Landscape and Urban Planning 221 (2022) 104370

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

The disparity in tree cover and ecosystem service values among redlining classes in the United States

David J. Nowak *, Alexis Ellis, Eric J. Greenfield

USDA Forest Service, Northern Research Station, 5 Moon Library, SUNY-ESF, Syracuse, NY 13210, USA

HIGHLIGHTS

- Redlined areas have lower percent tree cover and forest ecosystem services than non-redlined areas.
- Redlined areas in cities have higher percent impervious cover than non-redlined areas.
- Differences among redline classes are dominated by differences in impervious cover.
- As impervious cover increases, tree cover and associated ecosystem services tend to decrease.

ARTICLE INFO

Keywords:
Ecosystem services
Inequity
Redlining
Urban forestry
Urban tree cover

ABSTRACT

In the 1930's the Federal Home Loan Bank Board established a program to appraise real estate risk levels in several cities. Four classes indicating level of security for real estate investments were developed: A (green) – best, B (blue) – still desirable, C (yellow) – declining, and D (red) – hazardous. Recent studies have shown that heat island effects are greater, imperviousness is higher, and tree cover lower in areas that were formerly redlined (class D). This paper analyzed all redlined areas in U.S. cities and confirms that redlined areas (class D) have lower tree cover, greater impervious cover and lower forest ecosystem service values than other classes, with tree cover declining and impervious cover increasing as security risk class increased. Nationally, tree cover averaged 40.1 percent in class A and 20.8 percent in Class D; impervious cover averaged 30.6 in Class A and 53.0 percent in Class D. Loss of annual ecosystem services in riskier redlined areas (classes B-D) compared to the highest rated zone (class A) conservatively equates to $308 million nationally if classes B-D had the percent tree cover exhibited in Class A. At the city scale, these losses in foregone services can reach up to $100 million per year (New York, NY). As percent tree cover and percent tree cover stocking declines as percent impervious cover increases, differences in the physical impervious structure of the redlined areas at the time of designation influence tree cover differences. As redlined areas were often delimited in areas with higher population density and impervious cover, these areas tend have lower tree cover today. Even if stocking levels were increased to levels exhibited in Class A (57.8%) among all classes, tree cover would still decrease as class risk increases due to less available greenspace in lower graded classes. These patterns illustrate the importance of impervious cover on the distribution of ecosystem services and understanding the impacts of redlining practices. City policies could be directed to help offset these disparities by enhancing tree cover and reducing impervious cover in these under-resourced areas.

1. Introduction

Urban forests provide numerous benefits such as moderating climate, improving air and water quality, mitigating rainfall runoff and flooding, reducing energy building use and associated pollutant emissions, sequestering carbon, enhancing human health and social well-being and lowering noise impacts (Nowak & Dwyer, 2007). Vegetation can also negatively affect the local environment through allergen production, and other effects such as lowered wind speed and dispersion increasing local pollutant concentrations and winter shade increasing building energy use (e.g., Lyytimaki, 2017). These benefits are dependent upon the amount of tree cover, as well as species composition, tree sizes,

* Corresponding author.
E-mail addresses: david.nowak@usda.gov (D.J. Nowak), alexis.ellis@usda.gov (A. Ellis), eric.j.greenfield@usda.gov (E.J. Greenfield).

https://doi.org/10.1016/j.landurbplan.2022.104370
Received 10 May 2021; Received in revised form 14 January 2022; Accepted 20 January 2022
0169-2046/Published by Elsevier B.V.

location and tree health, as well as how the residents perceive/interact with nature and how that nature is maintained. Globally, urban tree cover averages 26.5 percent within Moderate Resolution Imaging Spectroradiometer derived (500 m resolution) urban land cover classifications (Nowak & Greenfield, 2020). In the United States, urban tree cover averages 39.6 percent based on population-density-derived Census urban land classifications (Nowak & Greenfield, 2018). These tree cover values illustrate the general magnitude of the urban tree resource. However, at the local scale, tree cover varies among land use classes and across the city landscape based on numerous factors such as available greenspace and management activities including tree planting, removals, mowing and tree care (Nowak & Greenfield, 2018).

Several recent papers have investigated the effect of historic redlining practices on current tree cover distribution and heat islands in cities (e.g., Gerrish & Watkins, 2018; Grove et al., 2018; Hoffman, Shandas, & Pendleton, 2020; Locke et al., 2021). Between 1935 and 1940, parts of hundreds of cities were delimited by the federal government's Home Owners' Loan Corporation (HOLC). HOLC assigned grades to delimited residential neighborhoods reflecting "mortgage security" that were visualized on color-coded maps. Four mortgage security risk classes were developed. Class A, the highest grade (Best), was colored green and were deemed as a minimal risk for lenders. Class B (Still desirable) was colored blue, Class C (Declining) was colored yellow, and the lowest grade, Class D, was colored red and considered "hazardous" (Nelson & Ayers, 2020).

