University of São Paulo
"Luiz de Queiroz" College of Agriculture

Urban tree cover change, income and crime assessments in Sao Paulo city, Brazil from 2010-2017

Bruna Lara de Arantes

Thesis presented to obtain the degree of Doctor in Science. Area: Forest Resources. Option in: Conservation of Forest Ecosystems

Piracicaba
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Licentiate and Bachelor's in Biological Sciences

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versão revisada de acordo com a Resolução CoPGr 6018 de 2011

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SUMMARY

RESUMO

Avaliação da mudança da cobertura arbórea, renda e crime na cidade de São Paulo, Brasil, período 2010-2017

A cidade de São Paulo é uma das cinco maiores cidades do mundo, a maior cidade da América Latina, e continua apresentando crescimento populacional urbano consistente o que faz com que a cidade se torne um importante objeto de estudo. Esta tese visa contribuir para preencher a lacuna de conhecimento nas cidades da América Latina e oferecer dados de boa qualidade para apoiar as políticas públicas. Dessa forma apresentamos no capítulo um, um mapa de Mudança de Cobertura Arbórea para identificar onde a cobertura arbórea urbana aumentou, diminuiu e não mudou na cidade de São Paulo no período 2010-2017. A cobertura arbórea foi derivada de duas imagens de alta resolução: Levantamento Aerofotogramétrico em 2010 ($1m^2$) e uma imagem Worldview-2 de 2017 (70 cm) e foram classificadas através de uma classificação orientada a objetos supervisionada com a Random Forest. Os resultados apontaram para uma mudança líquida de 0,30% nas áreas mais urbanizadas da cidade e uma mudança líquida nas áreas mais florestais da cidade de 10,34%, com domínio de uso privado do solo na cidade. No capítulo dois analisamos a correlação espacial entre cobertura arbórea e renda per capita e a interação dessas variáveis com outras coberturas do solo (gramado, prédios e sombras), para o ano de 2010. Os resultados mostram que a cidade de São Paulo apresenta uma distribuição desigual entre cobertura arbórea e renda, apresentando correlação espacial positiva em áreas urbanizadas. No capítulo três propomos testar a cobertura arbórea e a dependência espacial do crime e, uma vez que isso ocorre, vários modelos espaciais foram propostos com potenciais confundidores controlados. Nossos principais resultados mostraram que a cobertura arbórea da cidade de São Paulo está associada a menores taxas de crimes totais, patrimoniais e pessoais, mesmo quando diferentes áreas da cidade, escalas de estudo e denominador de crime são testados. Os resultados seguem a literatura que observou cobertura arbórea associada a menores índices de criminalidade, para diferentes tipos de crimes.

Keywords: Floresta urbana, Ecologia urbana, América Latina, Sensoriamento remoto, Análise espacial

ABSTRACT

Urban tree cover change, income and crime assessments in Sao Paulo city, Brazil from 2010-2017

Sao Paulo city is one of five largest cities in the word, the biggest city of Latin America, and continuing to show consistent urban population growth what makes the city become an important object of study. This thesis aims to contribute to filling the knowledge gap in Latin America cities and offering good quality data to support public policies. In this way, we present in chapter one an UTC Change map to identify where urban tree cover increased, decreased, and did not change in Sao Paulo city from 2010-2017 period. Tree cover was derived from two high resolution images: the Aero Photogrammetric Survey image in 2010 (1m²) and a Worldview-2 image from 2017 (70 cm) and were classified through a supervised object-oriented classification with the Random Forest. And the results pointed to XX net change in most urbanized areas of the city and XX net change in the most forest areas of the city, with domain of private land use in the city. In the Chapter two we analyzed the spatial correlation between tree cover and per capita income and the interaction of these variables with other land covers (lawn, buildings and shadows), to 2010 year. The results present that the city of São Paulo has an uneven distribution between tree cover and income, present positive spatial correlation to urbanized areas. In the chapter three we propose test the tree cover and crime spatially dependence, and once this occurs, several spatial models was carried out with potential confounders controlled. Our main results showed that Sao Paulo city tree cover is associated with lower total, property and person crime rates, even when different areas of the city, scales of study, and denominator of crime are tested. The results follow the literature that have observed tree cover associated with lower crime rates, for different types of crime.

Keywords: Urban forest, Urban ecology, Latin America, Remote sensing, Spatial analysis

INTRODUCTION

Understand how Urban Tree Cover (UTC) changes over time and its relationships with social aspects represents important management applications, once the integration of natural and social sciences in multidisciplinary research may be the key to improving public policies for urban greening (Locke et al., 2013, McGee III et al., 2012, Schwarz et al., 2015). Sao Paulo city is one of five largest cities in the word, the biggest city of Latin America, and continuing to show consistent urban population growth what makes the city become an important object of study (IBGE, 2010; United Nations, 2018).

Most research Urban Tree Cover change and its relationship with crime and income are concentrated in the United States of America and unfortunately it is a distant reality to a lot of cities around the world, including Latin American even with 81% of our population living in cities - the second world region with more urbanized areas (United Nations, 2014).

This thesis aims to contribute to filling the knowledge gap in Latin America cities and offering good quality data to support public policies. In this way, we present in chapter one a UTC change analysis, generated from high resolution satellite image from 2010-2017 and Geographic Information System techniques, to understand where urban tree cover increased, decreased, and did not change in the Sao Paulo city in this period, considering different boundaries of the city and land uses classes.

In next two chapter we assessment the socio-ecological relationships of the urban forest. In Chapter two we present spatial analysis to understand the relationship of income and tree cover, for 2010 year, to investigate if there is an equal distribution between the different tree cover and income levels, considering different city boundaries. In the Chapter three we proposes a series of spatial models to understand if tree cover distribution is spatial related with crime occurrence, for 2017 year. Once it is true, we investigate how this association occurs for different types of crimes and denominators of crime, and for different areas and delimitations of the city.

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CHAPTER I. URBAN TREE COVER CHANGE IN SAO PAULO CITY, BRAZIL FROM 2010-2017

Abstract

Sao Paulo city is one of five largest cities in the word, the biggest city of Latin America, and the principal center of Brazilian economy. Understanding how Urban Tree Cover (UTC) changes over time represents a massive management challenge. This study created an UTC Change map to identify where urban tree cover increased, decreased, and did not change in Sao Paulo city from 2010-2017 period. We analyze the UTC change for two main zones of the city: Urban and Environmental Macrozone, and for Administrative Districts. Land cover was derived from two high resolution images: the Aero Photogrammetric Survey image in 2010 ($1m^2$) and a Worldview-2 image from 2017 ($70\ cm^2$). The images were classified through a supervised object-oriented classification with the Random Forest, in ArcGIS version 10.7, in a paired digital image analysis process that allows choosing the sample trainers for each class respecting the same geographic location. For this research we considered just tree cover class. An accuracy assessment was done using a cross-validation process, with 1,000 sample points used to generate the confusion matrix. The matrix presented an overall Kappa Index of 84% in 2010 and 82% in 2017, and 96% and 95% accuracy, respectively for tree cover class. Sao Paulo city had a net increase of 10,34% in UTC in the 2010-2017 period. Considering the Macrozones, the Urban presented a net increase of 0.30% while the Environmental presented a net increase of 13%. Environmental macrozone, composed mainly of Atlantic Rainforest remnants, could be in an intense process of regeneration while Urban macrozone can be a major afforestation and maintenance challenge, mainly in a city such as Sao Paulo.

Keywords: Geographic Information System (GIS); urban forest.

1. Introduction

The rapid urbanization process observed in the last century was accompanied by an increase in the urban population in large cities, that gave rise to Megacities – an urban agglomeration with more than ten million inhabitants, which have become notable in importance and power of population and economic attraction (United Nations, 2014). Urban concentration is desirable in the sense of reducing the expenses of inter and intra-regional infrastructure and bringing more facilities to the population, but it also brings with costs arising from the malfunctioning of these spaces like pollution, inequality and loss of urban trees, which increasing the complexity of urban planning (Henderson 2002; Nowak and Dwyer, 2007).

The pression of urbanization process in urban trees are worrying, as trees are an important instrument to provide quality to the environment, having their presence directly related to the health of the population, increasing the feeling of human well-being, improving air quality and reducing pollutants emitted by traffic, balancing the microclimate, reducing direct sunlight and controlling temperatures, offering even more comfortable, aesthetically pleasing and healthy places to live (Grazuleviciene et al., 2015; Beyer et al., 2014; Tsao et al., 2014, McPherson, 1992; Dwyer et al., 1992; Nowak 1993; Wang et al., 2012;). Therefore, research focusing on quantitative diagnosis and changes of urban trees over time is extremely important to its preservation and urban forest management.

Most research on how Urban Tree Cover (UTC) changes over time and which processes are related with these changes is concentrated in the United States of America. A historical UTC change analysis was done to Worcester County (MA) considering the 1976-2009 period and found a forest cover loss that exceeded the state by 0,26% per year, being the main loss related to low-density residential land use expansion (Hostetler et al., 2013). Considering the years of 2008, 2010 and 2015 the city of Worcester (MA) presents a tree cover loss mainly in residential neighborhoods, where trees cover lost space for roads and grass surfaces (Elmes et al., 2017). Oklahoma City (OK) experienced a 2% net tree canopy loss between 2006 and 2013 (Ellis and Mathews, 2019), while in Los Angeles (CA) higher-income regions tended to have more tree canopy cover and lose it less over time (Locke et al., 2017).

Christchurch city (New Zealand) presents 0.56% of tree canopy loss between 2011 and 2015, being this loss mainly related to properties that were in underwent redevelopment (Guo et al., 2019). These subtle changes founded by these studies were possible to detect due to the use of high-resolution imagery and remote sensing techniques, which provides an ideal basis for UTC detection, as they allow mapping in a fine spatial resolution (Neyns and Canters, 2022). The inclusion of LiDAR data and digital surface models combined with high resolution satellite images can help to increase the accuracy tree canopy mapping in urban environments, due to their three-dimensional data (O'Neil-Dunne et al., 2014).

Understanding how UTC changes over time represents important management applications and is also an excellent opportunity to build better urban planning. Knowing the spatial distribution of urban tree cover is a first step that will allow you to link it with goals of urban forestry, maintenance programs, and do a more inclusive urban planning (Locke et al., 2013, McGee III et al., 2012, Schwarz et al., 2015).

Unfortunately, it is a distant reality to a lot of cities around the world, including Latin American even with 81% of our population living in cities - the second world region with more urbanized areas (United Nations, 2014). In Brazil, urban forest spatial distribution and its gain and loss over time remain mostly unknown. This creates a lack of knowledge and makes it difficult to generate stronger urban public policies, even with city managers' efforts.

In this way, Sao Paulo city becomes an important object of study once continuing to show consistent urban population growth, that follows an urban sprawl dynamics – a tendency observed in Latin American cities (Inostroza et al., 2013; IBGE, 2010). Sao Paulo city presents two main areas, the Urban Macrozone composed of most central and urbanized areas of the city, and the Environmental Macrozone composed of most peripheral areas, with big patches of Atlantic rainforest reminiscent. Sao Paulo city urban expansion occurs in direction of Environmental Macrozone, with low density population in horizontal low-income settlements, frequently non-regular, that are pressuring the Atlantic Rainforest remnants - a hotspot of biodiversity in tropical regions (Rolnik 2001a, Joly et al., 2014, Rezende et al., 2018). This research aims to contribute to filling the knowledge gap in Latin America cities and offering good quality data to support public policies, creating a UTC Change map for Sao Paulo city.

1.2. Research question, objectives and hypothesis

The general goal is to create a high-resolution UTC change map for the 2010-2017 period to Sao Paulo city. The research questions are: Did UTC increase, decrease, remain the same from 2010 to 2017 period? Does the UTC change vary in the environmental and urbanized areas? How does tree canopy change vary by Administrative Districts? Does the different types of land use, as private and public, relate to UTC change?

The hypothesis to be tested are: (i) UTC increase, decrease and not change in 7 years; (ii) urban and environmental macrozone present different UTC changes; (iii) Administrative District presents different UTC changes rates; (iv) the types of land use have influence in UTC Change; (v) private and public have influence in UTC changes. These hypothesis have been corroborated for preview studies that discuss the different process of urbanization between the Sao Paulo city macrozones and our relationship with Atlantic rainforest remnants (Souza, 1994, Nobre et al. 2010, Rolnik 2001b), and that types of land use has present different role in UTC changes, as private and public (Elmes et al., 2017; Guo et al., 2019; Clark, Ordóñez and Livesley 2020).

2. Methodology

2.1. Study area

Sao Paulo city is the capital of the state of Sao Paulo, Brazil, at an average elevation of 802 meters, latitude 23º37’ and longitude 46º39’ W, inserted in a Humid Subtropical Climate zone (Köppen and Geiger, 1928). Sao Paulo city has a population of 12 million inhabitants distributed in 1,521.110 km², with a projections of 23.5 million inhabitants for 2030, a 110% of growth (IBGE, 2010), being the largest urban area in Latin America by population and one of the world's five largest cities (United Nations, 2018). The city was founded in an extensive area of Atlantic Rainforest biome, a global biodiversity hotspot, that was extensively explored during the city development and nowadays is still suffering with urbanization pressure (Rezende et al., 2018, Joly et al., 2014).

Sao Paulo official delimitation is comprised of 96 Administrative Districts (AD) regulated by Sao Paulo (1992). The ADs can be in two main zones of the city, the i) Urban Macrozone, that is composed by most urbanized areas of the city, and concentrate the most of business areas, economical centers, public transportation; and the ii) Environmental Macrozone, that is composed most peripheral areas of city with horizontal settlement, popular housing, and non-regulated areas occupied, with big patches of Atlantic rainforest reminiscent, agriculture activities and with fragile geological and geotechnical characteristics for human occupation. These divisions are defined by the Strategic Director Plan review (PL 688/13) (Sao Paulo, 2014). All divisions are illustrated on Figure 1. The city still has the division generated by the Brazilian Statistics Institute (IBGE, 2010) the Census Sector (CS), defined as a grouping of blocks and the small boundary for the city, very close to the international pattern urban divisions.

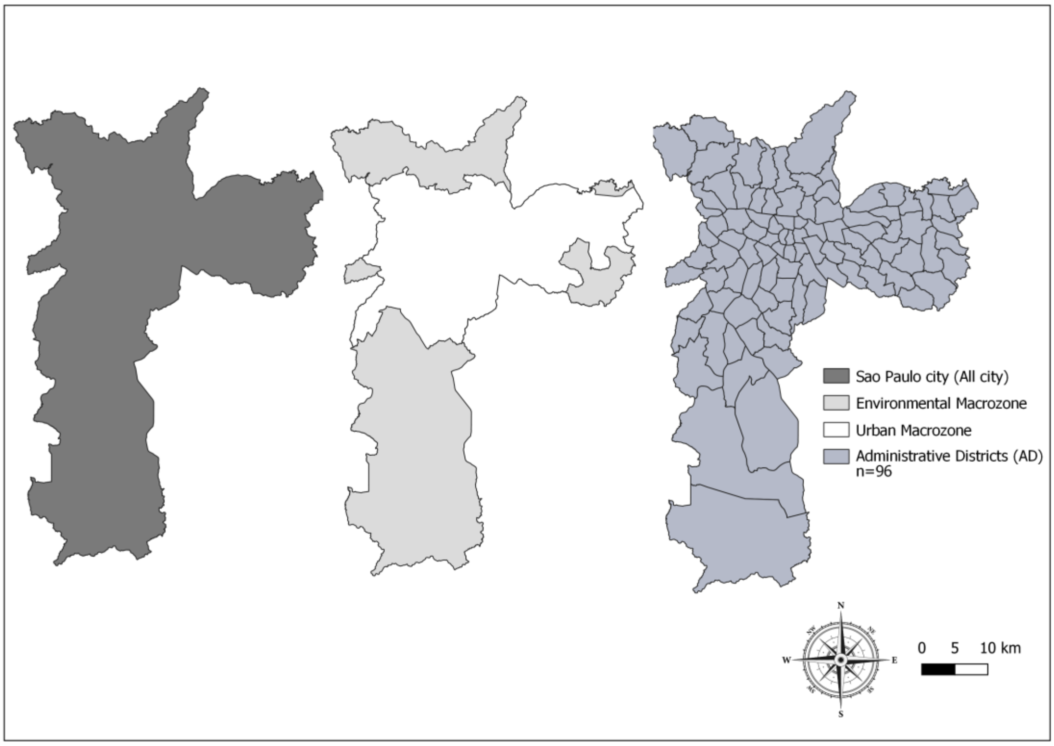

Figure 1. Sao Paulo city delimitations, being all city, environmental and urban macrozones (n=2), and Administrative Districts (AD) (n=96).

Historically, Sao Paulo city had flawed urban planning where the poorer classes moved to the peripheral areas carrying out an intense and disorderly urban expansion with lack of state support (Souza, 1994). Studies gather evidence of this non-harmonious urban configuration, highlighting peripheral regions that are socially and environmentally fragile, with landslides and floodplains, through the irregular use of natural resources, such as deforestation for housing construction and which without basic sanitation, pollute rivers and soil, increasing flood risks and put pressure on natural reserve areas (Nobre et al. 2010).

2.2. Database

Sao Paulo city's land cover classification was derived from two high resolution images: the Aero Photogrammetric Survey image in 2010, with 1m² resolution (Sao Paulo, 2012) and a Worldview-2 image from 2017, with 70 cm^2 resolution (Geosampa, 2017). Both images were orthorectified and have blue, red and near infrared spectral bands. The images were classified through a Supervised Object-Oriented classification, a Geographic Information System (GIS) technique, available on ArcGIS version 10.7 (ArcGIS, 2021a). The classification was developed following the steps: i) image segmentation, ii) sample trainers,

iii) Random Forest classifier, iv) image classification, v) manual corrections, vi) Kappa index of Accuracy. This process is illustrated on Figure 2.

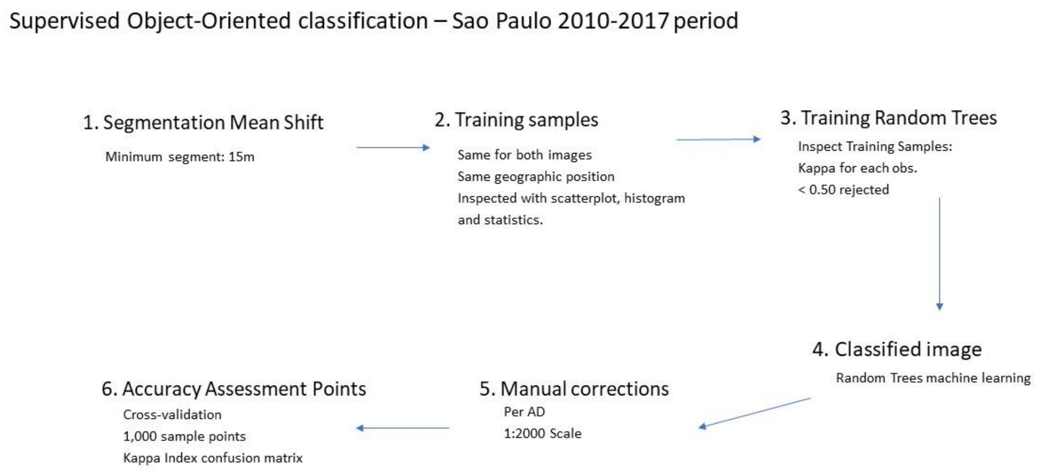

Figure 2. Supervised Object-Oriented classification, using the tool set available at ArcGIS version 10.7.

Segmentation was carried out in image to create objects through an aggregation of adjacent pixels that are similar in spectral and spatial characteristics, such as texture, size, form, and value (ArcGIS, 2021). Segmentation method has shown more accurate results when compared with pixel-based classification, that aggregates samples only for pixel value (Elmes et. al 2017). In this study we used the Segmentation Mean Shift tool with Minimum Segment Size of 15 meters - the minimum map unit. The value was defined after tests of ideal size and shape of objects.

A paired digital image analysis process was carried out, where the training samples were chosen with the overlapping images, which allows them to be chosen at same time and with the same geographic location to both images. The paired digital image analysis allows to reduce errors on a UTC map generation, once possible select objects that accurately represent tree cover, in both years, being more suitable to be the trainers on the classification model (Nowak and Greenfield, 2012). For example, the trainers for tree cover had the same geographic position and respected the rule of be tree cover in 2010 and 2017 year (Figure 3). The same rule was applied for all classes.

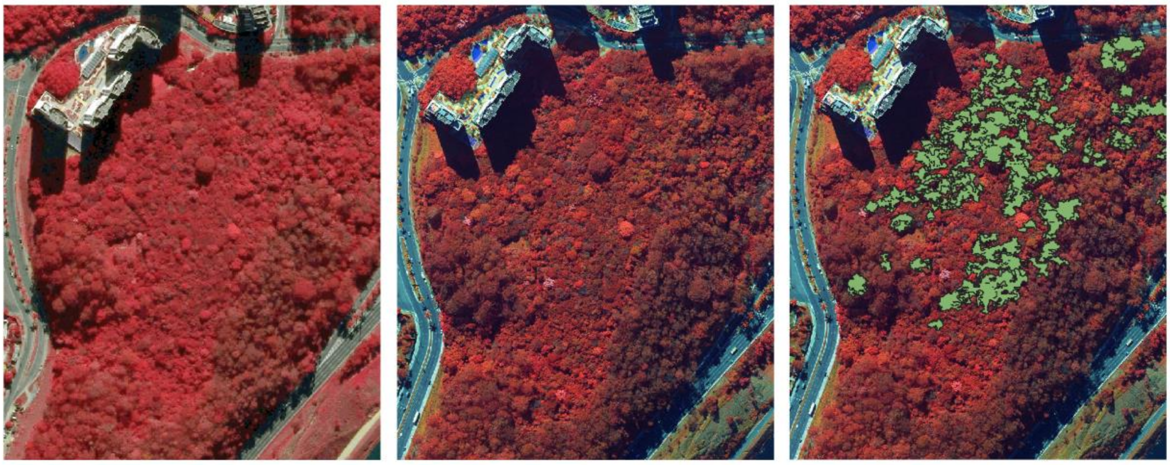

Figure 3. Sample trainers to tree cover class, selected in a paired digital image analysis process. They have the same geographic position in 2010 and in 2017.

To analyze the accuracy of the set of segments chosen as training samples, scatterplot, histogram, and statistics tools were done for each segment that explored its distribution between the samples. Through the Inspect training samples tool, the accuracy of each individual trainer was estimated through a cross validation method, keeping in the sample just the trainers that closest represent the class. Once identified, the miss classification and non-accurate samples were excluded and only classifiers above 50% of accuracy were maintained.

After the segment set was created and refined, the training sample was applied to classification through Random Forest machine learning technique. Random Forest is an algorithm of decision trees collector, where each tree is generated from different samples and subsets of training data, which make it resistant to overfitting and make it the most effective technique of image classification nowadays (Rodriguez-Galiano, 2012).

Twelve land cover classes were mapped: tree cover, lawn, lawn with soil, soil, pavement, shadow, roofs (write, dark, gray, orange), water and swimming pool. After classification the classes were aggregated into seven classes: tree cover, lawn (that include lawn and lawn with soil), soil, pavement, buildings (that include all roofs and swimming pool), shadow, and water (Figure 4 Supplementary Material). Since the goal of this work is a UTC map generation only the Tree cover class was considered from this point.

