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Original article

Turning a new leaf: Social and land use drivers of urban tree canopy change in the Chicago Metropolitan Area 2010–2017

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ABSTRACT

Increasing the equitable distribution of tree canopy is a priority for many cities, and tree canopy change studies are needed to inform natural resource managers on how and for whom canopy is changing. This study examines relationships between tree canopy change, socioeconomic/demographic characteristics, and land use at the block group and county scales, in Cook County, Illinois from 2010 to 2017. At the block group level, spatial Random Forest Regression models the nonlinear relationships between six canopy metrics and socioeconomic, demographic, and land use predictors. We also tabulated canopy change across land use categories at the county scale. Tree canopy decreased by 11,634 ha—1.1 % of Cook County's land area. Residential and transit land use types experienced the highest canopy gains and losses. Block groups with higher proportions of residential land, higher median income, home ownership rates, and lower housing densities experienced more canopy gains and losses. High housing density areas possessed less canopy, but lost less proportionally. Vacant and natural land were associated with canopy growth and persistence respectively. Diverse modeling suggests net canopy change calculations mask the presence of canopy turnover and that there is a need for a unification of canopy tabulations in the field. Protection of existing canopy as well as the investigation of vacant space for canopy growth may improve urban forest equity in a city where it could be on the rise.

1. Introduction

Urban tree canopy (UTC) makes cities more livable; it decreases the urban heat island effect, reduces stormwater runoff, provides habitat for wildlife, and improves the physical and mental health of people (Turner-Skoff and Cavender, 2019). Given UTC's importance, much research has been devoted to examining UTC distribution and how it relates to socio-economic patterns. Broadly, this research has found that UTC is not distributed equitably. Instead, minoritized and low-income communities tend to have less tree canopy cover (Gerrish and Watkins, 2017; Watkins and Gerrish, 2018). Published research suggests that inequity is the result of a long history of environmental racism and segregation in the United States which has deprived minoritized neighborhoods of investment for decades (Holifield, 2001; Locke et al., 2021; Schell et al., 2020). These trends extend beyond the United States; similar tree canopy cover disparities by income and visible minority status have also been reported across Canadian cities (Quinton et al., 2022).

There is a surge of interest and investments to plant trees and expand tree canopy in many North American cities, and these projects are often targeted at redressing longstanding inequities (Eisenman et al., 2024; Locke et al., 2017; Young and McPherson, 2013). Support for this work

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is evidenced by the creation of tools that allow cities to quantify canopy inequity (e.g., American Forest's Tree Equity Score (American Forests, 2024)), as well as by extensive funding–the US federal government allocated $1.5 billion to urban and community forestry to increase canopy cover and decrease UTC inequities (US Forest Service, 2023). Yet it remains unclear if these ongoing efforts are achieving their goals, in part because urban tree canopy changes are poorly characterized.

The small but fast-growing literature on urban tree canopy change can be grouped into a few categories: 1) studies examining relatively long time horizons (i.e. 50–90 years), often using manual tracing of digitized historic aerial imagery; 2) shorter term studies spanning 5–10 years, typically using object-based image analyses, a) without social correlates, b) with social correlates, and c) with time-varying social correlates. The methodological differences between these different studies make direct comparisons and synthesis results to identify general patterns difficult, but we identify some overarching trends here.

Longer-term studies (~50–90 years) generally reveal relatively consistent total canopy cover, yet the spatial distribution changes over time. Manual polygon tracing of forest patches along an urban to rural gradient in and around Baltimore Maryland, examined forest cover in 1914, 1938, 1957, 1971, 1999, and 2004 (Zhou et al., 2011). Over those 90 years forest cover was approximately equal in 2004 and 1914, but the average patch size dropped dramatically as forests became increasingly fragmented (Zhou et al., 2011). Circular plots (n = 250) with digitized tree canopy polygons did not indicate change over 59 years (from 1951 to 2010) in either Detroit, MI or Atlanta, GA (Merry et al., 2014). Healy and colleagues (2022) manually traced all of the tree canopy cover in two Massachusetts cities, Holyoke and Chelsea, in 1952, 1971, 2003, 2014 and found that during periods of economic prosperity, tree canopy declined and during economically depressed periods tree canopy cover increased. A unique study used a convolutional neural network model called "U-NET" to classify historic images of Utica, NY in 1957 and 2017 and found that tree canopy gains were most common in uninhabited natural areas and losses were most common in residential areas coinciding with the onset of urban renewal (Kropp, 2024). However, low classification accuracy means caution is warranted with interpretation.

Shorter-term (~5–10 year) tree canopy change studies are more common. High-resolution tree canopy change maps using object-based image analysis (OBIA) minimize errors from shadows, differences in look angle, and other spurious methodological artifacts. In Tampa, FL there was a 3 % increase in tree canopy cover from 2006 to 2011 (Landry et al., 2013). Tree canopy was aggressively removed to stop the spread of the invasive Asian Long Horned Beetle in Worcester, MA in 2008. Elmes and colleagues (2017) used OBIA to map tree canopy change in 2008, 2010, and 2015. Despite a background warming trend in land surface temperature, areas experiencing canopy loss warmed significantly faster (Elmes et al., 2017) highlighting the important role trees provide in mitigating the urban heat island effect. Despite the widespread removal of the Asian long-horned beetle's preferred host tree species, maples, most of the canopy decline from 2008 to 2010 in Worcester could be attributed to development (Hostetler et al., 2013). It is common to find that development is a major driver of canopy loss, examples include Melbourne Australia from 2008 to 2017 (Croeser et al., 2020), Oklahoma City from 2006 to 2013 (Ellis and Mathews, 2019), Christchurch, NZ from 2011 to 2015 (Guo et al., 2019), in Denver, CO from 2008 to 2013, and in Milwaukee, WI from 2010 to 2015 (Ossola and Hopton, 2018). Aside from development, natural disasters such as earthquakes in Christchurch, NZ (Morgenroth and Armstrong, 2012) and hurricanes in Houston, TX (Thompson et al., 2011) were associated with canopy losses when using OBIA, and field-based plot sampling, respectively.