The neighborhood grades were based on quality of housing, proximity to industry, recent history of sale and rent values, and race, ethnicity, religion, and class of residents. The presence of immigrants, poor households, and non-White racial groups were considered detrimental to a neighborhood's assessment by appraisers and other real estate professionals (Aaronson et al., 2021). These maps helped set the rules for real estate practices that made it difficult or impossible for people in "higher risk" classes to access mortgage financing and become homeowners. Redlining practices directed capital to native-born white families and away from African American and immigrant families (Nelson & Ayers, 2020). Recent studies have investigated environmental differences among redlining classes in various cities and how the redlining practices influenced generational-scale socioeconomic outcomes (e.g., Aaronson et al., 2021).

An analysis of recent tree cover in 37 metropolitan areas reveals that Class D areas average ~ 23 % tree canopy compared to ~ 43 % tree cover in Class A areas. Percent tree cover declined as class risk severity increased (Locke et al., 2021). Other studies of recent tree cover have shown that areas with lower income or more racial minorities tend to have lower tree cover (e.g., Gerrish & Watkins, 2018; Watkins & Gerrish, 2018; McDonald et al., 2021). In Baltimore, MD, Class D areas had denser development and less available space for trees and tree planting; Class A areas were mainly single-family homes on larger lots that could sustain more trees (Grove et al., 2018). In a study of seven cities there was a strong positive correlation between urban tree cover and median household income (Schwarz et al., 2015). However, substantial variability exists in the patterns of urban tree cover and ecosystem service distribution across socioeconomic groups (Riley & Gardiner, 2020).

Summertime land surface temperature differences among redline classes in 108 urban areas reveal that 94 % of studied areas had elevated land surface temperatures in formerly redlined areas (Class D) relative to their non-redlined neighbors, by up to 7° C. On average, land surface temperatures in redlined areas (Class D) were approximately 2.6° C warmer than in non-redlined areas. Higher temperatures in Class D are partly due to relatively high levels of impervious surfaces (Hoffman et al., 2020). Exposure to airborne carcinogens and respiratory hazards have also been found to be higher in lower rated classes (Namin, Xu, Zhou, & Beyer, 2020).

The intent of this paper is to investigate to what extent these disparities in tree cover exist among the various redlining classes for all cities in the United States where redlining data are available. In addition, the difference in ecosystem service values among the redlining classes is also investigated. A goal of this paper is to help illustrate the overall national impact of the legacy of redlining practices on current tree and impervious cover in cities and its associated impact on current annual urban forest ecosystem service values.

2. Methods

National U.S. redlining data were combined with national tree and impervious cover maps and U.S. Census place boundary data to quantify the tree and impervious cover within each redlined class for all places that had redlining data. Tree cover data were then combined with local environmental data to assess annual ecosystem services and values for each redline class in all places related to air pollution removal, carbon sequestration and avoided stormwater runoff.

2.1. *Redlining data*

All redline class maps (c. 1935–1940) for United States (Nelson & Ayers, 2020) were overlaid with 2010 U.S. Census place boundaries (incorporated places and census-designated places) to map the redlining class locations within each place (U.S. Census Bureau, 2020). Overall 1,259 census places had at least one redline class with 889 places having multiple classes (Supplemental Tables 1–2).

2.2. *NLCD tree and impervious cover data*

The redline class map for each place was combined with 2011 NLCD 30-meter resolution tree cover and impervious cover maps to quantify the amount and percent tree and impervious within each redlining class by place. As the 2001 NLCD cover maps are known to underestimate tree cover by 9.7 % and impervious cover by 1.5 % (Nowak & Greenfield, 2010), NLCD 2011 tree and impervious cover estimates were compared with random sampling of aerial images from c. 2011 using Google Earth. A total of 4,000 random points were interpreted across the conterminous United States to estimate percent tree and impervious cover along an associated standard error of the estimate. With 4,000 points, the maximum standard error for an estimate of cover would be 0.8 percent. Most images were high resolution in-leaf imagery. If out-of-leaf, imagery could still be accurately interpreted for cover classes. Only points on images with cloud cover or poor resolution were not interpreted and a new random point was selected.