To increase the accuracy of tree cover classification manual corrections were performed to eliminate obvious and non-systematic errors of tree cover classification, in a scale that ranges closely to 1:2000. This step is very important once a map generated on an automatic feature extraction hardly achieves perfect accuracy, mainly in an urban environment with so many types of land covers, and tree cover variation of size and physical aspects (O'Neil-Dunne et al., 2014).

To generate the confusion matrix an Accuracy Assessment Points with cross-validation process was carried out (ArcGIS, 2022). In this process, 1,000 sample points are randomly distributed within each of seven classes, with the number of points proportional to its relative area and assigns a class to them based on reference data. Once these reference points are created, the classifier will reclassify the sample points and manually assign a class to them based on the segmented image and your experience. The reference points are then compared with the result of the reclassification in each of the samples. Based on this the Kappa Index confusion matrix is calculated. This process was done for each image, with a total of 2,000 sample points, and it is illustrated on Figure 5.

The UTC Change generation was carried out with a raster calculator, all the steps with 2010 and 2017 raster are illustrated on Figure 6, highlighting the importance of each step on the GIS data management to make the UTC Change more detailed and accurate.

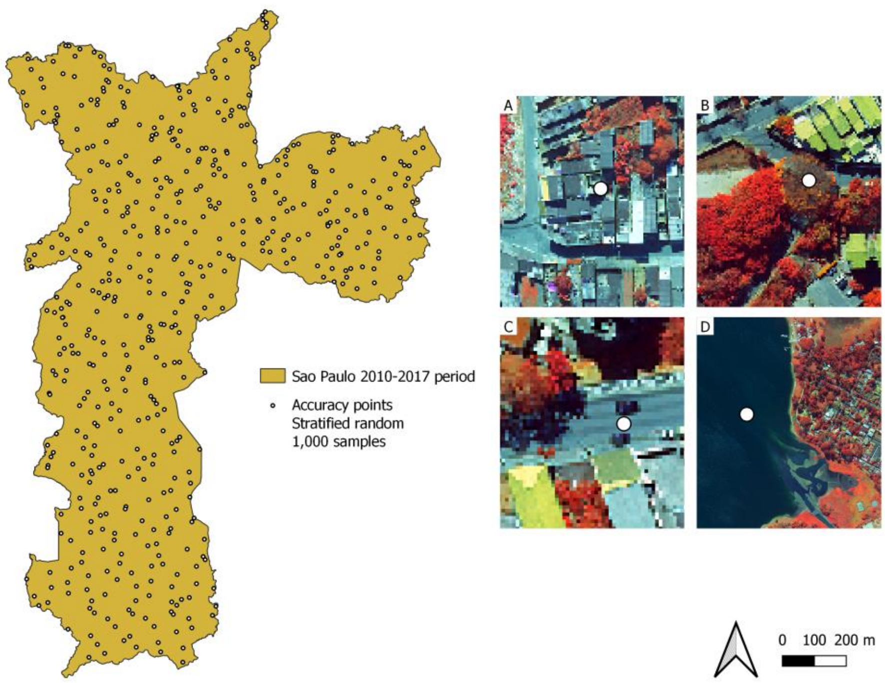

Figure 5. Accuracy Assessment Points to 2010-2017 images, chosen with cross-validation process, carried out ArcGIS version 10.7. Samples of points to A) Building, B) Tree Cover, C) Asphalt, D) Water.

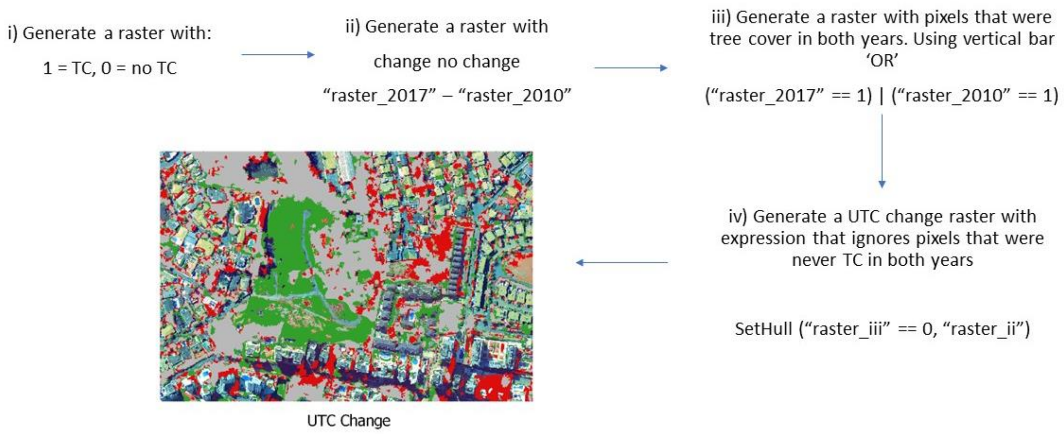

Figure 6. Steps to generate the UTC change map, using raster calculator available at ArcGIS 10.7.

The UTC was calculated in four measures: no change, loss, gain, and net change. For UTC Change analysis were chosen two study areas: i) Urban Macrozone; ii) Environmental Macrozone; one city boundary iii) Administrative District (n=96) and two subdivisions: land use and private and public (n= 58389). The definition for the metrics are defined on Table 1.

Table 1. Urban tree cover (UTC) change metrics and its definitions

Metric	Definition
UTC	The urban tree cover for one year, estimated in square meters (m^2).
UTC Change	When two years of urban tree cover for the same region are compared, through overlapping high-resolution images, estimated in square meters (m^2).
Loss, gain and no change	UTC Change measures, estimated in square meters (m^2). Loss are the negative values, gain are the positive and no change are the zero.
UTC Change Percentage	The UTC loss, gain and no change divided by study area, since it is expressed in percentages (%).
Net change	The difference in percentage point, or absolute values, between the percentages of UTC Change for both years.

The land use predominance mapping for Sao Paulo city is based on predominance use, equal or superior to 60% of each city block, considering 2014 year, and was performed by Municipal Secretary of Urban Development SMDU, available in GeoSampa (2022). The data presents some limitations as generic and imprecise information and year not matched with the most recent satellite image. The analysis will be carried out even considering the limitations, once land use is an important driver on UTC Change (Elmes et al., 2017; Guo et al., 2019; Clark, Ordóñez and Livesley 2020) and this is the unique data available to Sao Paulo city.

Sao Paulo city land use predominance mapping presents 16 classes and does not include the natural reserve areas and the urban dams, but includes urban parks (Figure 7 Supplementary Material). For land use analysis we regrouped the 16 original classes into 9 classes: commercial and services, industrial and residential, private, public, residential, schools, vacant lots, industrial, and unknown (Figure 8). These classes were further regrouped in 3 classes: private, public and unknown (Figure 9). Histograms, basic statistics and spatial maps were done to understand the distribution of the data in the different study areas.

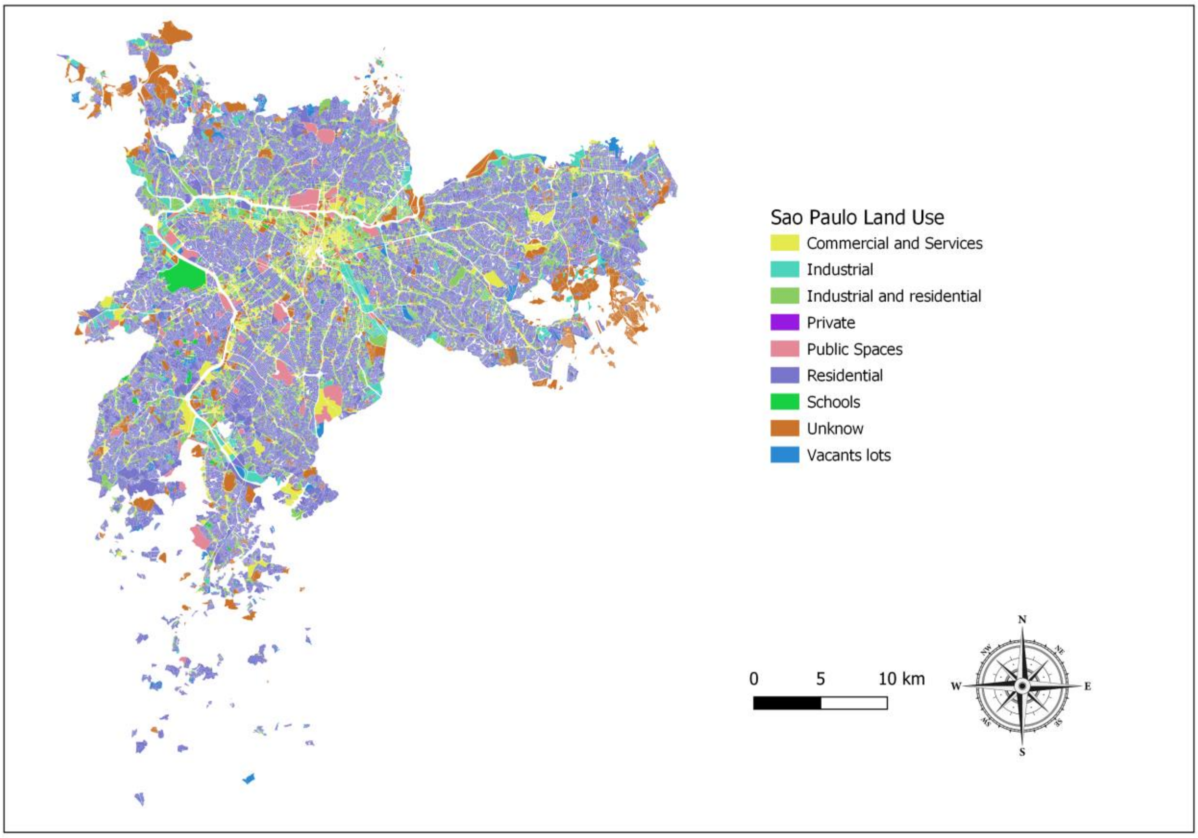

Figure 8. Sao Paulo city land use predominance mapping with 9 classes.

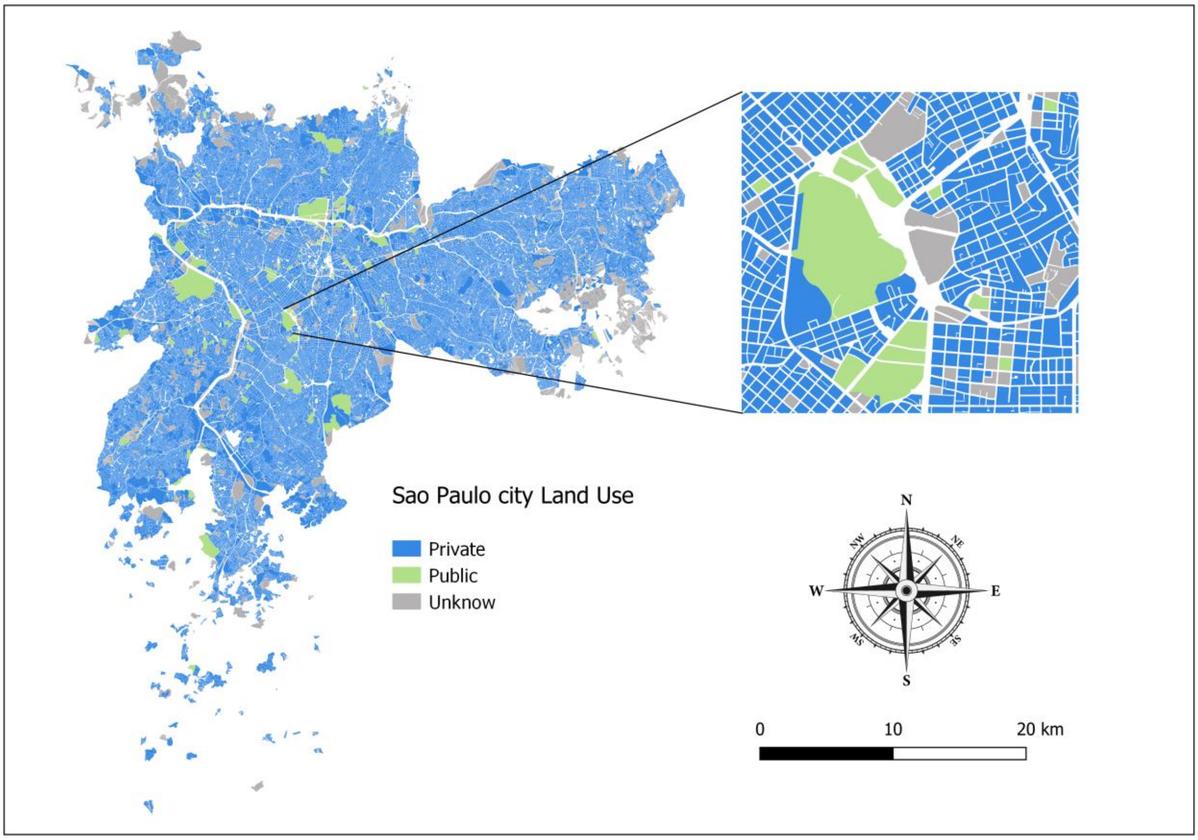

Figure 9. Sao Paulo city land use predominance mapping with 3 classes: public, private and unknown.

3. Results

3.1. Accuracy

The classification presents a Kappa Index of 84% for the 2010 image and 82% for the 2017 image. The tree canopy class was 96% and 95% accurate, for 2010 and 2017, respectively. The manual corrections for tree cover class for 2017 image represented a difference of -0.61% for the total area of the city, while the ADs presented a minimum rate of -5% in the southern zone and maximum rate of +13% in easter zone. A test with the Census Sector (CS) was done, the minor boundary available for the city, with the goal to understand how this misclassification occurs on small scales. We could find correction rates that ranged from -99.44% to +99.61%. These three scales of analysis for misclassification allows us to understand how important this step is to contribute to achieve high accuracy in all city scales.

Figure 10 illustrates the ADs manual corrections to the 2017 image. Two main misclassification trends can be found for tree cover classification: overestimation in the east zone and an underestimation in the south zone. This occurs due to the city has a very large territorial extension (1,521.110 km²) and naturally has a very wide variety of land covers when considering urban and environmental macrozones, both in natural elements as exposed soil and tree cover (native, planted, large areas of reserve, small urban patches, different phenologies) as well in built elements such as roofs, pavements and others. This wide variety of textures, colors and elements within the same class decrease the classification power of the algorithm.

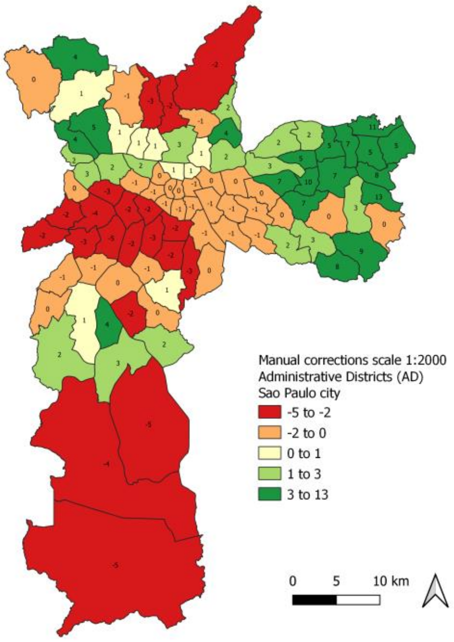

Figure 10. Manual corrections rates presented in percentages by Administrative Districts boundary, for the 2017 image.

3.2. How much UTC Does Sao Paulo have?

Sao Paulo city presented a UTC of 36.25% in 2010 and 41.21% in 2017. The 2010 and 2017 UTC classification results are illustrated in Figure 11. The both years present a similar pattern of spatial distribution: the most covered areas of the city are the pheriferical in south, north and west - most of them located in the Environmental Macrozone, and the less covered are the midwestern regions.

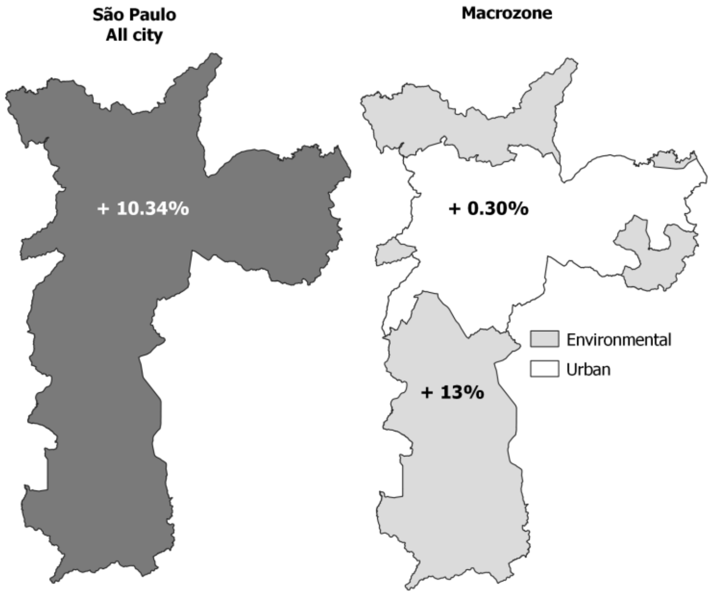

Figure 11. Urban tree cover classification results to 2010 and to 2017, and UTC net change map for 2010-2017 period. All maps are considering Administrative Districts (AD) delimitations.

3.3. How much has UTC changed between 2010 and 2017?

Sao Paulo city had a net increase of 10.34% in UTC in the 2010-2017 period. Considering the Macrozones, the Urban presented a net increase of 0.30% while the Environmental presented a net increase of 13% (Figure 12). A summary of UTC change for the three study areas is presented in Table 2, with no change presenting a higher percentage, followed by gain and loss.

Table 2. Urban Tree Cover (UTC) loss, no change, gain and net change to All city and Urban and Environmental Macrozones.

	All city		Urban Macrozone		Environmental Macrozone	
UTC	km²	%	km²	%	km²	%
No change	454668610	63.10	70710602	45.51	383958008	67.94
Gain	170204720	23.62	42570834	27.40	127633886	22.58
Loss	95687305	13.28	42108600	27.10	53578705	9.48
Net Change		10.34		0.30		13.10

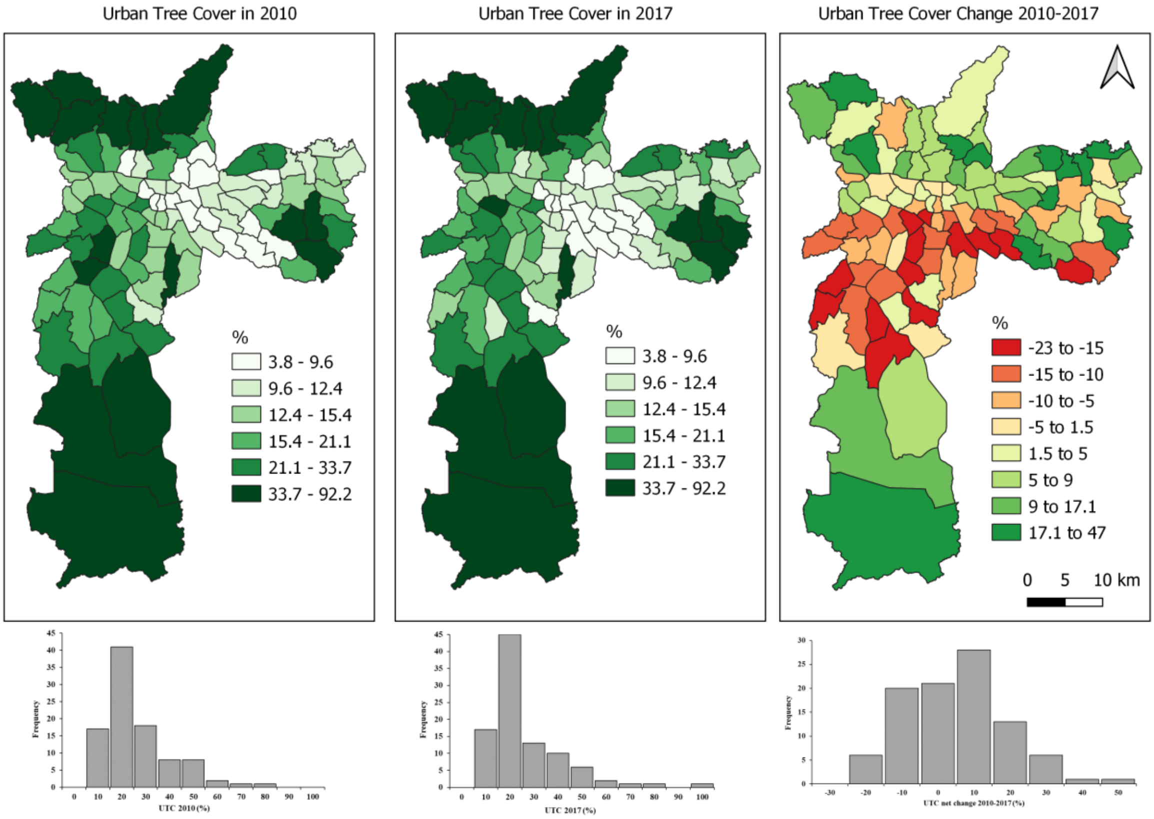

Figure 12. Urban Tree Cover (UTC) net change to Sao Paulo (all city) and to Environmental and Urban macrozones.

The UTC net change map, considering AD division, is illustrated on Figure 11. The AD net change presented positive net changes in the peripherical south, north and west and negative net change in north central regions, with higher frequencies of net change between -10% to 10%. Descriptive statistics for UTC change considering AD boundary are presented in Table 3.

Table 3. Descriptive statistics for UTC change, considering Administrative Districts (n=96).

Variable	Minimum	Mean	Maximum	Median	SD
Loss	2	26.89	43	28	8.49
No change	26	45.24	76	43	10.97
Gain	10	27.90	61	26	9.06
Net change	-23	1	47	1.5	13.74

3.4. How much has UTC changed across Land Uses (LU)?

In Sao Paulo city the most common LU are residential, industrial and residential, and unknown which together represent more than 80% of the city territory (Figure 13 Supplementary Material). When the LU are regrouped in private and public, private represents 81% of the city territory, followed by 14% of unknown and 5% of public (Figure 14 Supplementary Material).

Considering the UTC change map results for LU, the residential areas present the most expressive changes with 13.77% of gain and 14.66% of loss, which gives a net change of -0.89% (Figure 15). In all other LU classes the net changes varied in the range of +0.83 and -0.34. When the LU are regrouped in private and public, the private presents the most expressive changes, with 20.24% of loss and 19.44% of gain, which gives a net change in UTC of -0.80%, followed by public with -0.46% and unknown with 1.16% (Figure 16).

The net change found in both LU presented values very close to zero, which corroborates the UTC net change found for urban macrozone, once the most of LU availables are included in this zone, and few of them are included on the environmental which presented more expressive UTC net changes.

