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Satellite Image Based Classification Mapping For Spatially Analyzing West Virginia Corridor H Urban Development

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Satellite Image Based Classification Mapping For Spatially Analyzing West Virginia Corridor H Urban Development.

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By

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ABSTRACT

Using Remote Sensing Techniques to Track and Analyze Urban Development Along ADHS Corridor H in West Virginia

By Chandra L. Inglis-Smith

The study area for this project is Corridor H, a designated Appalachian Development Highway located in Lewis, Upshur, Barbour Counties which are part of the Appalachian Plateau Province, and Randolph, Tucker, Grant and Hardy Counties which are Part of the Ridge and Valley Province in West Virginia. The region has a long history of occupation and a traditional economic structure consisting of mainly agriculture, timbering and coal mining. The final objective of the study was to perform change detection, using two Landsat datasets obtained from the USGS of the study area from 1987 and 2005 to determine if economic development, via change to cropland/ pasture and Urban Built Up Areas, could be measured and detected along Corridor H by using remote sensing techniques. Geometric Registration, Principal Component Analysis, Radiometric Normalization, Accuracy Analysis, Unsupervised Classification, and Spatial Analysis logical operators were utilized in IDRISI, ERMapper, and ESRI to complete the study. The total land change for the study area for Urban was 1.4% of the total 2,573,351 acres and 4.9% for change in Cropland/Pasture. More significantly there is a 2.7 %increase in Urban development within a 1-mile buffer around the length of Corridor H in the study area. When a buffer was placed 1-mile around Corridor H from Weston to Elkins the percentage of change increased to 4.5% for Urban areas and 7.5% for Cropland/Pasture. These results indicate economic change is occurring already along Corridor H before its completion. The development of this data will provide a baseline on which to base future studies of the area for tracking the expected economic growth of the region, and for Appalachian corridor highway systems in general. This data should be used with more traditional methods of economic impact and growth reporting and measurement, to focus these studies, and supply spatial relevance to changes in rural Appalachia.

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CHAPTER I

Introduction

Overview of Corridor H

The United States Congress established the Appalachian Regional Commission (ARC) in 1965. The goal of the commission is to encourage and foster economic growth and social development in the Appalachian Region, which includes all of West Virginia and portions of 13 other states stretching from New York to Mississippi. One of the programs proposed by the ARC was the Appalachian Development Highway System (ADHS), which was subsequently approved by the U.S. Congress. Corridor H is a designated Appalachian Development Highway and when completed will be part of a total of 3,090 miles of economic development highway system (Reference 40, 41). Figure 1 below is an image of the proposed location of Corridor H in West Virginia

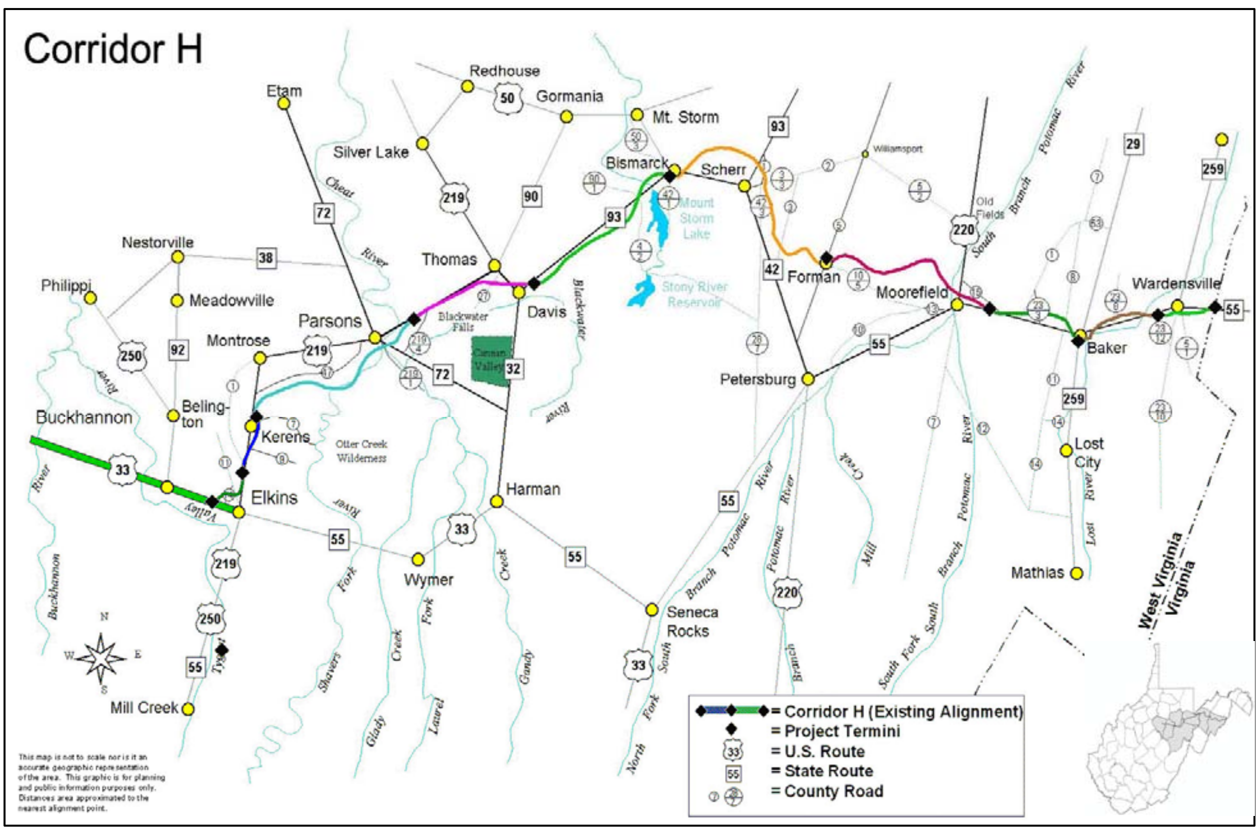


Figure 1: Corridor H, image from www.corridorh.com

In the Late 1970's a possible construction route of corridor H was studied from Elkins to I-81 in Virginia. By 1981 a Draft Environmental Impact Statement had been produced with a preferred alignment picked and a portion of what was to become Corridor H, from I-79 at Weston to Elkins had been completed and opened to traffic. By 1984 however, the project was put on hold due to lack of funds. During the 1990's environmental and regional studies of the proposed project area were resumed. By 1999 Corridor H had been divided into nine separate sections, with logical termini and by February of 2000 construction and planning for Corridor H was fully resumed. On May 31, 2000, WVDOH officials, and state and national leaders broke ground on the Moorefield to Baker section of the project. In 2002 a 5.48 mile segment of Corridor H opened to traffic between Elkins and Kerens and a three mile section opened in Hardy County. By 2003 another 5.35-mile section of Corridor H east of Moorefield opened to traffic in Hardy County (Reference 22, 36).

The main goal of Corridor H is to foster economic growth in the region, by improving east-west travel, inter-community travel, emergency response time, freight travel, and increasing access to recreational facilities in the area by linking the existing north-south interstates in the region (West Virginia, Virginia, Pennsylvania, and Maryland). The foundation of the Corridor H project rests on the belief that improved travel routes and travel efficiency leads to an increase in economic production, job opportunities, wages, population, and the growth of recreation, hotels/motels, forests, parks, golf courses, outfitters, and conference facilities (Reference 22, 32, 36, 41).

Land-Use, Land-Cover, and Change Detection

Land-use and land-cover are considered as two completely distinct classifications of the earth's surface but are closely linked. Land-use is the way that humans use and modify the land and its resources, such as agriculture, mining, timber extraction, and urban development. Land cover refers to the physical state of the surface of the land, such as streams, wetlands, grasslands, forest, and human modifications like roads, and buildings. Land-use and Land-cover affect each other, and that is why they are so closely linked. Changes in land cover by land use are either by modification, change in the condition within a particular cover type, or conversion, as in change from one cover type to a different one (Reference 3, 16, 19).

The use of multi-spectral reflectance data for mapping land-use and land-cover change has become an integral component of contemporary land use studies (Bottomley, 1998). Multi-spectral remote sensing satellite systems, like Landsat, collect multiple images in multiple electro-magnetic spectrum bands (wavelengths) specifically in the visible and near to mid infrared ranges. The information needed for the analysis will define the bands needed in the study. The satellite systems take the reflectance values recorded and convert this data to pixels of brightness values which are images. Associated with the images are four different resolution types, spatial, spectral, temporal and radiometric (Reference 18).

Spatial Resolution is the ability to distinguish between two closely located objects in an image. It is the minimum distance between two objects at which the images appear separate and distinct. High spatial resolution is a finer, more detailed ground resolution cell. An example of high spatial resolution satellite imagery is Spot or Quickbird, both very useful in urban areas for distinguishing between structures, but very expensive to obtain (Reference 42). Low spatial resolution is a less detailed ground resolution cell. An example of this type of imagery is Landsat MSS, very useful in larger areas, deserts plains, etc., where you need to make general land classifications, but not useful if you need finer data. The Landsat TM data, at 30 x 30m ground cell resolution, falls somewhere in the middle of the spatial resolution spectrum of the currently available data, while also being reasonably priced (Reference 1, 12, 18).

Spectral resolution is the ability of a sensor to define fine wavelength intervals. A wavelength interval is recorded at 50% of the peak response of a detector. The finer the spectral resolution the narrower the wavelength range for a particular channel or band, the more bands of information can be collected. An example of high spectral resolution would be multi-spectral or hyper-spectral satellite sensors like Aster and Landsat ETM, or Modis, and AVRIS, because they detect multiple ranges of bandwidths. Low spectral resolution would be black and white film, or panchromatic, because you only have one spectral region over a wide available band for study (Reference 18).

Temporal resolution has to do with the re-visit period of the satellite system, or the length of time it takes to do one complete orbit. The temporal resolution of a system depends on a variety of factors including the satellites capabilities, and the swath and overlap of the path. Another aspect of temporal resolution has to do with the time of year/day an image is procured. Radiometric resolution determines how fine the sensor can distinguish between two objects of similar reflection. The higher the radiometric resolution the easier it is to distinguish between subtle differences in reflection (Reference 18).

Once the satellite imagery is obtained with the desired spatial, spectral, temporal and radiometric characteristics, classification of land-use and land-cover classes can be derived by utilizing computer assisted image classification techniques. There are two common techniques in image classification; unsupervised and supervised. Unsupervised classification groups pixels with similar characteristics into like classes and similar groupings and assigns those groups numbers without any guidance from the user (Reference 12, 14). Supervised Classification uses predefined training sites that define specific areas of land cover/use types to and uses those sites to classify the images based on those training sites spectral signatures (Reference 12). Both techniques can be used in change detection analysis, depending on the final requirements of the study. Or as in the case of Lo and Choi‘s(2004) study in the Atlanta, Georgia metropolitan area, a combination of both techniques can be utilized for classification, by clipping out certain areas from the unsupervised classified image for use with supervised classification.

> Classifying land use/cover in the urban environment presents a major challenge because of the diversity within and between the urban landscapes, where continuous and discrete elements occur side by side (Alpin, 2003). Recognizing the high frequency of detail in the urban land use/cover, Welch (1982) recommended that high spatial resolution image data, at least 5m or higher, should be used to improve urban classification. However, research conducted by Irons et al. (1985) and Cushnie (1987) found that classification accuracy decreased with an increase in spatial resolution. This is because while increased spatial resolution has reduced mixed pixels, it has resulted in an increase not only in inter-class spectral variability but also intra-class spectral variability, thus causing poor accuracy for per-pixel classification. Toll (1985), who compared the differences in classification performance between Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM), concluded that spectral and radiometric properties were more

> important that spatial resolution in determining the accuracy of land use/cover classification. (Lo & Choi, 2004)

There is usually a simple relationship between the multi-spectral reflectance recorded by remote sensing devices and the dominant land cover type found on the ground. The same cannot be said for land use. Residential areas frequently comprise a mixture of tarmac and concrete (roads), grass, trees, soil and water (gardens), each of which may have a different spectral response. These same sets of land cover types may also be present on an industrial or commercial district. Often it is not possible for software to distinguish unambiguously between these types of land use/cover solely in terms of detected spectral reflectance. This is commonly referred to as a mixed pixel problem. (Reference 10, 11)

Change detection is determined by typically using map algebra, direct multi-date classification, or post-classification comparison techniques. Typical Map algebra in spatial analysis uses Boolean logic and is used within cartographic modeling as one means of combining two or more input map layers to produce a final map output layer. Direct Multi-date classification is usually done by taking a band from each image and overlaying them to see where changes occur via a change in color. Post-classification methods typically consist of running an unsupervised classification or supervised classification on multiple images, reclassifying them to the same number and types of classes, and then running an image differencing algorithm to determine the specific areas of change (Reference 12, 18, 20, 26).

Integrating remote sensing images and other data in Geographic Information Systems (GIS) may provide a way to produce more accurate land-use and land-cover maps especially for use in change detection. Change detection is useful in such diverse applications as land use analysis, monitoring shifting cultivation, assessment of deforestation, study of changes in vegetation phenology, seasonal changes in pasture production, damage assessment, crop stress detection, disaster monitoring, day/night analysis of thermal characteristics as well as other environmental changes (Singh, 1989 in Bottomley, 22). Change detection may also be important for tracking urban and economic growth.

Objective

The purpose of this project is to look at change in the study area over time by mapping present day West Virginia and comparing it to the past through the use of satellite imagery and GIS data. The objective of the study is to perform change detection, using two datasets obtained from the USGS of the study area from 1987 and 2005 to determine if economic development as seen through urban change can be measured along Corridor H. This is done by identifying the pattern of land-cover change in the study area from satellite images. Since the aim of this study is to determine change in land use in a general manner it does not matter if the change is specifically residential, commercial, industrial, or transportation since all are considered urban or built up areas. Any change in use from forest, or soil to urban will be considered a sign of economic impact in the area through the creation of jobs. The goal of this study is to determine if remote sensing techniques, specifically change detection, can be utilized to help measure urban and economic growth along Corridor H.

CHAPTER II

Methods and Techniques

Study Area

Corridor H is located in Lewis, Upshur, Barbour, Randolph, Tucker, Grant and Hardy Counties as shown in Figure 2 below. Lewis, Upshur, and Barbour counties are part of the Appalachian Plateau Province that is only structurally a plateau. The ancient surface has been eroded by stream action over millions of years into what is today a region of high relief and is characterized by small, narrow valleys (or hollows) which twist through the resulting mountains. The original plateau surface is evident in the pattern of hilltops that all tend to reach the same elevation, and is commonly known as a dissected plateau (Reference 43).

