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# Exploring the Spatially Heterogeneous Effects of Street-Level Perceived Qualities on Listed Real Estate Prices Using Geographically Weighted Regression (GWR) Modeling

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**Abstract:** The listed price of real estate is a subjective reflection of its value by sellers, usually related to structural, neighborhood, and environmental attributes. Although previous studies have proposed the hedonic pricing model, factors related to perception are rarely seen in explanatory variables. This study aims to explore the impact of street-level perceived qualities on the listed price per square meter of plot set by the seller of the real estate using the Geographically Weighted Regression (GWR)-based hedonic pricing model and analyzes the spatially heterogeneous effects of the coefficients. In the city of Eindhoven, the Netherlands, Google Street View photos collected at 200 m intervals were employed to calculate representative variables of perceptual quality via a validated convolutional neural network, alongside structural and neighborhood attributes. The final model includes eight explanatory variables, and the results indicate that, apart from the plot area and the number of rooms, the influencing mechanisms of other factors are different. The impact of perceived beautiful quality on listed real estate prices demonstrates obvious distinctions between the north and the south. Perceived livability (positive) and depressing (negative) qualities show similar heterogeneous characteristics. This study offers a comprehensive approach to promote diverse strategies for real estate development across urban areas and recommends a heightened emphasis on the design quality of residential streets.

**Keywords:** hedonic pricing model; spatial heterogeneity; geographically weighted regression; perceived quality; urban design

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## 1. Introduction

The listed price of real estate is the subjective reflection of its value by the sellers and is influenced not only by the quality of the building structure but also by the neighborhood-level and street-level environments [1]. The advent of the internet information era has generated massive data resources, which, inevitably, have had a profound impact on the real estate appraisal industry [2]. Although previous studies have proposed hedonic pricing models to explain spatial heterogeneity (spatial heterogeneity means that overall parameters estimated for the entire system may not adequately describe the process at any given location), most of these variables regarding neighborhood environments focus on the number and distance of facilities and lack effective explanatory variables reflecting the quality of street space at the micro-scale [3]. Streets are considered not only the richest public space in cities [4] but also the main venues for residents to interact [5]. Safe, accessible, and comfortable street environments contribute to residents' sense of place, safety, and community [6], making it more relevant than ever to model subjective perceptions and residential values [7]. Some previous studies suggest that urban spaces at multiple scales

are closely related to residents' lives and trips [8,9], but capturing the quality of streetscape design from a macro perspective is challenging, and statistics on street-level elements are difficult to extend to a larger urban scale [10,11]. Due to limitations in data and methods, there is currently a lack of quantitative research to prove the correlation between street-level qualities and real estate prices.

This study aims to explore the impact of street-level perceived qualities on the listed real estate price. For validation, the estimation models of the listed real estate price per square meter of plot were established using publicly available data from May 2021 in the city of Eindhoven, the Netherlands. A trained convolutional neural network was used to identify six categories of perceived quality from street view images acquired at 200 m intervals on the roads. In addition to the generally agreed structural, neighborhood, and environmental attributes, the street-level perceived qualities were also added to the hedonic pricing model based on Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR). The second method took into account the locational differences of the samples and was used to explore whether there was spatial heterogeneity in traditional factors and perceived qualities. The findings offer a comprehensive approach to promoting diverse strategies for real estate development across urban areas and recommend a heightened emphasis on the design quality of residential streets. The research effort should be viewed as a stepstone in the systematic inclusion of urban design-related factors into real estate pricing models.

The paper is structured as follows. Section 2 conducts a literature review on the built environment factors that affect real estate prices and their measurement methods. Sections 3 and 4 present the methodology and data sources, respectively. Section 5 compares the results and performance of the OLS and GWR models. Section 6 discusses the spatial heterogeneity of influencing factors and their possible causes. Section 7 summarizes the conclusions and limitations.

## 2. Literature Review

### *2.1. Physical Features of the Built Environment*

Questionnaires and interviews [12–14] are commonly used methods to record perceived neighborhood characteristics and typically include Likert scales, rating scales [15,16], and open-ended questions [17,18]. The Microscale Audit of Pedestrian Streetscapes (MAPS), proposed by Cain et al. in 2012, is one of the tools to effectively measure microscopic street quality with a detailed manual survey form designed for four types of streets [19]. The limitation of these methods lies in their subjectivity of the environment assessments and susceptibility to individual differences [20].

