# CHANGE DETECTION ANALYSIS OF THE LANDUSE AND LANDCOVER

# OF THE FORT COBB RESERVOIR WATERSHED

By

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**FOR THE FORT COBB WATERSHED**

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# CHAPTER ONE

## *Background*

Landcover generally refers to the biophysical material on the earth's surface such as forest and urban areas while landuse refers to the human use of the land at a particular point in time and examples of this will include wheat farms, and wild life parks.

Deforestation, agriculture, expanding farmlands and urban centers are a few of the ways in which man is changing the world's landscape (Foley et al., 2005). Although these activities vary from one place to the other, their impact on the earth's surface is usually the same. Combined, these activities paint a picture of man's contribution in degrading the environment. The quest to develop better means of using natural resources and at the same time understand their impact on the environmental has, over the years led to the development and improvement of maps and other methods of landscape analysis. Our ever increasing use of the earth's resources have led to both short and long term effects on the environment, and for decades remote sensing has played a major role in the understanding of the consequences of man's actions. Change detection (monitoring changes in pixel value between images of a given location acquired at different times) using remote sensing has been considered of great importance in the monitoring of the earth's well being (Van Oort P.A.J., 2007). Change detection analyses are used to monitor the dynamic nature of biophysical and anthropogenic features on the earth's surface. As earlier mentioned, it is important that such changes be monitored so that their contribution to global environmental change can be fully understood (Morawits et al., 2006).

Change detection analysis is performed using multi-date imagery. Single date imagery show the landuses and landcovers for a particular point in time but multi-date imagery show the landuse and the landcover of a particular place at different points in time, (t1, t2… tn). Land use (commercial, residential, transportation, utilities, cadastral, and land cover (agriculture, forest and urban etc) (Jensen, 2005) mapping have been especially improved over the years by the use of multi-date imagery, which have been used in cases of progressive or gradual environmental changes such as erosion or reforestation for which more than one image may be necessary (Le Hegarat-Mascle and Seltz, 2004).

Of the many different change detection techniques that exist, two main categories can be identified. One category involves techniques which first detect change and then assign classes to the detected change (e.g., principal component analysis and image differencing). A second category of techniques first assigns classes and then detects the changes between the different classes. An example of this second category of techniques is the post classification method of change detection (Van Oort P.A.J, 2007).

Change detection analysis takes into consideration image characteristics such as spatial (and look angle), radiometric, temporal and spectral resolutions. For the most part, the type of land use or land cover to be studied and the level of detail needed in the study, determines the type of sensor to be used (Landsat 5 (5 band image), Landsat TM (7 band image), SPOT, or Landsat Enhanced Thematic mapper (ETM) etc) (Jensen, 2005).

Visual change detection analysis (the act of comparing the difference between two or more image visually (without any band analysis)) is a basic form of change detection and cannot be grouped under any of the above category. It has been successfully used by the National Wetlands Inventory (Wilkie and Finn, 1996).Unfortunately, visual change detection is time consuming and tedious, thus making automated (software driven) change detection analysis attractive. Our ability to monitor successional changes in the environment has been made more practical since the launch of earth resource sensing satellites.

Change detection analysis, may be enhanced through anniversary date synchronization, (Lillesand and Kiefer 2000). Using anniversary date images ensures that the sun's angle of incidence is the same on both days of image capture. However this approach does not ensure that the temperature and precipitation between the years will be the same, both of which affect the phenology of the region. Thus in some cases phenology synchronization should provide a better analytical approach than anniversary synchronization.

In the case of post classification change detection analysis, it is necessary that both images have high classification accuracy. (Accuracy assessment determines how well the classified image corresponds with what actually exist on the earth surface.) Accurate spatial registration, similar acquisition sensors same spatial, spectral and radiometric resolutions, of the images are all necessary for an effective change detection analysis to be performed. In most cases, the above factors depend on the feature under study (Jensen, 2005). Climatological factors like lake levels, tidal stage (affected mostly by the moon), wind and soil moisture, might also be important in change detection analysis (Lillesand et al., 2004).

## *Problem Statement*

Landuse and Landcover changes can either be natural for example a mud flow or human induced (increase in paved surfaces), and their impact on the environment can range from a short period after which the environment recovers, to recovery periods that are decades to centuries long. In a watershed changes in the landuse and landcover can be as glaring as the change from forest to farmland, or as trivial as the rotation of crops on a particular piece of land. What ever their nature, change always has an effect on the environment.

The Fort Cobb Reservoir watershed (FCRW) is one of the 14 USDA-Agricultural/Research services (ARS) bench mark watersheds in the nation wide Conservation Effects Assessment Program (CEAP) that was created in 2003 as a result of the 2002 Farm Bills. The CEAP aims at assessing and quantifying the effects and the benefits of USDA conservation practices implemented in agricultural watersheds. Conservation practices in the FCRW were implemented as a result of the high loads of suspended sediments, low levels of dissolved oxygen, high levels of phosphorus and nitrogen, and the presence of nuisance algae in the reservoir. SWAT (Soil and Water Assessment Tool) will be used to assess the impact of conservation practices on selected environmental outcomes (e.g., water quality, wildlife habitat, etc,) (USDA-ARS. 2007). The SWAT is a model designed to assess the impact of landuse practices. However, these landuses change overtime thus making it important to monitor these changes. The output change detection analysis may serve as input for SWAT and, hence, support policy decision and conservation project implementation.

Suspended solids and other non-point source pollutants result from agricultural chemical inputs like fertilizers and pesticides, whose application vary depending on the use of a particular piece of land. Change detection analysis determines the landuse type before and after the implementation of a conservation practice, and therefore should play an important role in the CEAP analysis. The goal of this project is to develop an output that can be used in the SWAT or USLE models to evaluate and better implement management practices.

## *Goal and Objectives*

The main goal of this project is to analyze changes in the landuse and landcover in the FCRW. A change analysis will be performed for a short term and a long term period. The short term change analysis will determine how much change took place in the watershed between 2001 and 2005, while the long term change period will determine the change in the landcover between 1992 and 2005. Therefore, the objectives of this study are as follows:

- Develop a Geospatial database for the watershed.
- Develop a landuse and landcover map for the year 2005
- Evaluate the change in the landuse and landcover between 1992 and 2005, and between 2001 and 2005.

## *Study Area*

The Fort Cobb Reservoir Watershed (FCRW) is located in southwestern Oklahoma in the Caddo, Washita, and Custer Counties (Figure 1). The basin area is 314 square miles and the surface area of the Fort Cobb Reservoir is 4,100 acres. This watershed is dynamic in terms of the agricultural practices, crops grown and diversity of land management practices. The Fort Cobb Reservoir and six stream segments in its basin are listed on the Oklahoma 303(d) list as being impaired by nutrients, pesticides, siltation, suspended solids, and unknown toxicity (Storm et al., 2006) . This watershed has been the site of recent research from different government and environmental agencies interested in its water quality, erosion rates and soil conditions. Recently, the U.S Environmental Protection Agency named the Fort Cobb Reservoir Watershed Implementation Project by the Oklahoma Conservation Commission as one of the six best in the nation. This project is designed to improve water quality in the Fort Cobb Reservoir using non-point source pollution controls (OCC, 2007). The objectives included protecting and reestablishing buffer zones and riparian areas, and to demonstrate conservation practices necessary to reduce sediment, nutrient and pesticides loadings to improve water quality. Another agency actively involved in this watershed is the USDA ARS, which uses this watershed as a benchmark watershed studied as part of the Conservation Effects Assessment Program (CEAP). The CEAP as earlier mentioned is a program aimed at assessing the environmental benefits of the USDA implemented conservation programs in the watershed (USDA. ARS, 2007). The program was started in 2003 as a result of a farm bill, and is ongoing in selected watersheds in the nation including the Fort Cobb watershed.

Other agencies involved in this watershed are Oklahoma Department of Water Quality (OKDEQ), the Oklahoma Conservation commission (OKCC), and the United States Geological Survey (USGS). Figure 1 shows the watershed, and its location in southwestern Oklahoma.

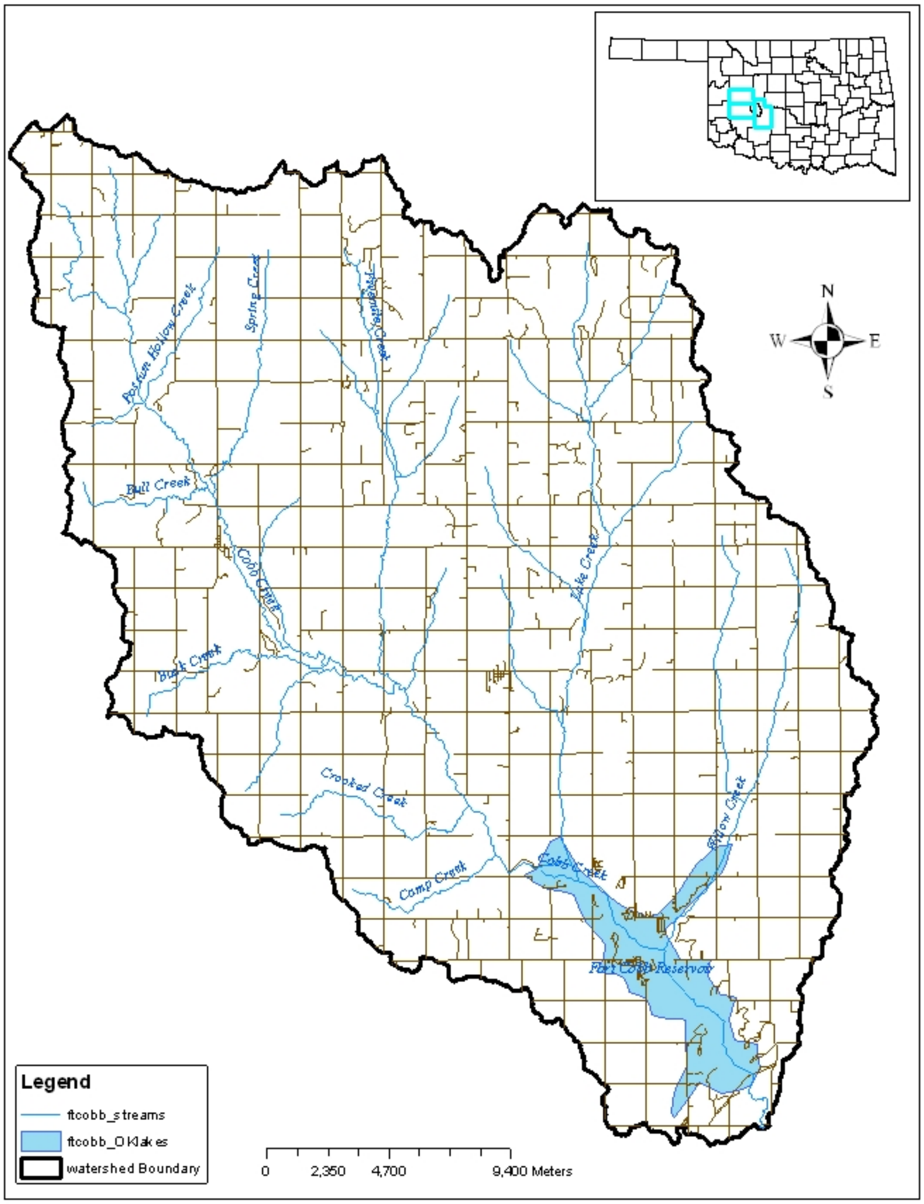


**Figure 1. The Fort Cobb Reservoir Watershed in southwestern Oklahoma.**

# CHAPTER TWO

## *Literature Review*

Landuse and landcover change is concerned with the detection and quantification of alterations of the land surface and its biotic cover. The difference between landuse and landcover is that while landuse denotes the human employment of the land and is largely studied by social scientists. Landcover denotes the physical and biotic character of the land surface and is mostly studied by natural scientists (Meyer and Turner II, 1992). Landuse and landcover also have a time element tied into their definitions: For example, in an agricultural context, landuse refers to the surface conditions observed at a point in time (plowed, fallow, wheat etc.) Landcover of a particular piece of land would be an integration of the landuses of that piece of land. For example, freshly plowed land in September, emerging cover crop in October, complete green canopy in November, through April, senescing canopy in May and harvested crop in June would indicate an agricultural landcover.

"Environmental changes as a result of landcover or landuse change become global either by affecting a global fluid system (atmosphere, world climate or sea level) or by occurring in a localized or patchwork fashion in enough places to sum up to a globally significant total"(Meyer and Turner II 1992).

Meyer and Turner (1992) defined land cover change as a change that takes place in two forms; conversion from one category of  land to another, and the modification of the conditions within a category. So while conversion will be the complete change of a forested area into a built up area, modification will be the conversion of the same forested land into secondary forest. In further discussions, they state that conversion in the landcover is more documented and monitored than modification is, and because of this, important forms of landcover modifications are obscured.

Li et al. (2003) studied the landcover changes in the Tarim basin of China between 1964 and 2000. Owing to its special landforms, this basin, considered one of the most representative regions of the arid and semi arid worlds, has been attracting more and more scientists as a result of changes taking place within it; such as expansion in its oases, soil salinization and dying poplar forests. To characterize the changes in this watershed they used Landsat ETM for the year 2000, and Corona Panchromatic images for the year 1964. Using the post classification change detection method, they noticed changes in the size of the land reclaimed from water and soil, the death of an old poplar forest around the Tarim River and also changes in the level of salinization. Payatos et al (2003), studied landuse and landcover changes in the Catalan Pre-Pyrenees using 1957 and 1996 orthophotographs, they noted that the expansion of forest areas was basically the main landcover change and that this was caused by the abandonment of traditional agricultural activities, and by the use of other materials and energy sources, instead of forest resources.

Although natural environmental factors also account for changes in the environment, humans remain the main cause for most of the landuse and landcover changes. Hayes and Sader (2001) in their study of forest clearings and regrowth in tropical moist forest noticed that Guatemala’s Maya Biosphere Reserve had faced increasing rates of deforestation due to human migrations and the expansion of the cultivated frontier. Using, three dates of Landsat TM images, each two years apart, they radiometrically corrected and preprocessed the images removing clouds, water and wetlands. What followed next was their use of three (normalized vegetation index (NDVI) image differencing, Principal Component Analysis, and red, green and blue (RGB)-NDVI classification) different change detection techniques to analyze the changes in this reserve. The RGB-NDVI method yielded the highest Kappa value (the Kappa index determines the degree of agreement between two images), and an accuracy rate of 85% and the least was the Principal Component Analysis method.

Contrary to Hayes and Sader (2001), Lambin et al. (2001) state that neither population nor poverty alone is the major cause for landuse and landcover change. Rather, man’s responses to economic opportunities as mediated by institutional forces, and the opportunities created by local and national markets and policies are also to be blamed for the landuse and landcover change. By this they mean, the market forces of demand and supply coupled with marketing policies, trade zones, and other policies affect landuse and landcover changes as well as population growth.

The importance of landuse and landcover change has led to a sea of literature that exists on change detection and on the different algorithms used in detecting change (e.g. Lillesand et. al. (2004), Wilkie and Finn (1996), and Jensen (2005). Berry (1998) used the Kauth-Thomas Greenness vegetation index to determine multi-temporal landcover dynamics in the Little Washita watershed. He used this algorithm because it was developed specifically for agricultural applications, containing more information than a two band NDVI ratio and also represents ground cover better. However change detection analysis can be described as work in progress because the methods used, depend on the nature of the project. It therefore becomes difficult to discuss all these techniques/algorithms in this literature review. Here, only the main ideas behind each method and not the different algorithms will be discussed.

Change detection requires careful attention to environmental characteristics and remote sensor systems considerations. Sensor considerations include sensor characteristics such as temporal spatial, spectral, and radiometric resolution. Temporal resolution refers to the time it takes the satellite to revisit the same point on the earths surface. There are two aspects associated with temporal resolutions that are important to note: anniversary dates, and the time of the day the images are acquired (for the Landsat Thematic Mapper it is 9:45 am). Failure to understand the impact of these aspects on the change detection result may lead to inaccurate results (Yuan and Elvidge, 1998). For example, the use of anniversary images will ensure similar solar illumination angle, and if the images are taken at the same time of the day, the sun earth distance too will be the same, and this further reduces the illumination differences between the two dates.

Spatial resolution (the total area covered by a pixel in an image), varies from one sensor to another (For example the Landsat Thematic Mapper is 30x30m while that for a SPOT HRVS image is 20x20m) and is important in change detection analysis because it determines the amount of detail that can be extracted from an image. The smaller the spatial resolution, the greater the amount of detail that can be extracted from a particular image and the greater it is the less the detail.

