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An urban forest-inventory-and-analysis investigation in Oregon and Washington

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ABSTRACT

The U.S. Department of Agriculture (USDA) Forest Service, Forest Inventory and Analysis program recently inventoried trees on 257 sample plots in the urbanized areas of Oregon and Washington. Plots were located on the standard grid (≈1 plot/2428 ha) and installed with the 4-subplot footprint (≈.067 ha with 4 circular subplots). Using these data, we examined: 1) use of the land use classification data from the National Land Cover Database (NLCD) for post-stratification; 2) the resolution of the inventory data to make inferences about subdomains (specifically sub-regions) and subgroups (species and diameter classes); and 3) the i-Tree Eco software as a tool for data compilation, estimation, and reporting.

Ideally post-stratification would enable us to achieve greater precision in sub-regions (Seattle, Portland, and eastern Oregon and Washington), but our analyses indicated that NLCD land use classes did not aid us in estimation of trees per ha and basal area in Oregon and Washington urbanized areas. Due to the small sample size and lack of effective post-stratifying variables, the data support few inferences about sub-regions. It is likely, however, that another set of stratifying variables can improve precision and enable a greater diversity of sub-region inferences from these data.

1. Introduction

Urban forests provide a myriad of environmental, social, and economic benefits for what the US Census estimates is approximately 80 percent of the U.S. population. The term "urban forest" is used to define all trees within an urban area, including those along parking strips, in yards, and on public lands such as parks (Cumming et al., 2008). It is a mosaic of both the planted landscape and native forest remnants that have been left behind, intentionally or unintentionally, as our cities have developed. Even vacant or previously cleared land, when left long enough, can revert back to forest by natural processes. Research conducted in the last several decades has begun to quantify many of thebenefits provided by urban trees, which include reduced storm water runoff (Sanders, 1986), cleaner air (Nowak, 1994; Nowak et al., 2006), support for better mental and physical health (Ulrich et al., 1991; Dwyer et al., 1991; Donovan et al., 2013; Kardan et al., 2015), reduced crime (Kuo and Sullivan, 2001; Donovan and Prestemon, 2012), reduced home energy costs (Akbari, 2002; Donovan and Butry, 2009), and trees make neighborhoods more desirable places to live and work (Westphal, 2003; Wolf, 2003; Kinzig et al., 2005; Nowak and Dwyer, 2007). The Arbor Day Foundation reports that more than $1 billion is spent on planting, maintaining, and managing the urban forest in the over 3400 cities awarded Tree City USA status ("Arbor Day Foundation," n.d.). Given the importance of urban forests, and the large amounts of public funds spent to manage them, very little is actually known about the health, extent, and characteristics of the nation's urban forest resource. To help remedy this situation, the Forest Inventory and Analysis (FIA) program of the USDA Forest Service has recently begun several projects to collect data in urban areas for the purpose

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of preforming analyses and informing the public on the status and trends of urban forests.

The FIA program originated in 1930 as an effort to "make and keep current a comprehensive inventory and analysis of the present and prospective conditions of, and requirements for, the renewable resources of the forest and rangelands of the U.S." (U.S. Department of Agriculture Forest Service, 1992). Every year, in every U.S. state, the FIA program collects data from a set of permanent ground plots, then analyzes and later reports information on the extent and health of states' forest resources. While the FIA plot sample grid covers all the land area in each state, for a plot on the grid to be installed it had to intersect a forested area, defined as at least 0.4 ha in size, at least 36.5 m wide, and at least 10 percent stocked with tree canopy and containing an understory that is undisturbed by another land use (U.S. Department of Agriculture Forest Service, 2012). The plots located outside of these conditions have been considered nonforest or developed, and they were not installed. In the last decade, an effort has begun to include urban land in the sample. This is based on the understanding that across the landscape there is a gap in the ability to account for trees and their potential benefits outside of the traditional forests. As part of an all-lands approach, FIA acknowledged the importance of urban trees and they have focused recent efforts on installing plots located in several urban areas.

Many cities rely on ground based tree inventories of street and park trees, or on aerial based canopy coverage studies to obtain data for planning and management purposes. Effective forest inventory design, analyses, and reporting typically require a suite of specialized skills that may not be available within an organization. Some cities look to contractors and volunteers to assist in inventory collection, and it is common for cities to perform minimal inventories that are on decade intervals and on limited land use types. This can prove problematic for data continuity if different contractors or measurement protocols are used between inventories. Additionally, since the inventories are not standardized among cities, they may prove useless for policy and planning at the state, regional or national level (Cumming et al., 2008).

The difficulties described in implementing a forest inventory suggest that there is a need for infrastructure to support consistent urban inventory practices, as well as to provide inventory analyses and to communicate inventory results. Software packages that provide inventory guidance, analyses, and reporting capacity may help alleviate some of the difficulties associated with urban inventory and reduce the overhead associated with planning and maintaining an inventory system. In addition, if municipalities across the region adopted a standard methodology, reporting and planning may be feasible at a larger scale.

The first FIA inventory of nonforest conditions in urban areas was in 1999, when FIA initiated an assessment of all non-forest plots in the 5 counties surrounding the city of Baltimore, including both urban and rural lands (Riemann, 2003). In 2001, the USDA Forest Service, Forest Health and Monitoring (FHM) program initiated an assessment of urban forest conditions (Cumming et al., 2001). This assessment delimited urban boundaries and then collected tree information from established plots within the urban boundaries. This was the first attempt to apply national forest health monitoring protocols to aid in the planning and management of the urban forest. Statewide urban pilot studies were later conducted by FIA incorporating the protocols developed by the FHM program. More recently, urban areas in five states were inventoried by FIA including Indiana, Wisconsin, Colorado, New Jersey, and Tennessee (Nowak et al., 2011; Cumming, 2007; Lake et al., 2006). Data obtained from plots can be used to monitor the health, condition, and trends of the urban forest, giving managers an important tool for long range planning.

