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Vegetation cover in relation to socioeconomic factors in a tropical city assessed from sub-meter resolution imagery

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Abstract. Fine-scale information about urban vegetation and social-ecological relationships is crucial to inform both urban planning and ecological research, and high spatial resolution imagery is a valuable tool for assessing urban areas. However, urban ecology and remote sensing have largely focused on cities in temperate zones. Our goal was to characterize urban vegetation cover with sub-meter (<1 m) resolution aerial imagery, and identify social-ecological relationships of urban vegetation patterns in a tropical city, the San Juan Metropolitan Area, Puerto Rico. Our specific objectives were to (1) map vegetation cover using sub-meter spatial resolution (0.3-m) imagery, (2) quantify the amount of residential and non-residential vegetation, and (3) investigate the relationship between patterns of urban vegetation vs. socioeconomic and environmental factors. We found that 61% of the San Juan Metropolitan Area was green and that our combination of high spatial resolution imagery and object-based classification was highly successful for extracting vegetation cover in a moist tropical city (97% accuracy). In addition, simple spatial pattern analysis allowed us to separate residential from non-residential vegetation with 76% accuracy, and patterns of residential and non-residential vegetation varied greatly across the city. Both socioeconomic (e.g., population density, building age, detached homes) and environmental variables (e.g., topography) were important in explaining variations in vegetation cover in our spatial regression models. However, important socioeconomic drivers found in cities in temperate zones, such as income and home value, were not important in San Juan. Climatic and cultural differences between tropical and temperate cities may result in different social-ecological relationships. Our study provides novel information for local land use planners, highlights the value of high spatial resolution remote sensing data to advance ecological research and urban planning in tropical cities, and emphasizes the need for more studies in tropical cities.

Key words: airborne imagery; green infrastructure; land use planning; object-based classification; Puerto Rico; residential vegetation; social-ecological relationships; tropical city; urban ecology.

Introduction

Urban vegetation provides important ecosystem services such as reduction of water runoff and regulation of local temperature (Nowak and Dwyer 2007, Weber 2013). Urban vegetation is also very important for people and local economies, affecting individual well-being, public health, and property values (Escobedo et al. 2014, Holtan et al. 2015). However, most urban areas are heterogeneous and complex social-ecological systems, making both urban planning and urban ecological research challenging. This is why both monitoring of urban vegetation and understanding the relationship between urban vegetation and socioeconomic factors is a major need for urban ecological research, city planning, and sustainable urban development (Pickett et al. 2001).

High spatial resolution remotely sensed data (i.e., <4 m resolution) has opened new opportunities for mapping urban vegetation and understanding social-ecological relationships in cities (Jensen and Cowen 1999, Grove et al. 2006, Landry and Pu 2010, Weng 2012). This is because high spatial resolution imagery is ideal for mapping small urban features, which is typical for urban vegetation. However, previous assessments of urban vegetation with remote sensing have been typically conducted in cities in temperate zones, and mostly in the United States (e.g., Lo and Faber 1997, Troy et al. 2007, MacFaden et al. 2012, Grove et al. 2014, Locke et al. 2016). Tropical regions are expected to see high rates of urban growth (UN 2014), yet little is known about urban vegetation and social-ecological relationships in these regions (Tapiador et al. 2011, Hetrick et al. 2013).

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Hence, there is an urgent need to advance urban ecology and urban remote sensing in tropical cities.

High spatial resolution maps of vegetated vs. non-vegetated surfaces provide important information for city planning and assessments of urban ecosystem services. Previous studies showed that separating vegetated vs. non-vegetated surfaces with high spatial resolution imagery is most successful when employing object-based classification approaches rather than per-pixel classifications (Yu et al. 2006, Blaschke 2010, Wentz et al. 2014). Object-based approaches, which first aggregate image pixels into spectrally homogenous image objects and then classify the individual objects, are better suited to handle the high, intra-class, spectral variability inherent in high spatial resolution data, resulting in higher classification accuracies (Myint et al. 2011). Little is known, however, about the ability of high spatial resolution data and object-based classifications to map urban vegetation in tropical cities. Vegetation in moist tropical cities can be highly diverse in terms of spectral signatures and three-dimensional structure (Lugo 2014, Meléndez-Ackerman et al. 2014), which combined with the already high spectral variability of urban areas challenges remote sensing applications. Moreover, tropical countries often lack the basic geospatial information to support city planning that is available in many cities in temperate regions. Hence, high spatial resolution maps of urban vegetation cover can be of great value to advancing the understanding and management of tropical cities.

In addition to mapping vegetation cover, distinguishing residential vegetation from non-residential vegetation is important for urban planning and ecological research. These two types of urban vegetation have different social and ecological functions, and are managed for different purposes (Grove et al. 2006). Residential vegetation includes gardens, yards, and street vegetation, while non-residential vegetation includes parks, riparian vegetation, and other large greenspaces. High spatial resolution imagery has been used to separate vegetation types such as grass, shrubs, or tree cover (Walker and Briggs 2007, Moskal et al. 2011, Myint et al. 2011, Li and Shao 2013) as well as forest types (Zhang et al. 2010, Pu and Landry 2012, Tigges et al. 2013) in urban settings. However, the suitability of high spatial resolution data to separate residential vs. non-residential vegetation is less well understood. A major challenge to do so is that the distinction between these two types of urban vegetation does not necessarily depend on the type of vegetation itself, and hence its spectral characteristics, but rather on its relative location (e.g., inside or outside a residential property). Previous studies in temperate zones have separated residential vs. non-residential vegetation using auxiliary spatial information such as property parcel boundaries and rights of way (e.g., Grove et al. 2014), which are the ideal data for such a purpose but rarely available in tropical countries. Distinguishing residential and non-residential vegetation is important, though, to elucidate relationships of vegetation cover with socioeconomic conditions. For example, in Baltimore (USA), socioeconomic factors were important predictors of residential vegetation but poor predictors of riparian (i.e., non-residential) vegetation (Grove et al. 2006). Simple approaches based on spatial pattern analysis, which describes the geometry and connectivity of image pixels, have been explored as a potential way to separate residential and non-residential vegetation when auxiliary spatial information is missing (Ramos-González 2014), but the accuracy of this approach has not been quantified.