The percentage of each cover class (p) was calculated as the number of sample points (x) hitting the cover attribute divided by the total number of interpretable sample points (n) within the area of analysis ($p = x/n$). The standard error of the estimate (SE) in cover class j was calculated as $SE_j = [p_j(1\text{-}p_j)/n]^{0.5}$ (Lindgren & McElrath, 1969). The total sample 95-percent confidence internal (cover estimate +/- 1.96 × SE) was contrasted with the national NLCD cover estimates. If the NLCD cover was outside the confidence interval, the NLCD estimate was statistically different from the photo-interpreted estimate. This comparison was conducted to calculate the potential difference between NLCD estimates and photo-interpreted values.

Statistical differences were found between NLCD values and photo-interpreted cover estimates for tree cover, but not impervious cover. The overall statistical difference in tree cover was added to each risk class tree cover values to provide better estimates of actual tree cover and aid in ecosystem service assessments. As the same adjustment factor was added to all classes, the actual NLCD differences were used to contrast cover differences among the redlining classes.

Tree cover stocking levels were calculated to contrast stocking differences among classes. Percent stocking = percent tree cover / (100 – percent impervious cover) and is an indication of the proportion of non-impervious area occupied by tree canopies (Nowak et al., 1996; Nowak & Greenfield, 2018).

Each city was assigned to its biome (forest, grassland, desert) based on global biomes data (Bailey, 1995; Olson & Dinerstein, 2002; Nature Conservancy, 2018). Differences in percent tree cover among redline classes within each biome were used to illustrate how differences among classes might vary by biome.

2.3. Ecosystem services and values

Three ecosystem service values derived from tree cover were estimated for each risk class in each place. Air pollution removal and associated health impacts were based on methods in Nowak, Hirabayashi, Ellis, & Greenfield (2014). Estimates vary by local tree cover, weather, pollution concentration and human population data. The value of health impacts was calculated using functions that estimate the health-care expenses (i.e., cost of illness and willingness to pay to avoid illness) and productivity losses associated with specific adverse health events, and on the value of a statistical life in the case of mortality.

Annual carbon sequestration by trees was based on methods in Nowak, Greenfield, Hoehn, and LaPoint (2013) and uses state average annual sequestration rates (kgC/m^2 of urban tree cover/year) times local tree cover (m^2) to estimate local carbon sequestration rates (kgC/yr). Sequestration rates are determined based on U.S. urban forest field data estimates, which vary by the length of growing season for each U.S. state. Carbon value is estimated at $188 per tonne based on the estimated social costs of carbon for 2020 with a 3 percent discount rate updated to reflect 2018 dollars (Interagency Working Group on Social Cost of Carbon, 2016).

Avoided runoff was estimated based on methods detailed in Hirabayashi (2015) and Nowak (2020). For each U.S. county, potential evaporation, potential evapotranspiration, evaporation, transpiration, precipitation interception, and avoided runoff from trees per m^2 of tree cover was estimated based on local hourly weather data (2010) and tree cover (2011 NLCD). The local standardized estimate of avoided runoff in m^3 per m^2 of tree cover per year was multiplied by local tree cover in each risk class (m^2) to estimate avoided runoff (m^3/yr). A U.S. national average dollar value of \$2.36/m^3 was used to estimate the value avoided runoff due to trees. This value is based on 16 research studies on the costs of storm water control and treatment (Nowak, 2020).

All results were calculated at the place level for each redline class and then aggregated to calculate population totals. Place and redline class information are given in Supplemental Tables 1–2.

3. Results

3.1. Tree and impervious cover – Photo-interpretation vs NLCD estimates

Statistical differences were found between NLCD and photo-interpreted estimates for tree cover, but not impervious cover. NLCD underestimated tree cover by 10.5 percent nationwide. NLCD also underestimated tree cover in each general land cover class (Table 1).

3.2. Cover differences among risk classes

Percent tree cover was highest in Class A and lowest in Class D, with tree cover and tree stocking decreasing as class risk increased. Likewise, percent impervious cover was lowest in Class A and highest in Class D, with these values increasing as class risk increased. Stocking differences would be even greater among the classes if impervious cover was constant among the classes; the increase in impervious cover as class risk increases reduces available spaces for trees and thus increases the stocking levels in areas with high impervious cover. The percent of area not occupied by tree or impervious cover was similar among all risk classes, averaging 27 percent (Table 2).

The differences among the classes were fairly consistent, but not universal. Class D had lower tree cover values than: Class A in 88.6 % of the places with multiple classes; Class B: 73.4 %; and Class C: 65.7 % (Table 3). Class D also had the higher impervious cover values than Class A in 86.4 % of the places with multiple classes; Class B: 74.6 %; and Class C: 64.8 % (Table 4).

