

Efficient assessments of urban tree planting potential within or near the southern Piedmont region of the United States



Krista Merry^{a,*}, Jacek Siry^a, Pete Bettinger^a, J.M. Bowker^b

^a University of Georgia, 180 E. Green Street, Athens, GA 30602, United States

^b U.S. Forest Service, 320 Green Street Athens, GA 30602, United States

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ABSTRACT

Urban forest carbon offset projects have the potential to draw substantial amounts of carbon dioxide (CO₂) from the atmosphere, increase green space, and possibly generate revenue for landowners in cities capable of trading credits associated with these projects. The area of 15 cities in or near the Piedmont region of the southern United States on which trees could be potentially planted was explored in this analysis. The objectives were to assess a straightforward time-efficient method of classifying land and to determine the extent of the open and plantable areas in these cities. Overall accuracy of the classification process ranged from about 69% to 95%, and on average was 80.1%. The average producer's accuracy for all land classes in all 15 cities was 84.2%, while the average producer's accuracy for the open land class was 78.7%. The average user's accuracy for all land classes and the open class was about 80%. We estimate the amount of open, tree-plantable area in these 15 cities to be a little over 43,300 hectares (ha), comparable to the size of Washington, DC, or about 36 new Harvard Forests (Massachusetts). Extrapolating these results to the entire Piedmont region, the total plantable area in cities would amount to about 438,500 ha, and potentially allow 108 million tons of CO₂ to be sequestered, with a value of about 1.084 billion U.S. dollars. Given the small sample size and the variation within the results, the most conservative 95% confidence interval around these estimates suggests that the plantable area today is between about 274,300 ha and 645,100 ha.

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1. Introduction

Global climate change is an important topic for natural resource managers, in part due to the potential to reduce additional atmospheric carbon dioxide (CO₂) levels through the photosynthetic processes of healthy plants. From a resource management perspective, sequestering carbon in trees is viewed as a relatively safe, environmentally acceptable, aesthetically appealing, and in many cases cost-effective option to address this issue (McHale, McPherson, & Burke, 2007). Several broad initiatives have been introduced to address the reduction in atmospheric greenhouse gas concentrations, including the Kyoto Protocol, the European Union's Greenhouse Gas Emission Trading Scheme (EU ETS), and the Regional Greenhouse Gas Initiative (RGGI) in the United States. The carbon sequestration options suggested through the forest management practices noted in the Kyoto Protocol can be used to help offset carbon dioxide emissions (Fang, Chen, Peng, Zhao, & Ci, 2001). Had the U.S. Congress passed into law the American Clean Energy and Security Act of 2009, it would have set targets for reductions in green-

house gas emissions and provided mechanisms for forest carbon offsets in the United States.

In some areas of the world, financial incentives have emerged to encourage additional tree planting efforts on current treeless land; these include tradable carbon credits (Cairns & Lasserre, 2004). However, there is considerable risk and uncertainty in the carbon credit market, due to world-wide economic instability and security concerns of the various carbon registries (ICIS Heren, 2011). For example, prices of tradable European Union Allowances (EUAs), which are equivalent to 1 metric ton of CO₂ emissions, have ranged from 7 to 20 Euros over the past 2 years (Thomson Reuters Point Carbon, 2012), and Internet attacks on carbon registries have been documented (ICIS Heren, 2011). Voluntary forest carbon markets account for most of the forest carbon transactions, and a majority of these have originated in North America. However, a key trading mechanism, the Chicago Climate Exchange, recently (2010) collapsed. On a positive note, approval of registered afforestation/reforestation projects under the Clean Development Mechanism (CDM) seems to be increasing (Neeff et al., 2010). While risk exists, creating a carbon offset project and selling the associated carbon credits is one method to encourage the tree planting in urban areas. These efforts may lead to reductions in atmospheric CO₂, making it necessary to assess potential planting opportunities.

* Corresponding author. Tel.: +1 706542 4298; fax: +1 706542 8356.

E-mail address: kmerry@warnell.uga.edu (K. Merry).

Unlike commercial forests that are usually situated in rural areas and occasionally harvested and regenerated, urban forests can, under certain conditions, be considered as a permanent repository of carbon. In cities across the United States, research efforts have sought to identify the potential for carbon sequestration. For example, [Hutyra, Yoon, and Alberti \(2011\)](#) used site visits and data obtained from sample plots throughout Seattle, WA in order to develop land cover data across varying degrees of urban development, and to identify potential carbon stocks. While site visits may be ideal in estimating carbon potential in an urban environment, they can be cost prohibitive and time consuming efforts.

The use of remotely sensed data provides an alternative to on-the-ground sampling processes. Using Landsat TM/ETM+ data from 1991 and 1999, [Zhao, Brown, and Bergen \(2007\)](#), combined housing density and land cover classification to estimate changes in gross primary production (GPP) in the Detroit-Ann Arbor-Flint Metropolitan Statistical Area of Michigan. They concluded that low density development in urban areas that maintain a combination of productive trees and grasses can increase the CO₂ sequestration in the area, while high density development will decrease sequestration. [Nowak and Crane \(2002\)](#) once suggested that Atlanta, GA stored approximately 1,220,000 metric tons of carbon in urban trees. [Nowak \(1994\)](#) also suggested that Chicago's Cook and DuPage counties were capable of storing approximately 855,000 metric tons of carbon in urban trees, with residential land (1–3 occupants), parks, forests, and open areas having the greatest potential for carbon storage and sequestration. Certain types of land in urban areas (vacant lots, open areas along roads and among housing developments) can support additional tree plantings, and therefore contribute to reductions in atmospheric CO₂. Given the capacity of urban forests to store carbon in trees and soils and the interest in research linking urban forests to carbon storage, there is a need to develop procedures and protocols that would facilitate assessments (financial, environmental, social) of carbon projects and transactions.

