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The relationships between Urban Tree Canopy Cover and Crime in São Paulo City, Brazil

Bruna Lara Arantes[a,1,*], Dexter Henry Locke[b,2], Gustavo Carvalho Moreira[c,3], J. Morgan Grove[b,4]

[a] Forest Sciences Department, Luiz de Queiroz College of Agriculture (Esalq), University of São Paulo (USP), Avenida Pádua Dias, 11, Agronomia, Piracicaba, São Paulo 13418900, Brazil

[b] USDA Forest Service, Northern Research Station, Baltimore Field Station, Suite 350, 5523 Research Park Drive, Baltimore, MD 21228, USA

[c] Department of Economics, Administration and Sociology, Luiz de Queiroz College of Agriculture (Esalq), University of São Paulo (USP), Avenida Pádua Dias, 11, Agronomia, Piracicaba, São Paulo 13418900, Brazil

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ABSTRACT

Prior research has indicated lower crime rates in areas with greater tree canopy cover predominantly in the Global North. There are few studies from the Global South, and more specifically in Latin America. Given the high prevalence of crime in Latin American cities, the need to address social and environmental inequalities using nature-based solutions is urgent. This study examines crime and tree canopy cover through a series of spatial analyses for São Paulo city, Brazil, while controlling for potential confounders. We tested six levels of data aggregation that were combined with three different crime types and two denominators of crime, to account for spurious findings from Modifiable Areal Unit Problems (MAUP). Of the 36 models, a majority of 27 models (75 %) indicate a negative relationship between crime and tree cover canopy, while 4 models (11 %) show a positive correlation, and 5 models (14 %) suggest no statistically significant relationship. Our best models allow us to infer that 10 % greater tree canopy cover is associated with a 1.20 % fewer property, personal and total reported crimes, with statistical significance at the $p < 0.001$ level. These findings support our hypothesis that there is a negative relationship between tree canopy cover and crime, with a stronger association observed for property crime than personal or total crime. The negative relationship persisted independently of the level of data aggregation, crime types, crime denominator and spatial models specifications (lag and SARMA), avoiding statistical bias of MAUP. The results follow the literature that have observed tree cover associated with lower crime rates, for different types of crime, while adding a new climatic and cultural context to the evidence base.

1. Introduction

Urban tree canopy - the layer of leaves, branches, and stems when viewed from above - provide numerous environmental and social benefits (Westphal, 2003; Nesbitt et al., 2017), and are often associated with lower crime rates in US cities (Gilstad-Hayden et al., 2015; Troy et al., 2012; Wolfe and Mennis, 2012). Crime and crime opportunities are neither uniformly nor randomly distributed in space and time (Ratcliffe, 2010). Opportunities for crime vary across space and over time (Cohen and Felson, 1979; Brantingham and Brantingham, 1981; Weisburd et al., 2012) and are predicted in part by environmental characteristics (Jeffery, 1971; Newman, 1972), including tree canopy cover.

Latin American cities contain some of the highest levels of violent crime in the world and are considered to be at epidemic levels by the World Health Organization (United Nations Development Programme, 2014). In São Paulo city, reported crime rates highlight theft as the most frequent crime type, but assaults and homicides rates have been decreasing every year since 2000 (Appendix A, Fig. 1A) (Public Security

* Corresponding author.
E-mail addresses: blarantes@alumni.usp.br (B.L. Arantes), dexter.locke@usda.gov (D.H. Locke), gustavocmoreira@usp.br (G.C. Moreira), Jonathan.Grove@usda.gov (J.M. Grove).
[1] ORCID: 0000–0001-9708–7218
[2] ORCID: 0000–0003-2704–9720
[3] ORCID: 0000–0001-9526–0267
[4] ORCID: 0000–0002-7803–074X

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Department, 2022). In the early 2000s, São Paulo city was the most violent city in Brazil and Latin America, but the combination of social policies, police intelligence, and other changes decreased homicide rates from 50 cases per 100,000 in 1999 to less than 5 in 2020, representing a global crime reduction success story (Justus et al., 2018). Although constant efforts are being made to further reduce crime, the literature shows that characteristics intrinsic to São Paulo such as high population density, extensive size, chronic poverty, and historical social exclusion with low investments in some regions, are strongly associated with high violent crimes rates (Ceccato et al., 2007). Given the high prevalence of crime in São Paulo, Brazil, research is needed to address social and environmental inequalities using nature-based solutions (Torres et al., 2023), and to understand how reported crime is related to tree canopy cover.

Previous research has measured the relationships between tree canopy and crime in US cities. For example, a negative association between tree cover and crime was found in New Haven (CT), where 10 % greater tree cover is associated with 15 % lower violent crimes and 14 % lower property crimes (Gilstad-Hayden et al., 2015). Negative relationships were also found in Baltimore County (MD), where 10 % greater tree cover was related to 12 % lower crimes (Troy et al., 2012). Troy et al. (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). In Philadelphia (PA) vegetation abundance was also associated with lower rates of assault, robbery and burglary, with the exception of theft, which did not exhibit a statistically significant relationship (Wolfe and Mennis, 2012). In Austin (TX), tree canopy was negatively associated with violent and property street crime and thought to be attributable in part to creating more walking-friendly neighborhoods (Lee, 2021).

The literature on crime and urban tree canopy cover has almost exclusively focused on the United States and Europe (Sreetheran and Van Den Bosch, 2014), with only a limited number of studies from the Global South (i.e. Maruthaveeran and Van den Bosh, 2015; Potgieter et al., 2019). In South Africa, Venter et al. (2022) conducted national-scale research and found similar results to US cities, where 1 % greater green space was related to 1.2 % lower violent and 1.3 % lower property crimes. However, these results diverged when specific green spaces, such as public parks, were considered. It is important to consider that ideas about crime-tree canopy relationships developed in the United States and Europe may or may not apply in Global South and Latin American cities, where relatively less research on this topic has been conducted. Care and adaptation considering local factors such as cultural differences, poverty and income rates, organized crime, and the lack of a state presence might be needed (Ceccato and Paz, 2017; Justus et al., 2018; Loureiro et al., 2018; Melo et al., 2016). For example, one of the best-studied relationships in urban forestry predominantly in North American cities is that higher income areas tend to have more tree canopy cover (Gerrish and Watkins, 2018). A similar path of unequal distribution of income and urban forest was found in São Paulo city (BR) (Arantes et al., 2021). Yet analyses in other tropical climates such as those found in San Juan (PR) and the Dominican Republic have found different relationships between socioeconomic status and tree canopy cover (Martinuzzi et al., 2018; Martinuzzi et al., 2021).

Latin America, one of the world’s most urbanized regions, is also home to one of the most biodiverse areas on Earth, making it a global hotspot for conservation efforts (UNEP-WCMC, 2016, United Nations, 2022). Despite the importance of Latin America in terms of both biodiversity and urbanization, little research about urban tree canopy and crime can be found. A notable counterexample is research, in Bogotá (Colombia), which showed the spatial distribution of large and high-density urban trees are linked with lower occurrence of homicides, while the non-harmonious combination of high street lighting and tree height can contribute to more dark and unsafe areas (Escobedo et al., 2018). Despite the example from Bogotá, the question about a tree canopy-crime relationship in Latin American cities is relatively unexplored.

