High-Resolution Land Use and Land Cover Mapping
Boone, North Carolina

by

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Honors Project

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Abstract

Traditional Land Use and Land Cover (LULC) datasets typically occur on a coarse spatial scale. With the accessibility of more sources of higher spatial resolution imagery, the overall accuracy of these datasets can be enhanced. The increase in spatial resolution often comes at a cost to the spectral information contained within imagery. A two-step object based image analysis (OBIA) technique along with thresholding of spectral bands and a Normalized Difference Vegetation Index (NDVI) were used to create a LULC map for the Boone area in North Carolina.

Introduction

Appalachian State University, and the town that it resides in, Boone, North Carolina is moving towards compiling GIS data online. In this program, a land use and land cover (LULC) map is needed. LULC maps are valuable in that they allow us to see the current state of both natural and anthropogenic factors on the surface of the earth (Knight and Voth 2011). This project aimed to delineate 10 separate spectral features on the ground using high resolution 6-inch 4-band imagery (visible and near-infrared). These features included urban or built-up, cropland/ Pasture, orchards/vineyards, deciduous forest, evergreen forest, mixed forest, water, wetland, bare exposed rock, and strip mines, quarries and gravel pits. The spectral dimensionality was assessed prior to the final image processing. The focus of this research is: 1) can land cover be separated spectrally with the available high resolution imagery and 2) can local knowledge or other techniques provide valuable insight to successfully classify land cover and land use.

