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A comparison of two sampling approaches for assessing the urban forest canopy cover from aerial photography

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ABSTRACT

Two different sampling approaches for estimating urban tree canopy cover were applied to two medium-sized cities in the United States, in conjunction with two freely available remotely sensed imagery products. A random point-based sampling approach, which involved 1000 sample points, was compared against a plot/grid sampling (cluster sampling) approach that involved a 1.83 m square grid of points embedded within 0.04 ha circular plots. The imagery products included aerial photography from the U.S. Department of Agriculture National Agricultural Imagery Program (viewed within ArcGIS), and Google Earth imagery. For Tallahassee, Florida, the estimate of tree canopy cover was 48.6–49.1% using Google Earth imagery and 44.5–45.1% using NAIP imagery within ArcGIS. Statistical tests suggested that the two sampling approaches produced significantly different estimates using the two different imagery sources. For Tacoma, Washington, the estimated tree canopy cover was about 19.2–20.0% using Google Earth imagery and 17.3–18.1% when using NAIP imagery in ArcGIS. Here, there seemed to be no significant difference between the random point-based sampling efforts when used with the two different image sources, while the opposite was true when using the plot/grid sampling approach. However, our findings showed some similarities between the two sampling approaches; hence, the random point-based sampling approach might be preferred due to the time and effort required, and because fewer opportunities for classification problems might arise. Continuous review of urban canopy cover estimation procedures suggested by organizations such as the Climate Action Reserve and others can provide society with information on the accuracy and effectiveness resource assessment methods employed for making wise decisions about climate change and carbon management.

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1. Introduction

An urban forest can be described as the woody vegetation within a city that includes street trees located on both public and private lands, urban parks, and other trees located on residential properties, commercial land, and other lands. This resource provides a number of essential benefits to human beings, a few of which include providing aesthetic value, reducing energy use, facilitating cooling effects, improving water and air quality, providing diverse wildlife habitat, and increasing human health and well-being (Nowak, 1993; Jensen et al., 2004; Leuzinger et al., 2010; Nowak et al., 2010; McPherson et al., 2011; Richardson and Moskal, 2014). The ecosystem services derived from an urban forest are often directly related to the amount of tree canopy cover, which is ideally composed of healthy and functioning vegetation (Nowak and Greenfield, 2012). Tree canopy cover, generally estimated as the percentage of a site covered by tree canopies, is the simplest and most often used metric to quantify urban forest extent (Richardson and Moskal, 2014) and can be used to inform management decisions and policy analyses. For instance, a tree canopy assessment was conducted for Los Angeles to determine the capacity of the city to plant an additional one million trees (McPherson et al., 2011).

The human population of the United States increased from 281.4 million to 308.7 million between 2000 and 2010, and over 83.7% of the population now lives in metropolitan areas (large cities), where the population grew almost twice as fast as micropolitan areas (small cities with 10,000 to 50,000 people) (Mackun et al., 2011).

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Unless the administrative boundaries of cities expand, growth in the human population applies certain types of pressure upon the urban forests found there (Nowak, 1993; McPherson et al., 2011). For many United States cities, developed areas were created from areas once previously forested. In the 1990s, approximately 0.4 million hectares (ha) of forested land was converted each year to developed or other uses. Even if tree canopy cover increases in association with urban expansion of Great Plains and desert states, it is estimated that by 2050, an additional 9.3 million ha of forested area will become some other land use in the United States due to urbanization (Alig et al., 2003), thus population growth may result in direct or indirect negative impact on the structure, pattern and function of urban ecosystems in and around urban areas (Nowak, 1993).

In recent years, various approaches such as aerial photography interpretation, satellite-based image analysis, and aerial LiDAR (Light Detection and Ranging) analysis have proved useful for estimating tree canopy cover. These remotely-sensed sources of information can be both cost-effective when compared to field sampling, and can facilitate comparable analyses among different cities (McPherson et al., 2011). As examples, Irani and Galvin (2003) used 4 m resolution remotely sensed imagery to assess tree canopy cover in Baltimore. Nowak and Greenfield (2012) conducted a study using paired aerial photographs to determine tree canopy cover changes in 20 cities in the United States. Parlin (2009) also used digital land cover maps developed from 0.6 m resolution remotely sensed imagery to estimate tree cover change in Seattle. Remotely sensed imagery thus provides an opportunity to efficiently and effectively measure canopy cover across both space and time.

Specific tree canopy cover estimates can be developed using several different sampling approaches. The most common sampling approach involves random point-based sampling, where random points are located within the boundary of a city, and then are classified through aerial photo interpretation as either falling on a tree crown or not falling on a tree crown. The observation value from this sampling approach is binary (yes/no or 1/0), indicating presence or absence of tree canopy at the sample point, as interpreted from the imagery. As suggested above, for 20 cities in the United States, Nowak and Greenfield (2012) used random point sampling to assess tree cover change over a five year period. They found that there was a decreasing trend in tree cover, about 0.27% per year on average, in these cities. Walton et al. (2008) also used a random point sampling approach and compared their results to classified satellite images.

A second sampling approach for estimating tree canopy cover might be to create random polygons and delineate tree crowns within these polygons. Nowak et al. (1996) were perhaps the first to use a fixed polygon approach like this for estimating tree cover. Nowak et al. (2008) studied the impact of polygon size on urban forest estimates, and noted that an increase in polygon size meant (logically) an increase in time required to perform the assessment. For Detroit and Atlanta, Merry et al. (2014) used a polygon approach to estimate tree canopy cover from aerial photography, and noted that the estimate of tree canopy cover using a polygon sampling approach could be slightly different than the estimate derived from using a point-based approach. The combined effects of mis-registration, feature displacement, and shadows could have imposed minor challenges to either method.