In addition to monitoring different types of vegetation cover, it is necessary to investigate the relationship between patterns of urban vegetation and socioeconomic factors (e.g., income, housing density, etc.), to understand the interaction between people and green infrastructure, and to inform sustainable development plans. High-resolution urban vegetation maps can provide key information to assess those relationships. In cities in temperate zones, where most studies have taken place, there is typically a positive relationship between urban vegetation cover and indicators of socioeconomic status such as income or home value (Lo and Faber 1997, Jensen et al. 2004, Troy et al. 2007, Landry and Chakraborty 2009, Grove et al. 2014). However, recent studies in tropical countries did not find those associations (Hetrick et al. 2013, Meléndez-Ackerman et al. 2014). Moreover, previous studies in tropical countries that used high spatial resolution data focused mostly on the extraction of socioeconomic information, such as social classes or wealth (e.g., Tapiador et al. 2011, Stow et al. 2013, Jean et al. 2016), but analyses of the relationship of residential and non-residential vegetation with socioeconomic factors are particularly lacking (Hetrick et al. 2013). At the same time, prior studies evaluating the relationship between urban vegetation cover and socioeconomic characteristic were based on global models that did not capture local spatial variations in social-ecological relationships (e.g., Troy et al. 2007, Landry and Chakraborty 2009, Grove et al. 2014). Last but not least, while both socioeconomic and environmental conditions (e.g., topography) can affect urban vegetation patterns (Davies et al. 2008, Lowry et al. 2012), there are relatively few assessments of social-ecological relationships that integrated both socioeconomic and environmental variables. More studies are therefore needed to understand patterns and feedbacks in social-ecological relationships in different latitudinal regions (Cook et al. 2012), and especially in tropical cities.

Our goal was to evaluate the use of high spatial resolution imagery to characterize urban vegetation and social-ecological relationships in a moist tropical city using the San Juan Metropolitan Area in Puerto Rico as a case study. Our specific objectives were to (1) map vegetation cover using sub-meter spatial resolution (0.3-m) imagery, (2) quantify the amount of residential and non-residential vegetation, and (3) investigate the relationship between patterns of urban vegetation and local socioeconomic and environmental characteristics.

Methods

Study area

We conducted our study in the San Juan Metropolitan Area along the northern coast of Puerto Rico. The metropolitan area includes six municipalities (San Juan, Carolina, Trujillo Alto, Guaynabo, Bayamón, and Cataño), covers 51,000 ha, and is inhabited by about one million people, or one-fourth of Puerto Rico's population. Our study area is part of the San Juan-Carolina-Caguas Metropolitan Statistical Area as defined by the U.S. Census, and commonly known as the San Juan Metropolitan Area. The climate is moist tropical with a mean temperature of 23°–27°C and an annual precipitation of 1,500–2,300 mm. The northern half of the study area is coastal lowlands, relatively flat, and dominated by impervious surfaces and high-density urban development. The southern half is mountainous (up to 400 m elevation), densely forested, and characterized by low-density development (Martinuzzi et al. 2007). The study area is well drained by a dense network of streams.

Residential vegetation in the San Juan Metropolitan Area includes mostly yards, mowed lawns, and street trees and grasses. Non-residential vegetation, on the other hand, represents a mix of city parks, including areas managed for natural vegetation, planted trees, mowed lawns, and sports fields, as well as areas of natural vegetation, including secondary forests (mostly in the mountains), mangroves and wetlands along the coast, and corridors of riparian vegetation throughout the city.

Data

Imagery.—We analyzed 0.3-m resolution, digital, airborne, orthographic imagery acquired by the U.S. Army Corps of Engineers (USACE) in 2010 with a Leica ADS40 (Leica Geosystems Inc., Norcross, GA) digital sensor with four channels including blue, green, red, and near-infrared. The image was orthorectified by USACE and provided in 8-bit format.

Socioeconomic and environmental variables.—To investigate the relationship between patterns of urban vegetation and local socioeconomic and environmental characteristics, we analyzed socioeconomic and environmental data at the census block group level, which is a summarization unit of the U.S. Census Bureau. There are 789 census block groups in the San Juan Metropolitan Area. We extracted socioeconomic variables from the U.S. Census Bureau American Community Survey. American Community Survey data are not available for single years, but in 5-yr rolling averages. The 2008–2012 data and corresponded most closely to the 2010, the year of the remotely sensed data. We extracted socioeconomic variables that are related to urban vegetation in other cities, such as housing density, income, and housing characteristics, among others, based on previous studies (e.g., Troy et al. 2007, Grove et al. 2014; Table 1). In addition, we summarized environmental characteristics including mean elevation, riparian area, and area of wetlands and water, using auxiliary GIS layers (Table 1). The final list included 17 independent variables, 14 of them socioeconomic variables and three environmental.

Table 1. Socioeconomic and environmental variables used in this study.