1.1. Research objectives and questions

This research aims to begin to remedy the gap in urban ecological research in Latin America that links crime and urban tree canopy through a series of spatial analyses of urban tree canopy cover and crime for São Paulo city, Brazil. Based on previous literature, it is hypothesized that crime and tree canopy cover are negatively related and the relationships between tree canopy cover and crime vary based on the

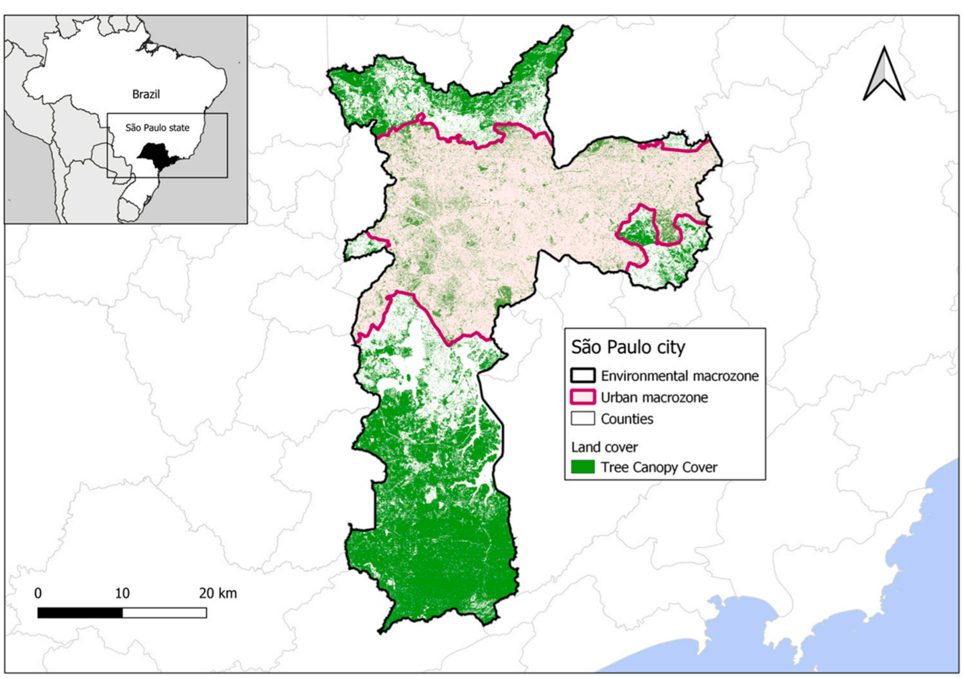

Fig. 1. São Paulo city subdivisions, with highlights to the urban macrozone (purple line) and environmental macrozone (black line), and Tree Canopy Cover (green). In detail is São Paulo state location in Brazil, South America.

crime type (Escobedo et al., 2018; Venter et al. 2022). We ask,

1) How are crime and tree canopy cover related across São Paulo city?
   Because different types of crimes have different motivations, there could be different relationships between different types of crime and tree canopy cover, which motivates our second research question:
2) How are different types of crime related to tree canopy cover?
   Recognizing that how reported crimes are standardized (i.e. crimes per capita versus crimes per square kilometer) may influence the findings, we ask:
3) Do the relationships vary by crime denominator?
   The geographically large, socially diverse, and topographically variable nature of São Paulo city necessitates that we ask:
4) Are the findings different when considering the whole city as opposed to the urban area?
   Understanding that statistical results of analyses using spatial data can be sensitive to geographic boundaries chosen, we ask:
5) Is the spatial correlation sensitive to statistical bias from the modifiable areal unit problem (MAUP)?

The results may provide better information for management and policy-making by identifying the specific contexts in which reported crime occurs or not. The general objective for this research was to estimate the relationship between tree canopy cover and crime, while controlling for key confounders, in São Paulo city for 2016.

1.2. Theoretical background: urban tree cover and socioeconomic factors related to crime

There are several hypotheses about the relationships between crime and the built environment. One explanation for a positive relationship between urban trees and crime is concealment: tree canopy cover can offer physical concealment to criminals and limit prospects and escape for victims, which can increase the opportunities of attacks and decrease safety (Fisher and Nasar, 1992). Donovan and Prestemon (2010) found view-obstructing trees were associated with greater crime in Portland, Oregon. In Milwaukee, WI, mixed tree heights and patterns were correlated with different crime types, highlighting a complex relationship of mixed associations and a lack of spatial uniformity (Deng, 2015). In Cape Town (South Africa), a positive relationship between perceived crime risk and vegetation structure densification by invasive alien trees and shrubs was observed (Potgieter et al., 2019). From this perspective, urban trees may create opportunities for criminals since surveillance is limited or blocked by trees.

There are several additional hypotheses about negative relationships between crime and urban trees. One explanation is about care and signs of care. Neighborhood characteristics indicating a lack of maintenance, may signal that residents' lack interest in taking care of their surroundings, including trees, which may increase crime. This has been called "Broken Windows theory" (Kelling and Wilson, 1982). Home maintenance can act as a "territorial marker" (Brown and Bentley, 1993), indicating care and investment. Neighborhood characteristics such organization and cleanliness, and perceived-positive landscaping via high maintenance are so called "cues to care" (Nassauer, 1995). Surveillance can be related to neighborhoods where people know, communicate, and care for each other, stimulating social cohesion and creating a passive community surveillance with more "eyes on the street" (Newman, 1972; Jacobs, 1961). The main idea is that visual indicators of care may subconsciously indicate that other residents are watching and will lookout for each other. Donovan and Prestemon (2010) also found that in some regions of the city where there were well-maintained trees, which may convey greater care, had lower crime rates.

The rationale of the negative relationship between urban trees and crime also aligns with the context of Sampson and colleagues' Collective Efficacy Theory (Sampson et al., 1997; Sampson, 2012), as well as Crime Prevention Through Environmental Design (CPTED) (Jeffery, 1971; Newman, 1972). Urban trees and well-maintained green spaces may enhance social interactions and community engagement, thereby strengthening collective efficacy. Additionally, CPTED principles advocate for the strategic design and management of the physical environment to reduce opportunities for crime. Trees and green spaces can contribute to natural surveillance and an overall sense of safety and order.

To control for the relationship between urban tree cover and crime, socioeconomic, demographic and environmental variables need to be included in empirical models, taking into account criminological theories such as disorganization theory (Shaw and McKay, 1942; Sampson and Groves, 1989), collective efficacy theory (Sampson et al., 1997; Sampson, 2012), rational choice (Becker, 1968), routine activity theory (Cohen and Felson, 1979), as well as considering previous empirical crime studies conducted worldwide and specifically in the Global South (Ceccato et al., 2007; Resende and Andrade, 2011; Justus and Kassouf, 2013; Biderman et al., 2014; Justus et al., 2015; Steeves et al., 2015; Melo *et al.,* 2016; Ceccato and Paz, 2017; Justus et al., 2018; Dix-Carneiro et al., 2018; Loureiro et al., 2018; Moreira and Ceccato, 2021a; Alves et al., 2022; Venter et al., 2022).

Population density has been shown to have both positive and negative associations with urban crime rates (Shichor et al., 1979). When population density is high, it can be positively related with higher crime rates because there are more opportunities to commit crimes, via more potential targets and potentially less social organization (Cohen and Felson, 1979; Kassem et al., 2019; Watts, 1931). On the other hand, in areas of low population density, there is relatively less informal surveillance to protect would-be victims (Troy *et al.,* 2012). Alternatively, high population density can have a negative association with crime rates, as high population density may offer more surveillance and more chances to be caught, which may inhibit crime (Newman, 1972; Jacobs, 1961), or low population density offers fewer crime opportunities, particularly for property crime (Cohen and Felson, 1979).

Another variable that may have an ambiguous relationship with crime is income. On one hand, one might expect that the higher the income of individuals in an area, the greater the potential returns from criminal activities (Becker, 1968), thus increasing the risk of victimization and the occurrence of crimes in wealthier regions. On the other hand, populations with higher incomes also tend to have more resources to protect themselves and more opportunities to frequent safe and monitored environments, such as shopping malls and private schools, which could reduce the risk of victimization (Justus et al., 2015; Sant'Anna et al., 2016).

A relevant variable frequently considered in studies on the determinants of crime concerns the demographic composition of the population, particularly regarding the participation of young men (typically aged 15 to 29) in the population, as this group is known to be the most involved in criminal activities (Cohen and Land, 1987; Murray et al., 2013; Biderman et al., 2014; Alves et al., 2022; Venter et al., 2022). Therefore, a positive relationship between this variable and crime is expected.

An additional variable regarding characteristics of the young population concerns their literacy or level of education. The more literate the young individuals are and the higher their level of education attainment, the lower their vulnerability to crime, since education enhances future opportunities and discourages involvement in criminal activities (Becker, 1968; Ceccato and Paz, 2017; Justus et al., 2018; Lochner, 2020).

To incorporate Shawn and McKay's (1942) social disorganization theory, which was empirically evaluated by Sampson and Groves (1989), holistically analyzing crime includes considering specific environmental variables. Initially, Shawn and McKay (1942) emphasized the importance of ethnic homogeneity in maintaining effective social control, where the greater the ethnic homogeneity, the lower the incidence of crimes (Trawick and Howsen, 2006; Gu et al., 2023). Subsequent theoretical and empirical studies have also highlighted the importance of additional environmental characteristics that can affect the social stability of an environment and create conducive conditions for crime (Jeffery, 1971; Newman, 1972; Sampson et al., 1997; Sampson, 2012; Ioannidis et al., 2024), such as open sewers and garbage, which represent neighborhoods and settlements with social vulnerability and/or low collective efficacy, typical of Latin American cities (Melo *et al.,* 2016), and owner-occupied properties, since ownership often correlates with a deeper sense of belonging, personal investment and care in maintaining the property (Lauridsen *et al.,* 2013; Nassauer, 1995).