In addition to canopy change studies about development and/or disasters, some have investigated who lives in neighborhoods experiencing tree canopy loss, persistence and gain. Foster and colleagues (2022) found the inequitable distribution in tree canopy cover in Philadelphia worsened between 2008 and 2018. In coastal Los Angeles higher income areas had more tree canopy and lost less from 2009 to 2014 (Locke et al., 2017). There were similar findings in Washington, D. C. from 2006 to 2011: low-income areas lost more canopy in both percentage and absolute terms despite having less to begin with (Sanders et al., 2015). Backyards in Baltimore, MD had more tree canopy cover than front yards, and they appear to be gaining tree canopy cover from 2008 to 2013 (Locke et al., 2025). In these four tree canopy change studies, the social correlates of canopy change were static.

A few studies have examined tree canopy change alongside time-varying demographic and socioeconomic measures. Both increases and decreases in median household income experienced tree canopy gain in Washington, D.C. from 2006 to 2011 (Chuang et al., 2017). In Philadelphia, PA, census tracts with increasing homeownership, income, and educational attainment from 1980 to 2010 had higher probabilities of tree canopy persistence (Locke et al., 2023). Census block groups in Portland, OR with increasing population density, non-white population, and decreasing incomes all experienced higher rates of canopy loss between 2014 and 2020 (Ock et al., 2024).

The studies described above used a variety of tree canopy change metrics, complicating direct comparisons. We expand on previous work by considering canopy gain, loss, persistence, and net change side by side to better understand canopy turnover more comprehensively. Turnover refers to the dynamic process of how urban tree canopy changes over time, encompassing tree growth, the introduction of new plantings, and the loss of canopy due to tree removal, maintenance, and senescence. While net change simply tells us if the urban forest has expanded or contracted, canopy turnover paints a more complete picture of how urban form, management practices, environmental conditions, and social fabrics work in concert to impact forest composition and structure. Future analyses may be designed to capture canopy turnover in addition to conventional metrics.

Given the expansive, nation-wide efforts to increase tree canopy and decrease canopy inequities (Eisenman et al., 2024), it is reasonable to question for whom, where, and why canopy is changing. Research has demonstrated the importance of neighborhood-scale analyses (as approximated with US Census geographies (Landry and Chakraborty, 2009; Troy et al., 2007), and their Canadian equivalents (Greene and Kedron, 2018; Pham et al., 2012, 2017)); as they can demonstrate links between socioeconomic and demographic data to UTC dynamics. Tree management decisions are often made at the parcel scale and can heavily depend on land use, or the economic and cultural activities practiced on a piece of land (Nedd et al., 2021). Therefore multi-scalar analyses are needed. By examining only how socioeconomic and demographic data relates to UTC change, one then excludes the effects of the other land uses, and by extension their unique management fingerprints on, and exposure to the benefits of the urban forest.

Future tree canopy is persistence plus gain minus losses (Luley and Bond, 2002). Persistence comes from tree protection; gains occur from plantings, succession, and the growth of existing canopy; and losses are attributable to senescence, removal, blowdown, pests, and diseases. Tree canopy change dynamics therefore have a mix of natural and anthropogenic factors, and multi-scale approaches with multiple measures of persistence and changes are needed to effectively capture these diverse drivers (Roman et al. 2018; Locke et al. 2025). Ample research has shown that significant changes in net urban tree canopy can occur over relatively short periods of time (Chuang et al., 2017; Ellis and Mathews, 2019; Guo et al., 2019; Landry et al., 2013; Locke et al., 2025). We expect that looking at these additional metrics of canopy changes will offer insights on how the forest is changing. For example, while the impact of new plantings may not yet be remotely-sensed, the growth and/or removal of existing trees will likely have impacts on urban tree canopy that could influence efforts to make it more equitable.

Our goals were 1) to summarize recent, short term canopy change over a seven-year period in a large, North American urban region. 2) To model how socioeconomic, demographic, and land use factors simultaneously relate to canopy distribution, gain, loss, and persistence using nonlinear, machine-learning methods to better understand canopy turnover and the trajectory of canopy equity. The goals are therefore to characterize patterns and uncover relationships. Thus far, UTC change research has been conducted using correlations and other linear methods (Chuang et al., 2017; Kiani et al. 2023; Ock et al., 2024). We sought to characterize the relationships of canopy correlates beyond static and possibly non-linear relationships to increase the applicability of our findings to homeowners, urban foresters, and policy makers managing and serving diverse landscapes. Analyses were conducted at two scales: the block group level with random forests, and at the parcel scale via descriptive statistics.

2. Methods

2.1. Study area

This study examined canopy change in Cook County, IL. Cook County contains the City of Chicago, the third most populous city in the United States. In 2020, the county had a population of 5.2 million people (U.S. Census Bureau, 2020). The county is 244,800 ha and contains 134 municipalities in addition to Chicago (Cook County, n.d). Cook County is highly segregated and communities of color have less tree canopy (Fan et al., 2019). Cook County is currently rebounding from an infestation of emerald ash borer (*Agrilus planipennis*), an invasive insect that girdles and kills trees in the ash (*Fraxinus*) genus. A 2010 inventory estimated that 8 % of Cook County's trees were ashes, and that they made up nearly 20 % of street trees (Nowak et al. 2013). By 2020, nearly half of these trees had been removed and the remaining ones were generally in poor health (Kua et al. 2020). Residential and transit (including roads, the adjacent right of ways where street trees may live, and associated facilities) land use types are the most common in the county, composing approximately a third and a quarter of the entire study area respectively (Brandt et al., 2017), but the distribution of land uses are heterogeneous (Fig. 1, Table 2).

Cook County lies at the intersection of the tall-grass prairies of the central United States and the temperate forests of the east; in the pre-colonial era, the majority of the county was a prairie with forests dotting the landscape (Bowles and Mcbride, 2002). Given this ecological history, Cook County had relatively sparse canopy cover before Euro-American colonization, although the City of Chicago has always had a strong ecological focus; its motto is *Urbs in Horto* (City in a Garden). In the County's early development, landscape architects including Frederick Olmstead and Daniel Burnham planned rings of parks and treed boulevards and preserved expansive forests (Cronon, 1991). There have also been intentional efforts to increase tree canopy in recent decades. From 1989 – 2011, Mayor Richard M. Daley created the Bureau of Forestry and Department of the Environment to guide a massive street tree planting campaign (Daley, 2003). These policies did not consider tree equity, and likely prioritized tree plantings in more affluent neighborhoods that were better able to advocate for investment. Like in many metropolitan areas in the United States, there are canopy inequities in Cook County, with wealthier communities having more tree canopy (Fan et al., 2019). Further, this inequity is rooted in the region's history, with areas that had more forests in the pre-colonial era currently having more tree canopy (Fahey et al., 2012; Darling et al., 2025). However, the region is currently working to increase tree equity. In 2022, the City of Chicago committed to planting 75,000 trees over 5 years primarily in minoritized communities (The City of Chicago, 2022). Within the broader region the Chicago Region Trees Initiative (CRTI) regularly identifies inequitable tree deficits, disseminates high quality information and training, and helps communities acquire funding for tree plantings and care (Chicago Region Trees Initiative, 2019). The region's historical inequity, recent struggles with invasive pests, as well as its current efforts to invest in minoritized communities is representative of many other cities within the US, and therefore examining how canopy has changed in this region offers insights to other cities.