Variable	Description	Mean	SD
Population density†	people per square kilometer	5,048.3	3,992.5
Housing density†	no. housing units per square kilometer	2,368.5	2,190.4
Median household income†	median household income of the block group in 2012	27,960.9	18,435.6
Home value†	median value of owner-occupied housing units	167,927.5	110,451.0
Percent vacant housing†	percent vacant properties	16.2	12.2
Building age†	average age of buildings as of 2012	42.4	10.8
Building age squared†	average age of buildings as of 2012, squared	1,916.7	904.9
Percent African American†,‡	percent of population that is Black or African American	24.4	15.3
Percent detached homes†	percent of detached housing units	47.2	27.3
Percent family homes†	percent family households	55.9	18.4
Percent 3 person households†	percentage of households with three or more people	40.7	14.9
Percent owner occupied†	percentage of owner-occupied housing units	52.2	22.8
Percent open space§	percent of land within protected areas	1.5	9.4
Percent married†	percent of households that are married-couple families	34.5	17.1
Elevation¶	mean elevation	33.7	44.6
Riparian zone#	area within 15 m of streams relative to census block area (%)	5.9	7.2
Water#	percent cover of water	1.6	7.1

Note: The list includes 14 socioeconomic variables (top) and three environmental variables (bottom).
†From 2008 to 2012 American Community Survey, U.S. Census Bureau.
‡Includes Black or African American alone or in combination with one or more other races.
§From Protected Natural Areas of Puerto Rico (Gould et al. 2011)
¶From National Elevation Dataset (NED) U.S. Geological Survey, spatial resolution 30-m pixel.
#From Puerto Rico Municipal Revenue Collection Center (CRIM).

Mapping urban vegetation

We mapped vegetated vs. non-vegetated surfaces via an object-based classification algorithm implemented in eCognition Developer 8.9 and Server 8.9 (Trimble Inc., Westminster, CO). We classified the imagery by developing a simple rule-based object-based classification framework composed of three steps: image segmentation, NDVI thresholding, and refining (the full rule set is included in Appendix S1). First, we segmented the imagery into objects using the multiresolution and spectral-difference segmentations, which are standard segmentation approaches. Then, we calculated the average Normalized Difference Vegetation Index (NDVI) for each object and applied a threshold to separate vegetated from non-vegetated objects. Vegetation results in positive NDVI values, making NDVI data useful for separating vegetation vs. non-vegetation with high spatial resolution data and object-based classifications (Zhang et al. 2010, Belgiu et al. 2014, Voltersen et al. 2014). Finally, during the last step (refining), we used information about the object's brightness and size to incorporate image objects that appeared falsely classified as non-vegetation after the other rules and procedures. To summarize our results, we report the amount of vegetation cover in the San Juan Metropolitan Area both in terms of total area (ha) and percent cover by census block groups.

In our initial analyses, we found that different NDVI thresholds performed better in different regions, which is why we developed three variants of our rule sets, one for each region. In image tiles for the lowlands and dominated by built-up surfaces, we used a high NDVI threshold (>0.2) to separate vegetation, but in tiles in the mountains that were heavily forested, we used a lower NDVI threshold (>0.01). For intermediate landscapes, we used a mid-value of NDVI (>0.1). We assigned the image tiles to the different regions visually (see rule set in the Appendix S1).

Last, we conducted an accuracy assessment based on 1,000 random pixels and visual interpretation of those pixels in the original 0.3-m resolution imagery. We calculated overall accuracy, user and producer accuracies, and the kappa statistic, which are standard accuracy statistics for land-cover type classifications. The validations points used in the accuracy assessment were independent observations and not used for building the rule set.

Separating residential from non-residential vegetation

We classified the vegetation layer into residential and non-residential based on spatial pattern analysis, using Morphological Spatial Pattern Analysis (MSPA) in GuidosToolbox (Vogt 2016). MSPA has been successfully used to characterize green infrastructure and connectivity (Wickham et al. 2010, Saura et al. 2011). MSPA uses image morphology to divide a particular class of interest, in our case "vegetation," into seven classes based on the geometry and connectivity of each pixel, and a user-specified edge width. The seven classes are Core, Islet, Perforation, Edge, Loop, Bridge, and Branch (see Appendix S2). Increasing the edge width will increase the non-core area at the expense of the core area. In a previous study, Ramos-González (2014) used MSPA to characterize green infrastructure from 4-m resolution Ikonos data in a portion of our study area and found that the class "Islet" (defined as disjoint objects that are too small or narrow to contain Core) from an edge width of 4 Ikonos pixels (16 m) is a good proxy for residential vegetation. However, the approach has not been tested for its accuracy. We applied the same rule using an edge width of 50 0.3-m pixels (15 m), which was the closest option in MSPA to the 16 m edge width used by Ramos-González (2014). Our class "residential vegetation" therefore included the MSPA class Islet, and "non-residential vegetation" included all other MSPA classes combined.

For the separation of residential vs. non-residential vegetation, we conducted a pixel-based accuracy assessment based on 500 random points (250 in each vegetation class) and visual interpretation of the high spatial resolution imagery, and calculated overall accuracy, user and producer accuracies, and kappa. The most common type of building is houses and these are easy to identify by visual interpretation, and we used our local knowledge to assist in the separation of apartment buildings vs. commercial buildings. Commercial buildings tend to be associated with shopping malls and are concentrated in certain neighborhoods (e.g., the banking district), while apartment buildings tend to be concentrated in a few neighborhoods near the coast. When in doubt, we discarded the point and used a new random point. To summarize our results, we compared the residential and non-residential vegetation in the San Juan Metropolitan Area both in terms of total area (ha) and percent cover by census block group. We decided to use MSPA here, instead of eCognition, because it provides land use planners and urban ecologists with a simple, freely available software that can be applied to any other available land cover map, in contrast to eCognition, which requires considerable expertise and is not free. In summary, we calculated three urban vegetation variables for each census block group: (1) percent vegetation cover, (2) percent residential vegetation cover, and (3) percent non-residential vegetation cover. These percentages were calculated relative to the census block group's land area, i.e., excluding water.