Spectral resolution, which can also be called band width of the sensor, is the portion(s) of the electromagnetic spectrum recorded by the sensor and varies from one sensor to another. For example, the Landsat 7 ETM records reflectance's in six optical bands and one thermal band while the SPOT 1, 2, and 3 HRV sensor collects data in three multi-spectral bands and one panchromatic band (Sabins, 1996).

Radiometric resolution refers to the brightness values of images from different sensors which may range from 6 bit to 8 bit images. These bits signify the number of shades of gray the picture can be recorded in, and the higher the number of bits, the better the representation. The Landsat TM has an 8 bit radiometric resolution which yields 256 shades (0-255) (Lillesand et. al. 2004)

Environmental conditions, on the other hand, will include vegetation phenology, those aspects of the vegetation that vary with the climate such as leaf shedding. Flowering and seed dispersal are important aspects of the vegetation that should be considered in change detection analysis, especially if the study involves monitoring the changes in plant growth. Soil moisture level and content is another environmental aspect that should be considered when performing change detection analysis. The presence or absence of soil moisture in the ground affects the color of the plant leaves which in turns affects the stoma structure and thus the angle direction and amount of energy reflected. Atmospheric conditions, cloud cover, dust particles, and atmospheric moisture are also important environmental aspects to consider because they determine how visible the image will be and how useful it will be in change detection analysis. Also, effects of tidal stage and urban-suburban phenological cycles are factors worthy of consideration, because these factors affect the immediate (local) atmospheric conditions (Jensen 2005).

Change detection methods, according to Chen (2007), can be separated into two main types; supervised and unsupervised methods. The supervised methods involve the use of ground truth data (training data) to perform a supervised classification on an image and later, use of the same ground control points to identify those areas of change on the classified image. Three main forms of change detection techniques fall into this category: compound classification, supervised direct multi-data classification and post classification comparison (Chen, 2007). Contrary to the supervised forms of change detection, the unsupervised techniques include: univariate image differencing, change vector analysis, image ratioing, vegetation index differencing, the tasselled cap transformation, and Principal Component Analysis (PCA). These techniques do not involve the use of ground truth data (Chen, 2007). The main difference between the supervised and the unsupervised change detection methods is that while the supervised methods require a supervised classification to be performed before the change analysis is performed, the unsupervised change detection methods do not. In fact in the unsupervised methods of change analysis can be performed using the raw (unprocessed) bands of the landsat images.

The post classification change detection method is a highly quantitative method and is widely used. In this technique, two individually geometrically rectified and classified images are compared on a pixel-by-pixel basis using a developed change detection matrix (Jensen, 2005). Because the outputs from two individual maps are used in performing post-classification change detection, the overall accuracy of the change image depends on the accuracy of the independently classified maps (Lillesand et al., 2004). In other words, the total accuracy of the image is close to the product of the accuracies yielded by the individual images. The advantage of this kind of method is that most of the time, it does not require atmospheric correction. It provides from- and to change class information and also the already classified images can be used as base maps for other change detection analysis (Wilkie and Finn, 1996). In their study of the natural environmental change in the Danube delta based on SPOT and HRV images, Noaje and Turdeanu (2004) used the post classification change detection method and noticed that this method of change detection analysis minimized difficulties that arose because of the use of different sensors and the atmospheric conditions at the time of capture.

The supervised direct multi-date classification determines the direct transition of pixels from one class of pixels to another by the use of a trained classifier. This method shows the time difference correlation between the two images used in the analysis. The disadvantage of this method is that the training pixels used must be the same points on the ground in the two different dates (Pons et al., 2002).

The compound classification is similar to the supervised direct multi-date classification, but does not require the same ground truth data to be used to classify both images (Chen, 2007). Therefore, two different sets of ground truth data can be used, and the advantage lies in the fact that the more diverse and spread out the ground data are, the more represented the field is and therefore the better the results.

Unsupervised methods of change detection as the supervised methods are dependent on the spectral differences of the different images, but do not require the use of ground truth data. They usually require a lot of preprocessing, and detailed comparison of the two images (Chen 2007).

Image differencing is a popular method in performing a change detection analysis between two images. It entails the subtraction of the digital numbers (DN) of the cells in the second image from the DN values of the cells in the first image. The difference in the areas of no change will be near zero, while the difference in the areas with change will be high (Lillesand et al., 2004). In 8 bit images, the range of the value difference is usually between -255 to +255 and because negative values are avoided, a constant of 255, is added to each difference image value for display purposes. The change image produced yields a brightness value (*BV)* distribution approximately Gaussian in shape, where the pixels of no *BV* change are distributed around the mean and pixels of change are found at the tail of the distribution (Civco et al., 2002). Image differencing does not have to be limited to the individual bands of an image, but can be extended to include the Normalized Difference Vegetation Index (NDVI) of the two images. Tardie and Congalton (2001), in their study of the progression of development into Essex County in Massachusetts, used the image differencing technique to determine change between a 1990 and a 2001 image. In their analysis, they performed image differencing on the first four raw bands of the images (blue, green, red, and near infrared) and based their threshold values are standard deviation from the mean, to determine changed from unchanged pixels. In this case there are no clear cut rules in picking the threshold for change versus no change pixels, but a common rule of thumb is to assume that pixels in the difference image that fall outside the limit where 95% of the values fall, are considered to have changed. For example in the figure 2, 5% of the observations in the change image will be considered to represent change (2.5% of pixels in each tail).

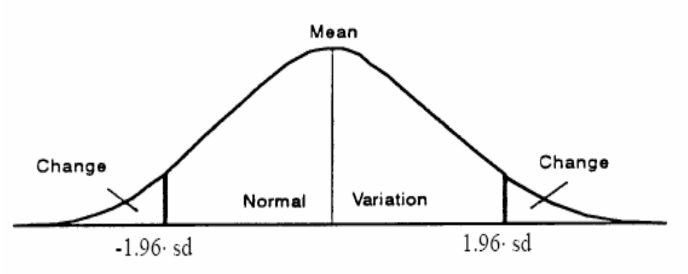


**Figure 2. Creating a Threshold of change and No-change pixels**

However, the problem with thresholding is that there are no clear guidelines on how to set limits for change against no change pixels (Congalton and Green, 1999).

Image ratioing or band ratioing is very similar to image differencing and are all forms of algebraic image change detection. Image ratioing is simply dividing the DN values of the cells in image one by the DN values of the cells in image two. In this technique, the ratios computed range from 1/255 to 255, with no change pixels having a ratio value of 1 in the change image. Important to note is how the analyst determines the threshold boundaries between the change and the no change pixels displayed in the change image histogram. This change point is never known and analysts have developed different means of defining it. One standard deviation from the mean has been used in some cases, while in others empirical experiments have been used.

Sangavongse (1995) used this method in his study of the changes in the Chiang Mai area in northern Thailand. Using image data from two landsat 5 TM images, they performed image ratioing on a pixel by pixel basis dividing band 3 of the first image by the band 3 of the second image. Band 3 (visible red, 0.63-0.69 m) was used because of its ability to differentiate different soil boundaries and also because of its usefulness in differentiating many plant species. The change image was enhanced by the use of a false color composite (FCC), in which the different image bands were assigned to different filters (guns) in order to identify specific features in the images. In this case, TM 3 of date one was assigned the red gun, and the TM 4 of date 2 was assigned the blue gun.

Principal Component Analysis (PCA) is also used in change detection analysis and is performed based on the variance - covariance matrices or on correlation matrices with the result being in the computation of the eigen-value, and factor values used in producing a new uncorrelated PCA image dataset. In a PCA analysis, the before and after images with their N bands are combined in to a single 2 *N*-dimensional image from which an equal number of principal components are computed. Several of the uncorrelated principal components computed from the combined data set can be related to areas of change. The disadvantage in using this method is that it is often difficult to interpret.

Change Vector analysis (CVA) is similar to image differencing, but takes into consideration the distance and direction of the change. In this method two spectral variables, which may be data for two different bands or data from two different types of vegetation, are plotted for a particular pixel at time T1 and at time T2. For this pixel the direction and distance of change is determined by the vector connecting the two dates. If it appears that the pixel position on the feature space has changed between time T1 and time T2, then it means the land cover represented by the pixel has undergone some change in the time interval. The vector that determines this change is called the *spectral change vector*.

The CVA method was used by Kuzera et al. (2005) in their study of vegetation regeneration and deforestation on Mt. St. Helens in Skamania County, Washington. Using Landsat TM images for the years 1988 and 1996, they used the Tasseled Cap Transformation (TCAP) inputs of brightness and greenness to monitor the deforestation and regeneration of the forest between these two periods. Placing brightness along the X-axis and greenness along the Y-axis the angle of the change vector from a pixel was measured at time 1, to corresponding to a pixel measured at time 2. A regeneration of the vegetation was represented by angles measured between 90 to180 degrees which indicated an increase in greenness and a decrease in brightness. Angles measured between 270 and 360 degrees indicated a decrease in greenness and an increase in brightness representing areas of deforestation. Angles between 0 and 90 degrees and the angles between 180 and 270 indicated either a decrease or and increase in both greenness and brightness. Furthermore, four categories were used to signify the amount of change ranging from low (8-25), medium (25-50), high (50-75), and lastly extreme (75-100). These values indicated the length of the change value in the measurement space, and values between 0 and 8 were considered as noise and classified to represent persistence. The change direction and its magnitude were cross tabulated and classified into 9 categories, consisting of four categories of regeneration and four for deforestation, plus the persistence category.

According to Jensen (2005), there are several other methods by which a change detection analysis can be performed. The binary change masks detection analysis technique that has the attributes of both the post classification change detection method and the image differencing method. A traditional classification is performed on the date 1 image, while image differencing is performed on any two bands on the two original images. This method has the advantage of reducing change detection errors such as the errors of commission (adding pixels that should be absent) and omission (exclusion of pixels that should have been added). It also provides detailed “from-to” data change class information and also very little effort is needed on the part of the analyst because he can focus on the very small areas that have changed between the two dates. Jensen, 2005 suggest that “This method of change detection is very effective”.

The change detection method using an ancillary source as date 1 involves the use of a land cover data similar to the date 1 image in place of the image. For example the use of a digitized National Wetland Inventory map in place of remotely sensed image of the coastal areas in a coastal change detection project. Other methods of change detection include the chi square transformation change detection method, the cross correlation method, the knowledge based systems method and the visual on screen change detection and digitization method.

Although all these methods are used in performing a change detection analysis, they all have their advantages as well as their disadvantages. In reality, the unsupervised methods of change detection are preferred to the supervised methods because they do not require the use of ground truth data which, for the most part, is expensive and time consuming to collect. For this project, a hybrid form of image classification was used that involved the strong aspects of both the supervised and the unsupervised classification methods. This method ensured that the images were adequately classified with very high accuracies. As concerns change detection, the post classification change detection method was used because the other images to be used in the analysis had been classified. The simplicity involved in the use of this technique was an added advantage.

# CHAPTER THREE

## *Methodology*

### Overview

In this chapter, the different stages followed and techniques used in developing a composite landuse image for 2005, and for performing a post classification change detection analysis will be addressed. The procedures followed can be divided in to three main stages (Figure. 3) image preprocessing, image classification and the development of the composite landuse image, and lastly the steps used to perform a post classification change detection analysis. The first stage of the methodology will involve image importing, sub-setting, and atmospheric correction. The second stage consists of hybrid image classification, accuracy assessment, and image composition. Stage three of the analysis will involve, image reclassification (ASSIGN), format transformation, cross tabulation, change analysis and accuracy assessment.

Both raster and vector formats were used in this project and are summarized in Table 1. This table shows the different dates, paths and rows of the images that were used and also the dates of the ground truth data used for the supervised image classification.

**Table1. Spatial Data types used and their sources.**

| Data Type | Source |
|---|---|
| Vector layer files (transportation, water bodies, counties, and cities) | Oklahoma Centre for Geospatial Information (OCGI) website www.seic.okstate.edu |
| • Landsat TM image data and their path (p) row (r)<br>-March 9,2005 p28 r36<br>-March 9,2005 p28 r35<br>-June 29, 2005 p28 r36<br>-June 29, 2005 p28 r35<br>-September 9, 2005 p28 r36<br>-September 9, 2005 p28 r35<br>-November 4, 2005 p28 r 36<br>-November 4, 2005 p28 r 35<br><br>• Ground truth data<br>-March 24,2005<br>-June 29,2005<br>-August 01,2005<br>-November 03,2005<br><br>• Boundary shapefile of the Ft. Cobb Reservoir watershed. | USDA-ARS Grazing Lands Research Laboratory El Reno, Oklahoma. |
| 2003 National Agriculture Imagery Program (NAIP) images for the Caddo, Grady and Comanche Counties. | Oklahoma Centre for Geospatial Information (OCGI) website www.seic.okstate.edu |
| National Landcover Data (NLCD) for 1992 and 2001 | Multi-Resolution Land Characteristics Consortium (MRLC) website www.mrlc.gov USGS website |

### *Landsat data*

Sixteen different Landsat Thematic Mapper (TM) images were provided by the USDA ARS Grazinglands Research Laboratory (GRL) at El Reno, Oklahoma, of which eight cloud- free images were chosen for the project (Table. 1). The (TM) is a sensor that records energy in the visible, reflective-infrared, middle infra-red, and thermal infrared regions of the electromagnetic spectrum (USGS, 2007), and has a spatial resolution of 30x30m. All the images were geometrically corrected by the USGS, and were projected to UTM zone 14, GRS 1980, NAD 83. 1992 and 2001 National Landcover data (NLCD) were downloaded from the USGS website.

### *Ancillary data*

GIS layers for roads and water bodies were downloaded along with other raster data sets like the National Agriculture Imagery Program (NAIP) image to support image classification, accuracy assessment and also to serve as a reference to the different landsat images. Boundary shape files were used to subset the Landsat images to the actual boundary of the watershed. This reduced the data sizes and increased computer storage space. It also reduced the run time of the different processes. Ground truth data for the image classification was provided by the Grazingland research laboratory (Table. 1), and consisted of photographs, coordinates of sampling location and notes concerning landcover at the sampling sites.

### *Software*

Three different type of softwares were used to complete this project; ArcGIS 9.2, (ESRI, 2007), Erdas Imagine 9.1 (Erdas 2007) and Idrisi Andes (Idrisi, 2007). ArcGIS was used for mapping out ground truth points, perform image overlay, add images and to add attributes to some images. These processes can be performed in Erdas imagine and Idrisi Andes but the ArcGIS software was used because it was easier to use for these analysis. The Erdas Imagine software was used for image classification, image subsetting and for other image analysis like the atmospheric rectification that require the use of models.

Idrisi Andes was used only for change detection analysis. It was used particularly because it provided a more detailed change output (e.g. the Kappa statistics of agreement, the cross tabulation table) than the Erdas imagine.

Figure 3 shows a summary of the different procedures used in achieving the goals of this project.