The process for estimating plantable areas is often achieved through interpretation and classification of remotely sensed imagery. For example, [Nowak and Greenfield \(2009\)](#) used National Land Cover Data (NLCD) to determine plantable areas in certain cities using a planting priority index. While NLCD is readily available and relatively easy to use, the data was derived from either 2001 or 2006 era Landsat imagery ([Fry et al., 2011](#); [Xian, Homer, & Fry, 2009](#)). Further, the NLCD was created using an unsupervised classification process, and a formal accuracy assessment of the latest NLCD product has not yet been reported ([Fry et al., 2011](#)). Although of value for many purposes, we assume that 5–10 year old data is not appropriate for timely assessments of open, plantable land in areas that may be rapidly developing from a human infrastructure, business, and housing perspective. Due to increases in population between 2000 and 2010 in cities within our scope of analysis ([Table 1](#)), and the rapidity with which landscapes change in urban environments, we feel it is important to use the most current available remotely sensed imagery ([Bowman, Thompson, Tyndall, & Anderson, 2012](#)).

Several analytical methods and types of remotely sensed imagery have been used to estimate the extent of plantable lands within urban areas. For example, [Wu, Xiao, and McPherson \(2008\)](#) used QuickBird high resolution imagery to identify plantable areas in Los Angeles, California, and developed an automated process for identifying plantable areas. However, QuickBird imagery may be cost-prohibitive for municipalities that seek to periodically replicate assessments of urban carbon tree planting potential. For instance, each 1 km² image from QuickBird can cost between 14 and 23 U.S. dollars ([Land Info World Mapping, 2011](#)) while other imagery sources (e.g., Landsat) may be free of charge. More recently, [McGee, Day, Wynne, and White \(2012\)](#) explored the

Table 1
Population change and land area of cities within or near the Piedmont of the southern United States.

City	Estimated population ^a (2000)	Estimated population ^a (2010)	Land area ^a (km ²)
Athens, GA	101,489	116,714	306.3
Atlanta, GA	416,474	420,003	343.2
Auburn, AL	42,987	53,380	241.7
Charlotte, NC	540,828	731,424	628.5
Chattanooga, TN	155,554	167,674	370.7
Columbia, SC	116,278	129,272	330.5
Greenville, SC	56,002	58,409	67.6
Hickory, NC	37,222	40,010	68.5
Laurens, SC	9916	9139	27.4
Lynchburg, VA	65,269	75,568	128.8
Mount Airy, NC	8484	10,388	21.7
Richmond, VA	197,790	204,214	162.1
Roanoke, AL	6563	6074	49.6
South Boston, VA	8491	8142	31.8
Toccoa, GA	9323	8491	21.7

^a Within a city boundary, and not representative of a larger metropolitan area.

potential of using U.S. National Agriculture Imagery Program (NAIP) digital aerial photography for the purpose of identifying broad land classes. NAIP imagery is freely available, yet with a 1 m spatial resolution it requires relatively more computer storage space and perhaps requires extensive image processing time. Additionally, NAIP imagery has only three spectral bands compared to other imagery platforms like Landsat 7 ETM+ with 8 bands, which may limit its utility. The methods employed by [McGee et al. \(2012\)](#) may lead to greater accuracy for certain types of land classes, yet multiple intermediate data management steps are necessary to alleviate classification errors including initial classifications using spectral signature groupings and ISODATA to develop “shadow” and “mixed” classes in order to reduce the impact of pixels not representative of land cover classes.

The goal of our research is to assess methodology for estimating the amount of urban area potentially plantable with trees within or near the southern Piedmont area of United States. The intent is to illustrate methods that can be employed for timely and cost-efficient data analyses. Therefore, we focus on a relatively straightforward method that could be used by city- or county-level planners for estimating plantable areas and for assessing the accuracy of the classification process. Extensions of the results are then made to assess land area plantable with trees, and the potential storage of carbon in urban areas of the southern Piedmont through additional tree planting efforts.

2. Methodology

2.1. Study area

This research focused on 15 cities ([Table 1](#)) within or near the Piedmont region of the southern United States. This region is situated between the Atlantic Coastal Plain and the Appalachian Mountains ([Fig. 1](#)) of the southern United States. Due to interests of the collaborative research team and the physical location of larger established cities, we were unable to select samples that were entirely contained within the Piedmont ecosystem of the southern United States. The 15 cities were selected based on their human population levels and their distribution throughout the study area. We selected five cities each from what we consider the small (population less than 10,000), medium (population greater than 10,000 but less than 110,000), and large (population greater than 110,000) population classes. These population classes were created because we wanted to assess whether differences in plantable area were

