Multi-Scale Ground Filtering of Dense Lidar Point Clouds for Modeling Shrub Mangrove Canopies in Coastal Environments

Author: Travis Meyer

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Abstract

Coastal wetland managers face difficulties monitoring shrub mangroves at large scales using traditional remote sensing methods employed in forest stock monitoring due to the low stature of the vegetation and the dense nature of its canopy structure. The goal of this project is to assess the qualitative accuracy of ground filtering algorithms applied at varying scales to model shrub mangrove canopies using dense lidar point clouds and object-based feature extraction methods. High-resolution imagery and dense lidar point cloud data sets were used to delineate and extract mangrove and waterbody features as shapefile layers using Object-Based Image Analysis (OBIA) rule sets in eCognition. Three separate object scales were used to classify three differing outputs for mangroves areas (Scale of 3, 5, and 10 in eCognition). These layers are later used to classify mangrove points for volumetric extraction within LP360. Ground filtering algorithms were applied to the unclassified point data at 5-meter, 10-meter, and 20-meter filtering grids for the purpose of deriving ground surface models. The three imported mangrove feature shapefiles are then used to assign the remaining mangrove surface points to a unique mangrove class for each ground model. Canopy Height Models (CHM) were produced by generating Normalized Digital Surface Models (nDSM) within mangrove areas, for a total of 9 different ground filtering and object scale combinations. Volumetric differencing was then used to determine how much Above-Ground Biomass (AGB) is lost or "gained" due to interpolation approximations reported in percentage values and volumetric units (cubic meters) by comparing subsequent CHMs to a baseline CHM (the model with best resolution). By applying the workflow designed in this project to coastal wetland monitoring projects, wetland managers may be able to better observe carbon sequestration and ecological improvements in mangrove habitats at appropriate scales over long periods of time.

Introduction

Mangroves are a species of wetland vegetation receiving more attention by climate scientists and coastal conservation groups lately as their contributions to the global climate budget and coastal ecology draw increasingly scrutiny (Kauffman, et al., 2014, Kauffman, et al., 2012, Lagomasino, et al., 2016, Luna, et al., 2017, Maeda, et al., 2016). Mangroves exist at the littoral interface between ocean and land and play a pivotal role in coastal ecology. Mangroves sequester large amounts of carbon (Bouillon, et al., 2008, Fatoyinbo, 2010, Kauffman, et al., 2014, Kauffman, et al., 2012, Maeda, et al., 2016, Mcleod, et al., 2011), establish breeding grounds for maritime species of birds and fish safe from predation, deposit sediment along coastlines, and help dissipate storm surge produced by tropical cyclones. Not all mangroves are created equal, and due to varying environmental factors found in the differing geographies of their global extent, there can often be large discrepancies in the areal extent and vegetative structure of mangroves found in the wild (Alsumaiti, 2014, Heenkenda, et al., 2015, Kauffman, et al., 2012, Son, et al., 2015, Wannasiri, et al., 2013).

Scientists from a wide range of communities have a vested interest in monitoring mangroves at large scales due to their role in regulating the carbon budget and coastal ecology—climatologists, wetland ecologists, biogeochemists, etc. (Bouillon, et al., 2008, Fatoyinbo, 2010, Kauffman, et al., 2014, Luna, et al., 2017). These researchers often have a difficult time monitoring mangroves at large scale due to the inaccessible nature of certain wetlands, and aerial or space-borne imagery is often used to identify and delineate wetland areas that mangroves inhabit instead (Alatorre, et al., 2011, Fatoyinbo, 2010, Heenkenda, et al., 2014, Heenkenda, et al., 2015, Luna, et al., 2017, Myint, et al., 2008, Simard, et al., 2006). While digitizing the areal and even volumetric extent of mangroves using modern remote sensing techniques to generate Canopy Height Models (CHMs) is relatively easy, accurately modeling *shrub* mangroves in coastal wetlands at large scale has been a difficult challenge for wetland scientists for decades due to their dense vegetative structure and their low stature in an inundated environment (Everitt, et al., 2008, Giri, eta l., 2011, Meng, et al., 2017, Osland, et al., 2014, Wannasiri, et al., 2013).

Few studies have been conducted seeking better methods for developing Canopy Height Models (CHMs) of shrub mangroves in coastal environments for use in quantifying vegetative biomass using modern remote sensing methods like Object-Based Image Analysis (OBIA) or statistical point cloud filtering (Dronova, 2015, Everitt, J. H., et al., 2008, Fatoyinbo, 2010, Feliciano, 2015, Luna, et al., 2017, Meng, et al., 2017, Wannasiri, et al., 2013). Vegetative biomass quantification can be used to approximate the carbon sequestered by mangroves over a given area—which can then be subsequently factored into global carbon budget models, but accurate CHMs must first be produced to quantify these values (Boegh, Eva, et al., 2002, Feliciano, 2015, Kauffman, et al., 2012, Khosravipour, et al., 2014, Lagomasino, et al., 2016, Thapa, et al., 2015).

Producing an accurate CHM is difficult because the vegetative canopy is so dense and thick that few lidar pulses can penetrate them using traditional airborne lidar altimetry and surface-differencing methods on the data-processing side (see Figure 1). Without good data collection capabilities, the generated model will not be resolute enough to characterize the above-ground biomass and relate it to overall vegetative structure and carbon sequestration rates (Heenkenda, et al., 2014, Heenkenda, et al., 2015, Kamal, et al., 2014, Karlson, et al., 2014, Kauffman, et al., 2014, Maeda, et al., 2016). A better methodology must be derived for remotely collecting and processing imagery and elevation data to accurately model shrub mangroves in coastal environments.