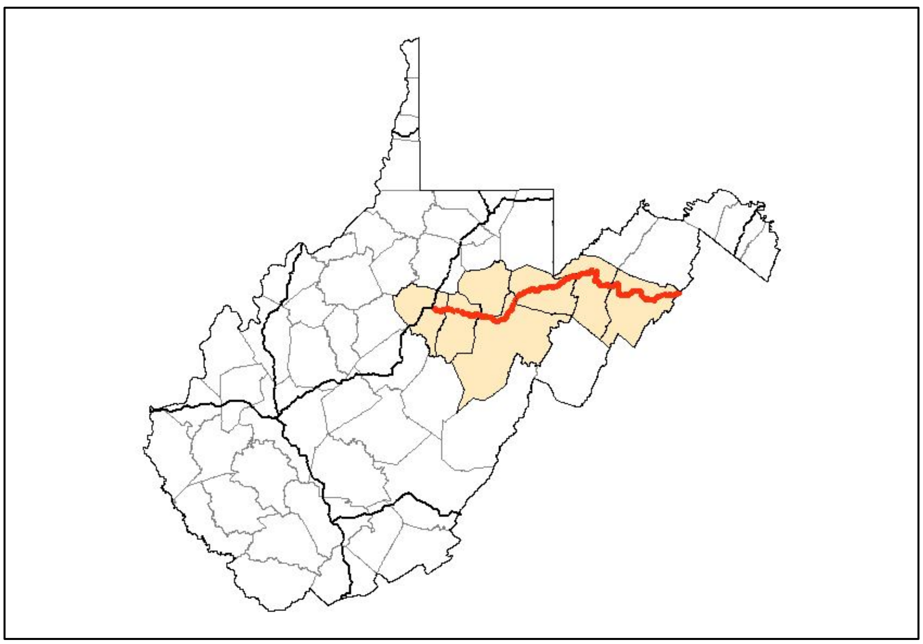


Figure 2: Study Area

The transition from the Appalachian Plateau Province to the Ridge and Valley Province, which Randolph, Tucker, Grant and Hardy Counties are part of, is called the Alleghany Front. This is the area where the horizontal beds of the plateau change into the folded geologic beds of the Valley and Ridge province. The Ridge and Valley province is characterized by long parallel mountain ridges that are heavily forested separated by valleys with rich soils that are useful for agriculture (Reference 44).

The earliest, late 18th century, Euro-American settlements in this region, can be characterized as scattered, with Europeans occupying the bottomlands flanking the river. These settlement patterns followed those initiated by Native Americans, who had inhabited West Virginia for thousands of years. Native Americans in the valley had practiced agriculture for centuries, and their presence is indicated on early maps of the region (Baker, 1997). In this early period settlement would have consisted of large homesteads or farmsteads spread throughout the area. Transportation systems were poorly developed consisting of dirt roads and Native American Trails. By the mid-1800's settlement was still fairly scattered in West Virginia, but there were a few areas with concentrations of population and by this time most places had taverns, stores, tailors, churches, etc. Improvements to the transportation network during this period with the development of Turnpikes led to continued economic growth for the area (Michael, 1997).

The regions main economic focus throughout its history has been agriculture and resource extraction. Only the dynamics of what is produced has changed, the earliest products being cattle and grain, and more recently corn and poultry farming. When the railroad came in the early 20th century there was a surge in the timber industry of the area, which eventually diminished by mid-century. Areas like Tucker County also had a surge in coal and coke production in the early part of the 20th century, an industry that diminished rapidly in the 1930's. Currently construction, transportation, service and health industries, and government and leisure industries are some of the leading employers in the counties where Corridor H is located (Reference 22).

Data Acquisition

Satellite images (raster data) are a convenient source of visual information for separating the urban built environment from open spaces and vegetation. With the availability of multi-spectral remotely sensed data in a digital form and the developments in digital processing, remote sensing supplies a new prospective for land-cover/land-use analysis (Betktas and Goskel, 2004). Vector datasets such as census data, line data, and DEM's can be incorporated with raster datasets to produce improved land-use and land-cover measurements and classification for change detection in economic development. Vector data is readily available on the internet for download and use in a GIS platform. Geographical Information Systems have already been used for assessing environmental problems, since they provide a flexible environment and a powerful tool for the manipulation and analysis of spatial information for land cover feature identification, and maps of all variables are combined to extract information to better understand the analysis (Weng, 2001).

Landsat TM data is being used because its spectral and temporal characteristics are useful and the systems have been collecting data in the time period of concern for this study. Data was obtained from the USGS via the Nick Joe Rahall II Appalachian Transportation Institute (RTI) and the West Virginia Department of Transportation (WVDOT). The imagery was chosen because it was temporally similar, and was perceived to be the best available of the area during the time frame of the study. A total of four images were procured (2 for Path 16 Row 33, and 2 for path 17 Row 33), however the final analysis was completed on the 1987 and 2005 images of Path 17 Row 33. Figure 3 shows how Path 17 fits in WV with the alignment of Corridor H shown as a white line. The specifications of the data utilized for the analysis are shown in Table 1.

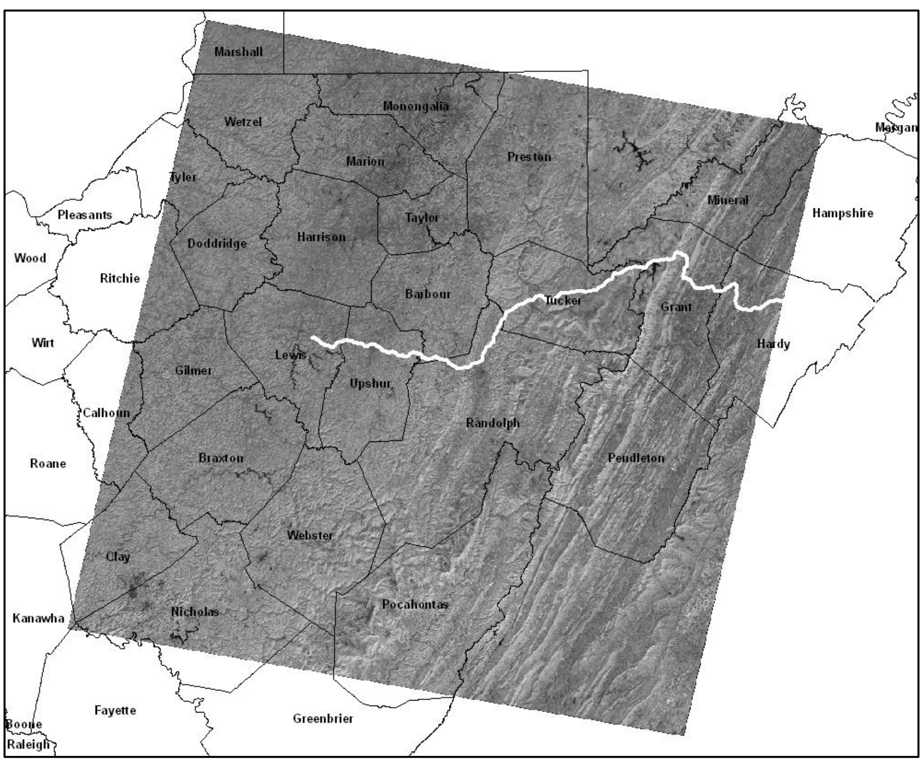


Figure 3: Landsat Path 17 and how it fits in WV.

Table 1

Path/Row	Date of Acquisition	Landsat Number	Imager Type	Spatial Resolution (m)	Sun Elevation (degrees)	Sun Azimuth (degrees)	Cloud Cover (%)
33/17	05Oct1987	5	TM	25	40.61	145.54	0%
33/17	03Aug2005	5	TM	25	59.58	127.58	0%

File Conversion

With the use of three software packages in the analysis, a number of file conversions were necessary to transfer data from one package to another. The three software packages utilized were ErMapper 7.0, IDRISI 3.2, and ESRI ArcGis 9.1. The software's were utilized to optimize on their capabilities for analyzing data and performing analysis. The file type most utilized was ASCII or ".asc", as it was easily imported and exported across all the software's used. There was no need for conversion between ERMapper and ESRI since there is an ECW and ERMapper download available, that allows ERMapper ".ers" files to be loaded directly into ESRI ArcMap.

Only two shapefiles were converted for use in the other packages, these were the Corridor H polyline, and a created Corridor H Boundary polyline. They were imported in IDRISI and ERMapper, utilizing their ERSI Import functions, and then converted to each software's native vector data file type for use.

Spatial Reference

The USGS imagery was supplied in UTM Zone 17N, and utilized the datum WGS 1984. The data downloaded from the WVU GIS Tech center was in UTM Zone 17N, and utilized the NAD 1983 datum. ArcMap is able to do on-the-fly projection, so the vector data was used without re-projection. The raster NLCD layer was re-projected to UTM Zone 17N, WGS 1984, in ArcToolbox to insure no conflict during spatial analysis.

Preprocessing

Images were imported into ERMapper from the GEOTIFF format. The images were purchased from the USGS were geo-registered to the same coordinate system (UTM Zone 17N) and to one another. Some rectification was completed in ERMapper to ensure that the data was aligned properly. This was completed by geometrically rectifying the images by registering them to one another using the 2005 image as the reference image. Two methods were undertaken to insure the images aligned properly. First, the registration coordinates were corrected manually to insure proper alignment and second, a polynomial transformation was completed using ground control points to manually resample the 1987 image. Vector data such as stream and road data, and the WV State Addressing and Mapping Board (SAMB) aerial photography was also utilized to ensure the accuracy of the registrations, by visual comparison in ESRI ArcMap. The Path 17 1987 and 2005 images were then loaded into an algorithm that displayed all six of the seven bands (band 6, thermal, was not utilized in the study) and saved as a virtual dataset. Figure 4 is a screen shot of the georectified images overlain. The bright yellow areas display unchanged/matched pixels, indicating areas where there is no difference between 1987 and 2005. While the red and green pixels display changed/unmatched pixels, giving a good

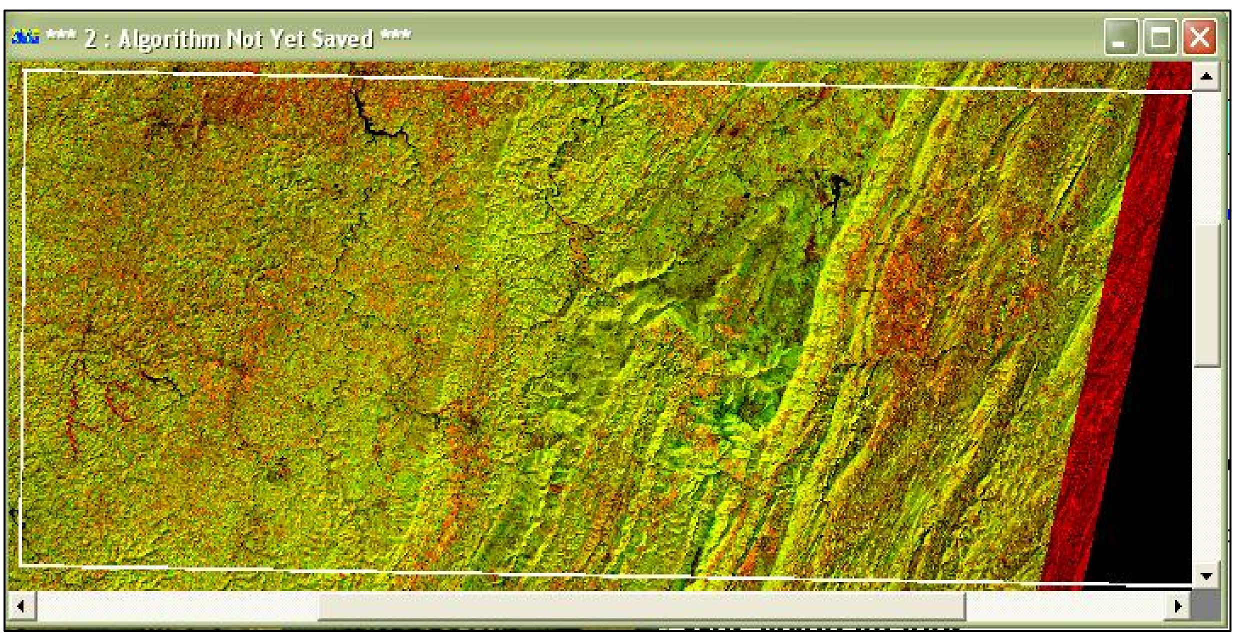


Figure 4: Overlay of the Geo-rectified 1987 and 2005 Images. Red and Green indicate Areas of Change.

indication of where areas of change are occurring to help guide the analysis. The white outline box is the border of the study area and is a vector layer that was used to clip the images.

Principal Components Analysis

Principal Components Analysis (PCA) is a statistical procedure of data compression that transforms a number of correlated or possibly correlated variables into a smaller number of uncorrelated variables (ErMapper). PCA reorganizes the data based on the transform axis. The first principal component usually accounts for as most of the variability in the data, and each component calculated thereafter accounts for some percentage of the remaining variability up to the number of components being analyzed. PCA takes the cloud of data points, and rotates the axis such that the maximum variability is visible on the first axis. This allows the analyst to pick out patterns and relationships in the variables and to reduce the size of the dataset without a significant loss of information. Exploratory multivariate data analysis like PCA are useful for extracting data that is scattered or noisy and helps to make the final image more meaningful (Jarupath, 2004).

Initially Principle Components Analysis in IDRISI was run on the images for bands 1-7. Statistics were calculated by IDRISI for the PCA Images, these are located in Appendix B. The testing of the PCA procedures produced three color composite images. One using bands 2, 3, & 4, one using bands 3, 4, & 5, and one using PCA bands 1, 2, & 3. It was determined that PCA bands produce component axis based on variability, with more colorful color composite images than spectral color composite images because the data is uncorrelated and this allows you to see more distinct differences in the data patterns. The TM and PCA color composite images were then used as the seed images for CLUSTER in IDRISI. The parameters set up for the initial clustering were for the software to do fine clustering, and to retain all clusters. HISTO was then run on the resulting images to determine where the clusters of features were located and what an appropriate maximum number of clusters would be. Then CLUSTER was run again on the seed images producing a final image containing only the maximum number of clusters needed as seen from the breaks in the histograms. The final images were then compared to 2003 SAMB aerial photography to determine the general accuracy of the classifications in relation to features on the ground.

