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Uncertainty in urban forest canopy assessment: Lessons from Seattle, WA, USA

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ABSTRACT

Increasing urbanization around the globe is leading to concern over the loss of tree canopy within cities, but quantifying urban forest canopy cover can be difficult. We discuss methods of assessing canopy cover within cities, and then use a case study of Seattle, WA, USA to examine issues of uncertainty in canopy cover assessment. We find that uncertainty is often not reported, and when reported, may be biased. Based on these findings, we provide a list of recommendations for those undertaking canopy cover assessment in complex urban environments.

Introduction

The amount of tree canopy within a city has become a growing concern in municipalities worldwide as urbanization has led to land-use conversion and a corresponding loss of urban forests (Pauchard et al., 2006; Nowak et al., 2010). The benefits of tree canopy in mitigating the negative effects of air pollution, atmospheric carbon dioxide, storm water runoff, and other environmental problems (Xiao et al., 2000; Brack, 2002) have led to an increasing desire to stop or reverse the losses in canopy cover to provide a public benefit. In addition, tree canopy has been found to positively impact social factors such as human health, property values, and well-being (Ulrich et al., 1991; Tzoulas et al., 2007; Wolf, 2007). Potential negatives of urban forests such as property hazard and loss of garden space are often overlooked, but the overwhelming trend is to associate tree canopy with a societal benefit.

Municipalities have sought to precisely quantify these benefits to understand the value of their urban forests and set management goals (McPherson et al., 2011). While any number of measures can be used to quantify canopy, the simplest and most often used is the percent canopy cover (CC). This is a measure of the fractional projected area of tree canopy above ground-level expressed as a percentage ranging from 0 to 100 (Walton et al., 2008). It should be noted that there are issues with the implementation of CC as a measure: the term is often confused with canopy closure, there is often confusion as to whether inter-leaf gaps within a canopy should be accounted for or ignored, and it is often unclear where the threshold lies between tree canopy and the canopies of shrubs and other low vegetation (Jennings et al., 1999). For example, an investigator measuring CC from the ground will be better able to directly observe the tree/shrub height threshold and observe or measure smaller gaps in the canopy (King and Locke, 2013) than an investigator interpreting an aerial photograph with 0.5 ft pixel resolution. Despite these issues, the CC measure is still widely adopted, and can serve as a useful benchmark for assessing a municipality's quantity of urban forest.

Methodologies of canopy cover assessment

The methodologies most often used to assess urban forest CC fall into two groups: remote sensing based raster methods that produce a census of a city's land cover, and sampling-based methods that estimate city-wide CC via a subset of points or plots within a city. Walton et al. (2008) provided a thorough overview of remote sensing techniques, highlighting the various methods based on aerial and satellite imagery. In these cases, raster surfaces are used to either classify a scene into canopy and non-canopy components, or used to directly estimate the amount of CC within each pixel. Of note among remote sensing-based methods is the increasing use of both object-based image analysis (OBIA) techniques and aerial LiDAR (Light Detection and Ranging). OBIA is a technique that breaks an aerial or satellite image into individual clusters of pixels (segments) and then classifies those segments based on rules related to color, shape, or texture to identify areas of canopy cover. Aerial LiDAR datasets consist of a three-dimensional point cloud collected using an airplane or helicopter that can be used to produce rasters of CC and the related leaf area index (LAI) alone or in conjunction with imagery (Riaño et al., 2004; Lee and Lucas, 2007; Richardson et al., 2009). OBIA and LiDAR can also be combined to produce estimates of CC (MacFaden et al., 2012).

Sampling-based methods are different in that they rely on sampling CC to produce areal wide-estimates. They require less

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technology and the individual samples are often considered to be "true" since technicians are manually measuring CC. Sampling is often performed in the field using fixed radius plots or based on manual photo interpretation of remotely sensed imagery (USDA Forest Service, 2012). Sampling-based methods rely on a sampling design and statistical inference to arrive at city-wide estimates of CC. Because of the perception that field or photo interpretation based methods are more accurate, these methods are often used to assess the accuracy of CC derived from a remote sensing based raster methodology. A field-based census of all trees within a city could potentially be also used to assess CC, but methods to obtain such a census, such as those utilizing citizen scientists, are only in their infancy (Urban Forest Map, 2012).