With the rapid development of big data, computer vision, and artificial intelligence technologies [21], large-scale measurements of spatial features such as the sky [22], shadows, and plants have been conducted [23]. Semantic segmentation of street images to identify types and proportions of elements therein, thus establishing the connection between objective features and subjective perceptions, is the commonly used method. The MIT Scene Parsing Benchmark has provided a standard training and evaluation platform for 150 semantic categories, including the sky, road, grass, and discrete objects like persons and cars [24]. A German team has used the Cityscapes dataset to perform semantic labeling tasks based on 30 labels in seven categories: Flat, Human, Vehicle, Construction, Object, Nature, and Sky [25], and the tool has been used to objectively assess the recreational walkability [26]. Several studies have used streetscape data to assess the greenery of urban streets [27,28] and to establish a link between physical activity and elderly health [29].

### *2.2. Perceived Qualities of the Built Environment*

Many widely used qualities are subjective terms, such as distinctiveness, focality, intricacy, and spaciousness [8]. While they help convey design intent, they are difficult to measure. To quantify such unmeasurable perceptions, some studies have included them as latent variables in structural equation modeling to establish a link between the

objective environment and subjective satisfaction or behavior. The choice of perceived quality affects the explanatory power of the dependent variable, usually based on existing environmental psychology findings [30] or theories related to urban design [9]. Ewing screened five qualities from nine urban design qualities that primarily affect walkability, including Imageability, Enclosure, Human Scale, Complexity, and Transparency, and used them to evaluate different streets [31]. Ma chose five metrics to measure the quality of streetscape design as perceived by the human eye [7]. Zhou proposed the Integrated Visual Walkability indicator [32], which contains four components: Psychological Greenery, Visual Crowdedness, Outdoor Enclosure, and Visual Pavement.

### *2.3. Three Types of Influences on Real Estate Prices*

The hedonic pricing model used to evaluate the value of real estate typically considers factors such as structural, neighborhood, and environmental attributes. Structural attributes significantly impact pricing [33,34], with higher floors generally less expensive unless elevators are available [2]. Detached and low-rise homes are often more costly [35], and the number of bedrooms boosts prices [36]. Balconies and curb appeal can increase apartment prices by EUR 200/$m^2$ [37], and curb appeal can add up to 7% to the sale price [38]. Sustainability attributes are increasingly valued, notably in Singapore [39]. The neighborhood is the fundamental component of the city and the basic area where residents live and work [30,40]. Schools, malls, and parks positively affect property values, while distance from city centers and subway stations can reduce them [34,41]. Sports facilities and natural facilities like Seoul's greenbelt increase rents [42], but proximity to polluting factories has a negative impact [43]. Mixed land use and better road connectivity are preferred [44].

As for environmental attributes, urban green spaces, parks, and preserved landscapes have been shown to augment property prices, with larger and closer green areas being more beneficial [33,45]. More neighboring visible greenery and larger lakes enhance the economic value of residences in Beijing [46]. Plant identified a significant correlation between the trees on the sidewalk and real estate prices [47]. Greenways can boost real estate values [48], but proximity to the coast has mixed effects due to pollution [49]. In addition, the design of street space from a microscopic perspective is more closely related to living quality [21]. The proportion of windows along the street and the density of street businesses were found to be the principle determinants of the perceived quality [50]. Streets characterized by a higher sense of enclosure and slower traffic speeds were shown to provide a greater sense of safety [51]. However, street-level factors, especially perceived qualities, are rarely used in real estate price estimation, underscoring the necessity for thorough analysis and discussion of their contributions.

## 3. Data

### *3.1. Study Area*

The study was conducted in Eindhoven, the fifth-largest city located in the south of the Netherlands. The area of the study area is 88.57 square kilometers, containing 20,583 streets totaling 2151 km, 3314 facilities, and 481 real estate samples (since the dependent variable is the listed price per square meter of plot, only the real estate samples of houses and villas are retained, while apartments are excluded because their plots are shared) (Figure 1). The total listed price (since the actual transaction price is confidential and difficult to obtain, it is replaced by the listed price [2,52]), locational coordinates, and structural attributes of houses were obtained through the real estate website (https://www.funda.nl/, accessed on 20 May 2021). In the same month, Facility and road network data were obtained through the Google Maps Platform and Open Street Map, and these were used to calculate distance and density metrics in ArcGIS 10.2 software. Based on the collecting points evenly arranged in the road network, street view data were acquired through Google Maps.

