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# Extracting human perceptions from street view images for better assessing urban renewal potential

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ABSTRACT

Accurate and efficient assessment of large-scale urban renewal potential is an indispensable prerequisite for managing and facilitating projects. However, few studies consider the built environment when assessing urban renewal potential because it is difficult to measure. Street view images can show the physical setting of a place for humans to perceive the built environment. Hence, we separately extracted emotional and visual perceptions from street view images to construct a new comprehensive indicator set to assess multi-class urban renewal potentials. To establish the assessment model, we applied a backpropagation neural network based on the presence and background learning (PBL-BPNN). The renewal potential assessment based on the proposed indicator set can reach the highest accuracy. Emotional perceptions contribute more to assessing renewal potential than visual perceptions because they are more consistent in portraying the blighted built environment. Emotionally, the ratings of safety, boring, depression, and lively are stable in the blighted built environment. Visually, greenness and imageability often remain at lower values, highlighting the importance of greenspace and urban furniture in determining urban renewal. Furthermore, multi-class renewal potentials can be used for scenario analysis by assuming different renewal intentions. The results can support governments and planners in making efficient urban renewal decisions.

## 1. Introduction

Urban renewal mainly refers to the regeneration of a community with decaying scenes, harsh environments, or a backward economy that can no longer meet the demand of modern society and residents (Wang, Shen, Tang, & Skitmore, 2013; Zhang & Fang, 2004). By attracting private or public assets, urban renewal aims to beautify the urban appearance, enhance the quality of life, and restore economic vitality (Chan & Lee, 2008; Forouhar & Hasankhani, 2018; Liang, Lee, & Yong, 2020). Urban planners and government agencies consider that urban land parcels with low land-use efficiency or unreasonable utilization deserve urban renewal, which is an effective solution to solve the shortage of available land resources (Hui, Wong, & Wan, 2008; Zheng, Shen, & Wang, 2014). The parcels can be renewed through development strategies such as renovation, redevelopment, and conservation (Zhou, Lan, & Zhou, 2021). Many megacities have been undergoing urban renewal activities in China since the 21st century (Yi, Liu, Lang, Shrestha, & Martek, 2017; Zhuang, Qian, Visscher, Elsinga, & Wu, 2019). To effectively promote urban renewal, it is a vital prerequisite to accurately assess the renewal potential of urban land parcels, determine the priority, and clarify the proposed land-use types in the future.

There are two methods for assessing the renewal potential of urban land parcels. The first method is the field survey, mainly conducted by applying stakeholder surveys, expert interviews, and comparisons with completed urban renewal cases (Han, Kim, Jin, & Pettit, 2021; Li, Hui, Chen, Lang, & Guo, 2019; Liu, Wang, Xia, & Ni, 2018). The urban land parcels with renewal intention are declared by the landowners first. After confirming the renewal project, the developer will collect data and do field surveys on the urban land parcels (Jiang, Mohabir, Ma, Wu, & Chen, 2020; Zhuang et al., 2019). Based on the survey results,

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developers can assess the renewal potential of urban land parcels to help formulate the renewal strategy. This assessment method is crucial to the designation and implementation of a specific urban renewal project, as it can accurately assess each factor, such as the land price, building materials, and economic benefits (Cheng, Geertman, Kuffer, & Zhan, 2011; Liu, Wei, Gu, Zhou, & Liu, 2020). However, the field survey is not conducive to renewal project management in a large-scale area since it increases labor and time costs, which cannot meet the increasing demands of urban renewal in megacities.

To effectively assess the renewal potential of urban land parcels in large-scale areas, the technology based on geographic information system (GIS) has been applied in many studies as the other assessment method. The GIS-based technology enables professionals to collect and manage statistical data with geospatial location information and a large amount of crowdsourced geospatial data. They can mine the feature information related to urban renewal to build an indicator set to realize the renewal potential assessment. Therefore, the results are closely related to the type and quality of data since the assessment strategy is data-driven. This data-driven method can reduce labor and time costs to improve the efficiency of renewal potential assessment, which is suitable for large-scale promotion and application (Doğan, Güngör, Bostancı, & Bakır, 2020). Previous studies extracted the traditional indicators from the official statistical data to assess the urban renewal potential (Coffin, 2003; Hayek, Novak, Arku, & Gilliland, 2010; Pizzol et al., 2016). With the popularization of network information technology, many crowdsourced geospatial data can be generated every day since location-based space services usher in a period of rapid development (Wu et al., 2020). Crowdsourced geospatial data can better reflect information related to urban development in multiple aspects, such as human activities, social economy, and environmental pollution. Previous studies often applied crowdsourced geospatial data to present urban characteristics at a fine-scale level to make up for the defects of statistical data (Liu et al., 2015; Liu et al., 2017). Currently, crowdsourced geospatial data has been widely used in many studies of urban planning and land resource management (Chen et al., 2017; Liu et al., 2018; Yao et al., 2017). There is little research in this area for the urban renewal potential assessment due to the unclear correlation between crowdsourced geospatial data and renewal potential. Frantál et al. (2015) believed that population, economic activities, and facility levels are the key factors determining urban renewal promotion. Liu et al. (2019) collected time-series population density data to obtain population distribution to measure overpopulation and economic activities of urban renewal projects. However, the urban renewal potential assessment still ignores some crucial influencing factors, especially the built environment. Over the decades, the built environment has continuously changed due to human migration and rapid urbanization. The human perceptions of the built environment also change over time, subtly affecting the quality of life (Ahlfeldt, Maennig, & Richter, 2017; Huang, Kuo, Tzeng, & Lai, 2020; Park, Ewing, Sabouri, & Larsen, 2019). Especially in blighted built environments, abandoned buildings, backward economic levels, and filthy streets elevate the possibility of violence and compromise their security (Loukaitou-Sideris, 2011; Pope et al., 2015; Zavadskas, Cavallaro, Podvezko, Ubarte, & Kaklauskas, 2017). The residents living there are prone to negative emotions such as anxiety and depression (Pearson et al., 2019). The human perceptions of the blighted built environment can also reflect the developers' willingness to invest and landowners' willingness to "sell" their apartments from the landowners (Xu, Xue, & Huang, 2022). Hence, the blighted built environment can be one of the main hallmarks for judging whether an area should implement renewal.

As a kind of emerging crowdsourced data, street view images can directly show the realistic built environment of a community. The community organically combines the natural environment and architecture to construct a complex living system that allows humans to socialize, live, and do other daily activities (Carmona, Gabrieli, Hickman, Laopoulou, & Livingstone, 2018; Kim, Lee, Hipp, & Ki, 2021). Therefore, human perception extracted from street view can depict the built environment and provide data to support urban-related analysis. For example, Liu, Silva, Wu, and Wang (2017) extracted the building facade and building interface continuity of the street to assess building structure and spatial quality. Dubey, Naik, Parikh, Raskar, and Hidalgo (2016) collected approximately one million street view images from 56 cities in 28 countries. The street view images are scored by several emotional perceptions (beautiful, boring, depressing, safety, lively, and wealthy) to construct the emotion score dataset of human perceptions for the first time. Ma et al. (2021) applied several human perceptions based on the ground object components in street view images. By comparing the human perceptions of communities in different periods, the results show that the time-series changes in human perceptions are affected by urban renewal. In short, human perceptions extracted from the street view images can also be one of the indicators to assess the urban renewal potential.

Inspired by the above facts, this study carries out the renewal potential assessment of urban land parcels integrated with human perceptions (including objective visual and subjective emotional perception). In this paper, human perceptions were obtained from the various components of the ground objects. We applied an advanced semantic segmentation model to get the components of ground objects efficiently. Then four visual perceptions (greenness, openness, enclosure, and imageability) and six emotional perceptions (beautiful, boring, depressing, safety, lively, and wealthy) were integrated to construct the indicator set. To complete the assessment indicator set, we also applied the traditional indicators to describe the factors from social, economic, and physical aspects. All traditional features are taken from crowdsourced data and official statistics, including topography, buildings, land parcels, accessibility, facility abundance, and population distribution. Finally, we conducted experiments under different indicator sets to demonstrate the positive impact of human perceptions on the assessment of urban renewal potential. The multi-class urban renewal potentials were also applied to urban-relate metrics to demonstrate their validation and practical implication. The main contribution of this paper can be listed as follows:

1) To our knowledge, it should be the first time that street view images are used to extract human perceptions to assist the renewal potential assessment in making a better result.
2) Through accuracy comparisons and case studies, we summarized the contribution of each type of human perception to urban renewal assessment.
3) We constructed multiple PBL-BPNN-based assessment models to obtain multi-class urban renewal potentials. The results can explore potential urban renewal land parcels and provide a reference for the renewal intention by comparing multi-class renewal potentials.

## 2. Study area and datasets

### 2.1. Study area

The proposed methodology uses Dongguan as a case study to assess the potential for urban renewal. As an important transportation hub and foreign trade port in Pearl River Delta, Dongguan is in the south-central region of Guangdong Province, with adjacent borders of Guangzhou, Huizhou, and Shenzhen. With the rapid economic development of the Pearl River Delta, Dongguan has developed industries to drive economic growth and attract more migrant workers guided by international industrial transfer (Chen, Xu, & Yang, 2017). In the past few decades, Dongguan has grown from a rural area to a megacity with a high urbanization rate. However, rapid urbanization has also brought a series of problems. Most obviously, the rapid urban expansion quickly breeds many urban land parcels with unreasonable utilization. Therefore, urban renewal has become the core policy for future sustainable development in Dongguan, where there is a shortage of available land. Dongguan has completed 1693.33 ha of urban renewal area by 2018.

Benefited from the economies of its two neighboring cities, Shenzhen and Guangzhou, Dongguan has a massive demand for urban renewal in the future (http://nr.dg.gov.cn/ztpd/csgx/bszn/content/post_2213311.html).

### 2.2. Urban renewal documented data

To assess the renewal potential of urban land parcels, we collected the urban renewal projects from Dongguan Urban and Rural Planning Bureau, which have been documented in the past ten years with detailed information and geographic location as the training data of the assessment model. Fig. 1 shows the urban renewal projects and other urban land parcels in the study area. The renewal condition of the urban renewal projects is either pending or ongoing. Table 1 presents the typical information of several urban renewal projects. We can see that the renewal areas can be identified as old factories, old villages, or old neighborhoods (Li et al., 2019). The demand for urban renewal is also related to the economic activities of local communities. For example, Dongcheng and Humen, two major towns (urban districts) of Dongguan, are densely populated with many old factories, resulting in high demand for urban renewal. Instead, Songshanhu, an emerging urban district, has only a small demand for urban renewal, dominated by high-tech industries.