A third sampling approach may be to create a random polygon and then create a grid of points within the polygon in order to estimate canopy cover. Therefore, rather than draw the outline of tree canopies within the polygon and compute the proportion of tree canopy cover using the tree canopy and non-tree canopy areas (as in Merry et al., 2014), the proportion of grid points that fall on tree canopies within the polygon is used as the estimate of canopy cover for the polygon. From this juncture forward we will refer to this cluster sampling process as the *plot/grid sampling approach*. This approach was proposed by the Climate Action Reserve (Nickerson, 2014a), in their draft Urban Forest Project Protocol. The Climate Action Reserve is a private nonprofit environmental organization and leading entity in the measurement of forest resources for carbon policy implementation. Their aim is to provide support to activities that decrease greenhouse gas emissions (GHG) by assuring the environmental entirety and economic benefits of emissions reduction projects. Along these lines, the Climate Action Reserve has a goal of establishing high quality standards for carbon offset projects and supporting activities that reduce air pollution, enhance growth in new green technologies, and facilitate the attainment of emission reduction goals. Since the cluster sampling approach for estimating canopy cover (when proposed) was different than other approaches described in the literature, we embarked on a study of its effectiveness for this purpose.

Interestingly, the cluster sampling process described in the draft Climate Action Reserve protocol (Nickerson, 2014a) was absent from the final protocol to allow people involved in these assessments the flexibility to respond to improvements in methodological and technological tools. However, they refer to desired sampling error in the *Quantification Guidance* (Climate Action Reserve, 2014a) and to verification of tree canopy cover estimates through a point-based sampling approach in the final protocol. Comments received with respect to the draft Urban Forest Project protocol (Climate Action Reserve, 2014b) suggested that the plot/grid sampling approach may have been reasonable for large, contiguous forest areas, but may have been unsuitable for urban areas that include a scattered arrangement of trees (street trees and others). However, this limitation would also seem to affect a point-based sampling approach. Further, it was suggested through feedback on the draft protocol that the processes used for estimating urban canopy cover needed to be less detailed and structured, and needed to allow for the use of other equally valid tree canopy cover sampling protocols. While not included in the final protocols for urban forest projects by the Climate Action Reserve, the plot/grid sampling approach has not heretofore been assessed; therefore, it is the focus of this study.

Our goal was to compare two sampling approaches for estimating urban tree canopy cover in two United States cities (Tacoma, Washington and Tallahassee, Florida), using remotely sensed imagery from two different sources. We wanted to determine the feasibility of each sampling approach and to compare the results of canopy cover estimates using the two different remotely sensed imagery sources. The two sampling approaches are (a) the random point-based and (b) the plot/grid approach. The two remote sensing imagery sources used in this study included (a) U.S. Department of Agriculture National Agriculture Imagery Program (NAIP) imagery viewed within ArcGIS (ESRI, 2013) and (b) Google Earth imagery (Google Inc., 2014). The NAIP imagery presents features in natural color (0.4–0.7 μm wavelengths of energy), is contained in compressed county mosaic form, and has a 1 m spatial resolution. The imagery is provided by the U.S. Department of Agriculture's Farm Service Agency (U.S. Department of Agriculture, 2013), and was captured between September 16th, 2013 and October 28th, 2013. Google Earth imagery arises from a variety of sources such as the U.S. Department of Agriculture, DigitalGlobe, GeoEye-1, Ikonos, MODIS Terra, city or state governments, and commercial aerial photographers (Taylor, 2014). Thus due to the use of third-party sources of imagery contained in Google Earth, and because the imagery is aggregated, the spatial resolution varies. The Google Earth imagery was dated as May 5th, 2013 and April 1st 2013 for Tacoma and Tallahassee, respectively. The most recent imagery available through Google Earth also presents features in natural color; the historical imagery available through Google Earth may be panchromatic. These two imagery sources (NAIP and Google Earth)

were selected because they are freely available and temporally current. The Google Earth imagery is also temporally consistent with the NAIP imagery within the two cities studied. NAIP imagery has been used in other recently published assessments of urban tree canopy cover (e.g., McGee et al., 2012; Merry et al., 2014), while Google Earth imagery has not.

In summary, we conducted a study to determine the percentage of tree canopy cover using NAIP imagery within ArcGIS and using Google Earth imagery in order to compare whether estimated tree canopy cover levels would be comparable when using either imagery source. We also conducted the study in a manner that would allow us to compare the two sampling approaches. Statistical tests were employed to determine whether significant differences existed. The following hypotheses were developed:

H_1: When employing the random point-based sampling approach across Tallahassee, there is no significant difference in the estimated tree canopy cover derived from using the NAIP imagery in ArcGIS and the estimated tree canopy cover derived from using the Google Earth imagery.

H_2: When employing the random point-based sampling approach across Tacoma, there is no significant difference in the estimated tree canopy cover derived from using the NAIP imagery in ArcGIS and the estimated tree canopy cover derived from using the Google Earth imagery.

H_3: When employing the plot/grid sampling approach across Tallahassee, there is no significant difference in the estimated tree canopy cover derived from using the NAIP imagery in ArcGIS and the estimated tree canopy cover derived from using the Google Earth imagery.

H_4: When employing the plot/grid sampling approach across Tacoma, there is no significant difference in the estimated tree canopy cover derived from using the NAIP imagery in ArcGIS and the estimated tree canopy cover derived from using the Google Earth imagery.

2. Methods

In the sections below, the study areas (cities) and the remotely sensed data around which the study was conducted are described, along with the sampling approaches employed and the statistical tests used to address the hypotheses.

2.1. Study areas

As we suggested earlier, we selected two United States cities (Tallahassee, Florida and Tacoma, Washington) as case studies within which to estimate tree canopy cover using two sampling approaches and two imagery sources. We wanted to select two medium-sized cities that were located in two different regions of the United States, which contained in theory different forms of vegetative cover. These two cities were further selected based on the availability of both NAIP imagery and Google Earth imagery for the year 2013, and because Tallahassee and Tacoma have similar human population sizes. According to the Census Bureau (2014), Tallahassee was the seventh largest city in Florida with an estimated total population of about 186,000 people in 2013 and a population density of about 700 people per square kilometer (km^2). Comparably, Tacoma was the third largest city in Washington with an estimated total population of about 203,000 people in 2013 and a population density of about 1541 people per km^2. The percent change in population from April 1, 2010 to July 1, 2013 was 2.5% for Tacoma and 2.8% for Tallahassee.

