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Tree canopy cover and carbon density are different proxy indicators for assessing the relationship between forest structure and urban socio-ecological conditions

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ABSTRACT

Forest canopy cover and carbon density are two pivotal biophysical parameters for assessing urban forest structure and its ecosystem services. While canopy cover (horizontal structure) has been extensively studied for understanding the relationship between socio-ecological dynamics and urban forests, carbon density (vertical structure) received little attention in the urban setting. The goal of this study was twofold: (i) exploring the differences between canopy cover and carbon density, and their relationships with socio-ecological factors across an urbanizing landscape, and (ii) assessing the effect of neighborhood category (i.e., low, medium and high development intensity) on the relationships at the neighborhood level. We used Mecklenburg County located in the Charlotte Metropolitan area of North Carolina, United States as a case study area, where rapid urban sprawl has fragmented the pine-oak-hickory dominated forests into a range of low to high housing density neighborhoods. We observed two major findings. First, canopy cover and carbon density demonstrated a generally weak correlation across various types of residential neighborhoods, although such relationship became relatively stronger in areas featuring a higher level of development intensity. Second, ecological factors (e.g., landscape spatial patterns) were found to dominate the statistical models explaining the variance in both canopy cover and carbon density compared to urban socioeconomic factors (e.g., income and age). However, the models and the explanatory factors were different for the two forest parameters, and they varied across neighborhoods of diverse development intensities. Based upon these findings, we argue that canopy cover and carbon density are different proxy indicators of forest functioning in the urban setting, and should be independently treated in urban forest management. The best management practices should be developed at the inner-city, neighborhood level, rather than the typical city level, owing to the significant, variable influence of socio-ecological conditions across neighborhood types.

1. Introduction

Urban forests are essential for maintaining a plethora of ecosystem services that affect human wellbeing (Dwyer et al., 1992; Nowak et al., 2006; Nesbitt et al., 2017). These benefits have led to many efforts into managing, conserving, and preserving trees. Nonetheless, trees are exposed to a wide range of disturbances such as land conversions, insect outbursts, microclimate change, and plant invasions that disturb trees and their capacity to sequester carbon often for the long-term and with slowed or no opportunity for recovery (Alberti, 2005; Poland and McCullough, 2006; Drummond and Loveland, 2010; Hawthorne et al., 2015; Singh et al., 2018). A growing concern for forest managers is how to increase tree cover and their capacity to sequester carbon in rapidly urbanizing landscapes to minimize the negative impacts of disturbances. Success relies on a rarely studied relationship between forest structure (e.g., canopy cover, and carbon density) and diverse socio-ecological conditions of urban landscapes.

Previous studies have often utilized canopy cover as a proxy indicator to assess forest ecosystem services in the urban setting (Kabisch et al., 2015). Canopy cover is typically defined as a proportion of land

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area occupied by tree crowns when viewed from the sky. Setting a clear goal of future canopy cover is widely employed by city managers in their forest management plans (e.g., Baltimore County, 2018; City of Charlotte, 2017a; City of Seattle, 2013; City of Toronto, 2013). Perhaps, our advancements in mapping canopy cover from remote sensing data contrary to estimating other forest biophysical/biochemical parameters is one of the main reasons for using canopy cover as the main input. To date, socio-ecological conditions of urban landscapes have proven to be relevant to canopy cover. For example, tree cover in urban landscapes is associated with property value (Anderson and Cordell, 1988), water cycle (Wear et al., 1998), air quality (Nowak et al., 2013), inequalities (Escobedo et al., 2015b), and the crime rate (Gilstad-Hayden et al., 2015).

Forest's capacity to assimilate atmospheric carbon and reduce greenhouse gas emissions depends on the age of trees, species types, and the local environment control. Therefore, carbon density (carbon storage per unit area) is an equally important parameter along with canopy cover in ecosystem service assessments (Escobedo et al., 2015b). In contrast with canopy cover that describes the horizontal structure of trees, carbon density emphasizes the vertical structure. While carbon density has been intensively studied in the natural environment, it received much less attention in the urban setting, particularly for analyzing the relationship between forest structure and socio-ecological conditions. Only a few examples exist in the literature. For example, Conway and Bourne (2013) studied Toronto's neighborhood plants and concluded that forest vertical structure is a vital factor to complement canopy cover for understanding the impacts of wealth, demographics, and housing on tree patterns. Escobedo et al. (2015a) found that both tree cover and vertical foliage affect human perceptions of local greenspaces and hence property value. Godwin et al. (2015) discovered varying relationships between carbon density and urban spatial patterns across four different densities of residential neighborhoods. The results from Singh et al. (2017) suggested a strong effect of impervious surface on forest biomass, which is directly related to carbon storage. While bigger trees tend to have larger canopy cover and higher carbon density, those studies indicate that canopy cover and carbon density may not be used interchangeably in studying urban forests, which are subject to complex disturbances resulting in a high level of landscape fragmentation. To date, it remains uncertain how differently tree cover and carbon density relates to socio-ecological conditions in an urban environment.

