Residential housing segregation and urban tree canopy in 37 US Cities.

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Abstract

Redlining was a racially discriminatory housing policy established by the federal Home Owners' Loan Corporation (HOLC) during the 1930s. For decades, redlining limited access to homeownership and wealth creation among racial minorities, contributing to a host of adverse social outcomes, including high unemployment, poverty, and residential vacancy, that persist today. While the multigenerational socioeconomic impacts of redlining are increasingly understood, the impacts on urban environments and ecosystems remains unclear. To begin to address this gap, we investigated how the HOLC policy administered 80 years ago may relate to present-day tree canopy at the neighborhood level. Urban trees provide many ecosystem services, mitigate the urban heat island effect, and may improve quality of life in cities. In our prior research in Baltimore, MD, we discovered that redlining policy influenced the location and allocation of trees and parks. Our analysis of 37 metropolitan areas here shows that areas formerly graded D, which were mostly inhabited by racial and ethnic minorities, have on average ~23% tree canopy cover today. Areas formerly graded A, characterized by U.S.-born white populations living in newer housing stock, had nearly twice as much tree canopy (~43%). Results are consistent across small and large metropolitan regions. The ranking system used by Home Owners' Loan Corporation to assess loan risk in the 1930s parallels the rank order of average percent tree canopy cover today.

Keywords: Urban Tree Canopy, Environmental Justice, Mortgage loans

1 Introduction

Spatial, social, and environmental inequities pose significant challenges for American cities (1, 2). Urban inequity is the result of historical and systemic forces, including structural racism and segregation, which have enduring effects on the ways cities function socially, economically, and ecologically (3–5). For instance, decades of racial discrimination in housing policy created barriers to homeownership, employment, and access to quality education for people of color, making it difficult to build wealth across generations (6–8). While the mechanisms linking structural racism to wealth creation and socioeconomic status are well understood (9), it is less clear how housing segregation may have played a role in shaping urban ecosystems.

This paper investigates how the historic practice of redlining, one of the most consistent, wide-spread, spatial, and racial forms of US housing practices, relates to the contemporary distribution of urban tree canopy, commonly understood as a vital component of urban ecosystem health and sustainability (10, 11). Trees provide a host of ecosystem services and social benefits, including heat island mitigation (12, 13). In the United States, approximately 1,500 heat-related deaths occur each year (14), and the impact of heat stress is likely to increase given current climate projections (15). Existing tree canopy cover (13) and the replacement of impervious surfaces with tree canopy can lower urban temperatures (12) and save lives. But trees and tree canopy are not distributed equitably (16–18). Recent meta-analyses show that lower-income urban areas (16) and areas with more racial minorities (17) have less tree canopy cover, an environmental injustice that can exacerbate health problems for already disadvantaged groups. The space to plant, however, is often a legacy of the urban built environment, which in the United States stems from histories of deliberate and systematic racial discrimination in housing and urban development (19, 20). In 1933, the US Congress created the Home Owners' Loan

Corporation (HOLC) to assist Americans struggling to pay their mortgages in the wake of the Great Depression. To guide lending criteria, the HOLC developed neighborhood appraisal maps for 239 urban areas, ranking the perceived risk of investing in particular neighborhoods using a color-coded scale of "A" (green), "B" (blue), "C" (yellow), and "D" (red) (21). Appraisals were based primarily on an area's demographic characteristics and the age and physical condition of its housing stock. Areas with predominantly U.S.-born, white populations, and newer housing stock were often codified as the "safest" places for banks to invest and were graded "A" and "B." Meanwhile, areas with somewhat older structures and/or a presence of foreign-born residents were commonly ascribed a "C" grade, while areas with significant numbers of racial and ethnic minorities, foreign-born residents, families on relief, and having older housing were almost always viewed as "hazardous" and given the lowest grade, "D." The term "redlining" is used because areas graded "D" were shaded red on the HOLC maps. In effect, while race was not the only criterion considered in designating grades, the maps formally embedded race into neighborhood appraisal processes by systematically factoring in the race of an area's occupants into the perceived long-term value of an area (22, 23).

