

Using feature analyst & NAIP imagery to conduct a statewide tree canopy assessment of Georgia

Abstract

Background: A collaboration between agencies to conduct a statewide canopy assessment of Georgia was formed in order to develop a baseline dataset from 2015 NAIP imagery to be used as comparison to archival data and future data analysis to measure canopy growth/loss over time. Using Feature Analyst software, analysts processed the imagery running a minimum of 1 iteration on each tile, checking for accuracy at 70% or higher. If under 70% accuracy, up to 4 additional iterations were conducted until accuracy confirmed for some tiles at 90%. Random point checking was conducted by field foresters to confirm accuracy of the binary: canopy/no canopy. Due to size of the imagery on a statewide scale, the state was divided into 24 physiographic regions as specified by the Department of Natural Resources and then into 269 tiles to create manageable data files. This article will summarize the process for analyzing imagery to generate a statewide canopy assessment and recommend ways in which to use the results to manage forestry resources or to conduct further comparative analysis.

Keywords: tree canopy, forestry, feature analyst, imagery, remote sensing

Volume 3 Issue 1 - 2019

Allison J Bailey,¹ Charles O Bailey Jr²

¹Institute for Environmental & Spatial Analysis, University of North Georgia, USA

²Georgia Forestry Commission, USA

Correspondence: Allison J Bailey, Institute for Environmental & Spatial Analysis, University of North Georgia, 3820 Mundy Mill Road, UNG-Gainesville Campus, Oakwood, GA, 30566, USA, Tel +1 678-717-2276, Email alison.bailey@ung.edu

Received: December 13, 2018 | **Published:** February 05, 2019

Introduction

Like many states or countries, government agencies responsible for the conservation and protection of forest resources have a need for accurate datasets. McGee III¹ stated in their study that this information is vital for urban forestry management support. After realizing that other states in the United States (Texas, Virginia) had published tree canopy data on state agency websites, Georgia realized the need for a statewide canopy assessment.² At the time of funding, the 2015 imagery from United States Department of Agriculture³ was determined to be the most complete statewide file which could feasibly be analyzed. Other researchers have used LiDar⁴⁻⁷ or aerial imagery from UAV;⁷ however neither of these options fit the objectives of the Georgia Forestry Commission (GFC). First, there is not a currently complete and available LiDar imagery for the state of Georgia; just now in 2018, Georgia has only just began collecting LiDar data and only 82 of the 159 counties in Georgia have been flown.⁸ This project began in 2016, so the 2015 NAIP imagery was the most recent imagery available at a consistent standard. Secondly, LiDar is most often used for smaller scale projects using ground sensing equipment for species identification in addition to canopy coverage in urban.^{4,9} Since the state of Georgia has extensive portions of the state in undeveloped national forest lands or large tracts of timber, this type of analysis would not be appropriate. Aerial imagery from UAV or manned aircraft are only available for specific locations and so not sufficient for the scope of this project. Similarly, Ucar et al.,¹⁰ used NAIP imagery to analyze tree canopy in two medium-sized cities in the United States which is a smaller undertaking compared to an entire state. And some geospatial analysts are fusing LiDar with satellite imagery to produce urban tree canopy cover analysis.¹¹

Some of the objectives of the project was to capture 'exurban' and low density sites as well as interface, create a baseline dataset for site specific comparison to historical data as well as future data as it becomes available. Grant funding became available for this type of

project from The Sustainable Community Forest Program (SCFP), an ongoing program initiative under the GFC which promotes the value of forest resources in community settings including urban, exurban, and interface areas. This canopy assessment will: spatially identify and quantify tree canopy resources within the state, develop a standard methodology that may be utilized to conduct change assessments against future canopy conditions, and utilize the deliverable canopy layer data within a variety of standardized GIS applications. These activities are part of the GFC SCFP's ongoing community forestry program and are focused on identifying current canopy resources and evaluating future impacts from development related activities. The 24 Department of Natural Resources (DNR) physiographic regions include a mixture of urban, exurban, low density, and interface sites and also allowed an organized way to have region specific tiles to be used by other state agencies wanting to compare forestry resources to whatever is under their purview.