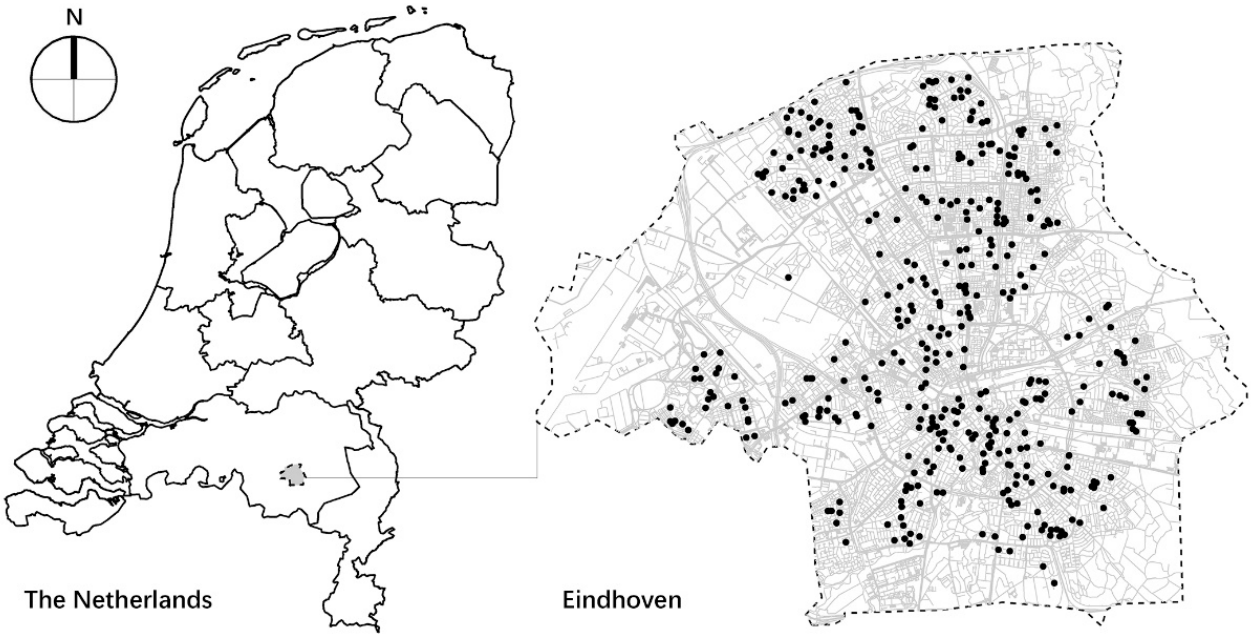



**Figure 1.** Study area and real estate samples.

To obtain a database containing sufficient street view photos and fully reflect the neighboring spatial characteristics of all sample points, the collecting points of street view data were distributed on simplified roads every 200 m (Figure 2). The measurement of street-level perceived qualities for each street view collecting point was represented by the mean of scores over the four cardinal directions (0, 90, 180, and 270 degrees) of all collecting points within a 1000 m service area.

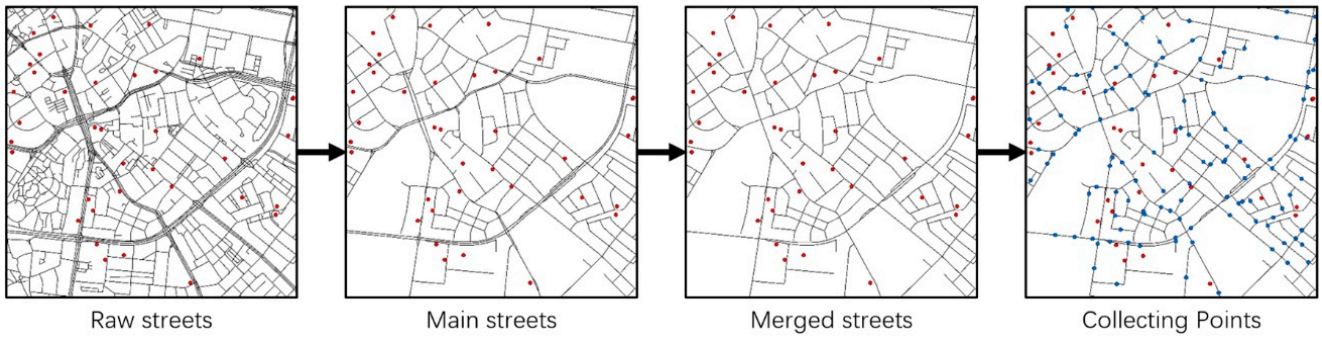



**Figure 2.** Real estate samples (red) and street view collecting points (blue).

### *3.2. Variables*

Since the real estate value is generally influenced by the land price at that location [53], the total listed price of real estate on the website divided by its plot area (including the projected area of house and the area without house in the plot) was calculated as the dependent variable. This dependent variable reflects the payable price per square meter of land set by the seller of the real estate.

