (2), 106–111. doi:10.1080/01944367008977291.

Ren, M., *et al*., 2020. Examining the effect of land-use function complementarity on intra-urban spatial interactions using metro smart card records. *Transportation*, 47 (4), 1607–1629. doi:10.1007/s11116-019-09977-7.

Roberts, H.R., 2013. *City health check: how design can save lives and money*, Architecture. Com: Royal Institute of British Architects (RIBA)[online], 1–48.

Salat, S., Bourdic, L., and Nowacki, C., 2010. Assessing urban complexity. *International Journal of Sustainable Building Technology and Urban Development*, 1 (2), 160–167. doi:10.5390/SUSB.2010.1.2.160.

Shao, S., *et al*., 2018. Analyzing jobs-housing spatial relationship based on floating car data. *In*: *2018 5th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS*), 489–494. Hangzhou, China.

Simonyan, K. and Zisserman, A., 2014. *Very deep convolutional networks for large-scale image recognition*, arXiv preprint arXiv:1409.1556.

Szegedy, C., *et al*., 2015. Going deeper with convolutions. *In*: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1–9. Boston, United States.

Ta, N., *et al*., 2017. Understanding jobs-housing relationship and commuting pattern in Chinese cities: past, present and future. *Transportation Research Part D: Transport and Environment*, 52, 562–573. doi:10.1016/j.trd.2016.11.011.

Tang, L., *et al*., 2018. Exploring the influence of urban form on urban vibrancy in shenzhen based on mobile phone data. *Sustainability*, 10 (12), 4565–4585. doi:10.3390/su10124565.

Tu, W., *et al*., 2017. Coupling mobile phone and social media data: a new approach to understanding urban functions and diurnal patterns. *International Journal of Geographical Information Science*, 31 (12), 2331–2358. doi:10.1080/13658816.2017.1356464.

Turner, M.G., *et al*., 2001. *Landscape ecology in theory and practice*. New York: Springer.

Van Acker, V. and Witlox, F., 2011. Commuting trips within tours: how is commuting related to land use? *Transportation*, 38 (3), 465–486. doi:10.1007/s11116-010-9309-6.

Wan, N. and Lin, G., 2013. Life-space characterization from cellular telephone collected GPS data. *Computers, Environment and Urban Systems*, 39, 63–70. doi:10.1016/j.compenvurbsys.2013.01.003

Wan, N. and Lin, G., 2016. Classifying human activity patterns from smartphone collected GPS data: a fuzzy classification and aggregation approach. *Transactions in GIS*, 20 (6), 869–886. doi:10.1111/tgis.12181.

Wang, R., *et al*., 2019a. The linkage between the perception of neighbourhood and physical activity in Guangzhou, China: using street view imagery with deep learning techniques. *International Journal of Health Geographics*, 18 (1), 18. doi:10.1186/s12942-019-0182-z.

Wang, R., *et al*., 2019b. The relationship between visual enclosure for neighbourhood street walkability and elders' mental health in China: using street view images. *Journal of Transport & Health*, 13, 90–102. doi:10.1016/j.jth.2019.02.009.

Wang, R., *et al*., 2019c. Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. *Health & Place*, 59, 102186. doi:10.1016/j.healthplace.2019.102186.

Wang, Y.P. and Murie, A., 1999. Commercial housing development in urban China. *Urban Studies*, 36 (9), 1475–1494. doi:10.1080/0042098992881.

Wang, Y.P. and Murie, A., 2000. Social and spatial implications of housing reform in China. *International Journal of Urban and Regional Research*, 24 (2), 397–417. doi:10.1111/1468-2427.00254.

Wu, C., 2013. Research on unified boundary code at E-documents filing format. *Land and Resources Informatization*, 1, 3–6.

Wu, F., 2004. Residential relocation under market-oriented redevelopment: the process and outcomes in urban China. *Geoforum*, 35 (4), 453–470. doi:10.1016/j.geoforum.2003.10.001.

Xin, M. and Wang, Y., 2019. Research on image classification model based on deep convolution neural network. *EURASIP Journal on Image and Video Processing*, 2019 (1), 40. doi:10.1186/s13640-019-0417-8.

