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Assessing the Effects of Subjective and Objective Measures on Housing Prices with Street View Imagery: A Case Study of Suzhou

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Abstract: The price of a house is affected by both the subjective and objective factors of the street environment in a neighborhood. However, the relationships between these factors and housing prices are not fully understood. Street view imagery (SVI) has recently emerged as a new data source for housing price studies. The SVI contains both objective and subjective information and can be used to extract objective measurements describing the physical environment and subjective measurements depicting human perceptions. Compared to conventional methods, there is consistency between subjective and objective information extracted from SVIs, and the two types of information are acquired from the perspective of the human visual perceptual system. Therefore, using both objective and subjective information extracted from street view images to study their relationship with housing prices has several advantages. In this study, focusing on the city of Suzhou, China, we extracted subjective perception and objective view indices from SVIs and systematically assessed their effects on housing prices. The global ordinary least squares (OLS) regression model and the local geographically weighted regression (GWR) model were used to model the correlations between these measures and housing prices. The OLS reveals that overall objective measures have stronger explanatory power, and built environment factors have a greater impact on housing prices. GWR shows that subjective factors can explain more variance in housing prices on the local scale and that home buyers care more about the subjective perceptions of the neighborhood's surroundings. The map of the GWR local coefficients demonstrates that the perception indicators have both positive and negative effects on housing prices in different places. In addition, a Monte Carlo test was performed to verify the spatially varying relationships between these measures. Our findings provide important references for urban designers and guide various applications, such as safe neighborhood design and sustainable city planning.

Keywords: street view imagery; housing prices; human perception; Simpson's paradox; geographically weighted regression

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1. Introduction

Housing price studies have received growing attention in recent years because of the availability of housing data and the important role of housing in human life [1–3]. Housing prices are determined by several groups of characteristics, such as structural, locational and neighborhood attributes [4]. Streets near houses can provide residents with opportunities for strolling and socializing [5]. The streetscape is the "outdoor room" one encounters when turning the corner or stepping out the door into the street [6]. The quality of a streetscape is associated with user well-being [7]. People tend to live in houses surrounded by high-quality streetscapes with many trees or that are perceived as beautiful and safe [8,9]. Understanding the relationship between streetscapes and housing prices can provide new insights into the composition of housing prices and is beneficial for applications, such as urban planning and real estate.

Conventional approaches to streetscape evaluation include field surveys and interviews. These methods may lead to potential biases and are costly and time consuming [10]. Street view imagery (SVI) has recently become widely used as an emerging source of big data [11,12]. The SVI is publicly available and provides an alternative to traditional methods [11]. Owing to machine learning and deep learning, the SVI has become highly effective for assessing streetscapes in urban environments. There are two types of indicators for measuring streetscape qualities from the SVI [13]. The first is an objective measure that describes the physical appearance of streets, such as the green view index (GVI) [14], pedestrian volume [15], and sidewalk length [16]. Prior studies have mainly used objective measures to study the relationship between streetscape quality and housing prices [8,17]. For example, visible street greenery has been found to have a significant positive effect on housing prices [8]. However, we can only learn about one side of a street from objective measurements. Specifically, they do not capture a street's human perceptions, which may have subtle or complex relationships with physical elements [18]. The second category includes subjective measures depicting human perceptions, such as beautiful, safe and enclosure [19]. They described the raters' overall perceptions of street view images. Analyzing the effects of the street environment's human perceptions on housing prices may provide a comprehensive understanding of housing prices [13]. For example, the enclosure measurement was found to have a negative relationship with housing prices [13]. Although objective and subjective measures have distinct effects on housing prices, the strength of the association between these measures and housing prices is not fully understood.

Previous research has focused on the perceptions favored by urban planners [13,20,21]. These perceptions included enclosure, human scale, complexity, imageability, safety, greenness, and walkability. These are the professional opinions of urban planners, which are difficult for ordinary house buyers to comprehend. Personal perceptions, which are more subjective than professional perceptions [18], such as safety, wealthy, lively, beautiful, boring, depressing [9], class, and uniqueness [22], are closely related to residents' daily lives. Therefore, for housing buyers and renters, these personal perceptions offer additional references and values. However, prior studies usually employed the Place Pulse dataset (Place Pulse 1.0 and 2.0) [9] created by MIT Senseable City Lab researchers to measure the visual perceptions of Google Street View images, which may not be appropriate for Chinese cities. The Place Pulse 2.0 dataset contains 110,988 SVIs spanning 56 cities in 28 countries [23] and does not include SVIs from mainland China. Although the Place Pulse 2.0 dataset can be applied to other cities, each city has its own socio-economic status or physical environments, such as building styles [24–26], which may pose problems and lead to perceptual biases in people. To estimate premiums on housing prices, it would be ideal to use a perception dataset with locally obtained SVIs and local evaluations.

This study aimed to understand the impact of subjective emotional and objective view measures on housing prices using locally obtained SVIs in China through a comprehensive assessment. In this study, we extracted subjective perception and objective view indices from SVIs and systematically compared their effects on housing prices. We considered Suzhou City, China, as an example. The subjective perceptions were safety, wealthy, lively, beautiful, boring, and depressing, and they were more relevant to people's daily lives. Locally collected SVIs were used to train a deep learning model to predict human perceptions of the street environment. The effects of subjective and objective measures on housing prices were assessed with ordinary least squares (OLS) regression. To account for spatial heterogeneity, GWR was also performed.

This study makes three main contributions to the literature. First, we comprehensively assessed the relationship between objective/subjective measures and housing prices. Second, we discussed how certain perceptions may affect housing prices. Third, we explored the effects of these measures on housing prices, both globally and locally. We do not intend to make any causal statements. Our study aims to use this correlation to demonstrate the need to incorporate human perceptions into housing price studies. Our study provides a significant reference for urban planners to enhance urban environments from the viewpoint of human perception.

2. Literature Review

2.1. Housing Price Modeling and Spatial Heterogeneity

Extensive research has been conducted to analyze the different factors that affect housing prices [1,27,28]. The willingness to pay for these attributes can be inferred using the hedonic price modeling (HPM) method [4] in environmental economics. Due to its simplicity and interpretability, OLS regression is the most popular HPM technique.

OLS provides a set of coefficients for all observations and is, therefore, a global model. OLS ignores spatial heterogeneity, implying that different locations within a given area exhibit distinct features or patterns. This may lead to the Simpson's paradox, which refers to the reversal of results when datasets are analyzed separately and then combined. This indicates that it is risky to analyze aggregated data. It is essential to mitigate this problem by modeling spatially varying relationships [29].

Geographically weighted regression (GWR) [30] has been used as an effective model to detect spatially varying relationships. GWR estimates different coefficients for observations at different locations and is, therefore, a local model that can reduce the problem of Simpson's paradox. While OLS establishes the baseline, GWR is recommended for improving the estimation of housing prices.

2.2. Streetscape Measures from SVI

Both the objective and the subjective groups of information can be derived from SVIs. Examples of common objective measurements include the GVI [31,32], the sky view index (SVI) [33], blue spaces (e.g., rivers, lakes) [34], and frontage [35]. As objective measures are simpler to extract than subjective measures, some studies first extract view indices from SVIs and then use view indices to compute subjective human perceptions through specific mathematical models. For example, the view indices of psychological greenery, visual crowdedness, outdoor enclosure, and visual pavement were combined to constitute an integrated visual walkability index [36]. Ito employed both objective and subjective SVI indicators and other non-SVI indicators to construct a comprehensive bikeability index [37]. Ma [38] used objective view indices to form perceptions of openness, greenness, enclosure, walkability, and imageability. Subjective measures are believed to depict the environment more completely than objective measures [16]. Subjective measures have complex and subtle relationships with objective measures. Ewing presented operational definitions of five perceptions (imageability, enclosure, human scale, transparency, and complexity) and provided novel insights into the relationships between physical features and perceptions [18]. Street-level perceptions can be measured subjectively through surveys or objectively by recombining view indices extracted from SVI [38].

2.3. Effects of Streetscape Measures on Housing Prices

An important aspect of assessing the effectiveness of environmental policies in improving streetscapes is the quantitative measurement of the economic value of the benefits. Houses surrounded by better streetscapes will have this benefit capitalized into their value, and this should be reflected in a higher sales price. Regarding objective measures, Ye found that visible street greenery had a significant positive effect on housing prices [8]. Fu showed that greenery and sky view indices could significantly increase housing prices [17]. Chen found that the impacts of the green view index and sky view index on housing prices were nonlinear; the green view index had a positive effect, whereas the sky view index had a negative effect [39] on housing prices. Objective measures can only describe the physical settings of the street environment and cannot fully capture people's overall perceptions of the streetscape [18].

For subjective measures, Buonanno confirmed that security perception was positive for a property's average value in Barcelona [40]. Kang incorporated six human perceptions (safe, beautiful, depressed, lively, wealthy, and boring) into the HPM and found that positive perceptions (beautiful, lively, safe, and wealthy) had a positive correlation with housing prices, and negative perceptions (depressing and boring) had a negative correlation [9]. The US cities of Boston and Los Angeles were selected as case studies for Kang's study. Based on the assumption that subjective indicators provide a more complete picture of the street environment, Qiu compared the strength of objective measures and subjective urban design-related measures (enclosure, human scale, complexity, imageability, and safety) and revealed that the subjective measures individually had stronger strength than the objective measures [13]. Despite employing the GWR to map the effects of various measures on housing prices, Qiu neglected to thoroughly examine the positive and negative effects of objective and subjective measures. Qiu subjectively and objectively measured six perceptions (greenness, safety, walkability, imageability, enclosure, and complexity) and found that the collective strengths of perception indicators were nearly equal for both subjective scores and objective counterparts; however, the subjective and objective indicators all had opposite individual signs in explaining price variance [20]. Xu took a similar approach and discovered that subjective scores explained more variance than objective scores and that perceptions could not be fully represented by objective indicators [21]. For professional perceptions (e.g., imageability), subjective indicators can explain more variance, but for self-evident perceptions (e.g., greenness), objective indicators perform better. Qiu and Xu used only the global model and did not consider local models, such as GWR [20,21]. Table 1 summarizes the models and measures used in studies on the effects of streetscape perceptions on housing prices.

