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ESTIMATING URBAN FOREST CARBON SEQUESTRATION POTENTIAL IN THE SOUTHERN UNITED STATES USING CURRENT REMOTE SENSING IMAGERY SOURCES

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ABSTRACT:
With an increased interest in reducing carbon dioxide in the atmosphere, tree planting and maintenance in urban areas has become a viable option for increasing carbon sequestration. Methods for assessing the potential for planting trees within an urban area should allow for quick, inexpensive, and accurate estimations of available land using current remote sensing sources. Here we use Landsat 8, launched in February 2013, and the USDA's NAIP program to perform supervised classification of land cover classes in six southern cities. These supervised classifications were used to determine the availability of plantable open area in each city. The results of the assessment using the two different imagery sources are compared, and in terms of overall accuracy, were found to be similar for the two data sources. Both the producer's and user's accuracies when using NAIP imagery were slightly lower than when using Landsat 8 imagery. However, each of the classifications met our desired accuracy levels for open area delineation in five of six cases.

Key-words: *Urban forestry, Landsat 8, NAIP, Supervised classification, Carbon sequestration.*

1. INTRODUCTION

Climate change and associated options for carbon sequestration in forests have become important societal issues over the last decade. Although identification of carbon sinks and estimations of net carbon flux are important in understanding the global carbon cycle (Woodbury, Smith & Heath, 2007), on a regional or local scale an understanding of the current condition and future potential of land areas to support sequestration through forestry efforts is also important and may be used as an indicator of ecological performance (Whitford, Ennos & Handley, 2001).

Urbanization can significantly alter the ecology of land from its natural state, resulting in changes to the vegetation, hydrology, biodiversity, ecosystem services, and climate previously found or available there (Tratalos et al, 2007). While the activities on city lands can be producers of large amounts of CO_2, these lands can also be viewed as potential areas to sequester carbon and provide environmental benefits through the development, planting and maintenance of trees (Strohbach, Arnold & Haase, 2012), although some maintenance activities can offset the carbon storage gains (Nowak & Crane, 2002).

Trees grown in urban areas can provide shading, cooling, and wind mitigation services to nearby human infrastructure (Jim & Chen, 2009), although the potential space available is a concern due to the wide variety of uses of land within urban areas (Akbari, 2002). With

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respect to forest carbon sequestration opportunities within urban areas, prior research has evaluated the use of satellite imagery (McPherson, Xiao & Aguaron, 2013; Merry et al, 2013a; Merry et al, 2013b; Zheng, Ducey & Heath, 2013) and aerial photographs (Akbari, 2002; Huang, Robinson & Paker, 2014) for timely, cost effective, and accurate assessments of land available for the development of forest carbon projects.

Since 1972, the U.S. government has facilitated the collection of broad-scale medium-resolution satellite imagery through the Landsat program. The Landsat 5 mission was launched in 1984, and was decommissioned in 2013. In the last few years of its useful life, the satellite suffered from problems with the operating current within the data transmission segment and the inability to adjust equatorial inclination due to low fuel and failure of a redundant gyroscope, leading to drift (Wulder et al, 2011; National Aeronautics and Space Administration, 2014). The mission was only expected to last five years, and thus its useful life (28 years) lasted much longer than anticipated.

The Landsat 7 mission was launched in 1999, yet since 2003 has suffered from technical issues, specifically the failure of the scan line correction (SLC), that led up to 22% of an image lost in "no data" wedges (Wulder et al, 2011). Landsat 7 continues to collect data of the Earth's surface as of this writing. The Landsat Data Continuity Mission (Landsat 8) was launched in February 2013, and imagery became available shortly thereafter. Landsat LCDM is designed to become a standard source of satellite imagery for at least a decade, possibly much longer. With the operation of Landsat 8, imagery is enhanced with additional bands for coastal and water resources analysis and an additional near infrared band useful in detecting cirrus clouds, and two push-broom instruments, a Thermal Infrared Sensor (TIRS) and the Operational Land Imager (OLI).