For both cities, we used NAIP imagery viewed within ArcGIS and Google Earth imagery, both captured in 2013. Google Earth compiles imagery from multiple imagery sources including USDA NAIP imagery. However, through visual analysis we confirmed that the imagery used when analyzing sampling methods in Google Earth was not NAIP imagery.

2.1.1. Sampling approaches for tree canopy cover estimates

Two different approaches were employed: a random point-based approach and a plot/grid approach. We randomly located 1000 points each within the boundaries of each city (Fig. 1). Suggested minimum samples were 100 per class for a large area by Congalton and Green (2009). Our sample size, 1000 points, goes beyond the minimum requirements presented by Congalton and Green (2009) and is comparable to recent studies by Nowak and Greenfield (2012) and Richardson and Moskal (2014). These random points were created using the random point generator in ArcGIS. They were converted to a .KMZ format for use in Google Earth. For the plot/grid approach, the plots were centered on the points of the point-based approach.

The point-based approach uses binary data that is typically expressed as a proportion or percent when reported for an entire population (or sample area). The samples involve a determination from a random or systematic dot grid whether tree canopy is present or absent. This metric is often reported as the percent canopy cover for the sample area. In this study, through aerial photo interpretation we determined whether the location of every single point fell onto a tree crown (1), or did not fell onto a tree crown (0) representing a presence/absence type of analysis. We used the same 1000 sample points to assess canopy cover with the NAIP imagery in ArcGIS and with the Google Earth imagery. Points were analyzed simultaneously in the two imagery sources in order to make sure they fell on the same location and to limit mis-classification, but the order of the sample was randomly assigned for each data set, so as to not introduce bias into the presence/absence decision. Also, in estimating canopy cover a fixed scale was utilized (1:600–1:800) when interpreting NAIP imagery within ArcGIS, and a fixed eye altitude was utilized (200–300 m (m)) when interpreting Google Earth imagery. The percentage of tree canopy cover (p) was calculated by dividing the number of samples (x) indicating tree canopy cover by the total number of sample points (n) within each city ($p = x/n$). The standard error (SE) for the tree canopy cover of an individual sample was defined using following equation:

$$SE = (p(1-p)/n)^{0.5} \quad (1)$$

We also derived the pooled sample proportion

$$p* = ((p_1 * n_1 + p_2 * n_2)/(n_1 + n_2)) \quad (2)$$

for the estimates of tree canopy cover between NAIP imagery (p_1) and Google Earth imagery (p_2) (Macfie and Nufrio 2006), and the SE from pooled sample proportion:

$$SE* = (p*(1-p*))((1/n_1) + (1/n_2)))^{0.5} \quad (3)$$

where p^* is the pooled sample proportion, n_1 is the size of sample 1, and n_2 is the size of sample 2.

For the plot/grid (cluster sampling) approach, the original 1000 randomly sampled points were buffered in ArcGIS to create circular polygons of a size (0.04 ha) that was suggested by Nickerson (2014a) as appropriate for this type of analysis. A grid of points was then placed inside each plot in order to estimate canopy cover. The spacing between the points within the circular plots was 1.83 m, and a large number of points (121) were created for each circular plot (Fig. 1). Thus, 121,000 points were interpreted (1000 plots x 121 points per plot) for each imagery product. Some plots were very quickly interpreted, if all or most points fell inside or outside of tree canopies, thus the average rate of interpretation per point in this method is much faster than the per-point rate for the