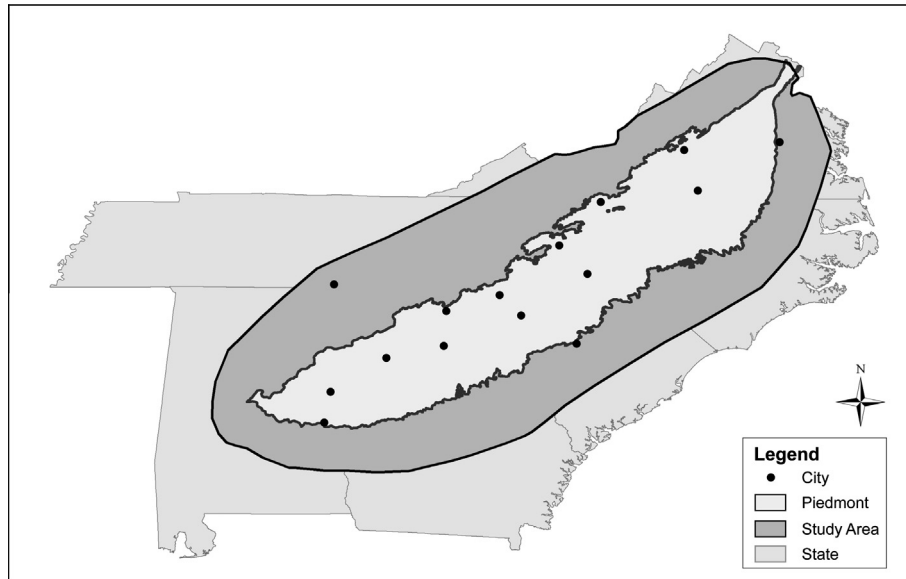


Fig. 1. The physiographic region of the analysis of cities falling within or near the Piedmont region of the southern United States.

attributable to human population levels and the additional infrastructure necessary to support these populations. While the U.S. Census Bureau (2012) includes in its definition of urban area the adjacent areas that contain non-residential urban land, we use the administrative boundary of each city to define the extent of our assessment. In doing this, we restrict our analysis to the urban core and omit surrounding areas with lesser populations.

2.2. Preprocessing

We obtained 30 m Landsat 7 ETM+ imagery from the U.S. Geological Survey (2012). Landsat 7 imagery was orthorectified by the U.S. Geological Survey prior to acquisition, which reduced the amount of pre-analysis processing steps required. However, after Landsat 7 imagery was acquired, several other processing steps were necessary before the imagery could be analyzed. For example, Landsat 7 imagery contains data gaps due to the failure of the scan line corrector (SLC) within the satellite (Chen, Zhu, Vogelmann, Gao, & Jin, 2011). Several methods are available for correcting or filling these data gaps. For this research, a simple histogram matching technique was employed (Figs. 2 and 3). Histogram matching merges pieces of an auxiliary image with the original image in a manner that best matches the area surrounding gaps (Rulloni, Bustos, & Flesia, 2012); it relies on a comparison of the relative distribution of land cover of one image (with data gaps) to the auxiliary image (ERDAS, Inc. 1999). We used the most recently acquired, complementary auxiliary image available to fill the gaps in the original image obtained from the U.S. Geological Survey. With the exception of Mt. Airy NC, each city's original Landsat image required histogram matching using an auxiliary image. Mt. Airy fell within the middle of the Landsat scene where no data gaps from SLC failure occurred. When available, the auxiliary images were acquired within a month or two of the original Landsat image. This was not always possible due to data gap overlaps between the original image and the auxiliary image, or due to poor image quality of the auxiliary image. Collection years for auxiliary images ranged from 2009 to 2011. Following the histogram matching process, the satellite imagery was radiometrically corrected to convert the raw Landsat data from digital numbers (DN) to spectral reflectance values.

2.3. Image classification

Once the raw Landsat imagery for each of the 15 cities was pre-processed, the data within each city boundary was extracted, and then a supervised classification process (Lillesand, Kiefer, & Chipman, 2004) was used in order to delineate four land classes: water, developed, open, and forest. The developed class included roads and buildings while the open class included forest clearcuts, agricultural land, bare ground, and grassy areas. For each of the four land classes, sixty training sites were selected within each city (with the exceptions due to limited sample areas). These training sites contained a minimum of 20 Landsat pixels. NAIP imagery (1 m resolution) was used as the reference data for identifying the true class of the training sites. Every effort was made to avoid training sites that contained "mixed pixels" (high variation in spectral reflectance values), but this was difficult to accomplish in open areas. Due to the small number of land cover classes and the relatively small areas being classified, 60 training sites for each land class were deemed appropriate (Lillesand et al., 2004).

2.4. Classification accuracy assessment

In order to assess the accuracy of the supervised classification, an equalized random sample of each class within each city was developed using 60 independent sample points per land cover class. An accuracy assessment of the land cover classification database was then completed for each city using temporally consistent NAIP imagery as reference, with a goal of obtaining an overall accuracy of 70% and a within-class user's and producer's accuracy of at least 70%. Given the purpose of this research, we focus on the accuracy of identifying the *open* land class, a portion of which might be plantable with trees that can sequester additional carbon. While there are a number of methods for assessing the accuracy of image classification, we relied on error matrices and omission/commission tables (Foody, 2002). Error matrices are important in reporting accuracy (Steham, 1997) as they are useful in identifying between-class confusion from supervised classification. Relying solely on the overall accuracy of the classification process may be misleading, and attention needs to be paid to the user's and producer's accuracy levels, which allow one to focus on individual class