Difference in tree cover among redlining classes were fairly consistent among the three biomes (forest, grassland, desert) with tree cover greatest in the forest biome and lowest in the desert biome (Table 5). The differences among tree cover by city between Class A and Class D are illustrated in Fig. 1.

Table 1
Comparison of 2011 percent tree cover estimates between NLCD and photo-interpreted (PI) estimates among land cover classes in the conterminous United States.

	Tree Cover			
Cover Class[a]	NLCD	PI	Diff[b]	95 % CI[c]
Forest	60.3	77.3	−17.0*	74.7–79.9
Developed	16.4	31.6	−15.2*	27.5–35.7
Pasture	14.2	24.8	−10.6*	21.0–28.6
Other	2.6	9.5	−6.9*	7.7–11.3
Crop	2.3	8.0	−5.7*	5.6–10.4
Water	0.4	5.4	−5.0*	3.4–7.4
Total	22.3	32.7	−10.5*	31.5–33.9

* statistically significant difference between NLCD and PI estimates (alpha = 0.05).
[a] Based on land cover classes from Brooks, Coulston, Riitters, and Wear (2020).
[b] NLCD cover minus PI cover.
[c] 95-percent confidence interval of PI estimate.

Table 2
Average percent tree cover, impervious cover and stocking by redlining class. Tree cover was adjusted upward by 10.5% in all classes based on photo-interpretation comparison with NLCD tree cover estimates.

Redline Class	Tree (%)	Impervious (%)	Stocking[a] (%)	Open Space[b] (%)
A - Best	40.1	30.6	57.8	29.3
B - Still desirable	28.8	44.1	51.4	27.2
C - Definitely declining	23.8	50.3	47.8	26.0
D - Hazardous	20.8	53.0	44.3	26.2

[a] Percent of greenspace (non-impervious area) filled with tree cover.
[b] Percent of area not covered by trees or impervious surfaces (i.e., grass, soil and water areas). Open space = 100 - (percent tree cover + percent impervious cover).

Table 3
Proportion of differences in tree cover among redlining classes. Table values are the percent of cities that had greater percent tree cover in column classes compared with row classes. For example, 80.1 percent of the cities had greater percent tree cover in Class A than Class B.

Class	A > Class	B > Class	C > Class
B	80.1		
C	85.4	69.0	
D	88.6	73.4	65.7

Table 4
Proportion of differences in impervious cover among redlining classes. Table values are the percent of cities that had lower percent impervious cover in column classes compared with row classes. For example, 83.6 percent of the cities had lower percent impervious cover in Class A than Class B.

Class	A < Class	B < Class	C < Class
B	83.6		
C	88.4	71.7	
D	86.4	74.6	64.8

Table 5
Percent tree cover among redlining classes by biome.

Biome	Redline Class A	B	C	D
Desert	23.9	16.4	15.2	13.1
Forest	41.2	29.4	24.0	20.9
Grassland	36.8	26.7	23.0	21.2

3.3. Ecosystem service values

Total annual ecosystem service values for air pollution removal, carbon sequestration and avoided runoff varied from $669/ha of land in Class A to $384/ha in Class D, with values declining as class risk increased (Table 6). If all classes had the same per hectare value as found in Class A, the ecosystem services in all redlined areas would increase by $308 million/year. This estimate is likely conservative as most cities did not have a Class A, but had other classes, thus loss of services could not be calculated for these cities. At the city scale, results varied based on the amount of land within each class and tree cover conditions. For the 466 cities that had a Class A, the average loss in potential annual services within Classes B-D relative to performing like Class A was $662,000 and ranged from $0 (i.e., cities where Class A had the lowest percent tree cover) to $100 million. Cities with the greatest loss of potential services were New York, NY ($100 million in foregone service per year), Philadelphia, PA ($16 million/yr), Chicago, IL ($14 million/yr), Boston, MA ($9 million/yr) and Oakland, CA ($9 million/yr). Individual city information can be found in Supplemental Tables 1 and 2.