In previous work, Landsat 7 data was used to estimate the amount of open, plantable area contained within the administrative boundaries of fifteen southern Piedmont (USA) cities (Merry et al, 2013a). Imagery from Landsat 7 was further compared to imagery obtained from Landsat 5 and the U.S. Department of Agriculture's National Agricultural Imagery Program (NAIP) for the same purpose (Merry et al, 2013b). Supervised classifications were used to identify open, plantable areas, and the process was consistently applied to each of the imagery sources. The research presented here is an extension of urban carbon tree planting potential (Merry et al, 2013a; Merry et al. 2013b) where a methodology was developed for the southern United States. The aim of the present research is to further illustrate the potential of Landsat 8 to provide timely, cost-effective, and precise estimates of urban resources for the identification of open, plantable areas with respect to the potential development of urban forest carbon projects. An additional goal is to compare plantable estimates across two imagery sources with different resolutions is accomplished by using the same methodology with recent NAIP imagery.

2. METHODS

2.1 Study areas

This research concentrated on the identification of open areas suitable for urban carbon tree planting projects in six cities located in the southern United States using Landsat 8 and NAIP imagery. Several of the cities selected had been analyzed using Landsat 5, Landsat 7, and NAIP imagery (Merry et al, 2013a, Merry et al, 2013b). Landsat 5 and 7 data selected ranged in time from 2010 to 2011 while the available NAIP data was from 2009. Here, we are using Landsat 8 imagery from 2013 and NAIP imagery from 2013 as well.

Landsat 8 imagery of an acceptable quality (less than 10% cloud cover) was not available for all 6 of the cities previously analyzed (Atlanta, GA, Charlotte, NC, Greenville, SC, Mount Airy, NC, Roanoke, AL, South Boston, VA), therefore, we used several of the cities available from a larger 15 city analysis (Merry et al, 2013a) and added Birmingham, AL (**Table 1**). We selected two cities (Roanoke, AL and Toccoa, GA) where the 2010 population was less than 10,000 people, three cities (Athens, GA, Columbia, SC, and Greenville, SC) where the 2010 population was greater than 10,000 yet less than 120,000 people, and one larger city (Birmingham, AL). Three population sizes were used in order to assess whether differences in plantable area might be related to population size with larger population cities having fewer opportunities for planting. The administrative boundary of each city was used to delineate the extent of the analysis even though urban transitions may continue into other nearby urban centers or adjacent counties that contain non-residential and residential urban characteristics. Urban areas ranged in size from approximately 22 km^2 to 393 km^2.

Table 1. Population of cities where urban carbon potential will be assessed

City	Estimated population[a] (2000)	Estimated population[b] (2010)	Land area[a] (km^2)
Athens, GA	101,489	116,714	306.3
Birmingham, AL	242,216	212,237	393.4
Columbia, SC	120,563	129,272	342.4
Greenville, SC	56,002	58,409	67.6
Roanoke, AL	6,563	6,074	49.6
Tocoaa, GA	9,323	8,491	21.7

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

2.2 Imagery Pre-Processing

We obtained 30 m spatial resolution Landsat 8 imagery from the United Stated Geological Survey (USGS) to use in identifying plantable areas. Landsat 8 imagery is an excellent source of data for broad and efficient land cover assessments because it is available free of charge and downloadable from the Internet. The imagery used for this assessment was collected during the time period May 2013 to September 2013. Prior to acquisition, the imagery was orthorectified by the USGS. Following acquisition of the data, the imagery was radiometrically corrected in order to convert to spectral reflectance values from the digital numbers (DN) that were assigned to each pixel in each database. Pre-processing time using Landsat 8 data was reduced from the time allocated to pre-processing Landsat 7 imagery since the user no longer needs to correct for the failure of the scan line collecter. This failure resulted in data gaps on the edge of each imagery scene that needed to be filled using a secondary image and processes such as histogram correction before any analysis could be conducted.