We divide the proposed land-use types of renewal into four categories: industrial, commercial, residential, and public management-services land. Please note that some urban renewal projects have multiple proposed land-use types. The main reason is that the renewal intention is uncertain and needs further detailed investigation according to policies, building conditions, and economic benefits. To facilitate subsequent model and analysis, we assumed that if an urban land parcel has multiple proposed land-use types, it can be renewed to any one of them. In other words, some urban land parcels may be simultaneously trained and assessed as samples for multiple assessment models.

### 2.3. Street view images

Real-world images with geographic coordinates have been hotspot data in recent years, such as street view images and social media check-in photos (Ahlfeldt et al., 2017; Kaneko & Yanai, 2016). Street view images have rich visual features, which allow humans to perceive the built environment in the most realistic scenario. We collected Dongguan's street view images to extract the human perceptions related to urban renewal. The API of Baidu Map (https://map.baidu.com/) was applied to crawl street view images along with the road network in Dongguan. However, the dense distribution of the shooting points can easily cause unnecessary information redundancy. We performed a sparse preprocessing of the shooting points by taking one of every three shooting points of street view images. Fig. 2 shows the spatial distribution of the final acquired 257,335 shooting points, covering most areas in Dongguan. Only a few areas still lack street view images, such as Huangjiang, Zhangmutou, and Xiegang. We collected four street view images based on the four relative angles of each point, among which a small number of points did not contain images from all directions. Finally, we collected 1,024,724 street view images for extracting human perceptions.

**Table 1**
Information of documented urban renewal projects.

| ID | Year of planned renewal | Original land-use type | Proposed land-use types of renewal |
|---|---|---|---|
| 1 | 2020 | Old factory | Commercial land; Public management-services land |
| 2 | 2020 | Old factory | Public management-services land |
| 3 | 2019 | Old village | Residential land |
| 4 | 2011 | Old neighborhood | Commercial land |
| 5 | 2011 | Old village | Residential land; Commercial land |
| 6 | 2017 | Old factory | Residential land; Commercial land |

### 2.4. Other geospatial data

#### 2.4.1. Basic geospatial data

The basic geospatial data includes the Digital Elevation Model (DEM) and the road networks. The road networks have six categories: railway, highway, expressway, arterial road, secondary road, and branch road. The accessibility was then calculated based on these road networks.

#### 2.4.2. Building and land survey data

The building and land survey data include the building footprint,

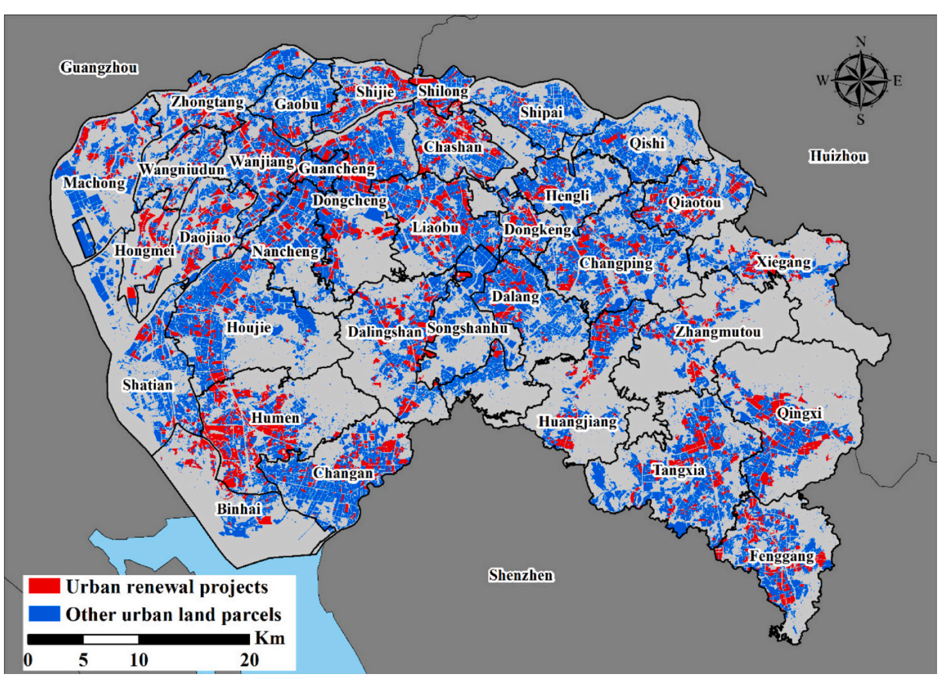


**Fig. 1.** The study area and the spatial distribution of documented urban renewal projects (sources: Dongguan Urban and Rural Planning Bureau).


**Fig. 2.** Spatial distribution of shooting points for requesting street view images.

housing price, and land value data. The building footprint consists of 1,695,515 buildings in Dongguan. In addition to building area, the building footprint also records information such as building height and construction materials, which can be used to calculate building density, floor area ratio, and volume related to the implementation of urban renewal projects.

### 2.4.3. Crowdsourced data

In addition to the street view images, we also collected points of interest (POIs), Didi trajectory, and dynamic population density distribution. 403,080 POIs were crawled from Baidu Map (https://map.baidu.com/).

The POIs are divided into 16 categories according to their coding. We performed spatial kernel density analysis on each type of POIs separately and extracted their kernel density to express facility abundance. Appendix Fig. 1 shows the kernel density of POIs.

We obtained the Didi trajectories for the one-week interval from May 6 to May 12, 2019 (https://outreach.didichuxing.com/). The Didi trajectories record the coordinates of the Original and Destination (OD) points of each trajectory. We can obtain the commuting distance and time of the Didi trajectory based on the map API (https://lbs.amap.com/) and integrate the features to perform K-means clustering on the OD points. According to Calinski-Harabasz index, the OD points of both weekdays and holidays can be divided into four clusters (Maulik & Bandyopadhyay, 2002). The processing flow of OD points after clustering is similar to that of POIs. We applied the spatial kernel density of clustered OD points and the Euclidean distance to the road networks to represent the accessibility. Appendix Fig. 2 shows the accessibility maps.

We also collected real-time Tencent user density (RTUD) data from the Tencent Location Big Data service (https://heat.qq.com/bigdata/index.html) for the one-week interval from July 1 to July 7, 2015. The RTUD data are raster images with a spatial resolution of 114.28 m. We treated the urban land parcel as the basic unit for the calculation. The average population density and total population were obtained on workdays and holidays to provide information on human activities. Appendix Fig. 3 shows the RTUD data in the study area.

## 3. Methodology

The framework of this study consists of two main parts: indicator set construction and renewal potential assessment (Fig. 3). We conducted experiments under different indicator sets to highlight the impact of street view images on assessing urban renewal potential. The framework can be divided into six steps: 1) The shooting points of street view

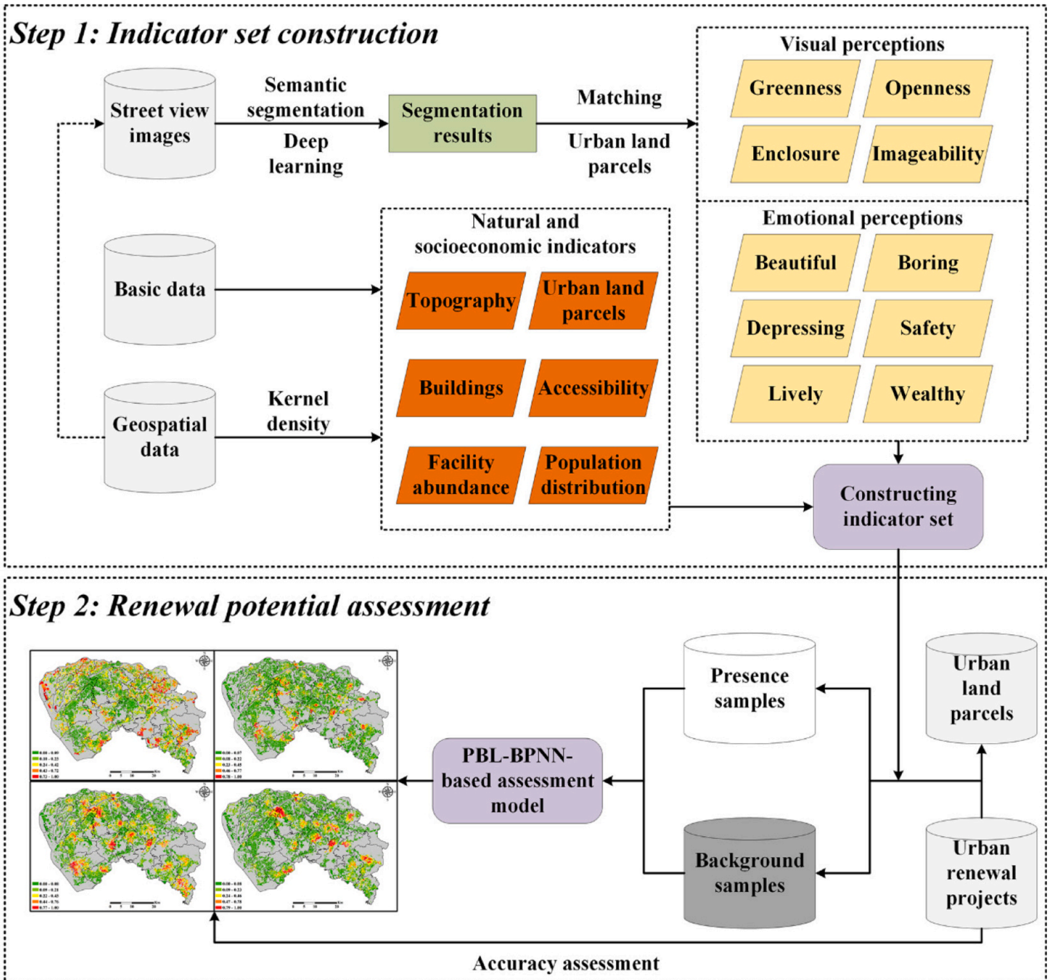


**Fig. 3.** Overall flowchart of urban renewal potential assessment.

images were generated along the road network. We collected the street view images based on the relative angle of each shooting point; 2) The street view images were segmented using a semantic segmentation model to obtain the components of various ground objects; 3) We set a visual distance to match the street view images with the corresponding urban land parcels; 4) Human visual and emotional perceptions extracted from the components of various ground objects were combined with other geospatial variables to construct a comprehensive indicator set for renewal potential assessment; 5) A presence and background learning-based backpropagation neural network model (PBL-BPNN) was applied to assess urban renewal potential; 6) By comparing the accuracy and renewal potential under different indicator sets, we analyzed the impact of human perceptions on assessing urban renewal potential.