Table 1. Models and measures of studies related to the effects of streetscape perceptions on housing prices.

Research	Model	Measures	Case Study
Buonanno [40]	OLS	security perception	Barcelona, Spain
Kang [9]	OLS, GWR, PCA	beautiful, lively, safe, wealthy, depressing and boring	Boston and Los Angeles, USA
Qiu [13]	OLS, GWR, Spatial Regression	enclosure, human scale, complexity, imageability, and safety	Shanghai, China
Qiu [20]	OLS	greenness, safety, walkability, imageability, enclosure, and complexity, with subjective survey and objective equations	Shanghai, China
Xu [21]	OLS	greenness, safety, walkability, imageability, enclosure, and complexity	Shanghai, China
this study	OLS, GWR	beautiful, lively, safe, wealthy, depressing and boring	Suzhou, China

2.4. Summary

The following three knowledge gaps regarding the effects of streetscape measures on housing prices are summarized:

First, personal perceptions have received little attention in the research on housing prices. The perceptions (safe, beautiful, depressing, lively, wealthy, and boring) are more relevant to local residents than Qiu and Xu's chosen perceptions (enclosure, human scale, complexity, imageability, and safety), which are based on urban planning theory [18]. Subjective measures of urban design are more readily available to designers and planners than to the general public. Therefore, they have fewer actionable implications for homebuyers and residents [13]. The effects of these perceptions on housing prices are not very clear, and they have not been assessed or compared with objective measures.

Second, little research has been conducted on personal perceptions of housing prices in China. Kang's study focused on American cities, and the human perception dataset was the Place Pulse dataset, which primarily comprised Western cities. However, each city has unique characteristics. Urban perceptions obtained from the global Place Pulse dataset may not apply to Chinese cities. Using a perception dataset with locally obtained SVIs and local evaluations may be more appropriate for predicting perceptions.

Third, the global and local models have rarely been considered simultaneously. Most studies have employed global models, such as OLS. However, inferring a policy from the average results of a global model may be misleading. Local models, such as GWR, should be used to reveal the spatially varying effects of streetscape measures.

Based on the aforementioned analysis, we assessed and compared the effects of personal perceptions of housing prices with those of objective measures. Locally collected SVIs were used to train a deep learning model to predict human perceptions. The effects of these measures were assessed using OSL. To avoid misleading interpretations, GWR was employed to account for the spatial heterogeneity of these measures.

3. Data and Methods

3.1. Research Framework

The major steps of the research framework are listed below and presented in Figure 1. First, street view images were collected from the Baidu online map and fed into the deep learning models PSPNet and convolutional neural network (CNN) separately to obtain objective view indices (sky view index, tree view index) and subjective perception scores. Community housing price data and other related variables were gathered from the Anjuke online platform, and community price was set as the dependent variable. The road network and the point-of-interest (POI) datasets were used to calculate hedonic variables. Finally, the subjective perception scores and objective view indices were regarded as two groups of interpretable variables and added with control variables. Using these two groups of variables, we compared and analyzed the results of stepwise regression and GWR.

3.2. Study Area

Our analysis was conducted in Suzhou, a city located in the Jiangsu province of China ranging from 119° 55′ E to 121° 20′ E longitude and from 30° 47′ N to 32°02′ N latitude. The total area of Suzhou was 8657.32 km^2 and its population was 12.75 million as of 2020 [41]. Suzhou lies with Shanghai to the east and is the most populous city in Jiangsu Province. It is one of the first national historical and cultural cities, known as "the heaven on the earth". The central city consists of the Gusu District, Industrial Park District, Wuzhong District, Xin District, and Xiangcheng District. In 2020, the GDP of Suzhou exceeded 2 trillion Chinese Yuan(CNY) for the first time, making it the sixth 2 trillion CNY city in China, and the city's housing prices have been growing rapidly in recent years. Suzhou is characterized by a network of canals, rivers, and numerous small lakes. These waterways have earned Suzhou the nickname "Venice of the East". The city is known for its traditional architecture, with well-preserved historic areas featuring narrow streets, stone bridges, and traditional Chinese buildings. The central region of Suzhou was selected as the study area in the present study.

3.3. Data

3.3.1. Housing Prices

Housing prices for 1389 communities as of December 2022 were collected through web crawling technology from the Anjuke website [42]. Anjuke is a large website that offers real-estate information services and serves numerous cities in China. Community attributes, such as address, building year, property fee, floor area ratio, and greenspace proportion, were also gathered. Duplex flats and villas were not included in the scope of this study, thus avoiding potential biases and increasing the reliability of the findings. Price is the average price of the properties currently on sale for the current month. The latitude and longitude coordinates of residential communities were gathered using Baidu Map's geocoding service, and community attributes were combined with housing price data, as shown in Figure 2.

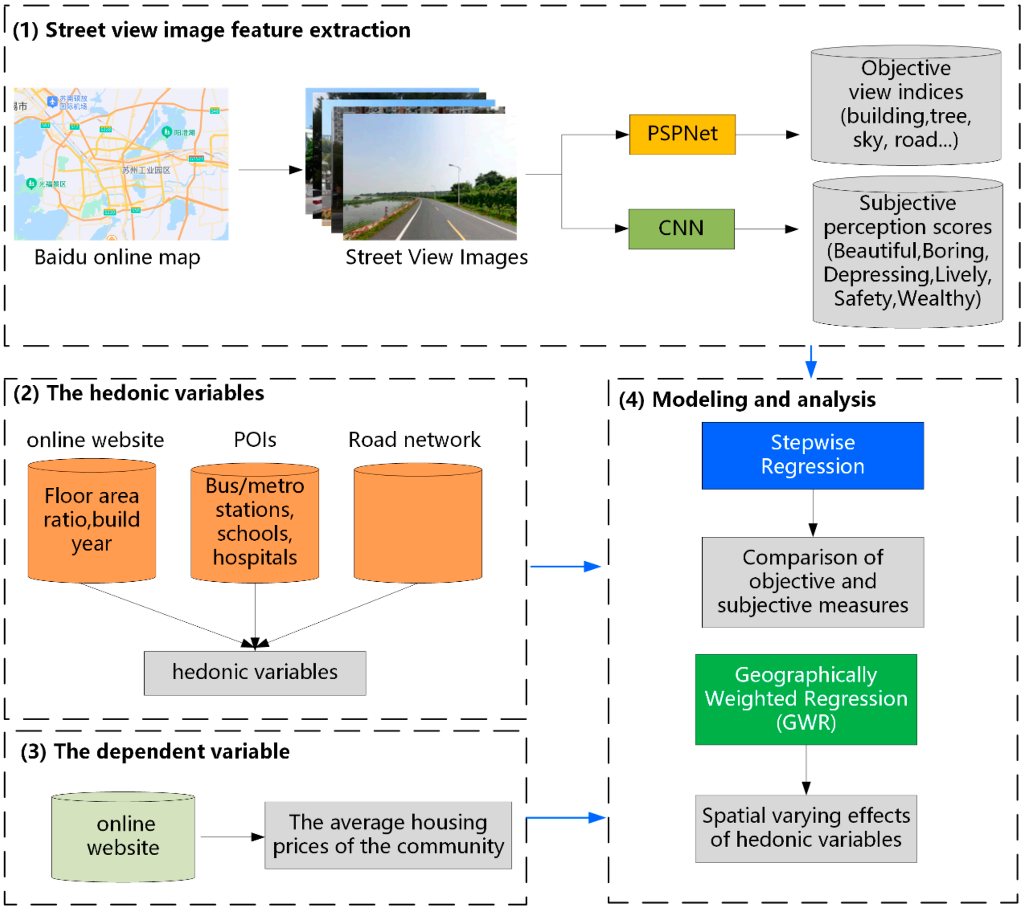


Figure 1. Research framework.

3.3.2. POI and Road Network

Additionally, POI data for Suzhou were gathered from the Baidu map platform using web crawling technology. The categories in the POI data were utilized to extract bus stations, metro stations, primary/middle schools, and hospitals, which were then used to compute the locational and neighborhood attributes in the HPM. The road network of Suzhou was extracted from the Open Street Map (OSM, https://www.openstreetmap.org (accessed on 21 May 2023)) and used to calculate the network distances between communities and amenities.

3.3.3. Street View Images

Subjective human perceptions and objective view indices of the street environment were obtained using SVIs. The SVIs of Suzhou were collected from the Baidu Map in December 2022. Baidu Maps, a Chinese map service provider, is comparable to Google Maps in that it provides street viewing services to numerous Chinese cities. We used the road network data of Suzhou City to construct sampling points for street view images at 100 m intervals along the streets. Based on the location of the sampling points, images in the horizontal direction closest to the sampling points were obtained through web requests. Four acquisition directions (90°, 180°, 270°, and 360°) were specified at each sampling point to capture its full view. Each image had a resolution of 960 × 720 pixels. There were 43,382 sampling points in the study area, and 173,528 images were collected.