Methods

The base imagery for analysis used for this project was APFO NAIP for Georgia, 2015 4 band (rgb-nir) 1m resolution. The number of bands and the resolution is extremely important to having viable results at this scale. Textron Overwatch provided support services after development of Feature Analyst Plug-In for analysis of the imagery. Another software which could have been used for this project is eCognition software,⁹ but was not chosen due to cost. Analysis of imagery was conducted using ArcGIS for Desktop 10.3 with Overwatch Feature Analyst Extension/Plug-In after dividing into the imagery files into the provided map layer of the 24 GA DNR physiographic regions. Within each region, training polygon specifications were established under the following conditions: minimum size 200m², no maximum all within grid; training polygon edge content \geq 20% of polygons with edge content; classification threshold at 64m²; and output raster resolution at 1m² nominal pixel size (Figure 1).



Figure 1 Map of Physiographic Regions and 2015 NAIP Imagery of Georgia.

Upon analysis of each training polygon, random points were generated for inspection (n=435 per region) and field foresters were assigned point inspection data records on mobile devices to be verified. Huang et al.,¹² also extrapolated from field inventories to determine

accuracy of canopy coverage calculations. Some aspects of the raster analysis were verified for accuracy in both ArcGIS for Desktop 10.3 and ArcPro. The flow of the imagery processing is modeled in Figure 2.

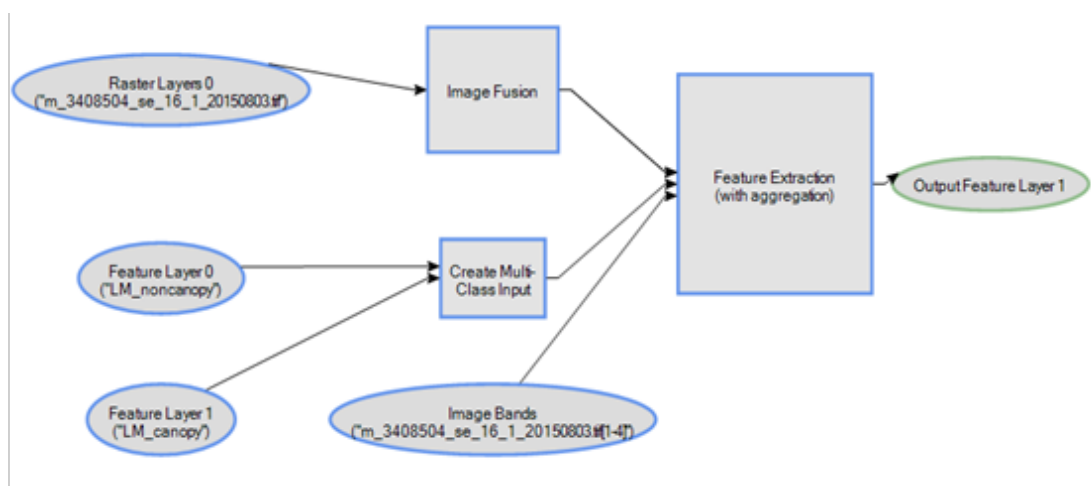


Figure 2 Flow of Imagery Processing.

The parameters for image tile selection in the Feature Selector window under four categories: input bands, input representation, masking, and output options. Four bands (R,G,B,NIR) were selected based on reflectance, with the NIR band additionally used for textural analysis. No stretching was done for the histogram, with the learning floor set at 1 m/pixel to take full advantage of the image resolution. Wall-to-wall (exhaustive) classification and feature rotation were enabled with the algorithm settings. The input representation pattern was set for a bulls-eye covering 4 pixels at the center with an outer width of 15 pixels.

The main purpose of choosing Feature Analyst as the analysis tool was to utilize the advanced machine learning algorithms to automate the classification process.² A time intensive analysis did not necessarily need to be a labor intensive process.¹³ Each region made up of multiple tiles with multiple training polygons averaged 22 hours of batch processing time. The technician simply selected the classification training files for the model and the images to be

processed and moved to another computer station to begin the flow for processing the next tile. Ultimately 269 NAIP tiles were processed using 19 canopy sample training modules and 20 non-canopy sample training modules (Figure 3).

