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 Jitse Ruurd Nauta Thomas Nibbering

2023-04-14

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. 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

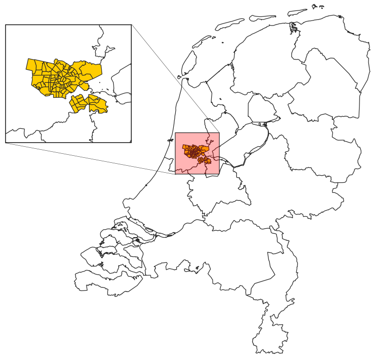

Figure 1: Overview of the study area.

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].

$$NDVI = \frac{(N-R)}{(N+R)} \qquad (1)$$

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 [40]. 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 [41]. As a result, variables $NDVI_{100}$ and $NDVI_{500}$ 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.

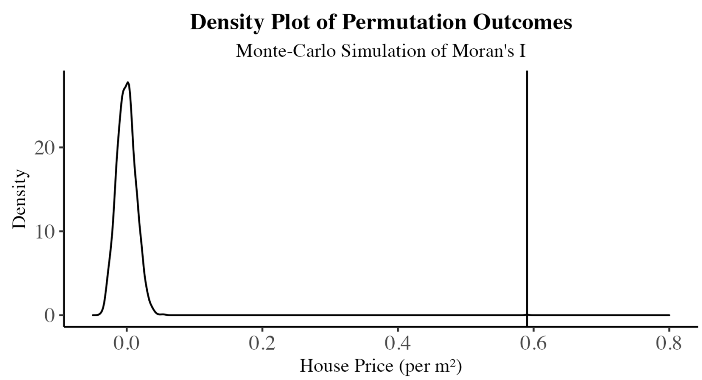

Figure 2: Density plot of Monte-Carlo Moran's I Permutation Outcomes.

Furthermore, similar studies found evidence for the existence of non-stationarity in both house prices and green spaces [39, 42]. 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 [43]. Doing so, provided estimates for each location in the study area. Finally, an overview of the scripts used throughout this study may be found on: GitHub.

3. Results and Discussion

The results showed that urban green spaces provide significant economic value, indicated by their positive association with residential property prices in the local regression model. However, this association was not

Table 1: Descriptive statistics of property characteristics, public amenities and greenness measures of Amsterdam real-estate.

Independent Variable	Mean	SD	Description
	Summary Statistics (N = 1,719)		
Property Characteristics[1]			
Living Area (m2) [38]	105.7	71.0	Size of livable area of the property
Number of Bedrooms [38, 39]	2.5	1.4	Number of bedrooms of the property
Number of Bathrooms [23]	1.1	0.7	Number of bathrooms of the property
House Age (years) [23, 38]	76.9	63.2	Age of the property in 2023
Design[2]			
NDVI_{100} [36, 39, 40]	0.200	0.073	Average NDVI at 100 m around property
NDVI_{300} [36, 39, 40]	0.212	0.069	Average NDVI at 300 m around property
NDVI_{500} [36, 39, 40]	0.216	0.067	Average NDVI at 500 m around property
Transit Distance[3,4,5]			
Distance to Train Station (m) [22]	1703.7	958.2	Euclidean distance to nearest train station
Distance to Tram Station (m) [22]	689.1	1024.7	Euclidean distance to nearest tram station
Distance to Metro Station (m) [23]	1303.2	951.8	Euclidean distance to nearest metro station
Destination Accessibility[4]			
Distance to City Center (m) [38]	3770.5	2288.1	Euclidean distance to city center
Distance to Business District (m) [38]	4659.2	2228.3	Euclidean distance to business district
Distance to School (m) [23]	268.3	183.8	Euclidean distance to nearest school
Distance to Convenience Stores (m) [38]	266.7	206.9	Euclidean distance to nearest store

Sources: [1]Funda.nl, [2]Sentinel-2, [3]ArcGIS, [4]OpenStreetMap.org, and [5]Amsterdam Municipality

consistent across all locations, as presented in Figure 3. Since the local model captured both the spatial dependence and non-stationarity present in the data, this section primarily focuses on the results of this model. A detailed overview of both models is presented in Appendix I.