The final principal component analysis was done in ERMapper on the virtual dataset, made up of the geo-rectified TM bands, produced during the preprocessing. PCA was run using a predefined algorithm included in the software under the classification toolbar. Only the Principal Components (1, 2, & 3) which contained 99.57% of the total image variance from Path 17 1987, and the Principal Components (1, 2, & 3) which contained 98.40% from Path 17 2005 were utilized for the continuation of the study. The resulting images (p17_87_vd_pca.ers and p17_05_vd_pca.ers) were saved as virtual datasets and were clipped to the boundary of the study area.

Radiometric Normalization

This process involves radiometrically normalizing the separate bands from one multi-spectral image date to a second date over the same geographical location acquired at approximately the same time of year. The procedure consists of extracting brightness values from the reference band (RGB), deriving regression coefficients from these values between the two dates, and applying the coefficients to the entire first date image. In this way, the first date image is corrected for differences in atmospheric conditions and/or sun angle differences that may occur between the acquisitions of the two images (i.e., the first date is Radiometrically Normalized to the second, reference date) (Reference12). Distribution-based relative radiometric correction techniques, such as histogram matching (e.g. Chavez and MacKinnon 1994), eliminate the subjectivity problem and reduce the dependence on a geometrically accurate spatial match between multi-data images through their use of the entire dataset (Nelson et al, 2005). Radiometric Normalization via histogram matching of the principal component images was done in ERMapper. This process was completed because the two images had different radiometric (pixel brightness) characteristics due to their different temporal collection times. It was important to complete this step for accurate classification and comparison purposes. Histogram matching transformed the final output histograms of the red, green, blue, principle component 1987 layers to match the final output histograms of the 2005 layers of the same type. Both principal component images (1987 &2005) were added to an algorithm window with six bands, two red, two green, and two blue (RGB for 1987 and RGB for 2005). The 1987 bands were then matched band by band to the 2005 image by editing the transformations.

Image Classification

Land cover classification based on statistical feature extraction for pattern recognition is one of the most common techniques of information extraction (Jenson, 2005, Brumfield, 1997). As previously stated there are two basic types of classification techniques, unsupervised and supervised. For this study the method employed was unsupervised classification of the PCA transformed images. Unsupervised classification groups pixels with similar characteristics into like classes or similar groupings and assigns those groups numbers. A number of different methods were employed to figure out the best classification technique. IDRISI and ErMapper software were both utilized to determine the optimum number of classes and which software classified the images more succinctly. Initially both PCA images were classified in IDRISI using both the Broad and Fine clustering techniques. The histograms of the classified images were studied to determine where the appropriate class break was. Figure 5 is an example of path 17 2005, showing where the results become asymptotic around 14 classes, and this indicated the optimum number cluster classes. Both images returned similar results for maximum number of classes.

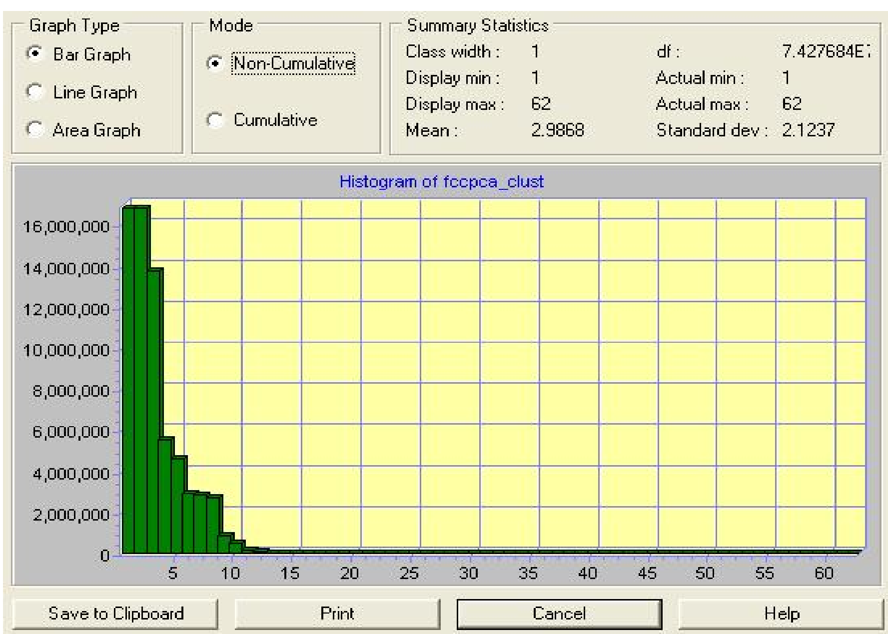
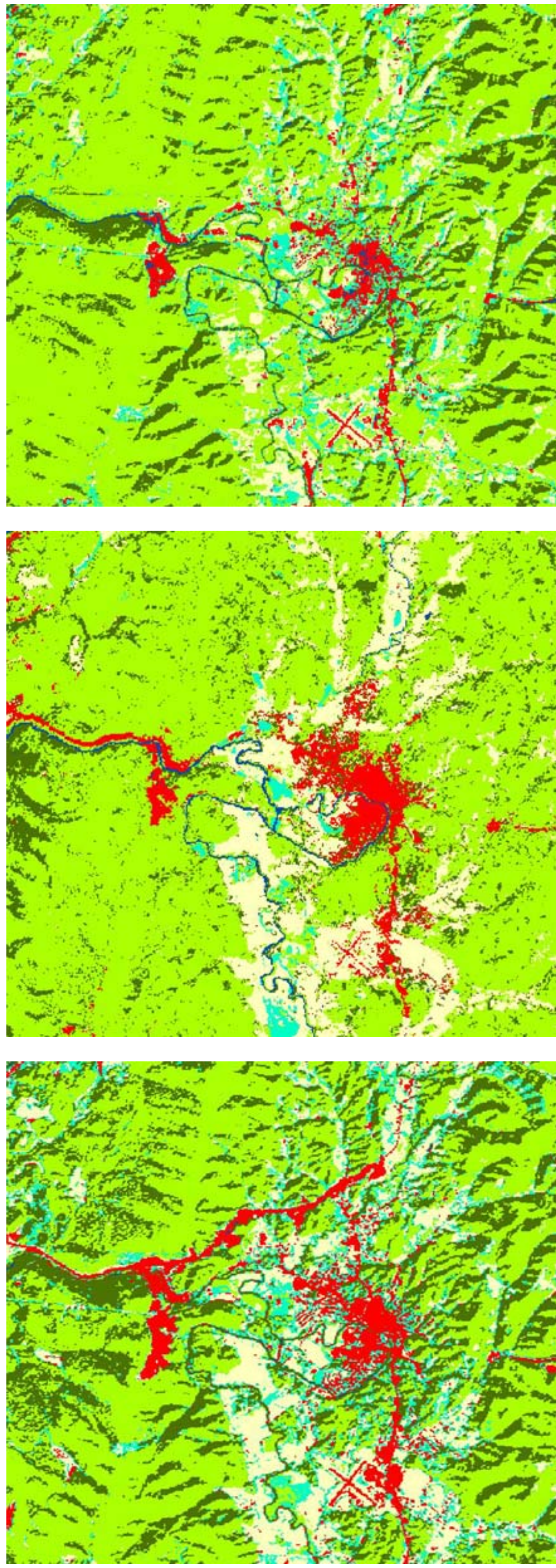


Figure 5: Histogram of Path 17, 2005 Principal Components Analysis Image

The images were then classified in ERMapper. The analysis constraints for both images in ERMapper were: a maximum number of 15 classes, 99 iterations, and 0.1% for minimum members in a class, zero values were set to null and not classified. All the other options were left as default.

After executing the classification algorithm, the classified images were returned and the clusters were labeled and identified as to land cover/use type. The classified PCA images were then brought into ESRI for Spatial Analysis. Vector data such road and river polylines, and raster data like the National Landuse Map (NLCD) and SAMB Aerial Photography, were processed in ESRI GIS software, to supplement the imagery analysis results originally produced in ERMapper. These vector and raster datasets were used to determine the accuracy and type of classifications completed by the software algorithms, by visual comparison. This step was taken to make sure the analyst had classified the land covers/uses correctly, by utilizing additional datasets and feature attribute information available. ESRI software was utilized for this because of its ability to easily open ERMapper images without conversion from software to software. Each class was assigned a land cover type such as coniferous, deciduous, water, transportation, residential, etc. Some land cover types, like those in urban areas, were classified ambiguously because of spectral confusion, as expected. To ensure the best possible results when the images were compared via spatial analysis, the original numbers of classes returned were combined and reclassified into 6 distinct classes for each image. The types and definitions, modified from Anderson Level II definitions, of these classes can be found in Table 2. An example of the classifications can be seen in Figure 6, which shows a view of the classified images around Elkins, WV.



A)

B)

C)

Figure 6: Classified PCA images before ESRI Spatial Analysis operations from top to bottom of Elkins: A) 1987, B) NLCD, C) 2005

Table 2: Classification Descriptions

Class Number	Class Type	Description
1	Open Water	All areas of open water, generally with greater than 95% cover of water, including streams rivers, lakes and reservoirs.
2	Deciduous	Includes all forested area having a predominance of trees that lose their leaves during a growing season
3	Evergreen, Transitional	Includes all forested areas in which the trees are predominantly those which remain green throughout the year
4	Emergent and Woody Wetlands	Dominated by both woody vegetation and herbaceous vegetation. Can include freshwater meadows, and open bogs.
5	Croplands and Pastures	Characterized by high percentages of grasses of grasses, other herbaceous vegetation and crops: including lands that are regularly mowed for hay and or grazed by livestock, and regularly tilled and planted cropland
6	Mixed Urban or Built up land	Comprised of areas of intensive use with much of the land covered by structures. Included in this category are cities, towns, villages, Residential areas, strip developments, transportation, industrial, commercial, shopping centers, commercial enterprises, strip mines, and quarries.

Accuracy Assessment

The accuracy assessment undertaken did not utilize the IDRISI or ERMapper assessment methods. Errors in the accuracy assessment results in both IDRISI and ERMapper continually occurred and the results were unsatisfactory and inaccurate. Instead an error matrix quantitatively assessing the National Landuse Classification Dataset (NLCD) reference layer and the classified images was used instead. This method was found during an internet search at University of Alberta Biological Sciences Web Page (Reference 45). There is only one NLCD available as a reference layer so it was used to compare both images. The analysis was a non site-specific accuracy assessment method which measures the total amount of each class irrespective of its location. The error matrix, which is also known as a confusion matrix, correlation matrix, or covariance matrix summarizes the relationship between the two datasets to assess accuracy.

The 1987, 2005, and NLCD images were brought into a new map in ESRI. The Raster Calculator in Spatial Analyst was utilized for the following formulas:

Nlcd_87 = combine ([clip_87], [pronlcd_clip])
Nlcd_05 = combine ([clip_05], [pronlcd_clip])

Where Nlcd_87 and Nlcd_05 are the resultant images from the accuracy analysis, and clip_87, clip_05, and pronlcd_clip are clipped images from the same geographic location in the interior of the study area of the classified PCA images and NLCD images on which the accuracy analysis is being performed.

The tables for each image were then exported to a .dbf and then opened in MS Access. Then a crosstab query was produced and the resulting table was exported to MS Excel. Four accuracy assessments were derived from the analysis in Excel:

- Omission Error (producer's accuracy) – Takes into account the accuracy of individual classes and indicates the probability of the cell value in reference map being the same as in the classified image.
    - $= X_{ii} / X_i \times 100\%$ where X_{ii} is equal to the total number of correct cell in a class and, X_i is the sum of cell values in the column.
- Commission Error (user's accuracy) – Takes into account the accuracy of individual classes and indicates the probability of the cell value in reference map being the same as in the classified image.
    - $= X_{ii} / X_{i+} \times 100\%$ where X_{ii} is equal to the total number of correct cell in a class and, X_{i+} is the sum of cell values in the row.
- Overall Accuracy – Summarizes the total agreement/disagreement between the maps, only incorporates the major diagonal and excluded the omission and commission errors.
    - $= D / N \times 100\%$ where D is the total number of correct cells as summed along the major diagonal and N is the total number of cells in the error matrix.
- Kappa Analysis (K_{hat}) – A measure of agreement or accuracy, useful for comparing maps of similar categories to determine if they are significantly different.

Image Comparison

Image comparison was done in ESRI using the Spatial Analyst procedure DIFF. The result of this function, which analyzes the two images entered on a cell-by-cell basis, is a resultant image that shows those areas that have changed, and returns the type of class change that has occurred. Those areas that remain unchanged are returned with a zero value. The Raster Calculator in Spatial Analyst was utilized for the following formula and the resulting image can be seen in Figure 7:

landdiff = [p17_05] diff [p17_87]

Where landdiff is the resultant image produced by the differencing (diff) algorithm and p17_05 and p17_87 are the classified PCA images the operation was performed on.

