Assessing Potential Urban Tree Planting Sites in the Piedmont of the United States

A Comparison of Methods

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There is a growing interest of late to enhance our ability to reduce carbon dioxide levels in the atmosphere through tree growth. Although the spread of development in urban areas may, in some cases, cause a reduction in forest cover, there may be opportunities to establish additional trees in open areas within cities and metropolitan areas. We assess three freely available aerial or satellite imagery products for their ability to correctly identify open areas in six southern United States cities. A standard supervised classification process and a statistical assessment of plantable open areas are employed. Results suggest that while the United States National Agriculture Imagery Program (NAIP) aerial imagery may require more computer processing time and more computer memory, classification accuracy is acceptable for the purpose of identifying open areas where trees might be planted. Therefore, the use of NAIP for this purpose is as sufficient as Landsat 5 and 7. Given recent uncertainties in the availability of Landsat 5 and 7 imagery, and given analytical needs such as the one proposed here, improvements in estimates of urban carbon potential can be made over less intensive methods.

En los últimos tiempos hay un creciente interés para mejorar nuestra capacidad para reducir los niveles de dióxido de carbono en la atmósfera a través del incremento de árboles. Aunque la propagación del desarrollo en las zonas urbanas, en algunos casos, causa una reducción de la cobertura forestal, puede haber oportunidades para establecer nuevos árboles en zonas abiertas dentro de las ciudades y áreas metropolitanas. Evaluamos tres productos de imágenes aéreas o de satélite disponibles gratuitamente para determinar su capacidad para identificar correctamente los espacios abiertos en seis ciudades del sur de los Estados Unidos. Un proceso estándar de clasificación supervisada y una evaluación estadística de áreas abiertas plantables se emplearon. Los resultados sugieren que mientras que las imágenes aéreas del National Agriculture Imagery Program (NAIP) de los Estados Unidos pueden requerir más tiempo de procesamiento y equipos con mayor capacidad de *memoria, la precisión de la clasificación es aceptable para el propósito de identificar áreas abiertas donde los árboles pueden ser plantados. Por lo tanto, el uso de NAIP para este propósito es tan adecuado como Landsat 5 y 7. Teniendo en cuenta las incertidumbres recientes en la disponibilidad de las imágenes Landsat 5 y 7, y teniendo en cuenta las necesidades de análisis como el que aquí se propone, las mejoras en las estimaciones del potencial de carbono urbano se puede hacer con métodos menos intensivos.*

KEY WORDS: urban forests, carbon sequestration, supervised classification, remote sensing

PALABRAS CLAVE: bosques urbanos, secuestro de carbono, clasificación supervisada, teledetección

INTRODUCTION

Over the last two decades natural resource managers, planners, and policy makers have made great advances in identifying the importance of climate change to natural resource management. More specifically, a number of natural resource professionals have focused on the role plants' photosynthetic processes can play in reducing atmospheric carbon dioxide (CO_2) in urban environments (Dwyer et al. 1992; Nowak 1993; Nowak 1994; McPherson 1998; Nowak and Crane 2002). Urban forests are beneficial to urban environments for their carbon sequestration capacities because they are environmentally acceptable, often cost-effective, and aesthetically pleasing (McHale et al. 2007). By intercepting and reflecting solar radiation, urban trees help prevent local warming (mitigating heat islands), cool buildings and surfaces (reducing energy costs), and cool ambient air by absorbing thermal energy. In many cases, urban forests also act as windbreaks, intercept particulate matter, absorb gaseous pollutants, and help reduce stormwater runoff (Millward and Sabir 2011).

An understanding of how urban tree cover is distributed among development zones, land ownerships, and special areas is essential to the success of urban forestry programs. Gaps in the landscape and opportunities for tree-planting efforts are therefore of value for reasons beyond additional sequestration of carbon. Through the availability of carbon storage credits, forestry programs are beginning to recognize the economic benefits arising from carbon sequestration through carbon exchanges (Cairns and Lasserre 2004). However, due to the uncertainty of financial markets and the recent global economic crisis, relying on revenue derived from these carbon exchanges is risky (ICIS Heren 2011). For example, recent tradable carbon allowances for the European Union Allowances (EUA's) (one metric ton of carbon dioxide emissions), have ranged in price from 7 to 20 Euros (Thomson Reuters Point Carbon 2012). Additionally, the security of carbon registries has come into question following documented Internet attacks (ICIS Heren 2011). Finally, while there are several voluntary forest carbon markets originating in the United States, the key trading mechanism, the Chicago Climate Exchange, recently (2010) ceased trading carbon credits, leading to additional scrutiny of the risk involved in these carbon trading markets (Neeff et al. 2010). While uncertainty exists in markets, an assessment of the potential tree planting opportunities available to municipalities and private landowners is of value simply due to the carbon sequestration potential of these efforts.

Productive forestland has been under pressure from rapidly growing urban and suburban areas in the southern United States (Wear and Greis 2011) leading to a gradual reduction in commercial forest land area. In a number of cases, urban development has converted forests and greenspace into reserves managed by local governments, non-profit groups, and private individuals or families. Urban reserves have the potential to become permanent carbon repositories. Further, trees planted in urban areas along roadsides and in residential areas and vacant lots can serve a similar function. Nowak and Crane (2002) found that Atlanta, GA stored approximately 1,220,000 metric tons of carbon in forests. Additional research in Chicago found that within Cook and DuPage counties, approximately 855,000 metric tons of carbon could be stored in urban trees, with the greatest potential found in open spaces, parks, and urban forests (Nowak 1994).