Some context is important to better understand HOLC's residential security maps and its practices from 1934 to 1951. While the HOLC created uniform guidelines for neighborhood appraisal, because appraisals were produced in direct consultation with local municipal officials, loan officers, appraisers, and realtors, evidence suggests some variation in the grading across cities (24). Still, these agents were familiar with their city's specific patterns of residential segregation. More importantly, many local actors were already part of the power structures that had created, maintained, or profited from the prevailing racist housing policies and practices. These policies and practices included segregation ordinances, racially-restrictive deed covenants, and zoning plans that promoted their agendas of racial and immigrant exclusion (25–29). Thus, the HOLC maps helped codify the local real estate industry's consensus of perceived neighborhood value, which often institutionalized existing local inequities in borrowers' access to credit (23, 30).

The extent to which the HOLC's maps, guidelines, and practices influenced the actual distribution of mortgages remains uncertain. Some evidence suggests that lending practices varied by lender and geography, despite the HOLC's systematic guidelines (24). Additionally, some have argued that it is unlikely that the Federal Housing Administration (FHA), which issued long-term mortgages, cooperated directly with the HOLC (24). Yet it has been demonstrated that the FHA overwhelmingly prioritized granting mortgages for new homes, which would have been located in areas graded "A" by the HOLC. For instance, between 1934 and 1962, the FHA and the Veterans Administration lent over $120 billion for new housing, and 98% of this money was distributed to white residents compared to less than 2% for African Americans and other people of color (31, 32). During this period, African Americans represented ~10% of the US population (33). Studies in Houston and Boston show that even when controlling for income, whites were nearly three times as likely to receive a mortgage loan (3, 34).

A large consensus among housing policy scholars is that the federal government helped institutionalize a two-tiered racialized lending system: one tier provided federally-backed mortgages to higher graded neighborhoods (with predominantly U.S.-born, affluent, white populations with newer housing stock) and a second that subjected residents in the "yellow" and "red" neighborhoods (comprised of predominantly low-income African Americans and immigrants in older housing stock) to predatory lending schemes or no mortgage lending at all

(27, 35). For decades, many whites benefited from privileged access to credit, home ownership, and wealth accumulation based on home equity, while African Americans were largely denied this route to economic prosperity (3, 25, 36–38). Redlining created systematic disinvestment in minority communities that were located in the denser, older urban core while protecting the property values and resources of white communities moving into desirable homes in the suburbs. Indeed, the post-World War II suburban development supported by federal subsidies created new, exclusively white geographies that generated enormous new wealth (23, 39).

Although Congress officially outlawed racial discrimination in housing with the Fair Housing Act of 1968, studies continue to document its enduring effects. Many formerly redlined areas continue to struggle with segregation, poverty, unemployment, low educational attainment, and poor health outcomes today (3, 40, 41). Research shows that compared to areas receiving higher grades by the HOLC, lower graded areas exhibit declines in home ownership, housing value, and credit scores (42).

Despite the abundance of evidence on the social and economic impacts of racist housing policy, little is known about the relationships among redlining, social disadvantage, and environmental quality. It is well-documented that various social disadvantages are bundled in racially segregated urban areas (3). It has also been documented that lower-income areas (16) and areas with more racial minorities (17) tend to have less tree canopy cover. However, the relationships among long term discriminatory housing practices and contemporary environmental conditions remain poorly understood. The distribution of current urban tree canopy cover offers one perspective on environmental inequities related to housing segregation.

Research in Baltimore, MD has shown that redlining and other racially-biased housing practices have historically shaped the location of investments in environmental amenities such as trees and parks and the allocation of environmental disamenities via non-conforming zoning (2, 30, 44, 45). Redlined, African American neighborhoods of East and West Baltimore, graded D in the HOLC system, had overcrowded and poor quality housing and higher exposure to noise and other pollution from nearby industries (2). These denser, D-graded areas had less available space for trees and tree planting, while A-graded areas comprised of single-family homes on larger lots could maintain, grow, and plant additional trees. Race-based evaluations of credit-worthiness also shaped access to wealth accumulation and related political power. Residents in A-graded areas directed municipal investments into street tree plantings, creating public parks with trees, and invest their own resources into trees on their private lands (19, 45). At the same time, residents in D-graded areas had less access to public investments and were more likely to spend their lower wages on other necessities such as rent, food, or transportation. Thus, differences in lot sizes, money, and access to power along HOLC neighborhood lines played an important role in shaping the distribution of Baltimore's urban tree canopy over the long term (2).