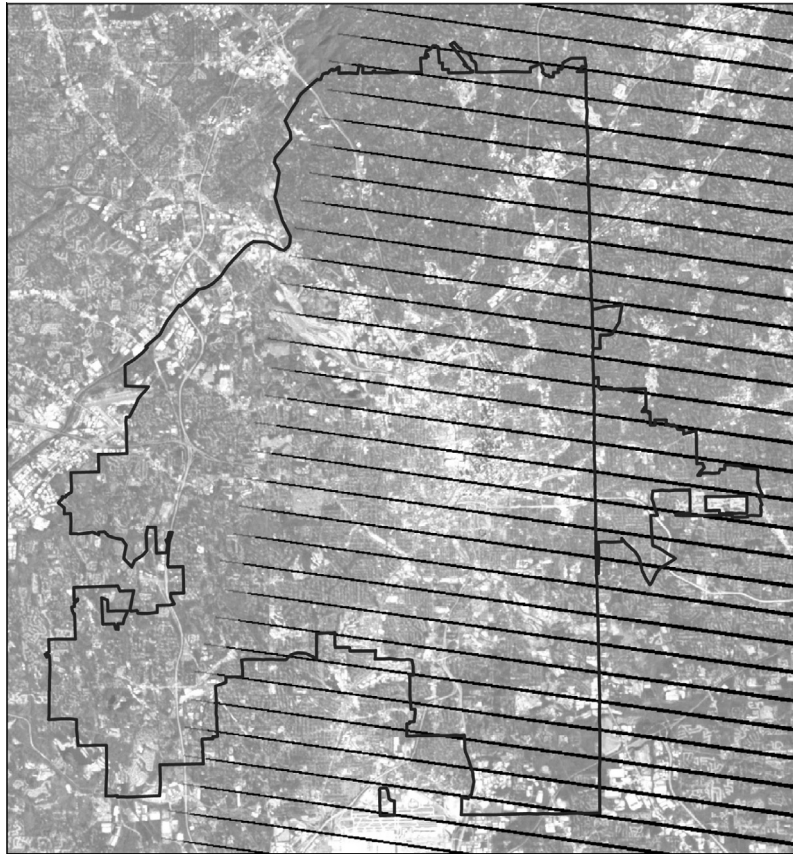


Fig. 2. An example of imagery containing data gaps resulting from the failure of the scan line corrector.

classification accuracy. User's accuracy (commission) indicates the likelihood that a pixel classified as one distinct class is actually representative of that class. Producer's accuracy (omission) illustrates how well training sets represent classes.

2.5. Assessment of open areas

After the supervised classification process and accuracy assessment were completed, 100 sample points were randomly located within the set of pixels classified as the *open* land class of each city. An assessment was then made to verify whether these points represented areas that were (within reason) plantable with trees, and thus to determine the percentage of open areas in each city were actually plantable with trees. The size of the sample is consistent with recent research. For example, in an assessment of Los Angeles, McPherson, Simpson, Xiao, and Wu (2011) sampled 50 parcels to assess land cover accuracy, and 100 parcels (randomly located) to determine plantable area accuracy. NAIP imagery was employed to determine the current state of the land, and whether the points represented areas that were plantable with trees. Our reasoning process, developed through much discussion, concluded that residential lots, powerline rights-of-way, areas sufficiently inside highway on/off ramps, farmland (what little occurred within the administrative boundaries of the cities), edges of roadways that followed existing vegetation patterns, and large forest clearings (not small gaps) would all be classified as plantable with trees.

A 30 m Landsat pixel classified as an open area would be large enough to support the development of about four trees. However, if one of the verification sample points was located within a single pixel that was classified as an open area, yet in reality represented a small, natural forested gap according to the NAIP imagery, the

point was not classified as plantable. However, if a sample point fell within a large, recent clearcut, the point was classified as plantable. Our contention was that small (one Landsat pixel) forested gaps, as subsequently viewed with NAIP imagery (which included shadows) were likely to contain advanced tree regeneration that was not recognizable, and therefore these areas likely would not need a tree to be planted in order to take advantage of the available growing space. Open areas within or around airports, sports facilities (e.g., baseball fields, golf courses), cemeteries, and open public areas with a specific purpose were classified as non-plantable with trees. For instance, Fig. 4 illustrates two random sample points placed in an area classified as *open*, yet they are located adjacent to an airport runway. In our assessment, these points would have been considered non-plantable. Further, if any of the one hundred sample points located in a pixel classified as *open* was situated on land misclassified as *open* land (i.e., the land was actually one of the other three classes), these points were considered non-plantable with trees.

2.6. Extension of results to potential storage of carbon in urban areas

There are over 550 other cities in the southern Piedmont of the United States that have a population of over 2500 people. We will extend the results concerning the overall average area plantable to the size of these cities in order to estimate land area plantable with trees. In doing so, we first apply the average percentage of open, plantable land area to the land area of all cities in the Piedmont that had a population of 2500 or more people. However, we also assess the amount of land area plantable by applying the average plantable area for each of the three 5-city population groupings to cities falling within those groupings. In this latter case, we