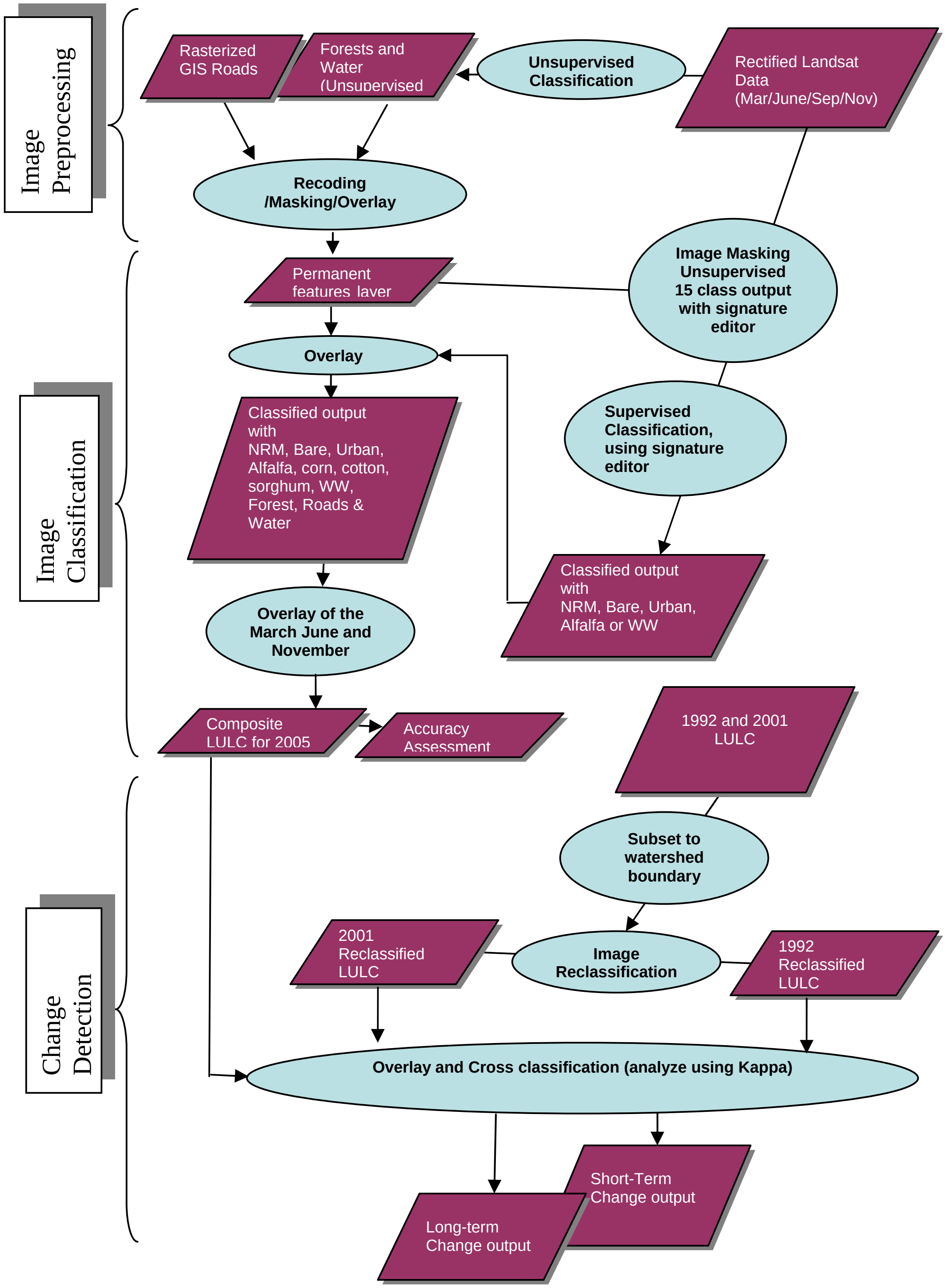


**Figure 3. Stages in the Methodology.**

The methods used in this project will be discussed in three different stages; image preprocessing, image classification and change detection analysis.

### *Image Preprocessing*

This section of the methodology includes radiometric correction, image mosaicing, and image subsetting. All of the Landsat TM images provided by the Grazinglands Research Laboratory El Reno OK, were in Geo TIFF format, and were later converted and stored in an image format (.img) compatible with the softwares to be used. Image subsetting, was performed in two different stages. First, band six (thermal band) was removed from all the images because of its properties. Thermal bands receive heat emissions from objects on the earth i.e. they sense heat from earth objects, and not their spectral reflectance. Furthermore, the pixels sizes for band six are generally larger than the normal pixel sizes. The spatial resolution of all the other bands in a landsat TM image is 30 x 30m but for band six, it is 120 x 120m. After the removal of band six from images, the next preprocessing step was the atmospheric correction of the images.

Atmospheric constituents, both gaseous and particulate, affect the amount of solar radiant reaching the earth's surface. Phenomena such as Rayliegh scattering add brightness to images whereas atmospheric absorption reduces the brightness of the Landsat images. Atmospheric correction adjusts the image for changes in the reflectance of ground features at different times or location (Lillesand et al., 2004). In applications like this, it is necessary to correct for a solar elevation and earth-sun distance difference. This process is only necessary for change detection image analysis, involving multi-temporal images as is the case with this study. The FCRW images were corrected for solar illumination angles by normalizing the pixel brightness values, assuming the sun was at the zenith on each date of image acquisition.

The normalization process used the model proposed by Chavez (1998) and developed into an algorithm by the GIS and Remote Sensing department of the University of Utah (Remote Sensing and GIS Laboratory, Utah State University, 2007) http://www.gis.usu.edu/docs/projects/swgap/ImageStandardization.htm, accessed 10/12/2007)

. The algorithm implemented in the spatial modeler in Erdas Imagine:

$$\rho_{BandN} = \frac{\pi((L_{BandN} * Gain_{BandN} + Bias_{BandN}) - (H_{BandN} * Gain_{BandN} + Bias_{BandN})) * D^2}{E_{BandN} * (COS((90-\theta) * \pi / 180)) * \tau}$$

Where,

$\rho_{BandN}$ = Reflectance for Band N

$L_{bandN}$ = Digital Number for Band N

$H_{bandN}$ = Digital Number representing Dark Object for Band N

D = Normalized Earth-Sun Distance

$E_{bandN}$ = Solar Irradiance for Band N

$\tau$ = Atmospheric Transmittance expressed as $(COS((90-\theta) * \pi / 180))$

The outputs from this preprocessing stage were Landsat images with little or no cloud cover, or other atmospheric impurities that could adversely affect the classification of the images.

Image preprocessing continued with image mosiacing, which required two images of similar paths but different rows to be joined in order to extract the area of the images covered by the watershed. Landsat paths refer to the satellite’s north to south orbit system, while the row is an individual sensor frame. In this case, as a result of the watershed shape and the path of the satellite, the complete shape of the watershed, could not be captured in a single satellite frame (row). This therefore necessitated a join of the landsat images that had portions of the watershed (path 28 row 35 and path 28 row 36) and then a subset of the join to the actually watershed boundary (Figure. 4).

The watershed boundary file was then used to extract only the portion of the imagery needed for the project. The portion of the watershed extracted was slightly larger than the extent of the watershed boundary (figure 5), so as to include ground-truthed GPS points that were crucial in classifying the image and in assessing its accuracy.

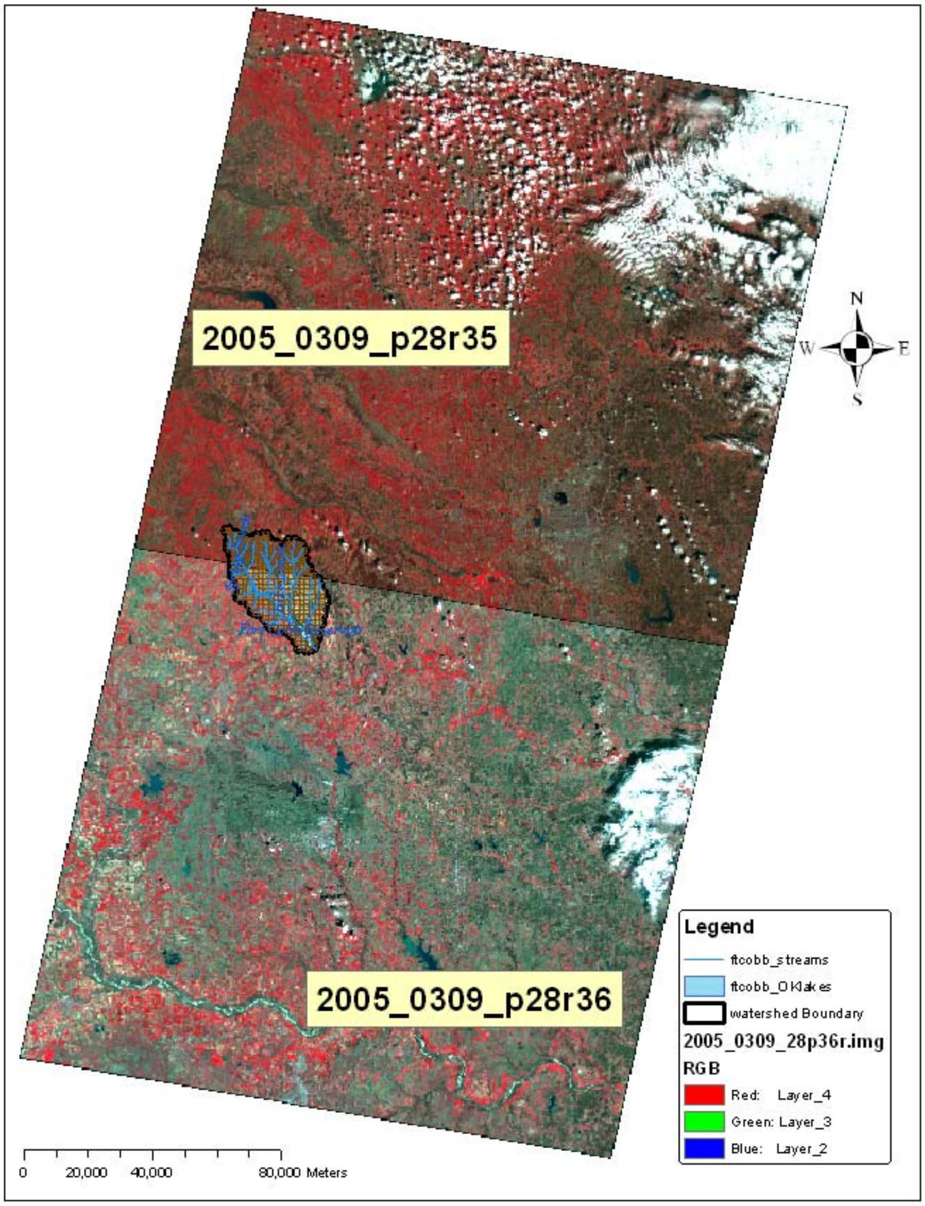


**Figure 4. The Fort Cobb Watershed Located between Two Landsat Images of Paths 35 and 36.**

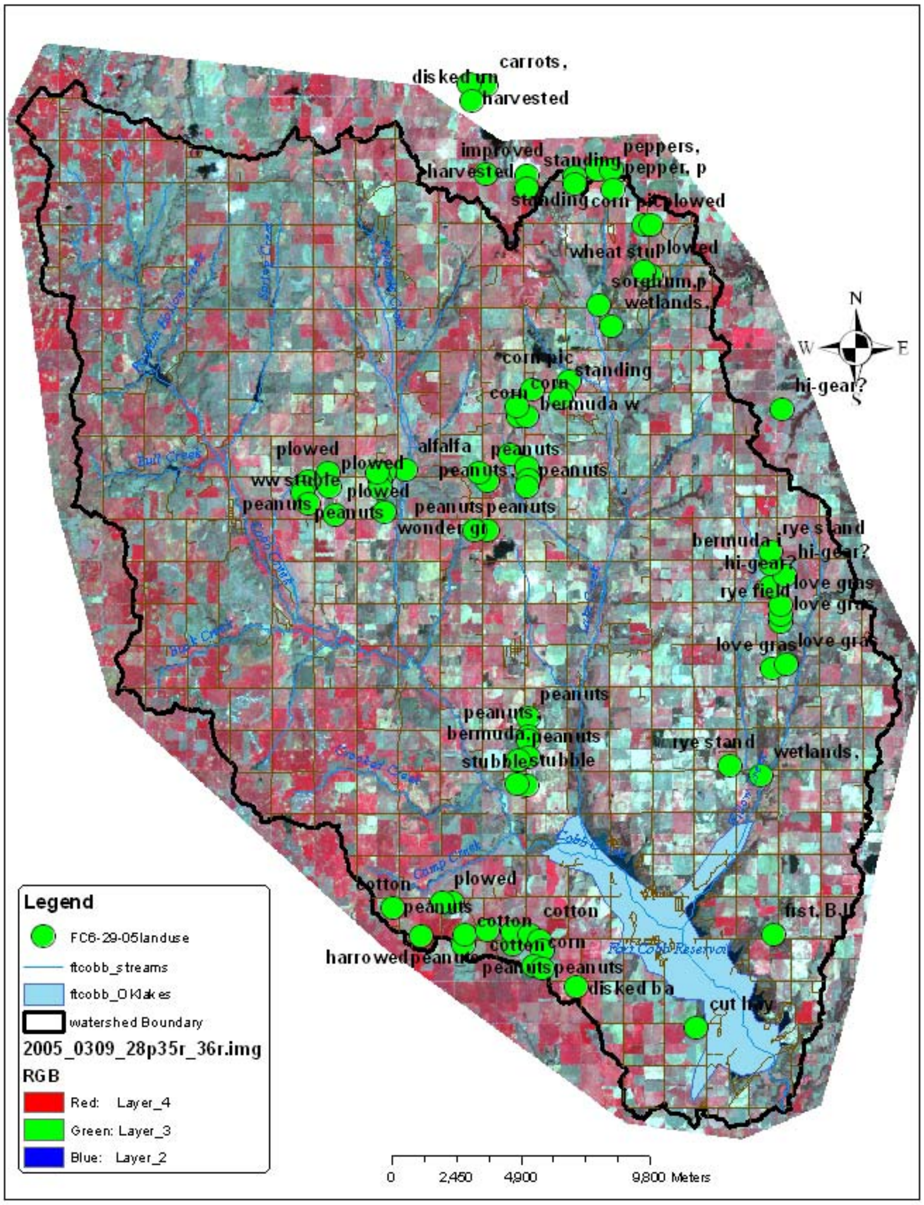


**Figure 5. The Landsat image subsetted to contain the watershed boundary and showing outlying ground truth location.**

### *The Creation of a Permanent Layer*

The last stage in the preprocessing stage was the creation of a permanent image layer. The reason for this was to avoid confusions in spectral signature during the image classification stage. For example, plowed fields have a similar spectral reflectance with bare surfaces like un-paved roads and in some cases, quarries and this becomes a potential cause for misclassification. It becomes advisable therefore, if possible to separate layers with similar signatures like roads in the FCRW that had similar signatures with plowed and recently tilled fields.

Roads were extracted from every image, with the aim of reducing this spectral confusion with plowed fields but forest and water features were extracted because they did not change in total area or extent in the course of the year. The GIS layer for road was converted from vector to raster (cell) format at resolution of 30m x 30m, to make it compatible with the other raster layers. Before rasterization, the vector layer was reprojected to USGS 1983, NAD 83, UTM zone 14 to match the other layers in the project. The road layer was then saved as an image file.

In order to indentify the water and forest features, an unsupervised classification (image classification that does not require the use of ground truth information or any prior knowledge of the classified area) was performed on the June image generating about 15 classes. This image was used because June is the month of the year in which most vegetation is actively growing. The NAIP imagery and the alarm tool in Erdas Imagine were then used to identify those classes that represented either water bodies or forested areas in the watershed. After the classification, these landuse features water, roads, and forest were combined using the overlay “AND” operation to form one permanent feature layer using the Erdas Imagine overlay module. A recoding process in Arc GIS attributed to them (the layers) unique codes for identification and easy overlay with the other landuse types that were to be coded. For example 1 = forest, 2 = water, and 3 = roads. This layer was used to mask out the roads, forest and water layers from all the selected landsat images.

### *Image Classification*

Image classification can be defined as the technical grouping of the cells in an image into specific landuse and landcover types. Generally speaking, images can be classified using three different methods; unsupervised, supervised, and the hybrid (a combination of the supervised and unsupervised methods) methods of classification. The hybrid classification method is a technique that incorporates the positive aspects of the supervised and unsupervised methods, ignoring their short comings. The Hybrid classification though is time consuming and in some cases very expensive to perform. In the supervised classification of an image, the identity and location of the different landcover types are known by the analyst before the classification. This means that the analyst is guided in his classification by field information such as ground truthed data, or some other ancillary data such as aerial photographs. This method of classification, is limited by accessibility to ground sampling sites, accessible areas or areas with availability of ancillary data and may be potentially expensive is field work is required (Wilkie and Finn, 1996).

In an unsupervised classification the analyst has no ground information and the generation of different landuse and landcover categories is dependent upon DN values of the cells categorized into a number of different classes specified by the analyst. Though limited in this aspect, it has the advantage of not being biased and of being less costly. A major disadvantage of this classification type is that inexperience can very well lead to the misclassification of landcovers with similar spectra signatures. (Wilkie and Finn, 1996; Lillesand et al 2004).

After creating and recoding, the permanent feature layers (roads, forest and water), Erdas Imagine was used to mask out the permanent features from all four Landsat images of the watershed. In this procedure, the first input image was the six band Landsat image, while the permanent layer served as the second input image with the possibilities of being recoded. In this recoding process, the features in the permanent layer (roads, water and forest) were recoded to zero while the background of the image was recoded from zero to one. This recoding ensured that in the output was a six band image with all the roads forest and water areas absent. This image was then classified using the unsupervised form of image classification generating 15 different classes and an output signature file.

The classification process was completed by using ground truthed points to develop areas of interest (AOI) to extract spectral signatures from the Landsat images for the different landuses. Spectral signatures were extracted for different landuses using the ground truth data provided for the different months. The spectral signatures developed using the AOIs were added to the output signature file produced from the unsupervised classification procedure. Fine tuned, the signature files were then used to perform a supervised classification on the masked six band images. The out put was a classified image of the watershed with no roads, forest, or water. At this point, the road, water and forest layers that were separated out earlier were added to each of the four individually classified images of the watershed, to complete the classification process. This process of combining the two layers was done using the overlay “AND” method in Arc GIS.

