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Tree Canopies, Urban Green Amenities and the Residential Real Estate Market: Remote Sensing and Spatial Hedonic Applications to Lisbon, Portugal

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Abstract

This paper explores the use of remote sensing techniques and hedonic pricing methods for the valuation of urban green amenities and in particular street trees. The classification and study of these amenities in an urban area is challenged by the high level of spatially detailed data required.

While tree canopies are important not only for their aesthetics and ecological benefits, it is difficult to obtain such data to be used for informed policy discussions. A classification algorithm is tested and applied to high resolution aerial photographs of Lisbon to assess the usage of remote sensing techniques for the detection of tree canopies in the city. Results indicate that 8% of Lisbon is covered with tree canopy with a high accuracy rate of approximately 90%.

We further explore how the heterogeneity of urban green amenities influence the residential real estate market under the hedonic valuation framework with a spatial error specification, focusing on the impact of parks, urban forests, cemeteries, playgrounds and Monsanto Forest Park. Results indicate that different types of green spaces are valued differently and further that there is varying effects in how the real estate market values different types of street trees. Residential real estate capitalizes these trees based on their heterogeneous characteristics such as foliage type and location, with results showing that trees have significant positive amenity values in mitigating flood risk in the urban area. This highlights the importance in considering how different trees are contextualized in an urban environment.

Remote sensing techniques of tree canopies are thus worthwhile in providing additional dimensions from which urban green amenities can be valued via the hedonic framework. In this way, our findings contribute to the broader debate on applying remote sensing and hedonic pricing to the valuation of ecosystem and environmental services and to assess strategies to increase the level of greenness within urban areas.

Keywords: Environmental amenities, tree canopy, hedonic pricing, remote sensing

JEL CODES: Q51, R21

1. Introduction

Urban green amenities in a city range from planted street trees, manicured parks and gardens, green infrastructure including green walls and roofs, and more natural urban forests and agricultural areas. The amenity value of these local public goods not only service residents and visitors of a city but further have an important relationship with the local ecology. Urban green amenities and street trees influence storm water runoff, noise and air pollution, shade and urban heat, and bio-diversity all with additional important spillover influences on neighborhood ambiance and aesthetics, human quality of life and health (see Zupancic et al. 2015 for a meta-analysis).

Increasingly, municipalities use tree planting and maintenance as a core component of their green infrastructure and environmental programs. Still little appears to be known about the value and role of urban trees and tree canopies in Mediterranean climates such as in Lisbon, Portugal and developing cities where vegetation thrives allowing for a high diversity of plant types. In recent years the municipal authority of Lisbon, *Câmara Municipal de Lisboa* (CML), has prioritized the environment and green spaces within its city planning, being among 12 nominees for the European Green Capital 2017 (CML, 2014). Embedded in the planning of the city is the development of green corridors and green spaces throughout the city with the aim of promoting community interaction and healthy living (CML, 2015). Further, the city aims to increase biodiversity 20% by 2020 focusing on promoting native species of plants and trees while realizing the importance of exotic species, which were primarily introduced in imperial gardens during the Portuguese colonial period, in preserving the ecological cultural heritage of the city (CML, 2015).

This paper explores the amenity value that urban residents place on a variety of local green amenities in Lisbon, Portugal, with particular emphasis on how the residential real estate market is influenced by urban street trees and tree canopies. Traditional studies of urban green amenities have been limited by data to focusing on broad categories of open spaces and omitting the analysis of individual trees and tree canopy coverage. Our analysis is unique in that we use the results of a one-class support vector machine (SVM) supervised learning algorithm to capture urban tree canopy coverage using high resolution aerial photography of the study region. These results highlight the strength of remote sensing techniques and its application to the economic literature for obtaining environmental data related to urban tree canopies. Using both an ordinary least square (OLS) and spatial hedonic framework we show the importance of capturing the heterogeneity of urban green amenities and street trees with different attributes having markedly different impacts on the residential real estate market.

Understanding the value of urban green amenities and the relationship to urban real estate markets is important to developers who could profit from building more desirable residential communities, but also to city planners and local officials in order to foster the adequate provision of the local public goods

provided by urban green spaces by designing better land-use regulations and promoting sustainable neighborhoods.

The remote sensing algorithm developed for detecting tree canopies yields an overall accuracy of approximately 90%, highlighting the value of this technique in gathering highly detailed spatial environmental data for urban analysis. Our estimates indicate that approximately 8% of Lisbon is covered by urban tree canopy. Traditional methods of data collection involve in situ sampling or the usage of municipal inventory databases, which can be both costly and time consuming or subject to data availability. Thus remote sensing is a valuable tool for economists to accurately classify tree canopy coverage, further increasing the dimensionality through which the effects of urban street trees can be analysed and used for policy purposes related to the greening and beautification of urban areas.

Empirical results of a hedonic analysis on housing prices and the location of urban street trees and green amenities indicate that there are significant impacts on the residential real estate market. Namely, we find that the heterogeneity of street trees are valued differently depending on specific attributes such as foliage type.

Results indicate that while deciduous trees (which lose their foliage in the winter) have a positive impact on housing prices in the range of 0.08%, evergreen trees are negatively valued by 0.1%. This may be due to the shading effect from evergreens, especially during the winter season when sunlight is highly valued. We further see that neighborhoods with higher coverage of tree canopies have a negative influence on prices, likely for the same reason as why evergreen trees are valued negatively.

While certain trees may have a negative impact in general on prices, we see that when considering these trees in areas of high potential flood risk, there are positive amenity values such as evergreen trees having a positive amenity value of 0.3% in zones of high flood risk. Although aesthetically, high levels of tree canopy and evergreens may have a negative impact, we see that these amenities still have positive ecological spillover effects in mitigating flood risks. This has important policy implications for the decision on where to plant and how to maintain different types of trees. Further, we see that palm trees have positive interaction effects in historic protected zones owing to the fact that these trees are primarily aesthetic and contribute to the overall landscape, while evergreen trees continue to have a negative influence in these protected zones where view and ambience are valued by residents.

The remainder of the paper is structured as follows. Section 2 highlights the existing literature related to both the remote sensing of tree canopies and the hedonic framework for valuing urban green amenities. Section 3 describes the study region of Lisbon, Portugal, while section 4 presents the data. Results from the one-class SVM procedure are presented in section 5 while section 6 presents the results from the OLS hedonic valuation of urban green amenities and street trees. Finally, section 7 provides overall conclusions.

2. Literature Review

2.1. Remote Sensing Studies

Remote sensing has been used extensively for the classification of tree canopies at the region or country level (see for example Iizuka and Tateishi, 2015; Karlson et al., 2015). Relatively fewer studies have focused on tree canopies in an urban area, due to the high spatial resolution images required. Significantly detailed images are needed to accurately identify and classify tree canopies located among the mixture of private residences, commercial buildings, public spaces and dense networks of roads.

Xiao and McPherson (2005) use high spatial resolution images of 20 centimeters to map the tree canopy of the University of California Davis campus. Spectral bands available include near-infrared (NIR), red and green – further allowing for the calculation of the normalized difference vegetation index (NDVI).¹ This research assesses the spread of tree disease among 8,962 trees located on the campus combining remote sensing, a GIS tree database and ancillary GIS data on roads, buildings and parking lot. Trees are classified as broadleaf deciduous, broadleaf evergreen, conifer or palm and based on their height (small: < 10 meters; medium: 10-20 meters; and large: > 20 meters). The NDVI is used to assess vegetation on the campus and specific tree canopies are matched to the tree database to link respective canopies to trees species, height, and width (diameter at breast height).

Applications of remote sensing techniques include studies on the relationship between green spaces and crime. While higher densities of vegetation and tree canopy increase the chance of crime concealment, appropriately designed green and open spaces may foster community interaction and usage of these spaces, thus increasing the natural surveillance of the area. In Baltimore, Troy and Grove (2008) include proximity to parks and crime interaction effects to examine heterogeneity of impacts from different parks using remote sensing to classify parks as minimum two hectares with threshold level of NDVI coverage. Parks are valued positively up until a certain threshold level of crime of over 400% the national average, after which there is a negative effect on housing prices.

Troy, Grove and O'Neil-Dunne (2012) use 1 meter remote sensing data to estimate that a 10% increase in tree canopy coverage in the city yields an approximate 12% decrease in crime rates. Wolfe and Mennis (2012) obtain a negative relationship between urban vegetation and crime with a decrease in levels of assault, robbery and burglary for census tracts with higher vegetation levels.

2.2. Hedonic Pricing Methods

The value of green space has been the topic of a vast number of studies using hedonic and stated preference methods as surveyed in McConnell and Walls (2005) and Waltert and Schläpfer (2010). The results are generally mixed with positive, negative and insignificant effects found for the same types of amenities. With the exceptions of Anderson and West (2006) and Irwin (2002) much of the existing literature focuses on specific types of green space (e.g. nature preserves or agricultural fields)

¹ NDVI is calculated using the spectral bands as follows: $NDVI = [NIR-Red] / [NIR+Red]$.

or categorization of green space by size and accessibility. Studies on the value of alternative forms of urban green amenities however, in particular urban trees, are still quite scarce.

Donovan and Butry (2010) estimate a spatial hedonic regression to obtain the marginal impact of street trees on property values in Portland, Oregon. The authors collect data on the number of street trees fronting a house, tree crown areas in the front and within 100 feet of the house, height, volume and whether the trees are flowering, fruiting, coniferous, deciduous, appears to be sick or poorly pruned. Of these variables only meaningful results are obtained with the number of trees and the area of tree canopies within 100 feet, suggesting that in situ sampling of trees to collect detailed data may not be necessary. Remote sensing techniques can be used to obtain the most relevant data such as tree location and canopy at a much lower cost.

There are a number of different types of open spaces which may have heterogeneous impacts on housing prices. Both Sander and Polasky (2009) and Anderson and West (2006) consider proximity to parks, trails, lakes and rivers. While Sander and Polasky test and reject spatial autocorrelation in their data, Anderson and West do not explicitly account for spatial autocorrelation in housing prices. The authors include a range of interaction effects to estimate open space and its heterogeneous influence with neighborhood demographics, crime rates, distance to central business district (CBD), income levels, density and lot size. Parks have positive impacts on housing properties, and the effect of being closer to a park is nearly three times as high in neighborhoods which are twice as dense as the average while approximately four times as high in neighborhoods with twice as high income levels.

Urban forests have a positive impact on housing prices with prices increases approximately 5.9% for 1 kilometre increase in proximity or 4.9% for views of forests (Tyrväinen and Miettinen, 2000). Czembrowski and Kronenberg (2016) group open and green spaces into 9 different categories: small, medium and large parks and forests, the single largest forest, cemeteries and allotment gardens in Lodz, Poland. The authors correct for spatial dependence with a spatial autoregressive with autoregressive disturbances model and find that proximity to large parks and the Lagiewniki forest, which are well known, have the strongest positive impacts on housing prices with property values increasing approximately 1.5% for square meter as proximity increases. Cemeteries had the opposite effect with prices per square meter decreasing as dwellings were located closer in the range of 2%.

In Castellón, Spain, Morancho (2003) find that distance to open space is a more significant determinant than the size of the open spaces with 100 meters increase in proximity provides a premium of €1,800. In terms of valuing amenities through the housing market Cho et al. (2006), Cho et al. (2008) and Nilsson (2014) use the geographically weighted regression technique to value open spaces and natural amenities via property prices allowing this effect to vary over space as an alternative to including interaction effects to determine heterogeneity across neighborhoods.

