Application of Ancillary Data In Post-Classification To Improve Forest Area Estimates In A Landsat TM Scene

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Abstract

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To Improve Forest Area Estimates In A Landsat TM Scene

In order to produce a more current inventory of forest estimates along with change estimates, the Forest Inventory Analysis (FIA) program has moved to an annual system in which 20% of the permanent plots in a state are surveyed. The previous system sampled permanent plots in 10-year intervals by sampling states sequentially in a cycle (Wayman 2001, USDA FIA). The move to an annual assessment has introduced the use satellite technology to produce forest estimates. Wayman et al (2001) researched the effectiveness of satellite technology in relation to aerial photo-interpretation, finding the satellite method to do an adequate job, but reporting over-estimations of forest area. This research extends the satellite method a step further, introducing the use of ancillary data in post-classification.

The US Forest Service has well-defined definitions of forest and nonforest land-use in its (FIA) program. Using these definitions as parameters, post-classification techniques were developed to improve forest area estimates from the initial spectral classification.

A goal of the study was to determine the accuracy of using readily available ancillary data. US Census data, TIGER street files, and local tax parcel data were used. An Urban Mask was created based on population density to mask out Forested pixels in a classified image. Logistic Regression was used to see if population density, street density, and land value were good predictors of forest/nonforest pixels.

Research was also conducted on accuracy when using contiguity filters. The current filter used by the Virginia Department of Forestry (VDoF) was compared to functions available in ERDAS Imagine. These filters were applied as part of the post-classification techniques.

Results show there was no significant difference in map accuracies at the 95% confidence interval using the ancillary data with filters in a post-classification sort. However, the use of ancillary data had liabilities depending on the resolution of the data and its application in overlay.

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Chapter 1: Introduction and Objective

1.1 Introduction

Multiple studies have been conducted using ancillary data to improve classification of highly confused areas in a remotely sensed image (Mesev 1998, Northcutt 1991, Richetti 2000). The purpose of creating an Urban Mask is to improve the precision of forest estimates in a remotely sensed image, above the initial spectral classification. An urban mask is a feature defined by an analyst to overlay over an image that reclassifies pixels based upon parameters set by the analyst.

The mask will specifically target areas of human use. These areas may have high population densities, high street densities, and/or high tax values. Three hypotheses will be tested. First, it is believed areas containing dense population will likely not support the parameters of FIA definition of forested land. It is believed that a creation of an Urban Mask based upon population demographics will highlight such areas in an image. Secondly, parcels of higher tax value will identify commercial areas where the land value is too high to be used as forest. The third hypothesis, deals with street density. Areas containing a greater density of streets per square mile have dense urban features i.e. business districts, commercial centers, industrial areas, etc., that would otherwise be missed by using population demographics alone.

The latter two hypotheses will be tested using logistic regression, while the first will be tested by creating a model that uses a population density threshold in a vector file to overlay over a classified image and reclassify forest pixel values to nonforest. Accuracy assessments on the resulting images will be performed by a script available from the Virginia Department of Forestry (VDoF).

1.2 Objective:

The objective of this study is two fold. First, use ancillary data to improve the forest estimation of a Landsat Scene of Montgomery Co., VA based upon the "land use" definition of forest by the FIA. It is believed that the addition of ancillary data such as population demographics, street density, and tax parcel values will make a significant difference in forest estimations between the initially classified Iterative Guided Spectral Class Rejection (IGSCR) image and the IGSCR image with the addition of the ancillary data.

Secondly, compare methods of contiguity checks. The VDoF has developed an ArcView script that checks for contiguity based upon FIA definitions of forested and nonforested lands. This script is to be compared to readily available functions provided by ERDAS Imagine 8.5.

Chapter 2: Literature Review

2.1 Forest Inventory Analysis

In 1928 the US Congress enacted the McSweeney-McNary Forest Research Act, then in 1974 created the Forest and Rangeland Renewable Resources Planning Act. These acts were implemented to monitor the condition, extent, volume of growth, and health of the United States' forests and the impacts of management practices upon them. These acts and their latter revisions are the basis for the Forest Inventory Analysis (FIA) Program (Patrick et al 2001). "FIA is the Nation's forest census (USDA FIA http://fia.fs.fed.us/about.htm)." The FIA program is unique in that it is currently the only such program that monitors forest ecosystems across all ownerships (SAF 2000). This is important because it sets a standardization for monitoring that previously did not exist.

FIA data are of prime importance to policy making by federal, state, and local governments. FIA data is influential in analysis that affects both economical and ecological decision policies at all levels of government. The use of the data is not limited to public forest planning but is also of great importance to the private industry. Having the most up-to-date and correct forest area estimates helps in such policy decisions as strategic planning for the timber industry, reporting national forest carbon budgets, and assessment of ecological and economic change resulting from natural disasters (SAF 2000).

Previously, the FIA program was conducted on a periodic basis, sampling states sequentially in a cycle. As part of the 1998 Agricultural Research, Extension and Education Reform Act, the US Forest Service has developed a strategic plan for a continuous inventory for the program, in which every state is sampled annually. It is a

three-phase initiative that is applied to monitoring across all forest ownerships (SAF 200).

The first phase defines the strata. The second phase focuses on tree measurements while the third phase deals with forest health. Sampling one plot per some number of acres makes up the second and third phases. Phase two has a sampling intensity of one plot per 6,000 acres while the third phase has a sampling intensity of one sample per 100,000 acres (SAF 2000).

Originally, Phase I strata were defined using a grid of points draped over aerial photos. The photos were mostly at 1:40,000 scale from the National Aerial Photography Program (NAPP). A classification of forest or nonforest was given to each point in the systematic grid based upon photo interpretation (Wayman et al 2001). Reams and Van Duesen (1999) cited two inefficiencies of using this method for collecting data to define strata; it is both time consuming and costly. Wayman et al (2001) have researched the use of satellite remote sensing compared to photo interpretation. They found the use of satellite remote sensing to be "comparable" in defining Phase I estimations, yet believed that these procedures produced overestimations of forest area (Wayman et al 2001).

Using satellite imagery to monitor forest quantity is not an easy task. There are fundamental differences between spectral classes, data from the satellite; and information classes, those defined by humans that the spectral data are placed into (Jensen 1996). Satellite data provide land-cover (spectral) information, but what is needed is land-use information (human defined) (Northcutt 1991). Many times these are not one and the same, and this where the difficulty occurs in defining forest and nonforest areas. Multiple variables must be taken into account when classifying forest and nonforested

areas. The FIA program has set definitions it uses as guides to do this. These definitions standardize what is a “forested area” and what is a “nonforested area”. Examples of difficulties in classification occur in determining harvested areas in a forested tract, from those areas that are agriculture or another form of human impact. Another source of difficulty is when there is a high amount of forest/nonforest variation. Examples of such areas will be introduced later on in the study.

2.2 Ancillary Data

Jensen defines ancillary data as:

> Any type of spatial or nonspatial information that may be of value in the image classification process, including elevation, slope, aspect, geology, soils, hydrology, transportation networks, political boundaries, and vegetation maps (Jensen, 1996, p. 244).

This is by no means an exhaustive list. Ancillary data is used to improve image classification. Analysts can choose to use ancillary data in any of three stages of image classification: 1) preclassification scene stratification, 2) post-classification sorting, and 3) during classification through modification of a priori probabilities (Hutchinson 1982, Mesev 1998). Hutchinson found that preclassification stratification and post-classification sorting were the most efficient, but were limited to their decision rules. An advantage of post-classification sorting is the fact it is done after classification and only deals with "problem classes" i.e. those areas that would be affected by the decision rules (Hutchinson 1982).

The post-classification technique is used to refine the class assignment of a pixel after its initial classification. Hutchinson (1982) applied this method in his classification

of a desert scene in Flynn, California. He used slope data to separate steep, sunny, dunes from flat playa surfaces. Many other studies have incorporated the use DEM data in post-classification (Ricchetti 2000) and (Eiumnoh, Shrestha 2000).

Studies conducted by Mesev (1998) and Harris et al (1995) used demographic data in the classification process. Both studies used ancillary data to improve classification in urban areas. The demographic data used by Mesev (1998) was housing density. A weighted estimator template based upon centroid distance of housing density was calculated and used in all three stages. He used the template to help in the acquisition of training data (preclassification), during classification as a component in Bayesian-modified maximum likelihood estimator, and in post-classification sorting. Mesev (1998) used an urban mask as a post-classification sorting template. Others have successfully used the urban mask. Northcutt (1991) reported that the addition of an Urban Mask in a post-classification sort improved classification and accuracy in urban areas, especially in easily confused areas; i.e. where human impact can spectrally look like natural surfaces.

2.3 Census Data

Little research has been conducted on the practice of integrating satellite imagery with demographic data (Radeloff et al 2000). The work that has been done has been aimed primarily toward improving broad scale land cover classifications (Vogelmann et al 1998, Luman 1996).

The 2000 Census data from the US Census Bureau is one of the data layers to be used here as ancillary data. The smallest unit of measure published by the Census is the

census block (US Census Bureau 2000). Census blocks are vector polygon data of varying shapes and sizes. The census block has the highest spatial resolution of all census data (Radeloff et al 2000).

2.4 Tax parcel Data

Another avenue of research is whether the addition of data above and beyond the readily available data (i.e. census data) improves accuracy and whether any improvement is significant.

Land value was chosen as a variable to measure, because it can be used across all government and zoning laws. Land value is not restricted to specific county laws. More and more municipalities are switching from hard copy to soft copy documentation and record keeping for tax parcel data. Because of up to date digital tax maps, land value was seen as the best additional variable. It is contended that areas of high land value could not be expected to be in a forest land use, because such areas would be incompatible with those of high commercial value.

Montgomery Co., Virginia tax parcel data was obtained from the Virginia Tech Library and the Blacksburg GIS Office. The Shape File of the County contained over 36,000 polygons. The associating database had upwards of 20 fields. The only fields of concern were land value and tax parcel ID.

2.5 FIA Program Definitions

Wayman et al's (2001) results indicate that satellite derived classification, in two out of three study areas, overestimated the amount of forest area up to 2.75%. It is

believed the addition of ancillary data will improve these estimations, and make them more comparable to the photo-based methodology for forest area estimates. The classifications must meet standards set by the FIA program. Below are the three definitions that are of importance in the post-classification techniques. The classification model outputs had to meet these requirements. The definitions are from the Field Instructions For Southern Forest Inventory, a manual from the US Forest Service and the Department of Agriculture.

> *Nonforest Land* -- Land that does not support, or has never supported, forests, and lands formerly forested where use for timber management is precluded by development for other uses. Includes areas used for crops, improved pasture, residential areas, city parks, improved roads of any width and adjoining rights-of-way, power line clearings of any width, and noncensus water. If intermingled in forest areas, unimproved roads and nonforest strips must be more than 120 feet wide, and clearings, etc., more than one acre in size, to qualify as nonforest land.
>
> *Forest land*—Land at least 10 percent stocked by forest trees of any size, or formerly having such tree cover, and not currently developed for nonforest uses. The minimum area for classification of forest land, or subclasses of forest land is 1 acre. Roadside, streamside, and shelterbelt strips of timber must have a width (based upon stem-to-stem distance) of at least 120 feet wide to qualify as forest land. Unimproved roads, trails, and clearings in forest areas (if not urban and other) shall be classed as forest if less than 120 feet in width.
>
> *Urban and other*- Areas of intensive use with much of the land covered by man-made structures, e.g., towns, strip developments along highways, power and communication facilities, industrial complexes, and institutions. Areas include those developed for residential, industrial or recreational purposes; school yards, cemeteries, roads, railroads, airports, beaches, power lines, and other rights-of-way. For land use classification, this includes other nonforest land areas not included in any other specified land use class. Urban and other areas do not need to meet the 120 feet wide and 1 acre in size requirement. Urban and other areas may be any shape and size.

The above definitions for "Nonforest Land" and "Urban and Other" are almost contradictory. However, the main point needs to be in the last line of the "Nonforest Land" definition. Nonforested areas need to be at least 120 ft wide and one acre in size

only when intermingled in forested areas, i.e. tracts of forested land. Forest land however, must always be one acre in size anywhere it occurs. This puts one into a predicament when trying to classify an area. Are the pixels of nonforest land immersed in a forested tract or are they nonforest pixels in an area of confusion? Which definition should be applied, and how does one tell the difference in a classification? Using just the "Urban and Other" is not a viable option for the study. The "Nonforest Land" definition is all-inclusive. It is these areas of confusion, which the addition of ancillary data is designed to help in pixel classification.

Chapter 3: Methods

3.1 Study Area

The study area is Montgomery County, Virginia located in Southwest VA. It is a found within Landsat TM Scene 17/34 from Virginia taken 04/03/00 (Figures 1 and 2).

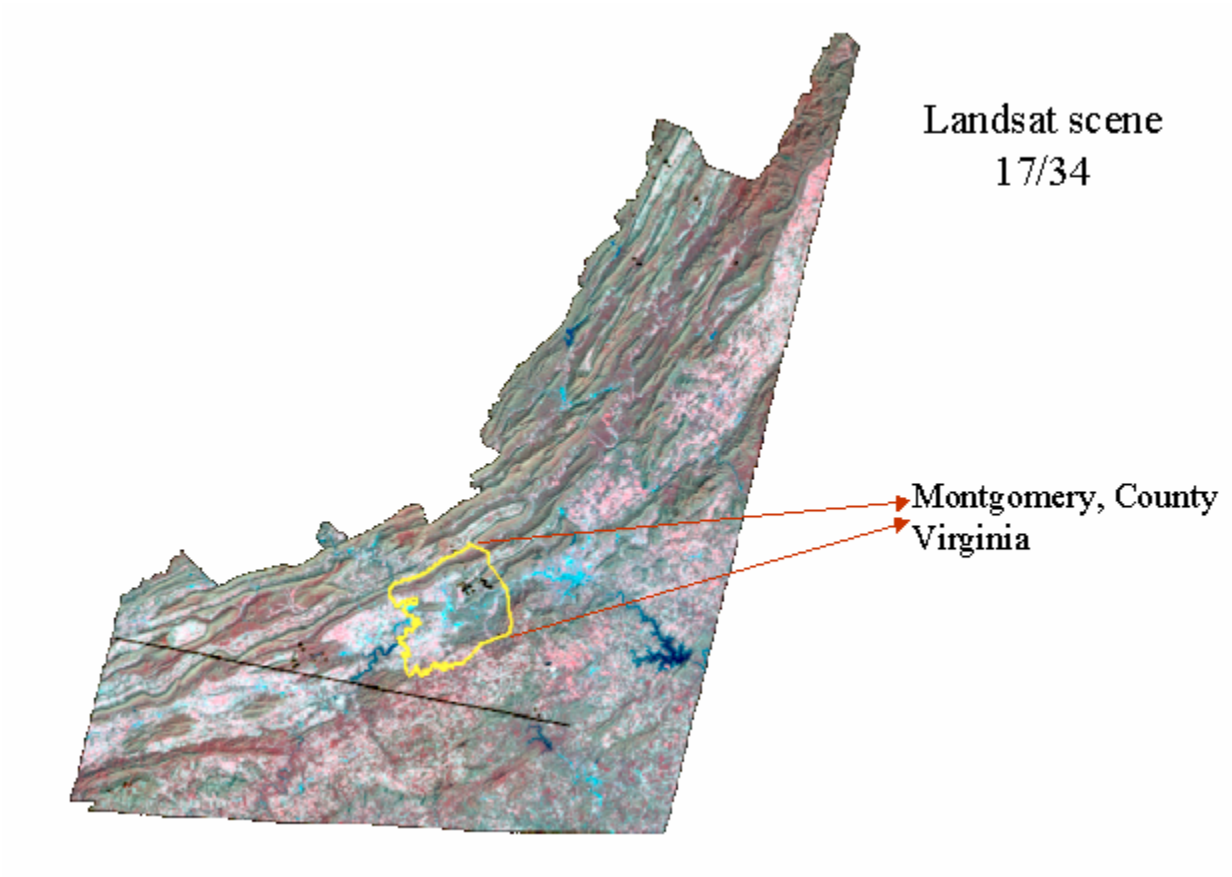

Figure 1: Landsat TM Scene 17/34 with spatial location of Montgomery County, VA.

Montgomery County was chosen for multiple reasons. First, was the availability of tax parcel data in a useable digital format. The second was logistics, living in the study area provided ease of data collection. Third, when compared to state percentage of forest area (61% forest land), Montgomery County was similar (Johnson 1992).

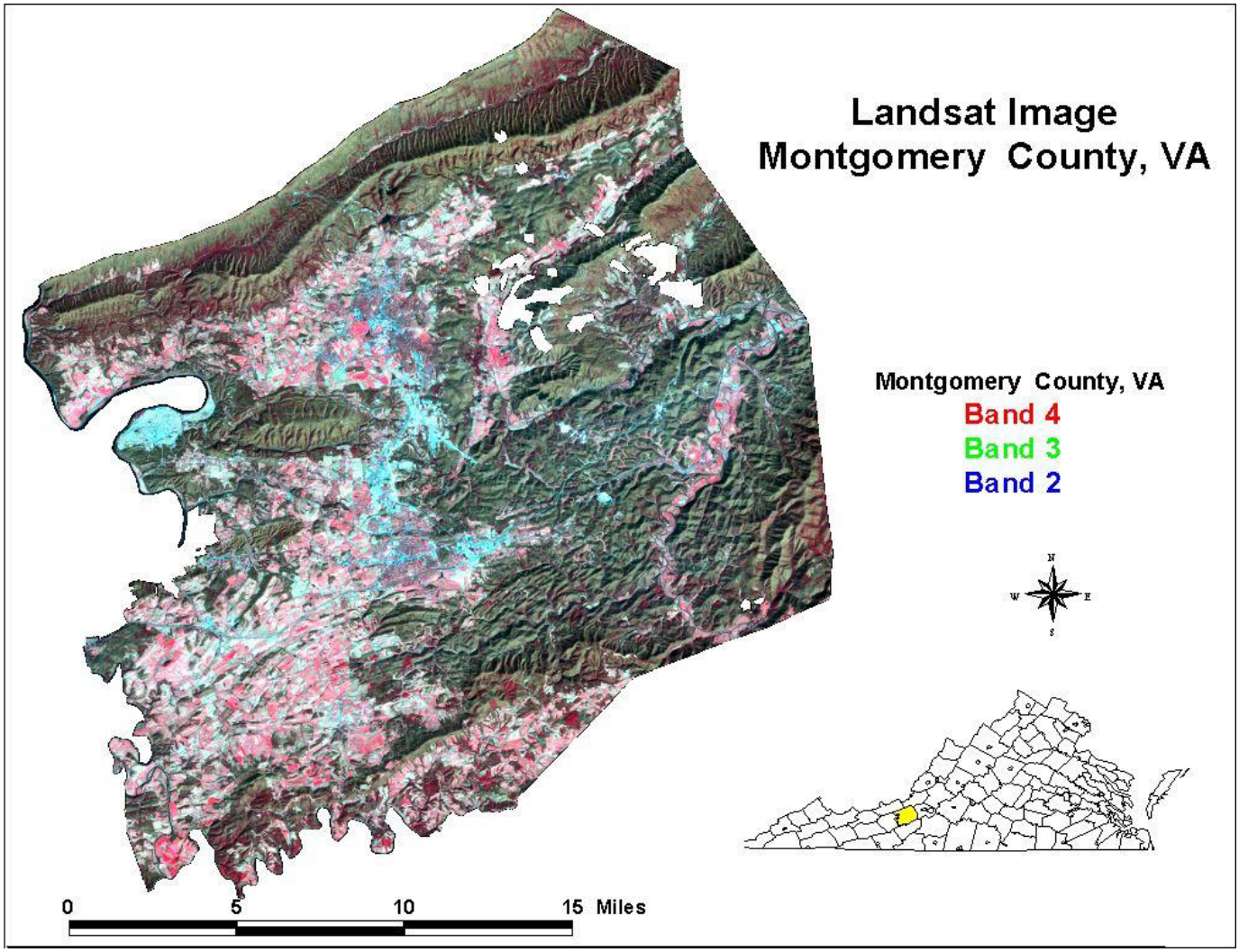

Figure 2 Close-up of clipped area of Montgomery County, VA from Landsat TM Scene 17/34

3.2 Data Sets

The classified forest/nonforest image used in the study comes from VDoF's Forest Inventory Analysis project (FIA Program in VA). It was classified using Iterative Guided Spectral Class Rejection (IGSCR); a hybrid classification technique of both supervised and unsupervised classification (Wayman et al 2001). The classification is unsupervised and iterative in that spectral classes are clustered and grouped based upon their spectral signature. Pixels not meeting a homogeneity threshold value are rejected

from the class and set aside. When a class is created it is removed from the raw image and a new image is created. This image is made up of the unlabeled pixels. They are clustered into new spectral classes. Pixels are again grouped, labeled, and removed. These iterations continue, until user-defined parameters of percentage classified are met. The known spectral classes are then put into a signature file, which is the basis for a supervised classification using the maximum likelihood decision rule. Pixels in the image are classified into the information classes of "forest" and "nonforest" (Wayman et al 2001).

An important point in my study is that this research is specifically post-classification in context. The initially classified image can be done by any technique GAP, NLCD, etc. My research was not concerned with initial classification techniques.

An aim of the study was to use readily available GIS data layers for the creation of the Urban Masks. US Census data was chosen to fulfill this requirement. The 2000 TIGER Census data was retrieved from two locations. The TIGER Line data of Montgomery County was downloaded from ESRI's website (ESRI). The matching Census Data was obtained from the Census Bureau's SF1 disk made available from Virginia Tech's library.

The ancillary data used to create the Urban Masks are as follows:

- 2000 US Census Data at the census block level (US Census)
- 2000 TIGER Line Files for the census block level (ESRI)2000 TIGER Line Files for Roads (ESRI)
- Tax Parcel Data for Montgomery County in shapefile format (Blacksburg GIS Department).

Data for collecting validation points:

- 2000 TIGER Line Files of the county outline and roads for Montgomery, Co.
- Digital Ortho Quarter Quads (DOQQ's) for the entire county downloaded from the Virginia Economic Development website. The image dates range from 1996-2000, and are to USGS specifications.

- National Land Cover Dataset (NLCD) Land Cover Class Definitions as a basis for land cover from the US Geological Survey (USGS)

3.3 Software Equipment

- ArcView 3.2 with Image Analyst and Grid Analyst
- ArcGis 8.1 (ArcTool Box, and ArcCatalog)
- ERDAS Imagine 8.5
- IDRISI
- NCSS
- PC GPS
- Corvallis GPS unit

3.4 Validation Points

Validation points were field collected for two reasons. First, was due to the wide spacing of FIA sample plots at the county level. It was determined that the FIA plot data did not provide a robust enough data set at the county level. It was deemed more appropriate at the multi-county level. The second reason for field collecting validation points was because of the current laws for FIA plot data release. Currently FIA policy on public release of coordinates must be rounded to the nearest 100 seconds (approx. 1 mile) (Federal Registrar). The findings in this study can be extrapolated upward and used at a broader scale.

The collection of validation points for the accuracy assessment was based on a random stratified sample. A 7x7 grid was overlaid on the county outline and roads files. A 7x7 grid allows for 35 cells to have at least some portion of the county to be in a cell (*Appendix i* Figure 18). A minimum of two points were collected in each grid cell, depending on the amount of area encompassed within the grid cell more points were taken. This allowed for a more robust data set of validation points (*Appendix i* Table 12 gives the UTM coordinates and value of each validation point). The limiting factor for

point collection was access from the road and property ownership. To alleviate the property ownership factor, DOQQ's in the correct projection were used to eyeball land-use from a viewable point. If both matched then the point was digitized on screen with the DOQQ as the base map. Figure 3 compares the relative FIA plot locations and the field collected validation points.

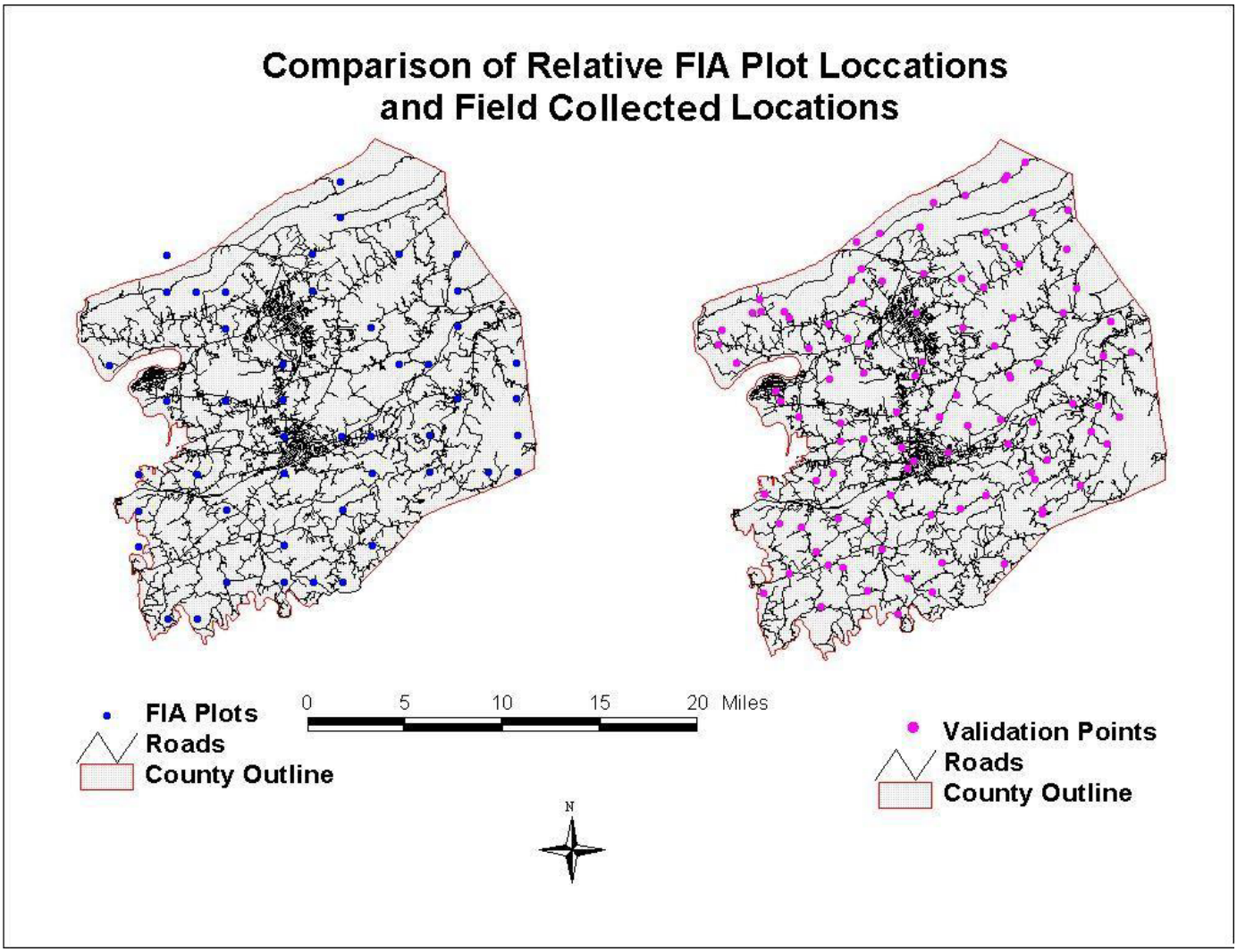

Figure 3 Comparison of relative FIA plot locations and the field collected validation points.

After acquisition of the data, the GIS layers were projected into the following projection using ArcTool Box.

Projection

Spheroid: GRS 1980
Datum 1983
UTM Zone: 17N
False northing at origin - 0.00 meters
False easting at central meridian – 500,000.00 meters

3.5 Urban Mask

Before urban and nonurban areas were found, population density for each census block was calculated. The US Census Bureau releases the demographic data for each census block. Each census block's area was calculated in square miles. Dividing the population by the area derived the population density. The US Census Bureau defines an Urban Area (UA) as having core census block groups or blocks with a population density of 1,000 people per square mile, with surrounding census blocks having an overall density of at least 500 people per square mile. All other areas are defined as rural (US Census Bureau 2000). The rural(nonurban)/urban interface is an area of large confusion in remote sensing classification. It can be best defined as "suburban". This "suburban" area belongs within the urban framework as it pertains to land-use classification. It is in these areas that land use classification is the most difficult. The urban area defined in this study was set to 300 persons per square mile. Figure 4, shows the created Urban Mask, with an inset focused on Blacksburg, VA.

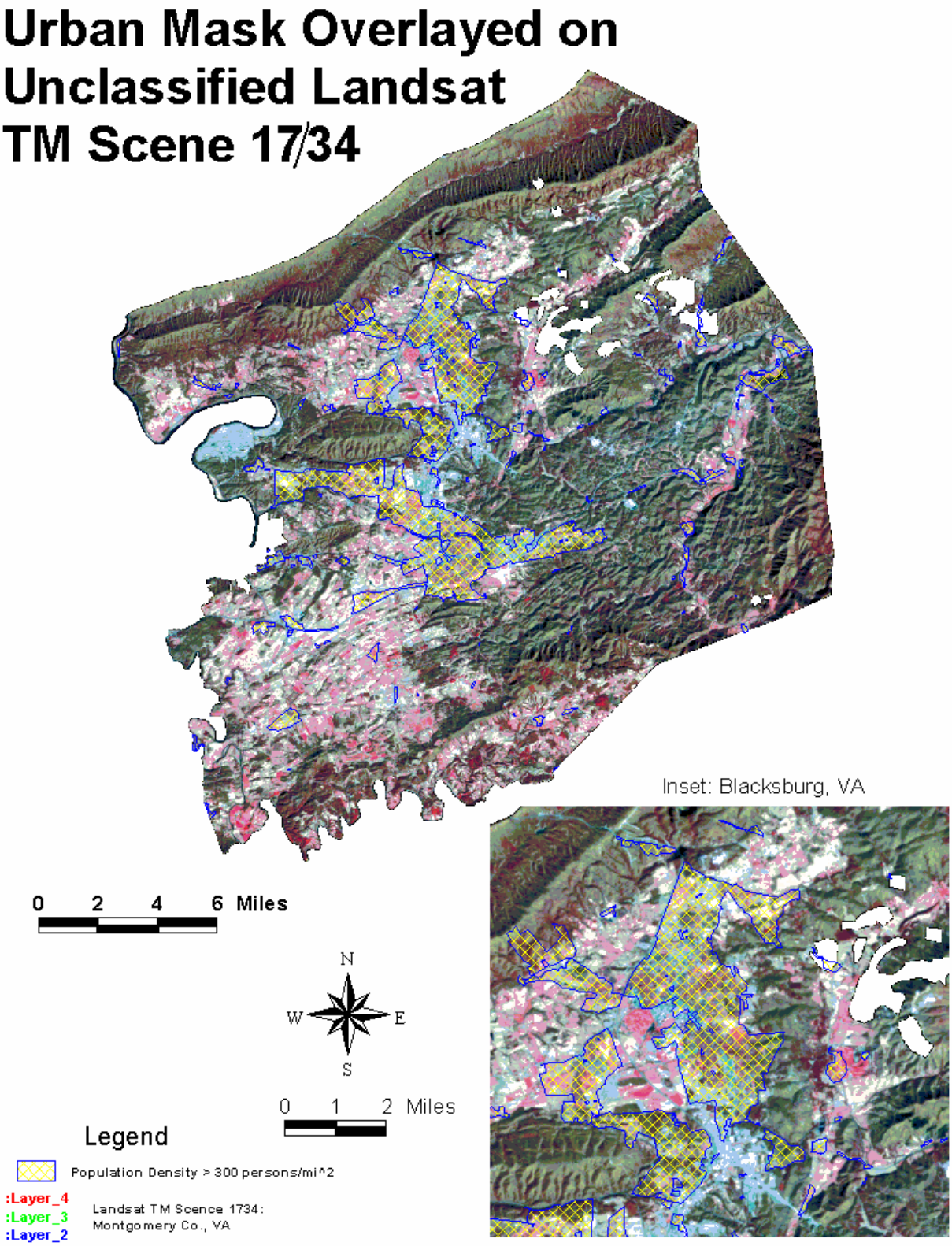

Figure 4 Urban Mask overlaid over Landsat TM Scene 17/34

The Urban Mask was a shape file made of merged blocks imported into ERDAS from ArcView. Once in ERDAS, the vector shape file was converted into an Area of Interest (AOI) file. Using the Mask Tool in ERDAS a separate image file of the masked area was created then recoded to reflect nonforested area. The original reference image classified by IGSCR and the mask image were then placed into a model I created (*Appendix ii Figure 20*). The output image was a post-classification sort using the mask image as ancillary data. An accuracy assessment was then conducted on the resulting image based upon known land use pixel values from the validation sample.

