sustainability

MDPI

Article

The Unequal Impact of Natural Landscape Views on Housing Prices: Applying Visual Perception Model and Quantile Regression to Apartments in Seoul

Hyejin Lee [1], Byoungkil Lee [2,*] and Sangkyeong Lee [3,*]

[1] Facility Infra Division, NCSOFT, Seongnam 13494, Korea; vocalise6@naver.com
[2] Department of Civil Engineering, Kyonggi University, Suwon 16227, Korea
[3] Department of Urban Planning and Landscape Architecture, Gachon University, Seongnam 13120, Korea
* Correspondence: basil@kgu.ac.kr (B.L.); skylee@gachon.ac.kr (S.L.);
Tel.: +82-31-2499713 (B.L.); +82-31-7508765 (S.L.)

Received: 8 September 2020; Accepted: 6 October 2020; Published: 8 October 2020

check for updates

Abstract: Natural landscape views have positive sides, such as providing restorative effects to urban residents, and negative sides, such as deepening wealth inequality. Previous studies have mainly focused on the positives and rarely on the negatives. From this perspective, this study aimed to analyze the unequal impact of natural landscape views on housing prices for apartments in Seoul. We proposed a visual perception model to analyze natural landscape views and, based on a hedonic price model, we used ordinary least squares and quantile regression to estimate the marginal impacts on housing prices. The results show that: (1) natural landscape views had positive impacts on housing prices, but their impacts did not reach the level of structural and locational characteristics such as apartment area and the distance to subway stations; (2) natural landscape views had different marginal impacts by housing price range and, in particular, had much higher value-added effects on higher-priced apartments, meaning that if old apartment complexes are redeveloped into high-rise ones, the improvement in natural landscape views generates great profit for apartment owners and intensifies wealth inequality; (3) the geographic information system-based visual perception model effectively quantified the natural landscape views of wide areas and is thus applicable for the rigorous analysis of various landscape views.

Keywords: natural landscape; views; visual perception; housing price; hedonic price model; quantile regression; marginal impact; wealth inequality

1. Introduction

A natural landscape consists of a collection of landforms such as mountains, rivers, and lakes as well as natural vegetation [1]. Views of such landscapes have restorative effects and provide psychological comfort to urban residents [2,3]. Therefore, consumers are willing to pay more for homes with good natural landscape views [4]. In light of this, researchers have attempted to analyze the impacts of natural landscape views on housing prices, generally using hedonic price models [5]. A hedonic price refers to the unit price of structural, locational, and environmental characteristics of housing, such as area, floor level, and proximity to a primary school [6]. The hedonic price is typically estimated by using ordinary least squares (OLS) regression, and the estimated coefficient is also described as a marginal impact [7]. The marginal impact of a natural landscape view refers to the change in housing price for a unit change of the view variable, all other independent variables being constant. Most studies have found that the marginal impact of the natural landscape view had positive values, supporting that natural landscape views positively affect urban residents [4,8–23].

Based on the mean of price distribution, OLS regression estimates marginal impacts equally for all housing. However, this is not an appropriate analysis method for segmented markets, such as low-, mid-, and high-end housing markets [7,24]. Several studies have indicated quantile regression as an alternative to OLS regression, as quantile regression coefficients are estimated differently across the conditional distribution of housing prices [7,19,25–30]. OLS minimizes the sum of squared residuals, whereas quantile regression minimizes the sum of asymmetric weighted absolute values [31]. Indeed, several studies have used quantile regression to analyze the impact of natural landscape views on housing prices. Some showed that natural landscape views had a much higher value-added impact on higher-priced housing than on lower-priced housing [32], whereas others found the opposite [7,28]. To draw definite conclusions, a complementary study using quantile regression should be performed. Moreover, previous studies have focused mainly on measuring the marginal impacts of natural landscape views, and have not been concerned with the related social problems. Considering the public nature of natural landscape views, it is necessary to examine the related social issues. In the study, we tried to address these issues by examining the Seoul housing market.

In Seoul, the capital of Korea, housing prices have risen significantly in recent years. As housing prices rose, wealth inequality between homeowners and non-owners deepened, and as the prices of expensive housing rose even further, wealth inequality among homeowners grew as well [33]. In particular, the housing prices of apartment complexes preparing for redevelopment rose significantly. In Korea, an apartment is a self-contained housing unit and a type of residential real estate. An apartment complex consists of one or more buildings, with more than five floors, divided into units that are owned and sold individually. The rise in the housing prices of old apartment complexes along the Han River has attracted particular attention. The reason for this lies in the expectation that redeveloping the old apartment complex into a high-rise one with a good view of the Han River will provide great benefits to apartment owners. This expectation is based on the fact that new apartments along the Han River are the most expensive in Seoul [34]. The Seoul Metropolitan Government strictly controls such redevelopment projects, as profits are attributed to apartment owners. For these reasons, natural landscape views are often criticized as being a cause of deepening wealth inequality.

The situation in Korea shows us that natural landscape views have both positive sides, such as providing restorative effects to urban residents, and negative ones, such as deepening wealth inequality. Despite the importance of reducing wealth inequality in terms of sustainability, previous studies have focused mainly on the positives, and rarely on the negatives. Quantile regression can be effectively used as an analytical method to examine these negative sides. When analyzing the marginal impact by housing price range through quantile regression, it is possible to determine which price ranges get premiums from natural landscape views. From this perspective, this study aimed to analyze the impact of natural landscape views on housing prices for apartments in Seoul. First, we analyzed the marginal impacts of natural landscape views using OLS regression analysis. Next, we analyzed the variation of marginal impacts by price range using quantile regression. Based on the analysis results, we discuss the impact of natural landscape views on deepening wealth inequality.

In order to effectively analyze the impact of natural landscape views on housing prices, it is necessary to measure such views accurately. In many studies, views were analyzed using dummy variables, and categorized as visible and invisible, or visible, partially visible, and invisible [4,5,9,10,15,35–37]. However, these studies did not show an objectively testable method of measuring views; it is difficult to know how the view was measured and how much was measured. To overcome this limitation, the quantification of views is being attempted. Viewing is possible when there is line-of-sight between the viewpoint and the target object, and visibility analysis is based on this nature of viewing. Viewshed analysis is performed by accumulating visibility analysis for target objects within a certain radius around a viewpoint. As for landscape analysis, various methods have been developed using Geographical Information System (GIS) or Computer-Aided Design (CAD) software as well as a digital elevation model (DEM), which comprises numerical information on terrain topography.

Two major groups of studies on landscape quantification have been performed. One concerned calculating the area of various objects that can be viewed using viewshed analysis [12,17,38–41], and the other involved determining a visual perception using the spatial relationship between a specific target object and a viewpoint to determine the psychological effect of the target object on the observer [42–47]. The former group involved evaluating the landscape by calculating the planimetric area for each target object, although recent studies have improved the accuracy of the analysis by using more precise three-dimensional data [17,41]. The area to be viewed is obtained by overlaying the results of viewshed analysis and land use or land cover information. This analysis technique is limited in that it is impossible to quantify the human visual perception of view by using the planimetric area of the landscape included in the visual field. The latter group of studies quantified the view analysis results using the concept of visual perception. However, the study [42] only evaluated openness among factors affecting property value, and [43] did not analyze irregular topography. Studies [44] and [45] attempted to quantify exact visual perceptions using a solid angle as a viewing unit, but it is necessary to improve the algorithm for applying it to a large area, as these were experimental studies on a small research site. By considering only the vertical view of an object, the entire view and visual perception are not appropriately integrated and analyzed [46]. Since the algorithm in [47] evaluated the landscape using the depth view obtained by projecting the view onto a cylinder, not a hemisphere, it was not able to evaluate the correct visual perception.

As such, conclusive studies have not yet been conducted to evaluate the value of landscapes using the results of view analysis based on visual perception targeting large urban areas where natural and artificial features are mixed. In the study, to analyze the value of natural landscapes in the Seoul metropolitan area, an analysis method was proposed to apply visual perception-based view analysis to wide areas.

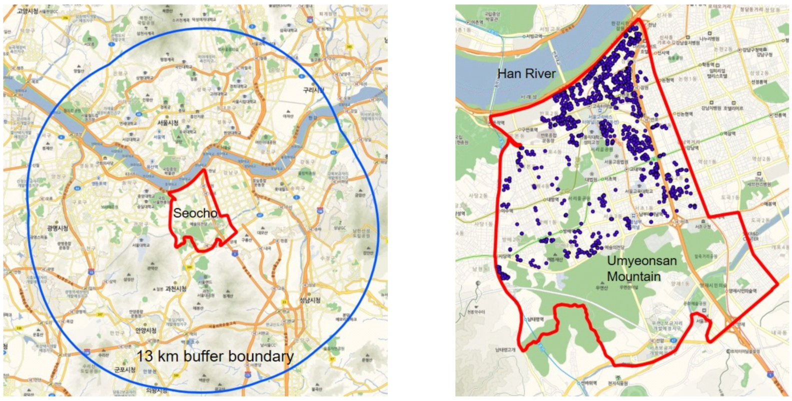
The rest of this paper is organized as follows. Section 2 introduces study area and data, discusses research methods focused on the visual perception model, the hedonic price model, and the quantile regression model, and describes independent variables such as natural landscape view variables and other independent variables. Section 3 presents and discusses the results of an empirical analysis using OLS and Quantile regression. Section 4 discusses wealth inequality, which is the negative side of natural landscape views in connection with apartment redevelopment in Seoul, and additionally discusses the utility of the visual perception model. The final section summarizes the key findings and suggests policy implications.