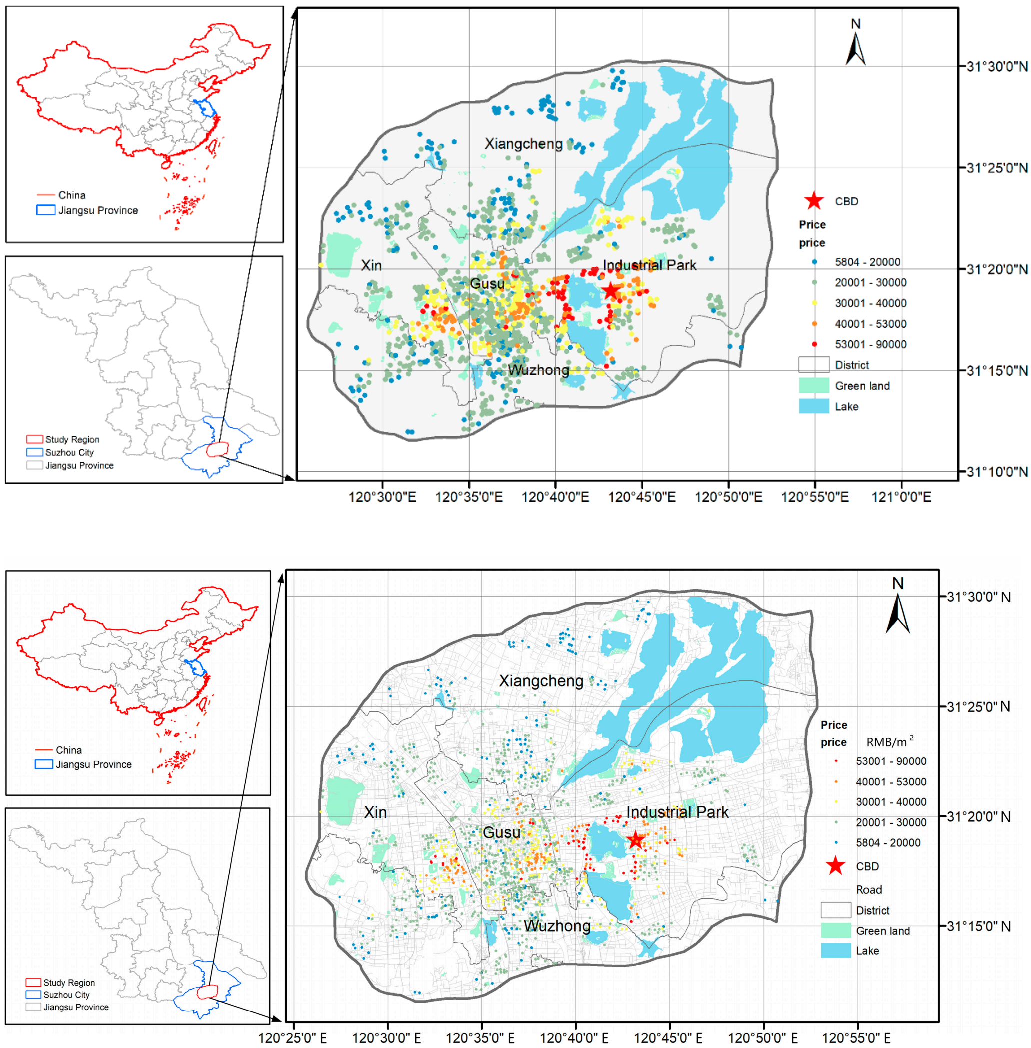


Figure 2. Spatial distribution of community housing prices in Suzhou.

3.4. Data Preprocessing

3.4.1. Calculation of Subjective Perception Scores

Deep learning is the primary method used to extract human perceptions from SVIs. Deep learning can be used to obtain human perception in two ways. One fits the human perception scores directly and automatically learns the deep features of an image. For instance, Dubey et al. trained an end-to-end Siamese-like convolutional neural model on the Place Pulse 2.0 dataset to predict the human perception score of a street view image [23]. Wang et al. [43] designed a CNN model based on VGGNet and trained it on a Chinese urban perception dataset [44]. Another method extracts image features using deep learning semantic segmentation techniques and uses additional machine learning models, such as the random forest model, to fit the human perception scores. For example, Yao et al. employed a fully convolutional network to semantically segment the features of SVIs and estimate the areal ratio of each semantic object [24]. The areal ratios were then fed into a random forest model to fit human perceptions. Zhang et al. developed a CNN model based on a residual network to learn the deep features of SVIs and trained an SVM classifier to predict the human perception score [19].

The accuracies of the CNN approach and Yao's method were compared by Wang et al. [24], and it was discovered that the former was superior to the latter because it considered the topological properties of semantic objects [44]. The former method is faster and simpler. Furthermore, the CNN model introduced by Wang et al. was open-source (https://doi.org/10.6084/m9.figshare.12552233 (accessed on 23 May 2023)), trained on a Chinese (Wuhan city) urban perception dataset, and was more suitable for the present study than other models trained on the global Place Pulse 2.0 dataset. Therefore, we employed Wang's CNN model to quantify the human perception scores of the SVIs.

The architecture of Wang's model is illustrated in Figure 3. Traditional CNN models are typically used for image classification tasks. Wang modified the traditional CNN model and replaced the softmax layer used for classification with a fully connected layer to gather deep-image features and predict human perceptions.

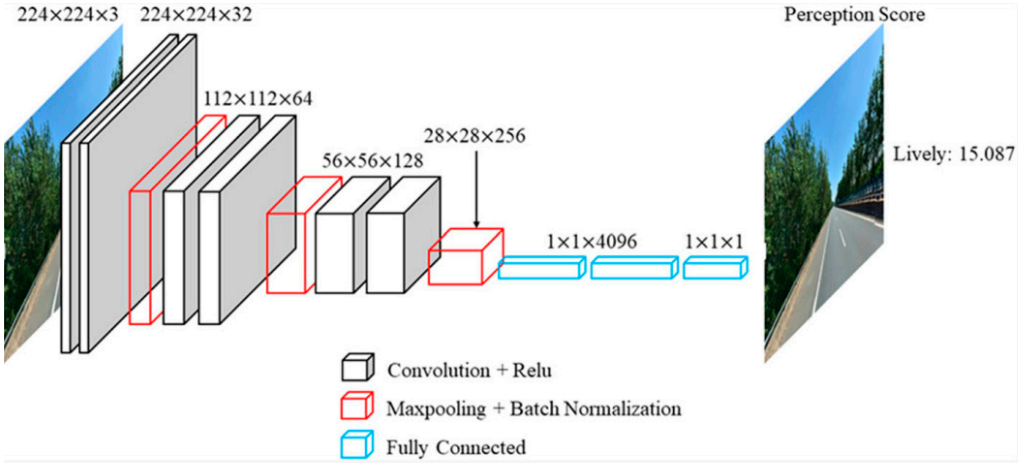


Figure 3. Subjective perception score calculations via the CNN model [44].

After predicting the six perception scores for each SVI, the average SVI scores for the SVIs of all four directions at each sampling point were calculated. Then, the scores of the SVIs with a 1 km buffer (15 min walking distance) of a community were averaged to represent the street perception of the community [13,36]. Descriptive statistics for the six perceptions are presented at the bottom of Table 2.

3.4.2. Extracting Objective View Indices

The objective view index of a street view image is the areal ratio of a semantic object to the total number of pixels in the image. This can be calculated using Equation (1).

$$VI_{obj} = \frac{\sum_{i=1}^{m} Area_{obj\_i}}{\sum_{i=1}^{m} Area_{total\_i}} \times 100\% \tag{1}$$

where $Area_{obj\_i}$ is the number of pixels of a particular object obj (e.g., building, sky, or tree) obtained by the deep learning semantic segmentation algorithm in direction i. $Area_{total\_i}$ is the total number of pixels of one SVI. The number m represents the number of SVI orientations that a camera will capture at one sample point, which was four in this study.

To extract semantic features from the SVIs, the Pyramid Scene Parsing Network (PSPNet) model [45] was employed. PSPNet is a deep-learning-based semantic segmentation network that extracts scene information from global to local scales to better recognize and distinguish between various objects. Figure 4 shows the PSPNet architecture. PSPNet has a wide range of applications in image segmentation and scene understanding tasks, with advantages such as high accuracy, high speed, and low computational cost. This is appropriate for various high-level computer vision tasks.

Table 2. Descriptive statistics of all variables.

Variable	Definition	Mean	Std
Ln_Price	RMB (Chinese currency)/m^2, dependent variable, the natural logarithm of the original price	10.197	0.354
Structural attributes	**Description**	**Mean**	**Std**
FAR	Floor area ratio	1.68	0.835
Age	Age of the building	18.862	7.322
Locational attributes	**Description**	**Mean**	**Std**
D_CBD	Network distance (km) to the CBD (the Suzhou Industrial Park)	13.739	6.213
D_Bus	Network distance to the nearest bus station (km)	0.306	0.210
D_Metro	Network distance to the nearest metro station (km)	1.042	1.249
D_School	Network distance to the nearest primary/middle school (km)	0.424	0.369
D_Hospital	Network distance to the nearest hospital (km)	0.552	0.542
Neighborhood attributes	**Description**	**Mean**	**Std**
N_Bus	Number of bus stations in 1000 m walking distance	7.534	4.837
N_Metro	Number of metro stations in 1000 m walking distance	1.433	1.368
N_School	Number of schools in 1000 m walking distance	6.34	4.536
N_Hospital	Number of hospitals in 1000 m walking distance	2.788	1.309
Subjective perceptions	**Description**	**Mean**	**Std**
S_Beautiful	Beautiful perception	37.818	4.416
S_Lively	Lively perception	36.256	2.817
S_Safe	Safe perception	37.143	1.725
S_Wealthy	Wealthy perception	42.717	2.482
S_Boring	Boring perception	60.134	1.516
S_Depressing	Depressing perception	53.568	2.391
Objective view index	**Description**	**Mean**	**Std**
O_Sky	Sky view index	30.069	7.13
O_Building	Building view index	20.976	9.237
O_Tree	Tree view index	17.369	6.917
O_Road	Road view index	13.796	3.053
O_Wall	Wall view index	2.856	2.148
O_Car	Car view index	2.548	1.372
O_Sidewalk	Sidewalk view index	2.67	0.963
O_Plant	Plant view index	2.335	1.26
O_Grass	Grass view index	1.534	1.256
O_Earth	Earth view index	0.867	1.136
O_Fence	Fence view index	0.831	0.592
O_Ceiling	Ceiling view index	0.52	1.417

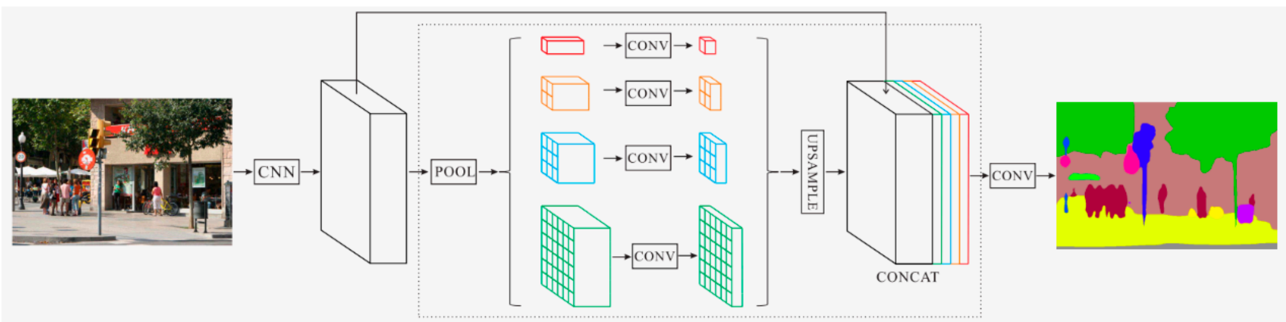


Figure 4. PSPNet model to semantically segment an SVI [45].