Multicollinearity is considered one of the main causes of the unreliability of the GWR model, so it is important to first diagnose all potential explanatory variables for collinearity. Independent variables with correlations were simplified by comparing the Variance Inflation Factor (VIF). To ensure reliability, the model was required to satisfy an adjusted R-Square value greater than 0.5, a coefficient *p*-value less than 0.05, a VIF value less than 7.5, and a Jarque-Bera value greater than 0.1. Screening the independent variables by exploratory regression and comparing changes in indicators revealed that only when the dependent variable is the listed price per square meter of plot (MLP) could a compliant

model be produced. The independent variables used for the pricing model are shown in Table 1.

**Table 1.** Descriptive statistics (N = 481).

| | Variable | Explanation | Mean | Std. Deviation |
|---|---|---|---|---|
| Dependent variable | MLP | listed price per square meter of plot (EUR/$m^2$) | 1748.25 | 783.91 |
| Structural attributes | PA | plot area ($m^2$) | 303.61 | 239.61 |
| | EA | exterior space area ($m^2$) | 15.53 | 21.26 |
| | RN | number of rooms (amount) | 4.54 | 1.55 |
| Neighborhood attributes | DoF | density of facilities (amount/$km^2$) | 0.75 | 0.90 |
| | DtS | distance to the shopping center (m) | 3.43 | 1.71 |
| Environmental attributes (Street-level qualities [1]) | Beautiful | positive quality—people perceive that the street has a beautiful view, and the design quality makes people feel happy. Influencing factors include trees, flower beds, street sketches, and open sky. | 32.61 | 2.03 |
| | Lively | positive quality—people perceive the energetic and lively design quality on the street. Influencing factors include public art and abundant shops. | 32.61 | 2.63 |
| | Depressing | negative quality—people perceive that the street space is not open and the interface is opaque. | 54.00 | 1.37 |

[1] According to the citation [54], street-level qualities are represented using a rating range of 1–100, with 0 being the lowest and 100 being the highest level of a perception.

## 4. Methodology

The analysis process of this study includes three main steps. First, the traditional independent variables for the hedonic pricing model were calculated. Second, a convolutional neural network was trained to recognize the six street-level perceived qualities. Third, the contribution of all variables to the listed real estate prices was analyzed using GWR based models considering spatial heterogeneity.

### *4.1. Measuring Traditional Variables*

Density reflects the intensity of land use developments for housing, employment, or other purposes [55]. An outcome of higher densities is not only a lower level of solo commuting but also an increased sense of public safety [56]. The density of facilities in this study was calculated based on a 1000 m service area starting from the sample points of real estate. Some public places, such as commercial centers, train stations, hospitals, and stadiums, can serve residents of larger areas, so homes closer to them have better accessibility. Numerous studies have found that these attractive destinations enhance the value of properties and contribute more than other factors [57,58]. Based on the road network data within the research area, the shortest path analysis tool of ArcGIS 10.2 software was used to measure the distance of samples to these important destinations.

### *4.2. Measurement of Street-Level Perceived Qualities*

Compared to the structural and neighborhood attributes, environmental attributes, especially the perceived quality of the street, are the most difficult to measure. There is a lack of sufficient evidence that urban design has a significant impact on the value of real estate, so the inclusion of street-level variables in the hedonic pricing model is an important supplement and innovation. In recent years, computer-assisted methods have been developed to measure the design quality of streets, compensating for the lack of attention to street-level factors in previous studies [59]. Online images have been used to create reproducible quantitative measures of urban perception and characterize the inequality of different cities [60]. Crowd-sourcing ratings on streetscape images of 0.7 million streets have been used to evaluate perceptions of safety and beauty [61]. With the

help of machine learning, the convolutional neural network has been used to semantically segment street view pictures into different elements, from which human perceptions have been derived using a support vector machine [62].

Referring to the existing research [63], six street perception qualities were considered: safe, lively, beautiful, and wealthy (positive qualities) and depressing and boring (negative qualities). Several studies conducted in other countries have also demonstrated that these six types of perception can be effectively applied to the evaluation of large-scale urban perception [54]. A convolutional neural network trained on human–machine adversarial scoring was used for prediction, which is based on a dataset of 25,000 street images and achieves an overall accuracy of over 90% [27].

### *4.3. GWR-Based Hedonic Pricing Model*

The hedonic pricing model is based on the premise that listed real estate prices are influenced by both internal and external factors. Due to the insufficient goodness of fit demonstrated by the OLS model in exploratory analysis of global data, the GWR-based hedonic pricing model, considering the coordinates of sample positions, is finally used to explain spatial heterogeneity.

