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Exploring the relationships between tree canopy cover and socioeconomic characteristics in tropical urban systems: The case of Santo Domingo, Dominican Republic

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A R T I C L E I N F O

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A B S T R A C T

Understanding the distribution of urban tree canopy cover and its relationship with socioeconomic characteristics is critical for informing urban planning and ecological research. However, most knowledge on this topic comes from studies in high-income countries (e.g., North America), and thus, little is known for other cultural, ecological, and political contexts. Here, we derived a high-spatial resolution (1.2 m) land-use/land-cover map for the tropical city of Santo Domingo, Dominican Republic, and examined how socioeconomic characteristics (i.e., population density, socioeconomic status, detached homes, homeownership, and householder's age) relate to residential tree canopy cover at the neighborhood scale. We found that previous theory developed in North American cities applied only partially to Santo Domingo. Of the five socioeconomic variables examined, only two showed relationships with tree canopy consistent with previous findings from North American cities. In particular, socioeconomic status, one of the better-studied correlates of urban tree canopy, was not positively associated with tree canopy cover. At the same time, our new land-use/land-cover map revealed the presence of important areas with low levels of tree canopy cover, which may require additional attention by city planners. Our study reinforces the value of high-spatial resolution satellite data for examining urban areas, and highlights the need for further understanding the characteristics related to the distribution of tree canopy cover outside North America.

1. Introduction

Understanding the distribution of urban tree canopy cover and its relationship with neighborhood socioeconomic characteristics is key to informed decision-making, urban planning, and environmental justice (Schwarz et al., 2015; Gerrish and Watkins, 2018; Watkins and Gerrish, 2018; Grove et al., 2018). Urban tree canopy provides important ecological, social, and psychological benefits (Livesley et al., 2016; Endreny, 2018). However, knowledge of tree canopy cover and its relationship with socioeconomic factors comes mostly from studies of cities in high-income countries and the temperate zone, particularly from North America (e.g., Troy et al., 2007; Pham et al., 2012a, b, Giner et al., 2013; Shakeel and Conway, 2013; Grove et al., 2014; Locke et al., 2017; Kolosna and Spurlock, 2018; Nesbitt et al., 2019). Advancing urban planning and environmental research requires testing whether previous theory developed mostly in North America applies to other regions of the world (McHale et al., 2013).

Previous studies predominantly from North America suggest that population density, income (a proxy for socioeconomic status), presence of detached homes, homeownership, and lifestage are important factors

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related to the distribution of tree canopy cover on residential lands in urban areas (e.g., Troy et al., 2007; Bigsby et al., 2014; Grove et al., 2014; Locke et al., 2016). Specifically, population density has been found to be negatively associated with residential tree canopy cover (Troy et al., 2007; Grove et al., 2014; Locke et al., 2016). The negative association between population density and tree canopy cover could be explained by the fact that people and buildings displace trees and green spaces in general (Troy et al., 2007; Grove et al., 2014; Locke et al., 2016). Moreover, detached houses typically have more available space for trees and green vegetation than areas with attached houses, which could explain the positive association with tree canopy cover (Troy et al., 2007; Grove et al., 2014). Income, one of the best-studied correlates of tree canopy cover in cities, has typically been found to be positively associated with residential tree canopy cover (Troy et al., 2007; Grove et al., 2014; Schwarz et al., 2015; Locke et al., 2016; see meta-analysis by Gerrish and Watkins, 2018). The positive association could be explained by the fact that residents of more affluent neighborhoods or with higher socioeconomic status may choose to plant and care for more trees, and/or to move to greener neighborhoods. Nesbitt and colleagues found a strong positive correlation between urban woody vegetation and income in eight out of ten US cities analyzed (Nesbitt et al., 2019). In the United States, historic socioeconomic conditions are also predictive of contemporary tree canopy cover. Specifically, a race-based housing policy called Redlining in the 1930′s categorized neighborhoods by racial composition and housing stock. Studies of more than 100 metropolitan regions show that areas formerly inhabited by racial minorities and immigrants have less vegetation overall today than neighborhoods formerly consisting of US-born, white residents (Hoffman et al., 2020; Namin et al., 2020). A study using high-resolution, high-accuracy tree canopy maps for 37 US cities found that predominantly US-born white neighborhoods have on average 43 % tree canopy today, whereas the areas where racial and ethnic minorities have on average 23 % tree canopy cover (Locke et al., 2021). In summary, both historic and present-day socioeconomic characteristics relate to urban tree canopy.