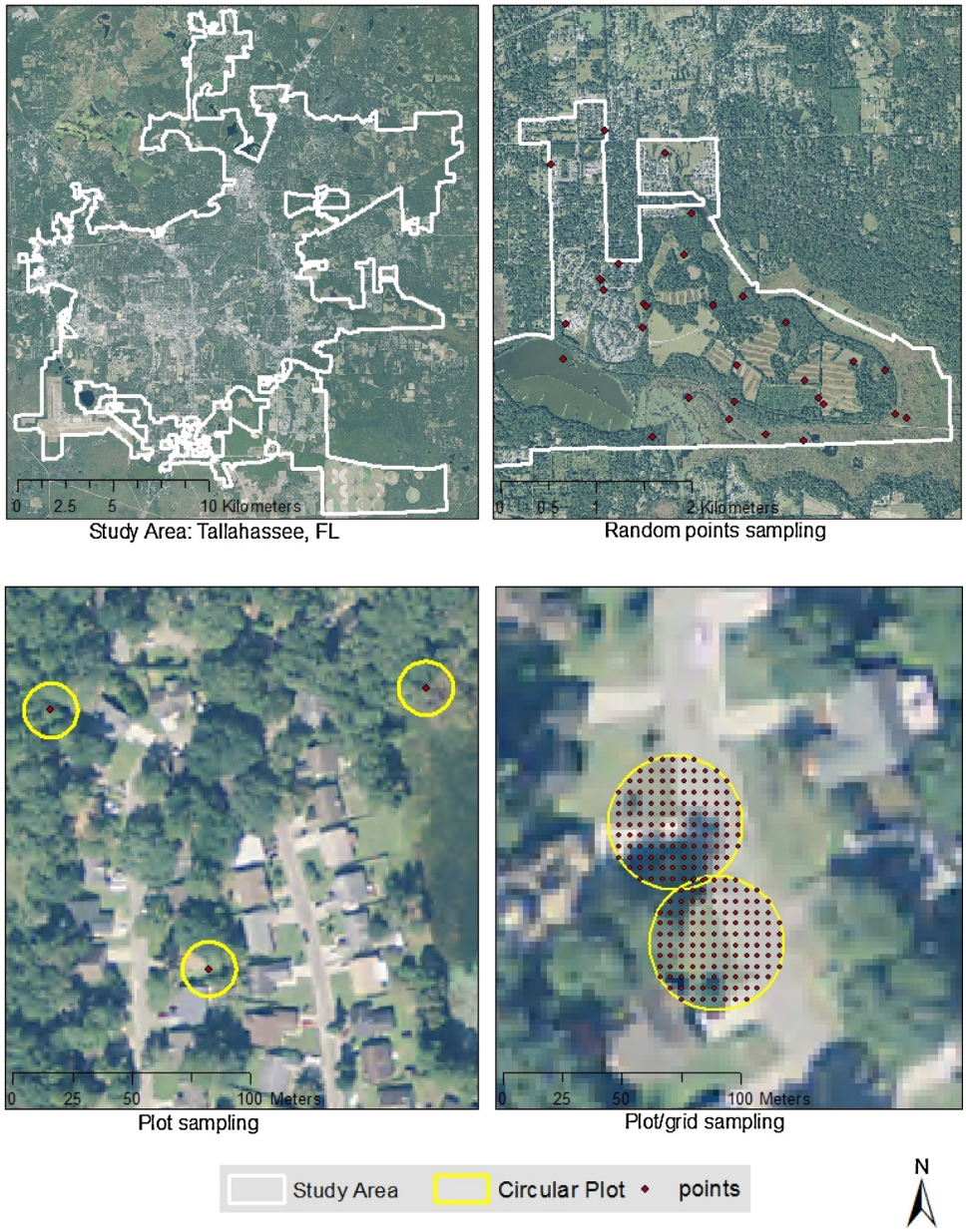

Fig. 1. The Tallahassee city boundary (upper left), an example of the random point-based sampling approach (upper right), 0.4 ha plots (lower left), and the 1.83 m grid embedded within the 0.4 ha plots (lower right).

point-based approach. A Visual Basic program was used to create the grid of points based on the center location of the plot. A shapefile of these grids was created for use in ArcGIS, and a .KMZ file was created for use in Google Earth. The number of the points within the circular points that fell on a tree canopy was counted and the percentage canopy cover was estimated for each plot by dividing through by the total number of points in the grid. While the order of plot assessment was randomized, for consistency, we followed the same order for assessing the grid of points within each plot (north to south and laterally west to east). Also, some of the circular plots overlapped, overlapping points were not discarded but treated as a separate plot/grid sample. After interpretation of the grid within each plot, each plot became associated with an observation of the percentage canopy cover that ranged between 0 and 100 percent.

For the plot/grid approach, the mean and standard error for the entire sample within each city were calculated, along with 95% confidence intervals for tree canopy cover. We also calculated SE for each plot to compare with standard error of the entire sample. Similar to the point-based sampling approach, we reordered the sample randomly for each imagery source (NAIP and Google Earth) to avoid introducing sampling bias in the tree canopy cover estimation. We also used the same fixed viewing scale for the random point-based sampling approach (1:600–1:800 for NAIP imagery within ArcGIS and 200–300 m eye altitude for Google Earth imagery, respectively). Although Nickerson (2014a) suggests progressive sampling of plots until "a confidence estimate for average canopy cover for each urban forest class is achieved at ±10% at the 90% confidence interval", we initially used the same number of samples (1000) as we used in the point-based sampling approach. However, we re-analyzed the data collected to determine how many samples would have been required had the stopping point been determined where the ±10% range in average canopy cover equaled the 90% confidence interval for canopy cover.

The plot/grid (cluster sampling) approach that we employ is a form of simple random one-stage cluster sampling process that involves a geographic sampling frame or cluster (a city) in which there are listing units (the 0.10 acre plots) and elementary units (the collection of points within the plots) from which we estimate the proportion of tree cover. The clusters (cities) however are not selected randomly from the entire population (sampling frame) of cities within the United States. The listing units were randomly dispersed (or selected) within each city. Given that the plots could differ in tree canopy characteristics by simply shifting them a meter or so in any direction, the sampling frame for the plots might be considered infinite or very large. The feasibility and economics of cluster sampling have been noted as reasons for using this type of sampling process. In our case these reasons may not be viewed as advantages for our sampling effort, since the listing units are positioned in the same locations as the random sample points, and since more time is required to assess the elementary units (points) within the plots. High standard errors within samples have also been suggested as a disadvantage of cluster sampling approaches (Levy and Lemeshow, 1991). However, an estimate of the percent canopy cover for each of the listing units (plots) is obtained from the binary data associated with each elementary unit (the points within the plots). This continuous value (range 0–100 percent) is then used to determine canopy closure within each city rather than the binary value associated with the point-based sampling approach noted previously.

2.1.2. Statistical tests related to tree canopy cover estimates

For hypotheses H_1 and H_2 (referencing the random point-based approach) we tested the difference between proportions (H_0: $p_1 = p_2$, H_a: $p_1 \neq p_2$). We developed the pooled sample proportion and the standard error of the sampling distribution difference between two proportions. A Z-score was determined using the following equation;

$$Z = (p_1 - p_2)/\mathrm{SE}* \tag{4}$$

We then assessed the probability (P-value) associated with the Z-score to determine whether significant differences existed, and to determine whether to accept or reject the hypotheses. Because the data collected from the plot/grid sampling approach resulted in a continuous value estimate (from 0 to 100%) of tree canopy cover (as opposed to the presence/absence response from the random point-based sampling approach), to test H_3 and H_4 we first examined the normality of the data by employing the Shapiro-Wilk test, since our data set was smaller than 2000 elements. The results indicated that the tree canopy estimates from the plot/grid sampling approach, using both the NAIP imagery viewed within ArcGIS and the Google Earth imagery, were not normally distributed. Hence, the non-parametric Wilcoxon Signed Rank Test was used to test hypotheses H_3 and H_4.

2.1.3. Assessment of classification error, mis-Registration and feature displacement

Inevitably when conducting analysis with two remotely sensed imagery sources, issues such as image mis-registration and the resulting mis-classification of a point between imagery sources will need to be addressed. As suggested by Nowak and Greenfield (2012) these components of image analysis may lead to incorrect estimations of land cover, for example a point may be reported as falling on tree canopy in one imagery source and not falling on a tree in a different imagery source. Using a second interpreter can help mitigate this mis-classification; therefore, we randomly selected 10% of the points from the 1000 sampling points in each city and with a second interpreter analyzed the presence/absence of trees using the NAIP and Google Earth imagery in the two cities. There was a 95–98% agreement between the analyses of the two interpreters across the two imagery sources and two cities, which is similar to that found in Nowak and Greenfield (2012). Differences were due to the subjective nature of the classification near the edges of tree crowns.