Relatively fewer studies have focused on the impact of tree canopies on property values given the difficulty in obtaining such data. Sander et al. (2010) use the National Land Cover Database in the United States which provides tree canopy cover across the country. This data however is available only

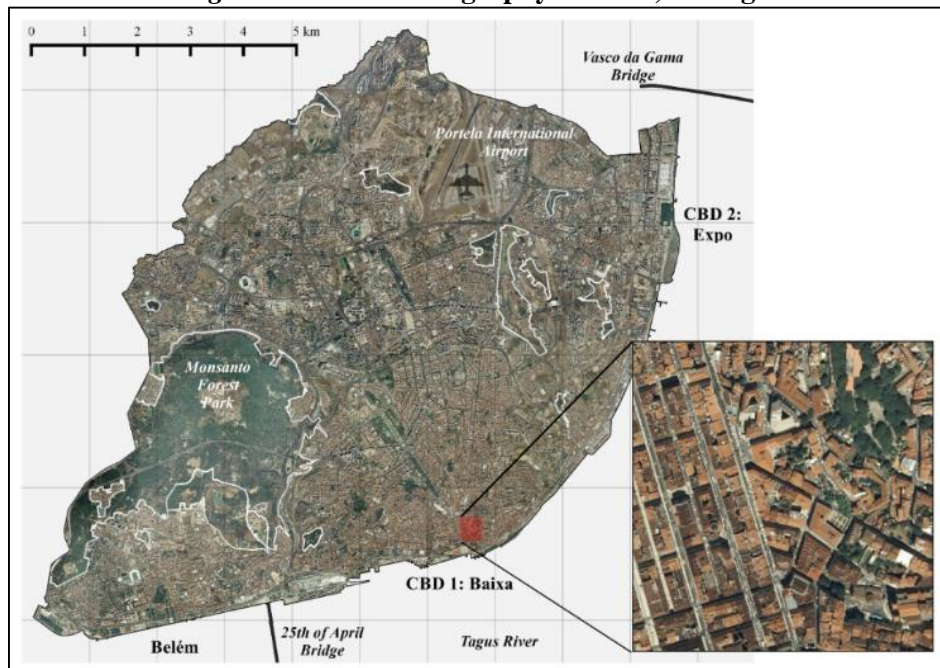
at a 30 meter resolution inhibiting the specificity of identifying individual trees and providing an overall average for dwelling neighborhoods. Under a spatial error specification, the authors argue that tree canopies are valued in direct proximity to dwellings with little influence further away in the magnitude of a 0.48% and a 0.29% increase in dwelling prices for a 10% in tree coverage within 100 meters and 250 meters respectively.

Our analysis contributes to the broader literature on the valuation of environmental amenities by using an extensive database on the location of these amenities complemented by the location of urban trees in the city. Making use of highly detailed aerial photography we are able to extend the analysis to include tree canopy vegetation, an important urban environmental variable which is traditionally overlooked.

3. Study Region

The study area is the European capital city of Lisbon, Portugal (lat: 38.707, long: -9.136), covering an area of approximately 100 km² with a 2007 population of 552,118 and slightly over 2 million residing in the greater metropolitan area (see figure 1).² Lisbon has a rugged topography built on seven historic hills rising from sea level where the Tagus River flows to the Atlantic Ocean. The Monsanto hill dominates the cityscape and is located in the west. It is the largest natural urban forest, covering approximately 10% of the city and reaching 227 meters above sea level. The city has a Mediterranean climate with two distinctive seasons: a hot dry summer where temperatures commonly exceed 30°C and a cool wet winter, which allows for a variety of tree species to thrive in the urban environment.

Figure 1. Aerial Photography: Lisbon, Portugal



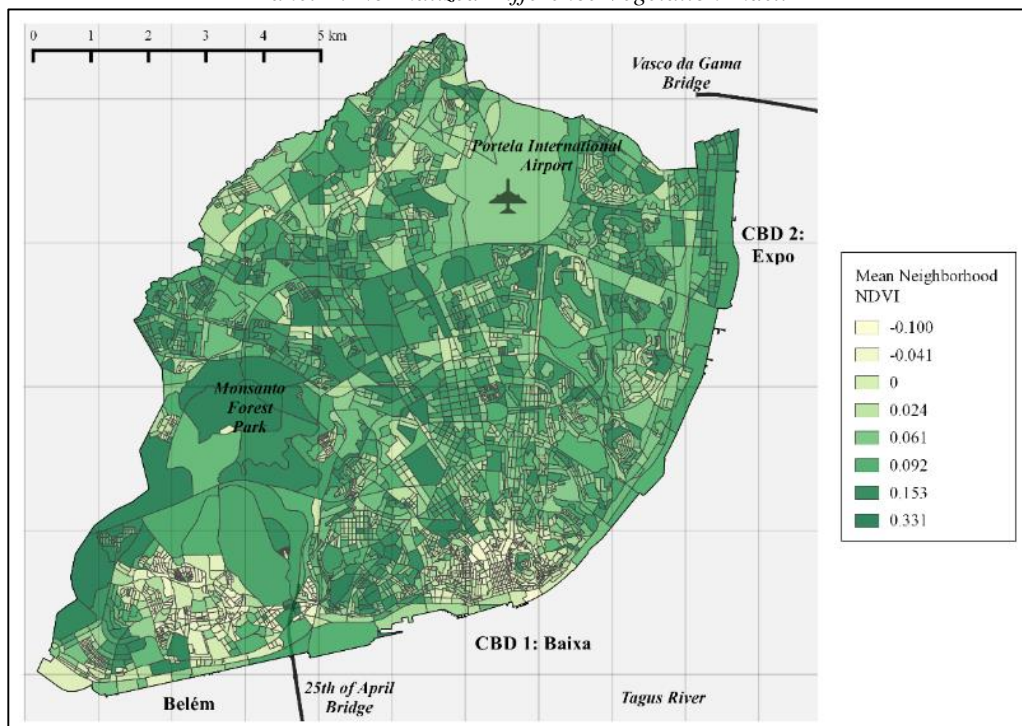
² Population for the year of study from which data is available and defined as the total sum of individuals of all ages residing within the city limits of Lisbon.

The primary CBD and historic hub of Lisbon, known as *Baixa Pombalina*, is located in the downtown core bordered by the Tagus in the south. This part of the city was completely rebuilt after the 1755 earthquake by the Marquês de Pombal and greatly differs from the spatial layout of the other historic neighbourhoods, with wide sprawling boulevards and open squares. While this central area serves as the main employment center, in 1998 Lisbon leveraged its hosting of the World Expo to redevelop a previously idle industrial area into a secondary CBD. This area, known as *Parque das Nações* or "Expo", is now an active commercial and residential area of the city located further inland along the river.

The main transportation hub is the Portela international airport with two further international train stations, one in each CBD, linking Lisbon to destinations in Spain and France. Two bridges connect the city to municipalities and motorways on the south of the Tagus River: The 25th of April Bridge inaugurated in 1966 and situated between *Baixa* and the mouth of the river and the Vasco da Gama Bridge, currently the longest bridge in Europe, opened in 1998 and located in the Expo area.

Lisbon has a long history, and its historic buildings and cobblestone streets are juxtaposed against the newer buildings of modern Lisbon. The city has a wide variety of historic amenities representing Portuguese culture and history throughout the centuries and these monuments are dotted throughout the city and complemented by ornate imperial and botanical gardens, tree-lined boulevards and a rich ecological diversity. These ornamental gardens allowed for the introduction of exotic species of trees and plants, primarily introduced during the 15th and 16th century Portuguese Golden Age of Discovery (Rosa, 2013).

Figure 2. Lisbon NDVI
 Panel A: Normalized Difference Vegetation Index



The city is rich in ecological diversity and vegetation. Using aerial photography we calculate continuous NDVI values across the city which is spatially aggregated to Census tract neighborhood blocks in figure 2. Different land covers yield different values of NDVI which ranges from -1, typically representative of water to, +1 which is representative of healthy vegetation. This measure provides a relative index of the levels of trees, shrubs and flora in a given neighborhood highlighting the spatial variability in vegetation with noticeably less in the primary CBD where there are many impervious surfaces (i.e. roads, buildings).

There is evidently strong implications for the city of Lisbon with regards to urban green policy and the broader impact on its residents. While remote sensing techniques allow for the accurate collection of green data in the city, hedonic pricing allows for informed discussions on the broader effects of how urban green amenities and street trees interact with society.

4. Data

4.1. Remotely Sensed Images

Orthorectified aerial photographs covering all of Portugal are taken by the Portuguese *Direção Geral do Território* (DGT) under the national Ministry of the Environment. Images are available with a high spatial resolution of 0.5 meters in four spectral bands: blue, green, red, and NIR. Although aerial photographs are captured approximately every two years, we make use of those taken between July 27 and August 23, 2007. Images are obtained using an Intergraph Digital Mapping Camera DMC01-0037 and UltraCam-D. Each band has a radiometric resolution of 8-bit with digital numbers ranging from 0 to 255.

While remote sensing techniques have been extensively used for the classification of tree canopies at regional or even country levels, the classification of tree canopies within an urban area requires data with a very high spatial resolution. Each image from DGT covers a respective land area of 20 km² in 4 km × 5 km blocks. In total, 11 images are used to cover the study area of Lisbon with spectral layers stacked and clipped to the city boundaries. Images are projected to the EPSG: 3763 (ETRS89/ PT-TM06) coordinate reference system.

4.2. Hedonic Pricing Variables

Geo-coded residential property data for 2007 is obtained from *Confidencial Imobiliário*, a Portuguese organization providing data regarding the national real estate market. The database contains the asking bid price and price per square meter of the property, a vector of structural characteristics (e.g. area, parking, view) and location characteristics (partial address, zip code, *freguesia*/civil parish) for

11,616 two-bedroom apartment dwellings in the city.³ Average income at the *freguesia* level comes from the Ministry of Finance and obtained via CML. Average income in this respect is based on IRS tax submissions for the 2007 year.

Within each *freguesia*, further subsections are used for the collection of Census 2011 data at the city block level. The city block serves as the primary unit of analysis for neighborhood level variables including population density, socio-demographic variables on education level and age, and variables related to the stock of buildings including the percentage of non-residential buildings and percentage of buildings built in different decades since 1919. In total Lisbon is divided into 3,623 city blocks with an average of 69 per *freguesia*, of which our observations fall into 307 unique ones.

We further control for the number of dilapidated buildings within a 200 meter buffer of each dwelling, which refers to entire buildings or complexes which are abandoned and unsightly and further may attract illegal squatting, crime or increase the risk of large fires and influence neighborhood perception.

Local urban amenities in Lisbon are obtained through the *Lisbon City Service Development Kit API* providing the geo-coded locations of different categories of amenities in the city. Using these locations we calculate variables to control for proximity to employment centers, airport, health (e.g. hospitals, pharmacies, clinics), education (e.g. primary, secondary, post-secondary institutions), train stations, shopping centers, art amenities (i.e. galleries and museums) and culture amenities (i.e. libraries, theatres, auditoriums and cinemas).⁴ Accessibility to amenities is explored in two ways, firstly by Euclidean distance and secondly by considering dummy variables to represent being located in mutually exclusive concentric rings surrounding the amenity of interest.