3.6 Kurtzinator

Part of the analysis for this project was to compare existing methods of post-classification. The Virginia Department of Forestry (VDoF) has developed an ArcView script to be run on an image after it has been classified (*Appendix iii*). The script specifically targets shape-area-adjacency, and is to be run on classified images before an accuracy assessment is conducted. Currently there are no published studies that have been conducted testing the validity of the Shape-Area-Adjacency script, so it has not been open for peer review nor does it have a specific title. Robert Kurtz, an employee of the VDoF, wrote the script and in my study it will be referred to as the "Kurtzinator."

To run the script, a classified image must be converted to a grid in ArcView. The grid is reclassified to 1's for nonforest and 0's for forest. A second grid of nonforest features that are to be preserved i.e. roads and water bodies, may also be used. It is important to note that the grids have been resampled to 15m resolutions from the 30m resolution of the image, because of the parameters of the FIA definition.

The script looks at both forested and nonforested pixels in its algorithm. It is an iterative algorithm that looks at an orthogonal neighborhood for adjacency. According to FIA definitions a forested area must at minimum be 120 feet wide and an acre in size. A nonforested area surrounded by forest must also be 120 feet wide and an acre in size.

The script first runs though nonforested pixels looking for adjacency. The kernel targets the 4 cardinal directions as shown in Figure 5. Each pixel is 15x15m, meaning the minimum pixel width for FIA standards is 3 pixels wide (>120 ft) for a neighborhood. A neighborhood must have at least 3 pixels together in any of the four directions, including the center pixel. The script iterates through an image checking for adjacency. The script will iterate through until all pixels have been verified, or until the user defined threshold for iterations is met. If adjacency is met, pixels are patched out, and groups are formed. Pixels not meeting the adjacency standard are reclassed to forest. The next parameter the script checks for is area. If groups of patches are less than 17 pixels (0.9452 acres in size) then these pixels are reclassed to forest also.

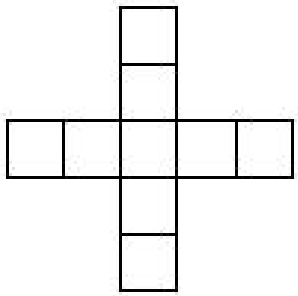

Figure 5: Orthogonal kernel used the check adjacency in the shape-area-adjacency ("Kurtzinator") script.

Shape-area-adjacency is then checked for forested pixels. The same protocol is used on these pixels, but instead of being reclassed to forest, pixels not meeting the standards are reclassed to nonforest.

Outputs of these operations are combined. If a second grid of preserved features is present, these classified pixels are added back as is. The resulting grid is reclassified back to 1's for nonforest and 2's for forest and imported back to ERDAS to create an *img* file for accuracy assessment.

Each time the script was implemented on an image, it was run with and without roads as a preserved feature. Road data for the county came from TIGER. The vector line file was converted to a grid with a 15m-pixel resolution. Roads were classified as 1 and No Data areas within the county boundary were classified as 0, as per the requirements of the " Kurtzinator" script.

3.7 Clump/Eliminate

To compare shape-area-adjacency techniques, the clump/eliminate functions of ERDAS were implemented on the classified reference image. The clump/eliminate method is currently used by the Minnesota Department of Forestry as their post-classification contiguity check (Wynne 2002). The clump function is used for contiguity analysis. Contiguous pixels of the same class are grouped together. These groups are known as raster regions. The clump function identifies the raster regions by their size. Once groups of raster regions, "clumps", are found, the findings can be manipulated as needed, for example eliminating groups that are too small for a set of parameters (ERDAS 1997).

In order to compare against the results of the "Kurtzinator" script, the classified reference image was resampled from 30m to 15m resolution. In the classified image the nonforest classification (1) was recoded to unclassified (0). The clump function, using 8

neighbors, was then run on the recoded image. The clumping function groups like coded pixels together, in this case it grouped the forest class (2). The resulting image was then sent through the eliminate function. Each pixel in the resampled Landsat TM image is 15x15m. To match FIA definition for a forested land, clumps containing less than 18 pixels (1.001 acre) were eliminated from the image. I chose 18 pixels because it was a more precise measure for acreage compared to the "Kurtzinator" at 0.9452 acres (17 pixels). These eliminated areas now have an unclassified pixel value of 0. To decipher between background values of 0 and eliminated areas of 0, a model was created in ERDAS to reclassify eliminated areas back to 1 (*Appendix ii* Figure 21).

As with the "Kurtzinator" script, nonforested areas must be evaluated. In the reference image the forested pixels were reclassed to 0 and the nonforested pixels were left as 1. The same clump/eliminate method was implemented on the image. A modification to the above model in *Appendix ii* Figure 21 was made. It still deciphers between background values of 0 and eliminated areas of 0, however eliminated areas were reclassified back to the forested value of 2 (*Appendix ii* Figure 22).

Two images now exist, one for removed and reclassified forest pixels and one for removed and reclassified nonforested pixels. A methodology was developed to combine the results of these two images into one image. The overlay functions of IDRISI were used in this stage. First each eliminated image was subtracted from the reference image:

A. Reference – eliminated forest = nonforest (1)
B. Reference – eliminated nonforest = forest (-1)
   Reclass output value of B from –1 to 2

The output of A shows the areas that were forest reclassified to nonforest. The output of B shows the areas that were nonforest reclassified to forest. An image addition overlay function was used to add the resulting outputs into a single image. IDRISI has an overlay function called "First covers second except where 0." The function produces an image that uses the value of the first image (the change image in this case) unless the value equals 0, then it uses the value of the second image (the original reference image). The outcome of this overlay function was then exported as an *.img* file in ERDAS to run an accuracy assessment. ***Note:*** The clump/eliminate methodology that was run on the population model image uses the population image as the reference when doing subtractions.

3.8 3x3 Majority Filter

In the Wayman et al (2001) study, a marked difference in overall accuracy was achieved when a 3x3 majority filter was applied to the IGSCR classified image. Overall accuracies increased anywhere from 1.5% to 6.5%. To see if the same results could be achieved, a 3x3 Majority Filter was applied to the reference image. This filter acts as contiguity filter also, but not as complex an algorithm as the "Kurtzinator" script or Clump/Eliminate method.

3.9 Images

Eleven different images were created using multiple combinations of the above procedures. Population density was looked at for the entire image, but once areas were eliminated based upon the population density threshold, the Urban Mask was only concerned with pixels within the masked area. On the other hand the "Kurtzinator" script

and Clump/Eliminate method looked at pixel classification in the entire image. These two techniques take into consideration the FIA definition of Nonforested area. Images were created using combinations of the Urban Mask and these two techniques. Table 1 shows all of the images that were created and their accompanying procedures that were used to create them.

Table 1 Images created and the procedure used for each.

Image Name	Procedure
IGSCR	This is a clipped image of the originally classified Landsat TM scene 17/34.
3x3 Majority	This is the output of a 3x3 majority filter on the original reference image.
Urban Mask	This is the output using the "Urban Mask," of population density on the reference image.
Clump/Eliminate	This is the output of the clump/eliminate functions of ERDAS.
Urban Mask – Clump/Eliminate	This is the output of running the clump/eliminate functions of ERDAS on the "Urban Mask" model image.
Clump/Eliminate – Urban Mask	This is the output running the "Urban Mask" model on the clump/eliminate image.
Kurtz-No Roads	This is the output running the "Kurtzinator" script on the original reference image, without having roads as a preserved feature.
Kurtz-Roads	This is the output running the "Kurtzinator" script on the original reference image, with roads as a preserved feature.
Kurtz-No Roads – Urban Mask	This is the output of the "Kurtzinator" script on the original reference image, without having roads as a preserved feature, then applying the "Urban Mask."
Kurtz-Roads – Urban Mask	This is the output of running the "Kurtzinator" script on the original reference image, with roads as a preserved feature, then applying the "Urban Mask."

Image Name	Procedure
Urban Mask – Kurtz-No Roads	This is the output of the "Urban Mask." The "Kurtzinator" script was then applied to the image without having roads as a preserved feature.
Urban Mask – Kurtz-Roads	This is the output of the "Urban Mask". The "Kurtzinator" script was then applied to the image with roads as a preserved feature.

3.10 Logistic Regression

Logistic Regression was used to see if other data layers were good predictors of forest/nonforest pixel, and, if so, what threshold values could be used to create other urban masks. Logistic regression was chosen because of its binary nature, yes-or-no, forest-or-nonforest. Logistic regression is a widely used and accepted statistical analysis for this type of binary response (NCSS 2000).

The logistic regression was run using four variables: (1) land-vaule/10m^2 (2) Street Density (3) Population/mi^2 and (4) the Classified reference image. Each variable was input into the model individually, then all combinations of these four variables were used. This was done to explain the percent of variation each variable had within the model.

Before the logistic regression could be performed, the image data for each variable needed to be converted to a raster format to obtain tabular data. Initially the land value image was a shape file of tax parcel data. Area for each tax parcel polygon was obtained and the land value per 10m^2 was calculated. The shape file was then converted to a grid. Ten-meter resolution was chosen for the grid, because use of 30m cells (resolution of Landsat TM scene) would lose information, as some tax parcels in downtown areas were less than 30m wide. Using 10m grid cells preserved the data.

As with the tax parcel data, the road data was a shapefile in vector format. The file was converted to a grid. A filter was run on the grid to obtain a quantitative measure of street density. A mean filter was used. Multiple kernel sizes were tested, and a 7x7 kernel size was chosen.

As with the other variables, the population data was also in vector format. The data layer needed to be transformed to match the resolution of the reference image that was in pixel format. Essentially, population density needed to be converted into a continuous surface. The census block is the smallest unit for measuring census data. At this level, census information is not always available for every unit, creating gaps. To circumvent this problem and create a continuous surface an adaptive technique was implemented. The technique was based upon research conducted by Mesev (1998). Mesev (1998) used an algorithm that used distance decay from the centroid of each census tract (a reporting unit for census in the United Kingdom, different from the US census tract). Each centroid contained the census information for that tract. The distance decay algorithm attempted to measure "where within the tract the greatest concentration of residential land use [was] located" (Mesev 1998). An interpolated surface was derived from the centroids using this technique.

The technique that was implemented in this study did not take into account the distance decay from centroids as part of an algorithm as did Mesev's (1998). Population density per square mile was calculated for each census block. Centroids of each census block were calculated using the AddXY Script in ArcView 3.2. The centroid shape file was then used as mass points to create a TIN in ArcMap (Figure 6). The TIN is an interpolated continuous surface of population density. In order to create a TIN of the

entire county, census data from surrounding counties were needed. Once the TIN was created, it was clipped by the county and converted to a raster surface. The raster surface had a resolution of 30m per pixel to coincide with the reference image (Figure 7).

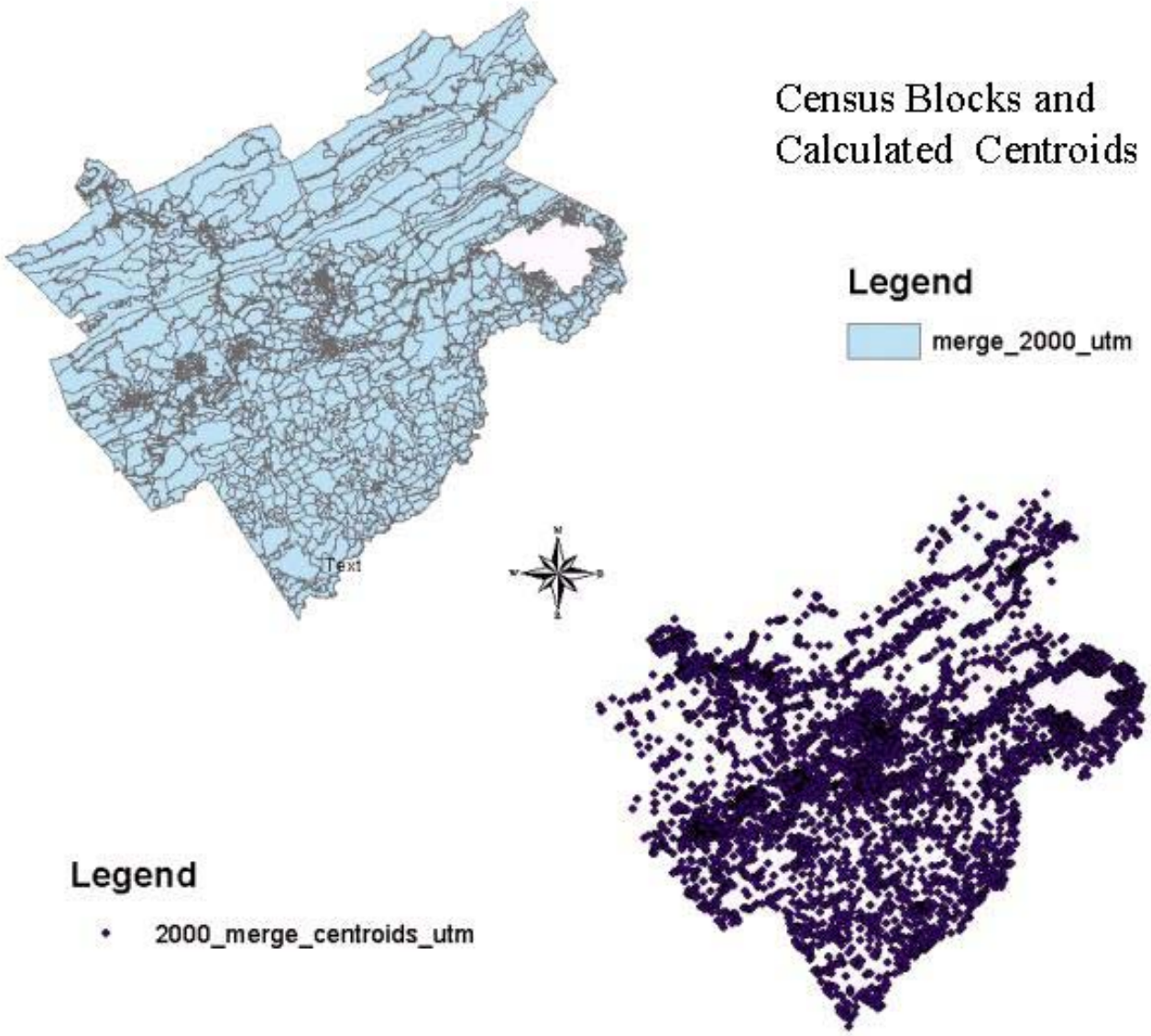

Figure 6 Census Blocks and accompanying Centroids for Montgomery and surrounding counties for interpolation.

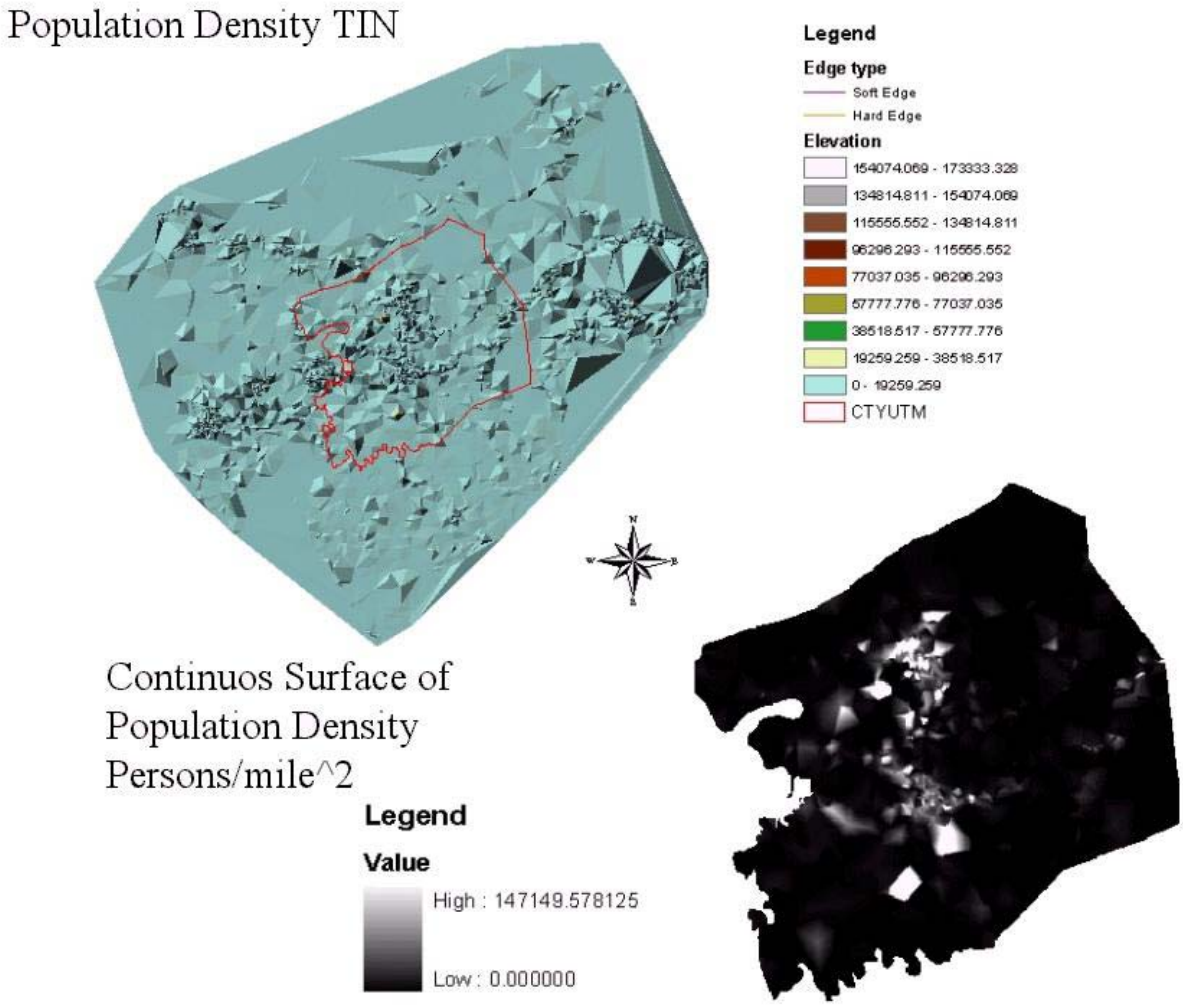

Figure 7 TIN created from centroid mass points and the resulting grid.

The points for the logistic regression would be the validation points in the study. Once all of the variables were converted to a raster format the Grid Analyst 1.1 extension (Extract X, Y, and Z values for point theme from grid theme) in ArcView was used to obtain the Z values of each grid for each validation point. A table then could be created to use in NCSS for the logistic regression model.

3.11 Accuracy Assessments

Accuracy assessments were conducted on the 12 images in Table 1. An ArcView script developed by the VDoF was used to perform this task (*Appendix iii*). The script was a pixel-to-pixel algorithm to develop an error matrix. User's and Producer's accuracies of each category were calculated along with an overall image accuracy and Kappa. Kappa is "a measure of agreement or accuracy" (Jensen 1996). The input file for the script had to be an ERDAS Imagine file (*.img*). To compare the accuracies of each image to the original reference, Kappa and its variance were used to calculate Z-scores to determine if the differences between the classifications were significant at a 95% confidence interval.

3.11.1 Equations used

Kappa Variance

$$\sigma^2_K = \frac{1}{N} \bullet \left[\frac{T(1-T)}{(1-U)^2} + \frac{2(1-T)(2TU-V)}{(1-U)^3} + \frac{(1-T)^2(W-4U)^2}{(1-U)^4} \right]$$

Where

$$T = \frac{\sum x_{ii}}{N}$$

$$U = \frac{\sum x_{i+}x_{+i}}{N^2}$$

$$V = \frac{\sum [x_{ii} \bullet (x_{i+}x_{+i})]}{N^2}$$

$$W = \frac{\sum\sum [xij \bullet (x_{i+}x_{+i})^2]}{N^3}$$

(Congalton 1982)

Z-Score for Significant Difference

$$Z = \frac{K_1 - K_2}{\sqrt{(\sigma^2_{K1} + \sigma^2_{K2})}}$$

3.12 Image Differencing

A qualitative analysis was also a parameter of the study. Where and how, did the reclassification techniques affect the original reference image? The Cross Tab function in IDRISI was used to perform the image differencing. The IGSCR classified image was Cross Tabbed with the results of each post-classification technique. The output of the function was an image that showed pixel changes, i.e. Forest–to–Nonforest and Nonforest-to-Forest. This allowed for visual examination of where pixels changed in the post-classification techniques.

Chapter 4: Results

4.1 Image Comparison

Overall image comparisons by classification are reflected in Table 2. Figure 8, the original classified reference image (*IGSCR*) had 65.14% of the pixels classified as Forest and 34.86% classified as Nonforest. The Urban Mask decreased the amount of forested area by 2.39%. Techniques that made use of the Urban Mask had a net decrease in forested area in the overall image. The "Kurtzinator" script with both roads preserved and not preserved along with the 3x3 majority had net increases in forested area; while the Clump/Eliminate method was almost unchanged compared to the reference image with a decrease in forested area by 0.01%. Figure 9 gives a graphic representation of each images' net result of forested area.

Table 2 Classification comparisons of study images.

	IGSCR	Urban Mask	Kurtz-No Roads
Pixel Forest	2885712	2779685	2922316
Pixel Nonforest	1544012	1650039	1507408
% Forest	65.14	62.75	65.97
% Nonforest	34.86	37.25	34.03
Area Forest	160442.00	154547.00	162477.00
Area Nonforest	85845.10	91740.00	83809.90

	Urban Mask – Kurtz-No Roads	Urban Mask – Kurtz-Roads	Clump/Eliminate
Pixel Forest	2814352	2800026	2885180
Pixel Nonforest	1615372	1629698	1544544
% Forest	63.53	63.21	65.13
% Nonforest	36.47	36.79	34.87
Area Forest	156474.00	155678.00	160412.00
Area Nonforest	89812.60	90609.10	85874.60

	Kurtz-No Roads – Urban Mask	Kurtz-Roads – Urban Mask	Urban Mask – Clump/Eliminate
Pixel Forest	2820018	2805220	2782496
Pixel Nonforest	1609706	1624504	1647228
% Forest	63.66	63.33	62.81
% Nonforest	36.34	36.67	37.19
Area Forest	156789	155967.00	154703.00
Area Nonforest	89497.6	90320.30	91583.70

	3x3 Majority	Clump/Eliminate – Urban Mask	Kurtz-Roads
Pixel Forest	2888680	2783337	2903816
Pixel Nonforest	1541044	1646387	1525908
% Forest	65.21	62.83	65.55
% Nonforest	34.79	37.17	34.45
Area Forest	160607.00	154750.00	161448.00
Area Nonforest	85680.10	91537.00	84838.50

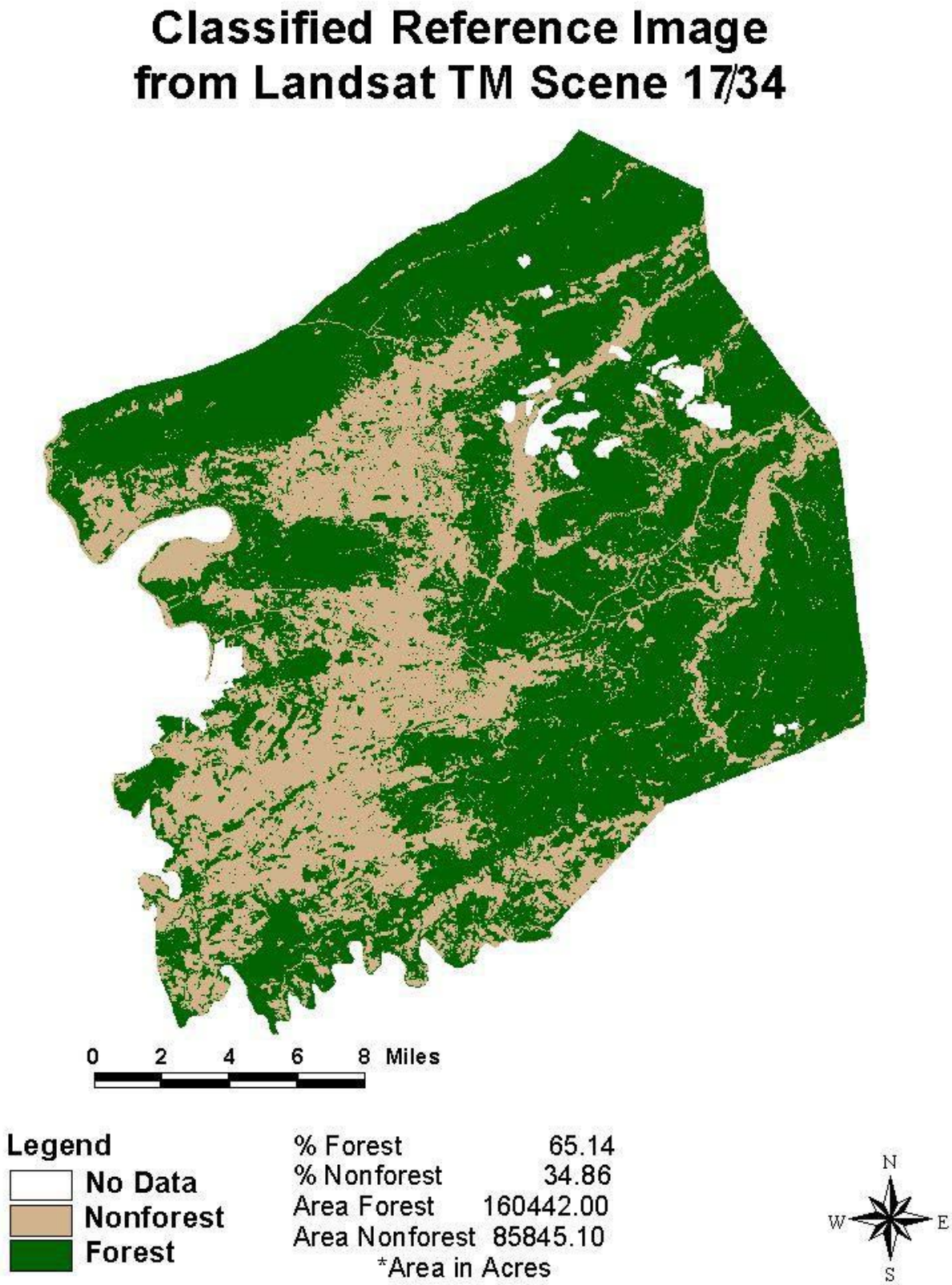

Figure 8 Clipped image of the originally classified Landsat TM scene 17/34.

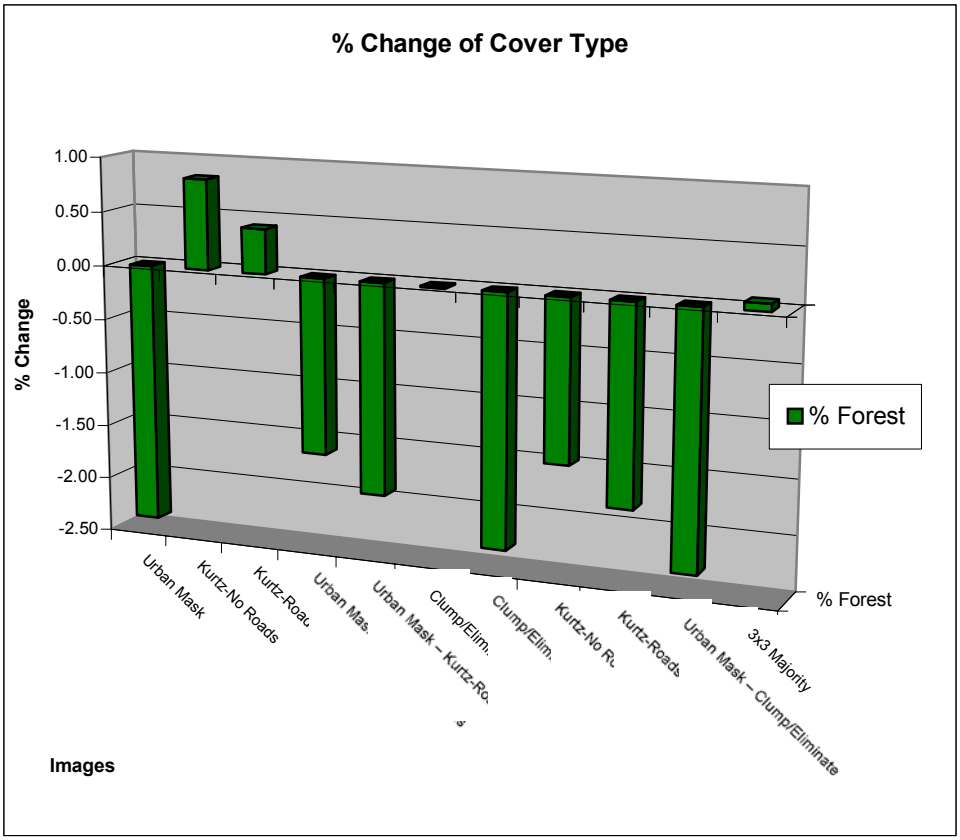

Figure 9 Percent Change of Forested area per image.

Why did the variations of the "Kurtzinator" script and the 3x3 Majority show net increases in forested area when compared to the Urban Mask? Population density was computed for the entire image, but once areas were eliminated based upon the population density threshold, the Urban Mask was only concerned with pixels within the masked area. On the other hand, the "Kurtzinator" script, Clump/Eliminate Method, and 3x3 Majority filter looked at pixel classification in the entire image. This explains the net increase in forested area for the variations of the "Kurtzinator" script and 3x3 Majority and the negligible loss of forest for the Clump/Eliminate Method. The "Kurtzinator", Clump/Eliminate, and to a degree the 3x3 Majority take into consideration the FIA definition of Nonforested area. Images were created using combinations of the Urban

Mask and the "Kurtzinator" script and Clump/Eliminate Method. Figures of the multiple techniques are located in *Appendix iv*.