Our goal in this paper is to examine whether there are similar patterns in the distribution of tree canopy by HOLC-graded neighborhoods in other cities. These analyses are possible because redlining was a national process, initiated by the Federal government in collaboration with state and local governments. It was a practice that was spatially-explicit, and applied to 239 cities in the same time period throughout the country. These characteristics make the practice of redlining particularly well-suited for within and cross-city comparisons. We examined whether historic redlining is statistically associated with contemporary spatial distributions of tree canopy for a range of metropolitan areas across a spectrum of area, population, and climate. This paper assesses whether there are differences in current tree canopy cover among historic HOLC classes and whether differences among HOLC classes are consistent among cities.

2 Results

There is a strong relationship between HOLC grades and tree canopy: areas formerly graded D have 21 percentage points less tree canopy than areas formerly graded A. One-way ANOVA showed significant differences in tree canopy by HOLC grade [$F(3, 3184) = 253.9$, $p < 0.001$]. Post hoc comparisons using the Tukey HSD test indicated that the same hierarchical ranking system used by HOLC to assess loan risk in the 1930s is paralleled by the rank order of average percent tree canopy cover today. Areas formerly graded D have significantly less tree canopy ($M = 20.9$ percentage points, $SD = 12.2$), than areas graded C ($M = 24.6$, $SD = 10.9$), B ($M = 32.4$, $SD = 13.8$), or A ($M =41.1$, $SD =14.7$). All six pairwise combinations were significantly different at the $p < 0.0001$ level. The same model was re-fit as a linear regression so that areas graded A are the reference, with differences in means as estimated coefficients, as a baseline model (Table 1, Model 1).

To test for unobserved city-specific factors, a separate unconditional one-way ANOVA was performed. This second ANOVA showed significant differences in tree canopy by city [$F(36, 3151) = 21.60$, $p < 0.001$]. The intra-class correlation coefficient (ICC) indicated that 23% of the variance in tree canopy cover was from city to city (Table 1, Model 2). A mixed effects model with fixed effects for HOLC grade and random effects for city (Table 1, Model 3) showed that the areas given less-favorable grades by HOLC have significantly less canopy cover than their higher-graded counter parts, with overlap between C and D areas (i.e., $D \leq C < B < A$). Comparing the three model specifications (fixed effects for HOLC grade only, random effects for city, and a specification with both HOLC fixed effects and city random effects) with an AIC-minimization criterion showed that Model 3's added complexity provided the best fit (Table 1).

Model 3's regression-adjusted estimates of tree canopy cover suggest that areas formerly graded D had 21 percentage points less tree canopy (γ_{30} = -20.79, 95% [-22.27, -19.31]) (or 22% cover) than areas formerly graded A (γ_{00} = 43.44, 95% [40.80 to 46.07]) and the HOLC categories explained 19% of the tree canopy variance while city-to-city variation explained an additional 25%.

Results of further tests and robustness checks

A-graded neighborhoods were often the rarest, making within-city analyses under-powered statistically. In cities with 10 or more A-graded neighborhoods (Figure 1), within-city analyses of tree canopy cover by grade confirmed the pooled analyses' findings (Figure 2). Wilcoxon tests showed lower median tree canopy in D neighborhoods compared to A neighborhoods, except in Seattle ($p = 0.093$). Although the sample sizes for many cities do not permit statistical analyses of within city analyses of canopy by HOLC grade, the boxplots in Figure S1 are provided to illustrate variation among classes within each city. Tree canopy today is almost always in rank order of HOLC grades.

It is possible that the main results reported in Model 3 are driven by the patterns and sample size in the largest 16 cities with at least 50 HOLC-defined neighborhoods. We therefore re-fit Model 3 excluding the largest 16 cities and the results were substantively the same (Table S1); formerly D-graded areas have about 23% tree canopy, while formerly A-graded areas have nearly twice as much canopy today (43%). Therefore, the findings are not attributable to the patterns found in the largest cities.