Study Area and Data Collection

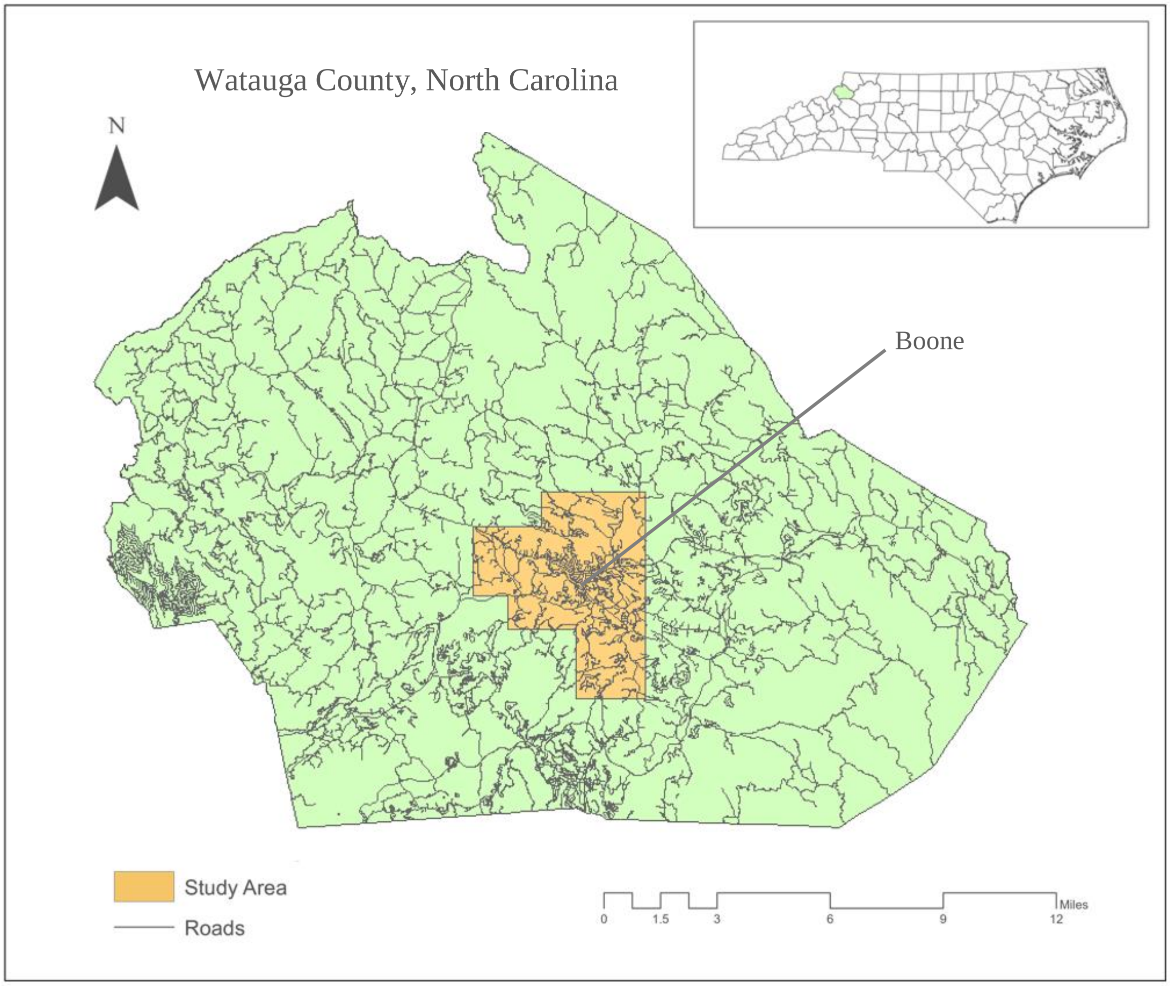


Figure 1: Study area within Watauga County, North Carolina.

The study area for this project is in and around the town of Boone, North Carolina (Figure 1). The area is limited by the extent of the aerial orthophotography provided by the university that was to be used in this classification. The spatial area of focus for this study is the town of Boone, Appalachian State University Campus, properties owned by the University, and the New River Light and Power service region. The town of Boone is in the Blue Ridge Mountains of northwestern North Carolina.

The biophysical characteristics of interest are the vegetation, trees, agricultural land, the built environment surrounding them and other environments that can be classified spectrally within the study area.

The dataset that was used is a 4-band multispectral image with 6-inch spatial resolution. This dataset is of aerial imagery that was collected for clarity on March 10, 2014, the winter season. The original intent of this imagery was for emergency management and mapping of utility infrastructure. The bands in this dataset are red, blue, green (RGB) and near-infrared (NIR). The time that this data was collected was during a break at the university to lessen the impact of cars in the imagery. The imagery was collected at a time where leaf cover was off, this helps in providing reference for an accuracy assessment and the classification of evergreen forests which will have the highest NDVI while other vegetation is dormant or bare.

Spectral Assessment of Aerial Imagery

No Pre-processing correction was done to the dataset after acquisition from the geodatabase. The imagery has been mosaiced and corrected through methods that are not noted in the metadata. The quality of the data was assessed through the histogram of both the original 6-inch 4-band imagery and resulting NDVI outputs. The distribution of the histograms is somewhat normal with a unimodal distribution. The pixels in the imagery were first resampled at 10 feet, 15 feet, and 30 feet using the pixel aggregate method. This was done to reduce both the amount of noise in the image and ground objects such as cars that would interfere with the classification. Decreasing the spatial resolution also helped reduce processing time.

NDVI outputs were then created for the three spatially resampled images. The outputs display the highest brightness in the evergreen vegetation and the lowest brightness values in the urban and built environment.

From the NDVI outputs and the pixel resampled imagery, ISODATA unsupervised classifications were done with 5-10 resulting outputs to assess the spectral dimensionality of the data and how the imagery naturally separates into spectral classes (Figure 2). This process can be used to determine the location of unique spectral classes and results in a higher standard deviation that that of a trained classification method.