Results of the local regression model revealed that urban green spaces were significantly associated with residental house prices at a 300m spatial scale ($p < 0.05$). Here, property premiums per m2 ranged from -82,657.5 to 125,978.4 euros for each unit increase in the vegetation index. This result aligns with previous studies [23, 36, 39, 40]. One explanation for this wide range might be related to the direct-use value placed on these areas [23]. In other words, particular green areas might attract more residents to benefit from the perceived value of greenness, prompting more people to purchase houses nearby [44]. Hence, highlighting the spatial variability and non-stationary nature of the association of interest, as illustrated in Appendix II. Finally, the findings of this study provide empirical evidence of the capitalisation of greenness characteristics in residential real-estate prices.

Limitations of this study were three-fold. First, distinctions between vegetation types were not considered. However, it was demonstrated to affect the scope and magnitude on house prices differently [45]. Second, the presence of property and neighbourhood characteristics that were unobserved but associated with urban green space and/or house prices may have biased the estimations. Lastly, the temporal dimension was not considered in this study. Hence, this may limit the generalisability of the study as the dynamic nature of the data might not be captured.

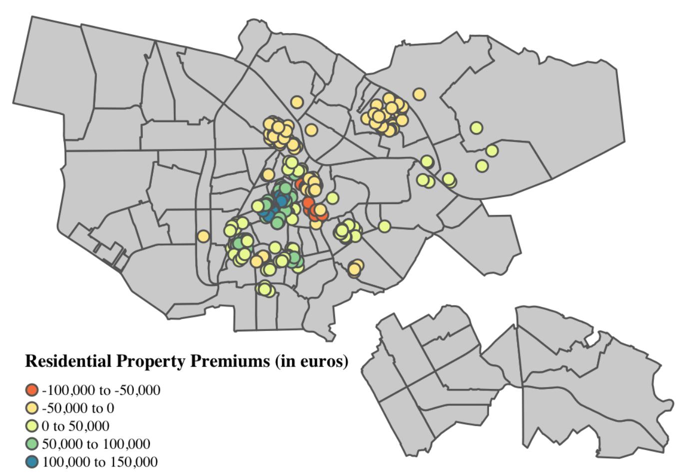

Figure 3: Overview of statistically significant ($p < 0.05$) urban green space coefficients at a 300m spatial scale in Amsterdam.

4. Conclusion

This study aimed to examine the economic value of urban green spaces in Amsterdam, as reflected in the real-estate prices of 2023. Here, property characteristics, public amenities and greenness measurements were obtained from a variety of sources. In line with topical literature, independent variables were identified and constructed to either adjust or explain the economic value of urban green spaces. In doing so, the local hedonic pricing model revealed that urban green spaces provided significant economic value. However, this association was not consistent across all locations, as the property premiums per m2 ranged from -82,657.5 to 125,978.4 euros for each unit increase in the vegetation index. The main theoretical explanation for this range might be related to the direct-use value placed on these areas. As a result, the outcomes of this study provide empirical evidence for the capitalisation of greenness characteristics in residential real-estate.

Further research may consider the usage of eye-level greenness in addition to aerial-view greenness, as it was demonstrated that this type of information might be an important valuation indicator of residential real-estate prices [46, 47]. Moreover, additional studies may consider the relationship between various types of urban green vegetation and property valuations.

