Abstract

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Advancements in remote sensing technology continue to aid natural disaster damage assessment. Quick and accurate damage assessment significantly increases the speed of recovery efforts and allows aid to reach those most severely affected. Object-oriented classification techniques require minimal user input to remotely classify large areas and may be utilized to provide timely and accurate damage assessments of affected areas. In this study, I explored the use of object-oriented classification techniques to classify downed timber areas in the Dare County Bombing Range in North Carolina. The spatial resolution of scanned color-infrared aerial photography was degraded from 0.2-meter to 3 other spatial resolutions (1-meter, 5-meter, and 10-meter). Training data developed from the 0.2-meter pixel imagery were used to establish training data for all spatial resolutions. Each set of images was classified using object-oriented classification techniques. Results were compared statistically to each other and to results obtained from a manual delineation and a conventional supervised classification. Before the accuracy assessment began, we anticipated that the classification produced by the 0.2-meter imagery would be the most accurate due to the high level of detail in the imagery. After comparing the results of the classifications, there was no statistically significant difference among the object-oriented classifications, but there was a significant difference between the object-oriented results and the other classifications. Using the training data created on the high-resolution imagery to classify the coarser spatial resolution imagery did not cause classification accuracy loss. The potential damage assessment impact of this technique is that low-resolution imagery can be utilized to quickly classify damaged areas, provided high-resolution imagery is used to create training data. This classification technique demonstrates that damage assessment can be accomplished less expensively, without sacrificing accuracy and speed.
THE EFFECT OF SPATIAL RESOLUTION ON AN OBJECT-ORIENTED CLASSIFICATION OF DOWNED TIMBER

by

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A thesis submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Master of Science

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Dedication

I would like to dedicate this to my wife, Laddie, who has put up with continual promises to have this research done and has stood by me through thick and thin. I would also like to thank my parents, without their support and guidance none of this would have been possible.
Biography

The author is originally from Milford Delaware and moved to North Carolina in 1993. He has an undergraduate degree in Environmental Studies from Elon University where he graduated with honors in 1997. He served in the North Carolina National Guard from 2000 to 2006 and was activated as part of Operation Noble Eagle in 2003. He currently lives in Apex with his wife.
Acknowledgements

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1. Background:

Natural disasters have occurred throughout modern history and have varied in frequency and severity. Relief and recovery efforts have also changed to meet new challenges. There are many factors that hinder relief efforts especially concerns about where to allocate resources, how much is needed where, and who is affected most. All of these decisions are based on best available information. The manner in which disaster recovery information is collected has changed in many ways. Eyewitness reports and ground surveys are giving way to modern remote sensing techniques using aerial imagery and advanced image interpretation technology.

While there are many factors propelling improvements in remote sensing technology, disaster recovery applications have received added attention in the wake of Hurricanes Katrina and Rita and the Sumatra-Andaman earthquake. As the severity and graphic extent of a disaster increases, so does the value of remote sensing to aid recovery efforts. Remote sensing technology was used to identify damaged areas and facilitate the allocation of resources in the Sumatra-Andaman earthquake. Comparing before and after images of the coastline guided the rebuilding of the coastline and the coordination of activities among government organizations (Polngam 2005). Commercial and military imagery was utilized to help The Federal Emergency Management Agency coordinate relief efforts for Hurricanes Katrina and Rita (Adams 2005). In these cases, remote sensing technology and satellite imagery assisted relief efforts through visual inspection. In my research, I will validate the use of object-oriented classification as a remote sensing technique for rapidly identifying areas of downed trees.
Technological advances in aerial and space-borne imagery have improved the quality and availability of information. Imagery is now available through many commercial entities at many different spatial resolutions. Satellite imagery is available from many different sensors, such as, IKONOS, Quickbird and SPOT. Airborne sensors from aircraft can provide imagery at even finer spatial resolutions.

Improvements in classification technology have also increased the quality of information that can be acquired through remote sensing. Pixel-based and object-oriented classification techniques harvest useful data for planners and scientists from satellite imagery. Pixel-based classification techniques are used to classify coarse spatial resolutions, like Landsat imagery (Blaschke and Strobl 2001). Pixel-based classification ignores any spatial characteristics and focuses purely on spectral qualities. Object-oriented classification examines the spatial relationship of pixels as well as spectral qualities. This technique is designed to classify images with a finer spatial resolution (Jensen 2005). The “objects” identified consist of similar pixels that are in close proximity, producing a series of numerous polygons. The primary advantage that object-oriented classification has over pixel-based classification is that the pixels are not classified in isolation but in context with the rest of the image.

Object-oriented classification can be achieved through segmentation or user specified algorithms. Segmentation divides an image into areas of like pixels and users define the class of each group of pixels. The ‘user specified’ algorithm requires the user to define areas on an image before classification can begin. Once the training datasets are defined, the software uses the input to define the image. Visual Learning System Inc.’s Feature Analyst 4.0.2.21 in ArcGIS 9.1 is a software package that uses object-oriented
comparison techniques to classify images. Feature Analyst uses a supervised classification method in which the program “learns” what each class is according to user input. With well-developed training data, the software package can correctly recognize and classify pixels faster and more thoroughly than manual classification, which can greatly aid recovery and restoration efforts in areas devastated by natural disasters, such as hurricanes. Object-oriented classification may be the best way to access more useful and timely information for disaster recovery efforts.

