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Measuring urban tree loss dynamics across residential landscapes

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Abstract

The spatial arrangement of urban vegetation depends on urban morphology and socio-economic settings. Urban vegetation changes over time because of human management. Urban trees are removed due to hazard prevention or aesthetic preferences. Previous research attributed tree loss to decreases in canopy cover. However, this provides little information about location and structural characteristics of trees lost, as well as environmental and social factors affecting tree loss dynamics. This is particularly relevant in residential landscapes where access to residential parcels for field surveys is limited. We tested whether multi-temporal airborne LiDAR and multi-spectral imagery collected at a 5-year interval can be used to investigate urban tree loss dynamics across residential landscapes in Denver, CO and Milwaukee, WI, covering 400,705 residential parcels in 444 census tracts. Position and stem height of trees lost were extracted from canopy height models calculated as the difference between final (year 5) and initial (year 0) vegetation height derived from LiDAR. Multivariate regression models were used to predict number and height of tree stems lost in residential parcels in each census tract based on urban morphological and socio-economic variables. A total of 28,427 stems were lost from residential parcels in Denver and Milwaukee over 5 years. Overall, 7% of residential parcels lost one stem, averaging 90.87 stems per km^2. Average stem height was 10.16 m, though trees lost in Denver were taller compared to Milwaukee. The number of stems lost was higher in neighborhoods with higher canopy cover and developed before the 1970s. However, socio-economic characteristics had little effect on tree loss dynamics. The study provides a simple method for measuring urban tree loss dynamics within and across entire cities, and represents a further step towards high resolution assessments of the three-dimensional change of urban vegetation at large spatial scales.

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Keywords

multi-temporal LiDAR; urban forestry; remote sensing; vegetation dynamics; socio-ecological systems; urban ecology

1. Introduction

When viewed from above, most urban landscapes contain trees and vegetation. These can provide humans a number of important ecosystem services ranging from stormwater runoff and pollution reduction to urban heat island mitigation and psychological wellbeing (Dobbs et al. 2011, Livesley et al. 2016). As such, it is not surprising that over the last two decades the increased availability of remotely sensed imagery has fueled research on urban tree canopy cover (Iverson and Cook 2000, Mennis 2006, Jiang et al. 2017). These investigations have largely focused on the assessment of factors regulating canopy cover, such as the morphological characteristics of urban landscapes (e.g., land use, parcel size, age of development) (Luck et al. 2009, Lowry et al. 2012, Bigsby et al. 2014) and socio-economic characteristics of neighborhoods (e.g., education, income) (Grove et al. 2006, 2014, Schwarz et al. 2015).

Advancements in data collection, storage, and processing have made LiDAR (*Light Detection And Ranging*) technology much more efficient for accurate assessments of the three-dimensional structure of urban trees and vegetation (Alonzo et al. 2014, Raciti et al. 2014, Mitchell et al. 2016). These investigations are important because the structure of vegetation, rather than its cover *per se*, can significantly affect the biophysical and micro-climatic characteristics of urban greenspace (McPherson et al. 1997, Davis et al. 2016), ecological and hydrological processes (Ossola et al. 2015a, Ossola et al. 2016), and the provision of habitat for biodiversity (Stagoll et al. 2012, Le Roux et al. 2014, Ossola et al. 2015b).

However, the structure of urban vegetation is not a static measure because it is continuously re-shaped through human management and environmental factors. For example, it is estimated that about 4 million urban trees are lost each year in the United States (US), corresponding to about 1% of urban forests of the entire country (Nowak and Greenfield 2012). On the other hand, hundreds of exotic and native species of trees and shrubs are regularly planted in urban greenspace (Clarke et al. 2013, Threlfall et al. 2016). As such, the evaluation of spatial and temporal changes of vegetation and trees in urban landscapes can provide insights on the environmental and social factors driving these dynamics. This is particularly relevant in residential landscapes where the diversity of people's preferences and attitudes toward trees and vegetation can greatly affect management practices of vegetation (Cook et al. 2012, Kendal et al. 2012, van Heezik et al. 2013, Pearce et al. 2015, Conway 2016, Visscher et al. 2016).

Similar to assessments of urban tree cover, those evaluating urban forest dynamics (e.g., growth, mortality, etc.) have relied on the comparison of multi-temporal medium-and high-resolution imagery to date (Zhao et al. 2013, Zhao et al. 2016). Studies based on field-collected data examining temporal changes in vegetation structure have been generally restricted to small geographical areas due to the costs associated with field surveys, limited access to sites of interest (Quigley 2002, O'Brien et al. 2012, Briber et al. 2015, Enloe et al. 2015, Vogt et al. 2015), or the sporadic occurrence of atmospheric events such as storms and hurricanes (Burley et al. 2008, Staudhammer et al. 2011). Similarly, few manipulative experiments designed to evaluate the effects of urbanization on tree and vegetation growth or productivity have been focused on comparisons between urban and rural sites (Gregg et al. 2003, Ziska et al. 2004, Searle et al. 2012, Singh et al. 2017). At large spatial scales, most literature on urban tree loss dynamics has focused on changes in canopy cover (Nowak and Greenfield 2012, Hostetler et al. 2013). These studies, however, provide little information on location and structural characteristics (e.g., stem height) of trees lost, and as such, on the potential environmental and socio-economic factors driving these changes.

The recent availability of multi-temporal LiDAR datasets for some rural forests and plantations has allowed the investigation of vegetation structural dynamics over spatial scales ranging from individual plots to entire landscapes. For example, numerous attempts have been made to measure short-term (2–11 years) tree growth (Næsset and Gobakken 2005, Hopkinson et al. 2008) and changes in tree biomass (Meyer et al. 2013, Økseter et al. 2015, Cao et al. 2016). Similarly, canopy gap opening and closure in rural forests and tree harvesting in plantations have been monitored using LiDAR (Yu et al. 2004, Vepakomma et al. 2008, Vepakomma et al. 2010, Vepakomma et al. 2011). The only LiDAR-based study investigating dynamics of vegetation structure in urban systems was restricted to a single urban park in Osaka, Japan, over a six-year period (Song et al. 2016).

This study addresses the following objectives: i) to devise a method based on medium-resolution LiDAR collected at a 5-year interval to measure dynamics of urban tree loss across entire residential landscapes, and ii) to apply this method in two US cities to identify potential relationships between dynamics of tree loss (i.e., number of stems lost in a 5-year period and their height), and the morphological and socio-economic characteristics of residential landscapes.

2. Methods and data

2.1. Study areas

The metropolitan areas of Denver, CO and Milwaukee, WI were selected for this study due to their contrasting urbanization trajectories and availability of geospatial datasets (Fig. 1).

Denver's metropolitan area is situated in the Colorado Piedmont of the Great Plains, between the High Plains and the Rocky Mountains in the South Platte River Valley. Located at an altitude ranging from 1564 and 1768 m above sea level, the area has a semi-arid continental climate (Kottek et al. 2006) with mean annual temperature of 10.3°C and mean annual precipitation of 440 mm (PRISM Climate Group 2015). Denver was founded in 1858 and its population has recently grown to more than 750,000 people, making it one of the fastest growing US cities (US Census Bureau 2010).

Milwaukee's metropolitan area is located on the western shore of Lake Michigan at an altitude between 179 and 259 m above sea level. Due to its proximity to the Great Lakes, Milwaukee has a humid continental climate (Kottek et al. 2006) with a mean annual temperature of 9.0°C and mean annual precipitation of 861 mm (PRISM Climate Group 2015). European immigrants settled in the area in the 1830's and the population peaked in the 1960's to then decrease to 850,000 inhabitants to date (US Census Bureau 2010). As such, Milwaukee is currently considered a shrinking city. The Milwaukee study area (516 km^2) is larger than that in Denver (448 km^2), comprising some peri-urban forest and agricultural land intermixed with developed areas.

2.2. Data sources

Two airborne LiDAR point cloud datasets with similar point density were used for each city (Table 1).

LiDAR point clouds were collected in 2008 and 2013 for Denver, and in 2010 and 2015 for Milwaukee, resulting in LiDAR datasets collected at a 5-year interval. LiDAR datasets for Denver and Milwaukee were acquired by USGS and the Southeastern Wisconsin Regional Planning Commission, respectively, and are publicly available for download (Denver, http://nationalmap.gov/; Milwaukee, http://county.milwaukee.gov/mclio/geodata.html). Ground returns were already classified by the data provider. Aerial 4-band visible (RBG) and near-infrared (NIR) imagery at 1 m resolution were obtained from the National Agricultural Imagery Program (NAIP, United States Department of Agriculture; http://datagateway.nrcs.usda.gov/). NAIP imagery for Denver was acquired in 2009 and 2013, and for Milwaukee in 2010 and 2015. The collection of LiDAR and NAIP data was not simultaneous because LiDAR data are preferentially collected in winter when leaves are absent ("*leaf off*"), and NAIP imagery is acquired in summer at the peak of the growing season ("*leaf on*"). A time offset up to 3 years in the collection of LiDAR data and NAIP imagery was assumed to not significantly change urban vegetation structure in Chicago, IL (Davis et al. 2016). In this study, the maximum offset between LiDAR and NAIP data was limited to 1 year (i.e., Denver 2008–2009).

Land use/zoning and parcel maps were used to locate residential properties within the urban landscape (n=187,478 and 213,227 for Denver and Milwaukee, respectively). Publicly available land use and parcel data for Denver were acquired from the City of Denver (https://www.denvergov.org/opendata/), the City of Aurora (https://apps2.auroragov.org/opendata/) and Arapahoe County (http://www.arapahoegov.com/), whereas data for Milwaukee were acquired from Milwaukee County (http://county.milwaukee.gov/mclio). Socio-economic indicators related to population, education, employment, income inequality (Gini Index), and house physical characteristics for the year 2010 (Appendix A) were obtained from the *American FactFinder* (US Census Bureau 2010), and summarized at the census tract level as a proxy for neighborhoods (n=177 and 267 for Denver and Milwaukee, respectively).