At the same time, home ownership in the US is often associated with higher tree canopy cover (e.g., Heynen et al., 2006; Szantoi et al., 2012; Grove et al., 2014; Mills et al., 2016). A potential explanation is that owners have decision making control over their properties and may choose to plant trees, while renters may not have permission, or economic resources to modify the landscape via tree plantings (Landry and Chakraborty, 2009). Yet, in some cases null and insignificant (Troy et al., 2007) or even negative associations (Miller and Bourne 2013, Locke et al., 2016) between home ownership and tree canopy cover have been observed, with little rationale provided. These findings highlight the need for further understanding the role of home ownership.

Further, members of different demographic groups reflecting life-stage and lifestyle characteristic, such as young couples, retirees, recent parents, or grandparents have been found to have different amounts of tree canopy cover, even when they have similar socioeconomic status (Troy et al., 2007; Grove et al., 2014). This phenomenon can be explained by the fact that different demographic groups are expected to have different motivations, capacities and interests in yard care, including participation in residential tree planting programs (Locke and Grove, 2016). For example, greater tree canopy cover might be expected with older householders, because more established households may have had more time for trees to grow.

Detailed information on urban vegetation from land-use/land cover maps is a key input for assessing social-ecological relationships in urban areas. The increasing availability of high-spatial resolution (≤ 5 m pixel) remotely-sensed data has opened new opportunities for mapping tree canopy cover and urban land-use/land-cover in cities around the globe (e.g., Moran, 2010; Pu and Landry, 2012; O'Neil-Dunne et al., 2014; Santos and Freire, 2015; Fundisi and Musakwa, 2017; Morgenroth and Östberg, 2017). In particular, the combination of high-spatial resolution imagery with object-based classification techniques has been shown to be a powerful approach for mapping and characterizing urban areas. Object-based classifications are more effective at handling the spectral complexity of high-spatial resolution data than traditional pixel-based classifications (Blaschke, 2010), resulting in land-use/land-cover maps with higher accuracy (Zhou et al., 2008; Myint et al., 2011; Pu et al., 2011; Momeni et al., 2016). Contrary to pixel-based classification that classifies the image based on the pixel's spectral information, object-based classification identifies clusters of pixels with similar spectral properties, size, shape, and texture (i.e., "objects") and uses them for classification (Yu et al., 2006; Myint et al., 2011; O'Neil-Dunne et al., 2014). Moreover, high-spatial resolution maps of urban land-use/land-cover provide not only information on the distribution of urban tree canopy cover necessary to evaluate relationships between residential vegetation and socioeconomic characteristics, but also elements of urban form including built surfaces and building density, which can be important to urban planning and ecological research efforts. Urban land-use/land-cover data is especially needed in countries that have historically had limited access to data (Luederitz et al., 2015; Ziter, 2016).

Latin America is one of the most urbanized regions of the world (United Nations, 2018). However, assessments of the relationships between urban vegetation and socioeconomic characteristics are limited, particularly in the tropical region of Latin America (see review by Dobbs et al., 2019, but see Martinuzzi et al., 2018). Further understanding of patterns of urban vegetation and social-ecological relationships in tropical Latin American cities is key for advancing urban ecological research and urban planning there.

Our main goal was to understand the extent to which prior theory developed in North American cities applies to a tropical Latin American city, using Santo Domingo, Dominican Republic, as a case. Our objectives were to: i) derive a high-spatial resolution land-use/land-cover map of the city of Santo Domingo, and ii) examine how socioeconomic characteristics relate to tree canopy cover on residential lands. We focused on five socioeconomic variables, including population density, socioeconomic status, presence of detached homes, homeownership, and householder's age. We tested five hypotheses: 1: Population density will be negatively correlated with tree canopy cover on residential land; 2: The percentage of houses that are detached structures will be positively correlated with tree canopy cover on residential lands; 3: Socioeconomic status will be positively correlated with tree canopy cover on residential lands; 4: The percentage of owner-occupied housing will be positively correlated with tree canopy cover on residential lands; and 5: The average age of households heads will be positively correlated with tree canopy cover on residential lands.

2. Methods

2.1. Study area

We conducted our study in National District of Santo Domingo (hereafter Santo Domingo), the capital of the Dominican Republic in the Caribbean island of Hispaniola, and the oldest colonial city in the Americas (Fig. 1a). Santo Domingo covers 91.6 km^2 and supports a population of 965,040 people according to the 2010 Census (https://censo2010.one.gob.do/). Santo Domingo is a low elevation, coastal city bordered by the Caribbean Sea to the south, the Ozama and Isabela Rivers to the east and north, and other territories of the metropolitan area to the west. The climate is tropical with average annual temperature and precipitation of 26 °C and 1661 mm respectively, corresponding to the subtropical moist forest life zone according to the Holdridge's life zones classification. Santo Domingo is the center of a broader Metropolitan area and is divided into seventy neighborhoods or "barrios" ranging from 0.3 km^2 to 6.1 km^2 in size (Fig. 1b).