2. Literature Review

2.1 Hurricane Damage to Forest Stands

Hurricanes are tropical cyclones that can produce extremely high winds, tornadoes, torrential rain, and drive storm surge onto coastal areas (Anonymous 2007). Large-scale canopy disturbances caused by windstorms or other catastrophic events affect many forests (Merrens and Peart 1992). The two major types of damage to forest stands caused by hurricanes are defoliation and flooding. While defoliation is the most common type of damage, branch loss and uprooting of stems also occur (Brokaw and Walker 1991). Windfalls caused by hurricanes consist mostly of uprooted trees (Berg 2004), but stand gaps caused by wind can have an irregular shape with many trees still standing within each gap (Greenburg and McNab 1997). According to Berg, “hurricanes create unique understory plant microsites and massive amounts of tree debris,” which “vary substantially from man made gaps” (Berg and Van Lear 2004).

2.2 Advancements in Remote Sensing Applications for Hurricane Damage

For more than a decade, the United States Department of Agriculture’s Forest
Service has used Geographic Information Systems (GIS) to manage resources and aid in land management planning (Parsons and Orleman 2002). To fully understand the scope and magnitude of storm events, “quick and reliable information on the extent of forest damage is required.” (Sewarz et al. 2003). According to Adams (2005), recent deployments of remote sensing technology have yielded many benefits including “detailed visualization, regionwide assessment, safe surveying of dangerous areas, timely information about inaccessible locations, and a permanent record of perishable damage.” Rejaie and Shinozuka (2003) believe that recent advancements in remote sensing technology have made it possible to remotely assess areas damaged by natural disasters. Rapid deliveries of remote sensing products and on-site GIS have become invaluable tools that increase the accuracy and timeliness of results (Parsons and Orlemann 2002).

2.3 Current Natural Disaster Remotely Sensed Damage Assessment Techniques

Remotely sensed data are being used more frequently to classify and assess damaged areas all over the world. One of the most widely used remote sensing techniques is change detection, which determines damage through a temporal analysis of a location; areas that have changed are considered damaged. New techniques that utilize user input to develop algorithms that classify damaged areas directly from one set of imagery are becoming more prevalent.

Change detection has been the most widely used remote sensing technique to assess damaged areas, but there are other techniques, such as principle component analysis, maximum likelihood and complex coherence analysis. Rejaie and Shinozoka (2003) used principle component analysis on 8-bit gray level images before and after the
1995 Kobe earthquake to determine damage. They attempted to classify each image into changed and unchanged classes but were limited in application to places where illumination conditions were identical. Kaya et al. used change detection to determine damaged forest areas in Instanbul, India (1998). Thirty-meter pixel Landsat 5 Thematic Mapper (TM) imagery taken in 1984 and 1997 were classified with a maximum likelihood classification algorithm and compared visually to demonstrate the growth of the mining industry at the expense of forested areas in India. Yamazaki compared the backscattering characteristics of Landsat TM imagery in a complex coherence analysis to synthetic aperture radar in Kobe, Japan to detect damaged buildings (2001).

Object-oriented classification techniques have also been used to classify damaged areas. Redmond and Winne (2001) used Feature Analyst to classify two, thirty-meter pixel Landsat 7 images according to burn severity. The thematic maps produced were far more accurate than those created using principal component analysis (Redmond and Winne 2001). Feature Analyst was also used to update fire load datasets in the Petersburg National Battlefield and Shenandoah National Park (Shedd et al. 2005). To classify downed woody debris, they used one-half meter true color and color infrared aerial photography. Feature Analyst was successfully used to classify woody debris and update the fuel load datasets in an accurate and time efficient manner.

2.4 Advantages of Object-Oriented Classification over Pixel-Based Classification

By incorporating both spectral and spatial image information, object-oriented classification interprets information as the human eye does, yet has the advantage of automation (Laliberte et al. 2004). Perception of an image’s content is primarily based
on objects, or “homogeneous groups of pixels” that relate to items of interest (Blaschke et al. 2000). Single pixels are not as critical to understanding an image’s information as objects and their relationships are (Blaschke et al. 2000). By incorporating user input, object-oriented classification takes advantage of the user’s insight to identify image objects (Blaschke et al. 2000).

2.5 Similar Studies

My study was built upon the results of three similar studies. Benson and Mackenzie (1995) examined the effects of spatial resolution on remotely classified maps of the Wisconsin Lake District. The objective of their study was to examine how different spatial resolutions affected the classification of land cover on satellite imagery. They used three different sensors: 20-meter SPOT multi-spectral, 30-meter Landsat 4 and 5 TM, and 1.1 kilometers Advanced Very High Resolution Radiometer (AVHRR). Each image was classified with Leica Geosystems Erdas Imagine into two classes; water and land. Classification values from these three thematic maps were used to extrapolate several landscape parameters including percent water, number of patches, and average area of patches. The extrapolation algorithm simulated classifications starting at 20 meters and then degraded by a factor of two until a spatial resolution of 1280 meters was reached. Benson and Mackenzie (2005) found that as spatial resolution was degraded, the number of water bodies identified, the percentage of total water and average patch size decreased.

Swarz et al. (2003) evaluated different classification algorithms on images with differing spatial resolutions. The sensors used were 30-meter Landsat TM, 10-meter Spot
IV, and 1-meter IKONOS. Object-oriented and supervised pixel-based classification algorithms were used on each image and compared to a hand-delineated thematic map. Schwarz et al. (2003) used image segmentation by Defines’ eCognition software and compared it to a supervised pixel-based classification method. After all the images had been classified, the accuracy was assessed and a Kappa statistic was generated. They found that manual classification of the 1-meter IKONOS imagery was the most accurate, followed by the object-oriented classifications of the IKONOS and SPOT images. The most accurate pixel-based classification was the 10-meter SPOT IV image. Although the object-oriented classification was not the most accurate classification, it was more accurate than traditional pixel-based supervised classification at different spatial resolutions.