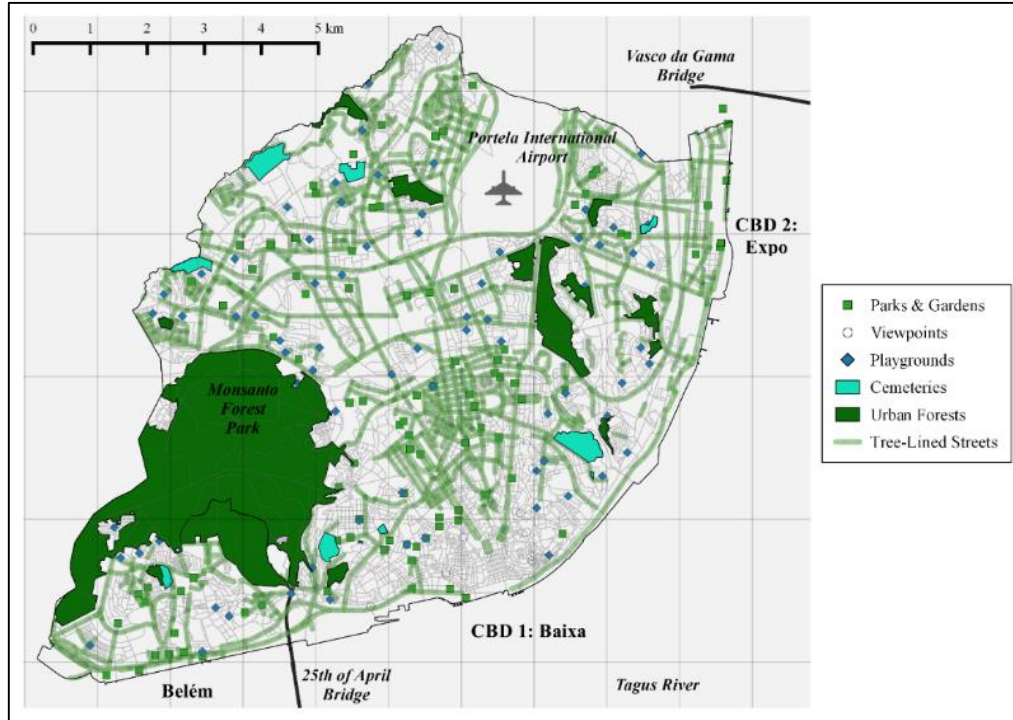
The municipality maintains a number of maps with data used for urban planning which are available for public use. These include the road and freeway network of Lisbon including both bridges crossing the Tagus, and the location of metro stations in the city (of which we consider only those constructed prior to 2007). These maps further include geological hazards of which the city may be prone including regions of high seismic risk (based on soil quality) and regions of high flooding risk.

The location and size of urban green amenities are obtained from CML. Finer disaggregation's related to the type of these green spaces and usages are obtained making reference to the 2007 aerial photographs in order to correctly classify land usage at the time of the study. We are interested in how the real estate market values accessibility of open spaces with different functions using classifications of: 7 cemeteries, 8 urban forests, 135 parks and gardens by size, 110 playgrounds and the Monsanto Forest Park.

³ Although transaction prices are favored we are limited to using asking bid prices, which may introduce a positive bias in the results. This bias is consistent across all observations, and estimation results remain meaningful.

⁴ Endogeneity is expected due to a potential causal relationship between housing prices and the location where developers decide to situate their businesses. Without an appropriate instrument, we include only those arts and culture amenities established in their location for at least ten years prior to the listing of the dwelling in 2007, with amenities developed after 1997 excluded.

Figure 3. Environmental Amenities: Green Spaces, Urban Forests, Tree-Lined Streets



Data provided by CML allows us to identify the specific location of 52,507 publically managed urban trees across Lisbon. From this we estimate the number of trees located within each neighborhood across the city. We are further able to classify trees based on heterogeneous characteristics, namely their foliage type. This is important as trees with different types of foliage are perceived differently by residents. The most common type of tree in the city are deciduous trees which lose their leaves in the winter time, with approximately 26,287 planted and managed by the city. Evergreen trees, which remain green for the entire year, can be categorized as broadleaf or conifers (pine trees) of which there are 1,884 and 2,311 respectively. Further we identify 493 palm trees, 272 shrubs and bushes, and 139 monumental trees which are considered as living history of the city (see figure A1 of the Appendix for tree locations).

This extensive database on tree location does not however include those which are located in public parks or gardens, urban forests or on private properties. It is estimated that there are up to 600,000 individual trees located in Lisbon including up to 200 different species ranging in size, colour, shape and region of origin (CML, 2010). Thus, in order to capture the full range of trees across the city remote sensing techniques are required.

5. Remote Sensing of Tree Canopies

With the increasing availability of high resolution satellite and aerial images, it is possible to distinguish detailed urban land use allowing for important urban policy and planning discussions. The remote sensing of tree canopies in an urban area is particularly important for the tracking and

management of trees, to which significant municipal resources are devoted in terms of planting and maintenance costs.⁵

Balancing these costs, there are a number of benefits ranging from purely aesthetic and contributing to neighbourhood quality to more complex ecological benefits in terms of pollution and air quality, rain and storm water runoff, noise, urban heat and harmful UV radiation. As such, accurately quantifying the size and location of tree canopy in a city is an important source of information to be used for research and decision making.

The value of the stock of urban trees in Lisbon on property value is estimated to be approximately \$5.97 million, or \$145 per tree, while \$1.9 million (\$45.64 per tree) is invested in their maintenance which includes planting, pruning, removals, pest control and watering (Soares et al., 2011). This research uses a tree valuation software specifically developed to estimate the contribution of trees to a city in terms of environmental and socio-economic benefits.⁶

Urban tree canopies are distinctive in that they are one of the main sources of carbon sequestration in cities and significant in offsetting total carbon emissions.⁷ While measures of vegetation such as the NDVI highlight areas rich in plant life, it may be unsuitable for more detailed analysis of ecological interactions since different urban environmental amenities have very heterogeneous functions. For example, while both a closed canopy urban park and sport field may yield high NDVI values, urban parks have an important role to play in carbon sequestration and balancing urban (micro) climate while sport fields are primarily recreational for residents of the area.

Given the importance of capturing tree canopies, and further since the number of publically managed trees represents only a fraction of total tree vegetation, in order to capture a comprehensive coverage of tree canopy in Lisbon (including publically managed trees, urban forests, public gardens and those on private grounds) remote sensing techniques are required.

5.1. One-Class Support Vector Machine Learning Methodology

Remote sensing for land use classification with high spatial resolution images in this scenario can be conducted focusing only on the single class of interest (i.e. tree canopies). This one-class classification technique has been applied to a number of ground objects including tree canopies, vegetation, water, rooftops and vehicles among others. In terms of classifying the data, an algorithm is applied to aerial images using the underlying data to value pixels as being either positive (i.e. the class of interest, in our case tree canopies) or negative (i.e. all other classes).

This research uses a one-class SVM supervised machine learning algorithm as outlined by Schölkopf et al. (2001). SVM methodologies analyze underlying patterns in the spectral information

⁵ Tree canopies defined as the above ground collection of branches and leaves forming the crown of the tree which cover a ground area when viewed from above.

⁶ See Sarajevs (2011) for an overview of three popular tree valuation software: i-Trees, CAVAT and Helliwell.

⁷ Nowak and Crane (2002) estimate that urban street trees in the USA store 700 million tons of carbon and sequester an additional 22.8 million tons annually, equivalent to \$460 million per year.

(and synthetic bands as estimated from these, such as the NDVI) to classify ground objects.⁸ Under the one-class SVM, a function is estimated based on n positive training samples to estimate a high dimensional hypersphere which separates positive training samples from all others based on the spectral information of each pixel with the largest margin possible. This methodology rests on the assumption that negative classes are uniformly distributed around the positive samples outside of the hypersphere.

This algorithm however is sensitive to free parameters which has led to studies on the efficiency of the one-class SVM compared to others such as the Positive and Unlabeled Learning (PUL) algorithm (Li et al., 2011).

5.2. Training Sample Collection

Four spectral bands are available from the aerial images of the study area, from which further synthetic bands are calculated. In addition to the standard blue, green, red and NIR bands, the NDVI values are obtained and converted from a range of [-1, +1] to a range of [0, 255] to align with the data from the spectral bands which are in 8-bit format.⁹

With these five bands at our disposal, we obtain additional information from each to assist in the classification and the detection of tree canopies versus all other land uses. For each band (R-G-B-NIR-NDVI) we estimate the mean value of surrounding pixels with a three pixel window. This determines, for example, whether a pixel classified as vegetation is surrounded by additional vegetation. Such a measure is used to help in distinguishing the boundaries and interiors of ground objects.

One important feature of tree canopies that we make use of is the texture of the vegetation in comparison to other types of vegetation such as grass and lawns. Again with a three pixel window, we estimate the standard deviation of the surrounding pixels. Vegetation is detected based on the original spectral bands, and combined with the standard deviation of surrounding pixels it is possible to determine highly textured vegetation. Thus we have 15 dimensions of digital numbers at our disposal for each pixel in an image to use in the training and classification of the data: blue, green, red, and NIR spectral bands, NDVI values, and further the mean and standard deviation for surrounding pixels of each band. Using positive training samples, the one-class algorithm determines the hypersphere surrounding the cluster of training points and values located within the hypersphere are classified as positive cases (tree canopies) and values outside are classified as negative cases (all others).

We use 506 positive training samples collected from throughout the city capturing a wide variety of tree canopy including individual trees planted in urban planters, clusters of trees in parks, urban forests and from a wide range of tree species with different vegetation levels (both healthy with strong green pigment or not). Visual detection at such high spatial resolution was used to classify the training samples, making use of underlying shadows to distinguish between trees and shrubs which have similar

⁸ Using the digital number associated to each pixel in respective bands as our data.

⁹ Rather than normalizing all variables to a range of (0,1) they are kept in 8-bit format (0,255) so that they remain integers as opposed to floating points which increases file size and computation time significantly.

texture and comparison with satellite images from Google Earth. These training samples feed the algorithm used to determine which cells correspond to tree canopies.

Photographs are stacked and clipped using the *raster* package with **R 3.2.2** with visual collection of the training data and interpretation of the images using **QGIS 2.10.1**. Further, estimation and application of the one-class SVM model along with the cross validation to obtain optimal parameter values is conducted in **R** under the *e1071* and *dismo* packages.

5.3. Remote Sensing Results

Remotely sensed urban tree canopies across Lisbon are presented in figure 4. Our estimates indicate that approximately 8% of Lisbon is covered by urban tree canopy. Using these results, we are thus able to approximate the percentage of each neighborhood covered by urban tree canopies.

In order to assess the accuracy of the resulting map covers, 500 random points were plotted in two different study areas with the resulting true land cover and value from the SVM compared. For each of these 500 points we determined how each point was classified in the SVM map and how it should be classified in real life. Within both study areas there is an approximate 90% accuracy rating (see figure A2 of the Appendix).

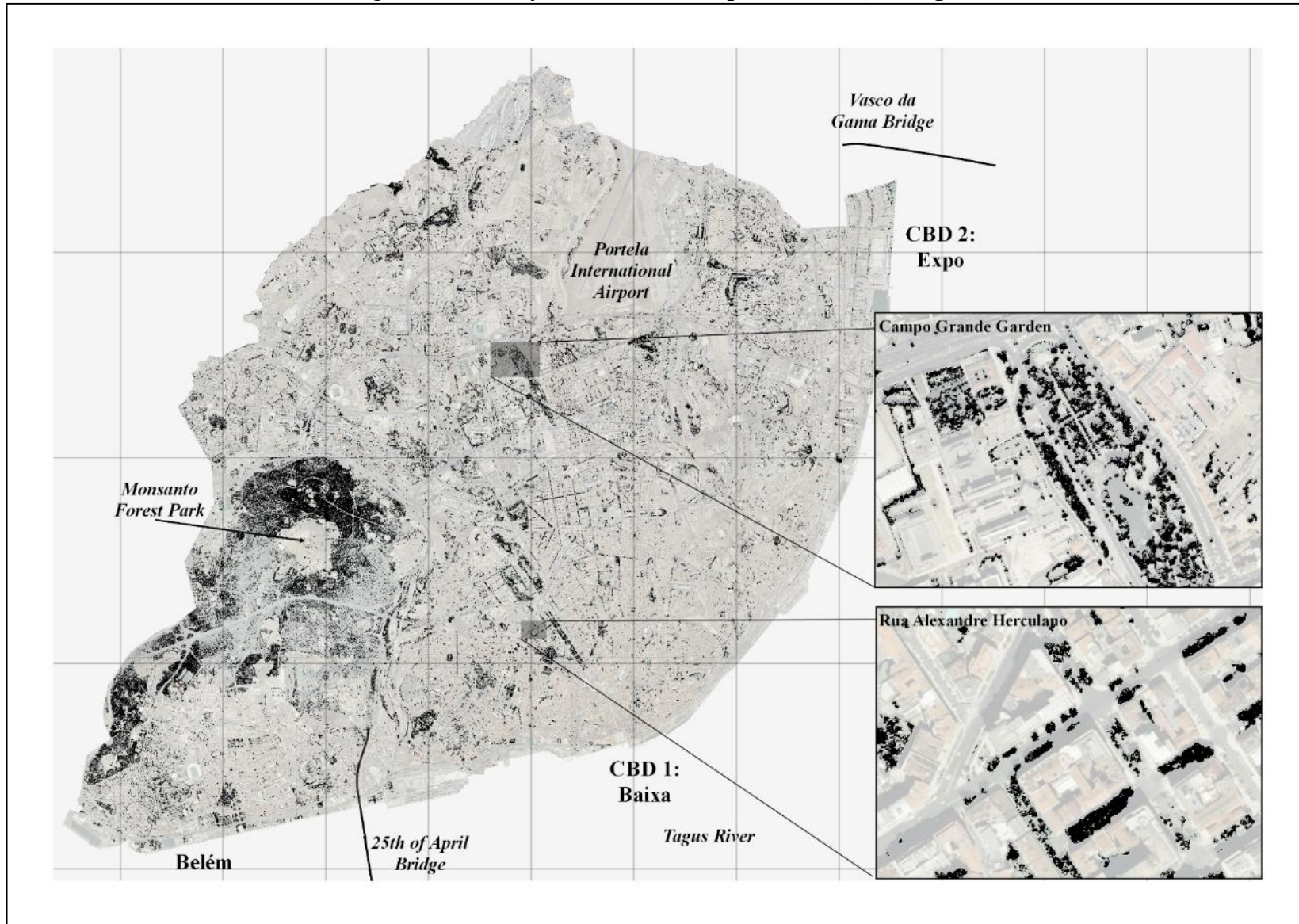
The user accuracy for positive cases tend to be greater than the producer accuracy while the reverse is true for negative cases. This indicates that tree canopies that are classified via the SVM have a high probability of corresponding to actual tree canopies on the ground, while for negative cases where we have high producer accuracy this indicates that all other classes on the ground (e.g. roads and buildings) have a high probability of being correctly classified.