Using MIT ADE20K [46], the largest open-source dataset for semantic segmentation and scene parsing, PSPNet achieved a high accuracy of 80.13%. ADE20K is a collection of 20,000 photographs with pixel-level annotations covering 150 object types in various scenes, including street scenes. It is useful for comprehending the semantics of urban environments. This study used the PyTorch implementation of a pretrained PSPNet based on the ADE20K dataset (https://pypi.org/project/mit-semseg/ (accessed on 19 May 2023)).

After semantic segmentation, 150 view indices were obtained. However, many view indices were zero because the ADE20K object categories contained a large number of indoor objects, which were uncommon in street scenes.

To eliminate objects whose view indices were extremely small for these 150 classes of objects, the average view indices of each class of objects in all street view images were calculated, and only objects with an average view index greater than 0.5% were retained. Twelve classes of objects—sky, building, tree, road, wall, car, sidewalk, plant, grass, earth, fence, and ceiling—were retained after preprocessing.

The average view indices for the SVIs in all four directions at each sampling point were calculated for the 12 classes of view indices. Then, the average view indices of the SVIs with a 1 km buffer (15 min walking distance) of a community were averaged to represent the view indices for the community. The descriptive statistics of the 12 view indices are shown at the bottom of Table 2.

3.4.3. Correlation Analysis

Zhang found that the Pearson's correlation coefficients of subjective perceptions were highly correlated, like beautiful–safe, beautiful–wealthy and depressing–safe [19]. The view indices were also correlated and could lead to multicollinearity issues in multiple linear regression (MLR). To inspect the linear relationship between the 12 view indices and the six subjective perceptions, pairwise Pearson's correlation coefficients were generated.

3.4.4. Analyzing the Importance of View Indices

View indices [13] or POI [24] can be used to predict and explain subjective perceptions to a certain degree. The lightGBM model [47] was fitted to examine the relative importance of each view index for each perception using the 12 view indices as explanatory variables and the 6 perception scores as response variables. LightGBM is a gradient boosting framework that uses a tree-based learning algorithm and is designed to be faster and more memory-efficient. To analyze the importance of a feature, LightGBM measures the extent to which each feature contributes to a model's accuracy by calculating the average gain of the splits where the feature is used.

3.4.5. Other Explanatory Variables

Other explanatory variables were selected based on data availability and a literature review [1–3,8,9] and can be divided into structural, locational, and neighborhood attributes. Building type, floor area ratio (*FAR*), and age of the building (*Age*) are common structural attributes. Owing to data availability, the latter two indicators were selected. Locational attributes are road network distances to various amenities, such as education, health care, and commercial facilities. Educational institutions, including primary and middle schools, can contribute to increases in housing prices. Healthcare facilities provide medical services to various types of hospitals. The central business district (CBD) plays a crucial role in the economic and commercial life of a city, and the CBD of Suzhou (the central region of the industrial park district) was considered a commercial facility in this study. The locational attributes comprised the distance to the CBD (*D_CBD*), nearest bus station (*D_Bus*), metro station (*D_Metro*), primary or middle school (*D_School*), and hospital (*D_Hospital*). The neighborhood attributes were the number of different facilities around the community, including the number of bus stations (*N_Bus*), metro stations (*N_Metro*), primary and middle schools (*N_School*), and hospitals (*N_Hospital*) in community neighborhoods within a radius of 1000 m. The locational and neighborhood attributes were computed using ArcGIS with POI and road network data. Table 2 provides the descriptive statistics for these variables.

3.5. Modeling Methodology

3.5.1. HPM

The HPM has been widely used to estimate the willingness to pay for a house based on its characteristics, quality, and features [9,48]. The HPM assumes that the price of a house is influenced by its characteristics, as well as the characteristics of market demand and supply [4]. The HPM estimates the contribution of each feature to the house price and helps identify the relative importance of each feature in determining the final price.

This study aimed to compare the contributions of subjective perception scores and objective view indices to community housing prices. The subjective perception scores and objective view indices belong to neighborhood attributes, and we distinguished these two groups of neighborhood attributes from traditional neighborhood attributes. All of these attributes are independent variables of the HPM, and Table 2 shows their descriptive statistics.

The dependent variable of the HPM is community housing prices. We used the natural logarithm of community housing prices as the dependent variable, which is called the semi-logarithmic form of the HPM. It has several advantages over other functional forms, including interpretability, flexibility, improved accuracy, and reduced heteroscedasticity.

3.5.2. Stepwise Regression

The conventional HPM uses the MLR model to model the relationship between two or more attributes and community housing prices [13,28,49]. OLS is the most common method for estimating the coefficients of variables in the MLR model.

We employed a specific type of MLR called stepwise regression, which is a variable selection technique that iteratively adds or removes variables from the model and tests for statistical significance after each iteration until the best set of variables is obtained [50]. By selecting the most influential variables, stepwise regression can produce a more parsimonious model that is easier to interpret. Therefore, stepwise regression rather than MLR was chosen for this study.

Seven attributes were chosen using stepwise regression out of 11 structural, locational, and neighborhood attributes, with a backward stepwise regression model that iteratively removed variables. These seven attributes were *FAR*, *Age*, *D_CBD*, *D_Hospital*, *N_Bus*, *N_Metro*, and *N_School*.

Using the seven attributes as control variables and subjective perception scores and objective view indices as interpretable variables, two groups of backward stepwise regression models were constructed. There were seven control variables plus six subjective perception scores and seven control variables plus twelve objective view indices. The threshold for significance was set at $p < 0.05$. Variables with p-values > 0.05 were removed, and significant variables were retained. Finally, S_Boring and S_Safe from the subjective perception score group and *O_Sky*, *O_Tree*, *O_Building*, *O_Plant*, *O_Car*, *O_Fence*, and *O_Ceiling* from the objective view index group were retained and regarded as explanatory variables. The MLR model is expressed by Equations (2) and (3) for subjective perception scores and objective view indices, respectively.

$$\begin{aligned} Ln\_Price = \beta_0 + \beta_1 * FAR + \beta_2 * Age + \beta_3 * D\_CBD + \beta_4 * D\_Hospital \\ + \beta_5 * N\_Bus + \beta_6 * N\_Metro + \beta_7 * N\_School + \beta_8 \\ * S\_Boring + \beta_9 * S\_Safe \end{aligned} \tag{2}$$

$$\begin{aligned} Ln\_Price = \beta_0 + \beta_1 * FAR + \beta_2 * Age + \beta_3 * D\_CBD + \beta_4 * D\_Hospital + \beta_5 \\ * N\_Bus + \beta_6 * N\_Metro + \beta_7 * N\_School + \beta_8 * O\_Sky + \beta_9 \\ * O\_Tree + \beta_{10} * O\_Building + \beta_{11} * O\_Plant + \beta_{12} * O\_Car + \beta_{13} \\ * O\_Fence + \beta_{14} * O\_Ceiling \end{aligned} \tag{3}$$

where β_0 is the intercept, and $\beta_i (i = 1, \ldots, 9)$ in Equation (2) and $\beta_i (i = 1, \ldots, 14)$ in Equation (3) represent the coefficients of the independent variables.

The MLR model can also be expressed in matrix form:

$$\boldsymbol{Y} = \beta_0 1_n + \boldsymbol{X\beta} + \varepsilon \quad (4)$$

where $\boldsymbol{Y}$ is an $n \times 1$ column vector of dependent variables for each community $\boldsymbol{i}$ in the sample ($\boldsymbol{i} = 1, \ldots, \boldsymbol{n}$), 1_n is an $n \times 1$ column vector of ones associated with intercept β_0, $\boldsymbol{X}$ is an $n \times p$ matrix of the explanatory variables, $\boldsymbol{\beta}$ is a $p \times 1$ column vector of coefficients, ε is an $n \times 1$ column vector of random errors, n is the number of communities, and p is the number of explanatory variables.

3.5.3. GWR

MLR is a global stationary regression model. This implies that the coefficients of the MLR are constant in space. However, owing to the complex spatial heterogeneity caused by urban spatial structures, the modeling relationships vary across space.

To capture the spatially varying effects in modeling the relationships between the dependent and independent variables, GWR establishes local functions corresponding to each observation. The GWR model is expressed in Equation (5).

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i, \quad i = 1, \ldots, n, \quad (5)$$

For each location i, y_i is the dependent variable, β_{i0} is the location-specific intercept term, β_{ik} is the local regression coefficient of the kth explanatory variable, x_{ik} is the kth explanatory variable, and ε_i is the random error following a normal distribution. In this study, a bisquare kernel function was selected to calculate the spatial weight matrix.

4. Results

4.1. Extracting Perceptual Scores and View Indices

Figure 5 displays four sample SVIs, semantic segmentation results, six predicted perceptual scores, and eight dominant view indices. Different SVIs have different perceptual scores and viewing indices. The perceptual scores and results of the semantic segmentation appeared to be reasonable.

Owing to the Image A's large tree and sky view indices, Image A had the highest beautiful perceptual score. Despite being in a shopping district, Image B's wealthy perceptual score was low, likely because the image lacked trees. Image C appeared to be the wealthiest, safest, lively, and boring image because of its extensive collection of urban scene objects. Image D was believed to be the most depressing. This may be because the majority of the images consisted of artificial buildings and were dark in hue.

4.2. Correlation Analysis

Six different types of perceptions are correlated, as Zhang (2018) showed [19]. The Pearson correlation coefficients for the six indicators are displayed in Figure 6. Some correlation pairs had a strong positive correlation, including "lively–safety" (0.56), "lively–wealthy" (0.64), and "safety–wealthy" (0.52). In contrast, "beautiful–depressing" had a strong negative correlation (−0.55).