Shedd et al. (2005) used Feature Analyst to classify downed woody debris on 0.5-meter aerial photography of Petersburg National Battlefield and Shenandoah National Park. My decision to use Feature Analyst as the object-oriented classification software was based on the success that Shedd et al. (2005) had using it. A true color 1:6000 photo mosaic with a one-half meter spatial resolution was used for classification. Shedd et al. (2005) were able to successfully classify individual downed timbers through multiple classification runs. The ‘downed timber’ polygons were then used to augment fuel load data in fire modeling maps.
3. Objectives

3.1 Purpose:

In this study, I used infrared aerial photography to identify and classify areas of downed timber. I compared an object-oriented classification approach with results obtained from hand-delineation and supervised classification. The study area was part of the Dare County Bombing range, which has been affected by Hurricanes Dennis (1999), Floyd (1999), and Isabel (2003), creating large sections of downed timber. Three spatial resolutions derived from the original aerial photography were chosen to simulate several satellite sensors. The original imagery had a spatial resolution of 0.2-meters and was degraded to 1-meter (IKONOS), 5-meter (SPOT IV Panchromatic), and 10-meter (SPOT V Panchromatic). By degrading the spatial resolution of the imagery, the effect of pixel resolution on object-oriented classification was also evaluated.

3.2 Hypotheses:

I evaluated four hypotheses:

1. An object-oriented classification can be used to accurately identify and classify downed timber on high-resolution imagery.

2. The classification can be replicated for images with similar characteristics.

3. Feature Analyst can be used at variable resolutions to identify downed timber.

4. Feature Analyst’s results are similar to results achieved through a pixel-based supervised classification and a manual delineation.
4. Methods and Materials

4.1 Study Area

The study area was located in the Dare County bombing range along the eastern coast of North Carolina (Figure 1). The bombing range has been used by the United States Air Force and Navy for air-to-surface target training and consists of 46,000 acres of marshland, mixed forest land, low lying conifers, and open land. Atlantic white cedar forest, pond pine woodland, cypress domes, streamhead pocosins, bay forest, basin shrub-dominated types, and depression pocosins are the primary vegetation (Robinson et al. 1998). Only a few old-growth stands remain due to the heavy timber harvest of Atlantic White Cedar during World War I. The bombing range was constructed in 1965 on land leased from West Virginia Pulp and Paper. The Air Force obtained the range in 1978 and has shared it with the Navy for use in training bomber pilots since then (Global Security 2007).
4.2 Imagery

Images used for classification were 1: 6,000 color-infrared (CIR) aerial photography of the Dare County bombing range flown during the spring of 2004. The images were taken by Kucera International with a Kodak CIR 1443 camera with a focal length of 152.850 mm at an altitude of 917 meters (3010 ft). Film positives were scanned on a high quality consumer-grade Epson desktop scanning bed with a transparency unit using 24-bit color at a resolution of 800 dots per inch (dpi) resulting in a nominal spatial resolution of 19 cm (7.5 in) per pixel. Leica Photogrammetry Suite softcopy software was used to orthorectify the images, which were then exported as uncompressed,
georectified Erdas Imagine files (Leica Geosystems 2006). Each file represented 418 acres on the ground and was 172-megabytes in size.

Based on visual inspection, ten images were selected for their similarity in color variation and sun glint. We used Visual Learning System Inc.’s Feature Analyst (v 4.0.2.21) in ArcGIS 9.1 to classify areas of downed timber. To degrade the pixel resolution of the original imagery we used the ‘degrade’ tool in Leica Geosystem’s Erdas Imagine 8.7 that reduces the resolution of images. The actual process used to alter the pixels is a proprietary technique that is not explicitly explained in the manual. User input determines how far the pixel boundary is extended. The 0.2-meter resolution imagery was degraded by a factor of five to create 1-meter resolution imagery. The spatial extent of the original pixel was expanded horizontally and vertically by the specified integer factor. Spectral values of the original pixel and surrounding pixels (within and adjacent to the new spatial extent) were resampled to produce a new pixel with adjusted spectral values. In the resampling process, spectral values of the original pixel were weighted more heavily than those of surrounding pixels during the process and the relative weighting increased as output pixel size increased (Leica Geosystems 2006).

4.3 Training Procedure

Our classification scheme was adapted from techniques developed by Miller (2005) and Shedd et al. (2005). After examining the image, we determined that there were three primary classes: downed timber, trees, and soil. We developed training sites for each of the classes by hand-digitizing polygons that represented multiple examples of each class, using the 0.2-meter imagery. Initial classification attempts revealed
considerable class confusion, especially within the tree and downed timber classes. Although Feature Analyst provides clutter removal tools to modify existing classifications and re-classify, modification attempts in this study compromised the training set and decreased the ability to correctly classify the areas with downed timber. Miller (2005) had the same problem with the clutter removal tools, finding the tools could effectively improve the classification within an image but decreased the accuracy of subsequent classifications of other images. Full descriptions of the imagery problems encountered and software observations discovered during the training procedure can be found in the appendix (Appendix 8.1).

To improve the classification over all images; more training polygons were added for the confused classes. The downed timber and tree classes were also divided into subclasses because of the spectral variability within each primary class. The “downed timber” class was divided into two subclasses: high amount of debris and low amount of debris. Training classes that combined coniferous and deciduous trees increased the classification run time and misclassified many areas, so the tree class was also subdivided into deciduous and coniferous trees. An additional class was created for black film edges and fiducial marks that were visible on individual images. There were a total of six classes used in the object-oriented classification: high amount of debris downed timber, low amount of debris downed timber, coniferous trees, deciduous trees, soil and photo remnants.

The Feature Analyst software includes a series of preset wizard-driven options that modify the classification algorithm to suit particular image types. These options affect how objects are classified and the qualities of individual classified objects.
The options were (1) image band selection, (2) input representation, (3) inclusion of rotated objects, (4) classification approach, and (5) aggregate areas.