No matter the method used to assess CC for a municipality, the estimate will contain some uncertainty. One difficulty is in how to quantify, express, and interpret this uncertainty (Atkinson and Foody, 2006), a set of issues further confounded by the complexities facing municipalities that may have political and economic pressures to achieve a certain level of CC. A long history of canopy assessment in Seattle, WA USA serves as a case study for exploring issues of uncertainty in CC assessment.

History of canopy cover assessment in Seattle

The city of Seattle has a climate that is well suited for growing large trees. The area of the city was almost completely logged by the early 20th century, but contains many mature second-growth trees and an extensive network of parks and green spaces. Rapid urbanization in Seattle and the surrounding region in the last 40 years has led to land-use change and a subsequent loss of canopy (American Forests, 1999; Alberti et al., 2004). The initial reports of canopy loss led the City of Seattle to produce an Urban Forest Management Plan that called for increasing the city wide CC from 18% in 2004 to 30% by 2037 (City of Seattle, 2007). The plan cited CC of 40% in Seattle in 1972, although the accuracy of that estimate is unclear. Several studies have been performed since the Management Plan was published. The City of Seattle commissioned NCDC Imaging (no longer in business) in 2008 to produce two CC estimates for 2002 and 2007. The company created categorical rasters of land use. The canopy portions of these maps were summed to produce CC estimates of 22.5% in 2002 and 22.9% in 2007 (NCDC Imaging, 2009). An i-Tree Eco analysis was performed in 2010 to quantify urban ecosystem services, and also produced a CC estimate of 26.3% (Ciecko et al., 2012). As part of the present paper, the authors created their own CC estimate for Seattle using an OBIA method, estimating CC at 29.6%. A point-based accuracy assessment of the OBIA method yielded a CC estimate of 26.3%. The i-Tree Canopy web application (USDA Forest Service, 2012), which uses a point-based methodology, was also used by the authors of this study to produce a CC estimate of Seattle in 2012 of 28.5%.

Lessons from Seattle

Table 1 shows a large variation in assessed Seattle CC over time, with multiple values for identical dates such as 1972, 2002 and 2009. While it is possible that a trend may exist within these findings, it is difficult to draw conclusions without a measure of uncertainty.

American Forests Assessments

Assessments used to determine the 1972 (15%) and 1996 CC (10% and 13%) values relied on classification methods based on Landsat imagery and limited plot-based sampling (American Forests, 1999). Nowak and Greenfield (2010) found that percent tree cover from the 2001 National Land Cover Database, which also uses Landsat imagery, significantly underestimated CC in developed lands by an average of 13.7% nationally. The relatively coarse pixel size of Landsat (30 m) can cause difficulty in urban areas, where individual and small clumps of trees dominate the canopy (Nowak and Greenfield, 2010) The plot-based method used to estimate CC in 1996 is based on 7 small rectangular plots within the city manually interpreted from aerial photos. While the sites were selected to represent the variability across the city, no sites within parks were obtained. This, coupled with the low sample size decreases the certainty of this estimate as a representation of mean city-wide CC.

A CC estimate of 40% was also reported for 1972 in the Urban Forest Management Plan (City of Seattle, 2007). The source of this value is unclear, but it may be a representation of the change in the broader Seattle metropolitan area captured in a (1998) American Forests report. If this is the case, the definition of the boundary of Seattle may be a source of uncertainty. A search for publicly available GIS data, for example, provides at least two different polygon boundary files for the city. The city-limits have also changed over time as neighborhoods were annexed (City of Seattle, 2012). These boundary-related sources of uncertainty can have a significant effect on the reported city-wide CC value.

Remote sensing raster based methods

Two assessments for 2002 and one assessment for 2007 relied on producing raster maps of CC derived from remote sensing and other geospatial data. Detailed methodologies were not published for any of the assessments, nor were accuracy assessments conducted (City of Seattle, 2007; NCDC Imaging, 2009). It is not uncommon for studies prepared for a non-academic audience to omit methods and accuracy assessments, but it also makes assessing uncertainty nearly impossible.

An (OBIA) approach was used in this study to produce a categorical raster map containing categories of tree, grass and scrub, bare ground, buildings, and ground impervious. Datasets used for this classification included: 2009 NAIP four band imagery, 2003 aerial LIDAR, City of Seattle polygon buildings layer, road polygon layer, and a polygon layer of major water bodies. By summing all the tree pixels within a finished classification and dividing by the total number of pixels for Seattle, a CC value of 29.6% was derived. Fig. 1 shows a map of CC for Seattle. While this result came from a census rather than a sample, biases are still present. One way to identify bias is by performing an accuracy assessment. 1000 points were randomly located within Seattle and assigned a class by a trained photo interpreter using 2009 0.5 ft Aerials Express true color imagery and georeferenced oblique angle aerial photographs. The accuracy assessment is presented as an error matrix (Table 2).