2.3. Geostatistical analyses and validation

LiDAR—LiDAR point clouds were imported in ArcGIS Desktop 10.4.1 (ESRI, Redlands, CA). Point outliers located at more than 100 m above the ground (e.g., bird returns) were reclassified as high-noise and excluded from analysis. Digital terrain models (DTMs) for each LiDAR dataset were interpolated from ground returns using a triangulation (natural neighbor) approach (Davis et al. 2016). To accommodate for differences in point density due to LiDAR swaths and urban morphology, a raster cell size of 1.5 m was set. Although this size is about double the suggested minimum size based on the average density of the first returns of the LiDAR datasets (Chen et al. 2006), it was used in Chicago, IL using a LiDAR dataset with comparable point density (Davis et al. 2016). Digital surface models (DSMs) for each LiDAR dataset were interpolated from the first returns of above-ground features using the same methodology used for the interpolation of the DTMs. From each DSM, the respective DTM was subtracted to calculate the normalized digital surface models (nDSMs), which represent the absolute altitude of urban features (e.g., vegetation, buildings, etc.) from the ground.

VEGETATION STRUCTURAL CHARACTERISTICS—The Normalized Difference Vegetation Index (NDVI) was calculated for each of the four NAIP datasets. Woody and herbaceous vegetation were distinguished from non-vegetated areas by using a supervised classification approach based on data fusion in ArcGIS Desktop 10.4.1 (ESRI, Redlands, CA). This approach allows the classification of urban features and land use over large geographic areas (Singh et al. 2012), and avoids the use of subjective thresholds in NDVI-based classifications. Thus, the NAIP 4 bands (RGB and NIR) were fused to the corresponding NDVI and nDSM layers for each city and temporal replication. A polygon training sample and the respective spectral signature were created by manually classifying a minimum of 100,000 pixels for each of three classes (woody vegetation, herbaceous vegetation, non-vegetated). The spectral signature was used as input for supervised classification using a maximum likelihood classifier (ML). Compared to other classifiers (e.g., classification trees) ML has been demonstrated to accurately map urban land use, particularly during large-scale assessments (Singh et al. 2012).

By using an ML on each fused dataset, a *canopy mask* was created based both on the spectral (i.e., RGB and NIR) and structural (i.e., LiDAR) characteristics of vegetation by selecting the woody vegetation class. Each canopy mask was used to crop the nDSMs and calculate canopy height models (CHMs) and canopy cover for each city and year. Vegetation volume (m^3) for each city and year was calculated by multiplying the canopy height by the pixel size (2.25 m^2), assuming the entire volume to be occupied by vegetation (e.g., stems, branches, leaves, etc.—from canopy to ground). Change in vegetation height (ΔCHMs, m) was calculated by subtracting CHM 2008 from 2013 for Denver, and 2010 CHM from 2015 for Milwaukee. The location and height of trees (> 5 m) lost during the 5-year period in each city was calculated by using the *rLiDAR* library (Silva et al. 2015) in R 3.3.1 (R Core Team 2016) on the inverted ΔCHMs (Fig. 2). The function *FindTreeCHM* of the *rLiDAR* library locates individual tree tops and their heights by using an algorithm that finds local maxima within a fixed window (Silva et al. 2015). To exclude shrubs and tree saplings from analyses, we assumed adult trees to be taller than 5 m and have a canopy footprint larger than 20 m^2. Thus, the window size in *FindTreeCHM* was set to 3 pixel units (i.e., 4.5 m) and the minimum detection height threshold to 5 m.

GEOSPATIAL ANALYSIS VALIDATION—The accuracy of the DTMs and nDSMs was calculated by comparing the two temporal models created for each city (i.e., 2008 and 2013 for Denver; 2010 and 2015 for Milwaukee). In particular, 100 points were randomly selected in correspondence of bare ground and paved surfaces and the values from each DTM were detected to test their correlation (Pearson) using R 3.3.1 (R Core Team 2016). Similarly, 100 points were randomly selected in correspondence of roof tops and values of each nDSM were detected to test the correlation of the two nDSMs for each city. In doing so, we assumed that ground and roofs did not significantly change over the 5-year periods, as was visually confirmed through inspection of the NAIP imagery.

The accuracy and reliability of the supervised classification of fused data for creating vegetation masks was performed by randomly generating 100 points for both vegetation classes (i.e., woody and herbaceous). Each point was visually truthed using the NAIP imagery to calculate a confusion matrix, and thus reliability (type I errors, false positives), accuracy (type II errors, false negatives), and the overall performance of classification (Kappa coefficient). The accuracy of the workflow used for identifying tree stems lost in residential areas in the 5-year period was tested by randomly selecting 200 stems out of the all tree stems lost in both Denver and Milwaukee using ArcGIS Desktop 10.4.1 (ESRI, Redlands, CA). These 400 stems were imported to Google Earth Pro™ to visually inspect their actual removal by comparing independent historic satellite imagery (DigitalGlobe, resolution <1 m) taken before 2008 and after 2013 in Denver, and before 2010 and after 2015 in Milwaukee. Accuracy was calculated as the ratio between the number of correctly classified tree stems lost and their total number (n=200).

2.4. Statistical analyses

DATA PREPARATION—Vegetation volume and canopy cover were summarized within each residential parcel and standardized based on the parcel area for each temporal replicate and city. Parcel level variables were summarized at census tract level by averaging all the values from all the residential parcels within each census tract. The total number of tree stems and average height was summarized at census tract level. Census tracts with fewer than 100 residential parcels were excluded from statistical analyses to allow a larger statistical base.

Racial composition and age of neighborhoods have been demonstrated to be related to canopy cover in numerous US cities (e.g., Grove et al. 2006, Lowry Jr. et al. 2012). Thus, a *racial diversity index* was computed from the proportion of the different races living in each census tract by calculating the Shannon-Weiner diversity index using the library *vegan* (Oksanen et al. 2014) in R 3.3.1 (R Core Team 2016). The *decade of maximum housing development* was calculated as the decade having the highest number of built structures in each census tract and it was used as a proxy for the age of neighborhoods.

STATISTICAL ANALYSES—Multivariate linear regression analysis was used to assess the relationship between urban morphological and socio-economic characteristics and i) total number of tree stems lost in each census tract and ii) average height of all tree stems lost in each census tract (response variables). In particular, three model types (i.e., *urban morphology*, *socio-economic*, and *global*) were fitted for each city. *Urban morphology* models were fitted using predictor variables related to vegetation, parcel, and physical characteristics of land use (Table 2), and previously used to model distribution of urban tree cover (Bigsby et al. 2014).

Socio-economic models were fitted based on predictor variables related to social and economic characteristics of census tracts (Table 2). *Global* models were fitted by using both urban morphology and socio-economic predictors. Before regression analyses, variables were checked to exclude outliers and test bi-variate relationships among variables (Zuur et al. 2009). To avoid multicollinearity of the predictor variables (Appendix B), these were selected using a stepwise procedure based on the variance inflation factor (VIF) with a set threshold of 3 ($R^2 = 0.66$) (Dormann et al. 2013) (Table 2). Variables were transformed using logarithmic and squared-root transformations as required to meet normality and heteroscedasticity assumptions. Small sample-size corrected Akaike information criterion (AICc) was used to determine the level of support for the three competing model types for each city and response variable, by selecting the model with the lowest AICc. Statistical analyses were performed in R 3.3.1 (R Core Team 2016) using the libraries *corrplot* (Wei and Simko 2016), *usdm* (Naimi 2015), *gvlma* (Peña and Slate 2015), to compute correlations, VIF-variable selections, and regression analyses, respectively. Average values are reported in Results with their standard errors unless otherwise stated.

3. Results

The DTMs and nDSMs calculated from the LiDAR datasets at i) the beginning and ii) the end of the 5-year periods were significantly correlated (ρ>0.98) both in Denver and Milwaukee (Appendix C). The supervised classifications of urban vegetation (woody, herbaceous, and non-vegetated) based on data fusion of NAIP, NDVI, and nDSM yielded accuracy and reliability of classification >91% for both temporal replicate datasets of the two cities (Appendix D). The accuracy of the *rLiDAR* detection of the tree stems lost based on the ΔCHMs was 95% on average (97% for Denver and 92% for Milwaukee).

A total of 13,427 and 15,000 tree stems (height > 5m) were lost in the 5-year period from residential parcels in Denver (2008–2013) and Milwaukee (2010–2015), respectively. On a per area basis, this corresponds to an average of 99.33 ± 3.49 (Denver) and 82.41 ± 2.14 (Milwaukee) tree stems per km^2 of residential area. The tallest stems lost in Denver and Milwaukee were 28.04 and 23.82 m high, respectively. Tree stems lost in Denver were taller on average (11.42 ± 0.03 m) compared to those lost in Milwaukee (8.95 ± 0.02 m) (Fig. 3).

Urban morphology and *global* models predicting the number of tree stems lost had the lowest AICc for Denver and Milwaukee, respectively (Table 3).

Initial canopy cover was positively related to the number of tree stems lost in residential landscapes in both cities, whereas the *decade of maximum housing development* and *racial diversity index* were negative predictors in Denver and Milwaukee, respectively (Table 4). The number of tree stems lost during a 5-year period was generally greater in neighborhoods having higher residential woody vegetation cover and volume in both cities (Fig. 4). In Denver, but not in Milwaukee, the number of tree stems lost decreased with the age of neighborhoods (Fig. 5A).

In both cities, *global* models were selected to predict the height of tree stems lost (Table 3). In Denver, stem height was negatively related to *percentage of families below poverty level* and positively to *Gini index* (Table 5).

The percentage of vacant housing units was a negative predictor for stem height in both cities, though this was marginally non-significant in Milwaukee (Table 5).

4. Discussion

4.1 LiDAR and tree loss dynamics in residential landscapes

The devised methodology, based on comparison of two CHMs calculated for different years (ΔCHMs) followed by stem loss detection with *rLiDAR*, held comparable results between Denver and Milwaukee. LiDAR point clouds had relatively low point density and were acquired by various providers using different sensors and flight and data processing settings. However, the methodology proved to be a simple procedure for the synoptic assessment of changes in urban forest structure within residential landscapes across two large urban areas (>250 km^2). LiDAR datasets have been recently used to measure vegetation attributes at smaller spatial scales, such as a few local neighborhoods or greenspaces (Raciti et al. 2014, Caynes et al. 2016), though some investigations covered entire urban areas (Singh et al. 2012, Davis et al. 2016, Mitchell et al. 2016). When attempts to evaluate structural changes of urban vegetation have been made, they were generally limited to a single urban greenspace (Song et al. 2016). As such, this study initiates the use of multi-source LiDAR and multi-spectral datasets for investigation of dynamics of urban forests within relatively short temporal scales (5 years) and across entire cities.