2.2. Dependent variables

We used a high-resolution, LiDAR-derived canopy change layer for this study (The Morton Arboretum, 2024). This layer was created by the

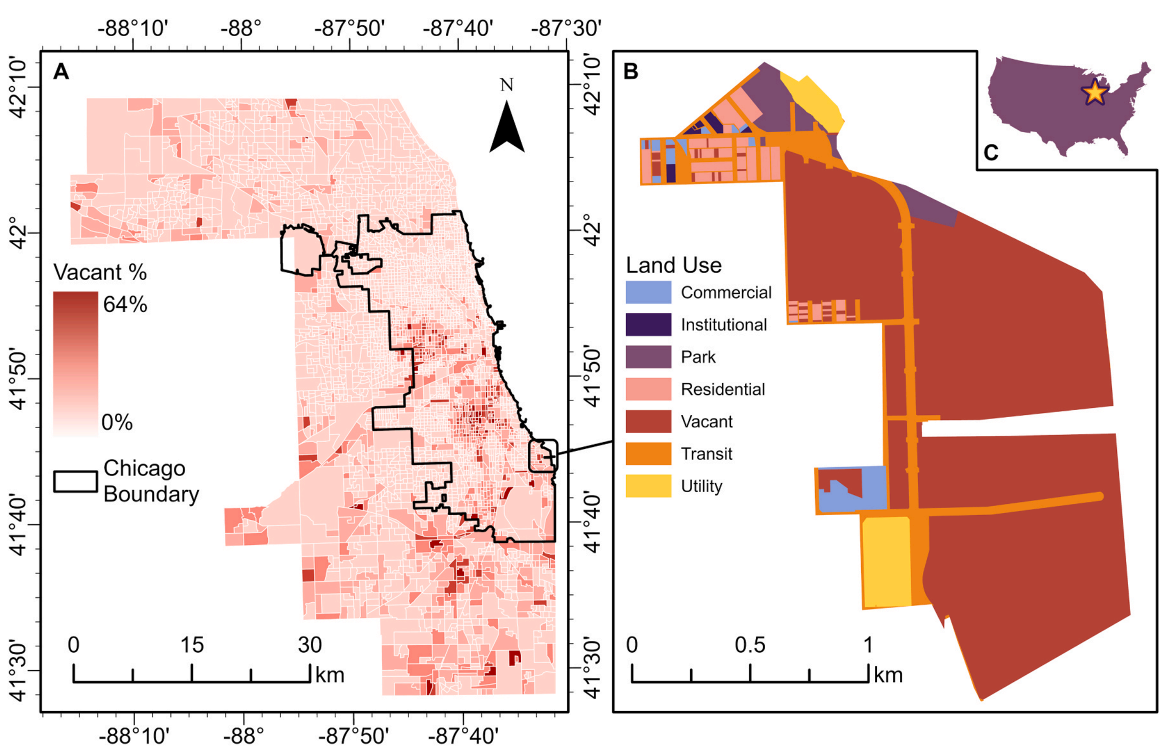

Fig. 1. Study Area. Cook County, IL is spatially heterogeneous, illustrated here by the distribution of vacant space both across (A) and within (B) Census block groups. Cook County is located in the Midwestern United States (C).

University of Vermont's Spatial Analysis Lab using Object-Based Image Analysis followed by manual corrections; these methods have been shown to identify tree canopy with 99 % accuracy (MacFaden et al., 2012; J. O'Neil-Dunne et al., 2013, 2014). The LiDAR for both years were captured in the early spring, before canopy leaf-out. Collecting LiDAR data when trees do not have leaves limits the possible impact of differences in phenology and climatic variation. Trees were defined as vegetation that was greater than six feet tall. The tree canopy change layer has 1 ft^2 resolution and has three values: persistence, growth, and loss. Persistence is defined as the canopy area that was measured in both 2010 and 2017, growth indicates no canopy was measured in 2010 but was present in 2017, and loss as canopy present in 2010 but not 2017.

Recognizing the multi-scalar nature of the drivers of UTC and canopy change (Chowdhury et al., 2011; Cook et al., 2012; Locke et al., 2016), analyses were conducted at both the neighborhood scale (approximated with block groups) and at the county scale (by land use type). Six measures of tree canopy and change were calculated at the block group level: 1) % canopy cover in 2010, 2) % canopy cover in 2017, 3) % canopy growth, 4) % canopy loss 5) % canopy persistence, 6) % canopy net change (Table 1.). Canopy metrics in the neighborhood scale analysis were normalized by, and expressed as a percent of block group area. Raw canopy area was not used as a dependent variable in modeling to avoid overrepresenting the effect of covariates in larger block groups. Raw area was included in the tabulation of canopy change at the county scale. The large suite of metrics was included to look beyond net canopy change. Net canopy change's additive nature underrepresents independent variables' effect on canopy in areas with equal levels of canopy gain and loss; those measures can cancel each other out, missing important canopy changes. The inclusion of additional measures better investigates canopy turnover—or how older canopy is succeeded by new canopy. Collectively, these related but distinct measures allow for a comprehensive appraisal and analysis of Cook County's changing UTC cover.

2.3. Covariates

Socioeconomic data were retrieved from the U.S. Census Bureau's 2015 5-year American Community Survey (ACS) using the tidycensus package in R version 4.3.2 with Rstudio (U.S. Census Bureau, 2016; Walker and Herman, 2024; Posit team.,2023; R Core Team, 2023). Data and code for this analysis are available at (Lyall, 2025). Block groups are the finest scale that many racial and economic data are made available. Their size is variable as they are drawn to contain between 600 – 3000 residents. We chose ACS variables that have previously been shown to be related to canopy cover (Table S1 (Gerrish and Watkins, 2017; Landry and Chakraborty, 2009; Quinton et al., 2022; Schwarz et al., 2015; Watkins and Gerrish, 2018)). This analysis included 3990 block groups in Cook County. Individual block groups with nonsensically high variable values were removed from the dataset (Housing densities greater than 1000 units/ha $n = 2$). Missing median age ($n = 8$) and housing age ($n = 16$) values were replaced with global medians.