This error matrix reveals several interesting statistics pertinent to CC. First, it shows 79.5% of the reference points were correctly classified as trees in the OBIA map (Producer's Accuracy). Secondly, it shows that 74.7% of the 1000 points that were coincident with a portion of the OBIA map classified as a tree were reference trees and not one of the other classes (User's Accuracy). Confusion with grass provided the largest source of misclassification of trees. Since producer's accuracy was greater than user's accuracy, more errors of commission occurred than omission and thus the OBIA map was biased toward an overestimate of CC.

Fig. 2 provides a different illustration of uncertainty within the classification. In Fig. 2, the percentage of tree canopy for 223 0.04 ha circular plots derived from the 2009 OBIA classification is compared to ocular estimates of canopy cover collected on the ground. This allows an interpretation of the precision of the OBIA CC estimates, as well as bias. A linear regression shows that LULC explains 69% of the variability within the ocular estimates of CC, with a RMSE of

Table 1
Estimates of city-wide canopy cover for Seattle. (RS, remote sensing; GS, ground sampling).

Year	Canopy cover estimate	Method	Data source	Citation
1972	15%	Landsat Sub-pixel	*RS*, Landsat	American Forests (1999)
1972	40%	Unknown	*RS*, Landsat	City of Seattle (2007)
1996	10%	Landsat Sub-pixel	*RS*, Landsat	American Forests (1999)
1996	10%	Plot-based photo interpretation	*RS, Aerial Photos*	American Forests (1999)
2002	18%	LiDAR Analysis	*RS*, 2000 LiDAR	City of Seattle (2007)
2002	22.5%	Categorical Raster Creation	*RS*, Unknown	NCDC Imaging (2009)
2007	22.9%	Categorical Raster Creation	*RS*, Unknown	NCDC Imaging (2009)
2009	26.4%	Point-based Random Sample	*RS*, 2009 Aerial Photos	This Study
2009	29.6%	Categorical Raster Creation	*RS*, 2003 LiDAR, 2009 Aerial Photos, Polygon Features	This Study
2010	26.3%	i-Tree Eco Plots	*GS*	Ciecko et al. (2012)
2012	28.5%	i-Tree Canopy Point-based Random Sample	*RS*, Google Maps	This Study