### *3.1. Semantic segmentation of street view images*

The human perceptions extracted from the urban appearance can express the psychological feelings of residents about the city, which affects the quality of life (Naik, Raskar, & Hidalgo, 2016; Senlier, Yildiz, & Aktaş, 2009; Tuan, 2013). Street view images are one kind of data source to present the urban appearance. Effectively describing the urban appearance in street view images provides a convenient way to reflect human perceptions (Dubey et al., 2016). To obtain the components of various ground objects in the urban appearance, we applied a semantic segmentation model (HRNetV2) to segment street view images (Sun et al., 2019).

As can be seen from Fig. 4, HRNetV2 has a group convolution structure. The core idea of HRNetV2 is to down-sample the input image multiple times to generate multi-scale feature maps. Then the multi-scale feature maps are fused to generate the final feature map for segmentation. There are four stages in HRNetV2 based on four down-sampling layers of the network. Each stage adds a new branch of the network to generate image features at a different scale. After down-sampling, the feature size of the new network branch is half of that of the original network branch, but the number of channels is doubled. However, the feature maps must be resampled to the same scale for subsequent feature fusion. HRNetV2 uses one or more convolutional layers with stride 2 and kernel size 3 × 3 to construct the resampling layers to unify the feature maps of different scales. A bilinear interpolation realizes both the down-sampling and up-sampling processing of the feature maps. The final feature map was fused through a 1 × 1 convolutional layer. To sum up, HRNetV2 can repeatedly fuse feature maps of different scales in each scale transformation layer. The scale transformation layers in HRNetV2 can promote the mutual enhancement of image features at different scales, thereby maximizing the preservation of the multi-scale feature maps of the image.

Due to a lack of an urban scene segmentation dataset in Dongguan, we applied the pre-trained HRNetV2 that was trained and tested on the ADE20k dataset (https://github.com/CSAILVision/semantic-segmentation-pytorch). The ADE20k dataset is an open-source semantic segmentation dataset released by the CSAILVision team from MIT (Zhou et al., 2017; Zhou et al., 2019). The ADE20k dataset contains 27,574 annotated scene images with 150 categories. In this study, the pre-trained

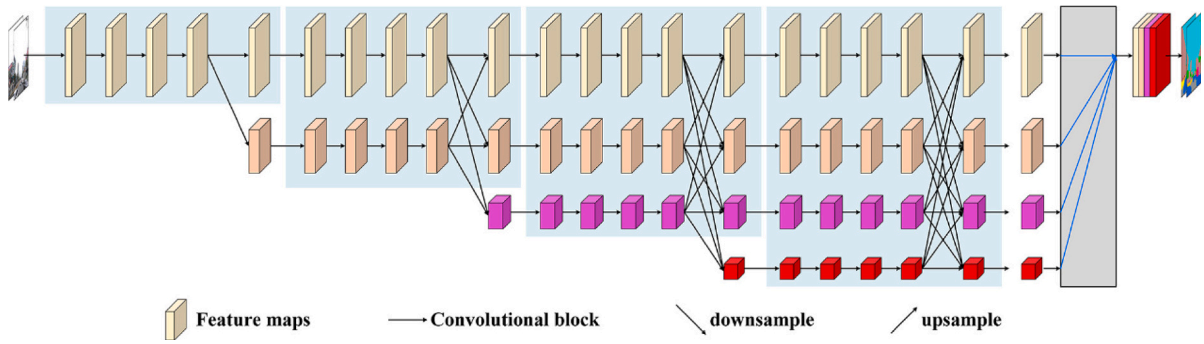


**Fig. 4.** Architecture of HRNetV2 (Sun et al., 2019) for segmenting street view images.

HRNetV2 (Mean IoU = 43.20 %) was used to segment the street view images of Dongguan. Fig. 5 shows the segmentation results of several examples in the study area. We can find that the generality of the ADE20k dataset is strong due to the coverage for the annotation of urban appearance. Visually, the segmentation results of some ground objects are accurate, such as cars, buildings, and roads. The accurate segmentation results can provide a reliable basis for the subsequent construction and calculation of human perceptions.

### *3.2. Matching of street view images with urban land parcels*

As the shooting points of street view images are distributed in the road networks, their coordinates cannot be set as that of street view images. Thus, we should match the street view images with the corresponding urban land parcels (Fang et al., 2021). In this study, we set the moving direction of the street-view car as the reference direction. Then we collected the street view images of four relative angles (0°, 90°, 180°, and 270°). The pitch angle and field of view (FoV) were set to 22.5° and 90° simultaneously to ensure street view images are close to what the human eye observes (Seiferling, Naik, Ratti, & Proulx, 2017). Fig. 6 shows the spatial relationship between the directions of the four street view images and the matching strategy. Based on the geographic coordinates of shooting points, we can calculate the geographic coordinates of four street view images from different angles (such as points a, b, c, and d in Fig. 6) using the trigonometric function with a fixed visual distance. As shown in Fig. 6(e), the geographic coordinate $(x_b, y_b)$ of point b can be calculated based on the geographic coordinate $(x, y)$ of the shooting point. The average width (approximately 40 m) of the road network is set as the fixed distance D to ensure that the newly generated coordinates can be located in urban land parcels. The locations of all street view images were generated and matched to the corresponding urban land parcels. However, some urban land parcels cannot include street view images. There are two reasons: one is that the shooting point cannot completely cover the research area; the other is that the street view image can only be matched with the adjacent urban land parcels of the road network. To obtain the renewal potential of the study area, we should carry out two sets of assessments. One is carried out based on the urban land parcels containing street view images, and the other is carried out based on the urban land parcels without street view images. Finally, we integrated two assessment results to generate the renewal potential map of the study area.

### *3.3. New comprehensive indicator set integrated with human perceptions*

As shown in Table 2, we proposed a new comprehensive indicator set for assessing the renewal potential of urban land parcels. Among them, housing price and land value affect developers' economic benefits and the landowners' compensations in urban renewal (Dowall, 1994; Guo, Xiao, & Yuan, 2017; Li, Lin, Li, & Wu, 2014). Floor area ratio, building density, and building structure also reveal the difficulty of developers in promoting renewal projects (Chen, Chau, & Yang, 2022; Cheng, Lai, & Tong, 2021; Shenvi & Slangen, 2018). Therefore, the indicators related to building and land parcels should be assessed before implementing urban renewal projects (Liu et al., 2019). In addition, previous studies have extracted other factors affecting sustainable urban development from crowdsourced geospatial data, such as topography, accessibility, and population distribution, to construct the traditional indicator set of the urban renewal potential assessment (Frantál et al., 2015; Zhou, Xu, Sun, & Deng, 2021). To complete the proposed indicator set, we finally added human perceptions extracted from street view images into the traditional indicator set to make up for the lack of the built environment depiction. Each street view image was first paired with the corresponding urban land parcels using the matching method in Fig. 6(e). Then we counted the average value of perceptions as the human

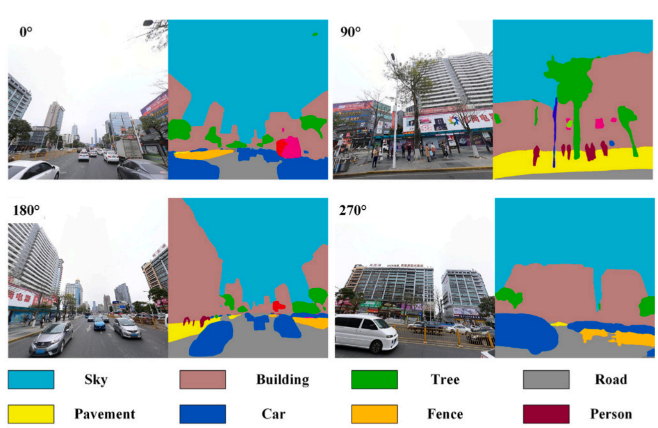


**Fig. 5.** Examples of semantic segmentation (the legend only shows the top 8 ground objects that are obvious in the segmentation results).