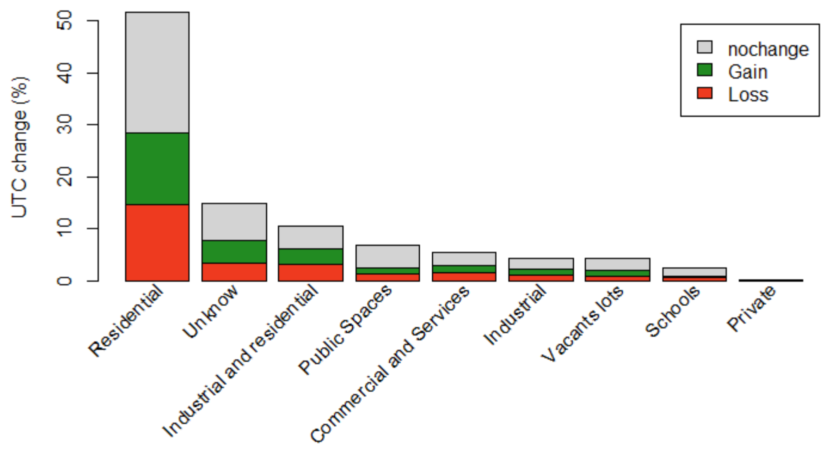

Figure 15. Urban Tree Cover (UTC) change map 2010-2017 period, for 9 classes of land use.

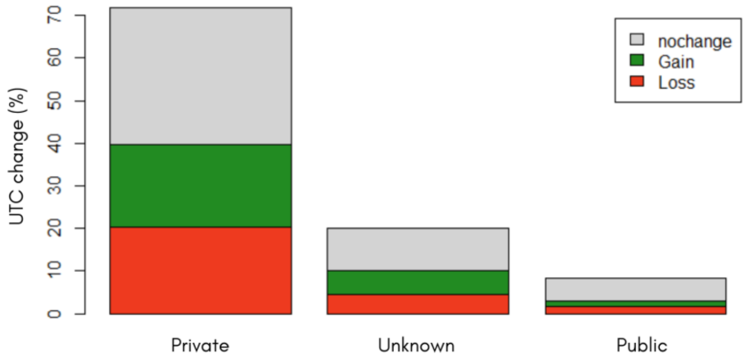

Figure 16. Urban Tree Cover (UTC) change map 2010-2017 period, for 3 classes of land use.

4. Discussion

Sao Paulo city had increases, decreases, and persistent tree canopy from 2010 to2017, which varied between the two macrozones, the AD boundary and between the land uses. But a tendency was followed by all study areas: a discrete net change in Urban macrozone close to zero and more expressive net changes in Environmental macrozone. These findings can be linked with two main points:

(i) Environmental areas, composed mainly of Atlantic Rainforest remnants, could be in an intense process of regeneration through the 2010-2017 period increasing the UTC, even persisting to urbanization expansion pressure. These findings follow the opposite trend of literature that points to reduction of this biome over the years mainly in urbanized areas (Rezende et al., 2018). The mainly reason for this is an urban sprawl dynamic of expansion present in Latin American cities, that presents fast increase population rates with falling densities trend (Inostroza et al., 2013), being the Sao Paulo city defined as “hollow city” in terms of verticalization, once it is elitist with low dwellers density (Rolnik 2001b, Rolnik et al., 1990). Despite the importance of these studies, any study was carried out in Sao Paulo city that demonstrated quantitatively the historical urbanization pressure in Atlantic Forest remains which does not allow us to compare our results.

(ii) It is a challenge to increase UTC in the Urban macrozone, mainly in a city with high rates of population and urbanization such as Sao Paulo, the biggest Latin American city (United Nations, 2014). This pattern of UTC losses and gain being so close can have as a driver the land use distribution in the city. Most of the existing tree cover is located in residential and private areas that represent more than 80% of land cover classes, while Public areas represent just 5%, and the rest is unknown. This distribution put several limits on the maintenance and reforestation through direct actions by public managers. Several cities around the world have identified that the main portion of UTC is located in private land and are discussing its consequences and challenges. Chicago has 60.6% of UTC in single and multi-family residential areas (Nowak et al., 2010), being the same pattern found in Sidney (Australia) where more than 50% of UTC is in residential areas, being the urban densification and inequality in income distribution related with less presence of UTC (Lin, Meyers and Barnett 2015). In this way, public management needs the agreement and the participation of residents to achieve goals of UTC, and this reveals how investing in the public-private relationship is crucial to planting and maintaining trees in the cities, including in Sao Paulo city. discuss that dwellers' support, rules and regulations is the key to maintenance of trees in private land (Clark, Ordóñez and Livesley 2020). UTC losses and gains so close in Urban Macrozone may reflect the mismatch in the public-private relationship.

Considering the image's classification process, the manual corrections highlighted how important it is to consider this step to achieve more accurate UTC maps. Even though the corrections rate looks discrete for all city, it is important to understand that a UTC map should be a product that can be used as a tool for mapping UTC changes both on large and small scales, as a group of city blocks. The two main misclassification trends found in AD boundaries reflect that some peripheral areas of the city were not so accurately classified as center regions (Figure 10) and can suggest best further strategies to generate more accurate class trainers. The accuracy in tree cover classification and UTC change map is still a big point to be developed and discussed in the literature.

Even with efforts, this study presents some limitations. The UTC change findings can be influenced by the non-standardization of the image's in sources, being 2010 from Aero Photogrammetric Survey and 2017 from WordView-2; and the non-standardization in image collection date, which mixed different seasons and tree phenologies in the same image. Still, LU database presents low precision, with high frequency the class "unknown" which impoverishes UTC change analysis for the study area.

5. Conclusion and Recommendations

Latin American cities face several difficulties in carrying out high-impact research and the spatial distribution of urban forest and its gains and losses over time remain largely unknown. This work presents importants international contributions, generating a UTC Change map for Sao Paulo city and offering good quality data to support public policies.

Remote sensing is the best option to manage urban land cover, quantify tree cover existent and watch it changing over time. Satellite images and GIS softwares provide products with high accuracy and have low cost and are fastly replicated than ground-base inventories, maily to large scale cities as Sao Paulo.

Sao Paulo city presents an increase in UTC of 10.34% for the 2010-2017 period when considering all territory of the city. This increased tendency is preserved when two main zones of the city are considered: Urban with 0.30% and Environmental with 13% - the first is the most central and urbanized zone of the city and the second is the most peripheral areas of the city with large areas of Atlantic Rainforest remnants.

This increased tendency and spatial distribution is presented when the AD boundary and land uses classes are tested: those located in Environmental Macrozone presents increase in UTC and those located in Urban Macrozone present UTC gain and loss very close to zero which can reflect challenges in increase and preserve UTC in urbanized areas, independent of study area scales.

The Land Use (LU) distribution pointed to important tendencies. The LU distribution in Sao Paulo city can put some limits on the maintenance and reforestation actions by public managers, once more than 80% of UTC are private areas, composed of residential and industrial zones.

In future studies the use of single sourced images can help increase the accuracy of result, just as the inclusion of LiDAR data, once the shadows on images can negatively influence UTC mainly at more verticalized areas (O'Neil-Dunne et al., 2014). The use of alternative accuracy methods to the Kappa index are important to be carried out, once it has been discussed and proposed in the remote sensing literature (Pontius Jr. & Millones 2011), and its application to the UTC map is a scientific field to be developed.

The authors also suggest for future research: the improvement of LU data for Sao Paulo city as corrections and the inclusion of streets areas (right of way); and the identification of the drivers of UTC changes in Sao Paulo city to this period. Some technical recommendations for future studies are done: i) Environmental and Urban macrozones if classified separately can be a better classification result, once it will consider the specific land cover patterns, probably resulting in an improvement of trainers class and less misclassifications.

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Supplemental Material

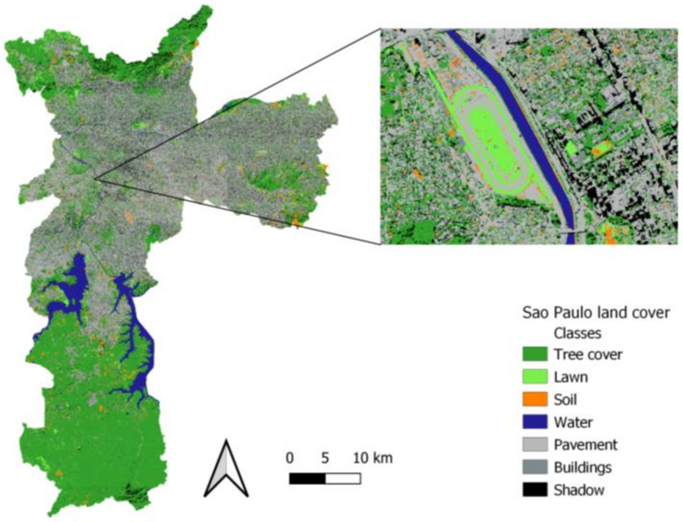

Figure 4. Seven land cover classes for high resolution image classification, for both years (2010-2017).

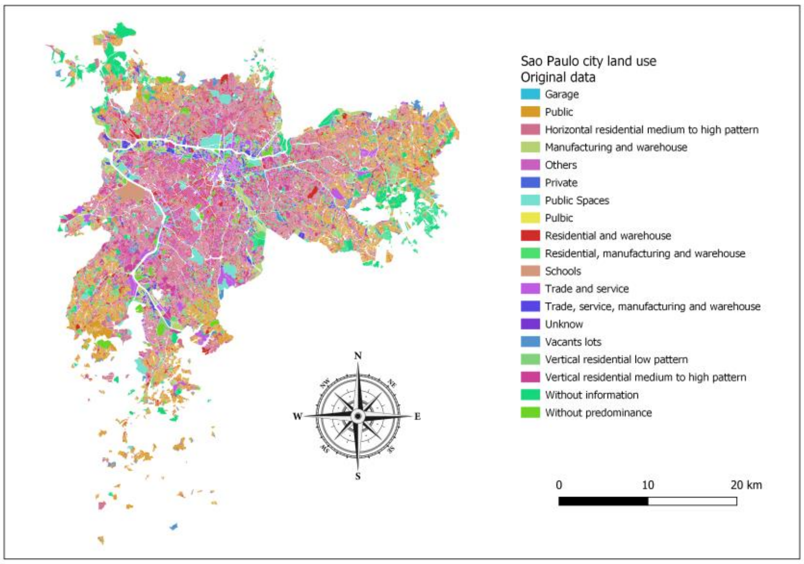

Figure 7. Sao Paulo city land use predominance original data, with 16 classes.

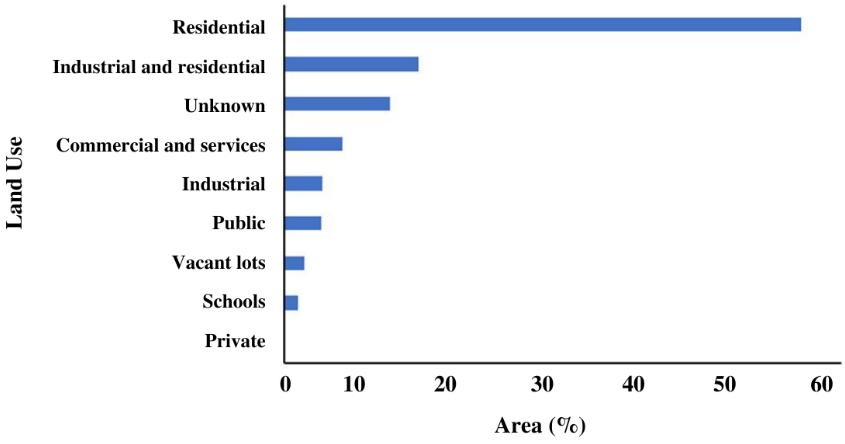

Figure 13. Land Use class area, presented in percentage (%).

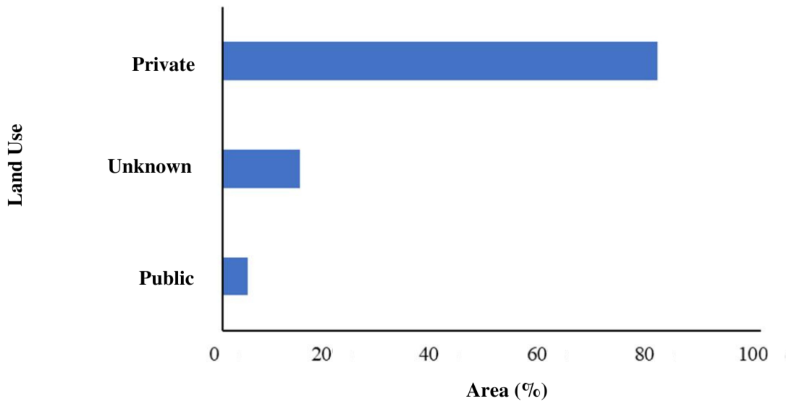

Figure 14. Land Use class area, for private, public and unknow classes, presented in percentage (%).

CHAPTER II. URBAN FOREST AND PER CAPITA INCOME IN THE MEGA-CITY OF SAO PAULO, BRAZIL: A SPATIAL PATTERN ANALYSIS[1]

Abstract
The integration of natural and social sciences in multidisciplinary research may be the key to improving public policies for urban greening. Analyses on the distribution of urban forests in relation to income are scarce for cities in developing countries, which is a crucial problem in view of the problematic and unplanned urbanization process common in these cities. Our study aims to fill this gap, focusing on the mega-city of Sao Paulo. We analyzed the spatial correlation between tree cover and per capita income and the interaction of these variables with other land covers (lawn, buildings and shadows). The city's land cover was estimated from a digital infrared orthoimage and Exploratory Spatial Data Analysis techniques. We found that Sao Paulo presents two patterns for the spatial correlation between tree cover and income, which may represent other mega-cities with similar characteristics. When considering the entire area of the city, the spatial correlation is negative, result contrary to most of the literature and strongly influenced by the presence of reminiscent forests in the peripheral regions, where lower-income population lives. When considering only more urbanized areas, the spatial correlation is positive, indicating an uneven distribution of urban forest that favors the wealthier neighborhoods.

Keywords: Geographic Information System (GIS); urban forest.

1. Introduction

Cities are heterogeneous, dynamic landscapes and complex socioecological systems, where society and ecosystems are widely connected (GRIMM et al., 2008). Therefore, to understand their dynamic forces and interactions, guiding and supporting society improvements, it is necessary to integrate the natural and social sciences in a multidisciplinary approach (GRIMM et al., 2008). This complexity has been amplified as the accelerated process of urbanization over the last century has led to the formation of mega-cities. Currently, 12% of the world's population, or about 453 million people, live in only 28 mega-cities worldwide (UNITED NATIONS, 2018).

The urban concentration with a compact landscape, as opposed to an sprawled one, can be more attractive for mega-cities, with verticalized buildings that promote dwellers densification, reducing the need for mobility and pollutant emissions and generating more free space for vegetation (ACIOLY; DAVIDSON, 1996; JENKS; BURGESS, 2001). However, without efficient planning, it also brings costs arising from the malfunctioning of the spaces, including an inefficient land use, traffic problems, loss of vegetation and social inequality, that can be caused and aggravated by poorly managed urban development (MCFARLANE,

[1] This study has been published on 21 January 2021 and can be found at: https://www.sciencedirect.com/science/article/abs/pii/S0264275120314475

2015; ROLNIK et al., 1990; HAALAND and VAN DEN BOSCH, 2015). One of these problems may be the uneven distribution of environmental benefits among the population (GERRISH; WATKINS, 2018).

Scientific literature shows that urban forests offer desirable effects on the environment and the urban population's health, contributing to reducing the level of stress, adding oxygen and reducing vehicle pollution, helping to balance microclimates, reducing direct sunlight, controlling the temperature, among other aspects; therefore, an uneven distribution of urban forest can be a form of environmental injustice (MCPHERSON, 1992; DWYER et al., 1992; NOWAK 1993; ROSENZWEIG et al., 2006; WANG et al., 2012; GRAZULEVICIENE et al., 2015; BEYER et al., 2014; TSAO et al., 2014; GERRISH; WATKINS, 2018).

Quantitative literature on environmental justice has traditionally focused on how low-income or minority communities are exposed to environmental hazards or how their benefits to environmental amenities can be limited (HETRICK et al., 2013; GERRISH; WATKINS, 2018). Several studies have analyzed the empirical distribution of the urban forest with respect to an array of socioeconomic variables, such as absolute or relative income, race, ethnicity, education, property value, and other (CUTTER, 1995; PEDLOWSKI et al. 2002; HEYNEN et al. 2006; PÄCKE; ALDUNCE, 2010; FLOCKS et al. 2011; JENNINGS et al. 2012; SZANTOI et al., 2012; PHAM et al., 2013; WOLCH et al., 2014; MARUTHAVEERAN AND VAN DEN BOSH, 2015; KABISCH et al., 2016; LOCKE; GROVE, 2016).

Specifically, regarding the relation between urban forest cover and income, most studies found a positive relationship between them (LANDRY; CHAKRABORTY, 2009; GERRISH; WATKINS, 2018). However, most studies focus on cities in developed countries and there is a lack of information on the distribution of urban forests with respect to income in cities in the developing world (PAUCHARD et al., 2006; HETRICK et al., 2013; ESCOBEDO et al., 2015; GERRISH; WATKINS, 2018).

This lack of information is a crucial problem, as these cities, opposed to cities of North America and Europe, often have irregular patterns of land use, social inequalities and socioeconomic instabilities — in lower-income countries, a troubled and unplanned urbanization process is more likely (ESCOBEDO et al., 2015). Our study aims to contribute to fill this gap, focusing on the city of Sao Paulo, a worthwhile object for the study of mega-cities in developing countries. Sao Paulo is currently one of the world's five largest cities, the largest in Latin America, with constant population growth and went through an unplanned process of intense urbanization that led to disharmonious urban configuration with socially and environmentally fragile peripheral regions (SOUZA, 1994; NOBRE et al., 2010, UNITED NATIONS, 2018).

Specifically, the objective of the study is to find out if there is a specific spatial pattern associating tree cover with per capita income in the Megacity of Sao Paulo, evaluating if there is convergence or divergence in the variables' spatial distribution. The different land coverings compete with each other for space and are a result of the historical process of urbanization of the city and, also, strongly determined by socioeconomic aspects. Therefore, to understand the spatial distribution of the Sao Paulo tree cover, and its relationship with income, the interaction of these variables with other land covers was also analyzed.

Throughout the study, urban forest is approached as the total of tree cover within the official urban limits of Sao Paulo, without discriminating between types, including from gardens and street trees to parks and residual forest in the bordering regions. The definition adopted allows formulating urban greening policy goals, in accordance with Brazilian law, which require that all green areas within municipal boundaries are the responsibility of municipal management.

Then, the study seeks to provide an overview of the distribution of green areas in relation to income in a mega-city in a developing country, thus bringing new evidence to an international literature that is still scarce. Evidence can support decision-making by urban managers in Sao Paulo and other mega-cities with similar urbanization processes.

Sao Paulo city's land cover was estimated from a digital infrared orthoimage date from 2010 using the Extraction and Classification of Homogeneous Objects (ECHO) algorithm. We organized the data, including per capita income, according to territorial division by Administrative District (AD) and used Exploratory Spatial Data Analysis (ESDA) techniques to explore the spatial associations. The theoretical framework that our study is based on is that of the 'inequality hypothesis', addressed in Heynen et al. (2006), which refers to the uneven distribution of environmental amenities, such as urban forests, between different sociodemographic groups.

2. Materials and Methods

2.1 The study area

The São Paulo city has a territorial extension of 1,521,110 km², with around 21 million inhabitants in its metropolitan region and 12 million in the city according to the last Brazilian census, and accounts for about 12% of the national GDP, being the greatest area of Brazilian urban development (IBGE, 2010). São Paulo was founded in a Brazilian Atlantic forest biome

(Atlantic rainforest), characterized by a high density of native forest and great water availability, still evident nowadays (SILVA, 2013).

Historically, the decision-making of municipal managers in the city has over the years created an uneven city in terms of opportunities, infrastructure and development. Economically, the city emerged as a commercial warehouse, but it really gained importance with the expansion of income promoted by the growth of coffee agriculture in the Brazilian historical context, which helped to provide the necessary income for the principle of industrialization in the country, becoming an industrial pole over the years; on the other hand, the urban expansion occurred from a horizontal process and with low urban planning (ROLNIK, 2001a; BENTES, 2011).

From the 1940s onwards, there were two simultaneous processes: the central verticalization, supported by the real estate appreciation in the region, and, at the same time, the continuous urban sprawl to the periphery, associated with irregular occupation and deficient infrastructure (TASCHNER; BOGUS, 2001). The "favelas" (typical Brazilian housing areas with poor and irregular constructions) have been regularized over time, forming low-income neighborhoods and migrating to even more precarious, remote settlements and without infrastructure; then the peripheral ring was formed, where there is little control over land use and occupation (TASCHNER; BOGUS, 2001; MARICATO, 2000).

If, on the one hand, there are skyscrapers and illuminated towers, with canalized rivers contained between wide marginal avenues in the central regions of São Paulo, which demonstrate the economic and employment strength, on the other hand, there is a strong contrast with the poverty in peripheral regions (ROLNIK, 2001a). This generates a clear spatial division by social classes, displacement problems, violence, worsening poverty, in addition to environmental problems such as thermal inversions, urban canyons, poor air circulation, population density, heat islands, among others (PEARLMUTTER et al., 1999; ROLNIK, 2001B; ARNFIELD 2003). Nowadays, this spatial pattern aggravates the mobility crisis – the city has a system dominated by private individual transport, with low investment in public transport, the latter being used predominantly by the low-income population (ROLNIK and KLINTOWITZ, 2011) – and causes an increase in emissions of traffic pollutants – exceeding the levels recommended by the World Health Organization (DE MIRANDA et al., 2012).

In summary, the intense urban and population expansion of Sao Paulo occurs sprawled, mainly in its peripheral portions, where they are faced with important reminiscences of the Atlantic Rainforest, as discuss by Silva (2013). The precarious horizontal expansion of São Paulo puts at risk the maintenance of the remaining forest, creates a mega-city occupied almost totally inefficiently and reduces the green spaces (SILVA, 2013). This aspect reinforces the importance of studies that reflect on the process of occupation of the city and distribution of the urban forest.

2.2. Data

Sao Paulo city’s land cover was estimated from a digital infrared orthoimage dated from 2010, which has spatial resolution of 1m per pixel, with each section of the mosaic encompassed 188 km² (13 km x 14.5 km), containing Blue, Red and Near Infrared spectral bands. The image was obtained by overflight and made available by the University of Sao Paulo (USP).

The presence of infrared sensitive film, with proper filters, allows to highlight vegetation, which makes it ideal for urban studies and a key tool for ecosystems conservation (OLIVEIRA, 1993; INOSTROZA et al., 2013; SZANTOI et al., 2012; GUINDON et al., 2004; XIAN, CRANE, 2005; BUCHANAN et al., 2018). At the same time, some limitations of the methodology are implicit. The result of image capture is influenced by Sun angle, solar irradiance and atmospheric conditions, causing distortions between acquired image by sensor and urban superficies. As discussed by Foster (1985), the high-quality resolution, presence of infrared band and all landscape elements registered on the same scale can mitigate possible geometric distortions.

Land cover classification was done through a supervised object oriented classification method. In this type of categorization, the image’s pixels are grouped so that an object's’ specific composition are shown as features different colors, allowing us to categorize them as specific land cover. Thus, the classification was assigned through application of the Extraction and Classification of Homogeneous Objects (ECHO) algorithm using the MultiSpec© 3.3 (BIEHL and LANDGREBE, 2002), with the input of 80 trainers (sample polygon) for each land cover class.