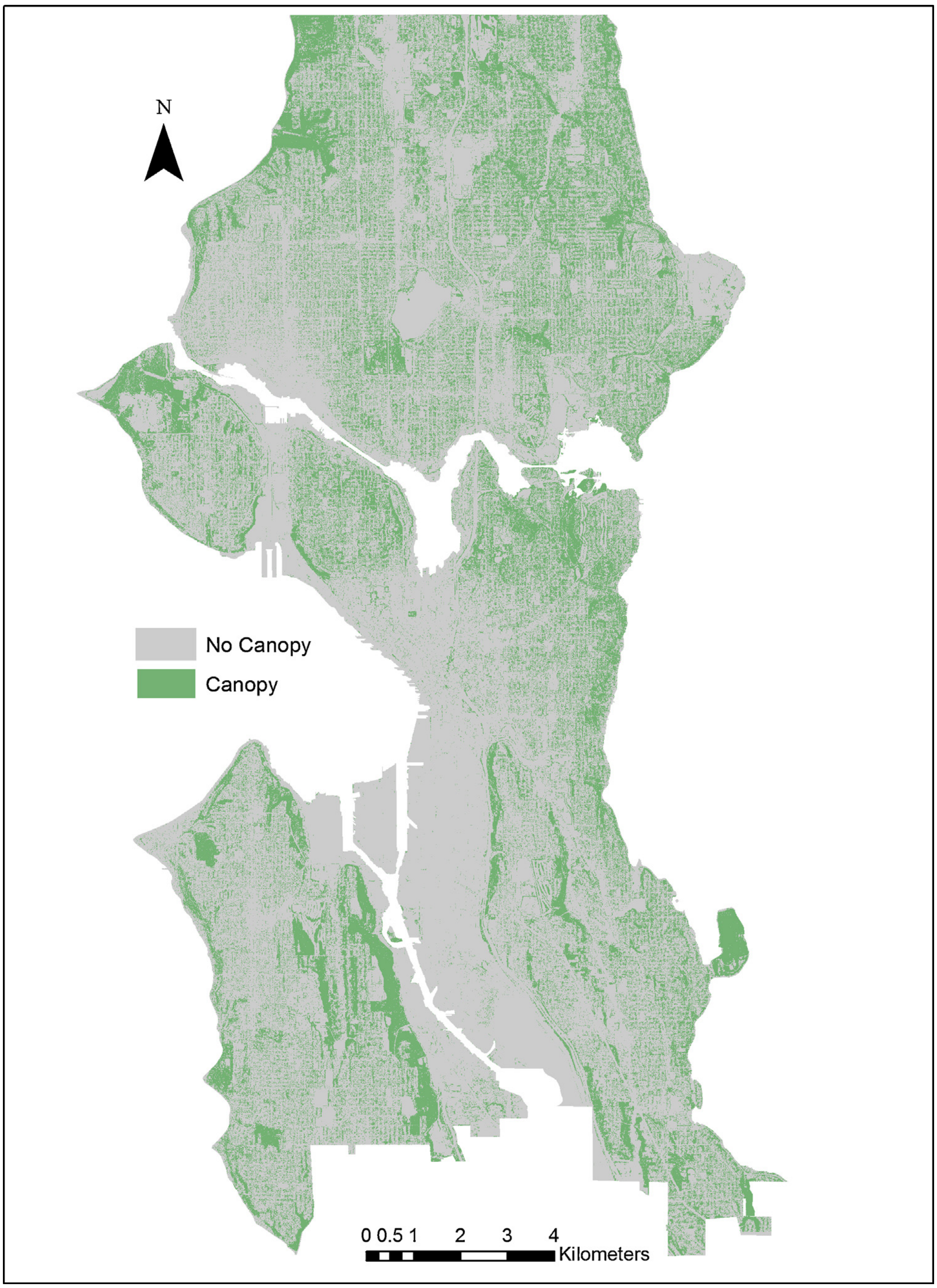

Fig. 1. Visualization of canopy cover pattern in Seattle derived from a categorical raster of land use/land cover. Pixels are 1 m^2.

Table 2
Error matrix showing accuracy for a categorical raster map of land use land cover in Seattle. Overall accuracy was 74.00%, and the Khat was 0.64.

	Classification data							
	Building	Impervious	Trees	Grass	Water	Bare ground	Total	Producer's accuracy
Reference data								
Building	148	42	17	3	1	1	212	69.81%
Impervious	11	288	18	10	0	0	327	88.07%
Trees	5	29	210	20	0	0	264	79.55%
Grass	2	72	36	73	0	0	183	39.89%
Water	0	0	0	0	7	0	7	100.0%
Bare Ground	0	5	0	2	0	0	7	0%
Total	166	436	281	108	8	1	1000	
User's accuracy	89.16%	66.06%	74.73%	67.59%	87.5%	0.00%		
Khat	0.86	0.50	0.62	0.60	0.87	0.00		

19%. The regression also suggests that the OBIA map overestimates CC compared to field measured CC.

Plot and point-based assessments

Several assessments have relied on points or plots to provide a sample of CC within the City of Seattle, and then have used that sample to estimate CC for the whole city. The 2010 i-Tree Eco Analysis for Seattle produced a CC assessment based on 223 randomly selected plots stratified by city management unit (Ciecko et al., 2012). One ocular estimate of CC, measured in categories of 5%, was observed at each 0.04 ha plot following the i-Tree Eco protocol, as well as individual tree biophysical variables (i-Tree). We could not find a published source that describes how the i-Tree Eco software produces city-wide estimates of CC given the field sampling design. i-Tree also produces a free online tool, i-Tree Canopy that can be used to quickly produce a CC assessment using freely available remote sensing data from Google Maps (USDA Forest Service, 2011). We performed an assessment for 1000 points generated by i-Tree Canopy by visually classifying each point as canopy or non-canopy. The application provided a CC estimate of 28.5% with a standard error of 1.4%. Confidence intervals may be more a more easily interpretable measure of uncertainty. The 95% confidence interval for the 28.5% CC estimate falls between 25.7% and 31.3%. Fig. 3 shows the relationship between increasing sample size and the decreasing range of the 95% confidence interval. The accuracy assessment conducted for the OBIA classification also provides a point-based measure of CC. Like the i-Tree Canopy analysis, 1000 points were visually classified into canopy and non-canopy using aerial imagery. Instead of Google Map imagery, we utilized high resolution aerial imagery collected in 2009 with a 1 ft pixel resolution, producing a CC estimate of 26.3% (Table 2).