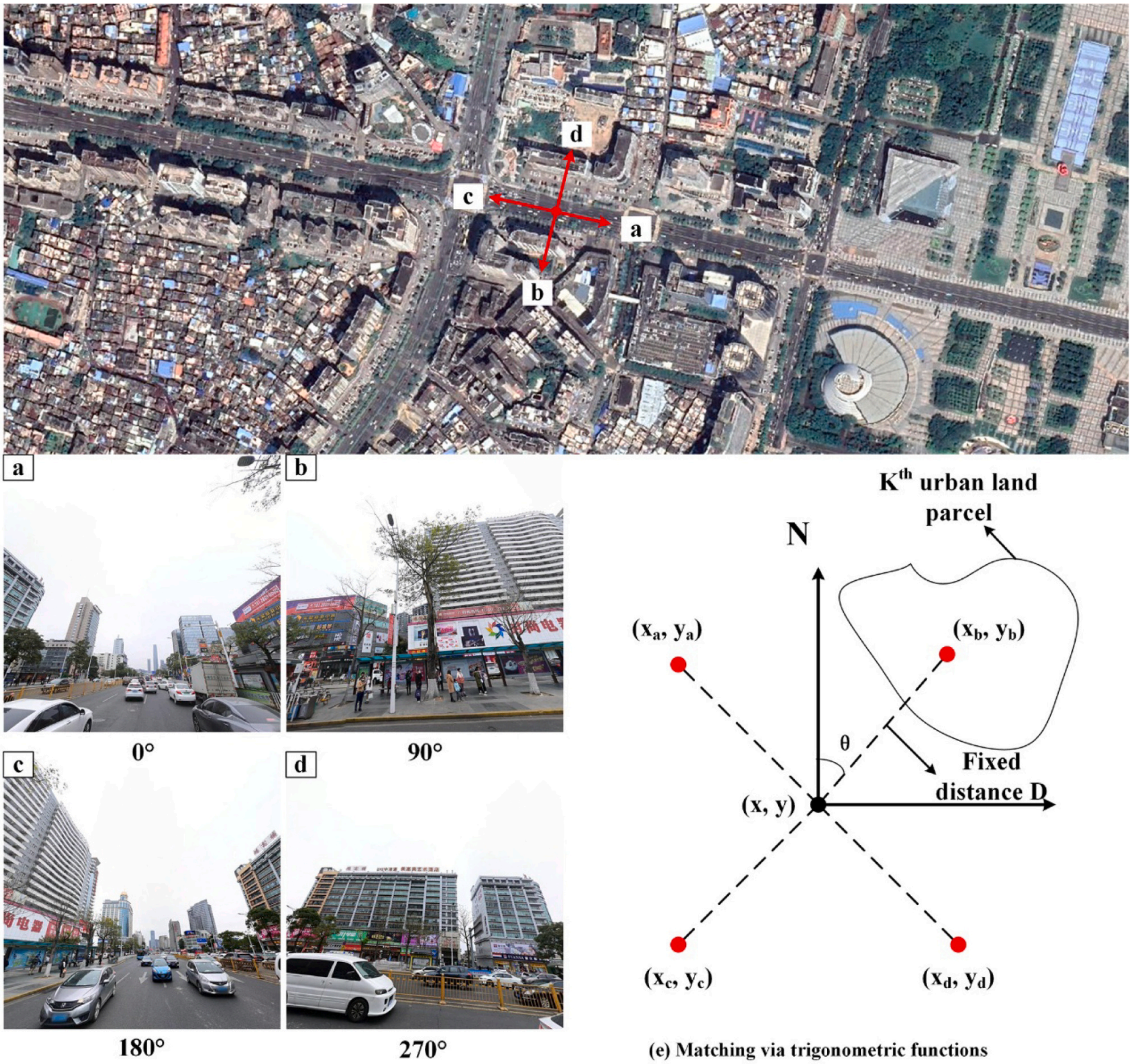


**Fig. 6.** Street view images from different angles and matching strategy.

perceptual features of the urban land parcels.

We selected ten human perceptual indicators that can depict the built environment according to (Zhang et al., 2018), (Ma et al., 2021), and (Dai et al., 2021). The selected human perceptions can be divided into objective visual and subjective emotional perceptions. Four visual indicators (greenness, openness, enclosure, and imageability) can be calculated directly from the components of various ground objects. The calculation formula and brief description of the four visual perceptions are shown in Table 3. The remaining six emotional perceptions (beautiful, boring, depressing, safety, lively, and wealthy) can be obtained by constructing a rating model based on machine learning algorithms. The features used to train the model are also the components of various ground objects (Wang, Han, He, & Jung, 2022). We employed an emotional perception dataset from (Yao et al., 2019) to construct the rating model. This emotional perception dataset was also collected from Baidu Map (https://map.baidu.com/), so it has little variability with the street view images of the study area due to the same data source.

### 3.4. PBL-BPNN-based assessment model of urban renewal potential

The core of assessing urban renewal potential involves the land-use suitability assessment, requiring the mapping relationship between multi-source factors and land-use suitability (Zhang, Liu, Lin, Zhang, & Zhang, 2020). However, the traditional assessment model constructed by binary classifiers is unsuitable for assessing the renewal potential. On the one hand, the assessment model can only select the urban land parcels that have completed renewal as negative samples, resulting in insufficient negative samples to support model training. On the other hand, whether the urban land parcel is to undergo urban renewal is sometimes determined by the report of landowners, so there is also the possibility that undocumented urban land parcels need to be renewed. Therefore, to solve the problem of missing negative samples in urban renewal assessment, this study used a presence and background learning (PBL) model specially designed for one-classification problems. The one-classification algorithm is mainly used to study the species distribution problem in ecology (Hernandez, Graham, Master, & Albert, 2006). The observation points of species are used as positive samples, but the area

**Table 2**
Summarized indicators of urban renewal potential assessment.

| Factors | Indicators | Brief Introduction |
|---|---|---|
| Topography | Elevation<br>Slope | Topography affects the cost and feasibility of urban renewal projects. |
| Building | Floor area radio<br>Building density<br>Number of floors<br>Building structure<br>Housing price | Floor area ratio, building density, number of floors, and building structure determine the intensity of urban renewal, which affect the economic benefits of developers. The housing price determines the reimbursements of the landowner. |
| Land parcels | Area<br>Type<br>Land value | The area and type of land parcels determine the priority and intensity of development. The land value determines the economic benefits of developers. |
| Accessibility | Euclidean distance to the road network<br>Kernel density of OD points | The Euclidean distance to the road network and the kernel density of OD points reflect the degree of transportation convenience, which determines the land-use efficiency and economic benefits after the land parcel is renewed. |
| Facility abundance | Kernel density of various facilities | The functional richness of the land parcel has an impact on the land value and housing prices. |
| Population distribution | Sum of population on weekdays<br>Population density on weekdays<br>Sum of population on holidays<br>Population density on holidays | Population distribution is used to measure the degree of abandonment of land parcels. |
| Visual perceptions | Greenness<br>Openness<br>Enclosure<br>Imageability | Visual perceptions are constructed by the visible features of the built environment, reflecting the living environment of residents. |
| Emotional perceptions | Beautiful<br>Boring<br>Depressing<br>Safety<br>Lively<br>Wealthy | Emotional perception is a subjective rating of the living environment scored by humans, expressing residents' assessment of the quality of life. |

without observation does not mean that there are no species. PBL has proven to be an effective method to accurately assess the probability of species distribution in the absence of negative samples (Li, Guo, & Elkan, 2010). Urban renewal potential assessment is like the case of species distribution. To accurately assess the renewal potential of urban land parcels, PBL only needs some positive urban renewal samples.

The principle of PBL is to convert the actual "positive-negative" scenario into the "presence-background" scenario for modeling. In the "presence-background" scenario, we can select an appropriate number of positive samples $Obs_{ur} = 1$ and background samples $Obs_{ur} = 0$ to construct the binary classifier to assess the observation probability $p_{obs}$. Let us assume that there are $p$ urban land parcels in the training set. Among them, $p_1$ urban land parcels (presence samples) are determined for urban renewal, while the remaining $(p - p_1)$ urban land parcels (background samples) are uncertain for urban renewal. Then we assume that there are $p_2$ urban land parcels for renewal and $(p - p_1 - p_2)$ urban land parcels not for renewal in the background samples. By constructing the relational expressions between the "positive-negative" and "presence-background" scenarios, we can estimate the probability of the "presence-background" scenario (Li, Guo, & Elkan, 2011). The relationship between the actual urban renewal potential $p_{ur}$ and the observed urban renewal potential $p_{obs}$ can be obtained as follows:

$$p_{ur} = \frac{p_2}{p_1} \times \frac{p_{obs}}{1 - p_{obs}} \tag{1}$$

**Table 3**
Formulas and introductions for visual perceptions.

| Indicators | Formula | Brief Introduction |
|---|---|---|
| Greenness | $Greenness = P_T + P_G + P_{Fl}$ | Greenness refers to the coverage of vegetation in human-eye observation, which can assess the greening level of urban streets. $P_T$, $P_G$, and $P_{Fl}$ respectively represent the components of tree, grass, and flora pixels. |
| Openness | $Openness = P_S$ | Openness refers to the composition of sky elements. The buildings and trees of this street are sparse and small, resulting in the enclosure is low. $P_S$ represents the components of sky pixels. |
| Enclosure | $Enclosure = P_B + P_T + P_{Fe} + P_W$ | Enclosure refers to the proportion of vertical elements such as buildings, trees, traffic signs, and fences in the street. The enclosure is an essential factor for pedestrians to perceive the surrounding environment, which also affects crime activities. $P_B$, $P_T$, $P_{Fe}$, and $P_W$ respectively represent the components of building, tree, fence, and wall pixels. |
| Imageability | $Imageability = P_B + P_{Si} + P_{Sc} + P_P$ | Imageability refers to residents' impressions of the street. Street elements such as buildings and traffic signs shape the richness and diversity of street features from the human eye's perspective. $P_B$, $P_{Si}$, $P_{Sc}$, and $P_P$ respectively represent the components of building, signboard, screen, and pillar pixels. |

Therefore, accurately estimating the value of $\frac{p_2}{p_1}$ becomes the key of PBL model since $p_{obs}$ can be obtained. PBL defines a constant $c = \frac{p_1}{p_1+p_2}$. $\frac{p_2}{p_1}$ can be transformed into $\frac{p_2}{p_1} = \frac{1-c}{c}$. The calculation formula of $p_{ur}$ is also updated as follows:

$$p_{ur} = \frac{1 - c}{c} \times \frac{p_{obs}}{1 - p_{obs}} \tag{2}$$

To estimate the constant c value, PBL introduces the concept of "prototypical presence". In species distribution, "prototypical presence" refers to the most suitable habitat for a species, meaning that there is a 100 % chance that the species will be observed in that habitat. In analogy, there are some urban land parcels that should undergo urban renewal. We define these urban land parcels as the "prototypical presence" of urban renewal. Previous studies generally set the first 50 percentile of the observed probability $p_{obs}$ in the "presence-background" scenario as the "prototypical presence" to estimate the value of c (Li, Guo, & Elkan, 2020). The formula used is as follows:

$$c = \frac{1}{n}\sum_{x \in O} p_{obs} \tag{3}$$

In summary, we must first apply traditional machine learning algorithms in the "presence-background" scenario to construct the PBL model. A backpropagation neural network (BPNN) is the appropriate binary classifier as it can estimate the posterior probability to fit the observed probability $p_{obs}$ in the "presence-background" scenario (Deng, Li, Liu, Guo, & Newsam, 2018; Richard & Lippmann, 1991). In the experiment, we sorted the observation probability $p_{obs}$ obtained by BPNN for the "presence-background" scenario. The first 50 % of $p_{obs}$ was taken as the "prototypical presence" of urban renewal. We counted the average value of the observation probability $p_{obs}$ of "prototypical presence" and set it as the estimated constant c. Finally, we can estimate the renewal potential $p_{ur}$ according to formula (2).