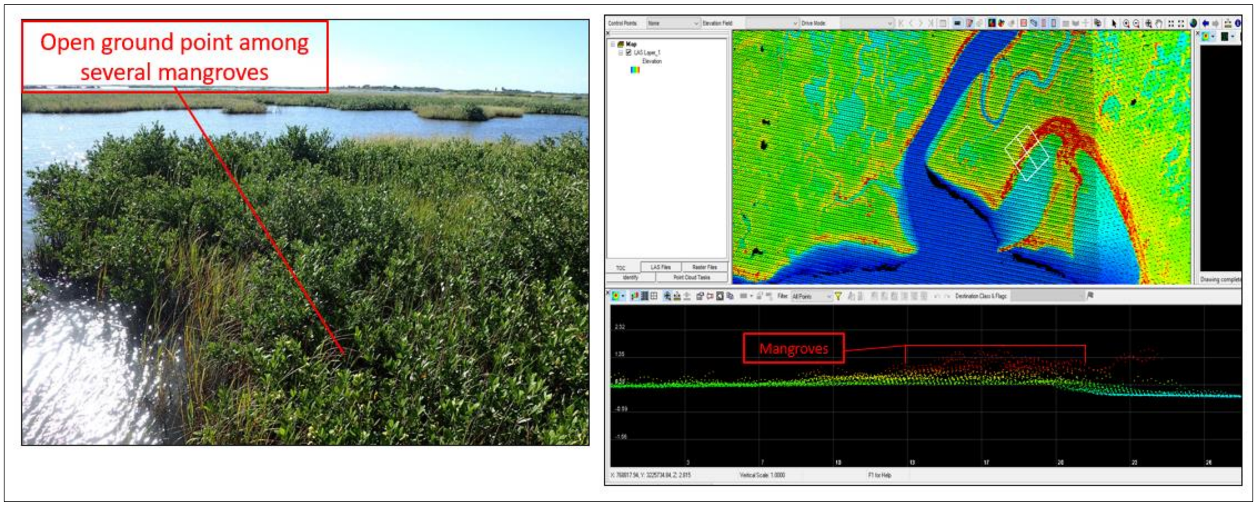

Figure 1: Open ground points between mangrove plots (left); mangroves in profile (below) and overhead view (above) within the point cloud.

Research Issues

This project seeks to address several gaps in data processing and modeling workflows for monitoring shrub mangroves at large scales in coastal environments. These shortfalls are related to:

A) The degree of accuracy with which researchers can extract coastal shrub mangroves from airborne imagery
B) Generating an accurate Digital Elevation Model (DEM) for use in canopy modeling
C) The ability to define degrees of accuracy in modeling scale parameters
D) Large area monitoring

Addressing the requirements with the best of contemporary data collection and processing software is not difficult, but defining the techniques used by that software will make or break the fidelity of the product model. The “solution” workflow needs to:

1) Delineate and extract coastal shrub mangroves from airborne imagery accurately
2) Produce a Canopy Height Model (CHM) from a statistically-approximated ground surface
3) Define the degree of influence that scale plays in the image and point cloud classification
4) Be “smooth” enough to approximate coastal shrub mangrove canopies at large scales

The goal of this project is to develop a procedure that satisfies the aforementioned requirements and can be used to address the challenges of monitoring coastal shrub mangroves worldwide.

Data Sources

The primary data sources for the project were dense lidar tiles and corresponding NAIP imagery acquired from the USGS Earth Explorer portal. The lidar data needed to have a high enough point density to get several pulses to pass through the dense mangrove canopy, so this was the primary selecting criteria for the data set. A lidar survey that produced a sufficiently dense point cloud for the study area (~6 points / m^2) was collected by Digital Aerial Solutions, LLC over the South Terrebonne Parish during leaf-off conditions in February of 2015 using an ALS-70-HP (see Table 1). A corresponding set of 4-band NAIP imagery (RGB+NIR) was acquired during leaf-on conditions using a Leica ADS100 sensor with a Ground Sampling Distance (GSD) of 1 m (see Figure 2).