1) Image band selection allows the user to specify which spectral bands are used and whether the reflectance or texture should be used. The reflectance and texture of all three input bands available were used in this study. Shedd et al. (2005) also used reflectance and texture to classify downed timber. Reflectance refers to the spectral qualities of the image and texture refers to the spectral uniformity of an object. The inclusion of texture was instrumental in differentiating between soil and individual tree stems. The spectral bands correspond to green, red and near infrared reflectance.

2) Input representation refers to the focal area used by the algorithm during classification. The focal area helps define pattern and width of the area analyzed.

There are input representations that simulate the way that the human eye recognizes different object patterns. Although there were many input representations, we chose the one recommended by the ‘Feature Selector’ under the ‘Learning Settings’ tab to identify natural features, ‘Bullseye 3’. Studies by Shedd et al. (2005) and Miller et al. (2005) also used a ‘Bullseye’ input representation to classify objects. A pattern width of thirty-three was used for the .2 meter class covering an areas of 43.56 square meters (thirty-three 0.2-meter pixels x thirty-three 0.2-meter pixels). A pattern width of 5 was used for the other resolutions. At the 1-meter spatial resolution an area of 25 square meters would be covered (five 1-meter pixels x five 1-meter pixels). The pattern width could
not be reduced below five pixels and still maintain the input representation pattern, so pattern width of 5 was used in all remaining classifications (Figure 2).

![Bullseye input representation](image)

**Figure 2: Bullseye input representation**

3) The option of including rotated objects allowed classification of downed trees no matter which way they fell. If this option is not selected, the algorithm will only classify downed timber that is in one orientation. For example, if the timber specified in a training class lies at a forty-five degree angle, only downed timber that falls at a forty-five degree angle will be classified.

4) There were three classification approaches available to determine how the ‘Learning Algorithm’ would classify the image. The default-learning algorithm, Approach 1, was described as ‘general purpose;’ Approach 2 was described as ‘good for removing clutter;’ and Approach 3 was ‘quick but not as accurate.’ Preliminary classifications resulted in no distinct advantage gained by selecting a
different approach for classifications, so the default, Approach 1 was selected as the ‘Learning Algorithm.’

5) The ‘aggregate areas’ option controlled the size of the objects classified. By selecting this option, we were able to eliminate areas that were too small to be downed timber. The number of pixels to be aggregated changed inversely with the pattern width (in pixels). At the 0.2-meter spatial resolution, there were thirty-six pixels aggregated into objects. The number of pixels aggregated decreased to five for all other spatial resolutions.

4.4 Classification

4.4.1 Object-Oriented

The first image was classified based on hand digitized training sites and algorithm settings described previously. Each classification produced an ArcGIS shapefile and a signature file that could be used to classify other images. Initially, each class had five training sites with spectrally pure examples. After each classification, the classified polygon was overlaid on the original imagery to determine how well the downed timber areas were classified. Any areas that were missed or that were misidentified were noted and adjustments to the training classes were made before the next classification attempt.

There are a few tools available with Feature Analyst that did not improve my classification results. The ‘clutter removal’ tool was used to select portions of classified polygons to be removed from the classification results and to specify which classified polygons were correct. Downed timber areas that were missed during the classification
could be added with the ‘add missed feature’ tool. However, these tools did not improve the classification, but tended to confuse the algorithm. After using the clutter removal tool, many areas that were not downed timber were erroneously added to the downed timber class and areas that had been correctly classified as downed timber were removed. Instead, training polygons were improved through the manual addition, deletion, and modification of training sites for each class. A total of fifty-nine training polygons were used in the final classification (Table 1).

Table 1: Number of Training polygons by class used for initial learning algorithm

<table>
<thead>
<tr>
<th>Class</th>
<th>Subclass</th>
<th>Number of Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low amount of debris</td>
<td>downed1</td>
<td>21</td>
</tr>
<tr>
<td>High amount of debris</td>
<td>downed2</td>
<td>5</td>
</tr>
<tr>
<td>Tree</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deciduous</td>
<td>tree1</td>
<td>9</td>
</tr>
<tr>
<td>Coniferous</td>
<td>tree2</td>
<td>11</td>
</tr>
<tr>
<td>Soil</td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>Film</td>
<td></td>
<td>4</td>
</tr>
</tbody>
</table>

In order to classify all of the downed areas, each image was classified twice. The batch process used the signature files for ‘downed1’ and ‘downed2’ to classify each image independently. Two polygon shapefiles were produced for each image for a total of twenty shapefiles at each spatial resolution. The twenty shapefiles were then merged to create one shapefile at each of the four spatial resolutions. The remaining signature files were not used to classify the images because we were only interested in classifying the downed timber areas.
4.4.2 Supervised Classification

I performed a supervised classification of the 1-meter spatial resolution dataset to directly compare how a conventional classification approach and an object-oriented classification. The software used for the supervised classification was Leica Geosystems Erdas Imagine. I chose the 1-meter spatial resolution imagery because it had the highest accuracy in the object-oriented classification. For direct comparison, the same training polygons used for the object-oriented classification were used in the supervised classification. Signature files for two ‘downed’ classes were used to classify all images independently. Once all the images were classified, the shapefiles were merged together to create one classified file for each spatial resolution.