The Chicago Metropolitan Agency for Planning produces a semi-regular land use inventory at the parcel scale for the Chicago region, and we used the 2015 version for this analysis (Chicago Metropolitan Agency for Planning, 2022). This dataset includes nearly 60 specific land use categories, including distinguishing between attached and detached residential housing as well as residential land that is under construction. To reduce the complexity of this analysis, we aggregated to 12 major land use categories (Table S2). Then, we calculated the percent of each land use coverage across all census block groups to examine land use's relationship to UTC alongside socioeconomic and demographic variables.

Table 1
Canopy metric calculations. Formulas for modeled dependent canopy variables.

Dependent Variable	Formula
2010 tree canopy cover (%)	(persistence + loss) / census block group area * 100
2017 tree canopy cover (%)	(persistence + gain) / census block group area * 100
Net canopy change (%)	(gain – loss) / census block group area * 100
Canopy growth (%)	gain / census block group area * 100
Canopy loss (%)	loss / census block group area * 100
Canopy persistence (%)	persistence / census block group area * 100

2.4. Statistical analyses

Both neighborhood (approximated with Census block groups) and parcel-level variables have been identified in prior research as important correlates of tree canopy cover (Locke et al., 2016) and changes (Locke et al., 2017) — analyses were conducted at both scales. Random forests are an ensemble machine learning technique suited to a wide variety of applications; for a full accounting of random forest regression modeling refer to Ho (1995) and Breiman (2001). Random forests have a number of advantages that complement large scale and socio-ecological datasets such as the data used here. The algorithm is insensitive to outliers, does not require normal distributions, functions at a variety of scales, and has quick processing times. For block group-level analyses, we used random forests because of the large number of input variables being processed as well as highly non-normal socio-economic data. Unlike spatial econometric approaches that assume and require linearity, random forests allow for non-linearities, and are therefore better-suited to the goal of finding and characterizing relationships. We used the R package *caret* (Kuhn, 2008) to train six random forest regression models based on an 80/20 train-test split. This commonly-used train-test split provides two benefits: first because predictions can be correlated with the hold out portion, it is easy to assess model performance, and secondly the chances that spatial autocorrelation will bias estimates are reduced because the random sampling removes observations from their spatial contexts. Training was performed with k-fold cross validation (a functionality within the *caret* package, $k = 10$). Number of variables tried at each split was optimized for each model using the tuneGrid parameter within the train() function. Model performance is evaluated in two ways: 1) with the internal validation metrics reported for the training data only (reported in Fig. 4), and 2) by calculating the correlation between predicted and actual values on the partitioned test set (Fig. 3). For all independent variables, importance is calculated as the increase in RMSE when the variable is randomly permuted in the out-of-bag validation data, averaged across all decision trees. Partial dependence plots (PDPs) are computed by fixing the plotted variable for all observations, keeping all other covariates at their actual observed values, then averaging the model predictions at the fixed values. Although multicollinear variables do not significantly impact random forest prediction accuracy, related variables can pose interpretability issues. For this reason, no independent variables with a Pearson correlation of $r > 0.6$ were included in our random forest models.

Because of apparent spatial patterning in the outcomes (Fig. 2) the model residuals were tested for spatial autocorrelation using a queen contiguity matrix, which defines block groups sharing an edge or vertex as neighbors via spdep and sfdep packages (Bivand, 2022; Bivand et al., 2013; Parry and Locke, 2024). The residuals exhibited significant spatial autocorrelation ($0.33 < \text{Moran's I} < 0.38$, p-value < 0.001). Therefore a spatially-lagged outcome variable was added as a predictor, and the residuals then satisfied the independence assumption ($-0.009 < \text{Moran's I} < 0.013$, p-value > 0.12).

Although other machine learning techniques were considered, random forest was selected because the results are more interpretable than black box algorithms like gradient boosting and support vector machines. This was critical as our goal was to interpret the factors that are related to canopy change, not to predict actual change. Our goal was to understand the underlying relationships, so interpretability is more important than prediction accuracy.