With the acknowledgement of the importance of urban forests in carbon sequestration, a need arises for assessing current urban forests and the potential for additional urban forests. It is important to develop a quick, cost-effective process for identifying potentially plantable locations within a city that could be implemented by local governments and non-profit organizations. These estimates can be used to assess the incremental carbon sequestration potential of an urban area, and can also be used to inform policies (e.g., tax credits) that might be developed to promote private landowner efforts. The use of aerial or satellite imagery for assessing the urban environment is a valuable tool for natural resource managers, planners, and the general public (Young 2010) due to the wide area of coverage and the ability to analyze the data within a computer system. Wu et al. (2008) developed a process whereby, in conjunction with classified satellite imagery (of a type not freely available), the number of tree-planting sites could be estimated in an urban area. After open areas had been identified using two classification processes, a model then assessed the area available for non-overlapping tree crowns (given certain local conditions), and attempted to fit small, medium, and large tree crowns onto the landscape. Our goal is different: we intend to assess the usefulness of three freely available image products, along with a straightforward classification system that may be implementable by a city or county-level planner, to determine an estimate of the area plantable with urban trees (rather than the number of trees plantable).

The research presented here is a significant extension of an initial urban carbon tree planting potential assessment where we developed and applied a methodology to 15 cities in or near the Piedmont of the southern United States. In the previous work, we used Landsat 7 satellite imagery and a supervised classification process to estimate the potential plantable area within the Piedmont region of the southern United States. Landsat satellite imagery has been widely used in landscape assessments, yet recent technological issues cloud its future (Chen et al. 2011). Given the results of the initial research and our goal of locating fast, cost-effective methods for assessing potentially plantable areas within cities, we felt it important to further investigate the use of different imagery products available free of charge to the public. For example, digital aerial photography in the United States, derived from the National Agriculture Imagery

Program (NAIP), has become freely accessible to communities despite large data storage requirements, and therefore may be an alternative to satellite imagery. Others have used paired-point analyses of randomly distributed sample locations on aerial photographs to determine recent changes in tree cover in cities (Nowak and Greenfield 2012) and other similar aerial photograph analyses (Hall et al. 2012). Rather than use sample sites within a city area, we considered it important to embark on an analysis that involves remotely-sensed imagery and a continuous surface classification of plantable areas.

Therefore, from our previous work we selected six cities (Atlanta, GA, Charlotte, NC, Greenville, SC, Mount Airy, NC, Roanoke, AL, and South Boston, VA) from the original 15 that were analyzed and had lower accuracy levels (overall, producer's, or user's accuracy) than our established accuracy threshold set for Landsat 7 data. The assumption here being that the use of other imagery may lead to increases in accuracy due to the perceived advantages of these sources over the data currently available through the Landsat 7 program. In sum, in this research we will compare the results of identifying plantable areas using Landsat 7, Landsat 5, and NAIP imagery.

METHODS

The cities selected fell approximately within the United States southern Piedmont region. The initial 15 cities were chosen based on population and distribution across the study region, and were divided into three population classes with populations less than 10,000 (small cities), populations greater than 10,000 and less than 110,000 (medium cities), and populations greater than 110,000 (large cities). Defining these population classes allowed us to test whether there were differences in plantable area that could be attributed to population size accompanied by the additional infrastructure necessary to support larger populations. We used the U.S. Census Bureau's Designated Places (U.S. Census Bureau 2000) database to define our city boundaries. This means that there may be instances, Atlanta, GA for example, where adjacent metropolitan areas with large human populations where not included in the analysis because they fell outside of the administrative boundary of the city.

Following the results of previous research, 6 of the original 15 cities (Figure 1) were chosen for further investigation of potential accuracy improvements using different satellite and aerial imagery sources. In order to be consistent with the previous research, the imagery needed to be readily available, free of charge, and cover the majority of the conterminous United States. Cities were selected based on accuracy values (overall, producer's, or user's accuracy) that were lower than our preferred threshold of 70 percent following analysis with Landsat 7 imagery. We also wanted to select at least one city from each population group (Table 1). The initial research used Landsat 7 imagery obtained from the U.S. Geological Survey (USGS) (U.S. Geological Survey 2012a) in order to identify potentially plantable areas in each city. Landsat 7 imagery has several advantages: 1) the imagery is available for the entire U.S. for a given year, 2) it is free, and 3) it is orthorectified by the USGS prior to distribution over the Internet, reducing the amount of pre-processing required. These characteristics also served as guidelines

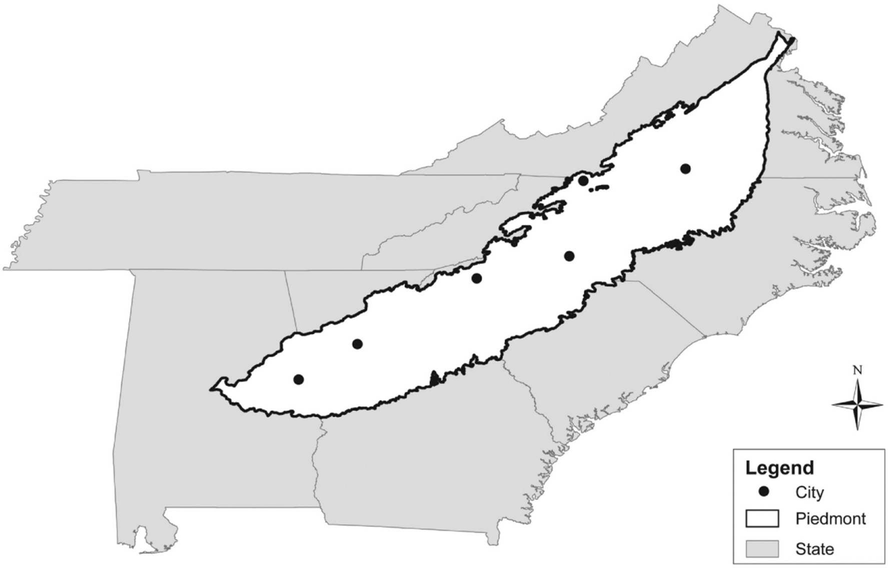

Figure 1. Study area including the 6 cities selected for analysis.

Table 1. Cities within the Piedmont of the southern United States where urban carbon potential will be assessed.

