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Relationships between population characteristics and nonresponse in urban forest inventories

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Abstract
Urban forest inventories are conducted to obtain important information regarding trees and the ecosystem services they provide in the urban environment. This information is derived from a sample of ground plots within which all trees are measured. It is common that some of the selected sample plots are unable to be measured, primarily due to lack of permission to access privately owned lands. At a minimum, nonresponse results in decreased sample sizes and eroded confidence in information derived from the inventory. Further, concern is raised regarding sample bias and its associated effects on analytical outcomes when the nonresponse cannot be considered random with respect to population characteristics. In this study, data from urban forest inventories conducted in 33 cities across the U.S. were used to assess amounts of nonresponse present. Total amounts of nonresponse ranged from 1.7% in Madison, WI to 36.8% in Bridgeport, CT. Examinations of potential nonrandom occurrence of nonresponse were conducted using plot location information in conjunction with various digital map layers and notable trends were found in relation to median income, median age, percent canopy cover, percent residential ownership, and percent impervious surface. In contrast, there appeared to be little correlation between nonresponse and percent of English-only speaking households. As a caveat to overly broad interpretation, in Houston, TX it was shown there was no correlation between nonresponse and median income and the relationship with percent canopy cover was opposing that of the general trend. The magnitude of potential nonresponse bias in estimates of tree biomass and tree frequency was investigated by substituting predicted values for nonresponse plots, with underestimation of both attributes ranging from approximately 1% to 10%. Thus, urban forest inventory practitioners should evaluate city-specific circumstances to effectively mitigate potential bias resulting from nonresponse in the sample.

Keywords Sample bias · Canopy cover · Socio-economic · Land use · Landowner · Ecosystem services

Introduction

The importance of trees and their many benefits to urban environments and human populations therein has gained increasing interest in the last few decades. Specific ecosystem services provided by trees in urban environments include carbon storage and sequestration, air pollution reduction, decreases in rainfall runoff, and energy effects (Nowak and Dwyer 2007; Irga et al. 2015; Kong et al. 2016). In many cities, quantification of amounts and monetary values of these ecosystem services arises from data collected while conducting urban forest inventories (Edgar et al. 2021; Östberg et al. 2018). For example, urban inventories conducted by the Forest Inventory and Analysis (FIA) program of U.S. Forest Service are typically based on approximately 200 sample plots (Nowak et al. 2008) spatially distributed within the city boundaries. Urban inventories differ from typical forest inventories in that all trees within the sample plots are measured regardless of land use (forest, residential, commercial, etc.). Annual data collection efforts are proportionally distributed depending on cycle length, e.g., 20% of the plots measured annually given a 5-year cycle (Edgar

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et al. 2021). This approach allows for updated estimates on a yearly basis. These data comprised of individual tree characteristics and related information provide inputs into statistical models that predict ecosystem service values (Nowak 2020; Scholz et al. 2018). City-wide estimates of ecosystem service contributions and other attributes of interest are then derived by summing the tree values on each urban inventory plot and using the plot values for estimation of population totals (Nowak 2020). These population values provide critical information for use by urban planners and policy makers in decision-making activities intended to improve local environmental conditions (Morgenroth and Östberg 2017).

Given the various uses of urban forest inventory information, most urban inventories implement well-established sampling designs to help ensure the estimates obtained from the inventory sample plots are unbiased. For example, FIA urban inventories use a spatially-distributed sampling paradigm that is enhanced via post-stratification to increase the precision of estimates (Edgar 2022). However, potential bias in the sample outcome due to nonresponse may be of concern when some inventory plots are unable to be measured, e.g., due to hazardous conditions or denial of access on privately owned land (Patterson et al. 2012). Often, forest inventory efforts assume nonresponse occurs randomly and thus bias is of minor concern and the primary negative effect is increased estimator variance due to the sample size reduction (Scott et al. 2005). However, in practice this assumption often is not tenable (Fattorini 2015; Särndal and Lundström 2005) and bias may be imparted to the sample when some population characteristics are more prone to nonresponse. In urban forest inventories, there may be site and/or socio-economic factors associated with nonresponse outcomes. For example, in traditional forest inventories it is more common that nonresponse occurs on private land compared to public land (Westfall et al. 2022). In the context of urban forest inventory, work by Westfall and Edgar (2022) suggest nonresponse bias can exceed 10 percent for estimates of numbers of trees and biomass density. Given that little research has been devoted to quantifying the magnitude of nonresponse present nor the potential estimation bias implications, the objectives of this study are to 1) assess nonresponse rates present in urban forest inventories, and 2) determine the correlation and direction of nonresponse rates with respect to socio-economic and land use factors present at inventory plot locations.