Our methodological approach seems to be particularly suitable in residential landscapes because these are characterized by scattered and relatively isolated trees, suggesting its potential application to other urban land uses having similar canopy structural characteristics, such as urban parks and streetscapes. In comparison, preliminary trials outside of Milwaukee's residential area, where the forest has a more closed and homogenous canopy cover, yielded slightly less accurate stem loss detections (results not shown). Using a similar approach based on co-registered LiDAR-derived CHMs collected at a 5-year interval and coupled with an object-based delineation technique, Vepakomma et al. (2008) were able to automatically detect naturally-occurring canopy gaps in a small 6 km^2 patch of Canadian boreal forest with 96% accuracy, which is comparable to the average accuracy achieved in this study.

A possible limitation of our methodological approach lies in the detection of tree stems through *rLiDAR,* which is based on the uppermost morphology of tree canopies (Silva et al. 2015). Thus, it is possible stems of smaller trees lost in the understory might not have been detected, and these are likely to be underestimated. On the other hand, two stems rather than two main branches might have been detected within the same canopy footprint in some instances (Fig. 2A), causing possible overestimations. This is a known limitation of the calculation of canopy metrics from CHMs, which is likely to have dissimilar effects on tree species based on their respective morphological traits (e.g., broadleaf vs conifer) and canopy architecture (Huabing et al. 2009). The detection of trees removed or still standing using remote-sensing data remains a challenging task in urban areas where the diversity of urban forests might be high (Gillespie et al. 2017). Despite the importance of field-based information to validate remote sensing data (Gillespie et al. 2017), in our study, the lack of available tree-loss datasets and the impossibility to locate tree stems lost with a targeted field survey impeded the validation of the tree loss dataset with independent field-based data. Though the resolution of the LiDAR and multispectral datasets used in this study did not allow the discrimination of tree genera or species, further improvements could be obtained through tree species classification based on LiDAR datasets with higher point density and novel remote sensing techniques (Alonzo et al. 2014, Asner et al. 2017). These are likely to become readily available in the future, allowing researchers to incorporate the variability arising from high tree species richness typical of residential landscapes (Clarke et al. 2013, Threlfall et al. 2016). A more detailed classification of urban features, structures, and infrastructure through LiDAR datasets with higher resolution could overcome few tree stem misclassifications observed in this study (e.g., powerlines overhanging herbaceous vegetation can create false positives).

Further, a 5 m threshold for the tree stem *rLiDAR* detection was selected in this study assuming: i) adult trees to be taller than 5 m and ii) a ΔCHMs > 5 m to be indicative of trees being completely removed rather than pruned or topped. As such, some of the stems detected with *rLiDAR* may have represented trees being drastically managed, rather than completely removed from residential parcels. Tree topping might partially explain some of the differences in the frequency distribution of observed stem height between Denver and Milwaukee. However, it is likely that the different height distribution of tree stems removed primarily depends on the different species composition of residential forest across the two cities. Despite tree topping and pruning being common and widespread practices in urban greenspaces, detailed information on these management practices is scant, particularly within the private realm and at city-wide scales (Kuhns 2009). As such, the collection of urban tree-care data from professionals and land-owners, possibly stratified for different tree species and age classes, could further refine assessments of changes to urban forest based on this or similar methodological approaches.

4.2 Tree loss patterns in residential landscapes

Regression models based on urban morphological variables best explained the dynamics of tree loss in Denver, but not in Milwaukee (Table 3). As such, this only partially resonates with previous evidence suggesting urban morphology as the main driver of urban tree cover (Bigsby et al. 2014). However, tree loss was higher in neighborhoods with more vegetation.

Thus, initial canopy cover was a significant predictor of stem loss in the multivariate regression analysis. This is reasonable because the number of trees lost over time increases with increasing canopy cover due to the likely higher initial number of stems that can be potentially lost.

The number of tree stems lost was higher in Denver's neighborhoods developed before the 1970s, and at a lesser extent in Milwaukee.

As such, in the latter, the *decade of maximum housing development* was not a significant term in the regression analysis. Although previous studies found significant relationships between vegetation cover and building or neighborhood age (Mennis 2006, Boone et al. 2010, Lowry et al. 2012), we argue that age of development could have different effects when comparing tree loss dynamics in cities characterized by different development histories and planning legacies. Except for the *racial diversity index* in Milwaukee, socio-economics variables were generally poor predictors of tree stem loss, as similarly reported by Raciti et al. (2014) investigating vegetation cover and biomass in Boston's residential neighborhoods. The effect of socio-economic variables on change in cover of urban vegetation that Luck et al. (2009) found in relation to neighborhood age was not observed in our study. Similarly, *housing density,* a significant predictor of urban tree cover (Luck et al. 2009, Bigsby et al. 2014), was not related to tree loss in either city.

Regression *global* models better predicted stem height of trees removed in both cities, though these had lower power (i.e., R^2) than those predicting the number of stems lost. This was particularly evident in Milwaukee were only *percentage of vacant units* had a marginally non-significant negative relationship with stem height of lost trees. The same relationship was significant in Denver. The generally poor and inconsistent relationship between tree stem height and socio-economics might indicate that factors accounted for in this study were weakly related to people's motivations for tree removal. This is in line with a recent study where removal patterns were not related to demographics or property characteristics, but rather aesthetic preferences, perceived tree health, and risk (Conway 2016). Koeser et al. (2015) noticed size of removed trees had little effect in risk perception of homeowners, property managers, and tree care professionals, suggesting relatively consistent effects determined by the various actors managing urban trees.

In general, identifying causal relationships related to trees loss in urban areas is a challenging task. In fact, beside factors accounted for in this study, sporadic events, such as those related to pest and disease outbreaks or extreme weather, can further complicate urban tree loss assessments (Hostetler et al. 2013). For example, ~30,000 trees were removed from urban areas in Worcester County, MA (~90 km^2) between 2008 and 2012 to limit the infestation of the Asian longhorned beetle (*Anoplophora glabripennis*) on maple tree species (Rogan et al. 2013). In comparison, Hurricane Ike making landfall over Houston, TX in 2008 caused the loss of only 4.3% of trees from 37 permanent research plots established in 2001–2002, whereas 31.8% of the original trees were actually removed due to urban development (Staudhammer et al. 2011). In this study, no extreme weather events were recorded in either Denver or Milwaukee during the 5-year periods considered (NWS-NOAA 2016, Western Water Assessment 2016). Although in the last few years both study areas have been affected by various tree pests (e.g., emerald ash borer), it is not possible to speculate about possible relationships with the tree loss dynamics observed.

5. Conclusions

This study demonstrated medium-resolution LiDAR can be used to measure tree loss dynamics across entire cities and landscapes. The growing availability of high-resolution LiDAR and multispectral imagery collected over time will greatly enhance our ability to assess and monitor urban forest dynamics at large spatial scales. New research is needed to evaluate the consequential impacts of urban tree loss on urban ecosystem services such as eco-hydrological processes, habitat provision for biodiversity, and air quality improvement. Future efforts based on similar methodological approaches could investigate other important processes driving urban vegetation change (e.g., growth, afforestation, post-planting mortality, pest, and pathogen epidemics, etc.) and how these are shaped by people and the urban environment.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Appendix A:

Details of the socio-economic indicators aggregated at census tract level obtained from the *American FactFinder* of the US Census Bureau for 2010 (https://factfinder.census.gov/).

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Socio-economic indicator	Description
DP0020001	Median age (both sexes)
DP0090001	White alone or in combination with one or more other races
DP0090002	Black or African American alone or in combination with one or more other races
DP0090003	American Indian and Alaska Native alone or in combination with one or more other races
DP0090004	Asian alone or in combination with one or more other races
DP0090005	Native Hawaiian and Other Pacific Islander alone or in combination with one or more other races
DP0090006	Some Other Race alone or in combination with one or more other races
DP0120002	Population in households
DP0120014	Population in group quarters
DP0130002	Family households
DP0130010	Nonfamily households
DP0160001	Average household size
DP0170001	Average family size
DP0180002	Occupied housing units
DP0180003	Vacant housing units
DP0210002	Owner-occupied housing units
DP0210003	Renter-occupied housing units
HC01_EST_VC16	Percent high school graduate or higher (table S1501)
HC01_EST_VC17	Percent bachelor’s degree or higher (table S1501)
HC01_EST_VC01	All families (table S1702)
HC02_EST_VC01	Percent families below poverty level (table S1702)
HD01_VD01	Gini Index (table B19083)
HC02_EST_VC02	Median income (dollars) per household (table S1903)
HC01_EST_VC24	Working-age population 20 to 64 years (table S2301)
HC02_EST_VC24	In labor population 20 to 64 years (table S2301)
HC03_EST_VC24	Employed population 20 to 64 years (table S2301)
HC04_EST_VC24	Unemployment rate 20 to 64 years (table S2301)
HD01_VD01	Median contract rent (table B25058)
HD01_VD02	Buildings built in 2005 or later (table B25034)
HD01_VD03	Buildings built 2000 to 2004 or earlier
HD01_VD04	Buildings built 1990 to 1999 or earlier
HD01_VD05	Buildings built 1980 to 1989 or earlier
HD01_VD06	Buildings built 1970 to 1979 or earlier
HD01_VD07	Buildings built 1960 to 1969 or earlier
HD01_VD08	Buildings built 1950 to 1959 or earlier
HD01_VD09	Buildings built 1940 to 1949 or earlier
HD01_VD10	Buildings built 1939 or earlier

Appendix B:

Correlation matrices of the urban morphology and socio-economic variables summarized at census tract level for Denver, CO and Milwaukee, WI.