6. Hedonic Valuation of Green Amenities and Urban Trees

There is a wide range of applications for the remote sensing of tree canopies, among others the economic valuation of urban green amenities and public street trees. We explore the values of urban green amenities, making use of the hedonic framework to estimate the impact of disaggregated green spaces by type, size and usage (e.g. parks, gardens, urban forests, playgrounds and cemeteries) and the location of urban street trees categorized by their heterogeneous characteristics and tree canopy.

The hedonic framework uses variability in dwelling prices and access to urban green amenities to estimate the marginal value of proximity to these amenities or higher concentrations of them within the neighborhood. Interaction effects between urban green amenities with broader neighborhood and ecological parameters are important for policy discussions on provision and accessibility of these amenities and their desirability by homebuyers.

Figure 4. Remotely Sensed Tree Canopies in Lisbon, Portugal



Our empirical hedonic specification is expressed as follows:

$$P = \beta_0 + S\beta_1 + B\beta_2 + D\beta_3 + G\beta_4 + \varepsilon$$

where housing price, P , for an observation is influenced by a vector of structural characteristics of the dwelling, S , neighborhood attributes, B , measures of accessibility to local urban amenities, D , and the variables of interest, G , which represent proximity and concentration of urban green amenities and street trees. The error term ε is classical, following a normal distribution with zero mean and constant variance.

6.1. Spatial Dependence of Housing Prices

House pricing techniques involve looking at the price of comparable dwellings in the neighborhood such that a dwellings listing price or assessment value is determined in part by the value of neighboring dwellings through a signaling mechanism. This implies a direct spatial relationship between property values in the sense that the price of a house will influence the price of other houses located relatively nearby, and vice-verse. OLS estimates may be biased or inefficient under the presence of this spatial dependence.

Alternatively, omitted or unobserved variables such as outdoor maintenance expenditures or public perception of certain areas in a city may be correlated in space through an externality mechanism, which in turn can influence property prices in a particular neighborhood. Under Gauss-Markov assumptions the covariance between error terms must be zero, and when this unobservable spatial dependence between housing prices is present, this assumption is violated. OLS tends to underestimate standard errors in hedonic regressions, and if these unobserved amenities are correlated with neighborhood housing prices, OLS also yields biased coefficient estimates.

The traditional OLS specification is augmented to model this underlying spatial structure. We define four spatial weight matrices to measure the influence of dwellings within proximity to each other and check for the robustness of the estimated spatial dependence and coefficients. Two binary matrices specify neighbors based on the 100 nearest dwellings and all dwellings within a radius of 500 meters, which has on average 400 neighbors and covers a handful of city blocks in which local amenities such as grocery stores are located. Specifying the 100 nearest dwellings allows for a tighter definition of neighbors and based on the dispersion of observations in the city, corresponds to dwellings located within a few streets of each other. We further estimate the spatial statistics and models with an inverse distance and inverse squared distance weight for neighbors within 500 meters. These spatial weight matrices are summarized in table 1.

For symmetric weight matrices based on neighbors within 500 meters and the inverse distance weights we use the Cholesky decomposition algorithm for sparse matrices to obtain numerical solutions for the coefficient and standard error estimates. When working with the non-symmetric nearest 100-neighbors matrix, we use the LU factorization method.

Table 1. Spatial Weights

	Description	Number of locations	Number of nonzero links	Percentage nonzero weights	Average number of links
SW1:	Inverse distance for all properties within 500 m	11,616	4,617,282	3.42	397.49
SW2:	Inverse distance squared for all properties within 500 m	11,616	4,617,282	3.42	397.49
SW3:	All properties within 500 m	11,616	4,617,292	3.42	397.49
SW4:	100 Nearest Neighbors	11,616	1,161,600	0.86	100

Spatial Hedonic Specifications

The general spatial hedonic form can be expressed as follows:

$$P = \beta_0 + \sum_{k=1}^m \beta_k z_k + \rho_{lag} \mathbb{W}P + \varepsilon$$

$$\varepsilon = \rho_{err} \mathbb{W}\varepsilon + u ; \quad u \sim iid(\mathbf{0}, \sigma^2 \mathbf{I}_n)$$

where the m regressors z capture the effects on housing prices attributed to dwelling characteristics, S , neighborhood attributes, B , accessibility, D , and urban green amenities, G . We account for spatial dependence by incorporating either the spatially lagged dependent variable $\mathbb{W}P$ where neighboring prices are weighted by each of the four spatial weight matrices in turn, \mathbb{W} . Alternatively the original OLS error ε can be modeled as an autoregressive error term accounting for spatial correlation, $\mathbb{W}\varepsilon$, or by the inclusion of both terms in a mixed model whereby u follows classical error term assumptions. Maximum likelihood is used to simultaneously estimate the lagged ρ and β_k parameters. From the above general specification, when $\rho_{lag} = 0$ we have a spatial error model (SEM) and with $\rho_{err} = 0$, the spatial autoregressive model (SAR). With economic intuition for the inclusion of both such spatial dependencies, we further estimate the mixed spatial autoregressive model with autoregressive disturbances (SARAR).

Spatial Statistics

We test for and find significant spatial autocorrelation in the dependent variable and the OLS residuals using the Moran I statistic. This test evaluates whether a pattern is clustered with positive autocorrelation, dispersed with negative autocorrelation or random. The spatial LM test diagnostics treat the standard OLS model as the restricted model (null hypothesis) and the spatial model as the unrestricted model (alternative hypothesis) and can thus effectively consider differences between spatial and non-spatial models and whether spatial dependence is a result of an omitted spatial lag of the

dependent variable or through the error component, ultimately indicating whether the SEM, SAR or SARAR models are appropriate.

Our results indicate significant positive spatial correlation in housing prices indicating that similarly priced dwellings cluster together more so than would be expected under a random spatial distribution (see table A1 of the Appendix). There is further evidence of underlying spatial processes with significant spatial autocorrelation through the residual terms of each model. These results are robust across all four spatial weight specifications. Significant LM statistics across all weight matrices further justify the modeling of the SEM, SAR and SARAR models with model selection to be based on the AIC criteria and variable significance.

Multicollinearity

With the inclusion of spatial variables measuring distances to different types of amenities, it is important to consider the impacts and manage multicollinearity in the models. The standard measure of multicollinearity in multivariate regression models is the variance inflation factor (VIF) which considers the explanatory power that regressors have on each other.¹⁰ We adopt a threshold VIF level of 10 above which estimates are considered to be heavily influenced by multicollinearity and from which inferences cannot be made. Although some variables have associated VIF values above 10, we draw no conclusions from these and care is made to ensure that the variables of interest have appropriate VIF levels. Since multicollinearity influences only the respective variables standard error, we are able to draw conclusions from the variables of interest for which the VIF levels are appropriate.

In order to manage multicollinearity, we limit the number of variables introduced in the model which measures distance to certain amenities. Alternative measures of proximity are explored by including dummy variables for location within mutually exclusive and concentric buffers surrounding such amenities as the primary and secondary CBD's, the airport and Monsanto Forest Park. This approach was explored by Tyrväinen (2000) and is a viable way of exploring accessibility to these types of amenities when there are a large number of observations.

6.2. OLS Hedonic Estimates

All hedonic specifications control for geographic and urban green amenities with urban street trees introduced according to foliage type: deciduous (loosing leaves in the winter), evergreen, palm or shrubs/ bushes. In addition to the number of street trees in each neighborhood, we control for the neighborhood tree canopy coverage.

We use a semi-log hedonic model to measure the percentage change in housing prices due to a unit change in the regressors. A number of OLS models are estimated with extensions to spatial modelling conducted on our preferred specification with models introducing interaction effects between trees and

¹⁰ The VIF for individual regressor j is defined as $\frac{1}{1-R_j^2}$, where R_j^2 is the coefficient of determination for regressing j on all other covariates.

both historic protected zones and areas of high flooding risk. Our baseline OLS specifications have R^2 values in the magnitude of 0.64.

For each spatial specification the SAR, SEM and SARAR are estimated each under the four chosen weight matrices. Based on the combination of the AIC criteria and variable significance, the preferred spatial specification is the SEM under the inverse squared distance within 500 meters as neighbors (SW2) and results presented focus on comparing baseline OLS to this specification.¹¹ Results indicate that for each specification, relative to the baseline OLS the spatial models have improvements in terms of the AIC criteria and reduction in the sum of squared errors. Estimated spatial parameters are significant and indicate positive spatial dependence in the models. Comparison results and spatial diagnostics for the preferred spatial model are in table 2.

Table 2. OLS and SEM Diagnostics (SW2)

	N	Global Adj. R2	AIC	SSE	Rho Err	Wald Statistic	LR Statistic
<i>Urban Street Trees by Type</i>							
OLS	11,616	0.643	-2336.9	550.27	-	-	-
SEM	11,616	-	-2355.0	548.86	0.0430***	56.31***	20.13***
<i>Urban Street Trees by Type (Interaction with Protected Zones)</i>							
OLS	11,616	0.644	-2345.6	549.39	-	-	-
SEM	11,616	-	-2362.5	548.06	0.0417***	17.67***	18.97***
<i>Urban Street Trees by Type (Interaction with Areas of High Flood Risk)</i>							
OLS	11,616	0.644	-2347.4	549.30	-	-	-
SEM	11,616	-	-2394.3	548.02	0.0669***	44.94***	48.86***

Notes: ***Significance at 1 p.c. level; **Significance at 5 p.c. level; *Significance at 10 p.c. level.

Table 3 highlights the results which pertain to urban green amenities and street trees for the OLS and spatial models. Full results with complete list of variables are found in table A1 of the appendix. Results indicate that different urban green amenities, and more specifically different types of urban trees, have heterogeneous impacts on the residential real estate market.

¹¹ Results presented are robust in terms of magnitudes across all spatial weights and model specifications. Additional empirical results available upon request.