The NAIP imagery consists of a natural color images, in the form of digital orthophotograph quarter quads (DOQQ), with a 1 m spatial resolution, and was obtained during the agricultural growing season of the continental U.S. (U.S. Department of Agriculture, 2013). At the time of this research, 2013 NAIP data was the most recently available imagery for the cities analyzed. No pre-processing was required to use NAIP imagery in a supervised classification.

2.3 Image Classification

A supervised classification process was employed to understand, based on spectral reflectance values, where open areas were located, along with developed areas, water, and forests. For the purpose of the NAIP imagery, we added an additional land cover class, a shadow class, as it was prevalent across the extent of each city. Prominent shadows across high resolution imagery in urban areas are not uncommon (Zhou et al, 2009). It was necessary to have a class specifically for shadows in the NAIP classification in order to reduce confusion between the spectral reflectance of areas impacted by shadows and other land cover classes. Additionally, where water appeared in an image, whether NAIP or Landsat 8, it was classified, but if water was not visible in an image, for instance in Greenville, SC, water was not classified.

Sixty (60) training sites were selected for each of the land classes in each of the six cities. A supervised classification was then performed using Erdas Imagine 2013 (Intergraph Corporation, 2012). An accuracy assessment was performed on the supervised classification through an equalized random sample of each class for each city using sixty sample points per class. One meter NAIP imagery from 2013 was used as the reference image for the accuracy assessment. An omission / commission matrix was developed to assist in our understanding of the accuracy of the supervised classification process and our understanding of the confusion that may exist between classes (Steham, 1997). We focused on the accuracy of identifying the open land cover class (**Table 2**).

Given the purpose of this research, accuracy in this class was important in determining the amount of potentially plantable area in each city. In addition to the overall accuracy of the classification process, the user's and producer's accuracy values were reported. For each accuracy index, we set a threshold of 70 percent as the minimum necessary for adequately identifying each class. The user's accuracy helps one to understand the likelihood that the land class assigned to a pixel was actually representative of that pixel on the ground in real life (illustrating commission). The producer's accuracy helps one to understand how well the training sites represented the respective land classes (illustrating perhaps omission).

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

Satellite System	City	Open area producer's accuracy (%)	Open area user's accuracy (%)	Overall accuracy (%)
Landsat 8	Athens, GA	85.00	85.00	78.75
	Birmingham, AL	95.00	95.00	92.96
	Columbia, SC	85.07	95.00	89.58
	Greenville, SC	87.76	71.67	81.11
	Roanoke, AL	80.00	93.33	79.17
	Tocoaa, GA	100.00	48.33	83.33
NAIP	Athens, GA	96.08	81.67	73.33
	Birmingham, AL	91.67	73.33	76.67
	Columbia, SC	82.61	63.33	76.33
	Greenville, SC	82.69	71.76	87.50
	Roanoke, AL	75.68	93.33	91.33
	Tocoaa, GA	86.67	73.33	93.67

2.4 Assessment of Open Areas

Upon completion of the supervised classification of the imagery, further analysis was conducted of the land considered open, since some of the open land is likely not suitable for tree planting projects. This process of identifying the proportion of open area suitable for tree planting projects is consistent with previously published research (Merry et al, 2013a). For example, golf courses and other defined sports facilities (baseball and soccer fields), cemeteries, and certain road rights-of-way would likely be unavailable for tree planting projects, and these exceptions needed to be removed from estimates of open area within a city.

Areas that were considered plantable with trees included residential lots, power line rights-of-way, farmland, large forest clearings, and edges of roadways that followed existing vegetation patterns. For example, in Athens a point falling on a sports field was not considered plantable while a point falling in an open field was considered plantable (**Fig.1**). NAIP imagery from 2013, which was temporally consistent with the Landsat 8 imagery, was used for ground truthing the land classified as open.