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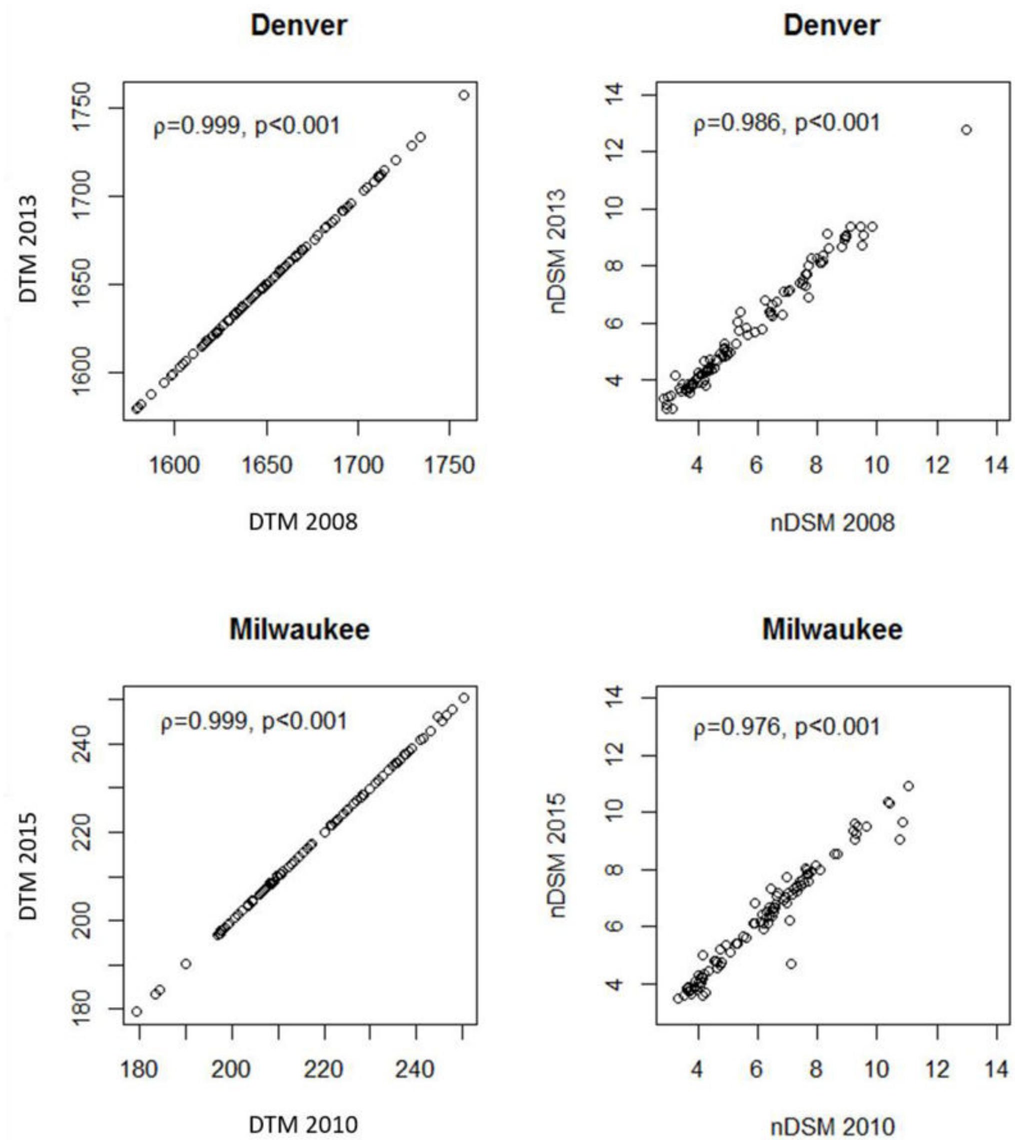
Denver, CO	**Median age**	**Racial diversity index**	**Family / non-family**	**Household size**	**% vacant units**	**% rented units**	**% high school graduate**	**% bachelor graduate**	**% below poverty**	**Gini index**	**Median annual income**	**% unemployed (20–64 y)**	**Median rent**	**Decade max development**	**Initial veg volume parcel**	**Initial veg cover parcel**	**Parcel size**	**housing density**	**% residential land use**
Median age	1.0	−0.6	0.1	−0.3	−0.1	−0.6	0.5	0.5	−0.5	0.0	0.5	−0.3	0.4	0.1	0.3	0.3	0.2	−0.1	0.0
Racial diversity index	−0.6	1.0	0.0	0.5	0.1	0.4	−0.7	−0.7	0.7	−0.2	−0.6	0.4	−0.5	0.2	−0.6	−0.5	−0.2	0.0	−0.1
Family / non-family	0.1	0.0	1.0	0.7	−0.2	−0.6	−0.2	0.0	0.0	−0.2	0.6	0.0	0.4	0.1	0.1	0.2	0.5	−0.5	0.1
Household size	−0.3	0.5	0.7	1.0	−0.1	−0.3	−0.7	−0.6	0.4	−0.4	0.1	0.3	0.0	−0.1	−0.2	−0.1	0.2	−0.5	0.1
% vacant units	−0.1	0.1	−0.2	−0.1	1.0	0.3	−0.2	−0.1	0.3	0.2	−0.2	0.2	−0.1	0.1	−0.2	−0.3	0.0	0.1	−0.3
% rented units	−0.6	0.4	−0.6	−0.3	0.3	1.0	−0.3	−0.3	0.5	0.3	−0.7	0.3	−0.6	0.1	−0.3	−0.4	−0.3	0.5	−0.3
% high school graduate	0.5	−0.7	−0.2	−0.7	−0.2	−0.3	1.0	0.8	−0.7	0.2	0.5	−0.6	0.4	0.2	0.4	0.4	0.2	0.1	0.0
% bachelor graduate	0.5	−0.7	0.0	−0.6	−0.1	−0.3	0.8	1.0	−0.7	0.4	0.7	−0.6	0.5	0.0	0.5	0.5	0.2	0.1	0.1
% below poverty	−0.5	0.7	0.0	0.4	0.3	0.5	−0.7	−0.7	1.0	0.0	−0.6	0.5	−0.5	0.1	−0.5	−0.5	−0.2	0.0	−0.2
Gini index	0.0	−0.2	−0.2	−0.4	0.2	0.3	0.2	0.4	0.0	1.0	0.0	−0.1	−0.1	0.0	0.1	0.0	0.1	0.2	−0.1
Median annual income	0.5	−0.6	0.6	0.1	−0.2	−0.7	0.5	0.7	−0.6	0.0	1.0	−0.4	0.7	0.0	0.4	0.4	0.6	−0.3	0.2
% unemployed (20–64 y)	−0.3	0.4	0.0	0.3	0.2	0.3	−0.6	−0.6	0.5	−0.1	−0.4	1.0	−0.4	0.0	−0.3	−0.3	−0.2	−0.1	−0.2
Median rent	0.4	−0.5	0.4	0.0	−0.1	−0.6	0.4	0.5	−0.5	−0.1	0.7	−0.4	1.0	0.1	0.2	0.3	0.3	−0.3	0.1
Decade max development	0.1	0.2	0.1	−0.1	0.1	0.1	0.2	0.0	0.1	0.0	0.0	0.0	0.1	1.0	−0.4	−0.3	0.1	−0.1	−0.4
Initial veg volume parcel	0.3	−0.6	0.1	−0.2	−0.2	−0.3	0.4	0.5	−0.5	0.1	0.4	−0.3	0.2	−0.4	1.0	0.9	0.3	0.0	0.5
Initial veg cover parcel	0.3	−0.5	0.2	−0.1	−0.3	−0.4	0.4	0.5	−0.5	0.0	0.4	−0.3	0.3	−0.3	0.9	1.0	0.4	−0.1	0.4
Parcel size	0.2	−0.2	0.5	0.2	0.0	−0.3	0.2	0.2	−0.2	0.1	0.6	−0.2	0.3	0.1	0.3	0.4	1.0	−0.2	0.2
housing density	−0.1	0.0	−0.5	−0.5	0.1	0.5	0.1	0.1	0.0	0.2	−0.3	−0.1	−0.3	−0.1	0.0	−0.1	−0.2	1.0	0.1
% residential land use	0.0	−0.1	0.1	0.1	−0.3	−0.3	0.0	0.1	−0.2	−0.1	0.2	−0.2	0.1	−0.4	0.5	0.4	0.2	0.1	1.0
Milwaukee, WI	Median age	Racial diversity index	Family / non-family	Household size	% vacant units	% rented units	% high school graduate	% bachelor graduate	% below poverty	Gini index	Median annual income	% unemployed (20–64 y)	Median rent	Decade max development	Initial veg volume parcel	Initial veg cover parcel	Parcel size	housing density	% residential land use
Median age	1.0	−0.4	−0.2	−0.6	−0.6	−0.7	0.6	0.4	−0.7	−0.3	0.6	−0.5	0.3	0.5	0.4	0.3	0.5	−0.4	0.2
Racial diversity index	−0.4	1.0	0.1	0.3	0.0	0.3	−0.5	−0.3	0.3	0.0	−0.3	0.1	−0.3	−0.1	−0.3	−0.3	−0.2	0.2	−0.2
Family / non-family	−0.2	0.1	1.0	0.9	0.1	−0.2	−0.4	−0.3	0.2	−0.1	0.1	0.3	−0.1	0.0	−0.1	−0.2	−0.1	−0.3	0.2
Household size	−0.6	0.3	0.9	1.0	0.4	0.1	−0.7	−0.5	0.5	0.0	−0.3	0.5	−0.3	−0.2	−0.3	−0.3	−0.3	−0.1	0.1
% vacant units	−0.6	0.0	0.1	0.4	1.0	0.6	−0.5	−0.5	0.7	0.4	−0.6	0.6	−0.4	−0.4	−0.2	−0.1	−0.3	0.2	−0.2
% rented units	−0.7	0.3	−0.2	0.1	0.6	1.0	−0.5	−0.4	0.7	0.5	−0.8	0.5	−0.4	−0.4	−0.2	−0.1	−0.3	0.5	−0.4
% high school graduate	0.6	−0.5	−0.4	−0.7	−0.5	−0.5	1.0	0.7	−0.7	−0.2	0.6	−0.5	0.6	0.3	0.4	0.3	0.4	−0.2	0.2
% bachelor graduate	0.4	−0.3	−0.3	−0.5	−0.5	−0.4	0.7	1.0	−0.6	0.0	0.7	−0.5	0.7	0.1	0.5	0.4	0.3	0.1	0.2
% below poverty	−0.7	0.3	0.2	0.5	0.7	0.7	−0.7	−0.6	1.0	0.4	−0.7	0.7	−0.5	−0.4	−0.2	−0.2	−0.3	0.2	−0.3
Gini index	−0.3	0.0	−0.1	0.0	0.4	0.5	−0.2	0.0	0.4	1.0	−0.4	0.3	−0.1	−0.1	0.1	0.1	0.0	0.3	−0.2
Median annual income	0.6	−0.3	0.1	−0.3	−0.6	−0.8	0.6	0.7	−0.7	−0.4	1.0	−0.6	0.6	0.3	0.4	0.3	0.4	−0.3	0.3
% unemployed (20–64 y)	−0.5	0.1	0.3	0.5	0.6	0.5	−0.5	−0.5	0.7	0.3	−0.6	1.0	−0.4	−0.3	−0.2	−0.2	−0.3	0.2	−0.1
Median rent	0.3	−0.3	−0.1	−0.3	−0.4	−0.4	0.6	0.7	−0.5	−0.1	0.6	−0.4	1.0	0.3	0.4	0.3	0.4	−0.2	0.2
Decade max development	0.5	−0.1	0.0	−0.2	−0.4	−0.4	0.3	0.1	−0.4	−0.1	0.3	−0.3	0.3	1.0	0.2	0.1	0.8	−0.4	−0.1
Initial veg volume parcel	0.4	−0.3	−0.1	−0.3	−0.2	−0.2	0.4	0.5	−0.2	0.1	0.4	−0.2	0.4	0.2	1.0	0.8	0.4	−0.2	0.0
Initial veg cover parcel	0.3	−0.3	−0.2	−0.3	−0.1	−0.1	0.3	0.4	−0.2	0.1	0.3	−0.2	0.3	0.1	0.8	1.0	0.3	−0.1	0.0
Parcel size	0.5	−0.2	−0.1	−0.3	−0.3	−0.3	0.4	0.3	−0.3	0.0	0.4	−0.3	0.4	0.8	0.4	0.3	1.0	−0.4	−0.1
housing density	−0.4	0.2	−0.3	−0.1	0.2	0.5	−0.2	0.1	0.2	0.3	−0.3	0.2	−0.2	−0.4	−0.2	−0.1	−0.4	1.0	0.3
% residential land use	0.2	−0.2	0.2	0.1	−0.2	−0.4	0.2	0.2	−0.3	−0.2	0.3	−0.1	0.2	−0.1	0.0	0.0	−0.1	0.3	1.0