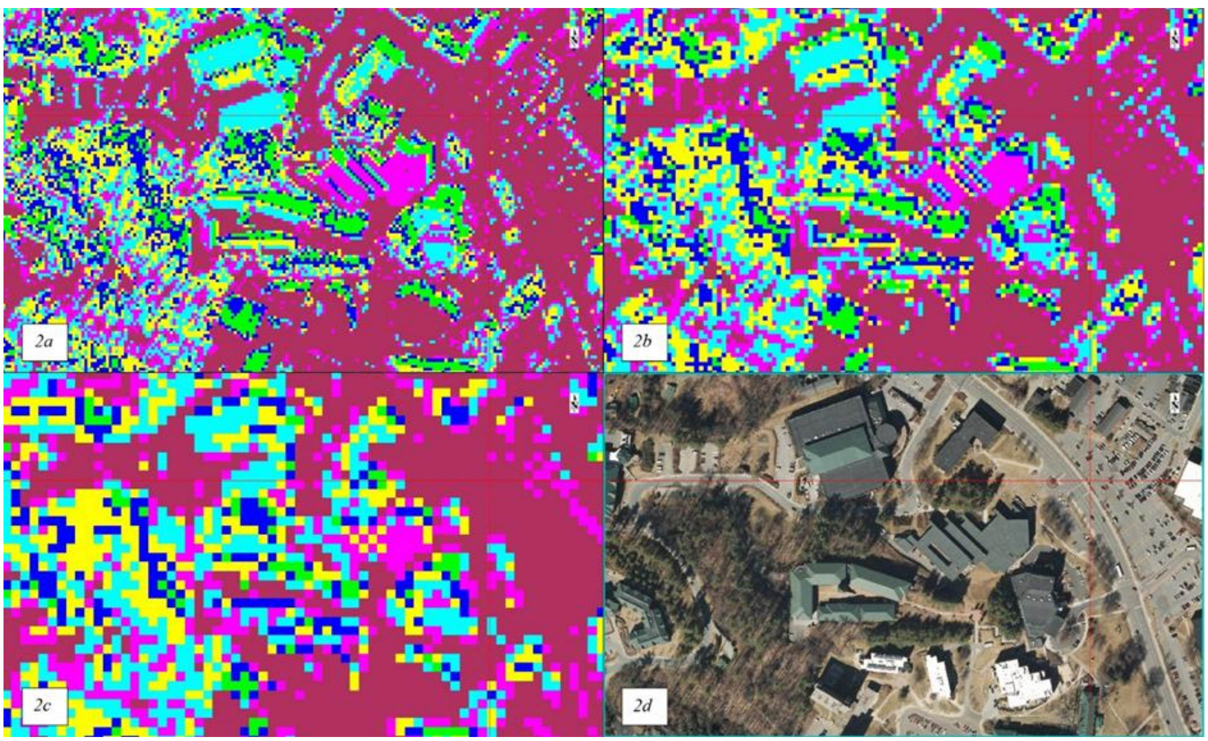


Figure 2a-d: ISODATA unsupervised classifications at various spatial resolutions. 2a: 15 feet, 2b: 20 feet, 2c: 30 feet, 2d: Original 6-inch imagery.

Based on the outputs, the 15-foot spatially resized imagery produced less noise than the 10-foot, 30-foot and 6-inch imagery without losing linear features such as roads and rivers within the study area. While the 10-foot imagery keeps those features, it does not eliminate noise created by cars and other small features. In the 30-foot imagery, noise is significantly reduced, but linear features are almost completely lost. However, some brightness is lost in both the 15-foot and the 30-foot spatial resolution NDVI imagery. A layer stack was created from the NDVI outputs to compare the distribution of the datasets.

Thresholds were then put on the NDVI output of the 15-foot spatially resampled imagery. Classes were created for urban and built-up land, water, grassland, pasture and recreation land, evergreen and deciduous forest. The remaining features (orchards/vineyards, wetland, bare exposed rock, and strip mines, quarries and gravel pits) did not separate spectrally.

A threshold was placed between 0.1428 and 0.41304 to map evergreen vegetation. This threshold was the most successful since all other vegetation during the time the imagery was collected was dormant. A threshold was placed between -0.1039 and -0.0085 on the NDVI scale to map impervious features. The distinction between impervious and other built-up land such as dirt or gravel roads, driveways, and parking lots were not made at this time. There was confusion between urban and built-up land, water, grassland and snow within the image because of the dormant state of the pasture and grassland areas within the study area. There are negative values present, interfering with the classification of urban and build-up land using this method. Snow cover in some areas and on ski slopes fall within the threshold placed on impervious features. Shadows also interact with urban features, which can be solved with radiometric enhancement of shadows but is dependent on the radiometric-post processing of the imagery (Dare 2005). With only 4-band imagery it is unclear how much information can be pulled from these areas even with post-processing techniques.

A threshold was placed on water features between -0.3174 and -0.1006. The areas were somewhat spectrally different but contained some small impervious surfaces within the threshold. The linear features of most rivers within the study area fell within this range along with ponds, lakes and Appalachian's reservoir.

Thresholds placed on both leaf-off deciduous areas and grassland had the greatest overlap and the most confusion in this process. Dormant grasslands and visible land between deciduous forest overlap and contain similar NDVI values, they cannot be successfully separated with this method due to their spectral similarity.