Relationship between urban vegetation and socioeconomic characteristics

Because we wanted to know if results from previous urban vegetation studies can be extrapolated to other locations, especially to urban areas in the moist tropics in developing countries, we emulated the approaches developed previously to relate urban vegetation and socioeconomic characteristics in temperate regions (e.g., Troy et al. 2007, Grove et al. 2014). To maintain comparability with prior theoretically supported and empirically tested work, we chose independent variables and methods that matched as closely as possible. Specifically, we estimated nine ordinary least squares (OLS) regression models. Our three dependent variables were (1) percent vegetation cover, (2) percent residential vegetation cover, and (3) percent non-residential vegetation cover. In the first set of OLS models, the independent variables were the socioeconomic variables, in the second set the environmental variables, and in the third set both socioeconomic and environmental variables. Next, we used a bidirectional stepwise process for the nine OLS models to drop redundant variables and identify the most parsimonious models, as in Grove et al. (2014). The variance inflation factors were low (<7; O'Brien 2007), except in models that retained both building age and the square of building age through the stepwise process. The squared value was included because trees can show peak canopy level decades after planted, and then senesce. Despite their multicollinearity, we retained these two variables as in previous studies (Grove et al. 2014).

Because all of the variables exhibited significant spatial autocorrelation ($P < 0.00001$; Appendix S3: Table S1), we expected that the OLS models' residuals may not be independent. Indeed, the global Moran's I test using a queen contiguity matrix to define neighboring block groups revealed moderate to medium and highly significantly spatial autocorrelation (Moran's I 0.20–0.40, $P < 0.00001$). We therefore used the Lagrange Multiplier test and the decision tree by Anselin (2005:198–200) to determine the more appropriate spatial model specification: either the spatial lag or spatial error. The suggested form was then fit for each dependent variable and each independent variable set, resulting in nine spatial regression models. We compared the nine final models based on pseudo-R^2 values and Akaike information criterion (AIC) scores.

As a robustness check for spatial non-stationarity, we fit geographically weighted regression (GWR) models for each spatial model (as in Locke et al. 2016). GWR creates a family of local regression models, one for each Census block group, using neighboring observations to identify local variation. It is possible, for example, that the relationship between vacant housing and residential vegetation is positive in one part of the study area, and negative elsewhere. The global spatial models cannot identify those geographically-varying relationships with a single lag (ρ) or error (λ) parameter, and GWR provides estimates at each location. For each independent variable in each GWR model we calculated the percentage of observations with statistically significant positive and statistically significant ($\alpha = 0.05$) negative relationships using pseudo t values (Charlton et al. 2006). The choice of which block groups are considered neighbors was informed using a cross-validation score that finds a search distance for neighbors so that the root mean square prediction error is minimized. By comparing the global (spatial regression) coefficient estimates to the percentage of locally significant (GWR-derived) estimates, we assessed the presence and degree of spatial non-stationarity, and examined how realistically our spatial models reflected the relationships between independent variable sets and dependent variables across the study region. The purpose of this analysis was not to identify causal relationships, but rather to explore social-ecological relationships and contrast them to previous studies. Statistical analysis was conducted within R software (R Core Team 2017) using the packages hmisc (Harrell 2017), car (Fox and Weisberg 2011), maptools (Bivand and Lewin-Koh 2017), spdep (Bivand et al. 2013, Bivand and Piras 2015), and spgwr (Bivand and Yu 2017).

Results

Vegetation cover

The accuracy assessment of the object-based classification of vegetated vs. non-vegetated surfaces for the San Juan Metropolitan Area revealed a high overall accuracy (97%) and Kappa value (94%; Appendix S3: Table S2). Vegetated surfaces covered 31,000 ha, or 61% of the metropolitan area. The median vegetation cover in the Census block groups was 32% (Table 2), and practically all census block groups (99%) had at least 10% vegetation cover. As expected, there was a strong north-south gradient in the amount of vegetation (Fig. 1) with less vegetation in the northern half of the study area, which is in the lowlands and dominated by impervious surfaces, and more vegetation cover in the southern half, which is more mountainous and less densely developed (Fig. 1).

Residential vs. non-residential vegetation

The accuracy assessment of the MSPA-based classification of residential vs. non-residential vegetation resulted in an overall accuracy of 76% and Kappa value of 52% (Appendix S3: Table S3), which is considered a moderate agreement for Kappa (Cohen 1960). In terms of total area, we found that 89% of the vegetation in the San Juan Metropolitan Area was non-residential and only 11% was residential (Table 2). However, at the Census block group level those differences were much smaller, and Census block groups had a median of 14% cover of residential vegetation and 15% cover of non-residential (Table 2). This discrepancy was due to the large census block groups in the mountains dominated by non-residential vegetation.

Table 2. Vegetation area and cover in the San Juan metropolitan area.

	Area (ha)	Part of total vegetation (%)	Median cover by census block group (%)
All vegetation	30,701	100.0	31.9
Residential vegetation	3,377	11.0	14.1
Non-residential vegetation	27,325	89.0	15.1