Methods

The entire FIA urban inventory dataset consisted of measurements taken from 2014–2019 in 33 cities across the U.S. (Fig. 1) using a consistent sample and response design. The primary field plot is defined as having the same 0.067 ha (0.166 ac) area as the FIA traditional forest inventory plot (Bechtold and Scott 2005). However, the urban inventory plot is a single 14.63 m (48.0 ft) radius circle to minimize

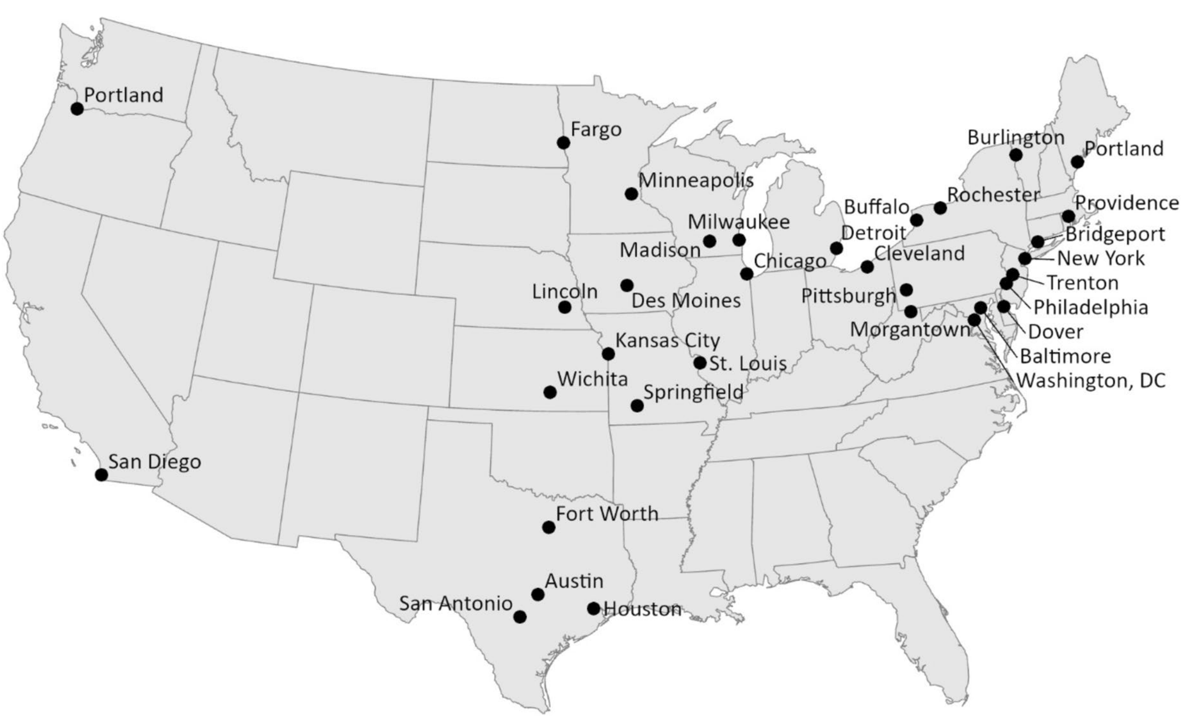

Fig. 1 Map of U.S. cities having FIA urban forest inventory

the number of landowner contacts in an urban setting (Edgar et al. 2021). Field crews are sent to each plot location to obtain measurements of various site factors and characteristics of any trees within the plot boundaries (U.S. Forest Service 2019). In some cases, crews are unable to access some or all of the plot area due to hazardous conditions or lack of permission for privately owned land. Regardless of underlying causes, inaccessible areas are considered nonresponse from a sampling perspective as no information was acquired. Thus, of particular relevance to this study is the mapping of boundaries within the and calculation of area percentage for portions of plots that could not be measured (nonresponse), with entirely inaccessible plots having a nonresponse percentage of 100. Thus, nonresponse can be partitioned into partial and complete components with the total nonresponse area being the component sum:

$$CNR\% = \frac{\sum_{i=1}^{n} p_{i(NR)}\delta_i}{n} \times 100 \quad (1)$$

$$PNR\% = \frac{\sum_{i=1}^{n} p_{i(NR)}\theta_i}{n} \times 100 \quad (2)$$

$$TNR\% = CNR\% + PNR\% \quad (3)$$

where $CNR\%$ is the percentage of plots having complete nonresponse, $PNR\%$ is the percentage of nonresponse due to partially nonsampled plots, $TNR\%$ is the percentage of sample plot areas having either complete or partial nonresponse, $p_{i(NR)}$ is the proportion of plot i area that was nonresponse, δ_i is an indicator variable (= 1 if plot i is complete nonresponse, 0 otherwise), θ_i is and indicator variable (= 1 if plot i has partial nonresponse, 0 otherwise), and n is the total number of plots selected for field measurement.