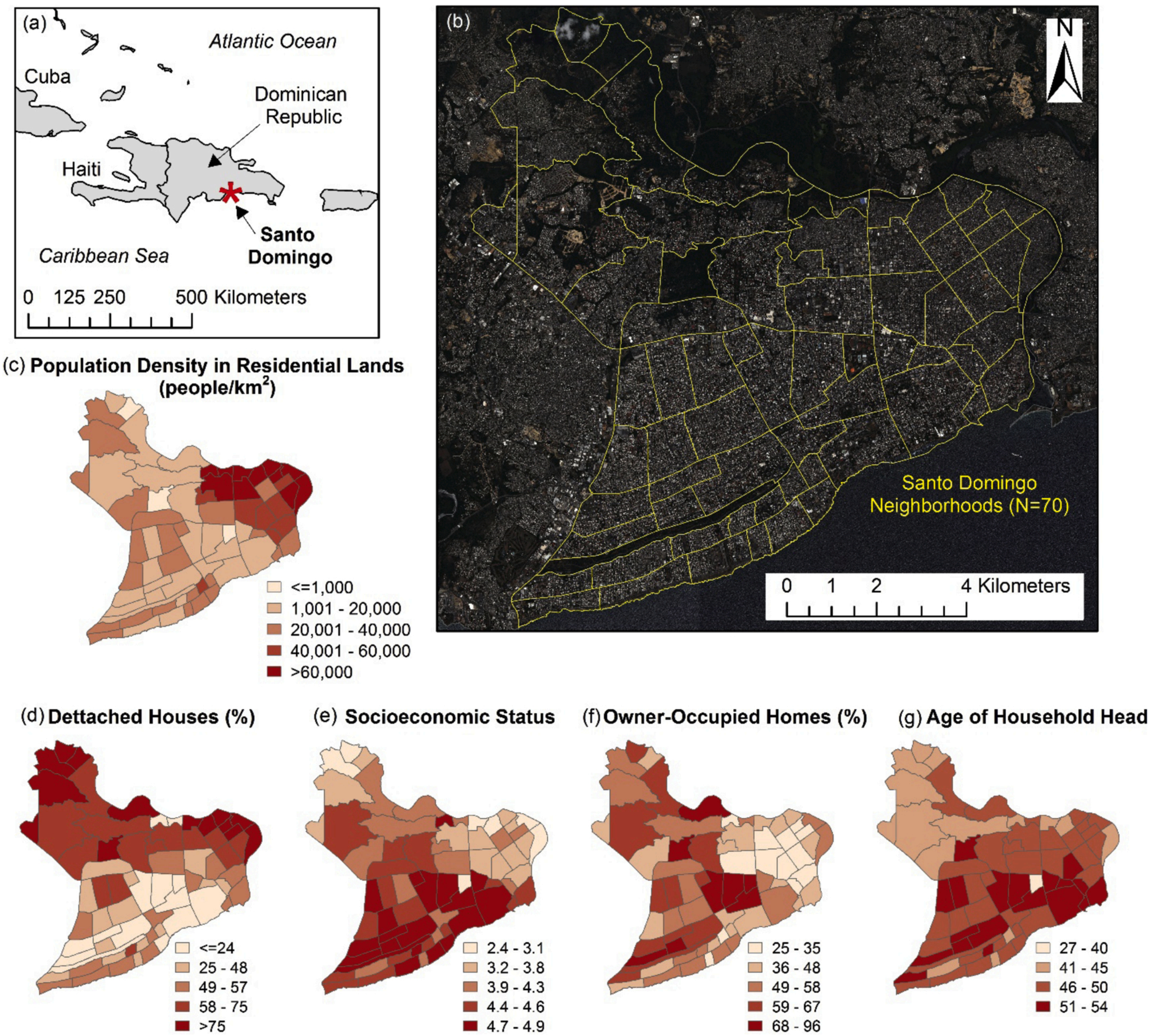

Fig. 1. Study area, including geographic location (a); neighborhoods or "barrios" (b); and socioeconomic characteristics (c-g).

2.2. Data

First, we created a high-resolution land-use/land-cover map, then we summarized it within Census-delineated units to associate with socioeconomic variables, then we used regression to test how socioeconomic characteristics relate to tree canopy cover on residential lands.