Methods

Due to the spectral similarity and overlapping of features at coarser spatial resolutions and through thresholding methods, further tests were done to assess a viable way to separate the urban and built-up land from other land cover features. Because of the high spatial resolution of the imagery, analysis can take place to better identify objects on the ground. While increasing spatial resolution does not always yield a better result, the use of Object Based Image Analysis (OBIA,) or sometimes referred to as Geographic Object Based Image Analysis (GOBIA,) analyses can take place on a group of pixels rather than individual pixels. The use of OBIA and GEOBIA is being used more widely in the GISciences (Blaschke 2009). While ESRIs ArcMap does not contain all the functionality of other programs such as Trimble's eCognition for OBIA, it has the capability to group pixels through mean-shift filtering to create a homogenous surface and reduce noise of areas while retaining overall spatial accuracy. The use of segmentation methods similar to this have been around since the 1980s (Haralick and Shapiro 1985). While the use of mean-shift filtering does not always lead to a good result due to texture and shadow, it does a relatively good job at dividing areas into homogenous regions based on texture, intensity, shape and color (Heng, et al. 2015). With a large range of spectral differences within urban and built-up landscapes, simplification is needed. The built environment is composed of features ranging from asphalt to bright reflective surfaces such as glass. Rooftops and building materials vary greatly. One aspect of this environment that does not vary is the negative NDVI values it has due to absorption of NIR energy. The NDVI along with mean-shift segmentation allows the image to be condensed and group areas outside of the pixel level because of the high spatial resolution

The spatial resolution of the imagery was determined using various spatial resolutions between 1 and 15 feet in combination with various mean-shift filtering parameters. Ninety combinations of mean-shift filtering parameters and resolutions were carried out on a spatial subset of the imagery to determine the spatial resolution that was to be used. The goal was to preserve the desired features while reducing noise such as vehicles, road markings, and small variations in somewhat spectrally similar surfaces. Used was a 4-foot spatial resolution. The three main input parameters for mean-shift filtering are spectral detail, spatial detail and minimum segment size noted in pixels. Higher values in the spectral and spatial detail parameters can be used to separate features that have spectrally similar characteristics and where smaller features are desired in the output (Figure 3). A balance between these values and minimum segment size are needed to result in an output that reduces the differences in the urban and built-up landscape while not excluding smaller areas of vegetation and features such as greenways. Through trial and error the mean-shift filtering parameters were set as follows: spectral detail: 15, spatial detail: 15 and minimum area size in pixels: 20. The determination of this is largely qualitative and visual, there are no statistics that can describe how well desired features are preserved.

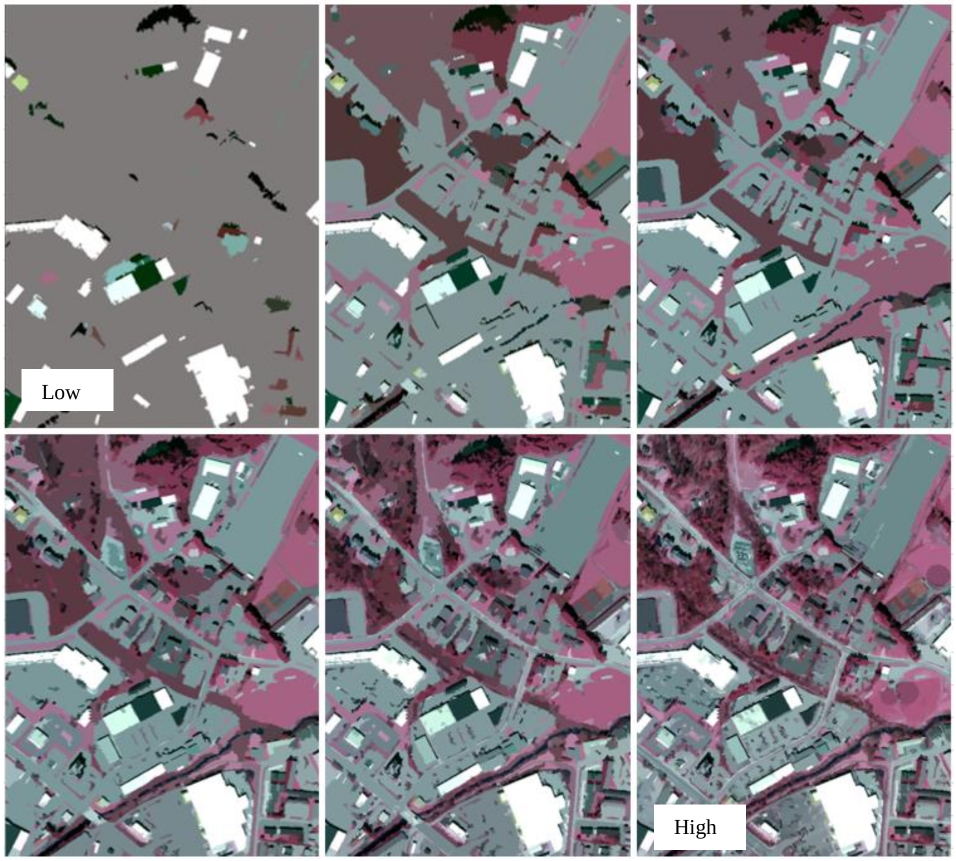


Figure 3: Mean-shift filtering spectral and spatial detail parameters from low to high done on a false color composite image.