This study aims to examine the relationship among canopy cover, carbon density, and socio-ecological factors of urbanizing landscapes at the neighborhood scale. Using Mecklenburg County in the Charlotte Metropolitan area of North Carolina as a case study, we estimated development intensities, urban spatial patterns, socioeconomic factors, tree cover, and carbon densities for urban residential neighborhoods, and established statistical relationships among these. This allowed us to: (1) explore the differences between two important forest parameters – canopy cover and carbon density, and their relationships with socio-ecological factors across urbanizing landscapes, and (2) assess the effect of development intensities (e.g., high *versus* low housing density) to these relationships at the inner-city level. Outcomes of this study helps shed light on the varying responses of urban forest productivity to socio-ecological dynamics, and complement urban forest management plans for maximizing ecosystem services in urbanizing landscapes.

2. Methods

2.1. Study area

The study area is Mecklenburg County, North Carolina, USA (Fig. 1). It is located within the center of the Charlotte metropolitan area and covers an area of 1,415 km^2. The elevation of the rolling topography ranges from 252 m above sea level in the north to 159 m in the south (Singh et al., 2012). The humid subtropical climate of the region is characterized by hot, humid summers and mild winters with three optimal growing seasons: spring, summer, and fall. Specifically, spring and fall have shorter days and cooler temperatures with an average temperature of 22 °C (average high) and 8 °C (average low), while long days and high temperatures are common in summer with an average high of 32 °C and average low of 20 °C at the peak of July. Average annual precipitation is 42 in. (1,067 mm), with an even distribution of rainfall throughout the year. Humidity ranges from 60% to 75%, with a peak in August. Wind speed is averaged at 6 mph, which remains relatively stable across the year. Average wind direction changes from southwest in the spring to northeast in the fall (National Weather Service, 2019).

As per the U.S. Census Bureau estimate in 2017, the population of the County is 1,076,837, a 17.1% increase from 2010. This trend is expected to continue. However, the rapid population growth, manifested by a low to high housing density, has replaced landscapes dominated by secondary forests and farmlands with an array of developed land use types, including managed treescapes and highly fragmented urban forests (BenDor et al., 2014). Mecklenburg County is comprised of 464 neighborhoods based on the Census Block Groups (City of Charlotte, 2017b). The planning designs (e.g., single-family *versus* multi-family residential, small *versus* large lot) and socio-demographic profiles (e.g., education and income) are relatively homogeneous within neighborhoods with high diversity and variation between neighborhoods (City of Charlotte, 2017b).

2.2. Measuring tree cover and carbon density

We acquired 2012 leaf-on season tree-cover data for the study area from the Geospatial Information Services of Charlotte. Data were developed using aerial photographs (1 m resolution), LiDAR (light detection and ranging) point cloud data (average point density – 1 pts/m^2), and field observations. We extracted carbon density from the urban forest carbon storage map (20 m resolution) produced by Godwin et al. (2015). In their project, the 2012 LiDAR data were applied to estimate forest carbon stocks by linking LiDAR-derived vertical structural variables (e.g., height percentiles) with field-measured carbon density samples. The relationship was extended to the entire county for mapping wall-to-wall carbon density in urban forests. Both tree cover and carbon density were averaged at the neighborhood scale (Fig. 2), which was consistent with that of the evaluated socio-ecological factors (see the succeeding sections).