In 2009, with funding from the America Recovery and Reinvestment Act of 2009, the USDA Forest Service Pacific Northwest Research Station (PNW) and the Oregon Department of Forestry (ODF) entered into an agreement to conduct an FIA inventory project in the 'urbanized areas' of five Pacific coast states (Alaska, California, Hawaii, Oregon, and Washington). Urbanized areas are defined by U.S. census to contain a core population of 50,000 people. This classification was chosen because 88 percent of the U.S. urban population lived in urbanized areas in 2010 and funding was not sufficient to install plots in the less densely populated land classification "urban clusters" (for classification information see: https://www.census.gov/geo/reference/ua/urban-rural-2010.html). In coordinating with the PNW FIA Program, ODF appointed a project manager, project coordinator, and quality assurance forester to help manage the project, and hired private urban forestry and forest inventory firms to collect the data. PNW formed an agreement with California Polytechnic State University, San Luis Obispo to collect the California urban data. The Hawaii and Alaska data will be published by the PNW FIA, but their relatively small urban areas limit analyses.

The objective of this study is to investigate our ability to make inferences about the character of the urban forest from urban FIA field data collected in 2010 and 2011 for Oregon and Washington. Initially we investigate whether NLCD data can be used to improve the precision of our estimates. We then investigate whether the collected inventory data support estimation within sub-regions and for subgroups. Finally, we examine i-Tree Eco (Nowak et al., 2013) software as a tool for estimation and reporting of selected base inventory estimates.

2. Methods

2.1. PNW urban inventory overview

Plots on the national FIA grid are spaced so each represents roughly 2428 ha. According to GIS layers provided by the U.S. Department of Commerce, Bureau of the Census (2011), there are 163 K ha of urbanized land in Oregon state and 460 K ha in Washington state. A total of 67 plots from the FIA grid fall within Oregon's urbanized areas and 190 fall within Washington's urbanized areas. Plot locations were mapped using coordinates derived from maps, aerial photos, and satellite imagery. Landowners were determined using GIS layers available from public agencies. All the plots in urban areas are part of the national FIA plot grid, and some plots on the edges of urban areas were already installed because they fell in area that met FIA's definition of forest. The majority of urban plots, however, were previously classified as nonforest and had not been installed. Forested FIA plots in the PNW region are measured on a panel system in which one-tenth of all the plots within a State are measured in a given year. Because this study was funded with a one-time grant, all plots in the urban areas were measured as urban plots in a two year window.

2.2. Data collection and field protocols

Field data were collected in the summer of 2010 and 2011. The standard FIA plot design was used, in which each plot consisted of four subplots, each 0.017 ha in size with a nested microplot covering 0.0013 ha (Fig. 1).

Urban protocols were based on a supplement to the standard FIA field manual that included a subset of tree health variables from Forest Health plots (Tallent-Halsell, 1994), and variables unique to the urban environment (e.g., poor pruning, conflicts with tree roots, etc.) (U.S. Department of Agriculture Forest Service, 2012). The spatial locations of plots were obtained in the field using GPS

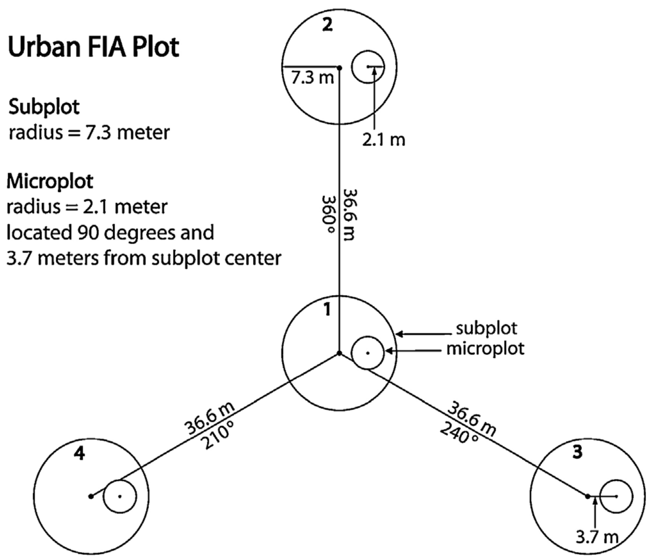

Fig. 1. FIA plot design.

Table 1
Summary statistics for selected field measure attributes.

	mean	med	sd	min	max
Tree DBH (cm, small[a])	6.7	6.3	2.7	2.5	12.4
Tree DBH (cm)	32.3	25.9	20.5	12.7	173.7
Tree crown base ht. (m)	7.5	5.0	6.8	0.0	38.3
Tree crown density (%)	37.8	35.0	16.8	0.0	99.0
Tree crown dieback (%)	3.9	5.0	4.9	0.0	99.0
Tree crown width (m)	7.2	6.7	3.2	0.3	34.6
Tree height (m)	18.6	17.1	9.6	1.5	58.8

[a] small tree measurements are from 110 live trees with dbh's less than 12.7 cm. The remainder of the measurements used to prepare this table are from 1,273 live Trees 12.7 cm in dbh and larger.

units—which became the official plot coordinates. All trees with a diameter at breast height (DBH) of 12.7 cm and greater were mapped and measured on each subplot and trees from 2.54 cm to 12.7 cm were measured and mapped on each microplot. Tree variables included: species, diameter, height, and several variables to assess tree health based on crown attributes, variables to account for tree damage, the presence or absence of pests, and the distance of tree to nearby buildings. Subplot variables include the percent of canopy, shrub, and ground cover on each subplot, the surface composition (impervious or permeable), and land uses. A summary of some basic measurements performed on field plots is provided in Table 1.

Field data were recorded using a personal digital assistant (PDA) running software specifically designed by the USDA Forest Service for the collection of urban FIA data. This software, known as Midas, was implemented nationally with versions for both forest and urban data collection.