To test the accuracy of the PBL-BPNN-based assessment model, we need to convert the renewal potential into the classification results. In particular, the renewal potential $p_{ur}$ can be divided into two parts through a fixed threshold. We used a proxy for the F1-measure ($F_{pb}$) to assess accuracy after threshold segmentation, as $F_{pb}$ can handle the confusion matrix for particular “presence-background” scenarios (Li & Guo, 2013). High values of $F_{pb}$ can likewise indicate that the model has low commission and omission errors. The F-score in the subsequent contents will directly represent this modified evaluation metric. The formula of $F_{pb}$ is as follows:

$$F_{pb} = \frac{2 \times TP}{TP + FN + FP} \tag{4}$$

where TP (True Positive), FP (False Positive), and FN (False Negative) refer to the number of observed urban renewal land parcels correctly identified, the number of observed non-urban renewal land parcels incorrectly identified, and the number of observed urban renewal land parcels incorrectly identified respectively.

## 4. Results and discussion

### 4.1. Model validation

The study area has 78,734 urban land parcels to assess the renewal potential, of which 39,138 urban land parcels contain street view images (Fig. 1). Since the street view images did not fully cover the study area, we divided the urban land parcels into two parts. We collected the documented urban renewal land parcels in Section 2.2 as the presence samples and other urban land parcels as the background samples for building the PBL-BPNN-based assessment model. Urban land parcels with multiple proposed land-use types might be sampled repeatedly, but the assessment results will not be affected. Table 4 shows the number of presence samples of each proposed land-use type. At the same time, the number of background samples was set to 5 times the number of presence samples. It can be found that most of the urban land parcels are planned to be commercial or residential land, so the number of selected samples is also relatively large. To verify the impact of human perceptions on urban renewal potential assessment, we designed three groups of comparative experiments using different indicator sets. Each group of experiments was repeated ten times via 10-fold cross-validation to reduce the randomness of the assessment model.

Table 5 shows the comparison of model accuracies. The F-scores of all the renewal potential obtained by PBL-BPNN are about 70 %. The proposed indicator set improves assessment accuracy by 5.16 to 7.64 % due to the inclusion of human perceptions. Except for industrial land, the F-scores of the other three types of land exceeded 80 % under the proposed indicator set. The high F-scores demonstrate the effectiveness of the assessment model with our proposed indicator set. Specifically, commercial land obtains the highest F-score of 83.59 %, while the F-scores of residential land and public management-services land are also above 80 %. The low standard deviation of the renewal potential assessment suggests that human perceptions have little influence on the stability of the model assessment. The comparison in Table 5 also demonstrates that emotional perceptions enhance the accuracy of the assessment model more than visual perceptions, reflecting that subjective human perceptions of the urban structure are more important for determining urban renewal. For example, urban land parcels used primarily to renew old factories generally have similar blighted urban structures such as backward facilities and environmental degradation.

**Table 4**
The number of urban land parcels collected for model training and testing.

| Proposed land-use type | Documented for renewal | Documented for renewal (with street view images) | Selected presence samples |
|---|---|---|---|
| Industrial land | 2921 | 1859 | 1000 |
| Commercial land | 7171 | 5079 | 3000 |
| Residential land | 10,525 | 7027 | 4000 |
| Public management-services land | 3105 | 1972 | 1000 |

**Table 5**
Assessment accuracy (F-score) based on different indicator sets. The values in parentheses indicate the standard deviation of the accuracies obtained from the 10-fold cross-validation.

| Proposed land-use type | Traditional indicators | With visual perception | With emotional perception | Proposed indicators |
|---|---|---|---|---|
| Industrial land | 72.28 (5.11) | 74.41 (6.00) | 75.15 (5.44) | 77.44 (6.22) |
| Commercial land | 77.74 (6.36) | 79.62 (9.78) | 81.70 (5.18) | 83.59 (5.78) |
| Residential land | 74.60 (3.54) | 78.06 (4.00) | 78.73 (4.38) | 80.73 (5.41) |
| Public management-services land | 74.34 (6.96) | 77.91 (7.03) | 79.12 (5.66) | 81.98 (8.00) |

Visual perceptions extracted by similar urban appearances can enlarge the identifiability of presence samples. However, there are still limitations in the ability of visual perception to discriminate decaying urban scenes. The main reason is that some typical objects depicting blighted built environments are challenging to identify in street view images, such as broken windows and dumped garbage. Therefore, some emotional perceptions that reflect the decay of the urban structure (e.g., safety, depressing, and lively) can be used to expand the variability of the feature between urban land parcels, thus improving the accuracy of the model assessment. In summary, the renewal potential assessment can be more accurate using the proposed indicator set integrated with human perceptions.

### 4.2. Spatial distribution of urban renewal potential assessment

The street view images cannot cover all the urban land parcels in the study area, so the complete renewal potential map needs to fuse the assessment results of two parts (according to whether the urban land parcels include street view images). The process is as follows: First, we assessed the renewal potential of all urban land parcels $A = \{U_1^{NSV}, U_2^{NSV}, \ldots, U_i^{NSV}\}$ based on the traditional indicator set, where $U$ represents the renewal potential, $NSV$ represents the indicator set without human perception, and $i$ represents the number of the urban land parcels. Then we assessed the renewal potential of urban land parcels $B = \{U_{j_1}{}^{SV}, U_{j_2}{}^{SV}, \ldots, U_{j_n}{}^{SV}\}$ based on the proposed indicator set, where $U$ represents the renewal potential, $SV$ represents the indicator set with human perceptions, $j = \{j_1, j_2, \ldots, j_n\}$ represents the urban land parcels containing the street view images. Obviously, $B$ is a subset of $A$, so replacing $B$ with the corresponding land parcel in $A$ is necessary to obtain the final assessment result $C = \{U_1^{NSV}, U_2^{NSV}, \ldots, U_{j_1}{}^{SV}, \ldots, U_{j_n}{}^{SV}, \ldots, U_i^{NSV}\}$.

This study uses the natural breaks (Jenks) to classify the various types of renewal potential $C$ into five levels (very low, low, moderate, high, and very high) (Chen, Yang, Li, Zhang, & Lv, 2013). Previous studies indicated that urban land parcels with high-value renewal potential should prioritize urban renewal (Liu et al., 2019). As shown in Fig. 7, we chose the first two levels of renewal potential as the high-value areas. Therefore, the selected thresholds for identifying the high-value renewal potential are 0.43 (industrial land), 0.46 (commercial land), 0.44 (residential land), and 0.47 (public management-serviced land). The area of high-value renewal potential parcels was counted to show the demand for urban renewal in each district (only the first ten districts). The spatial distribution of various renewal potentials also has apparent differences.

Except for the unique spatial distribution of renewal potential of industrial land, all other spatial distributions are urban land parcels with low-value renewal potential surrounding urban land parcels with high-value renewal potential. The reason is the rapid urbanization of Dongguan. With the expansion of new urban land from the boundary, the newly built-up area gradually surrounds the old built-up area, resulting in the spatial distribution of urban land parcels with high-value renewal

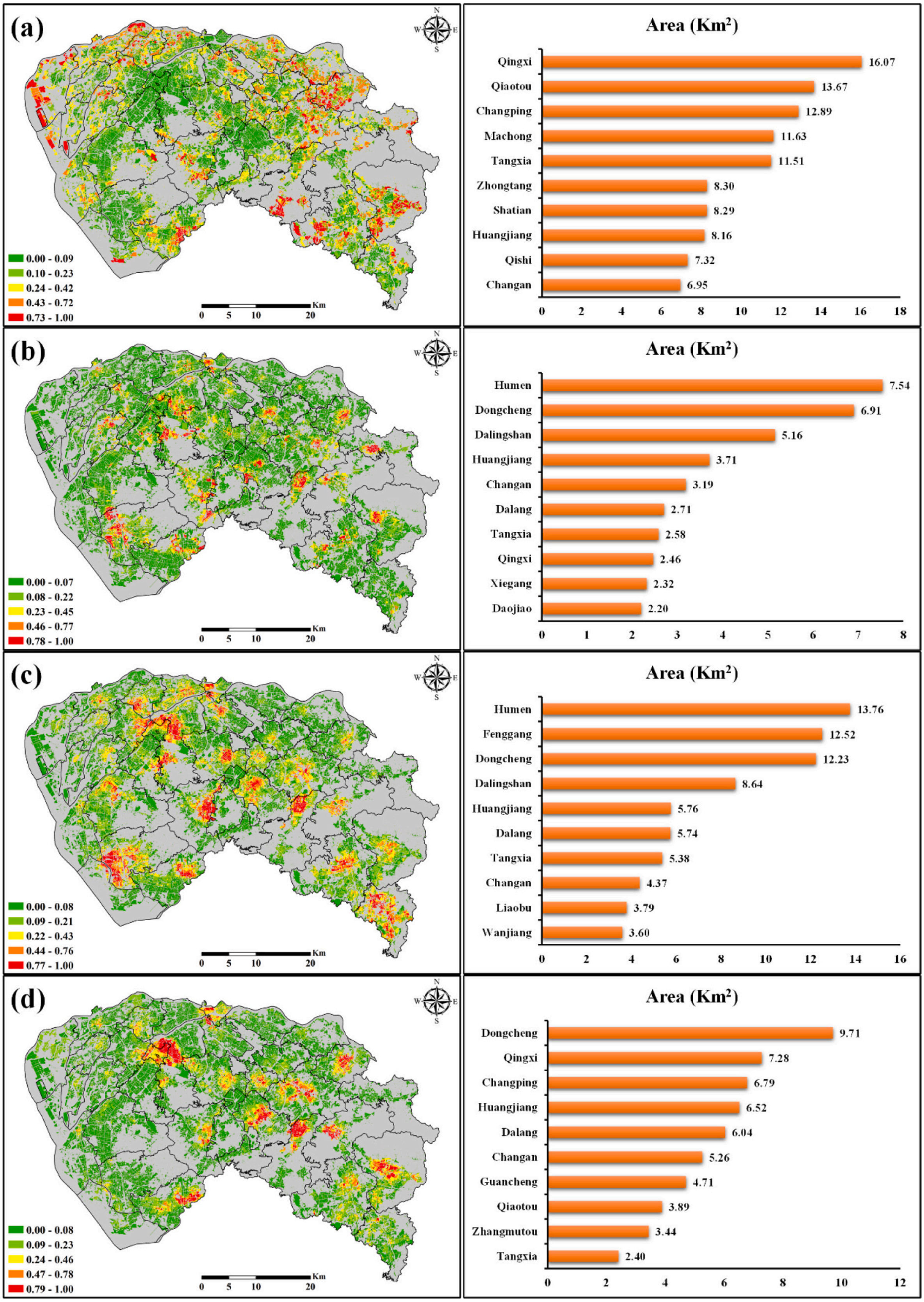


**Fig. 7.** Spatial distribution of various renewal potential assessments and the area of urban land parcels with high-value renewal potential (only the top 10 districts are displayed). The x-axis represents the area (Km$^2$), while the y-axis represents the district. (a) Renewal potential (Industrial land). (b) Renewal potential (Commercial land). (c) Renewal potential (Residential land). (d) Renewal potential (Public management-services land).