In contrast to the OLS model, which uses one equation to predict the dependent variable with a given set of independent variables, GWR considers the importance of the spatial location of regression points. Thus, GWR assumes that the association between a dependent variable and independent variables can be spatially variant and provides a set of equations to estimate coefficients of any regression point i [64]. The GWR model can be mathematically formulated as

$$y_i = \beta_0(u_i,\ v_i) + \sum_k x_{ik}\beta_k(u_i,\ v_i) + \varepsilon_i \tag{1}$$

where $y_i$ is the dependent variable of regression point i, $(u_i,\ v_i)$ is the locational coordinates of regression point i, $x_{ik}$ is the k-th independent variable of regression point i, and $\beta_k(u_i,\ v_i)$ is the coefficient of the k-th independent variable in the local equation of regression point i. $\beta_0(u_i,\ v_i)$ is the constant, and $\varepsilon_i$ is the error term of regression point i.

The current GWR model uses the adaptive bi-square kernel function to estimate the weights of nearby observations from regression point i, setting a rule that closer observations have a greater influence on the estimation of coefficients than observations farther away. The formula of weight $w_{ij}$ can be expressed as

$$w_{ij} = \begin{cases} \left(1 - \frac{{d_{ij}}^2}{{\theta_{i(n)}}^2}\right)^2 if\ d_{ij} \le \theta_{i(n)} \\ 0 \text{ if } d_{ij} \ge \theta_{i(n)} \end{cases} \tag{2}$$

where $d_{ij}$ is the Euclidean distance between regression point i and observation j. $\theta_{i(n)}$ denotes the adaptive bandwidth calculated by the n-th nearest-neighbor distance. It can be found by minimizing the cross-validation statistics, which only account for model prediction accuracy or Akaike's information criterion (AIC).

The regression coefficient $\hat{\beta}(u_i, v_i)$ for the GWR model for regression point i can be specified as follows:

$$\hat{\beta}(u_i, v_i) = \left(X^T W(u_i, v_i) X\right)^{-1} X^T W(u_i, v_i) y \tag{3}$$

where y is the dependent variable vector, X is the matrix of the independent variables with a column of ones for the intercept, and $X^T$ is the transpose of a matrix X. $W(u_i, v_i)$ is the diagonal matrix denoting the geographical weighting of each observed datum for regression point i [65].

## 5. Results

### *5.1. OLS Modeling*

The OLS model, without considering the locational differences, was first estimated as a reference. As shown in Table 2, the R-Square is 0.445, indicating that the model can explain about 44.5% of the sample. The Akaike Information Criterion (AIC) is an estimator of prediction error and thereby the relative quality of statistical models for a given set of data, and AICc is a modification for small sample sizes. Since the model with the smaller AIC and AICc values is the preferred model, they can be used to compare the OLS model and the GWR model in this study.

**Table 2.** Model summary (OLS).

| Model | R Square | Residual Sum of Squares | Log-Likelihood | AIC | AICc |
|---|---|---|---|---|---|
| OLS | 0.445 | 267.073 | −541.013 | 1100.026 | 1102.494 |

The statistic results of coefficients in Table 3 show that the VIF values of all variables in the model are less than five, indicating the absence of a multicollinearity problem. Because the results from the Koenker (BP) test are statistically significant, the robust coefficient standard errors and probabilities are consulted to assess the effectiveness of each explanatory variable.

**Table 3.** Summary statistics for coefficients (OLS).

| Variable | Coef. | Std. Coef. | Std. Error | t | Sig. | VIF |
|---|---|---|---|---|---|---|
| Intercept | 3587.990 ** | | 1588.055 | 2.259 | 0.024 | |
| PA | −1.867 *** | −0.571 | 0.135 | −13.781 | 0.000 | 1.457 |
| EA | 7.975 *** | 0.216 | 1.452 | 5.491 | 0.000 | 1.319 |
| RN | 238.880 *** | 0.472 | 18.805 | 12.703 | 0.000 | 1.174 |
| DoF | 119.423 ** | 0.136 | 42.295 | 2.824 | 0.005 | 1.985 |
| DtS | −91.897 *** | −0.200 | 23.963 | −3.835 | 0.000 | 2.314 |
| Beautiful | 80.128 *** | 0.208 | 15.277 | 5.245 | 0.000 | 1.334 |
| Lively | 37.714 ** | 0.126 | 13.830 | 2.727 | 0.006 | 1.825 |
| Depressing | −112.925 *** | −0.197 | 28.382 | −3.979 | 0.000 | 2.084 |

Note: *** represents significance at 0.001 level; ** represents significance at 0.05 level.