4.4.3 Manual Classification

Areas of downed timber on the Dare County bombing range were also delineated and classified manually using the aerial photography. An orthorectified mosaic was created from all of the 0.2-meter imagery and used for the manual classification. The minimum mapping unit was 1,000 square meters (0.1 hectare). The damaged areas were categorized into three different classes based on damage: less than 30% damage, 30% to 60% damage, and greater than 60% damage. Polygons were hand-digitized by two skilled map technicians using heads-up digitizing. Areas were checked for accuracy using stereo models and on-screen, 3-D visualization of the original images.
4.5 Accuracy Assessment

I conducted an accuracy assessment on the final classification of six data sets: 0.2-meter imagery, 1-meter imagery, 5-meter imagery, 10-meter imagery, manual delineation, and supervised classified data. Based on Congalton’s (1999) recommendation of 250 points with a minimum of 50 points per class, I created a new point shapefile with 300 randomly generated points and ensured that there were at least 125 points per class (Congalton and Green 1999). Because the final classified maps consisted of two categories, downed timber and other, each point was labeled as ‘downed timber’ or ‘other’ by visual comparison to the original 0.2-meter scanned imagery. Once all of the points were classified, we counted the number of ‘downed timber’ reference points that fell within areas classified as ‘downed timber’ and the number of ‘other’ reference points that fell within areas not classified as ‘downed timber.’

Overall accuracy, user’s accuracy, producer’s accuracy, a kappa statistic, kappa variance and kappa z statistic were calculated (Congalton and Green 1999). The overall accuracy of each classification was determined by dividing the total number of points correctly classified by the total number of reference points. The user’s accuracy, calculated by dividing the total number of correct points in a class by the total number of points classified in that class, estimates the probability that the classified point on the map actually represents that category on the ground. The producer’s accuracy, calculated by dividing the total number of correct points in a class by the total number of reference points in that class, estimates the probability that a point in a particular category is correctly classified. The kappa statistic was generated to describe the agreement between the classified data and the reference data (Jensen et al. 2005). The kappa z statistic
(Figure 3) and kappa variance were based on the kappa statistic and were used in a test to determine if two error matrices were significantly different (Congalton and Green 1999). This pair-wise test compared error matrices two at a time to determine if they were significantly different from one another (Figure 4).

\[ Z = \frac{\hat{K}_1}{\sqrt{\text{var}(\hat{K}_1)}} \]

\[ Z = \frac{|\hat{K}_1 - \hat{K}_2|}{\sqrt{\text{var}(\hat{K}_1) + \text{var}(\hat{K}_2)}} \]

\( K_1 = \) kappa statistic for an individual error matrix

\( K_2 = \) kappa statistic for an individual error matrix

**Figure 3: Kappa z statistic computation**

**Figure 4: Z statistic test computation**

5. Results

5.1 Accuracy

The final thematic maps had two classes: areas with downed timber and other areas. The accuracy at each spatial resolution varied from 58% for the manual delineation to 86% for the 1-meter classification (Table 2). The 1-meter resolution classification had the highest overall accuracy as well as the highest producer’s accuracy
with respect to the ‘downed timber’ class, and the highest user’s accuracy with respect to the ‘other’ classification; the kappa statistic was also the highest for this resolution (Table 3). The 5-meter classification had the highest user’s accuracy with respect to ‘downed timber’ and the highest producer’s accuracy with respect to ‘other area’.

A kappa statistic value greater than 0.8 indicates a strong level of agreement between the classified and reference data (Jensen 2005). The kappa statistic for each of the thematic maps demonstrated a moderate level of agreement between classification results using Feature Analyst because all fell between 0.4 and 0.8 (Jensen 2005). The kappa z-test was used to indicate superiority of one set of classification results over another. All of the object-oriented classifications had a higher kappa z – statistic than the supervised classification and the 1-meter classification was the highest (Table 2). However, the difference test did not show a significant difference ($z > 1.96$) among object-oriented classifications at different spatial resolution, but there were significant differences between the supervised classification, the manual delineation and the object-oriented classifications (Table 3). Overall, the 1-meter classification outperformed the other classifications, but none of the differences were statistically significant within object-oriented classifications (Figure 5).
Table 2: Summary of the classification accuracy results.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>0.2m</th>
<th>1m</th>
<th>5m</th>
<th>10m</th>
<th>Supervised</th>
<th>Manual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy</td>
<td>80%</td>
<td>86%</td>
<td>82%</td>
<td>81%</td>
<td>72%</td>
<td>58%</td>
</tr>
<tr>
<td>Downed Timber Class Producer's Accuracy</td>
<td>78%</td>
<td>92%</td>
<td>79%</td>
<td>78%</td>
<td>82%</td>
<td>59%</td>
</tr>
<tr>
<td>Downed Timber Class User's Accuracy</td>
<td>81%</td>
<td>76%</td>
<td>84%</td>
<td>83%</td>
<td>78%</td>
<td>40%</td>
</tr>
<tr>
<td>Other Area Class Producer's Accuracy</td>
<td>82%</td>
<td>81%</td>
<td>85%</td>
<td>84%</td>
<td>53%</td>
<td>58%</td>
</tr>
<tr>
<td>Other Area Class User's Accuracy</td>
<td>79%</td>
<td>94%</td>
<td>80%</td>
<td>79%</td>
<td>59%</td>
<td>75%</td>
</tr>
<tr>
<td>Kappa Statistic</td>
<td>0.60</td>
<td>0.71</td>
<td>0.63</td>
<td>0.62</td>
<td>0.36</td>
<td>0.15</td>
</tr>
<tr>
<td>Kappa Variance</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.009</td>
<td>0.003</td>
</tr>
<tr>
<td>Kappa Z Statistic</td>
<td>12.99</td>
<td>17.60</td>
<td>14.21</td>
<td>13.72</td>
<td>3.78</td>
<td>2.76</td>
</tr>
</tbody>
</table>

Table 3: Z statistic test between matrices.
A value greater than 1.96 indicates a statistically significant difference between classifications