4. Discussion

What is evident from this analysis and previous studies is that percent tree cover declines and imperviousness increases as redlining class risk increases from Class A to Class D. Percent tree cover in class A was about double that in Class D, similar to differences found from an analysis of 37 cities (A = 43 % tree cover; D = 23 % tree cover; Locke et al., 2021). Due to limitations of NLCD tree cover, cover adjustments were made to put tree cover in line with actual values. However, these adjustments would not affect the absolute differences in tree cover among classes as the adjustment (+10.5 %) was made to all classes. The adjustments will affect estimated ecosystem service estimates as tree cover was increased in all classes. It is likely that the average increase of 10.5 percent does not apply equally among all classes. As can be seen in Table 1, as tree cover increases the average difference between photo-interpreted tree cover and NLCD estimates increases. Thus, the correction factor should increase as NLCD tree cover increases. Using an average tree cover increase will lead to conservative estimates of tree cover and ecosystem service differences among classes. It is likely that

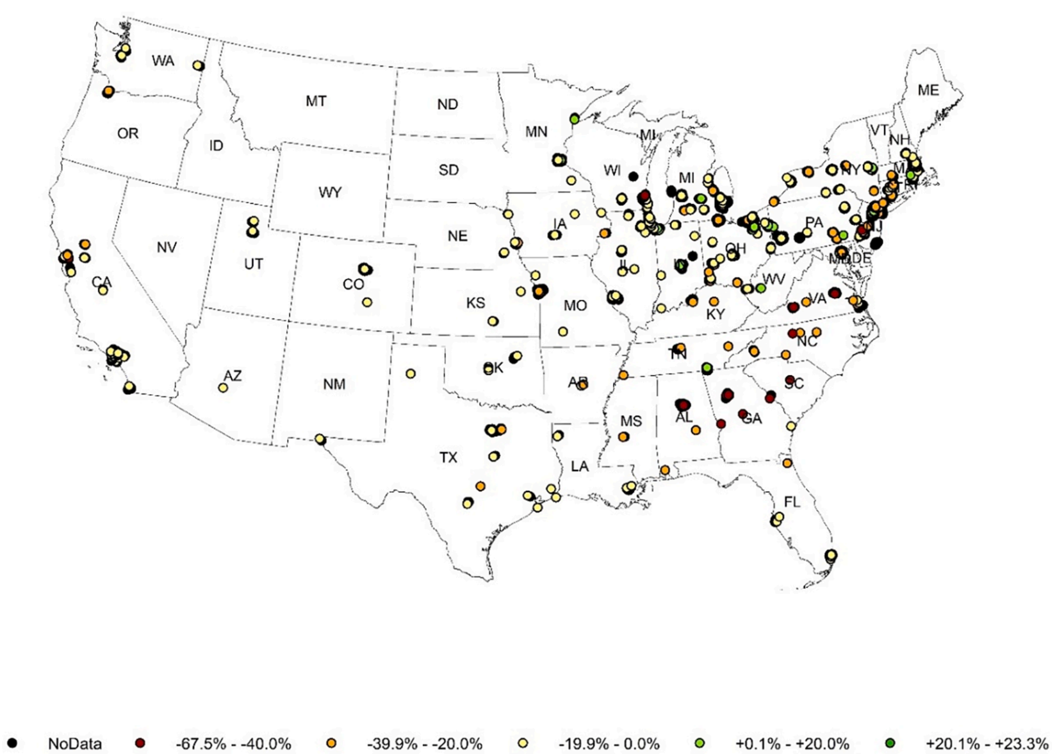

Fig. 1. Differences in percent tree cover between Class A and D (Class D cover minus Class A cover) among cities (i.e., negative value indicates reduced tree cover in Class D relative to Class A).

Table 6
Annual ecosystem service values (pollution removal, carbon sequestration, avoided runoff) by redline class and estimated loss in ecosystem services in classes B-D relative to having Class A tree cover.

Class	Area (ha $\times 10^3$)	Pollution ($ $\times 10^6$)	Carbon ($ $\times 10^6$)	Runoff ($ $\times 10^6$)	Total ($ $\times 10^6$)	Total ($/ha)	Lost Services ($ $\times 10^6$)
A	118.9	35.4	26.2	18.0	79.5	669	0
B	251.2	65.1	38.8	29.1	133.1	530	49.5
C	499.6	110.5	62.3	46.9	219.7	440	146.6
D	319.9	60.2	36.5	26.2	122.9	384	112.1

applying the average difference correction among all classes will overestimate tree cover in the higher risk classes (C, D) and underestimate tree cover in the lower risk classes (A, B), leading to conservative estimates of differences.

The differences among classes are fairly consistent across the United States. However, in addition to redlining, there are numerous other factors that affect local tree cover values. Dominant factors affecting tree cover in cities are the natural environment and land use / management activities. Based on 2014 tree cover data (Nowak & Greenfield, 2018), U.S. urban tree cover in forested regions averages 42 percent, in grasslands: 27 percent, and in deserts: 20 percent. These differences are largely due to natural regeneration, which readily occurs in forested areas where regeneration is not limited by outside forces (e.g., mowing, impervious surfaces, herbivory). In the United States and Canada, 2/3 of the existing urban forest comes from natural regeneration, with natural regeneration decreasing in more managed land uses (e.g. residential lands) and in dryer regions (Nowak, 2012).