potential. As Dongguan was once dubbed the "World Factory", the urban renewal land parcels in the main urban area are dominated by old factories with the renewal intention of other proposed land-use types. The renewal strategy of inner-city sites is mainly the relocation of old factories. Since the discharge of industrial waste will seriously affect the living quality of residents, the old factories located in the main urban area have become the focal area of urban renewal. With the demolition of old factories in the main urban areas, the suburbs became the main area for new factories. Hence, the spatial distribution of industrial land is unique. The urban land parcels with high-value renewal potential of industrial land are distributed in the suburbs of Dongguan, such as Qingxi, Qiaotou, and Changping. The other three types of urban land parcels with high-value renewal potential are generally distributed in the central area of each district. Even in some major urban areas, the distribution of urban land parcels renewed for residential and public management-services land is similar. As major urban areas of Dongguan, Humen and Dongcheng have generated a large amount of inefficient land due to the high population and economic growth in the past, thus requiring a relatively high demand for urban renewal. Probably due to inconsistent development goals, both districts have a high demand for the renewal of residential land, but Humen has little demand for the renewal of land for public management-services land. In addition, few urban land parcels have a high-value renewal potential in Guancheng and Songshanhu. Guancheng is the center of Dongguan with a small area, so the renewed land area is also tiny. Songshanhu is a high-tech zone in which urban construction and planning are very advanced, resulting in little demand for urban renewal.

To verify the effectiveness of the renewal potential assessment, we selected several urban land parcels from the testing samples for qualitative comparison. All the chosen urban land parcels were documented as urban renewal projects. As shown in Fig. 8, the renewal potential of most urban land parcels is similar to the recorded information, demonstrating the reliability of the assessment results. In particular, some urban land parcels have multiple high-value renewal potentials and show tentative undefined renewal intentions. These urban land parcels require further field surveys to decide on a specific renewal strategy. We can also find similar characteristics in the street view images of the renewed land parcels, such as low-rise buildings and narrow streets. The similar characteristics also confirm the feasibility of street view images in assessing urban renewal potential. With the proposal of the sustainable development goals, the old sites in Dongguan have promoted the urban renewal process. Among them, the proposed land-use type of the old factory might be commercial, residential, or public management-services land, as shown in Fig. 8(e). Generally, the old

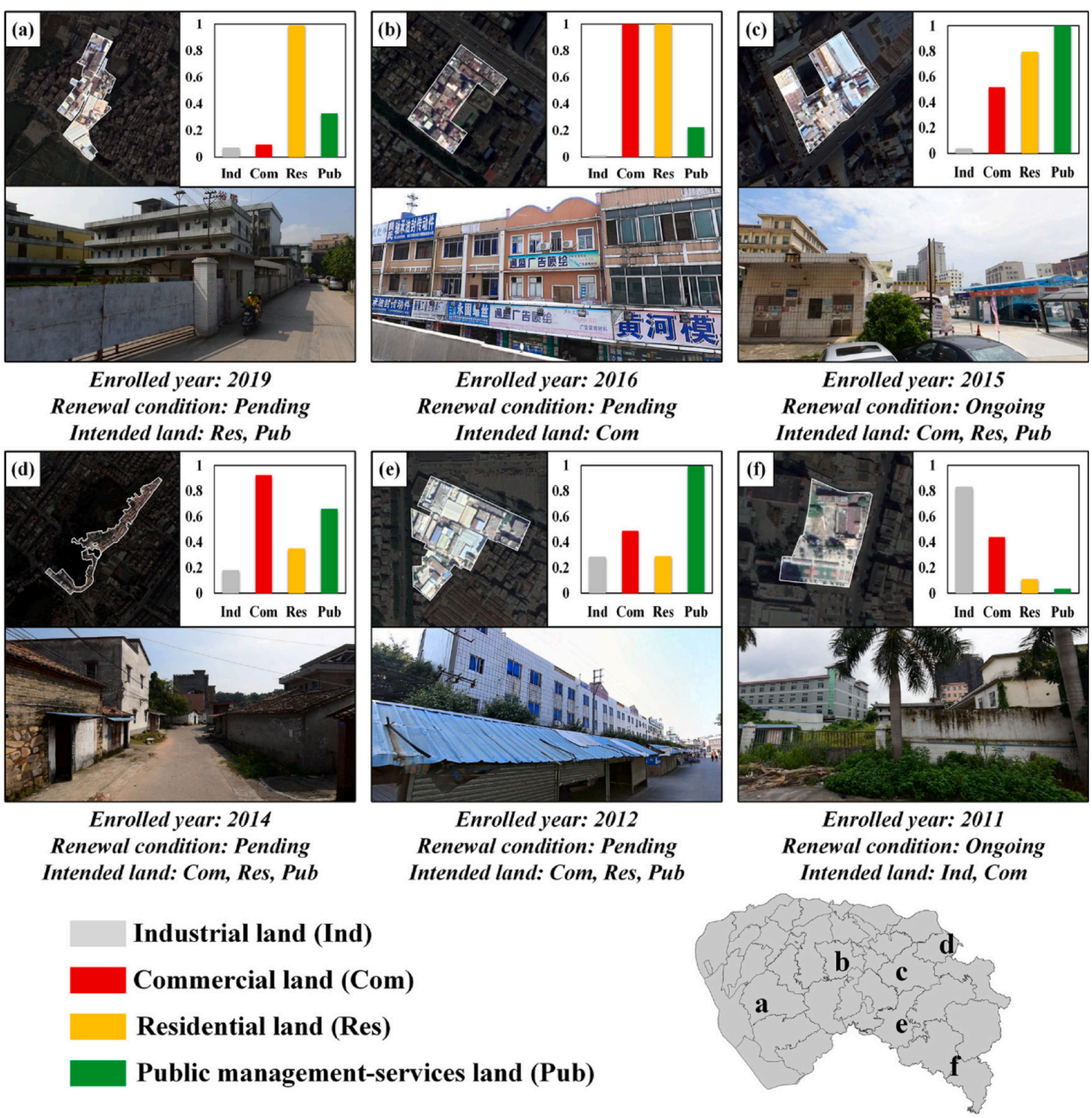


**Fig. 8.** Examples of urban renewal potential assessment based on the proposed indicators.

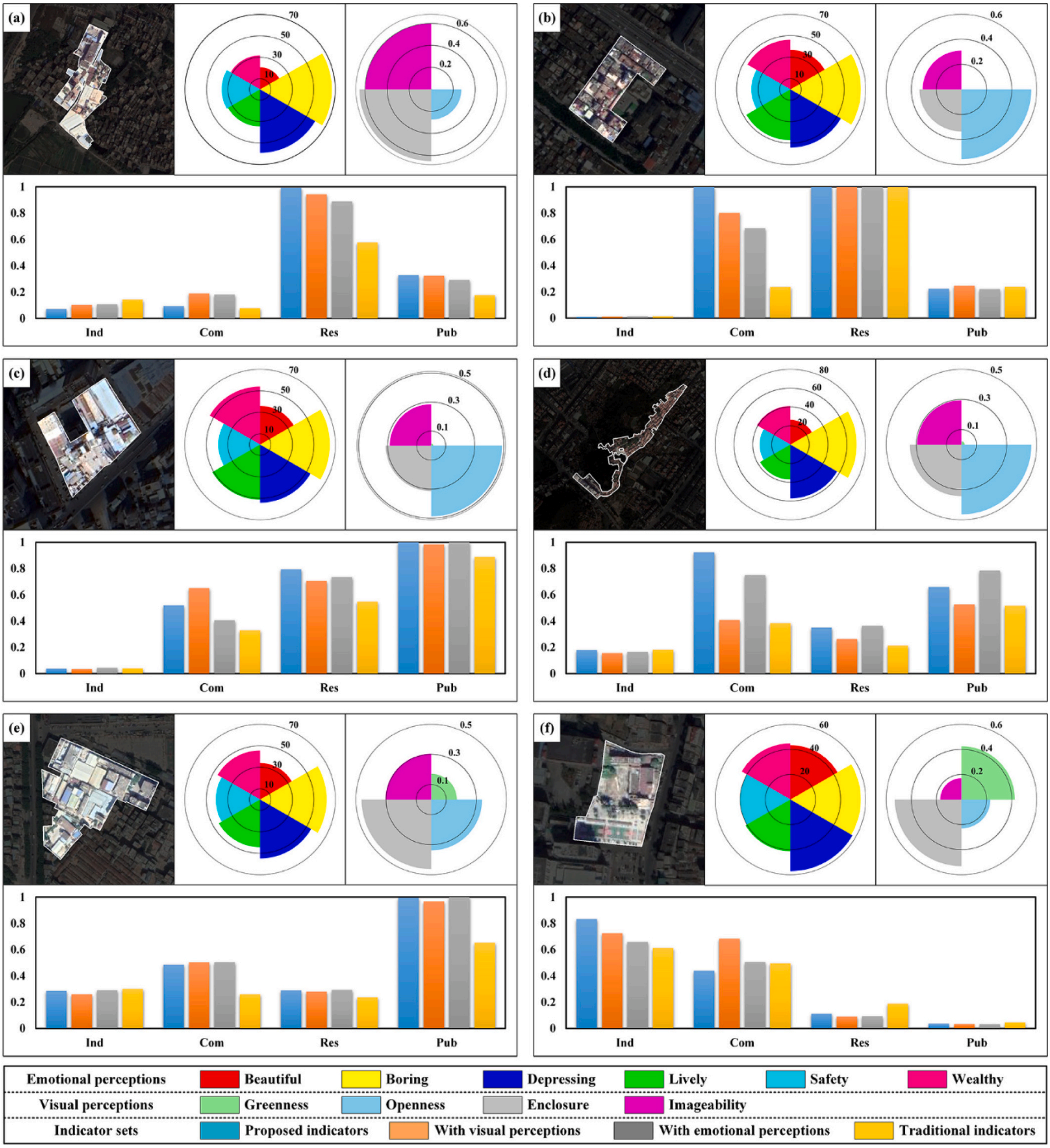


**Fig. 9.** Comparison of multi-class urban renewal potentials under different indicator sets. The abbreviations are industrial land (Ind), commercial land (Com), residential land (Res), and public management-services land (Pub).