One hundred (100) randomly located sample points were placed within each city's classified open area, and these were then assessed to determine whether they were plantable with trees. In addition to assessing whether these sample points were plantable with trees, if one the sample points was placed in an area mis-classified as an open area, and the underlying true state of the land was non-plantable, the sample area was considered non-plantable with trees.

Fig. 1 Example of points assessed to be not plantable and plantable in Athens, GA.

3. RESULTS

Overall accuracy for the six cities analyzed met and exceeded our goal of 70 percent ranging from about 79 percent (Roanoke and Athens) to 93 percent (Birmingham) accuracy using Landsat 8 imagery and from about 73 percent (Athens) to 94 percent (Toccoa) accuracy using the NAIP imagery.

3.1 Landsat 8

With Landsat 8 imagery, the average overall accuracy across the six cities was 84.1 percent compared to 83.1 percent using NAIP imagery. In addition to overall accuracy, the producer's accuracy illustrates how well training sets represent each land cover class. For all land classes, the average producer's accuracy when using Landsat 8 imagery was 87.3 percent, and the 95 percent confidence interval was 78.6 to 96.0 percent.

The producer's accuracy ranged from approximately 60 percent (forested class in Athens) to a high of 100 percent in several instances. The average producer's accuracy for the open land class of the six cities was 88.8 percent, and the 95 percent confidence interval was 82.9 to 94.7 percent. Specifically, the producer's accuracy for the open class ranged from 80 percent (Roanoke) to 100 percent in Toccoa (**Table 2**). Two areas of concern were found following the supervised classification in terms of the producer's accuracy when using the Landsat 8 imagery. Specifically, the producer's accuracy for the forested class in Athens and Roanoke fell below the 70 percent threshold set, 59.6 and 62.7 percent, respectively, indicating too much variability in the spectral signatures for the training sets used.

The average user's accuracy, or the proportion of pixels that were assigned to a land cover class and actually represented that land cover class, was 84.3 percent for all classes when using the Landsat 8 imagery, and the confidence interval was 74.5 to 94.0 percent. The user's accuracy ranged from 46.7 percent (the developed class in Roanoke) to 100 percent (both water and forested classes in Columbia). In the open class, the average user's accuracy was 81.4 percent (**Table 2**) and ranged from 48.3 percent (Toccoa) to 95.0 percent (Columbia and Birmingham) with a 95 percent confidence interval between 66.6 and 96.2 percent. There were four instances where the user's accuracy fell below our 70 percent threshold.

Using the error matrices (**Table 3**) derived from the accuracy assessment, in Athens developed (55.0 percent) was most often confused with the forested class. In both Columbia (63.3 percent) and Roanoke (46.7 percent), the developed class was most often misclassified as either open or forested (**Table 3**). The open class was rarely confused with another class with the exception of Toccoa (48.33 percent) the open class was most often confused with the developed and forested class.

Focusing on only the open class, it is clear that our classification meets the desired accuracy levels for open areas across all six cities with the exception of Toccoa. While 100 percent of the open areas have been correctly classified as open (producer's accuracy), only 48.3 percent of the areas identified as open are truly that class (user's accuracy). This may result in an under representation of the open class in the classification.

Table 3. Landsat 8 error matrices for six southern cities.

Satellite System	City	Class	Water	Developed	Forest	Open
Landsat 8	Athens, GA	Water	49	0	11	0
		Developed	2	33	20	5
		Forest	0	0	56	4
		Open	1	1	7	51
	Birmingham, AL	Water	59	0	1	0
		Developed	1	49	8	2
		Forest	1	0	58	1
		Open	1	1	1	57
	Columbia, SC	Water	60	0	0	0
		Developed	3	38	9	10
		Forest	0	0	60	0
		Open	0	1	2	57
	Greenville, SC	Water	-	-	-	-
		Developed	-	45	10	5
		Forest	-	1	58	1
		Open	-	6	11	43
	Roanoke, AL	Water	47	0	0	13
		Developed	1	28	18	13
		Forest	0	0	59	1
		Open	0	0	4	56
	Toccoa, GA	Water	58	2	0	0
		Developed	0	55	5	0
		Forest	0	2	58	0
		Open	0	20	11	29