With all the 4 Landsat images classified, the next task was the creation of a composite image, which would be compared with the 1992 and 2001 NLCD in the change detection analysis. The different classified images will be combined one at a time beginning with the March image and then progressing to the last image in the series, the November image. This will provide the analyst with greater control in determining how the cell landuse and landcover codes change from one image to another as the classified images are sequentially combined.

## *The Composite Image for 2005*

The process of adding images is simpified when the images have the same landcover codes. For this project, the landcover codes were standardized (Table 2).

**Table2. Standardized landcover codes used in this study**

| Codes | Lulc Types |
|---|---|
| 0 | Unclassified |
| 2 | Summer Crop |
| 3 | Winter Wheat |
| 5 | Native Range (NR)/Grass |
| 6 | Forest |
| 7 | Water |
| 8 | Roads |
| 9 | Plowed |

With a standardized landcover coding system in place, the analysis progressed to the development of permanent (static) layers for the classification. Static layers are defined as those landcover types that do not change in the course of the year, and to the already created permanent layer was added the native range/ grass (NRM/ Grass) layer and the winter wheat layer.

It should be noted that the NR/Grass and the winter wheat layers are made permanent only at this stage of the classification because it was only after classifying the images that a distinction could be made of the different landuses in the watershed. The winter wheat landuse was made permanent just for the months of March and November. The explanation for this is, winter wheat does not grow throughout the year, and the fields that grow winter wheat during the month of March are either plowed or planted with summer crops in June and replanted with winter wheat in November. In this region, upland winter wheat is seldom followed up by a summer crop. However, in irrigated areas, winter wheat may be followed by peanuts, corn, cotton, etc. Thus, winter wheat is only static for the months of March and November during which they are actively growing. The reason for making this layer static is to adequately map all the winter wheat fields in the months of March and November, and to also understand/follow up their change into other landcovers. To achieve this permanent layer, the winter wheat landcover from the March classified image was masked out and added to the November image. The goal was to be able to show accurately the winter wheat growing fields in both months although only half of the winter wheat shown in the month of March is shown in the November image. Therefore, fields classified as plowed or bare in November but classified as winter wheat in the March image were also reclassified as winter wheat fields. This procedure was adopted because most of the wheat is just beginning to grow in November and fields are likely to be wrongly classified as bare. Winter wheat from the month of March represents planted wheat from the previous fall and is fully grown and well represented in the classified image.

The native range (NR)/grass landuse category was also made a static layer, and eliminated the problem of confusing native range /grass with plowed or bare fields in the month of November when they both look the same on a Landsat image. Agricultural statistics and additional ground truthing revealed that alfalfa makes up a very insignificant portion of the FCRW. So, following the advice of scientists at the Grazinglands research Laboratory, alfalfa was combined to the NR/Grass class. The March image was then used to construct the NR/Grass mask to reduce the risk of miss-classification. NR/grass was easily masked out of the March image which had only three main landuses; winter wheat, plowed/bare and NR/Grass. NR/Grass was recoded as 1 and the other landuses as zero. This new NR/Grass layer was merged into the June image replacing, the NR/grass pixels in the image. The

Alfalfa pixels in the June image were then reclassified as NR/Grass, forming the final NR/Grass permanent layer. This layer was further masked out of the June image and used in replacing every NR/Grass and/or Alfalfa category in the other images (including the March image).The steps in the creation of this permanent layer can be summarized as follows;

i) NR is recoded (masked) from the classified March image layer.

ii) NR _mask (recode) is used to replace the NR in the June classified image.

iii) Alfalfa is reclassified to NR/grass in the June image, forming the final static NR/Grass layer.

iv) New and permanent NR/Grass layer is added to all the other images including the March image. The permanent Native Range/Grass layer is shown in Figure 6.

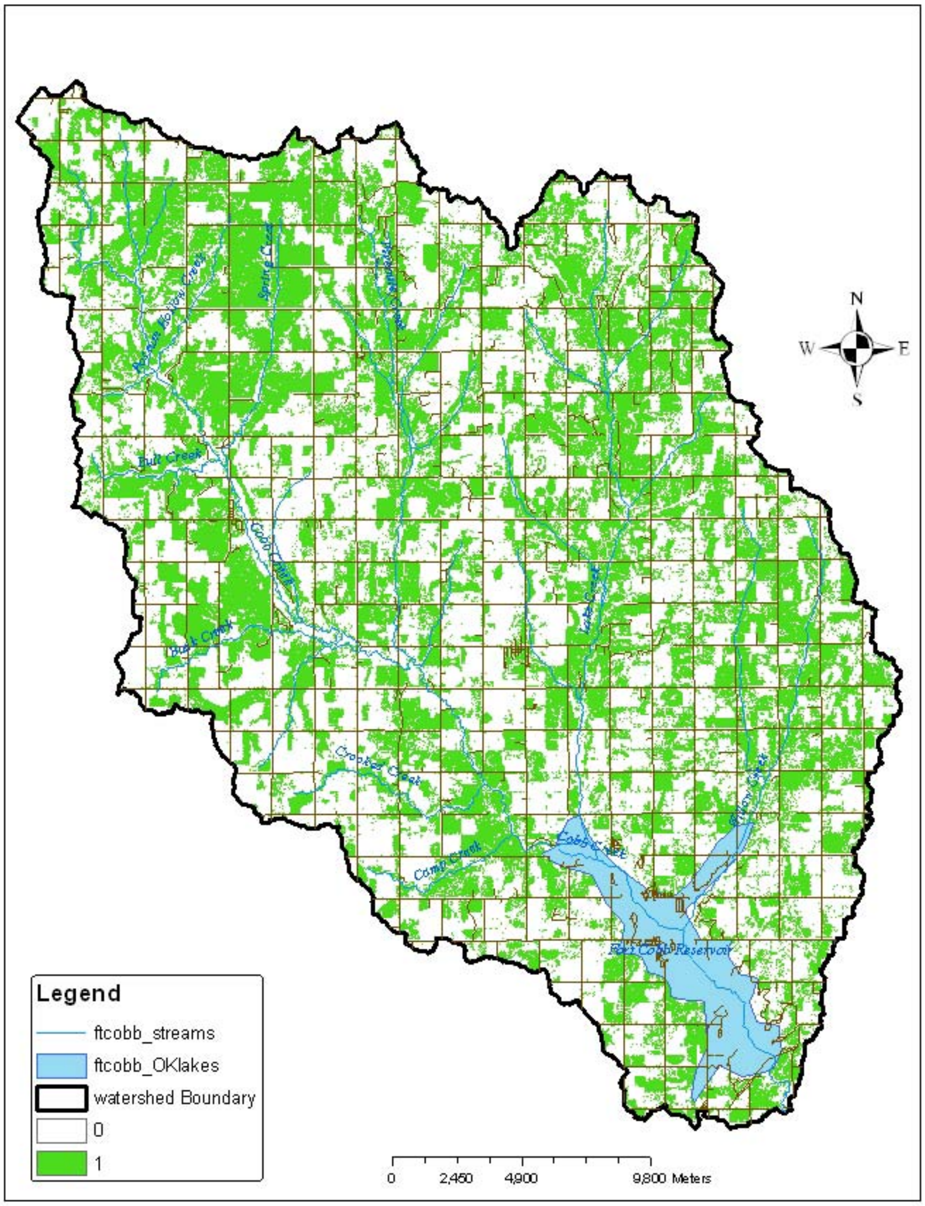


**Figure 6. Static Native Range/Grass layer, used in creating the 2005 Composite Image.**

The next step in the analysis was to develop a model to represent the different landuses in the watershed for the year 2005. The process started with computing the landuses of the March and June images in an Excel file to produce desired landuse outputs. The output at this stage was to be added to the classified images of the subsequent months, one at a time.

To combine the March and June images a few rules were required to guide the process. These rules were based on visual comparison of the raw images for these months, and also on the information obtained from the Oklahoma crop calendar (Oklahoma crop calendar, 2007). They were;

i) Combining any two images should not affect in any way the previously created layers (Roads, Water, Forest and NRM/Grass). Recall that winter wheat is not constant through out the year, so, its pixels were subject to change as the computation progressed.

ii) Plowed fields in the month of March were to be classified as summer crops in the month of June, especially those pixels that showed up as red (vegetated) in the Landsat image.

The next task was to decide on how to maintain the static layers in both images, such that their pixel total remains unchanged. To do this the landcover codes in Table 2 were used. The images were added together using the different image codes, and the output was determined with the use of the crop calendar.

**Table 3. Rule set used to combine the March (0309.img) and June (0629.img) images, while preserving the static landuse category.**

| Combinations | Output | March 09.img | June 29.img |
|---|---|---|---|
| 1 | **6** | 6 | 6 |
| 2 | **7** | 7 | 7 |
| 3 | **8** | 8 | 8 |
| 4 | **5** | 5 | 5 |
| 5 | **6** | 0 | 6 |
| 6 | **7** | 0 | 7 |
| 7 | **8** | 0 | 8 |
| 8 | **5** | 0 | 5 |
| 9 | **6** | 6 | 3 |
| 10 | **6** | 6 | 2 |
| 11 | **7** | 7 | 3 |
| 12 | **7** | 7 | 2 |
| 13 | **8** | 8 | 3 |
| 14 | **8** | 8 | 2 |
| 15 | **5** | 5 | 3 |
| 16 | **5** | 5 | 2 |
| 17 | **2** | 9 | 3 |
| 18 | **2** | 9 | 2 |
| 19 | **2** | 3 | 2 |
| 20 | **3** | 3 | 3 |
| 21 | **9** | 9 | 9 |
| 22 | **9** | 3 | 9 |
| 23 | **6** | 3 | 6 |
| 24 | **3** | 0 | 3 |
| 25 | **2** | 0 | 2 |
| 26 | **9** | 0 | 9 |

In the combination column, the first 16 combinations are meant to keep the permanent layer permanent and will stay constant in all the subsequent image combinations The output column in Table 3 represents the landuse and landcover codes of the resulting image after combining the landuse from the March and the June images. In other words, the output column shows the result of the different pixel combinations from both images. Columns 0309 and 0629 show the different landuse codes in the March and June images which if combined will give the desired code in the output column. For example, row 26 has the value 9 (plowed) for the June column, 0 (unclassified) for March column and 9 (plowed) for the output column. This means that if any pixel is classified with the code 0 (unclassified) in the March image and in the June image the same pixel is classified with the code of 9 (plowed); let the output image classify that pixel as a plowed pixel (9).

The above combination was then uploaded as a text file into the composite image model, in Erdas Imagine (figure 7).

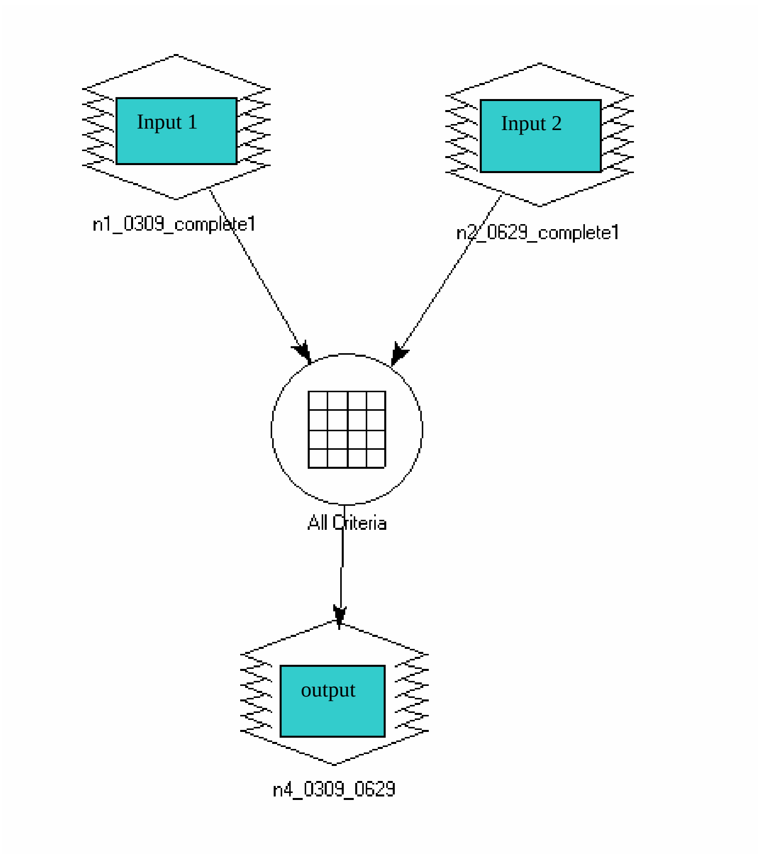


**Figure 7. Schematic showing the implementation of the composite image model**

*(The "All Criteria" performs a logical AND operation of the columns).*

Input one and two show the two classified images of March and June, used to produce the output image which will subsequently be added to the September image. The circle in the middle is the criteria model, which is where the criteria created as an excel file (Table 3) is uploaded as text and used in combining the classified images.

In this criteria model, the option to use the “all” criteria was chosen as opposed to the “any” criteria option. The “any” criteria performs a logical “OR” operation of the columns meaning, just one of the conditions have to be met for the combination to be valid. It therefore does not meet the goal of maintaining a permanent layer. The “all” criteria on the other hand, ensures that the output image meets all the condition specified in the criteria table (Table 3). The output after combining the March and the June image was named 0309_0629_composite (Figure 8). This image will be combined with the classified image for September.

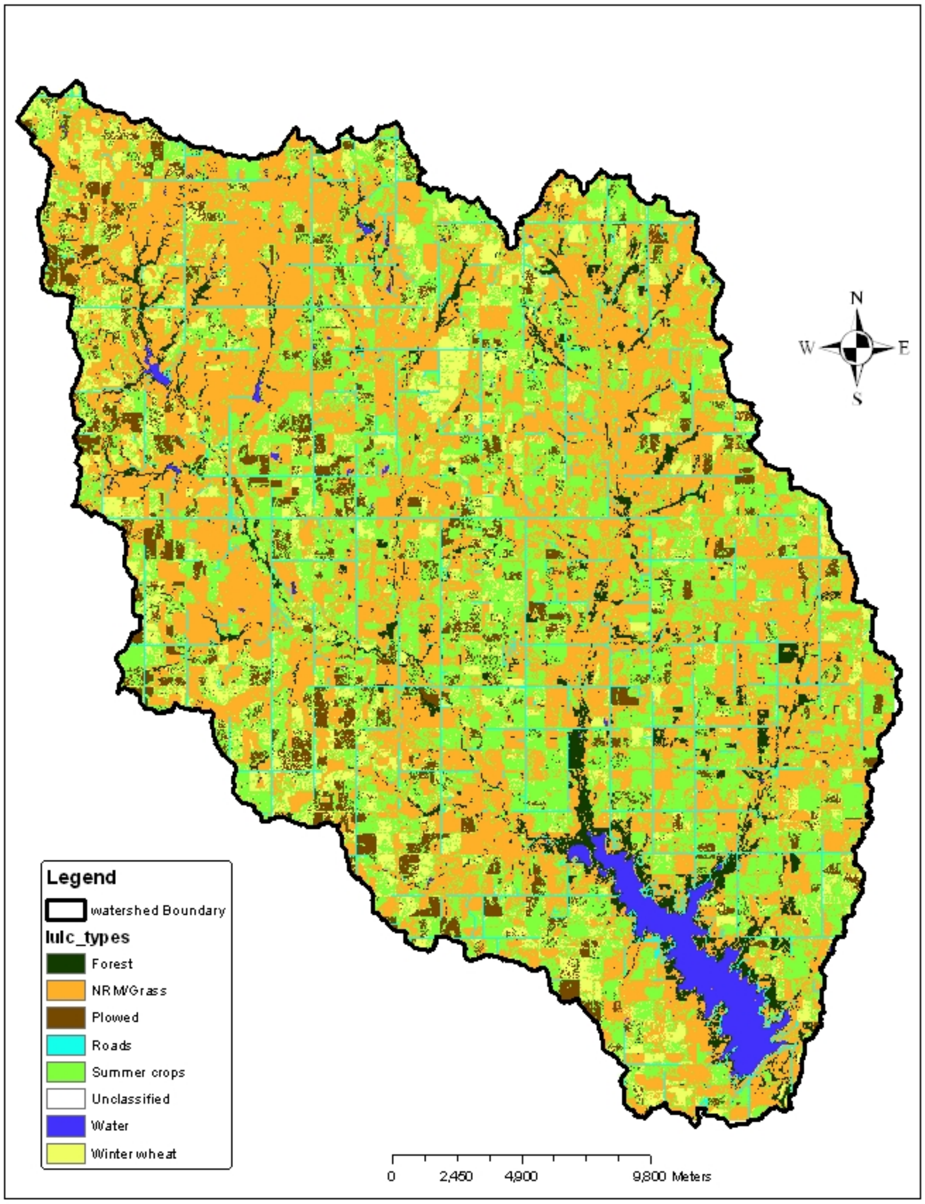


**Figure 8. Composite Image for March and June.**

Similar to the process used in combining the March and the June image, rules were also set to guide the addition of the classified September image to the composite image for March and June. The combinations were also based on observations from the

Oklahoma crop calendar and also from a visual comparison of the March, June and September images.

i) Pixels that were classified as plowed fields in the 0309_0629_composite, but are classified as cotton or peanuts in the September image were classified as summer crops in the composite output image.

ii) Winter wheat pixels in the 0309_0629_composite, that are classified as plowed in the 0901 image were reclassified as plowed, and the main reason for this is because at this time of the year, many fields are being plowed in preparation for the cultivation of winter wheat.