Image Generalization

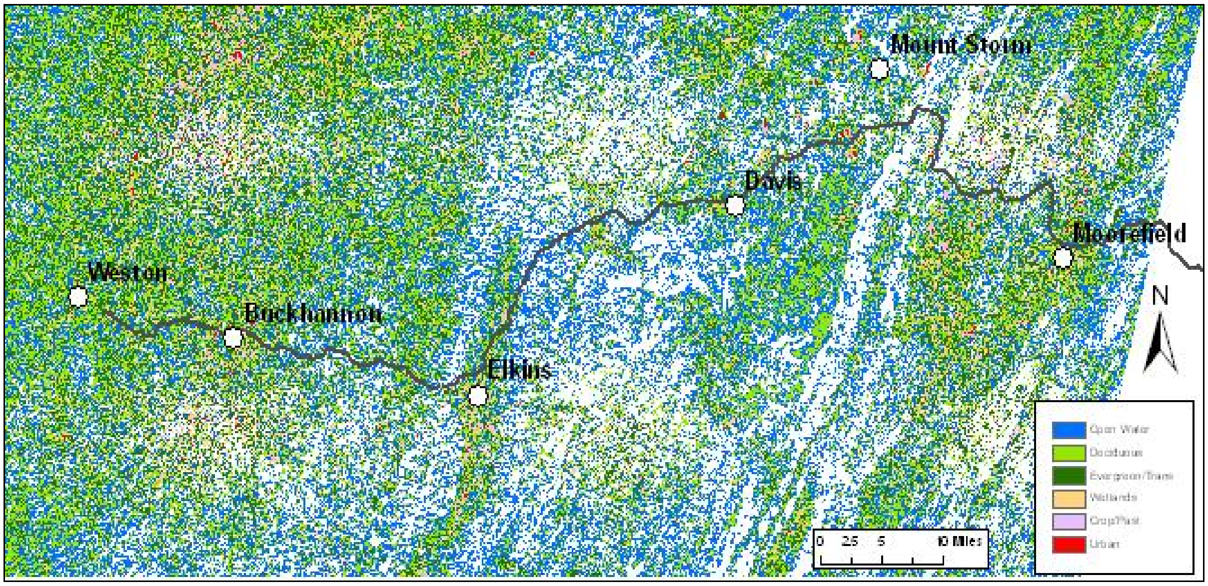
As can be seen in Figure 7 A & B, the image produced by DIFF showed significant areas of change but in its current state was too speckled and confusing to accurately analyze. To clarify the image and to reduce data, a series of image generalization analyses were undertaken in ESRI. The Raster Calculator in Spatial Analyst was utilized for the following formulas:

Land2 = majorityfilter ([landiff], eight, half)

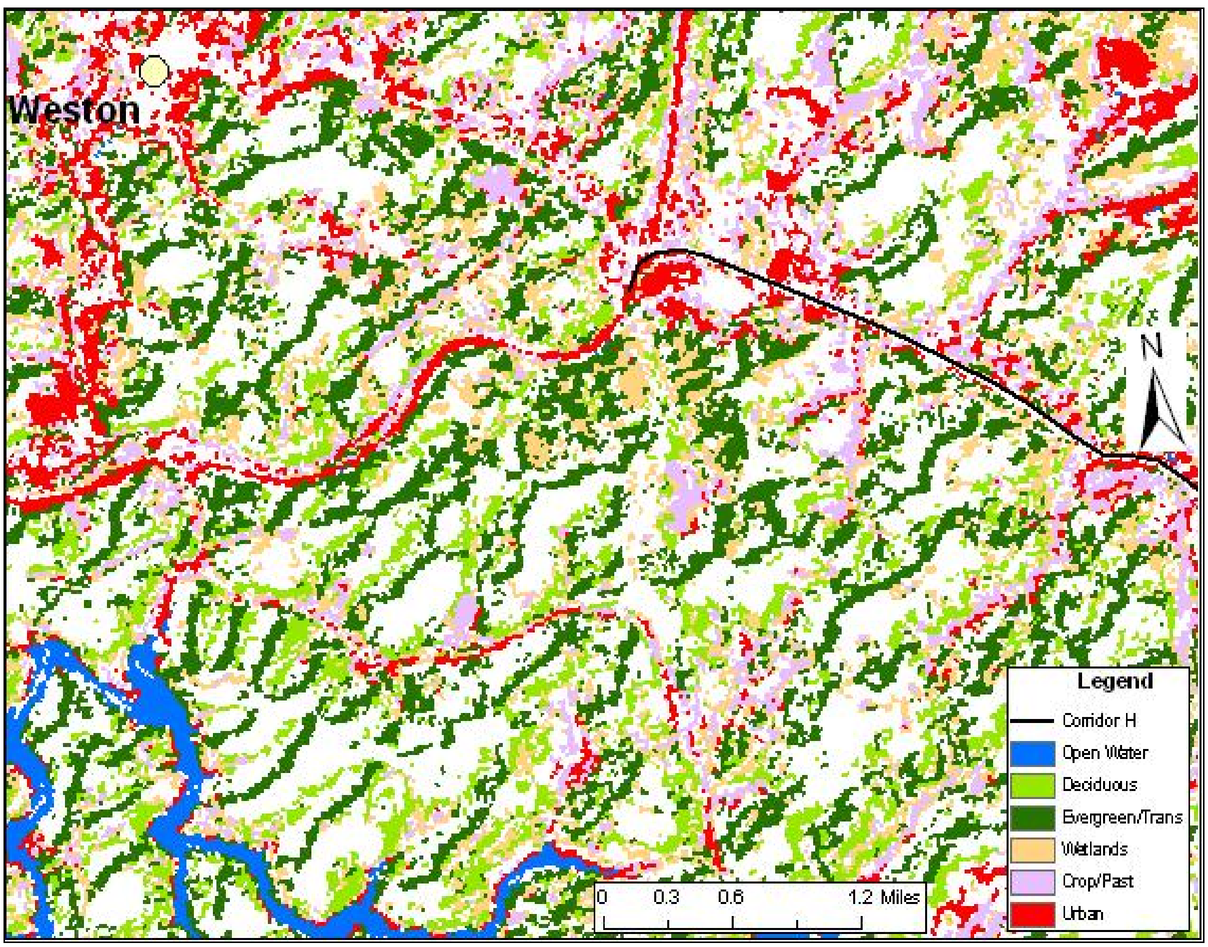
Majority Filter, a filter in the spatial domain, was used to replace cells based upon the majority of their contiguous neighbors. The use of eight in the formula smoothes corners while the use of half allows for more extensive filtering. Where Land2 is the resultant image produced by the majorityfilter algorithm and landdiff was the image the operation was performed on.

LndCvr56 = setnull ([Land2] <5, [Land2])

Setnull was utilized to extract only those areas classified as 5: Croplands and Pasture, and 6: Mixed Urban or Built up Land, by setting all other classes to null or NoData. It is useful for extracting out only those specific datasets the analyst is interested in looking at. Where LandCvr56 is the resultant image produced by the setnull algorithm and Land2 is the image the operation was performed on. The inclusion of <5 in the algorithm tells the computer system to set all values less than 5 to null (NoData), all other values should be returned as they are classified in the Land2 image.



A)



B)

Figure 7: Results of Spatial Analyst Diff. A) entire image and B) close up view of areas of change in the study area.

Region1 = regiongroup ([LndCvr56])

Nosmlarea = setnull ([Region1].count le 10, lndcvr56)

Region Group was applied to cluster connected cells into individual groups. This process produces a cell count for each individual region. Where Region1 is the resultant image produced by the regiongroup algorithm and LndCvr56 is the image the operation was performed on.

This allowed for a second use of Setnull to remove all groups with less than10 pixels, to help reduce speckling. Where Nosmlarea is the resultant image produced by the second setnull algorithm and Region1 is the image the operation was performed on.. The inclusion of ‘count le 10’ in the algorithm tells the computer system to set all values less than 10 to null (NoData), all other values should be returned as they are classified in the LndCvr56 image.

Figure 8 is the result of the analysis to this point and shows the extraction of classes 5 & 6 with the smaller areas excluded.

Finally the ZonalArea function was applied to calculate the area of change for the two classes in square meters, hectares, square kilometers, and acres.

Landmeter = zonalarea ([nosmlarea])

Landhec = zonalarea ([nosmlarea]) * 0.0001

Landkm = zonalarea ([nosmlarea]) * 0.000001

Landacre = zonalarea ([nosmlarea]) * 0.0002471

Where Landmeter, Landhec, Landkm, and Landacre are the resultant images produced by the zonalarea algorithm and mosmlarea is the image the operation was performed on. The numbers included at the end of the algorithm are the multipliers needed to obtain the proper area results for each type.

Vector Overlay

A number of vector layers were used in the analysis to provide spatial reference and to orient the analyst. These files were downloaded from the WVU WVGIS Tech Center internet site (http://wvgis.wvu.edu/index.php). The files downloaded and used are listed below. Additionally a Corridor Geodatabase was provided by the Rahall Transportation Institute that included the Corridor H feature class polyline.

- Rivers
- Cities
- Urban Areas
- Census Counties

The final raster file produced, nosmlarea, was converted to a vector polygon shapefile using ArcToolbox. Buffer polygons were then created around the Corridor H polyline shapefile at 1 mile, 5 mile, 10 mile, and 15 mile intervals. These buffer polygons were then used to clip the nosmlarea shapefile into four new shapefiles: clip_1mile, clip_5mile, clip_10mile, clip_15mile. For each shapefile the attribute table was opened, a new field, Area, was added. Then the Area field was selected and the option to Calculate Values outside of an editing session was selected. In the Field Calculator, the advanced option was utilized and the following VBA script was used to calculate the areas for each polygon.

```
Dim dblArea as double
Dim pArea as IArea
Set pArea = [shape]
dblArea = pArea.area
```

In the text box: dblArea

The attribute tables were then exported to .dbf, and opened in MS Excel, where calculations were done to determine the area of change for the two classes in square meters, hectares, square kilometers, and acres for each buffer zone. Figure 9 shows the locations of the buffers in relation to Corridor H and the raster file.

The steps taken for map generalization, map comparison, and the vector overlay portions of the analysis can be seen in model form in Figure 10.

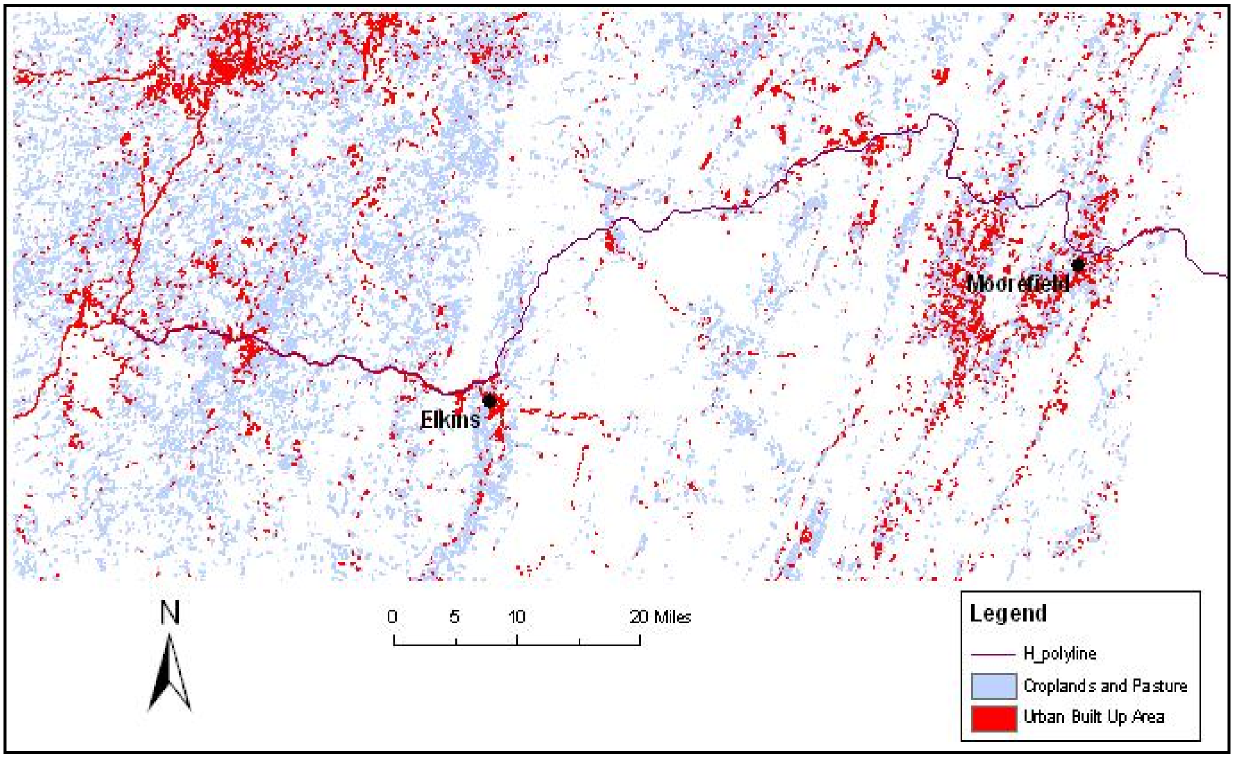


Figure 8: Area of change isolated, following the second setnull procedure done in ArcGis.

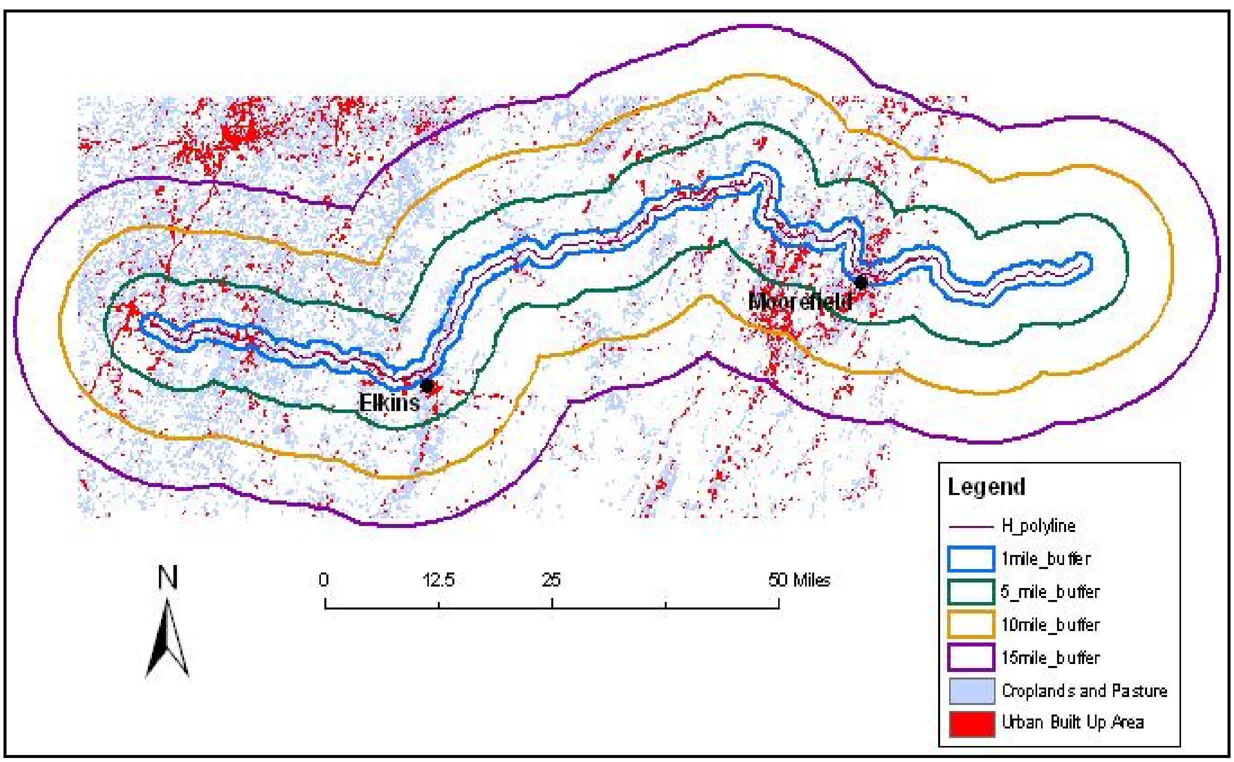


Figure 9: Relation of Corridor H and the buffer zones with areas of change.