3.2 NAIP

Due to the high resolution (1m) of the NAIP imagery, we introduced a shadow class to the classification. Initial classification trials indicated that a shadow class, due to the prominence of shadows across the images, would be necessary in order to reduce confusion amongst classes during the supervised classification. With the NAIP imagery, for the five land cover classes, the average producer’s accuracy was 85.3 percent, and the 95 percent confidence interval was 77.9 to 92.8 percent. The producer’s accuracy ranged from approximately 51 percent (forested class in Columbia) to a high of 100 percent in multiple instances. The average producer’s accuracy for the open land class was 85.9 percent, and the 95 percent confidence interval was 80.1 to 91.7 percent. Specifically, the producer’s accuracy for the open class ranged from 75.7 percent (Roanoke) to 96.1 percent (Athens) (**Table 2**). Again, there were areas of concern across the five classes used in the NAIP supervised classification in terms of the producer’s accuracy. Specifically, the producer’s accuracy for the forested class in Birmingham and Columbia fell below 70 percent, to 57.3 and 51 percent, respectively. Confusion between the forested class and the water class in Birmingham occurred 31 times (**Table 4**). In Columbia, confusion between the forested class and both the water and open classes occurred. The shadow class in Athens fell below 70 percent, specifically 55.6 percent, with confusion occurring most often with the water class highlighting the similar spectral signature of these two classes.

The average user's accuracy for all five land classes was 83.0 percent when using the NAIP imagery, and the 95 percent confidence interval ranged from 73.0 to 93.0 percent. User's accuracy ranged from 5.0 percent (water in Athens) to 100 percent in multiple instances. The average user's accuracy for the open class was 78.3 percent, and we found a 95 percent confidence interval to range from 69.6 percent to 87.1 percent (**Table 2**). Again, there were instances where the user's accuracy fell below 70 percent. This occurred predominantly in the water class in Athens (5 percent), Birmingham (25 percent), and Columbia (40 percent). Using error matrices (**Table 4**), it is clear that the water class in Athens was confused for the shadow class most often, 41 times specifically. In the case of Birmingham, the water class was confused for the forested class 31 times. Similarly in the case of Columbia, the water class was confused for the forested class 33 times. Additionally, the user's accuracy for the open class in Columbia was 63.3 percent with the open class being confused with the forested class 18 times.

Table 4. NAIP error matrices for six southern cities.

Satelite System	City	Class	Water	Developed	Forest	Open	Shadow
NAIP	Athens, GA	Water	3	1	15	0	41
		Developed	0	59	0	1	0
		Forest	1	2	49	1	7
		Open	0	3	8	49	0
		Shadow	60	0	0	0	0
	Birmingham, AL	Water	15	0	31	3	11
		Developed	0	59	0	1	0
		Forest	2	2	55	0	1
		Open	0	9	7	44	0
		Shadow	0	0	3	0	57
	Columbia, SC	Water	24	0	33	2	1
		Developed	0	57	0	3	0
		Forest	0	2	53	3	2
		Open	2	2	18	38	0
		Shadow	3	0	0	0	57
	Greenville, SC	Water	-	-	-	-	-
		Developed	-	60	0	0	0
		Forest	-	4	47	9	0
		Open	-	9	8	43	0
		Shadow	-	0	0	0	60
	Roanoke, AL	Water	53	0	1	4	2
		Developed	0	52	0	8	0
		Forest	0	0	53	6	1
		Open	1	0	3	56	0
		Shadow	0	0	0	0	60
	Toccoa, GA	Water	59	0	1	0	0
		Developed	0	59	0	1	0
		Forest	0	2	51	7	0
		Open	0	2	6	52	0
		Shadow	0	0	0	0	60

3.3 Open Assessment

Noting the accuracy across all six cities, the estimated amount of open area in the 6 cities for Landsat 8 is 16,140 hectares (ha) and for NAIP is 27,881 ha (**Table 5**). Using Landsat 8, the percentage of area classified as open ranges from 7.3 percent (Columbia) to 40.7 percent (Toccoa). Following the open area assessment, the percentage of the open class that is considered as plantable ranges from 35 percent (Greenville) to 70 percent (Athens). Across all six cities, the estimated plantable area is almost 9,000 ha using Landsat 8. Fifty-four percent of the total area classified as open across all six cities has the potential of being plantable.