For further clarity on the potential for mis-classification of a point due to its proximity to a tree canopy edge and potential mis-registration between the two imagery sources on the point classification, four independent sets of randomly selected points were generated from the original 1000 point-based sample. For both the NAIP and Google Earth imagery, 100 of the points classified as having fallen on a tree were selected. These were not paired points but 100 unique points for each imagery source. Additionally, 100 points that were classified as having not fallen on a tree were selected. For each point, a measurement was made to estimate the proximity of the point to the nearest tree canopy edge (those points not classified as having fallen on a tree) as well as the proximity of points classified as having fallen on a tree to nearest edge of the tree canopy. These measurements were of interest in assessing whether potential mis-classification by the interpreter may have contributed to the cause of some error.

For large areas, mis-registration of images may not be very important in estimating tree cover for a single point in time. Yet when comparing points between images taken at different points in time (e.g., to perform a landscape change analysis), the mis-registration of images may lead to false differences. When assessing two temporally different images, ideally an image interpreter may be able to account for mis-registration by locating on the second image the original position of each point from the first image. However, this is difficult in circumstances where points fall on tree crowns or within groups of trees. Therefore in order to further understand mis-registration (or registration inconsistencies) between the imagery sources, another 100 independent points of the original 1000 point sample were randomly selected for analysis in both cities. From these points, a linear distance measurement was made to a place on a clearly visible, permanent feature using both the NAIP imagery and the Google Earth imagery. Since it is impossible to know which of the two imagery sources is correct, the absolute difference in the distances between these measurements was used to understand the average mis-registration distance among the two imagery sources. These estimates of mis-registration distances are compared to the distances of points to the nearest canopy edge, using the sub-sets of sample points noted in the previous paragraph.

Finally, feature displacement can be a significant issue along the edges of individual aerial images, depending on a number of factors (flying height of the aircraft, focal length of the camera or sensor, etc.). With composited images, one would hope that feature displacement would be minimized, but through casual observation, the effects can occasionally be seen. Unfortunately, feature displacement depends also on the height of the features and the distance of the features from the nadir of each individual aerial image, two measurements that are elusive for a study such as ours; the image nadir is especially difficult to determine within composite images. To determine the nadir, one would need to locate the places in the composite images where feature displacement is negligible, which is difficult if these areas include a high density of trees, or if tree crowns are rounded (i.e., deciduous trees). For these reasons, we failed to provide a process for estimating feature displacement in the study areas.

3. Results

In evaluating the tree canopy cover of Tallahassee through the use of the point-based sampling approach, we estimated that 49.1% of the land within the boundary of the city was covered with trees

Table 1
Summary statistics for the point-based sampling approach (1000 randomly-located sample points) and the plot/grid sampling approach (1000 randomly-located sample plots) using imagery available through Google Earth and NAIP imagery viewed within ArcGIS.

	City											
	Tallahassee						Tacoma					
	Point-based Sampling Approach			Plot/grid Sampling Approach			Point-based Sampling Approach			Plot/grid Sampling Approach		
Imagery source	Estimated Canopy Cover (%)	Standard Error (%)	95% Confidence Interval (%)	Estimated canopy cover (%)	Standard error (%)	95% Confidence Interval (%)	Estimated Canopy Cover (%)	Standard Error (%)	95% Confidence Interval (%)	Estimated Canopy Cover (%)	Standard Error (%)	95% Confidence Interval (%)
NAIP	44.5	1.50	41.7–47.3	45.1	1.30	42.7–47.7	18.1	1.20	15.7–20.5	17.3	0.93	15.4–19.1
Google Earth	49.1	1.40	46.2–52.0	48.6	1.29	46.1–51.1	19.2	1.20	16.8–21.6	20.0	0.92	18.2–21.8

in 2013 when viewed with Google Earth imagery, while 44.5% was covered with trees when viewed with NAIP imagery in ArcGIS (Table 1). Therefore, the difference between two imagery sources seemed to be about 4.6% in tree canopy cover estimates (standard error of the difference = 2.23%). The standard errors employed for the confidence intervals were 1.50% for the Google Earth and 1.40% for NAIP analyses and the resulting 95% confidence intervals were [46.2 –52.0%] and [41.7–47.3%] for Google Earth and NAIP analyses, respectively. For Tacoma, through the use of the point-based sampling approach our estimate of tree cover in 2013 using the Google Earth imagery was 19.2%. The estimate of tree canopy cover was 18.1% when using NAIP imagery within ArcGIS. The estimated tree cover difference between Google Earth imagery and NAIP imagery within ArcGIS was thus 1.1% (standard error of the difference = 1.74%). The standard errors employed for developing confidence intervals were the same (1.20%) for both Google Earth imagery and NAIP imagery within ArcGIS, and hence the 95% confidence intervals were [16.8–21.6%] and [15.7–20.5%] for Google Earth imagery and NAIP imagery within ArcGIS, respectively.

With respect to the point-based sampling approach results, after performing the statistical tests associated with the hypotheses, we encountered some interesting findings. For Tallahassee, the results suggested that we cannot accept the H_1 null hypothesis ($p < 0.05$). There seemed to be a significant difference between the estimated percentage tree canopy cover using the random point-based approach with NAIP imagery within ArcGIS and the estimated percentage tree canopy cover using the random point-based approach with Google Earth imagery. On the other hand, the results for Tacoma suggested that we can accept the H_2 null hypothesis ($p > 0.05$). There seemed to be no significant difference between the estimated percentage tree canopy cover with the random point-based approach when using either NAIP imagery within ArcGIS or Google Earth imagery.