2.3. Post-stratification with NLCD classes

An important strategy to improve our capacity to make inferences from samples is to leverage auxiliary sources of information when performing estimation. Stratification is a common method to improve estimation precision in which plots are associated with homogeneous groups according to auxiliary information. This process may be performed before the inventory (pre-stratification, or simply stratification) or after the inventory is completed (post-stratification). One source of auxiliary information that has been used with favorable results with FIA data is the National Land Cover Database (NLCD). NLCD is a 30 m resolution raster dataset which uses Landsat data (30 m pixels) and unsupervised classification to predict land cover classes. The Landsat-based resource has the advantage of being free and available over the entire contiguous U.S. In inventories of forested areas this has worked well. Dunham et al. (2001), for example, obtained a 15% improvement in their standard error for the mean volume estimate by post-stratifying on NLCD classes (relative to estimation without stratification). The study by Liknes et al. (2006) observed slightly more dramatic improvements (21% to 68%) in precision by post-stratifying on NLCD for numbers of trees, biomass, and volume. Liknes et al. (2006) saw even slightly better post-stratification results by using data from the U.S. Department of Agriculture cropland data layer (http://www.nass.usda.gov/research/Cropland/SARS1a.htm), another remote sensing based classification system.

In this study we investigated our ability to post-stratify our sample into more homogeneous groups for our region of interest – urbanized areas in Oregon and Washington – based upon land cover classification. The data were grouped using 2006 version NLCD classes (Fry et al., 2011). The NLCD classification system was evaluated for its level of agreement with field data, as well as for its contribution to estimation. We used the level of association between NLCD and field-measured land use classes as a quasi-measure of accuracy. Four indices of association were used: Cramer's V (Cramér, 1946), Goodman–Kruskal lambda and tau (Goodman and Kruskal, 1954), and Theil's uncertainty coefficient (Theil, 1967). These statistics were computed using the StatMatch package (D'Orazio, 2012) in R (R Development Core Team, 2010). In a second strategy we evaluated land use classes by looking at the separation in a measured forest attribute between groups following grouping observations by land uses classes. Lastly, we compared standard errors with and without post-stratification.

2.4. Subdomains (sub-regions) and subgroups

Estimates were calculated for all urbanized areas in Oregon and Washington combined and for subdomains (sub-regions) Oregon, Washington, Portland in Oregon, Seattle in Washington, and urban areas in eastern Oregon and Washington (Fig. 2) where a subdomain is a partition of the target population. We estimated the number of trees per hectare (TPH) and square meters per hectare of tree basal area (BA) for all of the data combined and for the sub-regions by species and 5 cm diameter classes (DBH, diameter at breast height). Our evaluation of estimation in sub-regions and subgroups was based upon associated confidence intervals and t-statistics. For the indicated sub-regions and subgroups we were interested in whether there were sufficient numbers of observations to support inferences about TPH and BA. This analysis is meant to highlight the resolution of these data for making inferences about subcomponents of the population.

2.5. i-Tree eco software

We examined i-Tree Eco software as a tool for compilation and estimation of urban inventory data. Estimation of base variables with i-Tree Eco was compared with estimation performed in R. We did not attempt to validate i-Tree Eco model-based predictions of tree attributes such as biomass, carbon, or any of the other environmental attributes. Our examination of this software was chiefly aimed at feasibility and function for estimation of primary forest inventory attributes—e.g., were we able to integrate our urban FIA measurements with this free software and achieve reasonable estimates of TPH by species and size with associated errors.

A strength of the i-Tree Eco software is that it is free and easy to use (when data are collected with their software) and it is accompanied by a standardized measurement protocol. While the software is developed with the support of USDA Forest Service research, the

Fig. 2. Urban areas in Oregon and Washington by sub-regions.

Table 2
Statistical significance and measures of associations between NLCD and FIA land use classes on subplots when grouped and un-grouped.

Assoc. Measure	Un-grouped	Grouped
Cramer's V	0.38	0.49
Goodman–Kruskal lambda	0.21	0.30
Goodman–Kruskal tau	0.18	0.28
Theil's Uncertainty index	0.24	0.27
Chi-squared p-value	≪0.001	≪0.001

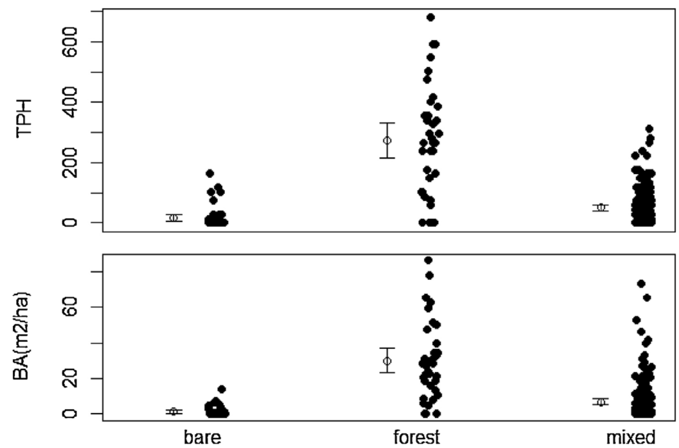

Fig. 3. Scatter plots and 95% CIs for means of BA and TPH by FIA land use for land use classes with more than 10 field plots.

software is not designed to accept field measurements directly from FIA plots. The i-Tree software was designed to utilize more intensive city inventories and output a broad suite of results at the city scale, rather than accept FIA field measurements from larger areas. Though the data collected is similar, one of the hurdles that may arise for organizations planning to use the software in conjunction with an FIA inventory is formatting the data for use with the complex structure of the i-Tree Eco database. This includes handling FIA's multiple subplots, measurements from subplots with different unit areas, and accepting data from multiple cities.

To evaluate i-Tree Eco with urban FIA data, the FIA data were reformatted in R and deposited into the appropriate tables in the i-Tree Eco. Our ad hoc solution used the RODBC package (Ripley, 2012) in R to interact with the i-Tree Eco database. Linking external data with i-Tree Eco required first parsing all of the spreadsheets to identify linked columns, and requires that the user parse each field and identify the data types of each record.