An examination of potential causal factors was conducted using spatial data sources to assess whether nonresponse occurred disproportionately in certain categories. As is commonly done in large-area forest inventory applications, the latitude and longitude coordinates of the plot center locations can be intersected with GIS map layers to assign map attributes to specific plots, e.g., eco-division or ownership information (Gormanson et al. 2018). For urban forest inventories, the plot location is usually determined with high accuracy due to clear landmark points of reference and the use of high resolution remotely-sensed imagery such as that from the National Agriculture Imagery Program (Farm Service Agency 2017). In this study, plot center locations were intersected with two sources of map data – the National Land Cover Database (NLCD) and the American Community Survey (ACS). The NLCD provides nationwide data on land cover at a 30 m resolution, including 16 discrete land cover classes, percent urban impervious surfaces, and percent tree canopy cover. Land cover and imperviousness were from the 2019 data release (Dewitz and U.S. Geological Survey 2021); tree canopy was from the 2016 data release (Coulston et al. 2012). The ACS is an ongoing survey of U.S. households that complements the decennial census to provide current information on housing, jobs, education, and many other topics (U.S. Census Bureau 2021). Demographic and economic information were extracted from the 2015–2019 ACS 5-year estimates at the block group level. Although numerous variables were present in the ACS data, a subset considered to be potentially correlated with nonresponse was chosen – median age, median income, percentage of owned residences, and percentage of only English-speaking households. With the exception of land cover class data, numerically continuous observations were binned with the mean and standard error of nonresponse proportions being calculated for each bin category. Linear regression models were used to assess the presence of systematic trends and rates of change. Model goodness-of-fit was assessed via the R^2 statistic, which indicates the proportion of variation in nonresponse explained by the model.

In some cases, similar trends in nonresponse may result from some factors that essentially supply very similar information. To help understand how some results may be correlated and aid in interpretation, a correlation matrix was constructed for the quantitative variables median income, median age, percent impervious surface, percent canopy cover, percent owned residence, and percent only English-speaking households.

To assess potential impacts of nonrandom nonresponse pattern, missing values of complete nonresponse plots were predicted for tree biomass and tree frequency using simple linear regression models where percent canopy cover served as the predictor variable. For 11 cities where the regression model R^2 was greater than 0.3 for both tree biomass and frequency, estimates of mean tree biomass and frequency attributes were then calculated for both the realized sample and the sample with model predictions substituted for missing values (i.e., imputation). Differences between the two means were considered an approximation of bias imparted due to the nonresponse in the sample.

Results

The assessment of nonresponse rates for each of the 33 cities showed considerable variability in results with $CNR\%$ ranging from 0.5%–26.5%, $PNR\%$ varying from 0.2%–13.4%, and $TNR\%$ fluctuating between 1.7%–36.8% (Table 1). Generally, cities with high $CNR\%$ tended to also have high $PNR\%$, with $CNR\%$ comprising the majority of $\%TNR$. However, there were exceptions such as Washington DC, Rochester NY, Portland OR, Wichita KS, and Burlington VT

Table 1 Complete (*CNR%*), partial (*PNR%*), and total (*TNR%*) nonresponse percentages from 33 urban forest inventory cities in the U.S. The sample size *n* is the number of plots selected for field measurement

CITY	*n*	*CNR%*	*PNR%*	*TNR%*
Bridgeport, CT	68	26.5%	10.3%	36.8%
Trenton, NJ	75	22.7%	13.4%	36.0%
Philadelphia, PA	199	20.1%	9.3%	29.4%
New York, NY	176	13.6%	9.3%	22.9%
Washington, DC	280	11.1%	10.1%	21.2%
Kansas City, MO	435	11.0%	6.9%	17.9%
Pittsburgh, PA	178	11.2%	5.3%	16.6%
Baltimore, MD	274	12.4%	3.6%	16.0%
Fort Worth, TX	74	14.9%	1.1%	16.0%
Providence, RI	229	10.0%	6.0%	16.0%
Springfield, MO	227	8.4%	7.1%	15.5%
Portland, ME	123	7.3%	7.9%	15.2%
Cleveland, OH	160	8.8%	4.3%	13.1%
St. Louis, MO	551	7.1%	5.0%	12.0%
San Antonio, TX	362	11.3%	0.6%	11.9%
Rochester, NY	140	5.7%	5.1%	10.8%
Buffalo, NY	72	6.9%	3.6%	10.6%
Detroit, MI	164	6.1%	3.5%	9.6%
Austin, TX	375	7.7%	1.4%	9.1%
San Diego, CA	258	6.2%	2.8%	9.0%
Portland, OR	228	4.4%	4.4%	8.8%
Morgantown, WV	58	3.4%	4.8%	8.3%
Minneapolis, MN	275	3.6%	4.5%	8.1%
Wichita, KS	98	4.1%	3.7%	7.8%
Dover, DE	60	6.7%	0.8%	7.5%
Chicago, IL	371	4.0%	3.4%	7.5%
Houston, TX	548	6.6%	0.2%	6.8%
Des Moines, IA	163	3.1%	2.2%	5.3%
Burlington, VT	126	2.4%	2.3%	4.7%
Milwaukee, WI	319	0.9%	1.7%	2.6%
Lincoln, NE	92	1.1%	1.2%	2.3%
Fargo, ND	87	1.1%	0.6%	1.8%
Madison, WI	187	0.5%	1.1%	1.7%
All	7032	7.8%	4.2%	12.0%

where *CNR%* and *PNR%* were similarly valued. The cities of Morgantown WV, Minneapolis MN, Milwaukee WI, Lincoln NE, and Madison WI had *PNR%* larger than *CNR%*. Across all cities studied, *TNR%* was 12.0% with *CNR%* and *PNR%* contributing 7.8% and 4.2%, respectively.