Using NAIP imagery, the percentage of area classified as open ranges from 20.9 (Toccoa) to 26.4 (Columbia) percent. This was a much smaller range of values than what was estimated using the Landsat 8 imagery. The percentage of open area considered plantable ranged from 29 percent (Columbia) to 69 percent (Roanoke). Roanoke and Athens generally had more area available that is potentially plantable, 69 and 56 percent, respectively. Of the total area classified as open across the six cities, 40 percent is potentially plantable, slightly less than when using the Landsat 8 imagery. In comparing the percent of area estimated to be plantable between Landsat 8 and NAIP imagery there is clearly a difference between the two estimates.

In Athens, Birmingham, and Columbia, the amount of open area plantable is between 13 and 14 percent less when using NAIP imagery while in Toccoa the NAIP imagery estimates are 15 percent greater when using NAIP imagery. However, estimates of plantable city area are greater when using the NAIP imagery, perhaps due to the finer-scale detail provided (1 m spatial resolution versus 30 m resolution). Further, large differences were noted between the two imagery sources in two larger cities (Birmingham and Columbia).

Table 5. Assessment of the "open" class in 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 8	Athens, GA	5.028	16.3	70	3.519
	Birmingham, AL	4.527	11.5	51	2.309
	Columbia, SC	2.407	7.3	42	1.011
	Greenville, SC	1.716	24.6	35	600
	Roanoke, AL	1.505	30.1	63	948
	Tocoaa, GA	958	40.7	35	335
	Total	16.140			8.723
NAIP 2013	Athens, GA	6.872	22.4	56	3.848
	Birmingham, AL	8.715	22.7	38	3.312
	Columbia, SC	8.695	24.4	29	2.522
	Greenville, SC	1.776	22.6	30	533
	Roanoke, AL	1.370	27.7	59	946
	Tocoaa, GA	454	20.9	50	227
	Total	27.881			11.386

4. DISCUSSION

Clearly there was variability between the open area estimations resulting from the classification of Landsat 8 and NAIP imagery. While accuracy was high using both imagery sources, in general, Landsat 8 accuracy levels are higher for overall, user's, and producer's accuracy. We were surprised by the differences found in Athens, Birmingham, and Columbia. After thoroughly reexamining the classifications, including the training sets and the accuracy assessment, we were satisfied that the classification process was reasonable with the resulting accuracy matrices supporting that. However, the user's and overall accuracy were greater for Landsat 8 than NAIP for these three cities, indicating an issue with the misclassification of NAIP pixels rather than an issue with the training sets.

In using high spatial resolution imagery, in this case 1 m resolution NAIP imagery, issues can arise in pixel-based classification techniques including the one used here, maximum likelihood classifier. This classification method assumes no interrelationship between adjacent pixels but instead treats each pixel as an individual (Cleve et al, 2008). This can result in a reduction in spectral separation (or increased spectral variation) between classes leading to misclassification or variation in class amongst neighboring pixels (Hayes, Miller & Murphy, 2014; Meneguzzon, Liknes & Nelson, 2013). Additionally, NAIP images are color balanced following collection in order to increase the functionality for the user (U.S. Department of Agriculture, 2013) reducing the validity of the resulting spectral signatures which may be exacerbated when working in larger areas (Hayes, Miller & Murphy, 2014).