Appendix C:

Pearson correlation (ρ) and p-value (p) of the digital elevation models (randomly-generated ground points for DTMs) and normalized digital surface models (randomly-generated roof points for nDSMs) in Denver, CO (2008 and 2013) and Milwaukee, WI (2010 and 2015).



Appendix D:

Confusion matrices calculated to test accuracy, reliability and Kappa statistic of the maximum likelihood supervised classification of urban vegetation in Denver, CO (2008, 2013) and Milwaukee, WI (2010, 2015) based on data fusion of the NAIP imagery (RGB, NIR), NDVI and nDSM. Reliability represents type I errors (false positives), accuracy represents type II errors (false negatives), and Kappa evaluates the overall performance of classification.

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Denver 2008		**Classification**					
		Woody vegetation	**Herbaceous vegetation**	**Non-vegetated**	**Total**	**Reliability**	**Kappa**
Validation	**Woody vegetation**	91	8	1	100	0.910	-
	Herbaceous vegetation	4	96	0	100	0.960	-
	Non-vegetated	0	0	0	0	0.000	-
	Total	95	104	1	200	0.000	-
	Accuracy	0.958	0.923	0.000	0.000	0.935	-
	Kappa	-	-	-	-	-	0.871

Denver 2013		**Classification**					
		Woody vegetation	**Herbaceous vegetation**	**Non-vegetated**	**Total**	**Reliability**	**Kappa**
Validation	**Woody vegetation**	91	4	5	100	0.910	-
	Herbaceous vegetation	4	95	1	100	0.950	-
	Non-vegetated	0	0	0	0	0.000	-
	Total	95	99	6	200	0.000	-
	Accuracy	0.958	0.960	0.000	0.000	0.930	-
	Kappa	-	-	-	-	-	0.864

Milwaukee 2010		**Classification**					
		Woody vegetation	**Herbaceous vegetation**	**Non-vegetated**	**Total**	**Reliability**	**Kappa**
Validation	**Woody vegetation**	96	3	1	100	0.960	-
	Herbaceous vegetation	4	96	0	100	0.960	-
	Non-vegetated	0	0	0	0	0.000	-
	Total	100	99	1	200	0.000	-
	Accuracy	0.960	0.970	0.000	0.000	0.960	-
	Kappa	-	-	-	-	-	0.920

Milwaukee 2010		**Classification**					
		Woody vegetation	**Herbaceous vegetation**	**Non-vegetated**	**Total**	**Reliability**	**Kappa**
Validation	**Woody vegetation**	91	9	0	100	0.910	-
	Herbaceous vegetation	7	93	0	100	0.930	-
	Non-vegetated	0	0	0	0	0.000	-
	Total	98	102	0	200	0.000	-
	Accuracy	0.929	0.912	0.000	0.000	0.920	-
	Kappa	-	-	-	-	-	0.840

References

Alonzo M, Bookhagen B, and Roberts DA. 2014 Urban tree species mapping using hyperspectral and lidar data fusion. Remote Sensing of Environment 148:70–83.

Asner GP, Martin RE, Knapp DE, Tupayachi R, Anderson CB, Sinca F, Vaughn NR, and Llactayo W. 2017 Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. Science 355:385. [PubMed: 28126815]

Bigsby KM, McHale MR, and Hess GR. 2014 Urban Morphology Drives the Homogenization of Tree Cover in Baltimore, MD, and Raleigh, NC. Ecosystems 17:212–227.

Boone CG, Cadenasso ML, Grove JM, Schwarz K, and Buckley GL. 2010 Landscape, vegetation characteristics, and group identity in an urban and suburban watershed: why the 60s matter. Urban Ecosystems 13:255–271.

Briber BM, Hutyra LR, Reinmann AB, Raciti SM, Dearborn VK, Holden CE, and Dunn AL. 2015 Tree Productivity Enhanced with Conversion from Forest to Urban Land Covers. PLoS ONE 10:e0136237. [PubMed: 26302444]

Burley S, Robinson SL, and Lundholm JT. 2008 Post-hurricane vegetation recovery in an urban forest. Landscape and Urban Planning 85:111–122.

Cao L, Coops NC, Innes JL, Sheppard SRJ, Fu L, Ruan H, and She G. 2016 Estimation of forest biomass dynamics in subtropical forests using multi-temporal airborne LiDAR data. Remote Sensing of Environment 178:158–171.

Caynes RJC, Mitchell MGE, Wu DS, Johansen K, and Rhodes JR. 2016 Using high-resolution LiDAR data to quantify the three-dimensional structure of vegetation in urban green space. Urban Ecosystems:1–17.

Chen Q, Baldocchi D, Gong P, and Kelly M. 2006 Isolating Individual Trees in a Savanna Woodland Using Small Footprint Lidar Data. Photogrammetric Engineering & Remote Sensing 72:923–932.

Clarke LW, Jenerette GD, and Davila A. 2013 The luxury of vegetation and the legacy of tree biodiversity in Los Angeles, CA. Landscape and Urban Planning 116:48–59.

Conway TM 2016 Tending their urban forest: Residents' motivations for tree planting and removal. Urban Forestry & Urban Greening 17:23–32.

Cook EM, Hall SJ, and Larson KL. 2012 Residential landscapes as social-ecological systems: a synthesis of multi-scalar interactions between people and their home environment. Urban Ecosystems 15:19–52.

Davis AY, Jung J, Pijanowski BC, and Minor ES. 2016 Combined vegetation volume and "greenness" affect urban air temperature. Applied Geography 71:106–114.

Dobbs C, Escobedo FJ, and Zipperer WC. 2011 A framework for developing urban forest ecosystem services and goods indicators. Landscape and Urban Planning 99:196–206.

Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, Marquéz JRG, Gruber B, Lafourcade B, Leitão PJ, Münkemüller T, McClean C, Osborne PE, Reineking B, Schröder B, Skidmore AK, Zurell D, and Lautenbach S. 2013 Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:27–46.

Enloe HA, Lockaby BG, Zipperer WC, and Somers GL. 2015 Urbanization effects on leaf litter decomposition, foliar nutrient dynamics and aboveground net primary productivity in the subtropics. Urban Ecosystems 18:1285–1303.

Gillespie TW, de Goede J, Aguilar L, Jenerette DE, Fricker GA, Avolio ML, Pincetl S, Stephanie T Johnston LW Clarke DE 2017 "Predicting tree species richness in urban forests." Urban Ecosystems 10.1007/s11252-016-0633-2.

Gregg JW, Jones CG, and Dawson TE. 2003 Urbanization effects on tree growth in the vicinity of New York City. Nature 424:183–187. [PubMed: 12853954]

Grove JM, Locke D, and O'Neil-Dunne JM. 2014 An Ecology of Prestige in New York City: Examining the Relationships Among Population Density, Socio-economic Status, Group Identity, and Residential Canopy Cover. Environmental Management 54:402–419. [PubMed: 25034751]

Grove JM, Troy AR, O'Neil-Dunne JPM, Burch WR, Cadenasso ML, and Pickett STA. 2006 Characterization of Households and Its Implications for the Vegetation of Urban Ecosystems. Ecosystems 9:578–597.

Hopkinson C, Chasmer L, and Hall RJ. 2008 The uncertainty in conifer plantation growth prediction from multi-temporal lidar datasets. Remote Sensing of Environment 112:1168–1180.

Hostetler AE, Rogan J, Martin D, DeLauer V, and O'Neil-Dunne J. 2013 Characterizing tree canopy loss using multi-source GIS data in Central Massachusetts, USA. Remote Sensing Letters 4:1137–1146.

Huabing H, Peng G, Xiao C, Nick C, and Zengyuan L. 2009 Improving Measurement of Forest Structural Parameters by Co-Registering of High Resolution Aerial Imagery and Low Density LiDAR Data. Sensors (14248220) 9:1541–1558. [PubMed: 22573971]

Iverson LR, and Cook EA. 2000 Urban forest cover of the Chicago region and its relation to household density and income. Urban Ecosystems 4:105–124.

Jiang B, Deal B, Pan H, Larsen L, Hsieh C-H, Chang C-Y, and Sullivan WC. 2017 Remotely-sensed imagery vs. eye-level photography: Evaluating associations among measurements of tree cover density. Landscape and Urban Planning 157:270–281.