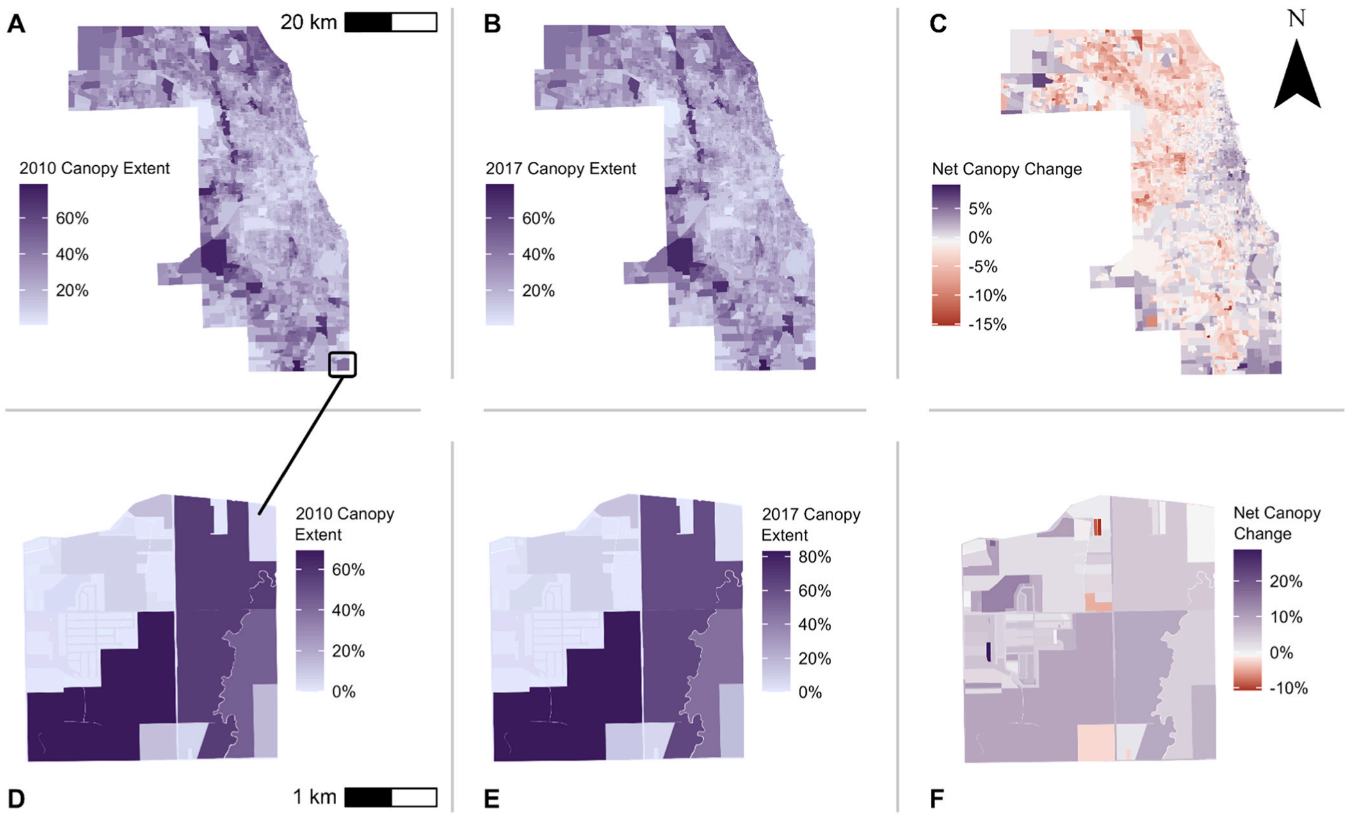

Fig. 2. Regional and local canopy heterogeneity. Canopy distribution and net change varies spatially across all block groups (top) and within block groups (bottom) in Cook County, IL from 2010 to 2017.

3. Results

3.1. Block group scale

Canopy covered 28.8 % of Cook County in 2010 and 27.7 % in 2017. Net change ranged from −15 % to + 9 % by block group (Fig. 2, top). Canopy cover was highest in the northern part of the county in both 2010 and 2017 and lowest in central Chicago, the most dense and urbanized portion of the study area. Within individual block groups, there is considerable heterogeneity of canopy change metrics across parcels as illustrated by Fig. 2, bottom.

Of all six models tested, canopy persistence, 2010 canopy distribution, and 2017 canopy distribution had nearly identical model fits, variable importances, and partial dependencies. To minimize redundancy, only 2017 canopy distribution is presented and discussed; the other models are shown in Figure S1. Correlations between predicted and actual results ranged from 0.65 (net canopy change) to 0.94 (2010 canopy cover, Fig. 3).

In the random forest models the spatially lagged predictor was always ranked highest (not shown). With the exception of residential, vacant, natural area, and commercial, the 9 socio-economic variables generally ranked higher in importance than the 11 land use variables; Residential land use was in the top four variables of all six models (Fig. 4A, B, C, D; Figure S1A, B). Residential land use was the most important predictor for net canopy change (Fig. 4B) and canopy loss (Fig. 4D). Block groups with more residential lost more canopy (Fig. 4H) and had higher net negative change (Fig. 4F). It was also the second most important predictor for canopy growth; areas with more residential land grew more canopy (Fig. 4G).

Median income appeared in five of the six models' most important variables. Income was the most important predictor for canopy growth. Block groups with higher median incomes experienced more growth (Fig. 4C). The variable was second most important for 2017 canopy distribution and the fourth most important for canopy loss. Higher-income areas lost more canopy than their counterparts (Fig. 4H) but had more overall canopy coverage in 2017 (Fig. 4E).

Houses/ha appeared two times in the models' top four most important variables. It was the third most important predictor for the net canopy change model. Areas with higher housing densities experienced more positive net canopy change (Fig. 4F). This effect stagnated beyond 100 households/ha. The variable was second most important for the canopy loss model. Higher housing densities lost less canopy (Fig. 4H). Similarly to net change, this effect was non-linear and leveled off beyond 100 houses/ha.

Percent owner occupied houses was the second most important variable in the net change model (Fig. 4B) and third in the loss model (Fig. 4D). Block groups with a higher proportion of owner occupied homes lost more canopy (Fig. 4H) and experienced more negative net canopy change (Fig. 4F). Percent of the population with a bachelor's degree was the third most important variable for canopy growth (Fig. 4C). Areas with greater educational attainment had higher amounts of canopy growth (Fig. 4G). Median house age was the fourth most important variable for net canopy change (Fig. 4B). Block groups with older homes experienced more negative net canopy change (Fig. 4G).

Percent vacant space was the fourth most important variable for predicting canopy growth. Block groups with higher amounts of vacant space saw more canopy growth, but this effect flattened at around 20 % vacant space (Fig. 4G). Natural area was the most important variable for the canopy distribution models (Fig. 4A, Figure S1B). The partial dependence plot displayed a positive linear relationship—block groups with more natural space possessed much higher levels of canopy in 2017 (Fig. 4E). Natural area was not an important predictor for any of the other models. Commercial land use was the third most important predictor for 2017 canopy distribution, with more commercial areas having less canopy. Commercial land use was somewhat important in the