This outcome deviates somewhat from that of Zhang's study. According to Zhang's examination of the six perceptual indicators for Beijing and Shanghai in China, "beautiful–safety" (0.819 and 0.667 for Beijing and Shanghai, respectively) and "beautiful–wealthy" (0. 834 and 0. 639 for Beijing and Shanghai, respectively) were strongly positively correlated. However, "beautiful–safety" (−0.06) and "beautiful–wealthy" (−0.07) were almost uncorrelated in our analysis. This can be noted in Image A in Figure 5, which had the highest beautiful score; however, its safety and wealthy scores were relatively low. This was probably caused by the distinct urban environments in these cities and the different datasets (Place Pulse 2.0 and the local dataset) used to train the perception prediction models.

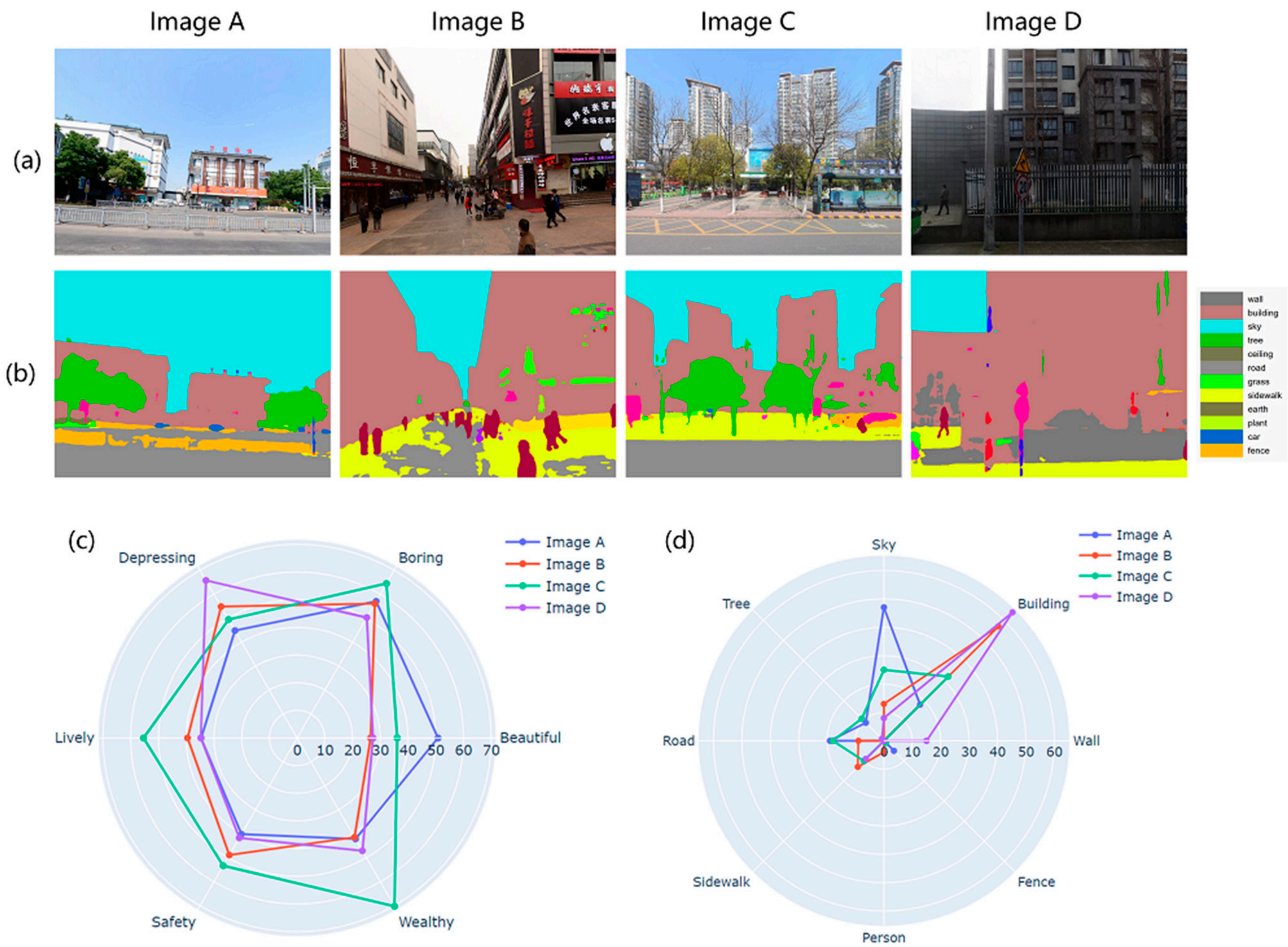


Figure 5. Sample SVIs. (**a**) Four SVIs. (**b**) Semantic segmentation result of SVIs. (**c**) Six perceptual scores for the SVIs. (**d**) Eight dominant view indices calculated with the semantic segmentation result.

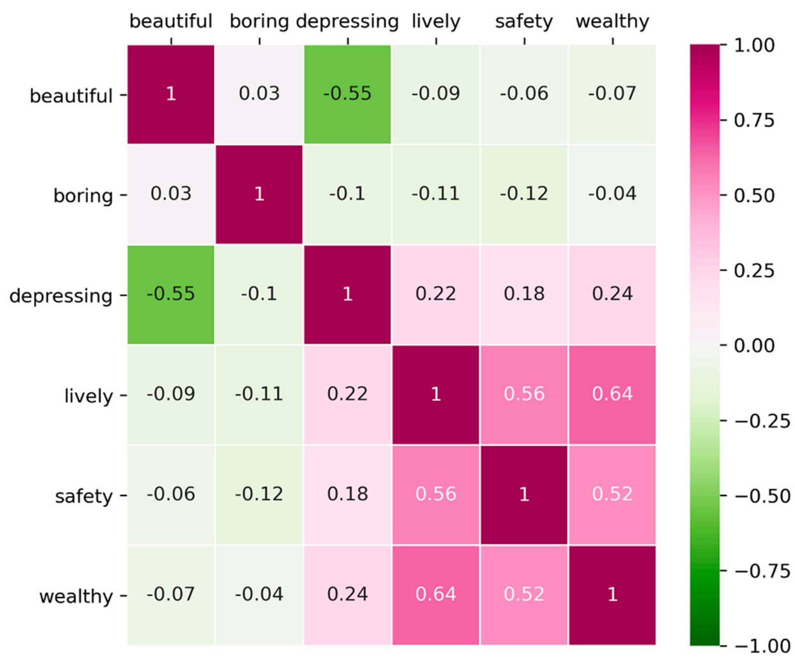


Figure 6. Pearson correlation coefficients of six perceptual scores.

In addition to the perceptual scores, the Pearson correlation coefficients of the top 12 view indices were calculated and are shown in Figure 7. Except for the "sky–tree" (−0.54) and "sky–building" (−0.48) pairs, which were relatively highly correlated, most correlations of view index pairs were weakly or moderately correlated, and this is consistent with Qiu's work [13].

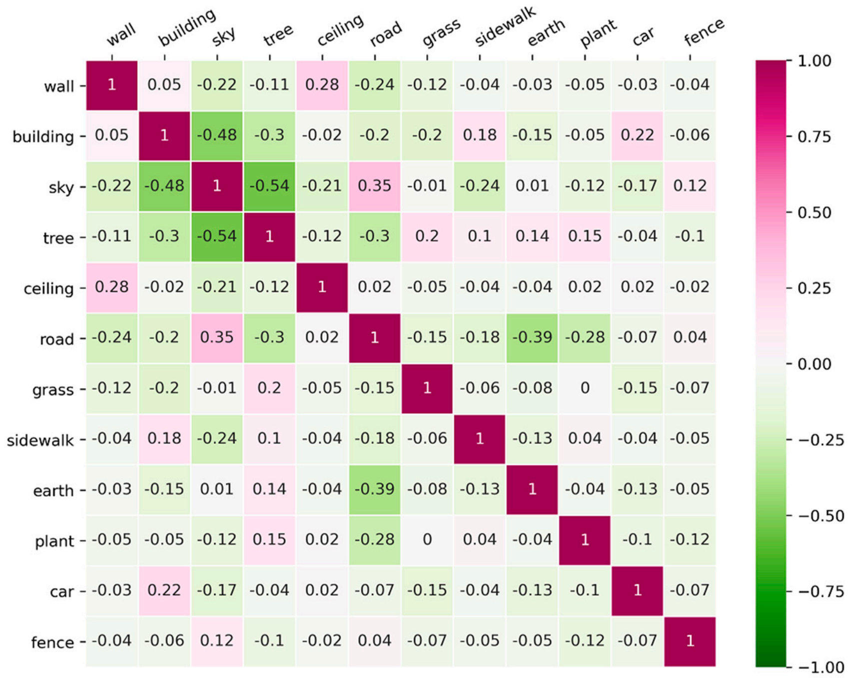


Figure 7. Pearson correlation coefficients of top 12 view indices.

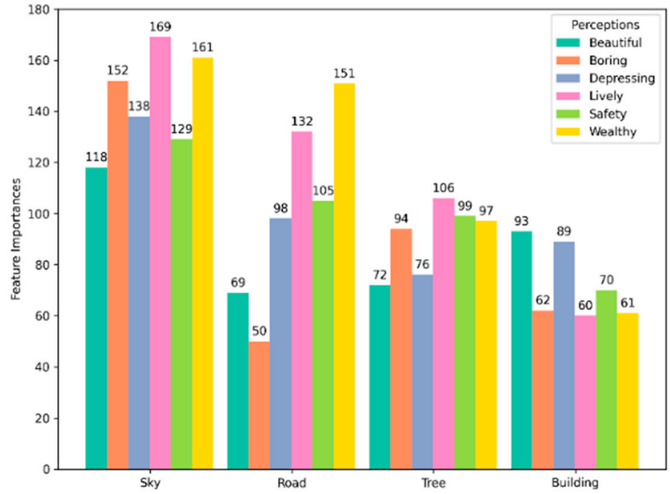
4.3. Feature Importance

The LightGBM was employed using the 12 most important view indices to predict the six perceptual scores. The R^2 metrics for measuring the fit performance of the six perceptions are presented in Table 3. The R^2 values for the six perceptions showed non-negligible variance. Depression had the highest R^2, which shows that the view indices could explain 54% of the variance in depression scores. Boring had the lowest R^2, and these view indices could only account for 17% of the variance in boring scores.