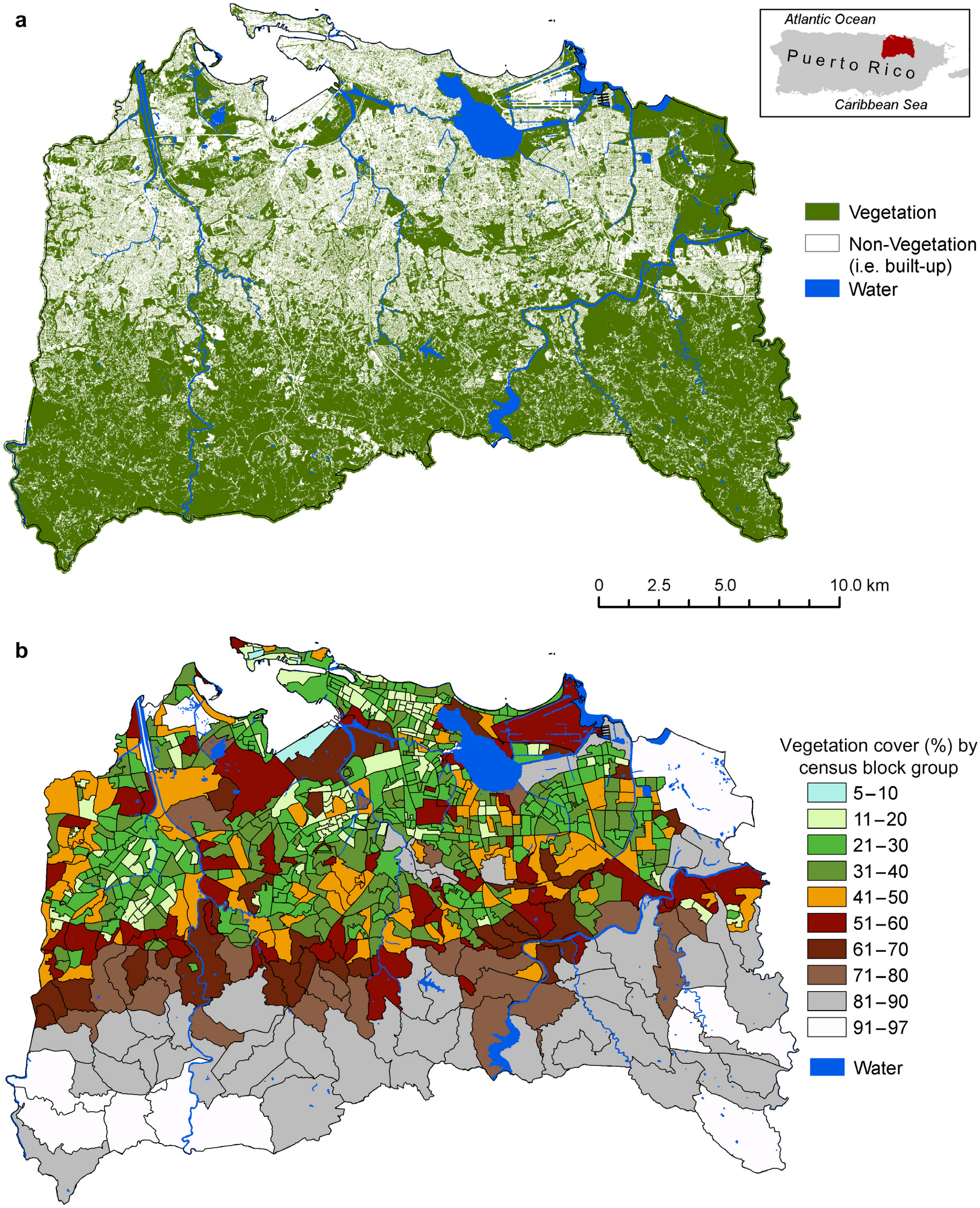

FIG. 1. Distribution of urban vegetation in the San Juan Metropolitan Area based on sub-meter resolution imagery. Panel a displays the 0.3-m resolution vegetation/non-vegetation layer. Panel b summarizes the vegetation cover by census block group (percent vegetation cover). The census block group limits are shown in black (b). Major hydrological features are shown as a reference (small streams are not shown).

We found that residential and non-residential vegetation were unevenly distributed among regions (Fig. 2). Residential vegetation was concentrated in the more developed coastal lowlands, reaching there a maximum of 32% cover per census block group (Fig. 2a), while non-residential vegetation occurred practically