City	Estimated population[a] (2000)	Land area[a] (km^2)
Atlanta, GA	416,474	343.2
Charlotte, NC	540,828	628.5
Greenville, SC	56,002	67.6
Mount Airy, NC	8,484	21.7
Roanoke, AL	6,563	49.6
South Boston, VA	8,491	31.8

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

for choosing additional imagery sources. Landsat 7 also has its disadvantages. For example, the imagery captured by Landsat 7 sensors contains data gaps that result in stripes across each scene, which are more prevalent toward the edges of scenes. This striping is caused by the permanent failure of the satellite's scan line corrector (SLC) which occurred in May 2003 (Chen et al. 2011). Correcting these data gaps can be accomplished by several methods, including the methodology used here, which involved using a secondary (auxiliary) Landsat scene to fill gaps through a simple linear histogram matching technique (Figure 2). Histogram matching is a process that merges pieces of older images with new images containing data gaps in a manner that best matches the area surrounding the gap (Rulloni et al. 2012), and thus has been used for filling data gaps of images by comparing the relative distribution of land cover of one (with data gaps) to another (without data gaps) (ERDAS, Inc. 1999). In order to account for potential land-cover changes between the reference scene and the secondary scene during the gap-filling process, collection years ranged for the secondary image from 2009 to 2011. In the

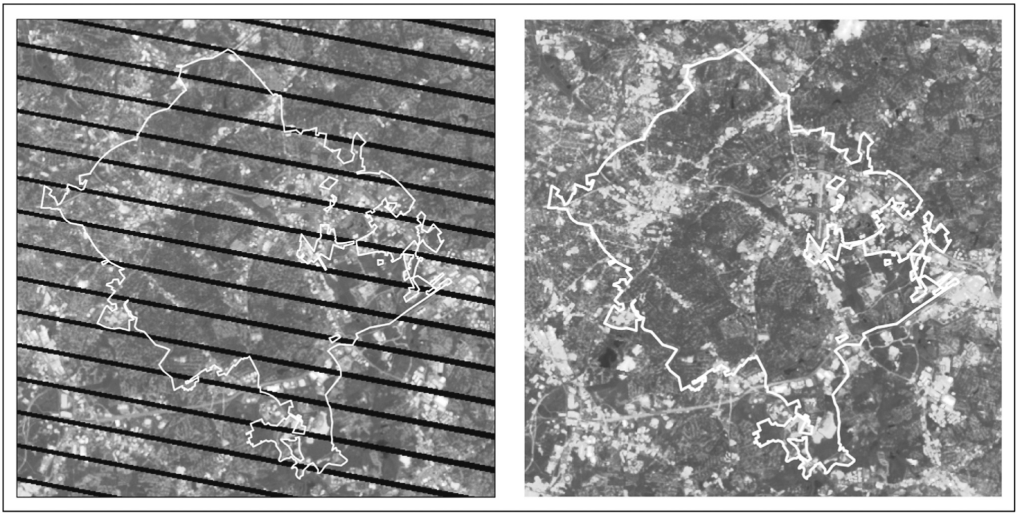

Figure 2. Example of a Landsat 7 scene prior to the data-gap filling process and the same scene following the data-gap filling process.

gaps that needed to be filled, inconsistencies in land use between the two images might arise. By acquiring a secondary image as close as possible in time to the first, we minimize the possibility of error propagating during the histogram matching process. While it is preferable to use a secondary scene obtained within two months of the reference image, this is not always possible due to image quality issues or overlapping data gaps in the reference and secondary image.

Due to the limitations of Landsat 7, we chose to select two additional imagery sources for comparison in order to assess if accuracy could be increased. We selected Landsat 5 satellite imagery and NAIP aerial imagery. Like Landsat 7 imagery, Landsat 5 is managed by the USGS (U.S. Geological Survey 2012a) while NAIP imagery is a product of U.S. Department of Agriculture Farm Service Agency (U.S. Department of Agriculture 2011). Landsat 5 and NAIP imagery are also free of charge, readily available for download via the Internet, and require minimal pre-processing activity. Additionally, both types of data have been orthorectified prior to distribution. Landsat 7 and Landsat 5 are comparable in that they both have a 30 m spatial resolution, although only Landsat 7 has a 15 m panchromatic band. The Landsat 5 program accommodates coverage of the United States, and is available through 2011. However, in November 2011, the USGS terminated imagery collection with Landsat 5 while they investigate a potential failure of the TM (Thematic Mapper) data retrieval system. At the time of this writing, Landsat 5 imagery collection is still paused (U.S. Geological Survey 2012b). Most importantly, Landsat 5 has had no failure of the SLC and, therefore, no data gaps occur across the imagery, reducing pre-processing time. Similar to our analysis of Landsat 7 imagery, the data selected for this analysis ranged from 2010 to 2011 dependent on its availability and quality. Without the SLC failure, only one Landsat 5 image was necessary for completing the current assessment, reducing the preprocessing time and the potential for introducing errors through the data-filling process.

NAIP imagery is available as natural color image digital orthoquarter quads (DOQQ) with a 1 m spatial resolution and is obtained during the agricultural growing season of the continental U.S. (U.S. Department of Agriculture 2011). At the time of this research, 2009 NAIP data was the most recently available imagery. Only after completion of this research did 2010 NAIP imagery become available. Since the dates of the three imagery products are not exactly the same, there is a risk of introducing bias into the analysis if significant land-use changes had occurred during this period of time. We failed to observe significant developmental changes amongst the three imagery products, perhaps given the recent economic situation of the United States. It should be noted that due to its fine spatial resolution, NAIP imagery can require a large amount of computational time to process and can require a large amount of computer storage space. In replicating our methodology, these storage and processing issues were noted. Further, a single quarter quad may contain data from more than one aerial image, therefore some tonal issues along the edges of the seams of the individual images may be present.