The rule set (Table 4) of this stage of the process looks very similar to that of the previous stage. Note that the first 16 combinations did not change.

**Table 4. Rule set used to combine the the march (0309.img), June (0629.img) and September (0901.img) images while preserving the static landuse categories**

| Combinations | Output | 0309_0629 img | 0901.img |
|---|---|---|---|
| 1 | **6** | 6 | 6 |
| 2 | **7** | 7 | 7 |
| 3 | **8** | 8 | 8 |
| 4 | **5** | 5 | 5 |
| 5 | **6** | 0 | 6 |
| 6 | **7** | 0 | 7 |
| 7 | **8** | 0 | 8 |
| 8 | **5** | 0 | 5 |
| 9 | **6** | 6 | 3 |
| 10 | **6** | 6 | 2 |
| 11 | **7** | 7 | 3 |
| 12 | **7** | 7 | 2 |
| 13 | **8** | 8 | 3 |
| 14 | **8** | 8 | 2 |
| 15 | **5** | 5 | 3 |
| 16 | **5** | 5 | 2 |
| 17 | **9** | 9 | 9 |
| 18 | **2** | 9 | 2 |
| 19 | **2** | 2 | 2 |
| 20 | **9** | 3 | 9 |
| 21 | **2** | 2 | 9 |
| 22 | **2** | 3 | 2 |

The same model used previously was used here but input image one was the output of the March and June composite, and image two was the classified September image. The resulting output image was named 0309_0629_0901composite (Figure 9 and as in the previous model, the “all” criteria condition was still used.

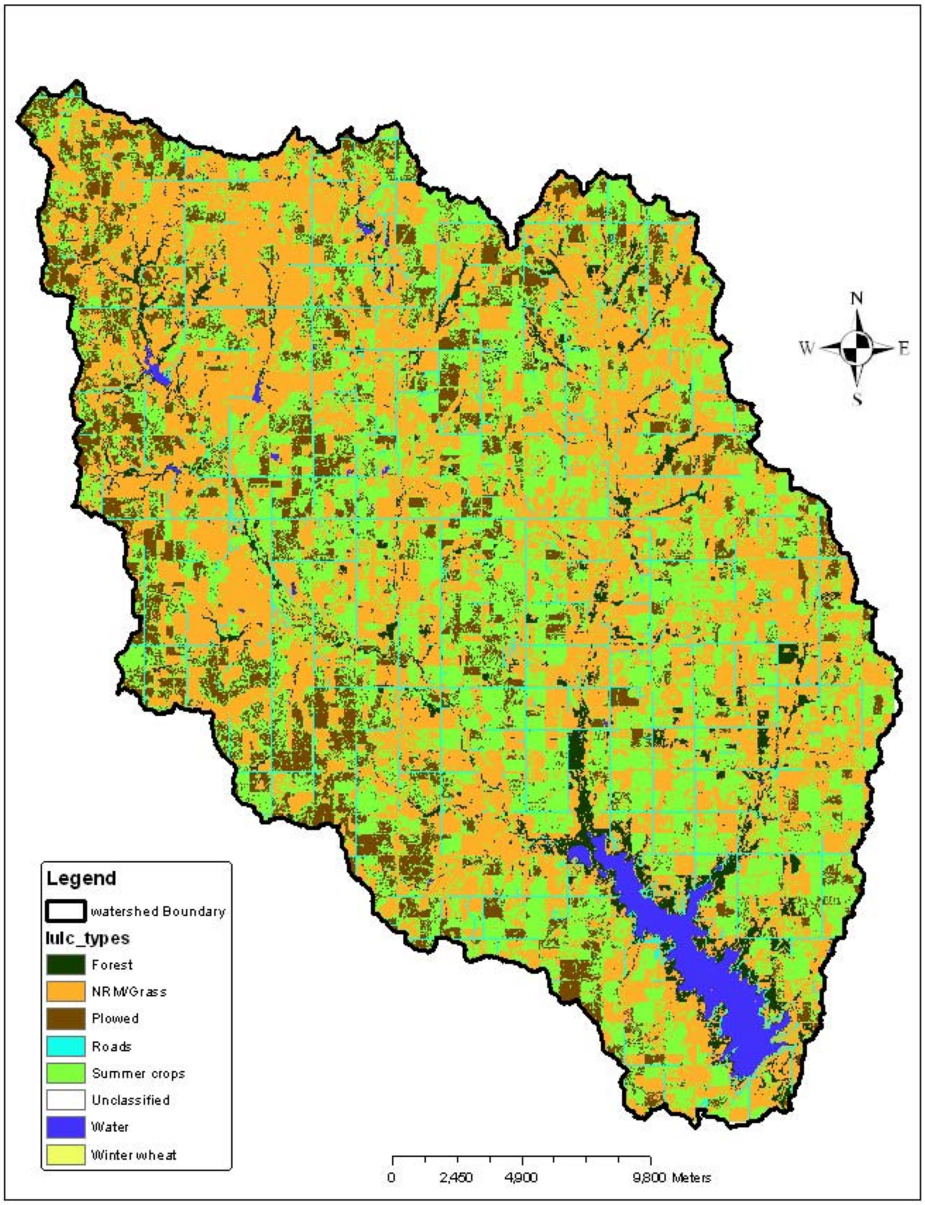


**Figure 9. Composite Image for March, June and September.**

The last stage in the analysis involved the adding of the classified November image to the output of the previous stage. The combination rule set for the two images is shown in Table 5.

**Table 5. Rule set used to combine the march (0309.img), June (0629.img), September (0901.img) and November (1104.img) images, while preserving the static landuse category.**

| Combinations | Output | 0309_0629_0901 | 1104_Image |
|---|---|---|---|
| 1 | **6** | 6 | 6 |
| 2 | **7** | 7 | 7 |
| 3 | **8** | 8 | 8 |
| 4 | **5** | 5 | 5 |
| 5 | **6** | 0 | 6 |
| 6 | **7** | 0 | 7 |
| 7 | **8** | 0 | 8 |
| 8 | **5** | 0 | 5 |
| 9 | **6** | 6 | 3 |
| 10 | **6** | 6 | 2 |
| 11 | **7** | 7 | 3 |
| 12 | **7** | 7 | 2 |
| 13 | **8** | 8 | 3 |
| 14 | **8** | 8 | 2 |
| 15 | **5** | 5 | 3 |
| 16 | **5** | 5 | 2 |
| 17 | **3** | 9 | 3 |
| 18 | **3** | 2 | 3 |
| 19 | **2** | 2 | 9 |
| 20 | **3** | 9 | 9 |

After completing the last computation, the final output (figure10) below, shows the landcover types within the FCRW for the year 2005.

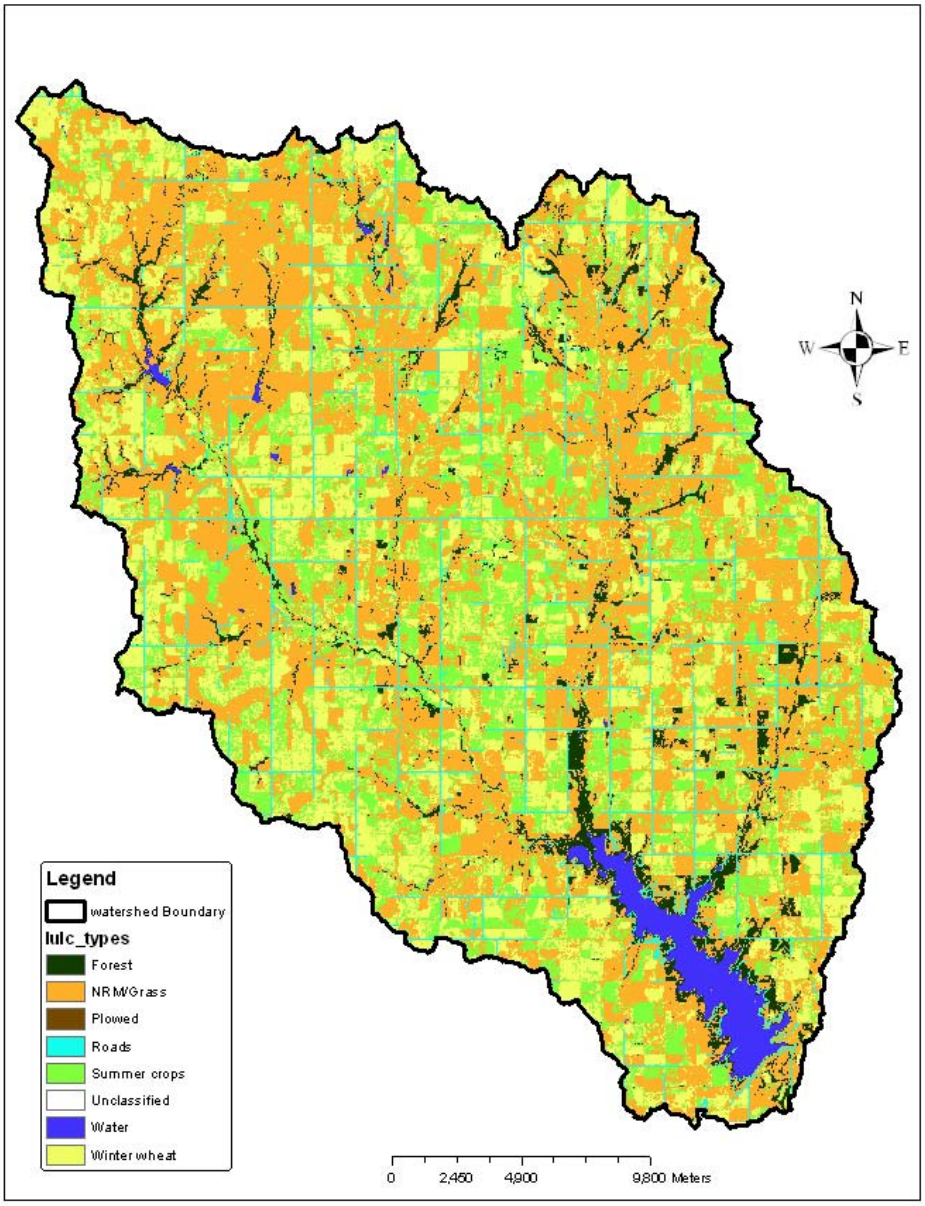


**Figure 10. Final Composite Image.**

## *Accuracy Assessment of the Composite Image*

The accuracy of any classified image is of utmost importance especially if that image is to be used for further analysis since it serves as the certificate of authenticity for any image. Accuracy assessment is particularly important in post classification change detection analysis where the accuracy of the final change image depends on the accuracy of the independently classified images (Yuan et al, 2005). In determining the accuracy of this image, the accuracy assessment module in Erdas Imagine was used. One hundred and twenty random points were selected by the Erdas Imagine Software software and using the NAIP image, the different landuse codes of those points on the composite image were determined. This is to say that with the NAIP image as a back drop, the landuses of the randomly selected point could be determined without looking at the classified image. The output matrix showed an accuracy of 92%, which was more than enough to permit its use for further analysis. Usually any accuracy above 80% qualified the image for further analysis.

## *Change Detection*

The first step in this section involves preprocessing the 1992 and 2001 datasets NLCD for the change detection analysis. The change detection analysis was done using the Idrisi Andes software. This software was used because of its simplicity of use and this particular version was used because it was the most recent version and the only one available.

Preprocessing of the NLCD entailed a reclassification of the landuse codes in the two NLCDs, and also sub-setting them to the boundary of the watershed. In the reclassification process (ASSIGN) Arc Map was used to match the USGS codes to those of the 2005 composite landuse map. Specific landuse types like deciduous forest, evergreen forest and shrubs were all combined to match the more generalized group "Forest" in the 2005 composite image. Other specific landuse types like, winter wheat, summer crops in the 2005 composite image, were combined together to match the more generalized group in the NLCD called cultivated groups. In effect a standard form of code was established for all three images ( Table 6 ).

**Table 6. Landuse and landcover types and codes**

| CODES | LULC |
|---|---|
| 2 | Cultivated Crops |
| 5 | Native Range/Grass |
| 6 | Forest |
| 7 | Roads/Bare |
| 8 | Water |

The 1992 NLCD layer was further preprocessed by recoding in Arc GIS, and this time it was due to the absent of a road layer in the grid. The rasterized road layer earlier used in the preprocessing stage was added on to it.

After reclassifying and sub-setting the 1992 and 2001 images, all the images were exported into Idrisi Andes where they were compared to each other by use of the CROSSTAB (Cross- Classification) model. This form of change detection is perhaps the most common approach (Jensen 2005), and has been used successfully by many researchers to detect and quantify change between two different dates. This approach provides "from-to" change information and the kind of change that has occurred can be easily calculated and mapped (Garcia-Aguirre et al., 2005, Yuan et al., 2005, Alphan et al., 2005).

Another advantage of the post classification change detection techniques is that it permits separately classified data to be compared, minimizing the problem of normalizing for atmospheric and sensor differences between the two dates (Liang-xu Li et al., 2003). This was the case with this project because no atmospheric correction or sensor normalization had to be done for the already classified 1992 and 2001 NLCDs.

CROSSTAB compares the number of pixels in a particular landuse between two dates. In a CROSSTAB table the numbers in the off diagonal signify the pixels (change pixel) that a particular landuse has either gained or lost between the two dates while the numbers on the diagonal signify the no change pixels.

Another way of identifying change (overall change) is by using the Kappa index of agreement (KIA) which ranges from -1 to 1. If no change has taken place between the two images, Kappa equals one (*K*=1). If all change can be accounted for by chance, then K equals zero (*K*=0). Lastly if there is no agreement between images, Kappa will equal -1 (*K*=-1) (Congalton and Green, 1999).The general formula used in calculating the Kappa Index of Agreement is:

$$\kappa = (p_0 - p_c)/(1 - p_c)$$

where,

$$p_0 = \sum_{i=1}^{c} p_{ii} = \sum_{i=1}^{c} n_{ii}/n = (1/n)\sum_{i=1}^{c} n_{ii}$$

$$p_c = \sum_{i=1}^{c} p_{i.}p_{.i} = \sum_{i=1}^{c} n_{i.}n_{.i}/n^2 = (1/n^2)\sum_{i=1}^{c} n_{i.}n_{.i}$$

Where:

P*o* = observed accuracy

P*c* = chance Agreement, and *n.i*, *ni.* and *n* are row, column and grand total numbers of pixels in the classification table.

The Kappa Index of agreement can also be used to determine the change per landcover category .In this case, the Kappa index expresses the degree to which a particular landcover type has changed between two dates. Per category the Kappa index is calculated using the following equation. Assuming that date 1 represents the rows, and date 2 the column of the matrix, date 1 is used as the reference map to which we compare the date 2 image.

$$\kappa_i = \frac{p_{ii} - p_{i.}p_{.i}}{p_{i.} - p_{i.}p_{.i}} = \frac{n_{ii} - (n_{i.}n_{.i} / n)}{n_{i.} - (n_{i.}n_{.i} / n)}$$

Where,

$P_{ii}$ = *nii / n* = the proportion of the entire image in which category *i* agrees for both dates

$P_{i}.$ = *ni. / n* = the proportion of the entire image in category *i* on Date 1

And

P.*i* = *n.i / n* = the proportion of the entire image in category *i* on Date 2

These images, 2005 composite image, and the two NLCDs (were uploaded into the Idrisi Andes CROSSTAB module and the change out puts were in two main formats;

images and tables. The images showed the changes from one landuse to another, and the tables (cross classification table) showed the actual number of pixels that changed between the two dates and the overall Kappa index.  The Cramer's index is another output index from the cross classification table. This index is not very different from the Kappa index of agreement (Yuan et al, 2005), but it shows the degree of association or dependency between the two images. This index, ranges from zero to one, with one signifying absolute agreement and zero no agreement between the two images.