2.2.1. Satellite imagery and auxiliary data

We used two high-spatial resolution satellite images from the WorldView-3 sensor (DigitalGlobe Incorporated, Longmont CO USA) acquired on August 2015, and covering the eastern and western half of the study area, respectively. WorldView-3 data has a spatial resolution of 1.2 m and eight spectral bands (coastal, blue, green, yellow, red, red edge, near infrared 1, near infrared 2). WorldView imagery have proved useful for separating land-use/land-cover classes in urban areas (Novack et al., 2011; Kumar et al., 2012; Pu and Landry, 2012; Belgiu et al., 2014; Hamedianfar et al., 2014; Ziaei et al., 2014; Hamedianfar and Shafri, 2015; Santos and Freire, 2015). Images were chosen to contain less than 10 % cloud cover and high atmospheric visual quality. As part of the image preparation, we removed the effects of atmospheric scattering and gas absorptions using the atmospheric correction tool FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) in ENVI version 5.3.1 software (Harris Geospatial Solutions, Broomfield, CO, USA), and converted the digital numbers to surface reflectance. Then, we mosaicked the two images into a single scene, covering our entire study area.

In addition, we used spatial layers with the distribution of residential areas from the Government of Santo Domingo, including a detailed parcel-level land-use map, and a thematic layer indicating the location of informal settlements, often colloquially called slums. The city-wide parcel-level map separates residential lands from industrial, commercial, transportation (i.e., streets, sidewalks), public lands, and other uses; however some informal settlements were not included. Thus, we created our own layer of residential vs. non-residential areas by combining the residential areas from parcel-level land-use map and the layer with the informal settlements. Other auxiliary data used in our study included a GIS layer of water features (rivers, streams), and 10 cm aerial photos from 2011, also provided by the local Government.

2.2.2. Socioeconomic data

We obtained socioeconomic data from the 2010 Census of the Dominican Republic (https://censo2010.one.gob.do/) at the level of individual person, house, and household. However, we aggregated the data at the barrio scale (n = 70) because it was the smallest mappable Census unit (Fig. 1b), and examined how socioeconomic characteristics relate to tree canopy cover exclusively on residential lands, because we were interested in the places where people live, and to maintain consistency with previous studies (Troy et al., 2007; Grove et al., 2014; Locke et al., 2016, among others). As part of the data preparation, we summarized five socioeconomic variables for each barrio: (1) population density in residential lands; (2) proportion of detached houses; (3) average socioeconomic status; (4) proportion of owner-occupied homes; and (5) average age of household head (Table 1, Fig. 1c-g). We calculated population density relative to the area of residential land per barrio. The proportion of detached houses, socioeconomic status, proportion of owner-occupied homes, and average age of household head were calculated from the Census.

The Census of the Dominican Republic does not make available household income data, but rather a unique socioeconomic status composite score, referred here as socioeconomic status. This multifaceted, socioeconomic status measure reflects the ability of each household to cover basic needs with ordinal values ranging from 1 (very low socioeconomic status) to 5 (medium-high socioeconomic status), and is based on house materials (roof, walls, etc.), available services (water, electricity, etc.), type of appliances in house, and level of education and health of the household members. We used the average value of socioeconomic status for each neighborhood, thus transforming the variable from ordinal to a continuous value between 1 and 5 (see Table 1 for a description of variables).

2.3. Analysis

2.3.1. Land-use/land-cover classification

We mapped seven land-use/land-cover classes through two main steps. First, we mapped three major land cover classes (tree, grass, and built-up surfaces) from the WorldView-3 imagery. Then, we combined the three land cover classes with our auxiliary GIS layers of residential/non-residential land, and water, resulting in our final map. We explain these two steps in detail below.

First, we mapped tree (including trees and shrubs), grass, and built-up land cover from the WorldView-3 imagery using object-based classification implemented in eCognition 9.2 (Trimble Germany GmbH, Munich, Germany). We segmented the satellite imagery into objects using the multi-resolution and spectral-difference segmentations, and then developed rule sets for separating tree, grass, and built-up surfaces based on the spectral, context, and size characteristics of the image objects, assisted by visual interpretation of the 10-cm aerial photos. We used the Normalized Difference Vegetation Index (NDVI) to broadly separate the three land-cover classes based on NDVI values, and then

Table 1
Socioeconomic and vegetation variables used in this study.

Variable Name	Indep.	Dep.	Description
Population Density in Residential Lands	X		People per km^2 of residential land.
Detached Houses	X		Proportion of houses that are detached, in percentages.
Socioeconomic Status	X		Average socioeconomic status of households. Values range from 1 to 5, where 1 = very low, 2 = low, 3 = medium-low, 4 = medium, and 5 = medium-high socioeconomic status.
Owner-Occupied Homes	X		Proportion of houses that are occupied by owners, in percentages.
Age of Household Head	X		Average age of household head in years.
Tree Canopy Cover on Residential Lands		X	Proportion of residential land covered by trees, in percentages.