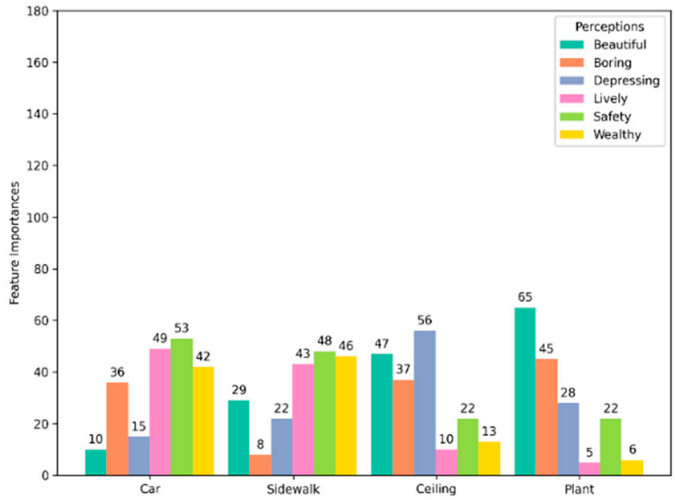
Table 3. The R^2 of LightGBM for the six perceptions.

Perceptions	Beautiful	Boring	Depressing	Lively	Safety	Wealthy
R^2	36%	17%	54%	33%	24%	39%

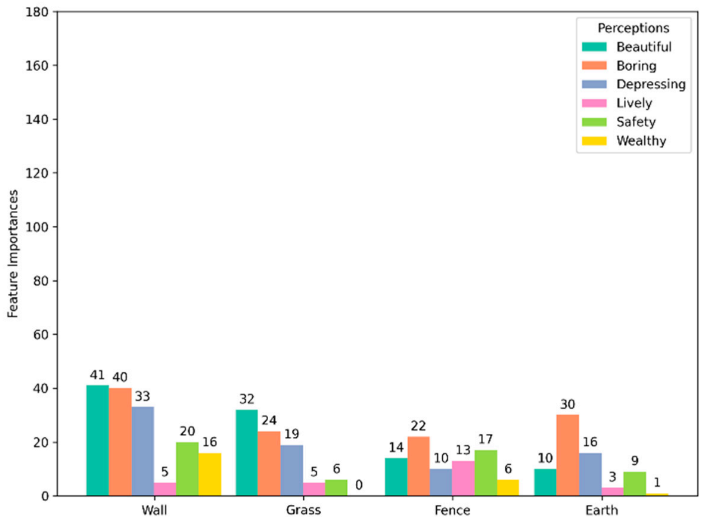
The feature importance of the view indices based on the total gain across all splits in LightGBM is displayed in Figure 8. In each view index group (sky, road, etc.), the six bars represent the importance of a specific view index in predicting the six perceptions. In general, the view indices with larger ratios are more important than those with lower ratios. For instance, the sky, roads, trees, and buildings are more important than walls, grass, fences, and earth. The contributions of the one-view index to the various perception scores varied significantly. Compared to the importance of the lively (132) and wealthy (151), the road view index for boring (50) was substantially less significant. The importance of the plant view index for the beautiful (65) was significantly higher than that for the lively (5) and wealthy (6). According to common sense, the earth view index can influence boring and depressing more than other perception scores. Trees, cars, and sidewalks contribute significantly to lively, safety, and wealthy, which is consistent with Zhang's research [19].



(**a**)



(**b**)



(**c**)

Figure 8. Feature importance for predicting the six perceptual scores. In each view index group (sky, road, and so on), there were six bars representing the importance of the specific view index in predicting the six perceptions. (**a**) The feature importance of sky, road, tree and building. (**b**) The feature importance of car, sidewalk, ceiling and plant. (**c**) The feature importance of wall, grass, fence, and earth.

4.4. Stepwise Regression

Stepwise regression was applied to select the significant variables. The baseline model, Model 0, was fitted with the attributes FAR, Age, D_CBD, D_Hospital, N_Bus, N_Metro, and N_School, accounting for 33.98% of the variance in housing prices. Then, stepwise regression was performed again to construct Models 1 and 2 using Equations (2) and (3), as follows:

Table 4 summarizes the regression diagnostic data for each model, including the adjusted R^2, AICc, AIC, and residual sum of squares (RSS). In terms of adjusted R^2, Model 1 (adjusted R^2 = 34.46%) and Model 2 (adjusted R^2 = 39.26%) improved by 0.48% and 5.28%, respectively, compared with Model 0 (adjusted R^2 = 33.98%). The values of the AICc, AIC, and RSS metrics of Model 0 were higher than those of Models 1 and 2. This indicates the effectiveness of the perception scores and view indices. Furthermore, the view indices were slightly stronger than the perception scores. This is consistent with Qiu's study [13], although our subjective and objective indicators were not exactly the same.

Table 4. Regression diagnostic information of OLS and GWR estimations.

	Model 0	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Model	OLS(Stepwise)			GWR	
Variables	Baseline	Perception scores	View Indices	Perception scores	View Indices
Adjusted R^2	33.98%	34.46%	39.26%	72.3%	70.1%
AICc	493.244	485.178	384.592	−453.945	−230.686
AIC	491.113	482.987	382.196	−276.803	−370.407

Table 5 lists the regression coefficients for each model. Notably, the absolute values of these coefficients were small because the dependent variable was the natural logarithm of the original house price. For Model 0, the signs of these coefficients were consistent with prior studies. The expected sign of the coefficient of D_Hospital was positive in some studies while negative in others, and it was positive in this study, indicating if a community is closer to a hospital, its price is lower. The signs of structural, locational, and neighborhood variables of Model 1 were the same as the ones of Model 0, and the magnitude of these variables changed little. The signs of S_Safe and S_Boring were both negative. All of the coefficients were significant at the 1% level, except that the coefficient of S_Safe was significant at the 5% level. The view index variables had positive and negative signs, and their coefficients were all significant at the 1% level.

4.5. GWR

In this study, the adaptive bisquare kernel function of the GWR model was employed. The adaptive kernel bandwidths (i.e., a fixed number of local observations) were estimated as 95 and 168 for Models 3 and 4, respectively. The effects of perception scores on housing prices were more localized than those of view indices.

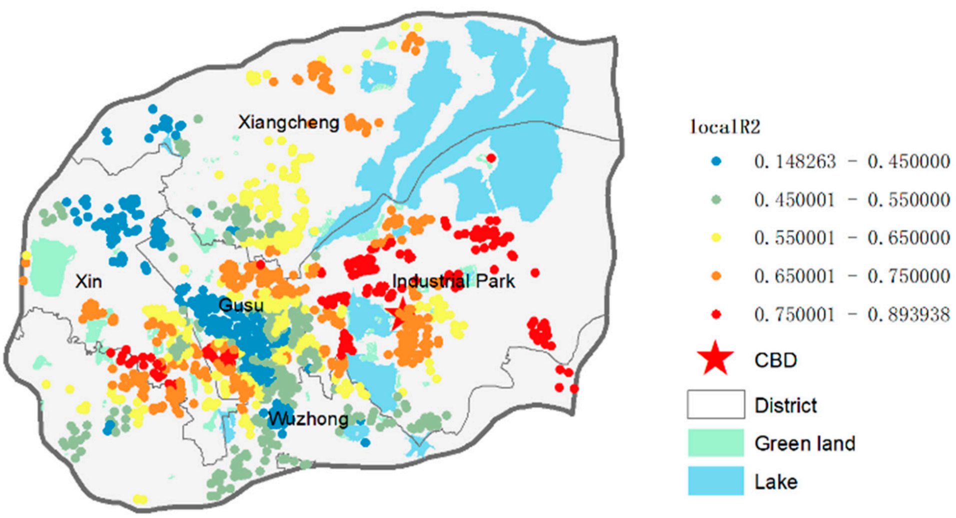
The GWR models offer better fitting performance than the OLS models. The adjusted R^2 values for Models 3 and 4 were 72.3% and 70.1%, respectively, which were much higher than those of the OLS. Interestingly, the adjusted R^2 of Model 3 (perceptions) was higher than that of Model 4 (view indices) for GWR, which is the opposite of the results of OLS, whose adjusted R^2 for perceptions was lower than that of the view indices. The high adjusted R^2 and low AICc values in Table 3 suggest that the GWR model had the strongest fitting performance.

Table 5. Regression coefficients of models.

Model	Model 0	Model 1	Model 2
cons	10.5238 ***	12.000 ***	12.437 ***
Structural attributes			
FAR	−0.0415 ***	−0.03956 ***	−0.0102 ***
Age	−0.0131 ***	−0.01281 ***	−0.0447 ***
Locational attributes			
D_CBD	−0.000024 ***	−0.000023 ***	−0.000022 ***
D_Hospital	0.000063 ***	0.000060 ***	0.000039 **
Neighborhood attributes			
N_Bus	0.01123 ***	0.01094 ***	0.00979 ***
N_Metro	0.01164 ***	0.01264 ***	0.01283 ***
N_School	0.00529 ***	0.00543 ***	0.00648 ***
Subjective perception			
S_Safe	/	−0.01226 ** (0.015)	/
S_Boring	/	−0.01722 ***	/
Objective view index			
O_Sky	/	/	−0.03284 ***
O_Tree	/	/	−0.02427 ***
O_Building	/	/	−0.02704 ***
O_Plant	/	/	0.02419 ***
O_Car	/	/	−0.02317 ***
O_Fence	/	/	0.04223 ***
O_Ceiling	/	/	−0.05011 ***

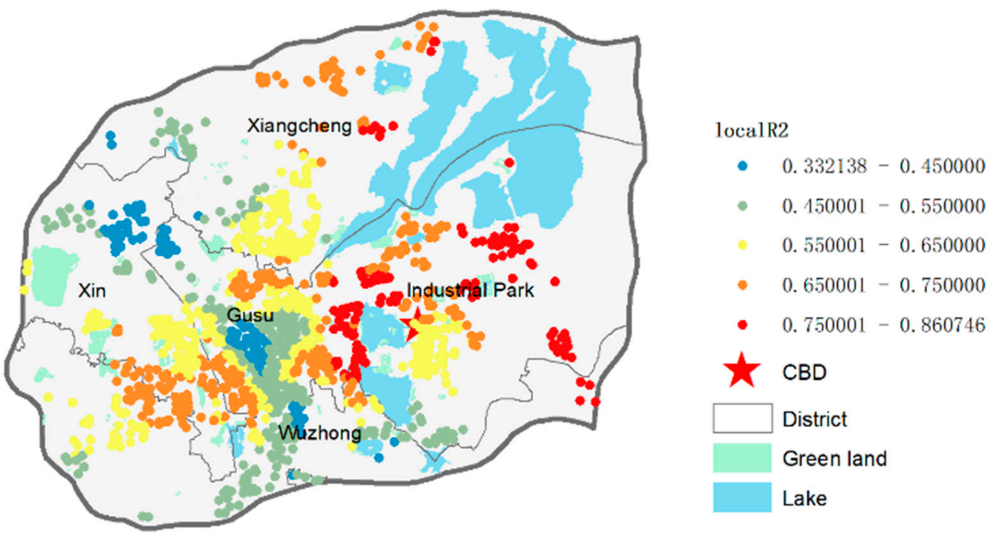
Note: Significant *p*-values are marked in parentheses: ** $p < 0.05$, *** $p < 0.01$.