4.2 Image Differencing

The results of the image differencing have had some interesting outcomes. They were analyzed in two areas. First, the area delineated as urban or populated by the Urban Mask was analyzed. A comparison of how each contiguity filter treated pixels in this area was to be established. Areas outside the Urban Mask (low populated or nonurban) area were analyzed and compared to the urban area.

First, the pixels that experienced a change in classification were analyzed. All four contiguity filters (3x3 Majority, Clump/Eliminate, Kurtzinator With Roads, and Kurtzinator Without Roads; Figures 10-13 respectively) had a significantly higher percentage change of Forest to Nonforest in the populated areas (those areas defined by the Urban Mask) than in the nonpopulated areas (those areas outside of the Urban Mask). The Clump/Eliminate had the highest amount of change, 85.41% of the total change in populated areas was Forest-to-Nonforest. The Kurtzinator with roads preserved had the second at 70.85%, the 3x3 Majority was third with 69.82%, and the Kurtzinator without roads preserved was fourth with 60.48%. These percentages are significant, in that they show the filters are doing a similar task to the Urban Mask, which reclassifies all the pixels in the specified area.

The nonurban or low populated areas had the opposite effect. In these areas Nonforest-to-Forest was the greater amount of overall change. The 3x3 Majority filter had the smallest amount of change with 54.61%, a net gain of 9.22% forest. The

Clump/Eliminate was the third with 56.51%, an overall net gain of 13.02% forest. Kurtzinator with roads preserved, had 63.13% Nonforest-to-Forest, an overall net gain of 26.26%. The Kurtzinator without roads preserved had the greatest amount of change of the four filters, with 69.25% of the overall change attributed to Nonforest-to-Forest, a net gain of 38.50%.

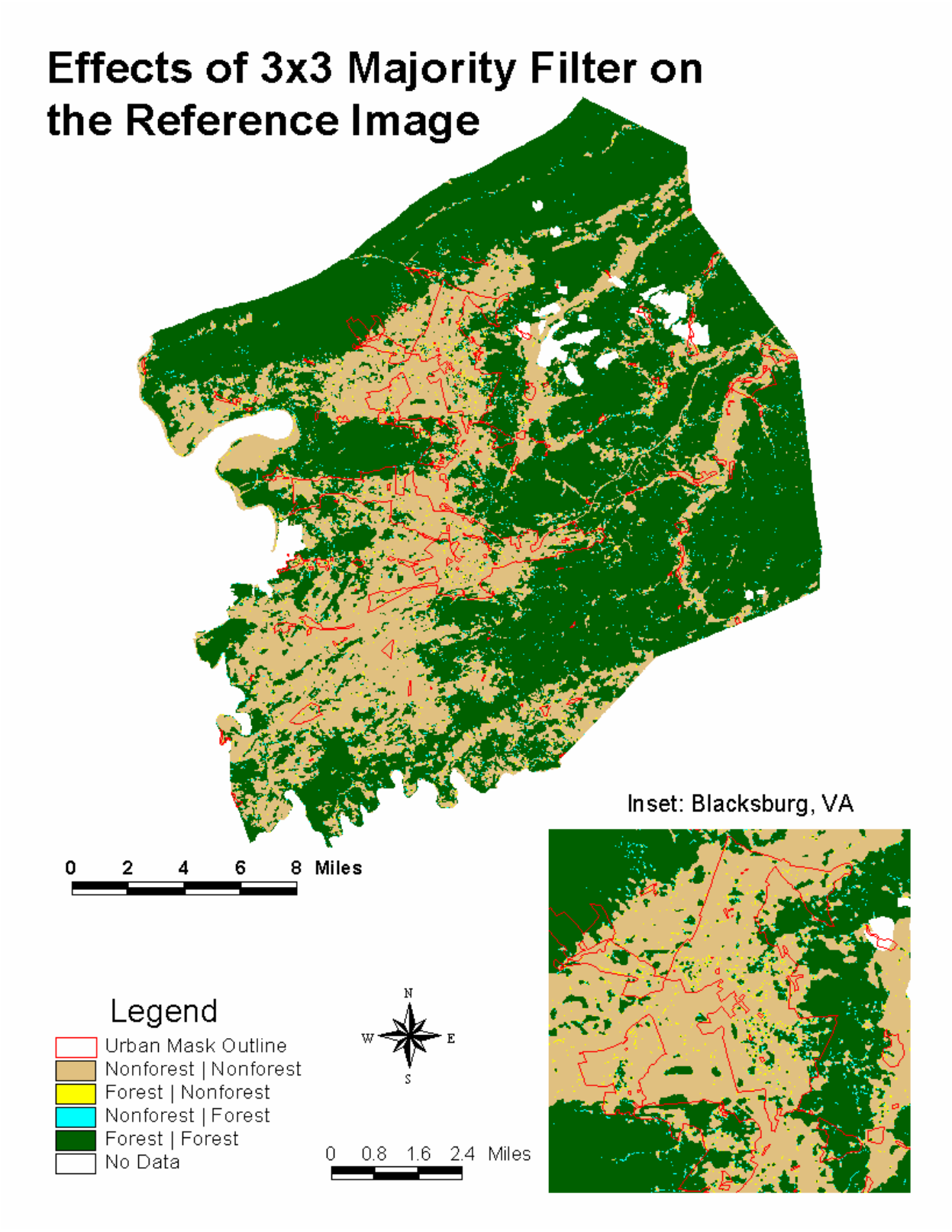

Figure 10 Effects of the 3x3 Majority Filter on the original IGSCR Classified Landsat TM Scene 17/34.

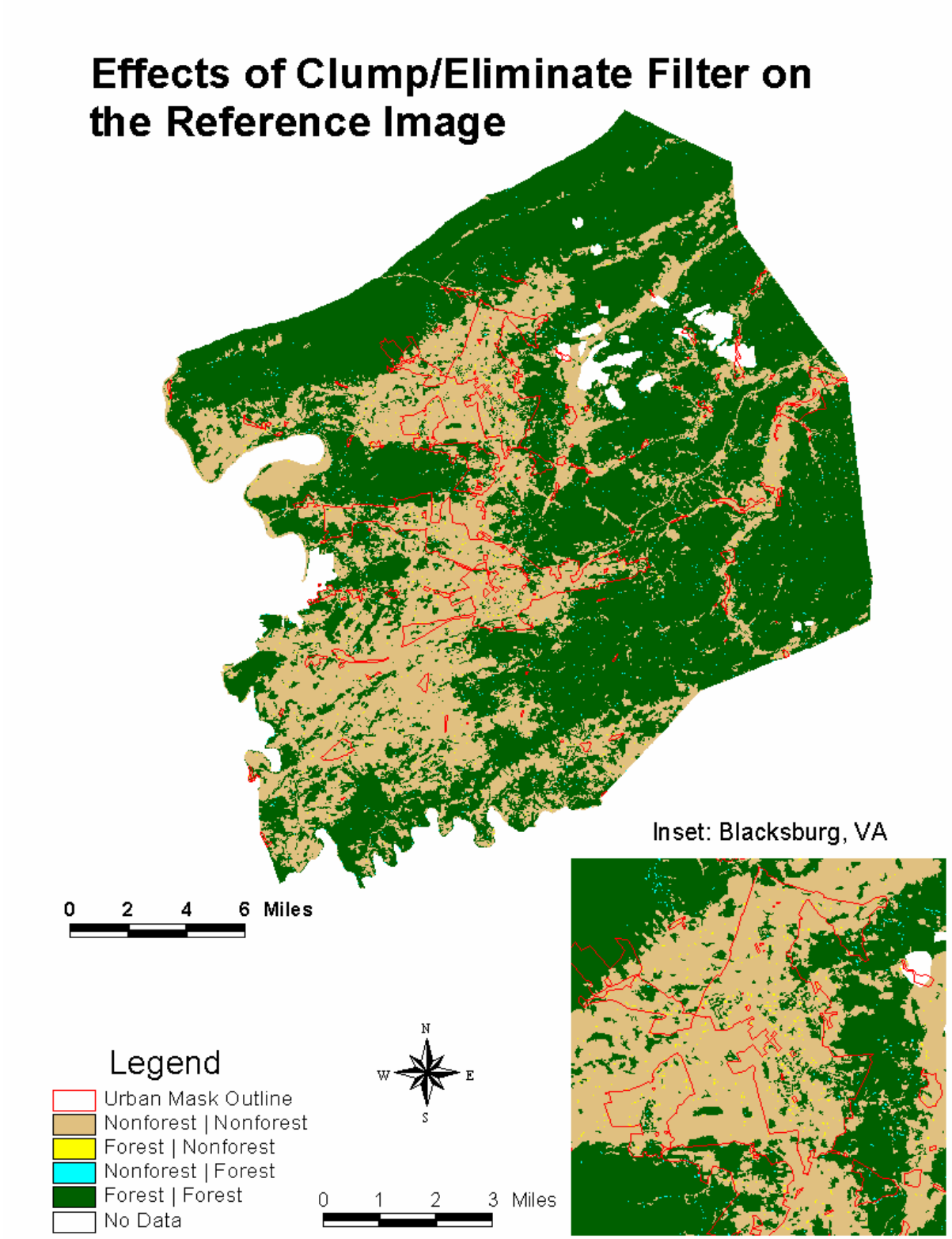

Figure 11 Effects of the Clump/Eliminate Filter on the original IGSCR Classified Landsat TM Scene 17/34.

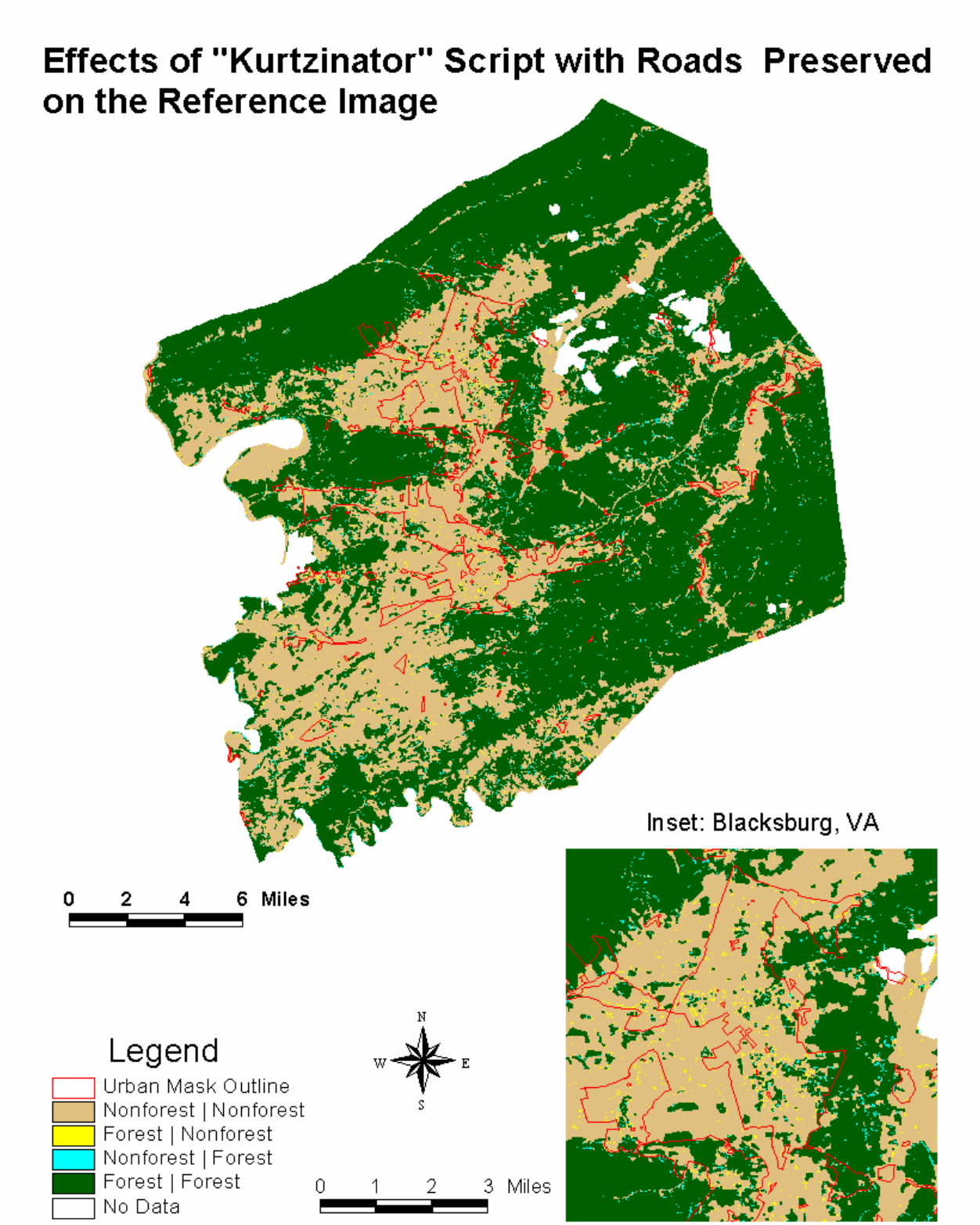

Figure 12 Effects of the "Kurtzinator" Script with Roads Preserved, on the original IGSCR Classified Landsat TM Scene 17/34.

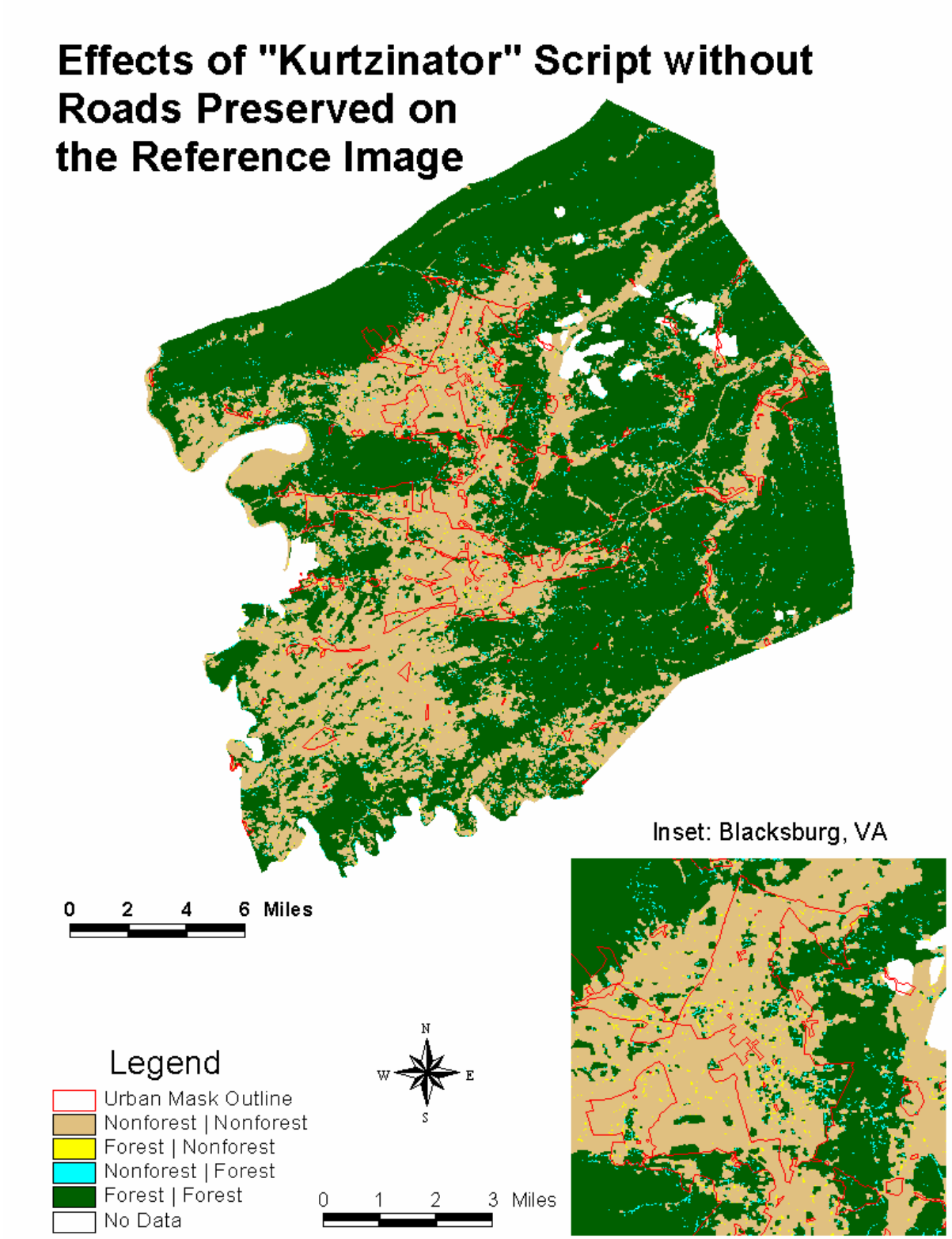

Figure 13 Effects of the "Kurtzinator" Script without Roads Preserved, on the original IGSCR Classified Landsat TM Scene 17/34.

When comparing the results of the filters to the same populated area defined by the Urban Mask, it was found that the amount of change attributed to the filters is much lower than that of the Urban Mask. In fact the percentage change attributed to each classification category was higher for Nonforest-to-Forest in all filters except the Clump/Eliminate (Table 3). However, the total area changed from Forest-to-Nonforest far out weighed that of Nonforest-to-Forest (Table 4).

Table 3 Percentage change attributed to each classification category.

Classification category	% change attributed to each category	Urban Mask	Kurtzinator w/out roads preserved	Kurtzinator w/roads preserved	Clump/Eliminate	3x3 Majority
Nonforest	Forest | Nonforest	27.21	3.95	4.37	1.78	5.39
Forest	Nonforest | Forest	NA	7.28	5.31	0.86	7.02

Table 4 Area in acres changed in each classification category.

Classification category	Area change of each category	Urban Mask	Kurtzinator w/out roads preserved	Kurtzinator w/roads preserved	Clump/Eliminate	3x3 Majority
Nonforest	Forest | Nonforest	5720.877	613.259	686.205	276.105	851.335
Forest	Nonforest | Forest	NA	400.759	282.277	47.148	368.067

The use of these filters had significant change in their respective areas, however the total amount of change for the entire image was not as drastic (Figure 9). Table 5 shows the total percentage change in forested area among the four filtering techniques. The total areas are almost unchanged. There was a less than 1% change in the total area. There was very little net loss or gain. The more important point is where the loss or gain occurred, as seen in the image differencing (Figures 10-13, and *Appendix v*).

Table 5 Total percentage increase in forested area for four filtering techniques.

Images	Kurtzinator w/out roads preserved	Kurtzinator w/roads preserved	Clump/Eliminate	3x3 Majority
% Change Forest	0.83	0.41	-0.01	0.07

4.2 Logistic Regression:

Logistic regression was used to determine if any of the four variables were significant in determining land use. The four variables tested in the logistic regression were: (1) land value/10m^2 [Tax Value] (2) Street Density (3) Population/mi^2 [Population Density] and (4) the IGSCR classified reference image. The full report of each variable and combination of variables are listed in *Appendix vi*. I was primarily concerned with the R-Squared and the Classification Table. The R-Squared is the percent of variation explained by the model. A model could contain an individual variable or a combination of variables. Table 6 shows each logistic regression model and its accompanying R-Squared Value. The highest reported R-square was 0.546398 by model **13**. This model contained all four variables. All models that had an R-Square of 0.50 and greater contained the IGSCR classified variable. In fact the IGSCR classified variable alone had an R-Square of 0.517033. The next highest model that did not contain this variable was model **7**, containing the variables Population Density, Road Density, and Tax Value; with an R-Square of 0.193781. The numbers show that the additional data layers can only explain 19% of the variation in the model.

Table 6 Logistic Regression model and R-Squared of each.

Model	Variables	R-Squared
1	Road Density	0.093134
2	Population Density	0.113166
3	Tax Parcel Value	0.130647
4	Population Density Road Density	0.153342
5	Road Density Tax Value	0.166927
6	Population Density Tax Value	0.168198
7	Population Density Road Density Tax Value	0.193781
8	IGSCR Classified Value	0.517033
9	Road Density IGSCR Classification Value	0.523265
10	Tax Value IGSCR Classification Value	0.528689
11	Population Density IGSCR Classification Value	0.531042
12	Road Density Tax Value IGSCR Classification Value	0.537571
13	Population Density Road Density Tax Value IGSCR Classification Value	0.546398

Within the output reports of NCSS for logistic regression, were classification tables of Actual vs. Predicted. These tables were useful indicators in seeing which variables were possible predictors of Forest and Nonforest. Of the three additional data layers, land value/Tax Parcel data proved to be the best predictor of Forested area; classifying 49 of 52 pixels correctly. Population Density was the second with 47 of 52 correctly classified pixels. Combinations of the variables did not prove to be as high as the individual variables themselves. None of the three variables were good predictors of Nonforest area. Road density had the highest number of pixels classified, 24 of 46. The

only other combination of the three that was close was the combination of Road Density and Population Density also classifying 24 of 46. These numbers proved to be too low to be considered good predictors.

Because of the low R-Squared values, and the similarities in classification tables in the NCSS reports; further research was conducted. Correlation matrices of the four variables were calculated to see if any correlation existed between the variables (Table 7).

Table 7 Correlation Matrices of the four variables used in the logistic regression using Pearson and Sperman Correlation Coefficients

Pearson Correlations Section (Pair-Wise Deletion)

	Population	Road	Tax Value	IGSCR Classification
Population Density	1.000000	0.457856	0.325337	-0.191414
Road Density	0.457856	1.000000	0.425934	-0.291031
Tax Value	0.325337	0.425934	1.000000	-0.221385
IGSCR Classification	-0.191414	-0.291031	-0.221385	1.000000

Cronbachs Alpha = 0.317591 Standardized Cronbachs Alpha = 0.268922

Spearman Correlations Section (Pair-Wise Deletion)

	Population	Road	Tax Value	IGSCR Classification
Population Density	1.000000	0.212427	0.322926	-0.204512
Road Density	0.212427	1.000000	0.235393	-0.262953
Tax Value	0.322926	0.235393	1.000000	-0.275656
IGSCR Classification	-0.204512	-0.262953	-0.275656	1.000000

The Pearson matrix revealed low to moderate correlation between the variables. Road Density and Population Density had the highest correlation, with a coefficient of 0.457856. Taking outlyers into account, the Spearman Correlation, revealed an even greater reduction in correlation between the variables showing the variables are not explaining the same variance reported in the R-Squared values.

4.4 Accuracy Assessments

Each accuracy assessment produced an error matrix with Producer's Accuracy, User's accuracy, Overall Accuracy, and Kappa. From this matrix the variance of Kappa was calculated and used to obtain a Z-Score comparison between each image and the reference image. Table 8 is an example of the error matrix for the reference image. Error matrices for the other images are found in *Appendix vi*. The VDoF, ArcView script uses a pixel-to-pixel comparison to generate the accuracy assessment. There was very little change in overall accuracy for all of the images created by the post-classification techniques. The largest reported drop was only 1.0204% and the largest gain was 1.0204%. Table 9 details each image's overall accuracy and its difference from the reference image. Images that had an increased accuracy used only the Clump/Eliminate method or the "Kurtzinator" script. The 3x3 Majority also resulted in an increase in overall accuracy. Any combination of techniques that used the Urban Mask had a decrease in overall accuracy, but as noted earlier the decrease was minimal, only 1.0204%.

Table 8 Error Matrix for IGSCR Classification of Landsat TM Scene 17/34 of Montgomery County, VA. Class 1 equals Nonforest and Class 2 equals Forest.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	43	1	44		97.7273
Class2	3	51	54		94.4444
Col Tot	46	52	98	*I*	
Producers acc	93.4783	98.0769			
Overall Acc	95.9184				
Kappa	0.917854				
T =	0.959183673				
U =	0.503123698				
V =	0.965847564				
W =	1.030841741				
Var of Kappa	0.001882329				

Table 9 Reported Overall Accuracy and % difference from classified reference image.

Alpha	Image	Overall Accuracy %	% Change
	IGSCR	95.9184	NA
1	Kurtz-No Roads – Urban Mask	94.8980	-1.0204
2	Kurtz-Roads – Urban Mask	94.8980	-1.0204
3	Urban Mask	94.8980	-1.0204
4	Clump/Eliminate	96.9388	1.0204
5	Clump/Eliminate – Urban Mask	94.8980	-1.0204
6	Urban Mask – Clump/Eliminate	94.8980	-1.0204
7	Urban Mask – Kurtz-No Roads	94.8980	-1.0204
8	Urban Mask – Kurtz-Roads	94.8980	-1.0204
9	Kurtz-No Roads	96.9388	1.0204
10	Kurtz-Roads	96.9388	1.0204
11	3x3 Majority	96.9388	1.0204

The overall accuracies proved to be quite high. To determine if the differences between the classifications were significant, Kappa and its variance were used to calculate Z-Scores. Significance at the 95% confidence level was obtained by comparing the calculated Z-Score to the equivalent value of 1.96 (from the normal (Gaussian) tables). Table 10 is a listing of each image, its Kappa value, Kappa Variance, and Z-

Score comparison to the originally classified image. It was determined that the classification accuracy results were not significantly different for all the images. None of the outputs from the combinations of post-classification techniques showed Z-Scores greater than 1.96.

Table 10 A listing of each image's Kappa value, Kappa Variance, and Z Score comparison to the originally classified image.

Alpha	Image	Kappa	Kappa Variance	Z score: Compared against Reference Image
	IGSCR	0.917854	0.001882329	NA
1	Kurtz-No Roads – Urban Mask	0.897704	0.002382863	0.30853592
2	Kurtz-Roads – Urban Mask	0.897704	0.002382863	0.30853592
3	Urban Mask	0.897959	0.002356592	0.30557393
4	Clump/Eliminate	0.938468	0.001373060	-0.36129405
5	Clump/Eliminate – Urban Mask	0.897959	0.002356592	0.30557393
6	Urban Mask – Clump/Eliminate	0.897959	0.002356592	0.30557393
7	Urban Mask – Kurtz-No Roads	0.897704	0.002382863	0.30853592
8	Urban Mask – Kurtz-Roads	0.897704	0.002382863	0.30853592
9	Kurtz-No Roads	0.938313	0.001378730	-0.35826559
10	Kurtz-Roads	0.938313	0.001378730	-0.35826559
11	3x3 Majority	0.938313	0.001378730	-0.35826559

Chapter 5: Discussion

The post-classification techniques were implemented to improve the precision of forest estimates in a remotely sensed image, beyond that of the initial spectral classification. IGSCR classification provides one with a land-cover image. It was believed that using multiple combinations of post-classification techniques would derive a land-use image. Some of these post-classification techniques used ancillary data in the form of an Urban Mask to reclassify pixels, while others reclassified pixels based solely on FIA parameters.

5.1 Urban Mask and Contiguity Filters

The addition of the Urban Mask lowered the amount of forested area, while still keeping a high overall accuracy. The Mask decreased the amount of forested area by almost 2.5%. The use of the Urban Mask statistically, showed no significant difference from the initially classified image (Refer to Table 10), and this reduction was solely within the masked area. This post-classification technique did not take into account nonforested areas within forested tracks. Applying the "Kurtzinator" script or the Clump/Eliminate method either before or after the application of the Urban Mask took nonforested areas in forested tracts into account, so the amount of overall forested area was still reduced, but at a lower amount. The order of application made a slight difference. Applying the Urban Mask before either the "Kurtzinator" or the Clump/Eliminate method reduced the amount of forested area by a greater amount than applying it after either of the filters. The change is attributed to the effects around the edges of the Urban Mask where the combination of pixels has changed within the filter

windows causing a change in pixel classification. Figure 14, shows the effects order has on the periphery of the Urban Mask. Figure 14a is a group of 22 pixels, classified as forest. Applying the Urban Mask causes the pixels contained in the Mask (those to the left of the red line), to be reclassed to nonforest (Figure 14b). When either the "Kurtzinator" or Clump/Eliminate method is then applied too few pixels remain in the new group (those to the right of the red line) to be considered a forested area anymore, and the pixels are reclassed to nonforest (Figure 14c).

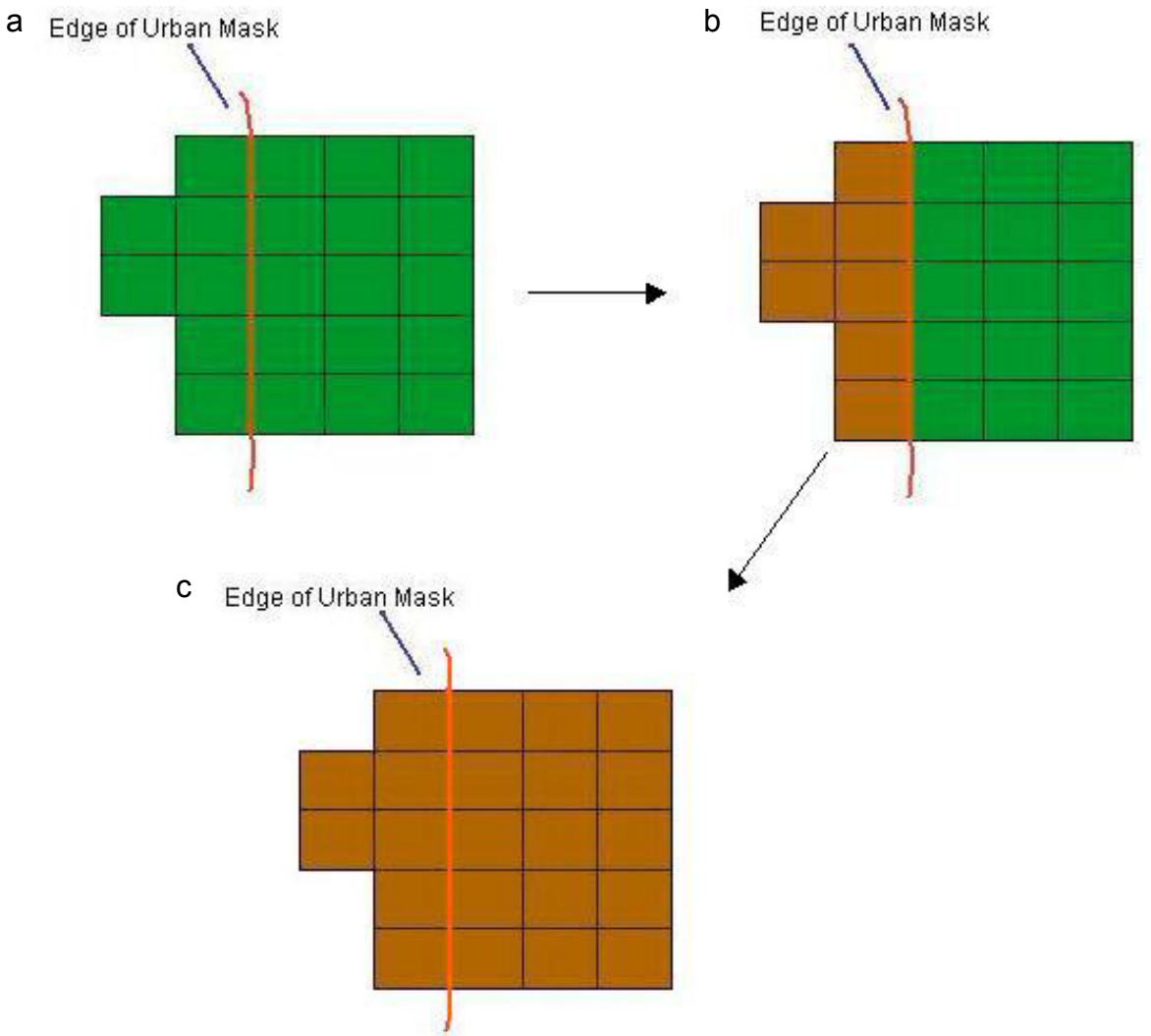

Figure 14: Effects of order at Mask edge. Urban Mask applied then Contiguity filter.