In addition to quantifying overall rates of nonresponse, the underlying causes were also examined. Approximately 93% of all nonresponses were attributed to field crews being denied access to some or all of the plot area. Denied access occurs primarily when private landowners prohibit field crews from entering their property. Most of the remainder of nonresponse (~6%) was attributed to the presence of hazardous conditions that precluded measurement activities due to safety concerns. FIA does not implement a replacement strategy for nonresponse plots to avoid creating a potential bias in the sample (Patterson et al. 2012).

Several socio-economic factors were found to have strong evidence of correlation with nonresponse rates, such that an assumption of nonresponse occurring at random may not hold in some cases. Patterns in nonresponse rates appeared to be associated with median income, median age, percentage of impervious surface, percentage of home ownership, and percent of tree canopy cover (Fig. 2). These trends were quite robust, with R^2 statistics ranging from 0.66 to 0.95. An example characteristic that seemed to have low correlation ($R^2 = 0.06$) with nonresponse rates was the percent of households speaking only the English language (Fig. 2).

Nonresponse also appeared to be nonrandom with respect to land cover class (Fig. 3).

The relationships shown above describe general findings across a range of cities. It is valuable to note that any given city may deviate from these results for one or more factors. For example, in comparison to the general trend (Fig. 2), patterns of nonresponse based on median incomes show increased rates in New York, NY, a weak relationship in Providence, RI, and a strong negative trend in Springfield, MO (Fig. 4). Similarly, a range of nonresponse patterns associated with percent canopy cover are depicted by Detroit, MI being similar to the national trend (Fig. 2), Washington, DC having no discernable trend, and Houston, TX where nonresponse decreased with increasing canopy cover (Fig. 5).

Results for correlations among factors indicated only weak to moderate strength of relationships (Table 2). The only correlation greater than 0.5 was between median income and home ownership; however, examination of the relationships between these two variables and nonresponse rates (Fig. 2) suggests differing patterns and thus each characteristic contributes a considerable amount of new information not contained in the other. The other two correlations worth noting were for median age and residence ownership (0.49) and canopy cover and impervious surface (-0.48). The rather mediocre strength of the latter result likely arises from canopy cover being an aerial phenomenon that can occur in areas primarily composed of either permeable or impervious surfaces.

Understanding biases that may be extant in the sample and the effect on population estimates is difficult because the true population values are unknown. However, substitution of imputed values from statistical models for missing