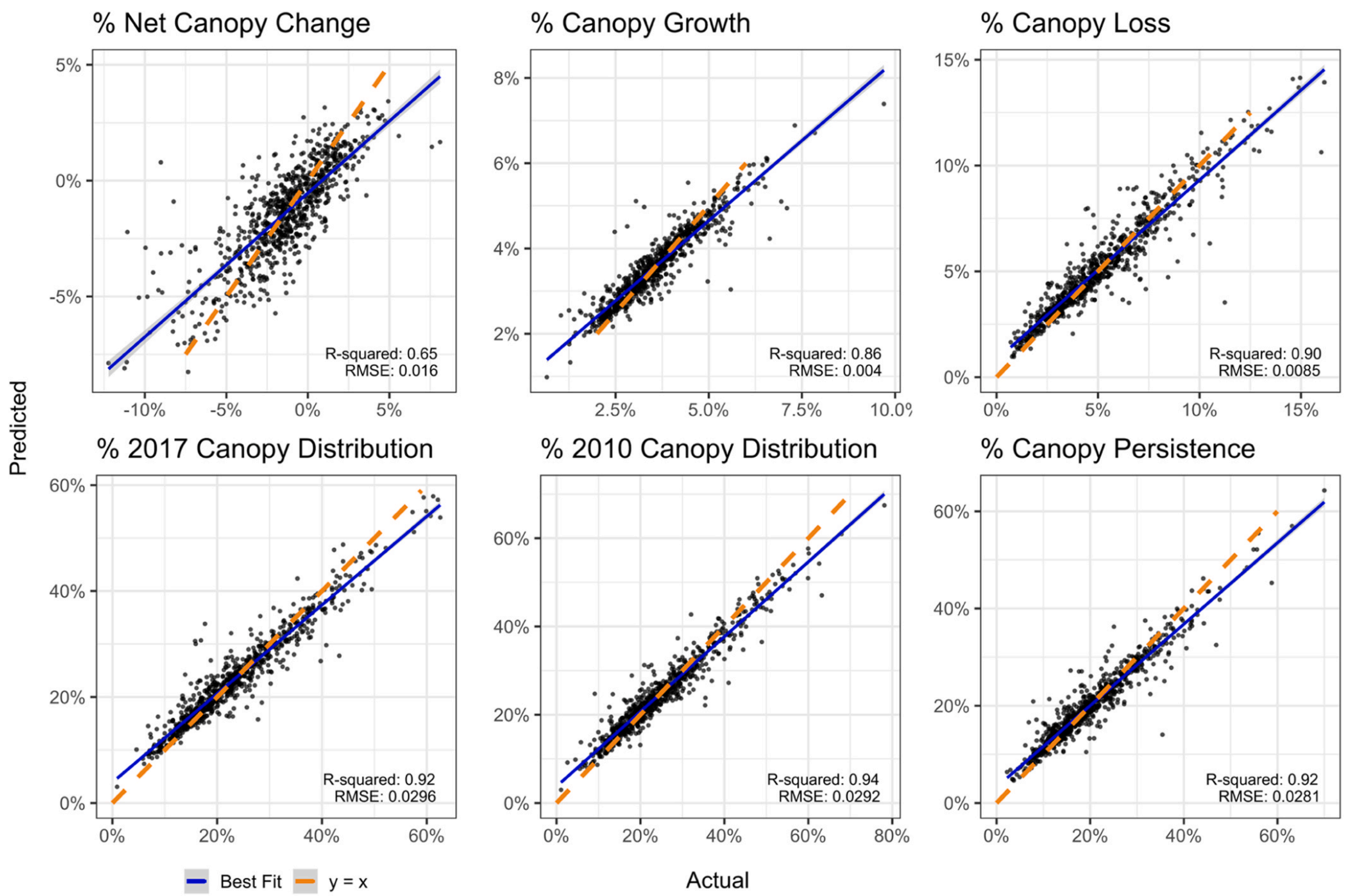

Fig. 3. Model fit external validation across canopy models. Random forest models built with an 80/20 train/test split and 10-fold cross-validation. Reported validation metrics are from the partitioned test dataset.

growth and loss models, but not important in the net change model.

3.2. Land use and canopy change

In 2010, Cook County possessed 70,520 ha of canopy cover; in 2017 canopy cover totaled 67,830 ha, a net loss of 1.1 % (2801 ha) of overall canopy (Table 2). However, there were considerable growths and losses that were obscured by overall canopy change. The county gained 8832 ha of canopy and lost 11,634 ha over the seven-year study period. Residential properties make up the plurality of land in Cook County and contain 37 % of Cook County's total 2017 canopy distribution. It also experienced high rates of canopy turnover–accounting for 39 % of the county's overall growth and 46 % of its loss. Transit, which includes right of way space alongside roadways, grew and lost the second most canopy of all land use types. Transit areas had an overall net change of −917 ha of canopy, or −1.6 % of its land area. Natural areas, which contained 25.5 % of Cook County's overall 2017 canopy remained relatively stable, with a slight net negative change of −0.8 %. Vacant land use contained just 4.5 % of Cook County's overall canopy in 2017 and was the seventh largest land use type by area. Despite this, vacant land use had the highest change area value and fourth highest growth area value of any land use type. The utility land use type also had the largest percent change (2.3 % corresponding to 109 ha of net change) but accounted for only 0.9 % of Cook County's overall canopy cover in 2017.

4. Discussion

4.1. Residential lands are especially important

Canopy turnover is pronounced in residential areas. We found that residential land lost and grew more hectares of UTC than any other land use category (Table 2), had high variable importance scores in random forest models (Figure 4A-D, S1A-B), and was strongly associated with higher amounts of negative net change, growth, and loss in the PDPs (Fig. 4F-H). Residential areas are not a monolith. Modeling census variables further articulated divisions in canopy change dynamics within residential lands by housing density and socio-economic characteristics. Highly residential areas, as well as block groups with high scocio-economic status (i.e. higher median incomes and rates of education and homeownership) possessed more UTC and had larger magnitudes of turnover. Block groups with less residential area and lower socio-economic status had less UTC and lower magnitudes of turnover. Relationships often changed significantly across their distribution as in Fig. 4G Median Income, which displays an important inflection point at $100,000, highlighting the importance of non-linear methods. Block groups with median incomes greater than $100,000 saw canopy growth rates approximately 1 % higher than block groups making less. Accurately representing non-linear relationships in future research might further assist policy makers to distribute resources and prioritize the needs of certain communities.

It is possible that construction caused canopy decline in residential areas but development-UTC relationships are not fully understood. Street widening and institutional development have been associated with canopy loss (Healy et al., 2022; McPherson and Luttinger, 1998) and with urban tree mortality (Hilbert et al., 2019; Roman et al., 2022).