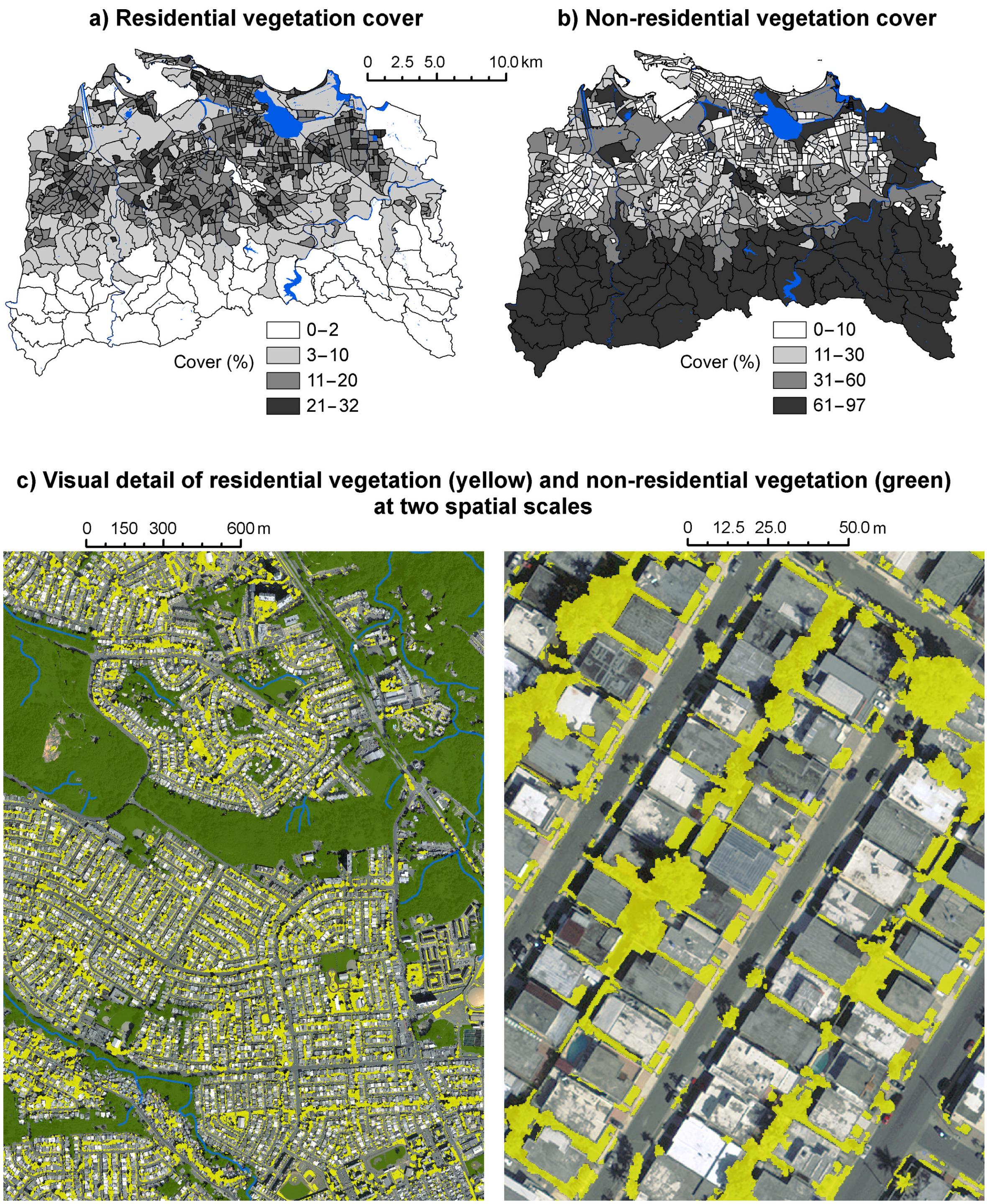

FIG. 2. Distribution of residential and non-residential vegetation. Panel a displays the percent residential vegetation cover by census block group; panel b displays the percent non-residential vegetation cover by census block group; and panel c shows the layer of residential vegetation (yellow) and non-residential vegetation (green) at two different spatial scales.

everywhere, but with the highest values in the mountains (up to 97% cover; Fig. 2b). As a result, the lowlands typically had both residential and non-residential vegetation, while the interior mountains in the south were strongly dominated by non-residential vegetation (Fig. 2).

TABLE 3. Nagelkerke pseudo-R^2 with Akaike information criterion values in parentheses for spatial regressions with different combinations of independent variables.

	Dependent variables		
Independent variables	Total vegetation	Residential vegetation	Non-residential vegetation
Socioeconomic	0.655 (6,172.6)	0.537 (4,615.7)	0.671 (6,491.0)
Environmental	0.660 (6,151.5)	0.460 (4,718.9)	0.661 (6,501.1)
All variables	0.749 (5,925.3)	0.586 (4,537.4)	0.760 (6,248.0)

Relationship between urban vegetation and socioeconomic characteristics

We found that models containing both socioeconomic and environmental variables had a better fit than models including either only socioeconomic or only environmental variables, even when accounting for model complexity (Table 3). This was true for all of our three dependent variables, including percent vegetation cover, percent residential vegetation cover, and percent non-residential vegetation cover (Table 3). At the same time, our spatial regression models explained a substantial amount of variation in vegetation, although the amount of variation in residential vegetation explained by the models (46–59%) was typically lower than that for total vegetation or non-residential vegetation (66–76%; Table 3).

When comparing socioeconomic and environmental variables, we found that socioeconomic variables alone explained about as much variance in non-residential vegetation as environmental variables alone (67% vs. 66% variance explained; Table 3). However, for residential vegetation, models based on socioeconomic variables alone explained substantially more variance than models based on environmental variables alone (54% vs. 46% variance explained; Table 3). Ultimately though, models containing both sets of independent variables were always best.

In addition, we found that both residential and non-residential vegetation were associated with many of the same individual variables, but in different ways (Table 4). In the majority of the observations (i.e., 67–99% of the GWR models), residential vegetation was positively and statistically significantly associated with population density, building age, and detached housing, and negatively associated with elevation, riparian areas, and public open spaces. On the other hand, non-residential vegetation was positively and statistically significantly associated with elevation, riparian areas, amount of water, and open public space, but negatively associated with population density and building age (Table 4). However, variables such as income and home value, which are important in temperate zones, were statistically significantly associated with residential and

TABLE 4. Spatial regression model coefficients’, their direction, and significance.

	Residential vegetation				Non-residential vegetation			
Variable	Coef.	P	% neg	% pos	Coef.	P	% neg	% pos
Rho	4.20×10^{-1}	**						
Intercept	7.51	**	0.0	93.8	2.21×10^{1}	**	0.0	99.4
Population density	8.84×10^{-4}	**	0.0	87.6	-2.28×10^{-3}	**	82.4	3.0
Housing density	-7.81×10^{-4}	**	49.6	3.5	7.79×10^{-4}	ns	10.9	15.8
Median household income	4.80×10^{-5}	**	0.0	17.5				
Home value	1.12×10^{-6}	ns	0.0	19.8	-7.13×10^{-6}	ns	10.9	0.0
Percent vacant housing	-3.92×10^{-2}	ns	2.8	0.0				
Building age	1.77×10^{-1}	**	0.5	67.4	-1.90×10^{-1}	**	86.8	0.0
Building age squared	-1.97×10^{-3}	**	49.0	2.0				
Percent African American	-3.85×10^{-2}	**	58.2	1.4				
Percent detached homes	4.67×10^{-2}	**	0.0	84.4	-1.16×10^{-1}	**	49.8	0.0
Percent family homes	-7.63×10^{-2}	**	39.2	0.0	2.39×10^{-1}	**	0.0	62.0
Percent three-person households	-2.19×10^{-2}	ns	13.1	0.0	4.49×10^{-2}	ns	0.0	2.9
Percent owner occupied	-3.30×10^{-2}	*	34.9	0.0				
Percent open space	-7.12×10^{-2}	**	83.7	0.0	4.66×10^{-1}	**	0.0	98.0
Percent married	2.99×10^{-2}	ns	0.0	15.5	-1.19×10^{-1}	**	44.2	0.0
Elevation	-2.34×10^{-2}	**	78.5	0.0	2.39×10^{-1}	**	0.0	97.2
Riparian zone	-1.73×10^{-1}	**	99.4	0.0	8.55×10^{-1}	**	0.0	99.0
Water	-3.63×10^{-2}	ns	44.6	0.0	3.56×10^{-1}	**	0.3	71.5
Lambda					5.66×10^{-1}	**		