2. Data and Methods

2.1. Data

In the study, we focused on natural landscape views such as views of greenery and the Han River, excluding views of artificial facilities. Seoul is made up of 25 local government districts called "gu". For the purpose of the study, Seocho-gu was selected due to its relative abundance of natural landscapes and its having the highest ratio of apartments (57.9% compared to 42.0% for the entirety of Seoul [48]). As shown in Figure 1, Seocho-gu has Umyeonsan Mountain to its south, Han River to the north, and the large Seoripul Park in the center. In a GIS-based viewshed analysis, natural landscapes both outside and inside Seocho-gu were analyzed. As shown in Figure 1a, the range for natural landscapes outside Seocho-gu was set to 13 km.

To analyze the impacts of natural landscape views on housing prices, we used apartment transaction data in Seocho-gu in 2013. These data, which were provided by the Seoul Metropolitan Government, consist of 1260 apartments in 193 complexes, and the locations of the apartments are shown in Figure 1b. The data include basic transaction information such as address, area, transaction date, and sale price. Using the addresses of apartments, we were able to locate them in three-dimensional space, which is a necessary prerequisite for GIS-based viewshed analysis.



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

Figure 1. Study area and the distribution of apartments: (**a**) Seocho-gu boundary (red line) and the 13 km buffer boundary (blue line) of the visible range of viewshed analysis; (**b**) the locations of apartments used for the study (blue points).

The structural characteristics of the apartment complex, such as the number of apartments and dwelling age, were extracted from the data provided by R114, a real estate consulting company. The locational characteristics of apartment complexes, such as the distances to subway stations and primary schools, were measured using the near function of ArcGIS.

In Korea, various kinds of spatial information are distributed through the National Spatial Data Infrastructure (NSDI). In the study, the DEM, building, and land cover information from the NSDI's spatial information distribution site [49] was used. A digital surface model (DSM) with a 2-m resolution was constructed using the DEM for Seoul and neighboring areas as well as the height values of the building map (Figure 2). The view of each land cover was analyzed to evaluate the landscape using the sub-class land cover map (2-m resolution) for Seoul and the mid-class land cover map (10-m resolution) for the neighboring regions. Land cover classes such as paddy fields, fields, broadleaf forests, coniferous forests, mixed forests, natural grassland, artificial grassland, and barren land were extracted for evaluation of natural landscape views, and inland wetland and inland water items were extracted for evaluation of the view of the Han River.

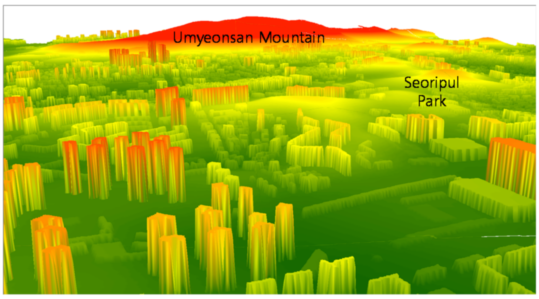


Figure 2. Part of the digital surface model (DSM) from the north.

2.2. Methods

2.2.1. Visual Perception Model

As humans perceive different landscapes differently, they also value them differently. To quantify the human perception of landscapes, all views in the viewshed must be converted into a single unit based on visual perception. Among studies on visual perception, the experimental studies [44,45] have quantified visual perception using a viewing angle. Based on this, we tried to develop a model for evaluating a visual perception in the study.

The visual field corresponds to the viewing angle of the camera, and is about 200° horizontally and 135° vertically in humans. All visible objects occupy a certain region on the retina to form the entire visual field. When an object forms an image on the human retina, it forms a three-dimensional angle proportional to the size of the object and inversely proportional to the square of the distance from the retina, as shown in Equation (1) [50]. As described above, if the area of the retina occupied by the object is converted into a solid angle, the visual angle can be quantified, based on which the value of the landscape can be evaluated.

$$\Omega \sim \frac{A}{r^2} \tag{1}$$

where Ω is the solid angle (in steradian), A is the projected area of the object, and r is the distance between the retina and the object.

Factors involved in visual perception include size, color, and texture, but color and texture are difficult to model because they are affected by irregularities such as weather and season. Therefore, in the study, we tried to quantify the viewing angle only in terms of size, which can be measured using a solid angle. In addition, we proposed a visual perception quantification model that can fully utilize the spatial analysis function of GIS to evaluate landscapes in metropolitan areas such as Seoul. While the viewshed analysis in previous studies did not rely on visual perception, the visibility of the entire area subject to landscape evaluation is still important, so the viewshed was extracted to limit the scope of the visual perception evaluation. As such, this study presented a general visual angle measurement model that can be applied to landscape evaluations by integrating viewshed analysis and visual angle quantification by solid angle. The proposed model is as follows:

(1) Viewshed analysis using a DSM. In an urban space where artificial features such as buildings interfere with the view, a DSM that includes the height information of buildings should be used, rather than a simple DEM. The viewshed analysis uses a distance and a viewing angle that can sufficiently include target objects required for landscape evaluation from a viewpoint. Viewshed analysis uses the raster analysis function of GIS;

(2) Using Equation (2), calculate the actual surface area from the angle of inclination, and generate raster data with the value of surface area only for the ground pixels on which a line of sight is created in the DSM. The angle of inclination is calculated using the slope function of GIS, and the calculation of the surface area uses the raster calculator function

$$A' = \frac{A''}{cos\theta} \tag{2}$$

where A' is the actual surface area, A'' is the planimetric area of pixel, and θ is the inclination angle of the ground surface;

(3) Using the dot product as in Equation (3), calculate the area where the actual surface area is projected in the direction of the viewing point, and create raster data. The normal vector of the ground surface is calculated using the elements of the aspect and slope of the DSM, the aspect is calculated using the raster analysis function of GIS, and the calculation of the projected area uses the raster calculator function

$$A = \vec{OP} \cdot \vec{A'} \times A' \tag{3}$$

where A is the projected area, $\vec{OP}$ is the direction vector of the line-of-sight with the target object as the origin and the viewpoint as the end point, and $\vec{A'}$ is the normal vector of the ground surface;

(4) The solid angle at which a pixel on the visible ground surface is perceived by a person is calculated by dividing the projected area by the square of the range of sightline using Equation (1). The distance from the observation point to the ground pixel to be analyzed is calculated as the Euclidean distance from the coordinates of the two points, and the raster calculator function is used to calculate the solid angle and generate raster data;

(5) The visibility angle is calculated by summing the solid angle of the raster data created in (4) for each natural landscape item of the land cover to be analyzed. Among the raster analysis functions of GIS, the zonal statistics function is used to sum solid angles.

2.2.2. Hedonic Price Model

A hedonic price model has been widely used to explore the determinants of housing prices. According to [6], the market price of a heterogeneous good like housing is determined by the sum of prices of its characteristics. As these characteristics are not transacted individually but in a bundle, these prices are not individually observed, unlike housing prices that are explicitly revealed. The characteristic price is described as the equilibrium price in the implicit market and is estimated by regressing housing price on the quantity of the characteristic [24]. The hedonic price model typically estimates coefficients using OLS regression. To test the impact of natural landscape views on the housing price P, we assume hedonic price model as the following form

$$P = \alpha + \sum \beta_i V_i + \sum \gamma_j S_j + \sum \delta_k L_k + \sum \theta_m T_m + \varepsilon \quad (4)$$

where V_i are the characteristics of natural landscape views, such as views of greenery and the Han River; S_j are structural characteristics, such as net area of housing and dwelling age; L_k are the locational characteristics, such as distance to subway stations and primary schools; T_m is dummy variables representing the season of transaction; ε is the error term; α, β_i, γ_j, δ_k and θ_m are coefficients to be estimated.

The estimated coefficient refers to the expected value of the partial derivative of the dependent variable with respect to an independent variable, depending the functional form of the hedonic price model. Linear, semi-log, and log–log forms are generally used as functional forms. In the linear form, both the dependent and independent variables go into regression without any transformation [24]. The estimated coefficient indicates the change in the dependent variable for a one-unit change of the independent variable when all other independent variables are held constant. This linear form has an advantage when interpreting the estimated coefficient because it means a marginal impact. In the semi-log form, a dependent variable is logged form and independent variable is linear [24]. The coefficient indicates the rate at which the housing price increases at a certain level, given an independent variable [24]. Marginal impact is found to be somewhat more complex than the linear form in that marginal impact is calculated by multiplying the estimated coefficient by the corresponding values for the mean of independent variables [7]. Since there is no economic theory that informs the selection of a functional form, it is generally selected by considering the research objective and comparing the goodness of fit [26]. In this study, the log–log form in which the dependent and independent variables are in logged form were excluded because the marginal impact is more complexly calculated. The appropriate functional form would be selected between linear form and semi-log form by comparing the goodness of fit.