3. Results

The results are presented in three sections. In the first section we evaluate NLCD land classes and examine their contribution to improve the post-stratification of field measurements. In the second section we evaluate our ability to make inferences from our field data for subdomains (Portland, Seattle, eastern Oregon and Washington) and for subgroups (diameter classes and species). In the third section we evaluate i-Tree Eco software to support inferences from these data.

3.1. Post-stratification

We use subplot-level data to assess the correspondence between field measured land use and NLCD land use classes to obtain a measure of the accuracy of the NLCD data. The other analyses in this section were based upon plot-level classifications. In both analyses, we followed an estimation strategy to classify the plot by using the NLCD classification observed at subplot center (land use recorded at the center of subplot 1 represented the plot-level observation).

3.2. Associations between NLCD and FIA land use classes

NLCD accuracy was evaluated by examining the association between NLCD classes and land use classes on subplots. Subplots are used here instead of plots, because plots may straddle multiple land use classes, where combining subplots adds additional noise. A contingency table for NLCD and land use classes with more than 10 observations (marginal totals) was prepared (not shown) and used to compute association statistics between NLCD classes and field measured land use classes. A simplification strategy was used to group NLCD and FIA land use classes into like land covers which generally translate to levels of forest cover (bare, mixed bare and forest, forest). The simplification is based on our objective to explain variability in the spatial distribution of trees. In Table 2 we observe that all four measures of association indicate a non-zero (and highly significant) association for both the grouped and un-grouped classes, but the strength of the association (variation described for numbers of subplots by land use class) is weak.

3.3. Post-stratification potential for land use classes

To assess the potential for post-stratification by land use classification we examined the amount of separation in response variables when grouped by field-measured FIA land use classes. If this classification scheme cannot aid in separation, it may suggest that land use is not a helpful variable for post-stratification of urban inventory plots in Oregon and Washington, even under ideal circumstances. In Fig. 3 we can see while the confidence intervals for BA and TPH (DBH > 12.7 cm) on accessible forest land do not over-

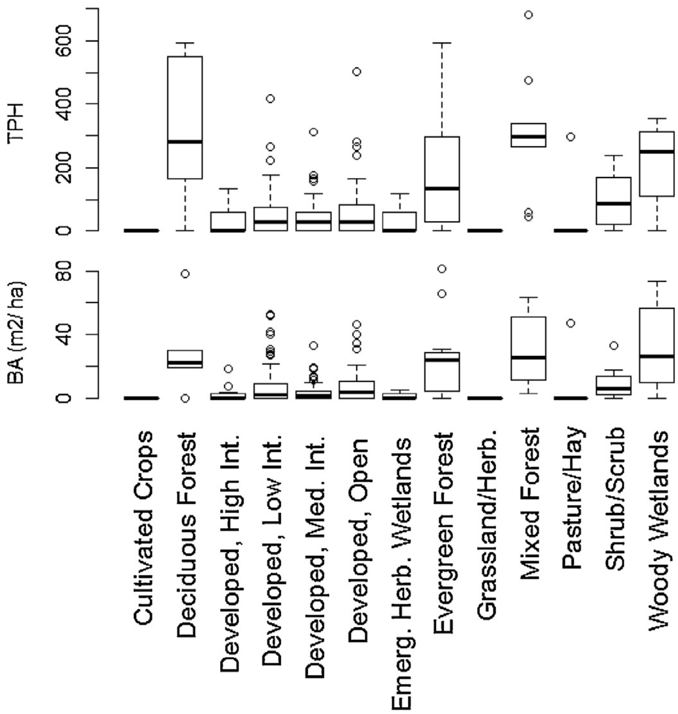

Fig. 4. Boxplot of TPH and BA by NLCD class on plots.

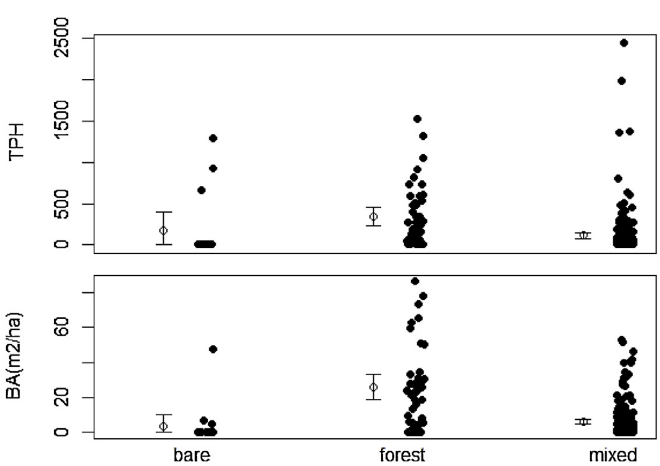

Fig. 5. Scatter plots and 95% CIs for means of BA and TPH by grouped NLCD classes with more than 10 field plots.

lap the other land uses (bare and mixed), the individual TPH and BA values on timberland do not appear to indicate that post-stratifying on timberland would, on average, appreciably reduce the variances within post-strata.

3.4. Homogeneity of responses by NLCD classes

Boxplots of TPH versus NLCD classes in Fig. 4 indicate that un-grouped NLCD classes provided poor separation of TPH and BA into homogeneous groups.

