Estimating the Effect of Urban Green Spaces on Residential House Prices in Amsterdam

An Empirical Study using Remote Sensing and Geographically Weighted Regression

Yúri Grings Thomas Nibbering Jitse Ruurd Nauta

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1. Introduction

Green spaces play an important role in urban ecosystems. As a natural purifier for cities, these areas help control soil erosion [1], improve air quality [2, 3], reduce the urban heat island effect [4–6] and are considered to be aesthetically pleasing [7]. Moreover, green areas in cities are shown to provide notable improvements in residents' physical and mental wellbeing [8, 9]. As the benefits of greenness in urban areas are increasingly recognised, numerous cities have developed urban greening programs to expand parks, build green roofs or plant more trees [10–12]. However, evaluating the effects of these initiatives to justify their costs remains a challenge, partly due to data sparsity.

A review of literature revealed several studies that aimed to examine the effect of urban green spaces on residential house prices [13–19]. Often these studies adopted a hedonic pricing approach to estimate the economic value that individuals place on particular property characteristics, as reflected in the real-estate prices [14, 15]. However, most literature only focused on the distance to urban green areas as a valuation indicator [20, 21]. Only a few studies considered a more comprehensive appreciation of greenness in cities by employing vegetation indices and the interaction with property and public amenities [16, 17, 22, 23].

Among the literature that explored the property value premium of urban green spaces more exhaustive, most adopted the normalised difference vegetation index (NDVI) [16, 22, 23]. Here, the relative abundance of vegetation was measured across varying buffer distances using remote sensing systems with various spatial resolutions. Moreover, most of these studies also considered the interaction with residential and public amenities, such as the number of rooms or proximity to convenience stores [16, 23]. However, these analyses were mainly performed in cities with conservative greening programs in place [23]. Lastly, the adoption of NDVI for identifying (urban) green spaces is often criticised due to its sensitivity to varying spatial scales and inability to differentiate between vegetation types [24]. Nonetheless, the index is widely accepted and can be considered almost a standard approach [25, 26].

Based on the examined literature, a hedonic pricing approach in combination with NDVI and the interaction with particular amenities emerges as an effective method to estimate the effect of urban green spaces on residential house prices. Given the limited literature available on property value premiums associated with greenness exposure in cities with more progressive urban greening programs, this study aims to answer the research question of what the economic value of urban green spaces is in the city of Amsterdam, as reflected in the real-estate prices of 2023.

2. Methods

2.1 Study Area

The geographical scope in this study concentrated on the city of Amsterdam, as presented in Figure 1. The city is situated in the Western part of the Netherlands and home to almost 880,000 residents [27], occupying a space of 219.3 km2 [28]. Surrounding the residential areas, the vast majority of land is occupied with vegetation [29]. Moreover, the municipality has progressive urban greening programs in place, stimulating and obligating residents and city districts to participate in greening initiatives [12]. As a result, these policies aimed at expanding urban green spaces may have the potential to increase nearby housing premiums.

2.2 Data Extraction

A total of 1,719 property listings were obtained from Funda.nl, a Dutch online real-estate platform [30]. Here, data included the sale price and property characteristics of homes in Amsterdam listed on the platform on 31 March 2023. Moreover, information about public amenities in Amsterdam were obtained from a variety of sources, including ArcGIS [31], OpenStreetMap.org [32, 33] and the municipality of Amsterdam [34]. Selection of public amenities, used as controlling variables, were based on applicable literature, as presented in Table 1. Adjusting for these variables was done to limit the effect of potential confounders on the association of interest.

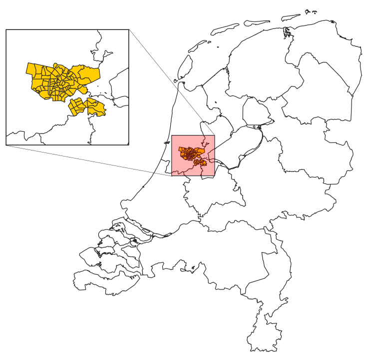

Figure 1: Overview of the study area.

Finally, remote sensing images were obtained from Sentinel-2 in August 2022 [35]. This allowed on the capitalisation of high greenness levels in that period, leading to improved differentiation between green and urban areas.

2.3 Data Enrichment

To examine the economic value of urban green spaces as reflected in the real-estate prices, coordinates for each property were obtained using geocoding and transformed into a single coordinate reference system, i.e. EPSG 28992, to ensure consistency and accuracy of the analysis. Exclusion criteria were in place for properties for which coordinates could not be obtained, i.e. future housing projects. Moreover, straight line distances from each property to the nearest public amenities were enumerated using the nearest neighbour algorithm in combination with Euclidean distance. This is a common approach to adjust for the implicit premium of local public amenities on house prices [36].

Furthermore, urban green vegetation was measured using NDVI. This vegetation index was derived from the Sentinel-2 satellite, based on Equation 1. Here, N and R refer to the spectral reflectance measurements obtained in the red and near-infrared regions, respectively. In general, the index ranges from -1.0 to 1.0 with positive values indicating greenness. The usage of this system provided more accurate images for identifying green spaces, i.e. 10x10m, compared to the moderate resolution of Landsat, i.e. 30x30m [37].

$$NDVI = \frac{(N - R)}{N + R}$$

Surrounding the residential properties, mean values of NDVI were obtained at varying spatial scales, i.e. 100, 300 and 500m. In doing so, the variation of greenness around the property could be included in the analysis. Moreover, the usage of these thresholds ensured that the results were less vulnerable to scaling effects given the resolution of the data [37]. Finally, based on the extraction and enhancement of data, several independent variables were identified and constructed, as presented in Table 1. These variables were included in the hedonic pricing model, as will be elaborated on in Section 2.4, to either adjust or explain the economic value of urban green areas in Amsterdam.