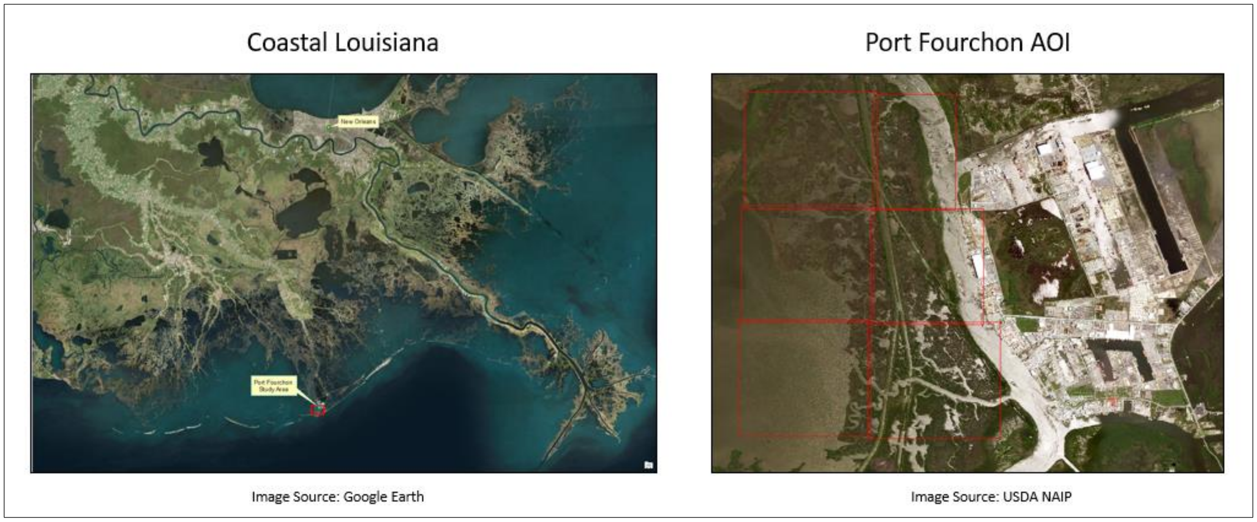

Figure 2: The location of the study area along the Louisiana coastline (left) and the portion of the study area encompassed by lidar coverage (right).

The combination of these data sets would be ideal because while the lidar point cloud was collected during leaf-off conditions—an optimum canopy structure for ground point collection, the imagery was collected during leaf-on conditions—an optimum canopy structure full of leaves for delineation using any band combination that incorporates the NIR channel for digital extraction. That the two data sets are very close in temporal period gives us the best snapshot we could get of both the bare ground surface and the full-bloom canopy for digital extraction and canopy modeling possible over the study area.

Table 1: Key metadata from the NAIP and lidar data

NAIP Imagery		Lidar Point Cloud	
Collection Date:	20150430	**Collection Date:**	20150213
Sensor:	Leica ADS100	**Data Format:**	LAS v1.2
Platform:	Cessna Conquest / Cessna 414	**Assigned Classes:**	1, 2, 7, 9, 10, 17, 18
Altitude:	16,000ft AGL	**Nominal Point Spacing:**	0.39 meters
Ground Sample Distance (GSD):	1-meter	**Nominal Point Density:**	6.36 pts / square meter
Spatial Reference System:	NAD83 UTM Zone 15N	**Spatial Reference System:**	NAD83 UTM Zone 15N
Bands:	4, R/G/B + NIR	**Vertical Datum:**	NAVD88 (Geoid 12B)
Bit Depth:	8-bit, 0-255	**Sensor:**	Leica ALS70-HP
Data Format:	JPEG 2000	**Vertical Accuracy Class:**	9.25cm (ASPRS '14 Standard)

Methodology

Three primary methods were applied to address the four requirements highlighted in the research issues section:

1. Object-Based Image Analysis (OBIA) in Trimble eCognition

2. Statistical ground filtering and surface generation in GeoCue LP360

3. Surface differencing and volumetric estimation in ESRI ArcMap (ArcGIS)

After the NAIP images and lidar tiles were pre-processed in ArcMap, they were imported into eCognition for initial planimetric (2D) feature extraction of the mangroves in the NAIP scene.

OBIA can be succinctly described as an attempt to train an automation program to process a multispectral image overlaid on an elevation dataset the way that a human eye can through the use of threshold-based boundaries set across a family of spectral, radiometric, allometric, textural, relative, and topographical values manually by a specially-trained imagery analyst. The OBIA software (eCognition) cracks the image up into "objects" containing similar pixels and then classifies the objects via rule sets developed by the analyst (see Figure 3). The advantage to this practice is that a machine can process these data sets and extract and export a digitized polygon of the desired features much quicker and more accurately than a human can.

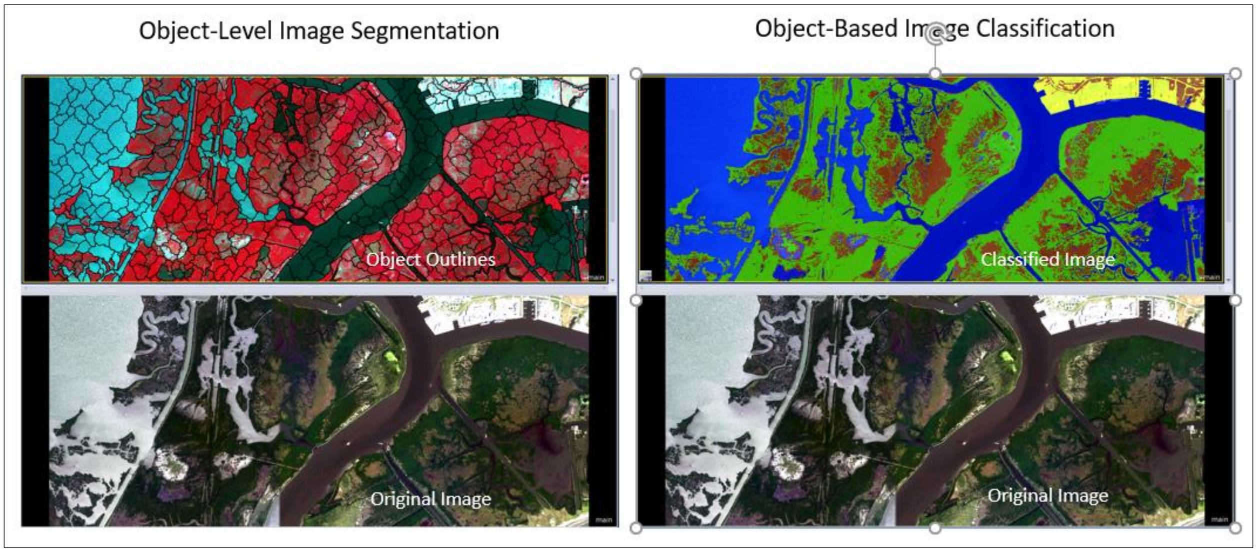

Figure 3: Image segmentation vs original image (left); classified image vs original image (right).