Our findings in the previous section for FIA land use are reflected here as well for NLCD classes. Fig. 5 shows mean estimates and 95% confidence intervals for TPH and BA estimates after grouping NLCD classes. For BA, the confidence interval for the mean in the forest class does not overlap the other groups, but the spread of points does not indicate that the standard deviation within groups is reduced by grouping observations. Two of the elevated TPH and BA values for bare land reflect misclassification of timberland (FIA)

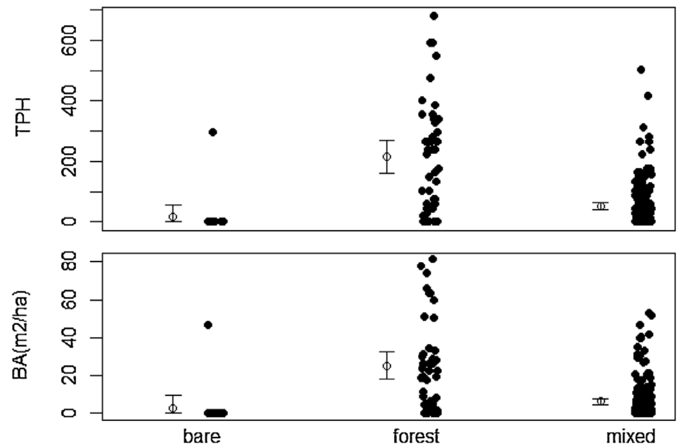

Fig. 6. Scatter plots and 95% CIs for means of BA and TPH by grouped NLCD classes for classes with more than 10 field plots and for trees larger than 12.7 DBH.

Table 3
Mean estimates and standard errors (SE, percent of mean) for un-stratified (No), post-stratified with NLCD (NLCD), and post-stratified with grouped NLCD observations (Grouped).

	All Trees		Trees < 12.7 cm	
	Mean	SE	Mean	SE
TPH—No	157.2	19.7	78.4	7.4
TPH—Grouped	163.2	19.9	83.5	7.0
BA—No	9.5	1.0	9.1	1.0
BA—Grouped	9.9	0.9	9.6	0.9

as pasture (NLCD) and a Christmas tree plantation (FIA) as cultivated crops (NLCD).

If we concentrate on trees larger than 12.7 cm (Fig. 6) we still do not see reasonable separation between groups, although without the smallest trees the confidence interval for TPH in forest lands does not overlap the two alternate grouped NLCD classes.

3.5. Effect of post-stratification on estimation precision

The results in Table 3 agree with our graphical findings from previous sections. When estimating population means for TPH and BA, post-stratification by NLCD classes does not appear to increase our estimation precision. Standard errors for mean estimates following post-stratification are not appreciably different from standard errors without post-stratification. Standard errors for mean estimates following direct post-stratification with NLCD classes (instead of overall estimates and precisions) are not provided because many of the classes had small numbers of observations (1–20).

3.6. Estimates for subdomains (subregions) and subgroups

Under ideal circumstances we would leverage post-strata to increase the precision of our estimates, but due to our finding that NCLD was not helpful for post-stratification, estimates for this section were computed without post-stratification. We initially look at whether the data support inferences base variables (TPH and BA) for selected subdomains, and then examine whether the data support inferences about subgroups and subgroups within subdomains.

3.7. Estimation for subdomains

Estimation in areal subdomains is equivalent to post-stratification by geographic boundaries. The objective is primarily motivated by our desire to make inference about sub-units in the population; there is no assumption that post-stratification on region will reduce the sampling variation within sub-region. The variation by species in sub-regions decline in some instances, however this is primarily the result of having smaller mean values, but in some instance results from reduced variability due to a smaller geographic extent. The numbers of observations in each post-strata are smaller than for the population, which will on average increase standard errors (decrease estimation precision) for sub-regions relative to estimation for the entire data extent.

The results in Table 4 represent estimates of TPH and BA for sub-regions of our area-of-interest. These results suggest that at the state level we can make basic inferences regarding TPH and BA. However, the magnitudes of standard errors for mean estimate with these data in subdomains indicate that this estimation strategy (including sampling design) provide minimal support for subdomain inferences. For example, the basal area in Seattle is 60% greater than in Portland, a difference which is likely of practical significant if substantiated. However, when we test the probability that this difference is statistically significant with a Welch's *t*-test (Welch, 1938), we observe a p-value larger than 0.08 which indicates that we do not have the statistical power to identify this size of difference between these cities.

3.8. Estimation for subgroups

The precision of estimates by subgroups, for example TPH or BA by species and DBH, will generally be lower relative to the mean than for the base variables. The greater percent variation in subgroups is the result of having fewer trees per plot to use for estimation. This will, for example, result in a greater number of plots with zero values in the subgroup, which increases the size of the variance relative to the size of the mean.

Increased variability for subgroups is demonstrated in Tables 5 and 6 in which we observe that percent standard errors for individual species and diameter classes all exceed the standard errors for the corresponding base variables and sub-regions in Table 4. The magnitudes of standard errors for subgroups indicate that, as with the base variables, the data cannot be used to support inferences for subgroups between sub-regions. However, the data do in some cases support inferences about subgroups for the entire region and in larger sub-regions (Washington and Seattle).

For the most populous species in Table 5, we are able to detect practically significant differences between species. For example, the difference between TPH for *Pseudotsuga menziesii* (Mirb.) Franco (Douglas-fir) and *Thuja plicata* Donn ex D. Don (western red cedar) for all of Oregon and Washington is arguably of practical significance (a difference of 4 TPH or 140% larger than *Thuja plicata*), but we would argue that the difference between *Pseudotsuga menziesii* and *Alnus rubra* Bong. (red alder) (1.2 TPH or 20% larger than *Alnus rubra*) is not practically significant. A paired *t*-test for the difference between *Pseudotsuga menziesii* and *Thuja plicata* was significant ($p = 0.007$), while the difference between *Pseudotsuga menziesii* versus *Alnus rubra* was not signification ($p = 0.50$). The differences between *Pseudotsuga menziesii* and *Thuja plicata* were also significant for Washington State (.009) and Seattle (.01), but not for any of the other sub-regions.

The results for 5 cm diameter-class subgroups are similar to those for species in that we are unable to compare across regions, but the data support some useful inferences within all of Oregon and Washington and within specific sub-regions. The standard errors for small trees (2.54–12.5 cm) are especially large, mostly due to the reduced sample areas for small trees, 0.0013 ha microplot versus 0.067 ha subplot for larger trees. However, for all of Oregon and Washington, Washington and Seattle, most of the 5 cm DBH classes up to 48 cm were significantly different from their neighbors at least at the 0.05 level. We also examined 10 cm diameter classes (table not shown), for which comparisons between the 3 smallest bins were pairwise significant in all sub-regions except for Eastern Oregon and Washington.