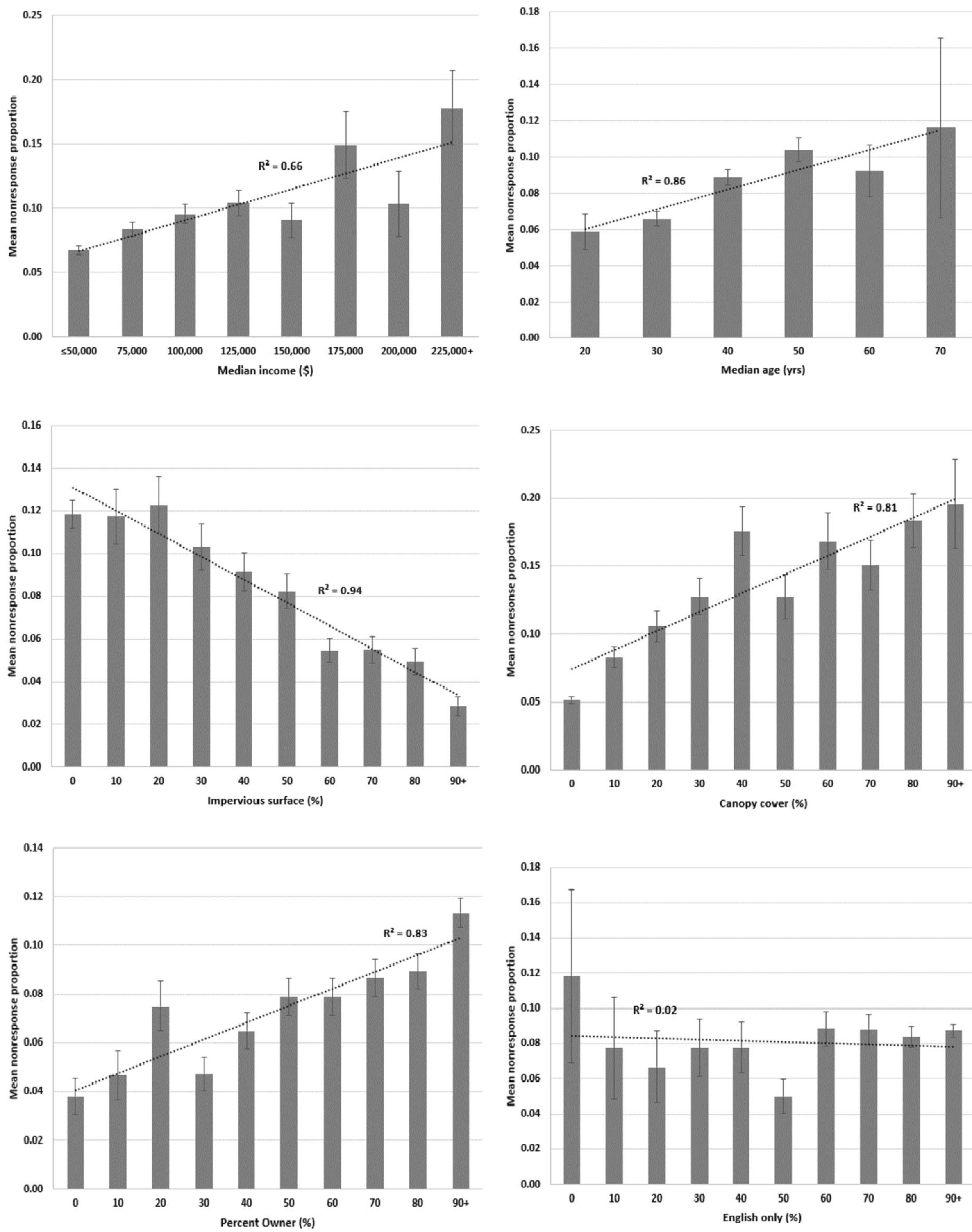

Fig. 2 Mean nonresponse proportion by category for median income, median age, percent impervious surface, percent canopy cover, percent home ownership, and percent only English-speaking homes across 33 cities in the U.S. Error bars represent ± 1 standard error

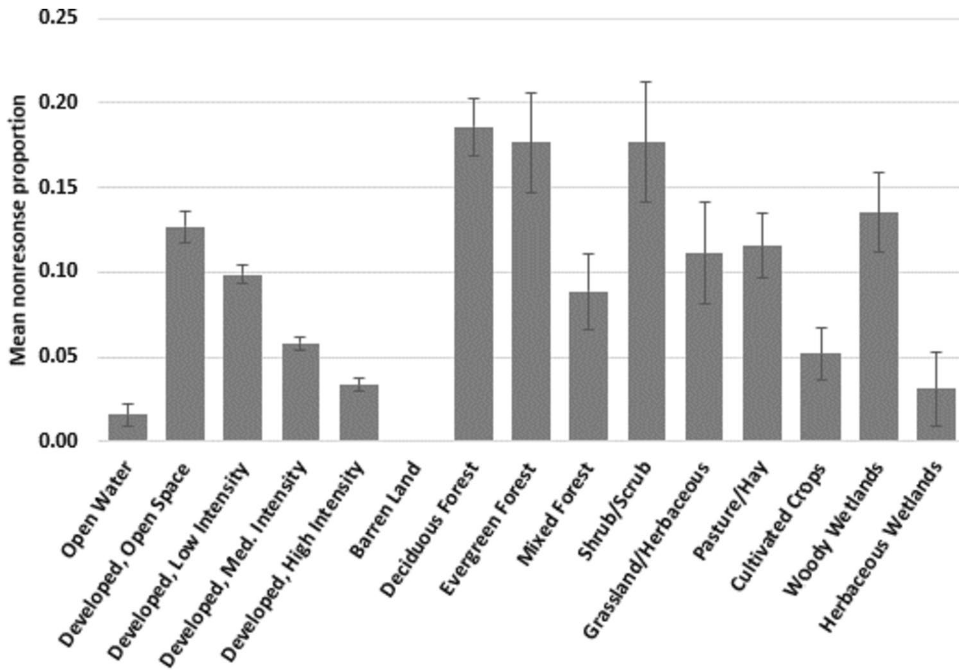

Fig. 3 Mean nonresponse proportion for 15 land use classes across 33 cities in the U.S. Error bars represent ± 1 standard error

data provides an approximation of nonrandom nonresponse consequences. Due to nonresponse primarily occurring for plots having trees present, it is often the case that nonresponse results in underestimation of attributes such as tree biomass and tree frequency. The analysis for 11 cities exhibiting a range of nonresponse showed this expected tendency, with negative potential biases generally ranging from about -1% to nearly -9%; with Washington, DC being an outlier with biases of approximately -14% and -17% for tree biomass and frequency, respectively (Table 3).

Discussion

Although practitioners strive to minimize the occurrence of nonresponse, it is encountered in virtually all sample surveys. The assessment of nonresponse rates in urban forest inventories revealed that some nonresponse occurred in every city, but rates varied widely among cities (1.7 – 36.8%). Perhaps the most prominent result was that over 10% of the plot areas intended to be measured were unsampled in approximately 50% (17/33) of the cities studied and about 15% (5/33) of cities had nonresponse areas exceeding 20%. For context, a recent study that examined nonresponse in the nationwide forest inventory of the U.S. showed slightly smaller overall *TNR%* rates of about 10%, but the range of nonresponse rates across survey units was similar to that found across cities in this study (Westfall et al. 2022). That study also reported that over 90% of the nonresponse was due to plots being complete nonresponse, whereas the urban analysis showed complete nonresponse was only about 65% of total nonresponse present. The increased presence of partial nonresponse in urban inventories is likely due to the relatively small parcel sizes encountered in urban environments that may require access permission from several landowners to measure the entire plot area. This phenomenon argues for compact field plot configurations, rather than cluster plot designs, in urban inventories to minimize the number of landowner contacts per plot.