The Winder Slope sample as shown in Figure 4 made a good fit for the pilot study of the project to establish the accuracy of the methodology; combined with the Greenville Slope, these two tiles represented between 4.5 and 5.5% of the statewide project area and included a diverse mixture of urban and rural environments to meet the objectives of the funding for the project. Within this region the classification accuracy was evaluated to exceed project requirements at approximately 91 percent. Given this favorable evaluation, the imagery files for the remainder of the state of Georgia were processed in the same fashion. Once the analysis was completed, the tiles had to be stitched to create a physiographic region mosaic to complete the statewide dataset as depicted in Figure 5.

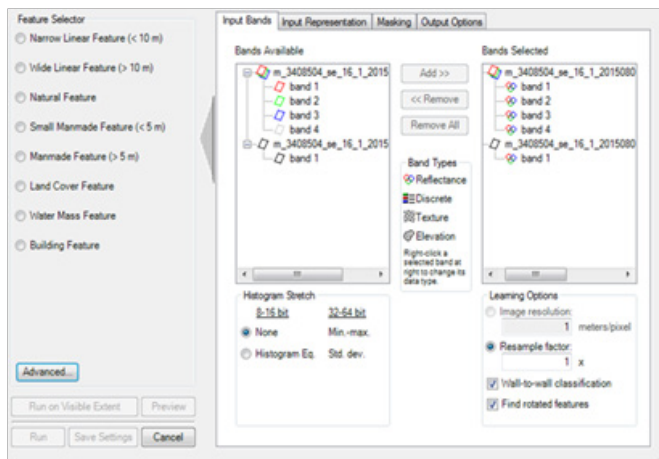


Figure 3 Parameters for Image Tile Selection in Feature Analyst.



Figure 4 Winder Slope Sample (1 of 269 NAIP tiles).

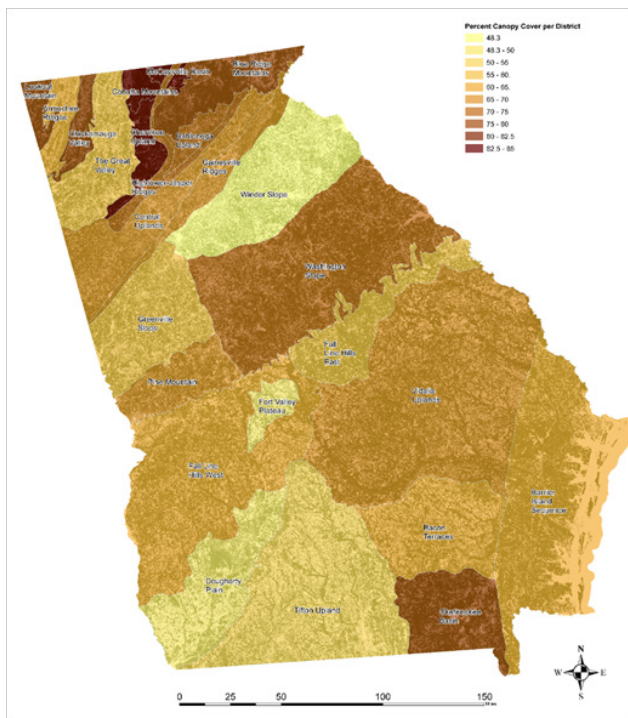


Figure 5 Percent of canopy cover per physiographic region.

Results

The deliverables to this statewide canopy assessment were packaged to include a binary raster as described in the specifications section, covering an extent equal to or greater than the state of Georgia using the classification of 1=defined canopy and 0=non-canopy with the projection of WKID 102039 USA_Contiguous_Albers_EA_USGS. Metadata records were written in compliance with US FGDC standards. A workflow document describing in detail the procedures used to produce desired outputs was generated and is reflected visually in Figure 2, so that forestry GIS specialists could recreate the workflow on other year datasets for comparative analysis of tree canopy loss/gain. The 2015 tree canopy coverage for the state of Georgia was determined to be 68.6% with the lowest percent canopy cover per physiographic region at 48.3% and the highest percent canopy cover per physiographic region at 85%.