When we examined TPH by species and diameter in combination (Table 7) the standard errors become quite large relative to the means. It quickly becomes clear that attempting further subdivision of the data by sub-regions will not support this level of analyses.

3.9. i-Tree eco software

3.9.1. Data initialization

Currently i-Tree Eco software cannot easily accept the inventory data collected by urban FIA. The FIA data were collected on data loggers using Midas software which has a specific data structure. Currently the i-Tree team is working on import facilities for FIA data. There is already an import facility which accepts external data that has been properly coded and placed in excel tables. Users can also build their own import tools to place the data directly into a MS Access database in the format used by i-Tree Eco. We used this approach (programmatic insertion of FIA data directly into an MS Access database) to place our FIA data in the i-Tree Eco data. Since i-Tree Eco provides a diverse array of outputs, the input data reside in a complex arrangement of 32 interconnected tables in an MS Access database. We found that a minimum of 11 of these tables were necessary to operate i-Tree Eco. However, once end users build a system to link their records with the i-Tree Eco database, the programmatic solution is easy to repeat.

3.9.2. Reporting

i-Tree Eco provides a rich set of tables, figures, and a detailed textual report to describe and provide background for many of the estimates in tables and figures. A list of available estimates (related to trees) from i-Tree Eco, referred to by the software as "resource structural analysis reports", is provided in Table 8.

i-Tree Eco additionally provides estimates of trees' influence on air quality, ecosystem services provided by trees, and information on trees' susceptibility to diseases. These should all prove useful in the various planning and reporting demands for an urban forestry office.

While i-Tree Eco outputs extensive reports derived from the data, the format of the output summaries is fixed and we felt that the selected format of the outputs inhibited interpretation. For example we were interested in seeing trees per hectare by species and diameter class, however the report provides the *percent* of trees by diameter class and standard errors in number of trees. In order to obtain estimates in trees per hectare would require a number of calculations by the user—who may not be familiar with forest biometrics calculations. This makes it difficult to use the report to obtain trees per hectare by diameter class. This style of reporting (tree per hectare in percent and SE in number of trees) is opposite of what we are familiar with; we believe it is more common and more interpretable to provide actual trees per hectare values and provide SE values in percent (although reporting SE values in number of trees is also fine). There is probably not a need for a custom reports module to meet each a multitude of user's different needs, but the software authors may wish to investigate how mainstream forest inventory software systems format their outputs.

3.10. Statistical inference

One of the strengths of the i-Tree Eco systems is that it generates a report based upon estimates from submitted data. Ideally we could levy these values to understand a city or cities. However, a requirement for sound inferences from these data is that SE values are available for reported values and correctly calculated. If the

Table 4
Mean estimates and standard errors (percent of mean) for BA and TPH for the entire area and for sub-regions.

	Mean Estimate (Standard Error%)					
	OR & WA	OR	WA	East OR & WA	Portland[a]	Seattle[a]
BA	9.5 (10%)	7.5 (21%)	10.1 (12%)	4.5 (21%)	7 (25%)	11 (15%)
BA (>12.7 cm)	9.1 (11%)	7.3 (22%)	9.8 (12%)	4 (22%)	6.6 (27%)	10.9 (15%)
TPH	157.2 (13%)	154.7 (25%)	158.1 (14%)	167.5 (33%)	204.3 (31%)	134.9 (16%)
TPH (>12.7 cm)	78.4 (9%)	59.7 (19%)	85 (11%)	47.3 (25%)	56.2 (20%)	96.8 (14%)
No. obs.	257	67	190	37	65	102

[a] Portland and Seattle refer to the Portland and Seattle standard metropolitan statistical areas respectively.

Table 5
TPH (>12.7 cm) estimates and standard errors for the 11 most populous species (common names) for all of Oregon and Washington and for sub-regions.

	TPH > 12.7 cm Mean Estimate (Standard Error%)					
species com.	OR&WA	OR	WA	East OR&WA	Portland[a]	Seattle[a]
Douglas-fir	16.9 (20)	10.6 (69)	19.1 (20)	1.2 (55)	5.3 (61)	23.7 (26)
red alder	13.7 (25)	5.3 (69)	16.7 (27)	0.4 (99)	9.8 (56)	19.6 (31)
bigleaf maple	8.6 (34)	2 (63)	10.9 (36)	0.8 (69)	6.2 (63)	15.7 (43)
western redcedar	7 (23)	3.8 (47)	8.1 (26)	0.8 (99)	4.2 (50)	6.7 (36)
ponderosa pine	3.5 (43)	4.1 (58)	3.3 (57)	23.4 (42)	0 (NA)	0 (NA)
sweet cherry	2.4 (26)	0.6 (99)	3 (27)	1.9 (70)	1.1 (70)	3.3 (36)
black cottonwood	1.9 (34)	0.7 (74)	2.3 (36)	4.4 (59)	0.8 (73)	2.2 (51)
Pacific madrone	1.6 (61)	0 (NA)	2.2 (61)	0 (NA)	0 (NA)	3.5 (70)
western hemlock	1.4 (31)	0 (NA)	2 (30)	0 (NA)	0 (NA)	1.9 (39)
paper birch	1 (48)	1.3 (70)	0.9 (63)	0 (NA)	1.7 (70)	0.7 (59)
Oregon white oak	1 (56)	2.9 (66)	0.3 (100)	0 (NA)	1.1 (78)	0.6 (100)

[a] Portland and Seattle refer to the Portland and Seattle standard metropolitan statistical areas respectively.

Table 6
TPH estimates and standard errors for 5 cm diameter classes (DBCL) for all of Oregon and Washington and for sub-regions.