Each of the three imagery products was georeferenced prior to acquisition. With both Landsat (7 and 5) satellite systems, scenes were radiometrically corrected in order to convert raw data from digital numbers (DN) to spectral reflectance values. The four bands of the NAIP imagery were also converted to spectral reflectance values for this analysis. Using spectral reflectance values allows the user to identify fine differences between bands that are not distinguishable under the umbrella of a digital number (Lillesand et al. 2004). Following pre-processing, each of the three imagery sources was clipped to the administrative boundaries of the 6 cities. The three types of image products (Landsat 5, Landsat 7, and NAIP) were then classified into four land-cover classes using the same supervised classification process. Land-cover classes were defined as water, developed, forested, and open. The developed class included roads and buildings while the open class included forest clearcuts, agricultural land, bare ground, and grassy areas. With these four classes, some confusion may occur during the classification process between agricultural fields and young pine forests, and an estimate of plantable area could be overstated. However, we use a sampling process (described below) to determine how much of the open class could actually be planted with new trees.

For each of the six cities, sixty training sets were selected for each land-cover class. With a relatively small area to classify and a minimal number of land-cover classes, we felt that sixty training sets were appropriate (Lillesand et al. 2004). In selecting training sets, every effort was made to minimize the inclusion of mixed pixels but this was difficult in some cases for the open class and water class. Further, in order to represent the diversity of spectral values for each land class, some training areas inevitably contained mixed pixels. For example, a pine forest that had been thinned may contain various reflectance values that represent parts of trees crowns in full sunlight, and parts of tree crowns that are shaded. Further, reflectance values for rivers, shallow ponds, and deep ponds could all be quite different depending on water conditions. Training sets were located within each city boundary and represented a diversity of conditions for each class. Training sets were devised for each city independent of the other cities. While differences in elevation and slope between cities could be problematic, these (we hope) were minimized. Utilizing NAIP imagery is somewhat problematic for large area landscape classification purposes, since each NAIP image is a composite of several digital aerial photographs. Therefore time of day and sun angle within a DOQQ composite could affect the ability to classify land using a supervised classification process. These issues (i.e., sun angle, time of day, elevation, slope) were not specifically addressed in our analysis, and could impact the ability to develop highly accurate land classifications. Finally, each training set contained a minimum of twenty pixels. This requirement was only an issue in one city (Greenville, SC) where areas of water large enough to use as training sites were limited within the city boundary.

After each image was classified, an accuracy assessment was undertaken. Fifty sample points were geographically located by employing an equalized random sample for each land-cover class. The objective of the accuracy assessment was to obtain an overall accuracy of 70 percent and a 70 percent user's and producer's accuracy amongst the classes using Landsat 5 and NAIP imagery. Specifically, we focused on the open land cover class in order to identify potentially plantable areas within the city. In assessing accuracy, we relied on omission/commission tables and error matrices. While overall accuracy is a useful tool in assessing the quality of a classification, it can be misleading. Therefore, attention to error matrices can help further identify accuracy between land-cover classes (Steham 1997). While our acceptable level of accuracy is subjective, the optimal level of acceptable accuracy is debatable, for which many examples are found in the literature. For example, Aguirre-Gutiérrez et al. (2012) found a wide range (41 to 93 percent) 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. And Im et al. (2012) found that producer's and user's accuracies ranged from 48 to 75 percent for bare ground in a recent hierarchical classification of Landsat imagery for an area of northern New York.

Following completion of the supervised classification process (Figure 3) and the accuracy assessment, 100 randomly sampled points within the open land-cover class of each city were examined to determine whether they were potentially plantable. Although a lack of specific information on buildings and other landscape features prevents us from taking all tree-planting factors into account (as in the case of Wu et al. 2008), we developed several assumptions to classify a pixel as plantable or not plantable. First, powerline right-of-ways, forest clearings, residential lots, and roadsides that follow existing patterns of vegetation were considered to be plantable with some type of tree species. Second, open areas within or near airports, athletic facilities (e.g., golf courses and baseball fields), cemeteries, and public areas with designated specific purposes were classified as not plantable. As an example, in Fig-

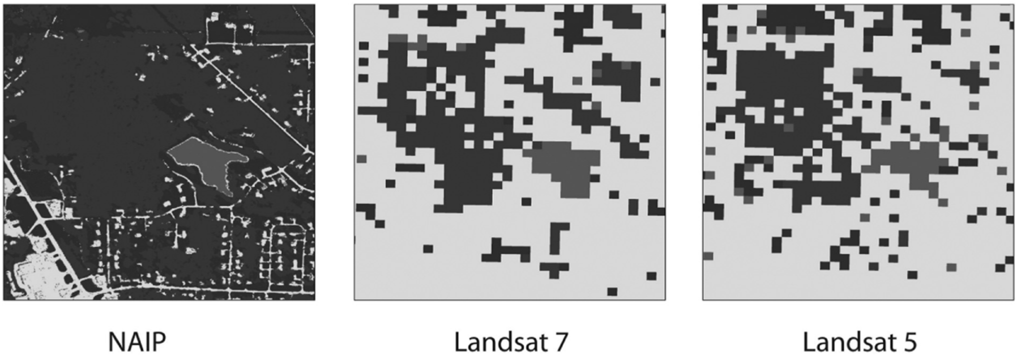

Figure 3. An example of each imagery source following the supervised classification.

ure 4 a randomly sampled point fell within a cemetery and would have been classified as not plantable. To be considered plantable, the area sampled also needed to be large enough to plant one tree. If an area were one pixel wide (in the case of Landsat data) or about 30 pixels square (in the case of NAIP data), they would have been considered plantable given the area required by at least one large-crowned tree. Obviously, spatial resolution differences between NAIP (1 m) and Landsat imagery (30 m) may bias this assessment since "open" areas defined using the NAIP imagery would require a collection of pixels, while with Landsat imagery, this would require a single pixel (and thus could accommodate more urban trees). These remote sensor spatial resolution issues are inherent in this assessment of urban forest planting sites.

Third, if a sample point fell within a forested area where there was space to plant one tree, it was not classified as plantable but instead classified as forest. However, if a point fell within a clear-cut, the point was classified as plantable. Finally, sample points within a pixel classified as open, but that were misclassified (were actually another class), were noted as being non-plantable with trees. Processing the imagery, completing the supervised classification, assessing accuracy, and determining plantable area within the city required, on average, two days for each image product.