Table 3. OLS and Spatial Hedonic (SEM) Estimations

	Street Trees		Street Trees by Type		Street Trees by Type (Protected Zone Interaction)		Street Trees by Type (Flood Risk Interaction)						
	OLS		OLS	Sp. Error	OLS	Sp. Error	OLS	Sp. Error					
<i>Neighborhood Geography and Historic Characteristics</i>													
Located in Historic Protected Zone	0.02371 *** 0.00889		0.02622 *** 0.00890		0.02684 *** 0.00921		0.03309 ** 0.01317		0.03297 ** 0.01348		0.02669 *** 0.00899		0.02752 *** 0.00949
Count of Historic Monuments 100 m	0.05547 *** 0.00833		0.05709 *** 0.00833		0.05718 *** 0.00864		0.05851 *** 0.00843		0.05881 *** 0.00873		0.05953 *** 0.00840		0.05915 *** 0.00888
High Risk of Flood	-0.00405 0.00928		-0.00158 0.00929		-0.00074 0.00963		-0.00303 0.00937		-0.00213 0.00969		-0.00895 0.01271		-0.00938 0.01324
View of Tagus River	0.05520 *** 0.00882		0.05614 *** 0.00881		0.05689 *** 0.00878		0.05690 *** 0.00881		0.05756 *** 0.00878		0.05609 *** 0.00881		0.05639 *** 0.00876
<i>Urban Green Amenities</i>													
Dist. to Nearest Urban Forest	-0.03661 *** 0.00727		-0.03606 *** 0.00729		-0.03707 *** 0.00756		-0.03634 *** 0.00734		-0.03742 *** 0.00760		-0.03873 *** 0.00744		-0.03995 *** 0.00787
Within 500 m of Monsanto	0.00897 0.01740		0.00718 0.01745		0.00641 0.01806		0.00573 0.01776		0.00494 0.01834		0.00670 0.01752		0.00574 0.01850
Within 500-750 m of Monsanto	0.00801 0.01366		0.00084 0.01398		-0.00003 0.01444		-0.00057 0.01424		-0.00101 0.01468		0.00194 0.01418		0.00011 0.01491
Within 750-1000 m of Monsanto	0.05062 *** 0.01009		0.04160 *** 0.01028		0.04197 *** 0.01065		0.04090 *** 0.01048		0.04148 *** 0.01084		0.04252 *** 0.01053		0.04284 *** 0.01113
Dist. to Nearest Cemetery	0.06012 *** 0.00704		0.05704 *** 0.00706		0.05762 *** 0.00732		0.05486 *** 0.00723		0.05537 *** 0.00748		0.05888 *** 0.00715		0.05959 *** 0.00757
Dist. to Nearest Playground	0.07609 *** 0.01540		0.07180 *** 0.01551		0.07151 *** 0.01609		0.07847 *** 0.01574		0.07821 *** 0.01630		0.07386 *** 0.01584		0.07478 *** 0.01677
Dist. to Nearest Small Park	-0.03548 *** 0.00940		-0.03265 *** 0.00942		-0.03254 *** 0.00977		-0.03420 *** 0.00970		-0.03422 *** 0.01004		-0.03310 *** 0.00946		-0.03297 *** 0.01003
Dist. to Nearest Medium Park	-0.02811 *** 0.00897		-0.03300 *** 0.00909		-0.03293 *** 0.00943		-0.03052 *** 0.00916		-0.03050 *** 0.00949		-0.03275 *** 0.00914		-0.03235 *** 0.00969
Dist. to Nearest Large Park	0.00678 0.00445		0.00901 ** 0.00451		0.00887 * 0.00468		0.00427 0.00488		0.00408 0.00504		0.00955 ** 0.00455		0.00902 * 0.00482

Urban Street Trees

Neighborhood Monument Trees	0.00404 *	0.00245	0.00254	0.00248	0.00261	0.00478 *	0.00439
	0.00239	0.00243	0.00243	0.00246	0.00246	0.00281	0.00283
Neighborhood Trees	0.00002						
	0.00002						
Neighborhood Deciduous Trees		0.00079 ***	0.00075 ***	0.00086 ***	0.00082 ***	0.00113 ***	0.00106 ***
		0.00015	0.00015	0.00016	0.00016	0.00017	0.00018
Neighborhood Evergreens		-0.00185 ***	-0.00170 ***	-0.00194 ***	-0.00180 ***	-0.00261 ***	-0.00237 ***
		0.00043	0.00043	0.00043	0.00044	0.00047	0.00047
Neighborhood Palm Trees		-0.00392 *	-0.00434 **	-0.00477 **	-0.00518 ***	-0.00486 **	-0.00533 *
		0.00205	0.00208	0.00220	0.00223	0.00219	0.00224
Neighborhood Shrubs		-0.00387	-0.00264	-0.00229	-0.00122	-0.00467	-0.00349
		0.00476	0.00481	0.00483	0.00488	0.00501	0.00508
% Neighborhood Tree Canopy	-0.01519	-0.08301 **	-0.07637 **	-0.10510 **	-0.09883 **	-0.15870 ***	-0.14789 ***
	0.03535	0.03814	0.03845	0.04209	0.04243	0.04644	0.04702
Historic Protected Zone*Deciduous Trees				0.00022	0.00018		
				0.00065	0.00067		
Historic Protected Zone*Evergreens				-0.00856 ***	-0.00844 **		
				0.00331	0.00338		
Historic Protected Zone*Palm Trees				0.02172 ***	0.02159 ***		
				0.00624	0.00640		
Historic Protected Zone*Shrubs				0.02182	0.02403		
				0.02148	0.02186		
Historic Protected Zone*Tree Canopy				0.05277	0.05911		
				0.09176	0.09342		
High Risk of Flood*Deciduous Trees						-0.00151 ***	-0.00143 ***
						0.00036	0.00036
High Risk of Flood*Evergreens						0.00339 **	0.00306 **
						0.00133	0.00134
High Risk of Flood*Palm Trees						0.01045 **	0.01019 *
						0.00531	0.00543
High Risk of Flood*Shrubs						0.00530	0.00556
						0.01247	0.01298
High Risk of Flood*Tree Canopy						0.22710 ***	0.23352 ***
						0.08756	0.08871

Notes: ***Significant at the 1 percent level; **Significant at the 5 percent level; *Significant at the 10 percent level.

Dwelling structural characteristics behave as expected with significant positive contributions to prices. The strongest drivers of prices include whether a dwelling is new, selling at a premium of 15%, whether the dwelling has air conditioning, with a premium of 14%, and whether a dwelling has a pool, with a premium of 11%. These structural characteristics are indicative of newer more modern dwellings with personal space. Floor space has a positive impact with each additional square meter contributing 0.9% to the price.

In terms of neighborhood characteristics, an increase in the *freguesia* average income level and the percent of non-residential buildings in a neighborhood both have positive impacts on the asking price of a dwelling. Neighborhoods with a higher population density however have negative impacts on prices in the range of 0.9% while neighborhoods with an older population similarly have lower prices of about 4%. Controlling for the percentage of buildings built in different eras, we see that there is heterogeneity in how the residential real estate market values the neighborhood composition of buildings of different ages, potentially due to varying architectural style and quality.

Using concentric rings to control for accessibility to the CBD's indicate positive significance for being located within 200 meters of *Baixa* of approximately 11% and of approximately 22% for being located within 750 meters of Expo. While there is a significant positive effect for being located within either CBD, we see that this effect drops off and is no longer present when we move further away from these areas. Dwellings located within the buffer of 750 to 1,500 meters from the airport have lower prices in the range of 13%, potentially due to noise and air pollution coming from large airport.

Other accessibility measures indicate that resident's value positively to be located near schools in the range of 6% increase in prices for a kilometer increase in proximity, and a 2% increase in prices for increased proximity to arts amenities (museums and galleries). Meanwhile, proximity to train stations tend to have a negative impact on prices in the range of 2%. Dwellings with a view of the Tagus River have a premium of approximately 5%.

Playgrounds

Proximity to playgrounds have significant negative impact on housing prices after controlling for spatial dependence in the order of a 7% decrease in prices for every kilometer closer to a playground. These amenities are catered towards specific demographics, namely those residents with children, and may be associated with increased noise and congestion with families frequenting playgrounds often, considering that few homes have private gardens or outdoor spaces for children.

Urban Forests, Monsanto, Parks and Gardens

Proximity to urban forests, which tend to be more dense and left to grow uninhibited, have a positive impact on residential real estate with these amenities providing benefits to residents in terms of recreational facilities and areas to enjoy nature away from the busy city life. These impacts are strongest

and most consistent in the spatial hedonic models in the range of 4% per kilometer increase in proximity, highlighting the benefit of spatial models over the baseline OLS specifications.

We extract the Monsanto Forest Park from overall urban forests due to its size and prominence to the city. In both the OLS and spatial models, we find no significant effects for being located in direct proximity to this park, however there are positive influences for being located at a slight distance, from 750 to 1,500 meters. Results from the spatial hedonic model are slightly greater in magnitude suggesting a premium of 4.2% for dwellings in this zone. While Monsanto has a range of natural and recreation amenities for residents, anecdotal evidence suggests that people perceive this area to be unsafe after dark and additionally many thoroughfares also pass through the park directly to link different areas of the city. This may explain why direct proximity does not yield any positive benefits to residents while being within driving distance does. Monsanto therefore has important amenity value to residents, and by introducing measures of concentric rings around the park we are able to capture the varying impacts of how the effect changes in relation to proximity. Thus implementing dummy variables for location within concentric rings of an amenity serve as an appropriate substitute for accessibility as measured by distance for determining how residents value varying degrees of proximity to the amenity while managing issues with multicollinearity.

Comparatively, parks and gardens are maintained and manicured by the municipal authority. We find that park size has important influences and that positive impacts on dwelling prices stem from proximity to smaller neighborhood parks (under 10,000 m²) in the range of 3.3% in the spatial models and 3.2% for proximity to medium sized parks (10,000 m² to 100,000 m²). There is some evidence to suggest that while small and medium neighborhood parks are valued by residents, large parks have little significance and in some cases a negative influence on prices. When residents decide on visiting urban green amenities, it may be that there is a stronger preference to visit urban forests with many recreational activities as opposed to large manicured parks of similar sizes, when the amenities found in larger parks can also be obtained in smaller neighborhood parks.

Cemeteries

While small parks and urban forests tend to be positively valued by the residential real estate market, other types of open spaces have a negative effect. Results show that proximity to cemeteries decrease housing prices in the magnitude of 6% for each kilometer closer. This is consistent across both OLS and spatial error specifications. While indeed cemeteries tend to be wide open spaces with lush greenery, the social context and interaction with residents is very different than with parks or gardens.

Urban Street Trees

In terms of urban street trees there is no significance for trees overall, however we find some indication that monumental trees, which are considered as living history of the city, have significant impacts of about 0.4% increase in prices for additional monumental trees in the neighborhood. While

trees on their own do not have any significant effects once we disaggregate by tree type, as defined by the foliage of the tree, we see that considering the heterogeneity of these trees are important for the residential real estate market.

Deciduous trees, which are the most numerous in the city, have a positive influence on housing prices with each additional tree in the neighborhood contributing 0.08% to housing prices. Deciduous trees include those which lose their leaves in the winter time and produce foliage, and potentially flowers, during the spring and summer.

Comparatively, evergreen trees tend to have a negative influence on the real estate market of approximately 0.1% per additional tree. While deciduous trees lose their leaves in the fall, evergreen trees remain lush all year round. When considering how a homeowner may perceive urban street trees, it is important to consider the shade which is provided by these trees. While trees may be aesthetically pleasing, large trees with lush vegetation all year round may actually be disliked by homeowners with potential blockage of view or shading of the sun, especially in the winter since many homes lack central heating and rely on sunlight during the day to provide warmth and light.

We disaggregate evergreen trees into both conifer evergreens and broadleaf evergreens and find that this negative result is driven exclusively by conifers, which tend to be more dense and dark than broadleaved trees. While we are able to disaggregate between the two, we conduct the analysis considering only evergreens in general since the disaggregation of sub-type increases the VIF and multicollinearity concerns.