2.3. Extracting ecological factors

Landscape metrics represent spatial characteristics of various types of patches or entire landscape mosaics, which have proven to affect biophysical characteristics of trees (Alberti, 2005). In this study, we extracted ecological factors by calculating landscape metrics (Herold et al., 2002; McGarigal and Marks, 1995), which quantify the spatial heterogeneity of the landscape patches (e.g., a tree cluster or an open space) using a range of indices at the neighborhood scale. To do so, first, we randomly selected 100 residential neighborhoods (Fig. 1) by excluding the commercial or industrial areas with low tree density. For considering urban development intensity, we categorized the selected neighborhoods into three groups using the percent built-up (PBU) criteria: low (PBU ≤ 15%); medium–low (15% < PBU ≤ 40%); and high (PBU > 40%) density (Table 1). The PBU is a ratio of built-up areas (i.e., impervious surfaces) divided by the total area in each neighborhood. Because the study area was in residential neighborhoods, the ratio of built-up areas was a strong indication of housing density. We derived PBU from a 1.0 m resolution land use/cover map (Godwin et al., 2015) developed using 2012 NAIP (National Agricultural Imagery Program) imagery with an accuracy of 83.92% and a kappa coefficient of 0.84. We utilized PBU thresholds of 15% and 40% for grouping neighborhoods into three broad categories. For example, low-density

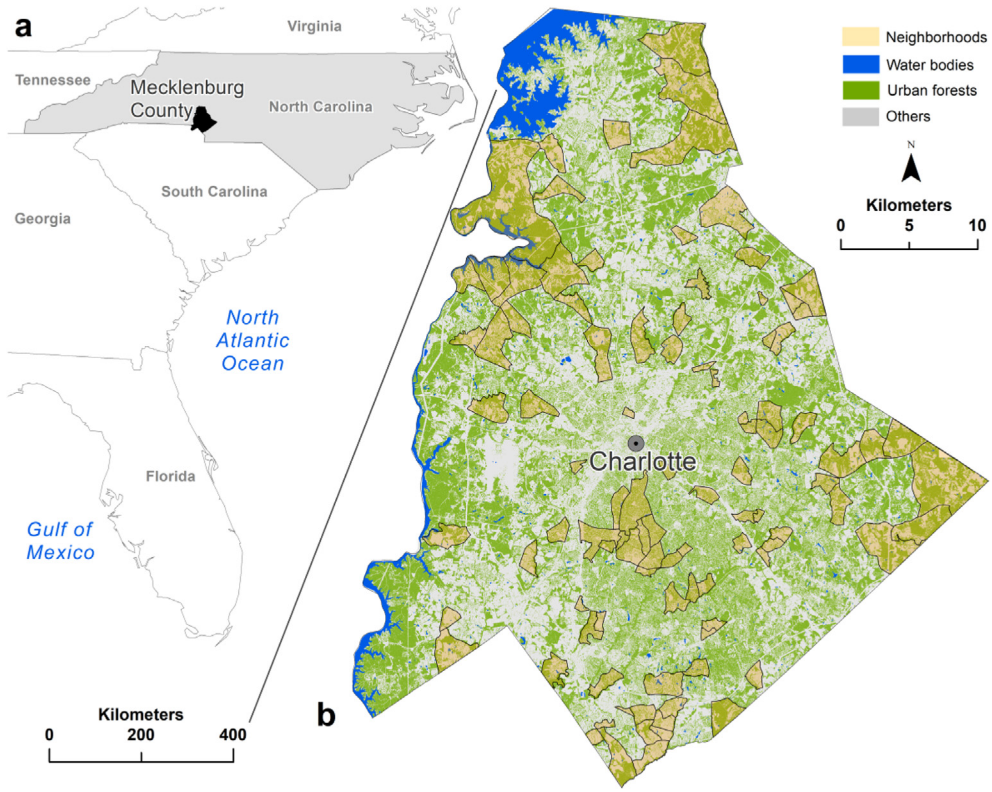

Fig. 1. Study area. (a) Mecklenburg County and the Charlotte Metropolitan area, North Carolina, USA and (b) Distribution of urban forests and water bodies with the selected residential neighborhoods overlay [modified after Godwin et al. (2015)].

neighborhoods are the suburban residences dominated by large patches of forested lands. High-density neighborhoods are close to the city center and sub-centers, containing a large percentage of residential areas along with small businesses. Medium-density neighborhoods are typically in the transitional areas between low- and high-density neighborhoods, with small to medium disaggregated clumps of trees. We did not categorize the neighborhoods into more detailed classes since the three types of neighborhoods are representative in many cities. Having more detailed classes will potentially make the conclusions tied to our study area only. More detailed classes will further reduce the number of neighborhoods, which is already limited for each class. It will lead to unreliable statistical analysis.