2.2.3. Quantile Regression Model

Based on the mean of price distribution, the OLS regression assumes that the marginal impacts of physical characteristics are constant across the conditional distribution of housing prices. However, recent studies have shown that marginal impacts are not constant because high-end home buyers value physical characteristics differently from low-end home buyers [29]. Several studies have identified significant variations in the marginal impacts across the conditional distribution of housing prices using quantile regression [7,19,26–29,51]. We assume that the marginal impacts of natural landscape views would vary differently across the conditional distribution of housing prices, in particular being much higher in higher-priced housing. Considering Equation (4), housing price for the quantile τ can be written as

$$P_\tau = \alpha_\tau + \sum \beta_{i\tau} V_i + \sum \gamma_{j\tau} S_j + \sum \delta_{k\tau} L_k + \sum \theta_{m\tau} T_m + \varepsilon \quad (5)$$

where τ represents a quantile point in the distribution of housing prices; and α_τ, $\beta_{i\tau}$, $\gamma_{j\tau}$, $\delta_{k\tau}$, and $\theta_{m\tau}$ are coefficients to be estimated.

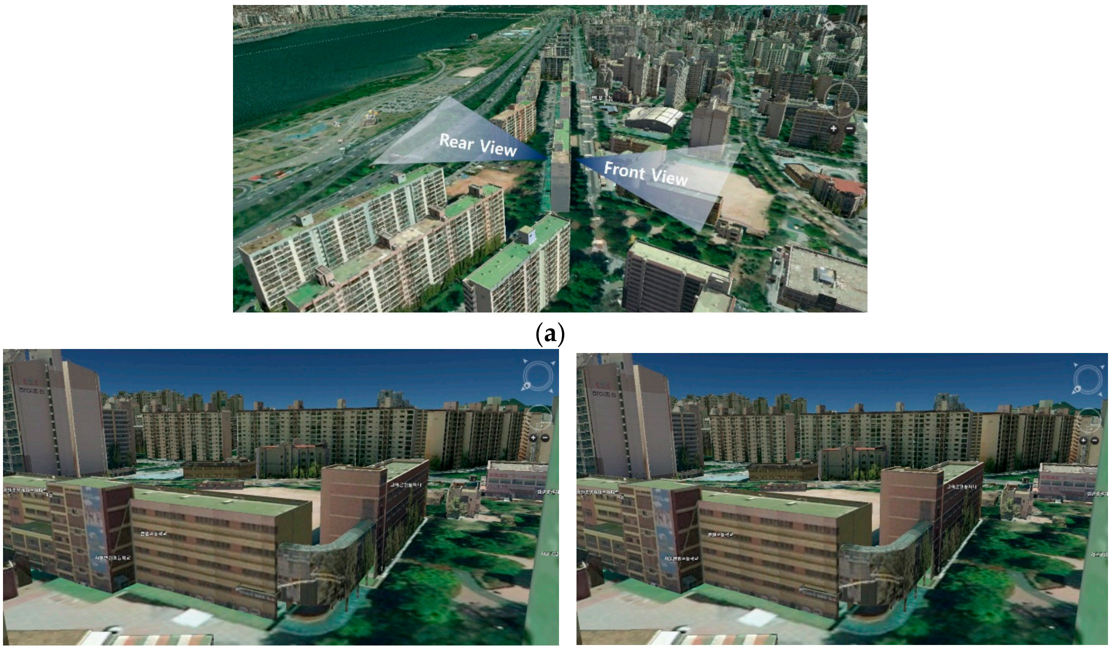
Quantile regression minimizes weighted absolute deviations to estimate conditional quantile functions [31]. For the median ($\tau = 0.5$), symmetric weights are used; for all other quantiles, asymmetric weights are used [7]. The standard errors of coefficient estimates can be feasibly estimated using bootstrapping [52].

2.3. Independent Variables

2.3.1. Natural Landscape Views

To analyze the impact of natural landscape views on housing prices, a database was constructed of the view characteristics. The view characteristic data were constructed by applying the visual perception measurement model described in Section 2.2.1 to the DSM and land cover, and the model was automated using the ArcGIS model builder.

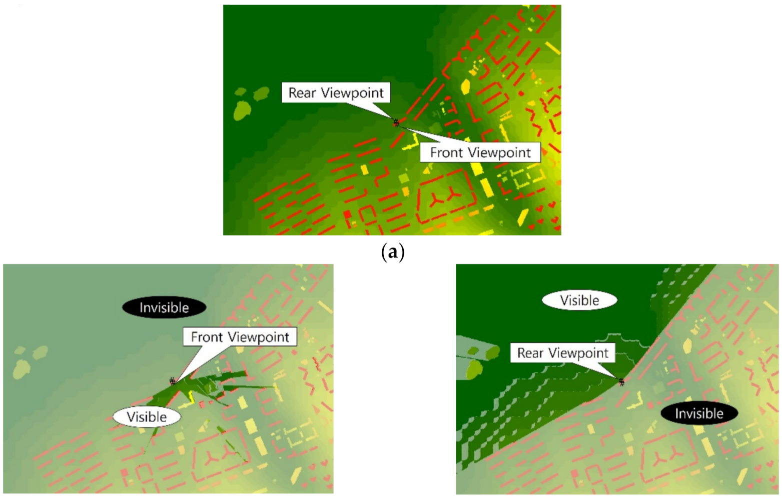
First, a viewshed analysis was performed using ArcGIS. The primary viewpoint for the viewshed was set in the front of the living room, and a secondary viewpoint was set to be spaced apart by the width of the building. The reason for having two viewpoints is that most apartments in Seoul are flat-type, and the views of the front and the rear are greatly different, as shown in Figure 3. As Korean culture values sunlight, the living room is usually located towards the south. As the study area is south of the river, to use Han River views as a variable for the landscape evaluation, both the front view and the rear view must be considered at the same time. In the study, the sum of the viewing angles of the natural landscape, quantitatively calculated for two or more viewsheds according to the shape of the apartment building, was used as the natural landscape view variable.



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

Figure 3. Front and rear views of an apartment in Seocho-gu, Seoul [53]: (**a**) two views of an apartment; (**b**) Part of the front view of (**a**); (**c**) Part of the rear view of (**a**).

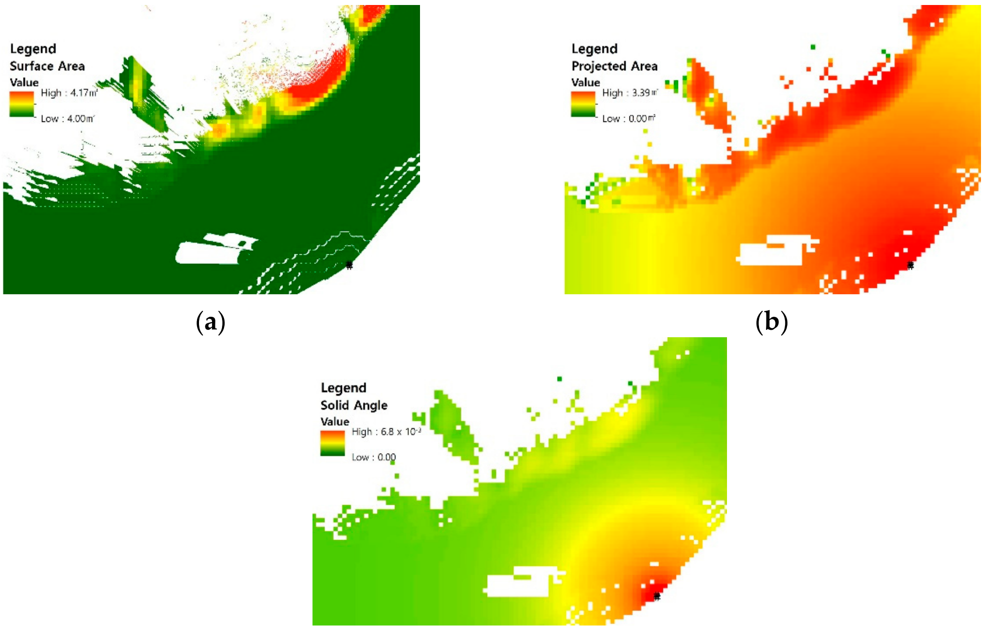
Next, viewshed analysis is performed so that the visual perception model can be applied to quantify natural landscape views. Viewshed analysis conditions were set as follows. The height of the viewpoint was given as an offset value considering the floor level of traded apartment. The visible range of the viewshed analysis was set to 13 km, the average visible range of Seoul (Figure 1a), as suggested in the annual air environment report [54], the observation orientation angle was set to the façade direction of the building, and the viewing angle was set to 180° for both the top, bottom, left, and right. Figure 4 shows an example of a viewshed analysis.



(b) (c)

Figure 4. Example of viewshed analysis results: (**a**) Viewpoint overlay with the DSM; (**b**) Viewshed analysis result of front view; (**c**) Viewshed analysis result of rear view.

The slope and aspect of the DSM and the azimuth angles from viewpoints to target points were analyzed using the Spatial Analyst function of ArcGIS. Since the resolution of the DSM is 2 m, the planimetric area of one pixel is 4 m^2. Slope, aspect, and azimuth angle are input into Equations (2) and (3) in ArcGIS Map Algebra to calculate the surface area (Figure 5a) and the projected area (Figure 5b), respectively. The surface area increases in proportion to the ground slope, and the projected area depends on the angle between the viewpoint and the surface.