Land use patterns and associated land management, including redlining practices, are the second most dominant factors affecting tree cover (behind the surrounding natural environment) as they determine the space available for trees and management activities that facilitate or limit tree cover (Nowak et al., 1996). A dominant factor of land use that affects tree cover is percent of the area occupied by impervious surfaces. Past studies have shown that tree cover is negatively correlated with percent impervious cover (Spearman correlation: $r = -0.72$, Nowak & Greenfield, 2012). Based on 2014 tree cover data (Nowak & Greenfield, 2018), percent tree stocking levels are also negatively correlated with percent impervious cover (Spearman correlation: $r = -0.66$). Thus, as impervious cover increases, tree cover and percent stocking decreases. Within the context of the natural environment and space available for trees, local management actions will further influence tree cover.

As differences in tree and impervious cover were found among redline classes, an interesting question, which is not addressed in this paper, is how much did redlining practices vs the existing development density at the time of redlining affect the current tree cover differences among classes? Both factors would influence tree cover. In viewing original redline maps (Nelson & Ayers, 2020), Class D areas were often in more densely developed downtown areas with higher impervious cover and Class A areas tended to occur in less densely developed areas on the outskirts of the city. Thus, for some redlined areas, even if redlining practices did not occur, it is likely that these areas would have lower tree cover due to higher impervious cover. This distinction is not to dismiss the impact of redlining. Redlined areas could also have developed or redeveloped with higher impervious cover and redlining practices could have limited mobility away from these areas. Rather, the current patterns of tree cover are a mosaic of both the physical and social environment. Further research is warranted to investigate the role of existing impervious cover at the time of redlining and its influence on current tree cover differences among redlining classes. As development density and impervious cover increase, surface temperatures will tend to increase and tree cover decrease. This influence of impervious cover on surface temperatures and tree cover exists regardless of redlining, exhibiting the influence of urban design, or lack thereof, on the local environment. Areas of high impervious cover could be improved through policies and management practices designed to increase tree cover and/or decreasing impervious cover within these areas to help sustain human health and well-being.

As noted by Schwarz et al. (2015), who found a positive correlation between tree cover and median household income, increasing income allows residents to move and buy larger lots and homes with lower percent impervious cover, but it does not necessarily increase tree cover in densely developed areas. Boone et al. (2010) also found that in the Baltimore region, key variables predicting tree cover were percent of pre-WWI housing (−), percent of post-WWII housing (+), and population density (−), indicating the influence of the vintage of development (likely lot size) and population density on tree cover. Population density influences are likely related again to percent impervious cover as percent impervious cover is positively correlated with urban population density (Spearman correlation: $r = 0.67$, Nowak & Greenfield, 2012).

The results (Table 4) indicate that all classes leave approximately 27 percent of their area open (grass/soil/water cover) and devoid of tree or impervious cover (i.e., tree + impervious cover =~ 73 percent). Thus, as impervious cover increases, the tree cover tends to decline on average. Also, as tree cover decreases, impervious cover increases, partially due to impervious cover that was previously covered by tree canopies being exposed on an aerial image.

The influence of impervious cover is substantial. Even if stocking levels were increased to levels exhibited in Class A (57.8 %) among all classes, tree cover would still decrease as class risk increases due to less available greenspace in lower graded classes. With Class A stocking levels, tree cover would increase to 32.3 % in Class B, 28.8 % in Class C, and 27.1 % in Class D, all still lower than the Class A average of 40.1 %.

While most of this reduction in tree cover comes from the physical structure of the impervious cover, social factors associated with income can affect local tree cover. In Baltimore, Class A residents directed municipal investments into street tree plantings, creating public parks with trees, and invested their own resources into trees on their private lands, while Class D 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 (Boone et al., 2010). Numerous social, physical and historical patterns interact to create current landscape distribution patterns (e.g., Grove et al., 2018) and these spatial patterns can be attributed to unequal stratification of wealth and power in human societies (Schell et al., 2020). More research is needed to better understand how factors such as urban morphology, impervious surface, land rents, past tree canopy cover, water budgets, tree planting policies, and dominant tree species affect urban tree cover (Schwarz et al., 2015). In addition, future analyses could include more recent and potentially higher resolution tree and impervious cover data, and historical census data to better assess factors associated with variations in tree and impervious cover distribution across the urban landscape.