General trends between socio-economic variables and nonresponse rates were apparent, with increases in median age, median income, and residential ownership being associated with increased nonresponse. There appeared to be no relationship between nonresponse and percent of english-speaking households. Site characteristics also seem to play a role, as larger amounts of canopy cover and smaller amounts of impervious surface were related to increased rates of nonresponse. Nonetheless, in any given city the relationships between nonresponse and the various factors studied may be different (Figs. 4 and 5). This variability among cities suggests more complex situations may be present, such as areas of low canopy cover occurring primarily on publicly-owned lands in one city in comparison to high canopy cover on public lands in another city. These outcomes indicate that city-specific analyses are often needed to understand local nonresponse dynamics. This presents a challenge when undertaking efforts to minimize nonresponse because

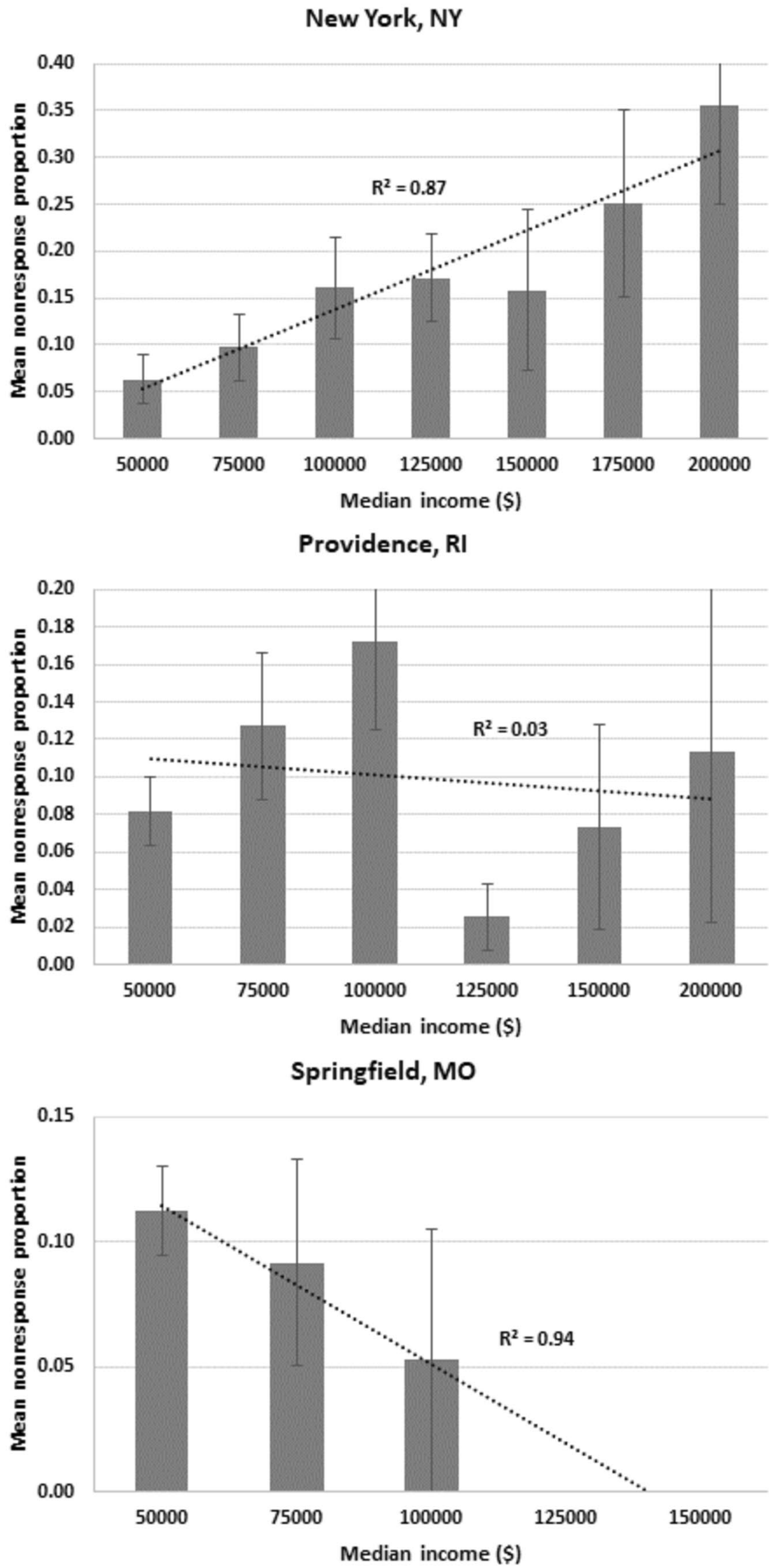

Fig. 4 Mean nonresponse proportion by median income class in New York, NY, Providence, RI, and Springfield, MO. Error bars represent ± 1 standard error