Indep. = independent, socioeconomic variables. Dep. = dependent, vegetation variable.

developed rule sets for correcting misclassified objects in shaded vs. non-shaded areas. Shaded areas from buildings, trees, etc., can be challenging for classification in high-spatial resolution imagery (Zhou et al., 2009; Adeline et al., 2013). Consequently, we developed two rule sets for refining the classification, with one shaded and another for unshaded areas. We also visited Santo Domingo before the mapping started in order to have a better understanding of the landscape. The segmentation parameters and full rule-set are available in the supplementary information (Appendix A).

Once we had classified tree, grass, and built-up surfaces, we separated them into residential and non-residential using our residential/non-residential layer, resulting in six land-use/land-cover classes (i.e., tree: residential; tree: non-residential; grass: residential; grass: non-residential; built-up: residential; and built-up: non-residential). Finally, we added the seventh class, water, from our auxiliary GIS data. Areas with persistent cloud cover in the satellite imagery and equivalent to 0.5 % of the study area were classified as “no-data”.

To assess the quality of our map we conducted an accuracy assessment of the tree, grass, and built-up land cover classes. We used a total of 450 points, 150 random points in each class, and conducted a visual interpretation of those points in the 10-cm aerial photos, and when in doubt, we used the high-spatial resolution imagery from Google Earth from circa 2015. We reported overall accuracy, user and producer accuracies, and the kappa statistic. We did not conduct an accuracy assessment on all of the seven classes because the information on residential and non-residential areas, as well as the water layer, are official data from the Government, and assumed to be truth. The 450 validation points were not used for training.

2.3.2. Socioeconomic relationships with tree canopy cover

The dependent variable, tree canopy cover on residential lands as a percentage of all residential land area per barrio, was log-transformed to aid in interpretation and because it was right-skewed. A multivariate, ordinary least squares (OLS) model was then fit with population density, the percentage of detached housing, socioeconomic status, percentage of owner-occupied housing, and the average age of the household head as independent variables. We excluded six barrios that were predominantly (>99 % of the land area) non-residential and support very little or no population, including Centro Olímpico, Jardín Botánico, Jardín Zoológico, San Diego, Centro de los Héroes, and Paseo de los Indios. The final number of barrios for statistical analysis was therefore 64 (out of 70).

In order to check that model assumptions were met, regression residuals were tested for spatial autocorrelation using Global Moran’s I. As in previous studies, we used a first-order queen contiguity matrix to define neighbors (i.e., barrios sharing an edge or vertex were considered neighbors; Pham et al., 2012a; Grove et al., 2014; Locke et al., 2016; Martinuzzi et al., 2018). The Global Moran’s I for regression residuals had a small absolute value (Moran’s I = -0.109) that was statistically insignificant (p-value = 0.47), indicating that the OLS model did not suffer from spatial autocorrelation in the residuals (Fig. S1). Further, the Lagrange multiplier tests (n = 5) for spatial dependence were also non-significant (p-values between 0.059 and 0.94), further confirming the lack of spatial autocorrelation in the residuals. Even though some of the independent variables were correlated (Table S1), variance inflation factors for the baseline OLS model were low (<6); ten is generally considered an upper threshold (O`Brien, 2007). Finally, a visual examination of the residuals confirmed the normality and homoskedasticity assumptions were met.

We defined relationships with tree canopy cover as statistically significant if the p-value was <0.01. However, because our sample size is relatively small (n = 64), we also discuss the consequences of interpreting the relationships using a less conservative p-value of <0.05, as many prior studies had larger sample sizes and used both thresholds (i.e., <0.01 and <0.05; Troy et al., 2007; Schwarz et al., 2015; Locke et al., 2016; Gerrish and Watkins, 2018). In addition to the multivariate

Table 2
Accuracy statistics of the land cover classes.

		Reference Data				User's Accuracy (%)	Producer's Accuracy (%)
		Grass	*Built-up*	*Tree*	Total		
Classified Data	*Grass*	113	8	29	150	83.7	75.3
	Built-up	2	148	0	150	94.9	98.7
	Tree	20	0	130	150	81.8	86.7
	Total	135	156	159	450		

Overall accuracy: 86.9 %. Cohen's Kappa: 0.80.

model, we regressed each variable separately against tree cover, and provide that information for comparison. All statistical analyses were carried out with R version 3.4.0 (2017−04-21).