<table>
<thead>
<tr>
<th></th>
<th>0.2 m</th>
<th>1 m</th>
<th>5 m</th>
<th>10 m</th>
<th>Supervised</th>
<th>Manual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2 m</td>
<td>NA</td>
<td>1.80</td>
<td>0.53</td>
<td>0.32</td>
<td>2.27</td>
<td>6.28</td>
</tr>
<tr>
<td>1 m</td>
<td>1.80</td>
<td>NA</td>
<td>1.27</td>
<td>1.48</td>
<td>3.39</td>
<td>8.24</td>
</tr>
<tr>
<td>5 m</td>
<td>0.53</td>
<td>1.272</td>
<td>NA</td>
<td>0.21</td>
<td>2.60</td>
<td>6.85</td>
</tr>
<tr>
<td>10 m</td>
<td>0.32</td>
<td>1.48</td>
<td>0.21</td>
<td>NA</td>
<td>2.47</td>
<td>6.62</td>
</tr>
<tr>
<td>Supervised</td>
<td>2.27</td>
<td>3.39</td>
<td>2.60</td>
<td>2.47</td>
<td>NA</td>
<td>1.91</td>
</tr>
</tbody>
</table>

Figure 5: Comparison of accuracy assessment results.
5.2 Maps

Using Feature Analyst, we were able to generate five thematic maps representing four spatial resolutions and the supervised classification. Each thematic map consists of ‘downed timber’ polygons and ‘other area’ polygons (Figure 6 and 7). Top images are a portion of the area classified and bottom images include light blue polygons representing downed timber areas overlaid on the image above.

Figure 6: Original 0.2-meter image and classification

Top images are a portion of the area classified and bottom images include light blue polygons representing downed timber areas overlaid on the image above.
Figure 7. 1-meter image and classification

Top images are a portion of the area classified and bottom images include light blue polygons representing downed timber areas overlaid on the image above.
5.3 Area Comparison

As a further comparison of the manual classification to digital classifications at different spatial resolutions, we decided to compare estimated total area of downed timber in each. The computer-based classifiers evaluated the imagery at a pixel level that manual delineation could not reach, so we also compared the relative size of the polygons in each classification. Polygons in the manual classification (Figure 8) were much larger than the computer classifications (Figure 6 and 7) and had fewer vertices, which made the polygon much more generalized. Polygons delineated manually contained damaged areas and undamaged areas, whereas the polygons derived digitally only contained damaged areas. Therefore the damaged area estimated by the manual classification was much larger than the acreage estimated from the computer-based classifications (Table 4 and Figure 9).

Table 4: Area of the downed timber estimated using different resolution imagery and manual classification

<table>
<thead>
<tr>
<th></th>
<th>10 m</th>
<th>5m</th>
<th>1m</th>
<th>.2m</th>
<th>Manual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acres</td>
<td>972</td>
<td>1,019</td>
<td>254</td>
<td>305</td>
<td>1,790</td>
</tr>
<tr>
<td>Square miles</td>
<td>1.52</td>
<td>1.59</td>
<td>0.40</td>
<td>0.48</td>
<td>2.80</td>
</tr>
</tbody>
</table>
Figure 8. Original image and manual classification

Top images are a portion of the area classified and bottom images include light blue polygons representing downed timber areas overlaid on the image above.
6. Discussion of Results

Hypothesis 1. *An object-oriented classification can be used to accurately identify and classify downed timber on high-resolution imagery.*

We found that an object-oriented classification can be used to identify downed timber on high-resolution aerial photography and that the classifications can be replicated on other images.

Hypothesis 2. *The classification can be replicated for images with similar characteristics.*

The training data I created on one image and used to classify the remaining images shows that one can replicate this classification on other similar images.
Hypothesis 3. *Feature Analyst can be used at variable resolutions to identify downed timber.*

Classification accuracy and kappa statistics demonstrated that downed timber areas can be identified at different spatial resolutions with an object-oriented classification technique (Table 3).

Hypothesis 4. *Feature Analyst’s results are similar to results achieved through a pixel-based supervised classification and a manual delineation.*

Using an object-oriented approach, classification accuracies at different spatial resolutions were not statistically different from each other, but were significantly different than results from manual delineation and conventional supervised classification approaches.

Before the accuracy assessment began, we anticipated that the classification produced by the 0.2-meter imagery would be the most accurate due to the high level of detail in the imagery. Although the classification results produced from the 5-meter and 10-meter imagery appeared to be coarse, statistically there was no difference between the object-oriented classifications at different spatial resolutions (Table 3).

The accuracy assessments provided a quantitative estimate of the success of each classification, but did not account for the visual quality of the classification. Visual comparison of each classification shows a reduction in number of polygons and increase in size of polygons as spatial resolution is decreased. Changes in the polygons are noteworthy. In the 0.2-meter imagery, the polygons are smaller, more numerous and have complex edges. Each polygon has a large number of vertices. The polygons generated from the 0.2-meter classification have more jagged edges than the 1-meter
classification, which softened some of the rough edges and reduced the number of smaller polygons, thereby reducing the “salt and pepper” appearance of the classification. The 5-meter classification looked “blocky” with larger pixels visible and polygon edges with ninety-degree angles. The 10-meter classification loses many of the smaller downed areas and exhibits more “blocky” appearance than the 5-meter classification.

Overall, the object-oriented classification approach was able to meet the challenge of identifying downed timber in an accurate and reasonably efficient manner. The level of detail and file size of the 0.2-meter pixel imagery increased classification runtime and required more attention to detail with respect to developing training sites. Classifying the 0.2-meter classification took an average of thirty-five minutes per image, yet the entire set of 10-meter imagery took twenty minutes. As the spatial resolution was degraded, the file size of the images decreased from 171 MB at 0.2-meter to 7 MB at 1-meter to 317 kb at 5-meter to 124 kb at 10-meter. There were fewer polygons with less detail classified as the spatial resolution increased from the original 0.2-meter resolution, yet the accuracy was not affected by this reduction. The file size on the 1-meter classification also decrease from the 0.2-meter classification (8,174kb vs 472,607 kb).