Notes: The percentage of locally significant at the 95% confidence interval (GWR-derived) estimates for positive and negative relationships (“% pos” and “% neg”) is also shown. Coef., coefficient; ns, not statistically significant; $*P < 0.05$; $**P < 0.01$.

non-residential vegetation in only a small proportion of local GWR models (18%, Table 4).

Finally, the use of GWR showed that the global study area-wide relationships generally maintained spatial stationarity, or in other words, that the local models mostly corroborate the global findings. The highly significant spatial lag and spatial error terms (ρ and λ, respectively; Table 4) had relatively high absolute values compared to other variables, which highlights the advantages of spatial models over OLS, and may suggest some omitted variable bias.

Discussion

Knowledge of urban ecology and urban remote sensing comes largely from cities in temperate zones. Our study in San Juan expand previous knowledge and (1) shows that temperate zone relationships between patterns of urban vegetation and socioeconomic factors do not necessarily hold in tropical moist cities, (2) demonstrates the value of simple spatial tools to separate key types of urban vegetation (residential non-residential), and (3) validates the effectiveness of high-resolution satellite data and object-based approaches to quantify urban green areas in locations with complex tropical vegetation. Overall, our study provides novel data products for local planners, and highlights the value of high spatial resolution remote sensing data to advance ecological research and urban planning in less studied tropical cities.

We found that the combination of high spatial resolution imagery and object-based classification was highly successful for mapping vegetation cover in a tropical urban area. Simple classification rules strongly based on NDVI, applied to our 0.3-m multispectral airborne data, allowed us to separate vegetated and non-vegetated surfaces with a very high accuracy, 97%. Although it is not surprising to see that the NDVI was a great index for separating vegetation from non-vegetation, it was encouraging to see it work well in a place with an immense variety of plant species and plant three-dimensional structure such as San Juan, which supports more than 350 types of trees, shrubs, palms, and ferns in people's yards alone (Vila-Ruiz et al. 2014). Our map revealed that a large proportion of the San Juan Metropolitan Area was green (61%), and that even the most urbanized neighborhoods (census block groups) had at least 10% vegetation cover. Overall, the high accuracy (97%) obtained here reinforces the value of high spatial resolution data and object-based classification for quantifying urban vegetation, expanding previous findings from temperate zones to tropical areas (Yu et al. 2006, Myint et al. 2011, O'Neil-Dunne et al. 2014, Weng 2014).

Residential and non-residential vegetation have different social and ecological functions, and we were able to separate these two vegetation types using spatial patterns analysis with an accuracy of 76%. Such accuracy is not as high as in our vegetation cover layer (97%), but it is comparable to other commonly used land cover maps (e.g., Wickham et al. 2013). This finding is promising because information on property parcel boundaries and rights-of-way, used in previous mapping efforts in developed countries to separate residential vs. non-residential vegetation, is typically absent in developing tropical countries (e.g., Troy et al. 2007, Grove et al. 2014). Simple tools such as MSPA, which are freely available, provide valuable means to enhance the understanding of types and patterns of urban vegetation. Object-based classifications may also be helpful (Stow et al. 2013), but MSPA has the advantage that is much simpler and easier to use, once a vegetation cover layer is available. In the San Juan Metropolitan Area, we found that residential and non-residential vegetation have very different spatial patterns, which are overlooked when assessing only total vegetation cover (Ramos-González 2014). Especially the substantial presence of non-residential vegetation, with a median cover of 15% at the census block group level, is interesting. We suggest that this is due to many riparian areas that provide non-residential vegetation cover within the city, and also the abundance of transportation corridors, non-compact land development, and sprawl in Puerto Rico (Martinuzzi et al. 2007).

In terms of social-ecological relationships, we found that residential vegetation in the San Juan Metropolitan Area was positively associated with population density, building age, and detached housing. These findings are not surprising, and can be explained by the fact that residential vegetation co-occurs where there are people, and detached houses in Puerto Rico commonly have vegetated yards (Meléndez-Ackerman et al. 2014, Vila-Ruiz et al. 2014). In addition, a positive relationship between building age and residential vegetation cover may be expected by the fact that it takes time for vegetation planted in a new development to grow and peak, which has also been observed in New York (Grove et al. 2006). However, such vegetation regrowth might be limited to high-income neighborhoods, because low-income neighborhoods in San Juan have been shown to substantially lose green cover as they age (Ramos-Santiago et al. 2014). On the other hand, non-residential vegetation was negatively associated with population density and building age, but positively associated with elevation and riparian areas. The reason for this is that the largest fragments of natural vegetation occur in the more mountainous, less populated parts of our study area, and along riparian zones. Overall, the combination of both environmental and socioeconomic variables explains urban vegetation patterns well, which makes sense in mountainous settings such as Puerto Rico.