	TPH Mean Estimate (Standard Error%)					
DBCL	OR & WA	OR	WA	East OR&WA	Portland[a]	Seattle[a]
2.5–7.4	48.6 (25)	81.1 (43)	37.1 (30)	65.1 (44)	106.1 (43)	27.3 (53)
7.5–12.4	29.2 (32)	11.7 (46)	35.4 (35)	50.1 (50)	39 (72)	11.2 (45)
12.5–17.4	18.9 (12)	15.3 (21)	20.1 (14)	11.2 (23)	17.1 (25)	22.5 (18)
17.5–22.4	12.8 (13)	10.8 (31)	13.5 (15)	9.6 (55)	8.9 (24)	16.1 (18)
22.5–27.4	11.8 (13)	9.4 (33)	12.7 (14)	8.2 (28)	8.2 (34)	13.9 (14)
27.5–32.4	8.1 (16)	5.5 (35)	9 (18)	4.3 (52)	4.7 (40)	10.4 (21)
32.5–37.4	6 (16)	4.1 (30)	6.7 (18)	3.6 (37)	4.3 (33)	7.7 (24)
37.5–42.4	4.5 (17)	2.2 (35)	5.3 (19)	2.4 (44)	2.2 (41)	6.2 (25)
42.5–47.4	3.2 (18)	2.4 (38)	3.5 (20)	1.6 (59)	1.7 (45)	3.3 (27)
47.5–52.4	2.4 (19)	1.8 (42)	2.6 (21)	1.6 (59)	1.7 (45)	3.7 (25)
52.5–57.4	2 (21)	0.4 (70)	2.5 (22)	2.4 (44)	0.6 (70)	2.6 (30)
57.5–62.4	1.6 (22)	1.8 (49)	1.6 (24)	1.2 (55)	1.7 (61)	1.9 (30)
62.5–67.4	1.2 (31)	0.2 (99)	1.6 (32)	0.4 (99)	0 (NA)	1.9 (42)
67.5–72.4	1.2 (27)	1.3 (51)	1.2 (31)	0 (NA)	1.4 (59)	1.5 (39)
72.5–77.4	1 (30)	0.4 (70)	1.2 (33)	0.4 (99)	0.3 (99)	1.2 (42)
77.5–82.4	0.6 (43)	0.2 (99)	0.8 (46)	0.4 (99)	0.3 (99)	1.2 (55)
82.5–87.4	0.5 (33)	0.4 (70)	0.5 (37)	0 (NA)	0.3 (99)	0.7 (44)
87.5–92.4	0.4 (42)	0.4 (70)	0.4 (53)	0 (NA)	0.3 (99)	0.4 (74)

[a] Portland and Seattle refer to the Portland and Seattle standard metropolitan statistical areas respectively.

Table 7
TPH by species and 5 cm diameter class (DBCL) for all of Oregon and Washington.

	TPH Mean Estimate (Standard Error%)								
DBCL	bigleaf maple	black cottonw.	Douglas-fir	Pac. madrone	paper birch	pond. pine	red alder	dom. cherry	west. hemlock
0–4.9	–	0.7 (100)	5 (87)	–	–	2.2 (100)	7.9 (73)	–	1.4 (100)
5–9.9	–	–	5.2 (61)	0.1 (100)	0.8 (93)	0.7 (100)	3.7 (65)	–	0.7 (100)
10–14.9	1.4 (40)	0.6 (37)	2.2 (33)	0.3 (72)	0.1 (71)	0.5 (53)	4 (31)	0.5 (36)	0.5 (39)
15–19.9	1.1 (34)	0.2 (50)	2.4 (33)	0.3 (53)	0.1 (100)	0.9 (76)	2.5 (31)	0.9 (39)	0.3 (44)
20–24.9	1.6 (27)	0.4 (37)	2.3 (31)	0.2 (58)	0.3 (53)	0.3 (52)	2.1 (35)	0.6 (31)	0.2 (58)
25–29.9	1.2 (45)	0.2 (71)	1.8 (36)	0.1 (100)	0.2 (61)	0.5 (64)	2 (37)	0.1 (71)	0.2 (74)
30–34.9	0.6 (65)	0.1 (71)	1 (31)	0.2 (61)	0.2 (74)	0.4 (42)	1.4 (30)	0.2 (58)	–
35–39.9	0.6 (73)	0.1 (100)	1.2 (35)	0.1 (71)	0.1 (100)	0.2 (58)	0.7 (39)	0.1 (100)	0.1 (71)
40–44.9	0.4 (55)	–	1.3 (25)	0.2 (100)	0.1 (100)	0.2 (74)	0.4 (51)	–	–
45–49.9	0.3 (44)	–	0.8 (40)	0.1 (100)	–	0.2 (74)	0.3 (53)	–	0.1 (71)
50–54.9	0.3 (47)	–	0.4 (46)	0.1 (100)	–	0.3 (53)	0.1 (100)	–	–
55–59.9	0.3 (52)	0.1 (100)	0.6 (42)	–	–	0.1 (100)	–	–	–
60–64.9	0.1 (71)	0.1 (100)	0.3 (47)	–	–	0.1 (100)	0.1 (100)	–	–

report estimates that we have a lot of trees of a given species, we can use the information to plan our management, but only if the SE values are sufficiently small to suggest that estimate is reliable. If, for example, the SE value is as large as the estimate then we would have some difficulty relying on the estimate (this suggests we need a larger sample to be able to make inference about the estimate). In some instances it is reasonable to omit SE values if they are available elsewhere, e.g. when reporting in graphical form, however this is not always the case in the i-Tree eco reports. For example, standard errors are not available for tables or graphs of tree density by land use—the user must compute these values from the total numbers of trees and divide by the number of acres. While the missing SE values can be calculated by the user from other tables, it would prove beneficial to associate standard errors with every mean or total estimate. We can imagine many users would not know to calculated trees per hectare, or calculate standard errors for trees per hectare before they can make inferences from reported values.