The object-oriented classifications were significantly different from the manual delineation and the supervised classification, but the supervised classification was not significantly different from the manual delineation. The lower accuracy of the supervised classification was most likely the result of spectral confusion between ‘soil’ and ‘downed timber’; these classes were confused more often in the supervised classification than in the object-oriented classification. The object-oriented classification incorporated surrounding pixels, which seemed to overcome this source of confusion.
Although the selection of 1-meter, 5-meter and 10-meter imagery was made to simulate available satellite sensors, the 0.2-meter imagery was actually acquired from an airborne camera rather than a satellite sensor. The initial 0.2-meter classification took a long time to produce because of the significant amount of time spent learning to operate Feature Analyst. Once the proper technique was developed, the classification was much quicker than manual, hand-delineated classification of the data. Manual classification of the area took nearly five hours while the 1-meter object-oriented classification took an hour and a half. The level of detail provided by the object-oriented classification was much greater than the manual classification and explains much of the disparity in total area calculation between object-oriented and other classifications. The difference in area among the object-oriented classifications at different spatial resolutions was most likely relative to the pixel size difference. Although downed timber areas consisted of several pixels for each spatial resolution, difference in pixel size increased the downed timber area estimates because the degraded pixels covered more area and consisted of more than just downed timber. Although the number of pixels that comprise an object is five pixels, the area of those objects increase from 25 square meters to 100 square meters as spatial resolution increased from 5-meter to 10-meter. There were multiple polygons generated by the object-oriented classification in each polygon manually classified. The manual classification polygons were much larger than those generated by the object-oriented classification since manual delineation tends to captures undamaged area along with downed timber. The ‘downed timber’ polygons from the object-oriented classification were more representative of the areas with only downed timber.
The same training polygons that were created on, and used to classify the 0.2-meter classification, were used to generate training data at all other spatial resolutions. Originally, the decision to use the same training polygons on every spatial resolution was made to avoid a bias in training data selection. However, the lack of significant difference among object-oriented classifications demonstrates that it is possible to use training polygons created on high-resolution imagery to generate training data on coarser resolution imagery. This technique can decrease the cost of natural disaster damage assessment by reducing the need for high-resolution imagery for the entire affected area. Instead, high-resolution imagery can be acquired for a portion of the affected area and used to generate training data to classify coarser resolution imagery over the larger area. Computer required to store and manipulate coarse resolution imagery would be less expensive to acquire and easier to manipulate because of smaller file sizes. Further study is needed to determine if this technique is applicable to other types of imagery at other spatial resolutions.

In conclusion, the classification accuracies demonstrated that object-oriented classification techniques can successfully identify downed timber areas. However, after comparing the results of the classifications, there was no statistically significant difference among the object-oriented classifications, but there was a significant difference between the object-oriented results and the other classifications. Using the training data created on the high-resolution imagery to classify the coarser spatial resolution imagery did not cause classification accuracy to diminish. The potential damage assessment impact of this technique is that low-resolution imagery can be utilized to quickly classify damaged areas, provided high-resolution imagery is used to
create training data. High-resolution imagery is more expensive and requires more disk space to store. Low-resolution imagery is less expensive and has a smaller file size, making it easier to manipulate. Remote sensing damage assessment is more appealing to government agencies as a less expensive, quick method to acquire the data necessary to quantify damaged areas and focus recovery efforts. This classification technique demonstrates that damage assessment can be accomplished less expensively, without sacrificing accuracy and speed.
7. List of References


8. Appendix

8.1 Discussion on the Imagery

Variable imagery quality issues caused many problems for Feature Analyst. In this study, the image quality varied between flight lines, images in each flight line, and within each image. Mosaics were generated to attempt to solve some of the quality issues and produce a uniform and consistent image to be classified. However, the mosaics often produced lower quality imagery due to the considerable variability described above. The mosaics lost spectral clarity and became grainy as Leica Geosystem Inc.’s Erdas Imagine attempted to generate a uniform consistency throughout. This lack of quality combined with the size of the images severely compromised the quality of the classification results produced by Feature Analyst. Often the classification runs would take several hours to compile and when finished would produce memory errors that would cause ArcMap to terminate and lose the entire set of data. The lean of the trees and sunspots on the images would generate false positive results during classifications. The exposed tree trunk of a tree exhibiting severe lean would be classed as downed timber and sun spots or glint would appear to be clearings of downed timber.

8.2 Discussion of Software

Feature Analyst proved to be effective object-oriented classification software, but it was not without its difficulties. There was a considerable learning curve with the software that was exacerbated by imagery issues. While the Feature Analyst software
package comes with a variety of wizard developed tools and menus, there are many topics that need to be discussed and solved before any classification job is attempted.

The Feature Analyst object-oriented classification approach was most effective when there were enough training classes to represent all of the objects that could be found on the image. In this study, using one training class (downed timber) to classify the entire image did not work effectively. Exporting one class from a complete classification works well, but simply classifying one class in the beginning does not. Based on this reasoning, it is important to add as many training sets and classes to classify a majority of the image before attempting to classify an image. When the “wall to wall” option was selected, objects that did not fall within specified training classes were forced into the class that it was most similar to. While this may produce a classification for the whole image, in this study we found that it actually confused the classifying algorithm in Feature Analyst because it forced unknown areas into one or more classes and diluting the quality of the classified polygons. Not selecting the “wall to wall” option produced a thematic map with polygons of pure downed timber rather than mixed polygons. Training polygons could then be refined or augmented to produce the desired results.