Segments within the mean-shift filtered image were selected to capture the still present variation in the urban and built-up areas. Increasing the parameters past this level lost the details that were desired in the final output. Areas were also selected to capture water features in the study area. These selected areas were used create a Support Vector Machine (SVM) classifier definition file. This file consisted of the grouped pixels. The SVM method of classification needs fewer training samples, does not require an even distribution of samples and handles large datasets more easily than other classification methods. The output SVM classification consisted of both urban and built-up land as well as areas of water. Those outputs were reclassified and converted into polygon data. The extent of the study area was then divided into sections to visually assess the accuracy of the classification. Areas outside of these land use and land cover classifications were removed manually if seen. Areas of disturbed land included in the urban and built-up category were recoded. The land use features in this category consist of a quarry and gravel supply area.

The 4-foot spatial resolution NDVI imagery used in the mean-shift filtering and SVM classification was also used in placing a threshold on evergreen vegetation in imagery. Due to the dormant nature of most vegetation in the early spring, the highest NDVI values are seen in the evergreen vegetation (Figure 4); NDVI values range from -1 to 1. A threshold was placed on this single band imagery between 0.142871-0.413043. There was not a distinction made between rhododendrons and other photosynthesizing evergreen vegetation at the time. The output was reclassified and converted into polygon data.

Figure 4: 4-foot NDVI imagery. Areas of evergreen vegetation can be seen in bright white in contrast to areas of urban and built-up land seen in black.

A second image was created with the 4-foot pixel aggregate resampled image. Band 4 (NIR) in the red color gun, band 3 (green) in the blue color gun, and band 2 (blue) in the green color gun (Figure 5). The color composite imagery was used for an alternative view of the imagery and was then used to distinguish shadows and grassland in the imagery. A threshold was placed on band 4 between 147-255 to separate grassland and agricultural land. A threshold was also placed between 0-64 to filter out shadows and areas of resting water on the built environment. This shadows layer was used for a visual assessment of potential inaccuracies within the landscape.

Figure 5: 4-foot False color composite. Band 4 (NIR) in the red color gun, band 3 (green) in the blue color gun, and band 2 (blue) in the green color gun.

The remaining land cover type to separate was deciduous forested land. Due to the time the imagery was collected, areas of deciduous forest are bare. While the spectral characteristics of this land cover is unique, to preserve the accuracy of the output and prevent gaps in the data, an alternative approach was taken to separate deciduous forest. Once all other polygon files were created, the erase feature was used to remove them from a polygon covering the extent of the study area. The remaining area that was not removed was labeled as deciduous forest.

The evergreen, deciduous, urban and built-up land, grassland and agriculture, water and disturbed land files were then merged to create one output (Figure 6). The smooth polygon function using Bezier interpolation was applied to enhance the character of the output.