RESULTS

Overall accuracy of the supervised classification of the four land-cover classes using Landsat 7 imagery ranged from a low of 69 percent to a high of 84 percent in Charlotte, NC and Atlanta, GA, respectively (Table 2). Each of the six cities should have had at least one measure (overall, producer's, or user's accuracy) below 70 percent when using Landsat 7 (the reason we chose them for this study). Although some of the overall accuracy values are above 70 percent, corresponding producer's or user's values are below 70 percent for the Landsat 7 imagery. Using Landsat 5 imagery yielded similar results with an overall accuracy ranging from 64 percent in Charlotte to 84 percent in Atlanta and South Boston, VA. With NAIP DOQQs, overall accuracy amongst the six cities ranged from

Figure 4. A randomly sampled point classified as non-plantable.

Table 2. Accuracy assessment results for six southern United States cities where a supervised classification process was employed to located open areas.

Remote sensing system	City	Open area producer's accuracy (%)	Open area user's accuracy (%)	Overall accuracy (%)
Landsat 7	Atlanta, GA	86.36	63.33	84.17
	Charlotte, NC	73.97	90.00	68.75
	Greenville, SC	86.84	55.00	78.33
	Mount Airy, NC	50.49	86.67	71.25
	Roanoke, AL	64.71	73.33	74.58
	South Boston, VA	69.05	96.67	82.08
Landsat 5	Atlanta, GA	94.59	58.33	84.17
	Charlotte, NC	86.11	51.67	63.75
	Greenville, SC	82.35	70.00	82.35
	Mount Airy, NC	87.50	81.67	87.50
	Roanoke, AL	62.07	90.00	74.17
	South Boston, VA	85.00	85.00	84.58
NAIP	Atlanta, GA	89.19	55.00	85.42
	Charlotte, NC	68.06	81.67	62.50
	Greenville, SC	77.27	85.00	73.75
	Mount Airy, NC	73.24	86.67	68.33
	Roanoke, AL	92.86	86.67	94.17
	South Boston, VA	56.70	91.67	67.08

63 percent in Charlotte to 94 percent in Roanoke, AL, averaging 75.2 percent. The highest average overall accuracy for the open class was derived from Landsat 5 imagery, with a 79 percent average overall accuracy. Both Landsat 7 and NAIP imagery had an average overall accuracy of 77 percent and 75 percent, respectively.

Overall Kappa coefficient values (Table 3) ranged from 0.922 (NAIP imagery, Roanoke) to 0.500 (NAIP imagery, Charlotte). The Kappa coefficient is an indicator of the extent to which the correct values in the error matrices are due to correct agreement with true landscape features and the extent to which they are due to random chance (Lillesand et al. 2004). An overall Kappa coefficient value of 0.922 suggests the observed classification is 92 percent better than one resulting from chance or random processes. There is no apparent pattern in our overall classification results that would suggest one of the three imagery products is superior in this regard to the others. Further, the larger cities were both high and low in this ranking, as were smaller cities. It is difficult to ascertain at this time whether topography had an influence, as all of the cities are contained in the Piedmont region of the southern United States. Further investigation of the correlation between topographic variables (slope, aspect, and elevation) and measures of overall classification may be assessed in the future.

In addition to overall accuracy, we ex-

Table 3. Ranked overall Kappa coefficient values for six southern United States cities where a supervised classification process was employed to located open areas.

Remote sensing system	City	Overall Kappa coefficient
NAIP	Roanoke, AL	0.922
Landsat 5	Mount Airy, NC	0.833
NAIP	Atlanta, GA	0.806
Landsat 5	Greenville, SC	0.800
Landsat 5	South Boston, VA	0.794
Landsat 7	Atlanta, GA	0.789
Landsat 5	Atlanta, GA	0.789
Landsat 7	South Boston, VA	0.761
Landsat 7	Greenville, SC	0.676
Landsat 7	Roanoke, AL	0.661
Landsat 5	Roanoke, AL	0.656
NAIP	Greenville, SC	0.651
Landsat 7	Mount Airy, NC	0.617
Landsat 7	Charlotte, NC	0.583
NAIP	Mount Airy, NC	0.578
NAIP	South Boston, VA	0.561
Landsat 5	Charlotte, NC	0.517
NAIP	Charlotte, NC	0.500

amined producer's and user's accuracy as indicators of the validity of our supervised classification. Producer's accuracy, or omission, represents the percentage of pixels that should have been assigned a given class, but were not by the supervised classification process. User's accuracy, or commission, represents the percentage of pixels assigned a given land class that actually belong to another class (Lillesand et al. 2004). With Landsat 7 imagery and for all four land-cover classes, the producer's accuracy ranged from approximately 51 percent for open areas in Mount Airy, NC to 100 percent for the water class for Atlanta, Roanoke, and South Boston. Additionally, producer's accuracy was 100 percent for the developed class in South Boston. With Landsat 7 imagery, for the open class, the producer's accuracy for all six cities ranged from 51 percent in Mount Airy to 87 percent in Greenville, SC, with an average producer's accuracy in the open class of 72 percent.

The user's accuracy with Landsat 7 imagery ranged from 10 percent for the water class in Charlotte to 100 percent for the forested class in South Boston. High user accuracies were also found in the forested class in Mount Airy (97 percent) and Roanoke (99 percent). Both Charlotte and Mount Airy had very low user's accuracies for the water class with 10 and 15 percent, respectively. The user's accuracies for the developed class in Roanoke (45 percent) and South Boston (57 percent) were also low. Both Atlanta and Greenville had lower user's accuracies for the open class (63 and 55 percent, respectively). The average open class user's accuracy when using Landsat 7 imagery was 77.5 percent.