(c)

Figure 5. Example of the calculation result for the rear viewpoint in Figure 4: (**a**) surface area; (**b**) projected area; (**c**) solid angle.

The distance of the target object from the viewpoint was calculated by using the three-dimensional coordinates of the two points. The solid angle of the visible pixels, as seen from the viewpoint, was calculated using Equation (1) in ArcGIS Map Algebra (Figure 5c). The sum of the solid angles for each land cover class within the viewshed was calculated using the Zonal Statistics function of ArcGIS. The GREENVIEW variable is the sum of the solid angles for land covers including paddy fields, fields, broadleaf forests, coniferous forests, mixed forests, natural grassland, artificial grassland, and barren land. The RIVERVIEW is the sum of the solid angles for the Han River.

2.3.2. Other Independent Variables

The structural characteristics were divided into apartment-level variables and complex-level variables. The independent variables of apartment-level include the net area of the apartment, AREA, floor level on which the apartment is located, FLOOR, and being south-facing, SOUTH. AREA was adopted as an independent variable because housing price generally increases with an increase in apartment area [4,10,15,18]. Likewise, higher floor levels have a better view, so their sale prices are also higher. For this reason, we adopted FLOOR as an independent variable, but this differs from the natural landscape view variables GREENVIEW and RIVERVIEW because both artificial and natural landscapes are included in the view object, and some apartments have poor views even if the floor level is high. Finally, previous studies show that the facing direction of housing has a significant impact on housing prices [25]. In Korea, south-facing housing commands higher prices due to advantages in heating, laundry drying, sterilization, and so on [55], so SOUTH was introduced as a dummy variable. As this is mainly related to sunlight, this variable was analyzed by classifying apartments facing south, southeast, and southwest into the same group, the south-facing.

Regarding the complex-level variables, we introduced dwelling age, AGE, age squared, AGESQ, and the number of total apartments in the complex, TUNIT. In general, the older the dwelling age, the lower the apartment price due to the negative impact of depreciation. However, as the dwelling age approaches the point when redevelopment is possible, old apartment prices turn and rise due to the expectation of redevelopment [56,57]. This phenomenon can be described effectively using a quadratic function on the AGE and AGESQ variables [56]. The turning point refers to the point that has a minimum apartment price and can be calculated by taking the partial derivative of housing price with respect to the AGE variable [57]. In the study, AGE is calculated by subtracting the year of apartment completion from 2013. Finally, the larger the complex, the better the housing service, so the price tends to increase [34]. TUNIT was adopted to test this hypothesis.

Regarding the locational characteristics, we introduce independent variables for the distance of the apartment complex from the boundary of Gangnam-gu, DGANGNAM, the distance to a subway station, DSUBWAY, the distance to a primary school, DPRIMARY, and the distance to a middle school, DMIDDLE. As Gangnam-gu is the commercial center of the southern area of the Han River, DGANGNAM was adopted to test the hypothesis that the closer the apartment complex is to Gangnam-gu, the higher the price of apartments will be. DSUBWAY is adopted to measure the impact of proximity to public transportation, as several studies have found such a relationship [34,55]. As Koreans highly value education, several studies have shown that the closer an apartment complex is to a primary or middle school [34,56], the higher the price of apartments. DPRIMARY and DMIDDLE were adopted to test this. The distance was measured to the nearest target from the apartment complex using ArcGIS, at 100-m measurement increments for convenience in analysis.

Korea has four distinct seasons that also affect housing transactions; for example, there are many in spring when the new school year begins due to the high interest in education. To test this, we introduced seasonal dummy variables with winter as the reference group. Given that Korea's real estate transaction reports had a time lag of 1-2 months, January to March was counted as winter, April to June as spring, July to September as summer, and October to December as fall.

Table 1 summarizes the definitions and basic statistics for the variables used in the study. The average and maximum of GREENVIEW were 0.063 and 0.320 steradians; viewshed in all directions was analyzed, so the possible maximum is 4π steradians. As the view from the zenith to the horizon forms one hemisphere, and the view from the horizon to the nadir forms the other, on average, both the blue sky and the landscape have 2π steradians. Therefore, the maximum of GREENVIEW, 0.32 steradians means that 5.1% (= 0.320/2π) of all view fields seen from the front and rear are the view of greenery. Looking the mean values of seasonal dummy variables, the most apartments were sold in spring (32.5%), and the least in summer (17.1%).

Table 1. Definition and statistical summary of variables.

Variable	Definition	Mean	S.D.	Min.	Max.
PRICE	Sale prices of apartments as dependent variable (million KRW) [1]	849.386	384.716	188.000	2850.000
Views					
GREENVIEW	Solid angle of the visible pixels for green views (steradians)	0.063	0.057	0.000	0.320
RIVERVIEW	Solid angle of the visible pixels for Han River views (steradians)	0.011	0.031	0.000	0.166
Structure					
AREA	Net area of the apartment (square meters)	98.850	37.697	23.700	254.450
FLOOR	Floor level on which the apartment is situated (story)	7.131	4.905	1.000	29.000
SOUTH	1 if the apartment is south-facing, otherwise 0 (dummy)	0.780	0.414	0.000	1.000
AGE	Subtracting the year of apartment completion from 2013 (years)	21.913	10.999	4.000	37.000
AGESQ	AGE squared (years squared)	601.044	458.871	16.000	1369.000
TUNIT	Number of total apartments in the complex	844.579	875.893	9.000	3410.000
Location					
DGANGNAM	Distance from the complex to Gangnam-gu boundary (100 m)	14.261	10.310	0.687	46.521
DSUBWAY	Distance from the complex to subway station (100 m)	4.433	1.920	0.242	9.428
DPRIMARY	Distance from the complex to primary school (100 m)	3.566	1.697	0.623	8.724
DMIDDLE	Distance from the complex to middle school (100 m)	4.076	1.982	0.259	9.553
Transaction					
SPRING	1 if reported from April to June, otherwise 0 (dummy)	0.325	0.469	0.000	1.000
SUMMER	1 if reported from July to September, otherwise 0 (dummy)	0.171	0.377	0.000	1.000
FALL	1 if reported from October to December, otherwise 0 (dummy)	0.220	0.414	0.000	1.000

Notes: [1] The average exchange rate in 2013 was USD 1.00 = KRW 1095.04 [58].

3. Results

3.1. OLS Regression Analysis Results

Table 2 shows the estimation results of OLS regression with linear and semi-log forms. When comparing the goodness of fit of two models, the R^2 of the linear form model is 0.8604 and that of the semi-log form model is 0.8403, indicating that the linear form model is better. In addition, comparing the significance of independent variables, SUMMER and FALL are not significant in the linear form model, while DMIDDLE, SPRING, SUMMER and FALL are insignificant in the semi-log form. The linear form model is superior in both the goodness of fit and the number of significant variables, so this study selects the linear form model.

Table 2. Analysis results of ordinary least squares (OLS) regression.

Variable	Linear: Dependent Variable = PRICE				Semi-Log: Dependent Variable = Ln(PRICE)			
	Unstandardized Coefficient	S.E.	Standardized Coefficient	VIF	Unstandardized Coefficient	S.E.	Standardized Coefficient	VIF
CONSTANT	341.474 ***	37.054			6.069 ***	0.041		
GREENVIEW	378.359 ***	80.715	0.056	1.259	0.226 **	0.088	0.033	1.259
RIVERVIEW	324.706 **	139.561	0.026	1.149	0.444 ***	0.153	0.035	1.149
AREA	7.253 ***	0.115	0.711	1.124	0.008 ***	0.0001	0.729	1.124
FLOOR	4.888 ***	0.939	0.062	1.278	0.006 ***	0.001	0.080	1.278
SOUTH	41.963 ***	10.395	0.045	1.117	0.055 ***	0.011	0.057	1.117
AGE	−15.854 ***	2.471	−0.453	44.446	−0.013 ***	0.003	−0.375	44.446
AGESQ	0.321 ***	0.058	0.383	42.942	0.0003 ***	0.0001	0.368	42.942
TUNIT	0.118 ***	0.006	0.269	1.800	0.0001 ***	0.00001	0.251	1.800
DGANGNAM	−0.792 *	0.475	−0.021	1.441	−0.002 ***	0.0005	−0.042	1.441
DSUBWAY	−34.427 ***	2.496	−0.172	1.383	−0.031 ***	0.0027	−0.150	1.383
DPRIMARY	−18.515 ***	2.997	−0.082	1.557	−0.023 ***	0.0033	−0.101	1.557
DMIDDLE	−5.890 **	2.594	−0.030	1.591	−0.004	0.0028	−0.020	1.591
SPRING	19.855 *	10.522	0.024	1.464	0.015	0.0115	0.017	1.464
SUMMER	3.130	12.644	0.003	1.368	−0.002	0.0138	−0.002	1.368
FALL	−11.577	11.711	−0.012	1.417	−0.014	0.0128	−0.015	1.417
R^2	0.8604				0.8403			
Adj. R^2	0.8587				0.8384			
N	1260				1260			

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

As the difference between R^2 and adjusted R^2 are small (R^2 = 0.8604; Adj. R^2 = 0.8587), it can be said that there are no multicollinearity among the independent variables. This is also confirmed through the variance inflation factor (VIF), which tests for multicollinearity: it is less than 2.0 for all variables except AGE and AGESQ, so it can be concluded that there is no multicollinearity. AGE and AGESQ can have high VIFs because although AGE and AGESQ are highly correlated, AGESQ is nonlinear functions of AGE [59]. Based on these observations, the GREENVIEW, RIVERVIEW, and FLOOR variables can be put into the model at the same time without worrying about multicollinearity.