Topographical characteristics of the environment can also influence crime occurrence because they affect visibility, accessibility, and escape routes. Topographical characteristics of the environment can influence crime occurrence by affecting visibility, accessibility, and escape routes. For example, in Tshwane, South Africa, greater altitude was associated with a lower risk of burglary victimization (Breetzke, 2012). In Bogotá, Colombia, areas with less homogeneous urban layouts, characterized by varying texture elements such as contrast, uniformity, and roughness, were linked to higher homicide rates (Patino et al., 2014).

Crime is acknowledged to be unevenly distributed across space (Clarke and Eck, 2003; Clarke and Eck, 2007). These areas, known as "hot spots", act both as generators and attractors of crime (Brantingham and Brantingham, 1995; Bowers, 2014; Ceccato and Paz, 2017; Moreira and Ceccato, 2021a; Moreira and Ceccato, 2021b). Therefore, the spatiality of crime needs to be considered or, at the very least, tested for the city of São Paulo to control the relationship between urban trees and crime.

The variables mentioned above have been integrated into our empirical model to control for the relationship between urban tree cover and crime. These variables are based on prior theories and empirical studies, and their inclusion is contingent on the availability of specific data for the city of São Paulo. They encompass a range of aspects that may influence both crimes against persons and crimes against property, reflecting rational choice theory, which views crime as an activity dependent on the relationship between benefits and costs, as well as criminological theories that regard crimes against persons as outcomes of social conditions and environmental instability (Watts, 1931; Shaw and McKay, 1942; Jacobs, 1961; Becker, 1968; Newman, 1972; Cohen and Felson, 1979; Sampson et al., 1997).

2. Methods

2.1. Study area

São Paulo city is one of five megacities in the world with a population of 12 million inhabitants, distributed across 1521.110 km^2, and the largest city in Latin America. São Paulo city is also one of the main centers of the Brazilian economy (IBGE, 2010; United Nations, 2018). São Paulo city was founded and developed in an area of the Atlantic Rainforest biome, a global biodiversity hotspot, that was extensively explored during urbanization and by coffee agriculture. Today, only small forest fragments remain that regulate regional climate, rainfall distribution, and stabilize soils, while providing other ecosystem services (Rezende et al., 2018, Joly et al., 2014).

To better manage the city of São Paulo's land cover the Strategic Director Plan review (PL 688/13) defined two main zones: i) the urban macrozone and ii) the environmental macrozone (São Paulo City, 2014), highlighted on Fig. 1. The urban macrozone, comprising the city's central urbanized areas, is made up of diverse land uses and land covers. This spatial heterogeneity encompasses concentrated businesses, economic centers, public transportation hubs, high real estate speculation and numerous opportunities within the city. In contrast, The Environmental macrozone is composed of large areas of Atlantic Rainforest remnants, agriculture activities, and with fragile geological and geotechnical characteristics where human occupation is at risk of flooding or landslides, and the soils are contaminated (São Paulo City, 2014). Despite comprising mostly forested areas, the environmental macrozone hosts some of the city's Administrative Districts with high population densities, that together have near 1 million residents. These districts are primarily concentrated in the northern and eastern regions (IBGE, 2010). Furthermore, the southern Administrative Districts, characterized by lower population density in 2010, stood out as the areas of the city with the most population growth by 2022, reaching growth rates of 38 % (IBGE, 2022). Predominantly the environmental macrozone is composed of the most peripheral Administrative Districts, dominated by horizontal settlement, popular housing projects, with poor investment, few job opportunities, and with high frequency of "favelas". Favelas are typical Brazilian housing defined by encroachment and non-regulated areas without any infrastructure. Favelas are built in conflict with urban and environmental laws, and are considered as the last housing alternative, offering risk to inhabitants and pressing the Atlantic Rainforest remnants around them (Maricato, 2010).

2.2. Data

Urban tree canopy cover was estimated from classification of a high-resolution image from WorldView-2, 70 cm of resolution, 2017 year, available at GeoSampa (2017). The chosen classification method was Supervised Object-Oriented, with manual correction performed to eliminate obvious and non-systematic errors at a scale of 1:2000 scale. An accuracy assessment was conducted through a cross-validation process, with 500 sample points to generate a confusion matrix. The classified image presents a Kappa of 82 %, whereas tree canopy cover presents a Kappa of 95 %. Based on the Pontius and Millones (2011) method, tree canopy cover attains a consistent global accuracy of 88.89 %, with a quantity disagreement of 3.53 % and an allocation disagreement of 11.11 %. For a systematic review of studies that have utilized remote sensing data for crime analysis from 2003 to 2023, see Ceccato and Ioannidis (2024).

The 2016 crime database was provided by municipal police records from the Public Security Secretariat of the State of São Paulo. It includes geocoded points (latitude and longitude) and crime type. Although São Paulo has an online system which facilitates the reporting of the vast majority of crimes by authorities, this can bias the estimation of the relationship between urban tree cover and crime. A limitation in using these data is the possibility that they may be underreported, which could introduce a bias that might be unevenly distributed across city areas, with higher rates of underreporting expected in peripheral regions with greater economic and social vulnerability. To address this bias, we have introduced a distinction between the "city as a whole" and "urban macrozone," with the goal of minimizing potential underreporting in areas characterized by greater socioeconomic vulnerability.

The crime types were classified into three major categories: (i) property crime made up of robbery and theft; (ii) personal crimes made up of assault, rape, and homicides, and iii) total crime, the combination of personal and property crimes. Those three categories are defined in accordance with the Brazilian Criminal Code (Brasil, 1998), and this organization is important because different types of crime have different motivations and outcomes, as described above.

The various units of analyses used (described next) are spatially heterogeneous with respect to size, total population, and population density. Crime rates were therefore standardized using two denominators: (i) crimes per 1000 people, and (ii) crimes per square kilometer (km^2). Crimes per capita (or per 1000 people) is commonly used as a denominator since it relates activities to criminals and victims (Newton *et al.,* 2021). However, it has limitations, since this denominator takes into account the people who live in the area (a static measure), not their routine data such as where they work or spend their leisure time (Boivin, 2013; Rummens et al., 2021). In this way, dense non-residential areas such as business centers, commercial buildings, parks, and other places that can be hotspots for crime can be underestimated (Sherman *et al.,* 1989). In some cases, using the crime per capita in low or non-populated areas can create bias by inflating rates from small denominators. Alternatively, using area as a denominator prevents that source of bias, but can introduce others. For example, when the denominator is square kilometers, crime hot spots may appear more severe owing to their small area. Both per capita and per area analyses have their strengths and weaknesses. This paper therefore uses and compares both of these commonly-used standardizations for more robust findings. Fig. 2 illustrates the distribution of reported crime by type and denominator, highlighting the differences in two subdivisions of São Paulo city.

All the analyses were carried out for two subregions: (i) the whole city, the entire territorial extension of the city of São Paulo, that is composed by the two macrozones, and (ii) the urban macrozone, the most urbanized regions of the city. The urban macrozone of the city has a privileged history of investments and development that has created a scenario of social and environmental inequality with the most peripheral areas of the city. Evaluating these two subregions helps us understand if this history of spatial inequality relates to the relationship between crime and tree canopy cover and control the influence of the large patches of Atlantic Rainforest remnants. Finally, three sets of geographic boundaries, representing three different levels of aggregation, were chosen for empirical analysis: (i) Administrative District (AD), regulated by São Paulo City (1992), (ii) the Human Development Unit (HDU), geographical units formed by a group of adjacent census sectors created by Sistema Estadual de Analise de Dados (SEADE, 2010), and (iii) Census Sectors (CS), the smallest unit of urban observation created by the Brazilian Institute of Geography and Statistics (IBGE, 2010). Each census sector belongs to one and only one HDU, and each HDU belongs to one and only one AD. In this way they are nested, akin to the American Census geographies: blocks within block groups and block groups within tracts.