If the "Kurtzinator" or Clump/Eliminate method is applied prior to the Urban Mask, the result is different. Since there are enough pixels in the group the area remains forested (Figure 15b). When the mask is applied to the area, only pixels inside the masked are reclassed to nonforest. The pixels to the right remain forested, even if there are not enough to meet the minimum one-acre size (Figure 15c). Applying the Urban Mask, first insures the area parameter of the FIA definition for size is met.

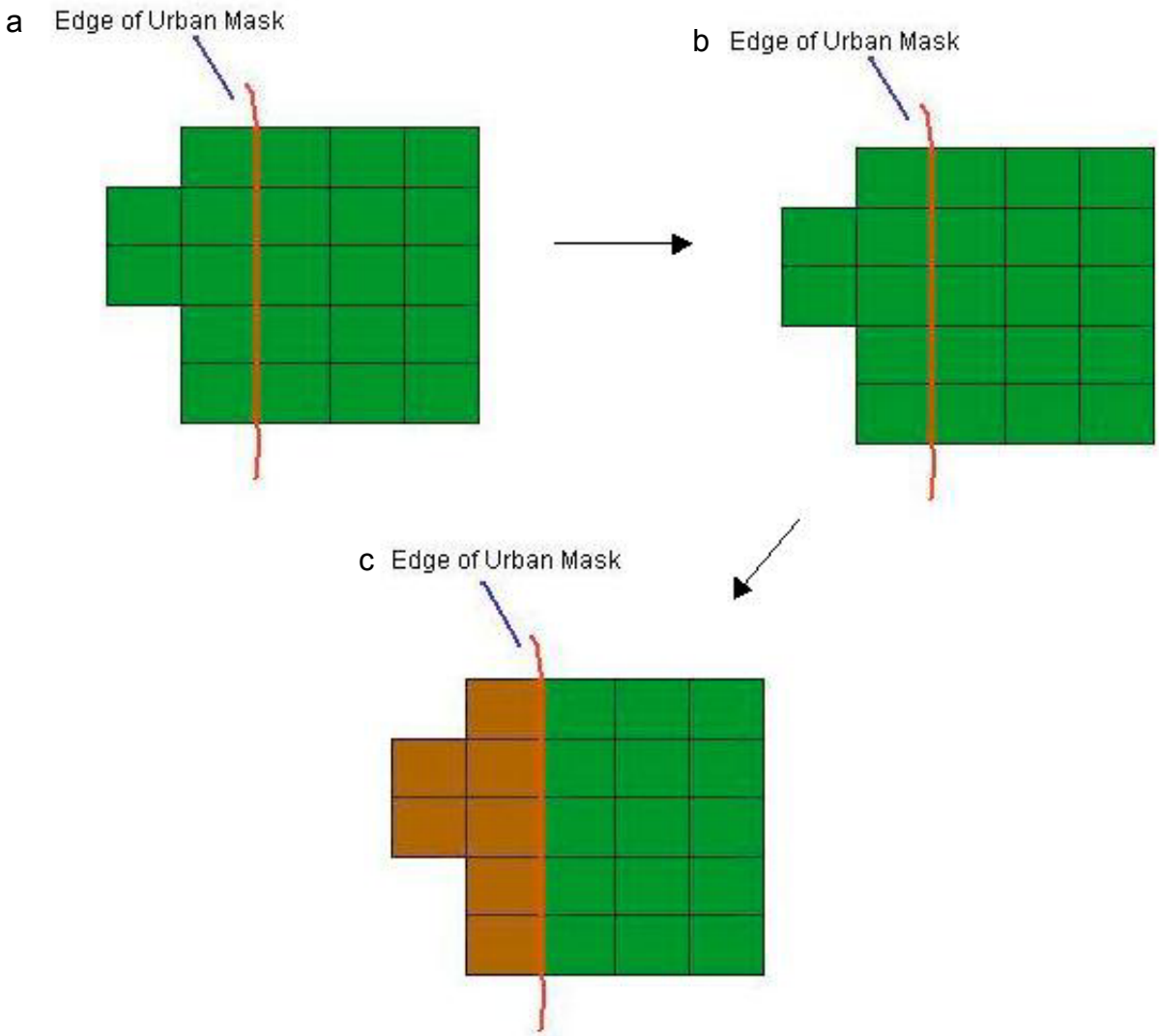

Figure 15: Effects of order at Mask edge. Contiguity filter applied then Urban Mask.

Looking at the four contiguity filtering techniques and how each one did in the populated vs. nonpopulated areas, to compare against the Urban Mask; it was found that in the populated areas all of the filters had a net loss of forested area and a gain in nonforested area, even though some pixels did change from nonforest to forest. Outside of the populated areas there was a net increase in forested area with a decrease in nonforested. This is significant in that the filters are doing a similar job to the Urban Mask filter, which reclassifies 100% of the forested areas in the populated areas to nonforest.

5.2 Map Accuracy

The post-classification techniques all performed properly without significant statistical difference in the classification accuracies. The Clump/Eliminate method, the two variations of the "Kurtzinator" script, and the 3x3 Majority had the highest overall accuracies, and the highest Kappa values. Finding no significant difference in the Z-Scores of the images, the Accuracy Assessments were all viable. Map accuracy does not suffer with the addition of ancillary data and contiguity filters. Figure 16 shows how much the amount of forested area can change within an image without statistical degradation to an image's overall accuracy.

It was conjectured that the location and number of validation points in the study did not provide a precise enough classification of forest. The VDoF, using the FIA points, with the selected error removed, carried out an independent validation on all of the images. The error matrices that the additional validation produced were combined with those produced from the field collected validation points. This increased the total number of validation points to 169. New Kappa, Kappa Variance, Overall Accuracy, and

Z-Scores were calculated (Table 11). Error matrices for the combination of validation points are found in *Appendix viii*.

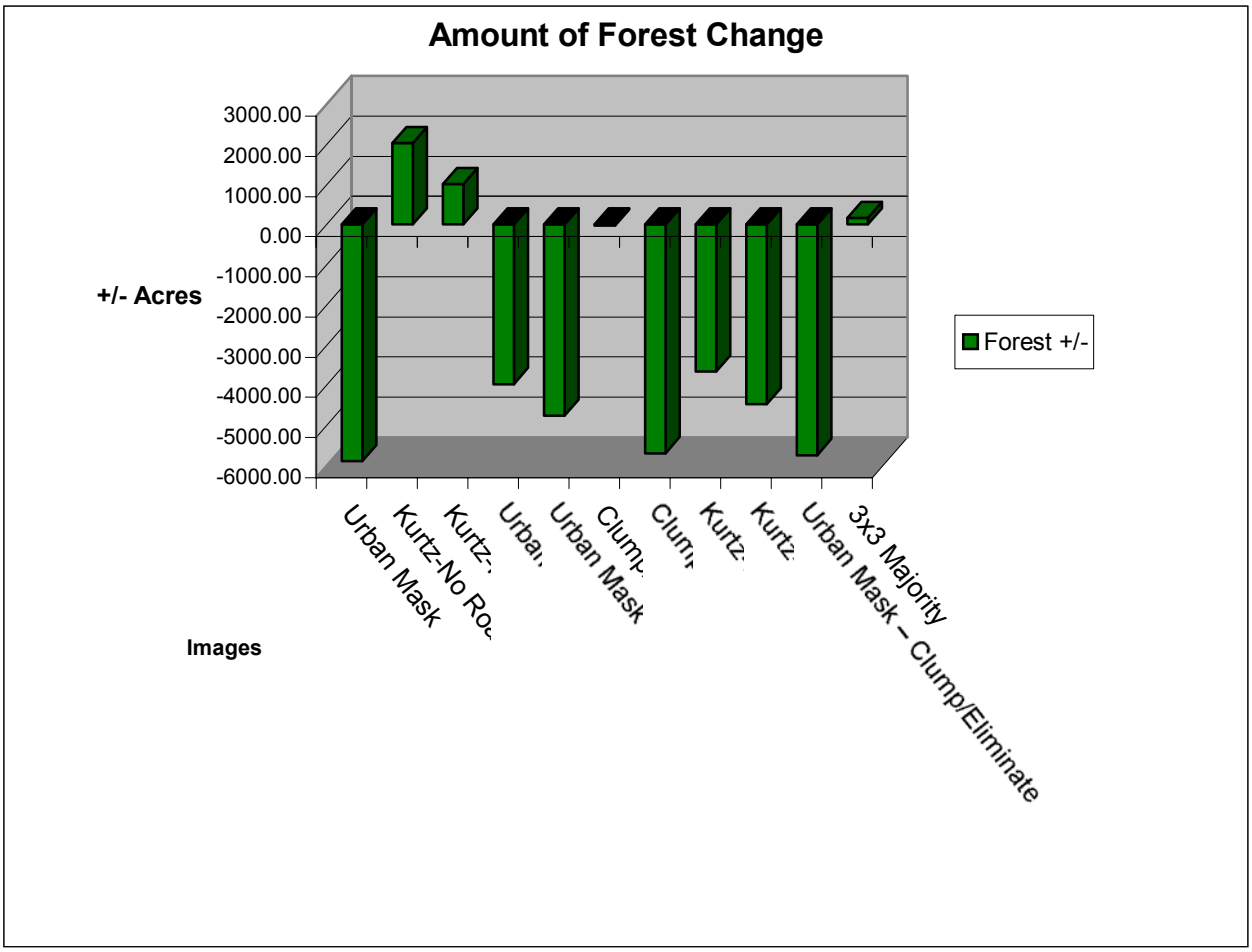

Figure 16 Amount of Forest change in acres for each classification technique.

The addition of the FIA validation points made no significant difference in overall accuracy. The initial classification accuracy dropped by less than 1%. All classification techniques experienced a slight drop in overall accuracy, with the 3x3 Majority filter having the highest overall accuracy with 95.2663. However, there was slight improvement in all Z-Score values. This was considered inconsequential though, because they all were still well below 1.96. There was still no significant difference at the 95% confidence interval with the addition of more validation points.

Table 11 Overall Accuracy statistics from the combination of Field Collected and FIA validation points.

Alpha	Image	Overall %	Kappa	Kappa Variance	Z-Score
	IGSCR	94.0828	0.8782	0.001716948	NA
1	Kurtz-No Roads – Urban Mask	92.8994	0.8539	0.002110413	0.3927865
2	Kurtz-Roads – Urban Mask	93.4911	0.8663	0.001905898	0.1977070
3	Urban Mask	93.4911	0.8671	0.001877806	0.1851349
4	Clump/Eliminate	94.6746	0.8906	0.001521246	-0.2179070
5	Clump/Eliminate – Urban Mask	93.4911	0.8671	0.001877806	0.1851349
6	Urban Mask – Clump/Eliminate	93.4911	0.8671	0.001877806	0.1851349
7	Urban Mask – Kurtz-No Roads	92.8994	0.8539	0.002110413	0.3927865
8	Urban Mask – Kurtz-Roads	92.8994	0.8539	0.002110413	0.3927865
9	Kurtz-No Roads	94.0828	0.8774	0.001733922	0.0136184
10	Kurtz-Roads	94.6746	0.8899	0.001537108	-0.2051040
11	3x3 Majority	95.2663	0.9023	0.001345106	-0.4355225

The map accuracy for the initial classification (IGSCR) was quite high. The type and location of validation points play an important role in map accuracy. The high overall accuracy seen in this study is attributed to these two factors. First, the collection of field validation points was not random enough. This is attributed to the private property issue. Validation points that could be GPS'ed, were limited to public lands or to private lands in which permission was gained. All other points were limited by visibility. Points could only be added through visual verification, limiting points close to roadsides. The second factor is location. More points were needed in areas where land-cover (satellite) and land-use (human) are not one and the same. Very few validation points were in these areas of where pixel flips occurred. The addition of the FIA field points alleviated this problem slightly, but not enough to offset the affects of the field collected validation points. More points in human impacted areas were needed for the study.

The 3x3 Majority had the highest overall map accuracy. Wayman et al (2001), explains the performance of the 3x3 majority in two ways. First, is a single pixel

classified as forest in a Landsat TM scene (0.22239 acres) is less than the minimum mapping unit of 1 acre for FIA parameters. The minimum mapping unit of the image is increased to almost 2 ¼ acres by the 3x3 majority filter. The FIA mapping unit is contained within the filter itself, and all is needed is a majority within the kernel for the classification. The second explanation given is that there is a "higher likelihood in a 3x3 majority-filtered image that if a point on the ground is forest, then the neighboring pixels will be forest", increasing the likelihood of classifying the pixel correctly (Wayman et al 2001 p.1161).

5.3 Logistic Regression

The other two layers of ancillary data used in addition to population density were land value (Tax Parcel data), and street density. Documented use of these two variables in delineating Urban and Nonurban areas did not exist as it did with the census data. Conventional threshold values were not available. Logistic Regression was used to find out if there were certain threshold values that could be used to predict Forest/Nonforest classes. The models developed did not have the desired affect. At most only 19% of the variance could be explained even with use of all three data layers. The models showed that the additional data layers were not good of predictors of Forest/Nonforest. Since the outputs of the logistic regression proved not to be a factor in Forest/Nonforest pixel determination there was no need to apply the classification models to the reference image.

Chapter 6: Conclusion and Recommendations

Wayman et al (2001) reported having correctly classified 83-89% Forest Land using satellite imagery, while the traditional photo-interpretation method classified 92-97%. In the current study, correctly classified Forest Land reached above 95%. With such a high initial classification it was difficult to make any marked improvements. It was believed having a greater number of validation points would improve the precision of forest classification in the initially classified image. This improvement in precision would lower the overall map accuracy of the initially classified image, allowing for a greater difference to be seen when ancillary data and post-classification techniques were applied. Additional validation points did not have the desired outcome. The addition of the FIA points increased the number of validation points from 98 to 169. Even with these additional points there was no significant difference in Z-scores at the 95% confidence interval. The effort to improve quantitative differences with the addition of more validation points failed.

The initial IGSCR classification proved to do very well. The use of the 3x3 Majority filter had similar increases in overall accuracy as seen in the Wayman et al (2001) study. It had the highest overall accuracy when the combination of field collected and FIA validation points were used. When using just the field collected validation points, all three contiguity filters; both variations of the "Kurtzinator", Clump/Eliminate, and 3x3 Majority, had identical overall accuracies.

The location of the validation points played a role in the very high accuracy of the initial classification. Because of limited access to private land, many validation points were along roadways. Only points that could be visually verified were used. This visual

verification limited point collection to what could be seen from the roadway. Along with visual verification of points, more points in areas of the Urban Fringe should have been collected. It is in these areas where the land-cover (satellite) and land-use (human) differ, making them more difficult to classify. More points in these areas would have had a better precision in the initially classified image.

An important finding in the study was the behavior of the contiguity filters. The Clump/Eliminate, both variations of the "Kurtzinator", and the 3x3 Majority all had higher amounts of change from Forest to Nonforest in populated areas. These filters were moving in the same direction as the Urban Mask, albeit at smaller amounts, clarifying areas of confusion and producing a land-use map. This movement explains why there was little variation in the accuracies assessments of the filtered images and that of the Urban Mask.

The addition of the Urban Mask statistically does not reduce accuracy levels in the image classification. However, it is too wide ranging in its reclassification, due to its scale. The smallest unit of measurement for the census data is still too coarse. This is evident in Figure 17.

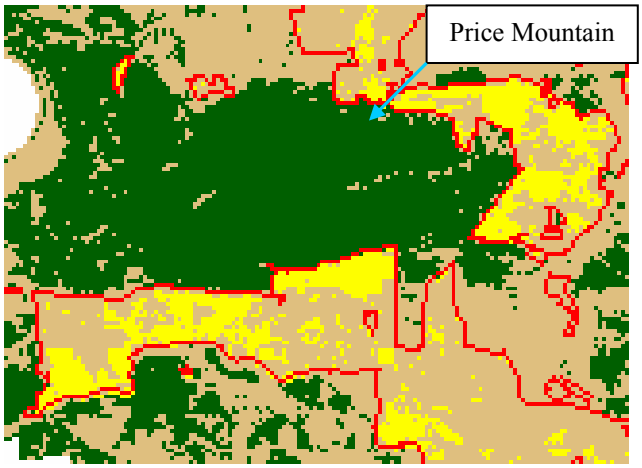

Figure 17: Zoomed area around Price Mountain, south west of Blacksburg, VA.

Large tracts of forested land around the mountain that are in census blocks that make up the Urban Mask are reclassed to nonforest. This is inaccurate based upon priori knowledge of the area. Unfortunately,

until US census data is available at a smaller unit of measure examples like this will be a continuing problem. Further research needs to be conducted on applying the Mask in a more selective manner. Perhaps a technique can be created that applies the Urban Mask to an area, after a shape-area-adjacency filter has gone through. The Mask would only target forested groups that did not meet the one-acre, 120 foot minimum set by the FIA parameters.

Statistically it is inconclusive which contiguity filter performed best with the Urban Mask. The "Kurtzinator" filter more readily follows the FIA definitions, because of its orthogonal kernel shape, compared to the Clump/Eliminate method and the 3x3 Majority. Time does play a factor with the "Kurtzinator" filter. The larger the study area the exponentially longer it takes to run the script. However, there are fewer steps in the process compared to the Clump/Eliminate method, causing less potential for human error. The 3x3 Majority is the quickest and easiest of all the contiguity filters.

There was no statistical degradation in map accuracy using the Urban Mask or any combination of contiguity filters. All decreased the amount of forested area by the overestimated percentage reported by Wayman et al (2001). However, overall map accuracy did not improve with the addition of the Urban Mask, and from the above example proved to be too coarse in it's reclassing.

The recommended post-classification techniques would be the "Kurtzinator" with roads preserved, the Clump/Eliminate method, or the 3x3 Majority. Overall accuracies were the same for all three using field collected validation points. The 3x3 majority showed a slight improvement with the addition of the FIA validation points. Because, of the concerns with the field collected validation points, a definitive method between the

three cannot be chosen. It should be noted that the current post-classification techniques in use today are the Shape-Area-Adjacency ("Kurtzinator") by the VdoF, and the Clump/Eliminate method by the Minnesota Forestry Department (Wynne 2002).

Multiple recommendations can be made with the completion of this study. First, would be to compare the post-classification techniques against the aerial-photography-derived FIA Phase I forest estimates. This might be a better validation of land-use vs. land-cover.

Second would be to perform the study on a broader scale. The County level is too small. More would be gained looking at a multi-county subset with FIA plot locations as validation points.

Third would be to further research the selective use of the urban mask with the combination of contiguity filters.

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Appendix i: Validation Points

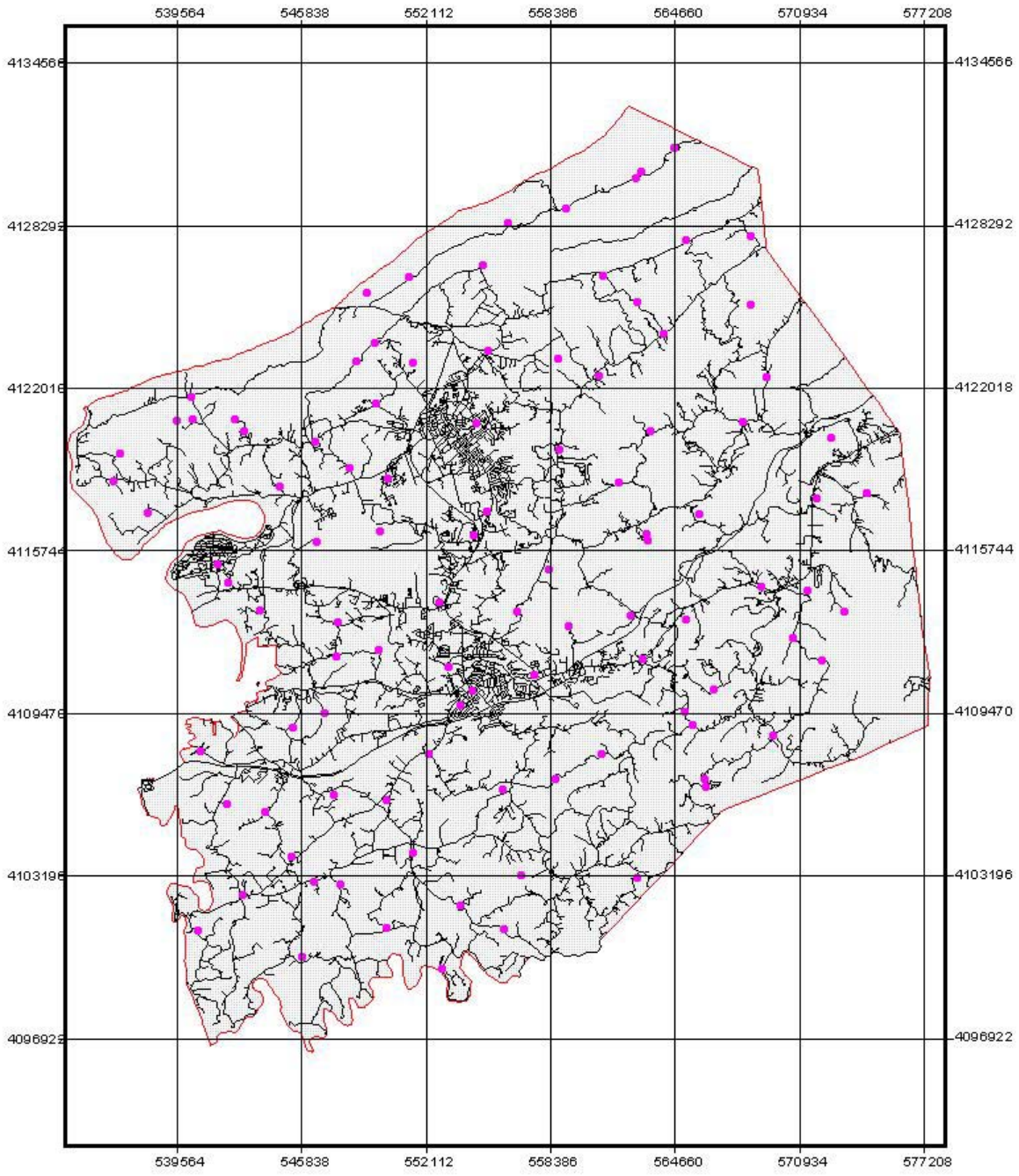

Figure 18: Grid of field collected validation points. Points were collected randomly within each grid cell, limited by access to private land.

Table 12 Field collected validation points: Easting and Northing coordinates are in Nad83 UTM Zone 17N; Value 1 = Nonforest, 2 = Forest**.**

Easting	Northing	Value		Easting	Northing	Value
563372.4171	4109364.781	2		556415.7982	4120215.617	1
560135.4544	4110722.893	1		558327.052	4106446.559	2
562040.3908	4108347.824	2		559594.0874	4112701.81	2
562963.5366	4105272.173	2		556822.1328	4112219.148	2
563014.6079	4104945.291	1		541352.9753	4104177.396	2
552487.4861	4116347.034	1		542073.0551	4100016.518	1
560067.4041	4132791.002	2		545776.5502	4108302.55	1
556669.7027	4131128.247	2		544353.078	4107630.11	2
549608.3866	4128045.973	2		548225.8745	4111136.199	1
548039.3508	4125072.558	2		546316.2742	4110847.879	2
547215.3817	4124205.388	2		546350.6195	4112399.681	1
547670.324	4127292.533	1		540153.6559	4106538.593	1
559875.6685	4132476.201	1		541435.3268	4114177.535	2
552651.9514	4121435.788	1		568297.1629	4110641.099	2
537783.5819	4117357.828	1		542877.8168	4112939.763	1
551397.7747	4110396.144	2		540966.1269	4115051.247	1
553124.0161	4117432.467	2		545436.78	4116032.598	2
568050.2194	4117978.37	1		536536.2621	4120051.229	2
565761.9033	4123480.628	1		536234.588	4118811.482	1
565766.6096	4123525.658	2		539744.0552	4122627.618	1
560392.6313	4116103.882	2		539062.0117	4121497.096	2
560307.3109	4116371.452	1		541711.2082	4121599.207	2
539819.0398	4121602.257	2		543714.6668	4118568.818	1
542123.6773	4121059.977	2		561560.2859	4133901.789	2
549769.2602	4124127.223	2		553176.7582	4124677.197	1
552428.2525	4109315.728	1		552909.5125	4128562.19	2
560517.7587	4121039.435	2		548122.9846	4122324.92	1
559901.076	4126917.794	2		545343.3962	4120543.637	1
556322.2287	4124302.614	1		546910.1859	4119358.675	1
559105.4336	4118718.125	1		550982.696	4113309.018	1
565067.4922	4129894.074	1		555264.8992	4109984.003	1
558181.1247	4123556.562	1		562409.2712	4107764.094	2
565020.7589	4126756.764	2		566078.7232	4107271.782	1
566970.4933	4111701.849	2		556204.2874	4105321.183	2
567584.4986	4113858.127	1		558388.5865	4128093.106	2
570319.1058	4118230.256	2		561107.8229	4125467.545	1
564685.5859	4121467.187	1		562137.1165	4129702.466	1
562702.8373	4117305.919	2		554507.5468	4112868.169	2
568675.8401	4120733.631	2		555911.6716	4114757.268	2
551111.7021	4096689.028	2		554061.721	4130500.435	2
548584.7049	4098550.73	1		548640.0492	4118912.246	1
546516.2477	4100546.416	2		569301.2572	4112858.706	2
545303.399	4100666.772	1		543093.4493	4103808.759	1
540029.8697	4098405.595	1		544307.4519	4101766.487	2

Easting	Northing	Value
544759.4726	4097237.206	2
548547.7376	4104326.163	1
553802.9383	4104808.062	2
554691.4854	4100917.488	2
551915.3237	4099596.312	2
553874.7531	4098476.724	2
559891.4688	4100792.633	1

Easting	Northing	Value
546164.6223	4104554.082	2
549794.3607	4101979.035	1
550492.0151	4106423.443	2
551907.2122	4108663.557	1
548282.1059	4116532.547	2
562148.1962	4112487.973	1
565539.8128	4113993.424	1

Appendix ii: **ERDAS Models**

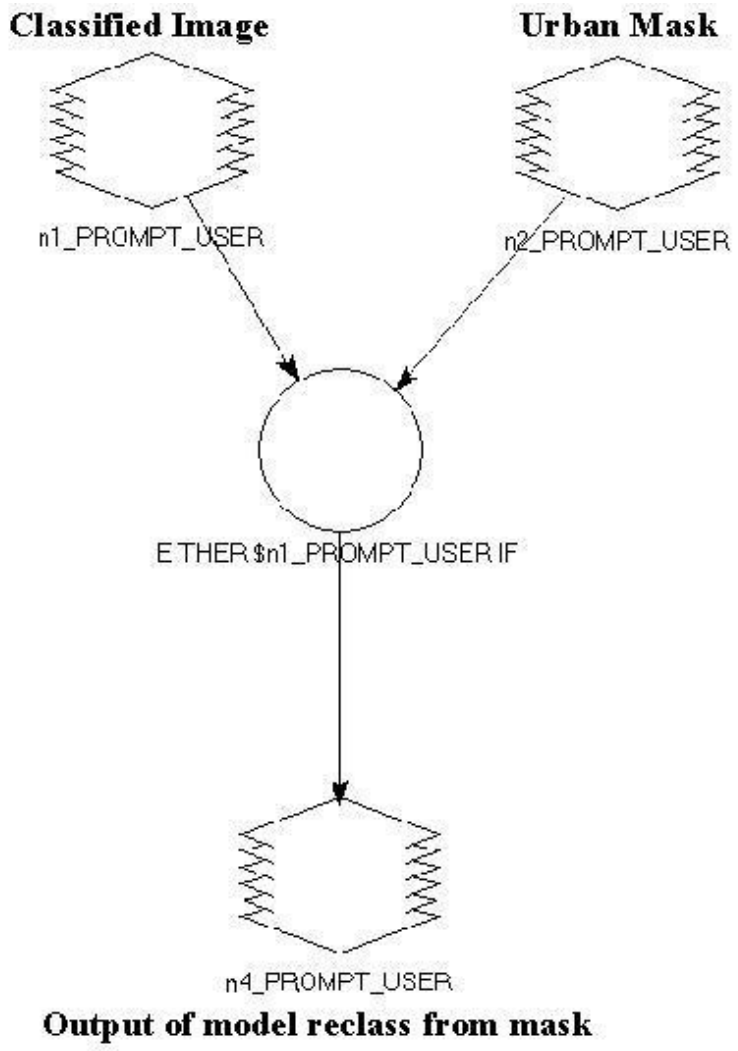

Figure 19 Model to combine Urban Mask image and IGSCR classified image

The above model combines the classified IGSCR image and Urban Mask image. The function reads in the IGSCR image, if the Mask image equals value 0 then it leaves the IGSCR image, however if the masked image equals 1 the function changes the value in the IGSCR to 1. The result is an image with the area of the mask classified as 1 (nonforest) and the rest of the image left alone.

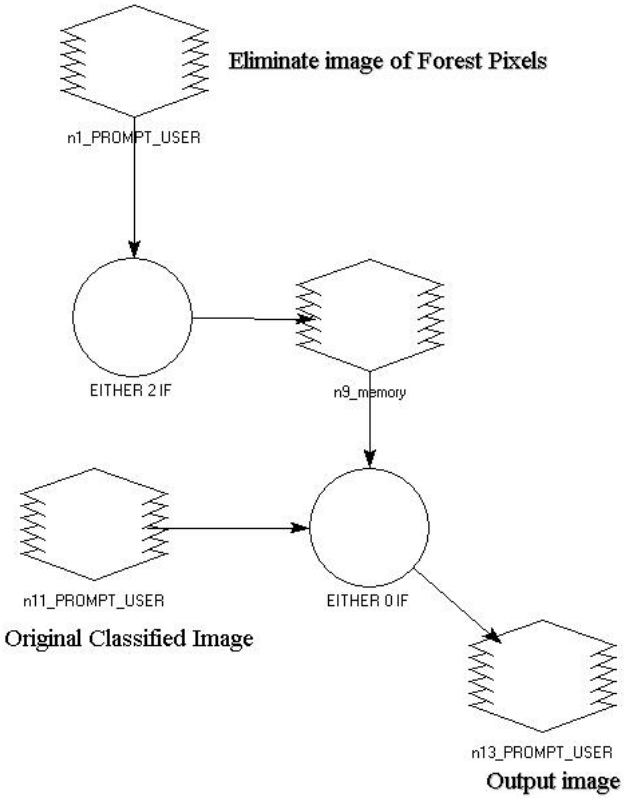

Figure 20: Model to decipher between background values of 0 and eliminated forest areas of 0.