3 Discussion

The link between redlining and socioeconomic outcomes such as poverty and home foreclosure have previously been documented (3, 21, 25, 36–38, 40–42, 46). The lack of access to wealth via homeownership had a powerful influence on real estate markets. People of color were deprived of an important path to wealth accumulation in many urban areas across the US (21, 25, 26). However, the relationships among historic discriminatory housing practices and current environmental conditions remain poorly understood. Redlining was one of the most consistent, wide-spread, spatial, and racial forms of US housing practices. The relationship between redlining and the current distribution of urban tree canopy cover offers a preliminary window into these larger, long term, and complex dynamics.

Trees are an important component of the urban environment. They reduce the urban heat island effect (12, 13) and provide a number of other public health benefits (47) such as crime reduction (48). In order to consider whether historic social disparities are paralleled by contemporary disparities in tree canopy, this paper examined variations in tree cover by HOLC-defined neighborhoods and the metropolitan regions containing those neighborhoods. The difference was significant: formerly D-graded areas have about 23% tree canopy today while formerly A-graded areas have nearly twice as much (43%). We found that just two variables, HOLC neighborhood grade and city, explained 43% of the variance (Table 1).

To be very clear, this study used a cross-sectional, observational quantification of social-ecological patterns that is fundamentally incapable of finding, identifying, and/or ascribing causality for complementary or competing explanations of process. The determinants of tree canopy cover in urban areas are complex (20). Our paper highlights one possible factor that may have played a role while also ruling out random chance. We argue that redlining is an understudied process in urban ecology and that our findings suggest that the role of redlining in shaping tree canopy, in concert with other explanatory factors, warrants further process-based research. HOLC's redlining was a moment in a long term history of discriminatory housing practices in the United States (23). Thus, in-depth and comparative research is needed to understand the systemic processes among long term discriminatory housing practices and contemporary environmental conditions (2).

There may be several systemic explanations for our pattern-based results. If redlining reflected existing differences in lot size and reinforced those differences through preferred investment over the long term, we could expect to see more extensive contemporary tree canopy within formerly A-graded areas. This contemporary distribution of canopy cover may be due in part to the fact that residential lots in these areas would have been larger and had more space for trees. A-graded areas were also more affluent, and households may have had higher disposable incomes to invest in landscaping such as trees. Further, because redlining helped shape wealth accumulation and related political power by race and geography, the privilege of those living in formerly A-graded neighborhoods may have served to direct public investments in tree canopy over the long term for street trees and trees in parks or through continued private household investment in landscaping on their own larger residential properties (49–52). In this way, complex and reinforcing positive feedback loops may have occurred, perpetuating relationships among housing markets, affluence, race, and trees. Such a positive feedback loop may have also been mirrored in formerly D-graded areas with lower tree canopy today due to smaller lots, industrial land uses not conducive to tree canopy cover, fewer resources for maintaining trees on properties, and less influence over public investments over the long term. Our results are consistent with both of these rationales. A process-based study is beyond the scope of this paper, but our findings provide a robust starting point to examine the longitudinal dynamics between redlining and tree canopy cover.

Our results point to at least three other areas that could benefit from further research. First, more research may be needed to understand the mechanisms for why the strong association between HOLC categories and urban tree canopy exists some 80 years after the HOLC maps were drawn and the roles that different actors may have played to maintain these differences. Many A-graded areas were suburban areas that had previously been zoned for single family housing with large lot sizes (53). D-graded areas had denser housing stock, but they may have also contained non-residential land uses, such as industrial sites, which might have been unfavorable for trees. A next step could be to examine different residential densities, land uses, policies, and tree planting programs in the different cities over time. For example, D-graded areas could have been more susceptible to urban renewal projects, supporting highways, and other large-scale infrastructure projects that could have required tree removals. Analyses of changing land uses, local policies, demographic trends, or historic aerial imagery could enable a greater understanding of the extent to which HOLC-grades 'locked in' urban forms that are more or less amenable to tree canopy.