3. Results

3.1. Land-use/land-cover classification

Map overall accuracy and kappa statistic were 86.9 % and 0.80 respectively, and the users' and producers' accuracies ranged between 75 % and 99 % (Table 2). The class tree had a user's and producer's accuracy of 81.8 % and 86.7 % respectively. The most expansive land cover in Santo Domingo was, unsurprisingly, built-up (61 %, 56.3 km^2), followed by tree (including trees and shrubs; 27 %, 25.2 km^2), and grass (9%, 8.5 km^2; Fig. 2a). In terms of land use, about one-third (36 %) of Santo Domingo's total area was residential, and two-thirds (64 %) was non-residential. Concomitantly, of the entire city's tree canopy cover (27 %), 30 % (7.6 km^2) was found in residential lands (i.e., in front yards and backyards) and 70 % (17.6 km^2) in non-residential lands (i.e., in parks, protected areas, greenways, streets, commercial areas, undeveloped private lands, etc.). Barrios in the northern part of the city, which are typically less urbanized than barrios in the southern portion, contain large areas (km^2) of non-residential forest cover (Fig. 2a,b).

The average tree canopy cover on residential lands, as a percentage of all residential land area per barrio, was 21 %. However, there was substantial variation depending on the barrio. In general, residential lands with the highest percentages of tree canopy cover (25 %–49 %) were located in the northern part of the city, followed by the west (17 %–24 %), and then by the east (7%–16 %; Fig. 2c).

3.2. Socioeconomic relationships with tree canopy cover

The OLS model fit with the five socioeconomic variables explained ($_{adj}R^2$) 68 % of the variation in tree canopy cover on residential lands (Table 3). Three variables were statistically significant at a p-value <0.01: population density (negatively associated), owner-occupied homes (positively associated), and average age of household head (negatively associated). Socioeconomic status was not statistically significant at p-value <0.01.

Interpreting of the relationships of the multivariate OLS model using a less conservative p-value (i.e., <0.05) changed the results for socioeconomic status, but did not the other variables. Using this lower threshold, socioeconomic status had a negative and statistically significant relationship with tree canopy cover (coefficient = -0.24; p-value = 0.025; Table 3).

In addition, we regressed each variable separately against tree cover (Table S2). Two variables were statistically significant at a p-value <0.01 in these single-predictor analyses, which included: population density (negatively associated), and owner-occupied homes (positively associated). These two variables also appeared as important in the multivariate model.

4. Discussion

The purpose of this study was to derive high-resolution land-use/land-cover data and assess social-ecological relationships in a relatively data-sparse and understudied urban area, i.e., the Caribbean moist tropical city of Santo Domingo. The analyses were motivated, in part, to understand if the often-studied correlates of urban tree canopy cover in high-income countries were also associated with tree canopy cover in a different climate and cultural context. Overall, we fail to reject hypotheses 1 and 4: tree canopy cover was negatively associated with population density and positively associated with owner-occupied housing. But we reject hypotheses 2, 3, and 5: detached housing, socioeconomic status, and age of household were not positively associated with tree canopy cover.

In relation to the remote sensing goal, we found that the combination of 1.2 m resolution WorldView-3 satellite imagery and object-based classification separated tree, grass, and other features with relatively high accuracy. The map kappa statistic was 0.80, which is considered substantial agreement, and the general, user's and producer's accuracies for the different classes were typically above 80 %, which is the standard for vegetation mapping by Federal Agencies like the US National Park Service (Environmental Systems Research Institute et al., 1994). The only exception was the producer's accuracy for the class grass (75.3 %) but this approximated 80 %. Remaining misclassification errors in our map were mostly due to the confusion between trees and grass. Multi-temporal imagery from wet and dry months may be able to refine the separation between the two classes further (Brown de Colstoun et al., 2003; Helmer et al., 2008; Gómez et al., 2016). Overall, our study reinforces the value of high-spatial resolution imagery coupled with object-based classification and auxiliary GIS data to characterize urban land-cover and land-use in the moist tropics.

On the social-ecological relationships, we did not find socioeconomic status, one of the better-studied correlates of urban tree canopy cover in North America (see meta-analysis by Gerrish and Watkins, 2018) to be positively related to residential tree canopy cover in Santo Domingo. Instead, we found a null or even negative relationship, depending on the p-value threshold used to interpret the model. Our results contradict not only the notion stemming from studies of North American cities, which typically result in positive relationships with income, but also recent consensus for Latin America by Dobbs et al. (2019). The study by Dobbs et al. (2019) reviewed the literature on urban ecosystem services for Latin American countries and concluded that high-income neighborhoods typically have greater quantity and better quality of vegetation than those of low-income (e.g., Pedlowski et al., 2002; Reyes Päcke and Figueroa Aldunce, 2010; Wright Wendel et al., 2012; de la Barrera et al., 2016). Different factors could explain the lack of a positive relationship with socioeconomic status found in our study. For instance, Santo Domingo is undergoing a rapid infrastructure transformation in which old houses are being replaced by multi-story apartment buildings, which typically leave little or no open and green space. This phenomenon may explain the presence of higher income neighborhoods with lower than expected tree canopy cover. At the same time, it is possible that natural vegetation is more common in certain lower-income areas, whereas intentionally planted tree canopy is present in higher-income areas. High tree canopy cover may be possible in moist tropical climates such as Santo Domingo, where productivity is high and vegetation can thrive year-round without human intervention. Conversely, the studies from Latin America cited in Dobbs et al. (2019) come mostly from colder