Both GREENVIEW and RIVERVIEW had significantly positive impacts on housing prices. As both are measured in steradian, their marginal impacts can be directly compared. The marginal impacts of GREENVIEW and RIVERVIEW are KRW 378.4 million and KRW 324.7 million, respectively. Given that the averages of GREENVIEW and RIVERVIEW are 0.063 and 0.011 steradians, respectively, the former has a greater impact. However, this interpretation must consider the location of apartments in Seocho-gu, as the views of the Han River were analyzed as the rear view of the apartment and the views of greenery as the front view in the study. Nevertheless, the fact that the values of their impacts are not very different supports the significant impact of the views of the Han River on housing prices.

Among the structural characteristics, AREA, FLOOR, TUNIT, and SOUTH had positive impacts on housing prices. Despite the limitation that floor level cannot directly express the level of the view, the fact that FLOOR had a positive impact can be seen as a result of the general perception that the higher the floor height, the better the view. Specifically, the floor level of the apartment has a limitation in that it cannot directly represent views. Nevertheless, the fact that FLOOR coefficient has a positive value can be seen as a result of reflecting the general perception that the view is better as floor level increases. Comparing south-facing apartments and non-south-facing apartments, the price of a south-facing apartment was about KRW 42.0 million higher.

With respect to AGE and AGESQ, the hypothesis of dwelling age assumes that the curve of housing prices represents a quadratic function, so the AGE coefficient should be negative and the AGESQ coefficient should be positive, and this is borne out by the results in Table 2. As a result of taking the partial derivative of housing price with respect to the AGE variable to find the turning point at which the housing price has the minimum value, the point was calculated as 24.8 years. This means that the housing price decreases over time up to about 25 years of dwelling age due to depreciation effect, but after 25 years, prices increase as the magnitude of the positive redevelopment effect overtakes the negative depreciation effect.

Among the locational characteristics, DGANGNAM, DSUBWAY, DPRIMARY, and DMIDDLE all had negative impacts on housing prices. Housing price decreases with greater distance between the apartment complex and Gangnam-gu (KRW 0.8 million per 100 m), the nearest subway station (KRW 34.4 million per 100 m), primary school (KRW 18.5 million per 100 m), and middle school (KRW 5.9 million per 100 m). When comparing primary and middle schools, the impact of primary schools is much higher because parents generally feel more needed to protect younger students from traffic accidents. When looking at the difference in housing prices by season, spring showed a statistically significant difference from winter, but summer and fall showed no significant difference from winter.

Comparing the marginal impacts using standardized coefficients, the following order is obtained, from greatest effect to smallest: AREA, TUNIT, DSUBWAY, DPRIMARY, FLOOR, GREENVIEW, SOUTH, DMIDLE, RIVERVIEW, SPRING and DGANGNAM. In summary, apartment area, complex size, and proximity to subway stations and primary schools, and floor level are important characteristics that determine housing prices. It can be seen that though the views of greenery and the Han River do not reach the impacts of these characteristics, they are significantly important characteristics.

3.2. Quantile Regression Analysis Results

In the OLS regression analysis, it was assumed that the marginal impact of the natural landscape was constant regardless of housing prices. To test our hypothesis that marginal impacts differ by housing price range, we used quantile regression. Table 3 shows the estimation results for the quantile regression. The results are summarized by increasing the quantile points by five percent to effectively represent the variation in marginal impact.

All GREENVIEW coefficients were positive but were not significant at quantile points 0.05, 0.15–0.4, and 0.8–0.85. As shown in Figure 6, the coefficients have similar values up to quantile point 0.85 and exhibit a sharp uptrend from quantile point 0.9. RIVERVIEW coefficients were significantly positive at all quantile points, showing a sharp uptrend from quantile point 0.85. Specifically, when comparing the marginal impact of the quantile point 0.95 and that of the quantile point 0.5, GREENVIEW was 4.0 times and RIVERVIEW was 4.3 times. The results indicate that natural landscape views have unequal impacts on housing prices by price range, in particular, having a greater positive impact on higher-priced apartments. In other words, this means that higher-priced apartments have a premium on natural landscape views compared to lower- and medium-priced apartments. Compared to the OLS estimate, GREENVIEW has less impact on lower- and medium-priced apartments, but has a much greater impact on higher-priced apartments. RIVERVIEW has less impact on medium-priced apartments, but has a greater impact on lower-priced apartments and much greater impact on higher-priced apartments. Methodologically, the results show that OLS regression underestimated marginal impacts on higher-priced apartments.

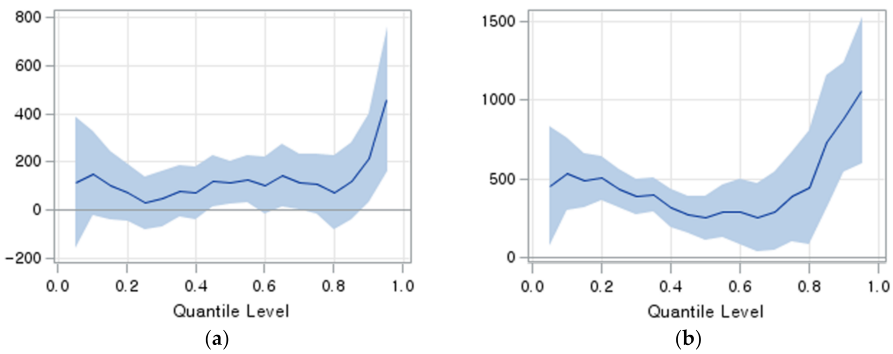


Figure 6. Quantile regression coefficients with 95% confidence limits: (**a**) GREENVIEW; (**b**) RIVERVIEW.

Table 3. Analysis results of quantile regression.

	OLS	Q0.05	Q0.1	Q0.15	Q0.2	Q0.25	Q0.3	Q0.35	Q0.4	Q0.45
CONSTANT	341.47 ***	45.94	76.27 *	138.54 ***	200.58 ***	271.76 ***	267.76 ***	289.66 ***	287.13 ***	298.36 ***
	(37.054)	(46.660)	(41.432)	(37.951)	(38.555)	(30.915)	(29.056)	(25.422)	(28.775)	(29.322)
GREENVIEW	378.36 ***	112.74	151.25 *	101.63	71.50	29.64	46.23	77.47	71.56	118.79 **
	(80.715)	(137.804)	(88.912)	(72.978)	(60.065)	(56.297)	(57.585)	(53.347)	(55.674)	(54.228)
RIVERVIEW	324.71 **	456.31 **	530.04 ***	486.33 ***	504.64 ***	438.63 ***	386.95 ***	401.38 ***	312.90 ***	271.82 ***
	(139.561)	(193.396)	(117.513)	(87.212)	(72.244)	(61.054)	(58.254)	(54.915)	(60.666)	(59.397)
AREA	7.25 ***	5.26 ***	5.54 ***	5.90 ***	6.25 ***	6.46 ***	6.78 ***	6.97 ***	7.17 ***	7.28 ***
	(0.115)	(0.183)	(0.141)	(0.141)	(0.142)	(0.140)	(0.164)	(0.144)	(0.139)	(0.134)
FLOOR	4.89 ***	2.66 **	5.31 ***	4.70 ***	5.10 ***	4.33 ***	4.27 ***	4.20 ***	4.69 ***	4.66 ***
	(0.939)	(1.163)	(1.027)	(0.925)	(0.731)	(0.688)	(0.678)	(0.644)	(0.642)	(0.536)
SOUTH	41.96 ***	78.87 ***	46.53 ***	32.72 ***	27.38 ***	21.29 ***	24.29 ***	20.49 ***	24.15 ***	24.23 ***
	(10.395)	(22.576)	(13.873)	(9.746)	(8.197)	(7.138)	(6.766)	(5.918)	(5.631)	(5.729)
AGE	−15.85 ***	7.09 ***	6.09 ***	4.72 **	−0.54	−6.91 ***	−8.81 ***	−10.28 ***	−11.40 ***	−12.63 ***
	(2.471)	(2.450)	(2.267)	(2.343)	(2.358)	(1.972)	(1.837)	(1.542)	(1.597)	(1.490)
AGESQ	0.32 ***	−0.14 **	−0.11 **	−0.10 *	0.01	0.13 ***	0.17 ***	0.20 ***	0.22 ***	0.24 ***
	(0.058)	(0.061)	(0.052)	(0.053)	(0.050)	(0.043)	(0.041)	(0.035)	(0.036)	(0.033)
TUNIT	0.12 ***	0.11 ***	0.11 ***	0.11 ***	0.11 ***	0.12 ***	0.12 ***	0.12 ***	0.11 ***	0.11 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
DGANGNAM	−0.79 *	−1.42 **	−1.41 ***	−1.94 ***	−2.22 ***	−2.26 ***	−2.08 ***	−2.03 ***	−2.15 ***	−1.88 ***
	(0.475)	(0.681)	(0.534)	(0.428)	(0.364)	(0.428)	(0.380)	(0.330)	(0.373)	(0.408)
DSUBWAY	−34.43 ***	−20.00 ***	−21.63 ***	−24.12 ***	−26.19 ***	−25.03 ***	−24.67 ***	−24.95 ***	−24.44 ***	−22.86 ***
	(2.496)	(4.376)	(3.032)	(2.457)	(2.114)	(1.697)	(1.729)	(1.642)	(1.955)	(2.080)
DPRIMARY	−18.51 ***	−7.94 *	−12.02 ***	−15.45 ***	−15.83 ***	−14.23 ***	−12.28 ***	−12.33 ***	−12.16 ***	−12.53 ***
	(2.997)	(4.413)	(3.474)	(2.648)	(2.274)	(2.107)	(2.444)	(2.375)	(2.435)	(2.567)
DMIDDLE	−5.89 **	−9.10 ***	−6.35 ***	−4.62 *	−5.11 **	−5.72 ***	−7.25 ***	−8.96 ***	−8.18 ***	−9.32 ***
	(2.594)	(2.623)	(2.380)	(2.374)	(2.251)	(2.182)	(2.039)	(1.719)	(1.898)	(2.093)
SPRING	19.85 *	17.74 *	19.12 *	12.43	9.62	6.59	8.02	5.88	9.10	10.67 *
	(10.522)	(10.168)	(9.943)	(10.005)	(8.333)	(7.572)	(7.074)	(7.185)	(6.973)	(6.444)
SUMMER	3.13	−8.46	21.13*	18.14 *	5.85	−0.35	3.08	2.43	1.63	2.56
	(12.644)	(22.069)	(12.721)	(9.809)	(9.251)	(9.181)	(8.769)	(8.062)	(7.209)	(6.914)
FALL	−11.58	13.85	17.67	12.30	4.44	0.94	−1.79	−2.61	−1.43	−1.58
	(11.711)	(21.190)	(12.129)	(8.706)	(7.454)	(6.956)	(7.307)	(7.003)	(6.926)	(6.659)