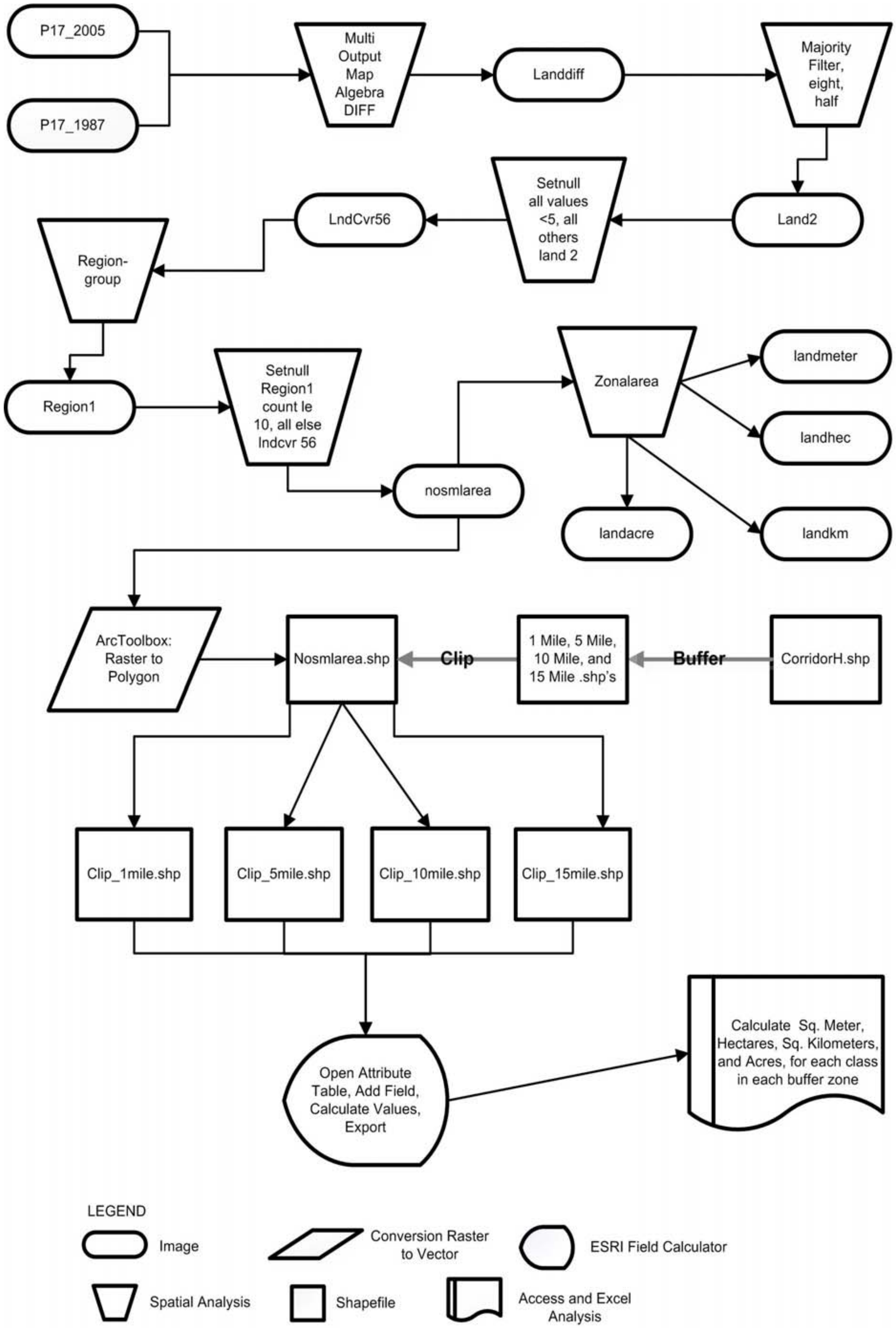


Figure 1 0: ESRI Raster and Vector Analysis Model, produced in Visio.

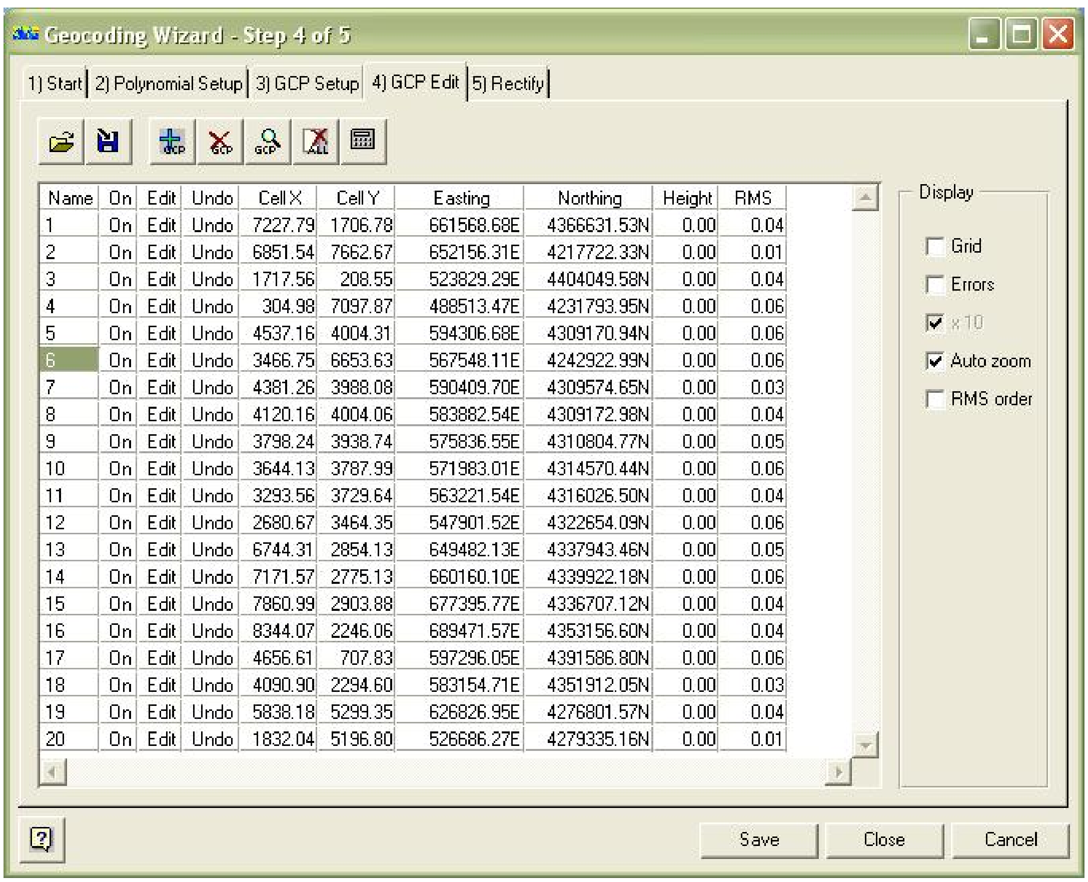
CHAPTER III

Results and Discussion

Procedural Analysis

Preprocessing

The results of the geometric registration returned a Root Mean Square error (RMS) of between 0.01 and 0.06 pixels, as seen in Figure 11. This is a fairly accurate result given the nature of the pixel size (30x30m or 0.222 acres), and results in an error of less than 55 square meters or 0.014 acres. When compared to the size of the study area, 10,414,210,255 square meters or 2,573,351 acres, the error is minor in comparison.



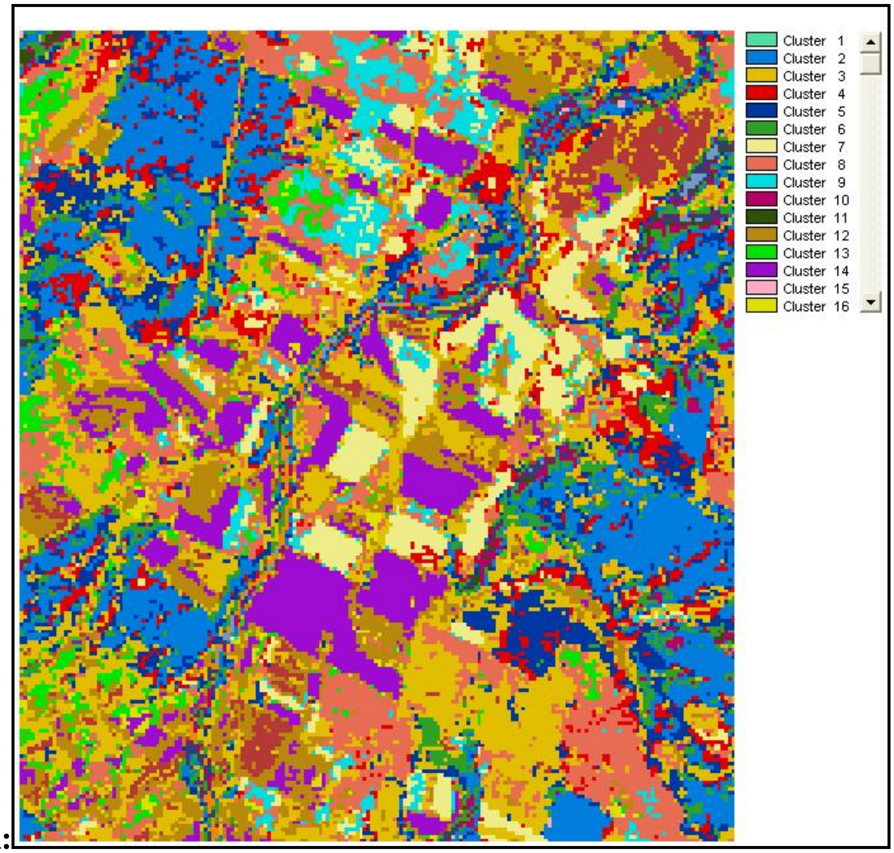
Name	On	Edit	Undo	Cell X	Cell Y	Easting	Northing	Height	RMS
1	On	Edit	Undo	7227.79	1706.78	661568.68E	4366631.53N	0.00	0.04
2	On	Edit	Undo	6851.54	7662.67	652156.31E	4217722.33N	0.00	0.01
3	On	Edit	Undo	1717.56	208.55	523829.29E	4404049.58N	0.00	0.04
4	On	Edit	Undo	304.98	7097.87	488513.47E	4231793.95N	0.00	0.06
5	On	Edit	Undo	4537.16	4004.31	594306.68E	4309170.94N	0.00	0.06
6	On	Edit	Undo	3466.75	6653.63	567548.11E	4242922.99N	0.00	0.06
7	On	Edit	Undo	4381.26	3988.08	590409.70E	4309574.65N	0.00	0.03
8	On	Edit	Undo	4120.16	4004.06	583882.54E	4309172.98N	0.00	0.04
9	On	Edit	Undo	3798.24	3938.74	575836.55E	4310804.77N	0.00	0.05
10	On	Edit	Undo	3644.13	3787.99	571983.01E	4314570.44N	0.00	0.06
11	On	Edit	Undo	3293.56	3729.64	563221.54E	4316026.50N	0.00	0.04
12	On	Edit	Undo	2680.67	3464.35	547901.52E	4322654.09N	0.00	0.06
13	On	Edit	Undo	6744.31	2854.13	649482.13E	4337943.46N	0.00	0.05
14	On	Edit	Undo	7171.57	2775.13	660160.10E	4339922.18N	0.00	0.06
15	On	Edit	Undo	7860.99	2903.88	677395.77E	4336707.12N	0.00	0.04
16	On	Edit	Undo	8344.07	2246.06	689471.57E	4353156.60N	0.00	0.04
17	On	Edit	Undo	4656.61	707.83	597296.05E	4391586.80N	0.00	0.06
18	On	Edit	Undo	4090.90	2294.60	583154.71E	4351912.05N	0.00	0.03
19	On	Edit	Undo	5838.18	5299.35	626826.95E	4276801.57N	0.00	0.04
20	On	Edit	Undo	1832.04	5196.80	526686.27E	4279335.16N	0.00	0.01

Figure 11: Ground Control Points and their RMS values during the registration process.

Principal Components Analysis and Radiometric Normalization

In the initial period of testing the PCA classification technique versus the 3-band classified images, there were distinct differences in the quality of classification produced. When the images were compared to each other and to the SAMB aerial photography, they showed distinct differences in the types and location of the classifications that were produced. There was obviously much more spectral confusion in the images classified from the original bands when compared to the image classified from the principal components bands. It was apparent that the principal components image provided a better basis for classification. By compressing all six bands of the TM images into the three principal components, the patterns in the data were highlighted. This resulted in less spectral confusion and created fewer mixed pixel occurrences in the classification results. An example of this spectral confusion was apparent in the classification of rivers. In the classified 3-band images, the rivers were not identified as a single feature, but more as a series of differently classified pixels, that in some cases matched the same classification as another type of land cover features like residential areas. Figure 12 shows an area in Moorefield that has an example of the river's mis-classification. This type of result was unacceptable given the nature of the study and the goal of extracting urban or built up areas from other types of land cover/use features. The images are not to scale, and the features in the clusters are not classified the same. For example cluster 13 in image A is the same as Cluster 6 and 10 in image B. Based on the initial IDRISI classification results, classifying the PCA bands provided better feature extraction for pattern recognition of the various types of land cover/use occurring in the study area by isolating the variability and showing the seperarability of the categories.