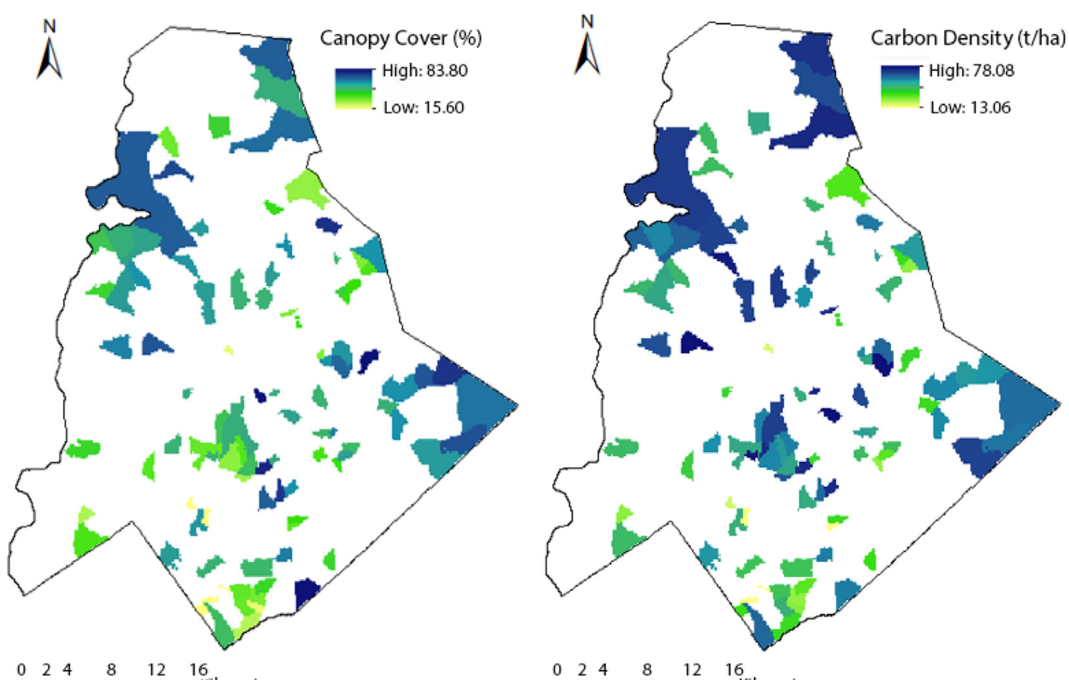

Fig. 2. Distribution of canopy cover and carbon density for the selected neighborhoods.

Table 1
Three neighborhood groups used in the study.

Category	Number	Mean size (ha)	Std. dev. (ha)	Minimum (ha)	Maximum (ha)
Low (PBU* ≤ 15%)	22	775	714.67	221.68	3454.74
Medium (15% < PBU ≤ 40%)	54	324	129.41	46.76	595.46
High (PBU > 40%)	24	128	160.62	33.21	809.46

* PBU = Percent built-up.

Table 2
Selected landscape metrics with description (McGarigal et al., 2002).

Variable	Description	Mean	Std. Dev.	Min	Max
Impervious	Percentage of impervious surface (%)	27.34	13.76	3.30	59.64
Open	Percentage of open space (%)	22.09	6.03	11.00	35.69
ED	Edge density (ED) is correlated positively with patch shape complexity where higher complexity corresponds to longer edge length and therefore higher ED.	1206.03	272.97	467.24	1787.95
CONTAG	Contagion index (CONTAG) quantifies the patch dispersion and interspersion effect. A higher CONTAG value may stem from landscapes with a few large, continuous patches.	57.33	4.29	47.70	72.41
SHDI	Shannon diversity (SHDI) index increases as the diversity of patch types increases.	99.53	0.25	98.72	99.95
COHESION	Patch cohesion index (COHESION) measures the physical connectedness of patches. A higher value represents an aggregated distribution.	1.24	0.11	0.83	1.43