# CHAPTER FOUR

## *Analysis and Results*

This chapter will present the results of the analysis performed on the images and will also examine the outputs in terms of changes in the watershed. The short term and long term changes in the watershed will be examined and the dominant landcover between the different time periods will be determined

## *Short Term Change Detection (2001 and 2005*).

Using the CROSSTAB module in IDRISI, the 2001 NLCD landcover map was uploaded as the "before" image, while the 2005 composite image was used as the after image. The output was a change image and a cross tabulation matrix showing the "change" and "no change" pixels (Figure 11). This is a generalized image because the individual landuses cannot be distinguished one from another.

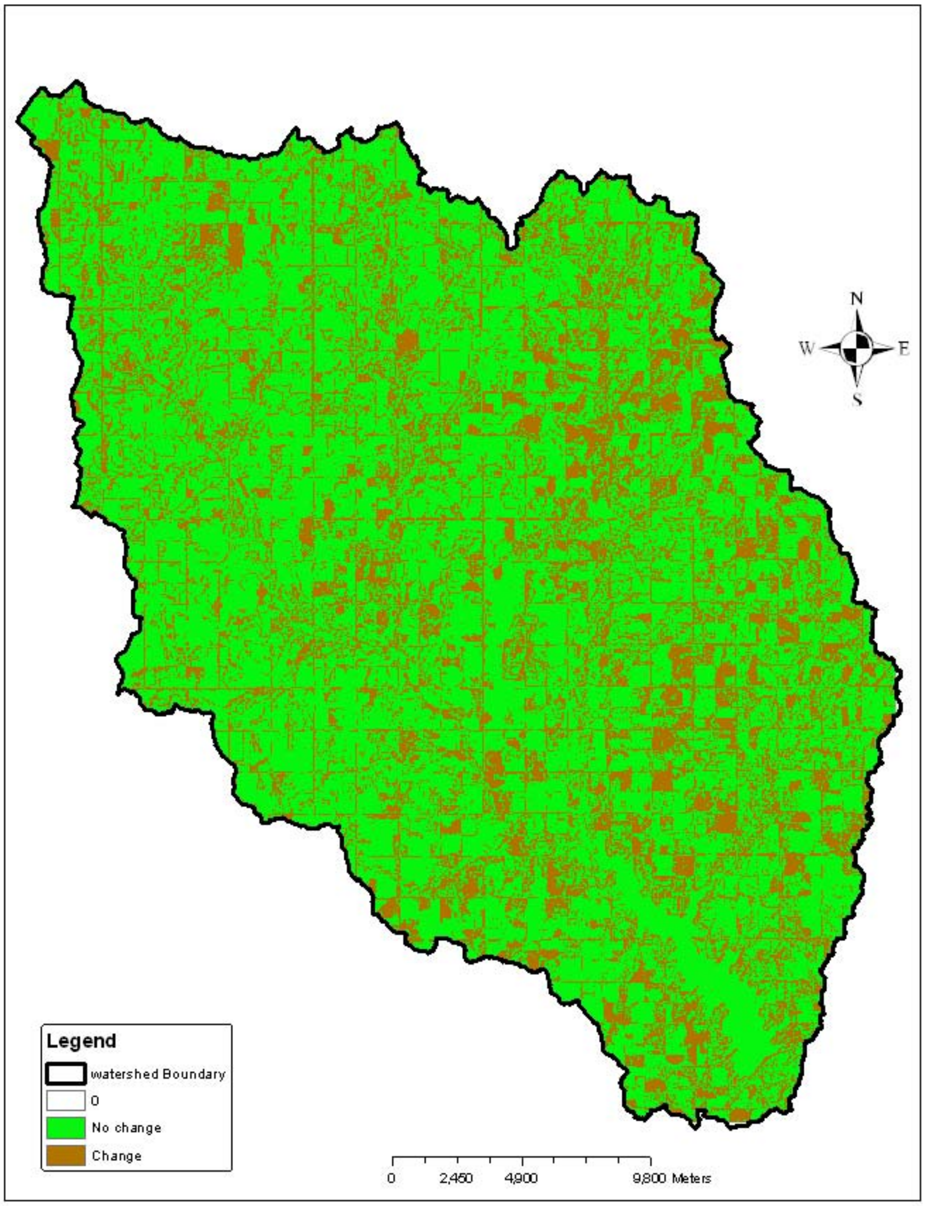


**Figure 11. Change image for 2001 and 2005**

To distinguish the different landuses in the image, a "from" and "to" change table and the area calculating tool in Idrisi Andes were used to create, a more detailed and explicit change image, (Figure. 12) that was better than figure 11.

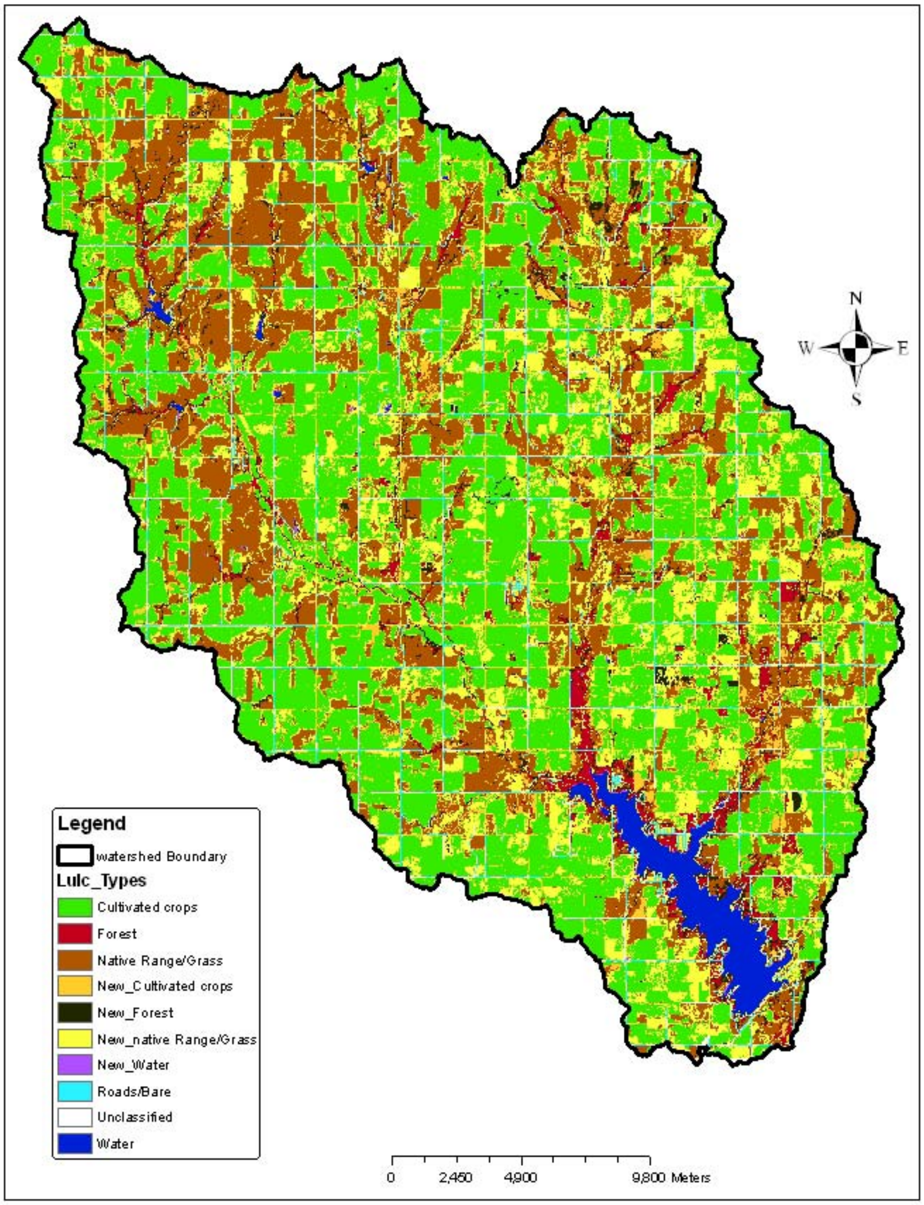


**Figure 12. Updated change Image 2001 and 2005 images**

In the above short term change image, the different landuses can clearly be distinguished one from the other. The legend shows two classes (new and old) of each landuse type aimed at facilitating the interpretation of the spatial distribution of the "change" and the "no change" areas. For most of the landuses, the distribution is uneven, with no particular area of concentration.

**Table 7. The Short-term cross-classification table.**

| 2005 \ 2001 | Unclassified | Cultivated Crops | NRM/Grass | Forest | Water | Roads/Bare | Total |
|---|---|---|---|---|---|---|---|
| Unclassified | **595714** | 602 | 57 | 0 | 0 | 16 | 596389 |
| Cultivated Crops | 1752 | **357341** | 39846 | 1510 | 746 | 10682 | 411877 |
| NRM/Grass | 925 | 141586 | **216911** | 7385 | 1563 | 14335 | 382705 |
| Forest | 29 | 3445 | 15900 | **19819** | 1177 | 1464 | 41834 |
| Water | 4 | 293 | 664 | 299 | **17778** | 161 | 19199 |
| Roads/Bare | 69 | 11355 | 7028 | 608 | 241 | **16965** | 36266 |
| Total | 598493 | 514622 | 280406 | 29621 | 21505 | 43623 | **1488270** |

The analysis of the cross tabulation table (Table 7) focuses on the comparison of the elements on the diagonal, which represent no change pixel between the two dates. The columns represent the 2001 image while the rows represent the 2005 image. For example, of the 514622 pixels that were classified as cultivated crops in 2001, about 39846 of them were transferred to the NR/Grass class in the 2005 date. To characterize the change between these years, consider the Kappa Index of Agreement (KIA) was calculated as 0.74. A KIA this high signifies that although change has taken place between both dates, 74.4 percent of the 2001 pixels did not change to other landuses in 2005. Also from the table, it is possible to determine the number of pixels transferred from one landuse to another between the dates.

The Cramer's index from the cross-classification table was also calculated as 0.70. This therefore supports the Kappa index signifying that there are great similarities between both images.

Another statistical output of CROSSTAB module is the kappa index for each individual landuse type for both years. In the output, the 2005 layer was used as the reference year for which to compare the 2001 layer, and the 2001 year layer was also used as reference to compare the 2005 layer. Comparing the Kappa for the different individual landuses makes it possible to analyses how much change has taken place between the two dates for the individual landuses.

**Table 8. The Kappa Index of Agreement on a per class basis (2001 and 2005).**

| **Landcover type** | **2005 as Reference image** | **2001 as Reference image** |
|---|---|---|
| Cultivated Crops | 0.79 | 0.57 |
| Native range/ Grass | 0.46 | 0.69 |
| Forest | 0.46 | 0.65 |
| Water | 0.92 | 0.82 |
| Roads/ Bare | 0.45 | 0.37 |

Table 8 shows the pattern of change between 2001 and 2005 in the watershed. By way of example, observing at the native range grass landuse, the Kappa figures can be interpreted as thus: of the pixels that were Native range/ Grass in 2001, most of them remained so in 2005 (Kappa= 0.69). However, when 2005 was used as the reference image (or the first image), much more land was native range/grass than in 2001 (Kappa = 0.46). This means that most of the pixels mapped as native range/grass in 2001 were also native range/grass in 2005, but more land has been added in to the 2005 native range/grass category at the expense of cultivated crop land and road/bare areas.

For the cultivated crop category it is observed using the 2001 image as reference that, very few of pixels remained as cultivated crops in 2005 (Kappa = 0.57). On the other hand, using 2005 as the reference image, a Kappa index of 0.79 signifies that of the pixels that stayed cropland in 2001 going to 2005, more have been lost to other landcover types like native range /grass.

The Forest landcover category experienced an increase between 2001 and 2005. The kappa statistics between the images using 2001 as the reference image is 0.65, signifying that more than three quarters of the total forest pixels in 2001 remained so in 2005. Using 2005 as the reference image, the Kappa index is 0.46, showing very little coherence with the 2001 image as a result of an increase in the total area covered by forest in the 2005 image.

The same can not be said for the water and road/bare classes which reduced in total area between both dates. These facts can be further supported when the total area covered by these landcovers in 2001 and in 2005 are considered. The change image can further show how the landuses succeeded each other over this time period and by what area. Figures 13, 14, and 15 show the total area covered by the different landcovers for the two dates.

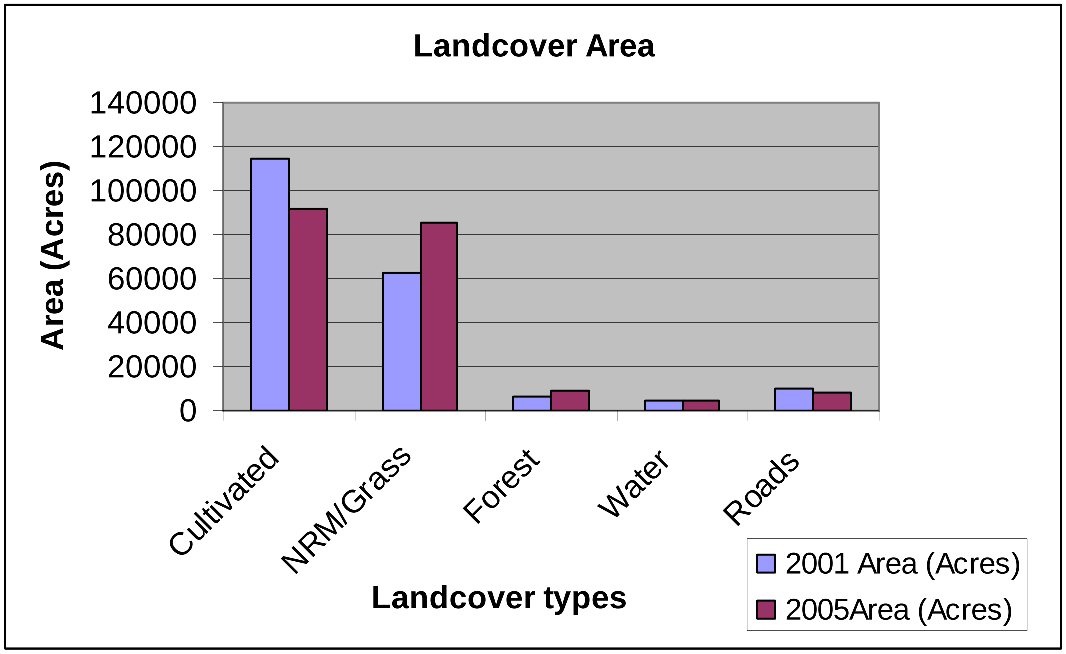


**Figure 13. Landcover area chart for 2001 and 2005.**

Figure 13 shows the total area in acres covered by the different landcover types in the watershed between 2001 and 2005. Cultivated crops in both 2001 and 2005 clearly cover the greatest acreage in the watershed in both years, followed by Native Range and Grass. Figures 14 and 15 below show the different landuse areas as a percentage of the total watershed area. The difference between the two years can be clearly seen.