Differences in atmospheric conditions, sensor calibration and solar illumination can often make it difficult to accurately compare images from different temporal periods if they are not radiometrically calibrated. Before classifying the principal components images the principal component bands from Path 17 1987 and 2005 were radiometrically normalized to standardize for effects outside of actual real surface change. This resulted in the two images having similar radiometric responses across feature types on which to base the classifications

A: 

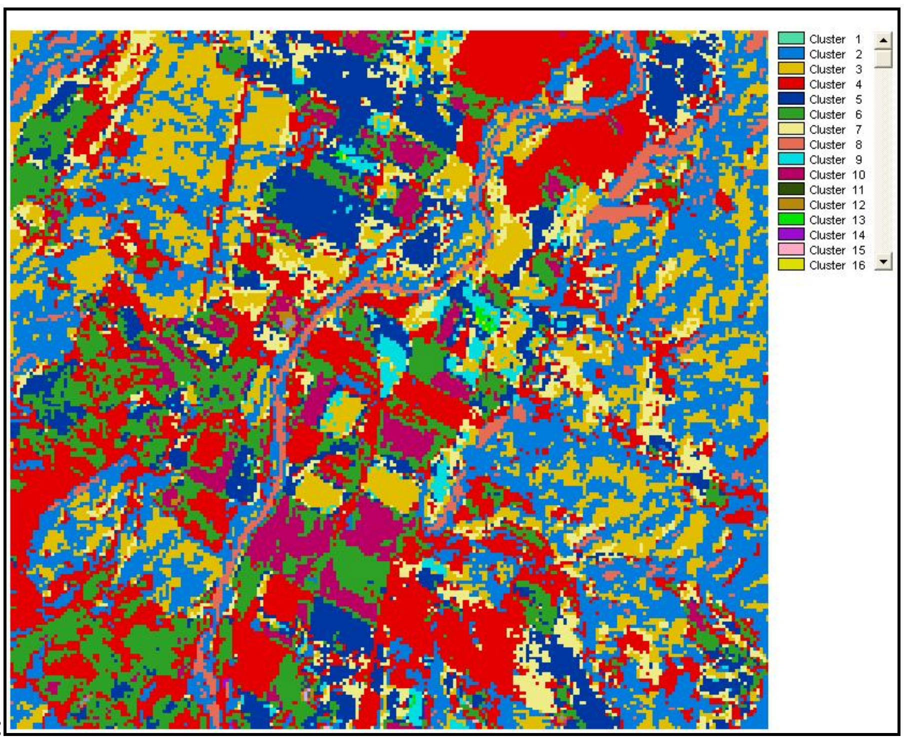
B: 

Figure 12: Comparison of classification results of bands 3,4,5 (A: top) and the PCA bands (B: bottom). Images are not to the same scale and are not classified the same.

Image Classification, Accuracy Assessment and Image Comparison

As discussed in the previous chapter the images were evaluated initially using a simple multi-data comparison to highlight potential areas of change (Figure 4). After the PCA images were radiometrically equalized they were classified using ERMapper's unsupervised classification process. Images were allowed the same parameters for classification, 15 classes, 99 iterations, and 0.1% for minimum members in a class, pixels with a zero value were set to null, and all other options were left as default.

The classification process was done more than once. The first classification was done on the entire TM image, this produced poor to fair classification results with class confusion between land cover like wetlands and residential. It is believed this is because the software has difficulty dealing with such a large data set, and producing consistent and accurate results across the entire image. Due to this confusion in the classifications across the image it was impossible to accurately narrow down like classes for comparison purposes. Each image from 1987 and 2005 had a different number of classes and different features contained in those classifications. This fact, combined with class errors like the classification of wetlands and residential into one class, made it difficult to par down the classifications into like categories.

A second classification was completed on the clipped study area. This produced much better results with no major class confusion. Path 17 1987 returned 10 classes and Path 17 2005 returned 12 classes. Both images were compared to both the NLCD dataset (date of 1992-1996) and SAMB aerial photography (date of 2003) to help determine which class was which land cover/use. The images were then reclassified into the exact same six classes for comparison purposes as shown in Table 2. This was done because the classification process still had difficulties separating land cover/uses like residential, from commercial, industrial, etc. This result was expected, however it was disappointing that more exact classifications couldn't be made at this level. However, for the scope of this study almost any change to the generalized class of Urban Built Up Area, is reflective of an economic impact in an area, via new construction and therefore indicative of job creation.

The initial accuracy assessment produced disappointing results, but not totally unexpected ones since only one reference image was available for use with both images, and did not fully cover the area on the satellite image since it was clipped to the outline of West Virginia. A subset of each the images was clipped and run through the accuracy assessment again to eliminate the impact of the NLCD image not completely covering the images. This assessment produced similar results. The overall accuracy returned was 58% for 1987 and 63% for 2005. Errors in the accuracy may be from a number of items such as geometric registration, the normalization process, the classification process, the accuracy assessment process itself (since it is not spatially dependent), or the fact that both images were being checked against a dataset (NLCD) that is not temporally relevant to either image. Complete statistics of both of the accuracy assessments are shown in Table 3.

The results of the differencing operation showed obvious changes in the land along Corridor H from 1987 to 2005, especially along the portion of the corridor that has already been completed, from Weston at I-79 to Elkins. There is also significant growth and change that is seen occurring in the Moorefield area of WV, which one can only guess is in partial anticipation of the completion of the east –west corridor, and the ability to more easily move goods and services to other areas of the country. Figure 13 is a screen capture of the study area with just the areas of Urban Change isolated. This is the direct result of the setnull procedure, which cleaned up the image by removing small areas, less than ten pixels, of change to make the image less confusing for interpretation. This does not negate those smaller areas of change as valid areas of change. It was simply a procedure to clean the image and make interpretation of large areas of change clear. In the image you can clearly see the existing location of Corridor H in the west, and the sections that are currently being worked on or which have recently opened in the east. Most of the change occurring directly along Corridor H is of a commercial nature. New businesses such as Wal-Mart, gas stations, restaurants, hotels, and car dealerships have been locating themselves along Corridor H. More businesses and developments are sure to follow as traffic volume increases when Corridor H is completed and the corridor becomes a major east–west thruway. Examples of some of the urban change within 1-mile of Corridor H are shown in Figure 15.

Table 3: Accuracy Assessment Results

Omission - Producers Accuracy

Classified File (1987)		Subset Classified File (1987)		Classified File (2005)		Subset Classified File (2005)	
1: Open Water	33%	1: Open Water	32%	1: Open Water	26%	1: Open Water	26%
2: Deciduous	67%	2: Deciduous	52%	2: Deciduous	76%	2: Deciduous	63%
3: Evergreen	31%	3: Evergreen	42%	3: Evergreen	27%	3: Evergreen	37%
4: Woody-Emrg Wetlands	50%	4: Woody-Emrg Wetlands	43%	4: Woody-Emrg Wetlands	30%	4: Woody-Emrg Wetlands	21%
5: Cropland, Pasture	56%	5: Cropland, Pasture	60%	5: Cropland, Pasture	51%	5: Cropland, Pasture	66%
6: Urban, Built Up Land	22%	6: Urban, Built Up Land	28%	6: Urban, Built Up Land	25%	6: Urban, Built Up Land	34%

Commission - Users Accuracy

Classified File (1987)		Subset Classified File (1987)		Classified File (2005)		Subset Classified File (2005)	
1: Open Water	41%	1: Open Water	66%	1: Open Water	42%	1: Open Water	42%
2: Deciduous	76%	2: Deciduous	78%	2: Deciduous	76%	2: Deciduous	79%
3: Evergreen	31%	3: Evergreen	27%	3: Evergreen	30%	3: Evergreen	27%
4: Woody-Emrg Wetlands	3%	4: Woody-Emrg Wetlands	2%	4: Woody-Emrg Wetlands	2%	4: Woody-Emrg Wetlands	1%
5: Cropland, Pasture	60%	5: Cropland, Pasture	60%	5: Cropland, Pasture	66%	5: Cropland, Pasture	64%
6: Urban, Built Up Land	35%	6: Urban, Built Up Land	20%	6: Urban, Built Up Land	50%	6: Urban, Built Up Land	31%

Overall Accuracy

Classified File (1987)	Subset Classified File (1987)	Classified File (2005)	Subset Classified File (2005)
58%	24%	63%	58%

Khat

Classified File (1987)	Subset Classified File (1987)	Classified File (2005)	Subset Classified File (2005)
28%	-17%	26%	27%

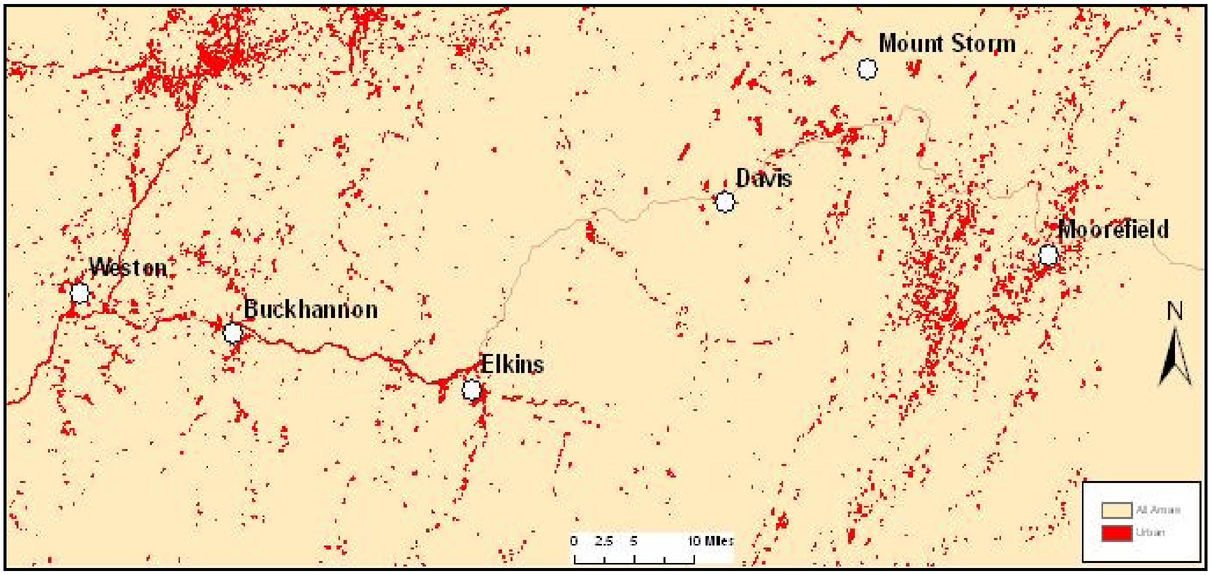


Figure 13: Urban Change in Study Area

Not only is there a change in urban development but there is an increasing change in land cover/use from 1987 to 2005 to Cropland/Pasture, as seen in Figure 14. These areas are indicative of where the next wave of economic development may begin, given the fact that the land is already likely cleared of any major construction impediments. This type of land is easily converted into Residential, Commercial, or Industrial uses and is already in some cases a sign of economic growth since it is most likely being used for agricultural purposes with the products being sold on the free market.

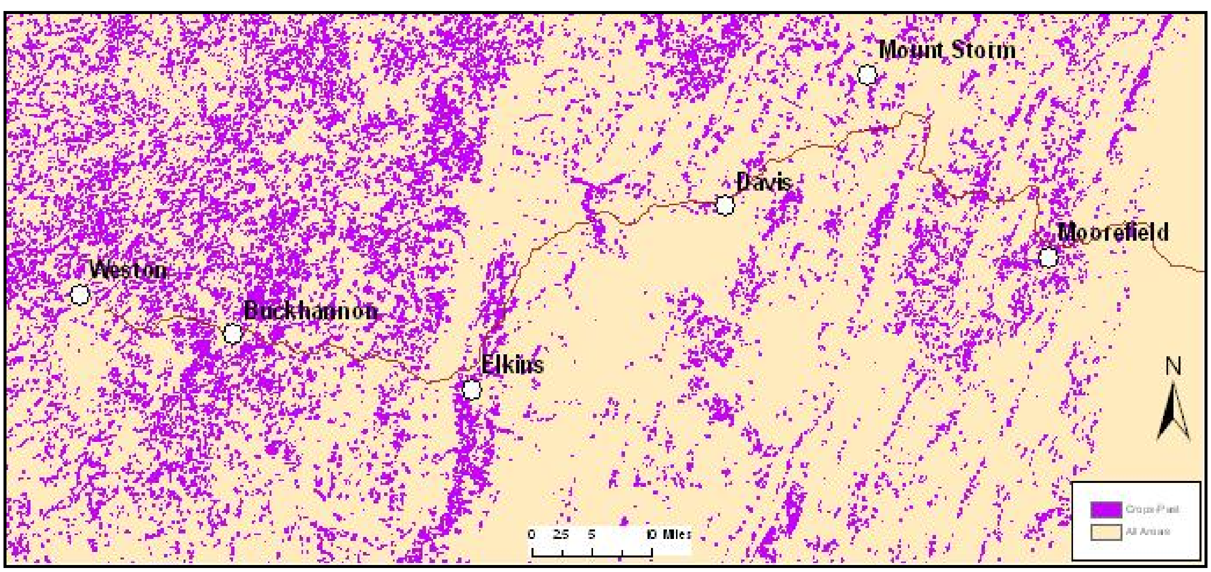
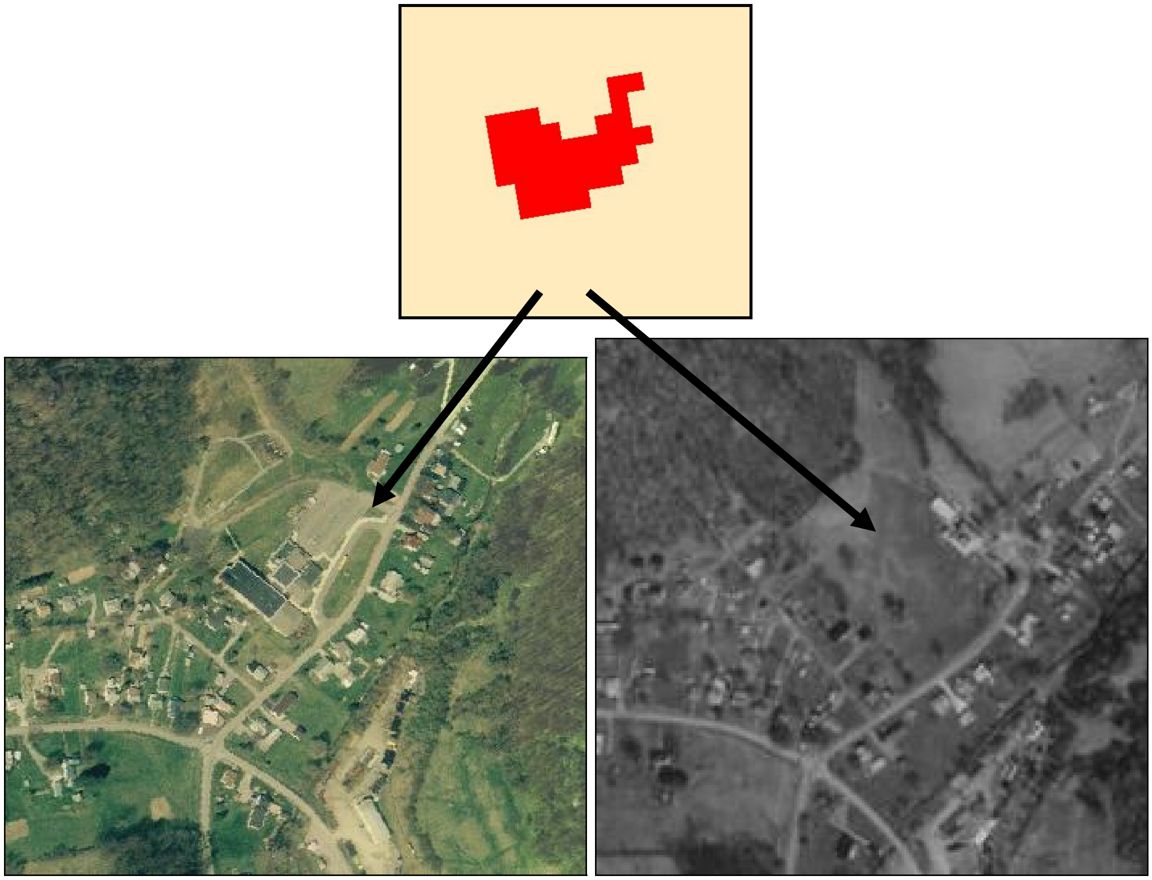