The nature of the study area makes the extraction of shrub mangroves a difficult task. Water, vegetation, bare earth, mangroves, and sea grass are all intertwined in a complex image for even the human eye to decipher at times. The nature of the mangroves themselves also make the elevation profile a difficult task to classify. Shrub mangroves are very low to the water/ground, and exist both in water and on land. Their root structure (pneumatophores) are often both submerged and exposed and their canopies are often rough, uneven, and dense in composition.

The image classification process began with an initial Multi-Resolution Segmentation (MRS) to establish initial objects, followed by an initial classification into overarching categories (Water, Wetlands, Manmade, etc.). The NIR channel is weighted twice as heavily as the RGB channels in the initial object segmentation with a scale parameter of 50, a shape parameter of 0.8, and a compactness parameter of 0.5.

The initial classification process is mostly spectral-based, making use of a family of indexes and values for the threshold-based classification, to include: Mean Normalized Difference Water Index (NDWI), Mean Normalized Vegetation Index (NDVI), Color Infrared (CIR) Ratio, Visible Brightness-to-Near Infrared Ratio (VBNIR), Green-Red Vegetation Index (GRVI), and Mean Brightness. Initial large-scale objects are used to avoid surface anomalies (ex: water reflection) at finer scales for initial classification. The initial objects are then segmented again using a much finer scale and the same classification values and indexes and then reclassified into new object classes (Mangroves, Water, Earth/Grass).

Because scale is of interest to the assessment of this solution, the finer scale segmentation was done at three separate scale parameters: 3 (finest scale), 5 (moderate scale), 10 (large scale). Once polygon features are extracted from the OBIA process, all three scale-derived extractions were then exported to LP360 for use in the deriving 3-dimensional elevation surfaces (Canopy

Height Models, or “CHMs”). The finest scale output was also exported to ArcMap for an accuracy assessment (see Figure 4).

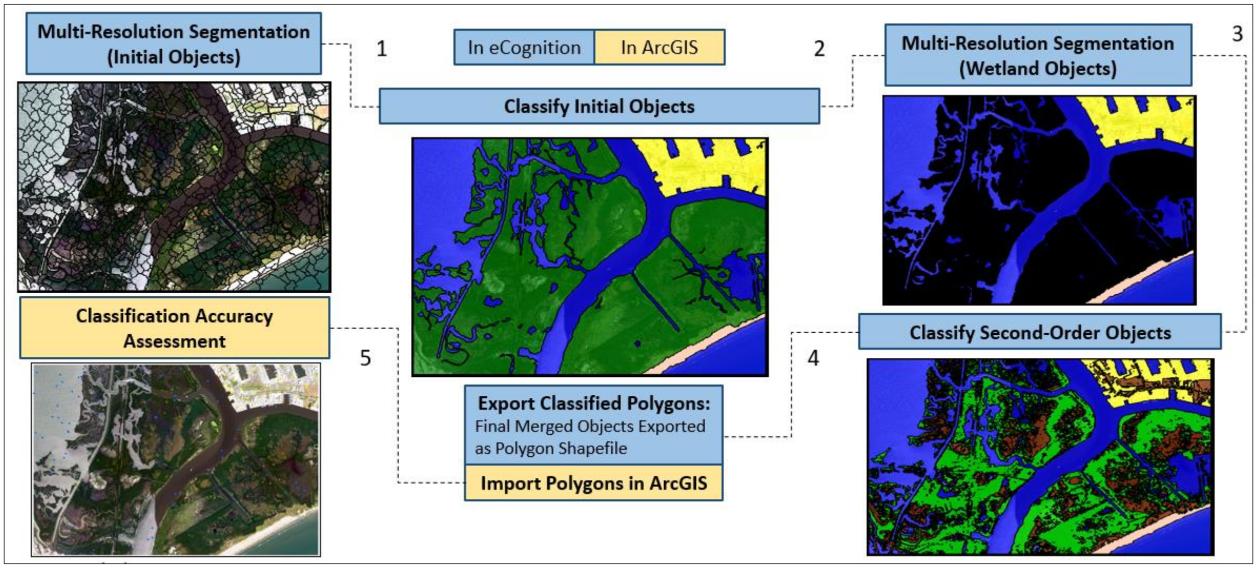

Figure 4: Overview of the object-based classification process in eCognition and ArcGIS.

The surface derivation process in LP360 began with importing the lidar data and doing a bit of pre-processing to get everything in the correct projection. The 2D mangrove polygons from the OBIA feature extraction were also imported (Scale of 3 = S3, same for S5 and S10). The first surface derived was the ground surface or Digital Elevation Model (DEM). This model is difficult to derive over the mangrove-vegetated areas, which is what we are primarily interested in for producing a shrub mangrove Canopy Height Model (CHM). In order to *approximate* the ground surface below the mangrove canopy to an empirically-justifiable degree, high and low noise points were first filtered out via statistically-derived thresholds, then lowest points were established and added in iterative fashion until a sufficiently-dense surface was derived below the canopy.