We control for both the number of trees accessible to residents in the neighborhood and further by the overall vegetation coverage of these trees. In line with this result, we find that neighborhoods with a higher coverage of tree canopies have a negative influence on prices in the range of a 10% decrease for every additional percentage coverage. Tree canopy coverage is measured via our work on remote sensing and thus captures large tree canopies as seen from a top-down perspective which stand out significantly among dwellings. With many homes concerned about energy efficiency and having sunlight during the day, increased tree canopy, and especially when this canopy is there all year round, makes for an undesirable dwelling trait.

Results indicate that palm trees tend to have a negative influence on housing prices in the range of 0.4%. This may be due to the fact that most palm trees in the city are planted along sprawling boulevards and freeways and this negative influence is capturing other aspects of the urban structure. Interestingly however we see that although palm trees in general have a negative influence, the interaction effect of palm trees and historic protected zone is positive and significant indicating that there is a positive amenity value of palm trees in these areas of about 2%. Given that palm trees are primarily aesthetic, they are complementary to historic protected zones indicating that residents value these green amenities when they contribute to the aesthetic or cultural aspect of an area in the city.

While palm trees have a positive interaction effect in historic zones, evergreen trees continue to have a negative influence in historic protected zone. Evergreen trees (such as conifers) are important

for urban forests however they may be unappealing for the general urban landscape and particularly in historically significant areas where aesthetics and views are important.

Urban Street Trees to Mitigate Flood Risk

The amenity value of urban street trees is highlighted when considering other aspects of the urban environment besides shade and views, namely when it comes to urban flooding. While in general evergreen trees, palm trees and tree canopy overall have a negative influence on the real estate market, when we consider interaction effects with these trees in locations of high flooding risk they have positive values of about 0.3% per evergreen and 1% per palm tree. Higher vegetation in the form of tree canopy is significant in terms of mitigating the negative influence of flood risk. Flooding in Lisbon is common and well publicized each year, and thus a relevant problem for households. While some households may dislike certain tree types due to shading or other reasons, there are clear ecological amenity values of trees in terms of managing urban flooding. As Lisbon experiences brief yet intense rainy seasons, this has important policy implications for municipalities in planning the planting of trees strategically to mitigate flood damage to dwellings.

7. Conclusions

This paper finds that the housing market values urban green amenities and street trees differently based on their attributes and characteristics. Empirical results show that not all types of trees are valued the same in the residential real estate market depending on location and relative ages. Remote sensing techniques are a promising avenue through which additional environmental data on tree canopies can be obtained to complement the ways in which trees can be classified.

With increasingly detailed data and computational power, remote sensing and GIS data continue to provide viable ways to explore urban policy analysis. High resolution aerial photography has shown itself to provide accurate data regarding the location of tree canopies, distinguishing them from all other land uses such as roads and buildings.

In modelling urban green amenities with a hedonic framework, it is important to take into account the differences between amenities and how they are perceived by individuals. Empirical results show that different types of green amenities and namely urban street trees can have very different influences on the housing market, and by simply considering the broad impact of trees without considering how they are perceived by residents, such results may mask important underlying impacts. Tree canopies have often been overlooked in hedonic studies due to the difficulty in obtaining the data, however increasing availability of spatially detailed data allow for studies on these impacts.

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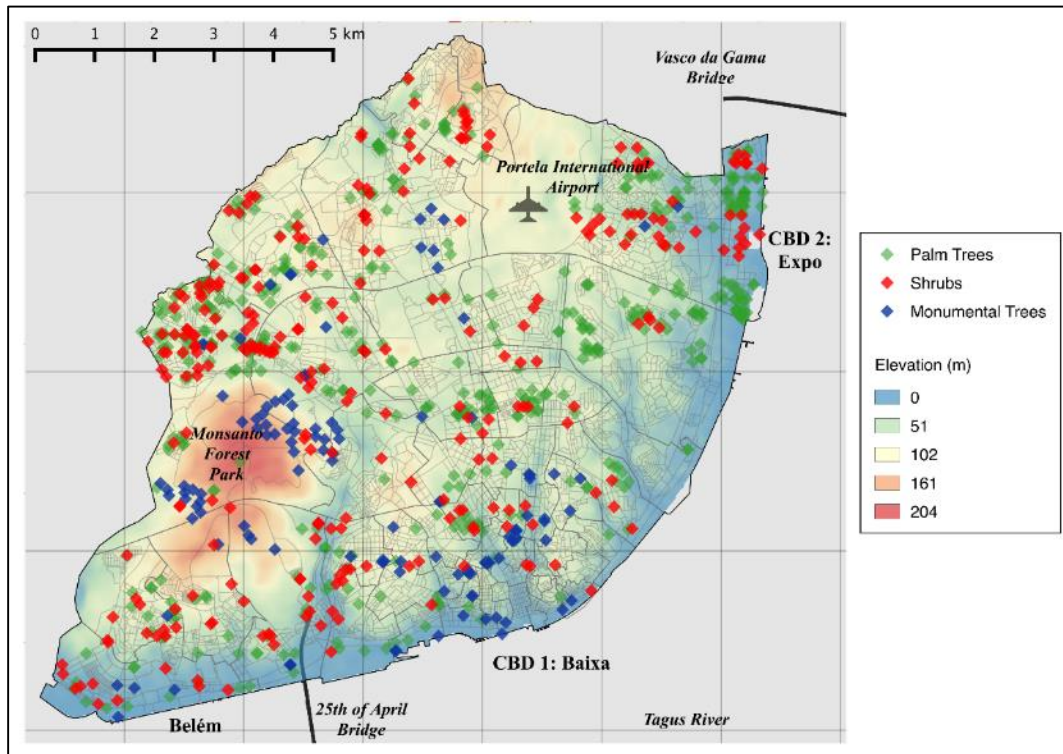
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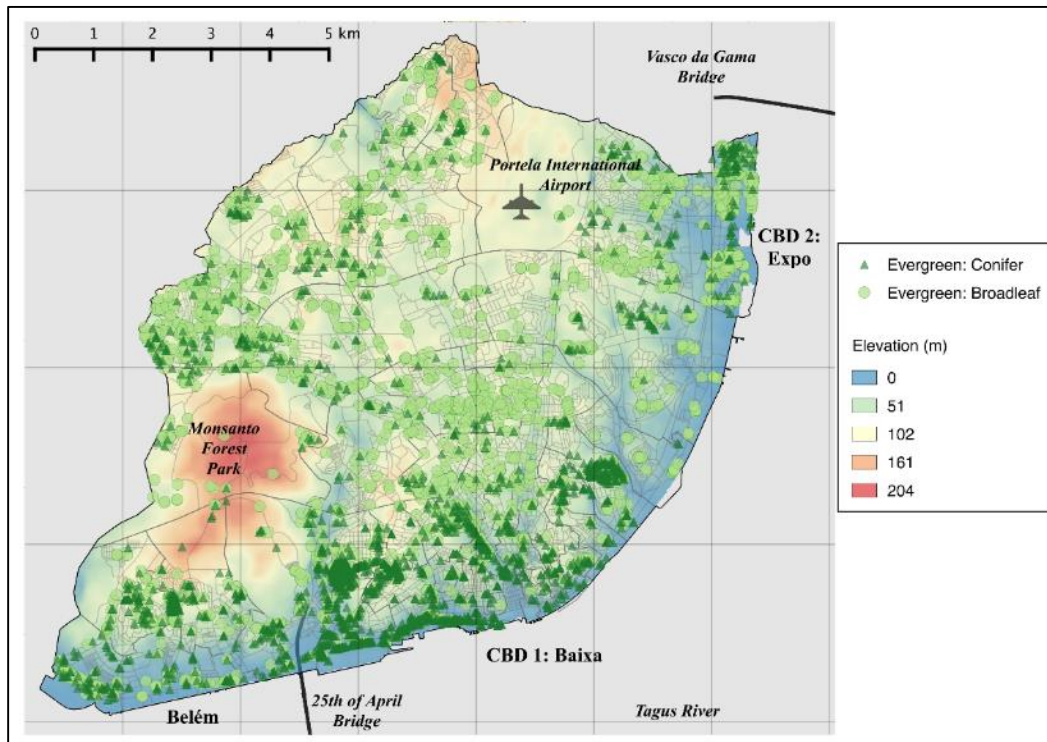
Appendix

Figure A1. Urban Street Tree Locations

Panel A: Monumental Trees, Palm Trees and Shrubs



Panel B: Broadleaf and Coniferous Evergreen Trees



Panel C: Deciduous Trees

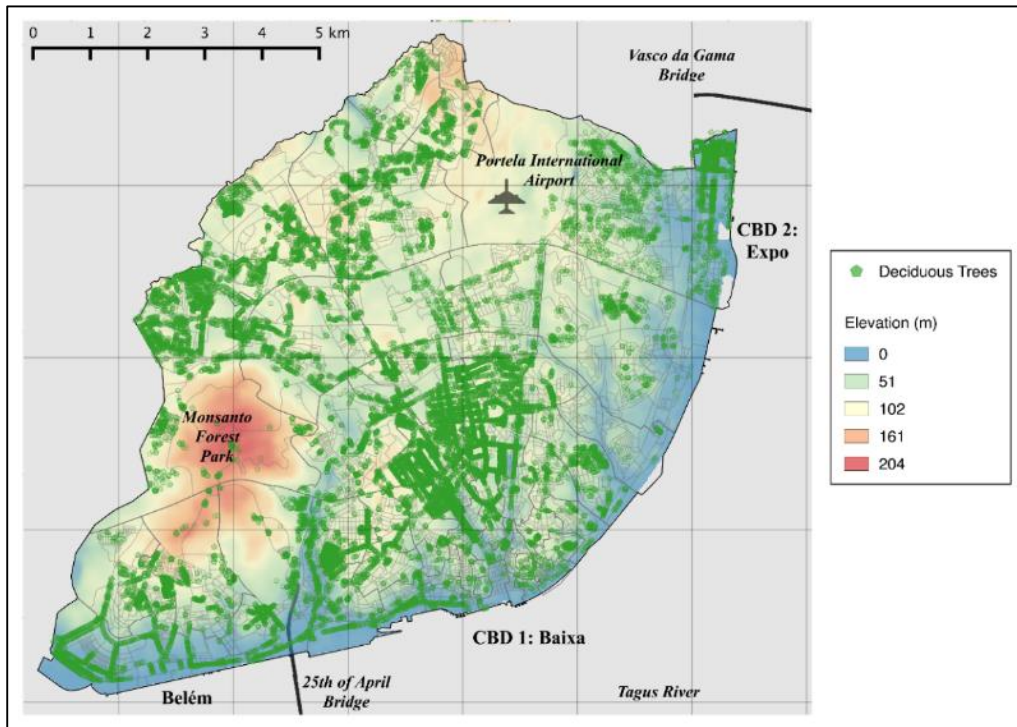


Figure A2.a. Remote Sensing Accuracy Assessment
Area A: Eduardo VII Park and Area B: Praça de Espanha