The image was classified using the classes: tree, lawn, shadow, roofs (ceramic, white, dark, gray), paving (asphalt, concrete, cement floor), exposed soil, pools and water. Information on areas with exposed soil, pools and water coverage was not analyzed in this study. Due the high resolution, this classification scheme provides a high level of detail of land cover, it allows to easily distinguish tree cover from herbaceous cover in accurate way. Once a city is richness in types of land cover, more simple indexes as Normalized Difference Vegetation Index (NDVI) and green areas index, what not allows distinguish trees from herbaceous, cannot offer accuracy needed in urban land cover researches (FOSTER, 1985; DAVIES et al., 2008). More information about the classification is available in Supplementary material.

Kappa Index (K), described in Landis and Koch (1977) and Moreira (2004), allows to statistically validate the acceptance or rejection of the classification, providing classification accuracy of results. Is considered K above 0.81 as accurate performance of classification.

We organized the data collection according to territorial division by Administrative District (AD), division that distributes the total urban area into 96 districts (GeoSampa, 2020) that varies greatly in area. Therefore, we express variables in percentages (AD classes area by AD total area). All the analyses of land cover were performed on Quantum GIS® 2.18.16 software.

As for income data, we used the per capita gross domestic product (GDP) per AD. These data were made available by the State Data Analysis System Foundation (SEADE, 2017) and were converted from Brazilian *reais* into US dollars, considering the exchange rate on May 1st 2018, 3.17 R$ = 1 USD, obtained from the Central Bank of Brazil (BCB, 2018)..

In summary, the variables analyzed in the study are tree, lawn, building (roofs and paving) and shadow percent covers and per capita GDP, by ADs. Tree cover was not distinguished by type (street, gardens, parks or residual forest), once the propose is provide an overview of equal or unequal distribution in relation to income.

In the land cover analysis, shadow can represent verticalization in cities. Mendes et al. (2015) in a research with high resolution image, suggest that shadow can be linked with verticalization in neighborhoods of Lisbon (Portugal), once the center of the city presented more buildings and more shadow, and this effect decrease towards periphery. To corroborate this affirmation, and test if shadow cover can express verticalization in Sao Paulo city, we implemented a simple regression analysis between the shadow coverage and the height of the buildings. The buildings height database is available in an official municipal website (GeoSampa, 2020). The height database contains approximately 2 million buildings georeferenced, by AD, and was made by overflight (2004), manual photogrammetric rendering and reading the height of the construction, whenever possible. The analyses were performed on RStudio© 1.2.5001. There was found a significant linear relationship between Shadow and Buildings height (r^2 adjusted of 0.84, $y= -4.6075 + 2.0356x$) with 99% confidence interval (the analysis can be found in the Supplementary material). Therefore, Shadow can represent the height of buildings, and its index express the verticalization in Sao Paulo city.

2.3. Exploratory spatial data analysis

As we intend to focus on spatial aspects of the evaluated database, we used Exploratory Spatial Data Analysis (ESDA) techniques. The ESDA assumes that every process that takes place in space is subject to Tobler's first law, which highlights the role of proximity in spatial interaction or dependence (ALMEIDA, 2013). The use of spatial techniques is justified by the process underlying urban space design, which responds to factors such as spatial diffusion and competition for space. The process is influenced by a combination of synergistic factors economy of scale and other types of increasing returns—and opposing dissonant factors—transportation costs and inefficiencies, such as congestion, crime, pollution and property price distortions (CHRISTALLER, 1933; KRUGMAN, 1991; VIEIRA, 2009).

The first step in the analysis of data spatial association is the definition of a spatial weights matrix, whose elements in this particular study indicate the spatial weight that relates one Sao Paulo AD with a neighboring Sao Paulo AD.

The most used matrix is the one constructed with spatial weights defined by proximity criterion (defined according to contiguity and / or geographical distance). In this study, we chose geographic Euclidean distance based on centroids using the ADs latitude and longitude data as the criterion. We also analyzed distance matrices for k nearest neighbors, with k = 5, k = 10 and k = 15. However, we consider that the Euclidean distance matrix had the best fit. The option for the geographic distances matrix is based on evidence from literature that contiguity matrices have less explanatory power than distance matrices as the sample size grows (TYSZLER, 2006).

Using the distance matrix, we performed three types of analysis: univariate global spatial autocorrelation, univariate local spatial autocorrelation and bivariate local spatial correlation.

The Moran's (1948) I statistic for the evaluation of global spatial autocorrelation is commonly used to verify the data's non-randomness in space (CARVALHO & ALBUQUERQUE, 2010), formally indicating the degree of linear association between the vectors of observed values and the weighted average of neighborhood values (or spatial lags). The null hypothesis to be tested is that of spatial randomness (CLIFF and ORD, 1973). Algebraically and in matrix notation, the statistics proposed by Moran (1948) reflect the cross product's auto covariance, as in equation (1) (ALMEIDA, 2013):

$$I = n/S_0\,(z'Wz)/z'z \tag{1}$$

Where n is the number of localities; z is the matrix with the variable values of interest; are the average values of the neighbors' standardized variable of interest, defined according to the spatial weighting matrix W; and S_0 is the sum of all the elements of the spatial weights' matrix W. The term of the numerator of (1) is spatial autocovariance, composed of cross products.

The indication of a global association pattern may not be in line with local association patterns. Three different situations may occur (PEROBELLI et al., 2007; ALMEIDA, 2013): (i) Moran's I is statistically non-significant when there are indications of significant local spatial autocorrelation; (ii) Positive indication of the global Moran's I that hides negatively or statically insignificant local spatial autocorrelation; (iii) evidence of a negative global spatial autocorrelation but accommodating evidence of positive local spatial autocorrelation.

To analyze local patterns, we use Local Indicators of Spatial Association (LISA) statistics, analyzing the local coefficients of Moran's I using the Moran Scatterplot and the map of spatial clusters, following criteria indicated in Anselin (1995; 1998). According to Almeida (2013), the local Moran's I decompose the global indicator of each autocorrelation in the local contribution of each observation into four categories, presented in the four quadrants of the Moran Scatterplot. The High-High (HH), or upper right quadrant, for example, is formed by regions with high values for the variable of interest surrounded by regions that also have above average values for this variable. Analogous logic explains the formation of the other categories: Low-Low (LL), High-Low (HL) and Low-High (LH). The regions located in the HH and LL quadrants have positive spatial autocorrelation and form clusters of similar values. The LH and HL quadrants have negative spatial autocorrelation and form clusters with dissimilar values.

The univariate LISA application allows identification of each variable's' spatial association pattern. We also analyze whether there is a specific spatial association pattern between some land cover variables (tree and shadow) and per capita income. According to Almeida (2013), local Moran's I can be adapted to a bivariate perspective. In general, we interpret the bivariate LISA statistic as the degree of linear association between the values of one variable in each location and the average values of another variable in a neighboring location.

For both univariate and bivariate analysis, we present the results as Moran Scatterplots and maps of spatial clusters. We use GeoDa© version 1.4.5 for analysis.

3. Results

Sao Paulo city in 2010 was covered by: 34% of tree, 31% roofs, 14% lawn, 12% paving, 5% shadows, 3% water (lakes, rivers) and the remaining 1% of swimming pools and exposed soil. The building areas (roofs and paving) covered 43% of the urban soil, and natural areas still were the dominant cover, with 51% (trees, lawn and water).

Figure 1 shows the spatial distribution of tree, building, lawn and shadow covers. The tree cover has a clear spatial pattern: greater percentages of coverage are concentrated in the city's peripheral zones, decrease in percentage cover as one approaches the city's center, and reach minimum covers in the most central-east zones (see in Figure 1a). Figure 1c shows the spatial distribution for lawn, which is similar to that of trees, with the presence of trees and lawn associated, mainly, with peripheral zones. In contrast, building and shadow follow an opposite pattern of spatial distribution, being higher in the central regions with decrease to peripheral zones (Figures 1b and d).

The spatial distribution of the building has higher values in the northern and northeastern ADs (Figure 1b). This area is highly populated, about 4 million inhabitants in 2010 or 35.6% of the city's population (IBGE, 2010), characterized by not verticalized neighborhoods and sprawl land cover. At the same time, shadow spatial distribution is divergent from building (Figure 1d), with the largest percentages is in the central zone, which has the city's smallest population share, just 3.8% in 2010 (IBGE, 2010). This corroborates that the central zones are dominated by high buildings areas mainly focused on commercial activities.

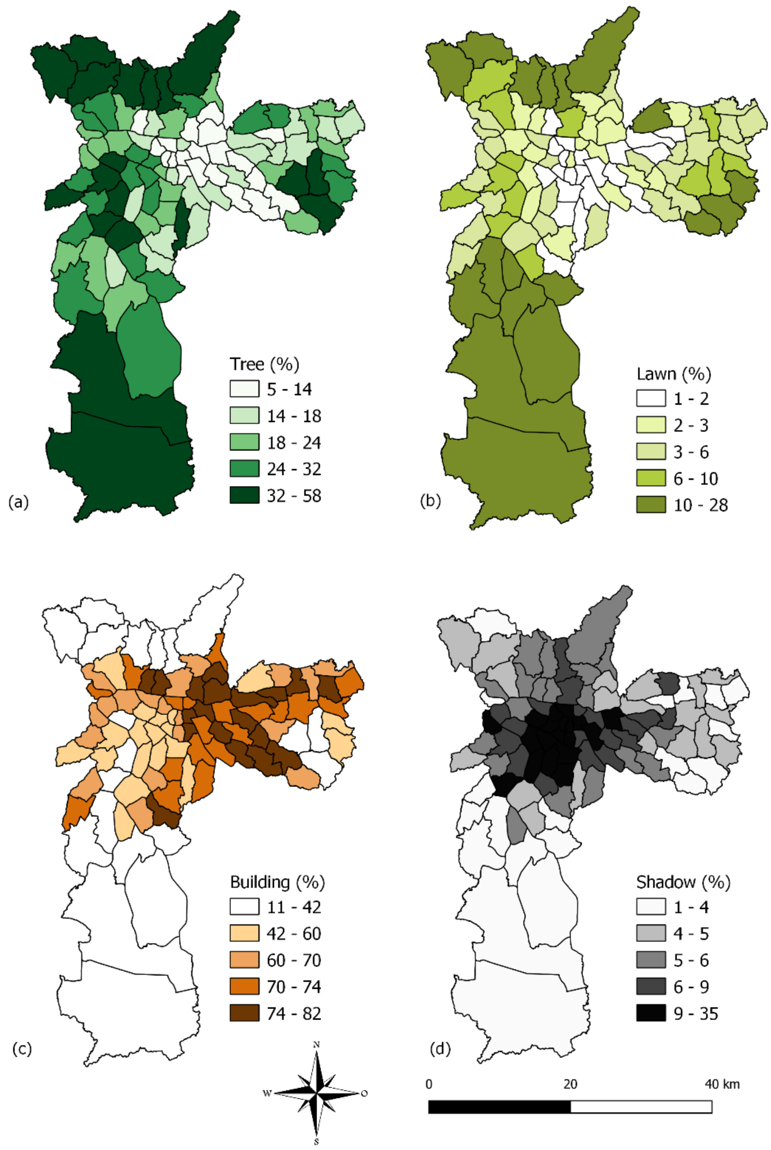

Figure 1. Spatial distribution of (a) tree, (b) building, (c) lawn, (d) shadow, all in percentage cover (%).

Information in Figure 2 indicate that per capita income is aligned in an overall radial-concentric configuration. Per capita income declines as one travels from the central ADs towards the peripheral ADs to the northwest and to the east. Residents with the highest income have an average per capita monthly income of between USD 663 and USD 1,567, while residents with lowest income have an average per capita income of between USD 110 and USD 175.

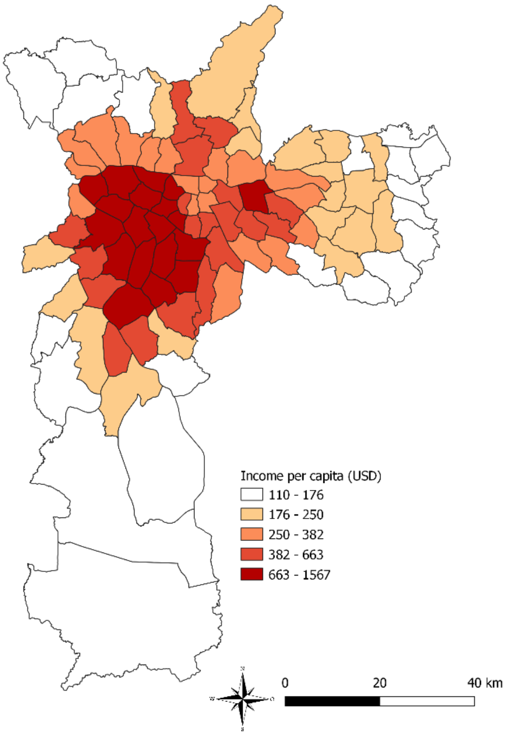

Figure 2. Per capita income spatial distribution (monthly average, in USD)

Although Figures 1 and 2 indicate that the distribution of the variables under study follows a spatial pattern, formal tests are necessary to make inferences, which is implemented in the next subsection.

3.1. Univariate spatial autocorrelation analysis

First, the Moran's I values for global autocorrelation were found to be statistically significant for tree and shadow covers and for per capita income: 0.228, 0.208 and 0.334 (all p-values less than 0.01), respectively. This indicates that these variables follow a concentration spatial pattern: districts with relatively high coverage of tree are surrounded by districts with the same characteristics and vice versa — and the same logic applies to the cases of per capita income and shadows.

Furthering the analysis for three of our main variables of interest we now present the Moran's diagram of dispersion and its resulting LISA cluster map, all of them with 95% confidence level (Figure 3). Figure 3a shows an important LL tree coverage cluster formed by ADs in the city’s central and eastern zones. This cluster is made up of districts with low tree cover surrounded by districts with the same characteristic. In addition, at the limits of this cluster, HL clusters were formed.

These HL ADs surround the central and eastern zones, which present the smallest quantiles of tree and lawn cover (Figures 1a and c), representing transition zones between the extremely urbanized central and eastern zones and more peripheral HH cluster zones. Figure 3a also shows that the predominant tree cover cluster is LL, representing 35% of the city's ADs. This cluster predominates in the central zone and is formed by several smaller sized ADs, reflecting the spatial force of the process of replacing green areas by buildings.

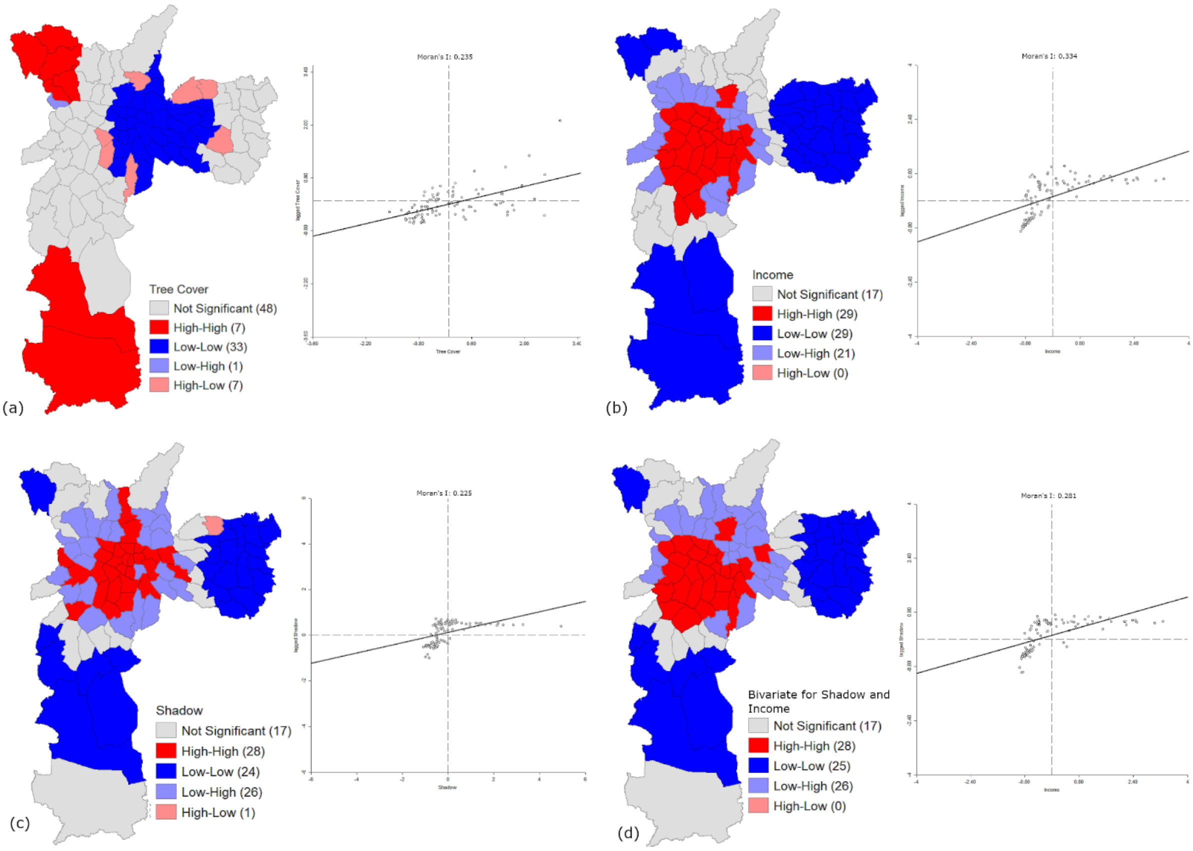

Figure 3. Local Indicators of Spatial Association (LISA): cluster map and Moran Scatterplot, respectively, being univariate for tree cover (a), per capita income (b), shadow (c), and bivariate for income and shadow (d).

Figure 3c shows the formation of an important shadow cover HH cluster, being dominant in the city's central zone. As previously pointed out, this zone is formed by high commercial buildings and has a small resident population. The HH cluster is surrounded by LH formations made up of regions in which tall buildings are less concentrated. Finally, LL shadow clusters are predominant in the peripheries of the city. This configuration evidences the existence of a process of spatial diffusion of verticalization, probably related to the value of land in and near the central zone.

The pattern of cluster formation for per capita income differs greatly from the tree cover pattern but shows some similarities with the shadow cover one (Figure 3b). There is a large HH cluster in the central zone, with some displacement to the west and north. The spatial displacement to the west of the HH per capita income cluster in relation to the LL tree cover cluster is caused by the existence of ADs that have high per capita income residents and also have high tree coverage; also, the displacement to the west in relation to the HH shadow cover cluster is caused by the existence of ADs that aren't in the central zone but whose residents have high incomes — these results are shown in the subsequent bivariate analysis. Again, the per capita income HH cluster is surrounded by LH per capita income formations that are composed by relatively poorer districts adjacent to the wealthy central zone. Three LL clusters were found in the city's periphery.

Figures 3a to 3c reinforces the concentrated and concentric spatial pattern of land covers and income distribution in Sao Paulo.

3.2. Bivariate spatial correlation analysis

Figure 4 shows the bivariate Moran's I diagram of dispersion and its resulting LISA cluster map comparing tree cover and per capita income (95% confidence level). Overall, there is a modest but significant negative global correlation between the variables (Moran's I: -0.093). This indicates that districts with relatively high tree coverage are usually surrounded by districts with relatively low per capita income. The global association may not perfectly reflect the more local associations. This can be seen in the LISA cluster —locally, the presence of clusters in the four possible quadrants is strong.

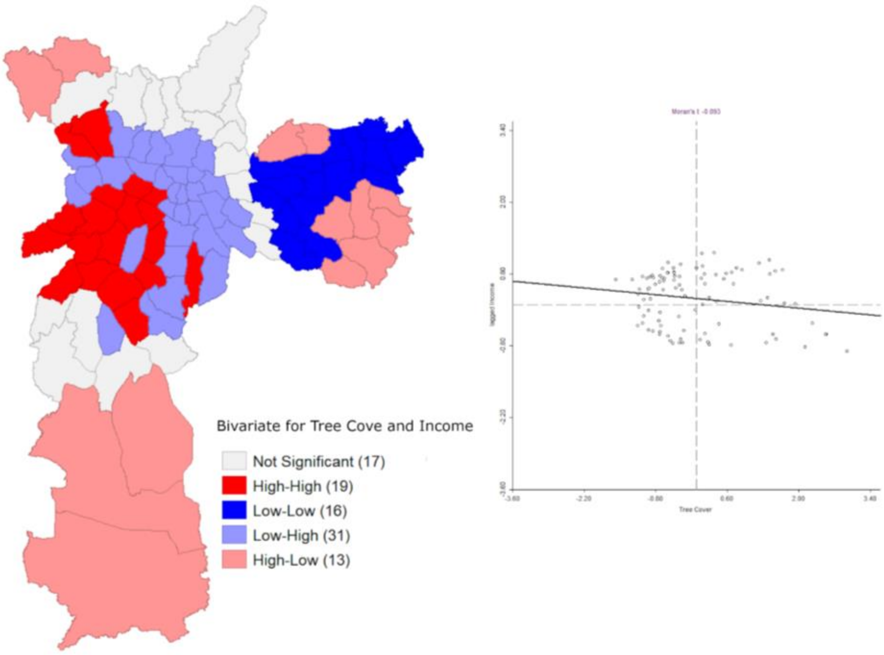

Figure 4. Local Indicators of Spatial Association (LISA): Cluster map (bivariate for tree cover and lagged per capita income) and bivariate Moran Scatterplot.

Significant HL clusters, high tree cover surrounded by below average per capita income, were found in all city's periphery, with exception of city's eastern periphery, that presents a LL cluster with low tree cover percentage and low per capita incomes. A HH cluster predominates in Sao Paulo's western zone, characterized by districts with above-average tree cover and neighbors showing the highest per capita income in the city. A large LH cluster predominates in Sao Paulo's central and surrounding zones.

Figure 3d shows the bivariate Moran's diagram of dispersion and its resulting LISA cluster map comparing per capita income and shadows. In this comparison, a significant positive global correlation was found (+0.281), indicating that districts with relatively high shadow are usually surrounded by districts with the relatively high per capita income. The local correlations between these features are also strong.

In the peripheral zones to the south and east, important LL clusters are formed, suggesting that a low level of income in a particular AD reduces the possibility of verticalization in neighboring ADs. The HH cluster in Figure 3d shows a right shift in comparison to the HH cluster in Figure 2. The Figure 3d cluster includes ADs in the central zone. These districts have a high degree of verticalization and high per capita incomes. Analogously, this analysis brings evidence that high per capita income and verticalization are highly associated in Sao Paulo city.

4. Discussion

We found that 34% of Sao Paulo's urban land was covered by trees, a percentage similar to that found in other world metropolis like Berlin (German) with 40% in 2016, Washington (DC) with 35% in 2019 and Boston (MA) with 29% in 2006 (LEFF, 2016; KABISCH et al., 2016). Endreny et al. (2017) analyzed the tree cover of 10 mega-city metropolitan areas around the world and found that they had an average tree cover of 21% and potential for more 19% of greening.