The two subregions combined with three levels of geographic boundaries has allowed us to create six levels of data aggregation for whole city, that presents AD (n = 96), HDU (n = 1490) and CS (n = 18,953); and for urban macrozone, that presents AD urban (n = 74), HDU urban (n = 1103) and CS urban (n = 14,220), see Fig.A2 in Supplementary material for a detailed illustration. The Modifiable areal unit problem (MAUP) explains that a correlation can be present just because of the size, shape, and configuration of a particular zoning system (Openshaw, 1984). MAUP is the product of both spatial autocorrelation

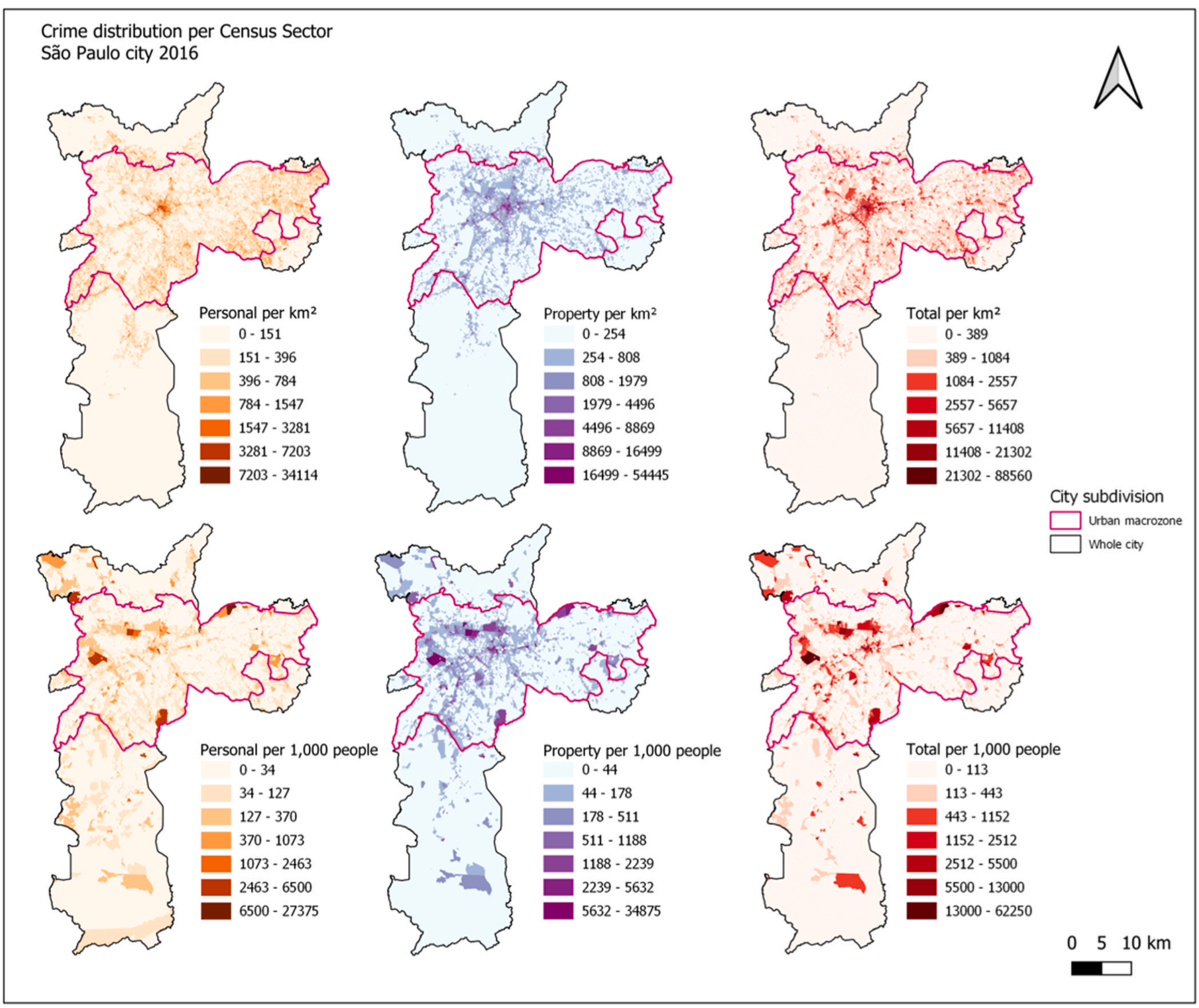

Fig. 2. Distribution of personal (orange), property (purple), and total (red) crime in São Paulo city, for 2016. Figures express the count of reported crimes by Census Sector (smallest urban unit in Brazil), for two crime denominators: per square kilometer (km^2) (above) and per 1000 people (below) and highlight the subdivisions: urban macrozone (purple line) and the whole city (black line).

and aggregation. To guard against spurious findings from MAUP, the analyses were carried out three times, once for each set of geographic boundaries.

In summary, 36 models were built with three types of crime: 1) total, 2) personal, and 3) property; with two denominators of crime: 1) per square kilometer (km^2), 2) per 1000 people; in three levels of geographic boundaries: 1) AD, 2) HDU, 3) CS combined with two areas of city: 1) the whole city, 2) urban macrozone.

Crime is the dependent variable and tree canopy cover the explanatory variable in this study, while controlling for potential confounders. The control variables chosen were income per capita, Blau index of ethnic heterogeneity, proportion of young men (15 to 29 years old), proportion of literate young (5 to 17 years old), proportion of households with garbage accumulated in front of the street, open sewer, percent of house that is owner occupied, elevation and roughness. The Blau Index (BI) is a measure of diversity and is calculated with $BI = 1 - \sum (p_i)^2$, where p_i is the proportion of individuals who are white, black, yellow, brown, and indigenous. The control variables are based on the general demographic census of Brazil, that is made available every 10 years (IBGE, 2010), and the topography data derived from the National Digital Elevation Model (MDE) (INPE, 2011). These chosen socioeconomic covariates have been shown to be related to crime and tree canopy cover in previous studies in US cities (Troy et al., 2012; Donovan and Prestemon, 2010; Wolfe and Mennis, 2012; Gilstad-Hayden et al., 2015; Deng, 2015), and they are also present in studies that sought to analyze the determinants of crime from different perspectives in Brazil described above (Ceccato et al., 2007; Resende and Andrade, 2011; Justus and Kassouf, 2013; Biderman et al., 2014; Justus et al., 2015; Steeves et al., 2015; Melo *et al.,* 2016; Ceccato and Paz, 2017; Justus et al., 2018; Dix-Carneiro et al., 2018; Loureiro et al., 2018; Moreira and Ceccato, 2021a; Alves et al., 2022). The chosen topography data were previously explored in Latin America and the Global South studies as significant and underexplored environmental components that can influence crime occurrence (Breetzke, 2012; Patino et al., 2014).

2.3. Statistical analysis

We computed descriptive statistics and conducted exploratory data analysis to examine the distribution, standard deviation, outliers, and tendencies of the data. This step was taken to avoid any bias in the regression models. To facilitate the substantive comparisons of interest (crime types, urban macrozone vs whole region) while investigating the sensitivity to standardization approach (per capita vs per area), choice of spatial units (AD, HDU, and CS), while appropriately addressing spatial autocorrelation, a model comparison and selection process was conducted. First, Ordinary Least Squares (OLS) was carried out for each dependent variable and set of explanatory variables, resulting in 36 OLS models. Multicollinearity was not an issue; the highest variance inflation factors were <8. However, OLS is a linear regression model which ignores spatial dependence and was used as baseline and as alternative when a model did not exhibit spatial autocorrelation (Almeida, 2013; Anselin, 2005). Then, global Moran's I was computed for the OLS residuals to test for spatial dependence, or the degree to which the linear association observed values correspond to the weighted average of neighboring values (or spatial lags) with a formal hypothesis test (Cliff and Ord, 1973). For this analysis a Queen contiguity spatial weights matrix was chosen, which defines spatial neighbors as contiguity between two spatial units that share a common edge or vertex (Almeida, 2013). The queen contiguity matrix was chosen due to the continuous tessellation of analytical units and for consistency with other published studies (Grove et al., 2014; Lin et al., 2021; Locke et al., 2017). Next, if Moran's I indicated spatial autocorrelation in the OLS residuals, spatially-adjusted regression models were carried out, using the Lagrange Multiplier Test to indicate which spatial regression model specification would be more appropriate: spatial lag, spatial error or Spatial Autoregressive Moving Average (SARMA) model, following the decision tree described by Anselin (2005). The spatial lag model assumes that spatial autoregressive process is an effect of lagged dependent variables (Eq. (1)); the spatial error model assumes that spatial dependency occurs like an effect in spatial errors correlated as a result of omitted variables (Eq. (2)); and SARMA which combines the spatial lag and spatial error model (Eq. (3)) (Anselin and Bera, 1998; Anselin, 2001; Almeida, 2013). In matrix notation:

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

$$y = \quad X\beta + \mu; \mu = \lambda W\mu + \sigma \tag{2}$$

$$y = \rho Wy + X\beta + \lambda W\mu + \sigma \tag{3}$$

where y is the dependent variable, W is a Queen contiguity spatial matrix, Wy is referred as a spatially lagged dependent variable, X is a matrix of regressors associated with parameter vector β and ε is the random error term with mean zero ($E(\varepsilon) = 0$) and variance constant ($E(\varepsilon\varepsilon') = \sigma^2 I$). The scalar ρ is a parameter to be estimated that will determine the spatial autoregressive relation between y and Wy. Additionally, in Eq. (2) λ is the autoregressive parameter to be estimated for the vector $W\mu$ and σ is the random error term, which has the same characteristics as the error term ε. The autoregressive parameter of the random term in Eq. (2) is incorporated into Eq. (1) in Eq. (3).

The spatial lag and SARMA models have the dependent variable on the right-hand side of the equation, complicating interpretation of their coefficients due to spatial spillovers (Golgher and Voss, 2016). Therefore, the betas are not adequate for inference. Impacts, in contrast to the coefficients correct for the reciprocal and spillover effects of neighboring units (Bivand and Piras, 2015). The error model includes the spatial dependence on the error term in the regression equation, and treats it as a nuisance to be adjusted for, and is free from the issues requiring impacts for lag models (Medina and Solymosi, 2022). Error models' coefficients can be interpreted like OLS models.

3. Results and discussion

3.1. Descriptive statistics and unadjusted relationships

To analyze the potential combinations and distributions of the 36 models proposed in this study, we have included facet graphics that depict the bivariate relationship between tree canopy cover and crime (Figs. 3 and 4). The panels in the graphic are categorized by geographic boundaries (AD, HDU, and CS), while crimes are displayed according to their types (personal, property and total) for the two denominators of crime (per square kilometer and per 1000 people), for the two subregions urban macrozone and whole city.

In both the urban macrozone (Fig. 3) and the whole city (Fig. 4), 75 % (n = 9) of the bivariate relationships between tree canopy cover and crime were negative correlations. This correlation is more pronounced when considering the square kilometer denominator and less pronounced when using the per 1000 people denominator, across all levels of geographic boundaries. However, some exceptions are observed, 25 % (n= 3) of the models present discrete positive bivariate correlations between tree canopy cover and crime per 1000 people within Human Development Unit (HDU) geographic boundaries. Overall, the unadjusted relationship between crime and tree canopy is weak and negative but exhibits heterogeneity depending on the level of geographic boundaries (AD vs HDU vs CS), crime type, and method of standardization of crime. For example, at low levels of tree canopy cover there is a wide range of crime per 1000 people in CS and, to a lesser extent, HDU.

Crime rates ranging from 2000 to 3000 crimes per square kilometer occur when tree canopy cover is less than 12 % (Figs. 3 and 4). On the other hand, no crimes per square kilometer are observed when tree

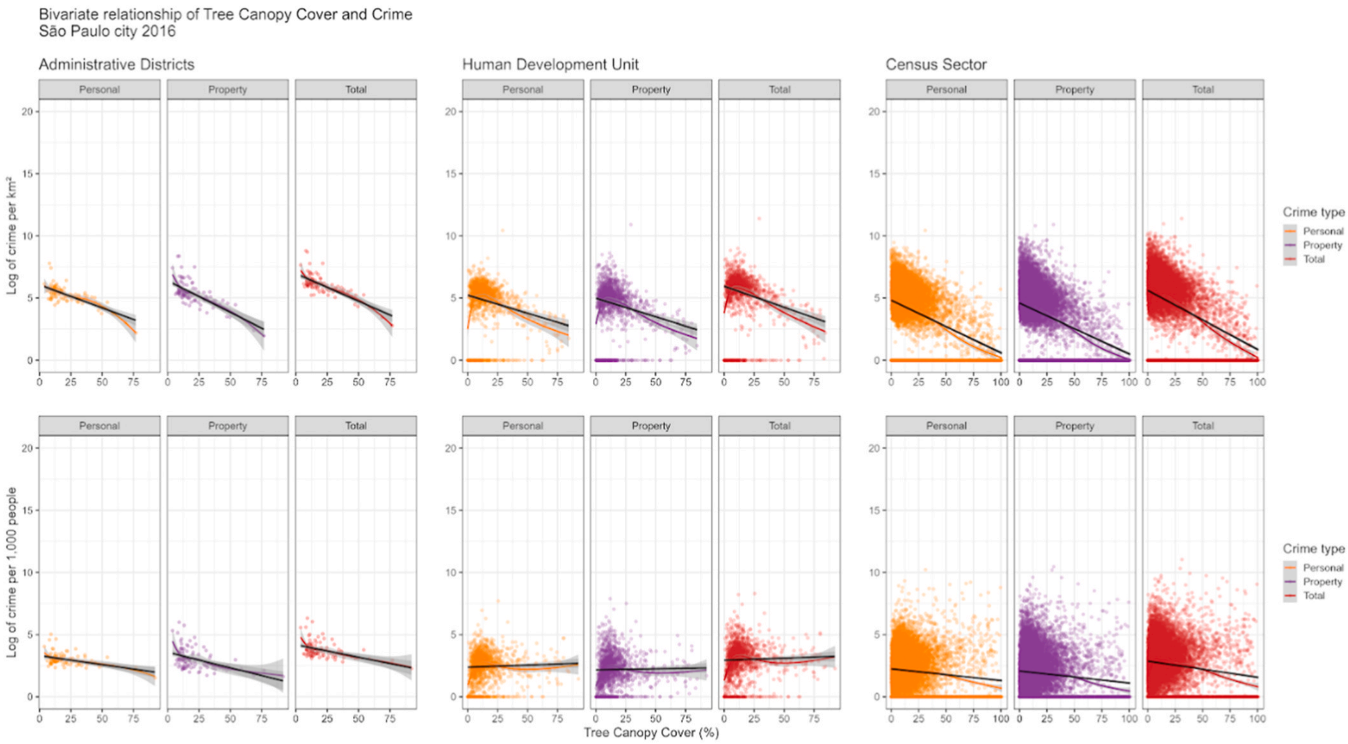

Fig. 3. Bivariate relationship of Tree Cover Canopy and Crime, composed of 18 models for the whole São Paulo city. Note: Panels are divided by three geographic boundaries: Administrative Districts (AD), Human Development Unit (HDU), and Census Sector (CS). The log of crime is plotted by type: personal (orange), property (purple) and total (red), for two denominators of crime: square kilometer (km^2) (above) and per 1000 people (below).