5. References

1. Morancho AB (2003) A hedonic valuation of urban green areas. Landsc Urban Plan 66:35–41. https://doi.org/10.1016/S0169-2046(03)00093-8

2. Selmi W, Weber C, Rivière E, et al (2016) Air pollution removal by trees in public green spaces in Strasbourg city, France. Urban For Urban Green 17:192–201. https://doi.org/10.1016/j.ufug.2016.04.010

3. Georgi JN, Dimitriou D (2010) The contribution of urban green spaces to the improvement of environment in cities: Case study of Chania, Greece. Build Environ 45:1401–1414. https://doi.org/10.1016/j.buildenv.2009.12.003

4. Wang C, Ren Z, Dong Y, et al (2022) Efficient cooling of cities at global scale using urban green space to mitigate urban heat island effects in different climatic regions. Urban For Urban Green 74:127635. https://doi.org/10.1016/j.ufug.2022.127635

5. Shishegar N (2014) The Impacts of Green Areas on Mitigating Urban Heat Island Effect. The International Journal of Environmental Sustainability 9:119–130. https://doi.org/10.18848/2325-1077/CGP/v09i01/55081

6. Huang M, Cui P, He X (2018) Study of the Cooling Effects of Urban Green Space in Harbin in Terms of Reducing the Heat Island Effect. Sustainability 10:1101. https://doi.org/10.3390/su10041101

7. Jim CY, Chen WY (2006) Perception and Attitude of Residents Toward Urban Green Spaces in Guangzhou (China). Environ Manage 38:338–349. https://doi.org/10.1007/s00267-005-0166-6

8. Groenewegen PP, van den Berg AE, de Vries S, Verheij RA (2006) Vitamin G: effects of green space on health, well-being, and social safety. BMC Public Health 6:149. https://doi.org/10.1186/1471-2458-6-149

9. Ayala-Azcárraga C, Diaz D, Zambrano L (2019) Characteristics of urban parks and their relation to user well-being. Landsc Urban Plan 189:27–35. https://doi.org/10.1016/j.landurbplan.2019.04.005

10. Department of Environmental Protection (2021) NYC Green Infrastructure. New York City

11. Lachmund J (2013) Greening Berlin. The MIT Press

12. Department of Planning and Sustainability (2020) Amsterdam Green Infrastructure Vision 2050. Amsterdam

13. Conway D, Li CQ, Wolch J, et al (2010) A Spatial Autocorrelation Approach for Examining the Effects of Urban Greenspace on Residential Property Values. The Journal of Real Estate Finance and Economics 41:150–169. https://doi.org/10.1007/s11146-008-9159-6

14. Saphores J-D, Li W (2012) Estimating the value of urban green areas: A hedonic pricing analysis of the single family housing market in Los Angeles, CA. Landsc Urban Plan 104:373–387. https://doi.org/10.1016/j.landurbplan.2011.11.012

15. Panduro TE, Veie KL (2013) Classification and valuation of urban green spaces—A hedonic house price valuation. Landsc Urban Plan 120:119–128. https://doi.org/10.1016/j.landurbplan.2013.08.009

16. Holt JR, Borsuk ME (2020) Using Zillow data to value green space amenities at the neighborhood scale. Urban For Urban Green 56:126794. https://doi.org/10.1016/j.ufug.2020.126794

17. Zambrano-Monserrate MA, Ruano MA, Yoong-Parraga C, Silva CA (2021) Urban green spaces and housing prices in developing countries: A Two-stage quantile spatial regression analysis. For Policy Econ 125:102420. https://doi.org/10.1016/j.forpol.2021.102420

18. Sander H, Polasky S, Haight RG (2010) The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. Ecological Economics 69:1646–1656. https://doi.org/10.1016/j.ecolecon.2010.03.011

19. Sander HA, Haight RG (2012) Estimating the economic value of cultural ecosystem services in an urbanizing area using hedonic pricing. J Environ Manage 113:194–205. https://doi.org/10.1016/j.jenvman.2012.08.031

20. Czembrowski P, Kronenberg J (2016) Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. Landsc Urban Plan 146:11–19. https://doi.org/10.1016/j.landurbplan.2015.10.005

21. Anderson ST, West SE (2006) Open space, residential property values, and spatial context. Reg Sci Urban Econ 36:773–789. https://doi.org/10.1016/j.regsciurbeco.2006.03.007