Then, we developed landscape metrics for each neighborhood considering five aspects: area, shape, dispersion/interspersion, diversity, and connectivity. We used the previously mentioned land use/cover map with six classes (i.e., deciduous tree, coniferous tree, impervious surface, open space, water, and bare earth). To quantify the five landscape aspects, we calculated five groups of landscape metrics (Table 2) that included percentage of impervious surface [Impervious (%)] and open space [Open (%)], edge density (ED), contagion index (CONTAG), Shannon's diversity index (SHDI), and patch cohesion index (COHESION). Both Impervious (%) and Open (%) are area-based metrics ranging from zero to 100, where 100 represents a neighborhood with a single patch. We did not consider water and bare earth land-cover types due to the lack of a significant correlation with forest structure in our preliminary analysis. Higher complexity in the shape of landscape patches corresponds to a longer edge length and therefore higher ED. The CONTAG quantifies the patch dispersion and interspersion effect. A higher CONTAG value may come from landscapes with a few large, continuous patches. The SHDI normally increases as the diversity of patch types increases. The COHESION measures the physical connectedness of patches. A high value represents a clumped or aggregated distribution. We applied the popular FRAGSTATS software (McGarigal et al., 2002) to calculate these ecological factors in each of the selected neighborhoods.

2.4. Extracting socioeconomic factors

We extracted socioeconomic factors from the Mecklenburg County and the City of Charlotte Quality of Life project that comprises socioeconomic factors at the neighborhood scale (City of Charlotte, 2017b). We evaluated all of the factors and identified four that are associated with the functioning of urban forest (i.e., a significant correlation with either canopy cover or carbon density) in our study area: Resident Age, Income, Ownership, and Neighborhood Age (Table 3). Socioeconomic factors such as Ownership may reflect the level of engagement of residents in tree care and management. For example, Szantoi et al. (2012) observed a positive correlation between canopy cover and owner-occupancy, while canopy cover correlated negatively with renter occupancy. Higher engagement of ownership indicates local residents' stronger willingness to maintain and improve the environment that would lead to more and/or healthier trees in a neighborhood. The factor Income has demonstrated a positive correlation with urban canopy cover (Holtan et al., 2015). Likewise, Resident Age may affect personal preferences and capacity to impact canopy cover and trees in a neighborhood. For instance, Szantoi et al. (2012) found a positive correlation between tree cover and resident with age between 40 and 64 years and a negative correlation with relatively young (22–39 years) residents. We also included Neighborhood Age to include the role of neighborhood development history.

2.5. Statistical analysis

We performed Pearson's correlation analysis followed by identification of outliers for developing multiple linear regression (MLR) models between canopy cover, carbon density, and socio-ecological factors. Pearson's correlation is a measure of the strength of the linear relationship between two variables, where '1' represents a perfect positive linear relationship. To identify the least collinear variables, we calculated VIF (*variance inflation factor*) for all the socio-ecological variables. We selected variables that produced VIF values smaller than 5 as a common rule of thumb to avoid the collinearity issue in the MLR models. We developed the models using the ordinary least squares method for estimating the unknown factors to establish the statistical relationship between socio-ecological conditions (i.e., landscape metrics, and socioeconomic factors), and tree cover and carbon density respectively at the neighborhood level. Socio-ecological factors were treated as independent variables while tree cover and carbon density were used as dependent variables. Because urban neighborhoods had varying development intensities, it is possible that socio-ecological

Table 3
Socioeconomic factors.

Factor	Description	Mean	Std. Dev.	Min	Max
Resident Age	Median age of population (year)	35.48	6.93	23	67
Income	Median income ($) by house	69,303	34,447	24,182	250,001
Ownership	Number of occupied housing units divided by the total number of housing units (%)	65.19	26.62	0.1	98.4
Neighborhood Age	Average age of housing (year)	30	17	7	95

Table 4
Statistics of tree cover and carbon density for the three neighborhood categories.

Neighborhood	Tree cover (%)				Carbon density (t/ha)			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Low density	60.15	10.36	35.30	83.80	61.15	9.34	41.74	78.08
Medium density	50.86	10.44	22.50	75.20	55.26	11.37	32.12	76.61
High density	34.46	10.43	15.60	52.10	42.30	17.83	13.06	73.46

conditions varied across neighborhood types. To assess the impact of development intensity on the evaluated relationship, we also developed models for the three neighborhood categories – low, medium, and high PBU neighborhoods, respectively. The MLR models were developed at a 0.05 significance level using adjusted R^2 and RMSE (Root-Mean-Square Error) as measures for performance assessment. The leave-one-out cross-validation method was used to assess the performance due to the low number of neighborhoods. The entire analysis was performed using the R statistical language (R Core Team, 2013).