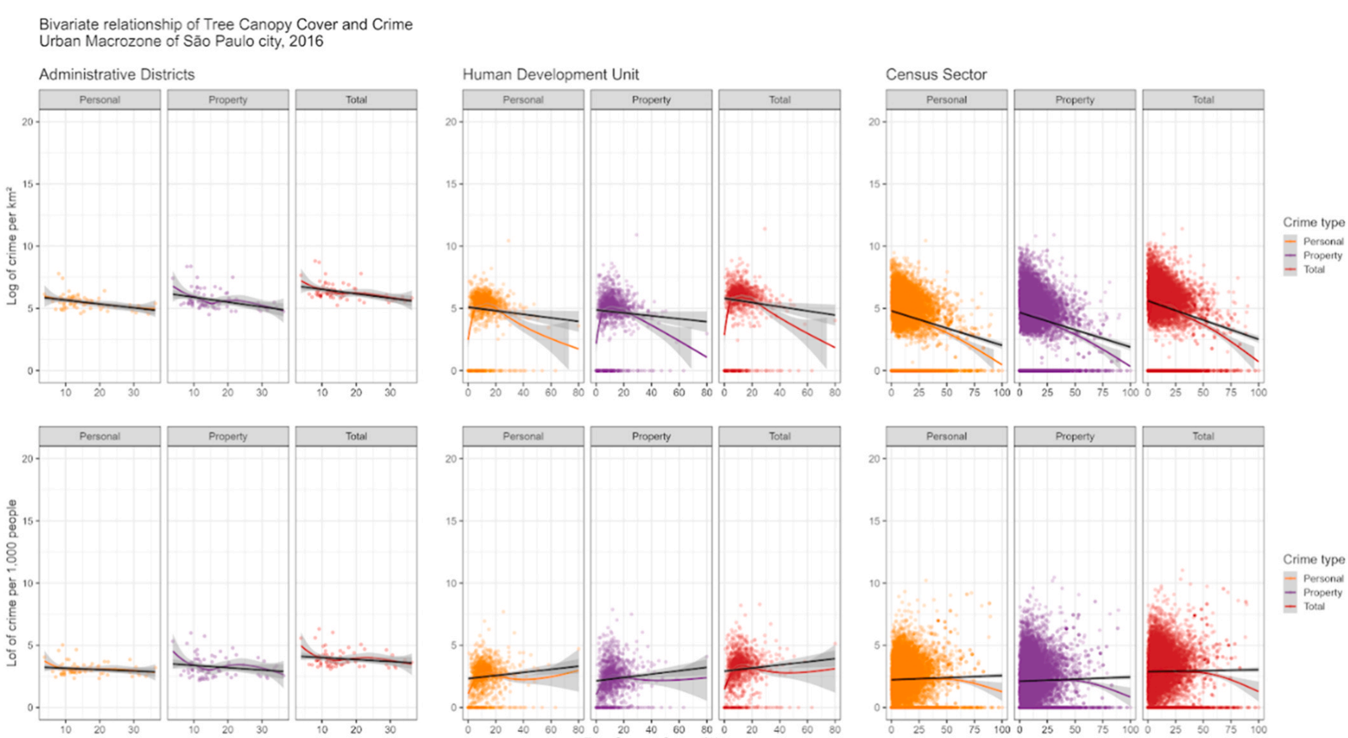

Fig. 4. Bivariate relationship of Tree Canopy Cover and Crime, composed of 18 proposed models for the Urban Macrozone of São Paulo city. Note: Panels are divided by three boundaries: Administrative Districts (AD), Human Development Unit (HDU), and Census Sector (CS), fitted to urban macrozone. The log of crime is plotted by type: personal (orange), property (purple) and total (red), for two denominators of crime: square kilometer (km^2) (above) and per 1000 person (below).

canopy cover is greater than 60 %. The bivariate correlations are stronger for total crime, and in the Administrative Districts (AD), but still seen in the other levels of geographic boundaries (HDU, CS). The crime per 1000 people presents very weak bivariate correlations in general, making it not possible to carry out consistent visual analysis.

The Moran's I test of each univariate distribution showed statistical significance for all crime types, tree canopy cover, and all control variables in both subregions - the whole city and urban macrozone - mostly at a 95 % significance level, except for Blau Index just for whole city (Tables 1 and 2).

3.2. OLS and spatial models

After accounting for the other independent variables influencing crime in the empirical model and addressing spatial dependence as necessary, 27 out of the 36 models (75 %) indicated a negative relationship between crime and tree cover canopy, while 4 models (11 %) show a positive correlation, and 5 models (14 %) suggest no statistically significant relationship. Residuals for 16 out of the 36 OLS models did not suggest a spatial model was necessary. Among those 16 OLS models, the association between tree canopy cover and crime was negative in 13 models, positive in 1 model, and statistically insignificant in 3 models. The regression-adjusted estimates for OLS and their respective confidence intervals are presented in Fig. 5. For the 20 spatial models, the decision tree outlined by Anselin (2005) and the Lagrange Multiplier (LM) tests suggested 7 lag models, 1 spatial error model and 12 SARMA models. Both OLS and spatial models specifications are described at Table 3.

Out of the 19 lag and SARMA spatial models that were fit, the relationship between tree canopy cover and crime was predominantly negative: 14 models (74 %) showed a negative relationship, 3 models (16 %) a positive relationship, and 2 models (10 %) statistically insignificant relationships. The estimated direct impacts for the lag and SARMA spatial models are illustrated in Fig. 6 and the sole error spatial model in Fig. 5. The direct impact of the spatial models are calculated as the average of the diagonal terms of the partial derivatives matrix. This metric helps to differentiate the spillover effects that arise from a change in the independent variable on the dependent variable, even when they occur in different regions (Golgher and Voss, 2016).

The Akaike Information Criterion (AIC) indicates that between the 14 negative spatial lag and SARMA models, those models that present lower AIC values for crime type (personal, property and total), for subregions (urban macrozone and whole city), and for both denominators (square kilometer and per 1000 people) are the SARMA models. All the 9 SARMA models are better adjusted to census sectors when compared with administrative districts, and present significantly lower AIC in general when compared with lag models (Table 3). Possibly, SARMA models present a better balance between best-fitting and complexity to data, once considering both autoregressive and moving average components (Anselin, 2001).

Based on the AIC-minimization criterion, the direct impact values mostly align with the mean value of the set, indicating a consistent impact distribution around −0.012 after controlling for potential confounders and spatial effects that influence crime. Consequently, 10 % greater tree canopy cover is associated with a 1.20 % lower property, personal, and total crimes, with statistical significance at the $p < 0.001$ level (Fig. 6). These findings support our hypothesis that there is a negative relationship between tree canopy cover and crime for São Paulo city, with a stronger association observed for property crime than personal or total crime.

Among the best-fitting spatial models revealing a negative crime-tree canopy association, most of them pertain to property crime (43 %), followed by total crime (36 %), and personal crime (21 %). The negative impact of tree canopy cover in property crime in São Paulo city can be supported by theories as "territorial marker" and "cues to care", that links care, investment and perceived-positive landscaping of a region as

Table 1
Crime and independent variables summary statistics, Moran's I index and p-value, by three geographic boundaries: Administrative Districts (AD), Human Development Unit (HDU) and Census Sector (CS), to the whole city of São Paulo.

		Administrative Districts (n= 96)					Human Development Unit (n= 1490)					Census Sector (n= 18,953)				
Crime	denominator	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value*
total count		4834	4246	2528	0.13	0.01	311	105	673	0.13	0.01	24	11	64	0.13	0.01
property count		2517	1890	1758	0.32	0	162	41	450	0.32	0	13	4	45	0.32	0
personal count		2317	2165	1277	0.21	0	149	60	250	0.21	0	12	6	22	0.21	0
total	square kilometer	629	428	933	0.45	0	522	377	2345	0.45	0	540	313	1361	0.45	0
property	square kilometer	372	201	661	0.49	0	254	145	1450	0.49	0	276	118	950	0.49	0
personal	square kilometer	257	199	290	0.34	0	266	206	909	0.34	0	264	156	507	0.34	0
total	1000 people	59	38	76	0.30	0	45	24	159	0.30	0	68	19	645	0.30	0
property	1000 people	35	18	57	0.33	0	23	9	96	0.33	0	36	7	399	0.33	0
personal	1000 people	24	18	20	0.22	0	22	14	68	0.22	0	32	10	289	0.22	0
Independent variables																
Tree Cover		21.48	15.46	15.88	0.57	0	15	11	13	0.57	0	14	9	16	0.57	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
income ln		7.54	7.40	0.68	0.72	0	7.08	7	0.77	0.72	0	7	7	1.53	0.72	0
literate young		0.82	0.82	0.03	0.50	0	0.81	0.82	0.07	0.50	0	0.79	0.82	0.18	0.50	0
young man		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
open sewer		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
owner occupied		0.30	0.31	0.03	0.64	0	0.32	0.32	0.07	0.64	0	0.30	0.31	0.14	0.64	0
Blau index		0.38	0.46	0.21	−0.03	0.61	0.45	0.52	0.16	−0.03	0.61	0.43	0.50	0.17	−0.03	0.61
elevation		773	768	30	0.47	0	776	774	28	0.47	0	778	776	29	0.47	0
roughness		7	6	3	0.55	0	7	7	3	0.55	0	7	7	4	0.55	0

Table 2
Crime and independent variables and our summary statistics, Moran's I index and p-value, by three geographic boundaries: Administrative Districts (AD), Human Development Unit (HDU) and Census Sector (CS), to the urban macrozone of São Paulo city.