Kendal D, Williams NSG, and Williams KJH. 2012 Drivers of diversity and tree cover in gardens, parks and streetscapes in an Australian city. Urban Forestry & Urban Greening 11:257–265.

Koeser AK, Klein RW, Hasing G, and Northrop RJ. 2015 Factors driving professional and public urban tree risk perception. Urban Forestry & Urban Greening 14:968–974.

Kottek M, Grieser J, Beck C, Rudolf B, and Rubel F. 2006 World Map of the Köppen-Geiger climate classification updated. Meteorologische Zeitschrift 15:259–263.

Kuhns MR 2009 Tree care and topping beliefs, knowledge, and practices in six western u.s. cities. Journal of Arboriculture 35:122–128.

Le Roux DS, Ikin K, Lindenmayer DB, Manning AD, and Gibbons P. 2014 The Future of Large Old Trees in Urban Landscapes. PLoS ONE 9:e99403. [PubMed: 24941258]

Livesley SJ, McPherson GM, and Calfapietra C. 2016 The urban forest and ecosystem services: Impacts on urban water, heat, and pollution cycles at the tree, street, and city scale. Journal of Environmental Quality 45:119–124. [PubMed: 26828167]

Lowry JH, Baker ME, and Ramsey RD. 2012 Determinants of urban tree canopy in residential neighborhoods: Household characteristics, urban form, and the geophysical landscape. Urban Ecosystems 15:247–266.

Luck GW, Smallbone LT, and O'Brien R. 2009 Socio-Economics and Vegetation Change in Urban Ecosystems: Patterns in Space and Time. Ecosystems 12:604.

McPherson EG, Nowak D, Heisler G, Grimmond S, Souch C, Grant R, and Rowntree R. 1997 Quantifying urban forest structure, function, and value: the Chicago urban forest climate project. Urban Ecosystems 1:49–61.

Mennis J 2006 Socioeconomic-Vegetation Relationships in Urban, Residential Land. Photogrammetric Engineering & Remote Sensing 72:911–921.

Meyer V, Saatchi SS, Chave J, Dalling JW, Bohlman S, Fricker GA, Robinson C, Neumann M, and Hubbell S. 2013 Detecting tropical forest biomass dynamics from repeated airborne lidar measurements. Biogeosciences 10:5421–5438.

Mitchell MGE, Wu D, Johansen K, Maron M, McAlpine C, and Rhodes JR. 2016 Landscape structure influences urban vegetation vertical structure. Journal of Applied Ecology:n/a-n/a.

Næsset E, and Gobakken T. 2005 Estimating forest growth using canopy metrics derived from airborne laser scanner data. Remote Sensing of Environment 96:453–465.

Naimi B 2015 usdm R library: Uncertainty Analysis for Species Distribution Models

Nowak DJ, and Greenfield EJ. 2012 Tree and impervious cover change in U.S. cities. Urban Forestry & Urban Greening 11:21–30.

NWS-NOAA. 2016.

O'Brien AM, Ettinger AK, and HilleRisLambers J. 2012 Conifer growth and reproduction in urban forest fragments: Predictors of future responses to global change? Urban Ecosystems 15:879–891.

Oksanen J, Guillaume Blanchet F, Kindt R, Legendre P, Minchin P, O'Hara R, Simpson G, Solymos P, Stevens M, and Wagner H. 2014 vegan: Community Ecology Package. R package version 2.2–0.

Økseter R, Bollandsås OM, Gobakken T, and Næsset E. 2015 Modeling and predicting aboveground biomass change in young forest using multi-temporal airborne laser scanner data. Scandinavian Journal of Forest Research 30:458–469.

Ossola A, Hahs AK, and Livesley SJ. 2015a Habitat complexity influences fine scale hydrological processes and the incidence of stormwater runoff in managed urban ecosystems. Journal of Environmental Management 159:1–10. [PubMed: 25989202]

Ossola A, Hahs AK, Nash MA, and Livesley SJ. 2016 Habitat Complexity Enhances Comminution and Decomposition Processes in Urban Ecosystems. Ecosystems 19:927–941.

Ossola A, Nash MA, Christie F, Hahs AK, and Livesley SJ. 2015b Urban habitat complexity affects species richness but not environmental filtering of morphologically diverse ants. PeerJ 3: e1356. [PubMed: 26528416]

Pearce LM, Davison A, and Kirkpatrick JB. 2015 Personal encounters with trees: The lived significance of the private urban forest. Urban Forestry & Urban Greening 14:1–7.

Peña EA, and Slate EH. 2015 gvlma R library: Global Validation of Linear Models Assumptions.

PRISM Climate Group. 2015 30-year Normals Oregon State University.

Quigley MF 2002 Franklin Park: 150 years of changing design, disturbance, and impact on tree growth. Urban Ecosystems 6:223–235.

R Core Team. 2016 R: A Language and Environment for Statistical Computing.

Raciti SM, Hutyra LR, and Newell JD. 2014 Mapping carbon storage in urban trees with multi-source remote sensing data: Relationships between biomass, land use, and demographics in Boston neighborhoods. Science of The Total Environment 500–501:72–83.

Rogan J, Ziemer M, Martin D, Ratick S, Cuba N, and DeLauer V. 2013 The impact of tree cover loss on land surface temperature: A case study of central Massachusetts using Landsat Thematic Mapper thermal data. Applied Geography 45:49–57.

Schwarz K, Fragkias M, Boone CG, Zhou W, McHale M, Grove JM, O'Neil-Dunne J, McFadden JP, Buckley GL, Childers D, Ogden L, Pincetl S, Pataki D, Whitmer A, and Cadenasso ML. 2015 Trees Grow on Money: Urban Tree Canopy Cover and Environmental Justice. PLoS ONE 10:e0122051. [PubMed: 25830303]

Searle SY, Turnbull MH, Boelman NT, Schuster WSF, Yakir D, and Griffin KL. 2012 Urban environment of New York City promotes growth in northern red oak seedlings. Tree Physiology 32:389–400. [PubMed: 22491523]

Silva CA, Crookston NL, Hudak AT, and Vierling LA. 2015 rLiDAR: LiDAR data processing and visualization.

Singh KK, Vogler JB, Shoemaker DA, and Meentemeyer RK. 2012 LiDAR-Landsat data fusion for large-area assessment of urban land cover: Balancing spatial resolution, data volume and mapping accuracy. ISPRS Journal of Photogrammetry and Remote Sensing 74:110–121.

Singh KK, Bianchetti RA, Chen G, and Meentemeyer RK. 2017 Assessing effect of dominant land-cover types and pattern on urban forest biomass estimated using LiDAR metrics Urban Ecosystems 20:265–275.

Song Y, Imanishi J, Sasaki T, Ioki K, and Morimoto Y. 2016 Estimation of broad-leaved canopy growth in the urban forested area using multi-temporal airborne LiDAR datasets. Urban Forestry & Urban Greening 16:142–149.

Stagoll K, Lindenmayer DB, Knight E, Fischer J, and Manning AD. 2012 Large trees are keystone structures in urban parks. Conservation Letters 5:115–122.

Staudhammer C, Escobedo F, Lawrence A, Duryea M, Smith P, and Merritt M. 2011 Rapid assessment of change and hurricane impacts to houston's Urban forest structure. Arboriculture and Urban Forestry 37:60–66.

Threlfall C, Ossola A, Hahs AK, Williams NSG, Wilson L, and Livesley SJ. 2016 Variation in vegetation structure and composition across urban green space types. Frontiers in Ecology and Evolution 4.

US Census Bureau. 2010 American FactFinder - 2010 American Community Survey. U.S Census Bureau's American Community Survey Office.

van Heezik Y, Freeman C, Porter S, and Dickinson KJM. 2013 Garden Size, Householder Knowledge, and Socio-Economic Status Influence Plant and Bird Diversity at the Scale of Individual Gardens. Ecosystems 16:1442–1454.

Vepakomma U, Kneeshaw D, and St-Onge B. 2010 Interactions of multiple disturbances in shaping boreal forest dynamics: a spa-tially explicit analysis using multi-temporal lidar data and high-resolution imagery. Journal of Ecology 98:526–539.

Vepakomma U, St-Onge B, and Kneeshaw D. 2008 Spatially explicit characterization of boreal forest gap dynamics using multi-temporal lidar data. Remote Sensing of Environment 112:2326–2340.

Vepakomma U, St-Onge B, and Kneeshaw D. 2011 Response of a boreal forest to canopy opening: assessing vertical and lateral tree growth with multi-temporal lidar data. Ecological Applications 21:99–121. [PubMed: 21516891]

Visscher RS, Nassauer JI, and Marshall LL. 2016 Homeowner preferences for wooded front yards and backyards: Implications for carbon storage. Landscape and Urban Planning 146:1–10.

Vogt JM, Watkins SL, Mincey SK, Patterson MS, and Fischer BC. 2015 Explaining planted-tree survival and growth in urban neighborhoods: A social–ecological approach to studying recently-planted trees in Indianapolis. Landscape and Urban Planning 136:130–143.

Wei T, and Simko V. 2016 corrplot R library: Visualization of a Correlation Matrix.

Western Water Assessment. 2016 Historical High-Impact Weather and Climate Events in Colorado, Wyoming, and Utah, 1862–2015 (version 5).

Yu X, Hyyppä J, Kaartinen H, and Maltamo M. 2004 Automatic detection of harvested trees and determination of forest growth using airborne laser scanning. Remote Sensing of Environment 90:451–462.

Zhao J, Chen S, Jiang B, Ren Y, Wang H, Vause J, and Yu H. 2013 Temporal trend of green space coverage in China and its relationship with urbanization over the last two decades. Science of The Total Environment 442:455–465. [PubMed: 23186616]

Zhao S, Liu S, and Zhou D. 2016 Prevalent vegetation growth enhancement in urban environment. Proceedings of the National Academy of Sciences

Ziska LH, Bunce JA, and Goins EW. 2004 Characterization of an Urban-Rural CO2/Temperature Gradient and Associated Changes in Initial Plant Productivity during Secondary Succession. Oecologia 139:454–458. [PubMed: 15021982]

Zuur A, Ieno EN, Walker N, Saveiliev AA, and Smith GM. 2009 Mixed Effects Models and Extensions in Ecology with R Springer.