The model above is used to reset background values back to 0. The first function recodes all values not equaling 2 to a value of 1 and writes this information to a temporary image. Second, it uses the original classified image, to recode background values back to 0. If a value equals 0 in the original classified image then the value in the temp image equals 0, otherwise the value in the temp image is kept.

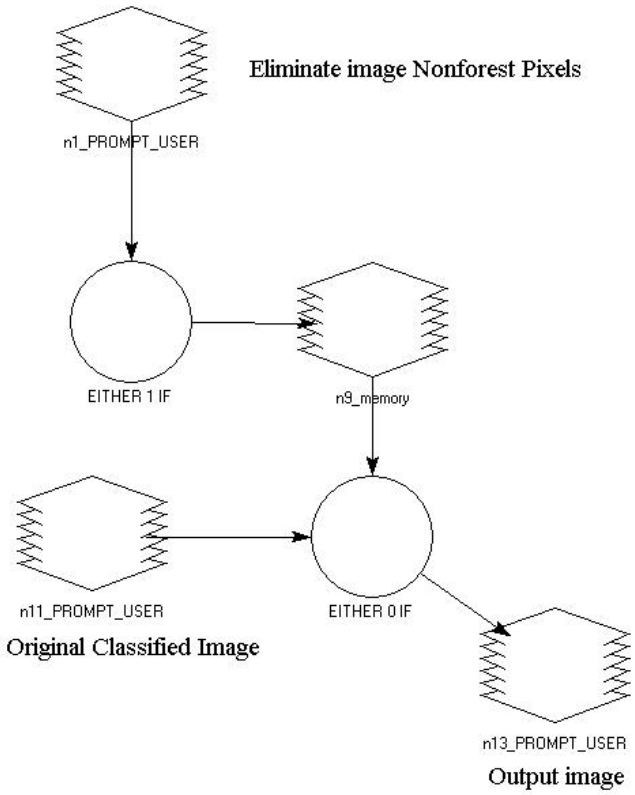

Figure 21: Model to decipher between background values of 0 and eliminated nonforest areas of 0

The model above is used to reset background values back to 0. The first function recodes all values not equaling 1 to a value of 2 and writes this information to a temporary image. Second, it uses the original classified image, to recode background values back to 0. If a value equals 0 in the original classified image then the value in the temp image equals 0, otherwise the value in the temp image is kept.

***Appendix iii* VDoF Scripts**

Accuracy Assessment Script for ArcView 3.x

```
' fGet the View
   theView = av.GetActiveDoc

' Convert the Image to a Grid (clssGrid)
   theTheme = theView.GetActiveThemes.Get(1)
   f = theTheme.GetSrcName.GetFileName
   clssGrid = Grid.MakeFromImage(f, 1)

' Get the reference point shapefile and FTab

  refTheme = theView.GetActiveThemes.Get(0)
  refFTab = refTheme.GetFTab


' Create Classification matrix2
  matrix2 = {0,0,0,0,0,0,0,0,0}
  Users = {0,0,0}
  Producers = {0,0,0}
  Overall = 0
  Total = 0

  refFTab.SetEditable(true)
  shapeF = refFTab.FindField( "shape" )
  classF = refFTab.FindField( "class" )
  referF = refFTab.FindField( "reference" )

' assign class values

  for each recno in refFtab
     refPoint = refFTab.ReturnValue(shapef, recno).ReturnCenter
     class = clssGrid.CellValue(refPoint, Prj.MakeNull)
     if (class.IsNull) then
        class = 0
     end

     refFTab.SetValue(classf, recno, class)
     if ((class > 0) AND (class < 4)) then
        lstindex = (class - 1)*3 + refFTab.ReturnValue(referF, recno) - 1
        matrix2.Set( lstindex, matrix2.Get(lstindex) + 1 )
     end
  end
  refFTab.SetEditable(false)
  for each i in 0..2
```

```
    for each j in 0..2
      Users.Set( i, Users.Get(i) + matrix2.Get(i*3 + j) )
      Producers.Set( i, Producers.Get(i) + matrix2.Get(j*3 + i) )
      if (i = j) then
          Overall = Overall + matrix2.Get(i*3 + j)
      end
      Total = Total + matrix2.Get(i*3 + j)
    end
  end

  'Write Results to Text File

  'CWD = FileName.Make("n:\15m\north\working").SetCWD
  Text1 = TextFile.Make( (f.AsString+"_accuracy.txt").AsFileName,
#FILE_PERM_WRITE )
  Text1.Write( "Accuracy for " + f.AsString, 72)

  ' Classification matrix2
  Text1.Write(NL,1)
  Text1.Write( NL+"Classification matrix2",72)
  Text1.Write(NL+NL,2)

  for each i in 0..2
    Text1.Write("Class "+(i+1).AsString+"  ", 9)
    for each j in 0..2
     Text1.Write( "  "+matrix2.Get(i*3 + j).AsString+"      ", 6 )
     end
     Text1.Write(NL,1)
  end
  Text1.Write(NL,1)

  ' Accuracy Stats
  Text1.Write(NL,1)
  Text1.Write(NL+" Total:            "+Total.AsString+String.MakeBuffer(72),72)
  Text1.Write(NL+" Total Correct:    "+Overall.AsString+String.MakeBuffer(72),72)
  Text1.Write(NL+" Overall Accuracy: "+(100*Overall /
Total).AsString+String.MakeBuffer(72),72)
  Text1.Write(NL,1)
  Text1.Write(NL+" Producers Accuracy"+String.MakeBuffer(72),72)
  Text1.Write(NL,1)
  for each i in 0..2
      Text1.Write(NL+"Class "+(i+1).AsString+"  "+(100*matrix2.Get(i*3 +
i)/Producers.Get(i)).AsString+String.MakeBuffer(72),72)
  end
  Text1.Write(NL,1)
  Text1.Write(NL+" Users Accuracy"+String.MakeBuffer(72),72)
  Text1.Write(NL,1)
```

```
  for each i in 0..2
      Text1.Write(NL+"Class "+(i+1).AsString+"  "+(100*matrix2.Get(i*3 +
i)/Users.Get(i)).AsString+String.MakeBuffer(72),72)
  end

' KAPPA
  kappa = 0
  for each i in 0..2
    kappa = kappa + (Producers.Get(i) * Users.Get(i))
  end

  kappa = (Total*Overall - kappa) / ((Total^2) - kappa)
  Text1.Write(NL+Nl+" Kappa = "+kappa.AsString+String.MakeBuffer(72),72)

  MsgBox.Info("Done","Accuracy Assessment")
```

VDoF Shape-Area-Adjacency Script
The Kurtzinator

```
'FIA Forest Cover

'Written by Robert Kurtz
'March 21, 2001

'Program requires 1 or 2 Active Themes in a View in the following order:
'1. A Forest\Non Forest grid with values (1) for Non Forest and (0) for Forest.
'    Note: Pixels that are to preserved from segmentation should have value (1).
'2. An optional non-forest pixel withholding grid with values (1) for those pixels to be
withheld from segmentation, and (0) or ('No Data') for all other pixels.
'    Note: Assure that the cell size of each grid is 15 meters

  theView = av.GetActiveDoc
  NwGrid = theView.GetActiveThemes.Get(0).GetGrid
  GridName = theView.GetActiveThemes.Get(0).GetName.AsString

  MsgBox.Report ("Program requires 1 or 2 Active Themes in a View in the following
order:"+NL+NL+
            "1. A Forest\Non Forest grid with values (1) for Non Forest and (0) for
Forest."+NL+
            "    Note: Pixels that are to preserved from segmentation should have value
(1)."+NL+NL+
            "2. An optional non-forest pixel withholding grid with values (1) for those
pixels to be withheld from segmentation, and (0) and\or ('No Data') for all other
pixels."+NL+
            "    Note: Assure that the cell size of each grid is 15 meters", "Instructions")
  W = MsgBox.Input("What Would You Like To Set The Working Directory To?", "Set
Working Directory", (FileName.GetCWD).AsString)
    if (W = nil) then return nil end
  N = MsgBox.Input("What Name Do You Want To Call The Output Grids?", "Grid Set
Name", GridName)
    if (N = nil) then return nil end
'  UW = MsgBox.YesNoCancel("Do You Want To Use A Second Grid To Remove
Values From Segmentation?", "Withhold Values?", TRUE)
'    if (UW = nil) then return nil end
  I = MsgBox.Input("How Many Iterations Would You Like to Run.", "Iteration Number
Request", 60.AsString)
    if (I = nil) then return nil end
  Q = MsgBox.YesNoCancel("Would You Like To Be Notified If Iterations Reach
"+I.AsString, "Notification?", FALSE)
    if (Q = nil) then return nil end
  Dit = MsgBox.YesNoCancel("Do You Want To Create Small Grids To Save Time On
Large Datasets?", "Large Datasets", TRUE)
    if (Dit = nil) then
```

```
      return nil
    elseif (Dit = TRUE) then
    Cu = MsgBox.Input("At What Count Would You Like To Create Small Grids?",
"Small Grids", "50").AsNumber
      if (Cu = nil) then return nil end
    else
      Cu = 0
    end

    CWD = FileName.Make(W).SetCWD
    Text1 = TextFile.Make( ("ForestCoverLog for "+GridName+".txt").AsFileName,
#FILE_PERM_APPEND )
    Text1.Write(GridName, 100)

   NwRect = NwGrid.GetExtent


'Non Forest Iteration

  Date1 = Date.Now
  Text1.Write(NL+NL+"Non Forest Iteration Initiation Time: "+Date1.AsString, 100)
  Text1.Write(NL+"Iteration #      Count #", 100)

' make the neighborhoods
firstLine = {0,0,1,0,0}
secndLine = {0,0,1,0,0}
thirdLine = {0,0,1,0,0}
forthLine = {0,0,0,0,0}
fifthLine = {0,0,0,0,0}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodA = NbrHood.MakeIrregular(theKernel)

firstLine = {0,0,0,0,0}
forthLine = {0,0,1,0,0}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodB = NbrHood.MakeIrregular(theKernel)

secndLine = {0,0,0,0,0}
fifthLine = {0,0,1,0,0}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodC = NbrHood.MakeIrregular(theKernel)

thirdLine = {1,1,1,0,0}
forthLine = {0,0,0,0,0}
fifthLine = {0,0,0,0,0}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodD = NbrHood.MakeIrregular(theKernel)
```

```
thirdLine = {0,1,1,1,0}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodE = NbrHood.MakeIrregular(theKernel)

thirdLine = {0,0,1,1,1}
theKernel = {firstLine,secndLine,thirdLine,forthLine,fifthLine}
theNbrHoodF = NbrHood.MakeIrregular(theKernel)

' run operation
proc = 0
Iteration = 0
InputGrid = NwGrid

While (True)

  iteration = iteration + 1
  A = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodA,FALSE)
  B = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodB,FALSE)
  C = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodC,FALSE)
  D = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodD,FALSE)
  E = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodE,FALSE)
  F = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodF,FALSE)
  OutputGrid = ((A = 3.AsGrid) or (B = 3.AsGrid) or (C = 3.AsGrid)) and ((D =
3.AsGrid) or (E = 3.AsGrid) or (F = 3.AsGrid))

    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName( ("Smoothed " + Iteration.AsString) )
    'theView.AddTheme(Smoothed)

  InpTab = InputGrid.GetVTab
  OutTab = OutputGrid.GetVTab
  InpCount = InpTab.ReturnValueNumber( InpTab.FindField("Count"), 1 )
  OutCount = OutTab.ReturnValueNumber( OutTab.FindField("Count"), 1 )

    if (iteration = 1) then
      Text1.Write(NL+"    0", 8)
      Text1.Write("         "+InpCount.AsString, 40)
    end

      Text1.Write(NL+"    "+Iteration.AsString, 8)
      Text1.Write("         "+(InpCount - OutCount).AsString, 40)

  cnt = InpCount - OutCount

  if ((cnt = 0) or (iteration >= I.AsNumber)) then
    if ((Q = TRUE) and (iteration >= I.AsNumber)) then
```

```
    MsgBox.Info( ("Iterations Have Reached "+I.AsString), "Attention")
    break
  end
  break

elseif ((cnt > 0) and (cnt <= CU) and (Dit = TRUE)) then

  Date2 = Date.Now
  Text1.Write(NL+"Count < "+Cu.AsString+" Iteration Time: "+Date2.AsString, 100)

  PatchedIn = InputGrid.RegionGroup(TRUE, FALSE, 0)
  PatchedIn = PatchedIn.Con(PatchedIn, 1.AsGrid.SetNull(0.AsGrid))
    'Smoothed = GTheme.Make(PatchedIn)
    'Smoothed.SetName("PatchedIn")
    'theView.AddTheme(Smoothed)
  pi = PatchedIn.GetVTab
  fpi = pi.FindField("value")
  fpic = pi.FindField("count")

  PatchedOut = OutputGrid.RegionGroup(TRUE, FALSE, 0)
  PatchedOut = PatchedOut.Con(PatchedIn, 1.AsGrid.SetNull(0.AsGrid))
    'Smoothed = GTheme.Make(PatchedOut)
    'Smoothed.SetName("PatchedOut")
    'theView.AddTheme(Smoothed)
  po = PatchedOut.GetVTab
  fpo = po.FindField("value")
  fpoc = po.FindField("count")
  b = po.GetSelection

  pic = pi.GetNumRecords
  poc = po.GetNumRecords
  if ((poc = pic).NOT) then
    InputGrid = OutputGrid
    continue
  end

  PatchedOutNeg = PatchedOut * 1
    'Smoothed = GTheme.Make(PatchedOutNeg)
    'Smoothed.SetName("PatchedOutNeg")
    'theView.AddTheme(Smoothed)
  pon = PatchedOutNeg.GetVTab
  bn = pon.GetSelection

  f = {}
  for each record in pi
    piv = pi.ReturnValue(fpi, record)
    f.Add(piv)
```

```
end

for each record in po

  pov = po.ReturnValue(fpo, record)
  povc = po.ReturnValue(fpoc, record)
  fnum = f.FindByValue(pov)
  pivc = pi.ReturnValue(fpic, fnum)
  if (pivc <> povc) then
    b.Set(record)
    po.UpdateSelection
  elseif (pivc = povc) then
    bn.Set(record)
    pon.UpdateSelection
  end

end

  S = PatchedOut.ExtractSelection
    'Smoothed = GTheme.Make(S)
    'Smoothed.SetName("S")
    'theView.AddTheme(Smoothed)
  Sn = PatchedOutNeg.ExtractSelection
    'Smoothed = GTheme.Make(Sn)
    'Smoothed.SetName("Sn")
    'theView.AddTheme(Smoothed)

  d = (FileName.GetCWD).AsString
  FileN = FileName.Merge (d, "poly.shp")

  anFTab = S.AsPolygonFTab (FileN, FALSE, Prj.MakeNull)
  shpfld = anFTab.FindField("Shape")
    'Smoothed = FTheme.Make(anFTab)
    'Smoothed.SetName("anFTab")
    'theView.AddTheme(Smoothed)

  shp = {}
  gs = {}
  for each record in anFTab

    aShape = anFTab.ReturnValue(shpfld, record)
    ext = aShape.ReturnExtent
      extO = ext.ReturnOrigin
        Xo = extO.GetX
        Yo = extO.GetY
    extX = Point.Make ((Xo - 45), (Yo - 45))
      extS = ext.ReturnSize
```

```
        Xs = extS.GetX
        Ys = extS.GetY
    extY = Point.Make ((Xs + 90), (Ys + 90))

    extN = Rect.Make(extX, extY)
    shp.Add(extN)

    Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extN)
    g = S.ExtractByRect(extN, Prj.MakeNull, FALSE)
      'Smoothed = GTheme.Make(g)
      'Smoothed.SetName("g")
      'theView.AddTheme(Smoothed)

    gnull = g.IsNull
    g = gnull.Con(0.AsGrid, 1.AsGrid)

    gs.Add(g)
      'Smoothed = GTheme.Make(g)
      'Smoothed.SetName("g")
      'theView.AddTheme(Smoothed)

  end

  gs1 = {}
  For each i in gs

    Date2 = Date.Now
    Text1.Write(NL+"Iterate Through Small Grids Initiation Time: "+Date2.AsString,
100)

  num = gs.Find(i)
  extN = shp.Get(num)
  Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extN)

  proc = 0
  Iteration = 0
  InGrid = i
  While (Proc = 0)

    iteration = iteration + 1
    A = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodA,FALSE)
    B = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodB,FALSE)
    C = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodC,FALSE)
    D = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodD,FALSE)
    E = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodE,FALSE)
    F = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodF,FALSE)
```

```
    OutGrid = ((A = 3.AsGrid) or (B = 3.AsGrid) or (C = 3.AsGrid)) and ((D =
3.AsGrid) or (E = 3.AsGrid) or (F = 3.AsGrid))
      'Smoothed = GTheme.Make(OutGrid)
      'Smoothed.SetName("OutGrid")
      'theView.AddTheme(Smoothed)


    OutCnt = OutGrid.GetVTab.GetNumRecords
    if ((OutCnt = 2).NOT) then
      OutGrid = OutGrid.Con(1.asGrid, 1.AsGrid.SetNull(0.AsGrid))
        'Smoothed = GTheme.Make(OutGrid)
        'Smoothed.SetName("Null OutGrid")
        'theView.AddTheme(Smoothed)
      gs1.Add(OutGrid)
      proc = 1
      break
    end

    InpTab = InGrid.GetVTab
    OutTab = OutGrid.GetVTab
    InpCount = InpTab.ReturnValueNumber( InpTab.FindField("Count"), 1 )
    OutCount = OutTab.ReturnValueNumber( OutTab.FindField("Count"), 1 )
    cont = InpCount - OutCount

    if (cont = 0) then
        extO = extN.ReturnOrigin
          Xo = extO.GetX
          Yo = extO.GetY
      extX = Point.Make ((Xo + 30), (Yo + 30))
        extS = extN.ReturnSize
          Xs = extS.GetX
          Ys = extS.GetY
      extY = Point.Make ((Xs - 60), (Ys - 60))
      extS = Rect.Make(extX, extY)
      Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extS)

      OutGrid = OutGrid.Con(1.asGrid, 1.AsGrid.SetNull(0.AsGrid))
        'Smoothed = GTheme.Make(OutGrid)
        'Smoothed.SetName("OutGrid nulled")
        'theView.AddTheme(Smoothed)
      gs1.Add(OutGrid)
      proc = 1
    else
      InGrid = OutGrid
    end

  end  'End of While (proc = 0)
```

```
    end  'End of For each in in gs

    break

  else  'End of (cnt > 0) and (cnt <= Cu)
    InputGrid = OutputGrid
  end
end  'End of While (True)

if (proc = 1) then

    Date2 = Date.Now
    Text1.Write(NL+"Merge Grids Initiation Time: "+Date2.AsString, 100)

  Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, NwRect)

Grid.SetAnalysisMask(NwGrid)  'Set Mask here?

  Sn = Sn.Con(1.AsGrid, 0.AsGrid)
  OutputGrid = Sn.Merge(gs1)
    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName( ("merged(gs1)") )
    'theView.AddTheme(Smoothed)

  OutputGrid = (OutputGrid.IsNull).Con(0.AsGrid, 1.AsGrid)

    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName("OutputGridNF")
    'theView.AddTheme(Smoothed)
end

    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName( ("NFSmoothed " + Iteration.AsString) )
    'theView.AddTheme(Smoothed)

    Date2 = Date.Now
    Text1.Write(NL+"Non Forest Iteration Completion Time: "+Date2.AsString, 100)

'Non Forest Patching

    Date1 = Date.Now
    Text1.Write(NL+NL+"NF Patching Initiation Time: "+Date1.AsString, 100)

  PatchNF = OutputGrid.RegionGroup(TRUE, FALSE, 0)

    Date2 = Date.Now
```

```
    Text1.Write(NL+"NF Patching Completion Time: "+Date2.AsString, 100)


'Query: NF Clip; Select > 17

  theVTab = PatchNF.GetVTab

    Date1 = Date.Now
    Text1.Write(NL+NL+"NF Query Initiation Time: "+Date1.AsString, 100)

  QueryNF = PatchNF.Test("([Count] > 17) and ([Link] = 1)")

    Date2 = Date.Now
    Text1.Write(NL+"NF Query Completion Time: "+Date2.AsString, 100)


'Calculation: NF Clip - (NF > 17)

  'theSrcName2 = Grid.MakeSrcName( "K:\county\SourceFiles\va_uw")
'  VAUW = theView.GetActiveThemes.Get(2).GetGrid  'Grid.Make(theSrcName2)

    Date1 = Date.Now
    Text1.Write(NL+NL+"NF Clip Calculation Initiation Time: "+Date1.AsString, 100)

  lst = theView.GetActiveThemes.Count
  if (lst = 2) then
    UW = theView.GetActiveThemes.Get(1).GetGrid
    Calc = NwGrid - QueryNF - UW
  elseif (lst = 1) then
    Calc = NwGrid - QueryNF
  end

    Date2 = Date.Now
    Text1.Write(NL+"NF Clip Calculation Completion Time: "+Date2.AsString, 100)


'Add Into Forest

    Date1 = Date.Now
    Text1.Write(NL+NL+"NF Adding Clips Initiation Time: "+Date1.AsString, 100)

   AddTo = ((Calc = 1.AsGrid) or (NwGrid = 0.AsGrid))  'AddTo = ((Calc = 1.AsGrid) or
(VANF = 0.AsGrid))

    Date2 = Date.Now
    Text1.Write(NL+"NF Adding Clips Completion Time: "+Date2.AsString, 100)
```

```
'Forest Iteration

   Date1 = Date.Now
   Name = "AddTo"
   Text1.Write(NL+NL+"Forest Iteration Initiation Time: "+Date1.AsString, 100)
   Text1.Write(NL+"Iteration #      Count #", 100)

' run operation
Iteration = 0
InputGrid = AddTo
While (True)

  iteration = iteration + 1
  A = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodA,FALSE)
  B = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodB,FALSE)
  C = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodC,FALSE)
  D = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodD,FALSE)
  E = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodE,FALSE)
  F = InputGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodF,FALSE)
  OutputGrid = ((A = 3.AsGrid) or (B = 3.AsGrid) or (C = 3.AsGrid)) and ((D =
3.AsGrid) or (E = 3.AsGrid) or (F = 3.AsGrid))
   'Smoothed = GTheme.Make(OutputGrid)
   'Smoothed.SetName( ("Smoothed " + Iteration.AsString) )
   'theView.AddTheme(Smoothed)

  InpTab = InputGrid.GetVTab
  OutTab = OutputGrid.GetVTab
  InpCount = InpTab.ReturnValueNumber( InpTab.FindField("Count"), 1 )
  OutCount = OutTab.ReturnValueNumber( OutTab.FindField("Count"), 1 )

   if (iteration = 1) then
      Text1.Write(NL+"    0", 8)
      Text1.Write("         "+InpCount.AsString, 40)
   end

     Text1.Write(NL+"    "+Iteration.AsString, 8)
     Text1.Write("         "+(InpCount - OutCount).AsString, 40)

  cnt = InpCount - OutCount

  if ((cnt = 0) or (iteration >= I.AsNumber)) then
   if ((Q = TRUE) and (iteration >= I.AsNumber)) then
     MsgBox.Info( ("Iterations Have Reached "+I.AsString), "Attention")
     break
   end
   break
```

```
elseif ((cnt > 0) and (cnt <= Cu) and (Dit = TRUE)) then

  Date2 = Date.Now
  Text1.Write(NL+"Count < "+Cu.AsString+" Iteration Time: "+Date2.AsString, 100)

  PatchedIn = InputGrid.RegionGroup(TRUE, FALSE, 0)
  PatchedIn = PatchedIn.Con(PatchedIn, 1.AsGrid.SetNull(0.AsGrid))
    'Smoothed = GTheme.Make(PatchedIn)
    'Smoothed.SetName("PatchedIn")
    'theView.AddTheme(Smoothed)
  pi = PatchedIn.GetVTab
  fpi = pi.FindField("value")
  fpic = pi.FindField("count")

  PatchedOut = OutputGrid.RegionGroup(TRUE, FALSE, 0)
  PatchedOut = PatchedOut.Con(PatchedIn, 1.AsGrid.SetNull(0.AsGrid))
    'Smoothed = GTheme.Make(PatchedOut)
    'Smoothed.SetName("PatchedOut")
    'theView.AddTheme(Smoothed)
  po = PatchedOut.GetVTab
  fpo = po.FindField("value")
  fpoc = po.FindField("count")
  b = po.GetSelection

  pic = pi.GetNumRecords
  poc = po.GetNumRecords
    'msgbox.info("pic, poc: "+pic.asstring++poc.asstring,"")
  if ((poc = pic).NOT) then
    'msgbox.info("break, iteration: "+iteration.asstring,"")
    InputGrid = OutputGrid
    continue
  end

  PatchedOutNeg = PatchedOut * 1
    'Smoothed = GTheme.Make(PatchedOutNeg)
    'Smoothed.SetName("PatchedOutNeg")
    'theView.AddTheme(Smoothed)
  pon = PatchedOutNeg.GetVTab
  bn = pon.GetSelection

  f = {}
  for each record in pi
    piv = pi.ReturnValue(fpi, record)
    f.Add(piv)
  end
```

```
for each record in po

  pov = po.ReturnValue(fpo, record)
  povc = po.ReturnValue(fpoc, record)
  fnum = f.FindByValue(pov)
  pivc = pi.ReturnValue(fpic, fnum)
  if (pivc <> povc) then
    b.Set(record)
    po.UpdateSelection
  elseif (pivc = povc) then
    bn.Set(record)
    pon.UpdateSelection
  end

end

  S = PatchedOut.ExtractSelection
    'Smoothed = GTheme.Make(S)
    'Smoothed.SetName("S")
    'theView.AddTheme(Smoothed)
  Sn = PatchedOutNeg.ExtractSelection
    'Smoothed = GTheme.Make(Sn)
    'Smoothed.SetName("Sn")
    'theView.AddTheme(Smoothed)

  d = (FileName.GetCWD).AsString
  FileN = FileName.Merge (d, "poly.shp")

  anFTab = S.AsPolygonFTab (FileN, FALSE, Prj.MakeNull)
  shpfld = anFTab.FindField("Shape")
    'Smoothed = FTheme.Make(anFTab)
    'Smoothed.SetName("anFTab")
    'theView.AddTheme(Smoothed)

  shp = {}
  gs = {}
  for each record in anFTab

    aShape = anFTab.ReturnValue(shpfld, record)
    ext = aShape.ReturnExtent 'ext = aShape.ReturnExtent
      extO = ext.ReturnOrigin
        Xo = extO.GetX
        Yo = extO.GetY
    extX = Point.Make ((Xo - 45), (Yo - 45))
      extS = ext.ReturnSize
        Xs = extS.GetX
        Ys = extS.GetY
```

```
      extY = Point.Make ((Xs + 90), (Ys + 90))
      extN = Rect.Make(extX, extY)
      shp.Add(extN)

      Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extN)
      g = S.ExtractByRect(extN, Prj.MakeNull, FALSE)
        'Smoothed = GTheme.Make(g)
        'Smoothed.SetName("g")
        'theView.AddTheme(Smoothed)

      gnull = g.IsNull
      g = gnull.Con(0.AsGrid, 1.AsGrid)

      gs.Add(g)
        'Smoothed = GTheme.Make(g)
        'Smoothed.SetName("g")
        'theView.AddTheme(Smoothed)

    end

  gs1 = {}
  For each i in gs

  Date2 = Date.Now
  Text1.Write(NL+"Iterate Through Small Grids Initiation Time: "+Date2.AsString,
100)

    num = gs.Find(i)
    extN = shp.Get(num)
    Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extN)

    proc = 0
    Iteration = 0
    InGrid = i
    While (Proc = 0)

      iteration = iteration + 1
      A = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodA,FALSE)
      B = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodB,FALSE)
      C = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodC,FALSE)
      D = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodD,FALSE)
      E = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodE,FALSE)
      F = InGrid.FocalStats(#GRID_STATYPE_SUM,theNbrHoodF,FALSE)
      OutGrid = ((A = 3.AsGrid) or (B = 3.AsGrid) or (C = 3.AsGrid)) and ((D =
3.AsGrid) or (E = 3.AsGrid) or (F = 3.AsGrid))
        'Smoothed = GTheme.Make(OutGrid)
        'Smoothed.SetName("OutGrid")
```

```
      'theView.AddTheme(Smoothed)

    OutCnt = OutGrid.GetVTab.GetNumRecords
    if ((OutCnt = 2).NOT) then
      OutGrid = OutGrid.Con(1.asGrid, 1.AsGrid.SetNull(0.AsGrid))
        'Smoothed = GTheme.Make(OutGrid)
        'Smoothed.SetName("OutGrid nulled1")
        'theView.AddTheme(Smoothed)
      gs1.Add(OutGrid)
      proc = 1
      break
    end

    InpTab = InGrid.GetVTab
    OutTab = OutGrid.GetVTab
    InpCount = InpTab.ReturnValueNumber( InpTab.FindField("Count"), 1 )
    OutCount = OutTab.ReturnValueNumber( OutTab.FindField("Count"), 1 )
    cont = InpCount - OutCount

    if (cont = 0) then
        extO = extN.ReturnOrigin
          Xo = extO.GetX
          Yo = extO.GetY
      extX = Point.Make ((Xo + 30), (Yo + 30))
        extS = extN.ReturnSize
          Xs = extS.GetX
          Ys = extS.GetY
      extY = Point.Make ((Xs - 60), (Ys - 60))
      extS = Rect.Make(extX, extY)
      Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, extS)

      OutGrid = OutGrid.Con(1.asGrid, 1.AsGrid.SetNull(0.AsGrid))
        'Smoothed = GTheme.Make(OutGrid)
        'Smoothed.SetName("OutGrid nulled")
        'theView.AddTheme(Smoothed)
      gs1.Add(OutGrid)
      proc = 1
    else
      InGrid = OutGrid
    end

  end  'End of While (proc = 0)

end  'End of For each in in gs

break
```

```
  else  'End of (cnt > 0) and (cnt <= 50)
    InputGrid = OutputGrid
  end
end  'End of While (True)

if (proc = 1) then

    Date2 = Date.Now
    Text1.Write(NL+"Merge Grids Initiation Time: "+Date2.AsString, 100)

  Grid.SetAnalysisExtent(#GRID_ENVTYPE_VALUE, NwRect)
  Grid.SetAnalysisMask(NwGrid)

  Sn = Sn.Con(1.AsGrid, 0.AsGrid)
  OutputGrid = Sn.Merge(gs1)
    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName( ("merged(gs1)") )
    'theView.AddTheme(Smoothed)

  OutputGrid = (OutputGrid.IsNull).Con(0.AsGrid, 1.AsGrid)
    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName("OutputGrid")
    'theView.AddTheme(Smoothed)

end

    'Smoothed = GTheme.Make(OutputGrid)
    'Smoothed.SetName( ("FSmoothed " + Iteration.AsString) )
    'theView.AddTheme(Smoothed)

  Date2 = Date.Now
  Text1.Write(NL+"Forest Iteration Completion Time: "+Date2.AsString, 100)


'Forest Patching

    Date1 = Date.Now
    Text1.Write(NL+NL+"Forest Patching Initiation Time: "+Date1.AsString, 100)

  PatchF = OutputGrid.RegionGroup(TRUE, FALSE, 0)

    Date2 = Date.Now
    Text1.Write(NL+"Forest Patching Completion Time: "+Date2.AsString, 100)


'Query: F Clip; Select > 17
```

```
  theVTab = PatchF.GetVTab

    Date1 = Date.Now
    Text1.Write(NL+NL+"Forest Query Initiation Time: "+Date1.AsString, 100)

  QueryF = PatchF.Test("([Count] > 17) and ([Link] = 1)")

    Date2 = Date.Now
    Text1.Write(NL+"Forest Query Completion Time: "+Date2.AsString, 100)

    theDirName = (CWD.GetName).AsFileName
    File1 = theDirName.MakeTmp( GridName, "" )
    QueryF.SaveDataSet (File1)

    theGTheme = GTheme.Make(QueryF)
    theGTheme.SetName(GridName+" FIA Forest Cover")
    theView.AddTheme( theGTheme )

  theLegend = theView.GetThemes.Get(0).GetLegend
  theLegend.Load ("K:\county\SourceFiles\fia forest cover.avl".AsFileName,
#LEGEND_LOADTYPE_ALL)


Return nil
```