Both the i-Tree Canopy and OBIA accuracy assessment point-based methods should provide unbiased estimates of CC assuming the points can be classified without bias or error. We have identified two potential sources of error in the classification of aerial photography used in this study: relief displacement and errors based on interpretation uncertainty. Relief displacement causes tall objects to appear displaced outward from their true location. In Seattle, trees are often the tallest object in a scene, and thus are strongly affected by relief displacement. The net effect of canopy relief displacement is that more area is covered by canopy in an aerial photograph than would be expected by a ground survey. Since trees in Seattle often grown singly or in small clusters, the effect of relief displacement is greater than in larger, more continuous forests because more non-canopy area is obscured by the displaced tree canopy. We also noticed a difference in the magnitude of relief displacement between the 2009 aerial imagery and the 2012 Google Maps imagery through a visual comparison of the two sets of imagery. Since relief displacement is more pronounced as the distance of an object from the location of the camera increases, not all trees will be affected by relief displacement to the same degree. Fig. 4 shows an example of relief displacement for a pair of tall trees in Seattle as seen in both the 2009 and 2012 imagery. The greater relief displacement observed in the Google Maps imagery compared to the aerial imagery is a possible explanation for the larger CC estimate derived from i-Tree Canopy (Table 1).

Interpretation errors are a result of the inability of the analyst to classify a point with complete certainty. We found that three issues affected the ability of the analyst to classify points with certainty: shadows, edges, and vegetation height. Table 3 details the 129 instances of uncertainty encountered by the analyst during the

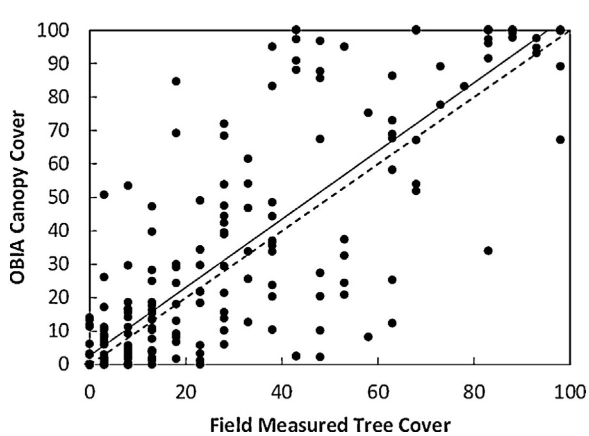

Fig. 2. Comparison of ocular estimates of tree cover collected on the ground to canopy cover derived from a categorical raster map of land use land cover for Seattle. Solid line is the best fit least squares regression and the dotted line represents unity.

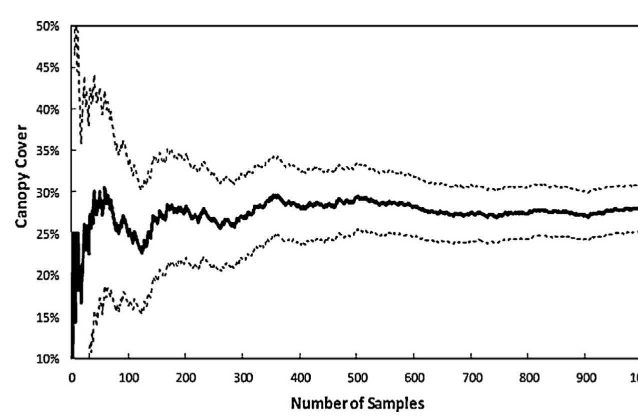

Fig. 3. Changes in Seattle city-wide canopy cover estimate with the addition of random points within the city. Upper and lower 95% confidence intervals are given by dotted lines.