In assessing tree cover using the plot/grid sampling approach, we estimated that 48.6% of the land within the city boundary of Tallahassee was covered with tree canopy in 2013 when viewed with imagery contained within Google Earth, and 45.1% was covered with tree canopy when viewed with NAIP imagery within ArcGIS (Table 1). Thus, the difference between the estimates of tree canopy cover was 3.5%. The estimate using Google Earth imagery was slightly lower than what we found using the point-based approach with Google Earth imagery, and the estimate from using NAIP imagery within ArcGIS was slightly higher than the result we found from the point-based approach. The standard errors were 1.29% and 1.30% for Google Earth imagery and NAIP imagery within ArcGIS, respectively, hence the 95% confidence intervals were [46.1%–51.1%] and [42.7%–47.7%] for Google Earth imagery and NAIP imagery within ArcGIS, respectively. For Tacoma, tree canopy cover was estimated to be about 20.0% in 2013 when viewed with Google Earth imagery, and 17.3% when viewed with NAIP imagery in ArcGIS, a difference in estimated tree canopy cover of 2.7%. Contrary to the Tallahassee results, the estimate from using NAIP imagery within ArcGIS was slightly lower than what we found using the point-based approach; however, the estimated tree canopy cover from using Google Earth imagery was slightly higher than the results we found from the point-based approach. The standard errors were 0.92% and 0.93% for the Google Earth imagery and using NAIP imagery within ArcGIS, respectively, hence the 95% confidence intervals were [18.2–21.8%] and [15.4–19.1%] for Google Earth imagery and NAIP imagery within ArcGIS, respectively.

With respect to the plot/grid sampling approach results, after performing the statistical tests associated with the hypotheses, we encountered some unexpected findings. The results suggested rejecting the H_3 and H_4 hypotheses ($p < 0.05$), since for both cities there seemed to be significant differences between the use of Google Earth imagery and NAIP imagery within ArcGIS for estimating tree canopy cover.

In re-analyzing the set of 1000 samples from the plot/grid approach, we found that the point at which the ±10% range in average canopy cover equaled the 90% confidence interval for canopy cover was greater when using the NAIP imagery than when using Google earth imagery for both cities. Further, the number of plot/grid samples that would have been required in Tacoma was greater than the number of plot/grid samples that would have been required in Tallahassee using this rule. For Tacoma, the number of plot/grid samples required would have been 796 using the NAIP imagery in ArcGIS, and 504 using Google Earth imagery. For Tallahassee, the number of plot/grid samples required would have been 200 using the NAIP imagery in ArcGIS, and 140 using Google Earth imagery. However, estimates of canopy cover using these sample sizes were greater (2–8%) than the estimates of canopy cover using 1000 samples.

From measurements made to a sub-set of sample points, on average for the two cities, those points that fell on a tree were within approximately 25 m (Tacoma) to 35 m (Tallahassee) of the edge of the canopy when using the NAIP imagery and approximately 15 m (Tacoma) to 24 m (Tallahassee) when using Google Earth imagery. Those points that were classified as not falling on a tree were, on average, approximately 37 m (Tallahassee) to 46 m (Tacoma) from a canopy edge when using the NAIP imagery and approximately 24 (Tallahassee) to 69 m (Tacoma) from a tree canopy edge when using Google Earth imagery. Therefore, the likelihood of a mis-classification due to a point falling on the edge of a tree canopy in one image and not in the other was deemed minimal for the point-based sampling approach. The variation in these distances to canopy edges was high, however. In Tacoma, when points within tree canopies were considered, 12% were within 1 m from the edge of the canopy. When points not falling on tree canopies were considered, 1.5% were within 1 m from the canopy edge. In Tallahassee, when the sub-sample of points within tree canopies were considered, 2.5% were within 1 m from the edge of the canopy. When points not falling on tree canopies were considered, 5.5% were within 1 m from the canopy edge. As a result, photo interpretation error due to close, subjective classifications along the edges

of tree crowns seems minimal, but likely contributes to some of the differences observed between sampling systems and imagery products. This is particularly of concern with the plot/grid approach where many points within a grid imposed within a plot may be close to the edge of a tree canopy.

The average absolute difference between specific points located on both the NAIP and Google Earth imagery, using locations of a sub-sample of paired points, was 1.19 m in Tacoma and 1.70 m in Tallahassee. These can be viewed as estimates of image registration differences. For Tacoma, using the NAIP imagery, 10% of the previous sub-sampled points classified as having fallen on a tree canopy were closer to the edge of the canopy than the corresponding image registration difference. Comparatively, none of the previous sub-sampled points classified as not being on a tree canopy were closer to the edge of the canopy than the corresponding image registration difference. When using Google Earth imagery, these were 20% and 4% of the previous sub-sampled points, respectively. For Tallahassee, using the NAIP imagery, less than 1% of the previous sub-sampled points that fell on a tree canopy were closer to the edge of the canopy than the corresponding image registration difference, while 3% of the points classified as not having fallen on tree canopy were closer to the edge of the canopy than the corresponding image registration difference. When using Google Earth imagery, these were 12% and 15% of the previous sub-sampled points, respectively. As a result of this analysis, it becomes obvious that some of the differences in tree canopy classification estimates may be associated with registration differences among the two imagery products. Again, this is particularly of concern with the plot/grid approach where many points within a grid imposed within a plot may be close to the edge of a tree canopy.

4. Discussion

In this study, our findings show similarities to other recent findings (e.g., Merry et al., 2014) that indicate tree canopy cover estimates can be statistically significantly different when different sampling approaches or imagery sources are employed, even when the sample units are basically positioned in the same location within the study areas. However, the sampling process itself should not be the cause of these differences; as we noted earlier the combined effects of mis-registration, feature displacement, and mis-classification could have imposed minor challenges to either method.

Given the large number of sample observations collected (1000 sample points, which exceeded the minimum requirement represented by Congalton and Green (2009)), it should be of no surprise that the standard errors are relatively small, and therefore slight differences in sample means might be considered statistically significant. For example, when employing point-based sampling, the differences in canopy cover between using NAIP imagery and Google Earth imagery were 4.6% and 1.1% for Tallahassee and Tacoma, respectively. Statistical test results showed that these were significantly different than the estimated tree canopy cover for Tallahassee but not Tacoma. However, when the plot/grid sampling approach was employed the differences in canopy cover between using NAIP imagery and Google Earth imagery are 3.5% and 2.7% for Tallahassee and Tacoma, respectively, and these were not significantly different. This might be a result of the plot/grid sampling approach minimizing the impact of image mis-registration and feature displacement. The SEs for the plot/grid sampling approach are slightly smaller than the SEs for the point-based approach. However, the average SE of each plot within the plot/grid sampling approach was 1.80% when using the NAIP imagery and 1.88% when using the Google Earth imagery for Tallahassee. For Tacoma, the average SE for the individual plots was 1.48% and 1.80% with the NAIP imagery and Google Earth imagery, respectively. These are slightly larger than the SEs for the point-based sampling approach. Even though many more points were employed in the plot/grid sampling approach, the SE of this approach should be similar to the SE of the point-based approach given that the plot is the sample unit, not the grid of 121 points used within each plot. Had a smaller number of sample observations been utilized, and larger standard errors observed, statistical tests may have suggested that there were no significant difference in the mean values of the Tallahassee results when using the point-based sampling approach. As it stands, the significant differences in results are more likely associated with some combination of mis-classification, mis-registration, and feature displacement issues of the sampling protocol.