Appendix iv: **Output Images From Post-Classification Techniques**

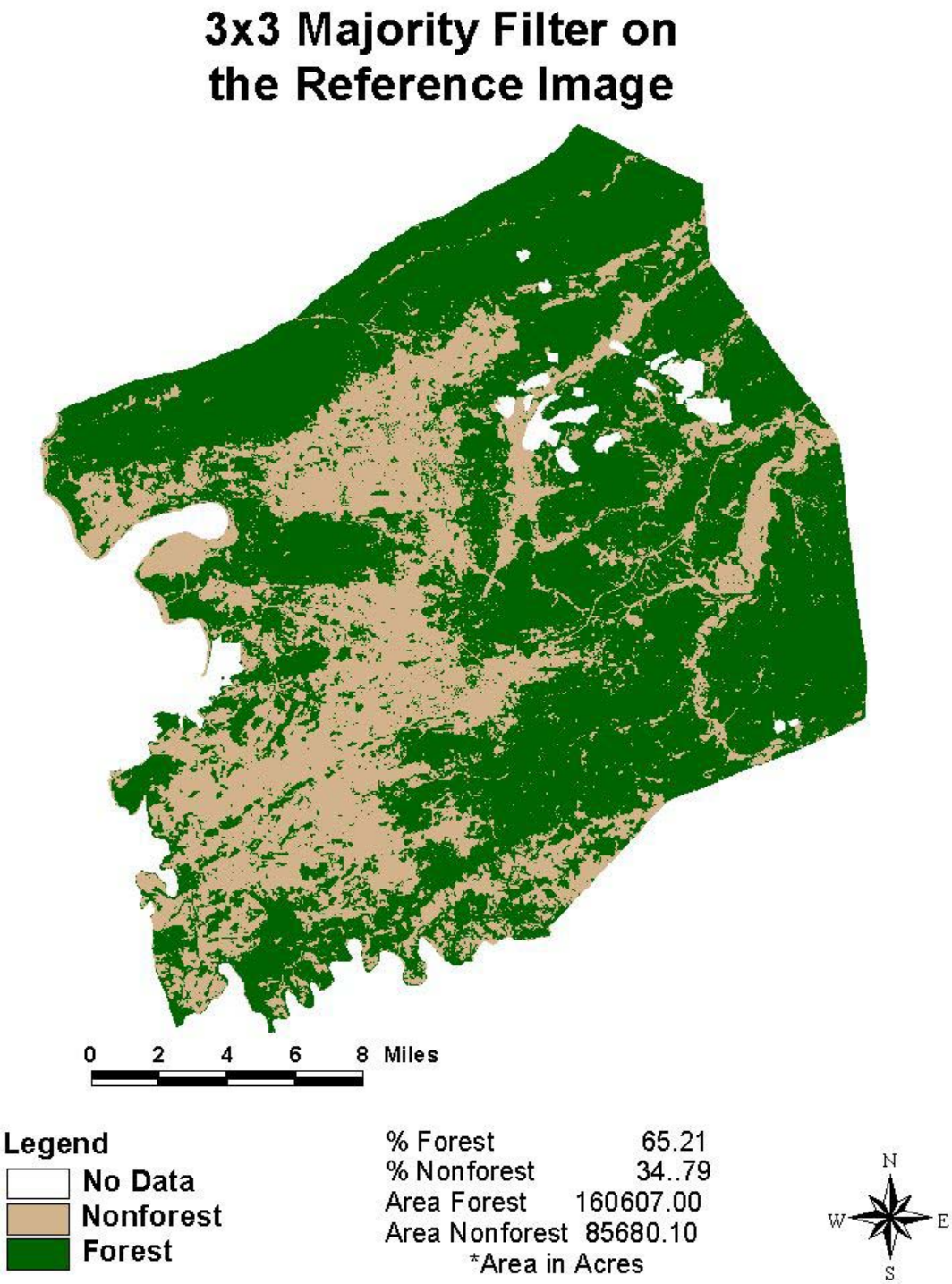

Figure 22 3x3 Majority Filter applied to the originally classified Landsat TM scene 17/34.

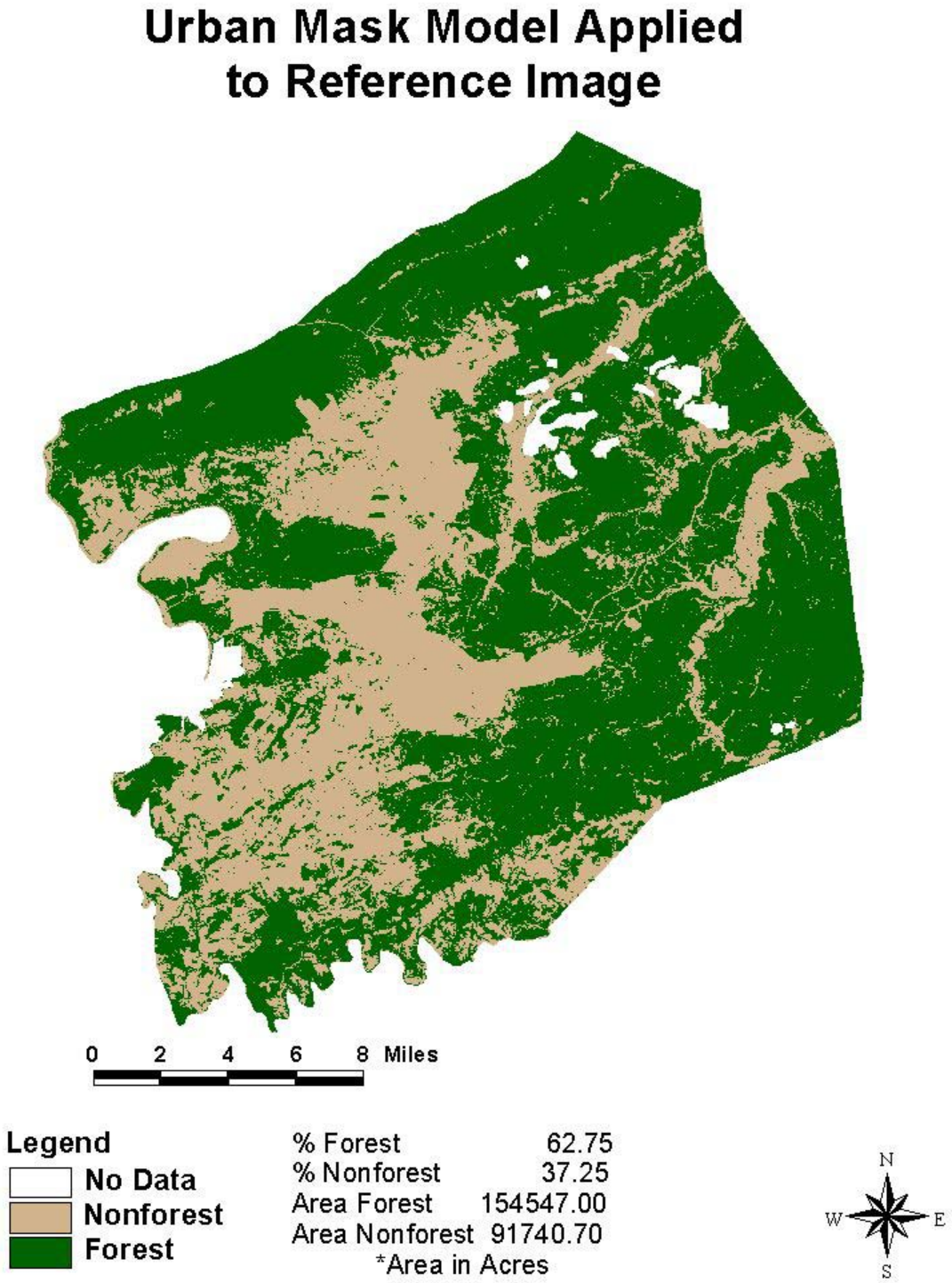

Figure 23 Urban Mask applied to the originally classified Landsat TM scene 17/34.

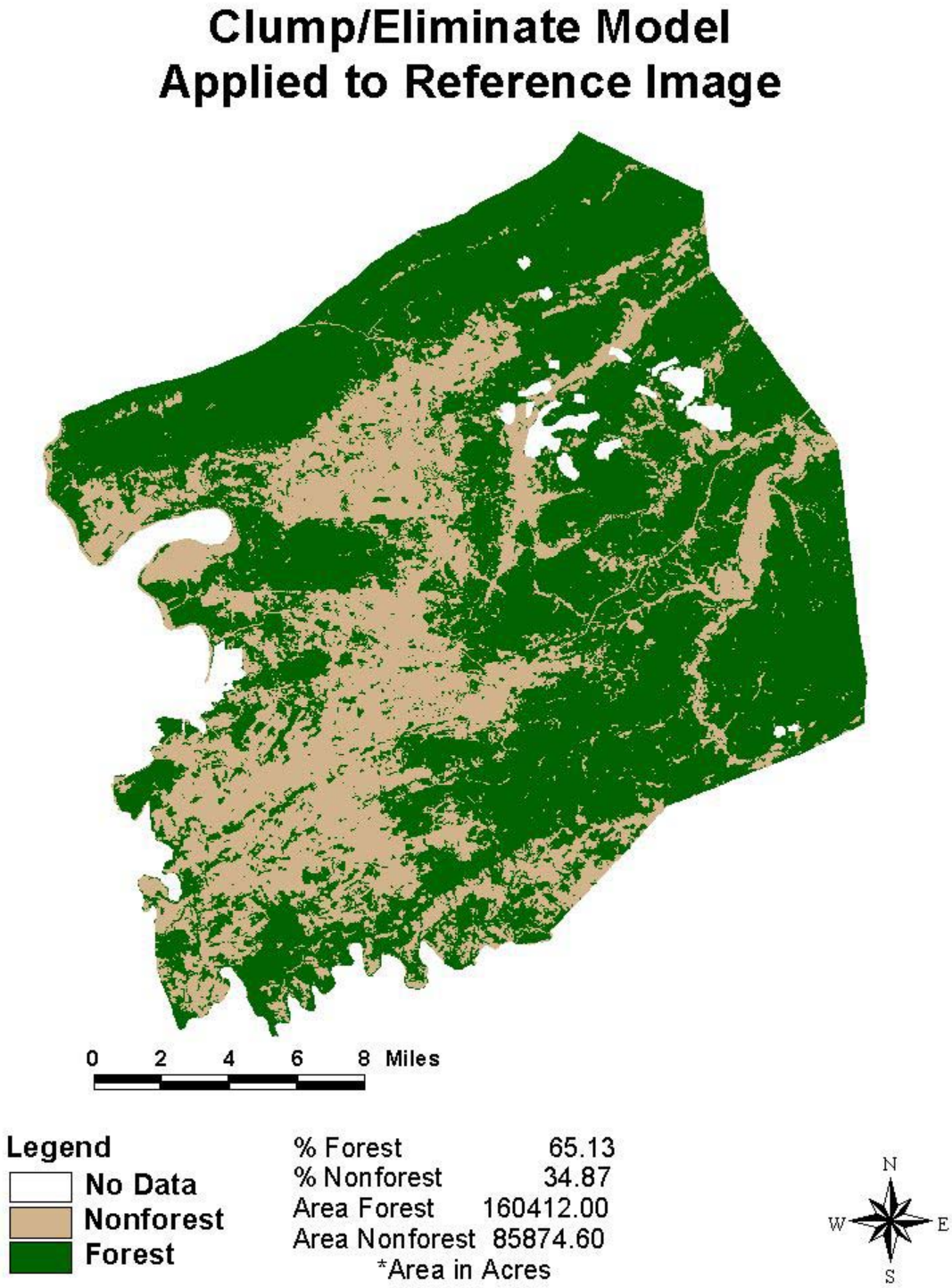

Figure 24 Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

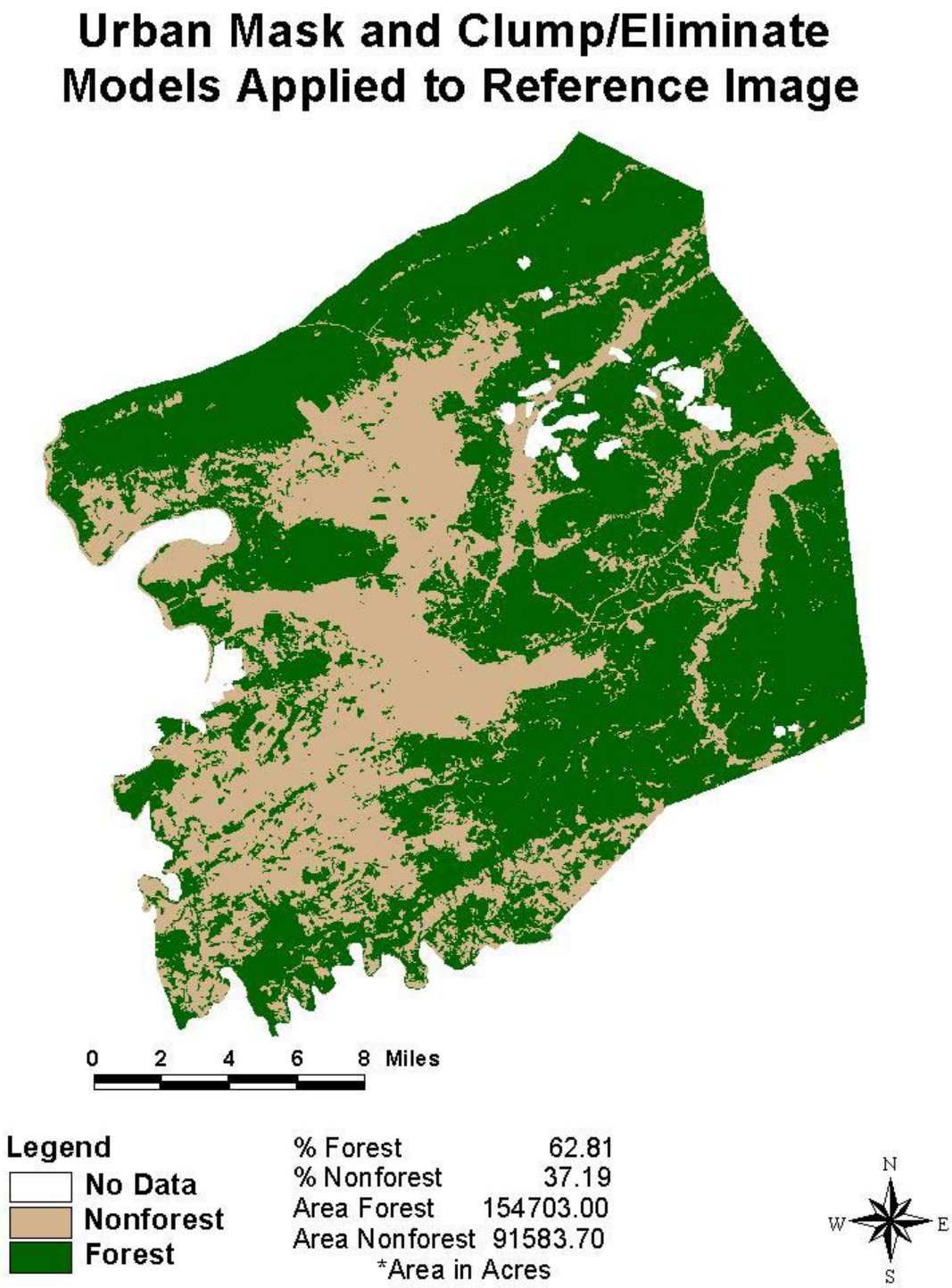

Figure 25 Urban Mask then the Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

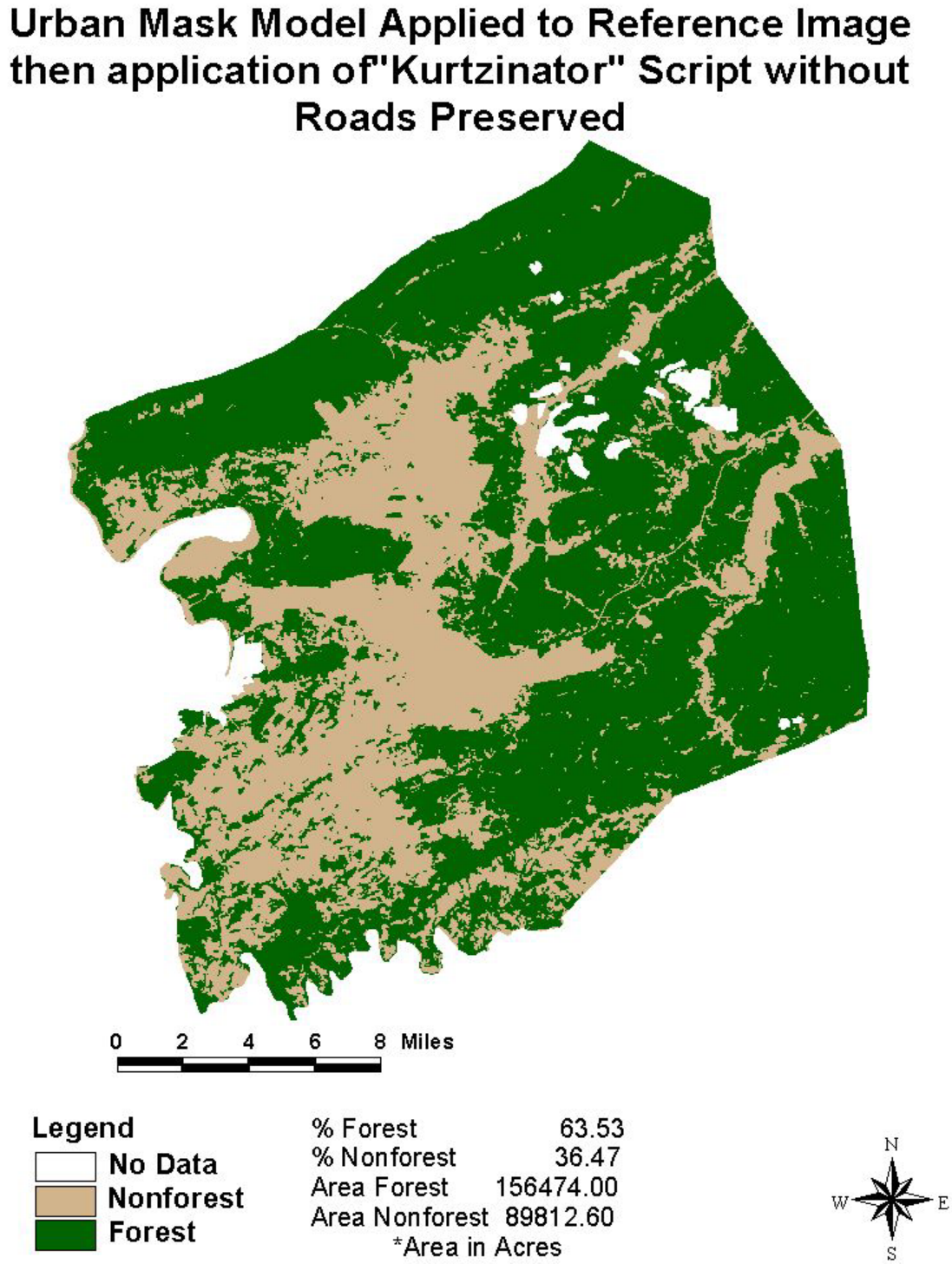

Figure 26 Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script without roads preserved.

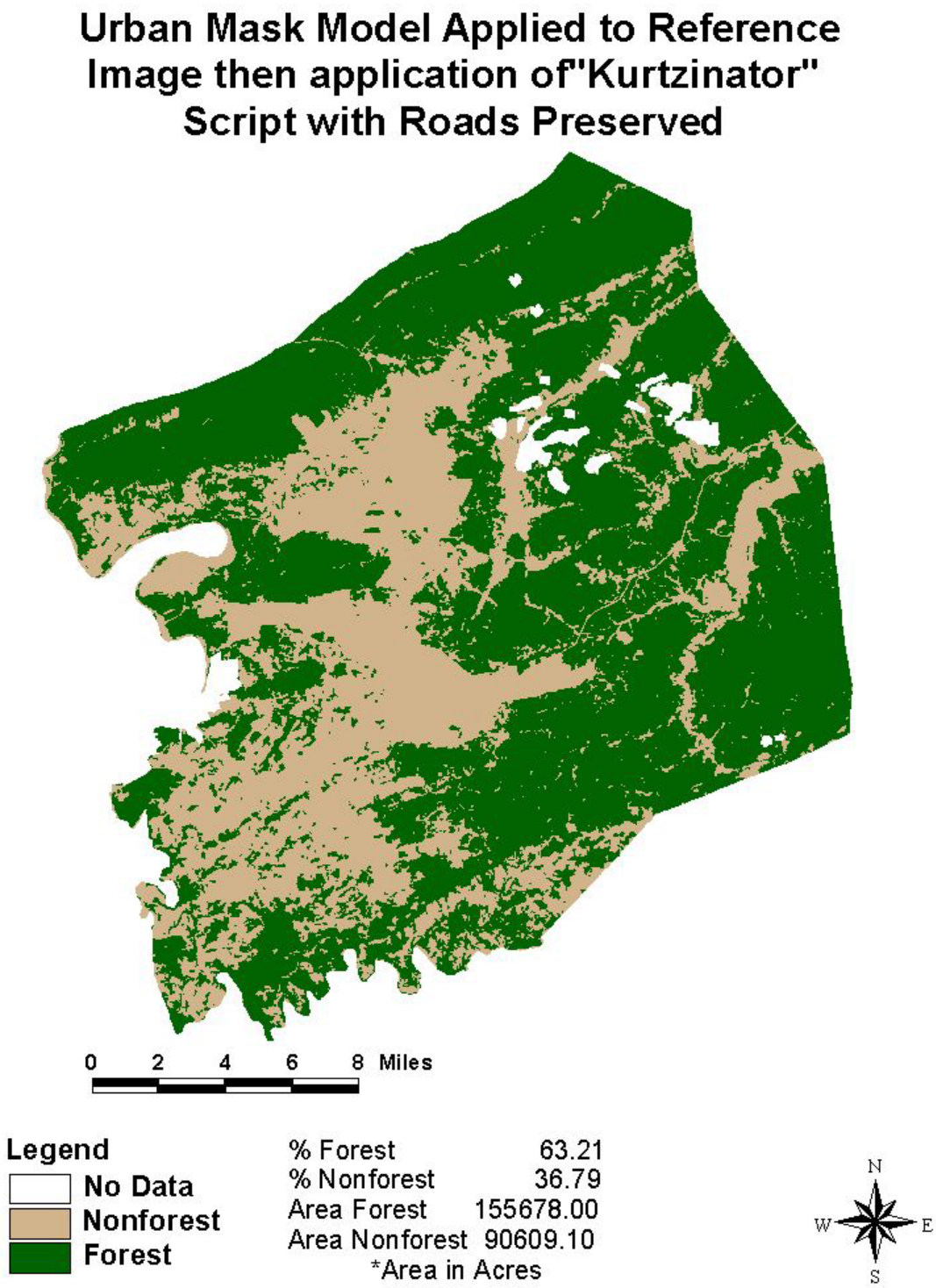

Figure 27 Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script with roads preserved.