In Sao Paulo city, tree cover is not evenly distributed in space, with a greater concentration in the peripheral areas and reduction towards the central regions. This is a common gradient of cities, as discussed by Bradley (1995), where areas with high urbanization can be found in the center of city occupy the land with such intensity that it leaves a limited space for forest areas in the urban landscape.

Considering that the spatial distribution of per capita income follows a pattern opposite to this, our bivariate analysis pointed to a negative global correlation between tree cover and income in Sao Paulo. This indicates that greater tree cover is spatially associated with lower per capita income – a result contrary to that of much of the scientific literature (LANDRY; CHAKRABORTY, 2009; GERRISH; WATKINS, 2018).

At the same time, it is noted that this result is mainly related to the fact that the historical urbanization process of Sao Paulo, and its expansion in the last decades, has been marked by growth towards the peripheral regions, especially with poor portions of the population, and to the fact that these peripheries hold important reminiscent forests. In addition, higher vegetation coverage can be expected in suburban areas – which in São Paulo, are those with the lowest income – than in the dense urban core (PHAM et al., 2013).

A similar result with similar underlying causes was found by Hetrick et al. (2013) for Altamira city, Brazil – a mid-sized city in Amazon. The authors explain that the positive relation between vegetative cover and income probably reflects the processes of agrarian frontier expansion and contraction in the Amazon and the fact that poorer households reside away from the most built up areas of the city, in areas of lower household density and lower ratios of impervious surface to vegetative cover. In contrast, also analyzing a Brazilian city, Campos dos Goytacazes, Pedlowski et al., (2002) have found a direct relationship between neighborhood wealth and tree abundance and explained that this result is associated to the fact that most urban areas created since the 1950s were built on former sugarcane fields, completely unvegetated areas.

Considering that presence of tree cover offers benefits to the population through its environmental services, the historical urbanization process of Sao Paulo, which did not have an environmental planning, created a central area with scarce urban forest that can offer insufficient ecosystems services to a high-income population; in contrast, it created peripheral zones with extensive urban forest (dominant by remaining forests) that can offer great value ecosystem services to the low-income population, although these regions are characterized by severe limitations of urban infrastructure, security and other social restrictions. In this sense, future studies are encouraged that consider that actually exposure and how accessible is the urban forest for the low-income population, considering all interfaces of these counterpoints, since access to and interaction with green areas is a fundamental part of urban quality of life (VAN HERZELE; WIEDEMANN, 2003).

The analysis of the results also suggests that Sao Paulo present two patterns for the relationship between tree cover and income. In addition to the negative global correlation already discussed, strongly influenced by remaining forests, there may be a second pattern, with positive correlations in areas of the city that are predominantly urbanized. To test empirically for the existence of this second pattern, a complementary analysis was performed.

The additional analysis estimates the bivariate spatial association between income and tree cover but excluding districts with an area predominantly covered by forests. In this case, we organized the data into Human Development Unit (UDHs), a geographical unit formed by a group of adjacent census tracts, totalizing 1189 observations. It was considered the Urban Macrozone delimitation, which contemplates the urbanized center, without the Environmental Macrozone (areas of permanent protections and of reminiscent of Atlantic Rainforest), both of which are official delimitations defined by the Director Plan (PL 688/13). Some of UDHs were between the Urban and Environmental boundaries of the Macrozones. We then exclude UDHs with 50% more forest-covered soil. Figure 5 shows the result of this analysis.

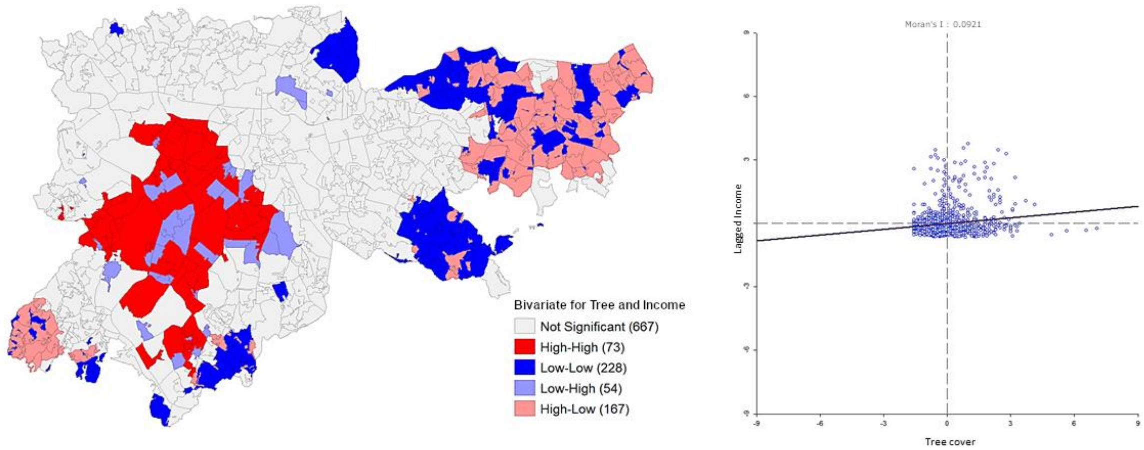

Figure 5. Local Indicators of Spatial Association (LISA): bivariate Moran Scatterplot (a) and cluster map (bivariate for tree cover and lagged per capita income) (b).* Without the areas covered predominantly by forests.

As expected, when forest areas are excluded from the analysis, the spatial association between income and tree cover becomes positive, indicating that in the predominantly urbanized areas greater tree cover is spatially associated with higher per capita income. This second relationship, that is less predominant in the previous overview analysis, reflects an inequality in the spatial distribution of the urban forest in relation to income, with opposition between two predominantly residential areas of São Paulo: the wealthier and forested western region and the low-income and poorly forested eastern region.

This second spatial pattern is convergent with most of the scientific literature in worldwide cities as Montreal and Toronto (Canada), several metropolitan regions of the southwestern United States (USA) (Albuquerque, New Mexico; Austin, Texas; Inland Empire region, California; Las Vegas, Nevada; Los Angeles, California; and Phoenix, Arizona), Miami-Dade and Chicago (USA), among others (IVERSON; COOK, 2000; LANDRY; CHAKRABORTY, 2009; PHAM et al., 2012; SZANTOI et al., 2012; CONWAY; BOURNE, 2013; JENERETTE et al., 2013; GERRISH; WATKINS, 2018); and Latin American cities, like Santiago (Chile), Bogotá (Colombia), including Rio de Janeiro and Campos Goytacazes (Brazil) (PÄCKE and ALDUNCE, 2010; ESCOBEDO et al., 2015, PEDLOWSKI et al., 2002).

In this case, different from the previous result, which is probably due to the unplanned urban expansion process of Sao Paulo city, the positive correlation between urban forest and income is probably related to a biased urban greening policy in favor of wealthier neighborhoods and to the fact that housing costs may be lower in residential areas with scarce urban forest, making them more affordable to low-income residents. These possibilities were raised by Pham et al. (2012), who found the same relationship between the variables for Montreal, Canada.

The same theory can be applied to verticalization process of the city – evidenced in land cover analysis. The bivariate analysis of shadow and per capita income (which have a positive global spatial correlation) together with the spatial distribution analyzes of the buildings and the shadows pointed to verticalized and wealthier center/western districts with low population density and non-verticalized and poorer peripheral districts, as well as a high building density in eastern districts – that are not high verticalized.

In this context, Sao Paulo city can be defined by a vertical and compacted city when considered your edifications and a "hollow city" in terms of dwellers density (ROLNIK et al., 1990; ROLNIK 2001a). Considering the Urban Macrozone (disregarding the highly forested peripheries) there is a contrast: the vertical, forested and highly infrastructure areas of the city are more expensive, being inhabited by high-income people to whom they are affordable; and sprawled parts of the city with less infrastructure and without the need for vegetation are cheaper, and concentrate parts of the population that have lower income. This is a pattern that originated at the beginning of the urbanization of the city and which is still explicit in the 2010 land cover distribution pattern.

The pattern of an elitist, vertical and greener western region and of low-income, low-vertical and poorly forested neighborhoods, highlighted in the Urban Macrozone analysis, aggravates the uneven distribution of urban forests in the city of São Paulo. A challenge for researchers and urban managers is to manage to create a compact and vertical city without loss of socioenvironmental quality, and a strategy for this is the use of greening technology and innovative public policies (HAALAND; VAN DEN BOSCH, 2015).

5. Policy Recommendations

The city of São Paulo has important regulatory documents for urban planning, the main ones being the director plan, the urban zoning laws, and the Municipal Plan for the Conservation and Recovery of the Atlantic Forest (SÃO PAULO, 2014, 2016, 2017). The director plan and the urban zoning laws regulate land use and occupation through generalist subdivision rules and efforts to establish quality standards for the urban landscape are rare (MACEDO, 2013; NETTO SABOYA, 2010). The Municipal Plan for the Conservation and Recovery of the Atlantic Forest deals with the reminiscent found mainly in periphery zones of the city and focuses on their quantification, conservation, the containment of deforestation and sustainable use.

All of these regulations were created recently and are still in the process of adaptation, and demonstrate how only recently has urban regulation planned for the expansion of the city and the conservation of the environment. The actual implementation of these regulations will take place in the coming decades. As the city of São Paulo is dominated by reminiscence of the Atlantic Rainforest, with a troubled history of expansion and in a constant process of urban expansion, urban administrations will face enormous challenges that a mega-city can offer.

In this context, some policy recommendations are made. To contain the constant sprawled expansion of the city, which puts at risk the forest remnants, as discussed by Silva (2013), it is necessary to invest in infrastructure and greening of the areas that dominate the east zone and that extend to the periphery. A factual densification of the city of São Paulo, in which ideal verticalized infrastructure accompanies the densification of residents, reducing the social inequality of access to these areas is desired, can be a key for urban forest preservation and increase (ROLNIK et al., 1990; ROLNIK 2001a). It is important to note that many cities around the world have achieved real densification and compact design, however many of them are associated with low urban forest, a paradox that is the main challenge for urban administrations (HAALAND; VAN DEN BOSCH, 2015).

6. Conclusion

The distribution of the urban space is a phenomenon typically sensitive to spatial effects. The definition of the land cover may reflect urban planning organized by the central power, or in the case of Sao Paulo, to be an organic movement with many spatial determinants, such as economic and social movements, real estate speculation, economies of scale, transportation costs, and levels of congestion and others. The spatial statistics and the formation of significant clusters highlighted the spatial dependence of land cover variables and per capita income in Sao Paulo city.

In summary, Sao Paulo city presents two patterns for the relation between tree cover and income. The first, when considering the entire area of the city, is a negative correlation between the variables. This atypical correlation is an unplanned and unwanted effect of a disorganized urban expansion process. In general, the historical occupation of Latin American cities has driven a spatial segregation guided by the preferences of the middle and upper classes, with the poorest classes being pushed to peripheral regions. But, unlike other cities, São Paulo has most of its Urban Forest in the peripheral areas, in the remnants of the Atlantic Rainforest. The historical social and environmental contrast and consequences is still very evident nowadays.

The second pattern is a positive correlation in the more urbanized areas of the city, indicating inequality in the distribution of urban forest. This probably reflects a biased urban greening policy in favor of wealthier neighborhoods and the fact that land prices may be higher in greener residential areas.

This pattern found for São Paulo can characterize other megacities that have undergone an urbanization process that segregates poorer populations in the peripheries, that creates an urban center without concern for environmental planning and that expands over regions where the previous landscape was forested. The continuation of a process of deterioration of green spaces associated with the economic inequality of the city, especially in peripheral areas, can cause important losses in the well-being of the city's inhabitants, which can aggravate already complex problems related to environmental and social issues in mega-cities.

By providing an overview of the distribution of green areas in relation to income in a mega city in a developing country, bringing new evidence and unpublished quantitative data, we aggregate knowledge in a still scarce literature, with evidence that can support decision-making by urban managers not only in São Paulo but in other megacities with similar urbanization processes.

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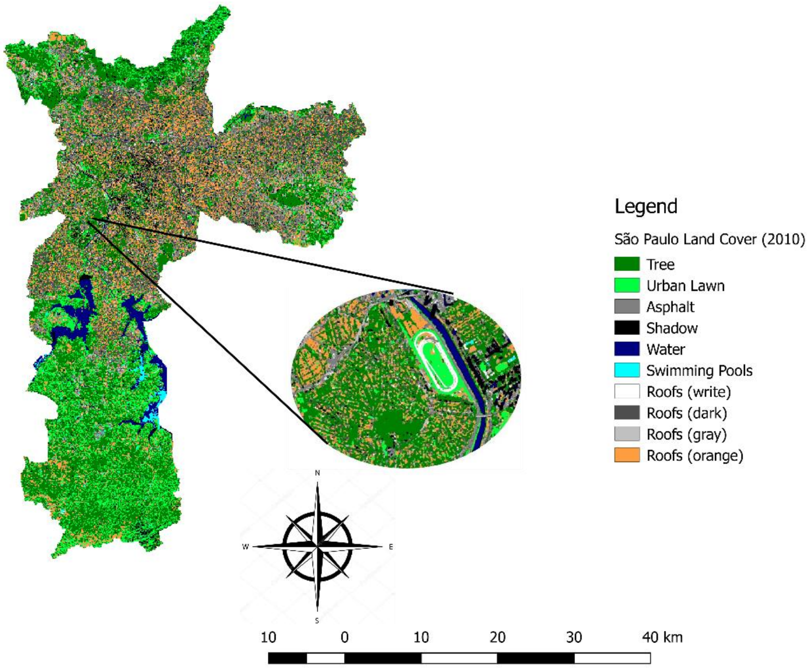
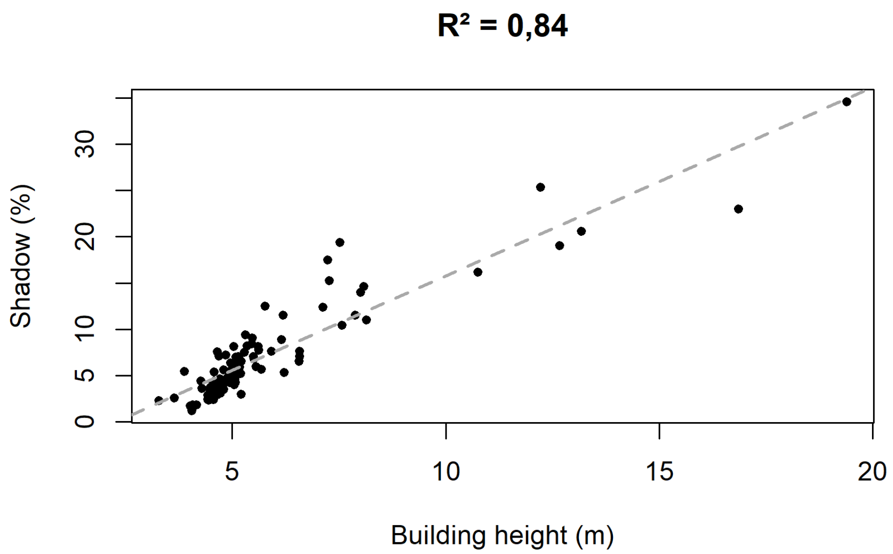
Supplementary Material

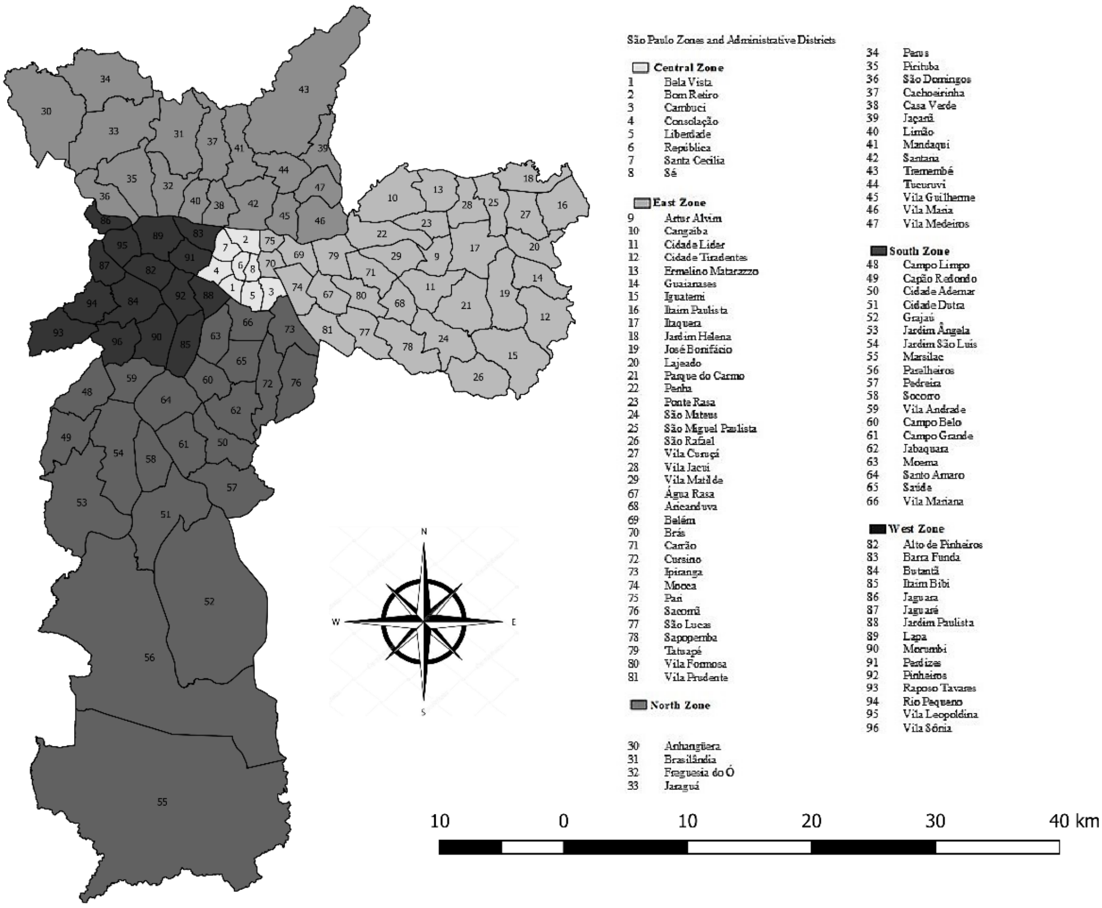
1. The land cover classes: tree, urban lawn, shadow, roofs (white, dark, gray, orange), asphalt, exposed soil, pools and water. For a high-resolution image, multispectral, satellite WorldView-2, year 2010 of the city of São Paulo / SP, Brazil.



2. Relationship between the variables shadow (percentage) and buildings height (meters) with 99% confidence interval of the simple linear regression equation.



3. Territorial division of the city of São Paulo in five zones (Central, East, North, South, West) and its respective Administrative Districts (AD’s).


São Paulo Zones and Administrative Districts
Central Zone
1 Bela Vista
2 Bom Retiro
3 Cambuci
4 Consolação
5 Liberdade
6 República
7 Santa Cecília
8 Sé
East Zone
9 Artur Alvim
10 Cangaíba
11 Cidade Líder
12 Cidade Tiradentes
13 Ermelino Matarazzo
14 Guaianases
15 Iguatemi
16 Itaim Paulista
17 Itaquera
18 Jardim Helena
19 José Bonifácio
20 Lajeado
21 Parque do Carmo
22 Penha
23 Ponte Rasa
24 São Mateus
25 São Miguel Paulista
26 São Rafael
27 Vila Curuçá
28 Vila Jacuí
29 Vila Matilde
67 Água Rasa
68 Aricanduva
69 Belém
70 Brás
71 Carrão
72 Cursino
73 Ipiranga
74 Mooca
75 Pari
76 Sacomã
77 São Lucas
78 Sapopemba
79 Tatuapé
80 Vila Formosa
81 Vila Prudente
North Zone
30 Anhangüera
31 Brasilândia
32 Freguesia do Ó
33 Jaraguá
34 Perus
35 Pirituba
36 São Domingos
37 Cachoeirinha
38 Casa Verde
39 Jaçanã
40 Limão
41 Mandaqui
42 Santana
43 Tremembé
44 Tucuruvi
45 Vila Guilherme
46 Vila Maria
47 Vila Medeiros
South Zone
48 Campo Limpo
49 Capão Redondo
50 Cidade Ademar
51 Cidade Dutra
52 Grajaú
53 Jardim Ângela
54 Jardim São Luís
55 Marsilac
56 Parelheiros
57 Pedreira
58 Socorro
59 Vila Andrade
60 Campo Belo
61 Campo Grande
62 Jabaquara
63 Moema
64 Santo Amaro
65 Saúde
66 Vila Mariana
West Zone
82 Alto de Pinheiros
83 Barra Funda
84 Butantã
85 Itaim Bibi
86 Jaguara
87 Jaguaré
88 Jardim Paulista
89 Lapa
90 Morumbi
91 Perdizes
92 Pinheiros
93 Raposo Tavares
94 Rio Pequeno
95 Vila Leopoldina
96 Vila Sônia
N
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E
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10
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10
20
30
40 km

CHAPTER III. DOES URBAN FORESTS MATTER FOR CRIME ANALYSIS? A SPATIAL ANALYSIS FOR SAO PAULO CITY, BRAZIL

Abstract

The link between tree canopy cover and crime has been discussed in the literature and its influence on social environment have been verified. Several studies were carried and has shown tree canopy associated with low crimes rates, mainly in the USA cities. Despite the importance of Latin American cities, few research about urban tree canopy and crime can be found. This study aims to fill this knowledge gap and proposes a series of spatial analysis models to tree cover and crime for Sao Paulo city (Brazil), with high quality data. Urban tree cover was estimated from 2017 satellite image, and geocoded crime database is from 2016 year, composed by robbery, theft, assault, rape, and all kinds of homicides. We test the tree cover and crime spatially dependence, and once this occurs, several spatial models are carried out, while potential confounders are controlled. We tested three crime types (person, property, total crime), three scales (crime per census sectors, human development unit, administrative districts), two areas of the city (all city versus the urbanized areas), and two denominators of crime (crime by population/1000 and by square kilometer). We found that there is a spatial association between the occurrence of crimes and the presence of tree cover, corroborating that these elements are not uniformly or randomly distributed in space. We fit 19 spatial models, being 11 SARMA and 9 LAG models, and 11 of them presented a negative relationship between tree cover and crime. Our main results showed that Sao Paulo city tree cover is associated with lower total, property and person crime rates, even when different areas of the city, scales of study, and denominator of crime are tested. The results follow the literature that have observed tree cover associated with lower crime rates, for different types of crime.

1. Introduction

The link between tree canopy cover and crime has been discussed in the literature and its influence on social environment have been verified. Research trends can be identified and categorized in four stages: linear analysis with regression models, as Ordinary Least Squares and Poisson regression (Kuo and Sullivan, 2001; Donovan and Prestemon, 2010); survey, applied for a group interviewed that can estimate perception, safety, fear of crime and others (Westover, 1985; Maruthaveeran, 2016); spatial analysis, in which spatial models and Geographically Weighted-Regression are applied, considering geographic effect on regression models (Deng, 2015; Wolfe and Mennis, 2012); and lastly, experimental or intervention studies, in which different treatments and control locations are applied in a time period defined to measurement of effects (Kondo et al., 2016).