factories are reconstructed for high-end residential areas, large shopping malls, or office buildings. However, single-handedly decommissioning factories can be a burden on economic development. Appropriate clearance and relocation to new sites are more suitable methods of reconstruction. The relocations of new factories are generally selected in the suburbs, thereby stimulating the economic development level of the suburbs of Dongguan. Therefore, the renewal type of old villages and neighborhoods in some suburbs will be industrial land. For example, the renewal intention of the suburban land parcels shown in Fig. 8(f) includes industrial land.

### 4.3. Impact of human perceptions on urban renewal potential assessment

In this section, we counted the human perceptions of the chosen urban land parcels in Section 4.2 to compare their renewal potentials under different indicator sets, as shown in Fig. 9. Overall, the renewal potentials of some urban land parcels, such as Fig. 9(b) and 9(d), are relatively low under the traditional indicator set, which is inconsistent with the recorded information. However, with the addition of human perceptions, the renewal potentials of most urban land parcels have significantly improved.

Several characteristics are summarized by analyzing the rose diagrams of the human perceptions of the selected samples. In terms of emotional perceptions, there are similarities in the composition of the scores depicting the blighted built environment, mainly in the form of lower scores for safety and lively and higher scores for boring and depressing. The reason for this composition is that the poor environment and decaying building structures are uninhabitable and can also reduce the human sense of security and raise anxiety, which is eventually presented as high or low values of emotional perceptions (Pearson et al., 2019). The similarity in the composition of emotional perceptions for the blighted built environment should also account for the high accuracy of urban renewal assessment compared to visual perceptions, indicating their more contribution to urban renewal assessment.

In terms of visual perceptions, the most intuitive characteristic is that most of the selected samples have a very low greenness. The composition of low-value greenness and middle-value enclosure indicates that buildings are the main components of the ground objects. Due to the intermediate enclosure, the low-rise buildings should be the primary building type of urban land parcel. For example, the building facades in Fig. 9(d) are hard to show continuity. Each household tended to have a single building, and the streets were sparsely vegetated. In the urban environment design concept, the enclosure and greenness in the central area should be higher than the average level of a city (Ma et al., 2021). High-value greenness has a positive impact on the livability of the built environment. The enclosure affects the spatial sense of residents, which is related to the crime rate. The crime rate represents lower in the area with a higher enclosure and vice versa (Deng, Yang, Chen, & Liu, 2022). At the same time, the urban land parcels with low values of enclosure lack the shelter of tree canopies and buildings. Therefore, the openness obtains a high value with the increase of the sky pixels. The imageability of the renewal land parcels is also essential in determining urban renewal since it can represent the residents' impression of an urban scene. If an urban scene contains many buildings, traffic signs, and billboards, especially landmarks, people will leave a deep impression on the urban scene. As shown in Fig. 9(d) and 9(f), the lower value of imageability indicates that there are few other ground objects apart from buildings (such as traffic signs and stores), which is in line with the single function of the renewal land parcels.

### 4.4. Practical implication

The urban renewal potential obtained by the proposed method is multi-class, thus providing a reference for urban land parcels with multiple renewal intentions to facilitate scenario analysis. This section examines one of the applications using the assessment results to

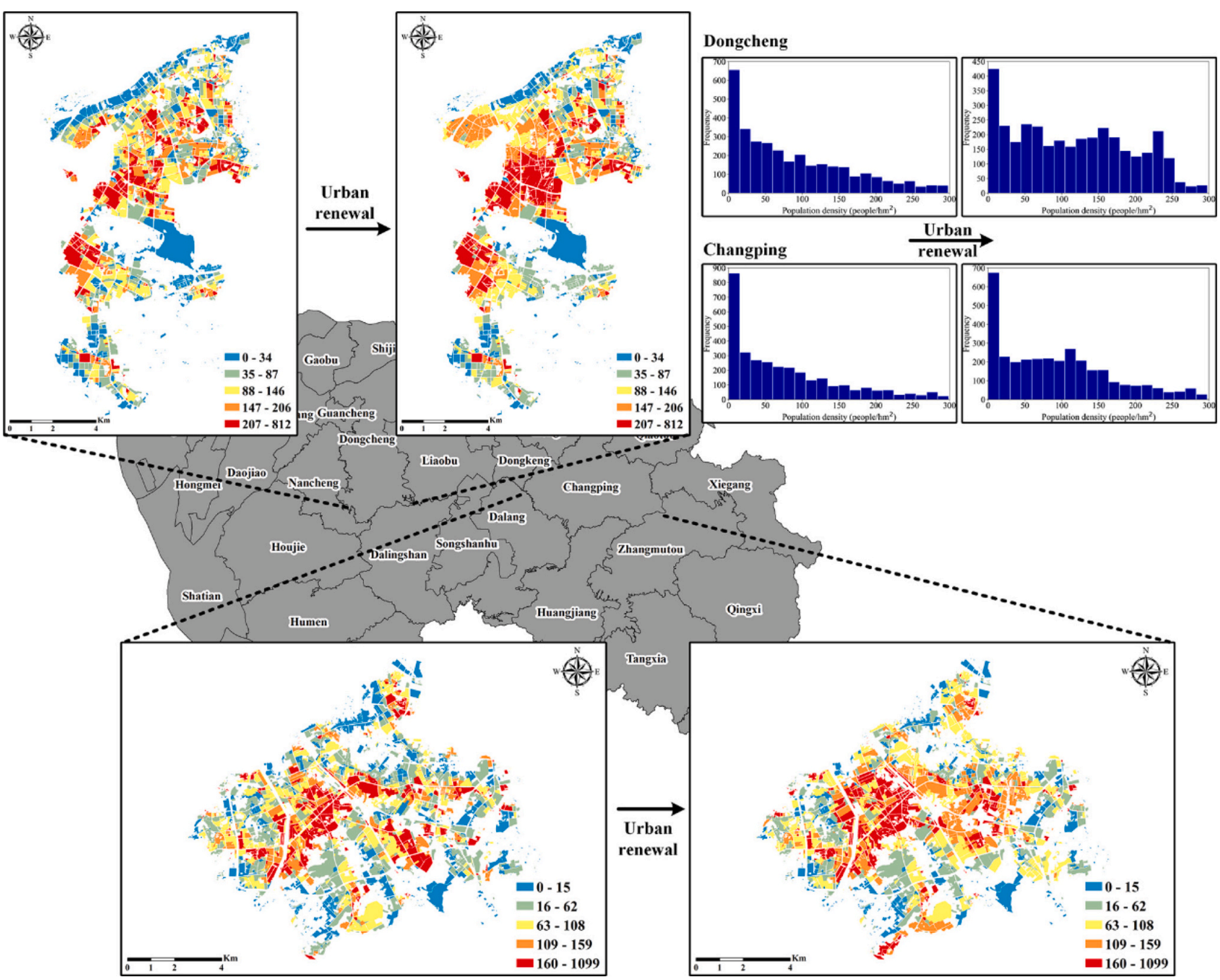


**Fig. 10.** Case study of population density estimation (unit: people/hm$^2$) before and after urban renewal. Dongcheng and Changping are two selected case districts.

demonstrate its impact on urban planning. Urban renewal is promoted to change the blighted appearance, improve the quality of life, and restore urban vitality. Previous studies have typically used population density as one way to measure urban vitality (He et al., 2018; Yue et al., 2021). Therefore, we applied topography, traffic, and facility abundance as the independent variables to estimate the population density before and after the implementation of urban renewal. The RTUD data in Appendix Fig. 3 are used as the dependent variable (Cheng, Wang, Feng, & Yan, 2021). A random forest-based regression algorithm to evaluate the population density of the renewed land parcels. Considering the variability of urban renewal demands between districts, we selected two districts with high-value renewal demands, Dongcheng and Changping, for the scenario analysis.

Fig. 10 illustrates the spatial variation and histogram distribution of population density under different scenarios in the two districts. Due to the high demand for urban renewal in these two districts, the population density of many parcels has changed. The results achieve an increase in population density, thus enhancing the urban vitality of the area when the land-use type with the highest value of renewal potential is selected for renewal. Please note that there is no upper limit set for the renewal potential for the comparison. In particular, the population density in the central area of Dongcheng has significantly increased. As shown in Fig. 7, Dongcheng includes many land parcels with high-value renewal potential, and the renewal intention of these land parcels is residential and public management-services land. The central area of Changping is changing similarly to Dongcheng. However, Changping is also one of the areas with the highest demand for emerging industrial land. These urban land parcels planned to be new industrial land are located in the suburbs of Changping. Even though there may be a decline in population density in the suburbs of Changping, the overall trend is upward. In a word, this section demonstrated that the multi-class urban renewal potential could support decisions on the problem of unclear renewal intentions for some urban land parcels. One possible approach is to evaluate the advantages and disadvantages of various renewal strategies through scenario analysis.