When conducting assessments like the one presented here, a decision needs to be made between the two resolutions available using NAIP and Landsat 8 imagery. While the detail of the NAIP imagery may be desirable, it may add confusion to the classification process where the Landsat 8 may be too coarse for some planners. In the NAIP classification, adding additional classes may be necessary in order to develop spectral seperability amongst the classes for example a shadow class, or multiple open classes (eg. bare ground, pasture, and clearcuts). Our intention here was to make the classification process simple and replicable. Therefore, we simplified the classes to four or five depending on the imagery used. More importantly, the results we found (and verified twice) argue that a compromise in spatial resolution may be necessary, and this may be the most important message. The NAIP imagery seems too fine for the purpose of detecting open, platable area, and the Landsat 8 data seems to course for this purpose. Resampling the NAIP imagery up to a spatial resolution of about 5 m will help maintain some of the fine-scale spectral variation that is important, rather than resampling the Landsat 8 data down from 30 m to 5 m resolution. Further, this extra processing step is relatively easy to perform and therefore is consistent with our desire to describe fast and effective ways to assess the amount of land available for carbon sequestration projects in urban areas.

Both imagery sources required similar time and effort for processing, classifying, assessing the accuracy, and quantifying the potential plantable area. Both imagery sources are free and readily available through internet downloading. NAIP imagery may take longer to process as well as require more storage due to the high resolution nature of the imagery. From start to finish for both imagery sources, each city took approximately one day to complete the assessment. In all six cities we reached our goal of an overall accuracy on 70 percent for both imagery sources making it difficult to postulate that one imagery source is better for plantable land and land cover assessments than another. However, NAIP imagery was more challenging to accurately classify due to its high resolution.

Additionally, Landsat 8 is available for every year with scenes captured every month compared to NAIP imagery that is available more sporadically and for the agricultural growing season. Each imagery source has its advantages and disadvantages which makes the research objectives or planning goals an important factor in deciding which imagery source is important for land cover assessments. Based on the results presented here, Landsat 8 imagery seems to be preferred for the purpose of estimating open plantable areas within cities of the southeastern United States.

Additional research would be useful to assess the overall accuracy and how much land area may be plantable with trees. For instance, additional geospatial data sets may be more informative in defining what is plantable and what is not plantable within a city. This methodology focuses on land cover and does not take into account land use and private land owner preferences. County level parcel data my provide insight into land use and help further define what is open and plantable across the landscape. While landowner preferences are complex and difficult to integrate into spatial assessments, land use can be integrated through parcels and land use plans.

Additionally, confusion between the developed class and the open class could be reduced using impervious surface data. Further, incorporating hydrological data into the land cover assessment would help reduce confusion with other classes and increase accuracy in defining the water class. Finally, we used leaf-on imagery for the assessment across the six cities. Open area assessments and plantable area estimations might benefit from a similar methodology using leaf-off imagery.

5. CONCLUSIONS

As we have shown with this work, very different estimates of land cover can arise using the same process applied to different imagery sources. While each estimate seems credible, the more compelling estimate was developed using the Landsat 8 imagery, although the results are somewhere coarse in nature as compare the finer-scale NAIP imagery. While previous work in this area showed a closer correspondence between open area estimates when using Landsat and NAIP imagery, the current work suggests that the utility of these data sources needs further research. Each city had its own classification issues across both imagery sources. These classification issues may be mitigated through the use of supplemental GIS data.

Overall, the accuracy of the land cover classification for both Landsat 8 and NAIP imagery was acceptable but the two imagery sources clearly varied in the resulting open area assessments and potential plantable area estimates. We have provided a reasonable methodology to assess areas that are potentially plantable within cities. However, careful consideration should be employed to decide which imagery source is appropriate when implementing the methodology.

Finally, the process should be extended one extra step to determine whether a mid-resolution imagery (NAIP imagery re-sampled up to 5 m spatial resolution) would be more effective in terms of overall accuracy of the spatial representation of open, plantatble areas given the variability in the NAIP classification and the coarse nature of the Landsat 8 classification.

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