Redlining has created systematic disinvestment in minority communities that were located in these denser, older urban core areas (Locke et al., 2021). People within these areas have lower tree cover and associated ecosystem services. The potential to add more trees in these areas is limited due to relatively high impervious cover. While physical conditions often dominate social influences on tree cover, social actions can change physical characteristics. Social actions could focus on redevelopment activities to reduce percent impervious cover within redline areas to help increase tree cover in these areas. While redevelopment opportunities may be limited, social policies could also focus on planting trees within redlined or highly impervious areas to help overcome the tree cover and tree stocking deficits.

The loss of potential ecosystem services due to lower tree cover in Classes B-D compared to Class A is conservatively estimated at $308 million per year. This loss is likely higher as many cities with Classes B-D did not have a Class A to compare with, so these cities are not included in the estimate. At the local city scale, increasing tree cover can enhance human health and well-being in these deprived areas by increasing forest ecosystem services.

5. Conclusion

There are clear and fairly consistent increases in impervious cover and reductions in tree cover and services as redline classes change from Class A to Class D. The differences in tree cover affect local ecosystem services derived from trees that affect the health and well-being of city residents, with loss in potential values that can reach millions of dollars annually in cities. Impervious cover has a substantial influence on tree cover and also influences local air temperatures with some of the impervious cover existing prior to the development of redline classes. Further investments in trees in redlined tree-deprived areas and other areas with high impervious cover can increase tree cover and associated ecosystem services in these underserved areas. However, substantial increases in tree cover may need to come from restructuring the physical environment by reducing the proportion of impervious cover. While reductions in impervious cover in currently developed areas is unlikely, the results illustrate the importance available greenspace in private lots and surround public spaces (e.g., parks) and limiting of impervious cover to enhance tree cover and associated ecosystem services when developing or redeveloping urban areas.

CRediT authorship contribution statement

David J. Nowak: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Alexis Ellis:** Methodology, Formal analysis, Investigation, Writing – review & editing. **Eric J. Greenfield:** Methodology, Formal analysis, Investigation, Writing – review & 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.

Acknowledgments

This work was funded by the USDA Forest Service. Thanks to Dexter Locke and Keith Nislow for review of an earlier draft of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2022.104370.

References

Aaronson, D., Faber, J., Hartley, D., & Mazumder, B. S. (2021). The long-run effects of the 1930s HOLC "redlining" maps on place-based measures of economic opportunity and socioeconomic success. *Regional Science and Urban Economics., 86*, Article 103622.

Bailey, R. G. (1995). *Description of the ecoregions of the United States* (2nd ed.). Misc. Pub. No. 1391, Map scale 1:7,500,000. USDA Forest Service. 108 p.

Boone, C. G., Cadenasso, M. L., Grove, M. J., Schwarz, K., & Buckley, G. L. (2010). Landscape, vegetation characteristics, and group identity in an urban and suburban watershed: Why the 60s matter. *Urban Ecosystems, 13*(3), 255–271.

Brooks, E. B., Coulston, J. W., Riitters, K. H., & Wear, D. N. (2020). Using a hybrid demand-allocation algorithm to enable distributional analysis of land use change patterns. *PLoS ONE, 15*(10), e0240097.

Gerrish, E., & Watkins, S. L. (2018). The relationship between urban forests and income: A 486 meta-analysis. *Landscape and Urban Planning, 170*, 293–308.

Grove, M., Ogden, L., Pickett, S., Boone, C., Buckley, G., Locke, D. H., … Hall, B. (2018). The legacy effect: Understanding how segregation and environmental injustice unfold over time in Baltimore. *Annals of the American Association of Geographers, 108* (2), 524–537. https://doi.org/10.1080/24694452.2017.1365585

Hirabayashi, S. (2015). *i-Tree Eco United States county-based hydrologic estimates.* Washington, DC: U.S. Department of Agriculture, Forest Service; Kent, OH: Davey Tree Expert Co.; and other cooperators. https://www.itreetools.org/documents/114/Eco_US_county-based_hydrologic_estimates.pdf Last accessed October 2020.

Hoffman, J. S., Shandas, V., & Pendleton, N. (2020). The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas. *Climate, 8*, 12; doi:10.3390/cli8010012.

Interagency Working Group on Social Cost of Carbon. (2016). *Technical support document: Social cost of carbon for regulatory impact analysis under Executive Order 12866*. https://www.epa.gov/sites/production/files/2016-12/documents/sc_co2_tsd_august_2016.pdf Last accessed October 2020.

Lindgren, B. W., & McElrath, G. W. (1969). *Introduction to Probability and Statistics*. MacMillan, London.