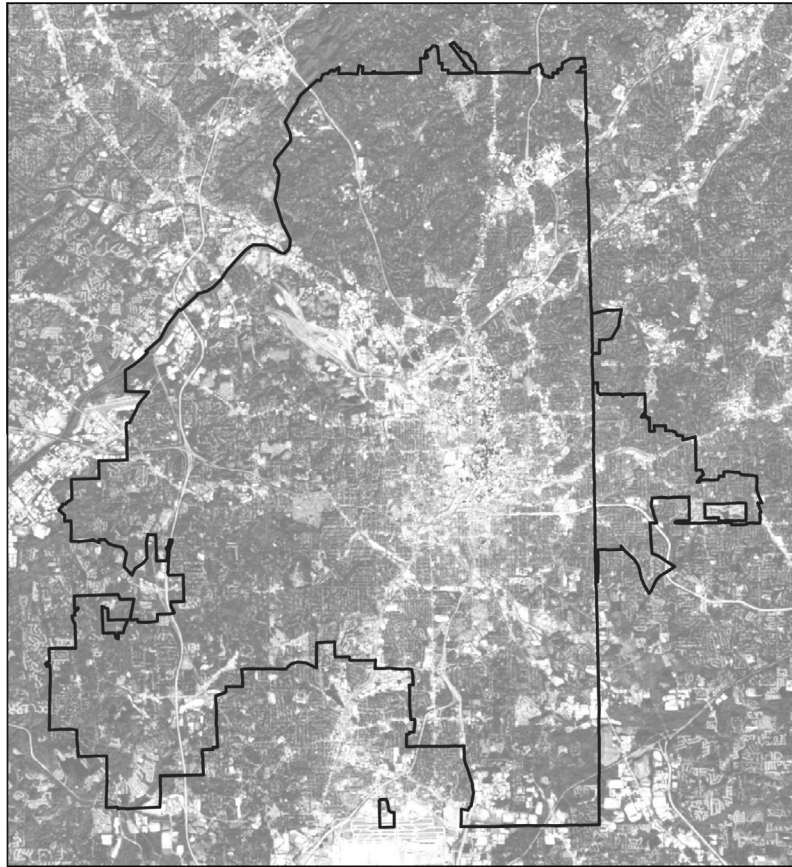


Fig. 3. An example of imagery following the histogram matching technique used for the gap-filling process.



Fig. 4. Two random sample points in an area classified as *open*, yet they were determined to be non-plantable.

attempt to describe open, plantable land using estimates from cities of relatively similar sizes rather than using the overall average results.

In assessing the potential carbon stored in these open, plantable land areas, we first assume a 100% tree planting rate, a target storage capacity of 247.1 tons of CO₂ per ha, and a price of 10 U.S. dollars per ton of CO₂ stored. In developing this estimate, we assumed full planting density as well as tree growth, wood volume, and car-

bon storage in above-ground biomass corresponding to 50% of what can be achieved on a typical southern pine plantation. This assumption results in a target storage capacity of 100 tons of CO₂ per acre (or 247.1 tons per ha) (Siry, Cubbage, & Malmquist, 2001). Our estimate is somewhat higher than estimated carbon storage in existing urban forests. For example, Nowak and Crane (2002) estimated that on average trees in Atlanta store about 35.7 tons of pure carbon per ha. This amount converted to CO₂

would yield 131 tons of storage per ha (53% of our previous assumption), and thus represents our second, more conservative assumption of the amount of CO₂ stored.

Prices for carbon credits vary greatly, from 0.10 to about 33 U.S. dollars per carbon credit in 2010 depending on project type and location (Diaz, Hamilton, & Johnson, 2011). The assumed average price of 10 U.S. dollars per credit corresponds to the average price of carbon credits issued under ISO-14064 standard (Diaz et al., 2011) as well as to a lower range of carbon credit prices under the EU Emissions Trading System (ETS) in 2010.

3. Results

The overall accuracy of the supervised classification process (Table 2) for determining developed, water, open, and forested areas was reasonably sufficient for the 15 urban areas around the southern Piedmont region of the United States, and ranged from about 69% (Charlotte) to about 95% (Chattanooga). On average, the overall classification accuracy was 80.1%; the 95% confidence interval about the mean of the 15 cities was 76.2 to 84.1%.

For all four land classes, the producer's accuracy ranged from about 49% (forested areas in Columbia) to 100% in several instances. The producer's accuracy is an expression of the error of omission, or the percentage of pixels that should have been assigned a given class but were not by the supervised classification process. The producer's accuracy therefore represents the percentage of a given land class that is correctly identified during the classification process. The average producer's accuracy for all land classes in all 15 cities was 84.2%, and the 95% confidence interval was 76.9–91.4%. More specifically, for the open land class the producer's accuracy (Table 2) ranged from about 50% (Mount Airy) to over 96% (Chattanooga). The average producer's accuracy for the open land class in all 15 cities was 78.7%, and the 95% confidence interval was 72.4–85%. Three areas of concern arose from this supervised classification process. First, the producer's accuracy of forested areas in cities representative of all three population classes was below 70% in several instances (Charlotte, Columbia, Athens, Auburn, Roanoke). Second, the producer's accuracy for developed areas was relatively low, below 70%, in two instances (Charlotte, Greenville). And third, the producer's accuracy of open areas in three small cities (Roanoke, Mount Airy, and South Boston) was below 70%.

For all four land classes, the user's accuracy ranged from about 10% (water in Charlotte) to 100% in several instances. The average user's accuracy for all land classes in all 15 cities was 80.1%, and

the 95% confidence interval was 69.7–90.6%. The user's accuracy is an expression of the error of commission, or the percentage of pixels that were assigned a given land class, yet actually belong to another class. The user's accuracy therefore represents the probability that a given pixel will appear on the ground as the class that it was assigned by the supervised classification process. For the open land class, the user's accuracy (Table 2) ranged from 55% (Greenville) to over 98% (Athens). The average user's accuracy for the open land class in all 15 cities was 80%, and the 95% confidence interval was 73.2–86.6%. Three areas of concern also arose when assessing the user's accuracy. First, the user's accuracy for the water class in four cities (Athens, Charlotte, Columbia, Mount Airy) was below 70%. Water was confused with forested areas in two cases (Athens, Columbia), open areas in one case (Mount Airy), and simply with the other three land classes in the fourth case (Charlotte). Second, the user's accuracy for the developed land class in five cities (Athens, Auburn, Lynchburg, Roanoke, South Boston) was below 70%. Each of these cities had instances where the developed land class was misclassified as forested or open areas. Third, the user's accuracy for open land in Greenville and Atlanta was below 70%. In the classification of Atlanta, there were several instances where open areas were assigned the forested land class, while in the classification of Greenville, many open areas were assigned to the developed land class.