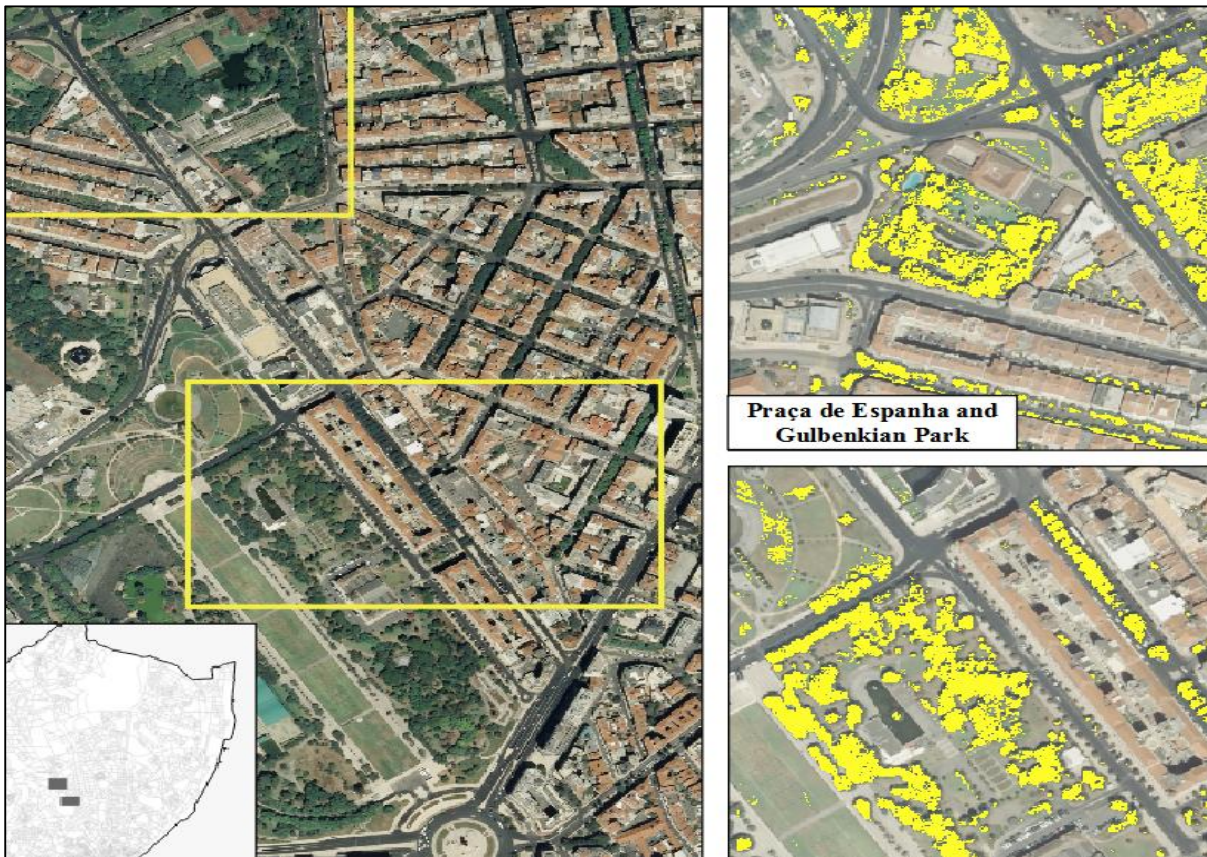


Figure A2.b. Remote Sensing Accuracy Assessment

<i>Study Area A</i>				<i>Study Area B</i>					
One-Class SVM				One-Class SVM					
		Negative (Other)	Positive (Canopy)			Negative (Other)	Positive (Canopy)		
Land Truth	Negative (Other)	420	5	425	Land Truth	Negative (Other)	358	20	378
	Positive (Canopy)	37	38	75		Positive (Canopy)	42	80	122
	457	43	500	400		100	500		

Figure A2.c. Remote Sensing Accuracy Assessment: User, Producer and Overall Accuracy

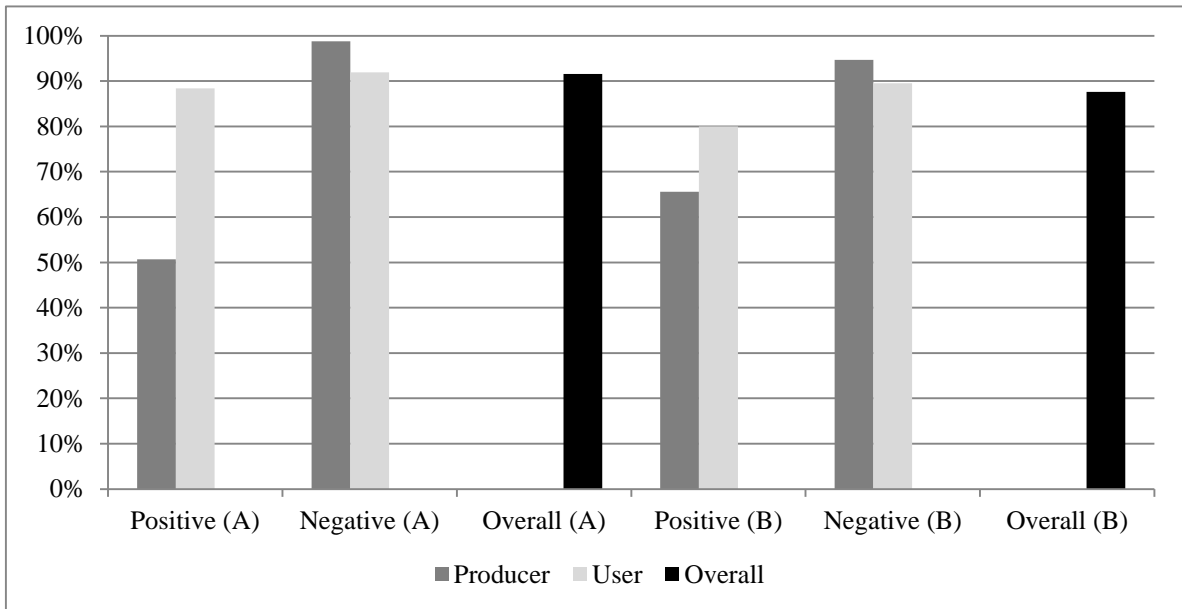


Table A1. Tests of Spatial Statistics

	Global Moran's I (Dep.)	Z-Value (Dep.)	Global Moran's I (Res.)	Z-Value (Res.)	LM Error	LM Lag	Rob. LM Error	Rob. LM Lag
Street Trees								
SW1	0.2640***	54.27	0.0562***	12.29	133.60***	52.01***	95.97***	14.42***
SW2	0.2743***	30.51	0.0675***	7.87	56.37***	49.56***	21.70***	14.89***
SW3	0.2267***	209.00	0.0267***	33.68	597.70***	33.03***	579.90***	15.22***
SW4	0.2350***	190.90	0.0344***	35.63	774.30***	607.80***	344.00***	177.50***
Street Trees by Type								
SW1	0.2640***	54.27	0.0420***	9.38	74.69***	39.83***	48.47***	13.61***
SW2	0.2743***	30.51	0.0403***	4.85	20.06***	30.29***	3.86**	14.09***
SW3	0.2267***	209.00	0.0249***	32.07	524.40***	32.31***	507.00***	14.92***
SW4	0.2350***	190.90	0.0296***	31.18	572.10***	543.20***	221.90***	192.90***
Street Trees by Type (Protected Zone Interaction)								
SW1	0.2640***	54.27	0.04084***	9.18	70.48***	38.34***	45.46***	13.33***
SW2	0.2743***	30.51	0.03897***	4.73	18.78***	29.02***	3.48*	13.73***
SW3	0.2267***	209.00	0.02408***	31.62	490.10***	31.44***	473.50***	14.82***
SW4	0.2350***	190.90	0.02825***	30.37	521.20***	509.50***	198.40***	186.60***
Street Trees by Type (Flood Risk Interaction)								
SW1	0.2640***	54.27	0.05177***	11.43	113.30***	45.92***	80.66***	13.25***
SW2	0.2743***	30.51	0.06266***	7.36	48.62***	44.35***	18.14***	13.87***
SW3	0.2267***	209.00	0.024***	31.19	484.00***	28.22***	469.20***	13.35***
SW4	0.2350***	190.90	0.03055***	32.34	609.30***	516.60***	257.70***	164.90***

Notes: ***Significance at 1 p.c. level; **Significance at 5 p.c. level; *Significance at 10 p.c. level.

Table A2. OLS and SEM Spatial Hedonic Full Results

	Street Trees			Street Trees by Type			Street Trees by Type (Protected Zone Interaction)			Street Trees by Type (Flood Risk Interaction)								
	OLS			OLS	Sp. Error		OLS	Sp. Error		OLS	Sp. Error							
Intercept	11.17 *** 0.03545	***		11.21 *** 0.03641	***		11.21 *** 0.03658	***		11.22 *** 0.03768	***		11.23 *** 0.03665	***		11.24 *** 0.03846	***	
Structural Characteristics																		
Area	0.00879 *** 0.00010	***		0.00879 *** 0.00010	***		0.00878 *** 0.00010	***		0.00877 *** 0.00010	***		0.00879 *** 0.00010	***		0.00876 *** 0.00010	***	
New Dummy	0.15420 *** 0.00584	***		0.15380 *** 0.00584	***		0.15326 *** 0.00582	***		0.15340 *** 0.00584	***		0.15292 *** 0.00582	***		0.15350 *** 0.00584	***	0.15328 *** 0.00581
Pool Dummy	0.11200 *** 0.02431	***		0.11220 *** 0.02429	***		0.11355 *** 0.02419	***		0.10920 *** 0.02429	***		0.11049 *** 0.02420	***		0.11210 *** 0.02427	***	0.11423 *** 0.02419
Parking Dummy	0.06793 *** 0.00757	***		0.06810 *** 0.00757	***		0.06908 *** 0.00754	***		0.06789 *** 0.00757	***		0.06884 *** 0.00754	***		0.06874 *** 0.00756	***	0.06998 *** 0.00752
Fireplace Dummy	0.01784 0.01343			0.01637 0.01342			0.01674 0.01338			0.01699 0.01342			0.01729 0.01337			0.01671 0.01341		0.01651 0.01332
Double Windows Dummy	0.01986 *** 0.00568	***		0.02010 *** 0.00567	***		0.02057 *** 0.00565	***		0.02040 *** 0.00567	***		0.02083 *** 0.00565	***		0.02011 *** 0.00567	***	0.01925 *** 0.00564
Air Conditioning Dummy	0.14830 *** 0.00684	***		0.14840 *** 0.00683	***		0.14730 *** 0.00682	***		0.14830 *** 0.00683	***		0.14727 *** 0.00681	***		0.14800 *** 0.00683	***	0.14716 *** 0.00678
Elevator Dummy	0.02327 *** 0.00576	***		0.02308 *** 0.00575	***		0.02225 *** 0.00574	***		0.02357 *** 0.00575	***		0.02275 *** 0.00574	***		0.02283 *** 0.00575	***	0.02248 *** 0.00572
Neighborhood Characteristics																		
% Buildings Built Pre 1919	0.04218 *** 0.01299	***		0.03292 ** 0.01331	**		0.02946 ** 0.01340	**		0.03756 *** 0.01342	***		0.03410 ** 0.01350	**		0.02475 * 0.01345	*	0.01985 0.01357
% Buildings Built 1919-1945	0.03168 0.01551	**		0.01610 0.01622			0.01476 0.01628			0.01664 0.01624			0.01551 0.01630			0.00675 0.01643		0.00542 0.01654
% Buildings Built 1946-1960	0.04833 *** 0.01510	***		0.04676 *** 0.01514	***		0.04530 *** 0.01523	***		0.05164 *** 0.01533	***		0.05033 *** 0.01541	***		0.03817 ** 0.01536	**	0.03557 ** 0.01549
% Buildings Built 1961-1970	0.02178 0.01600			0.02462 0.01674			0.02151 0.01682			0.02396 0.01685			0.02111 0.01692			0.01856 0.01681		0.01425 0.01693
% Buildings Built 1971-1980	0.06238 ***	***		0.04943 ***	***		0.04730 ***	***		0.05472 ***	***		0.05288 ***	***		0.03776 **	**	0.03399 *