In North America, several studies were carried out with spatial analyses. A negative correlation between tree cover and crime (robbery, burglary, theft and shooting) was found in Baltimore County (EUA), where 10% greater tree cover is related to 12% lower crimes (Troy, Grove and O'Neil-Dunne, 2012). A negative correlation was also found in New Haven

(EUA), where 10% greater tree cover is associated with 15% lower violent crimes and 14% lower property crimes (Gilstad-Hayden et al., 2015). The scientific literature of crime and urban forest have almost exclusively developed in the United States and Europe, being the last one more focused on fear of crime (Sreetheran and Van Den Bosch, 2014).

In Latin America, in Bogotá (Colombia), the spatial distribution of high size and high-density urban trees are linked with lower occurrence of homicides, discussing how urban forest can provide ecosystem service or disservice depending on municipal structure and management of these spaces (Escobedo et al., 2018). Tree canopy studies that mapped tree cover distribution and its relationship with socioeconomic characteristics were developed in the Caribbean, in Santo Domingo (Dominican Republic), where the socio-economic status was not positively associated with tree canopy cover (Martinuzzi et al., 2021), and in San Juan (Puerto Rico) where socioeconomic variables had a important explanatory hole in spatial variation of urban tree cover (Martinuzzi et al., 2018).

Latin America and the Caribbean are the second world regions with more urbanized areas, with 81% of our population living in cities, with projections estimating a peak of 752 million inhabitants around 2056 (UN, 2022). Your tropical climate houses one of the most biodiverse regions in the world, a global hotspot of conservancy (UNEP-WCMC, 2016). However, despite the importance of these regions, few research about urban tree canopy and crime can be found, creating a lack of scientific literature which leaves in question this relationship.

The under research is a case for the whole Latin America, main due the lack of information about urban forest and crime statistics, whereas robust and good quality geocoded database in this regard is needed, in order to be able to conduce high quality research (Schteingart, 2001; Dobbs et al., 2018; Ceccato, Haining and Kahn, 2007).

In this context, this research aims to fill this knowledge gap and proposes a series of spatial analysis models to tree cover and crime for Sao Paulo city (Brazil), with high quality data. Urban tree cover was estimated from 2017 satellite image, and geocoded crime database is from 2016 year, composed by robbery, theft, assault, rape, and all kinds of homicides. We test the tree cover and crime spatially dependence, and once this occurs, several spatial models are carried out, while potential confounders are controlled.

1.1. Crime review

Crime opportunities are neither uniformly nor randomly distributed in space and time (Ratcliffe, 2010). Opportunities for crime also vary over time and follow rhythmic patterns of human activities and are dependent in part on environmental characteristics. According to the Routine Activity Theory, most crimes depend on the convergence of a motivated criminal, susceptible victim, and a lack of perceived surveillance (Cohen and Felson, 1979). The urban forest is part of the urban environment, affecting when and how crime happens.

The theories of crime can be categorized in those that explain the positive correlation through i) Concealment. Tree cover can offer physical concealment to criminals and limited prospects and escape for victims, which can increase the opportunities of attacks and decrease safety (Fisher and Nasar, 1992); ii) Unoccupied. Neighborhoods with absence of neighbors, low density population as vast regions of cemented areas, industrial areas, that give rise to the feeling of lack of population and criminal supervision – no man's land and density population (Watts, 1931; Shichor, Decker & O'brien 1979, Troy, Grove, and O'Neil-Dunne, 2012); and iii) Disorder. Neighborhood characteristics such as lack of maintenance and care, and the resident's lack of interest in taking care of heritage, including trees, can increase crime – broken windows theory (Wilson & Kelling, 1982).

And those theories that explain the negative correlations through i) Care. Neighborhood characteristics such organization, clean, good landscape and high maintenance, due to the sense of belonging and care that the residents have in relation to the house and the neighborhood - care about, cues to care theories (Nassauer, 1995) and the absence of territorial concern, house good appearance and possible neighbors' reaction is a vulnerability to crime - territorial maker theories (Brown & Bentley, 1993); and ii) Surveillance. Neighborhoods where people know, communicate and care with each other stimulates territorial behavior and creates easy community surveillance – defensive space and eyes on the street theories (Newman, 1972; Jacobs, 1961).

Classical crime theories are important to explain correlations between urban forest and crime, as i) Social disorganization theory, which discusses that once the commons values are divergent and community structure are fragile the neighborhood will present lack of community effort to deal with each other, increasing crime rates (Shaw & McKay, 1942; Sampson and Groves, 1989). The studies point out population turn-over and ethnic heterogeneity as classicals indexes of social disorganization in literature. And ii) Social capital theory, which discusses that neighborhoods with high indexes of owners presents low crime index, once owners tend to dedicate more to maintenance and landscape care, when compared with renters, mainly because the owners usually stay more time in region and can develop the sense of invest on community (Lauridsen, Nannerup, & Skak, 2013).

These theories can substantiate the results found on the relation between urban forest and crime in several studies. View-obstructing trees are associated with increased crime, and houses with more trees convey the idea of greater care and may reduce crimes in Portland (OR) (Donovan and Prestemon, 2010). Troy, Grove and O'Neil-Dunne (2012) discussed that increasing trees in afforestation places can help to decrease "no man's land" and help to increase "eyes on the street" and "cues to care" in the Baltimore region (MD).

Positive correlations between trees and crime can be found in several papers, and are related with absence of maintenance on vegetation and landscape, presence of vacant lots, industrial areas and lack of harmony between the height of the street lighting and the trees, creating dark and no safe places (Sreetheran and Van Den Bosch, 2014; Locke et al., 2017; Escobedo, et al., 2018).

Although, is important considered that these theories were developed for Europe and North American cities, and their application on Latin American cities should requires care and adaptation, once factors as cultural differences, socioeconomic deprivation and income rates, organization crime, and the lack of a state presence are strong characteristics of this cities and can be milder in for Europe and North American cities (Melo, Andresen and Matias, 2017; Martinuzzi et al., 2021).

1.2. Research question, objectives and hypothesis

The general objective is to estimate the relationship between tree canopy cover and crime, while controlling for key confounders, in Sao Paulo city. Research questions: Have tree cover and crime a spatial pattern distribution? Is tree cover associated with crime rates? Do different crime types (person, property, total crime), delimitations (crime per census sectors, human development unit, administrative districts) affect the results? Does the relationship vary in the all city versus the urbanized areas only? Does the denominators of crime (crime by population/1000 and by square kilometer) generate different results?

It is expected that once tree cover and crime rates present a spatial pattern distribution along the city, the spatial analysis models allow to estimate tree cover positive or negative influence, when potential confounders are controlled. On the models, general index, person and property crime were tested, once one category can present more stronger correlation with urban forest than other; three different urban boundaries were tested, once a big or a small scale have different influence on spatial analysis; population/1000 and square kilometer were tested as crime rate denominators, once it can change the expression of crime rates in a region; and lastly, all city and just urban macrozone was tested as different regions of the city, once different types of urbanization process can present different results.

The hypothesis to be test are (i) there is spatial correlation between crime and tree cover on Sao Paulo city; once first is true, (ii) tree cover is associated with lower crime rates; (iii) different denominators, categories of crime, boundaries, and regions can influence the results.

2. Methodology

2.1. Study area

Sao Paulo city is one of five megacities in the world with a population of 12 million inhabitants distributed in 1,521.110 km², the largest city in Latin America, and the principal center of Brazilian economy (IBGE, 2010; United Nations, 2018) (Figure 1). The city was founded and developed in an area of Atlantic Rainforest biome, a global biodiversity hotspot, that was extensively explored during the city urbanization and by coffee agriculture. Today only small forest fragments remain that regulate regional climate, rainfall distribution, soil stability and other ecosystem services (Rezende et al., 2018, Joly et al., 2014).

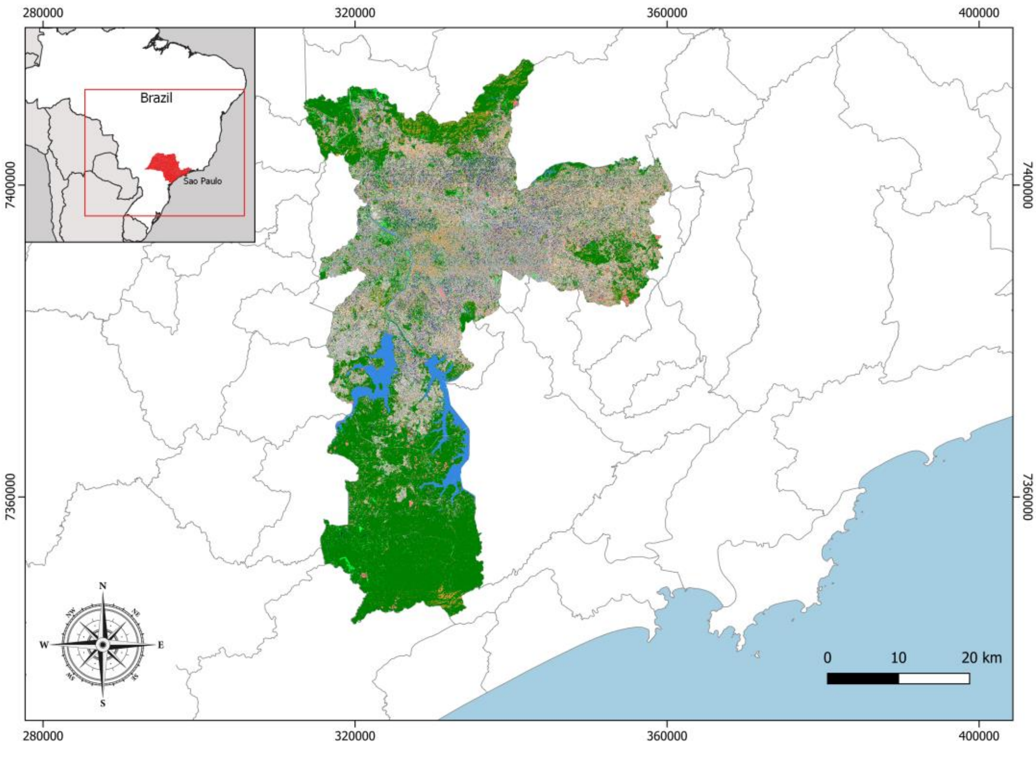

Figure 1. Sao Paulo city, in detail the location of the city related to Sao Paulo state (in red) and Brazil, South America.

To better manage Sao Paulo city land cover, the Strategic Director Plan review (PL 688/13) defined two main city zones: i) Urban Macrozone and ii) Environmental Macrozone (Sao Paulo, 2014). Illustrations can be found in Figure 2 (Supplementary Material).

The Urban Macrozone is the most urbanized areas of the city and is made up of diverse land covers and land use, the area is spatially heterogeneous due to urbanization. The Urban Macrozone is a concentration of businesses, economic centers, public transportation hubs, and opportunities in the city. The Environmental Macrozone is composed of large areas of Atlantic rainforest rements, agriculture activities, and with fragile geological and geotechnical characteristics for human occupation (Sao Paulo, 2014). The Environmental Macrozone is located in the most peripheral parts of the city, dominated by horizontal settlement, popular housing projects, with poor investment, few opportunities of jobs and education, and with high frequency of “favelas”. Favelas are typical Brazilian housing defined by invaded and non-regulated areas with any infrastructure, even contrary to urban and environmental laws, they are considered as the last housing alternative, offering risk to inhabitants and to Atlantic Rainforest remnants around them (Maricato, 2010).

Since Sao Paulo foundation investments and tax incentives were concentrated in the central and west side of the city, what started an intense process of verticalization and increase in real estate value in these areas (Rolnik, 2001). Due to this poor urban planning process the low-income inhabitants were “invited” to settle in peripheral areas, following a strong socioeconomic spatial pattern in America Latin cities, where high income groups are concentrated in the city metropolitan center (Ingram and Carroll, 1981). This pattern of social and economic inequality can be found in Sao Paulo nowadays and affects the function and development of the city, including an uneven tree cover spatial distribution.

A research that investigated the spatial correlation between tree cover and crime in Sao Paulo city shows that the wealthier neighborhoods have more tree cover in our territory, when considering most urbanized areas of the city, on Urban Macrozone (Arantes et al., 2021). The relationship is the inverse when including Environmental Macrozone on the analysis, being this inversion contrary to most of the literature, being explained by big patches of Atlantic Rainforest reminiscent around low-income neighborhoods.

2.2. Crime in Sao Paulo

Latin American cities present one of the highest levels of violent crime in the world, considered epidemic levels by the World Health Organization (ONU, 2014). An historical overview of Sao Paulo city crime rates is presented on Figure 3, highlighting theft as the highest crime rates, and the assaults and homicides rates decreasing every year. In the early 2000s, Sao Paulo city was the most violent city of Brazil and Latin America, but the combination of social politics, police intelligence and other factors decreased homicide rates from 50 cases in 1999 to 6 in 2017 - homicides per 100,000 population, being a worldwide known case of crime reduction (Justus et al., 2018). Since 2019 there has been a substantial worsening of available crime data which doesn't allow trustful analysis, mainly due to the beginning of the COVID 19 pandemic in the year 2020 and the increase in crimes via the internet (Cerqueira, 2021).

Although efforts are being constantly made to reduce crime rates, the literature shows that intrinsic characteristics of Sao Paulo as high population density, extensive territory, poverty, and a historical social exclusion with low investments in social regions, are strong contributions to the fact that the violent crimes rates stay high Ceccato, Haining & Kahn (2007).

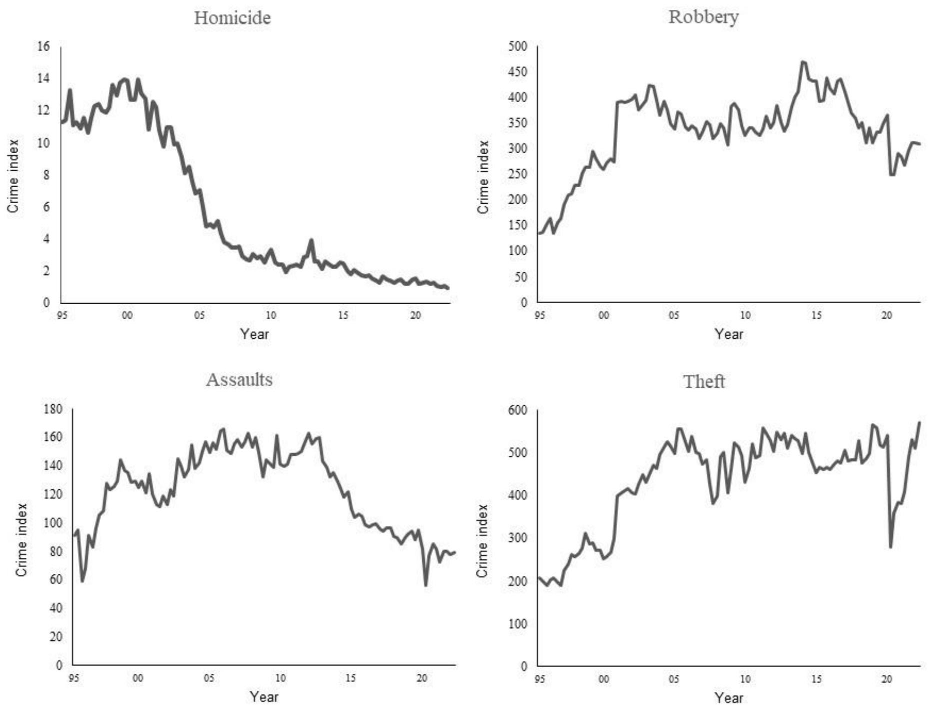

Figure 3. Crime rates (crime per 100 thousand inhabitants) for Sao Paulo city, 3rd trimester 1995 to 2nd trimester 2022. Source: Public Security Department, Sao Paulo state (2022).

2.3. Data

Urban tree cover was estimated from object-based classification of high-resolution images from WorldView-2, 70cm of resolution, 2017 year. This data was generated and described in Chapter 1 of this dissertation.

Crime database was provided by municipal police records from the Public Security Secretariat of the State of Sao Paulo (SSP-SP), from 2016 year. It includes information such as geocode points, type of crime, and police records. The crime database was organized in three categories: (i) total crime, the count of all crime points; (ii) property crime, the count of robbery and theft; (iii) crimes against the person, the count of assault, rape, and all kinds of homicides. Those categories are defined in accordance with the Brazilian Criminal Code (Brazil, 1998), and this organization is important once different types of crime have different motivations. On the one hand, property crimes such as robbery and theft involve taking and removing a private or public property and it is related with a decision involving benefits and costs to commit a crime (Becker, 1968). On the other hand, person crimes involve violet actions that are made against the will of a person and is related to elements described by social disorganization theory, as neighborhood characteristics, ethnic heterogeneity, unsupervised teenagers, social instability and others (Melo, Andresen and Matias, 2017).

Urban crime is a complex phenomenon and has multiple causes related to city size, routine activities, human behavior, victim characteristics, urban mobility, land use, environment, surveillance and an array of socioeconomic variables (Ceccato, Haining & Kahn, 2007; Ceccato e Paz, 2017). In this way, using just a general count of crime (raw frequencies) as an indicator can be a misleading picture of the real hotspots, for example, as the bigger the neighborhood the bigger will be the crime count, so standardizations are strongly recommended (Telep & Hibdon, 2017).

Thus, crime rates were created. Crime rate is defined by the count of points of crimes standardized by a denominator, being your impact on research results largely discussed in the criminology literature (Newton, Felson, & Bannister 2021). We used two types of denominators, where crime rates were generated divided crime counts by: (i) population divided by a thousand (pop/1000); and (ii) square kilometer (km²).

Population is a very common denominator in literature, that is usually a data based on census as number of houses or residential population and includes the human presence as standardization (Newton, Felson, & Bannister 2021). It has some limitations once population estimated by census considers the people that live in these areas, which will penalize business centers, commercial areas, parks, and others, that can be hotspots for crime (Sherman, Gartin

& Buerger 1989). In some cases, crime count can be standardized by low or zero population, creating a bias. Even though Sao Paulo city has significant business centers, parks and economic regions, few observations with zero denominator are found, being 3.2% considering census sector boundary, which cannot be an important impact.

Is very important for crime studies to test new denominators that differ from the classical residential population once types of crimes can have different responses to different standardizations (Andresen & Jenion 2010). The denominator square kilometer will be tested as an advantage, once it will not generate zero denominator, will reduce the effect of big areas, and will not penalize areas "where people don't live". It is important to highlight that it is a challenge, or sometimes is impossible, to find the most suitable denominator to crime analysis, mainly due the lack of information and open data, especially on Latin American cities.

Three geographical boundaries were used for empirical analysis: (i) Administrative District division, with 96 observations, regulated by Sao Paulo (1992). (ii) Human Development Unit, geographical units formed by a group of adjacent census sectors, with 1,490 observations, proposed by SEADE (2010), (iii) census sectors, the small unit of urban observation, with 18,953 observations, proposed by the Brazilian Institute of Geography and Statistics (IBGE, 2010). The test will be done once the official municipal divisions, like neighborhood or Administrative Districts, can better reflect political boundaries rather than a spatial distribution of a variable in space, as Tobler's first law of geography suggests. Another important statistical theory was tested in this study, the Modifiable areal unit problem theory. This theory explains that one correlation can present a strong statistical bias and occurs just because the type of scale choosed to the analysis, and it mainly occurs in spatial analysis (Openshaw, 1984). The literature points to census sectors as closer neighboring geographic units for spatial analysis and we will test how these differences can influence the results (CHAKRABORTY 2011, SCHWARZ et al., 2015, GERRISH and WATKINS 2018).

Finally, all the variables were tested for two areas: (i) all city and (ii) urban macrozone. The divisions for all city and for Urban Macrozone are illustrated respectively in Figure 4 and Figure 5 (SM).

In summary, 36 models were built with three variables of crime: 1) total, 2) person, 3) property; with two denominators of crime: 1) square kilometer (km^2), 2) population/1000; in three boundaries: 1) AD, 2) HDU, 3) CS; for two areas of city: 1) all city, 2) urban macrozone (Table 1). A list of the models in detail are presented in Table 2 (Supplementary Material).

Table 1. The models built for this study, considering three variables of crime: total, person and property; two denominators of crime: square kilometer (km²) and population by 1000 (Pop/1000); three boundaries: Administrative Districts (AD), Human Development Unit (HDU), Census Sector (CS); two areas of Sao Paulo city: all city and urban macrozone, in total of thirty-six models.

All city				Urban			
km²	**AD**	**HDU**	**CS**	km²	**AD**	**HDU**	**CS**
Total	model 1	model 4	model 7	Total	model 19	model 25	model 31
Property	model 2	model 5	model 8	Property	model 20	model 26	model 32
Person	model 3	model 6	model 9	Person	model 21	model 27	model 33
Pop/1000				Pop/1000			
Total	model 10	model 13	model 16	Total	model 22	model 28	model 34
Property	model 11	model 14	model 17	Property	model 23	model 29	model 35
Person	model 12	model 15	model 18	Person	model 24	model 30	model 36

In this study crime is the dependent variable and tree cover the explanatory variable, while potential confounders are controlled. The controllers are socioeconomic variables that can strongly influence crime rates and were chosen based on literature review of some important published papers of tree cover and crime analysis – a summary of these papers can be found in Table 3 (SM). Specialized review of literature is an important tool to define the controllers in crime analysis, as done by Justus et. al (2018) that proposed a model for understanding reduction in homicide rates in Sao Paulo city, defining its explanatory variables based on literature review, like family structure, demography, social programs, criminal organizations, and others.

The controllers chosen were population density, income per capita, proportion of write people, proportion of men young, literate young, households with open sewer and house that is owner occupied. All data was available in the demographic census from IBGE (2010). A summary of the chosen controllers, definitions and coefficient expected following the literature can be found at Table 4.

2.4. Statistical analysis

This study proposes a series of spatial statistics models to understand urban tree cover potential effects on crime rates, while controlling for socioeconomic factors. Spatial analyses are based on Tobler’s first law that said, "everything is related to everything else, but near things are more related than distant things” (Tobler, 1970) and investigates the relationship between near variables that are sensitive to geographic phenomena and can presents spatial autocorrelation and spatial dependence (Almeida, 2013).

It is known that crime is a phenomenon with non-aleatory distribution and highly sensitive to urban space. Criminologists affirm that those are concentrated in specific land uses, called hotspots, and acknowledge them as crucial for problem-oriented public policies, being well established on literature that crime rates in one neighborhood can easily influences surrounding regions (Goldstein, 1979; Troy, Grove, and O'Neil-Dunne, 2012).

First, descriptive statistics and exploratory data analysis was performed to check the database distribution, standard deviation, outliers, and tendencies, to avoid bias in regressions models. After that, the statistical models are proposed, being the statistical strategy summarized in Figure 6.

Table 4. Summary and literature review that substantiate the choice of social variables as controllers on spatial models.