		Administrative Districts (n= 73)					Human Development Unit (n= 1101)					Census Sector (n= 14,921)				
Crime	denominator	mean	median	SD	Moran's I	p-value*	mean	median	SD	Moran's I	p-value**	mean	median	SD	Moran's I	p-value*
total count		5156	4486	2624	0.11	0.05	356	115	762	0.26	0	29	14	71	0.35	0
property count		2842	2295	1852	0.28	0	195	47	515	0.35	0	15	5	51	0.35	0
personal count		2314	2003	1300	0.23	0	161	65	273	0.09	0	13	7	24	0.33	0
total	square kilometer	766	489	1033	0.41	0	599	417	2718	0.02	0	611	358	1506	0.29	0
property	square kilometer	465	235	734	0.46	0	303	168	1682	0.03	0	324	143	1060	0.30	0
personal	square kilometer	301	237	318	0.30	0	294	225	1050	0.01	0.07	286	177	542	0.25	0
total	1000 people	69	43	85	0.25	0	52	27	183	0.07	0	80	23	724	0.06	0
property	1000 people	43	21	64	0.28	0	28	10	111	0.10	0	44	9	449	0.05	0
personal	1000 people	26	20	22	0.16	0	24	15	79	0.03	0.04	36	12	321	0.08	0
Independent variables																
Tree Cover		15.46	13.00	7.41	0.27	0	12.60	10.99	8.38	0.28	0	12.27	9.17	11.00	0.52	0
garbage		0.03	0.03	0.02	0.27	0	0.05	0.01	0.11	0.07	0	0.03	0.00	0.12	0.20	0
income ln		7.72	7.63	0.65	0.68	0	7.19	7.13	0.74	0.38	0	7.33	7.27	1.22	0.40	0
literate young		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
young man		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
open sewer		0.02	0.01	0.03	0.03	0	0.03	0.00	0.10	0.14	0	0.03	0.00	0.12	0.25	0
owner occupied		0.30	0.30	0.03	0.62	0	0.31	0.31	0.07	0.07	0	0.30	0.30	0.13	0.10	0
Blau index		0.38	0.46	0.23	−0.01	0	0.44	0.50	0.16	0.27	0	0.42	0.47	0.16	0.62	0
elevation		765	762	19	0.45	0	770	770	22	0.74	0	773	772	24	0.90	0
roughness		6	6	2	0.27	0	7	7	3	0.51	0	7	7	3	0.61	0

* significant at 95 % level.
** significant at 90 % level.

crime inhibitors (Brown and Bentley, 1993; Nassauer, 1995). Property crimes, such as robbery and theft, are related to decisions that involve a balance between the perceived relative costs and benefits of committing the crime (Becker, 1968). The well-maintained landscape, with abundance of trees, can negatively unconsciously influence the crime decision and property crimes can be lower.

When considering the empirical models for the whole city, which take into account not only the urban macrozone but also the less densely populated areas with greater tree canopy cover, the results converge to a negative relationship between tree canopy cover and crime. The conditional estimated effect is stable across different types of crime and for different denominators. These findings are corroborated by the unadjusted, bivariate correlations presented in Fig. 3.For the urban macrozone with a denominator of square kilometers, the empirical model results converge to a negative relationship between crime and tree canopy cover, regardless of the type of crime and geographic boundaries analyzed. However, when using the per 1000 people denominator, the models converge to statistically insignificant or positive relationships, regardless of the type of crime and geographic boundaries analyzed. Results yielding distinct evidence regarding the relationship between green spaces and crime are also observed in other studies that employ spatial delineations or test different empirical specifications, as seen in the studies conducted by Escobedo et al. (2018) and Venter et al. (2022).

Overall, the negative relationship between crime and tree canopy cover for urban macrozones in São Paulo observed in this study is contingent upon the use of square kilometers as the denominator for crime rates. We contend that results from these models are more robust, and we argue that using the crime denominator per square kilometer may be more suitable in the context of São Paulo city. By using area as the denominator to weigh the number of crimes, we consider the routine activities of people rather than the static measure of residents (Boivin, 2013; Rummens et al., 2021). The use of the denominator of crime per 1000 people is a static measure that does not consider the flow of people and their daily activities, thus underestimating the convergence of victims and perpetrators without a capable guardian, as described by routine activity theory (Cohen and Felson, 1979). This has become a concern for empirical criminologists seeking new denominator measures for calculating crime rates (Boivin, 2013; Rummens et al., 2021). This is particularly important in the urban macrozone of cities like São Paulo, where millions of people commute daily for their activities and this consideration is crucial for areas of the city that are highly commercial but sparsely populated.

Due to the Modifiable Areal Unit Problem (MAUP), one of our research questions tested the spatial models with six levels of data aggregation (tree geographic boundaries vs two city subregions). A consistent negative spatial correlation was suggested by 14 models (74 %) across all levels of data aggregation. The negative relationships persist independently of the level of data aggregation, avoiding statistical bias of MAUP. Further, the relationships remain negative even between different crime types, crime denominator and spatial models specifications (lag and SARMA).

The overall findings align with prior studies indicating lower crime rates in areas with greater tree canopy cover, across various types of crimes. Studies conducted in the Global North converge on similar results for both property and personal crimes (Gilstad-Hayden et al., 2015; Troy *et al.*, 2012; Wolfe and Mennis, 2012; Lee, 2021). In the context of the Global South, particularly in Latin America, Escobedo et al. (2018) found that high tree density and size were associated with less homicide rates in Bogota, Colombia.

For other countries in the Global South that have also investigated the correlation between tree cover and crime, our findings also align with the overall results of Venter et al. (2022), who identified a negative association between green space and both violent and property crimes in South Africa, although with no relationship with sex crimes. However, Venter et al. (2022) findings diverged when considering green spaces such as public parks, a result that presents mixed evidence in the

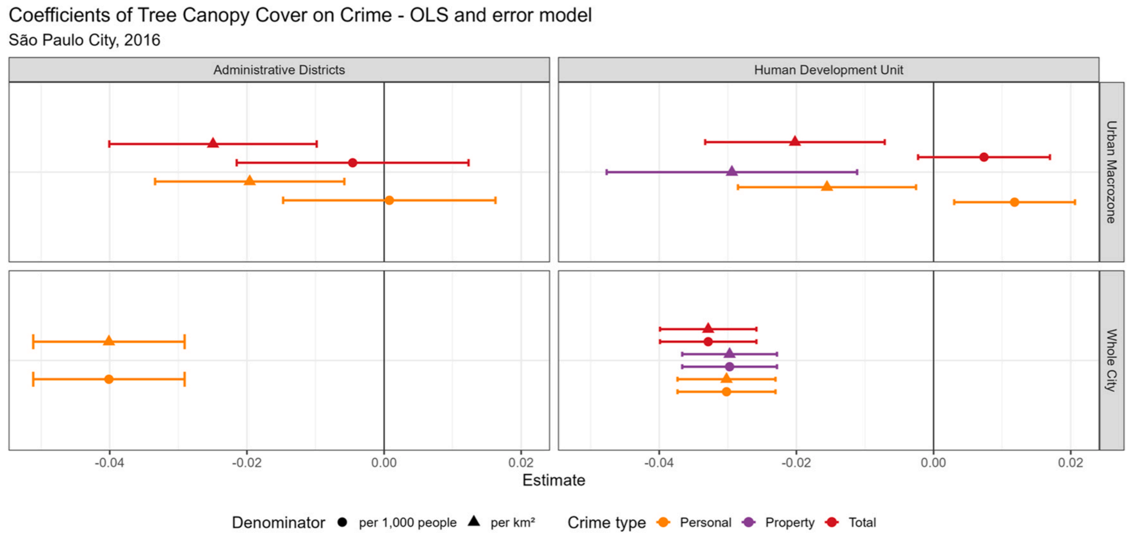

Fig. 5. The coefficient magnitude of Tree Canopy Cover on crime in 16 Ordinary Least Squares models and 1 error spatial model. The models encompass two regions of the city: Urban Macrozone and Whole city; two geographic boundaries: Administrative Districts (AD) and Human Development Unit (HDU); two denominators of crime: per square kilometer (km^2) and per 1000 people; as well as three crime types: personal (orange), property (purple) and total (red). The error spatial model is: Human Development Unit, urban macrozone, personal crime and pop/1000.

Table 3
Results of the recommended specification from the Moran's I of the OLS residuals and the Lagrange Multiplier (LM) tests. Results for the 36 models tested adjusted for OLS, lag, error and SARMA models, and respective Akaike information criterion (AIC). Results for urban macrozone and whole city, and for three geographic boundaries: Administrative Districts (AD), Human Development Units (HDU), and Census Sectors (CS).