22. Li W, Saphores J-DM, Gillespie TW (2015) A comparison of the economic benefits of urban green spaces estimated with NDVI and with high-resolution land cover data. Landsc Urban Plan 133:105–117. https://doi.org/10.1016/j.landurbplan.2014.09.013

23. Mei Y, Zhao X, Lin L, Gao L (2018) Capitalization of Urban Green Vegetation in a Housing Market with Poor Environmental Quality: Evidence from Beijing. J Urban Plan Dev 144:. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000458

24. Martinez A de la I, Labib SM (2023) Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. Environ Res 220:115155. https://doi.org/10.1016/j.envres.2022.115155

25. Rhew IC, Vander Stoep A, Kearney A, et al (2011) Validation of the Normalized Difference Vegetation Index as a Measure of Neighborhood Greenness. Ann Epidemiol 21:946–952. https://doi.org/10.1016/j.annepidem.2011.09.001

26. Jimenez RB, Lane KJ, Hutyra LR, Fabian MP (2022) Spatial resolution of Normalized Difference Vegetation Index and greenness exposure misclassification in an urban cohort. J Expo Sci Environ Epidemiol 32:213–222. https://doi.org/10.1038/s41370-022-00409-w

27. CBS Statline (2022) Inwoners per Gemeente. In: Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/visualisaties/dashboard-bevolking/regionaal/inwoners. Accessed 6 Apr 2023

28. CBS Statline (2022) Kerncijfers wijken en buurten 2022. In: Centraal Bureau voor de Statistiek. https://opendata.cbs.nl. Accessed 6 Apr 2023

29. Department of Planning and Sustainability (2018) Evaluatie project Groen in de buurt. Amsterdam

30. Funda (2023) Zoek huizen en appartementen te koop in Nederland. https://www.funda.nl. Accessed 6 Apr 2023

31. ArcGIS (2021) Stations in Nederland. https://www.arcgis.com/home. Accessed 6 Apr 2023

32. OpenStreetMap Contributors (2023) Convenience Store Amenities. In: OpenStreetMap.org

33. OpenStreetMap Contributors (2023) School Amenities. In: OpenStreetMap.org

34. Municipality of Amsterdam (2023) Datacatalogus. https://data.amsterdam.nl/datasets/zoek/. Accessed 6 Apr 2023

35. European Space Agency (2022) Sentinel-2 Level-2A. https://planetarycomputer.microsoft.com/dataset/sentinel-2-l2a. Accessed 6 Apr 2023

36. Daams MN, Sijtsma FJ, Veneri P (2019) Mixed monetary and non-monetary valuation of attractive urban green space: A case study using Amsterdam house prices. Ecological Economics 166:106430. https://doi.org/10.1016/j.ecolecon.2019.106430

37. Labib SM, Lindley S, Huck JJ (2021) Estimating multiple greenspace exposure types and their associations with neighbourhood premature mortality: A socioecological study. Science of The Total Environment 789:147919. https://doi.org/10.1016/j.scitotenv.2021.147919

38. Chen Y, Jones CA, Dunse NA, et al (2023) Housing Prices and the Characteristics of Nearby Green Space: Does Landscape Pattern Index Matter? Evidence from Metropolitan Area. Land (Basel) 12:496. https://doi.org/10.3390/land12020496

39. Zhang S, Wang L, Lu F (2019) Exploring Housing Rent by Mixed Geographically Weighted Regression: A Case Study in Nanjing. ISPRS Int J Geoinf 8:431. https://doi.org/10.3390/ijgi8100431

40. Sisman S, Aydinoglu AC (2022) A modelling approach with geographically weighted regression methods for determining geographic variation and influencing factors in housing price: A case in Istanbul. Land use policy 119:106183. https://doi.org/10.1016/j.landusepol.2022.106183

41. Kasmaoui K (2019) Linear Regression. In: Global Encyclopedia of Public Administration, Public Policy, and Governance. Springer International Publishing, Cham, pp 1–11

42. Wu C, Du Y, Li S, et al (2022) Does visual contact with green space impact housing prices? An integrated approach of machine learning and hedonic modeling based on the perception of green space. Land use policy 115:106048. https://doi.org/10.1016/j.landusepol.2022.106048