As scale is of interest to the assessment of this solution the statistical ground point filtering was done at varying scale windows to assess the degree that scale in the ground filtering process affects the CHM output compared to the degree that the scale of the OBIA process plays. Simple grids were used to define the iterative ground point filtering in a spatial metric using 5-meter, 10-meter, and 20-meter grid windows for a total of 3 separate DEM outputs. The mangrove points were then classified using the 3-separate scale OBIA feature extraction outputs using the “Classify by Feature” (CBF) Point Cloud Task (PCT) in LP360.

Once the ground points and the mangrove points were classified in each instance of scale combination (S3-3m, S3-5m, …S10-20m) the DEM and Digital Surface Model (DSM) were both exported to ArcMap. The DSM is the DEM combined with the surface features of interest, which in this case were just the mangrove canopy points. For the DSM generation, class 2 (ground) and class 3 (shrub mangrove) were the only points included and Inverse-Distance Weighing (IDW) using a 1-meter output scale. For the DEM export the same process was followed with the exception of only including the class 2 (ground) points. Both DSM &DEM were exported in .img format (see Figure 5).

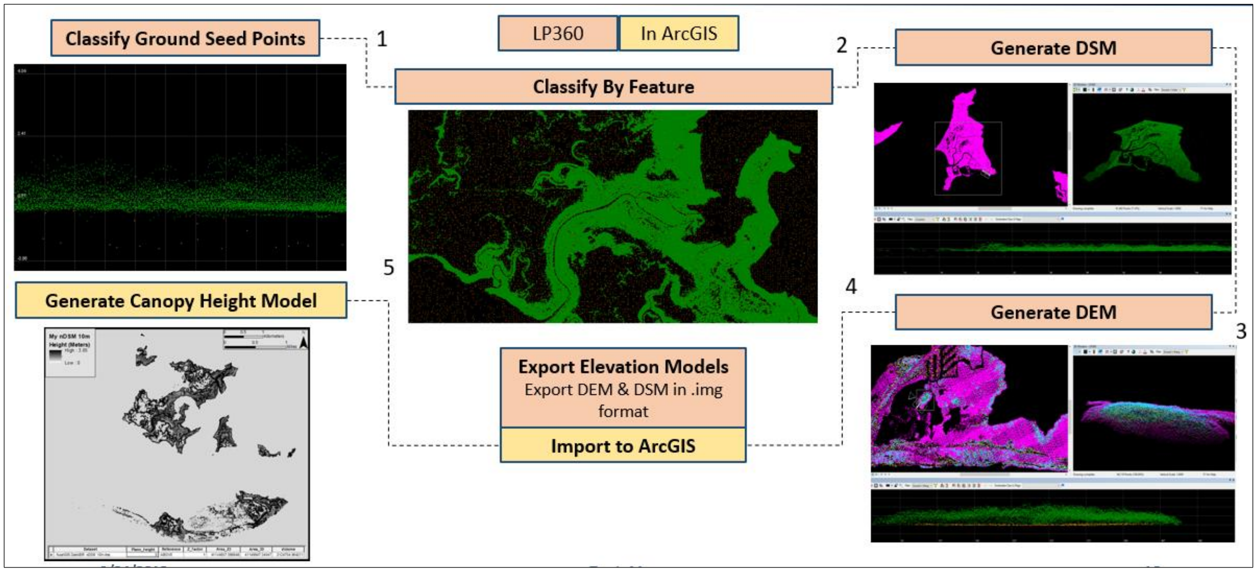

Figure 5: Overview of the CHM extraction process in LP360 and ArcGIS.

Once all 18 DEM/DSM .img files were imported into ArcMap, a simple surface volume differencing operation was done to normalize the resulting CHM, wherein the DEM was subtracted from the DSM to leave the shrub mangrove canopy behind with associated height values. Each DEM was subtracted from its corresponding DSM (ex: S3-5m DSM – S3-5m DEM) to derive 9 CHMs. Once all 9 CHMs were derived, the most well-defined data was used as the baseline model, and the remaining 8 CHMs were compared via volumetric surface differencing to assess the degree of influence that commissions and omissions induced at larger scales will play in the resultant CHMs. In this case, the S3-5m CHM was the most well-defined and was used as a reference baseline for the scale degree assessment (see Figure 6).