Table 3. *Cont.*

	Q0.5	**Q0.55**	**Q0.6**	**Q0.65**	**Q0.7**	**Q0.75**	**Q0.8**	**Q0.85**	**Q0.9**	**Q0.95**
CONSTANT	325.83 ***	342.60 ***	356.89 ***	383.15 ***	405.68 ***	424.72 ***	455.81 ***	440.41 ***	382.23 ***	395.90 ***
	(30.054)	(28.363)	(27.220)	(28.868)	(25.624)	(31.272)	(37.001)	(37.001)	(40.229)	(70.511)
GREENVIEW	114.74 **	127.95 ***	100.94 *	145.51 **	116.64 **	107.73 *	72.77	120.02	213.48 **	458.71 ***
	(45.034)	(48.643)	(60.593)	(65.955)	(57.354)	(62.947)	(78.983)	(78.983)	(92.476)	(151.891)
RIVERVIEW	249.66 ***	290.57 ***	286.47 ***	254.96 **	293.53 **	385.23 ***	445.58 **	730.81 ***	890.29 ***	1062.23 ***
	(69.545)	(85.274)	(105.407)	(111.051)	(127.246)	(146.622)	(184.104)	(184.104)	(179.130)	(237.457)
AREA	7.45 ***	7.59 ***	7.75 ***	7.89 ***	8.15 ***	8.27 ***	8.44 ***	8.59 ***	8.93 ***	9.75 ***
	(0.145)	(0.153)	(0.152)	(0.143)	(0.129)	(0.115)	(0.125)	(0.125)	(0.157)	(0.232)
FLOOR	4.72 ***	4.84 ***	5.11 ***	4.60 ***	4.40 ***	3.84 ***	3.26 ***	3.86 ***	3.39 ***	2.63 *
	(0.592)	(0.638)	(0.696)	(0.761)	(0.710)	(0.781)	(0.866)	(0.866)	(1.080)	(1.523)
SOUTH	21.13 ***	18.86 ***	14.69 ***	10.75 *	7.09	6.64	7.20	4.35	−1.20	−6.68
	(5.611)	(5.976)	(5.906)	(6.310)	(6.035)	(6.563)	(7.609)	(7.609)	(9.998)	(14.391)
AGE	−14.49 ***	−15.27 ***	−16.20 ***	−17.51 ***	−18.70 ***	−19.76 ***	−21.79 ***	−21.04 ***	−18.15 ***	−22.08 ***
	(1.599)	(1.531)	(1.578)	(1.545)	(1.428)	(1.676)	(2.161)	(2.161)	(3.021)	(5.282)
AGESQ	0.27 ***	0.28 ***	0.30 ***	0.32 ***	0.34 ***	0.35 ***	0.37 ***	0.35 ***	0.28 ***	0.34 ***
	(0.035)	(0.034)	(0.035)	(0.034)	(0.032)	(0.036)	(0.048)	(0.048)	(0.067)	(0.116)
TUNIT	0.11 ***	0.10 ***	0.10 ***	0.10 ***	0.10 ***	0.10 ***	0.10 ***	0.09 ***	0.10 ***	0.08 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)	(0.018)
DGANGNAM	−1.58 ***	−1.26 ***	−1.46 ***	−1.14 ***	−1.11 ***	−0.89 *	−0.56	0.82	3.13 ***	4.73 ***
	(0.454)	(0.437)	(0.428)	(0.430)	(0.413)	(0.495)	(0.734)	(0.734)	(0.888)	(1.073)
DSUBWAY	−23.44 ***	−24.51 ***	−25.21 ***	−25.85 ***	−29.44 ***	−30.43 ***	−32.22 ***	−32.71 ***	−31.61 ***	−30.40 ***
	(2.087)	(2.009)	(2.205)	(2.442)	(2.237)	(2.533)	(2.569)	(2.569)	(2.768)	(4.211)
DPRIMARY	−12.91 ***	−13.62 ***	−14.47 ***	−16.29 ***	−19.52 ***	−20.28 ***	−21.00 ***	−20.83 ***	−17.16 ***	−12.80 **
	(2.500)	(2.199)	(2.109)	(2.198)	(2.056)	(2.349)	(2.316)	(2.316)	(3.518)	(5.255)
DMIDDLE	−9.08 ***	−8.51 ***	−8.11 ***	−7.70 ***	−4.78 **	−3.69 *	−1.35	−1.87	−6.34 *	−12.38 **
	(2.308)	(2.249)	(2.223)	(2.238)	(2.060)	(2.234)	(2.602)	(2.602)	(3.712)	(5.232)
SPRING	9.16	6.14	8.97	5.54	11.47 *	13.62 **	15.60 *	20.90 **	21.89 *	32.60
	(6.543)	(6.760)	(6.576)	(6.512)	(6.425)	(6.518)	(8.117)	(8.117)	(11.929)	(20.018)
SUMMER	−4.47	−6.16	−3.03	−5.40	−1.99	4.87	5.57	3.18	2.17	8.05
	(7.296)	(7.567)	(7.633)	(8.018)	(7.618)	(7.891)	(8.860)	(8.860)	(9.946)	(13.576)
FALL	−5.36	−10.72	−9.28	−10.46	−2.96	−1.19	7.54	2.43	−1.86	8.19
	(6.342)	(6.718)	(6.877)	(7.444)	(6.869)	(7.199)	(7.269)	(7.269)	(9.413)	(12.286)

Notes: Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

All FLOOR coefficients had significantly positive impacts on housing prices like OLS estimate. Specifically, the coefficients of lower- and medium-priced apartments were larger than those of higher-priced apartments. This result is believed to have been influenced by the fact that the low- and mid-rise apartments being redeveloped were sold at high prices.

Redevelopment and natural landscape views are closely related. The owners of old apartments along the Han River are making great efforts to redevelop them into apartments with good views. In the study, the possibility of redevelopment is represented by the dwelling age of the apartment. According to the hypothesis that the curve of housing prices has a quadratic function with respect to the dwelling age, the AGE coefficient should be negative and the AGESQ coefficient should be positive. However, the signs of the coefficients up to quantile point 0.2 did not agree with the hypothesis, whereas they did from quantile point 0.25 onward. As in the OLS regression analysis, we took partial derivative of housing price with respect to the AGE variable to find the turning point at which the housing price has the minimum value. The turning points were found to be between 25 and 33 years longer than the 25 years of OLS regression. In particular, the turning points grow as quantile point increases, meaning that higher-priced apartments are redeveloped relatively later. This is related to the fact that higher-priced apartments are mainly located along the Han River and their redevelopment is strictly regulated by the Seoul Metropolitan Government.

Looking at other independent variables, the marginal impacts of AREA also increase as quantile point increases. The marginal impact at quantile point 0.95 of AREA is 1.6 times the marginal impact at quantile point 0.5. The marginal impacts of DSUBWAY also increase as quantile point increases. These results mean that the higher the price of the apartment, the more the price is affected by apartment size and the distance to subway stations. In other words, higher-priced apartments have a premium on apartment size and the distance to subway stations compared to lower-priced apartments. On the contrary, the marginal impacts of SOUTH and TUNIT decrease as quantile point increases, indicating that the higher the price of the apartment, the less the price is affected by apartment direction and the number of apartments in the complex. Except for these variables, other variables did not show notable trends with increasing quantile point. Compared to the OLS estimate, AREA has less impact on lower-priced apartments, but has much greater impact on medium- and higher-priced apartments. DSUBWAY, SOUTH and TUNIT have less impacts overall. Methodologically, the OLS regression overall underestimates the marginal impact of DSUBWAY, SOUTH, and TUNIT. For AREA, the OLS regression underestimates the marginal impact of medium- and higher-priced apartments, but rather overestimates that of lower-priced apartments.