A second approach would be to examine areas that do not match the overall pattern. So called statistical "deviant case analyses" (54) may help to build better theory about spatial, social, and environmental inequities, including historic processes of urban renewal and contemporary processes of gentrification and climatic conditions. For example, tree canopy cover in Seattle, WA in formerly A-graded neighborhoods is generally greater than in formerly D-graded neighborhoods (Figure 2), but the differences were not statistically significant ($p = 0.093$). Moreover, the two areas with the highest percent of tree canopy cover in Seattle were graded D. The distribution of tree canopy in Gary, IN appears relatively invariant to HOLC grades and may warrant further investigation, too (Figure S1). Third, additional research may disaggregate redlined neighborhoods by race and ethnicity to examine whether there are significant differences between neighborhoods with larger numbers of African-American residents, US-born white residents, and white immigrant residents, including Irish, Italian, Polish, German, and Jewish communities. A methodological challenge would be to identify realistic counterfactuals for analyzing the spatial distribution of urban tree canopy across metropolitan areas that were not redlined. Canadian cities may offer a point of comparison.

While urban trees mitigate urban heat island effects, it is important to acknowledge that trees can produce disservices (55, 56). Not everyone wants trees, so their absence may be a desired condition for some residents (57–61). Additionally, a pixel of tree canopy cover cannot reveal whether a tree was purposefully planted or sprouted through seed dispersal.

4 Conclusions

Given the long history of disinvestment in African-American communities in the United States, we sought to understand the extent to which a program in the 1930s that altered the distribution and flow of land and capital along racial lines is associated with contemporary tree canopy cover in urban areas. Our investigation into 37 cities reveals a strong association between HOLC grades inscribed on maps roughly nine decades ago and present-day tree canopy. The study design cannot identify causal pathways, but the inequity invites careful scrutiny of the social, economic, and ecological processes that have created the demonstrably uneven and inequitable distribution of urban tree canopy in the United States.

5 Methods

Sample and Data Two hundred and thirty-nine cities were redlined. As part of the Mapping Inequality project, the University of Richmond's Digital Scholarship Lab georectified and digitized more than 150 HOLC maps where HOLC-defined neighborhoods are represented as polygons (62). Shapefiles for areas with available land cover data, described below, were downloaded.

The heterogeneity of urban environments necessitates high-resolution and high-accuracy measures of tree canopy. $30m^2$ resolution datasets such as Landsat scenes or derivative products such as the National Land Cover Database (NLCD) are insufficient for mapping trees in a way that effectively operationalizes lived experience in cities (63, 64). For consistency, high-resolution tree canopy data were obtained from eleven sources.

Land cover data for twenty three areas were downloaded from The Spatial Analysis Lab (The SAL, http://gis.w3.uvm.edu/utc/, Table S2) at the University of Vermont. The SAL routinely maps large spatial extents such as counties and their methods are detailed elsewhere (65–67). Next, tree canopy data for the entire state of Pennsylvania were obtained for all HOLC-mapped cities in Pennsylvania from SAL (Altoona, Johnstown, New Castle, Philadelphia and Pittsburgh, http://letters-sal.blogspot.com/2015/09/pennslyvania-statewide-high-resolution.html). Tree canopy data for eight cities (Baltimore, MD; Johnson City-Binghamton, Syracuse, and Utica, NY; Lynchburg, Norfolk, Richmond, and Roanoke, VA) were obtained (Chesapeake Bay Program, https://chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/). Data for New Jersey (Atlantic City, Camden, and Trenton) were obtained (Pennsylvania Spatial Data Access, http://www.pasda.psu.edu/uci/DataSummary.aspx?dataset=3193). Finally, a literature review was used to identify (n = 8) sources for additional land cover data overlapping

HOLC-graded areas and corresponding authors were contacted for data access (Los Angeles and Sacramento, CA; Denver, CO; Miami and Tampa, FL; Hollyoke-Chicopee, MA; Toledo, OH; and Seattle, WA). In total, there were 3,188 HOLC-defined neighborhoods, from 37 of cities, in 16 of states from 11 sources (Table S2). Statistical analyses were conducted in R v. 3.6.1 (68) using the tidyverse (69), simple features (70), ggpubr (71), lme4 (72), sjPlot (73), and sjstats (74) packages.