43. Suryowati K, Ranggo MO, Bekti RD, et al (2021) Geographically Weighted Regression using Fixed and Adaptive Gaussian Kernel Weighting for Maternal Mortality Rate Analysis. In: 2021 3rd International Conference on Electronics Representation and Algorithm (ICERA). IEEE, pp 115–120

44. Lin I-H, Wu C, De Sousa C (2013) Examining the economic impact of park facilities on neighboring residential property values. Applied Geography 45:322–331. https://doi.org/10.1016/j.apgeog.2013.10.003

45. Crompton JL (2001) The Impact of Parks on Property Values: A Review of the Empirical Evidence. J Leis Res 33:1–31. https://doi.org/10.1080/00222216.2001.11949928

46. Ki D, Lee S (2021) Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning. Landsc Urban Plan 205:103920. https://doi.org/10.1016/j.landurbplan.2020.103920

47. Wang G (2023) The effect of environment on housing prices: Evidence from the Google Street View. J Forecast 42:288–311. https://doi.org/10.1002/for.2907

Appendix I

Table 2: Coefficients and statistical significance of the Ordinary Least Squares and Geographically Weighted Regression models.

Independent Variable	**Coef.**	**Min. Coef.**	**Median Coef.**	**Max. Coef.**
	OLS[1]		GWR[1,2]	
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				
$NDVI_{300}$	-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.

Appendix II

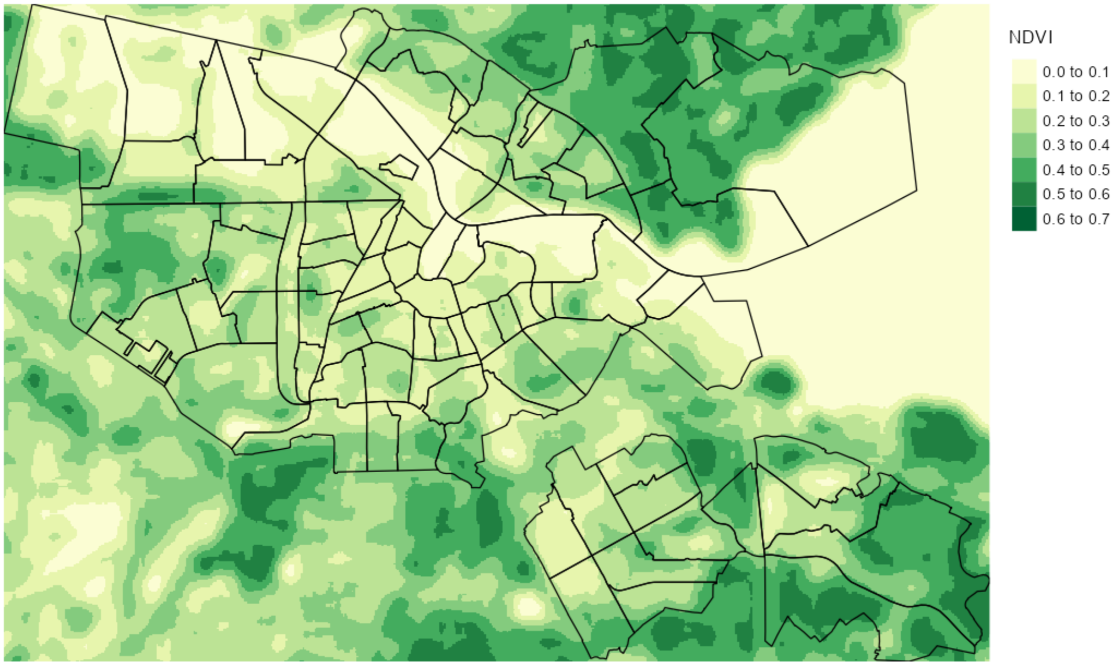

Figure 4: Overview of NDVI values in Amsterdam with a 300m Spatial Scale