Subregion	Geographic boundary	Denominator	Crime type	Model	Akaike information criterion (AIC)
whole city	AD	square kilometer	total	lag	120
whole city	AD	square kilometer	property	lag	145
whole city	AD	square kilometer	personal	OLS	127
whole city	AD	1000 people	total	lag	120
whole city	AD	1000 people	property	lag	145
whole city	AD	1000 people	personal	OLS	127
whole city	HDU	square kilometer	total	OLS	5796
whole city	HDU	square kilometer	property	OLS	5742
whole city	HDU	square kilometer	personal	OLS	5843
whole city	HDU	1000 people	total	OLS	5796
whole city	HDU	1000 people	property	OLS	5742
whole city	HDU	1000 people	personal	OLS	5843
whole city	CS	square kilometer	total	SARMA	4.04
whole city	CS	square kilometer	property	SARMA	3.88
whole city	CS	square kilometer	personal	SARMA	3.84
whole city	CS	1000 people	personal	SARMA	3.84
whole city	CS	1000 people	total	SARMA	4.04
whole city	CS	1000 people	property	SARMA	3.88
urban macrozone	AD	square kilometer	total	OLS	74
urban macrozone	AD	square kilometer	property	lag	85
urban macrozone	AD	square kilometer	personal	OLS	60
urban macrozone	AD	1000 people	total	OLS	90
urban macrozone	AD	1000 people	property	lag	113
urban macrozone	AD	1000 people	personal	OLS	77
urban macrozone	HDU	square kilometer	total	OLS	4363
urban macrozone	HDU	square kilometer	property	OLS	101
urban macrozone	HDU	square kilometer	personal	OLS	4346
urban macrozone	HDU	1000 people	total	OLS	3684
urban macrozone	HDU	1000 people	property	lag	3483
urban macrozone	HDU	1000 people	personal	error	3455
urban macrozone	CS	square kilometer	total	SARMA	4.02
urban macrozone	CS	square kilometer	property	SARMA	3.95
urban macrozone	CS	square kilometer	personal	SARMA	3.74
urban macrozone	CS	1000 people	total	SARMA	2.34
urban macrozone	CS	1000 people	property	SARMA	2.04
urban macrozone	CS	1000 people	personal	SARMA	1.93

literature, underscoring the importance of accounting for the specific conditions in which green space environments are situated. While employing a distinct methodology for analysis, Potgieter et al. (2019) conducted surveys to investigate the connection between vegetation and criminal activity in Cape Town, South Africa. Their analysis, based on surveys with 15 conservation managers, showed that most respondents agreed that crime could occur in areas dominated by both native and invasive plants, and that the vegetation's structure played a crucial role

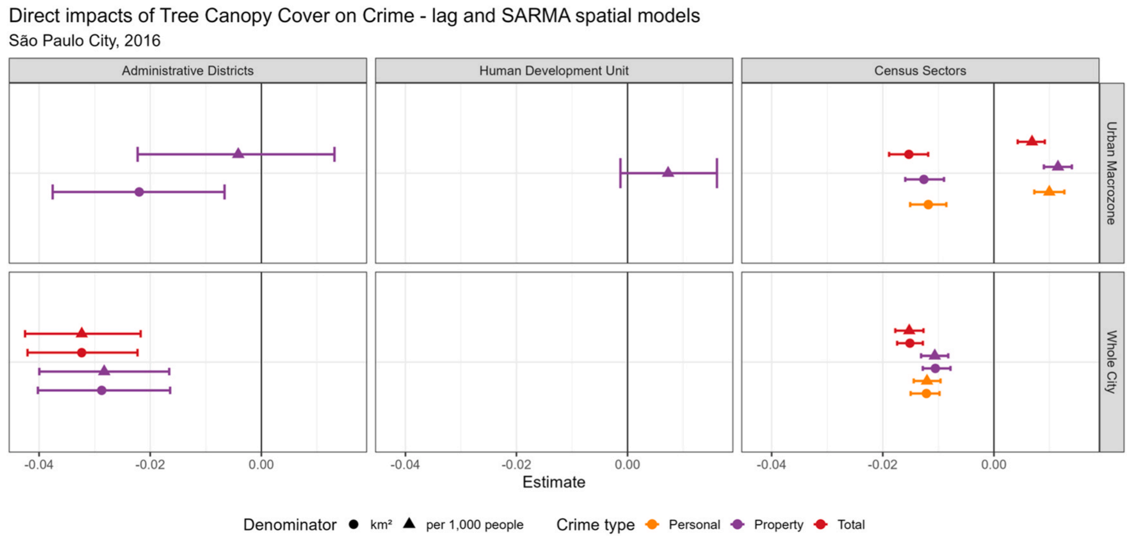

Fig. 6. Direct impacts of Tree Canopy Cover on crime in 7 lag spatial models, and 12 SARMA spatial models for Census Sectors. The spatial models encompass two regions of the city: Urban Macrozone and Whole city; three geographic boundaries: Administrative Districts (AD), Human Development Unit (HDU) and Census Sectors (CS); two denominators of crime: per square kilometer (km^2) and per 1000 people; as well as three crime types: personal (orange), property (purple) and total crime (red).

in facilitating criminal activity. This result differs from the findings of this study, which may be attributed to the different methodology and approach employed.

Additionally, the empirical findings align with theoretical factors that may be associated with the negative relationship between tree canopy cover and crime, such as the Broken Windows theory, territorial markers of home maintenance, cues to care in neighborhood organization and cleanliness, and the fostering of social cohesion and passive surveillance, all of which are consistent with Collective Efficacy Theory and Crime Prevention Through Environmental Design - CPTED principles (Jacobs, 1961; Jeffery, 1971; Newman, 1972; Kelling and Wilson, 1982; Brown and Bentley, 1993; Nassauer, 1995; Sampson et al., 1997; Donovan and Prestemon, 2010; Sampson, 2012). Urban tree canopy could be relevant for encouraging positive social interactions and building strong community ties. Tree canopy may naturally promote surveillance and unity among residents by creating cooler, more inviting spaces.

These results contribute to the literature by providing evidence of additional factors influencing crime in São Paulo city. This is rarely explored in empirical research on crime in the São Paulo city, which typically analyzes the phenomenon from different perspectives (Justus and Kassouf, 2013; Biderman et al., 2014; Cabral, 2016; Justus et al., 2018; Moreira and Ceccato, 2021a). Therefore, it highlights the importance of a holistic view of crime prevention that includes not only improvements in socioeconomic variables and public security, but also urban design and increased tree cover to create safer environments less prone to criminal activity.

4. Conclusion

This study showed negative relationships between tree canopy cover and crime in São Paulo city when using crimes per square kilometer as the denominator for both the whole city and the urban macrozone. By considering the routine activities of people instead of static measures of the resident population, we better capture the convergence of potential offenders and victims, especially in a mega-city like São Paulo. Our main results showed that 10 % more in tree canopy cover was associated with 1.20 % less crime, predominantly for property crimes. These findings corroborate previous studies indicating lower crime rates in areas with greater tree canopy cover in both the Global North and Global South, particularly in Latin America. Therefore, we provide evidence supporting the hypotheses that crime and urban tree canopy are negatively related. Future research may capture changes in crime and changes in the built environment, capturing "natural experiments" (Kondo et al. 2017; Locke et al. 2023.)

Although the negative relationship between crime and tree canopy cover holds for the whole city when considering crimes per 1000 people, positive relationships emerged for this denominator when examining the urban macrozone of São Paulo city, which has a high population density. Similar discrepancies are observed in the literature from the Global South when different measures are used to capture the relationship between urban space and crime (Escobedo et al., 2018; Venter et al. 2022). We argue that using the denominator of 1000 inhabitants introduces bias in the results, as it fails to accurately capture the true convergence between victims and perpetrators, which is better reflected by using crimes per square kilometer.

This study highlights the importance of a holistic approach to crime prevention and contributes to the international literature on urban ecology by: i) presenting robust results for the largest city in Latin America; ii) contributing to a line of research that is underdeveloped globally, primarily due to the scarcity of good public data on crime and tree canopy cover; and iii) testing the Modifiable Areal Unit Problem (MAUP) theory. Tree canopy cover remains an important component of the built environment, which is associated with lower crime.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2024.128497.

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