The values of local R^2 for Models 3 and 4 are shown in Figure 9. In general, for both models, the industrial park and Xin district had greater local R^2 values than the central region of the Gusu district. The spatial pattern of the local R^2 matched that of the housing price map shown in Figure 1. In other words, areas with higher housing prices exhibited a better fitting performance.



(**a**)

Figure 9. *Cont.*



(**b**)

Figure 9. Local R^2 of Model 3 and Model 4. (**a**) Local R^2 of Model 3 (perception scores). (**b**) Local R^2 of Model 4 (view indices).

The Monte Carlo test was used to evaluate the significance of the GWR-estimated coefficients and determine whether they were spatially stationary. The Monte Carlo test was performed 999 times with random permutations of the observations in space. The results of the descriptive statistics and the *p*-values of the Monte Carlo significance test for Models 3 and 4 are presented in Tables 6 and 7, respectively. The *p*-values of all coefficients in both models were zero, suggesting that the impact of the variables on housing prices varies spatially. Therefore, it was necessary to use GWR to model the spatial heterogeneity of these variables.

Table 6. Summary statistics and Monte Carlo significance test results for Model 3 (perception scores) parameter estimates.

Variable	Mean	STD	Min	Median	Max	*p*-Value
FAR	−0.074	0.096	−0.432	−0.072	0.178	0 ***
Age	−0.014	0.011	−0.046	−0.012	0.017	0 ***
D_CBD	0	0	0	0	0	0 ***
D_Hospital	0	0	−0.001	0	0.001	0 ***
N_Bus	0.006	0.013	−0.023	0.004	0.051	0 ***
N_Metro	0.007	0.024	−0.057	0.006	0.093	0 ***
N_School	−0.002	0.023	−0.093	0.002	0.055	0 ***
S_Boring	−0.005	0.038	−0.111	−0.001	0.116	0 ***
S_Safe	−0.012	0.04	−0.144	−0.008	0.098	0 ***

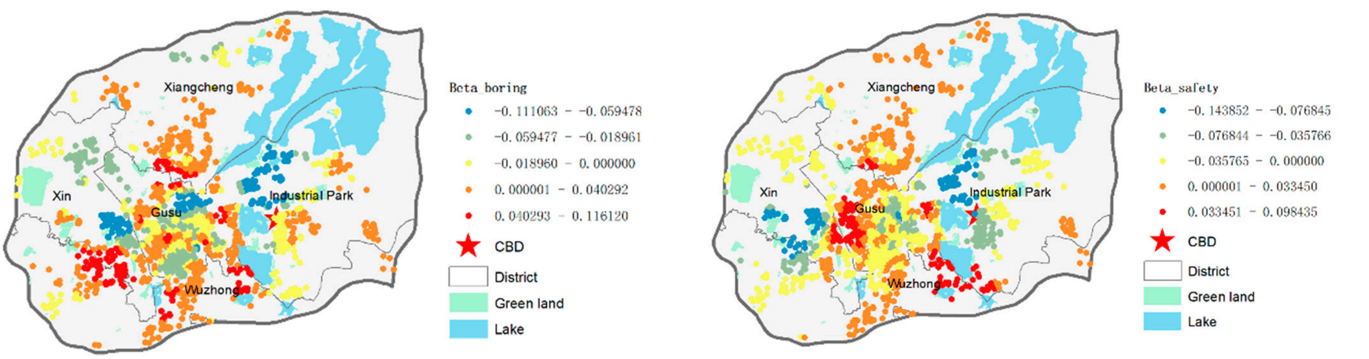
Note: Significance value, *** $p < 0.01$.

The estimated coefficients of the GWR varied from place to place. The spatial distributions of the coefficients for Models 3 and 4 are shown in Figures 10 and 11, respectively. The natural break (Jenks) classification method divides coefficients into five classes. To distinguish between the positive and negative effects of these factors on housing prices, a zero value was purposefully set in one of the classes to distinguish between the positive and negative coefficient groups.

Table 7. Summary statistics and Monte Carlo significance test results for Model 4 (view indices) parameter estimates.

Variable	Mean	STD	Min	Median	Max	*p*-Value
FAR	−0.064	0.075	−0.302	−0.062	0.118	0 ***
Age	−0.013	0.009	−0.034	−0.011	0.007	0 ***
D_CBD	0	0	0	0	0	0 ***
D_Hospital	0	0	0	0	0	0 ***
N_Bus	0.006	0.009	−0.017	0.005	0.032	0 ***
N_Metro	0.007	0.015	−0.032	0.008	0.059	0 ***
N_School	0.002	0.014	−0.048	0.004	0.033	0 ***
O_Sky	−0.021	0.027	−0.115	−0.019	0.035	0 ***
O_Building	−0.02	0.025	−0.114	−0.017	0.03	0 ***
O_Tree	−0.015	0.026	−0.105	−0.016	0.047	0 ***
O_Ceiling	−0.047	0.071	−0.286	−0.035	0.287	0 ***
O_Plant	0.018	0.033	−0.057	0.019	0.107	0 ***
O_Fence	0.018	0.077	−0.247	0.012	0.311	0 ***
O_Car	−0.017	0.036	−0.115	−0.022	0.067	0 ***

Note: Significance value, *** $p < 0.01$.



(**a**) (**b**)

Figure 10. Coefficient estimates for Model 3 (perception scores). (**a**) Coefficients of the boring score. (**b**) Coefficients of the safety score.

Boring is a negative and unlively perception [9], and a substantial portion of the boring coefficients were negative in Figure 10a, indicating that the boring perception in these communities was inversely proportional to housing prices. However, many communities had positive boring coefficients, such as several communities in the Wuzhong and Xiangcheng districts. This implies that an increase in boring scores may increase the housing price. Safety is a positive perception, and several communities in the Gusu, Xiangcheng, and Wuzhong districts had positive safety coefficients, indicating that safety perception is proportional to housing prices. Meanwhile, the safety coefficients were negative in certain outlying suburbs, indicating that an increasing safety score may decrease housing prices. This may be due to the fact that these areas are in suburbs and life is not convenient.

Figure 11a–c show similar spatial patterns for the sky, building, and tree-view index coefficients, respectively. Some communities in the city center had positive coefficients, whereas others in the surrounding regions had negative coefficients. The number of communities with negative coefficients was greater than those with positive coefficients. This indicates that increasing the sky, building, and tree indices may decrease housing prices in most communities. The spatial distributions of the other view index coefficients differed significantly from one another.