### *5.2. GWR Modeling*

The result of the GWR model based on the same sample and variables of the OLS model is reported in Table 4. The R square is 0.769 (an increase of 0.324), indicating that considering location information when estimating listed real estate prices can significantly improve the performance of the model. The AIC and AICc values are 797.883 and 820.914, clearly smaller than those of the OLS model. Its smaller index of residual sum of squares indicates that the GWR model can fit the data better.

**Table 4.** Model summary (GWR).

| Model | R Square | Residual Sum of Squares | Log-Likelihood | AIC | AICc |
|---|---|---|---|---|---|
| GWR | 0.769 | 111.340 | 330.590 | 797.883 | 820.914 |

By calculating Moran's I index and judging from the interval to which it belongs, the standardized residuals of the samples are in a random distribution ($-1.65 <$ z-score $< 1.65$ and $0.1 < p$-value), so the GWR model has a better confidence level. As can be seen from Table 5, the normalized residuals exhibit a clustered distribution in the OLS model result, while they are randomly distributed in the GWR model result. Table 6 shows the summary statistics of the final model. Since each sample point has a different geographic weight, each sample point in the GWR model has a separate set of coefficients.

**Table 5.** Moran's I summary (OLS and GWR).

| | OLS | GWR |
|---|---|---|
| Moran's I Index | 0.405 | −0.022 |
| z-score | 6.174 | −1.088 |
| *p*-value | 0.000 | 0.276 |
| Pattern | Clustered | Random |

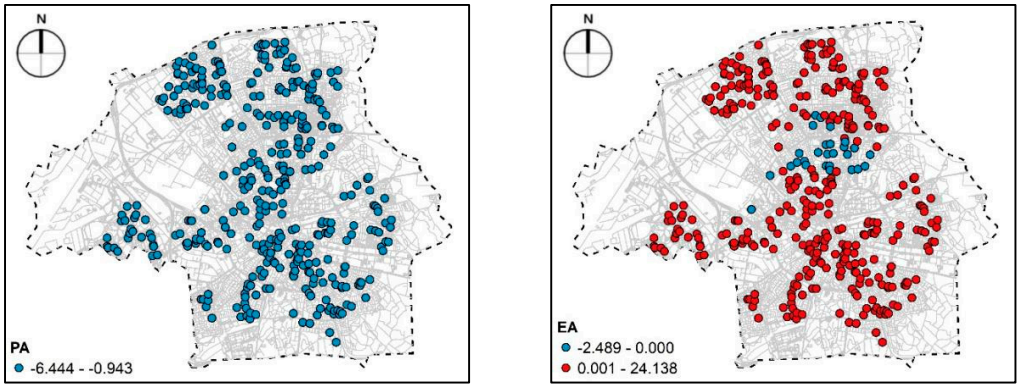
**Table 6.** Summary statistics for coefficients (GWR).

| | Coef. | | | | Std. Coef. | | | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Min** | **Median** | **Max** | **Mean** | **Min** | **Median** | **Max** |
| Intercept | 2349.214 | −9258.113 | 1192.809 | 21,186.664 | −0.169 | −1.014 | −0.191 | 1.049 |
| PA | −2.448 | −6.444 | −1.928 | −0.943 | −0.748 | −1.970 | −0.589 | −0.288 |
| EA | 6.344 | −2.489 | 5.815 | 24.138 | 0.172 | −0.068 | 0.158 | 0.655 |
| RN | 220.064 | 50.218 | 227.335 | 378.643 | 0.435 | 0.099 | 0.449 | 0.748 |
| DoF | 87.119 | −1095.102 | 146.230 | 825.185 | 0.100 | −1.251 | 0.167 | 0.943 |
| DtS | 13.729 | −376.744 | 9.672 | 655.519 | 0.030 | −0.820 | 0.021 | 1.427 |
| Beautiful | −4.686 | −178.349 | 15.526 | 107.351 | −0.012 | −0.463 | 0.040 | 0.278 |
| Lively | 1.452 | −147.933 | 3.666 | 101.499 | 0.005 | −0.496 | 0.012 | 0.340 |
| Depressing | −20.255 | −392.075 | −3.383 | 296.434 | −0.035 | −0.684 | −0.006 | 0.517 |