A number of factors could have introduced bias or error into our findings. These include problems inherent in the imagery, such as topographic displacement, spatial resolution, minor georeferencing problems, mis-registration, parallax, shadows, image tone and texture issues along edges of individual image frames, and other image processing issues for which users are unaware. During the image interpretation process, the majority of the differences were attributed to points falling on the edge of tree canopies within shadows of one imagery source and not within a shadow on the other imagery source. This was due to differences in the timing of the capture of the imagery (time of day, time of year). This was also particularly evident within the NAIP imagery. Further, due to the spatial resolution of the NAIP imagery, pixilation at a larger scale resulted in some challenges related to the classification of points. Google Earth imagery was advantageous in that regard because it has a finer spatial resolution at larger scales. Allowing the interpreter to vary the scale may also be beneficial to image interpretation efforts and canopy cover assessments using Google Earth imagery, but may have less benefits to similar efforts employing NAIP imagery. Finally, while the imagery used for analysis were captured within months of each other, the variation in season between the two imagery sources may have attributed to the differences in canopy estimates specifically when a point fell on a deciduous tree species.

Without sub-meter accurate horizontal positions to compare against, it is difficult to tell which of the two imagery sources had more mis-registration problems. Orthophotos like those offered by the USDA, by nature, have been processed and corrected to limit these sorts of issues (Lillesand et al., 2004) while the same corrections may not have been applied to the composite imagery offered from Google Earth. Overall, a small level of inconsistent registration was evident across both imagery sources and cities, and therefore likely had some impact on the point classification process. Given that both are composite images, the registration differences are not consistent across the landscape, and a correction process employed for an analysis such as this (estimating tree canopy cover in urban areas) would be time-intensive.

Shadows may result in urban trees not being easily distinguishable from other nearby features. Shadows can also result in mis-classification of the vegetation because of dense appearance of tree canopies (Merry et al., 2014). In addition, we assumed a fixed viewing scale for interpretation purposes, and this may compound the effect of the shadows; hence it may be better to change scales in order to more clearly interpret the image. Also, the finer spatial resolution of the Google Earth imagery may have played a role in the generally higher canopy cover estimates when compared to using the NAIP imagery. Other factors that could have played a role in the results we obtained included photo interpretation error caused by fatigue or distraction (blunders, random error), and photo interpretation error in the assessment of vegetation (e.g., trees vs. bushes). However, it is comforting to know that our estimated tree canopy cover for Tacoma was similar to other recent estimates (Nowak and Greenfield, 2012) and the results of our mis-registration and

mis-classification tests showed that these issues were minimal in influencing our analysis.

Estimation of tree canopy cover using different sampling approaches and different imagery sources provides us with an understanding of the time, effort, and complexity of the processes. The time required to implement each process associated with this study was important, as the use of different sampling approaches and imagery sources required a significantly different amount of time for interpretation and determination of tree cover. The plot/grid sampling approach may seem to represent a more precise way to estimate tree canopy cover, but it also required more time and attention to detail than when simply interpreting individual random points—when using the same number of sample. For instance, for the photo interpreter associated with this project, the plot/grid approach required approximately one hour to assess 100 plot/grid sample locations (1/10 of the sample size), but for the point sampling approach about 200–250 points were interpreted within same period of time (1/4 of the sample size). It may seem that the plot/grid sampling approach would be more time consuming than reported but the interpreter did not always have to count each point within each grid. There were many instances when the plot/grid fell completely onto a forested area or the area of canopy cover fell within one continuous section of the grid requiring only a portion of the points to be interpreted. Conversely, there were instances when the plot/grid fell completely onto a developed area or water, so only a minimal number of points within the grid (or no points at all) had to be analyzed, allowing the interpreter to move on to the next plot quickly. Had we ceased to sample using the plot/grid approach when the point at which the ±10% range in average canopy cover equaled the 90% confidence interval for canopy, the time required for sampling (as compared to the point-based approach) would have actually been less for Tallahassee, but not for Tacoma. This may be related to the lower level of canopy cover in Tacoma and the larger standard error as a proportion of the mean canopy cover. In addition, the higher spatial resolution of Google Earth imagery may reduce the number of samples required under this rule.

With regard to viewing scale, the NAIP imagery analysis within ArcGIS provided a fixed scale option which made it easier to provide and apply a consistent process for canopy cover estimation. However, the Google Earth imagery analysis required more attention on the photo interpreter's behalf to the fixed eye altitude in order to maintain a consistent scale while interpreting canopy cover for the sample points. Hence, more time was required for tree canopy cover analysis with the Google Earth imagery than when using the NAIP imagery within ArcGIS.