Dependent variables

The dependent variable was the percentage of tree canopy cover within each HOLC zone. Consistent with previously published literature (18, 75), we define and operationalize tree canopy as "the layer of leaves, branches, and stems of trees that cover the ground when viewed from above" (76). After projecting the HOLC polygons obtained from the Mapping Inequality Project to match the land cover data, the Tabulate Area tool was used in ArcMap Version 10.2.2 (ESRI, 2014) to calculate the percent of tree canopy cover for each polygon. In seven cities (Boston, Denver, Detroit, New Haven, New York City, Seattle, and Toledo), tree canopy data were not available for the entire extent of the HOLC-defined neighborhoods, which occasionally extended into suburban areas surrounding the municipalities of interest and 156 polygons had to be omitted. This represents 4.67% of the dataset and was unavoidable. As a robustness check, described below, our main regression model was re-fit with those seven cities entirely removed.

Empirical strategy

We conducted two analyses of variance (ANOVA) with tree canopy as the dependent variable. In the first ANOVA, the independent variable was the HOLC categories in order to test our main hypothesis that mean canopy cover varied by grade. A post-hoc Tukey HSD was then used to examine which pairs of grades differed from each other. This initial ANOVA was re-fit as a linear regression model so that Grade A would be the base-case for comparison, and letters B, C, and D would be estimated as differences in means from A. This is Model 1.

In the second ANOVA, the independent variable was the city in which each neighborhood was located (hereafter Model 2). This analysis was conducted because we were concerned that unobserved city-specific characteristics pertaining to such things as land use policy, urban form, climate, and other factors may have influenced tree canopy cover. The purpose of Model 2 was to test whether tree canopy cover varied across each study city.

As anticipated, tree canopy varies significantly by city. We therefore fit a mixed effects model with the four-category HOLC grades as the fixed effects, with random intercepts for city, as shown in Eq. 1 and termed Model 3.

$$\eta_{ij} = \gamma_{00} + \gamma_{10} HOLC_{grade\_B} + \gamma_{20} HOLC_{grade\_C} + \gamma_{30} HOLC_{grade\_D} + \mu_{0j} + e_{ij} \qquad \text{Eq. 1}$$

Where η_{ij} is tree canopy as a percentage land area for HOLC polygon *i* in city *j*. HOLC grade A is the reference, and γ_{00} is the intercept and mean value of percent tree canopy cover in formerly A-graded neighborhoods. γ_{10}, γ_{20}, γ_{30}, are the coefficients of interest, which represent the differences in mean tree canopy from A by HOLC grades B, C, and D, respectively. μ_{0j} represents the city-specific random intercept, which was included to capture unobserved aspects of each city, e_{ij} is the observation-level residuals, σ^2 is the within city variance, and τ_{00} represents the variance across cities. The variance partitioning coefficient, also known as the intraclass correlation coefficient (ICC) is “a population estimate of the variance explained by the grouping structure" (77), which was calculated as the between-group-variance (τ_{00}, random intercept variance) divided by the total variance (i.e. sum of between-group-variance τ_{00} and within-group σ^2 residual variance), shown in Eq. 2.

$$ICC = \tau_{00} / [\tau_{00} + \sigma^2] \qquad \text{Eq. 2}$$

T-statistics were treated as Wald Z-statistics for calculating the confidence intervals and p-values, assuming a normal-distribution. An approximate R^2 was computed as the proportion of variance explained in the random effect after adding the categorical HOLC fixed effect to the model. This is computed as the correlation between fitted and observed values (78). AIC minimization was used to compare Models 1, 2, and 3, and to determine the best fitting model (79).

Cities with enough A- and D-graded neighborhoods were examined in order to determine if the patterns from cross-city, pooled analyses hold within individual cities. D-graded areas are common, but A-graded areas were limiting. For each city with ≥10 HOLC-defined A-neighborhoods (n = 8: Los Angeles, Chicago, Cleveland, New York City, Lynchburg, Seattle, Pittsburgh, Philadelphia), Wilcoxon Rank-Sum tests were used to compare pairwise differences in tree canopy cover from A to D neighborhoods. All other pairwise tests were omitted for parsimony (Figure 2).