Table 3 provides an example of the error matrices that were developed for Athens and Chattanooga, and includes the conditional Kappa coefficients that were generated. These are provided to illustrate how the independent set of 60 validation points correspond to the classification of those areas through the supervised classification process. The overall Kappa coefficient indicates the extent to which the values in the error matrix are due to correct agreement with true landscape features, or due to random chance (Lillesand et al., 2004). For example, overall Kappa coefficient for Athens of 0.706 (Table 2) suggests an approximate 71% agreement between the ground truth and the overall image classification. The conditional Kappa coefficient is used to represent this agreement within individual classes (Gong, Marceau, & Howarth, 1992). For instance, in the classification of Athens, the water class was correctly identified 28 times, while it was incorrectly classified as forest 31 times. The water classification had a conditional Kappa coefficient of 0.396 suggesting about a 40% agreement between the result of the classification process of the water class and the ground truth. A conditional Kappa coefficient value of 0.396 suggests that the observed classification of the water class is 39.6% better than a classification resulting from chance or random processes. Comparatively, from the 60-point validation of our supervised classification of the forest class in Chattanooga, we observed a conditional Kappa value of 1.0, or 100% agreement between the classification of the forest class and the reference image and an overall Kappa value of 0.928, or approximately 93%.

With these levels of accuracy noted, we estimate that the amount of open area in these 15 cities to be a little over 61,000 hectares (ha) (Table 4). This ranges from 10.8% of a city's area (Charlotte) to about 47.8% of a city's area (Greenville) and there seems to be no general trend with human population size. Of course, not all of this land area is plantable with trees. Using a second independent set of random sample points solely located in the areas classified as having open land, we estimate that about one-half to over 90% is what we consider to be plantable with trees, depending on the city. For the 15 cities situated within or near the Piedmont of the southern United States, this plantable area amounts to roughly two-thirds of the estimated open areas (over 43,300 ha), and represents about 15.5% of the total 15-city area. To illustrate the magnitude of this area, it is comparable to the size of Washington, DC, or about 36 new Harvard Forests (Massachusetts). The cities with the highest percentage of open area that is

Table 2

Accuracy assessment results of the supervised classification for the 15 cities analyzed with a focus on the open class.

City	Open area producer's accuracy (%)	Open area user's accuracy (%)	Overall accuracy (%)	Overall Kappa coefficient
Athens, GA	80.82	98.33	77.92	0.706
Atlanta, GA	86.36	63.33	84.17	0.789
Auburn, AL	79.03	81.67	77.08	0.694
Charlotte, NC	73.97	90.00	68.75	0.583
Chattanooga, TN	96.55	93.33	94.58	0.928
Columbia, SC	87.04	78.33	70.42	0.606
Greenville, SC	86.84	55.00	78.33	0.676
Hickory, NC	86.21	83.33	84.58	0.794
Laurens, SC	74.14	71.67	82.08	0.761
Lynchburg, VA	79.37	83.33	86.67	0.822
Mount Airy, NC	50.49	86.67	71.25	0.617
Richmond, VA	76.27	75.00	81.25	0.750
Roanoke, AL	64.71	73.33	74.58	0.661
South Boston, VA	69.05	96.67	82.08	0.761
Toccoa, GA	89.36	70.00	88.33	0.844

Table 3

Example of error matrices derived following the supervised classification of Athens and Chattanooga.

City	Class	Water	Developed	Forest	Open	Conditional Kappa coefficient
Athens, GA	Water	28	0	31	1	0.396
	Developed	0	41	7	12	0.618
	Forest	0	0	59	1	0.972
	Open	0	0	1	59	0.976
Chattanooga, TN	Water	59	0	1	0	0.978
	Developed	0	52	6	2	0.829
	Forest	0	0	60	0	1.000
	Open	0	1	3	56	0.912

potentially plantable with trees are Athens and Mount Airy (90 and 92%, respectively). Atlanta had the largest total land area that is potentially plantable with trees. Finally, the least amount of plantable area was observed to be in Charlotte and Toccoa (52 and 53%, respectively).

Extending the results for the overall average area plantable to other cities in the southern Piedmont of the United States leads us to suggest that about 438,500 ha of open land could be plantable with trees today. Extending the overall average percentage of land area that is open and plantable to all cities within the southern Piedmont, we estimate that potentially 108.353 million tons of CO₂ could be stored, with a carbon credit market value of about 1.084 billion U.S. dollars. The 95% confidence interval about this estimate is large, about 348,000 ha to a little over 529,000 ha, given the small sample size and the relatively large variation among results (37.3% coefficient of variation). The estimated range of carbon potentially stored is thus about 86 million tons of CO₂ to 131 million tons of CO₂. The estimated market value ranges from about 860 million to 1.307 billion U.S. dollars. Using the more conservative Nowak and Crane (2002) assumption of carbon stored per unit area (53% of our assumption), we estimate that 57.427 million tons of CO₂ could be stored, with a market value of 574 million U.S. dollars and a range of 45.58–69.43 million tons.