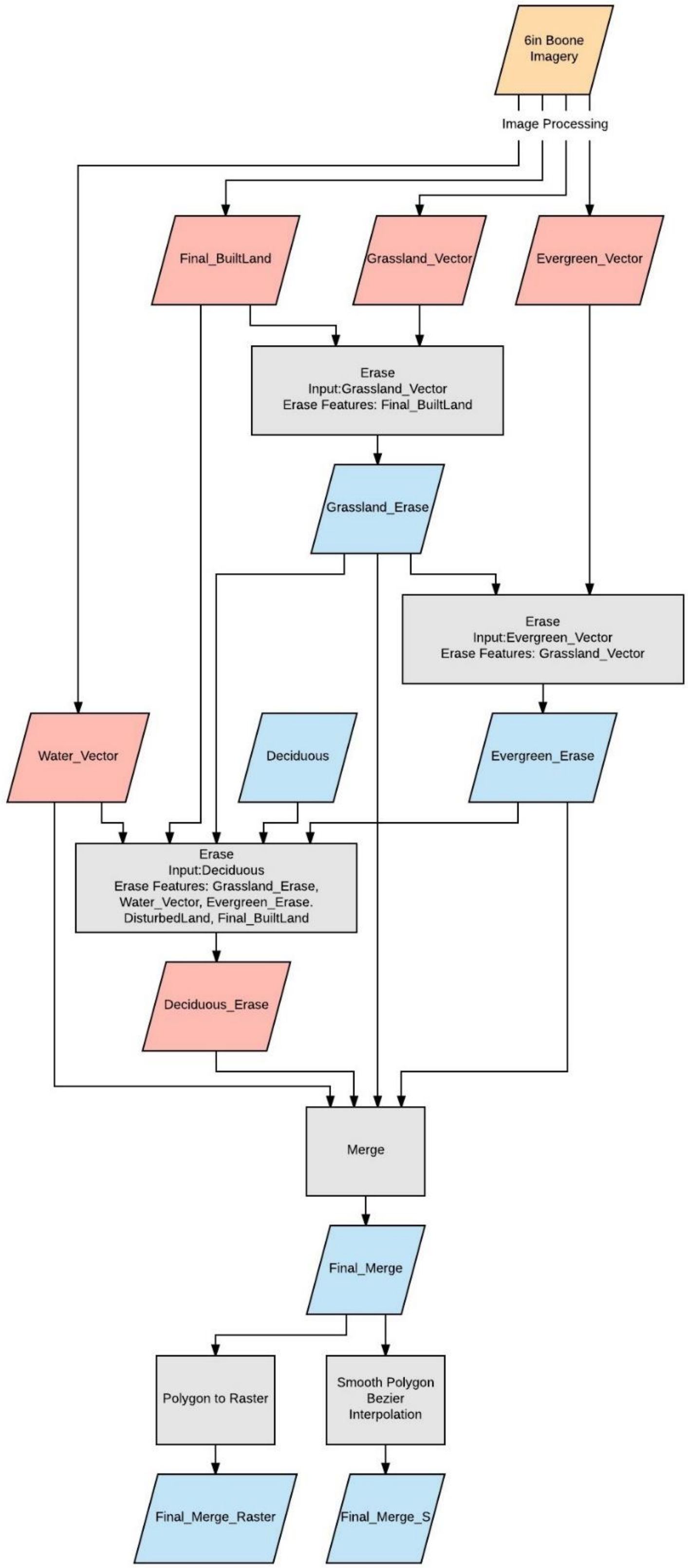


Figure 6: Compilation of map inputs. For full workflow see Appendix A.

Results

Once the output was finalized, a 300-point random sample accuracy assessment was conducted (Figure 7). The visual assessment was completed utilizing the original 6-inch imagery for ground truthing. An overall accuracy of 91.3% was calculated (Figure8).