Originally, the concept was to use an object-oriented classification to identify and classify the actual timber stems and root bundles. After several attempts, we realized that the varied color, texture, shape, and size of the downed timber proved too complex for accurate classification at the original spatial resolution. The individual timbers were confused with any tree that was upright and exposed as well as patches of soil and in some cases, parts of the dirt roads that wound through the study area. Many attempts
were made to change and add polygons to the training sites in hopes of eliminating this
class confusion. Different input representations and pattern widths were also used to try
and find any that would be able to identify the downed timber stems. Running multiple
classifications on the particular image to “mask” out areas that definitely were not
downed timber and to concentrate the search in areas that definitely had downed timber
did not improve the results.

I also tried increasing and decreasing the size of the image being classified to
reduce the variability among images and across the imagery, yet the results did not
improve. Classifying more than one image at a time increased classification run times and
introduced new classification errors and omissions. Many computer related problems
occurred including, unexpected crashing, loss of data and freezing by increasing the
image size. Reducing the image size decreased the run time but had little to no effect on
the quality of the classification. The smaller images did not produce training examples
that could be used to classify other images or even the rest of the image that the training
polygons were taken from.

8.3 Solutions

To solve these imagery and software problems, I classified areas with downed
timber and used a select group of original images. By classifying areas with downed
timber instead of individual timbers, I was able to take advantage of contextual object-
oriented classification system in Feature Analyst. Including texture of the objects in the
classification allowed Feature Analyst to differentiate between groups of downed trees
and soil patches. The pixels that made up soil areas were not that different from pixels
that made up downed timber in a pixel-based classification, but combining the edges and shadows that surrounded areas with downed timber proved to make the difference. Classifying areas instead of individual trees also helped eliminate the classification of tree trunks that were exposed.

Selecting images that had similar sun glint and tree lean had a dramatic effect on the quality of the classification possible and especially the ability to batch classify multiple images. There were a total of thirty-nine images that contained downed timber in the study area. Of those thirty-nine, ten images were selected that had similar image quality with respect to lean, glint and pixilation or sharpening. Taking advantage of the richness of the raw imagery rather than allowing a mosaic to wash out the images, provided an adequate amount of data to produce complete classifications. Using one image, also significantly reduced the run time on each classification. Once the signature files were generated for each spatial resolution, batch classification took less time and caused no computer related problems.

There were considerable problems and issues that occurred during this study. Feature Analyst, as an ArcGIS extension, is fairly hardy, but there are many quirky parts of the program that can give beginners problems. Using training files, for example can problematic if you begin working on different drives. Much of the study data were housed on a personal hard drive and much of the processing was accomplished on North Carolina State University lab computers. In order to use signature files that were generated on previous classification runs, the classified polygon shapefiles for which they were generated must be on the drive that housed the signature file. If the signature file was transferred to a new computer without the shapefile that it was generated from, then
the batch classification would fail and produce an error stating that there was “no training data” to run the classification on. To avoid this error, I create a new input combination file, run the classification and split the files out just prior to the classification run instead of using data generated earlier. It was also important to pay attention to the origin of the signature file. Batch classification generates signature files for the new classifications, but they cannot be used for batch classification later. Those signature files generate the same “no training data” available error mention earlier.

Another important consideration when using archival data is that any file generated by a tool in the Feature Analyst toolbar, including multiclass input layers, clutter removal files, combined feature and classification results, loses its symbology if it is not saved and kept in the .mxd file that created it. Feature Analyst must maintain the symbology in the .mxd file and not in the actual file. This is another reason to only work within in one .mxd file for each complete classification run.

8.4 Recommendations

8.4.1 Image Specific

In order to truly harness the full potential of an object-oriented classification software like Feature Analyst, image quality is critical. If there is one universal truth exposed by this study it is that imagery quality controls the quality of the classification, the level of difficulty in developing training data, and the time necessary to complete classification. Many of the pitfalls and problems developed ultimately from poor imagery. Object-oriented classifications cannot overcome sunspots or glint, image tilt
and color variations within images. When classifying objects rather than individual pixels, the size is not nearly as important as the recognition of that object.

8.4.2 Feature Analyst Specific

In this study, downed timber areas could be classified on the five spatial resolutions by using Feature Analyst. However, using Feature Analyst may not solve all classification needs. The best use for Feature Analyst is to identify objects that are relatively similar in all images and relatively homogenous. Using Feature Analyst to classify heterogeneous objects may be only partially successful unless the objects are in different training classes. The software has a wealth of options and settings that need to be explored before selecting one particular technique. Band selection, approach selection and input representation have a plethora of possibilities that can be used. Being mindful of the spatial resolution is also important when selecting the best input representation. This selection should be modified based on the size of the object that is to be classified. In this study, we were looking for downed timber and once the pixel size and subsequently the input representation started to be larger than the object being classified; the quality of the classification decreased. Overall, the Feature Analyst software package is a relatively robust classifier with its own limitations and advantages. Although it has seemed that the remotely sensed imagery technology has outpaced the classification software, classification technology will close the gap through the advancement of object-oriented classification algorithms, such as Feature Analyst.
Figure 10. Set up learning options for Feature Analyst

Figure 11. Input representation for 1-meter, 5-meter and 10-meter classifications
Figure 12. Input representation for 0.2-meter classification

Figure 13. Learning settings in Feature Analyst
Figure 14. Original 0.2-meter image and classification mid-view
Figure 15. Original 0.2-meter image and classification far-view
Figure 16. 1-meter image and classification far-view
Figure 17. 5-meter image and classification mid-view
Figure 18. 5-meter image and classification far-view
Figure 19. 10-meter image and classification close-view
Figure 20. 10-meter image and classification mid-view
Figure 21. 10-meter image and classification far-view
Figure 22. 0.2-meter image and manual classification close-view
Figure 23. 0.2-meter image and manual classification mid-view