2.4 Hedonic Pricing Models

Two forms of the hedonic pricing model were employed to examine the effect of urban green spaces on housing prices per square meter, namely ordinary least squares (OLS) and geographically weighted regression (GWR). In the models, the relation of interest was adjusted for using property characteristics, transit distances and destination accessibility. Here, the usage of OLS was mainly related to its superior interpretability [38]. However, the Durbin-Watson test and Variance Inflation Factor (VIF) revealed that observations were not independent and indicated some collinearity, respectively. Hence, violating two model assumptions [39]. As a result, variables NDVI100 and NDVI500 were excluded from the analysis, as these resulted in considerable collinearity (VIF > 5). Moreover, Moran's I indicated the presence of spatial dependency (0.590, $p < 0.05$), as presented in Figure 2.

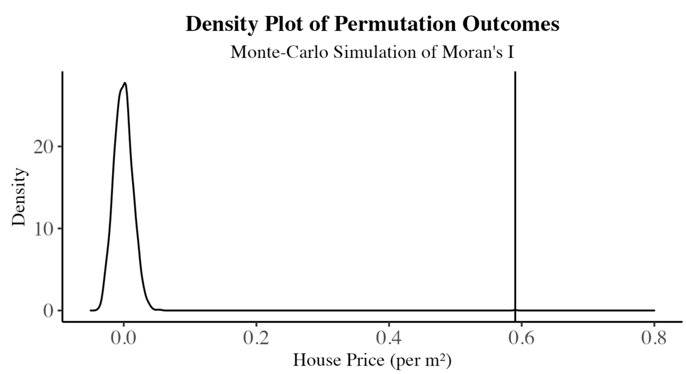

Figure 2: Density plot of Monte-Carlo Moran's I Permutation Outcomes.

Furthermore, similar studies found evidence for the existence of non-stationarity in both house prices and green spaces [40, 41]. Hence, a local regression approach, i.e. GWR with an adaptive bi-square kernel, was employed to account for both the spatial dependence and non-stationarity in the data. Here, a golden search algorithm was used to obtain the kernel bandwidth, as data was not uniformly distributed across space [42]. Doing so, provided estimates for each location in the study area.

Table 1: Descriptive Statistics of Property, Public Amenity and Greenness Characteristics of Properties in Amsterdam.

Independent Variable	**Mean**	**SD**	**Description**
Summary Statistics (N = 1,719)			
Property Characteristics			
Living Area (m2)	105.7	71.0	Size of livable area of the property
Number of Bedrooms	2.5	1.4	Number of bedrooms of the property
Number of Bathrooms	1.1	0.7	Number of bathrooms of the property
House Age (years)	76.9	63.2	Age of the property in 2023
Design			
NDVI100	0.200	0.073	Average NDVI at 100 m around property
NDVI300	0.212	0.069	Average NDVI at 300 m around property
NDVI500	0.216	0.067	Average NDVI at 500 m around property
Transit Distance			
Distance to Train Station (m)	1703.7	958.2	Euclidean distance to nearest train station
Distance to Tram Station (m)	689.1	1024.7	Euclidean distance to nearest tram station
Distance to Metro Station (m)	1303.2	951.8	Euclidean distance to nearest metro station
Destination Accessibility			
Distance to City Center (m)	3770.5	2288.1	Euclidean distance to city center
Distance to Business District (m)	4659.2	2228.3	Euclidean distance to business district
Distance to School (m)	268.3	183.8	Euclidean distance to nearest school
Distance to Convenience Stores (m)	266.7	206.9	Euclidean distance to nearest store

3. Results and Discussion

4. Conclusion

5. References

Table 2: Hier caption

Independent Variable	**Coef.**	**Min. Coef.**	**Median Coef.**	**Max. Coef.**
	OLS1		GWR1, 2	
Property Characteristics				
Living Area (m2)	4.7**	-45.7	-5.3	28.4
Number of Bedrooms	-329.6**	-1384.2	-136.0	957.8
Number of Bathrooms	318.3**	-1206.8	248.3	2,385.9
House Age (years)	1.3**	-121.1	-0.6	74.1
Design				
NDVI300	-1,674.1**	-82,657.5	262.5	125,978.4
Transit Distance				
Distance to Train Station (m)	-0.08	-79.7	1.0	297.5
Distance to Tram Station (m)	0.4**	-38.5	0.2	45.8
Distance to Metro Station (m)	0.5**	-66.0	0.5	39.1
Destination Accessibility				
Distance to City Center (m)	-0.5**	-495.3	-1.2	124.4
Distance to Business District (m)	-0.5**	-145.6	-0.02	162.1
Distance to School (m)	0.3	-21.5	-0.6	9.4
Distance to Convenience Stores (m)	1.2**	-15.4	0.2	18.1
Akaike Information Criterion (AIC)	30,487		29,720	

** Significant at $p < 0.05$

1 Statistical significance levels are only reported for the global OLS model, as p-values could not be easily presented for GWR due to its local approach.

2 Bandwidth of adjusted kernel corresponds to 67.