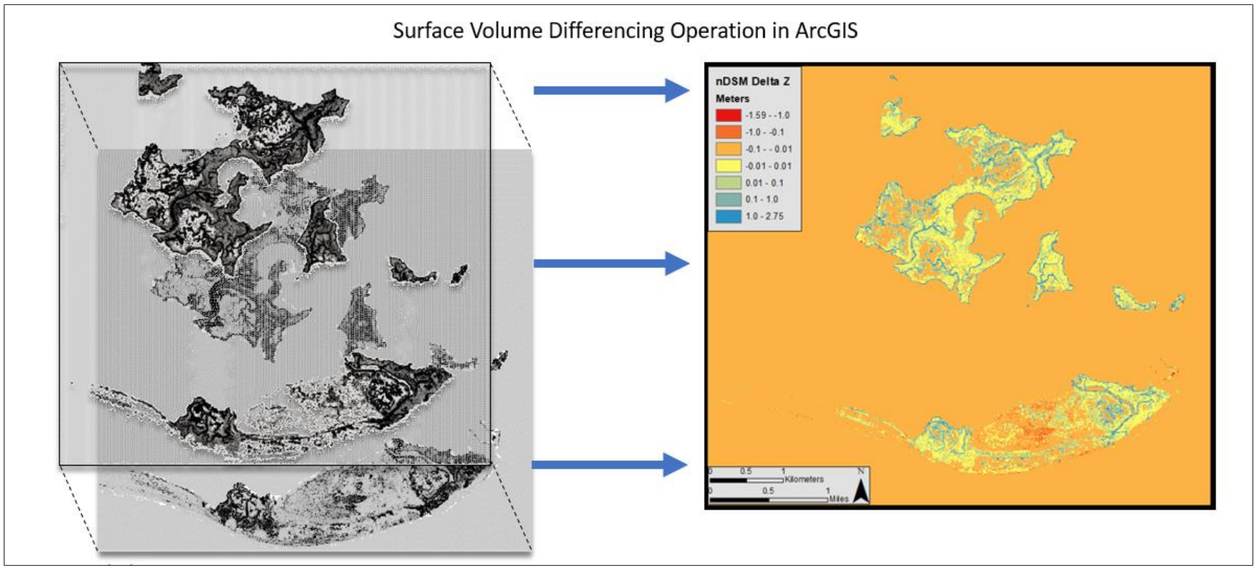

Figure 6: In the surface differencing process the CHM is differenced from the baseline to visualize commission/omission errors and to quantify the difference in volume and areal extent.

To assess the degree of influence that scales of OBIA objects and ground filtering grids play in the CHM output the 8 CHMs were differenced from the baseline CHM to produce an omission/commission (om/com) degree image with associated values for negative and positive elevation gains between surfaces. Eight om/com images were produced to visualize and quantify the degree of influence each scale factor plays in the CHM output. Finally, areal and volumetric calculations were made in ArcMap to quantify the AGB of the shrub mangrove CHMs. The outputs were compared to assess the degree of offset in the derived area and volume values. A diagram visualizing the entire workflow for the project in sequence can be viewed in Figure 7 below.

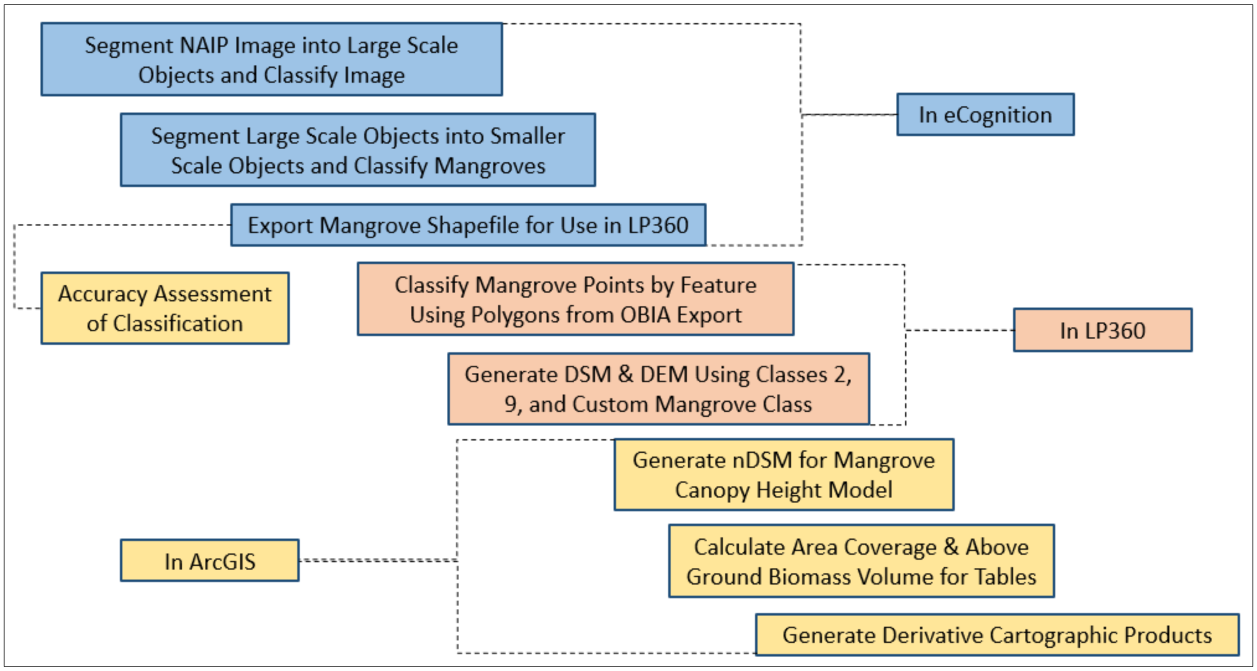

Figure 7: A step-by-step graphic of the entire remote sensing and geospatial workflow, excludes initial image processing (projections, etc.).

Results

The first thing to assess was the accuracy of the OBIA image classification process, which produced an overall accuracy of 93.6%. For the classification of shrub mangroves, the OBIA feature extraction workflow that was developed in eCognition produced a user's accuracy of 95.0% and a producer's accuracy of 93.44% (see Table 2). These results were deemed sufficient and the 2-D mangrove polygons were pushed into LP360 for the CHM extraction process.