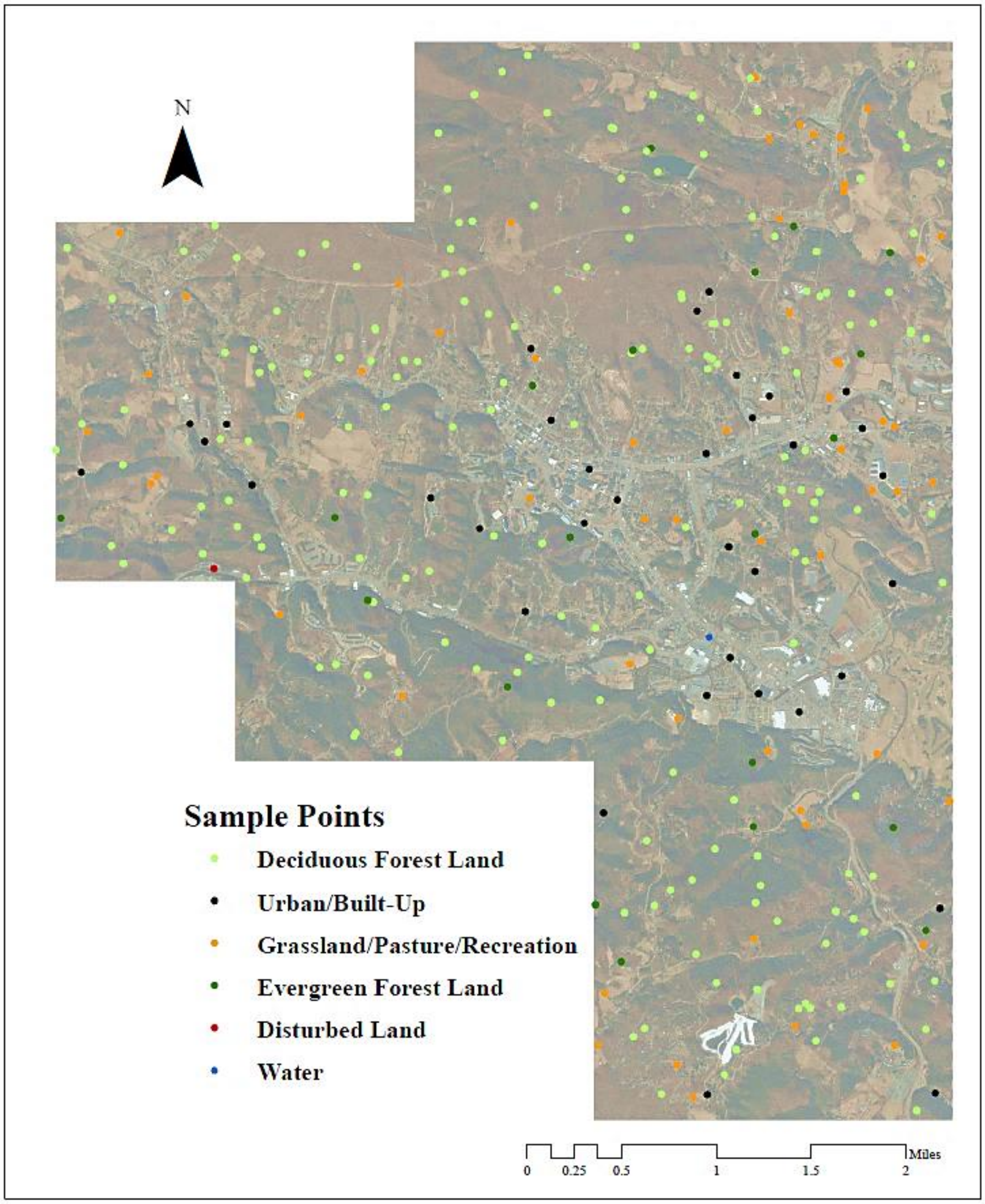


Figure 7: Distribution of randomly sampled accuracy assessment points on original 6-inch imagery Points are coded based on classified output.

Ground Truth

Classification	Deciduous	Urban/ Built-Up	Grassland/ Agriculture	Evergreen	Disturbed	Water	Total
Deciduous	154	2	15	4	0	0	175
Urban/ Built-Up	1	36	1	0	0	0	38
Grassland/ Agriculture	2	0	57	1	0	0	60
Evergreen	0	0	0	25	0	0	25
Disturbed	0	0	0	0	1	0	1
Water	0	0	0	0	0	1	1
Total	157	38	73	30	1	1	300
	Overall Accuracy		91.30%				
			274/300				

Figure 8: Confusion matrix calculated based on 300 randomly sampled points and validation from 6-inch imagery.