4. Discussion

4.1. Natural Landscape Views and Wealth Inequality

As discussed in the introduction, natural landscape views have both positive sides, such as providing restorative effects to urban residents, and negative sides, such as deepening wealth inequality. According to the results of our OLS regression analysis, natural landscape views such as the views of greenery and the Han River have significant positive impacts on housing prices, namely positive marginal impacts (Section 3.1). Based on the hedonic price model, this result is in line with several studies that suggest the positive value of natural landscape views. This also supports the common wisdom that natural landscape views positively affect urban residents. However, by comparing the standardized regression coefficients, we confirmed that the marginal impacts of natural landscape views did not reach the level of the effects of structural and locational characteristics such as the area of the apartment unit, the number of apartments in the complex, and the distance to subway stations and primary schools. OLS regression analysis is limited in that it is not able to effectively explain negative sides such as the deepening of wealth inequality, only estimating average marginal impacts on housing prices. Therefore, the only conclusion that can be drawn from these estimates is that housing prices rise with better natural landscape views. To overcome this limitation, we used quantile regression to estimate the impacts of natural landscape views on housing prices by price range.

According to the results of the quantile regression analysis, this study showed that the coefficients of natural landscape views have a sharp uptrend in higher price ranges, as shown in Figure 6 (Section 3.2). This means that natural landscape views have unequal impacts on housing prices depending on price range; specifically, the marginal impacts are higher for higher-priced apartments compared to lower- and medium-priced apartments. As discussed in the introduction, previous studies have found different results: one showed that natural landscape views had a much higher value-added effect on higher-priced housing than on lower-priced housing [32], and the others showed the opposite [7,28]. The results in the current study support the former group. The results also support that the Seoul housing market is segmented by housing level, such as the low-, mid- and high-end housing, which can respond to the needs of buyers by income level. This shows that "rich" households who can buy high-end housing have a high preference for housing with good natural landscape views, and they also appreciate the future value of such housing very high.

Linking natural landscape views to apartment redevelopment can allow us to address one aspect of deepening wealth inequality. Apartment prices tend to rise when dwelling age nears the time when redevelopment is permitted; however, the higher the housing price, the more severe the government's redevelopment regulation, so there is a tendency to delay the turning point at which prices increase in higher-priced apartment (Section 3.2). Nevertheless, the rise in the prices of old apartments is stronger in apartments along the Han River, as most buyers believe that redevelopment will provide more views of the Han River. It can be said that the prices of old apartments along the Han River reflect the average value of Han River views that will be secured in the future, plus a premium for higher-priced apartments. Redevelopment projects that improve natural landscape views result in a deepening of wealth inequality if development profits are attributed to homeowners. Improvement in natural landscape views is determined by urban planning activities such as height deregulation, but such decisions can worsen the views of neighboring houses and the city skyline. In this respect, natural landscape views should be strictly managed, and the development profits generated by improvement of the views need to be recouped to the public sector.

4.2. Visual Perception Analysis

Previous studies to analyze the impacts of landscape views on property value have considered the visible area by simply combining the results of viewshed analyses with information on land cover. However, the size of objects in the landscape as perceived by humans directly affects the value of the landscape. In the studies of [44,45], a method of quantifying the visual perception of a specific object was suggested, but it was difficult to use for general analysis work in metropolitan areas, such as real estate value modeling. We proposed the following analysis procedure to quantify the visual perception of the natural landscape views of wide areas. Using the spatial analysis function of GIS:

(1) Analyze the slope and aspect of the DSM, the azimuth between the viewpoint and the DSM pixel;
(2) Calculate the surface area using the slope of the DSM pixel where the visibility line is created;
(3) Calculate the projected area by applying directional cosine using slope, aspect, and azimuth angle to the surface area;
(4) Calculate the solid angle corresponding to the visual perception by dividing the projected area by the square of the distance between the viewpoint and the target pixel;
(5) Quantify the visual perception of the natural landscape by summing the solid angle for each land cover item included in the viewshed.

In the study, we constructed a GIS database using public data. By applying the proposed analysis procedure to the GIS database, the viewshed was analyzed for 843 km^2 including Seoul City and adjacent areas, and the visual perception area of each target object could be calculated from the results. By using the proposed method, it is possible to calculate the visual perception area for natural landscapes in a large urban area, rather than only a specific target, and analyze a large number of viewpoints. Using this visual perception-based landscape analysis, a more rigorous analysis of the impact of natural landscape views on property value is possible.

5. Conclusions

Natural landscape views have both positive and negative sides. From this perspective, we analyzed the impacts of natural landscape views on housing prices, and applied a visual perception model, OLS regression, and quantile regression to apartments sold in Seocho-gu, Seoul. The results are as follows. First, natural landscape views have a positive marginal impact, indicating that natural landscape views have positive sides. However, their marginal impacts did not reach the level of structural and locational characteristics such as apartment area and the distance to subway stations. Second, the study found that natural landscape views unequally affect housing prices by price range; the marginal impacts are higher in higher-priced housing than in lower- and medium-priced housing, indicating that natural landscape views have negative sides such as deepening wealth inequality. In particular, when old apartments along the Han River are redeveloped into high-rise apartments, the impact of natural landscape views on the housing prices is higher. Therefore, such redevelopment should be accompanied by efforts to recoup development profits to the public sector rather than leaving it in the hands of homeowners, to reduce wealth inequality. In addition, governments should consider how to properly impose property taxes to reduce wealth inequality caused by natural landscape views. In Korea, property taxes are levied on the basis of officially appraised prices. Despite the significant differences in natural landscape views, the appraised prices do not properly reflect this. It is necessary to introduce the visual perception model and quantile regression model used in the study as a valuation tool.

In the study, the research data were obtained using a GIS-based viewshed model, which effectively quantified the visual perception of natural landscape views in wide areas, unlike the similar model used in previous studies. However, this has a limitation in terms of analysis methods. The psychological effect of landscape on humans largely relates to its openness, along with the sense of stability given by natural landscape views of greenery and the river. We evaluated the natural landscape views only using viewshed analysis. However, unlike the viewshed, openness should be analyzed using a modified method of the daylight availability analysis represented by visual perception, which will require further research in the future.

Author Contributions: H.L., B.L. and S.L. led and contributed equally to this research—conceptualization, H.L., B.L. and S.L.; methodology, B.L. and S.L.; formal analysis, H.L. and S.L.; investigation, H.L.; data curation, H.L.; writing—original draft preparation, H.L., B.L. and S.L.; visualization, H.L. and B.L.; supervision, S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. National Geographic. Available online: https://www.nationalgeographic.org/encyclopedia/landscape/ (accessed on 30 August 2020).
2. Kaplan, R. Impact of urban nature: A theoretical analysis. *Urban Ecol.* **1984**, *8*, 189–197. [CrossRef]
3. Kaplan, R. The nature of the view from home. *Environ. Behav.* **2001**, *33*, 507–542. [CrossRef]
4. Jim, C.Y.; Chen, W.Y. Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landsc. Urban Plan.* **2009**, *91*, 226–234. [CrossRef]
5. Bourassa, S.C.; Hoesli, M.; Sun, J. What's in a view? *Environ. Plan. A* **2004**, *36*, 1427–1450. [CrossRef]
6. Rosen, S. Hedonic prices and implicit markets: Product differentiation in pure competition. *J. Political Econ.* **1974**, *82*, 34–55. [CrossRef]
7. Zietz, J.; Zietz, E.N.; Sirmans, G.S. Determinants of house prices: A quantile regression approach. *J. Real Estate Financ. Econ.* **2008**, *37*, 317–333. [CrossRef]