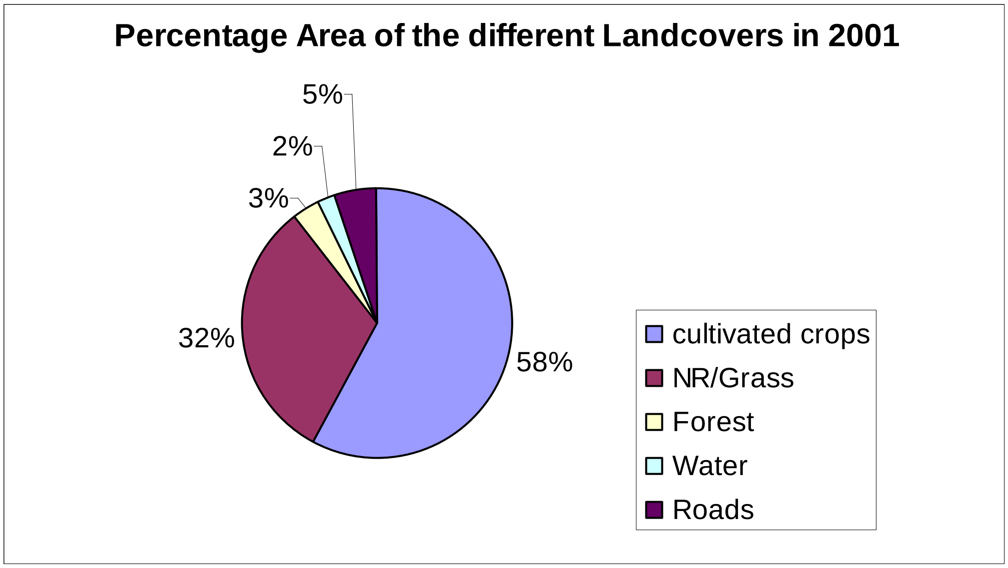


**Figure 14. Landcover area as a percentage of the watershed area in 2001.**
(Data from the 2001 NLCD was used to generate graph)

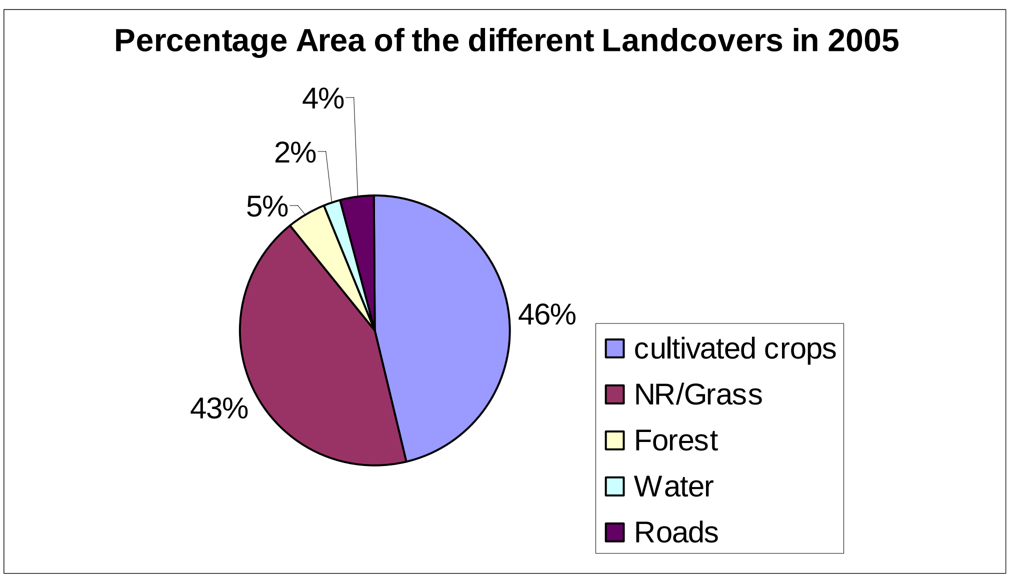


**Figure 15. Landcover area as a percentage of the watershed area in 2005.**
(Data from the 2005 composite landcover was used to generate the graph)

Figures 14, 15 and Table 8 support the results of the Kappa statistics. They show that while the native range/grass and forest landcovers, increased from 32% in 2001 to 43% in 2005, cultivated crops dropped from 58% in 2001 to 46% in 2005 as well as the roads / bare landcover that also decreased from 5% in 2001 to 4% in 2005. The water category changed little between the two years. The different landcovers and the actual area (in acres) that they lost to or gained from other landcovers can be calculated. Figure 16 shows exactly which landcover contributed most to the increase in other landcovers like forest and Native range/ grass.

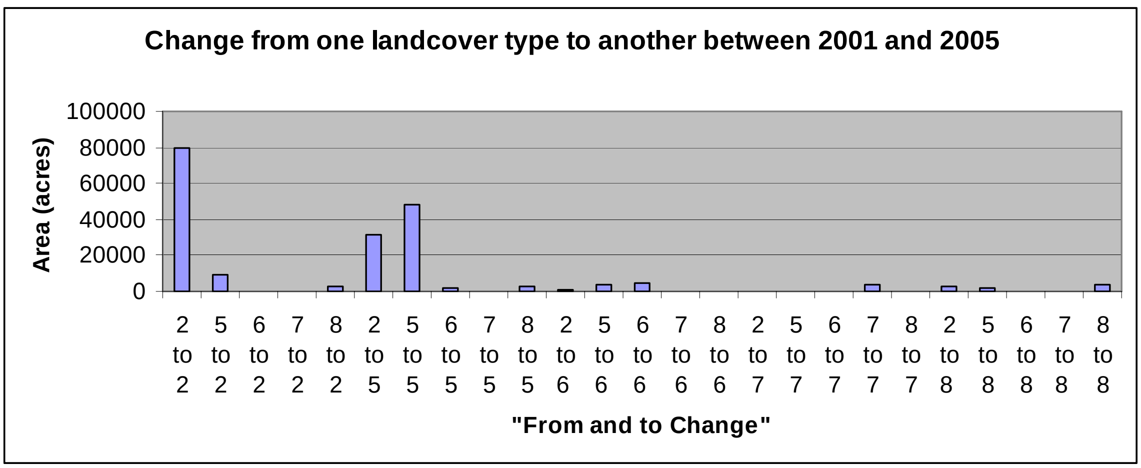


**Figure 16. "From and To" change between the 2001 and 2005 images.**

Figure 16 shows how the watershed changed from one landcover in 2001 to another in 2005, showing the amount of acreage that was transformed. From the Figure, 2 to 2 will signify the total amount of acreage that was cultivated crops in 2001 and stayed so in 2005. 5 to 2 will show the total acreage that was converted from NR/grass in 2001 to cultivated crops in 2005. It can be noticed that just about 9.000 acres were changed from NR/grass in 2001 to cultivated crop areas in 2005. On the other hand looking at the total acreage that was changed from cultivated crops in 2001 to NR/grass in 2005 i.e. 2 to 5, the acreage is about 30.000, about two times more than the change from NR/grass in 2001 to cultivated crops in 2005. These figures tell how much acreage was lost from one landcover type to another between the two years. The same statistics can be generated for the other landuses, but the main aim of all this is that this gives an idea of the landuses that have been seriously affected during this time period. It should be noted that although cultivated crop landcover lost much acreage to native range and grass, it still has the highest amount of acreage in the watershed.

The spatial distribution of this change can be analyzed when the change detection image in Figure 17 is analyzed. This image (Figure 17) does not show the actual change from one class to another but rather, the change from the no change areas.

### *Long Term change Detection (1992 and 2005)*

It is hypothesized that more changes occurred between 1992 and 2005 than 2001 and 2005 because of the longer time period under consideration. This analysis followed the same procedure as described above the CROSSTAB module in IDRISI was used and similar outputs to the short term analysis were developed. The change image is shown in figure 17.

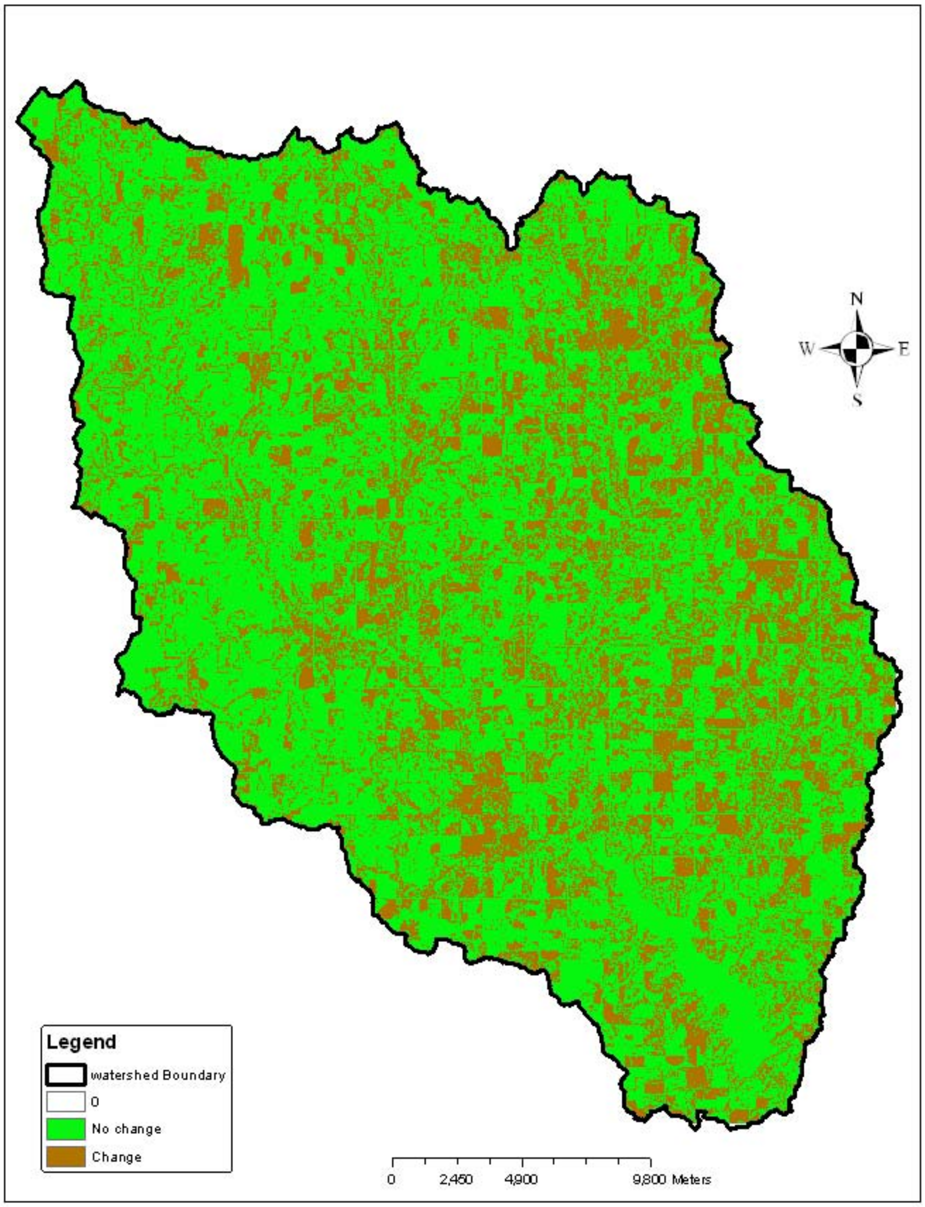


**Figure 17. Change Image for 1992 and 2005.**

Little can be deduced from the above image which shows just the change areas (brown) from the no change areas. From Figure 17 is evident that the change areas are well distributed throughout the watershed, but detailed information on the landcovers that changed is absent.  Similar to the short term change analysis, further processing of figure 17, with the help of the from and to change table produced by the Idrisi Andes software, led to the creation of a more detailed change image (Figure 18) between 1992 and 2005.

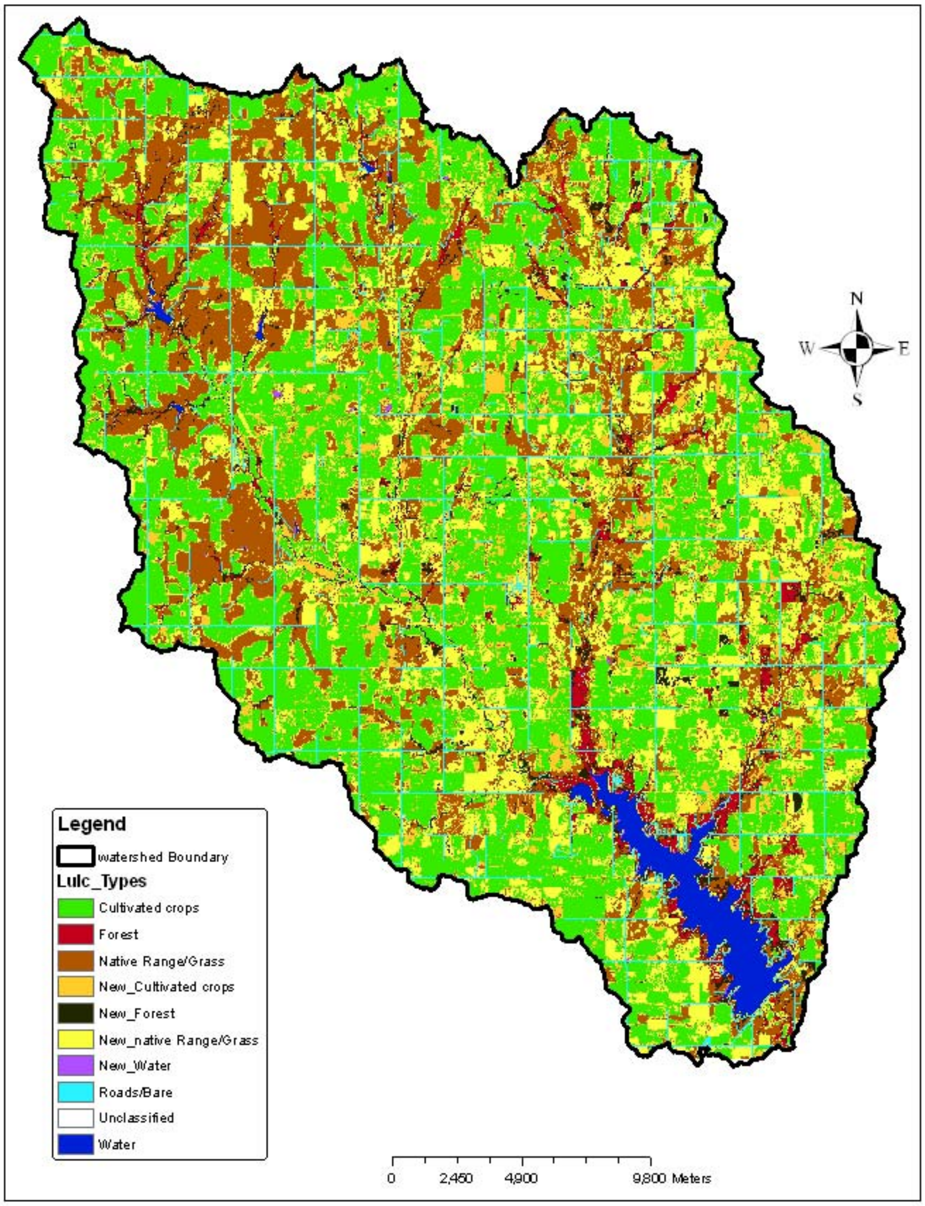


**Figure 18. Updated change Image for 1992 and 2005.**

Observation of figure 18 shows that there is no particular pattern in the spatial distribution of cultivated crops, water and forest in the watershed. The "new_Forest" landuse class is localized around streams and water bodies which is similar to the forest pixels that did not change between the two dates. Native range and grass have increased about 30 % of their total acreage located in the Northwest portion of the watershed. This portion of the watershed according to the Oklahoma Mesonet is the driest part of the watershed with temperatures up to about 26$^{o}$ C and wind speed of about 55mph (Oklahoma Mesonet, 2007). A few new water ponds (man made ponds) exist in the watershed and this must have been as a result of the droughts that this watershed experienced between 1992 and 2005.

**Table 9. The long-term Cross-classification table**

| | | **1992** | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Unclassified | Cultivated Crops | NRM/Grass | Forest | Water | Roads/Bare | Total |
| **2005** | Unclassified | **595710** | 503 | 163 | 4 | 0 | 9 | 596389 |
| | Cultivated Crops | 1752 | **347717** | 59404 | 1299 | 795 | 910 | 411877 |
| | NRM/Grass | 925 | 183071 | **189520** | 6121 | 1940 | 1128 | 382705 |
| | Forest | 29 | 7993 | 14672 | **16943** | 2169 | 28 | 41834 |
| | Water | 4 | 363 | 688 | 246 | **17895** | 3 | 19199 |
| | Roads/Bare | 0 | 0 | 0 | 0 | 0 | **36266** | 36266 |
| | Total | 598420 | 539647 | 264447 | 24613 | 22799 | 38344 | ***1488270*** |

The cross-classification table (Table 9), like the previous one, emphasizes the elements in diagonals which show the no-change pixels between the rows (2005) and the columns

(1992) while the off diagonals show the pixels that have changed. The rows show how much of a particular landuse in 1992 transformed into other categories in 2005, whereas the columns indicate composition and contribution of the 1992 class that created the categorical changes in 2005. Looking at the row and column totals, the change in a particular landcover can be easily determined. Cultivated crops for example, had a total of about 539647 pixels in 1992, but that number dropped to 411,877 pixels in 2005. The amount of change that has taken place between these data can also be determined from the value of the Kappa Index of Agreement. The Kappa value of this analysis was 0.72, signifying that about 72% of the land cover between these dates did not change. In other words there was a 28% decreased in the landuse from 1992 to 2005. The Cramer's V value for these images was 0.78 showing that there was a great amount of association between the two images.