	0.01706	0.01734	0.01745	0.01747	0.01758	0.01756	0.01769			
% Buildings Built 1981-1990	- 0.02759 0.02358	-0.03123 0.02374	- 0.03033 0.02381	-0.02803 0.02381	-0.02702 0.02387	-0.04230 0.02398	*	-0.03799 0.02411		
% Buildings Built 1991-1995	0.07367 0.02249	*** 0.05328 0.02283	** 0.05199 0.02309	** 0.02197 0.02536	0.02087 0.02559	0.03079 0.02379		0.02685 0.02418		
% Buildings Built 1996-2000	0.04758 0.02861	* 0.07050 0.02835	** 0.06739 0.02841	** 0.08827 0.02897	*** 0.08446 0.02904	*** 0.04207 0.03074		0.03695 0.03088		
% Buildings Built 2001-2005	- 0.00633 0.01959	-0.03469 0.02031	* 0.03210 0.02053	-0.02858 0.02054	-0.02579 0.02076	-0.04732 0.02053	**	-0.04243 0.02080	**	
% Non-Residential Buildings	0.03229 0.01128	*** 0.03215 0.01150	*** 0.03057 0.01162	*** 0.03356 0.01192	*** 0.03220 0.01204	*** 0.02369 0.01199	**	0.02079 0.01216	*	
Count of Dilapidated Buildings 200 m	- 0.00110 0.00052	-0.00085 0.00053	- 0.00085 0.00055	-0.00081 0.00053	-0.00081 0.00055	-0.00081 0.00053		-0.00076 0.00056		
Average Fregusia Income	0.00001 0.00000	*** 0.00001 0.00000	*** 0.00001 0.00000	*** 0.00001 0.00000	*** 0.00001 0.00000	*** 0.00001 0.00000	***	0.00001 0.00000	***	
Population Density	- 0.00966 0.00456	** -0.00979 0.00457	** 0.00913 0.00457	** -0.01042 0.00458	** -0.00974 0.00458	** -0.01036 0.00457	**	-0.00900 0.00456		
% Population w. Higher Education	- 0.00111 0.01454	-0.01129 0.01504	- 0.01252 0.01518	-0.01598 0.01531	-0.01734 0.01544	-0.00438 0.01530		-0.00582 0.01552		
% Population over 65	- 0.04396 0.01657	*** -0.04182 0.01662	** 0.03971 0.01668	** -0.04350 0.01674	*** -0.04113 0.01679	** -0.05099 0.01688	***	-0.04659 0.01698	***	
% Population under 19	- 0.03256 0.02482	-0.05047 0.02538	** 0.04578 0.02581	* -0.03731 0.02584	-0.03287 0.02623	-0.06383 0.02576	**	-0.05556 0.02642	*	
Accessibility										
Within 200 m of Baixa	0.11300 0.04685	** 0.11490 0.04691	** 0.11644 0.04878	** 0.11760 0.04704	** 0.11917 0.04884	** 0.13210 0.04745	***	0.13235 0.05043	***	
Within 200-750 m of Baixa	- 0.03221 0.01813	* -0.02760 0.01823	- 0.02743 0.01891	-0.02595 0.01855	-0.02575 0.01920	-0.02563 0.01829		-0.02543 0.01937		
Within 750 m of Expo	0.23610 0.02505	*** 0.22990 0.02512	*** 0.23185 0.02605	*** 0.22380 0.02522	*** 0.22587 0.02611	*** 0.22880 0.02518	***	0.23145 0.02666	***	

Within 750-1500 m of Expo	- 0.01862 0.11080	-0.01395 0.11070	- 0.01357 0.11518	-0.01182 0.11060	-0.01131 0.11496	-0.00741 0.11060	-0.01227 0.11783
Within 750 m of Airport	- 0.08552 0.04441	* -0.06879 0.04447	- 0.06936 0.04614	-0.06945 0.04447	-0.07012 0.04608	-0.06670 0.04457	-0.07017 0.04724
Within 750-1500 m of Airport	- 0.13010 0.01987	*** -0.12370 0.02036	*** - 0.12600 0.02103	*** -0.12600 0.02056	*** -0.12849 0.02120	*** -0.13350 0.02073	*** -0.13661 0.02179
Dist. to Freeway	0.01799 0.00733	** 0.00913 0.00755	0.00869 0.00781	0.01002 0.00767	0.00966 0.00792	0.00798 0.00765	0.00738 0.00807
Dist. to Nearest Culture Amenity	0.00055 0.00982	0.00143 0.00988	0.00237 0.01025	0.00051 0.00992	0.00140 0.01027	0.00254 0.00996	0.00409 0.01055
Dist. to Nearest Arts Amenity	- 0.01581 0.00914	* -0.02445 0.00930	*** - 0.02496 0.00964	*** -0.02176 0.00951	** -0.02222 0.00983	** -0.02512 0.00945	*** -0.02577 0.00999
Dist. to Nearest Public Parking	- 0.05138 0.00979	*** -0.04683 0.00983	*** - 0.04772 0.01019	*** -0.04638 0.01010	*** -0.04709 0.01046	*** -0.04932 0.01014	*** -0.05045 0.01073
Count of Metros in 100 m	0.01803 0.01895	0.01707 0.01897	0.01838 0.01964	0.01659 0.01898	0.01794 0.01963	0.01549 0.01896	0.01590 0.02005
Dist. to Nearest Train Station	0.02289 0.00803	*** 0.01695 0.00814	** 0.01725 0.00843	** 0.01589 0.00825	* 0.01619 0.00853	* 0.01689 0.00820	** 0.01705 0.00867
Dist. to Nearest School	- 0.07178 0.01963	*** -0.06399 0.01971	*** - 0.06593 0.02045	*** -0.06275 0.02027	*** -0.06484 0.02098	*** -0.05938 0.02005	*** -0.06425 0.02124
Dist. to Nearest Hospital	0.00364 0.00779	0.00324 0.00823	0.00176 0.00852	0.00118 0.00833	-0.00026 0.00860	0.00180 0.00854	-0.00026 0.00901
Dist. to Nearest Shopping	0.01255 0.00994	0.00686 0.01023	0.00629 0.01060	0.01030 0.01037	0.00978 0.01073	0.00423 0.01031	0.00413 0.01091
Dist. to Nearest Police	- 0.08054 0.01063	*** -0.07228 0.01089	*** - 0.07208 0.01129	*** -0.07148 0.01100	*** -0.07118 0.01139	*** -0.07103 0.01099	*** -0.07078 0.01163
Dist. to Nearest Fire Station	- 0.01806 0.00671	*** -0.01717 0.00680	** - 0.01687 0.00704	** -0.01605 0.00685	** -0.01577 0.00708	** -0.01595 0.00692	** -0.01584 0.00730
Neighborhood Geography and Historic Characteristics							
Located in Historic Protected Zone	0.02371	*** 0.02622	*** 0.02684	** 0.03309	** 0.03297	** 0.02669	*** 0.02752

	0.00889		0.00890		0.00921		0.01317		0.01348		0.00899		0.00949
Count of Historic Monuments 100 m	0.05547 ***		0.05709 ***		0.05718 ***		0.05851 ***		0.05881 ***		0.05953 ***		0.05915 ***
	0.00833		0.00833		0.00864		0.00843		0.00873		0.00840		0.00888
High Risk of Flood	-		-0.00158		-		-0.00303		-0.00213		-0.00895		-0.00938
	0.00405		0.00929		0.00074		0.00937		0.00969		0.01271		0.01324
View of Tagus River	0.05520 ***		0.05614 ***		0.05689 ***		0.05690 ***		0.05756 ***		0.05609 ***		0.05639 ***
	0.00882		0.00881		0.00878		0.00881		0.00878		0.00881		0.00876
Urban Green Amenities													
Dist. to Nearest Urban Forest	-		-0.03606 ***		-		-0.03634 ***		-0.03742 ***		-0.03873 ***		-0.03995 ***
	0.03661		0.00729		0.03707		0.00734		0.00760		0.00744		0.00787
Within 500 m of Monsanto	0.00897		0.00718		0.00641		0.00573		0.00494		0.00670		0.00574
	0.01740		0.01745		0.01806		0.01776		0.01834		0.01752		0.01850
Within 500-750 m of Monsanto	0.00801		0.00084		-		-0.00057		-0.00101		0.00194		0.00011
	0.01366		0.01398		0.00003		0.01424		0.01468		0.01418		0.01491
Within 750-1000 m of Monsanto	0.05062 ***		0.04160 ***		0.04197 ***		0.04090 ***		0.04148 ***		0.04252 ***		0.04284 ***
	0.01009		0.01028		0.01065		0.01048		0.01084		0.01053		0.01113
Dist. to Nearest Cemetery	0.06012 ***		0.05704 ***		0.05762 ***		0.05486 ***		0.05537 ***		0.05888 ***		0.05959 ***
	0.00704		0.00706		0.00732		0.00723		0.00748		0.00715		0.00757
Dist. to Nearest Playground	0.07609 ***		0.07180 ***		0.07151 ***		0.07847 ***		0.07821 ***		0.07386 ***		0.07478 ***
	0.01540		0.01551		0.01609		0.01574		0.01630		0.01584		0.01677
Dist. to Nearest Small Park	-		-0.03265 ***		-		-0.03420 ***		-0.03422 ***		-0.03310 ***		-0.03297 ***
	0.03548		0.00942		0.03254		0.00970		0.01004		0.00946		0.01003
Dist. to Nearest Medium Park	-		-0.03300 ***		-		-0.03052 ***		-0.03050 ***		-0.03275 ***		-0.03235 ***
	0.02811		0.00909		0.03293		0.00916		0.00949		0.00914		0.00969
Dist. to Nearest Large Park	0.00678		0.00901 **		0.00887 *		0.00427		0.00408		0.00955 **		0.00902 *
	0.00445		0.00451		0.00468		0.00488		0.00504		0.00455		0.00482
Urban Street Trees													
Neighborhood Monument Trees	0.00404 *		0.00245		0.00254		0.00248		0.00261		0.00478 *		0.00439
	0.00239		0.00243		0.00243		0.00246		0.00246		0.00281		0.00283
Neighborhood Trees	0.00002												
	0.00002												

Neighborhood Deciduous Trees		0.00079 ***	0.00075 ***	0.00086 ***	0.00082 ***	0.00113 ***	0.00106 ***
		0.00015	0.00015	0.00016	0.00016	0.00017	0.00018
Neighborhood Evergreens		-0.00185 ***	0.00170 ***	-0.00194 ***	-0.00180 ***	-0.00261 ***	-0.00237 ***
		0.00043	0.00043	0.00043	0.00044	0.00047	0.00047
Neighborhood Palm Trees		-0.00392 *	0.00434 **	-0.00477 **	-0.00518 ***	-0.00486 **	-0.00533 *
		0.00205	0.00208	0.00220	0.00223	0.00219	0.00224
Neighborhood Shrubs		-0.00387	0.00264	-0.00229	-0.00122	-0.00467	-0.00349
		0.00476	0.00481	0.00483	0.00488	0.00501	0.00508
% Neighborhood Tree Canopy	0.01519	-0.08301 **	0.07637 **	-0.10510 **	-0.09883 **	-0.15870 ***	-0.14789 ***
	0.03535	0.03814	0.03845	0.04209	0.04243	0.04644	0.04702
Historic Protected Zone*Deciduous Trees				0.00022	0.00018		
				0.00065	0.00067		
Historic Protected Zone*Evergreens				-0.00856 ***	-0.00844 **		
				0.00331	0.00338		
Historic Protected Zone*Palm Trees				0.02172 ***	0.02159 ***		
				0.00624	0.00640		
Historic Protected Zone*Shrubs				0.02182	0.02403		
				0.02148	0.02186		
Historic Protected Zone*Tree Canopy				0.05277	0.05911		
				0.09176	0.09342		
High Risk of Flood*Deciduous Trees						-0.00151 ***	-0.00143 ***
						0.00036	0.00036
High Risk of Flood*Evergreens						0.00339 **	0.00306 **
						0.00133	0.00134
High Risk of Flood*Palm Trees						0.01045 **	0.01019 *
						0.00531	0.00543
High Risk of Flood*Shrubs						0.00530	0.00556
						0.01247	0.01298
High Risk of Flood*Tree Canopy						0.22710 ***	0.23352 ***
						0.08756	0.08871

Notes: ***Significant at the 1 percent level; **Significant at the 5 percent level; *Significant at the 10 percent level.