Table 2: Accuracy assessment results for the object-based image classification process.

		Reference Class						
	Class Value	**Beach**	**Built**	**Earth/Grass**	**Mangrove**	**Water**	**Total**	**User's Accuracy**
Mapped Class	Beach	29	0	1	0	0	30	96.67%
	Built	0	39	1	0	0	40	97.50%
	Earth/Grass	0	0	51	2	7	60	85.00%
	Mangrove	0	0	2	57	1	60	**95.00%**
	Water	0	0	0	2	58	60	96.67%
	Total	29	39	55	61	66	250	**94.17%**
	Producer's Accuracy	100.00%	100.00%	92.73%	**93.44%**	87.88%	**94.81%**	**Overall Accuracy**
								93.60%

Following the CHM derivation and surface differencing operations, om/com images were produced to visualize the 3-dimensional offsets and highlight the degree of influence that scale plays in object segmentation and ground filtering. The om/com images produced revealed that there is substantially more degradation in the accuracy of the CHM output via opening up the areal extent of the ground filtering window. The results of the volumetric estimation can be viewed and compared in Table 3 below. Baseline comparison graphics are introduced in the following section.

Table 3: Results of the above-ground biomass volume estimates and mangrove area. Baseline values are highlighted in red.

	5m Ground Sampling	10m Ground Sampling	20m Ground Sampling
OBIA Scale of 3	Area: 10,633 sqr km Volume: 773,801 cu m	Area: 10,700 sqr km Volume: 848,588 cu m	Area: 11,074 sqr km Volume: 2,493,347 cu m
OBIA Scale of 5	Area: 10,633 sqr km Volume: 756,300 cu m	Area: 10,881 sqr km Volume: 1,520,329 cu m	Area: 11,073 sqr km Volume: 2,391,254 cu m
OBIA Scale of 10	Area: 10,693 sqr km Volume: 633,495 cu m	Area: 11,034 sqr km Volume: 1,280,187 cu m	Area: 11,097 sqr km Volume: 2,000,656 cu m

Discussion

The results of the baseline comparison indicate that there is substantially more accuracy degradation in the CHM via opening up the ground filtering window when compared to increasing the size of segmentation objects. These values are reflected in Table 3 but are visually evident when comparing the data layers visually, particularly when comparing om/com layers to the baseline CHM with a hillshade applied (see Figures 8-11). It is also possible to visually witness the difference in area and volume between the baseline CHM and other derivative CHMs.

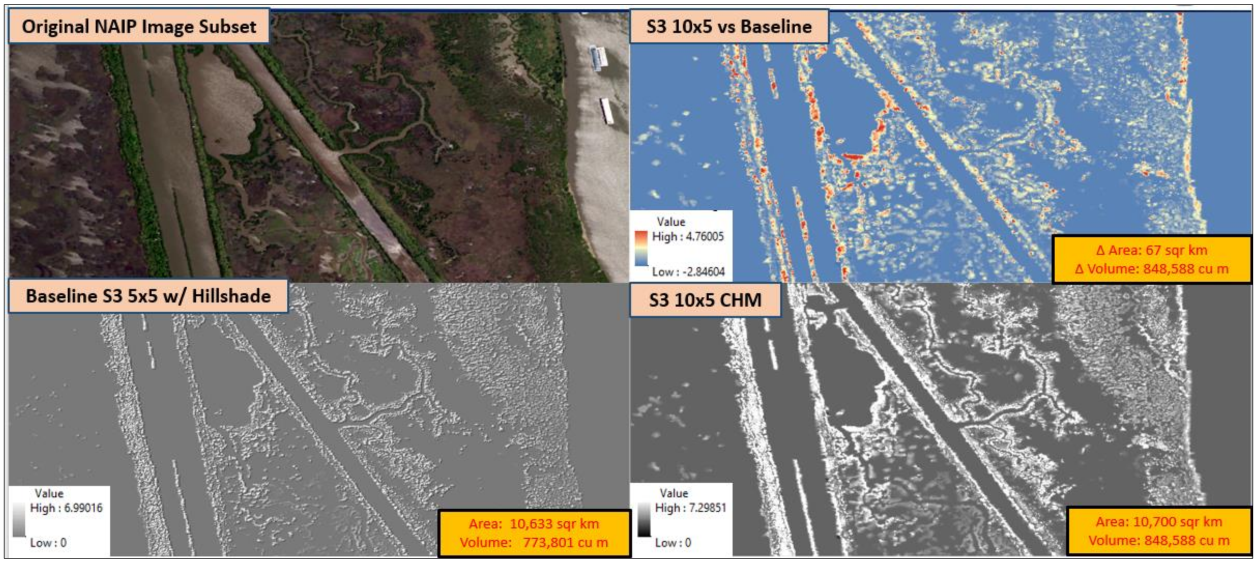

Figure 8: A subset of the original image (upper left); the baseline CHM with hillshade applied (lower left); the om/com image (upper right); the S3 10x5 CHM (lower right).