8. Boyle, M.; Kiel, K. A survey of house price hedonic studies of the impact of environmental externalities. *J. Real Estate Lit.* **2001**, *9*, 117–144.
9. Hui, E.C.M.; Zhong, J.W.; Yu, K.H. The impact of landscape views and storey levels on property prices. *Landsc. Urban Plan.* **2012**, *105*, 86–93. [CrossRef]
10. Jim, C.Y.; Chen, W.Y. Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landsc. Urban Plan.* **2006**, *78*, 422–434. [CrossRef]
11. Nicholls, S.; Crompton, J.L. The impact of greenways on property values: Evidence from Austin, Texas. *J. Leis. Res.* **2005**, *37*, 321–341. [CrossRef]
12. Schultz, S.; Schmitz, N. Viewshed analyses to measure the impact of lake views on urban residential properties. *Apprais. J.* **2008**, *76*, 224–232.
13. Bourassa, S.C.; Hoesli, M.; Peng, V.S. Do housing submarkets really matter? *J. Hous. Econ.* **2003**, *12*, 12–28. [CrossRef]
14. Garrod, G.D.; Willis, K.G. Valuing goods' characteristics: An application of the hedonic price method to environmental attributes. *J. Environ. Manag.* **1992**, *34*, 59–76. [CrossRef]
15. Jim, C.Y.; Chen, W.Y. External effects of neighbourhood parks and landscape elements on high-rise residential value. *Land Use Policy* **2010**, *27*, 662–670. [CrossRef]
16. Morancho, A.B. A hedonic valuation of urban green areas. *Landsc. Urban Plan.* **2003**, *66*, 35–41. [CrossRef]
17. Walls, M.; Kousky, C.; Chu, Z. Is what you see what you get? The value of natural landscape views. *Land Econ.* **2015**, *91*, 1–19. [CrossRef]
18. Liu, L.; Jakus, P.M. Hedonic valuation in an urban high-rise housing market. *Can. J. Agric. Econ./Rev. Can. d' Agroecon.* **2015**, *63*, 259–273. [CrossRef]
19. Liu, S.; Hite, D. Measuring the Effect of Green Space on Property Value: An Application of the Hedonic Spatial Quantile Regression. In Proceedings of the 2013 Annual Meeting, Orlando, FL, USA, 2–5 February 2013.
20. Wen, H.; Bu, X.; Qin, Z. Spatial effect of lake landscape on housing price: A case study of the West Lake in Hangzhou, China. *Habitat Int.* **2014**, *44*, 31–40. [CrossRef]
21. Wen, H.; Xiao, Y.; Zhang, L. Spatial effect of river landscape on housing price: An empirical study on the Grand Canal in Hangzhou, China. *Habitat Int.* **2017**, *63*, 34–44. [CrossRef]
22. Wen, H.; Zhang, Y.; Zhang, L. Assessing amenity effects of urban landscapes on housing price in Hangzhou, China. *Urban For. Urban Green.* **2015**, *14*, 1017–1026. [CrossRef]
23. Xiao, Y.; Hui, E.C.M.; Wen, H. Effects of floor level and landscape proximity on housing price: A hedonic analysis in Hangzhou, China. *Habitat Int.* **2019**, *87*, 11–26. [CrossRef]
24. Xiao, Y. Hedonic Housing Price Theory Review. In *Urban Morphology and Housing Market*; Springer: Singapore, 2017; pp. 11–40.
25. Ebru, Ç.; Eban, A. Determinants of house prices in Istanbul: A quantile regression approach. *Qual. Quant.* **2009**, *45*, 305–317. [CrossRef]
26. Mak, S.; Choy, L.; Ho, W. Quantile regression estimates of Hong Kong real estate prices. *Urban Stud.* **2010**, *47*, 2461–2472. [CrossRef]
27. Wen, H.; Gui, Z.; Tian, C.; Xiao, Y.; Fang, L. Subway opening, traffic accessibility, and housing prices: A quantile hedonic analysis in Hangzhou, China. *Sustainability* **2018**, *10*, 2254. [CrossRef]
28. Zhang, L.; Yi, Y. Quantile house price indices in Beijing. *Reg. Sci. Urban Econ.* **2017**, *63*, 85–96. [CrossRef]
29. Zahirovic-Herbert, V.; Chatterjee, S. Historic preservation and residential property values: Evidence from quantile regression. *Urban Stud.* **2012**, *49*, 369–382. [CrossRef]
30. Wen, H.; Xiao, Y.; Hui, E.C.M. Quantile effect of educational facilities on housing price: Do homebuyers of higher-priced housing pay more for educational resources? *Cities* **2019**, *90*, 100–112. [CrossRef]
31. Koenker, R.; Bassett, J.G. Regression quantiles. *Econom. J. Econom. Soc.* **1978**, *46*, 33–50. [CrossRef]
32. Kim, H.; Park, S.W.; Lee, S.; Xue, X. Determinants of house prices in Seoul: A quantile regression approach. *Pac. Rim Prop. Res. J.* **2015**, *21*, 91–113. [CrossRef]
33. Jeong, J.H.; Cheon, B.Y. Korea's wealth inequality structure from an international perspective: Comparing with wealth inequaliies in Korea, USA and Spain. *Geogr. J. Korea* **2017**, *51*, 149–164.
34. Kim, D.; Lee, S. The effect of characteristics of apartment complex on the count rate of house transaction. *J. Korea Real Estate Anal. Assoc.* **2018**, *24*, 53–68. [CrossRef]
35. Benson, E.D.; Hansen, J.L.; Schwartz, J.A.L.; Smersh, G.T. Pricing residential amenities: The value of a view. *J. Real Estate Finance Econ.* **1998**, *16*, 55–73. [CrossRef]

36. Hui, E.C.M.; Liang, C. Spatial spillover effect of urban landscape views on property price. *Appl. Geogr.* **2016**, *72*, 26–35. [CrossRef]
37. Luttik, J. The value of trees, water and open space as reflected by house prices in the Netherlands. *Landsc. Urban Plan.* **2000**, *48*, 161–167. [CrossRef]
38. Cavailhès, J.; Brossard, T.; Foltête, J.-C.; Hilal, M.; Joly, D.; Tourneux, F.-P.; Tritz, C.; Wavresky, P. GIS-based hedonic pricing of landscape. *Environ. Resour. Econ.* **2009**, *44*, 571–590. [CrossRef]
39. Baranzini, A.; Schaerer, C. A sight for sore eyes: Assessing the value of view and land use in the housing market. *J. Hous. Econ.* **2011**, *20*, 191–199. [CrossRef]
40. Poudyal, N.C.; Hodges, D.G.; Fenderson, J. Realizing the economic value of a forested landscape in a viewshed. *South. J. Appl. For.* **2010**, *34*, 72–78. [CrossRef]
41. Yamagata, Y.; Murakami, D.; Yoshida, T.; Seya, H.; Kuroda, S. Value of urban views in a bay city: Hedonic analysis with the spatial multilevel additive regression (SMAR) model. *Landsc. Urban Plan.* **2016**, *151*, 89–102. [CrossRef]
42. Yang, P.P.; Putra, S.Y.; Li, W. Viewsphere: A GIS-based 3D visibility analysis for urban design evaluation. *Environ. Plan. B Plan. Des.* **2007**, *34*, 971–992. [CrossRef]
43. Bartie, P.; Reitsma, F.; Kingham, S.; Mills, S. Advancing visibility modelling algorithms for urban environments. *Comput. Environ. Urban Syst.* **2010**, *34*, 518–531. [CrossRef]
44. Kwon, J.H. A Study on weighted visibility analysis of topographic landscape considering user's visual perception. *J. Reg. Assoc. Archit. Inst. Korea* **2011**, *13*, 85–92.
45. Domingo-Santos, J.M.; de Villarán, R.F.; Rapp-Arrarás, Í.; de Provens, E.C.P. The visual exposure in forest and rural landscapes: An algorithm and a GIS tool. *Landsc. Urban Plan.* **2011**, *101*, 52–58. [CrossRef]
46. Nutsford, D.; Reitsma, F.; Pearson, A.L.; Kingham, S. Personalising the viewshed: Visibility analysis from the human perspective. *Appl. Geogr.* **2015**, *62*, 1–7. [CrossRef]
47. Fisher-Gewirtzman, D. Integrating 'weighted views' to quantitative 3D visibility analysis as a predictive tool for perception of space. *Environ. Plan. B Urban Anal. City Sci.* **2018**, *45*, 345–366. [CrossRef]
48. The Seoul Institute. Regional Gap by Sector in Seoul (2) Dwelling and Housing. *Seoul Infographics* **2018**, *271*, 1–4. Available online: https://www.si.re.kr/node/60540 (accessed on 24 August 2020).
49. National Spatial Data Infrastructure Portal. Available online: http://www.nsdi.go.kr/lxportal/?menuno=2679 (accessed on 30 August 2020).
50. Groß, M. The analysis of visibility—Environmental interactions between computer graphics, physics, and physiology. *Comput. Graph.* **1991**, *15*, 407–415. [CrossRef]
51. Coulson, N.E.; McMillen, D.P. The dynamics of intraurban quantile house price indexes. *Urban Stud.* **2007**, *44*, 1517–1537. [CrossRef]
52. Koenker, R.; Hallock, K. Quantile regression: An introduction. J. *Econ. Perspect.* **2001**, *15*, 43–56. [CrossRef]
53. VWORLD. 3D Desktop API Reference. Available online: http://www.vworld.kr/dev/v4dv_dhapiguide_s001.do (accessed on 28 August 2020).
54. National Institute of Environmental Research. *Annual Report of Air Quality in Korea 2012*; National Institute of Environmental Research: Incheon, Korea, 2013.
55. Lee, J.S.; Kim, J.; Son, Y.H. A study on the influence of environmental factors on the apartment price: Focused on view quality and park accessibility in Songdo newtown. *Korea Real Estate Rev.* **2013**, *24*, 99–121.
56. Lee, S.-K.; Shin, W.-J. The effect of reconstruction probability on apartment price. *J. Korea Plan. Assoc.* **2001**, *36*, 101–110.
57. Lee, B.S.; Chung, E.-C.; Kim, Y.H. Dwelling age, redevelopment, and housing prices: The case of apartment complexes in Seoul. *J. Real Estate Finance Econ.* **2005**, *30*, 55–80. [CrossRef]
58. KOSIS. Exchange Rate. Available online: http://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_2KAA811&conn_path=I2 (accessed on 30 August 2020).
59. Gujarati, D.N. *Basic Econometrics*, 4th ed.; The Mc-Graw Hill: New York, NY, USA, 2004; pp. 226–229.