Several sampling approaches have been tested recently for their usefulness in assessing urban canopy cover in addition to the cluster sampling approach evaluated here. These include sampling processes that use satellite or aerial imagery (such as the random point and cluster sampling approaches) and integrated tools for field-based assessments of canopy cover. For example, the iTree application tool, developed by the U.S. Forest Service and their cooperators, was designed to help users assess and manage the character of urban forests (King and Locke 2013; Nowak et al., 2008). The iTree application tool allows one to collect field based measurements of urban tree canopy cover at sample points and to collect estimates of other forest information (tree size, species, etc.) needed for management purposes. In comparing different approaches using the iTree application tool, high-resolution land cover data (GIS), and skyward-oriented hemispherical photographs, King and Locke (2013) found that estimates of canopy cover from using these provided similar results. While we did not directly compare the cluster sampling approach described here to the use if the iTree application tool or hemispherical photographs, one might assume that the cluster sampling approach applied using high-resolution aerial imagery might also provide similar canopy cover estimates. If conducted well, a point-based sample should provide verifiable tree canopy cover estimates for use in carbon credit projects and carbon sequestration analyses. It also appears that the very latest versions of two freely available imagery products for the United States, Google Earth imagery and NAIP imagery, should both be adequate for providing estimates of tree canopy cover. Google Earth imagery may be more suitable for this type of analysis in urban areas due to its finer spatial resolution at varying scales. However, in using any composite aerial imagery, one must be aware of the potential for imagery mis-registration issues and feature displacement issues. In general, estimated tree canopy cover using NAIP imagery within ArcGIS and Google Earth imagery are similar when we compared the point-based sampling approach to the plot/grid sampling approach within the two cities of this study.

Protocols and procedures for estimating tree canopy cover from remotely sensed imagery continue to be tested for their usefulness in providing high quality information to support management decisions and policy analyses. The results of this study underline the importance of selecting resource assessment methods (sampling design, intensity, and frequency) for the development of protocols for urban forest carbon projects. Sampling costs and their relationship to carbon credit prices are essential for the economic feasibility of carbon projects under consideration. While some of the tested procedures may seem to advance our ability to provide more precise and realistic tree canopy cover estimates, given advances in the resolution (spatial and spectral) of remotely sensed imagery, estimates from various sampling approaches seem no better than those provided by point-based sampling, and provide no advantages in terms of time, effort, or reduction in complexity.

Clearly, to have a viable carbon market reliable resource assessment methods are required in order to generate marketable carbon credits and provide assurances that these represent real, meeting specific registry criteria, carbon emission offsets. At the same time, carbon credits have relatively low values. While prices of forest or tree-based carbon credits vary greatly depending on the trading platform and credit attributes the average price of California carbon allowance futures has been in the $12 to 13 per tonne CO_2 equivalent range since mid-2013 (Climate Policy Initiative, 2015). Climate Action Reserve carbon offset projects generate values of about $10 per tonne CO_2 equivalent on average (California Carbon, 2015). As of May 2015, several *improved forest management* and *reforestation* projects have been registered with the Climate Action Reserve, yet no specific urban forestry projects have been registered, likely because of high project development and implementation costs which include carbon verification and monitoring efforts. Kerchner and Keeton (2015) also noted that high project development and long-term monitoring costs may prevent forest landowners from developing carbon projects.

While recognizing the differences between urban tree resources and forests in rural settings, forest inventories are typically taken at the time of timber sale or purchase and then not more frequently than every five to ten years during the life of a forest stand (Borders et al., 2008). For example, planted pine stands in the U.S. South may be inventoried twice or three times during their lifetime, at the time of sale and then once or twice during mid-rotation. This sampling intensity is considered by and large as appropriate for the resources of such value. It can also be argued that timber stumpage prices in the U.S. South and carbon offset prices fall into similar ranges. Yet carbon inventories in forestry settings still require higher precision and frequency, and supplementary measurements (Holland 2013), which in turn rise project costs and may yield carbon project infeasible.

Therefore, there is a tradeoff between the stringency of project development and implementation rules and the volume of carbon

projects that are economically feasible. The challenge is, at least in our minds, to find a balance which would maximize environmental benefits expressed in additional carbon storage and offsets. It may be the case that the current rules may be too restrictive and therefore too expensive (given current carbon offset values), and this may prevent environmentally beneficial projects from being developed. Further research aimed at developing reliable yet cost-effective resource assessment methods may help to address these issues.

Organizations which are taking proactive leadership in the measurement of forest resources for carbon policy implementation should continue to allow their suggested protocols to undergo review. Deferring to the expertise of reviewers allows, in the case of the Urban Forest Management protocol (Nickerson, 2014b), landowners and agencies to select the process that best suits particular conditions. Research results, such as those presented here and elsewhere (e.g., Walton et al., 2008; Merry et al., 2014), provide guidance to others and help advance society's goals of making informed decisions with respect to climate change and carbon management.

5. Conclusions

The development of an accurate estimate of urban tree canopy cover can be a critical aspect of assessments of the carbon sequestration potential of an urban forest and the ecosystem services potentially provided by an urban forest (Nowak et al., 2008). Besides the more common sampling methods employed (point-based and polygon-based sampling approaches), a cluster sampling method was also proposed (Nickerson, 2014a), whose improvement in accuracy was heretofore unknown. While comparing point-based sampling approach to the plot/grid sampling approach, we found that the estimated tree canopy cover was similar within the two study areas (two medium-sized cities). Though with larger land coverage, the plot/grid sampling approach may represent actual tree cover better than the point-based sampling approach, yet the plot/grid sampling approach requires more time and effort. Like others have suggested, the point-based sampling approach may be the preferred method for assessments of tree canopy cover using remotely sensed imagery, particularly if fewer than 1000 samples are collected. However, in cities where the average canopy cover is relatively high and the resulting standard error of sampled canopy cover in proportion with the mean canopy cover is relatively low, using Google Earth imagery and a plot/grid sampling approach may require equal or less time than the point-based sampling approach if the stopping point for sampling is determined as the number of samples required for the $\pm 10\%$ range in average canopy cover to equal the 90% confidence interval for canopy cover. However, given a fixed time window within which the assessment must be completed, distributing more points to the point-based approach may reduce the SEs more quickly, and therefore providing greater confidence in the results.

In our study, it also seemed that using different remotely sensed sources may influence the estimates of percentage tree canopy cover under the two different sampling approaches. While some of the differences are statistically significant, the estimates of tree canopy cover were similar, and one should be comforted in knowing that some of the freely available remotely sensed data (e.g., airborne and satellite imagery) for the United States can provide reliable and repeatable results for purposes such as assessments of urban canopy cover. Remotely sensed imagery can help urban forest managers monitor current tree cover change levels and can facilitate processes that help to sustain desired tree canopy levels (e.g., McPherson et al., 2011), however when used for projects that influence financial outcomes or management policies, an explicit description of the sampling methods and data employed seems paramount.

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