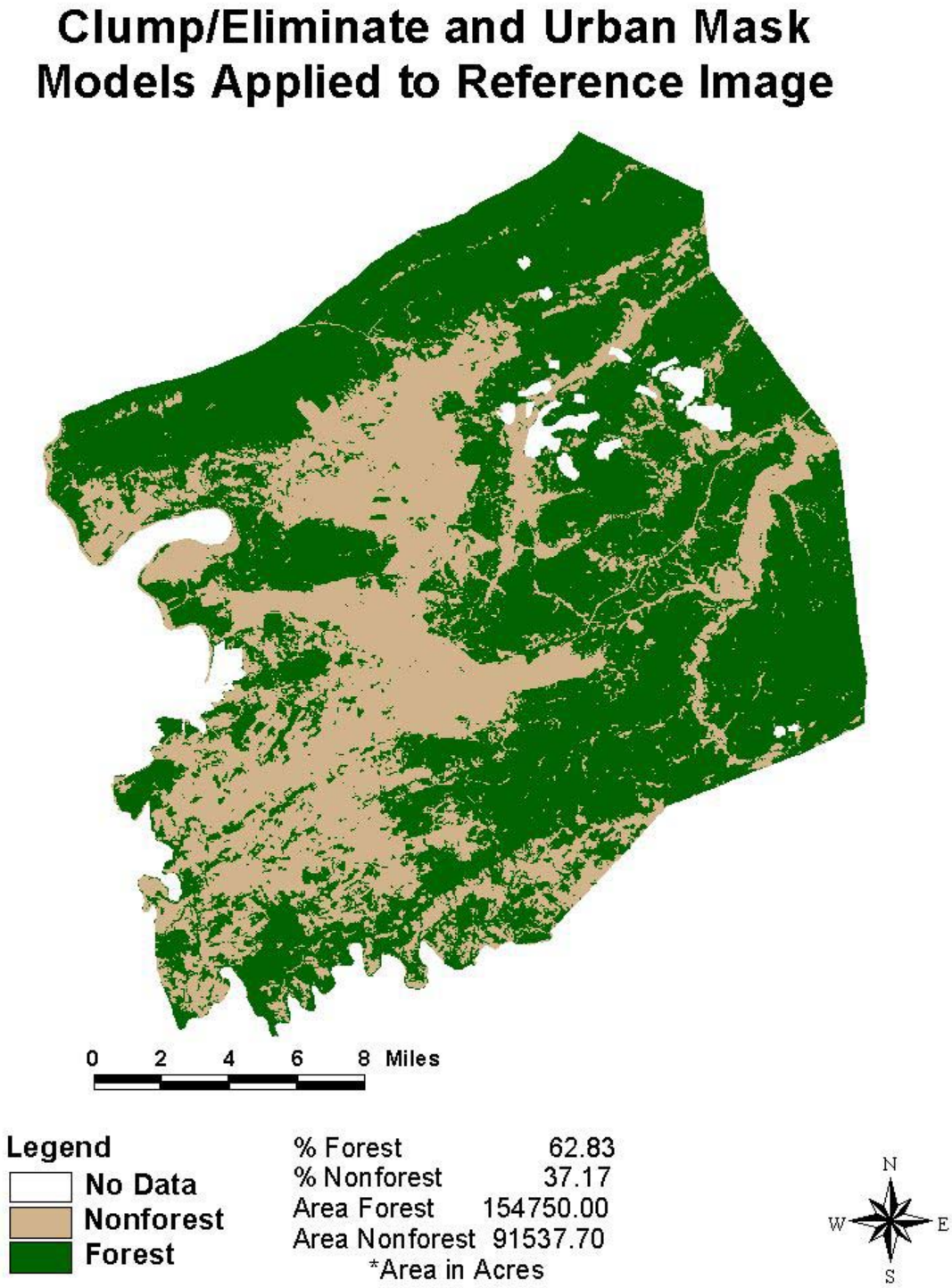

Figure 28 Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

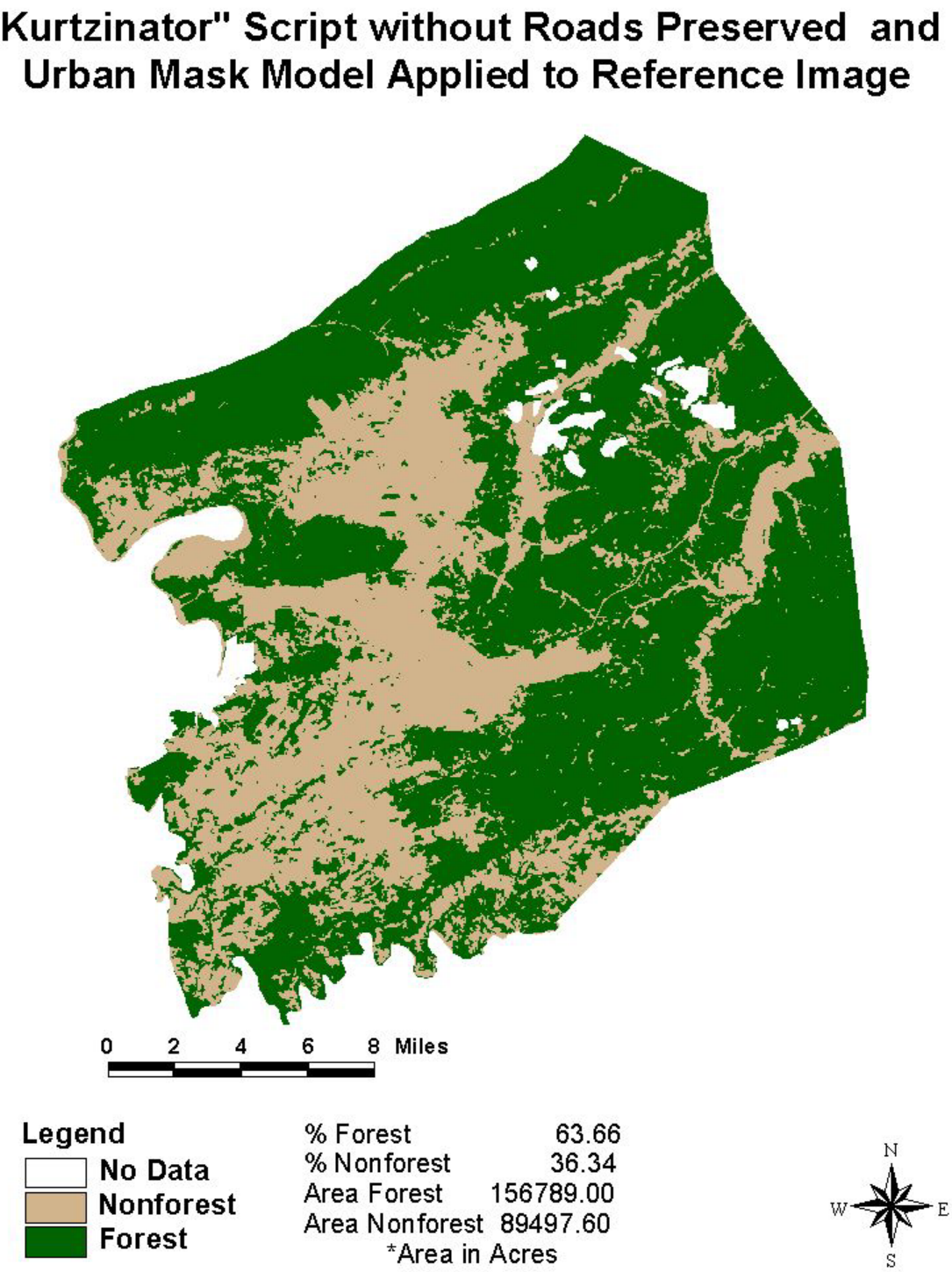

Figure 29 "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

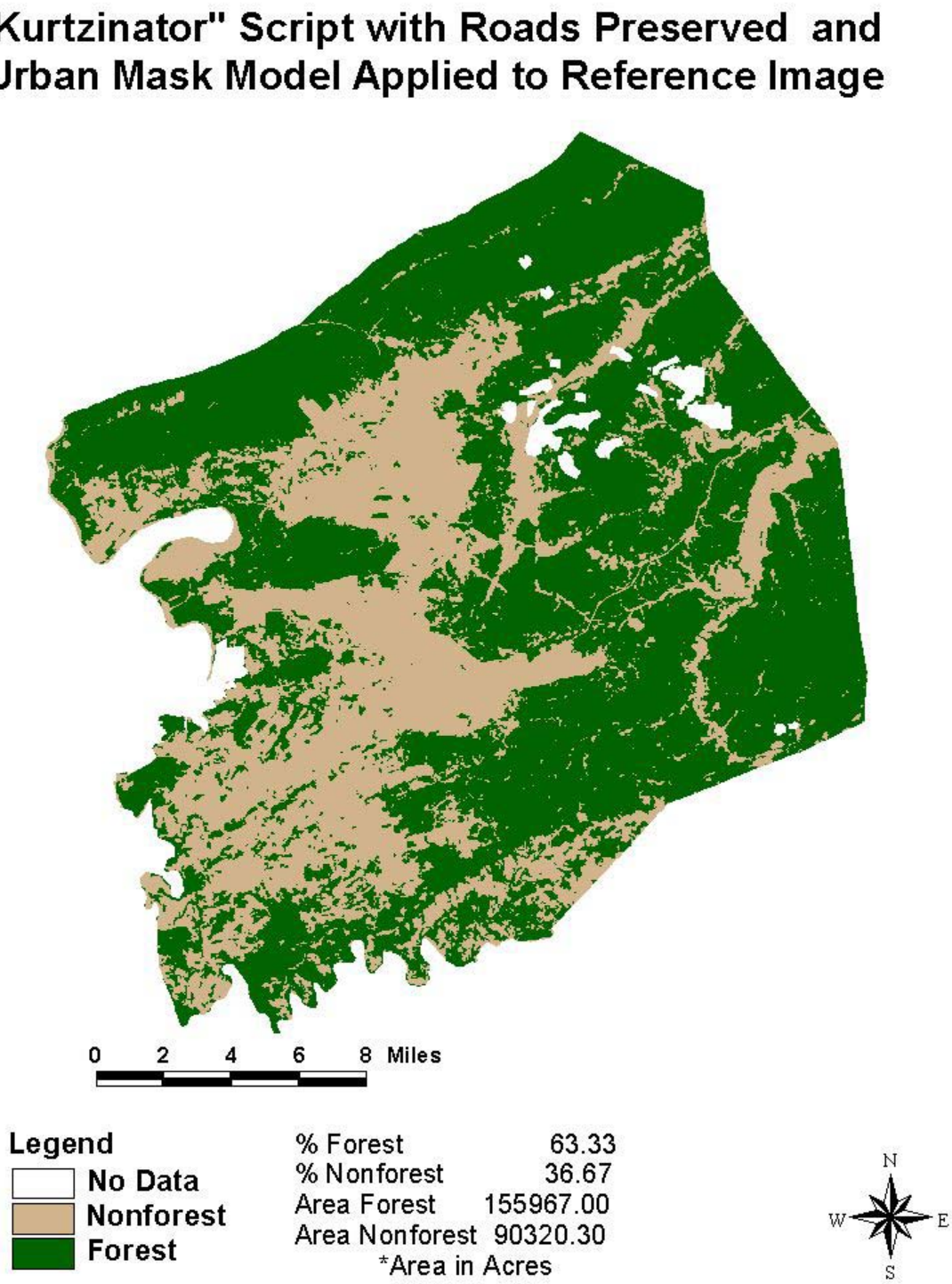

Figure 30 "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

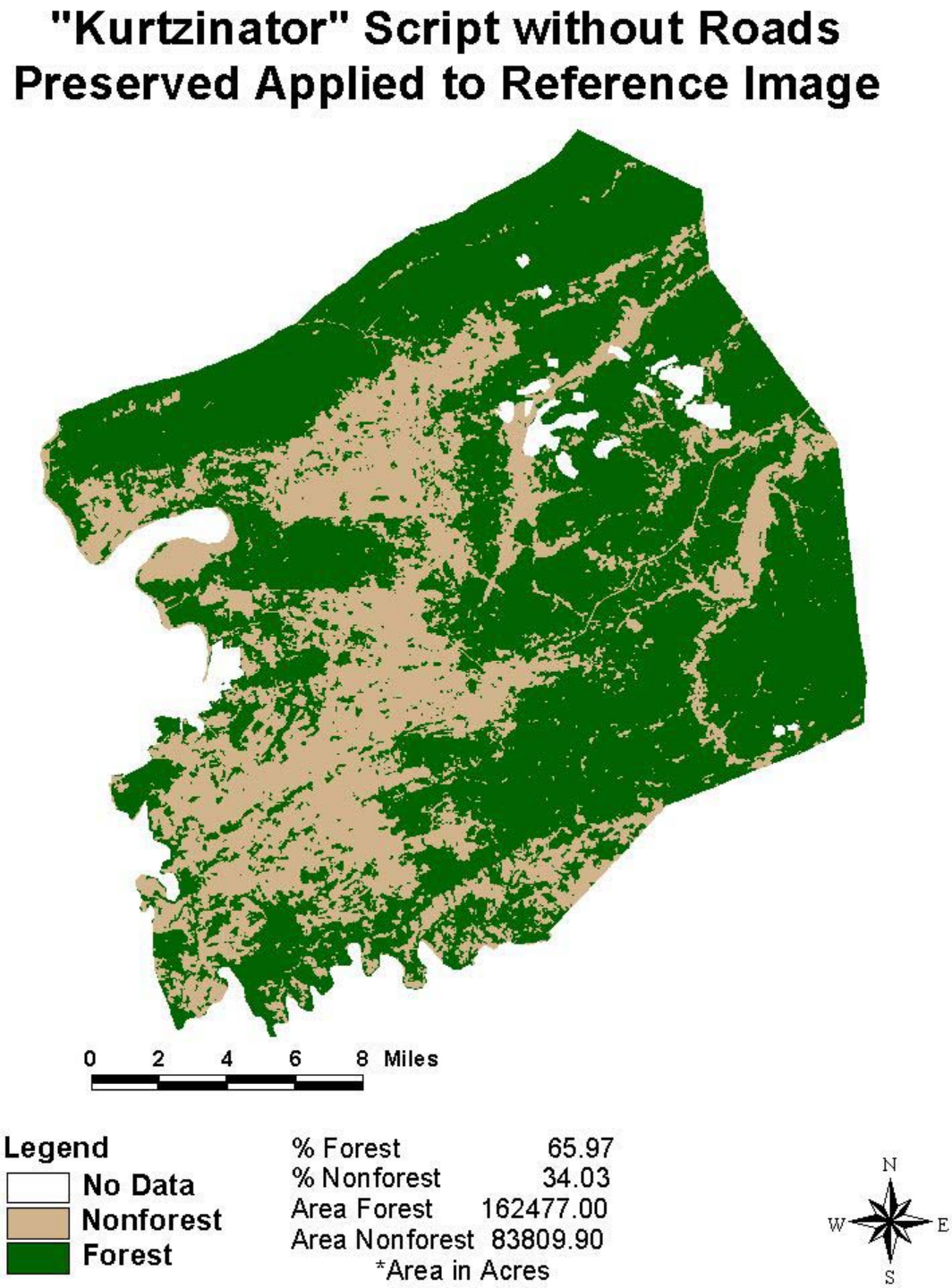

Figure 31 "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34.

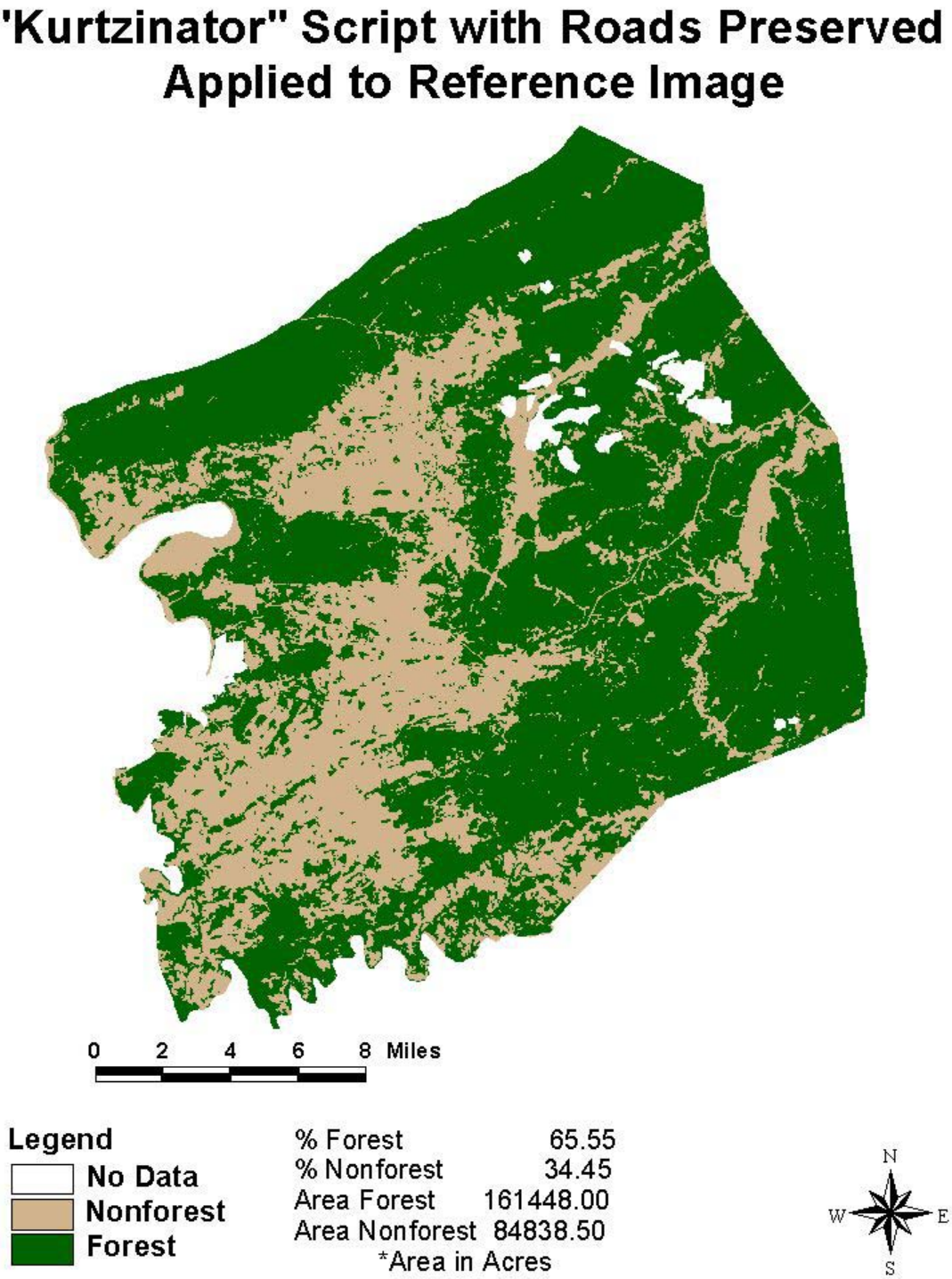

Figure 32 "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34.

Appendix v: **Image Differencing**

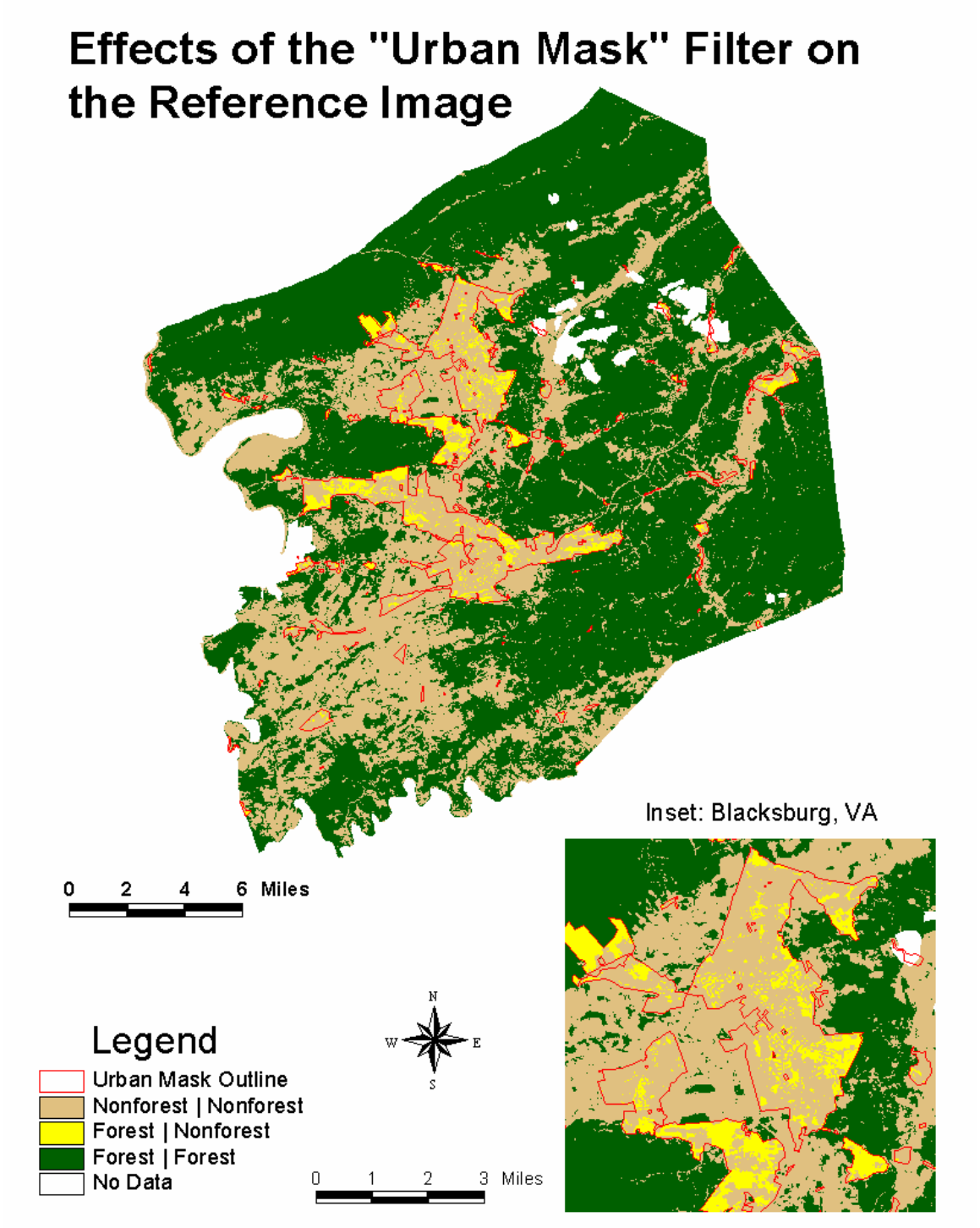

Figure 33 Effects of the Urban Mask on the original IGSCR Classified Landsat TM Scene 17/34.

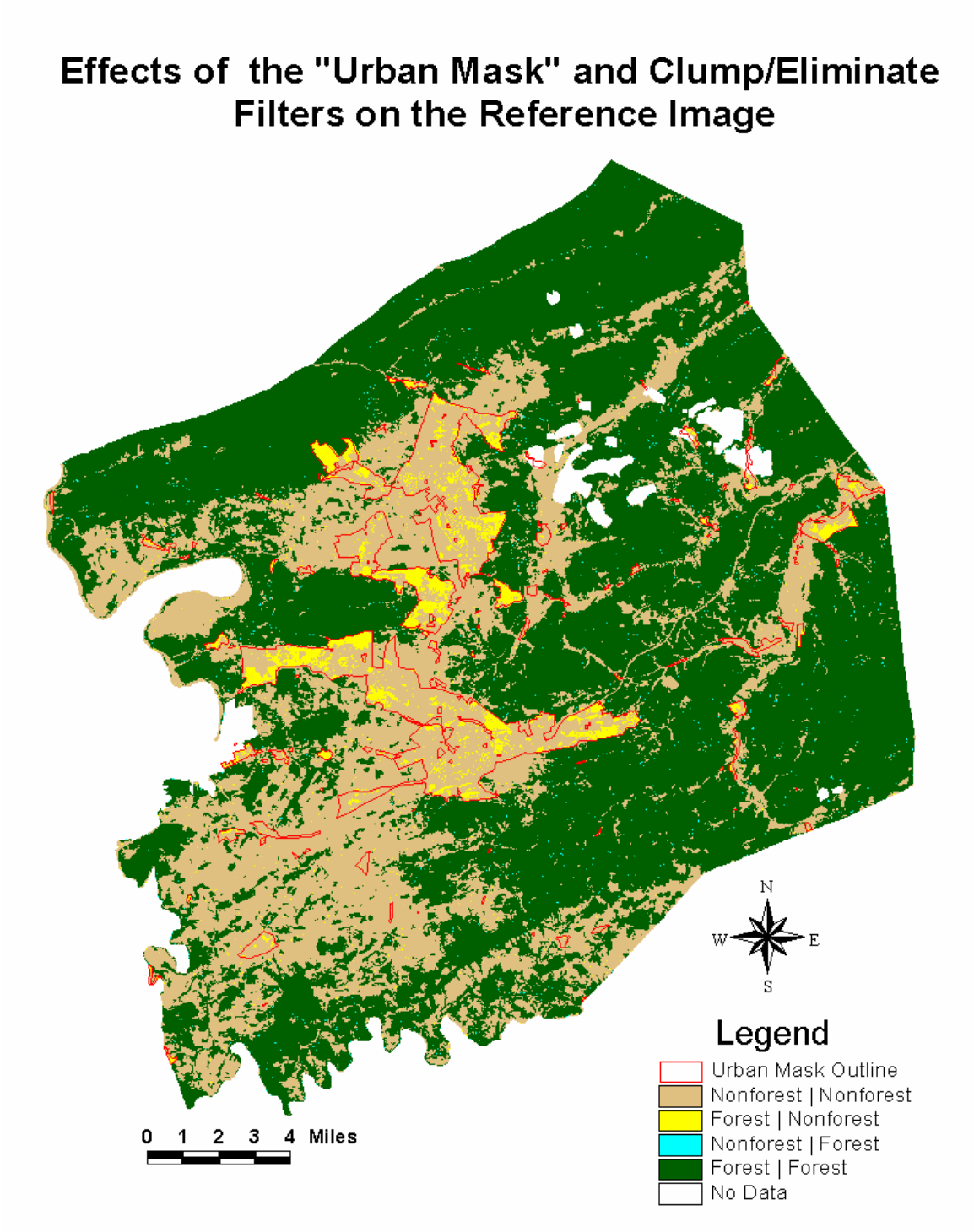

Figure 34 Effects of the Urban Mask and Clump/Eliminate Method on the original IGSCR Classified Landsat TM Scene 17/34.

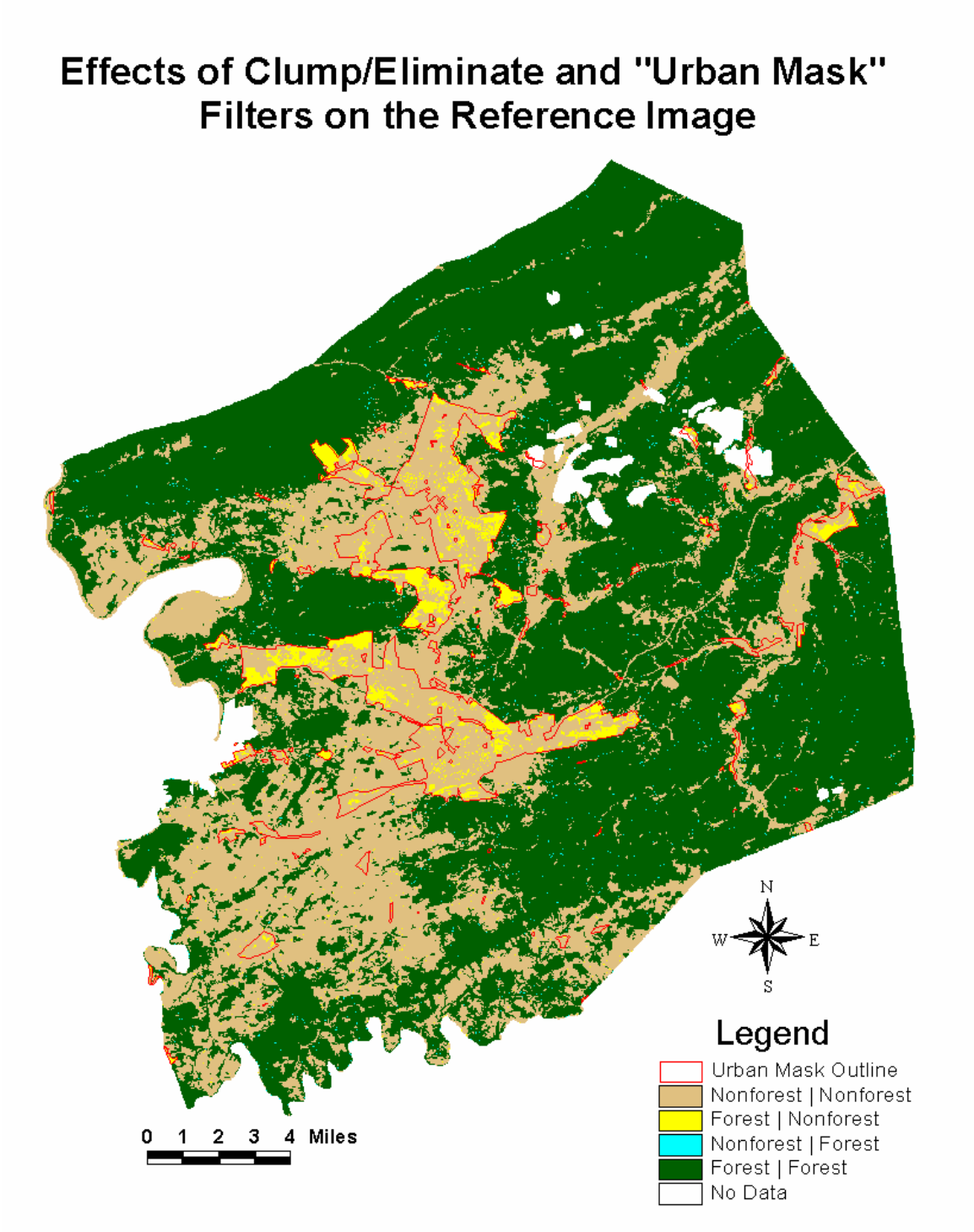

Figure 35 Effects of the Clump/Eliminate Method and the Urban Mask and on the original IGSCR Classified Landsat TM Scene 17/34.

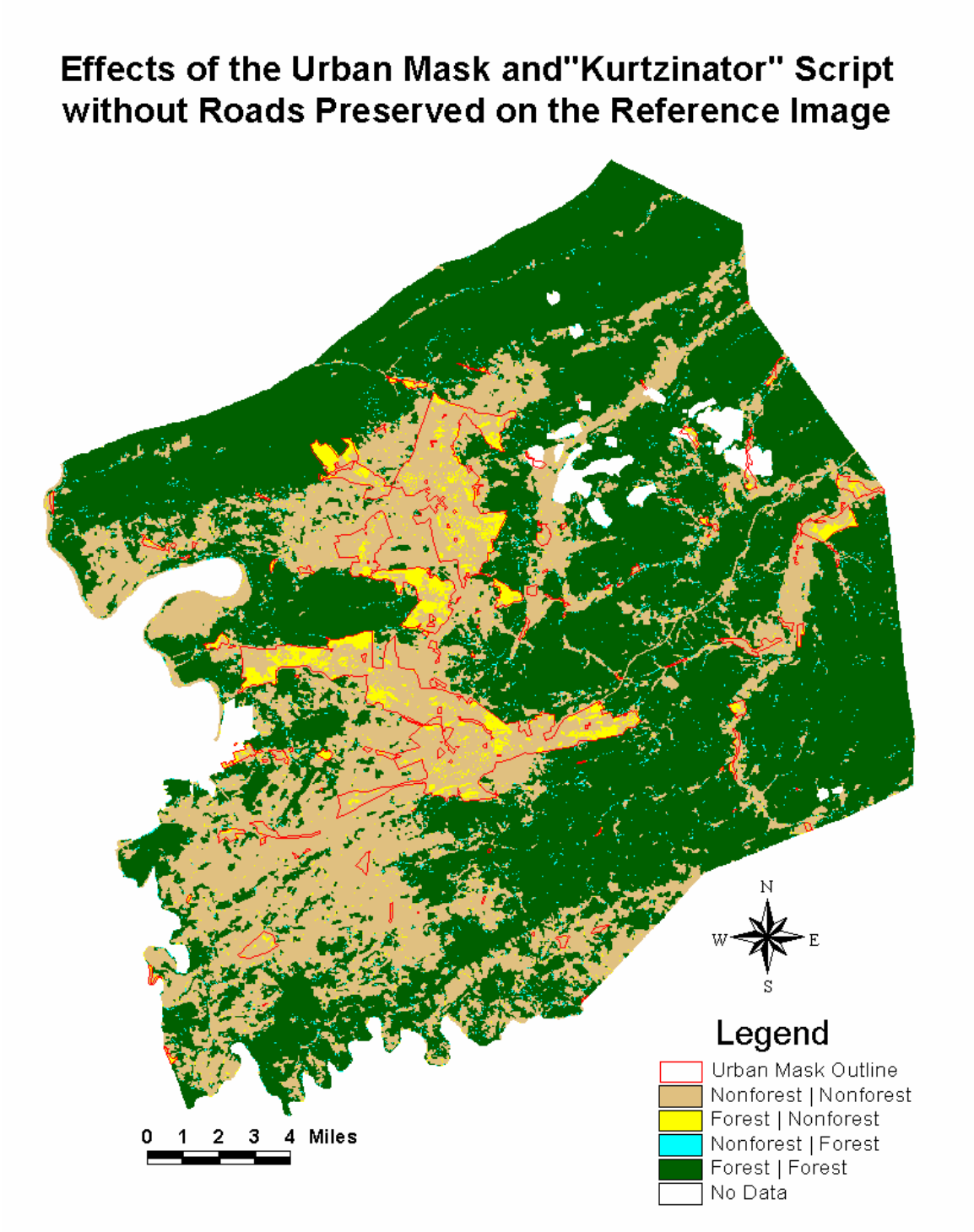

Figure 36 Effects of the Urban Mask and the "Kurtzinator" script without roads preserved, on the original IGSCR Classified Landsat TM Scene 17/34.

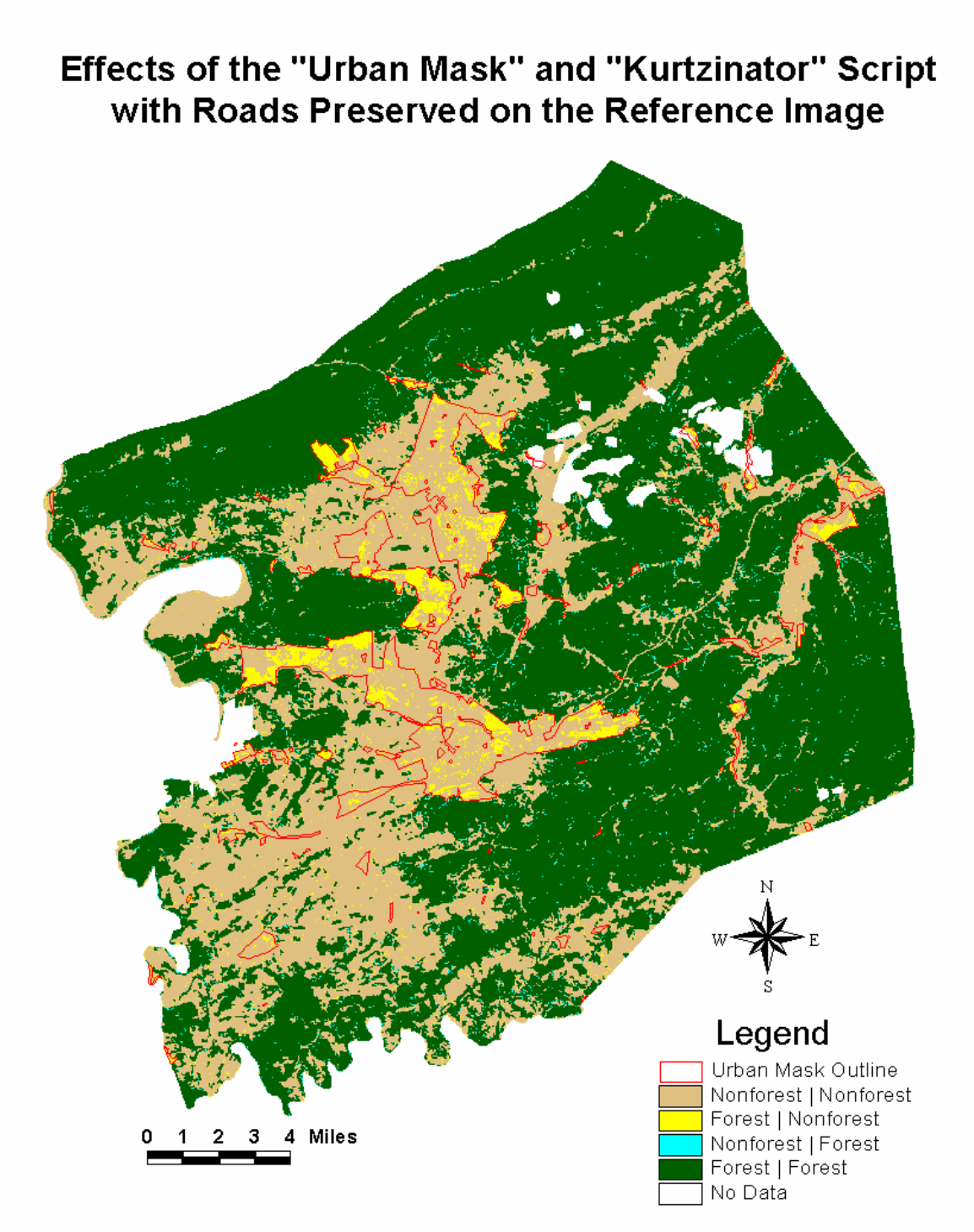

Figure 37 Effects of the Urban Mask and the "Kurtzinator" script with roads preserved, on the original IGSCR Classified Landsat TM Scene 17/34.