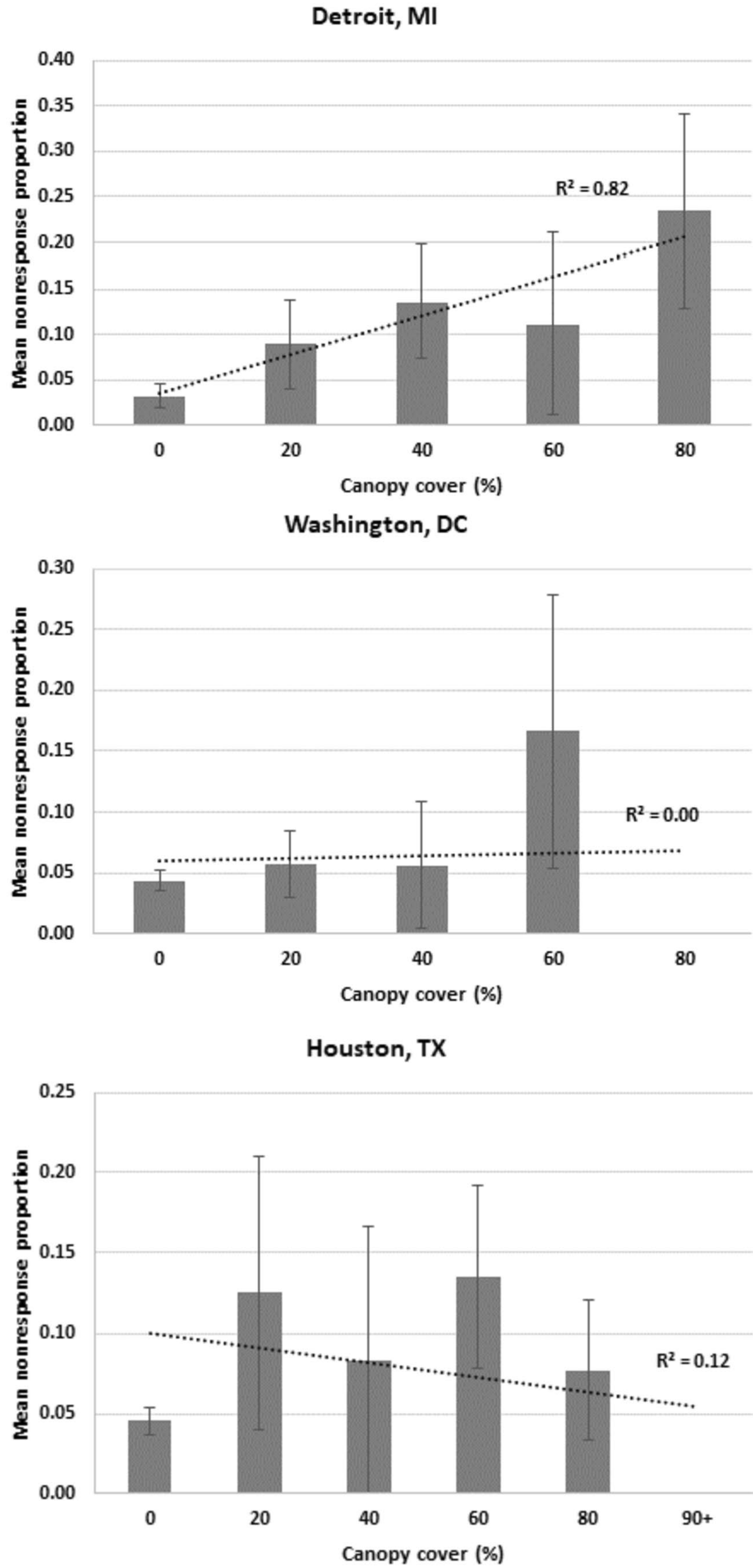

Fig. 5 Mean nonresponse proportion by percent canopy cover class in Detroit, MI, Washington, DC, and Houston, TX. Error bars represent ± 1 standard error

Table 2 Correlation matrix among quantitative population characteristics across 33 cities in the U.S

Population characteristic	Median Income	Median Age	Impervious surface	Canopy cover	Owned residence
Median Age	0.314				
Impervious surface	-0.259	-0.174			
Canopy cover	0.224	0.164	-0.482		
Owned residence	0.601	0.494	-0.303	0.215	
Speak English only	0.089	0.289	-0.106	0.100	0.316

formulation of effective strategies may need to be done on a city-by-city basis.