When using Landsat 5 imagery, the producer's accuracy ranged from 49 percent for the developed class in Charlotte to 100 percent for the water class for Atlanta, Roanoke, and South Boston. The producer's accuracy was low for forested areas in both Roanoke and South Boston (67 and 69 percent, respectively). Additionally, the producer's accuracy was below 70 percent in the open class in Roanoke (62 percent). There were several instances of 100 percent producers accuracies, including developed and water classes in Roanoke, along with the water class in both Atlanta and South Boston. The producer's accuracy was highest in Atlanta (over 94 percent) for the open and lowest in Roanoke (62 percent). When using Landsat 5 imagery, the average producer's accuracy in the open class was about 83 percent, which was the highest of the three imagery sources.

The user's accuracy for open areas in both Atlanta and Charlotte was below the 70 percent threshold (58 and 52 percent, respectively) when using Landsat 5 imagery. Additional issues arose with user's accuracy for the water class in the Charlotte analysis (17 percent) and the developed class in Roanoke (35 percent). There were instances of 100 percent user's accuracy in South Boston (the water land cover class) and in Roanoke (forested class). The average open area user's accuracy for all 6 cities using Landsat 5 imagery was about 73 percent with the highest user's accuracy for the open class found in Roanoke (90 percent) and the lowest in Charlotte (52 percent).

Using NAIP DOQQs, the producer's accuracy ranged from a low of 53 percent for the developed class of Charlotte to a high of 100 percent for the water class in Greenville, Mount Airy, and South Boston. The producer's accuracy was comparable for the developed class in Charlotte (53 percent), Greenville (57 percent) and Mount Airy (56 percent). In the open class, the producer's accuracy ranged from about 57 percent in South Boston to 93 percent in Roanoke. The average overall producer's accuracy for the open class was 76.2 percent.

There were several instances (Charlotte, Greenville, Mount Airy, and South Boston) where user's accuracies fell below 30 percent for the water class. This was surprising as water was more easily identified in the higher resolution NAIP imagery, yet was less often correctly classified. Additionally, forested pixels had a likelihood of 63 percent of being correctly classified in Charlotte while in Atlanta open pixels were correctly classified 55 percent of the time. Forested pixels had a one hundred percent likelihood of being correctly classified in South Boston and 95 percent in Atlanta. While Charlotte had a user's accuracy of 63 percent in the forested class, South Boston, VA had a 100 percent user's accuracy in the class. The developed class user's accuracy was lowest in South Boston (62 percent) but was above 90 percent in all other cities. With an overall average user's accuracy of 81 percent for the open class, the NAIP was the best in this regard among the three imagery sources.

Table 4 provides the error matrices with the conditional Kappa coefficients derived from the accuracy assessment. These matrices illustrate how randomly sampled validation points correspond with the results of the supervised classification process and indicate the agreement to which the correct values are real or the result of chance (Lillesand et al. 2004). Values greater than 0.75 indicate excellent agreement (Fitzgerald and Lees 1994) and a lower probability of agreement by chance (Banko 1998). Error matrices were generated for each of the three imagery systems for all land-cover classes across the six cities. Several patterns can be found using the error matrices. For example, issues arose in classifying the water class using both Landsat 7 and NAIP imagery. With Landsat 7 imagery, water was misclassified as the developed class 22 times, the forest class 21 times, and the open class 11 times in Charlotte resulting in a conditional Kappa coefficient of 0.073, and suggesting an approximate 7 percent agreement between the ground truth and the supervised classification. This may have occurred because of the striping problem and histo-

Table 4. Error matrices associated with the classification process for the six southern United States cities analyzed using Landsat 7, Landsat 5, and NAIP imagery.

Remote sensing system	City	Class	Water	Devel.	Forest	Open	Kappa
Landsat 7	Atlanta,	Water	53	0	5	2	0.850
	GA	Devel.	0	52	4	4	0.822
		Forest	0	1	59	0	0.975
		Open	0	7	15	38	0.551
	Charlotte,	Water	6	22	21	11	0.073
	NC	Devel.	0	48	6	6	0.714
		Forest	1	0	57	2	0.921
		Open	0	2	4	54	0.856
	Greenville,	Water	0	0	0	0	—
	SC	Devel.	0	56	1	3	0.875
		Forest	1	5	52	2	0.805
		Open	0	23	4	33	0.430
	Mount Airy,	Water	9	0	5	46	0.113
	NC	Devel.	1	52	3	4	0.824
		Forest	0	1	58	1	0.953
		Open	0	5	3	52	0.766
	Roanoke,	Water	49	2	5	4	0.770
	AL	Devel.	0	27	14	19	0.374
		Forest	0	0	59	1	0.973
		Open	0	0	16	44	0.628
	South Boston,	Water	45	0	0	15	0.692
	VA	Devel.	0	34	15	11	0.495
		Forest	0	0	60	0	1.000
		Open	0	0	2	58	0.949
Landsat 5	Atlanta,	Water	59	0	1	0	0.978
	GA	Devel.	0	52	7	1	0.812
		Forest	0	3	56	1	0.904
		Open	0	15	10	35	0.507
	Charlotte,	Water	10	37	10	3	0.127
	NC	Devel.	1	55	3	1	0.844
		Forest	0	2	57	1	0.925
		Open	0	18	11	31	0.431
	Greenville,	Water	51	0	4	5	0.808
	SC	Devel.	2	55	2	1	0.880
		Forest	0	1	56	3	0.908
		Open	0	13	5	42	0.619
	Mount Airy,	Water	56	0	4	0	0.912
	NC	Devel.	1	51	4	4	0.803
		Forest	0	3	54	3	0.860
		Open	1	3	7	49	0.761

Table 4. (Continued)