Discussion

The main objective for completing the statewide canopy assessment for Georgia was to develop a baseline dataset of canopy coverage in order to be able to do longitudinal studies of canopy loss/gain to monitor land cover change in national forest areas, timber agriculture areas, urban, and rural areas. Ucar et al.,¹⁰ compared two imagery sources to estimate canopy cover in cities within the state of Washington and the state of Florida in order to establish sampling approaches which would produce accurate results. In this project, the use of Feature Analyst to batch process imagery files produced results at 91% accuracy, well above the anticipated accuracy of 70%, thus establishing a method for assessing canopy coverage for large geographic areas. Now that the canopy cover is known for 2015 in all landscapes in the state of Georgia is known, looking back to older imagery could track in what landscapes tree canopy has increased or decreased. And then by focusing on areas with canopy loss, one could make inferences as to what may be the cause for that change. Is it urban sprawl or development in urban or interface areas? Is it changes in population density? How does population demographics affect canopy coverage? How can canopy assessment inform urban planners? Since timber is an agricultural crop in Georgia, how can canopy assessment inform timber managers? Agricultural landscapes – whether windbreaks for other crops¹⁴ or for orchards or silviculture – are crucial for the economics of a state like Georgia with its large agro-industry. Looking forward in time, how is canopy coverage in Georgia affected by climate change or natural disasters, such as, tornados, hurricanes, or wildfires? Since this canopy assessment was completed, a wildfire destroyed many acres of national forest areas in the northern part of the state and several hurricanes have taken out many stands of trees all across the state in urban, silviculture, and rural areas. What has happened to the Georgian tree canopy is only just now being captured in 2018 LiDar and aerial/satellite imagery, so the loss to canopy coverage has not yet been measured.

Assessing tree canopy cover has become a standard dataset required for forestry management in every state or country where preservation of forestry resources and ordinances for tree plantings in urban areas is policy. Ejares, et al.,⁹ mapped canopy cover for barangays in the Philippines using LiDar to analyze tree shade for public parks, Pahrmehr⁶ and Parmehr¹¹ mapped urban tree canopy in suburban areas of Melbourne, Australia. Forested areas are equally important to urban areas when discussing monitoring landscapes. Knowing the percent of canopy cover is useful to forest inventories.¹⁵ Sankey⁷ using multispectral data to create 3D models of canopy structure to visualize large-scale changes in northern Arizona. Livengood¹⁶

extracting timber harvest changes in canopy in the state of Tennessee. Tree canopy for agroforestry in North Dakota and South Dakota was assessed by Liknes¹⁴ to develop a classification tree algorithm. All studies attempting to determine tree canopy in recent years, even with their different methodologies, justification for their studies, and the differing locations did confirm the importance of having accurate tree canopy data and visualizing that data on maps.

Conclusion

In conclusion, knowing the actual canopy coverage for the entire state of Georgia informs forestry resource managers, municipalities, and the public about the importance of trees in the Georgian landscape. And so, this knowledge has many implications for practice. Urban planners could examine existing tree canopy to budget for tree planting programs; this would be especially useful in cities which have rapid urbanization.⁹ According to Parmehr¹¹ current maps of canopy are “important for sustainable development of urban green spaces” and this baseline 2015 map of canopy for Georgia will help to track future development within the state. Because preservation of forestry resources is a primary goal impacting state policy, this dataset will inform decision makers thereby assisting in improving environmental quality in urbanized locations and planning conservation activities in exurban, rural, or interface locations.⁵ The Georgia Forestry Commission is already using this dataset to inform policy makers regarding the health and abundance of trees in Georgia and hopes to fund new projects for comparative analysis soon.