In cities with high nonresponse rates, population estimates are subject to poorer precision due to smaller sample sizes. However, potentially nontrivial bias in the sample may be present due to nonrandom nonresponse regardless of the nonresponse rate. Strong trends in nonrandom nonresponse using the combined data across 33 cities were found for factors such as median age, percent impervious surface, median income, percent residence ownership, and percent canopy cover. The potential sample bias incurred depends on the site conditions, e.g., increasing percent canopy cover corresponding with increased nonresponse rates (Fig. 2) suggest that nonresponse areas with relatively large amounts of wood volume may be unsampled disproportionally in comparison to areas with relatively little/no volume present. This phenomenon is further exhibited by larger rates of nonresponse in land cover classes likely to have trees present (Fig. 3). As such, estimates of attributes such as tree biomass and frequency tend to be underestimated (Table 3). The magnitude of underestimation depends on the percent of nonresponse plots and the amount of tree biomass/frequency present on those plots. In the case of characteristics such as median income or median age, it is more difficult to ascertain as the site conditions associated with these characteristics may be highly variable and the potential creation of bias in the sample difficult to identify.

Clearly, urban forest inventory practitioners should actively seek to minimize nonresponse to the extent possible. Success in achieving this goal will likely require more focused investigation into potentially interrelated social, economic, and site factors at various spatial scales to better understand underly phenomena. Result of such studies could provide a basis for developing effective communication strategies to increase response rates, e.g., perhaps different interaction tactics based on landowner age, differences between renters versus homeowners, etc. From a practical perspective, eliminating nonresponse entirely seems unlikely and the results of this study suggest proceeding as though nonresponse is a random occurrence may be ill-advised. It is beyond the scope of this paper to delve into methods of accounting for nonresponse such that bias in population estimates is minimized. Interested readers are directed to general treatment of the topic by Särndal and Lundström (2005), as well as manuscripts specific to forest inventory nonresponse (McRoberts 2003; Fattorini et al. 2013; Goeking and Patterson 2013; Domke et al. 2014; Magnussen et al. 2017; Westfall 2022). The methods described in these papers should provide insights on addressing nonresponse bias, although some adaptation may be required for application in an urban forest inventory context (Westfall and Edgar 2022).

Table 3 Estimated means of tree biomass and frequency for the observed sample and with missing values imputed for nonresponse plots, the resultant percent bias, and the R^2 statistic for the imputation model

	Mean biomass (tonnes)				Mean tree frequency (ha^{-1})			
City	Observed	Imputed	Bias%	Model R^2	Observed	Imputed	Bias%	Model R^2
Burlington, VT	50.27	50.93	-1.32	0.61	461.48	466.74	-1.14	0.33
Cleveland, OH	44.11	46.79	-6.09	0.46	418.56	445.92	-6.54	0.47
Des Moines, IA	26.55	27.33	-2.93	0.32	274.65	285.82	-4.07	0.33
Fort Worth, TX	9.07	9.41	-3.75	0.68	373.96	386.90	-3.46	0.38
Houston, TX	17.58	17.88	-1.69	0.34	500.61	515.81	-3.04	0.35
Lincoln, NE	13.25	13.44	-1.44	0.36	240.75	247.77	-2.92	0.42
Morgantown, WV	66.36	69.54	-4.78	0.62	742.15	775.14	-4.45	0.46
New York, NY	49.65	53.55	-7.84	0.30	284.35	308.11	-8.36	0.31
Providence, RI	42.92	45.31	-5.57	0.55	501.95	531.30	-5.85	0.31
San Antonio, TX	16.53	17.51	-5.97	0.39	944.64	1027.96	-8.82	0.35
Washington, DC	39.34	44.71	-13.65	0.36	236.11	275.67	-16.76	0.38

Conclusion

Survey nonresponse is a complex, multi-faceted phenomenon that often defies straightforward analysis and rational explanation. There are likely numerous inter-related factors that affect whether an urban inventory field plot is subject to complete or partial nonresponse. This complexity was illustrated in the highly variable nonresponse rates found across different cities in the U.S. In this study, a simplifying assumption of linearity was imposed when examining effects of various factors on nonresponse rates and when evaluating correlations between factors. However, in some cases nonlinear methods of assessment may provide a more accurate depiction of the results. Also, potential interactions among the factors examined may be an area to concentrate further study. Nonetheless, the results provide insight into factors that appear to be correlated with urban inventory nonresponse patterns.

Although no steadfast guidance exists as to specific thresholds when nonresponse becomes a concern, it seems reasonable to suggest that the high nonresponse rates found in some cities may warrant attention. Further, the strength of systematic trends related to median age, median income, percent owned residences, percent canopy cover, and percent impervious surface imply a bias in the sample due to nonrandom nonresponse may be present in many cities. The issue may result in less accurate estimates of ecosystem services important to city managers such as carbon sequestration, energy savings, stormwater water run-off, and species diversity. Additional empirical studies should be undertaken to quantify the magnitude of nonresponse bias that may be present in urban forest inventories.

Author contributions James A. Westfall: Conceptualization, Formal analysis, Writing—Original Draft. Christopher B. Edgar: Conceptualization, Methodology, Writing—Review & Editing. Rebekah Zehnder: Resources, Writing—Review & Editing.

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Declarations

Competing interests The authors declare no competing interests.

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