Remote sensing system	City	Class	Water	Devel.	Forest	Open	Kappa
Landsat 5	Roanoke, AL	Water	43	0	2	15	0.655
		Devel.	0	21	21	18	0.288
		Forest	0	0	60	0	1.000
		Open	0	0	6	54	0.843
	South Boston, VA	Water	60	0	0	0	1.000
		Devel.	0	34	19	7	0.490
		Forest	0	0	58	2	0.949
		Open	0	2	7	51	0.800
NAIP	Atlanta, GA	Water	59	0	0	1	0.978
		Devel.	1	56	2	2	0.907
		Forest	0	1	57	2	0.927
		Open	0	11	16	33	0.468
	Charlotte, NC	Water	6	33	8	13	0.069
		Devel.	1	57	0	2	0.909
		Forest	1	13	38	8	0.532
		Open	0	5	6	49	0.738
	Greenville, SC	Water	16	34	1	9	0.214
		Devel.	1	58	0	1	0.942
		Forest	0	3	52	5	0.826
		Open	0	6	3	51	0.793
	Mount Airy, NC	Water	9	39	4	8	0.117
		Devel.	0	59	0	1	0.970
		Forest	0	6	44	10	0.656
		Open	0	2	6	52	0.811
	Roanoke, AL	Water	59	1	0	0	0.978
		Devel.	1	57	0	2	0.934
		Forest	0	0	58	2	0.954
		Open	0	1	7	52	0.826
	South Boston, VA	Water	9	10	22	19	0.117
		Devel.	0	37	0	23	0.523
		Forest	0	0	60	0	1.000
		Open	0	0	5	55	0.860

gram correction process. Similarly, Mount Airy had a conditional Kappa coefficient of 0.113 for the water class or an 11 percent agreement between the classification and the ground truth. Misclassification of the water class using Landsat 7 possibly resulted from too few instances of water across the scene, and the inability to develop robust training sets. In one instance (Greenville) no identifiable water pixels could be found resulting in no training sets for the water class.

With Landsat 7, confusion in the open class most commonly occurred with the forest and developed classes. For example, the open class in Atlanta was classified as developed 7 times and forested 15 times. In the developed class, forested and open pixels were most commonly misclassified as developed. A similar pattern of confusion in the open class occurred when using Landsat 5 imagery for classification. Misclassification of the open and developed classes was reduced using NAIP imagery but confusion occurred more frequently in the water class. Water was most commonly confused for the developed class in Mount Airy and for the forest and open classes in South Boston. In both Landsat 7 and Landsat 5 classifications, there were several instances of Kappa values of 1.0 or 100 percent for the forested class. On the whole, the greatest agreement between the ground-truth and classification of the open class occurred using the NAIP imagery. With one exception (Atlanta), all of the Kappa coefficients were above 0.70 or 70 percent in that class. Three instances of Kappa coefficients below 70 percent occurred in the open class using Landsat 7, while two instances occurred in Landsat 5.

As a function of total estimated open area, Landsat 7 and 5 are comparable (64 and 66 percent, respectively) in estimated area available for planting (Table 5). As one would assume, across all three imagery sources, Atlanta and Charlotte had the lowest percentage of plantable area. The density of these larger cities and the amount of land required to support their larger populations would be assumed to reduce the amount of open area available for planting. However, in terms of the estimated plantable area within the city, both Atlanta and Charlotte had the largest quantity of area available for planting across all three imagery sources. With Landsat 7 imagery, the city with the highest percentage of plantable open area was Mount Airy (92 percent). Similarly, Roanoke and Mount Airy (81 and 79 percent, respectively) had the greatest percentage of open plantable area estimated with Landsat 5 imagery. Using NAIP imagery, Roanoke was again identified as the city with the highest percentage of open, plantable area (88 percent).

In implementing this protocol for identifying potentially plantable areas, the computational time required to process the imagery as well as the computer memory required for storing the imagery needs to be considered. On average, classifying each imagery source through supervised classification, assessing the accuracy of the classification, and identifying potentially plantable areas within a city can be completed in two days. Computer storage requirements vary based on imagery source and size of the city being analyzed. Landsat 5 and 7 scenes can require 1 gigabyte of storage while NAIP imagery for a single city is downloaded in several quads and mosaicked into larger images that can require up to 15 to 20 gigabytes of storage for large cities such as Atlanta and Charlotte.

DISCUSSION

Our intent with this research was to assess three data sources for their value in determining and understanding the potential for increased urban tree planting, since the benefits derived from urban forests are directly related to tree cover (Nowak and Greenfield 2012). This is a complex issue, since the ability of an urban or metropolitan area to expand its tree cover and thereby increase the amount of carbon sequestered from the atmosphere is not only a function of land availability,

Table 5. Assessment of the "open" class in each of the six southern United States cities represented in this analysis.

Remote sensing System	City	Estimated total open area (ha)	Total city area (%)	Open area plantable (%)	Estimated plantable city area (ha)
Landsat 7	Atlanta, GA	10,919	31.8	64	6,988
	Charlotte, NC	6,778	10.8	52	3,525
	Greenville, SC	3,231	47.8	73	2,358
	Mount Airy, NC	560	25.8	92	515
	Roanoke, AL	1,027	20.7	84	770
	South Boston, VA	708	22.3	82	581
	Total	23,223			14,737
Landsat 5	Atlanta, GA	7,280	21.2	61	4,441
	Charlotte, NC	25,864	41.2	67	17,070
	Greenville, SC	2,000	29.6	75	1,500
	Mount Airy, NC	752	34.6	79	594
	Roanoke, AL	1,033	6.4	81	894
	South Boston, VA	743	23.4	70	520
	Total	37,672			25,019
NAIP	Atlanta, GA	7,952	23.2	55	4,692
	Charlotte, NC	12,985	20.7	70	9,090
	Greenville, SC	2,210	32.7	69	1,525
	Mount Airy, NC	634	29.2	80	507
	Roanoke, AL	1,567	9.7	88	1,379
	South Boston, VA	874	27.5	81	708
	Total	26,222			17,901

ownership, and development policy, but also a function of human behavior. Further, significant financial investment and ample labor supplies may be necessary conditions of the success of tree planting programs (Yang and Jinxing 2007). Some underlying demographic factors might also affect the distribution of tree cover within a city. The general affluence of landowners and age of a neighborhood positively influence the amount of tree cover, while increases in housing density decreases tree cover (Hall et al. 2012). Strategies for economic development and land-use planning vary from one city to another, and land development codes may require tree installation procedures to be followed (Gatrell and Jensen 2002). Land development policy, particularly in the area around roads, might also prohibit the planting of trees due to effects on road traffic and safety (Hall et al. 2012). On privately-owned land, incentives for landowners might be necessary to increase tree cover. These could include tax incentives or educational programs, as some landowners may prefer not to have trees near their structures. Finally, human behavior with regard to tradable carbon credit or carbon offset markets is unpredictable; humans may refrain from participating in tradable carbon credits due to distrust of the market mechanism or the volatility of prices (Sovacool 2011). These complexities aside, the potential area plantable with trees is important as tree cover decreased in some metropolitan areas in the last decade (Nowak and Greenfield 2012).