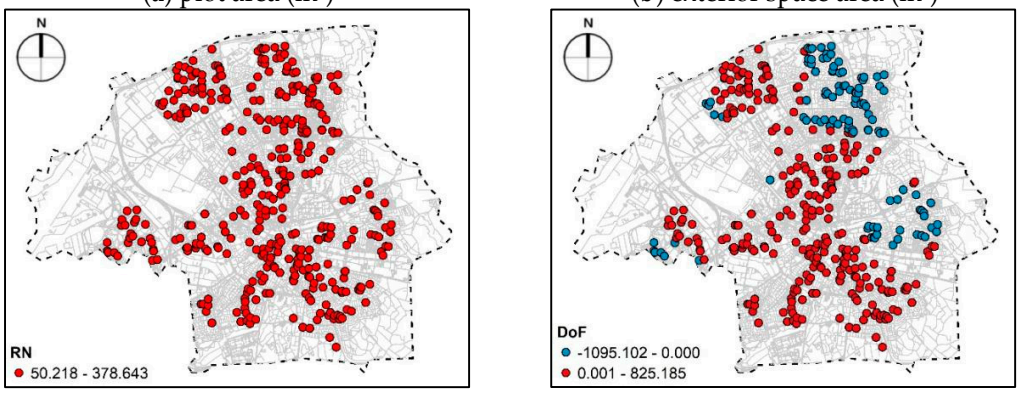
## 6. Discussion

Compared with some studies that also discuss the perception of the building environment [7,54], the innovation of this study lies in expanding the method proposed by Dubey et al. in 2016 and applying it to the real estate field. For the first time, it explores the spatial heterogeneity of street-level perceived quality as a factor influencing listed real estate prices through GWR-based hedonic pricing models. The important finding is that, in addition to traditional factors, the "beautiful", "lively", and "depressing" qualities at the street level also have a significant impact on the listed prices of real estate. In line with prior studies [2,63], after considering spatial heterogeneity, the GWR model exhibits superior performance compared to the OLS model in fitting and unveils the coefficient differences of each explanatory variable at different locations.

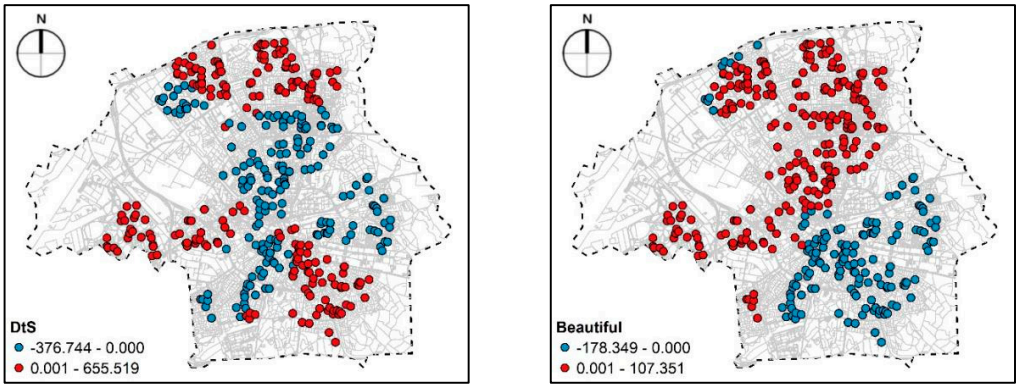
The map drawn based on the coefficients in GWR modeling results intuitively displays the spatial distribution of each independent variable. The plot size shows negative influence at all locations, indicating that the listed price per square meter of plot on larger plots is relatively lower (Figure 3a). The effect of the exterior space's size on the price shows a clear locational difference: its effect is positive in the periphery of the city but negative in the north-central area (Figure 3b). The reason for this may be that there is more ample buildable land away from the center and more villas, and the size of the yard is one of the bases for differentiating the value of these houses. The number of rooms is directly related to residential demand, so the impact on listed real estate prices is significantly positive within the study area (Figure 3c). The contribution of facility density to listed real estate prices is positive in the central area running through the north and south, which is the main residential area, but shows a negative effect in a small number of areas in the east, probably because these places pay more attention to natural resources (Figure 3d). The coefficient distribution of the distance to shopping center variable shows that in the area between the city center and the suburbs, the smaller the distance, the higher the listed price, while in other places, the opposite is true, indicating that the real estate in the city center is more dependent on large public facilities (Figure 3e).