Locke, D., Hall, B., Grove, J. M., Pickett, S. T., Ogden, L. A., Aoki, C., … O'Neil-Dunne, J. P. M. (2021). Residential housing segregation and urban tree canopy in 37 US cities. In *Npj Urban Sustainability 1:15*. https://doi.org/10.1038/s42949-021-00022-0

Lyytimaki, J. (2017). Chapter 12: Disservices of urban trees. In F. Ferrini, C. C. Konijnendijk, & A. Fini (Eds.), *Routledge Handbook of Urban Forestry* (pp. 164–176). New York: Routledge.

McDonald, R. I., Biswas, T., Sachar, C., Housman, I., Boucher, T. M., Balk, D., … Leyk, S. (2021). The tree cover and temperature disparity in US urbanized areas: Quantifying the association with income across 5,723 communities. *PLoS ONE, 16*(4), e0249715.

Namin, S., Xu, W., Zhou, Y., & Beyer, K. (2020). The legacy of the Home Owners' Loan Corporation and the political ecology of urban trees and air pollution in the United States. *Social Science & Medicine, 246*, 112758.

Conservancy, N. (2018). tnc_terr_ecoregions. Retrieved July 2018 from http://maps.tnc.org/files/metadata/TerrEcos.xml.

Nelson. R. K., & Ayers, E. L. (2020). *Mapping Inequality, American Panorama*. https://dsl.richmond.edu/panorama/redlining/ Last accessed October 2020.

Nowak, D. J. (2012). Contrasting natural regeneration and tree planting in 14 North American cities. *Urban Forestry and Urban Greening., 11*, 374–382.

Nowak, D. J. (2020). Understanding i-Tree: Summary of Programs and Methods. General Technical Report NRS-200. Madison, WI: U.S. Department of Agriculture, Forest Service. *Northern Research Station., 100*, 2021. https://doi.org/10.2737/NRS-GTR-200. Last accessed March.

Nowak, D. J., & Dwyer, J. F. (2007). Understanding the benefits and costs of urban forest ecosystems. In J. Kuser (Ed.), *Urban and Community Forestry in the Northeast* (pp. 25–46). New York: Springer.

Nowak, D. J., & Greenfield, E. J. (2010). Evaluating the National Land Cover Database tree canopy and impervious cover estimates across the conterminous United States: A comparison with photo-interpreted estimates. *Environmental Management, 46*, 378–390.

Nowak, D. J., & Greenfield, E. J. (2012). Tree and impervious cover in the United States. *Landscape and Urban Planning, 107*, 21–30.

Nowak, D. J., & Greenfield, E. J. (2018). U.S. urban forest statistics, values and projections. *Journal of Forestry, 116*(2), 164–177.

Nowak, D. J., & Greenfield, E. J. (2020). Recent changes in global urban tree and impervious cover. *Urban Forestry and Urban Greening, 49*, 126638.

Nowak, D. J., Rowntree, R. A., McPherson, E. G., Sisinni, S. M., Kerkmann, E., & Stevens, J. C. (1996). Measuring and analyzing urban tree cover. *Lands Urban Greening, 36*, 49–57.

Nowak, D. J., Greenfield, E. J., Hoehn, R., & LaPoint, E. (2013). Carbon storage and sequestration by trees in urban and community areas of the United States. *Environmental Pollution, 178*, 229–236.

Nowak, D. J., Hirabayashi, S., Ellis, A., & Greenfield, E. J. (2014). Tree and forest effects on air quality and human health in the United States. *Environmental Pollution, 193*, 119–129.

Olson, D. M., & Dinerstein, E. (2002). The Global 200: Priority ecoregions for global conservation. *Annals of the Missouri Botanical Garden, 89*, 125–126.

Riley, C. B., & Gardiner, M. M. (2020). Examining the distributional equity of urban tree canopy cover and ecosystem services across United States cities. *PLoS ONE, 15*(2), e0228499. https://doi.org/10.1371/journal.pone.0228499

Schell, C. J., Dyson, K., Fuentes, T. L., Des Roches, S., Harris, N. C., Sterud Miller, D., … Lambert, M. R. (2020). The ecological and evolutionary consequences of systemic racism in urban environments. *Science*. https://doi.org/10.1126/science.aay4497

Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., … Cadenasso, M. L. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLoS ONE, 10*(4), e0122051. https://doi.org/10.1371/journal.pone.0122051

US Census Bureau. (2020). *Tiger/line shapefiles - 2010*. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html (last accessed October 2020).

Watkins, S. L., & Gerrish, E. (2018). The relationship between urban forests and race: A meta-488 analysis. *Journal of Environmental Management, 209*, 152–168.