If we were to use the average plantable area for each of the three 5-city population groupings and apply these averages in estimating area plantable, this suggests that the 95% confidence interval is even larger, between about 274,300 ha and 645,100 ha. The estimated range of carbon potentially stored in this case is about 68 million tons of CO₂ to 159 million tons of CO₂. The estimated market value ranges from about 678 million to 1.594 billion U.S.

dollars. These ranges are more conservative than the previous set, but nonetheless help illustrate the enormous potential of these areas to support tree growth and therefore to capture carbon from the atmosphere. Using the Nowak and Crane (2002) assumption of carbon stored per unit area, 36.04–84.27 million tons of CO₂ could be stored, with a market value of 574 million U.S. dollars.

4. Discussion

One goal of this work was to develop and evaluate a method for rapidly determining the amount of land in cities of the southern United States (within or near the Piedmont region) that could be planted with trees in order to assist in assessments of carbon credit and sequestration potential. In an effort to assess efficient and reliable methods for timely assessments of urban carbon tree planting efforts in areas with evolving developmental status, we pursued a process that would allow a planning organization to acquire broad-scale satellite imagery free of charge, and to classify that imagery using known training areas. Therefore, we selected Landsat 7 imagery and a supervised classification processes to meet these needs. We postulate that remotely sensed imagery with higher spatial or spectral resolution may lead to an increase in the accuracy of classification as it is related to locating open areas in cities that may be planted with trees. However, higher spatial and spectral resolution images are often not freely available. Further, advanced classification methods may result in improved accuracy levels, yet the timeliness and the ability of county- or city-level planners to employ them is in question. When available, higher spatial resolution data may also require significantly more computer storage space and more extensive computer processing time. We intend to explore these options in the future, along with improvements in the efficiency of supervised classification.

We selected for this analysis 15 cities, five from each of three broad human population classes that were situated within or near the southern Piedmont of the United States. The land area representative of each city positively correlated (0.86) with the estimated population size. Processing the imagery, supervised classification, accuracy assessment, and the plantable assessment process can be completed in 1–2 days depending on issues that may arise with image quality. For each of these 15 cities, image classification confusion is evident in some cases, as indicated in the error matrices derived. In general, we were hoping for overall accuracy levels greater than 80%, and we achieved this in many cases. However, we noted several instances where the overall accuracy, and user's and producer's accuracy fell below 70%. Clearly, there are some cities within the analysis that do meet our expected standards. These problems may be the result of mixed pixels within training sites, shadows contained within images, or the data gap filling process that was required to mitigate the striping problem inherent in Landsat 7 imagery. However, the problems associated with identifying plantable, open areas are not unique to this study. Although we employed a straightforward supervised classification

Table 4

Assessment of the "open" class in 15 southern United States cities including estimated plantable area.

City	Estimated total open area (ha)	Percent of total city area (%)	Percent of open area plantable (%)	Estimated plantable area in the city (ha)
Athens, GA	4835	15.8	90	4351
Atlanta, GA	10,919	31.8	64	6988
Auburn, AL	7719	31.9	74	5712
Charlotte, NC	6778	10.8	52	3525
Chattanooga, TN	6526	17.6	82	5351
Columbia, SC	8929	27.0	65	5804
Greenville, SC	3231	47.8	73	2358
Hickory, NC	1553	22.7	68	1056
Laurens, SC	966	35.2	72	695
Lynchburg, VA	4344	33.7	78	3388
Mount Airy, NC	560	25.8	92	515
Richmond, VA	2196	13.5	84	1845
Roanoke, AL	1027	20.7	75	770
South Boston, VA	708	22.3	82	581
Toccoa, GA	742	34.2	53	393
	61,032			43,333

process, Im, Lu, Rhee, and Quackenbush (2012) found producer's and user's accuracies that ranged from 48% to 75% for bare ground in a recent hierarchical classification of Landsat imagery for an area of northern New York, and Aguirre-Gutiérrez, Seijmonsbergen, and Duivenvoorden (2012) observed a wide range (41–93%) of producer's and user's accuracies for bare soil in a recent object-based classification of Landsat imagery for an area of northern Mexico.

In cases where the producer's accuracy of developed areas was relatively low (Charlotte, Greenville), these problems were likely associated with cloud spots in the Landsat images, and over-estimation of open areas that were actually in a developed class. In these instances, many developed areas are surrounded by green space (open areas). In cases where the producer's accuracy of forested areas was relatively low (Charlotte, Columbia, Athens, Auburn, Roanoke), several issues emerge. For Athens and Roanoke, the misclassification may be the result of inadequate spectral signatures used to identify the water class. For both Athens and Roanoke, the number of training sets for the water class were only 33 and 34, respectively, therefore some misclassification with surrounding classes may have occurred. As we noted, the Charlotte Landsat image contained small clouds with shadows, and these may have led to classification error. In both the Columbia and Greenville Landsat images, there seemed to be significant latent striping in the images even after the data gap filling process. We had difficulty locating auxiliary images, free of overlapping data gaps, that would be of value in addressing this problem (as suggested in Pringle, Schmidt, & Muir, 2009). In the case of Auburn, the common image classification confusion seemed to be caused by similarities in spectral signatures between the forested class and other classes. After testing the protocols for identifying open, plantable areas, we noted that the producer's accuracy of open areas in the small cities may be relatively low. In one case (Roanoke) it seemed that the open areas were often misclassified as developed areas, perhaps because of the similar spectral signatures used in the training sets for the two classes. In the other case (Mt. Airy), many ponds and lakes were misclassified as open areas. This seemed to be the result of using too few training sets to represent the water class, which in turn may be related to the size of the city. The open class also included several different landscape features (bare ground, grassy areas, clearcuts, powerline cuts), which suggests that this class had a wider variety of mixed spectral signatures, and when these were used as training areas, it may have led to image misclassification.