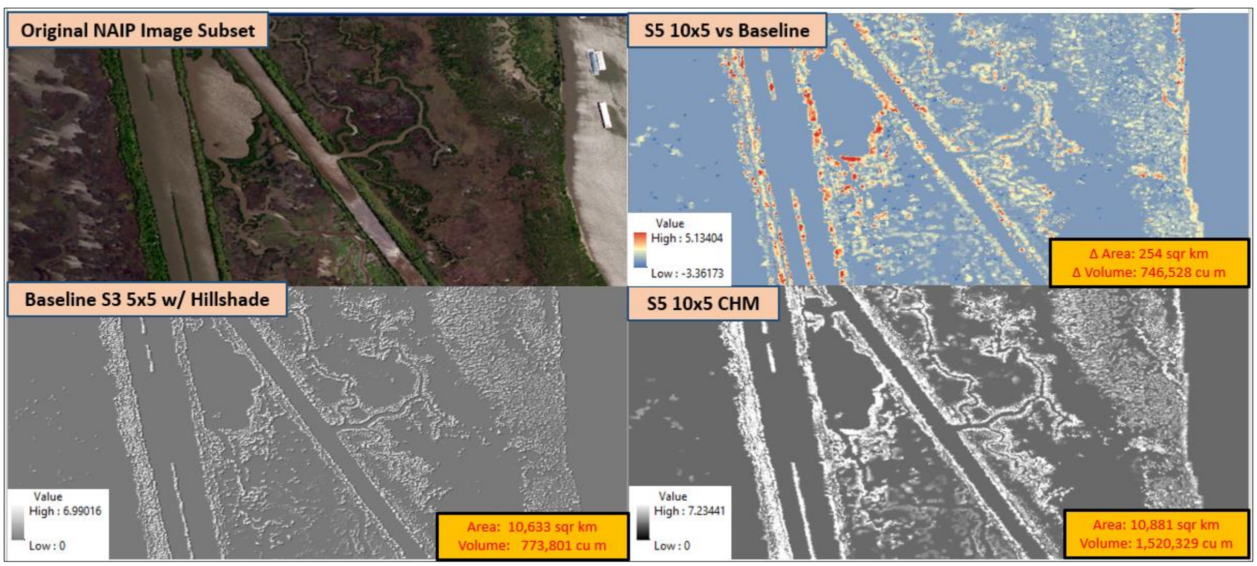

Figure 9: A subset of the original image (upper left); the baseline CHM with hillshade applied (lower left); the om/com image (upper right); the S5 10x5 CHM (lower right).

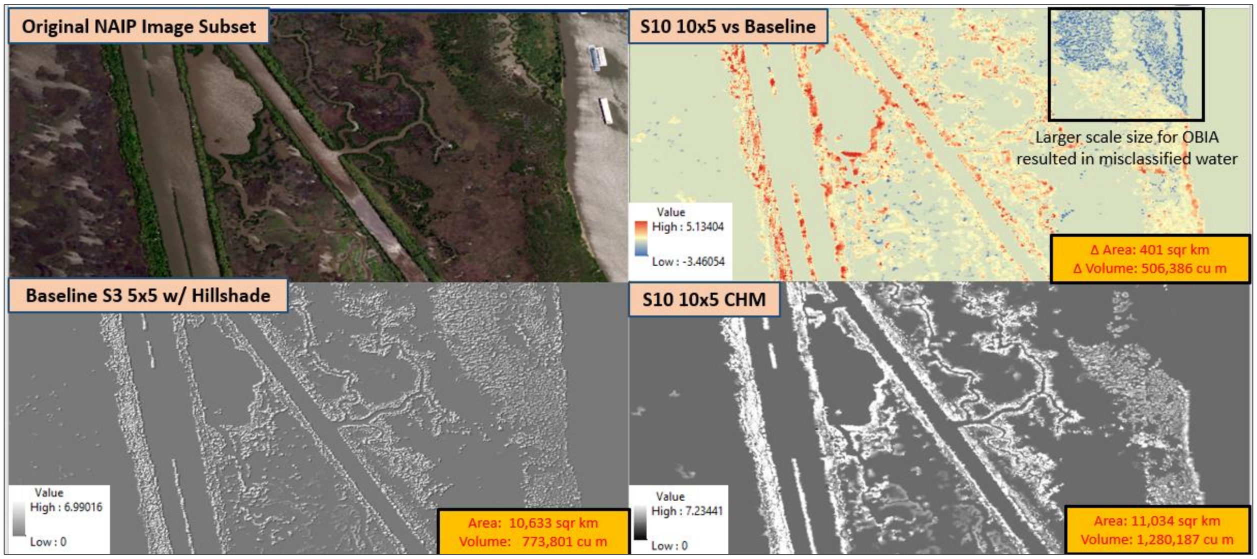

Figure 10: A subset of the original image (upper left); the baseline CHM with hillshade applied (lower left); the om/com image (upper right); the S10 10x5 CHM (lower right).

Conclusion

The goals of this project were to develop techniques capable of extracting coastal shrub mangroves from airborne imagery accurately, generate a CHM from a statistically-approximated ground surface, define the degree of influence that scale plays in the OBIA and ground filtering processes, and be capable of processing large areas across the Gulf Coast region. The results indicated that:

1. The methods developed successfully extracted shrub mangroves
2. Scales of ground filtering are more significant than scales of object size
3. These methods can be used to improve the study of global carbon budget estimates for coastal environments

Wetland researchers and global biogeochemists are encouraged to apply these remote sensing and geospatial methods to their modeling efforts in estimating CO_2 sequestration and tracking global mangrove decline in the Gulf Coast and similar environments abroad.

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