Yang, N., *et al*., 2019. Model loss and distribution analysis of regression problems in machine learning. *In*: *Proceedings of the 2019 11th International Conference on Machine Learning and Computing*, 1–5. Zhuhai, China.

Yang, X., *et al*., 2018. Understanding the spatial structure of urban commuting using mobile phone location data: a case study of Shenzhen, China. *Sustainability*, 10 (5), 1435–1448. doi:10.3390/su10051435.

Yao, Y., *et al*., 2017. Sensing spatial distribution of urban land use by integrating points-of-interest and Google Word2Vec model. *International Journal of Geographical Information Science*, 31 (4), 825–848. doi:10.1080/13658816.2016.1244608.

Yao, Y., *et al*., 2019. A human-machine adversarial scoring framework for urban perception assessment using street-view images. *International Journal of Geographical Information Science*, 33 (12), 2363–2384. doi:10.1080/13658816.2019.1643024.

Yao, Y., *et al*., 2020. Delineating mixed urban "jobs-housing" patterns at a fine scale by using high spatial resolution remote-sensing imagery. *Complexity*, 2020, 1–13. doi:10.1155/2020/8018629.

Ye, C., *et al*., 2020. Urban function recognition by integrating social media and street-level imagery. *Environment and Planning B: Urban Analytics and City Science*, 2399808320935467.

Ye, Y., *et al*., 2019. The visual quality of streets: a human-centred continuous measurement based on machine learning algorithms and street view images. *Environment and Planning B: Urban Analytics and City Science*, 46 (8), 1439–1457.

Yu, L., 2016. Revisiting several basic geographical concepts: a social sensing perspective. *Acta Geogr. Sin*, 71 (4), 475–564.

Yuxuan, L. and Nan, S.I., 2020. An empirical study of urban spatial structure based on social network analys is: a case study of urban update unit in Shenzhen as an example. *Journal of Landscape Research*, 12 (2), 35–39.

Zhang, F., *et al*., 2018. Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning*, 180, 148–160. doi:10.1016/j.landurbplan.2018.08.020.

Zhang, F., *et al*., 2019. Social sensing from street-level imagery: a case study in learning spatio-temporal urban mobility patterns. *ISPRS Journal of Photogrammetry and Remote Sensing*, 153, 48–58. doi:10.1016/j.isprsjprs.2019.04.017.

Zhang, J., et al., 2021. The Traj2Vec model to quantify residents' spatial trajectories and estimate the proportions of urban land-use types. *International Journal of Geographical Information Science, 35* (1), 193–211.
Zhang, P., Zhou, J., and Zhang, T., 2017. Quantifying and visualizing jobs-housing balance with big data: a case study of Shanghai. *Cities*, 66, 10–22. doi:10.1016/j.cities.2017.03.004
Zhao, P., Lu, B., and De Roo, G., 2011. Impact of the jobs-housing balance on urban commuting in Beijing in the transformation era. *Journal of Transport Geography*, 19 (1), 59–69. doi:10.1016/j.jtrangeo.2009.09.008.
Zheng, Y., 2015. Trajectory data mining: an overview. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 6 (3), 1–41. doi:10.1145/2743025.
Zhou, B., *et al*., 2014a. Learning deep features for scene recognition using places database. *In*: *Advances in neural information processing systems*, 487–495.
Zhou, J., *et al*., 2014b. Has the legacy of Danwei persisted in transformations? The jobs-housing balance and commuting efficiency in Xi'an. *Journal of Transport Geography*, 40, 64–76. doi:10.1016/j.jtrangeo.2014.04.008.
Zhou, J., *et al*., 2017. Jobs-housing balance and development zones in China: a case study of Suzhou industry park. *Urban Geography*, 38 (3), 363–380. doi:10.1080/02723638.2016.1152845.
Zhou, J. and Long, Y., 2014. Jobs-housing balance of bus commuters in beijing: exploration with large-scale synthesized smart card data. *Transportation Research Record: Journal of the Transportation Research Board*, 2418 (1), 1–10. doi:10.3141/2418-01.
Zhou, X., Yeh, A.G., and Yue, Y., 2018. Spatial variation of self-containment and jobs-housing balance in Shenzhen using cellphone big data. *Journal of Transport Geography*, 68, 102–108. doi:10.1016/j.jtrangeo.2017.12.006.