Methods for further tests and robustness checks

Four types of checks were conducted: one set to assess the potentially undue influence of cities with many HOLC-defined neighborhoods, a second to assess the influence of metropolitan areas with partially missing data, and a third to examine the sensitivity of grouping the five boroughs of New York City, and Chelsea and Cambridge with Boston, and a fourth to examine data from different sources.

Two strategies were used in order to evaluate whether the results of Models 1, 2, and 3 were driven by the metropolitan areas with the most HOLC-defined neighborhoods. First, the boxplots for all cities are provided in Figure S1 so that the within city patterns can be examined visually. Secondly, as a robustness check, Model 3 was re-fit without data from the metropolitan areas with ≥ 50 neighborhoods to see if the patterns would still hold (Table S1). The inferences from this smaller model remain unchanged, however the confidence intervals are larger by construction.

Tree canopy data were not available for the entire extent of the HOLC-defined areas in seven metropolitan areas. The missing data are usually at the edges of the geographic extent, and therefore non-random. Specifically, tree canopy data were not available for the entire extent HOLC-defined neighborhoods in Boston, Denver, Detroit, New Haven, New York City, Seattle, and Toledo, which collectively represent 4.67% of the total dataset's observations. To address non-random, partially missing data at the edges of these metropolitan regions, Model 3 was re-fit with these cities removed entirely (Table S1, Model 5). Model 5 provides substantively similar results and interpretation to the main Model 3 and the point estimates remain within the bounds of Model 3's confidence intervals.

The sensitivity of the analytical decision to group the five boroughs of New York City, and Chelsea and Cambridge with Boston was also examined. A version of Model 3 (Table S1, Model 5) was fit without grouping, which adds 6 additional random intercepts. Again, no substantive changes were observed.

Finally, land cover data for Sacramento, Denver, Miami, Tampa, Holyoke-Chicopee, Toledo, and Seattle all came from different sources (Table S1, Model 6). It is possible that data from those cities may have influenced the results if the land cover data were not comparable to those produced by SAL. Based on Model 6, no substantive changes were observed. All robustness check models supported the inferences of the main results: formerly D-graded areas had roughly half as much tree canopy as formerly A-graded areas.

Limitations

Cross-city analyses (80) and meta-analyses (16, 17) have demonstrated inequitable distribution of tree canopy by already disadvantaged groups. This paper builds on those studies by using a consistent approach across 37 cities. These 37 cities (or ~15% of all redlined cities) were chosen based on availability of data. However, this convenience sample nevertheless covers a range of characteristics in population from ~42,000 people (Lynchburg, VA) to ~7.2 million people (New York City) at the time they were redlined in 15 states. When they were redlined, these 37 urban areas analyzed housed ~28.7 million people.

Data availability

If accepted, we will make summarized tree canopy information per HOLC polygon available via an online data sharing platform and an R script that replicates all of the analyses performed in this paper.

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Contributions

D.H.L., B.H. and J.M.G. designed the research;

D.H.L and B.H. performed the research;

D.H.L. and J.O.D. analyzed the data; and

D.H.L, B.H., J.M.G., S.T.A.P, L.A.O., C.F.A., and C.G.B. wrote the paper.

The authors declare no conflict of interest.

Tables

Table 1. Regressions, for % tree canopy cover, by Home Owners Loan Corporation and metropolitan region

	Model 1: Fixed Effects of HOLC Grade			Model 2: Random Effects of City			Model 3: Mixed Effects		
Fixed Effects	*Estimates*	*95% CI*	*p*	*Estimates*	*95% CI*	*p*	*Estimates*	*95% CI*	*p*
(Intercept) HOLC Grade A: "Best" (γ_{00})	41.04	39.64 to 42.45	**<0.001**	29.31	27.03 to 31.59	**<0.001**	43.44	40.80 to 46.07	**<0.001**
HOLC Grade B: "Still Desirable" (γ_{10})	-8.66	-10.31 to -7.02	**<0.001**				-9.06	-10.51 to -7.61	**<0.001**
HOLC Grade C: "Definitely Declining" (γ_{20})	-16.41	-17.96 to -14.85	**<0.001**				-16.83	-18.21 to -15.45	**<0.001**
HOLC Grade D: "Hazardous" (γ_{30})	-20.11	-21.77 to -18.44	**<0.001**				-20.79	-22.27 to -19.31	**<0.001**
Random Effects									
σ^2				153.42			116.42		
τ_{00}				46.45 $_{city}$			50.88 $_{city}$		
ICC				0.23 $_{city}$			0.30 $_{city}$		
Observations	3188			3188			3188		
R^2 / adjusted R^2	0.193 / 0.192			0.000 / 0.232			0.187 / 0.434		
AIC	25084.874			25202.044			24336.329		