Fig. 4. Two images used for classification showing relief displacement of tree canopy. The top image is from Google Maps used by iTree Canopy. The bottom image was collected by Aerials Express for King County in 2009.

i-Tree Canopy analysis. Table 3 also shows if the analyst chose to classify the point as canopy or non-canopy, in order to help identify any biases in the analysis. Uncertainty due to height was caused by the inability of the analyst to determine if the vegetation met a certain height threshold to be considered tree canopy. An analyst can use shadows and other contextual information to judge the height of a tree, shrub, or low scrub such as brambles, but in many situations the height is not clear. In this study, we chose an arbitrary height threshold of 3 m to separate trees from other low vegetation. Uncertainty due to edge was a result of the point falling on or near the boundary between canopy and non-canopy. In a heterogeneous urban forest, these edges are very common. Lastly, shadowed areas in the image are difficult to classify. Large trees and buildings cast large shadows, making the boundary area between canopy and non-canopy classes in shadowed points difficult to ascertain. Overall, 65 uncertain points were classified as canopy and 64 uncertain points as non-canopy. This suggests that interpretation errors did not strongly bias the i-Tree Canopy CC results. The sub categories of uncertainty attribution do show that the analyst tended to classify uncertain points in shadow and on the edge as non-canopy and points of uncertain height as canopy. The analyst strongly favored classifying points that fell in shadowed areas within dense forests (Interior Forest Canopy) as canopy.

Table 3
Categorization of all photo-interpreted points not classified with 100% certainty.

	Classification	
	Canopy	Non-canopy
Attribution of uncertainty		
Height	19	13
Edge	15	19
Shadow	6	10
Edge/shadow	8	12
Edge/height	7	6
Height/shadow	1	2
Edge/height/shadow	0	1
Interior forest canopy	9	1
Totals	65	64

Conclusions and recommendations

We have demonstrated some of the complexities of assessing CC in municipal environments. The case study of Seattle highlights that uncertainties exist in all CC estimates independent of methodology used, and that it can be difficult to quantify the level of uncertainty. This presents a potential problem for those interested in accurate estimates of CC, especially when policy decisions and/or funding are tied to the level of CC in a city. In the case of Seattle, no assessment to date has produced a CC assessment with a clear quantification of uncertainty: The raster based American Forests estimates do not contain accuracy assessments and the plot-based estimate is limited by small, unrepresentative samples. The image interpreted point-based estimates are biased by relief displacement and also subject to uncertainty in the interpretation of more than 10% of points (Table 3). Categorical raster based measures either lack accuracy assessments or rely on accuracy assessments derived from uncertain point-based assessments. Point-based estimates are theoretically well suited to providing unbiased estimates of CC with quantifiable uncertainty through confidence intervals, but points must be classified accurately, which can be difficult.

We present the following recommendations as a guide to decision makers when faced with embarking upon or interpreting data related to municipal CC:

- Acknowledge that all CC estimates contain uncertainty. If the uncertainty cannot be reported quantitatively, provide a qualitative description of potential sources of uncertainty.
- Inspect the geography of the boundary used to determine the extent of the municipality. Ensure that the boundary is consistent if multiple CC estimates are to be compared.
- When comparing CC estimates for different years, compare uncertainties. If uncertainties are large or unknown for any of the dates in question, observed differences may not be significant.

See Nowak and Greenfield (2012) for a broader discussion of quantifying canopy cover change.

- If field collected data point or plot data were used, ensure that a large number of plots were collected.
- If a raster of CC was created, ensure than an accuracy estimate was performed.
- Record the methodology used to conduct the CC assessment. This should be sufficiently detailed that an independent investigator can reproduce the assessment.
- A random sample of points presents an unbiased method for assessing CC, but may require large numbers of points to achieve a high degree of certainty.
- Assessing points using aerial imagery may impart biases toward higher CC due to relief displacement. Visually assess imagery to determine the severity of relief displacement. Future research could be directed toward developing the quantifiable measures of relief displacement, and methods of correction.
- It can be difficult and imprecise to differentiate between trees, shrubs, and grass and low vegetation from aerial imagery due to the difficulty in assessing heights. Consider using a canopy height model derived from aerial LiDAR to aid in this classification. Alternatively, uncertain points can be visited in the field.
- Aerial imagery will be interpreted with greater certainty if it can be collected so shadows are minimized and resolution is high. Aerial LiDAR can be of aid if available and collected at the same time as the imagery.

Future research can help to refine methodologies of assessing CC in heterogeneous urban environments. Improvement in remote sensing technologies, such as the continuing development of Google Earth can improve the quality of imagery publicly available, thereby making accuracy assessments derived from manual interpretation more accurate. Methods should also be developed to eliminate or correct relief displacement from aerial and satellite imagery. Lastly, improvements in partnerships between municipalities and academic institutions can increase the rigor of CC assessments.

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