Figure 14: Cropland/Pasture Change in Study Area

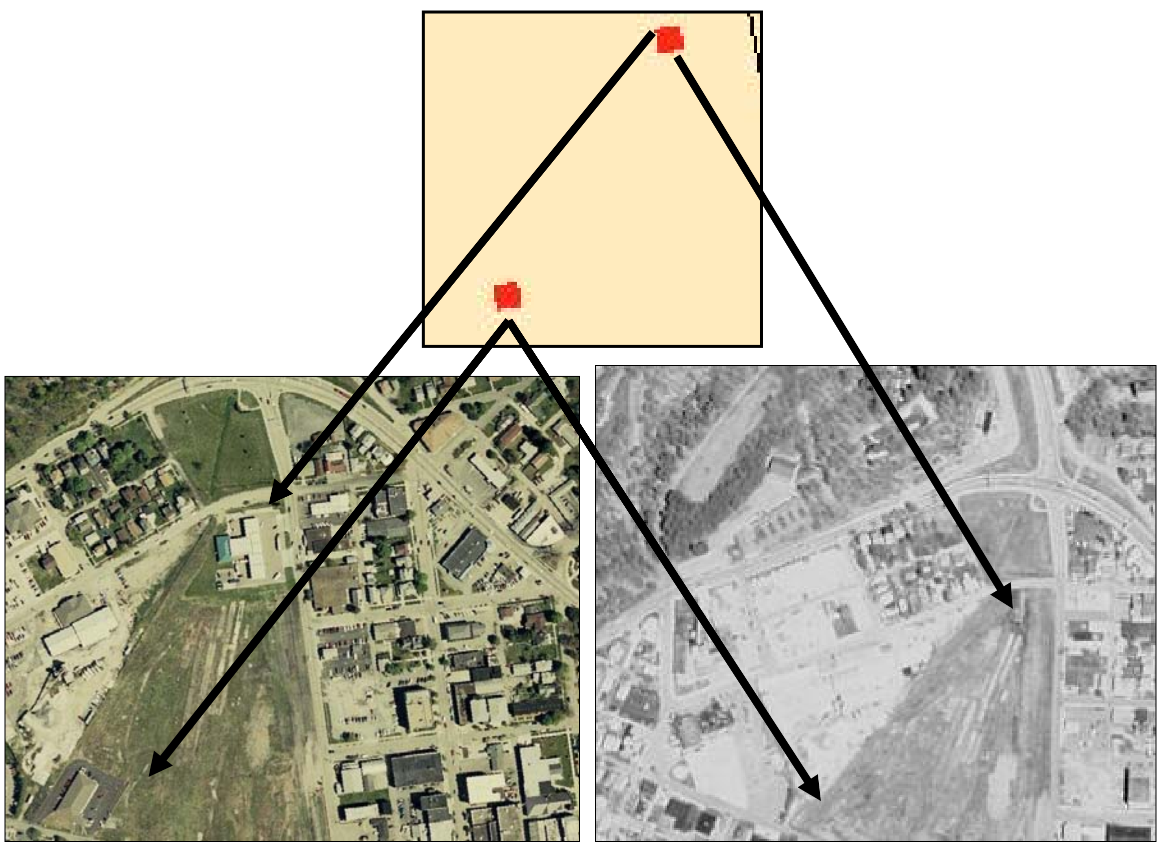
Table 4 documents the total land change and the percentage of change that has occurred in the study area for both Urban and Cropland/Pasture. To determine percentage of change the area of change was calculated and divided by the total acreage of the study area or acreage of the buffer zone. The total land change for the study area for Urban was 1.4% of the total 2,573,351 acres and 4.9% for change in Cropland/Pasture. More significantly there is a 2.7 %increase in Urban development within a 1-mile buffer around the length of Corridor H in the study area. When a buffer was placed 1-mile around Corridor H just from Weston to Elkins the percentage of change increased to 4.5% of total acreage for Urban areas and 7.5% for Cropland/Pasture. It is hard to subtract out exactly how much of this change can be attributed to the physical built environment of the road itself, especially since the developments that have occurred along Corridor H to date are located right along it's Right-of-Way and at the spatial resolution of the imagery these specifics can not be separated out. These changes are significant though and indicate urban development, which is indicative of some economic growth, is occurring along Corridor H, even prior to its completion and that these changes or features can be detected, extracted and measured using remote sensing techniques.

Table 4: Overall change in Land Cover/Use

Land Cover	Sq M	Hectares	Sq Km	Acres	% of Change
Urban Built up Land in Total Study Area	149,411,952	149,412	149	36,920	1.4%
Croplands and Pasture in Total Study Area	513,855,392	513,855	514	126,974	4.9%
Urban Built up Land in 1 mile buffer around H	18,746,612	1,875	19	4,632	2.7%
Croplands and Pasture in 1 mile buffer around H	32,021,191	3,202	32	7,912	4.6%
Urban Built up Land in 1 mile buffer around H from Weston to Elkins	10,649,236	1,065	11	2,631	4.5%
Croplands and Pasture in 1 mile buffer around H from Weston to Elkins	17,826,909	1,783	18	4,405	7.5%
Urban Built up Land in 5 mile buffer around H	53,344,840	5,334	53	13,182	1.5%
Croplands and Pasture in 5 mile buffer around H	145,763,807	14,576	146	36,018	4.2%
Urban Built up Land in 10 mile buffer around H	83,297,015	8,330	83	2,0583	1.2%
Croplands and Pasture in 10 mile buffer around H	289,096,934	28,910	289	71,436	4.1%
Urban Built up Land in 15 mile buffer around H	100,731,409	10,073	101	24,891	.9%
Croplands and Pasture in 15 mile buffer around H	394,467,561	39,447	394	97,473	3.6%

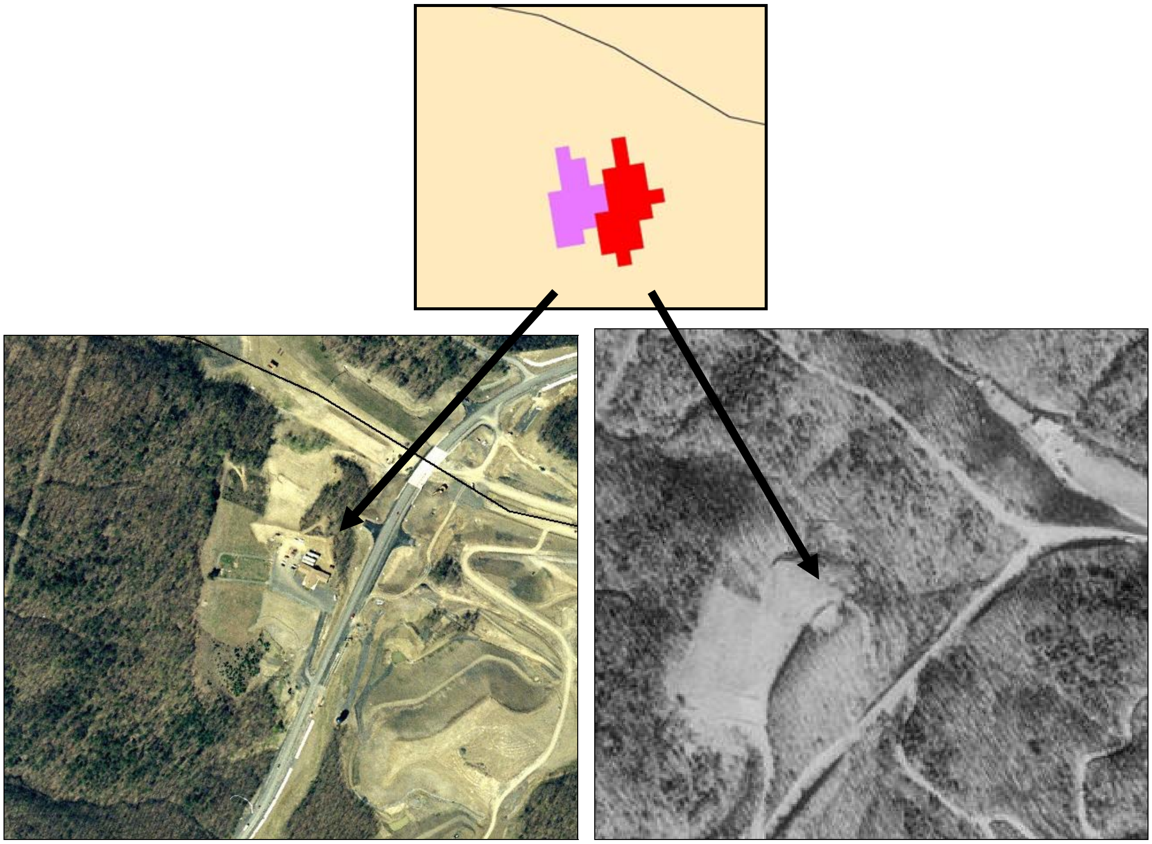


A: Weston Commercial Development as compared to 2003 and 1991

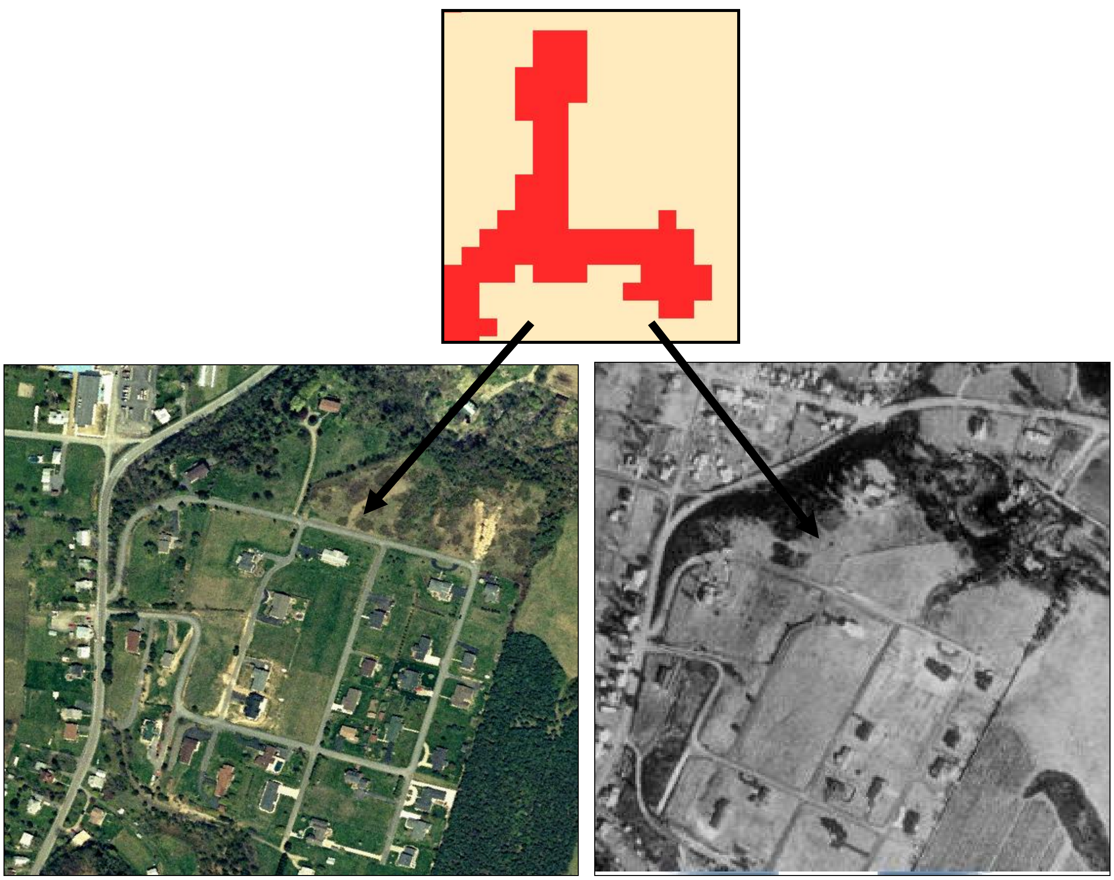


B: Elkins Commercial Development as compared to 2003 and 1991

Figure 15: Examples of Urban Change within 1-mile of Corridor H. Images not to scale



A: Moorefield Commercial and H construction as compared to 2003 and 1991



B: Moorefield Residential as compared to 2003 and 1991

Figure 16: Examples of Urban Change within 1-mile of Corridor H. Images not to scale.

CHAPTER IV

Summary and Conclusion

The concept of this project was to look at change in the study area over time by mapping present day West Virginia and comparing it to the past through the use of satellite imagery, GIS data and Remote Sensing change detection techniques. As proven through this study and many of the studies listed in the bibliography, remote sensing imagery analysis combined with GIS is an effective way to analyze data in a low-cost and efficient manner. The existence of systems like Landsat allow for efficient, consistent data collection for use in temporal studies. The wide availability of this satellite imagery along with the availability of higher spatial resolution imagery for comparison makes the use of this data effective for time series analysis especially for a topic like economic growth and development.