3. Results and discussion

3.1. Direct comparison between canopy cover and carbon density

The increase in built-up areas (e.g., high-density neighborhood) was linked to reduced tree cover and reduced carbon density (Table 4). For example, the high-density neighborhoods showed about half (34.46%) of the low-density (60.15%) tree cover. We observed similar but a less steep change in carbon density, such as an average of 61.15 t/ha for the low-density and 42.30 t/ha for the high-density neighborhoods. Our results confirmed that urban forests are severely affected by the increase of development intensities in terms of size and spatial pattern (Kong and Nakagoshi, 2006; Singh et al., 2017). While this was expected, our findings suggest that urban development may exert a greater impact on tree cover than carbon density. It was possibly linked to the development and management practices in urban areas where individual mature trees (high carbon stocks) are more likely to be conserved (Stagoll et al., 2012). It is also possible that isolated trees (e.g., street trees) appear more often in the highly fragmented urban environment and have received better care because of the Tree Ordinance adopted by the local government (City of Charlotte, 2018). The fact that high-density neighborhoods tend to retain larger trees than the lower-density neighborhoods offers some compensation for the loss of carbon. In addition, we found a consistent variation of tree cover (~10%) among neighborhood categories but carbon density increased from 9.34 t/ha (low-density) to 17.83 t/ha (high-density) (Table 4). This reveals a higher variability in the capacity of trees to sequester carbon in higher-density neighborhoods.

Pearson's correlation coefficients (r) for the tree cover and carbon density at the neighborhood scale were found to be weak across three neighborhood types: low (r = -0.11), medium (r = 0.48), and high (r = 0.60) (Fig. 3). However, the correlation became relatively stronger with the increase of development intensity from low to high. The findings support our assumption that a larger tree cover is not necessarily, and possibly not, leading to a higher carbon density in urban settings. As a result, urban forest structure in the horizontal (canopy cover) and the vertical direction (carbon density) should be considered as separate proxy indicators of forest ecosystem functioning. Carbon density may complement canopy cover for measuring the effectiveness of forest management practices and evaluating the benefits of trees in cities (Conway and Bourne, 2013; Escobedo et al., 2015a; Singh et al., 2017).

3.2. Impact of socio-ecological factors on canopy cover

We observed different relationships between socio-ecological factors and canopy cover across neighborhood categories (Table 5). For ecological factors, open space demonstrated a consistent, significantly negative correlation with canopy cover in all the neighborhoods. Similarly, impervious surface, ED (edge density), and SHDI (diversity) were negatively correlated with canopy cover, but the relationship did not hold significance across the neighborhood categories. Positive correlations were found between canopy cover and CONTAG (patch dispersion and interspersion effect) or COHESION (connectedness of patches). Effect of development on urban spatial patterns (e.g., land-cover fragmentation) has been well documented (Irwin and Bockstael, 2007). Tree canopy cover, as one typical land-cover type, is no exception (Kong and Nakagoshi, 2006). In urban areas, an increase in tree density would reduce the size of the open area in a neighborhood. Likewise, an increase in spatial heterogeneity increases edge density and that lowers contagion value for canopy cover, which means an increase in landscape fragmentation would impact contagion value for canopy cover in neighborhoods. Our findings further suggest that the relationship between ecological factors and canopy cover may not be equally significant across neighborhoods of different development intensities. The same conclusion applies to the relationship between socioeconomic factors and canopy cover. In our study, although resident age and neighborhood age have demonstrated moderately positive correlations with canopy cover, and the relationships were negative for income (Table 5), their significance did not hold across all the neighborhood categories. Property ownership even showed opposite correlations for high-density *versus* all neighborhoods (Table 5). Compared to the ecological factors, the socioeconomic conditions had less consistent correlations with canopy cover in the studied neighborhoods. As further proven in the regression analysis, the ecological factors were found to dominate the models (Table 6). This may be explained by the high variation in urban socioeconomic status across the city and even within the neighborhoods with similar tree cover. For example, Panduro and Veie (2013) argued that the same level of green space could have different relationships with property value, where accessibility and maintenance level also played a key role.