Controller name	Controller description	Coefficient expected		Reference
		positive	negative	
dpop	Population (per km²)	High population density offers more opportunity to commit crimes, more people, less organization. Social disorganization theory. Low population density offers an inhospitable environment, victim has few rescue resources. High association with crime against person and violent crimes. No man`s land theory.	High population density offers more surveillance, more chances to be caught and generates intimidation to commit crimes. Defensive space and eyes on the street theories. Low population density offers less crime opportunity, it is not an attractive region for criminals.	Watts (1931); Kassem, Ali, & Audi (2019); Shichor, Decker & O'brien (1979). Harries (2006); Newman, 1972; Jacobs, (1961); Sampson and Groves (1989)
incomeln	Log of mean income per capita	Is an attractive to crime, expected more intense in property and less in person, due its direct relationship with poverty.		Webster and Kingston (2014); Levitt (1999); Mehlum, Miguel, Torvik (2006)
whites	Proportion of write people		The greater the ethnic homogeneity the lower the incidence of crimes. In Brazil, due to miscegenation of races, this controller is important but has no notable effects as in other countries.	Trawick and Howsen (2006); Miethe, Hughes and McDowall (1991); Sampson and Groves (1989)
menyo	Proportion of men young (15 and 29 years old)	Is a strong controller. The literature indicates strong relationships due male gender and young people feeling that have nothing to lose, common related with low education level.		Murray, De Castro Cerqueira & Kahn (2013); Reichenheim et al. (2011) Cohen and Land (1987); South and Messner (2000); Steffensmeier et al. (1989); De Mello and Schneider (2010).
literatey	Proportion of literate young (5 and 17 years old)		The greater the education attainment lower is the vulnerability to crime rates, except for violent crimes. Education increases future opportunities and discourages crime participation.	Lochner (2020); Hjalmarsson and Lochner (2012); Sabates (2008); Machin, Vujić and Marie (2012)
opensewer	Proportion of households with open sewer	Social vulnerability. Neighborhood and settlements characteristics. Theories: social disorganization; care about, cues to care,		Melo, Andresen & Matias (2017); Melo (2016); Kuo (2003); Jacobs (1961); Troy and

garbage	Households with accumulated garbage in front of the street			Grove (2008); Sampson and Groves (1989)
owneroccup	Percent of house that is owner occupied. Includes residences rented or leased permanently		Owners have a sense of community and neighborhood care. Theories: social capital theory; care about, cues to care.	Lauridsen, Nannerup, & Skak (2013); Nassauer (1995).

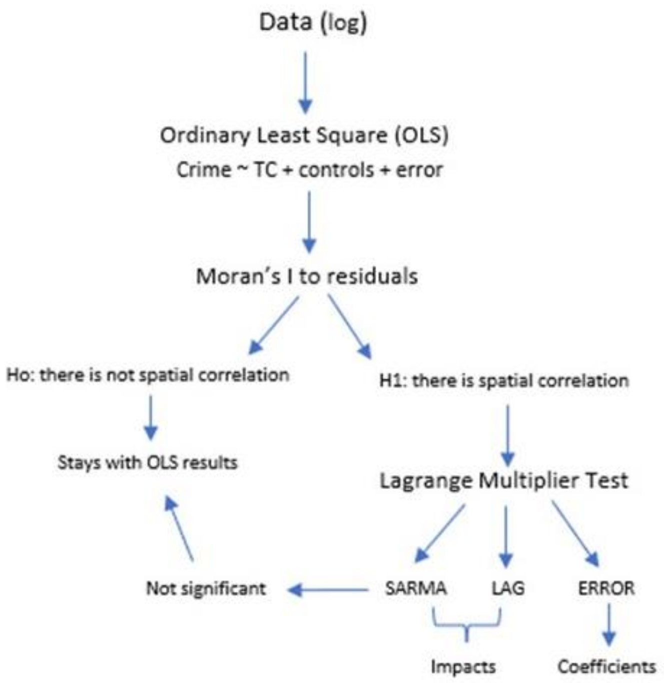

Figure 6. Statistical strategy proposed for this study, based on Anselin (2005).

Ordinary Least Squares (OLS) was carried out for each dependent variable and explanatory variables set, to identify associations between them, resulting in 36 models. OLS is a linear regression model which ignores spatial dependence and will be used as baseline and as alternative when a model does not present spatial autocorrelation (Almeida, 2013; Anselin, 2005).

Global Moran's I was carried out to OLS residuals as spatial dependence test, which indicates the degree of linear association between the vectors of observed values and the weighted average of neighborhood values (or spatial lags), testing the null hypothesis of spatial randomness (Cliff and Ord, 1973). For this analysis a Queen contiguity spatial weights matrix was chosen, which considers the contiguity between two spatial units that share a common edge (Almeida, 2013). The Queen matrix was chosen once the units of observations show a continuous urban fabric and allows it to be compared to other published studies (Grove, Locke, and O'Neil-Dunne, 2014; Locke et al., 2017; Lin, Wang, and Huang, 2021). Once Moran's I indicated spatial autocorrelation spatially adjusted regression models were carried out.

Lagrange Multiplier Test (LM) test was applied at OLS residuals to indicate which spatial regression model should be more appropriated: spatial lag, spatial error or SARMA model, following the decision rule described by Anselin (2005) shown in Figure 7 (SM). Lagrange is an asymptotic technique and a test of parametric hypothesis, which tests the first-order conditions effect for a maximum probability of imposing the hypothesis (Breusch and Pagan, 1980). Lagrange is strong against one-directional alternatives once two models can be suitable alternatives, as they are highly significant, but always one of them should be detected as the higher order alternative model (Anselin, 2005).

The spatial lag model assumes that spatial autoregressive process is an effect of lagged dependent variables; the spatial error model assumes that spatial dependency occurs like an effect in spatial errors correlations (a result of omitted variables); and SARMA model assumes that spatial dependency occurs for both (errors and lagged), being considered as a theoretical option, not applied (Anselin and Bera, 1998; Anselin, 2001; Almeida, 2013) The models are respectively described in the formulas 1, 2 and 3.

$$y = pWy + X\beta + \varepsilon \tag{1}$$

$$y = \lambda Wu + X\beta + \varepsilon \tag{2}$$

$$y = pWy + X\beta + \varepsilon \tag{3}$$

$$\varepsilon = \lambda W\varepsilon + \varepsilon$$

Where, y is dependent variable; p = spatial autoregressive coefficient; λ is a spatial autoregressive parameter; β is vectors of coefficient; X is matrix of covariates; u is a spatially dependent error term; ε is error term.

For the models that have been fit to Lag and SARMA spatial models an impact analysis was carried out to assist their interpretation. The coefficients of Lag and SARMA are not trustful once spillovers occur between the terms and spatial model present spatially lagged dependent variable and consequently their adjusted β coefficient values and standard errors does not provide a satisfactory basis for inference, being the impact coefficient the correct coefficient to consider (Bivand and Piras, 2015).

The interpretation of spatial models has been largely discussed in the spatial econometrics literature once the challenges that it offers (LeSage and Pace, 2009). In short, models with spatially lagged errors can be interpreted as simple partial derivatives once they not indicate spatial dependence in the dependent variable or in the explanatory variables; but models that are spatially lagged as LAG and SARMA model should be carefully interpreted due strength of spatial spillovers (Golgher and Voss 2016).

For interpretation of LAG and SARMA (combination of Error and LAG) models, we select the direct impact that is the mean value of the elements of the main diagonal of the partial derivatives matrix, which have its interpretation similar to a traditional (Golgher and Voss 2016). Just remember the importance of not considering the coefficients of these models, once they are not truthful due to spatial spillovers, even to LAG model that the spillover effect is strictly local - contiguous immediate neighbors (Bivand and Piras, 2015; Golgher and Voss 2016).

The Error model includes the spatial dependence on the error term in the regression equation and treats it as a nuisance once it does not attribute correlation to variables. In the case of Error models comparisons with OLS models are allowed once any spatial effect is measured (Medina and Solymosi, 2022).

To understand the significance of the LAG and SARMA models we consider Rho, that is a spatial autoregressive parameter that measures the explanatory variable effect on the dependent variable in each surrounding region defined by spatial weights matrix, with 95% of significance (Medina and Solymosi, 2022). The authors also discuss that the R square of this test is not trustful because it is a pseudo-R square, and instead of it we can consider analyzing the Akaike Information Criterion (AIC), a mathematical method for evaluating how well a model fits the data from which it was generated. To Error Model significance we can consider R-squared and AIC, as a more classic interpretation.

3. Results and Discussion

3.1. Descriptive statistics and exploratory data analysis

To analyze the possible combinations and distributions of the 36 models proposed in this study facet graphics are presented, where panels are divided by boundarie (AD, HDU and CS), with crimes plotted by type (total, person, property) for the two denominators of crime (p = person/1000 and k = square kilometer), to all city (Figure 8) and to urban macrozone (Figure 9).

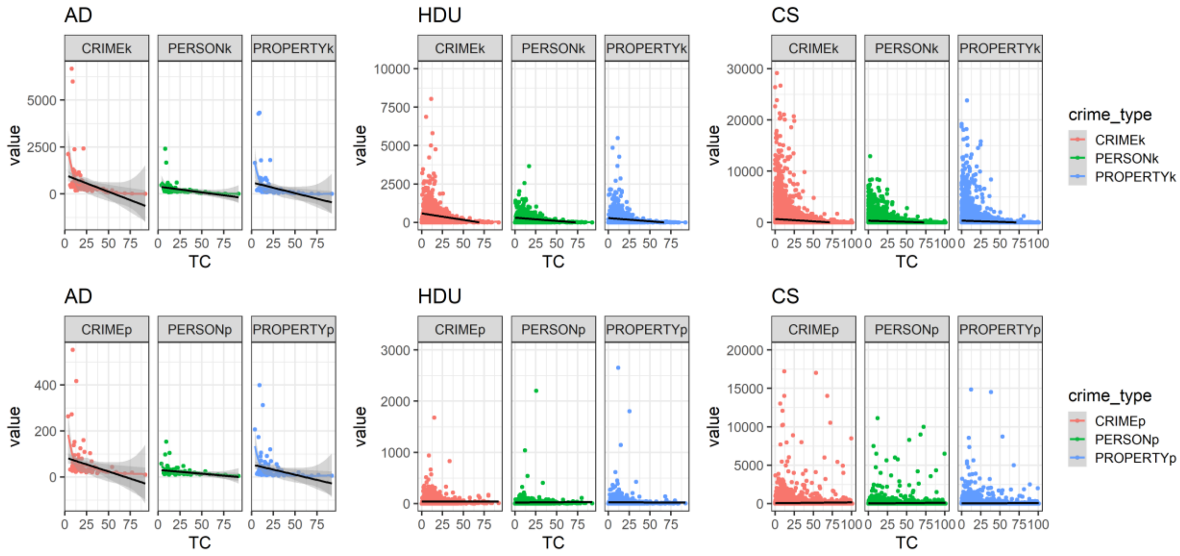

Figure 8. Distribution of 18 models proposed to all city region. Where panels are divided by boundaries (AD, HDU and CS); crime is plotted by the type, being total crime (red) , person (green) and property (blue); for the two denominators of crime, being p = person/1000 (above) and k = square kilometer (bellow).

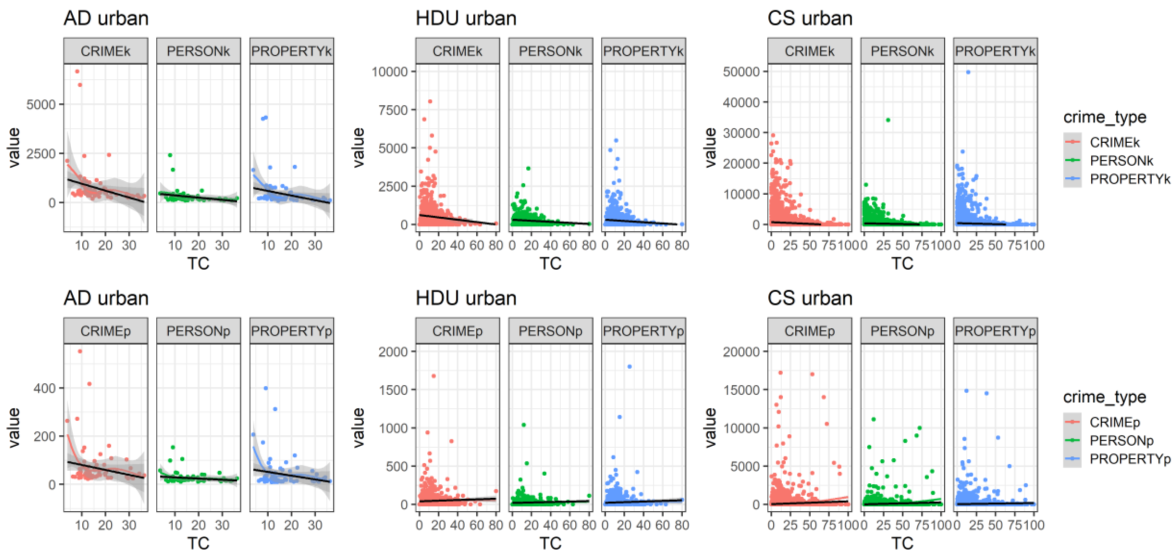

Figure 9. Distribution of 18 models proposed to urban macrozone region. Where panels are divided by boundaries (AD, HDU and CS); crime is plotted by the type, being total crime (red) , person (green) and property (blue); for the two denominators of crime, being p = person/1000 (above) and k = square kilometer (bellow).

Summary statistics (mean, median and standard deviation) and Moran's I for each variable of the models are presented for all city on Table 5 and for urban macrozone on Table 6. Ordinary Least Squares (OLS) to all city and urban are present in Supplementary Material (Figure 10 and 11). Moran's I presented significance at 95% level for all variables, except to open sewer AD urban, confirming the spatial dependence, which allowed us to proceed with the spatial analyzes. In this way, OLS is not considered as trustful analysis once it ignores the spatial dependence.

Table 5. Variables and our summary statistics, Moran's I index and p-value, by Administrative Districts (AD), Human Development Unit (HDU) and Census Sector (CS), to all city.

	AD (n= 96)					HDU (n= 1,490)					CS (n= 18,953)				
variable	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*
crimek	628.88	427.68	933.23	0.45	0	521.89	376.62	2345.24	0.45	0	540.25	312.72	1361.19	0.45	0
crimen	4833.79	4245.5	2528.4	0.13	0.01	311.44	105	672.61	0.13	0.01	24.48	11	63.53	0.13	0.01
crimep	59.04	37.69	76.11	0.3	0	45.28	24.31	158.5	0.3	0	67.75	18.81	644.88	0.3	0
dpop	11398	10974	5139	0.38	0	29985	16201	60628	0.38	0	33524	16898	71492	0.38	0
garbage	0.04	0.04	0.04	0.16	0	0.05	0.01	0.11	0.16	0	0.04	0	0.14	0.16	0
incomeln	7.54	7.4	0.68	0.72	0	7.08	6.97	0.77	0.72	0	7.05	7.07	1.53	0.72	0
literatey	0.82	0.82	0.03	0.5	0	0.81	0.82	0.07	0.5	0	0.79	0.82	0.18	0.5	0
menyo	0.12	0.12	0.01	0.47	0	0.13	0.13	0.02	0.47	0	0.12	0.12	0.04	0.47	0
opensewer	0.03	0.02	0.04	0.16	0	0.05	0	0.11	0.16	0	0.04	0	0.14	0.16	0
owneroccup	0.3	0.31	0.03	0.64	0	0.32	0.32	0.07	0.64	0	0.3	0.31	0.14	0.64	0
personk	257.17	198.59	290.04	0.34	0	266.05	206.15	909.08	0.34	0	264.17	156.11	507.21	0.34	0
personn	2316.69	2165	1276.96	0.21	0	149.26	59.5	249.67	0.21	0	11.73	6	21.98	0.21	0
personp	23.62	18.38	19.78	0.22	0	21.84	13.89	68.25	0.22	0	31.58	9.9	289.34	0.22	0
propertyk	371.71	201.23	660.83	0.49	0	254.31	145.17	1449.77	0.49	0	276.07	117.97	949.61	0.49	0
propertyn	2517.1	1889.5	1757.66	0.32	0	162.18	41	449.64	0.32	0	12.75	4	45.39	0.32	0
propertyp	35.42	18.18	57.32	0.33	0	23.44	9.05	96.33	0.33	0	36.18	7.03	398.71	0.33	0
TC	21.48	15.46	15.88	0.57	0	15.2	11.44	13.32	0.57	0	14.44	9.38	16.15	0.57	0
whites	0.65	0.66	0.14	0.69	0	0.58	0.56	0.17	0.69	0	0.6	0.61	0.22	0.69	0

* Significant at 95% level.

Table 6. Variables and our summary statistics, Moran's I index and p-value, by Administrative Districts (AD), Human Development Unit (HDU) and Census Sector (CS), to urban macrozone.

	AD urban (n= 73)					HDU urban (n= 1101)					CS urban (n= 14,921)				
variable	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*
crimek	765.95	488.53	1032.53	0.41	0	598.66	416.95	2717.75	0.02	0	610.64	358.05	1505.69	0.29	0
crimen	5156	4486	2624	0.11	0.05	356.15	115	762.44	0.26	0	28.58	14	70.54	0.35	0
crimep	69.26	43.22	84.66	0.25	0	51.77	26.71	183.04	0.07	0	79.95	22.51	724.07	0.06	0
dpop	12155	11696	4885	0.33	0	33252	16420	68516	0	0.53	35147	16686	75639	0.02	0
garbage	0.03	0.03	0.02	0.27	0	0.05	0.01	0.11	0.07	0	0.03	0	0.12	0.2	0
incomeln	7.72	7.63	0.65	0.68	0	7.19	7.13	0.74	0.38	0	7.33	7.27	1.22	0.4	0
literatey	0.83	0.83	0.02	0.27	0	0.82	0.82	0.06	0.06	0	0.81	0.83	0.13	0.15	0
menyo	0.12	0.12	0.01	0.47	0	0.13	0.13	0.02	0.23	0	0.12	0.12	0.03	0.31	0
opensewer	0.02	0.01	0.03	0.03	0.24	0.03	0	0.1	0.14	0	0.03	0	0.12	0.25	0
owneroccup	0.3	0.3	0.03	0.62	0	0.31	0.31	0.07	0.07	0	0.3	0.3	0.13	0.1	0
personk	300.84	236.79	318.45	0.3	0	293	224.94	1049	0.01	0.07	286	176.7	541	0.25	0
personn	2314	2003	1300	0.23	0	161.49	65	272.82	0.09	0	13.25	7	23.76	0.33	0
personp	26.08	20.38	21.91	0.16	0	23.89	14.83	78.67	0.03	0.04	35.83	11.59	321	0.08	0
propertyk	465.12	235.41	733.95	0.46	0	303.05	168.13	1681	0.03	0	324	143.04	1060	0.3	0
propertyn	2842	2295	1851	0.28	0	194	47	515	0.35	0	15.33	5	50.73	0.35	0
propertyp	43.18	20.95	63.79	0.28	0	27.88	10.2	111.27	0.1	0	44.13	8.85	449.49	0.05	0
TC	15.46	13	7.41	0.27	0	12.6	10.99	8.38	0.28	0	12.27	9.17	11	0.52	0
whites	0.7	0.7	0.12	0.62	0	0.61	0.62	0.17	0.46	0	0.65	0.68	0.2	0.63	0

* Significant at 95% level.

3.2. Spatial models

The Lagrange Multiplier (LM) test was not significant for 8 AD models, which suggests staying with OLS results once spatial models are not recommended. LM was significant for 28 models being 9 Error, 8 Lag and 11 SARMA model. The LM test result is presented on Table 7 (SM), and the models were chosen for each model following the decision rule described by Anselin (2005) (Figure 7 SM).

Once error models consider that the tree cover and crime relationship occurs because of coefficient errors, confirming the hypothesis for the non-existence of autocorrelation (Almeida, 2013), we will not focus on these models, being SARMA and LAG impacts more relevant for this study.

The strong tendency presented on the 19 spatial models was the negative relationship between tree cover and crime, with 13 negative models 4 positive models 2 models null models. The average direct impact, signs and magnitudes of tree cover in the Lag and SARMA models are presented in Table 8 and illustrated in Figure 12.

Table 8. Tree cover direct impact for Lag and SARMA models, orderly by average, with 95% of significance level.

Scale	Crime type	denominator	model	average	Rho	Rho p-value	Lambda	AIC
AD urban	property	pop/1000	LAG	-0.030	0.297	0.0004		101.22
HDU	total	km²	LAG	-0.030	0.238	0.0000		5298.43
AD urban	property	km²	LAG	-0.029	0.478	0.0000		104.85
AD	property	km²	LAG	-0.028	0.439	0.0000		157.72
HDU	property	km²	LAG	-0.028	0.250	0.0000		5336.12
CS urban	total	km²	SARMA	-0.024	0.456		-0.157	
CS	total	km²	SARMA	-0.022	0.607		-0.348	
CS urban	property	km²	SARMA	-0.021	0.532		-0.205	
AD	property	pop/1000	LAG	-0.019	0.317	0.0019		143.15
CS	property	km²	SARMA	-0.018	0.631		-0.357	
CS	person	km²	SARMA	-0.017	0.690		-0.406	
CS urban	person	km²	SARMA	-0.017	0.683		-0.341	
CS	total	pop/1000	SARMA	-0.001	0.244		0.081	
CS	property	pop/1000	SARMA	0.000	0.334		0.051	
CS	person	pop/1000	SARMA	0.000	0.322		0.057	
HDU	property	pop/1000	LAG	0.002	0.290	0.0000		4297.57
CS urban	property	pop/1000	SARMA	0.003	0.276		0.106	
CS urban	person	pop/1000	SARMA	0.004	0.316		0.074	
HDU urban	property	pop/1000	LAG	0.008	0.324	0.0000		3247.16

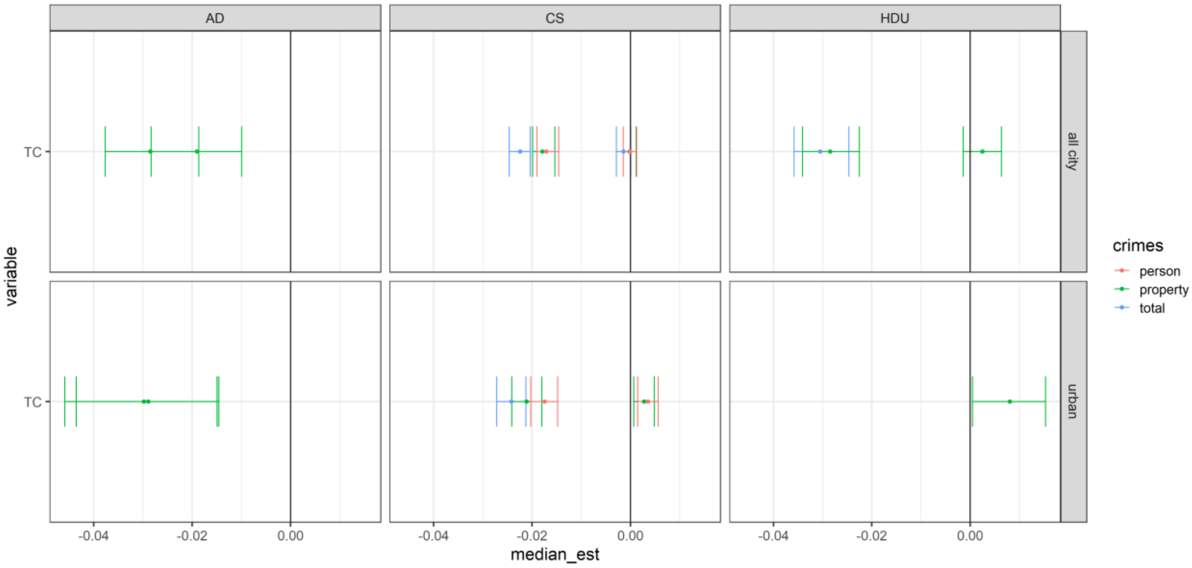

Figure 12. The magnitude of the tree cover direct impact in the LAG and SARMA models.