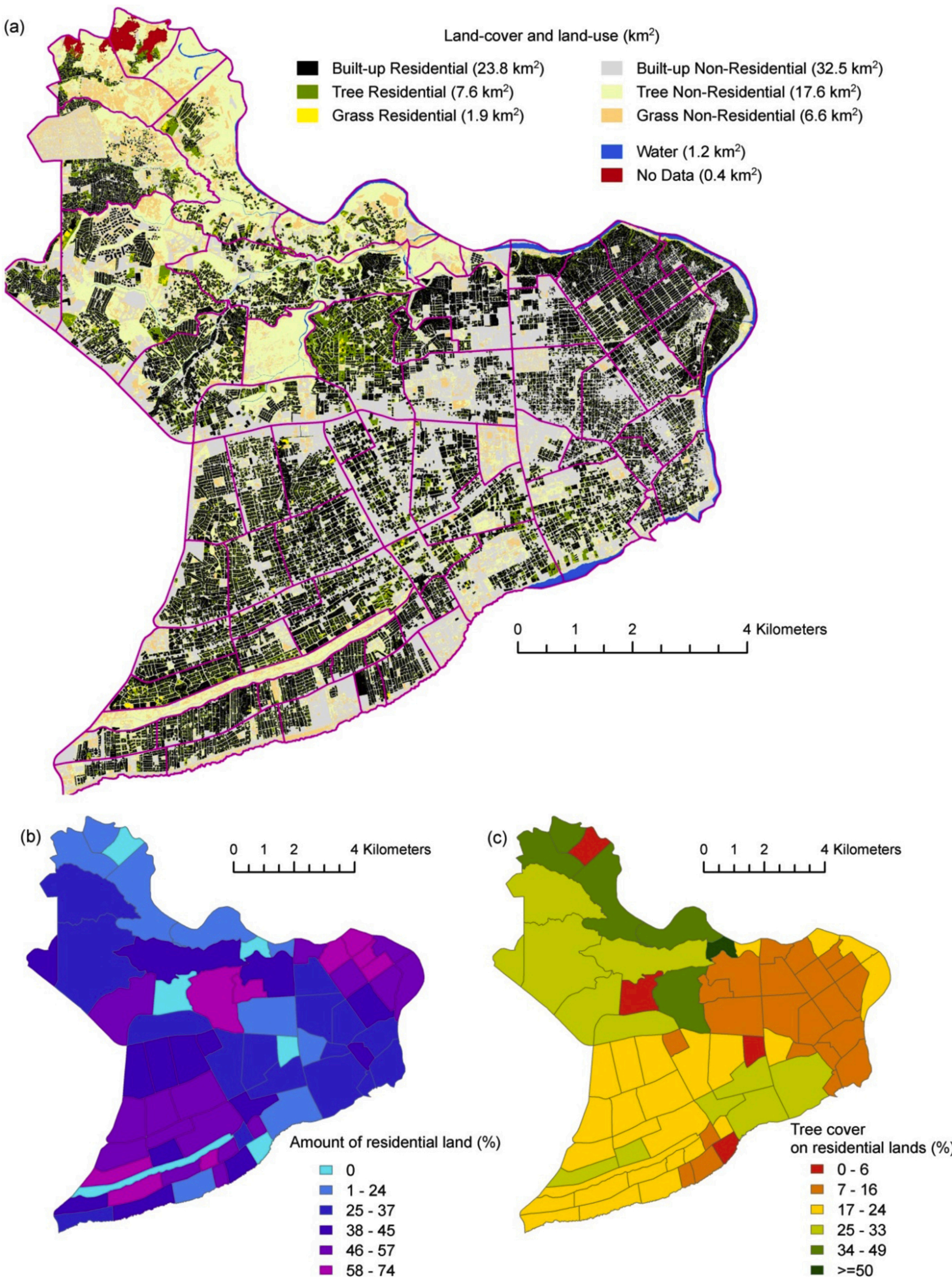

Fig. 2. Land-use/land-cover map (a); proportion of residential lands (b); and percent tree canopy cover on residential lands (c).

and/or drier climates that are less conducive to lush vegetation (e.g., Reyes Päcke and Figueroa Aldunce, 2010; Wright Wendel et al., 2012, de la Barrera et al., 2016, but see Pedlowski et al., 2002). In this sense, our results are consistent recent studies from San Juan, Puerto Rico, with a similar climate (Meléndez-Ackerman et al., 2014; Martinuzzi et al., 2018), suggesting a potential role of the moist tropical climate in shaping urban vegetation.