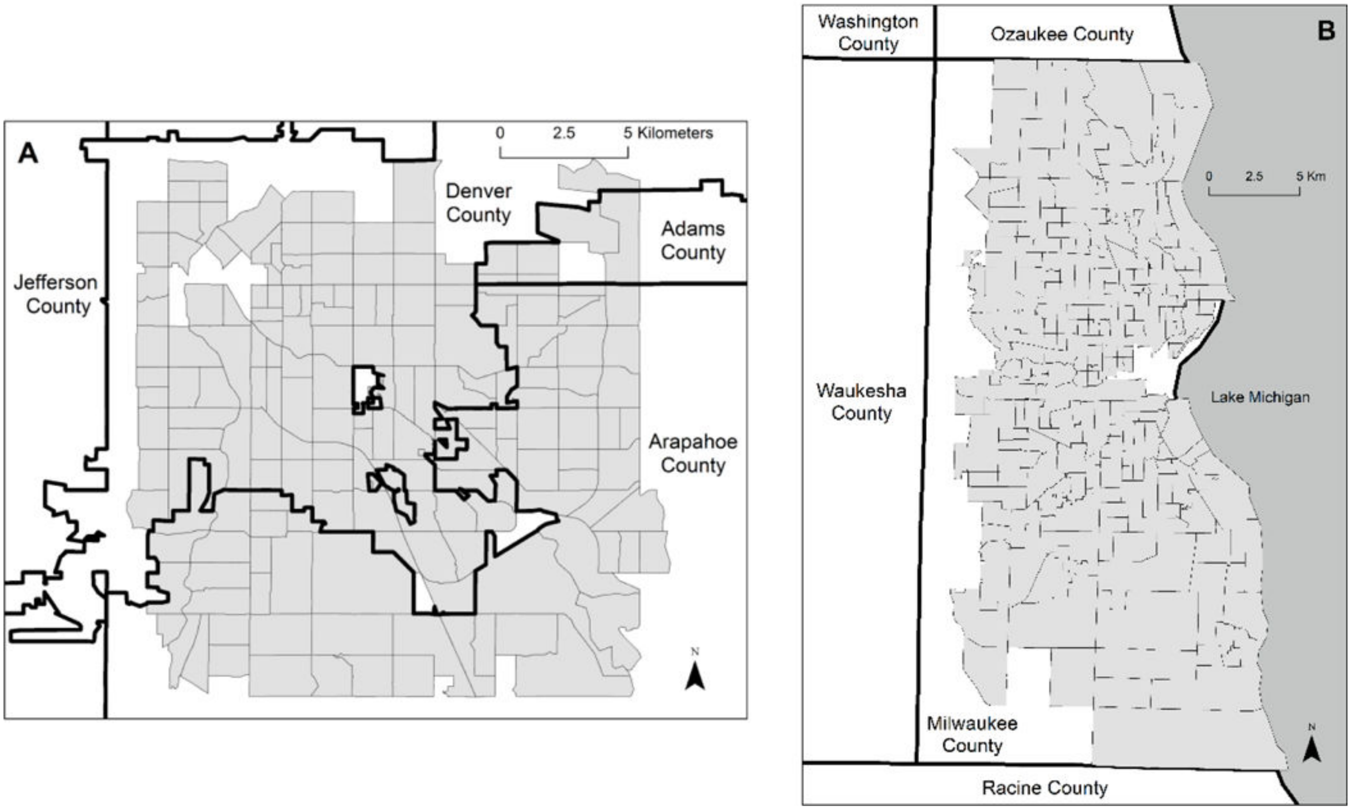

Figure 1:
Study areas in Denver, CO (A) and Milwaukee, WI (B). Light gray polygons represent the census tracts considered in the study, bold lines are the counties' perimeters.

Figure 2:
Example of tree stems lost within residential parcels in Denver, CO detected from the difference between the canopy height models (-ΔCHMs) calculated for the years 2008 and 2013 (A). Satellite images are from Google Earth™ and taken in July 2007 (B) and June 2014 (C), before and after the 5-year reference periods. Each dot represents the position of a tree stem lost, whereas the its radius is proportional to stem height. The complete tree datasets for Denver and Milwaukee are available as supplementary material.

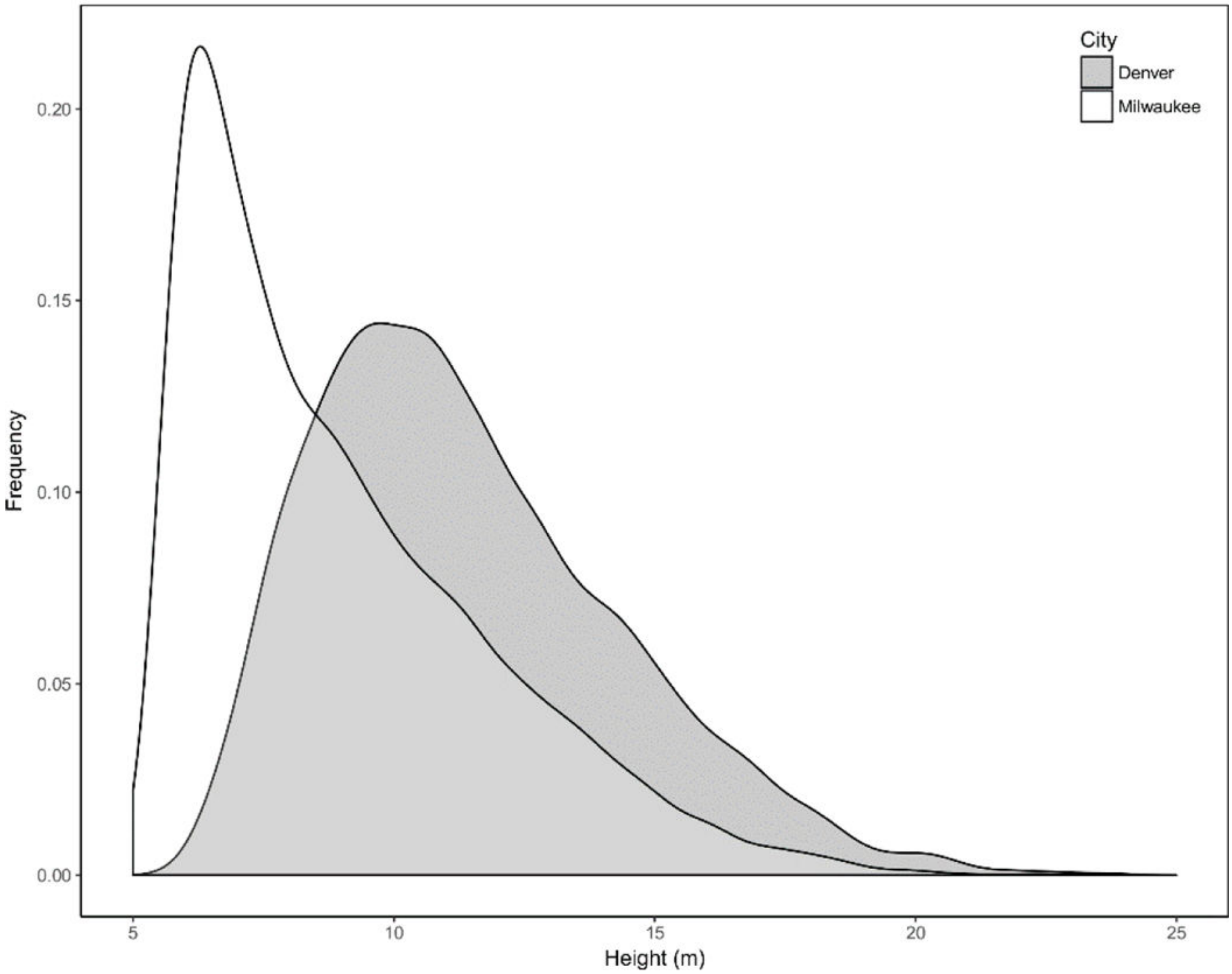

Figure 3:

Stem height frequency distribution for all the trees (height >5 m) lost within residential parcels in Denver, CO and Milwaukee, WI in a 5-year period.

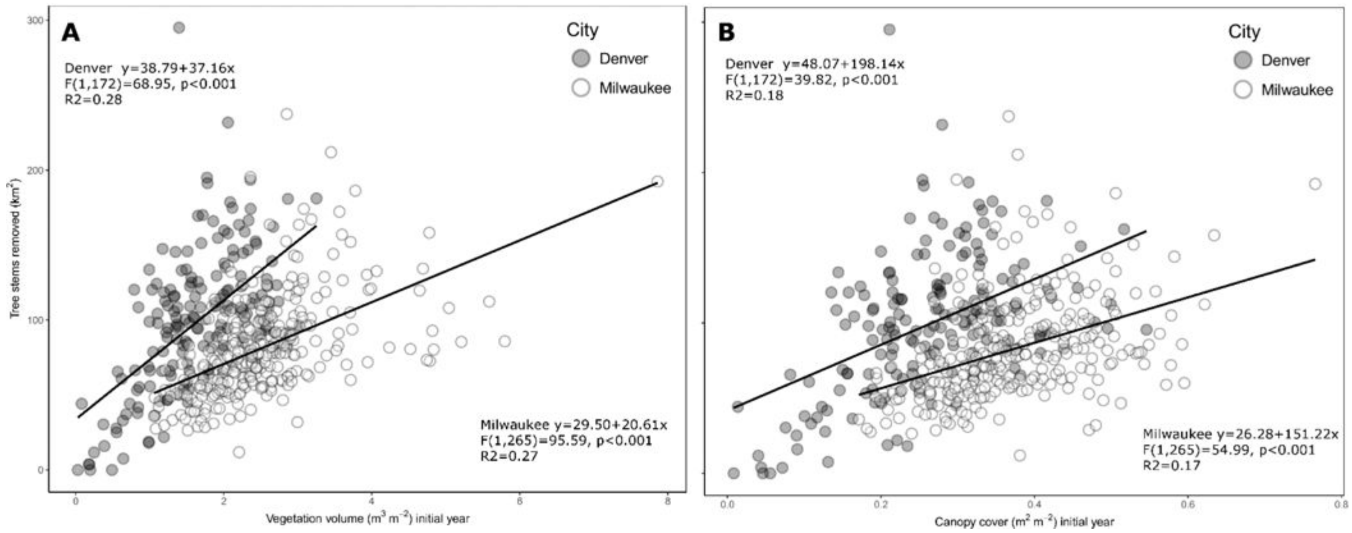

Figure 4:

Bivariate relationship between the total number of tree stems lost per unit of residential area and A) the average woody vegetation volume, and B) woody vegetation cover within residential parcels in the initial year (i.e. 2008 and 2010 for Denver and Milwaukee, respectively). Dots represent parcel-based values averaged at census tract level.