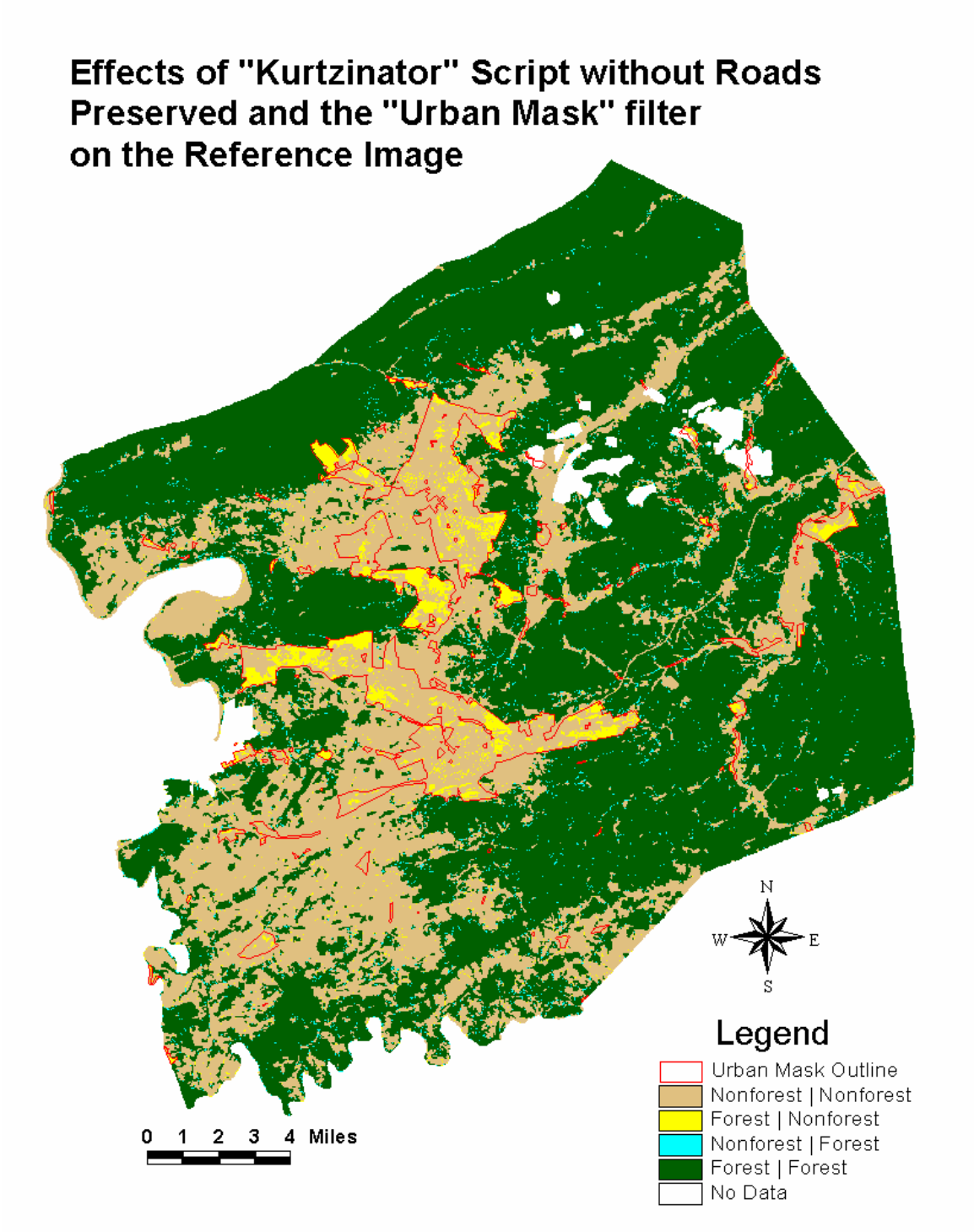

Figure 38 Effects of the "Kurtzinator" script without roads preserved and the Urban Mask on the original IGSCR Classified Landsat TM Scene 17/34.

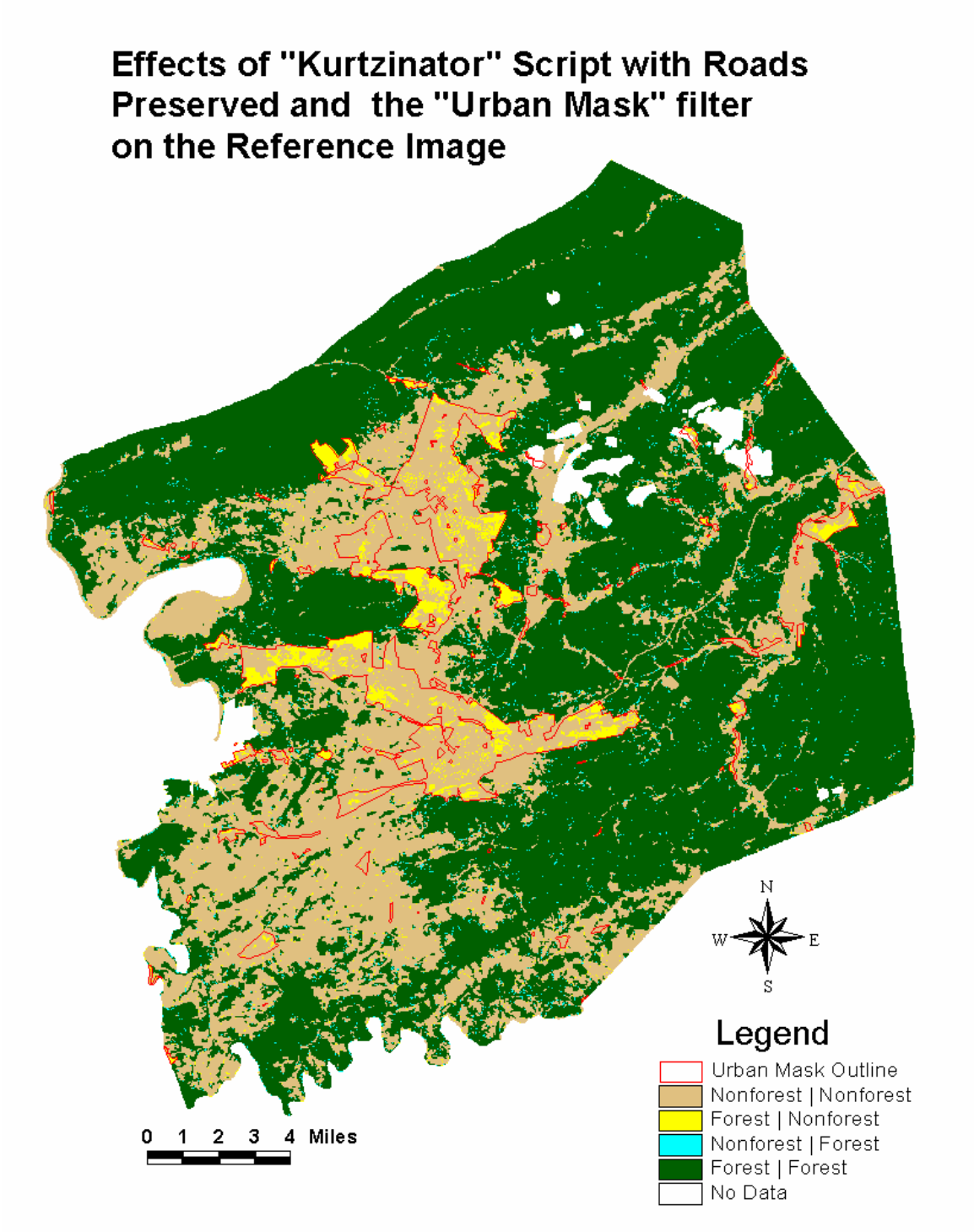

Figure 39 Effects of the "Kurtzinator" script with roads preserved and the Urban Mask on the original IGSCR Classified Landsat TM Scene 17/34.

Appendix vi: Logistic Regression Reports

Table 13 Logistic Regression Report: Tax Parcel Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.4419739	0.2267341	3.80	0.051259	0.038074
Tax_val	-1.04462E-03	4.977717E-04	4.40	0.035853	0.043864

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.130647	1	14.43	0.000146

Classification Table

Actual		Predicted 1	2	Total
1	Count	12.00	34.00	46.00
	Row Percent	26.09	73.91	100.00
	Column Percent	80.00	40.96	46.94
2	Count	3.00	49.00	52.00
	Row Percent	5.77	94.23	100.00
	Column Percent	20.00	59.04	53.06
Total	Count	15.00	83.00	98.00
	Row Percent	15.31	84.69	
	Column Percent	100.00	100.00	

Percent Correctly Classified=62.24

Table 14 Logistic Regression Report: Population Density

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.4597107	0.2343721	3.85	0.049826	0.038532
Pop_val	-7.54778E-04	3.678759E-04	4.21	0.040197	0.042007

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.113166	1	12.25	0.000465

Classification Table

Actual		Predicted 1	2	Total
1	Count	13.00	33.00	46.00
	Row Percent	28.26	71.74	100.00
	Column Percent	72.22	41.25	46.94
2	Count	5.00	47.00	52.00
	Row Percent	9.62	90.38	100.00
	Column Percent	27.78	58.75	53.06
Total	Count	18.00	80.00	98.00
	Row Percent	18.37	81.63	
	Column Percent	100.00	100.00	

Percent Correctly Classified=61.22

Table 15 Logistic Regression Report: Road Density

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.8203914	0.3166772	6.71	0.009580	0.065342
Roads_val	-4.744226	1.643666	8.33	0.003897	0.079853

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.093134	1	9.86	0.001690

Classification Table

Actual		Predicted 1	2	Total
1	Count	24.00	22.00	46.00
	Row Percent	52.17	47.83	100.00
	Column Percent	57.14	39.29	46.94
2	Count	18.00	34.00	52.00
	Row Percent	34.62	65.38	100.00
	Column Percent	42.86	60.71	53.06
Total	Count	42.00	56.00	98.00
	Row Percent	42.86	57.14	
	Column Percent	100.00	100.00	

Percent Correctly Classified=59.18

Table 16 Logistic Regression Report: IGSCR Classified Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-10.35561	2.108545	24.12	0.000001	0.200802
Mont_classval	6.594413	1.173114	31.60	0.000000	0.247642

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-10.355613	2.108545			
Mont_classval	6.594413	1.173114	730.999864	73.343346	7285.743394

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.517033	1	102.77	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	43.00	3.00	46.00
	Row Percent	93.48	6.52	100.00
	Column Percent	97.73	5.56	46.94
2	Count	1.00	51.00	52.00
	Row Percent	1.92	98.08	100.00
	Column Percent	2.27	94.44	53.06
Total	Count	44.00	54.00	98.00
	Row Percent	44.90	55.10	
	Column Percent	100.00	100.00	

Percent Correctly Classified=95.92

Table 17 Logistic Regression Report: Population Density, Road Density, Tax Value, and IGSCR Classification Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-10.12994	2.280901	19.72	0.000009	0.174978
Popval	-1.431387E-03	9.129624E-04	2.46	0.116916	0.025751
Roadsval	-4.058826	5.693449	0.51	0.475911	0.005435
Taxval	-2.576887E-03	1.225654E-03	4.42	0.035513	0.045374
Mont_classval	7.431474	1.482348	25.13	0.000001	0.212754

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-10.129942	2.280901			
Popval	-0.001431	0.000913			
Roadsval	-4.058826	5.693450			
Taxval	-0.002577	0.001226			
Mont_classval	7.431474	1.482348	1688.293588	92.399885	30847.822403

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.546398	4	112.03	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	44.00	2.00	46.00
	Row Percent	95.65	4.35	100.00
	Column Percent	97.78	3.77	46.94
2	Count	1.00	51.00	52.00
	Row Percent	1.92	98.08	100.00
	Column Percent	2.22	96.23	53.06
Total	Count	45.00	53.00	98.00
	Row Percent	45.92	54.08	
	Column Percent	100.00	100.00	

Percent Correctly Classified=96.94

Table 18 Logistic Regression Report: Population Density, Road Density, and Tax Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	1.053535	0.3591025	8.61	0.003348	0.083885
Pop_val	-5.215121E-04	3.771675E-04	1.91	0.166755	0.019934
Roads_val	-3.537067	1.970398	3.22	0.072637	0.033145
Tax_val	-8.058282E-04	5.529368E-04	2.12	0.145017	0.022095

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.193781	3	22.59	0.000049

Classification Table

Actual		Predicted 1	2	Total
1	Count	20.00	26.00	46.00
	Row Percent	43.48	56.52	100.00
	Column Percent	76.92	36.11	46.94
2	Count	6.00	46.00	52.00
	Row Percent	11.54	88.46	100.00
	Column Percent	23.08	63.89	53.06
Total	Count	26.00	72.00	98.00
	Row Percent	26.53	73.47	
	Column Percent	100.00	100.00	

Percent Correctly Classified=67.35

Table 19 Logistic Regression Report: Population Density and IGSCR Classification Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-10.24458	2.162113	22.45	0.000002	0.191150
Popval	-1.459277E-03	6.777591E-04	4.64	0.031312	0.046527
Mont_classval	6.899184	1.280599	29.02	0.000000	0.234024

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-10.244580	2.162114			
Popval	-0.001459	0.000678			
Mont_classval	6.899184	1.280599	991.465069	80.580372	12199.037564

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.531042	2	107.58	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	44.00	2.00	46.00
	Row Percent	95.65	4.35	100.00
	Column Percent	97.78	3.77	46.94
2	Count	1.00	51.00	52.00
	Row Percent	1.92	98.08	100.00
	Column Percent	2.22	96.23	53.06
Total	Count	45.00	53.00	98.00
	Row Percent	45.92	54.08	
	Column Percent	100.00	100.00	

Percent Correctly Classified=96.94

Table 20 Logistic Regression Report: Population Density and Road Density

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.964288	0.3412578	7.98	0.004718	0.077531
Pop_val	-6.704309E-04	3.657273E-04	3.36	0.066781	0.034164
Roads_val	-3.890574	1.821278	4.56	0.032665	0.045833

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.153342	2	17.21	0.000184

Classification Table

Actual		Predicted 1	2	Total
1	Count	24.00	22.00	46.00
	Row Percent	52.17	47.83	100.00
	Column Percent	82.76	31.88	46.94
2	Count	5.00	47.00	52.00
	Row Percent	9.62	90.38	100.00
	Column Percent	17.24	68.12	53.06
Total	Count	29.00	69.00	98.00
	Row Percent	29.59	70.41	
	Column Percent	100.00	100.00	

Percent Correctly Classified=72.45

Table 21 Logistic Regression Report: Population Density and Tax Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.6162873	0.2496606	6.09	0.013568	0.060276
Pop_val	-5.785351E-04	3.855416E-04	2.25	0.133465	0.023154
Tax_val	-8.637774E-04	5.418007E-04	2.54	0.110875	0.026058

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.168198	2	19.21	0.000067

Classification Table

Actual		Predicted 1	2	Total
1	Count	17.00	29.00	46.00
	Row Percent	36.96	63.04	100.00
	Column Percent	73.91	38.67	46.94
2	Count	6.00	46.00	52.00
	Row Percent	11.54	88.46	100.00
	Column Percent	26.09	61.33	53.06
Total	Count	23.00	75.00	98.00
	Row Percent	23.47	76.53	
	Column Percent	100.00	100.00	

Percent Correctly Classified=64.29

Table 22 Logistic Regression Report: Road Density and IGSCR Classification Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-9.634416	2.12194	20.62	0.000006	0.178308
Roadsval	-5.343105	4.584237	1.36	0.243801	0.014098
Mont_classval	6.605774	1.231698	28.76	0.000000	0.232406

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-9.634415	2.121940			
Roadsval	-5.343105	4.584237			
Mont_classval	6.605774	1.231698	739.351909	66.134506	8265.598113

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.523265	2	104.27	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	43.00	3.00	46.00
	Row Percent	93.48	6.52	100.00
	Column Percent	97.73	5.56	46.94
2	Count	1.00	51.00	52.00
	Row Percent	1.92	98.08	100.00
	Column Percent	2.27	94.44	53.06
Total	Count	44.00	54.00	98.00
	Row Percent	44.90	55.10	
	Column Percent	100.00	100.00	

Percent Correctly Classified=95.92

Table 23 Logistic Regression Report: Road Density and Tax Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	0.9614595	0.3466145	7.69	0.005540	0.074924
Roads_val	-3.962465	1.900663	4.35	0.037089	0.043749
Tax_val	-9.745127E-04	5.048835E-04	3.73	0.053585	0.037737

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.166927	2	19.04	0.000074

Classification Table

Actual		Predicted 1	2	Total
1	Count	23.00	23.00	46.00
	Row Percent	50.00	50.00	100.00
	Column Percent	76.67	33.82	46.94
2	Count	7.00	45.00	52.00
	Row Percent	13.46	86.54	100.00
	Column Percent	23.33	66.18	53.06
Total	Count	30.00	68.00	98.00
	Row Percent	30.61	69.39	
	Column Percent	100.00	100.00	

Percent Correctly Classified=69.39

Table 24 Logistic Regression Report: Road Density, Tax Value, and IGSCR Classification Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-9.954848	2.266176	19.30	0.000011	0.170320
Roadsval	-8.430015	5.461504	2.38	0.122701	0.024719
Taxval	-2.784556E-03	1.25893E-03	4.89	0.026978	0.049470
Mont_classval	7.377252	1.566653	22.17	0.000002	0.190869

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-9.954849	2.266176			
Roadsval	-8.430015	5.461505			
Taxval	-0.002785	0.001259			
Mont_classval	7.377252	1.566653	1599.188904	74.192929	34469.661571

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.537571	3	109.27	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	43.00	3.00	46.00
	Row Percent	93.48	6.52	100.00
	Column Percent	95.56	5.66	46.94
2	Count	2.00	50.00	52.00
	Row Percent	3.85	96.15	100.00
	Column Percent	4.44	94.34	53.06
Total	Count	45.00	53.00	98.00
	Row Percent	45.92	54.08	
	Column Percent	100.00	100.00	

Percent Correctly Classified=94.9

Table 25 Logistic Regression Report: Tax Value and IGSCR Classification Value

Parameter Estimation Section

Variable	Regression Coefficient	Standard Error	Chi-Square Beta=0	Prob Level	Last R-Squared
Intercept	-10.15474	2.155378	22.20	0.000002	0.189398
Taxval	-1.987614E-03	1.018975E-03	3.80	0.051105	0.038509
Mont_classval	6.752934	1.258098	28.81	0.000000	0.232701

Odds Ratio Estimation Section

Variable	Regression Coefficient	Standard Error	Odds Ratio	Lower 95% Conf. Limit	Upper 95% Conf. Limit
Intercept	-10.154737	2.155378			
Taxval	-0.001988	0.001019			
Mont_classval	6.752934	1.258098	856.568438	72.755704	10084.563121

Model Summary Section

Model R-Squared	Model D.F.	Model Chi-Square	Model Prob
0.528689	2	106.57	0.000000

Classification Table

Actual		Predicted 1	2	Total
1	Count	43.00	3.00	46.00
	Row Percent	93.48	6.52	100.00
	Column Percent	95.56	5.66	46.94
2	Count	2.00	50.00	52.00
	Row Percent	3.85	96.15	100.00
	Column Percent	4.44	94.34	53.06
Total	Count	45.00	53.00	98.00
	Row Percent	45.92	54.08	
	Column Percent	100.00	100.00	

Percent Correctly Classified=94.9

Appendix vii: Error Matrices

Table 26 Error Matrix : Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script with roads preserved.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	44	3	47		93.617
Class2	2	49	51		96.0784
Col Tot	46	52	98	*I*	
Producers acc	95.6522	94.2308			
Overall ACC	94.898				
Kappa	0.897704				
T =	0.948979592				
U =	0.501249479				
V =	0.951582674				
W =	1.041289131				
Var of Kappa	0.002382863				

Table 27 Error Matrix: Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script without roads preserved.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	44	3	47		93.617
Class2	2	49	51		96.0784
Col Tot	46	52	98	*I*	
Producers acc	95.6522	94.2308			
Overall ACC	94.898				
Kappa	0.897704				
T =	0.948979592				
U =	0.501249479				
V =	0.951582674				
W =	1.041289131				
Var of Kappa	0.002382863				

Table 28 Error Matrix: Urban Mask applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	45	4	49		91.8367
Class2	1	48	49		97.9592
Col Tot	46	52	98	***I***	
Producers acc	97.8261	92.3077			
Overall Acc	94.898				
Kappa	0.897959				
T =	0.948979592				
U =	0.5				
V =	0.949916701				
W =	1.044290644				
Var of Kappa	0.002356592				

Table 29 Error Matrix: Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	44	1	45		97.7778
Class2	2	51	53		96.2264
Col Tot	46	52	98	***I***	
Producers acc	95.6522	98.0769			
Overall ACC	96.9388				
Kappa	0.938468				
T =	0.969387755				
U =	0.502498959				
V =	0.974489796				
W =	1.026658748				
Var of Kappa	0.00137306				

Table 30 Error Matrix: Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	45	4	49		91.8367
Class2	1	48	49		97.9592
Col Tot	46	52	98	***I***	
Producers acc	97.8261	92.3077			
Overall ACC	94.898				
Kappa	0.897959				
T =	0.948979592				
U =	0.5				
V =	0.949916701				
W =	1.044290644				
Var of Kappa	0.002356592				

Table 31 Error Matrix: Urban Mask then the Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	45	4	49		91.8367
Class2	1	48	49		97.9592
Col Tot	46	52	98	***I***	
Producers acc	97.8261	92.3077			
Overall ACC	94.898				
Kappa	0.897959				
T =	0.948979592				
U =	0.5				
V =	0.949916701				
W =	1.044290644				
Var of Kappa	0.002356592				

Table 32 Error Matrix "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34.

		n_{IJ}	n_{IJ}	n_{J}		
		Class1	Class2	Row tot		Users acc
Class1		43	0	43		100
Class2		3	52	55		94.5455
Col Tot		46	52	98	n_{I}	
Producers acc		93.4783	100			
Overall ACC		96.9388				
Kappa		0.938313				
	T =	0.969387755				
	U =	0.503748438				
	V =	0.977821741				
	W =	1.023198242				
Var of Kappa		0.00137873				

Table 33 Error Matrix: "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34.

		n_{IJ}	n_{IJ}	n_{J}		
		Class1	Class2	Row tot		Users acc
Class1		43	0	43		100
Class2		3	52	55		94.5455
Col Tot		46	52	98	n_{I}	
Producers acc		93.4783	100			
Overall ACC		96.9388				
Kappa		0.938313				
	T =	0.969387755				
	U =	0.503748438				
	V =	0.977821741				
	W =	1.023198242				
Var of Kappa		0.00137873				

Table 34 Error Matrix: "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	44	3	47		93.617
Class2	2	49	51		96.0784
Col Tot	46	52	98	***I***	
Producers acc	95.6522	94.2308			
Overall Acc	94.898				
Kappa	0.897704				
T =	0.948979592				
U =	0.501249479				
V =	0.951582674				
W =	1.041289131				
Var of Kappa	0.002382863				

Table 35 Error Matrix: "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	44	3	47		93.617
Class2	2	49	51		96.0784
Col Tot	46	52	98	***I***	
Producers acc	95.6522	94.2308			
Overall Acc	94.898				
Kappa	0.897704				
T =	0.948979592				
U =	0.501249479				
V =	0.951582674				
W =	1.041289131				
Var of Kappa	0.002382863				

Table 36 Error Matrix: 3x3 Majority Filter applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	43	0	43		100
Class2	3	52	55		94.5455
Col Tot	46	52	98	***I***	
Producers acc	93.4783	100			
Overall Acc	96.9388				
Kappa	0.938313				
T =	0.969387755				
U =	0.503748438				
V =	0.977821741				
W =	1.023198242				
Var of Kappa	0.00137873				

Appendix viii: **Error Matrices Field plus FIA Validation Points**

Table 37 Error Matrix for IGSCR Classification of study area

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	65	2	67		97.0149
Class2	8	94	102		92.1569
Col Tot	73	96	169	***I***	
Producers acc	89.0411	97.91667			
Overall ACC	94.0828				
Kappa	0.8782				
T =	0.940828402				
U =	0.514092644				
V =	0.97027415				
W =	1.100392827				
Var of Kappa	0.001716948				

Table 38 Error Matrix: Urban Mask applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	67	5	72		93.0556
Class2	6	91	97		93.8144
Col Tot	73	96	169	***I***	
Producers acc	91.7808	94.79167			
Overall ACC	93.4911				
Kappa	0.8671				
T =	0.934911243				
U =	0.510066174				
V =	0.955078604				
W =	1.097707202				
Var of Kappa	0.001877806				

Table 39 Error Matrix : Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script with roads preserved

	IJ	IJ	J		
	Class1	Class2	Row tot		Users acc
Class1	64	3	67		95.5224
Class2	9	93	102		91.1765
Col Tot	73	96	169	I	
Producers acc	87.6712	96.875			
Overall ACC	92.8994				
Kappa	0.8539				
T =	0.928994083				
U =	0.514092644				
V =	0.958439831				
W =	1.108181409				
Var of Kappa	0.002110413				

Table 40 Error Matrix : Urban Mask applied to the originally classified Landsat TM scene 17/34 then application of the "Kurtzinator" Script without roads preserved

	IJ	IJ	J		
	Class1	Class2	Row tot		Users acc
Class1	64	3	67		95.5224
Class2	9	93	102		91.1765
Col Tot	73	96	169	I	
Producers acc	87.6712	96.875			
Overall ACC	92.8994				
Kappa	0.8539				
T =	0.928994083				
U =	0.514092644				
V =	0.958439831				
W =	1.108181409				
Var of Kappa	0.002110413				

Table 41 Error Matrix: Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	66	2	68		97.0588
Class2	7	94	101		93.0693
Col Tot	73	96	169	***I***	
Producers acc	90.4110	97.91667			
Overall ACC	94.6746				
Kappa	0.8906				
T =	0.946745562				
U =	0.51328735				
V =	0.974195581				
W =	1.095264801				
Var of Kappa	0.001521246				

Table 42 Error Matrix: Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	***IJ***	***J***		
	Class1	Class2	Row tot		Users acc
Class1	67	5	72		93.0556
Class2	6	91	97		93.8144
Col Tot	73	96	169	***I***	
Producers acc	91.7808	94.7917			
Overall ACC	93.4911				
Kappa	0.8671				
T =	0.934911243				
U =	0.510066174				
V =	0.955078604				
W =	1.097707202				
Var of Kappa	0.001877806				

Table 43 Error Matrix: Urban Mask then the Clump/Eliminate Method applied to the originally classified Landsat TM scene 17/34.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	67	5	72		93.0556
Class2	6	91	97		93.8144
Col Tot	73	96	169	*I*	
Producers acc	91.7808	94.7917			
Overall ACC	93.4911				
Kappa	0.8671				
T =	0.934911243				
U =	0.510066174				
V =	0.955078604				
W =	1.097707202				
Var of Kappa	0.001877806				

Table 44 Error Matrix: 3x3 Majority Filter applied to the originally classified Landsat TM scene 17/34.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	65	0	65		100
Class2	8	96	104		92.30769
Col Tot	73	96	169	*I*	
Producers acc	89.04109589	100			
Overall ACC	95.26627219				
Kappa	0.9023				
T =	0.952662722				
U =	0.515703232				
V =	0.986310003				
W =	1.094973511				
Var of Kappa	0.001345106				

Table 45 Error Matrix: "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	64	0	64		100.0000
Class2	9	96	105		91.4286
Col Tot	73	96	169	*I*	
Producers acc	87.6712	100.0000			
Overall ACC	94.6746				
Kappa	0.8899				
T =	0.946745562				
U =	0.516508526				
V =	0.982598649				
W =	1.100128884				
Var of Kappa	0.001537108				

Table 46 Error Matrix: "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	63	0	63		100.0000
Class2	10	96	106		90.5660
Col Tot	73	96	169	*I*	
Producers acc	86.3014	100.0000			
Overall ACC	94.0828				
Kappa	0.8774				
T =	0.940828402				
U =	0.51731382				
V =	0.978957319				
W =	1.105335223				
Var of Kappa	0.001733922				

Table 47 Error Matrix: "Kurtzinator" Script without roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	64	3	67		95.5224
Class2	9	93	102		91.1765
Col Tot	73	96	169	*I*	
Producers acc	87.6712	96.8750			
Overall ACC	92.8994				
Kappa	0.8539				
T =	0.928994083				
U =	0.514092644				
V =	0.958439831				
W =	1.108181409				
Var of Kappa	0.002110413				

Table 48 Error Matrix: "Kurtzinator" Script with roads preserved, applied to the originally classified Landsat TM scene 17/34 then application of the Urban Mask.

	IJ	*IJ*	*J*		
	Class1	Class2	Row tot		Users acc
Class1	65	3	68		95.5882
Class2	8	93	101		92.0792
Col Tot	73	96	169	*I*	
Producers acc	89.0411	96.8750			
Overall ACC	93.4911				
Kappa	0.8663				
T =	0.934911243				
U =	0.51328735				
V =	0.962361262				
W =	1.102990609				
Var of Kappa	0.001905898				

Vita

Brent Matthew Holoviak was born in Alamogordo, New Mexico, March 28, 1975. Being the son of an Air Force fighter pilot, he did quite a bit of moving around and became well traveled. He was able to see and experience other places and cultures, both here and abroad, not afforded to most young people.

He graduated from Tabb H.S. in Yorktown, VA in 1993. He earned his Bachelor of Science in Forestry and Wildlife from Virginia Tech in 1997. After graduation Brent worked for the Arizona Game and Fish department on an endangered species study where his interest in geography, specifically GPS and GIS was born. After his completion in Arizona, Brent obtained a job as an entry level GIS Technician with a firm in Colorado Springs, CO. With this firm Brent had the opportunity to work overseas for some time in Hyderabad, India. Upon his return to the United States, Brent migrated back to the East Coast and applied and was accepted as a graduate student in the Department of Geography at Virginia Tech, in the Fall of 2000. His interests in natural resource management, GIS, and remote sensing guided most of his course work and helped him earn an internship with the National Park Service in Yellowstone WY, as a GIS Analyst.

Upon completion of the master's program, Brent will remain in Blacksburg working for a local engineering firm, in a budding GIS department.