## 5. Conclusion

Accurately assessing the urban renewal potential in a large-scale area is beneficial for project promotion, which can meet the planning requirements for the proactive management of cities. The assessment of urban renewal potential can be conducted by constructing an indicator set based on crowdsourced geospatial and official statistical data. However, the existing framework for assessing urban renewal potential still has some limitations, especially the lack of a built environment assessment. The blighted built environment is an essential factor in determining urban renewal. Measuring the human sense of place can effectively reflect the residents' evaluation of the built environment design. Therefore, human perceptions of the built environment can be critical in improving the reliability of urban renewal assessment.

As emerging geospatial data, street view images present the built environment observed by human eyes. Therefore, street view images can be an essential data source for extracting human perception to assist urban-related research. We obtained the components of various ground objects from the street view images by applying a semantic segmentation model. Ten human perceptions (including four visual perceptions and six emotional perceptions) were constructed and obtained based on the components of ground objects. We assessed the renewal potential using a PBL-BPNN-based assessment model by integrating human perceptions with the traditional indicator set.

As a result, we achieved a higher renewal potential assessment accuracy based on the proposed indicator set than the traditional indicators. Under the proposed indicator set, all the assessment accuracies of urban renewal potential can exceed 77 %. The addition of human perceptions has increased the assessment accuracy of urban renewal potential, ranging from 5.16 % to 7.64 %. We further compared the composition of the human perceptions of several cases. Both emotional perception and visual perception were found to enhance the accuracy of urban renewal assessment. However, the superiority and stability of emotional perception in depicting blighted built environments contribute more to urban renewal assessment than visual perception. By integrating human perceptions, the proposed method can compensate for the shortcomings of the traditional method in incorrectly assessing some urban land parcels with a dilapidated urban appearance on a large scale. Besides, the large-scale assessment results are easy to manage and update, saving a lot of labor and providing data support for arranging subsequent field surveys. The multi-class urban renewal potential assessment can also give suggestions for the renewal intention of the parcel by comparing the renewal potential under different scenarios.

However, urban renewal potential assessment can be further improved in future research. Although the street view images can make up for the vacancy of the built environment in the traditional indicator set, some factors for urban renewal assessment are still insufficient. For example, the factors related to industrial output still lack complete and high spatiotemporal resolution geographic data, such as pollutant emissions and electricity consumption, which affect whether old factories undergo urban renewal. Moreover, the proposed method cannot assess the renewal potential of some urban land parcels because street view images do not fully cover the whole city. As smart city projects become more widespread in China, the proposed method should have broad application prospects when street view images can soon cover every corner of the city.

## CRediT authorship contribution statement

**Jialyu He:** Conceptualization, Methodology, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jinbao Zhang:** Methodology, Data curation, Visualization. **Yao Yao:** Resources, Methodology, Data curation. **Xia Li:** Conceptualization, Resources, Methodology, Supervision, Funding acquisition, Writing – review & editing.

## Declaration of Competing Interest

None.

## Data availability

The data that has been used is confidential.

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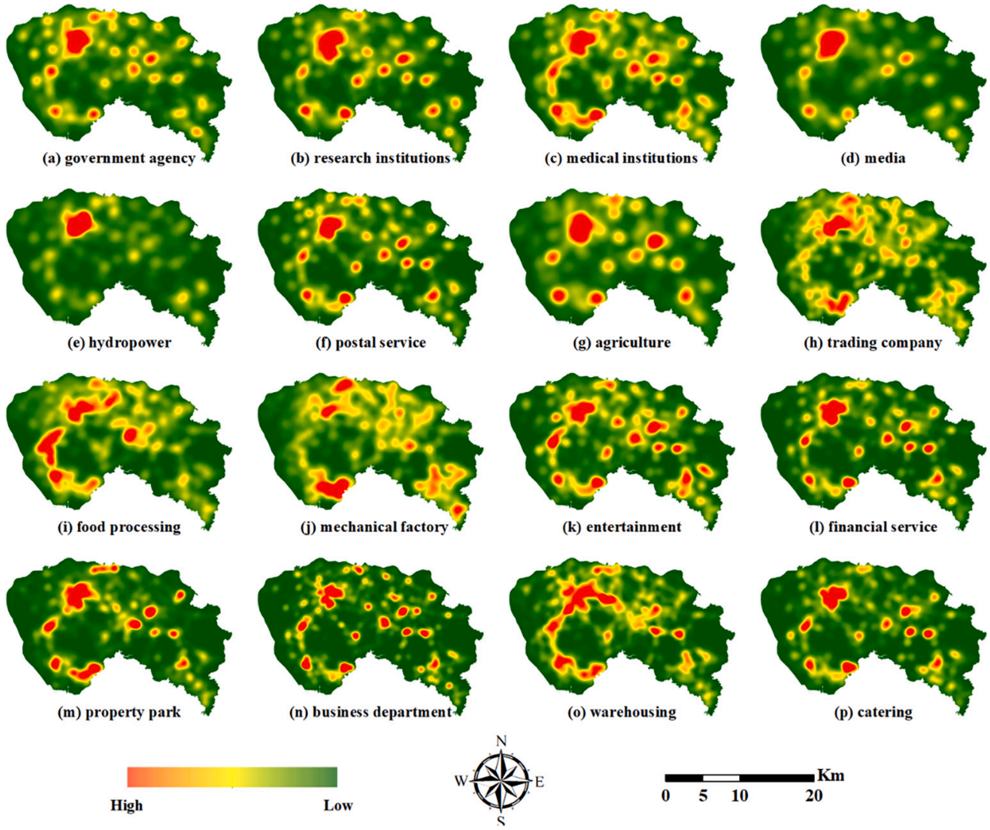
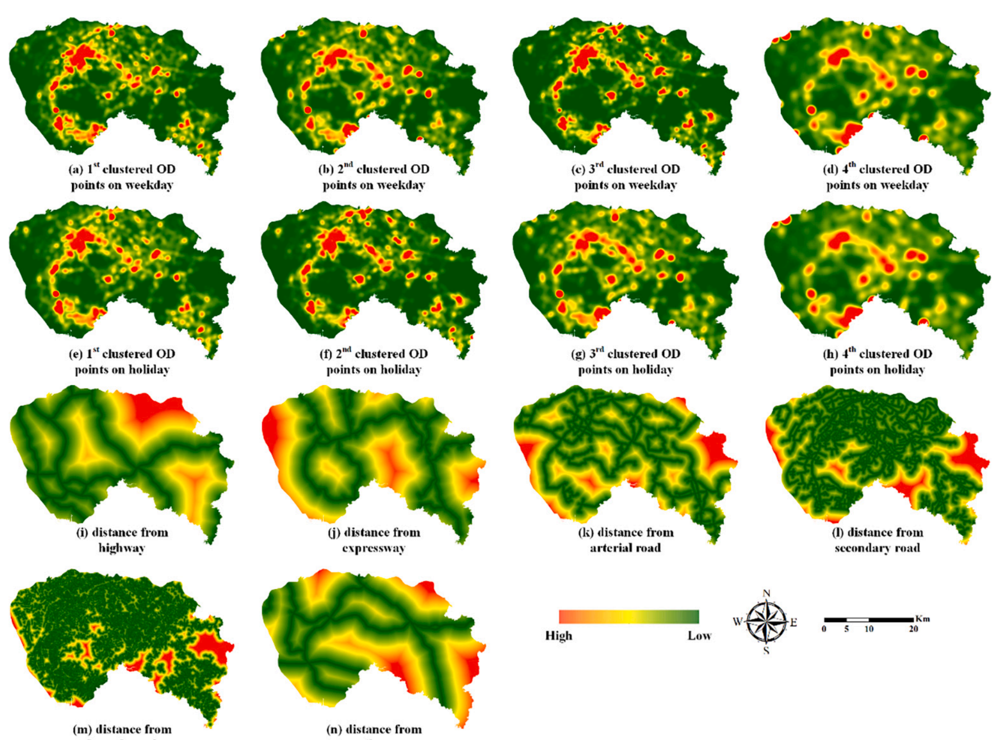
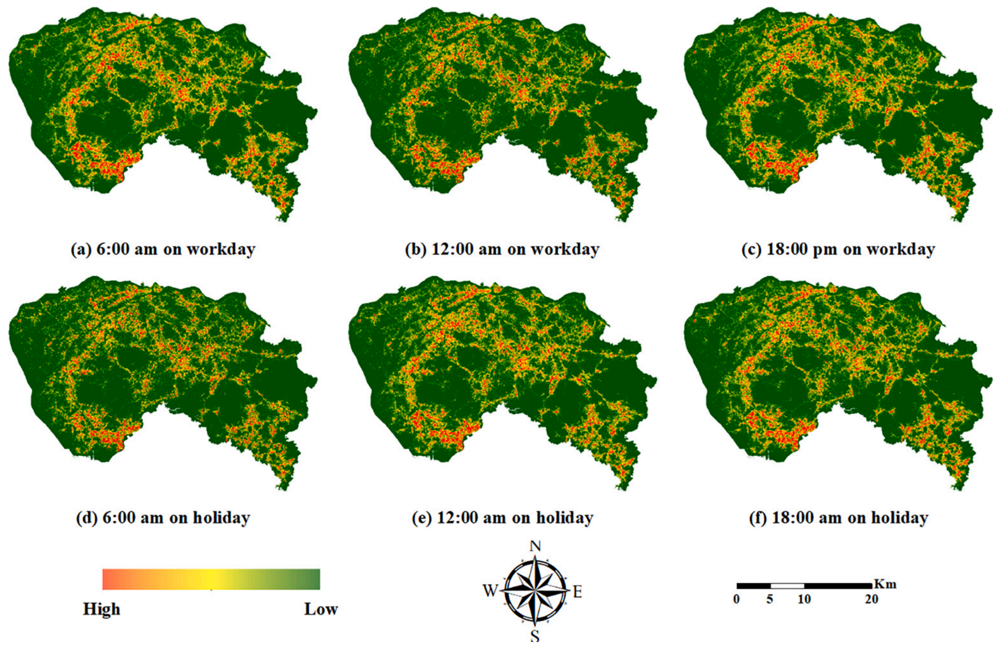
## Appendix A




**Appendix Fig. 1.** The facility abundance maps.




**Appendix Fig. 2.** The accessibility maps.




**Appendix Fig. 3.** The population distribution maps.

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