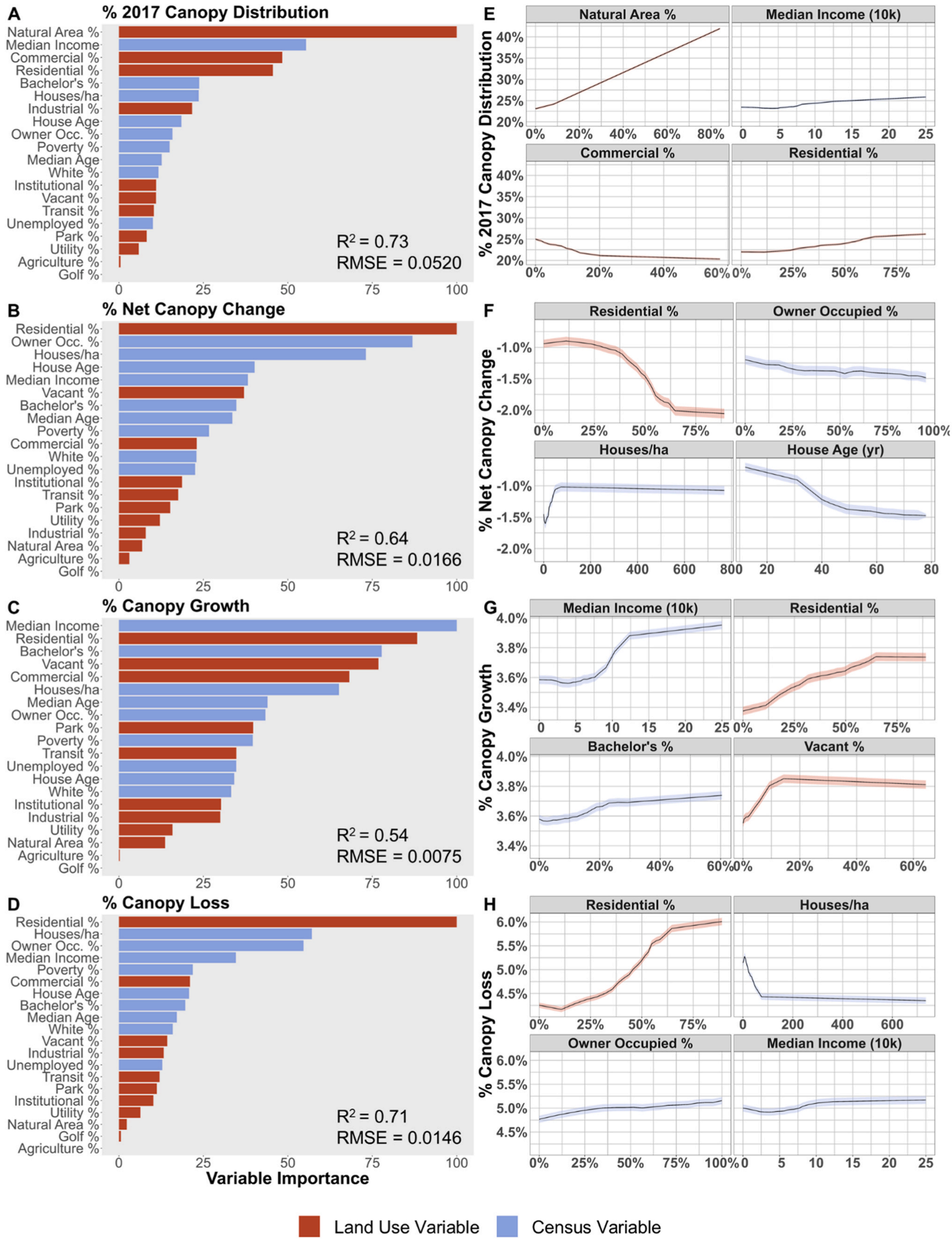

Fig. 4. Random forest variable importance (A-D) and partial dependence plots (E-H). Variable importance is defined as the increase in RMSE when the associated variable is randomly permuted in the validation data. Importances are scaled to the value of the most important predictor. R^2 and RMSE values are reported from internal training validation. The spatially-lagged predictor is omitted for clarity.

Table 2
Canopy metrics by land use type. Canopy change tabulations by land use for Cook County, IL 2010-2017.

Land use	Land area (ha)	% 2017 Canopy distribution	% Net canopy change	Change area (ha)	Growth area (ha)	Loss area (ha)
Residential	85,733	29.0	−2.2	−1872	3484	5356
Transit	56,362	23.7	−1.6	−917	2183	3100
Natural area	27,773	62.4	−0.8	−233	888	1122
Industrial	14,616	7.3	0.5	74	293	218
Institutional	14,244	17.6	−0.5	−69	391	460
Commercial	14,213	8.7	−0.1	−15	282	297
Vacant	9183	32.9	1.8	165	541	376
Park	6651	24.6	−0.4	−25	265	290
Agriculture	5983	12.4	1.6	96	151	54
Golf	5357	25.7	−2.1	−113	166	280
Utility	4744	13.2	2.3	109	185	75
Total	244,864	27.7	−1.1	−2801	8832	11,634

Conversely canopy growth has been linked with developing agricultural land (Berland, 2012) and urban renewal (via building demolition and the production of vacant lots) (Roman et al., 2021). Analysis of how land use succession, or the change of land's primary function over time, affects canopy change in the Chicago region may better elucidate these trends. Regardless, residential land, which makes up over a third of Cook County, had the second highest percent of UTC growth (~4 %), while having ~70 % of its land area uncovered by canopy as of 2017 (Table 1). This means residential land may offer opportunities to protect and expand UTC in the region. Tree protection ordinances, which can mandate the preservation of trees during construction, the planting of new trees after construction, and restrict the removal of mature trees on private residential lands, may be an effective strategy to maintain and grow canopy. Hill and colleagues (2010) found a significant relationship between meaningful tree ordinance clauses, as well as diverse residential zoning, and tree canopy preservation in the Atlanta metropolitan statistical area. In a similar vein, Hilbert et al. (2019) found that across 43 Florida municipalities, neighborhoods with heritage tree protection programs had 6.7 % more canopy cover. A survey of Floridian developers revealed a willingness to work with urban tree managers; subjects requested financial incentives and more flexible zoning allowing for increased density (Willis et al., 2024).

4.2. Transit hosts substantial areas of net canopy loss

The transit land use type, which is the second most abundant land use type in Cook County and includes road/railways, right-of-ways, and associated transportation facilities, grew ~2200 ha and lost ~3100 ha of canopy cover. Transit land use did not rank as important in our random forest models, despite growing the second largest volume of UTC. This is potentially due to how transit morphology pairs with block group level aggregation. Transit areas are present at fairly consistent levels across block groups, and its directions of change were likewise consistent. Regardless, similar to residential land, UTC loss outpaces growth on transit lands (Table 2). This indicates that changes in tree maintenance could be instrumental in suppressing losses and creating net gains. Unlike residential lands, the transportation category is under the municipal jurisdiction, authorizing local governments to preserve and increase tree canopy, and shifts in urban tree maintenance are already underway; in 2023, the City of Chicago began to proactively prune street trees on a regular basis (The City of Chicago, 2023). These lands are also a major focus for municipal tree plantings (The City of Chicago, 2023). These management efforts could increase tree health and promote longevity (Vogt et al., 2015).