We also found stark differences in terms of which variables explained vegetation cover best, when comparing our results with findings from previous studies in temperate zones. Income, an important variable explaining urban vegetation in the temperate north (Lo and Faber 1997, Mennis 2006, Troy et al. 2007, Landry and Chakraborty 2009), was not important in our non-residential vegetation model, and only statistically significant in 18% of the local models for residential vegetation. A previous study comparing six locations in San Juan also found no relationship between yard area and household's income (Meléndez-Ackerman et al. 2014), and our study using spatially explicit data corroborates that finding for a much larger area. A similar relationship was observed in a tropical moist city of Brazil (Hetrick et al. 2013). Similarly, home value, another important variable in previous studies in temperate zones (Troy et al. 2007, Grove et al. 2014), was not significantly related to residential vegetation either. Further, in places like Baltimore (USA), socioeconomic variables are important predictors of residential vegetation and poor predictors of non-residential, riparian vegetation (Grove et al. 2006). However, in our study area, socioeconomic variables explained more variation of non-residential vegetation than residential vegetation cover. The differences found here may be explained by a combination of climatic and cultural factors, including warm temperatures and abundant precipitation that, contrary to temperate zones, allows vegetation to thrive all year round (i.e., without a cold or dry season), the common practice of growing vegetables in backyards in San Juan (up to 60% of the people in some neighborhoods; Garcia-Montiel et al. 2014), and a strong legacy of Spanish city planning (Muñoz-Erickson et al. 2014). In general, our findings highlight the need to be cautious when extrapolating results across climates and cultural settings.

In addition, our study provides new insights into social-ecological relationships in urban areas. In particular, our results showed that the strength of the relationships between socioeconomic factors and urban vegetation cover varied somewhat across the study area, as highlighted by the GWR results. This is important because previous studies used only global models (e.g., Troy et al. 2007, Landry and Chakraborty 2009, Grove et al. 2014) and did not test for local spatial variation of the global relationships between socioeconomic variables and vegetation cover. For example, the fact that income was positively associated with residential vegetation in a small subset of the local models (18%), might suggest that there are similarities in the causes of temperate and tropical vegetation cover in these areas that may warrant further study. Such deviations from study-area-wide patterns may be important for developing social-ecological theory that global-only analyses preclude. Overall, we show here that vegetation cover is related to both social and environmental factors that need to be jointly considered across space.

While generally successful, our study was also subject to some limitations. During the mapping of vegetation cover, some flat rooftops were spectrally similar to grasses and wetlands, creating confusion with true vegetated surfaces. We suggest this was caused by the presence of algae and moss growing as a result of the accumulation of sediments, combined with a humid and warm climate, and potentially a lack of building maintenance. This is important because flat roofs are a common feature in hurricane-prone countries, and work in other tropical cities may encounter the same problem. In our case, having different rule sets for different regions circumvented this problem to some extent, but some spots with grasses that were shaded remained misclassified as non-vegetation. For the residential vs. non-residential vegetation classification, overall classification accuracy was lower (76%). In particular, small patches of planted vegetation in and around shopping malls, near other commercial and industrial land uses, and along avenues, were sometimes misclassified as residential because their spatial patterns were similar to vegetation in front yards. Similarly, vegetation in backyards directly connected with large areas of natural vegetation was sometimes classified all as non-residential due to the continuous vegetation cover. Additional uncertainties may exist due to the inability to visually separate apartment buildings from commercial buildings in some cases, or houses from small stores. However, small stores in the city do not commonly have vegetated yards, since available space is used for storage or parking.

Further evaluation of the errors in the residential/non-residential vegetation map revealed considerable underestimation of the residential vegetation in the southern parts of the study area. Error-adjusted area estimates following Olofsson et al. (2013; Appendix S4) suggests that there may be as much as 9,125 $\pm$ 1,490 ha of residential vegetation, vs. the 3,377 ha that were directly mapped. These underestimations were concentrated in the southern, mountainous and less populated part of the study area, where census blocks are large in size (see map in Appendix S4). Indeed, the largest 5% of census block groups alone contained 50% of all the underestimation errors. Because of this, the underestimation of residential vegetation should have only minor effects for our analysis of social-ecological relationships, which used census blocks as the unit of analysis, nor should it affect the general distribution of residential and non-residential vegetation in the SJMA. However, evaluating the error-adjusted area estimates revealed that our separation of residential from non-residential vegetation using MSPA worked better in the more populated lowlands, and that future efforts should try to improve the separation of residential vegetation in densely forested areas with lower housing densities.

Our approach for characterizing urban vegetation should be useful in other moist tropical cities, especially in Latin America and the Caribbean. We recognize, however, that the high costs of airborne imagery like the one used here can be a major limitation for other regions. High spatial resolution satellite imagery from WorldView-2 or QuickBird may provide alternative data with <2 m resolution, and similar or even more spectral bands than our airborne imagery. In future assessments of urban vegetation cover, users might find useful to test our rule sets to their study area, and then adapt them depending on the image type, objectives, local ecological conditions, and availability of auxiliary layers, and this is why we developed relatively simple rule sets (e.g., based on NDVI, object size, brightness) and provide them in Appendix S1. For land use planning in San Juan, our data products can serve to (1) identify patches of vegetation that can be converted to vegetable gardens, which is important for low income neighborhoods (Santiago et al. 2014), (2) improve precipitation runoff and flood models that require high-resolution vegetation cover data, and (3) evaluate the status of riparian vegetation, which is important for maintaining water quality in the city.

In summary, urban vegetation provides important ecosystem services and represents a vital component of cities, and we showed here that high spatial resolution imagery can be used to derive valuable information to advance urban planning and urban ecological research in tropical cities. We urge for ecological applications of high spatial resolution remote sensing to expand our understanding of urban vegetation, ecosystem services, and social-ecological relationships in tropical cities, because the lack of such information can lead to poor planning of these rapidly changing places.

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Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1673/full

Data Availability

Data available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.3vh79.