The process employed to identify and quantify opportunities for increased tree planting on open, plantable areas within cities of the southeastern United States was designed to be as time-efficient and cost-effective as possible. One of our main assumptions was that land-use planners may need to perform quick and timely assessments along these lines. Using error matrices, confusion in classification can be found across all three imagery sources. Whether we obtained our goal of increasing accuracy through the use of additional imagery sources is debatable. While the use of other imagery processing processes (object-based or neural networks) or imagery products (Lidar) may support higher levels of classification accuracy (Weng 2012), on the whole, we were hoping to reach an overall accuracy, producer's accuracy, and user's accuracy of 70 percent or greater in all cases using our methods and data. In most instances, we were able to achieve our overall threshold, with Charlotte as the only city that fell short of that criteria across all three imagery sources and in Mount Airy and South Boston when using NAIP imagery. Overall accuracies were very similar between the three imagery sources with Landsat 5 having the greatest overall accuracy. Focusing on the open class, the highest producer's accuracy was obtained when using Landsat 5 imagery, while the highest user's accuracy was obtained when using NAIP imagery. Lower accuracy values could be the result of several issues, including deficiencies in the quality of the imagery, insufficient data gap filling, cloud cover, shadows on the image, and the inclusion of mixed pixels in the supervised classification. For example, when using Landsat 7 imagery, Charlotte was left with visible striping in the image following the histogram matching (Figure 5).

Additional research would help to advance increases in overall accuracy and the ability to assess how much open land area may be plantable with trees. An exploration of the impact of shadows and higher heterogeneity of spectral reflectance values per unit area in NAIP imagery may be important. While NAIP imagery is visually more effective for identifying landscape features, due to high spatial resolution compared to Landsat imagery, these problems could amplify misclassification error. In addition, future research endeavors could replicate the methodology with leaf-off imagery and the identification of open areas may be enhanced with a reduction in the live forest cover within the imagery. Although we suggest this as an area of further research, at this time we are unsure whether leaf-off analysis would actually improve classification accuracy of some of the classes. We avoided including this process in our analysis because we were demonstrating reasonable cost-effective (and straightforward) methods for detecting the amount of open areas that could be plantable with urban trees using a single image source. The additional steps necessary to accommodate spectral changes observable during different periods of the year would add complexity to the process, and perhaps induce some error due to

Figure 5. Visible striping following the data-gap filling process.

land-cover changes that could have occurred. However, estimating potentially plantable open areas would benefit from multi-year assessments so that changes in plantable area can be estimated across space and time. Additionally, introducing supplemental GIS data sets, such as impervious surface cover or roads, may increase the accuracy of identifying developed areas. Either dataset could be used to mask areas in the imagery unavailable for planting prior to performing the supervised classification. Finally, the open assessment would benefit from an expansion in land-cover classes. With confusion amongst the classes evident in the error matrices, specifically the open class, the ambiguous definition of the class itself may be leading to a reduction in accuracy. For example, if the open class were further subdivided into bare ground and grass classifications, a reduction in misclassification of pixels might be achieved. These shortcomings aside, this work provides a reasonable, cost-effective methodology for estimating the potentially plantable area in a city. Also, using different imagery sources has shown that there is flexibility in implementing this methodology and it can be customized to meet the needs of planners and managers based on their familiarity with the imagery, their ability to process and store large datasets, and the desired resolution of their classification.

CONCLUSIONS

The focus of the research described here was to investigate the use of a variety of readily available, cost-efficient imagery sources and whether these could lead to increases in the accuracy of a classification process developed to quickly identify open, plantable opportunities within cities in the southern United States. The reasons that such an assessment is important range from the need to assess carbon sequestration opportunities to the need to perform zoning analyses. The results we have provided are promising and the methodology developed is flexible enough to be applied and implemented to areas beyond the southern United States. However, while NAIP imagery resulted in the greatest average user's accuracy for open areas and Landsat 5 imagery resulted in the greatest average producer's accuracy for open areas, some questions remain as to the utility of these data sources. In our analysis, the limited number of training sites for certain cities makes widespread application of a common protocol problematic to other cities. Further, each city seemed to have its own classification issue, with regard to one or more land classes, amongst the three imagery options. The future of Landsat 5 is also in doubt. As of June 2012, electronics problems continued to plague the system and further acquisition of data is questionable. Landsat 7 continues to have a SLC problem and about 25 percent of any image contains gaps that need to be filled using a process such as histogram matching. While the timeline for data availability is unclear at this time, a new Landsat satellite (Landsat Data Continuity Mission, or LCDM) is expected to be placed in orbit in early 2013. One may assume that hyperspectral imagery (e.g., Ikonos) might be used to alleviate these concerns, yet this type of imagery is not currently free of charge nor as widely applied as the imagery products assessed here. NAIP imagery is commonly used in conjunction with geographic information systems and on-line mapping tools. While other methods of processing NAIP imagery (e.g., McGee et al. 2012) may lead to greater image classification accuracy, these generally require greater knowledge of remote sensing and will likely require a larger time commitment for development of the final product. In sum, for timely and efficient estimates of plantable open areas, NAIP imagery seems adequate in conjunction with a supervised classification process. The other imagery products (Landsat 5 and 7) may also be adequate, yet their spatial resolution is larger, and their continued availability is in question.

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