4.3. Natural areas are important for the current distribution but not for change, the reverse is true for vacant land

The random forest models identified several other land use types important for predicting various aspects of UTC outside of residential space. Natural areas were the single most important variable for predicting 2017 UTC cover. Natural areas, along with the park land use type, were not highly important in canopy change models however. This finding indicates that while existing green spaces conserve large portions of UTC, their tree canopy cover does not change substantially over relatively short periods of time (≤10 years). Likewise, some parks and open spaces were found to have the most stable tree cover in Philadelphia, while others witnessed substantial gain (Roman et al., 2021). Investigating land use succession may reveal how recently constructed green spaces impact UTC.

Vacant space had the fourth highest variable importance for predicting canopy growth, but was not important for predicting UTC distribution. Vacant space also facilitated the highest positive net canopy change (165 ha), and the highest canopy growth relative to land area (~5.9 % of land area; Table 2). These results may suggest that vacant space is an emerging driver of canopy growth in Cook County. Marginalized communities often have a higher prevalence of vacant space. Canopy growth on vacant land, therefore, may mean canopy gains for these communities, and by extension increased ecosystem service provisioning. While this seems like improving environmental equity, the social and ecological considerations of spontaneous vegetation are varied and complex. While urban greenery is often an amenity, the quantity of vegetation is not always an indicator of environmental quality. Generally, spontaneous vegetation may be described as overgrown and disorderly, and is perceived negatively (Riley et al., 2018). Vacant spaces may also be common sites for dumping and other illicit activities (Berland et al., 2020; Chen & Rafail, 2020). Conversely, vacant spaces may be the most accessible form (both spatially and financially) of urban greenery, provide regulating/wildlife ecosystem services, and support diverse, well-adapted plant communities (Riley et al., 2018). The concentration of vacant lots in minority communities may make them ideal host sites for new, equity-minded green spaces. These properties are often already owned by city governments, and programs exist in many cities–including Chicago–to allow neighboring residents to purchase these lands for a nominal fee so that they may be developed or converted to neighborhood green spaces (Gobster et al., 2020a–c; Hadavi et al., 2021). Negative outcomes associated with vacant space may be curtailed by local ownership of these properties (Berland et al., 2023).

5. Limitations

Urban areas are highly heterogeneous, often at fine spatial scales. A single census block group may contain land use types and sociodemographic characteristics that have contradictory impacts on canopy cover and change. Our models explained between 54 % and 73 % of variation in canopy characteristics (Fig. 4). Future research may further expand our understanding of urban canopy change in several ways. We used the R package caret (Kuhn, 2008) to train six random forest regression models based on an 80/20 train-test split. our understanding of urban canopy change in several ways. It may be useful to examine localized hot and cold spots of canopy change and particularly areas of both high growth and loss. Future research may also test interactions between independent socioeconomic variables or stratify groups of variables clustered into categorical groups of communities as in Locke et al. (2016, 2025). This may be important for understanding tree equity and prioritizing communities most in need of tree maintenance and plantings. Finally, our models did not place a high importance on race/ethnicity despite Chicago's highly segregated past. This may be due to representing race as percent minority/nonminority population, collinearity with several other variables, or may be an inherent limitation of random forests. Random forest algorithms make predictions by averaging the results of many decision trees. For models with many explanatory variables, highly predictive variables may appear in most decision trees, preventing less influential variables from being selected, and suppressing their overall real-world contributions. Although our models did not attribute large importance to race/ethnicity, our findings may guide future research to investigate finer demographics questions within the broad trends revealed by our analysis, which may be more suited to traditional statistical analyses.

6. Conclusion

This study showed that better understanding the dynamics of canopy change in urban areas requires examining not only net change, but also canopy gains and losses. While net change is an important yardstick for measuring city-wide tree canopy and achieving policy goals, our results show that net change masks crucial aspects. Future tree canopy is tree canopy persistence plus gain from planting, growth, and succession and minus losses due to death and removal (Luley and Bond, 2002). In Cook County, overall net UTC declined 1.1 % from 2010 to 2017. However, this singular number masks the magnitude of considerable gains (3.6 %) and losses (4.7 %) (Table 2). We also demonstrated that non-linear methods provide further clarity of UTC dynamics. Canopy turnover was particularly impactful in residential and transit land use types. Lower density residential areas and areas of higher socioeconomic status experienced elevated turnover rates as compared to denser, lower socioeconomic status block groups. Vacant land was considerably important for predicting canopy growth and hosted the largest positive net canopy change area, while natural areas were the best predictor of persistent canopy in Cook County from 2010 to 2017. These two land uses, therefore, have differing but important relationships with UTC. Vacant space is a powerful recruiter of canopy, while natural areas are the best at holding onto their canopy. This indicates vacant space as an emerging driver of new UTC in the Chicago region and underscores the importance of analyzing measures beyond net canopy change.

Inconsistent definitions of tree canopy change make comparisons difficult across this small but fast-growing body of work. We emphasize the importance of explicitly defining canopy change (see Methods) to improve clarity, comparability, and replicability in future studies. Additionally, the majority of our models' independent variables displayed non-linear relationships with a suite of UTC metrics. Random forest and other non-linear methods will provide superior insight for managers attempting to optimize their limited resources.

Efforts in many cities to increase their canopy cover often emphasize the planting of new trees, but high mortality rates and time to maturity (Hilbert et al., 2019; Roman, 2014; Roman et al., 2016) are barriers to this strategy and can often result in net carbon emissions (Smith et al., 2019). The extensive area of canopy turnover that we found highlights another strategy to increase canopy cover: protecting existing trees. If Cook County had lost 25 % less tree canopy while growth remained the same, net canopy would have remained constant. If losses were curbed in just the two land use categories with highest turnover (residential and transit), UTC would have expanded by 1 percentage point of Cook County's total land area. Additionally, our understanding of equitable tree planting is contingent on said plantings and related institutions thoroughly documenting and sharing their efforts with the broader scientific community.

CRediT authorship contribution statement

Jackson D. Lyall: Writing – original draft, Validation, Data curation, Investigation, Formal analysis, Conceptualization, Writing – review & editing, Visualization, Software. **Lindsay E. Darling:** Writing – review & editing, Visualization, Supervision, Methodology, Formal analysis, Conceptualization, Writing – original draft, Validation, Project administration, Investigation, Data curation. **Dexter H. Locke:** Investigation, Writing – review & editing, Supervision, Project administration, Validation, Software, Methodology, Data curation. **Brady S. Hardiman:** Validation, Supervision, Project administration, Conceptualization, Writing – review & editing, Investigation.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2025.128999.

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