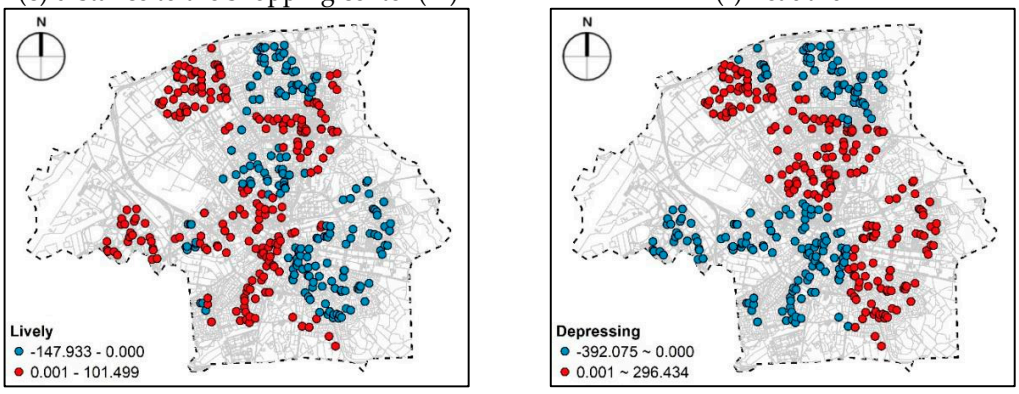

(**a**) plot area (m²) (**b**) exterior space area (m²)




(**c**) number of rooms (amount) (**d**) density of facilities (amount/km²)




(**e**) distance to the shopping center (m) (**f**) Beautiful




(**g**) Lively (**h**) Depressing

**Figure 3.** Distribution of the coefficients (GWR).

Regarding street-level perceived qualities, the coefficients of the three variables retained in the model all show notable spatial heterogeneity. Among them, the impact of perceived beautiful quality on listed real estate prices demonstrates obvious distinctions between the north and the south (negative correlation on the south side and positive correlation on the north side) (Figure 3f). Since the southern area of Eindhoven has many historic buildings and traditional-style residences, while the northern side has mostly new houses or apartments with a modern appearance, the subjective differences between the perceived scorers for the two architectural styles likely account for the opposite correlation. Furthermore, perceived livability (positive) and depressing qualities (negative) show similar heterogeneous characteristics, i.e., a positive effect in most of the southwestern area and a small part of the northern area of the city of Eindhoven (Figure 3g,h). The reason may be that the residential density in these areas is smaller and the residents are relatively young. They prefer the existence of energetic design factors in the surrounding streets and the more open and comfortable public spaces.

## 7. Conclusions

Based on the three types of factors outlined in the hedonic pricing model, this study comprehensively examines the contribution of street-level perceived quality to listed real estate prices. In the study area, in addition to the explanatory variables in the traditional model, Google Street View data with an interval of 200 m are collected to assess the street-level qualities in the service area where each house sample point is located. Employing neural network-based machine learning, we categorize perceived qualities into six distinct types. After eliminating redundant variables, eight retained explanatory variables are incorporated into the final model. The estimation results of the model reveal diverse mechanisms for the influence of factors other than plot size and number of rooms, which are recognized as common determinants. Unlike the OLS models, which only provide a universal formula, GWR models have the advantage of detecting those differences in the contribution of a given explanatory variable across regions due to locational differences, or even shifts in positive and negative correlations. In the final model, several explanatory variables are retained for all three types of factors, among which those belonging to structural attributes are plot area, exterior area, and number of rooms.

Furthermore, the street-level qualities of "beautiful", "lively", and "depressing" all show a significant impact on the listed real estate prices. Among them, there is a significant north–south difference in the expression of beauty quality, and the perceived livability (positive) and suppressed quality (negative) exhibit similar characteristics. Notably, spatial heterogeneity is observed across urban centers and suburbs, northern and southern regions, and areas with varying population density. These areas may differ in terms of population, facilities, transportation infrastructure, landscape, etc., consequently shaping people's demand for real estate. This study helps to provide urban planners and real estate investors with a more comprehensive assessment tool, avoiding the use of a single strategy to respond to housing construction in different areas, thereby overlooking the opposite contribution of certain factors. At the same time, it underscores the importance for urban designers to prioritize street quality, given its demonstrated impact on residential values.

Despite the significant methodological and practical implications of our findings, several limitations should be acknowledged. Firstly, due to the limited open-source data, this study is constrained in its sample size and does not encompass other environmental qualities considered in certain studies, such as noise and weather. Secondly, because the factors affecting listed real estate prices are spatially heterogeneous and vary across regions and countries, caution is necessary when directly applying our findings to other cities. Lastly, the currently used scoring model for perceived qualities still has deficiencies. Performance could be further improved through soliciting ratings from local residents regarding the perceived quality of neighborhood streets.

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