Future research will continue to inform praxis. Each physiographic region needs to be classified into landscape type especially denoting municipal boundaries in order to quantify the canopy coverage for each location. Areas of interest could then be analyzed using ground-based Portable Canopy Lidar for individual stands.⁴ Since this project did not focus on species identification, future research could expand to classify canopy cover of certain species. Hemlock trees would be of special interest in the North Georgia Foothills landscape and longleaf pine in South Georgia. And then the comparative analysis can begin to measure the economic benefits of tree canopy in the urban landscape, the social impacts of differences in tree canopy cover in wealthier communities versus poorer communities, and a comparison of road networks to determine carbon offset. The methods from this project can be applied to any state, country, or region of a larger geographic area to assess tree canopy cover where LiDar is not available and fused in areas where LiDar is available. Collaborations between other states in the Southeastern United States are underway to utilize this method to complete statewide tree canopy assessments for regional planning.

Acknowledgments

The authors would like to acknowledge the paid research team members who assisted with the processing of data and the random ground checks for accuracy: Andrew Hilliard, Jonathan Stewart, Christ Strother, & Michael Torbett, NAIP Imagery (2015) provided by the USDA-FSA-APFO Imagery Program, and Software support provided by staff at Textron Overwatch and ESRI.

Funding details

Funded by a grant of \$25,000 from the Georgia Forestry Commission in 2016

Conflicts of interest

Authors declare that there is no conflict of interest.

References

1. McGee III JA, Day SD, Wynne RH, et al. Using geospatial tools to assess the urban tree canopy: Decision support for local governments. *Journal of Forestry*. 2011;109(2):275–286.
2. Bailey AJ, Bailey Jr CO, Hilliard A, et al. Using Feature Analyst to Conduct Statewide Canopy Assessment of Georgia. Conference Presentation. Southern Group of State Foresters Annual Meeting: Raleigh, NC. 2017.
3. United States Department of Agriculture. (n.d.). GeoSpatial Data Gateway. 2016.
4. Hardiman BS, Bohrer G, Gough CM, et al. Canopy Structural Changes Following Widespread Mortality of Canopy Dominant Trees. *Forests*. 2013;4:537–552.
5. Mariappan M, Krishnan V, Murugaiya R, et al. Urban Forest Canopy Extraction Using Lidar Data. *Environmental Engineering and Management Journal*. 2015;4(10):2333–2340.
6. Parmehr EG, Amati M, Taylor EJ, et al. Estimation of urban tree canopy cover using random point sampling and remote sensing methods. *Urban Forestry & Urban Greening*. 2016;20:160–171.
7. Sankey T, Donager J, McVay J, et al. UAV lidar and hyperspectral fusion for forest monitoring in the southwestern USA. *Remote Sensing of Environment*. 2017 195:30–43.
8. Georgia Geospatial Information Office. (n.d.). State Imagery Program. 2018.
9. Ejares JA, Violanda RR, Diola AG, et al. Tree Canopy Cover Mapping Using Lidar in Urban Barangays of Cebu City, Central Philippines. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. XLI-B8, 2016. p. 611–615.
10. Ucar Z, Bettinger P, Merry K, et al. A comparison of two sampling approaches for assessing the urban forest canopy cover from aerial photography. *Urban Forestry & Urban Greening*. 2016;16:221–230.
11. Parmehr EG, Amati M, Fraser CS. Mapping Urban Tree Canopy Cover Using Fused Airborne Lidar and Satellite Imagery Data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, III-7.2016. p. 181–186.
12. Huang S, Ramirez C, Kennedy K, et al. A new approach to extrapolate forest attributes from field inventory with satellite and auxiliary data sets. *Forest Science*. 2017;63(2):232–240.
13. Bailey AJ, Bailey Jr CO, Hilliard A. Statewide Canopy Assessment of Georgia Using Feature Analyst. Conference Presentation. GIS-Pro 2017: Jacksonville, FL. 2017.
14. Liknes GC, Perry CH, Meneguzzo DM. Assessing Tree Cover in Agricultural Landscapes Using High-Resolution Aerial Imagery. *The Journal of Terrestrial Observation* 2010;2(1):38–55.
15. McRoberts RE, Liknes GC, Domke GM. Using a remote sensing-based, percent tree cover map to enhance forest inventory estimation. *Forest Ecology and Management*. 2014;331:12–18.
16. Livengood K. Extracting harvest sites from imagery. *The Forestry Source*. 2016. p. 16–17.