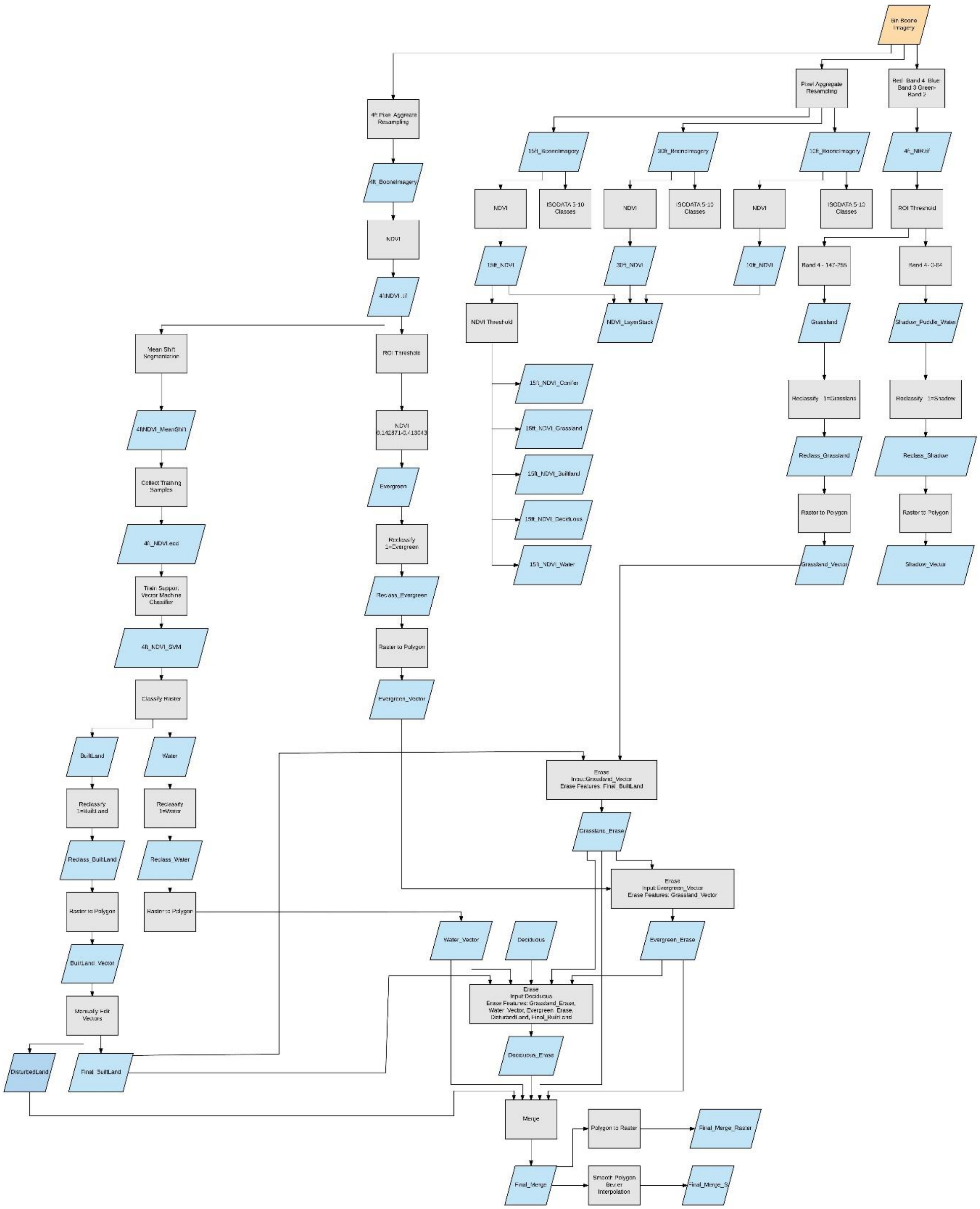
While classification using NDVI thresholds is an arbitrary means of delineating spectral features, this process can be used to determine spectral similarity in 4-band imagery. Because higher spectral resolution is not used in combination with high spatial resolution it can be difficult to determine spectral differences between ground features. With only visible and near-infrared imagery, spectral confusion can occur within the complexity of natural and urban landscapes (Chen, et al. 2007). This imagery, due to the high spatial resolution, may be used for object based image analysis methods to successfully identify urban and built-up land features in combination with spectral threshold methods to classify vegetation features. Some features within this study area, such as wetlands that can occur within areas covered by vegetation and are not visibly seen are not spectrally distinct in the 4-band imagery. Features such as this can only be mapped through local knowledge of the study area. The resulting data set is only a snapshot of March 10, 2014. It does not account for changes in vegetation or urban development within the study area.

Future Considerations

Future improvements can be made by integrating Light Detection and Ranging (LiDAR) data through programs such as Trible's eCognition where buildings and canopy can be segmented more easily and error in shadows can be minimized. In the absence of access to software such as this, height filtering of LiDAR data could be used to better distinguish buildings and canopy cover from lower land cover or use. The implementation of LiDAR would also reduce potential inaccuracies in areas covered in shadow. In forested areas, height filtered data would separate shaded areas between canopy or areas of bare ground. In the urban and built-up areas, height filtered data could also separate buildings from the ground and trees or other vegetation that may be lost in the shaded areas. North Carolina is currently processing Geiger-Mode LiDAR, these products, with a higher resolution in points per meter will better accommodate the high-resolution imagery that is available. If given the opportunity, similar high-resolution imagery collected later in the year could provide a greater spectral differentiation between land cover types. Collecting during the summer months could also provide for a higher sun angle at solar noon reducing shadows cast by objects on the ground. Snow cover and misclassification of snow would also not be an issue. Additional datasets such as aspect could provide for a greater sense of where error is occurring within the mountainous landscape. A greater sense of accuracy can also be attained through a larger sample size and combining stratified and random sampling of points. The urban and built-up features within the dataset have been visually assessed and are the most accurate layer within this classification. If separated from some other built features such as dirt roads, this classification in raster format could be converted to a coarser resolution and be used in potential run off modeling or other modeling procedures that require an impervious surfaces layer.

Appendix A

Complete Image Processing and GIS Workflow



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