3.3. Impact of socio-ecological factors on carbon density

Carbon density was also variously correlated with the evaluated socio-ecological factors (Table 7). We found that the factors have influenced canopy cover and carbon density in the same direction (i.e., positive or negative) with a few exceptions in the low-density neighborhoods. For example, Impervious, Open, and ED were negatively correlated with canopy cover; however, they demonstrated positive relationships with carbon density (Table 6; Table 7). Here, we should note that these positive relationships were not statistically significant. In fact, we were unable to fit a regression model for the low-density neighborhoods due to the low and insignificant correlations between carbon density and the tested socio-ecological factors (Table 8). For all the significant correlations (Table 7), the ecological factors – Impervious, Open and ED, and the socioeconomic factors – Income and Ownership showed negative relationships with carbon density, while the relationships for CONTAG, COHENSION, and Neighborhood Age were positive. Similar to the aforementioned findings for assessing canopy cover, our statistical analysis for carbon density again proved that the relationship between tree structure and socio-ecological conditions

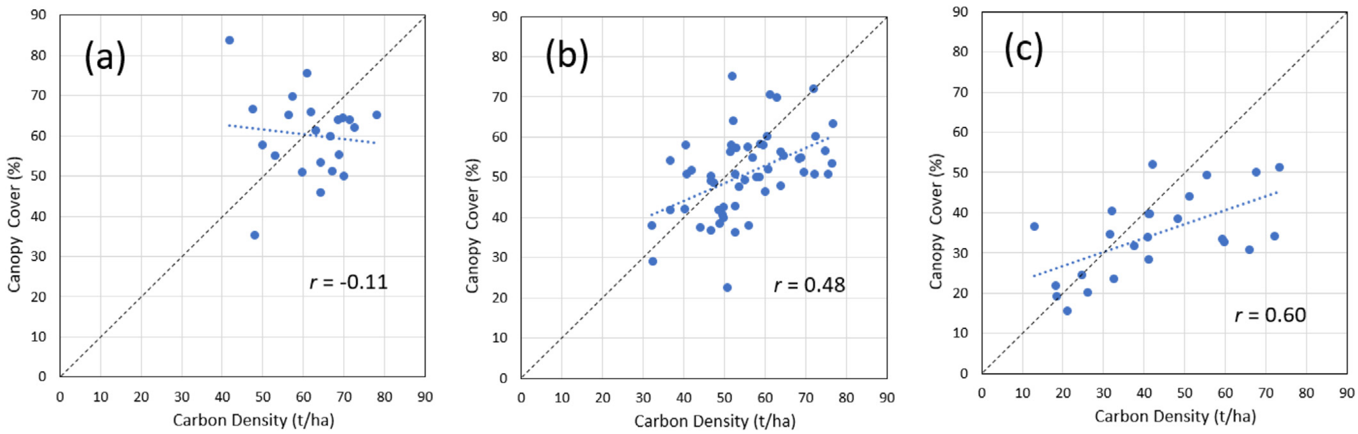

Fig. 3. Scatter plots showing canopy cover *versus* carbon density for (a) low-, (b) medium-, and (c) high-density neighborhoods.

Table 5
Pearson's correlation coefficients (r) between canopy cover and socio-ecological variables for low, medium, and high density, and for all neighborhoods.

Variable	Pearson's correlation			
	Low density	Medium density	High density	All neighbors
Impervious (%)	−0.50*	−0.32*	−0.02	−0.68**
Open (%)	−0.48*	−0.37**	−0.47*	−0.40**
ED	−0.37	−0.14	−0.47*	−0.37**
CONTAG	0.48*	0.26	0.48*	0.41**
COHESION	0.52*	0.04	0.35	0.29**
SHDI	−0.48*	−0.29*	−0.22	−0.32**
Resident Age	0.41	0.20	0.02	0.35**
Income	−0.07	−0.09	−0.46*	−0.01
Ownership	0.04	−0.23	−0.45*	0.25*
Neighborhood Age	0.31	0.33*	0.54**	0.16

* Correlation is significant at the 0.05 level.
** Correlation is significant at the 0.01 level.

Table 7
Pearson's correlation coefficients (r) between carbon density and socio-ecological variables for low, medium, and high density, and for all neighborhoods.

Variable	Pearson's correlation			
	Low density	Medium density	High density	All neighbors
Impervious (%)	0.07	−0.34*	−0.04	−0.50*
Open (%)	0.19	−0.55**	−0.59**	−0.43**
ED	0.22	−0.16	−0.65**	−0.33**
CONTAG	−0.16	0.29*	0.40	0.26**
COHESION	0.14	0.01	0.37	0.23*
SHDI	0.14	−0.22	−0.03	−0.12
Resident Age	−0.26	0.17	−0.16	0.15
Income	0.05	−0.14	−0.51*	−0.06
Ownership	−0.02	−0.13	−0.43*	0.11
Neighborhood Age	−0.07	0.34*	0.48*	0.23*