Change between two images can also be determined by calculating the KIA between the different landuses. Table 10 shows the KIA for the individual landuses for the two dates.

**Table 10. The Kappa Index of Agreement on a per class basis. (1992 and 2005)**

| **Landcover type** | **2005 as Referent image** | **1992 as Referent image** |
|---|---|---|
| Cultivated Crops | 0.75 | 0.50 |
| Native range/ Grass | 0.38 | 0.61 |
| Forest | 0.39 | 0.67 |
| Water | 0.93 | 0.78 |
| Roads/ Bare | 1.0 | 0.94 |

Interpreting Table 10 requires that both dates be considered at the same time. For example, using the 1992 image as the reference image, cultivated crops have a kappa index of 0.50 meaning that only 50% of the total number of pixels that were cultivated crops in 1992 were cultivated crops in 2005. Using the 2005 image as the reference image, the Kappa index of agreement is 0.75, signifying that of the total number of pixels that did not change between 1992 and 2005, a great portion was converted into different landuses. The situation is different for the Native range/grass landuse type which had a KIA of 61.8 using 1992 as the reference image and 0.38 when 2005 is used as the reference image. Therefore, 61.8% of the native range/grass pixels that existed in 1992 did not change in 2005, and when the 2005 image was used as the reference image, it was realized that the number of pixels or the area covered by this landuse type instead increased to 38%. Of all the landuse types, the road/bare category appears not to have undergone any change between the two dates, irrespective of what image was used as the reference. The reason for this is that the same road layer that was made permanent for the 2005 original image was added to the 1992 NLCD image that did not have a road layer. So, as discussed in the methodology, the road layer from the 2005 image was added to it, and thus the similarity. The statistics presented in Table 10 can be corroborated with the Figures 19 and 20.

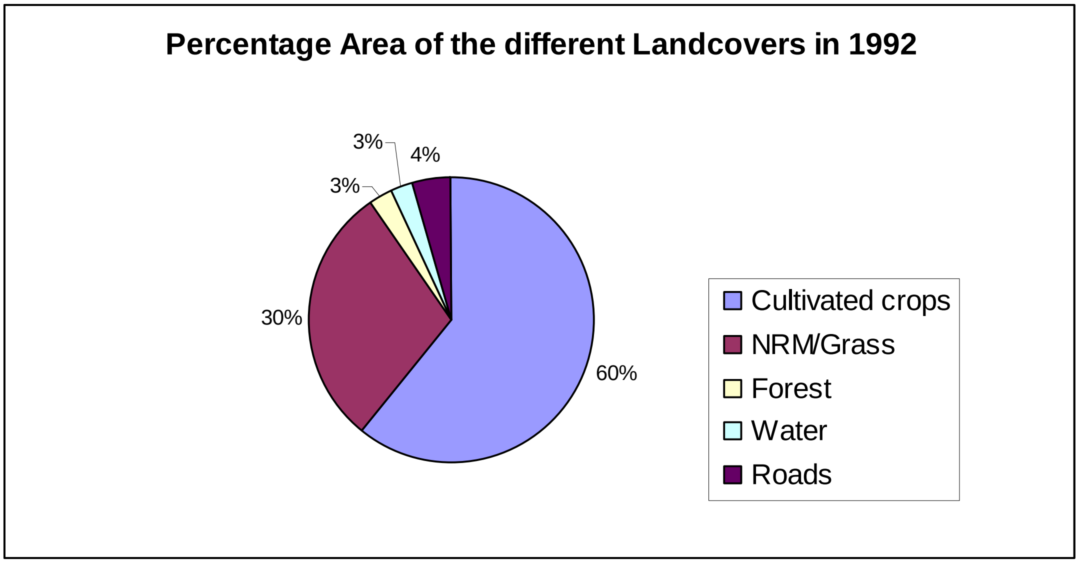


**Figure 19. Landcover area as a percentage of the watershed area in 1992.**

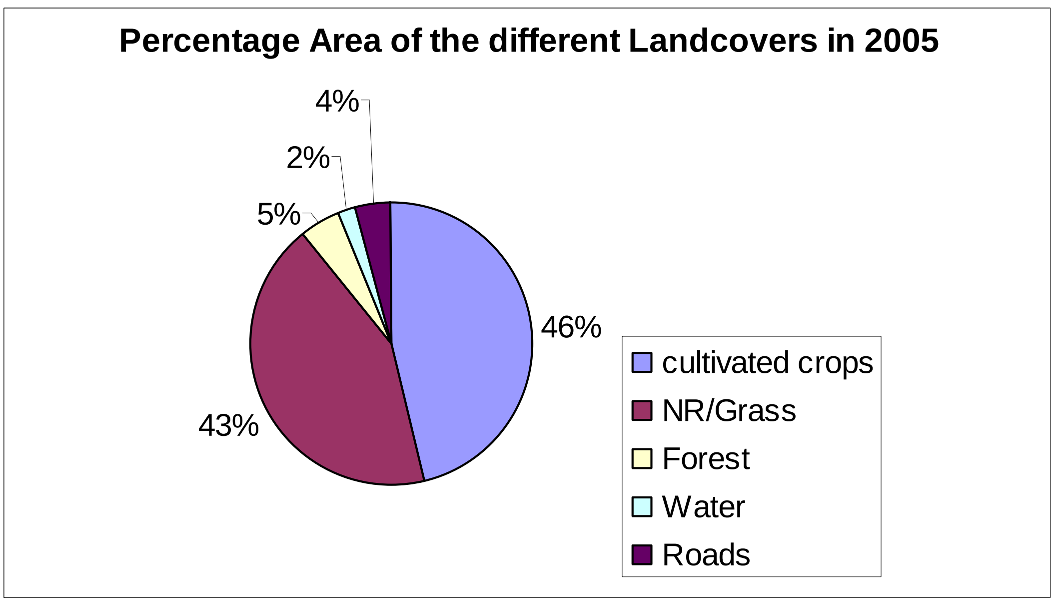


**Figure 20. Landcover area as a percentage of the watershed area in 2005.**

The above Figures show how the total area covered by cultivated crops has dropped between 1992 and 2005. Also clearly noticeable is the increase of the total area covered by the native range and grass category.

The amount of change from one year to another, and the amount of pixels that one landuse yields to another from one year to another can also be determined. This statistics is derived from the change image which will later be examined to analyze the spatial distribution of change in the watershed.

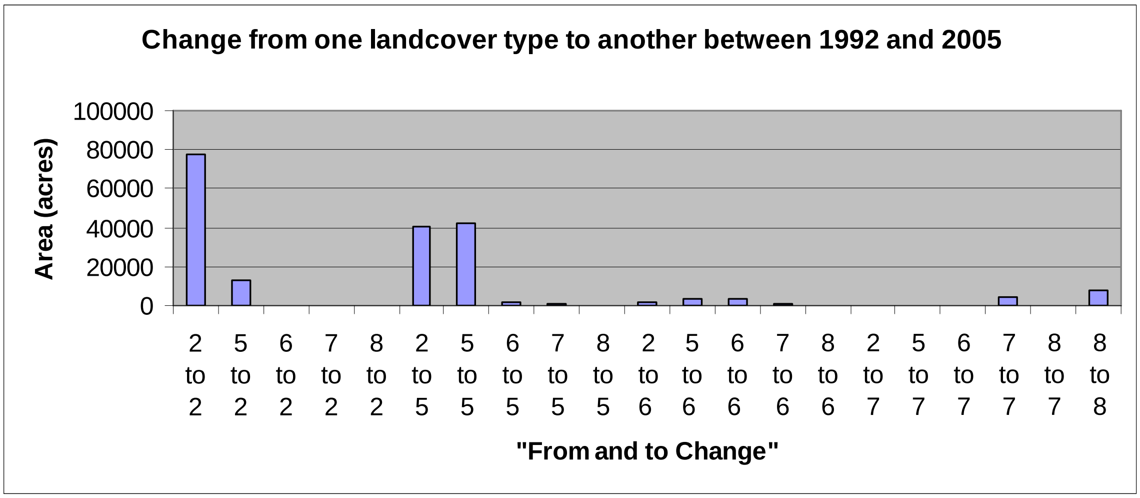


**Figure 21. "From and to" change between the 1992 and 2005 images.**

From figure 21, the noticeable changes are landuse types; 2 to 2, 5 to 2, 2 to 5, and 5 to 5. Although native range/ grass (5) had some areas classified as cultivated crops(2) between 1992 and 2005, the total area converted from cultivated crops to native range/ grass is about twice the size of the area from native range and grass to cultivated crops. This chart is important because it provides information that can help explain the reasons for such change in the watershed.

# CHAPTER FIVE

In this chapter, conclusions will be made based on the results and discussions of chapter Four.  Here attempts will be made to explain the findings of chapter four.  This chapter discusses some of the limitations to this study and also provides some recommendations for future research.

## *Discussions and Conclusion*

A major concern in change detection analysis is the accuracy assessment, which determines how accurately changes between the two dates have been documented. A major concern in change detection analysis is that both position and attribute errors can propagate through the multiple dates (Yuan et al, 2005). This is especially true when more than two dates are used in the analysis at the same time. The simplest method to detect the accuracy of a change image is to multiply the individual classification map accuracies to estimate the expected accuracy of the change map (Yuan et al 2005).

In this project, only two images were compared at the same time, and so, the problem of propagating both the positional and attribute errors though the map was not encountered. The accuracy of the change image in these analyses could not be determined because of all the images used, only the accuracy; of composite image for the 2005 was known (92%). Both the NLCD for 1992 and that for 2001 do not yet have a completed accuracy assessment, and so the accuracy of the final change image could not be determined.

Inspite of the fact the accuracies of the of these images could not be determined, the goal of the study was not to compare image accuracies, but to determine how much the landcover in this watershed has changed over the specified time periods and also to provide reason for the changes.

### *Change Trends*

The major change in the landcover between the two dates in the short and long term analysis, was the drastic increase of native range/ grass cover type from 32% to 43% in the short term change image (2001 and 2005), and from 30% to 43% in the long term change image between 1992 and 2005. This increase in the area covered by grassland, accompanied by an almost proportional drop in the cultivated area can be attributed to the Conservation Reserve Program (CRP) that was started in 1985. In their evaluation of CRP tracts in Texas County, (Oklahoma Panhandle), Rao and Raghavan (2002) noted that the most important period in the CRP program was between 1990 and 2000, during which thousands of acres of land were under fallow having been removed from active cultivation. Looking at the percentage area covered by native range/grass for all three years (1992 (30%), 2001 (32%), 2005 (43%)), it will be deduced that there was only a two percent increase in the total area covered by native range and grass between 1992 and 2001, and an increase to 43% between 1992 and 2005. This will also mean that there was a 41% increase in the total area of this landuse type between 2001 and 2005. Although the Fort Cobb watershed covers just a portion of the Caddo County and significantly smaller portions of Custer and Washita counties, the trends in the CRP enrollments and retirement between 1992 and 2005 in these counties can shed some light on the NR/grass changes between these periods. These trends are shown in Figure 22.

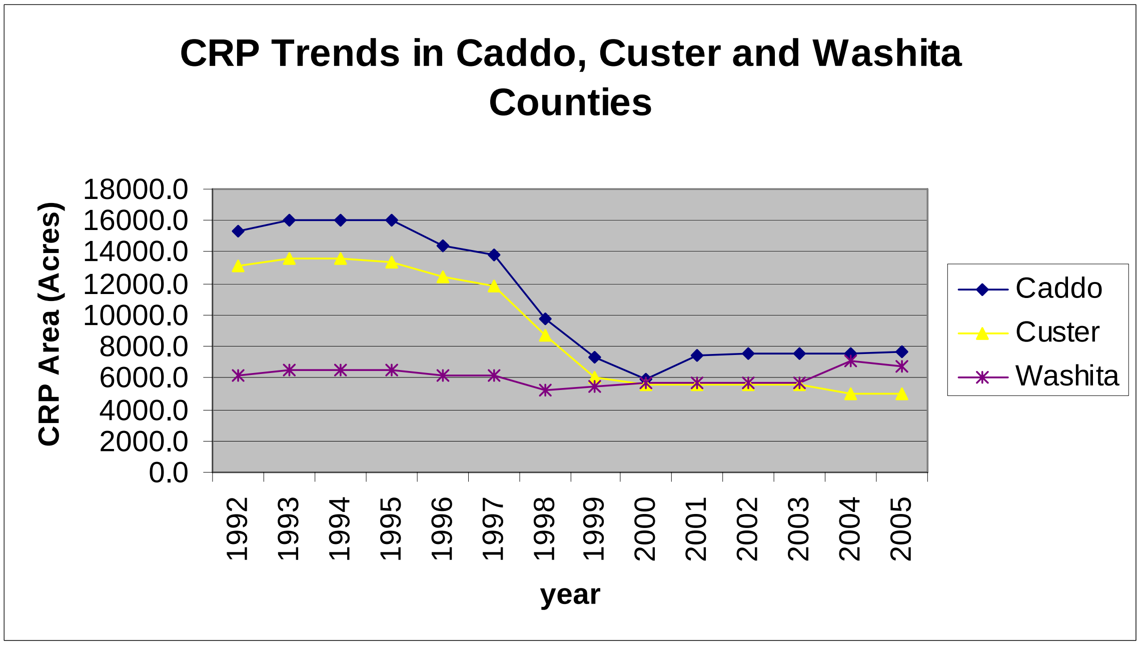


**Figure 22. CRP Trends in Caddo Custer and Washita Counties between 1992 and 2005.**

Figure 22 indicates that between 1992 and 2000 CRP enrolment was almost static for all three counties until 1997 when a significant drop in total enrolled acres is noticed. At this point in time, the total area of the watershed covered in agriculture should be increasing, at the detriment of the NR/grass cover type. But the increase in total enrolments between 2000 and 2001 is what accounts for the difference (2%) in area covered by NR/grass between 1992 and 2001.It is therefore safe to conclude that the difference in the acreage covered by NR/grass between 1992 and 2005 (13%), can be accounted for by the increase in enrolment between 2001 and 2005.

It is possible that the CRP is responsible for the rapid decrease in cultivated lands and a proportional increase in the native range and grass landuse. Furthermore in the two change images, native range and grass also lost some areas to the cultivated crops category. An explanation for this can be that lands which were already CRP designated lands by 1992, were being returned to crop cultivation by 2001 and 2005.

The changes noticed in the change images are the same. Some landuses have changed drastically in their area covered (cultivated crops and native range and grass) while others have had almost no change at all (roads). Change detection analysis has enabled this to be detected, and also the CROSSTAB module makes it possible for the actual amount of change to be documented. The advantages of the Hybrid image classification method cannot be over stated. The Hybrid image classification method made it possible for landuses and landcovers to be identified and then classified precisely between different dates. It minimized the risks of misclassification between the very similar monthly landsat images.

The Erdas Imagine software played the greatest role in the success of this project, but the difficulty involved in its use in post classification change detection cannot be neglected. This software became more complicated to use as the project advanced into its last stages. Idrisi Andes on the other hand provided a better and friendlier user interface to perform the change detection analysis using its in built cross tabulation module. The multiple statistical data produced by the Idrisi Andes software made it possible for the results to presented in different ways, and all still relevant to the changes in the watershed during this time period.

The analysis and findings of this study show that a composite landcover image can be easily and accurately computed by unifying the code names of the different images and by simply adding the different images one at a time. This process, as demonstrated, makes it possible to monitor the individual pixels as they change from one season to another. This project goes further to show the importance of post classification change detection methods, especially in situations where age-old images are to be used.

The purpose and objectives of this project have all been achieved; a personal geodatabase was created of all the vector and raster data used in this project, a composite landcover map for the 2005 was created and used in a change detection analysis performed for a the short and long term periods. Although these objectives were met, there were nevertheless several limitations in the execution of this project.

## *Limitations to the study and Recommendations for Future Research*

The most important factor in continuing research for this project is the use of better data set. The need for better and accurate NLCD maps can not be over emphasized. Using images like the 1992 and 2001 images with no known accuracy makes it impossible to determine the quality of the change result, and the importance of the results. Better ground truth data, with field pictures can also improve future research in this field. For example if consistent ground truth data were to be provided for every month for which there was an image, the classification, especially the supervised classification would be better than it was. Also if more advanced and more rigorous classification methods could be used such as the fuzzy classification and neural networks methods, the classification outputs could be better than they currently are. It would be beneficial to users if the national landcover data were updated and their accuracies determined.

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