Most tables do have standard errors, however there is no documentation for how standard errors were calculated. In a number of instances we attempted to reproduce the standard error values in the report and were unable to do so. An example computational errors in SE can be seen in the provided sample project which is distributed with i-Tree Eco as the "plot-based sample inventory project". When looking at species composition by diameter class, for example, there are a number of instances where there are estimates of number of trees by diameter and species for which the standard errors are listed as zero. This suggests that the software is excluding plots which do not have the observed species, resulting in severe under-estimates of error. Inclusion of zero values is important in the correct calculation of standard errors.

4. Discussion

4.1. Post-stratification

Unfortunately we did not observe any improvement in estimation performance as a result of post-stratification on NLCD land use class. This is perhaps not a surprising result as land use classification schemes are not optimized to explain variability in tree size, density, and species. This was demonstrated even for the ideal case in which we had actual on the ground measurements of land use. This preliminary examination of NLCD data served as our first attempt to post-stratify the Oregon and Washington urban inventory data. However, alternate classification data may provide more explanatory power – such as a vegetation-specific Landsat-based classification scheme, census demographics data, individual cities' land cover maps, or active remote sensing.

It is not clear how effectively another Landsat based classification system such as LANDFIRE (Rollins, 2009) would work for post-stratification in urban areas, but a Landsat based classification system aimed at tree size, density, and species instead of land use could potentially improve results. With respect to the majority of our study area, another alternative would be the use of lidar. Lidar is available extensively (but not comprehensively) over both Seattle and Portland metro areas ("Puget Sound LIDAR Consortium Home," n.d., "Oregon Lidar Consortium," n.d.). Although there would be concerns about the various ages of the datasets, it should prove feasible to identify coarse structure classes with respect to tree size and cover. These may enable estimation from this small sample size at a finer resolution for sub-regions and subgroups.

4.2. Estimation for sub-regions and subgroups

Estimation for sub-regions and subgroups was feasible for selected cases, however, due to the small sample size and lack of stratifying variables our ability to make inferences about sub-regions was limited. Inferences about trees in Portland and Seattle are likely of great interest to many, but these data essentially do not support looking beyond the base variables for these sub-regions. This is unfortunate given that it is likely that TPH by diameter class and species is of greater relevance than TPH alone. As previously mentioned, improved stratifying variables may help in this respect, increasing the resolution (sub-regions and subgroups) for which it is possible to make inference. However, given the sampling intensity of these data, it is still unlikely that even with better stratifying variables that inference can, for example, be made from these data about TPH by diameter class and species in sub-regions.

Table 8
Types of tree related estimates which can be acquired from i-Tree Eco.

Number of trees by land use
Number of trees per unit area by land use
Species composition by DBH class and land use
Species composition by DBH class
Most important tree species
Species richness, Shannon/Wiener diversity index
Origin of trees by land use
Condition of trees by land use
Condition of trees by DBH and land use
Leaf area of trees by land use
Leaf area of trees per unit area by land use
Leaf area and biomass of trees by DBH class and land use
Leaf area and biomass of trees by land use
Value of trees

4.3. i-Tree Eco

While limitations are bound to be present in a software tool as complex as i-Tree Eco, the software has a lot of potential as a tool to facilitate management and inferences regarding the condition of urban trees (Nowak et al., 2013). The diversity of figures, tables, and information that i-Tree Eco provides should prove helpful in preparing inventory data for human interpretation. Once the data were loaded into the i-Tree Eco database a complete report and numerous tables were available in less than 24 h (the data are processed "in the cloud"). In contrast, having every urban inventory group attempt to replicate the output from scratch would be tedious and redundant and the results may not be comparable between organizations.

While we were impressed by the simplicity and extensive reporting capacity of i-Tree Eco, we cannot yet recommend the software without an update to include measures of error for all estimated values, better descriptions of the estimation procedure and reported values, and perhaps a revised strategy for reporting estimates and standard errors. Fortunately, the development process for i-Tree Eco appears to be fairly responsive to external feedback, and we do not envision these issues being problematic to remediate. I-Tree Eco does have an import facility, which should enable most users to adopt the software regardless of their data collection system—although some programming is recommended to guarantee consistency in transferring data into the excel sheets to be imported by i-Tree Eco.

The limited number of reported statistics regarding urban trees is likely a stronger deterrent for users wishing to support management of urban trees from their inventory information. In evaluating this software it would be important to examine the outputs and evaluate whether they are sufficient to support the needs of the organization. This software will lend itself best to users who have minimal need to interact with the inventory database and do not require custom outputs, or who are more interested in estimates related to ecosystem services or air quality. In many instances having a rigid measurement and reporting protocol may even prove to be an advantage with respect to minimizing complexity and overhead.

5. Conclusions

Since the majority of people in the U.S. live in urban areas, and it is well known that trees play an important role in human well-being, understanding how trees are distributed in the built environment is critical to assessing how they affect human lives with respect to both their impact on the quality of human life and to the economic costs and value associated with the resource. In light of the impacts trees have on humans, the newly collected forest inventory data collected in a consistent manner across Oregon and Washington urbanized areas are an important resource for assessing the condition of the urban environment. However, it is also important to recognize the uses for which these data can be reasonably applied, and those for which additional data are likely necessary. Our analyses suggest that even without effective post-stratification, these data still enable defensible inferences about the distributions of trees by species and diameter at the state level. Estimation at the sub-region scale is also supported on a very limited basis, but would require supplementary inventory data or effective auxiliary information in most cases.

5.1. Future research

Our next objectives for these data are to assess whether use of alternative auxiliary data for post-stratification will better enable us to make inferences about sub-regions and subgroups. Incorporating data from inventories performed by individual cities is another option, but given increased precision, the consistent sampling and measurement protocol provided by urban FIA data would provide greater flexibility for compatible inferences within and between regions. We are also interested in examining the new urban FIA plot design (single 14.6 m radius, 0.067 ha area), and examining its efficiency properties in the urban environment, especially its interaction with post-stratification. The FIA plot is likely to be very efficient when using estimators appropriate for simple random samples, however with post-stratification it may be that the larger plot footprint could reduce estimation precision following post-stratification if there are a large number of plots which straddle multiple post-strata.

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