The completion of these studies has helped to define what procedures need to be completed to combine and analyze the data to end up with high quality classification results for this analysis. Geometric registration aligned the two datasets for comparison purposes, insuring some level of accuracy. The combination of the Principal Component images compressed the data in all the bands of the TM images, allowing for greater classification accuracy of features based on group/feature separability. Radiometric Normalization, equalized the two images brightness values, a task fundamentally needed for image classification and comparison. The images were classified using unsupervised classification and then the classification results were combined into six distinct classes for analysis in ESRI. The accuracy of the classifications were compared using confusion matrices, with acceptable results given the data available for comparison and the methods used. Finally spatial analysis was completed in ESRI, using logical operators to extract the changes from 1987 to 2005 and to make those areas of change clear.

Since the goal of this study was to determine change in land use in a general manner it did not matter if the change measured was specifically residential, commercial, industrial, or cropland/pasture since all were considered signs of economic growth or potential areas of future development in the area by the analyst. It was acceptable that some of these types of land cover/use were considered one class in the analysis at this point. It would be useful in future studies of these different classes could be broken out for more exact analysis. This may be possible by using techniques like those of Lo and Choi, 2004 which is a hybrid approach using both unsupervised and supervised classification to get more exacting results in urban areas. However the procedures and results of this study are ultimately considered successful.

There is currently an explosion of economic growth being experienced in the eastern panhandle of WV that is sure to follow along Corridor H when it is completed and the region is more accessible. Already areas linked on the eastern portion of the state near DC are experiencing growth as more and more people are moving to WV to live, because they can get more land, and more house for the money, then what they get in the city. In areas like Thomas, WV located near Davis WV, new businesses are moving into the area and re-utilizing abandoned buildings left from the coal/timber heyday, un-trackable by this study, but as more individuals and tourists come to the area via Corridor H, more businesses and vacation homes will be built increasing the economics of the area, which will be seen in the satellite imagery and can be tracked in the future. Economic development is occurring along Corridor H that currently connects the cities and towns like Buckhannon and Elkins to I-79. It has retained former businesses in the area and attracted new businesses, allowing them to expand their customer base and labor forces. It has also allowed individuals living in those areas to more easily obtain employment closer to home (Reference 32).

The final objective of the study was to perform change detection, using two datasets obtained from the USGS of the study area from 1987 and 2005 to determine if economic development could be measured and detected along Corridor H. This goal was accomplished by identifying the pattern of land-cover change in the study area from satellite images, classifying that data into appropriate land cover/use categories, comparing those images to determine patterns of change, and measuring that change by calculating the areas and percentage of total change. The development of this data provides a baseline on which to base future studies of the area for tracking the expected economic growth of the region and along the Appalachian corridor highway system in general. These methods should be combined with, and help redefine more traditional methods of economic growth reporting and measurement. The use of this data can help to focus these economic studies, and supply spatial relevance to changes in rural Appalachia.

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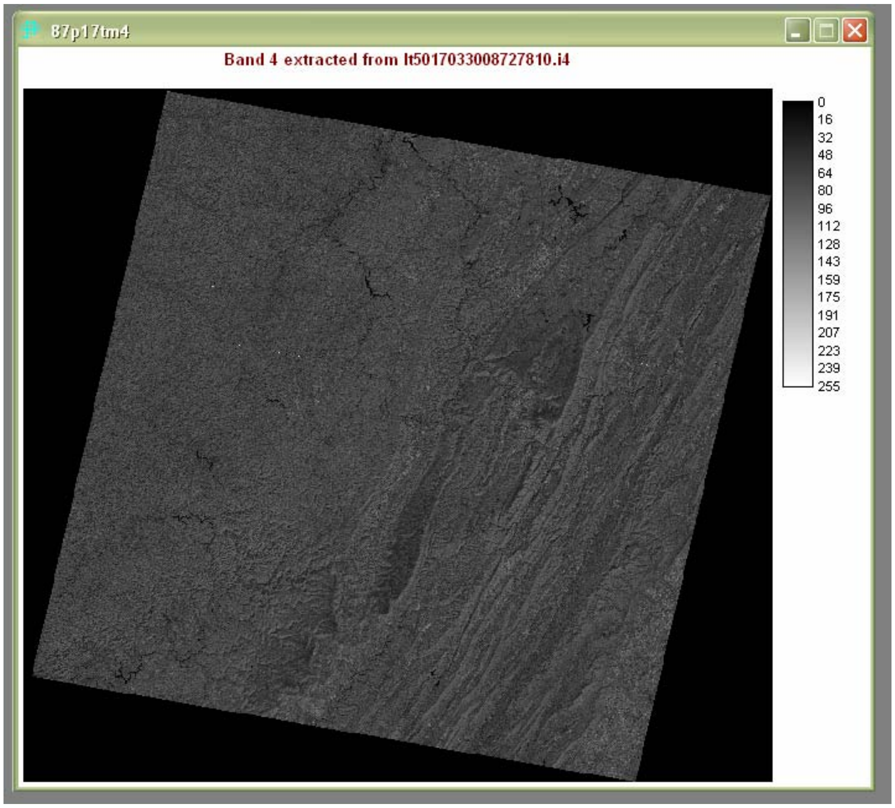
Software Utilized

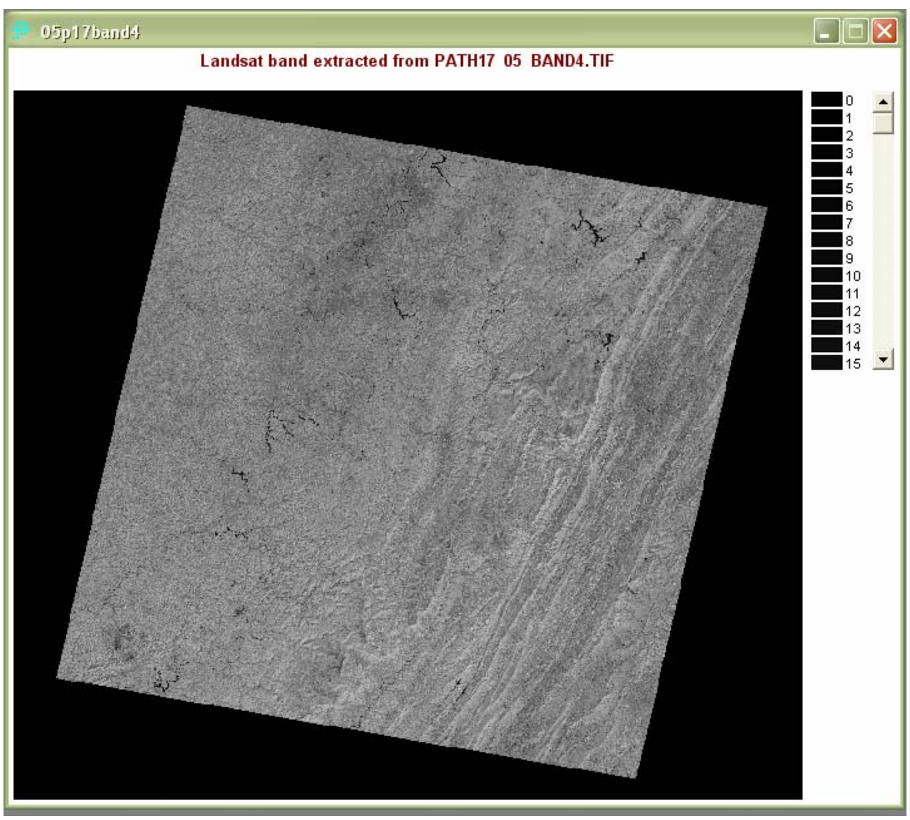
46. ESRI ArcGIS 9.1
47. ErMapper 7.0
48. IDRISI 3.2
49. Microsoft Access
50. Microsoft Excel
51. Microsoft Word
52. Microsoft Visio

APPENDIX A

Path 17 Images and H Images



TM Path 17 1987



TM Path 17 2005

Corridor H Buckhannon


Corridor H Construction by Lost River



Corridor H Elkins, Both Images

Images from www.vecelliogrogan.com & www.wearezen.com

Appendix B

Statistics

Statistics for Path 17 1987

VAR/COVAR	87p17tm1	87p17tm2	87p17tm3	87p17tm4	87p17tm5	87p17tm6	87p17tm7
87p17tm1	547.5	231.89	193.09	721.68	616.82	1177.94	208.59
87p17tm2	231.89	100.63	85	312.95	272.03	496.2	93.19
87p17tm3	193.09	85	77.13	254	236.36	405.54	84.5
87p17tm4	721.68	312.95	254	1136.07	884.1	1580.08	281.68
87p17tm5	616.82	272.03	236.36	884.1	821.17	1312.64	281.05
87p17tm6	1177.94	496.2	405.54	1580.08	1312.64	2588.81	433.9
87p17tm7	208.59	93.19	84.5	281.68	281.05	433.9	104.68

COR MATRX	87p17tm1	87p17tm2	87p17tm3	87p17tm4	87p17tm5	87p17tm6	87p17tm7
87p17tm1	1	0.987924	0.939617	0.915062	0.919915	0.989427	0.871312
87p17tm2	0.987924	1	0.964836	0.925552	0.9463	0.972152	0.907937
87p17tm3	0.939617	0.964836	1	0.858054	0.939182	0.90755	0.940376
87p17tm4	0.915062	0.925552	0.858054	1	0.915338	0.921351	0.816802
87p17tm5	0.919915	0.9463	0.939182	0.915338	1	0.900277	0.958589
87p17tm6	0.989427	0.972152	0.90755	0.921351	0.900277	1	0.833495
87p17tm7	0.871312	0.907937	0.940376	0.816802	0.958589	0.833495	1

COMPONENT	C 1	C 2	C 3	C 4	C 5	C 6	C 7
% var.	94.76	2.93	1.88	0.22	0.09	0.07	0.04
eigenval.	5094.32	157.52	101.32	11.86	5.06	3.89	2.05
eigvec.1	0.324384	-0.105997	0.138663	0.718189	-0.283607	-0.339125	-0.391252
eigvec.2	0.137909	-0.045064	0.058952	0.305333	-0.120573	-0.144177	0.920284
eigvec.3	0.114728	0.010191	0.088829	0.289318	0.945466	-0.035099	0
eigvec.4	0.452468	0.367409	-0.80558	0.051209	0.00461	0.093168	0
eigvec.5	0.380004	0.66835	0.4623	-0.313818	-0.012256	-0.31073	0
eigvec.6	0.705207	-0.585064	0.123497	-0.352465	0.022289	0.142837	0
eigvec.7	0.127067	0.2503	0.302446	0.286245	-0.102248	0.858685	0

LOADING	C 1	C 2	C 3	C 4	C 5	C 6	C 7
87p17tm1	0.989492	-0.056855	0.05965	0.105694	-0.027258	-0.028583	-0.023924
87p17tm2	0.981212	-0.05638	0.059151	0.104809	-0.02703	-0.028344	0.131256
87p17tm3	0.932395	0.014564	0.101808	0.11344	0.242109	-0.007882	0
87p17tm4	0.958136	0.136809	-0.240571	0.005232	0.000308	0.005451	0
87p17tm5	0.946484	0.292722	0.162384	-0.03771	-0.000962	-0.021384	0
87p17tm6	0.989258	-0.144319	0.024431	-0.023854	0.000985	0.005536	0
87p17tm7	0.886414	0.307038	0.297542	0.096339	-0.022475	0.165512	0

Statistics for Path 17 2005

VAR/COVAR	05p17tm1	05p17tm2	05p17tm3	05p17tm4	05p17tm5	05p17tm6	05p17tm7
05p17tm1	1296.9	597.77	586.85	1665.27	1314.25	1905.78	496.01
05p17tm2	597.77	297.11	302.94	721.03	606.04	783.13	247.37
05p17tm3	586.85	302.94	326.17	633.92	579.2	655.99	256.3
05p17tm4	1665.27	721.03	633.92	2766.49	1905.04	3076.83	608.92
05p17tm5	1314.25	606.04	579.2	1905.04	1527.34	2154.58	549.12
05p17tm6	1905.78	783.13	655.99	3076.83	2154.58	3889.26	663.66
05p17tm7	496.01	247.37	256.3	608.92	549.12	663.66	228.21

COR MATRX	05p17tm1	05p17tm2	05p17tm3	05p17tm4	05p17tm5	05p17tm6	05p17tm7
05p17tm1	1	0.962983	0.902294	0.87916	0.933809	0.848567	0.911736
05p17tm2	0.962983	1	0.97314	0.795291	0.899651	0.728511	0.949973
05p17tm3	0.902294	0.97314	1	0.667335	0.820614	0.582422	0.939411
05p17tm4	0.87916	0.795291	0.667335	1	0.92677	0.938006	0.766349
05p17tm5	0.933809	0.899651	0.820614	0.92677	1	0.884018	0.930109
05p17tm6	0.848567	0.728511	0.582422	0.938006	0.884018	1	0.704435
05p17tm7	0.911736	0.949973	0.939411	0.766349	0.930109	0.704435	1

COMPONENT	C 1	C 2	C 3	C 4	C 5	C 6	C 7
% var.	90.9	6.15	1.35	0.81	0.5	0.16	0.14
eigenval.	9390.81	635.76	139.87	83.33	51.42	16.22	14.08
eigvec.1	0.345172	-0.484089	0.114254	-0.282889	-0.411004	-0.420117	-0.456083
eigvec.2	0.142975	-0.235653	0.04738	-0.128951	-0.190378	0.907262	-0.213974
eigvec.3	0.144856	-0.404146	0.23191	-0.121517	-0.191184	0.001508	0.842959
eigvec.4	0.529514	0.100409	-0.62311	-0.454791	0.310748	0.007221	0.133478
eigvec.5	0.389615	-0.269117	-0.318375	0.821039	-0.016416	0.00005	0.006247
eigvec.6	0.624803	0.574073	0.51054	0.087409	-0.105785	0.017982	0.015983
eigvec.7	0.12987	-0.367049	0.425017	0	0.806385	0	-0.132334

LOADING	C 1	C 2	C 3	C 4	C 5	C 6	C 7
05p17tm1	0.928827	-0.338937	0.037521	-0.071706	-0.081841	-0.046982	-0.047525
05p17tm2	0.803803	-0.344712	0.032508	-0.068289	-0.079201	0.211974	-0.046583
05p17tm3	0.777254	-0.564234	0.151863	-0.06142	-0.075911	0.000336	0.17515
05p17tm4	0.975585	0.048134	-0.140106	-0.07893	0.042366	0.000553	0.009523
05p17tm5	0.966094	-0.173628	-0.096344	0.191773	-0.003012	0.000005	0.0006
05p17tm6	0.970871	0.232102	0.096817	0.012794	-0.012164	0.001161	0.000962
05p17tm7	0.833091	-0.612635	0.332731	0	0.382783	0	-0.032872