* Correlation is significant at the 0.05 level.
** Correlation is significant at the 0.01 level.

are not likely to hold significance across all the neighborhood categories. While previous studies have investigated similar relationships between forest structure and socio-ecological conditions (e.g., Escobedo et al., 2015b; Wang et al., 2016; Salvati et al., 2017; Singh et al., 2017), our study differs from theirs by evaluating the impact of neighborhood diversity (based on development intensity) on such relationships within the city boundary. The findings suggest that the two crucial forest biophysical factors – canopy cover and carbon density – are likely to show different relationships with socio-ecological conditions across residential neighborhoods. Consequently, they should be treated as different proxy indicators in urban forest management. This is important as urban forest vertical structure has received increasing attention (e.g., Conway and Bourne, 2013; Escobedo et al., 2015a; Singh et al., 2017) over the past decade. Advancements in high-resolution remote sensing (e.g., LiDAR) have made fine-scale urban forest 3D structure mensuration a feasible task (Godwin et al., 2015). Through quantitative analyses, our study indicates that experience gained for managing canopy cover is not a suitable guide for managing carbon density, as they are not necessarily correlated with each other. Further because urban neighborhoods typically exhibit a high variation of development intensity, best management practices should be developed at the neighborhood scale to improve the understanding of the influence of socio-ecological conditions on the two indicators of urban forests.

4. Conclusions

This study examined the relationship between urban socio-ecological conditions and two pivotal forest biophysical parameters – canopy cover (horizontal structure) and carbon density (vertical structure) – in the residential neighborhoods of Mecklenburg County, North Carolina, USA. We aimed to bridge a gap in understanding the difference between forest horizontal and vertical structure at the inner-city, urban neighborhood scale. Our study led to two major findings. First, canopy cover and carbon density demonstrated a stronger correlation in the

Table 6
Linear regression models of canopy cover for low, medium, and high density, and for all neighborhoods.

Neighborhood	Model	Adjusted R^2	RMSE (%)
Low density	−5911.856* + 59.860 × COHESION*	0.23	9.08
Medium density	97.170** − 0.767 × Open** − 0.654 × Impervious** − 0.173 × Ownership**	0.34	8.49
High density	24.226** + 0.261 × Neighborhood Age**	0.26	8.98
All neighborhoods	−790.856* − 0.647 × Impervious**- 0.580 × Open**+ 0.211 × Neighborhood Age**+ 8.670 × COHESION*	0.32	8.46

* Significance at the 0.05 level.
** Significance at the 0.01 level.

Table 8
Linear regression models of carbon density for low, medium, and high density, and for all neighborhoods.

Neighborhood	Model	Adjusted R^2	RMSE (t/ha)
Low density	n/a	n/a	n/a
Medium density	$91.758^{**} - 1.057 \times \text{Open}^{**} - 0.655 \times \text{Impervious}^{**} + 0.115 \times \text{Neighborhood Age}^{*}$	0.46	8.35
High density	113.343^{**}- $0.037 \times \text{ED}^{**} - 1.077 \times \text{Open}^{*}$	0.49	12.74
All neighborhoods	$78.215^{**} - 0.540 \times \text{Impervious}^{**} - 0.763 \times \text{Open}^{**} + 0.197 \times \text{Neighborhood Age}^{**}$	0.43	10.91

* Significance at the 0.05 level.
** Significance at the 0.01 level.

neighborhoods of higher development intensity. However, the correlations were generally weak ($r_{\max} = 0.60$), indicating different spatial distribution patterns of the two parameters at the urban neighborhood level. Second, socio-ecological conditions explained the variance in canopy cover and carbon density with diverse models and different explanatory variables. Our results suggest that tree canopy cover and carbon density are different proxy indicators for assessing the relationship between forest structure and urban socio-ecological conditions, and such relationship varies across neighborhoods of diverse development intensities. While cities across the world have been traditionally relying on canopy cover to evaluate the success in urban forest management, our study confirmed an essential role of tree vertical structure (i.e., carbon density) to underpin ecosystem services. Using high-resolution remote sensing to measure the two ecological indicators and quantifying their differences provide an operational solution to inform effective urban forest conservation and management.

CRediT authorship contribution statement

Gang Chen: research design, method development, results analysis, and writing & editing. **Kunwar K. Singh:** results analysis, writing & editing. **Jaime Lopez:** method development, and results analysis. **Yuyu Zhou:** results analysis, writing & editing.

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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