Figures

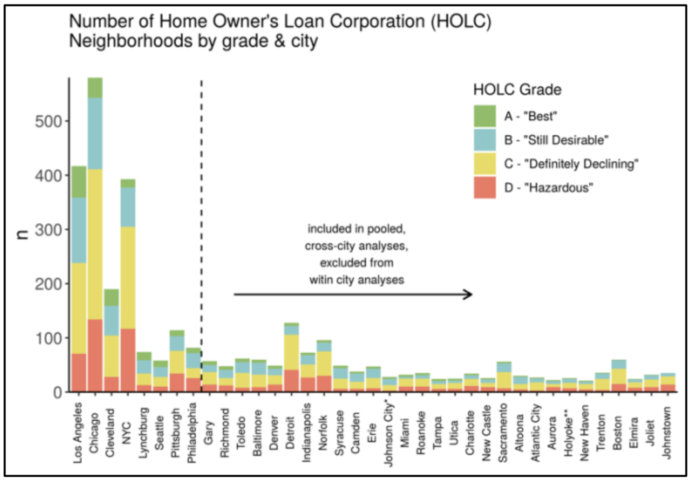

Figure 1. The distribution of HOLC neighborhoods by type and city. Cities are sorted by the number of A-graded neighborhoods. Only eight cities have ≥ 10 Grade-A neighborhoods (left) to permit within city analyses. In the main analysis, all neighborhoods are used.
*Johnson City / Birmingham, NY
**Holyoke / Chicopee, MA

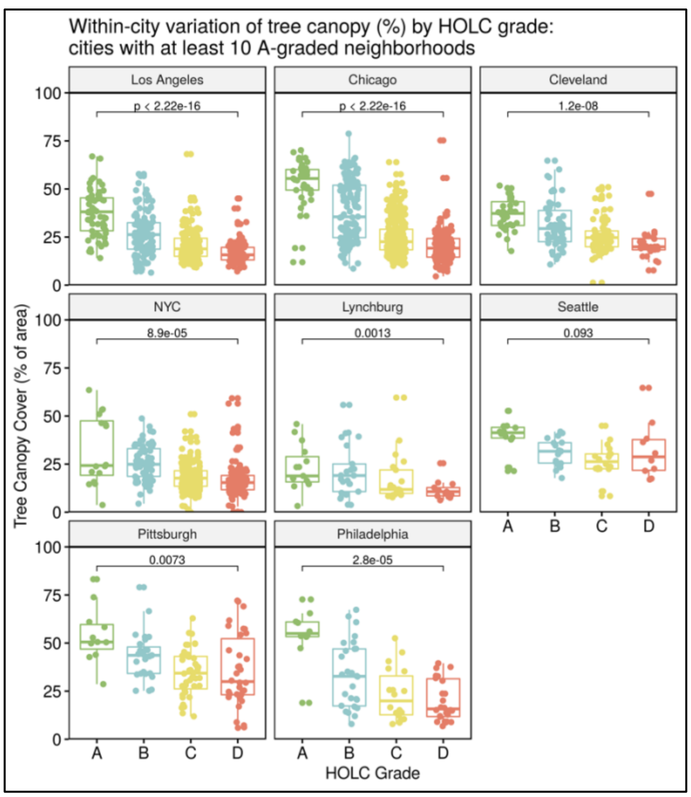

Figure 2. Within city analyses of tree canopy. The number of A-Graded neighborhoods constrains analyses within cities; only cities with ≥ 10 A-graded neighborhoods are shown. See Figure S2 for the distribution of tree canopy for all cities Note that the rank order of tree canopy cover mirrors the HOLC grades A through D. Significance tests for A to D provided via two-sample Wilcoxon test (aka Mann-Whitney test).

end January 4, 2020