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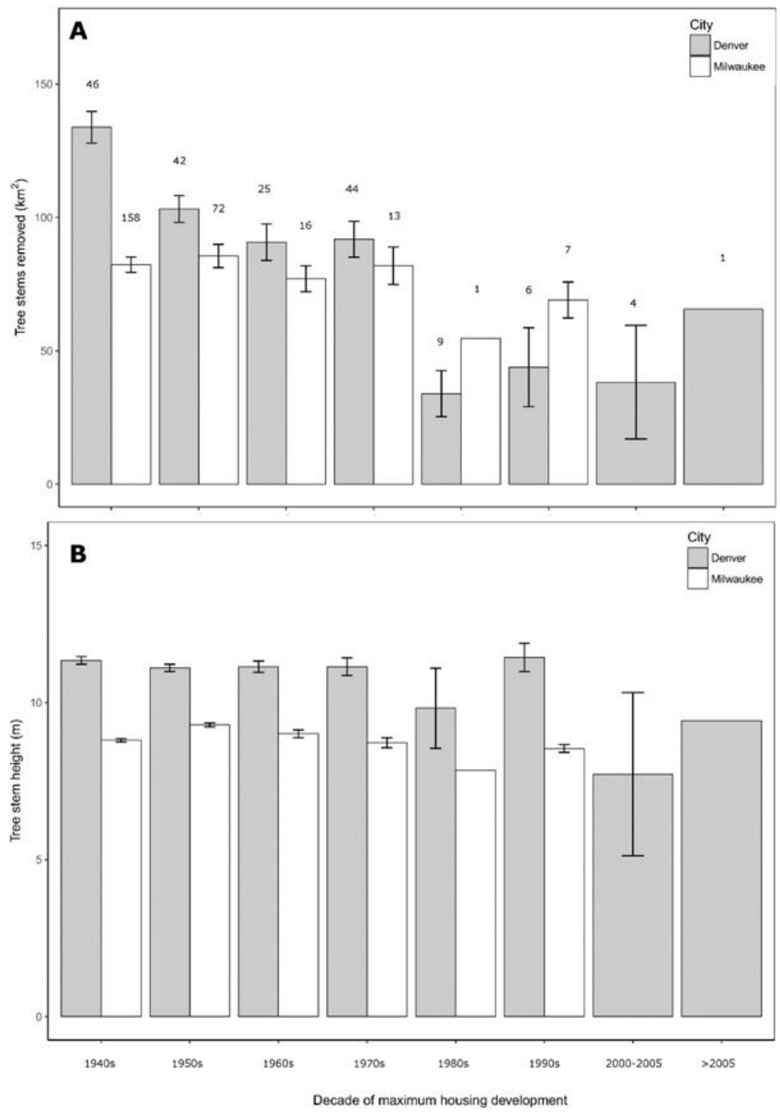

Figure 5:

Average number of tree stems lost (A) within a 5-year period per unit of residential area and their average height (B) in relation to the decade of maximum housing development of neighborhood (i.e. census tract) in Denver, CO and Milwaukee, WI. Numbers above bars represent the number of census tracts analyzed, errors bars represent standard errors of the mean.

Table 1:

Characteristics of the LiDAR datasets used in this study for Denver, CO and Milwaukee, WI.

Dataset name	USGS LPC CO Denver 2008	USGS LPC CO South Platte River Lot 5 – 2013	2010 Milwaukee County LiDAR	2015 Southeast WI Counties LiDAR
Study area	Denver, CO	Denver, CO	Milwaukee, WI	Milwaukee, WI
Collection period	25.03.2008 19.04.2008	25.10.2013 31.05.2014	16.04.2010 18.04.2010	24.03.2015 03.04.2015
Nominal point spacing (m)	0.7	0.7	0.7 *	0.7 *
Min. point spacing (m)	0.444	0.391	0.433 *	0.364 *
Mean point spacing (m)	0.603	0.439	0.542 *	0.457 *
Max. point spacing (m)	0.760	0.627	0.779 *	0.854 *
Vertical accuracy (cm)	6.3 RMSE	5.7 RMSE	8.0 RMSE	10.0 RMSE
Tile size (km)	1.5 × 1.5	1.5 × 1.5	1.5 × 1.5	3 × 3
N. tiles	196	196	291	88

*The original unit of measure of the 2010 Milwaukee County LiDAR and the 2015 Southeast WI Counties LiDAR datasets is the US foot, which has been converted to meter using the equivalency 1 foot = 0.3048 m.

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Table 2:

Variables selected using variance inflation factors (VIF) used as predictors in the multivariate regression analysis for each of the model types (i.e. *urban morphology*, *socio-economic*) in each city and having i) total number of tree stems lost in each tract and ii) stem average height as response variables. *Global* models were fitted by using both *urban morphology* and *socio-economic* variables for each city. Variable selection using variance inflation factors (VIF) was performed separately for each city, and as such, some variables (−) have been excluded from modeling to avoid multicollinearity.

Model type: *Urban morphology*	
Denver, CO	**Milwaukee, WI**
Canopy cover (initial year)	Canopy cover (initial year)
Decade max housing development	Decade max housing development
Average parcel area	-
Housing density	Housing density
Percent residential land use	Percent residential land use
Model type: *Socio-economic*	
Denver, CO	**Milwaukee, WI**
Median age	Median age
-	Racial diversity index
Family / non-family ratio	Family / non-family ratio
Percent vacant units	Percent vacant units
Percent families below poverty	-
Gini index	Gini index
Percent unemployed	Percent unemployed
Monthly rent	Monthly rent

Table 3:

Comparison of the competing models based on urban morphological, socio-economic, and all (global) variables performed using AICc. Model sets are ranked based on increasing AICc and the best models are italicized.

City	Response variable	Model type	n. parameters	AICc	ΔAICc	AICc weight
Denver	Number of tree stems lost	*Urban morphology*	*5*	*683.44*	*0.00*	*0.88*
		Global	12	687.33	3.89	0.12
		Socio-economic	7	765.94	82.5	0.00
Milwaukee	Number of tree stems lost	*Global*	*11*	*192.73*	*0.00*	*0.84*
		Socio-economic	7	196.02	3.29	0.16
		Urban morphology	4	239.17	46.44	0.00
Denver	Tree stem height	*Global*	*12*	*353.58*	*0.00*	*0.81*
		Socio-economic	7	356.48	2.90	0.19
		Urban morphology	5	382.76	29.18	0.00
Milwaukee	Tree stem height	*Global*	*11*	*504.39*	*0.00*	*0.88*
		Socio-economic	7	508.39	4.00	0.12
		Urban morphology	4	522.37	17.98	0.00

Table 4:

Summary statistics of the best fitting linear models (lowest AICc) predicting the number of tree stems lost in residential landscapes in Denver, CO and Milwaukee, WI.

Response variable: number tree stems lost (km^2)	**Denver**			**Milwaukee**		
Model type	**Urban morphology**			**Global**		
Predictor variables	**Estimate**	**Std. error**	**p**	**Estimate**	**Std. error**	**p**
Canopy cover (initial year)	*9.87*	*1.67*	***< 0.001***	*2.63*	*0.37*	***< 0.001***
Decade of max housing development	*−0.06*	*0.01*	***< 0.001***	−0.001	0.002	0.55
Average parcel area	−0.49	0.33	0.14	-	-	-
Housing density	−0.04	0.23	0.87	−0.03	0.08	0.73
Percent residential land use	0.01	0.01	0.13	−0.001	0.001	0.83
Median age	-	-	-	−0.32	5.61	0.11
Racial diversity index	-	-	-	*−0.38*	*0.15*	***< 0.05***
Family/non-family ratio	-	-	-	0.10	0.10	0.34
Percent vacant units	-	-	-	0.01	0.06	0.87
Gini index	-	-	-	0.74	0.91	0.22
Percent unemployed	-	-	-	−0.04	0.04	0.25
Monthly rent	-	-	−	0.01	0.15	0.94
Degrees of freedom	166			249		
R^2 / Adj R^2	0.48 / 0.46			0.28 / 0.25		
F-statistic (p-value)	30.2 (< 0.001)			8.848 (<0.001)		

Table 5:

Summary statistics of the best fitting linear models (lowest AICc) predicting stem height of trees lost in residential landscapes in Denver, CO and Milwaukee, WI.

Response variable: tree stem height (m)	**Denver**			**Milwaukee**		
Model type	**Global**			**Global**		
Predictor variables	**Estimate**	**Std. error**	**p**	**Estimate**	**Std. error**	**p**
Canopy cover (initial year)	0.72	0.82	0.38	0.42	0.67	0.54
Decade of max housing development	−0.001	0.001	0.65	−0.01	0.01	0.13
Average parcel area	0.14	0.15	0.38	-	-	-
Housing density	0.15	0.14	0.30	0.02	0.14	0.91
Percent residential land use	0.001	0.001	0.17	0.01	0.01	0.19
Median age	0.17	0.44	0.70	0.07	0.37	0.84
Racial diversity index	-	-	-	−0.09	0.27	0.72
Percent families below poverty	*−0.17*	*0.05*	***< 0.001***	-	-	-
Family/non-family ratio	0.03	0.23	0.91	0.14	0.18	0.43
Percent vacant units	*−0.33*	*0.16*	***< 0.05***	−0.23	0.12	0.053
Gini index	*2.90*	*0.89*	***< 0.01***	−1.89	1.11	0.08
Percent unemployed	0.05	0.08	0.53	−0.05	0.07	0.48
Monthly rent	−0.21	0.26	0.40	0.22	0.26	0.40
Degrees of freedom	156			249		
R^2 / Adj R^2	0.38 / 0.33			0.16 / 0.13		
F-statistic (p-value)	7.93 (< 0.001)			4.44 (< 0.001)		