Overall, a combination of population density, owner-occupied homes, and average age of householder explained the distribution of tree canopy cover on residential lands in Santo Domingo. The negative association with age of household head was particularly surprising, as it contradicts not only the general expectation but also the findings from San Juan, Puerto Rico. A field-based study of household yards in San Juan found positive associations between the amount of trees in yards

Table 3
Socioeconomic relationships with tree canopy cover assessed with OLS model.

	log(% Tree Canopy Cover on Residential Lands)		
Predictors	*Coefficients (in original units)*	*CI*	*P*
(Intercept)	5.55	4.19 to 6.91	<0.001
Population Density in Residential Lands	−0.00	−0.00 to -0.00	<0.001
Detached Houses	−0.00	−0.01 to 0.00	0.400
Socioeconomic Status	−0.24	−0.45 to -0.04	0.025
Owner-Occupied Homes	0.02	0.01 to 0.02	<0.001
Age of Household Head	−0.04	−0.06 to -0.02	0.001
Observations	64		
R2 / adjusted R2	0.708 / 0.683		
AIC	−0.607		

F-statistic: 28.17 on 5 and 58 DF, p-value: 2.306e-14.

and householder age (Meléndez-Ackerman et al., 2014). However, yard planting was not influenced by household age, and older residents were less likely to make yard improvements, which suggest that other factors, such as reduced maintenance or abandonment, may play a role in the relationship between age and vegetation (Meléndez-Ackerman et al., 2016). The relationship between age and tree canopy may be non-linear, and age may be an insufficient proxy for time. It is also possible that more theorization is needed to better link householder age and tree canopy cover. Additionally, our null relationship with detached houses contradicts previous studies that typically found a positive association between detached houses and tree canopy cover summarized to the Census block group scale (Troy et al., 2007; Grove et al., 2014). Our study was conducted at the barrio level, which is similar to US Census block groups, and it could therefore be important to corroborate for future research to examine if these relationships hold also at the parcel scale. More research is needed to better link the social and ecological drivers of urban vegetation, especially in tropical Latin America and the Caribbean.

Our study provides also timely information for urban planning. The government of Santo Domingo is developing a land-use plan that focuses, for the provision of ecosystem services, in the value of trees in public lands (i.e., in parks, streets, protected areas, etc.). While we agree with the value of public lands, our study revealed that about a third (30 %) of the city's tree canopy cover is located on residential lands, indicating that trees on private landholdings likely play an important role in the provision of ecosystem services in Santo Domingo. Thus, land-use planning efforts aimed at maximizing the provision of ecosystem services should try to preserve, or at least not ignore, the green areas on private lands. In addition, our map revealed that residential lands in the eastern part of the city, in particular, have very little tree canopy cover and should be given special attention by planners. Expanding the vegetation there may require connecting the interests of residents in this area with relevant messages and messengers to promote adoption of tree planting behaviors (Locke and Grove, 2016). However, the important presence of renter-occupied homes in that area, as reflected by the Census data, indicates that efforts aimed at expanding the vegetation should consider both homeowners and renters in order to be effective.

As are any modeling efforts, ours is subject to limitations. For example, Census data at the barrio level are useful for communicating our results to local institutions, but can reduce potentially important internal heterogeneity, such as variations in socioeconomic status within barrios at the household level. At the same time, we tested variables that are important in high-income countries, but it is possible that other variables not included here, such as building age, yard size, and architectural style, among others, might be playing a role too (Troy et al., 2007; Meléndez-Ackerman et al., 2014; Ossola et al., 2019). These data were not available for this study area. Finally, differences in statistical method, scales, and covariates could also be explaining some of the differences with the previous studies in both Latin America and North America. The findings from this study should be interpreted at the barrio level until further evaluations, e.g., at the household level, are carried out.

In conclusion, our study in the moist tropical city of Santo Domingo shows that socioeconomic variables that are important for explaining urban vegetation patterns in high-income countries are not necessarily important in the moist tropics, reinforcing the findings from recent tropical studies (Meléndez-Ackerman et al., 2014; Martinuzzi et al., 2018). For local planners, we provide new land-use/land-cover data, and call for the inclusion of residential lands in current city planning efforts as residential lands contain a substantial amount of the city's tree canopy cover. Finally, our study reinforces the value of high-spatial resolution satellite data for studying urban areas, and highlights the need for further understanding the factors affecting the distribution of the controls of tree canopy cover outside North America.

Author statement

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Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ufug.2021.127125.

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