Considering the areas of the city in i) all city, tree cover mostly presented negative signs for all scales, except for HDU property crime; in ii) urban, tree cover mostly presented negative signs on all scales, except for one HDU model and two CS models. Considering crime type tree cover presented negative signs for total, person and property, in all scales (AD, HDU, CS). The most frequent crime type was property crime (11 models). Considering the two crime denominators the i) km² presents just negative signs to tree cover while ii) pop/1000 presents negative signs and all the positive signs found to tree cover.

The negative relationship between tree cover and crime occurs to all types of crime, areas of the city, scales, and denominators. The positive models are mostly for urban macrozone, HDU and CS scale, for property crimes and for pop/1000 denominator.

The presented models even with differences in their approaches (LAG, SARMA) and with differences in the components (area, scale and denominator) present the same tendency: tree cover presents a negative spatial correlation with total, person and property crime, although they are discreet. In this way, the Modifiable areal unit problem theory was tested with different scales, and once the negative correlation stayed we understood that correlation occurs independent of scales, not being the scale a statistical bias.

3.3. One model to tell the history

Once we have 36 models and it is not interesting to describe them one by one, we select the best fitted model to represent the variables that we set out for this study. We selected the AD all city, to property crime and pop/1000 denominator (model 11) and its average direct impacts and magnitudes, Rho and AIC model, with 95% of significance are presented in Table 9.

Table 9. LAG model direct impact to AD (all city).

Crime type	Denominator	Variable	Conf. Low	Median	Conf. High	Average
property	pop/1000	TC	-0.028	-0.019	-0.010	-0.019
		dpop	-0.000083	-0.000060	-0.000038	-0.000060
		incomeln	0.033	0.424	0.795	0.418
		whites	0.300	2.604	4.921	2.608
		menyo	13.067	30.047	47.708	30.274
		opensewer	-5.331	-2.316	0.538	-2.370
		owneroccup	-10.380	-4.899	0.577	-4.901
		garbage	-0.716	2.928	6.566	2.926
		literatey	-14.318	-7.317	-0.513	-7.382
Rho	0.3173	p-value: 0.00191				
AIC lm	143.15					
LM model	-60.57					

In this model tree cover presents a negative relationship with crime, considering all city, AD scale, property crime and pop/1000 denominator. Almost all the controllers followed the literature. Population density presents negative impacts, and even if it is discreets, they can mainly be related to surveillance and less crime opportunity (Watts 1931; Shichor, Decker & O'brien, 1979). Income presents positive impacts, which is expected once it can be attractive, mainly to property crime (Webster and Kingston 2014; Levitt 1999; Mehlum, Miguel, Torvik 2006). Men young is strongly associated with the crime increase, as expected, being the strongest controller (30.27), once represent the since it represents the age group and sex most suffers from crimes, mainly violent, being strong even in this model of property crimes (Murray, De Castro Cerqueira & Kahn 2013; Reichenheim et al., 2011; Cohen and Land 1987). Literate young is strongly associated with the crime decrease (-7.38), as expected, once greater the educational attainment lower is the vulnerability to crime (Lochner, 2020; Hjalmarsson and Lochner 2012; Sabates 2008). Owner occupied is associated with reduction in crime once it creates a sense of community and neighborhood care (ref), and lastly garbage is associated with increase in crime rates, once representing neighborhood and settlements with social vulnerability (Lauridsen, Nannerup, & Skak 2013; Nassauer, 1995). More literature reviews for each controller and signs expected can be found at Table 4.

Two of the controllers did not follow the literature. Open sewer presents negative impacts in all 19 spatial models. We expected that open sewer presents positive impacts to crime once it represents neighborhoods and settlements with social vulnerability and could be linked with Social disorganization theory how it happens with garbage (Melo, Andresen & Matias 2017; Melo 2016). However, our test showed, for all models, that this control needs to be better worked out since it did not effectively represent the areas of interest.

Writes presents positive impacts in 16 models, but we expected that writes presents negative impacts to crime once the literature points out that the greater the ethnic homogeneity the lower the incidence of crimes (Trawick and Howsen, 2006; Miethe, Hughes and McDowal 1991). In São Paulo studies studies have shown that black people suffer more from violence due to prejudice, as they live in more socially fragile regions, especially young black people (Caldeira, 2000) and that homicide rates in the city tend to increase for blacks and decrease for whites (Soares Filho, 2011). In this way, Writes should present a negative impact to crime. Future adjustments will be needed for both variables.

4. Conclusion

In this study we found that there is a spatial association between the occurrence of crimes and the presence of tree cover, corroborating that these elements are not uniformly or randomly distributed in space and the closer they are, the more related they are (Tobler, 1970; Ratcliffe, 2010).

Our main results showed that Sao Paulo city tree cover is associated with lower total, property and person crime rates, even when different areas of the city, scales of study, and denominator of crime are tested. The mais results follow the literature that have observed tree cover associated with lower crime rates, for different types of crime (Troy, Grove and O'Neil-Dunne, 2012; Gilstad-Hayden et al., 2015; Escobedo et al., 2018).

This study contributes to international literature once i) presents robust results about the largest city of Latin America, contribute to fill the gap of scientific knowledge in this areas; ii) contributes to a line of research that is poorly developed in the world, mainly due to the scarcity of good public data on crime and tree cover; iii) innovates in testing different scales of the city and demonstrates that even being influenced by the different areas of study, the negative association of tree cover and crime occurrences remains true.

Some limitations of this study are the controllers that do not follow the literature, as open sewer and writes, and demonstrate that future adjustments in the model can be done, with the objective of giving more robustness to the model. For future studies we suggest more controls are tested, and analysis with Geographically Weighted- Regression (GWR) that was used to challenge the spatial model results and have been discussed in tree cover and crime literature (Locke et al., 2016, Troy et al., 2012).

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Supplementary Material

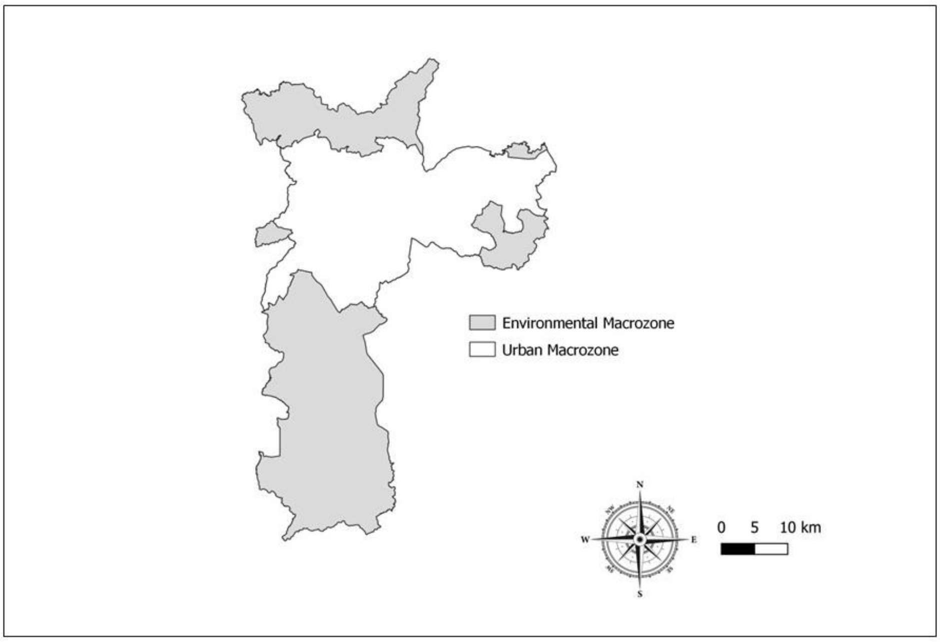

Figure 2. Sao Paulo city two main city zones: i) Urban Macrozone and ii) Environmental Macrozone.

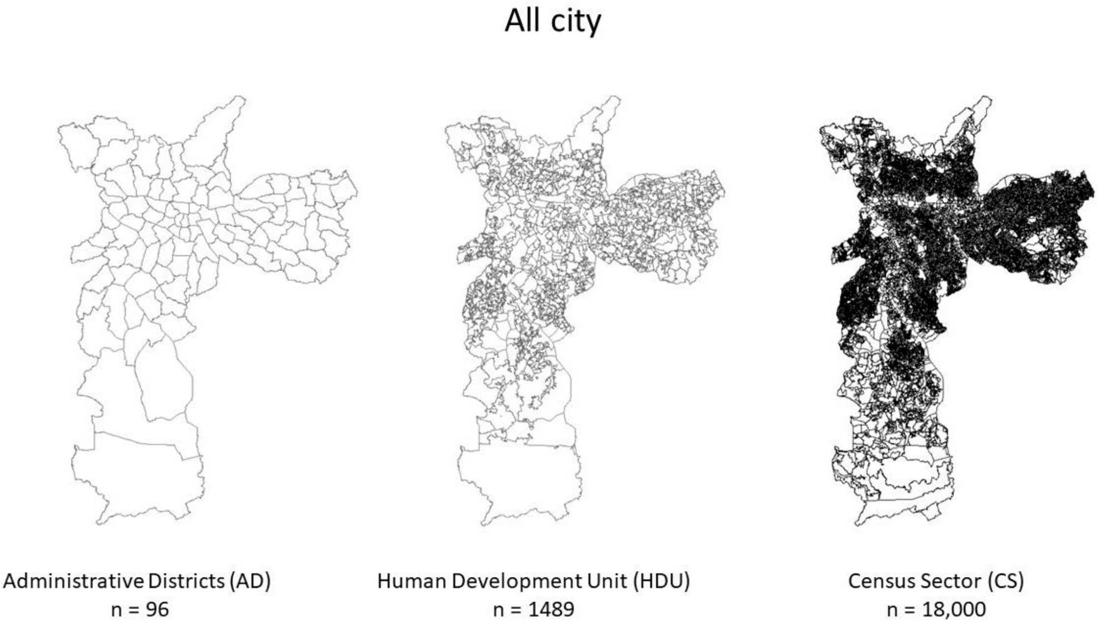

Figure 4. Sao Paulo city (all city) and boundaries.

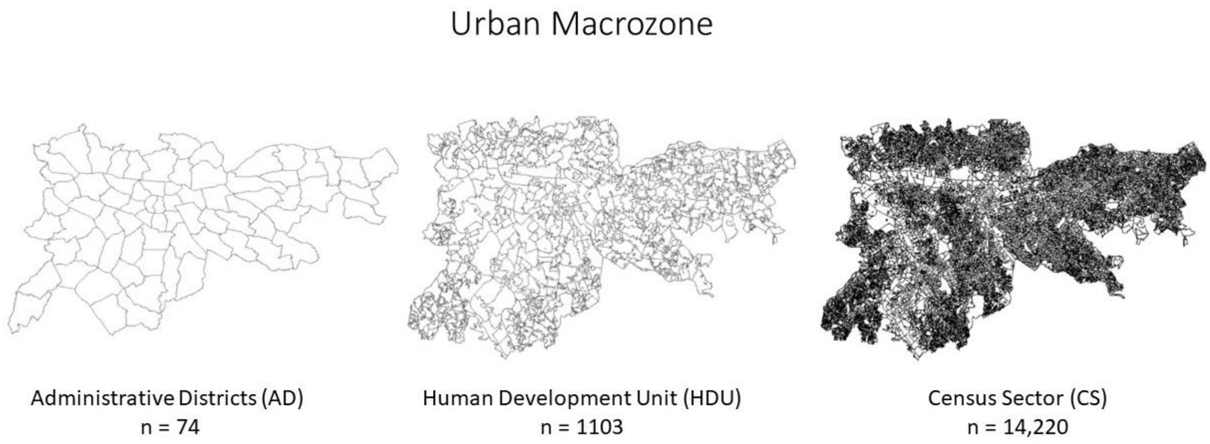

Figure 5. Sao Paulo city Urban Macrozone and boundaries.

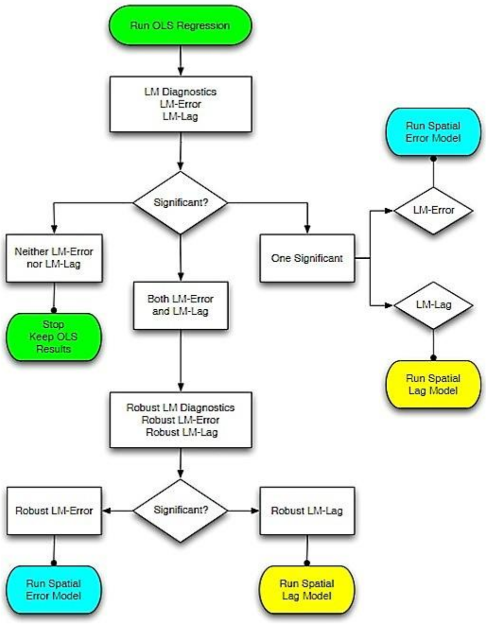

Figure 7. Decision rule to Lagrange Multiplier test, to choose spatial regression model more appropriated: spatial lag, spatial error or SARMA model.
Source: Anselin (2005)

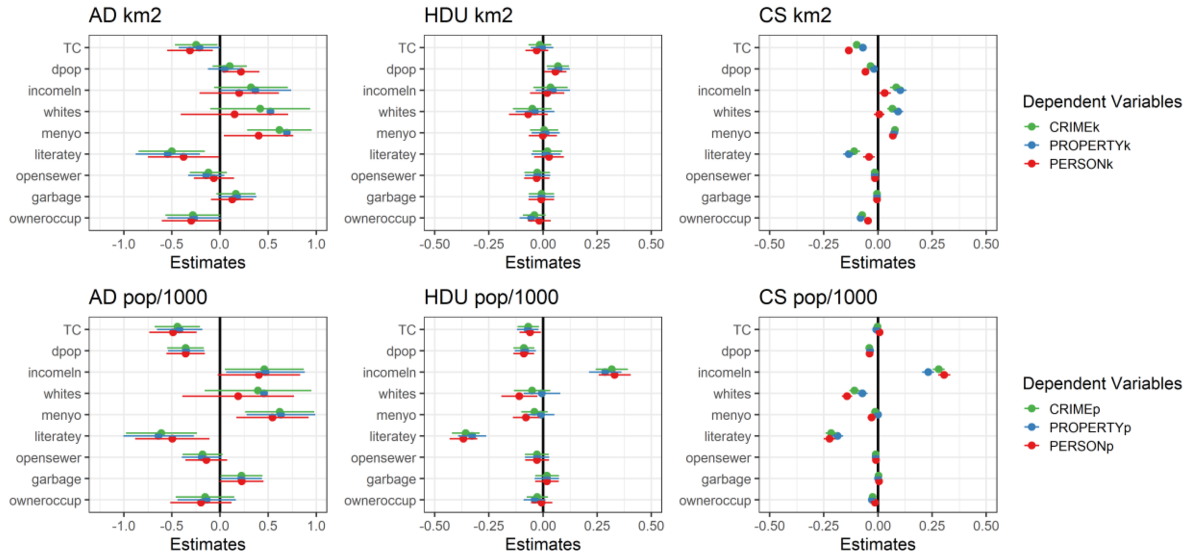

Figure 10. Ordinary Least Squares (OLS) results to all city.

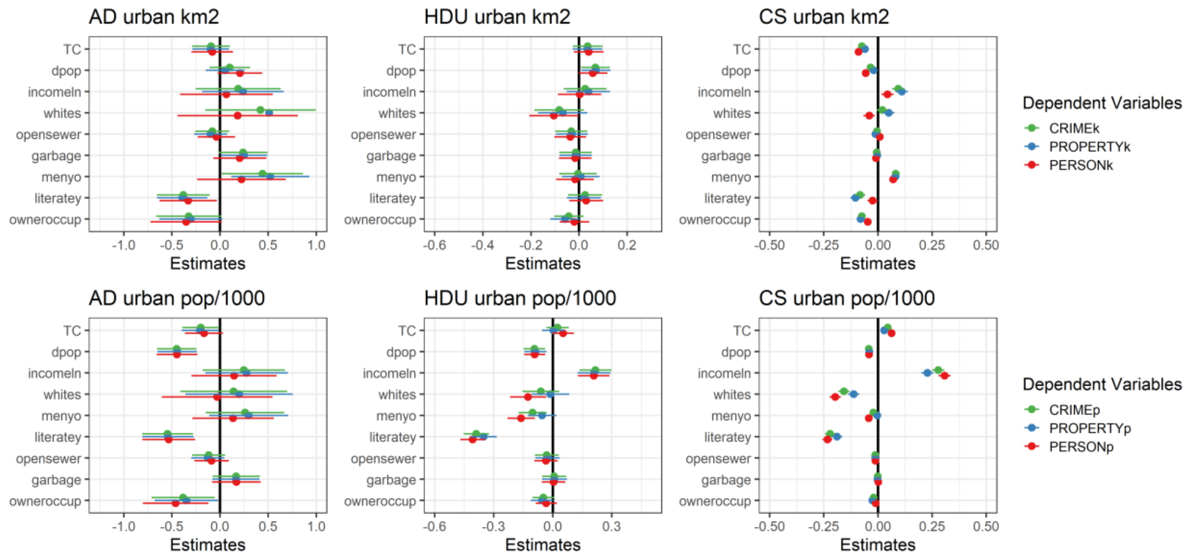

Figure 11. Ordinary Least Squares (OLS) results to urban.

Table 2. List of the models

1. **All city**
2. **km²**

AD

1. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
2. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
3. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

HDU

4. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
5. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
6. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

CS

7. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
8. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
9. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

B. pop / 1000

AD

10. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
11. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)
12. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

HDU

13. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
14. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)
15. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

CS

16. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
17. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)
18. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

A. Urban Macrozone

B. km²

AD

19. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
20. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
21. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

HDU

22. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
23. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
24. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

CS

25. CRIMEk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
26. PROPERTYk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup
27. PERSONk ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup

B. pop / 1000

AD

28. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
29. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)
30. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

HDU

31. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
32. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

33. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

CS

34. CRIMEp ~ TC + dpop + incomeln + whites + menyo + literatey + opensewer + garbage + owneroccup)
35. PROPERTYp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)
36. PERSONp ~ TC + dpop + incomeln + whites + menyo + opensewer + owneroccup + garbage + literatey)

Table 3. Literature review to choose the controllers, the socioeconomic variables that can strongly influence crime rates.

Controllers	**Variable of**	**Troy et al. (2016)**	**Donovan and Prestemon (2010)**	**Wolfe and Mennis (2012)**	**Gilstad-Hayden et al (2015)**	**Deng (2015)**	**Arantes et al. (2022)**
Income per capita	Inequality	x			x	x	x
Poverty (%)	Poverty			x			
Percent of houses with single family/multifamily	Poverty	x	x				
Percent of house that is owner/rented occupied	Poverty	x			x		x
Real estate/mean assessed values of houses	Poverty		x			x	
Population density per km²	Agglomera tion	x		x	x	x	x
Proportion of men young or mean housing age	Age					x	x
Proportion of literate young people between 5 and 17 years	Education				x		x
Population without a high school degree or equivalency	Education			x	x		
Proportion of households with open sewer	Social instability						x
Households with accumulated garbage in front of the street	Social instability						x
House with garage, driveway, windows with bars	Social instability		x				x
Vacant housing units	Social instability				x		
Median year of construction	Land cover	x					
Percent of land that is protected open space	Lan use	x					
Percent of land that is preserve designation	Land use	x					
Percent of rural population	Rural areas	x					
Proportion of black people	Ethnic				x	x	

Proportion of write people	Ethnic	x				x	x
Proportion of Asian people	Ethnic					x	
Proportion of Hispanic people	Ethnic				x	x	
Variables		**Troy et al. (2016)**	**Donovan and Prestemon (2010)**	**Wolfe and Mennis (2012)**	**Gilstad-Hayden et al (2015)**	**Deng (2015)**	**Arantes et al. (2022)**
Tree Cover source							
High resolution image classification		x	x		x	x	x
NDVI				x			
LIDAR		x				x	
Tree count and crown variables			x				
Crime data							
General crime index		x	x		x	x	x
Against property			x		x	x	x
Against person							x
Violent crimes			x		x	x	
Aggravated assaults			x	x			
Robberies			x	x			
Burglaries			x	x			
Larceny			x				
Motor-vehicle theft			x				
Simple assault			x				
Vandalism			x				
Thefts				x			

Table 7. Lagrange Multiplier (LM) test results.

All city				Urban			
km²	AD	HDU	CS	km²	AD	HDU	CS
Total	Not significant	Lag	SARMA	Total	Not significant	Error	SARMA
Property	Lag	Lag	SARMA	Property	Lag	Error	SARMA
Person	Not significant	Error	SARMA	Person	Not significant	Error	SARMA
Pop/1000				Pop/1000			
Total	Not significant	Error	SARMA	Total	Not significant	Error	Error
Property	Lag	Lag	SARMA	Property	Lag	Lag	SARMA
Person	Not significant	Error	SARMA	Person	Not significant	Error	SARMA

GENERAL CONCLUSION

Remote sensing is the best option to manage urban land cover, quantify tree cover existent and watch it changing over time. Satellite images and GIS softwares provide products with high accuracy and have low cost and are fastly replicated than ground-base inventories, maily to large scale cities as Sao Paulo.

In chapter one, Sao Paulo city presents a net increase in Urban Tree Cover (UTC) of 10.34% for the 2010-2017 period when considering all territory of the city. This increased tendency is preserved when two main zones of the city are considered: Urban with 0.30% and Environmental with 13% - the first is the most central and urbanized zone of the city and the second is the most peripheral areas of the city with large areas of Atlantic Rainforest remnants. The Land Use (LU) distribution pointed to important tendencies. The LU distribution in Sao Paulo city can put some limits on the maintenance and reforestation actions by public managers, once more than 80% of UTC are private areas, composed of residential and industrial zones.

In chapter two, Sao Paulo city presents two patterns for the relation between tree cover and income. The first, when considering the entire area of the city, is a negative correlation between the variables. This atypical correlation is an unplanned and unwanted effect of a disorganized urban expansion process. In general, the historical occupation of Latin American cities has driven a spatial segregation guided by the preferences of the middle and upper classes, with the poorest classes being pushed to peripheral regions. But, unlike other cities, São Paulo has most of its Urban Forest in the peripheral areas, in the remnants of the Atlantic Rainforest. The historical social and environmental contrast and consequences is still very evident nowadays. The second pattern is a positive correlation in the more urbanized areas of the city, indicating inequality in the distribution of urban forest. This probably reflects a biased urban greening policy in favor of wealthier neighborhoods and the fact that land prices may be higher in greener residential areas.

In the chapter three, we found that there is a spatial association between the occurrence of crimes and the presence of tree cover, corroborating that these elements are not uniformly or randomly distributed in space. Our main results showed that Sao Paulo city tree cover is associated with lower total, property and person crime rates, even when different areas of the city, scales of study, and denominator of crime are tested. The mais results follow the literature that have observed tree cover associated with lower crime rates, for different types of crime.