We understand the need for standardization of land use and land cover classifications, as suggested by Anderson, Hardy, Roach, and Witmer (1976). Data interpretation and aggregation problems can arise, and analytical efforts might be duplicated within an organization, when employing an ad-hoc land cover class estimation process. The Level I classification suggested by Anderson et al. (1976) for use in conjunction with satellite imagery includes Level I and Level II forest and water classes we used in our assessment. Our classification of developed areas would have included the buildings and roads associated with the Anderson Level I and Level II urban and built-up land classes. However, there are some disharmonies between our approach and the Anderson classification approach. For example, our classification of open areas would have included the bare, plantable land that would normally have been found in the Anderson Level II classifications of residential areas, commercial and service areas, industrial areas, and others within the Level I urban and built-up land class, less buildings and other infrastructure that would be found there. Further, our classification of open areas would have also included Level II classifications of cropland and pasture, within the Anderson Level I agricultural land class. Anderson et al. (1976) suggest classifying these various areas separately. While our approach to locating open areas may have been more direct than the Anderson et al.

(1976) approach, and while the potential for work inefficiencies may exist within planning offices, we feel our approach adequately addresses the spirit of the objective.

In addition to replicating this methodology with higher resolution imagery, several future research efforts would be helpful in enhancing the process of identifying plantable areas. Specifically, we used leaf-on imagery for this analysis while future research would benefit by replicating this methodology with leaf-off imagery to assess changes in plantable estimates and possible increases in classification accuracy. Using multiple years to assess the change in plantable areas estimates across cities over time would be of interest. This methodology focuses solely on land cover characteristics and does not account for land use which will have an impact on what land is actually plantable. This shortcoming can be easily remedied through the use of auxiliary data representing parcels or land use plans. A classification process could also benefit from the use of additional GIS datasets, such as those representing impervious surface areas. Further, while our training data seemed sufficient, an increased number of training sets could enhance the classification accuracy for land classes with significant spectral diversity. Additionally, the classification process might benefit from the identification of additional land cover classes. For instance, the open class accuracy may improve if the class was separated into bare land or grass classifications. Also, datasets like roads could be manipulated to mask open areas that are not plantable due to easements required to mitigate transportation safety concerns. However, on the whole, this work provides a reasonable guide for developing a timely and cost-effective assessment of potentially plantable areas that can be implemented by cities across the southern United States and customized to meet their needs.

While we estimated the potential carbon stored through tree planting efforts in open urban areas, carbon sequestration in plants encompasses both above- and below-ground pools. Soil carbon levels in urban areas may approach or exceed that of native temperate forests after several decades following conversion from forests to residential uses, thus the age of urbanized land has been shown to be positively correlated with accumulation of carbon (Gough & Elliott, 2012). Therefore, urbanization of land from a previously forested state can lead to lower below-ground carbon sequestration levels that require decades to alleviate (Zhang et al., 2012). While planting urban trees in open areas may not result in the same type of above-ground forested ecosystem prior to urbanization, one estimate of above ground carbon storage in an urban environment indicates that forested areas contain over twice the carbon per unit area than "green urban area" (Strohbach & Haase, 2012). Agricultural fields in urban areas may have low amounts of above-ground carbon storage due to periodic harvesting activities. However, in terms of biomass produced, optimistic (29.7 metric tons ha^{-1}) sweet corn (*Zea mays* var. *rugosa* Bonaf.) production (Russo & Fish, 2012) is about 1.56 times greater than one optimistic estimate of dry urban lawn biomass (Springer, 2012) harvested per growing season (19 kg ha^{-1}). The latter may be about the same as about 23 mature red maple trees grown on the same area that are 25 cm in diameter and 20 m tall (using relationships from Clark, Phillips, and Frederick (1986)), although the trees would require two to three decades to grow this large.

5. Conclusions

The research described here had the objective of testing a time-efficient supervised classification process to assist with the estimation of plantable areas within cities of various sizes in the Piedmont region of the southern United States. As the character of urban areas change, timely assessments such as these may be

necessary in order to prudently react to economic and political opportunities that are presented. Further, as carbon markets evolve and mature, urban forest carbon projects may provide a method for not only increasing the amount of carbon dioxide stored in trees, but also a method for cities to earn revenue through the offering of carbon credits. This work thus is one step in the testing and development of tools for assisting in the assessments of urban carbon tree planting areas. Most of the results are promising, suggesting that identification of the potential of an urban area to further sequester carbon through tree planting efforts can be accomplished relatively quickly with sufficient accuracy to inform policy decisions. However, the percent of open area (11–48%), and the amount of open area that can potentially be planted with trees (52–92%) both vary considerably for the cities studied. Thus a simple relationship between city size and urban carbon offset potential seems elusive at this time. In fact, the range of opportunities in this region is from about 274,300 to 645,100 ha. Further exploration of the value of publicly available remotely sensed imagery seems necessary. For example, some classification error was associated with inherent image problems, while other error was associated with the ability of the imagery to represent, spectrally, the features of interest to us across the landscape. Understanding the potential for this environmentally friendly, socially acceptable, and cost effective sequestration option may therefore be of value to cities and municipalities that have the capacity and interest to trade the credits associated with these projects. The additionality, permanence, and quality of urban forest carbon offsets should then be relatively easy to establish and measure.

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