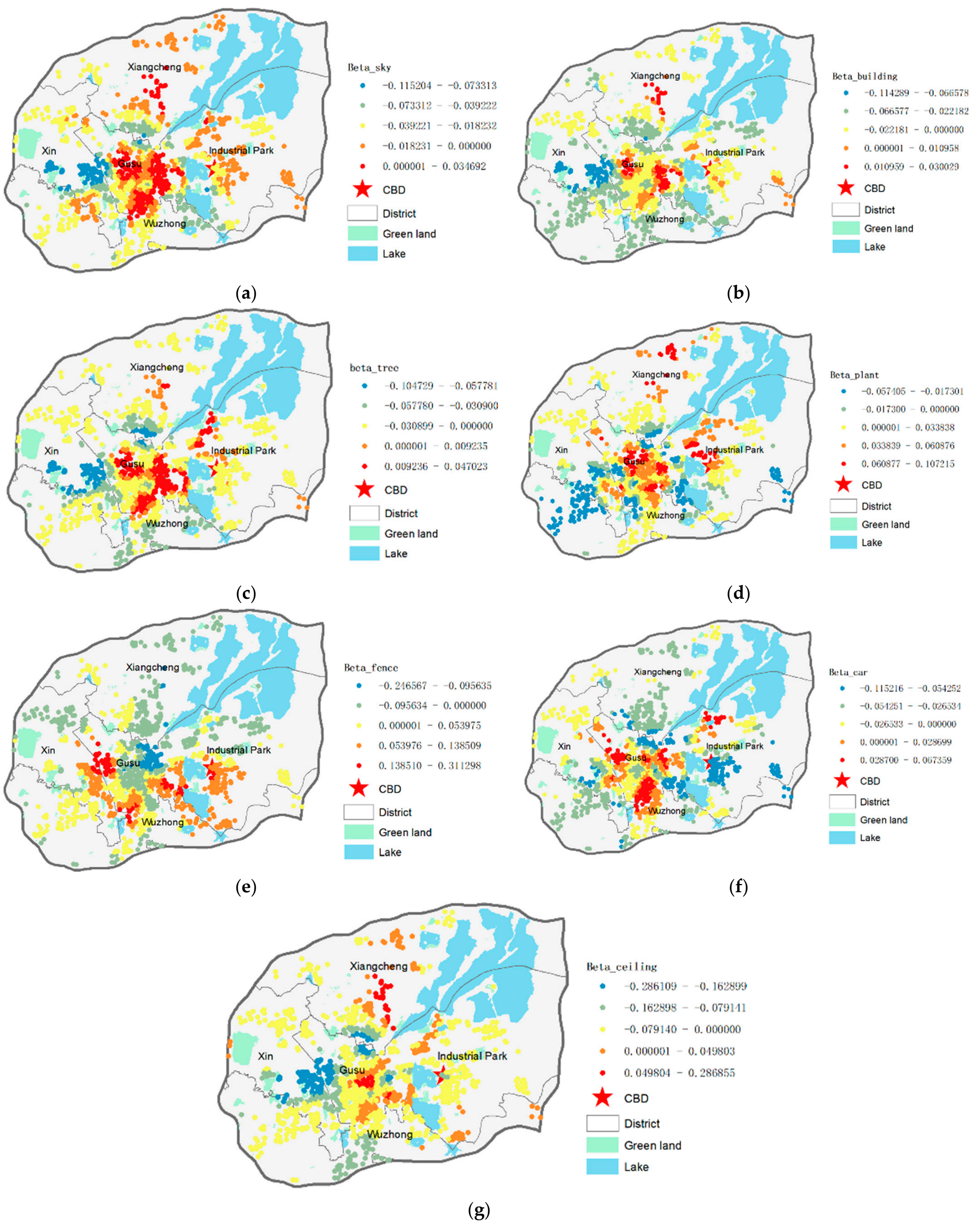


Figure 11. Coefficient estimates for Model 4 (view indices). (**a**) Sky view index coefficients. (**b**) Building view index coefficients. (**c**) Coefficients of the tree view index. (**d**) Coefficients of the plant view index. (**e**) Coefficients of fence view index (**f**) Coefficients of car view index. (**g**) Coefficients of the ceiling view index.

5. Discussion

5.1. Effects of Subjective and Objective Measures on Housing Prices

The objective measures may generally explain more variance than the subjective measures, according to the adjusted R^2 of the OLS in Table 3. The adjusted R^2 of Model 2 (39.26%) for OLS was 4.8 percentage points higher than that of Model 1 (34.46%). Overall, the objective measures had stronger explanatory power, and built environment factors had a greater impact on housing prices. This is in line with a study by Qiu [13]. In addition to the sky, tree, and building view indices having the largest proportions, the plant, car, fence, and ceiling view indices also have a considerable impact on housing prices.

The global OLS model determines a single corresponding parameter for each variable in each observation. By contrast, GWR is a local model that estimates the model parameters for every observation within a local neighborhood. In Table 3, the adjusted R^2 of Model 3 (72.3%) was greater than that of Model 4 (70.1%), which is an interesting contrast to the OLS relationship. This contradicts Qiu [13] and demonstrates that for GWR, perceptual measures can explain more variance in housing prices than view indices on the local scale. This indicates that home buyers care more about their subjective perceptions of their neighborhoods' surroundings.

The GWR produces a different result than OLS, suggesting that the result of the local model is opposite to that of the global model. This phenomenon is, in fact, the Simpson's paradox. It is essential to mitigate this problem by modeling spatially varying relationships [29]. The results of the Monte Carlo test also demonstrate that the impacts of the explanatory variables vary spatially.

Specifically, the coefficients of the boring and safety scores were both negative for OLS. For GWR, some communities had positive coefficients for boring and safety scores, whereas others had negative coefficients. Boring is a negative perception that usually has a negative impact on housing prices, indicating that a boring community environment is associated with low housing prices. Safety is a positive perception and usually has a positive impact on housing prices. This indicates that people are prepared to pay premiums for safe communities.

However, some communities had positive coefficients for boring perceptions. This appears counterintuitive. One reason is that older residential communities usually have stores on the first floor and are cheaper, whereas newer residential communities do not have stores on the first floor and are usually more expensive than older communities. Owing to stores and shoppers, older and cheaper residential communities have lower boring scores. By contrast, newer residential communities had higher boring scores. Therefore, the boring coefficients were positive for some communities.

A potential explanation for the negative safety coefficients was provided. According to Figure 8b, the car and sidewalk view indices (53 and 48) had the highest feature importance in predicting the safety perception. More cars can bring not only safety but also more air pollution and noise. This has a negative effect on housing prices. This justification is comparable to the effect of metro stations on housing prices [51]. The closer a community is to a metro station, the more convenient it is to travel. Thus, property prices property will increase. However, if they are too close, housing prices may be lowered due to noise and other considerations.

In addition, the effect of the tree view index on housing prices was negative for the OLS. This is counterintuitive and inconsistent with Ye's work [8]. Figure 11c shows that the tree view index had both positive and negative effects. The positive effects were mainly concentrated in the city center. The negative effects were in the suburbs, and a possible reason was that trees around new residential communities in the suburbs were not tall or large because of their relatively young age, resulting in a low tree view index. Thus, new communities have high housing prices and a low tree view index.

It is critical to pay attention to both the model and the selected variables when analyzing housing prices because the result of OLS is the opposite of that of GWR. In particular, the Simpson's paradox may result from utilizing global models, such as OLS. Thus, OLS should be used with caution when attempting to explain the influence of various variables on housing prices. It is indispensable to use a local model, such as GWR, to analyze the spatially varying effects of variables.

The outcomes we obtained differed from those of Kang's study [9]. Kang first employed the principal component analysis technique and then used OLS to analyze the effects of various factors on housing prices. The principal components were linear combinations of individual perceptions. Kang analyzed only the principal components' impacts on housing prices rather than individual perceptions. In addition, although Kang applied GWR, Kang did not demonstrate or analyze the spatially varying coefficients.

5.2. Pros and Cons of Subjective and Objective Measures

The GWR discloses that subjective perceptual scores can explain more variance in housing prices than objective view indices. This highlights the importance of "sense of place" and humanistic insights in evaluating the effects of various features on housing prices [9]. Perceptual scores measure how people perceive a place psychologically and are related to the socioeconomic environment, such as land use [52], poverty status [53], and crime rates [54]. Human perceptions of places depict a complete picture. Table 3 shows that the 12 most important view indices could only explain a small proportion of the perceptual variance (17–54%). The boring and safety perceptions had the two lowest R^2 values (17% and 24%, respectively), and the two perceptions were selected using the stepwise regression model to fit housing prices. This reflects the fact that the two perceptions contain more sensory information than view indices. The multicollinearity issue with subjective measurements makes it challenging to incorporate all of them into OLS, which is one of their drawbacks.

Objective view indices can supplement subjective perceptual scores even if they cannot fully characterize a place, such as subjective measures. The view indices are distinct, unambiguous, easy to measure, and have a low correlation.

5.3. Implications for Urban Planning

This research integrates and compares the effects of subjective perceptions and objective view indices on housing prices and has broad and practical applications in urban planning. First, housing prices were significantly affected by subjective perceptions. Governments and policymakers should pay attention not only to the built environment, but also to perceptions of the micro-scale street environment around residential districts. Sidewalks and fences, which may affect residents' perceptions of safety, should receive more attention. Currently, only the green ratio and road construction have received attention in other cities. Perception indicators should be carefully selected because of the multicollinearity problem. Second, a street environmental fee can be imposed to compensate for public funds invested in improving streetscapes [8]. This is because real estate developers profit financially from the surrounding street environment, whereas cities create, invest in, and maintain streetscapes. Tax amounts can be determined using both subjective and objective indices. Third, boring and safety perceptions were selected to represent negative and positive perceptions, respectively. This study can serve as a reference for future research. These subjective perceptions can be used to model economics and other urban plans outside of settlement assessments. For example, they can provide new measures for street design guidelines [38]. Urban designers and practitioners can examine the social, psychological, and emotional meanings of the street environment and better guide various applications, such as lively and safe neighborhood design, sustainable city planning, and urban micro-renovation.

5.4. Limitations and Potential Improvements

This study has several limitations that should be addressed in future studies. First, human perception may have been biased. The deep learning model used to appraise the SVIs of Suzhou was trained using SVIs collected in Wuhan City. Although both cities are located in China, each city has a unique street environment [55]. These two datasets have distinct data distributions. To assess the performance of the model in future studies, Suzhou's sample SVIs may need to be collected and annotated by humans.

Second, human perceptions were predicted with a deep learning model. Experiencing a place does not involve the observation of specific objects. In addition to the visual elements in SVIs, other elements are related to human perceptions. Quercia pointed out that the history, culture, interactions, and experiences of a place cannot be easily captured by images [56]. Future research could expand the incorporation of additional datasets, such as social media datasets.

Third, previous studies have shown that the spatial scale impacts the hedonic price model's results. The scale of the research object has a modifiable areal unit problem [57]. A fine-scale community was selected as the study object. More coarse-level regions (such as zip code regions) can be applied in other research to conduct experiments [2].

6. Conclusions

Using SVIs, this study analyzed the effects of subjective perceptions and objective view indices on housing prices. Subjective perceptions and objective view indices were extracted from the SVIs using deep-learning models. The effects of the subjective and objective measures were analyzed and compared using OLS and GWR. The global model OLS explored the overall impact of these measures on housing prices. GWR was employed to reveal the spatial variation in these factors from a local perspective, as opposed to the global approach that OLS uses. The main findings are summarized as follows:

First, for OLS, the overall objective measures explained more variance than the subjective measures. This result is consistent with that reported by Qiu et al. [13]. This suggests that the built environment factors have a greater impact on housing prices.

Second, compared to the view indices, the perceptual scores for the GWR exhibited stronger explanatory power. This indicates that home buyers care more about their subjective perceptions of their neighborhoods' surroundings. The results of the local GWR model were opposite to those of the global OLS model. The GWR result highlighted the importance of "sense of place" and humanistic insights in evaluating the effects of various indicators on housing prices. Furthermore, human perceptions of a place can provide a more complete picture.

Third, the results of the Monte Carlo test showed that the effects of the explanatory variables varied spatially and were statistically significant. However, this demonstrates the value of using GWR.

These results have important implications for governments and urban planners. They should focus on the perceptions of the microscale street environment around residential areas, as well as the built environment. Urban designers and practitioners can examine the social, psychological, and emotional meanings of street environments and guide various applications.

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