USING REMOTELY SENSED IMAGES TO ASSESS ABANDONED MINE LAND RECLAMATION

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Abstract

Surface mining of coal has been occurring in Missouri since the 1840s, and there have been significant environmental impacts of such operations, especially before the enactment of the Surface Mining Control and Reclamation Act in 1977. The agency responsible for reclamation of mined land that was affected before 1977 is the Missouri Department of Natural Resources, Land Reclamation Program, Abandoned Mine Land Section. The application of remote sensing methods for assessing these effects has not been utilized by the Section thus far. A preliminary study was done to evaluate their feasibility and usefulness. The primary objective of this study is to apply methods of image classification, change detection analysis and NDVI calculation and determine their feasibility on a study area in Henry County, Missouri. This was accomplished by producing classified and NDVI images from Landsat TM imagery acquired in 1984 and 2011. The results indicate that these methods could be successfully applied to assist in reclamation assessment and monitoring.

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I. INTRODUCTION

The Missouri Department of Natural Resources (MDNR), Land Reclamation Program (LRP), Abandoned Mine Land (AML) section is responsible for completing reclamation on public and private lands that were mined for coal prior to the enactment of the Surface Mining Control and Reclamation Act (SMCRA) of 1977. Problems associated with abandoned mine lands are classified based on the threat to public health, safety and the environment. Each problem area is ranked according to a system that assigns values based on the priority of the features within them. Priority I problems are those that protect the public from extreme danger, Priority II problems are those that protect the public from danger that is not considered extreme and Priority III problems are those that restore land resources, water resources and the environment.

AML staff selects reclamation projects based on an inventory that was completed in the 1980s by the LRP and the MDNR Division of Geology and Land Survey. In addition to the original inventory, new problems are occasionally encountered that were either not accessible, or were not problematic, at the time the initial investigations were done. The majority of the problems the AML section is responsible for are related to abandoned coal mines; however, occasionally issues caused by pre-law, abandoned lead-zinc mines are also considered for reclamation. Currently, lead-zinc-related issues that are able to be addressed by the AML section are limited to open shafts that are considered an extreme danger to the public. Some examples of work that is done to address coal-related problems include grading and revegetation of barren spoils, backfilling dangerous highwalls, closing open mine shafts and treating acid mine drainage (AMD).

The use of digital image processing to assist in the identification of abandoned mine lands that are not in the inventory as well as in the assessment of reclamation that has been completed by the program has not been widely used by the program. Visual interpretation of aerial photographs and satellite images has been the sole method utilized. Image classification, change detection analysis, and Normalized Difference Vegetation Index (NDVI) are three methods that have the potential to contribute to the efficiency and overall success of AML related activities done by the program.

Image classification of remotely sensed images can be used to identify land cover types that are related to AML features such as barren and vegetated spoil. The classified maps created from remotely sensed images could be used to distinguish areas that have been disturbed by mining activities from areas that are unaffected. This data can be used to identify features that are currently not in the inventory. Classifications can also be used to assess the success of reclamation activities by determining the extent and distribution of problem associated classes after work has been completed. This could be especially useful for monitoring project sites after the program no longer has regular access to the property.

Change detection analysis can be used to compare classified images from different years. In particular, classifications from images taken during pre-reclamation can be compared to those taken after reclamation is complete. Changes between land cover types can be distinguished with a change detection matrix. This could also assist in verifying that areas disturbed by mining have been successfully reclaimed.

NDVI can be used to assess the vigor of vegetation established on reclaimed lands. This could assist AML staff in identifying areas that may need additional soil amendments or replanting. This would also allow the review of reclamation practices so that adjustments can be made to revegetation practices in the future. As with image classification, NDVI could be applied to project areas where staff does not visit on a regular basis.

1.1 Research Objective

The application of these remote sensing methods has not occurred in the MDNR AML section thus far, so a preliminary study was done to evaluate their feasibility and usefulness. The primary objective of this study is to apply methods of image classification, change detection analysis and NDVI calculation and determine their feasibility on a study area in Henry County, Missouri.

1.2 Study Area

The study area is in Henry County, Missouri, just north of the city of Montrose. The area is approximately 4,500 acres of which about 3,000 have been surface mined, mostly before the enactment of SMCRA (Figure 1). Some of the problems that were created by surface coal mining within the study area are clogged stream lands, dangerous highwalls, barren spoil piles, hazardous equipment facilities, waste dumps and polluted pit impoundments (Figure 2). There have been four reclamation projects completed by the AML section within the study area, the first was completed in 1984. One of the four is the Noah Reclamation Project, which involved grading and revegetating barren spoils and backfilling of dangerous highwalls (Figure 3). The study area also includes acreage that is proposed for future reclamation, as well as some mined areas that are not currently in the inventory.

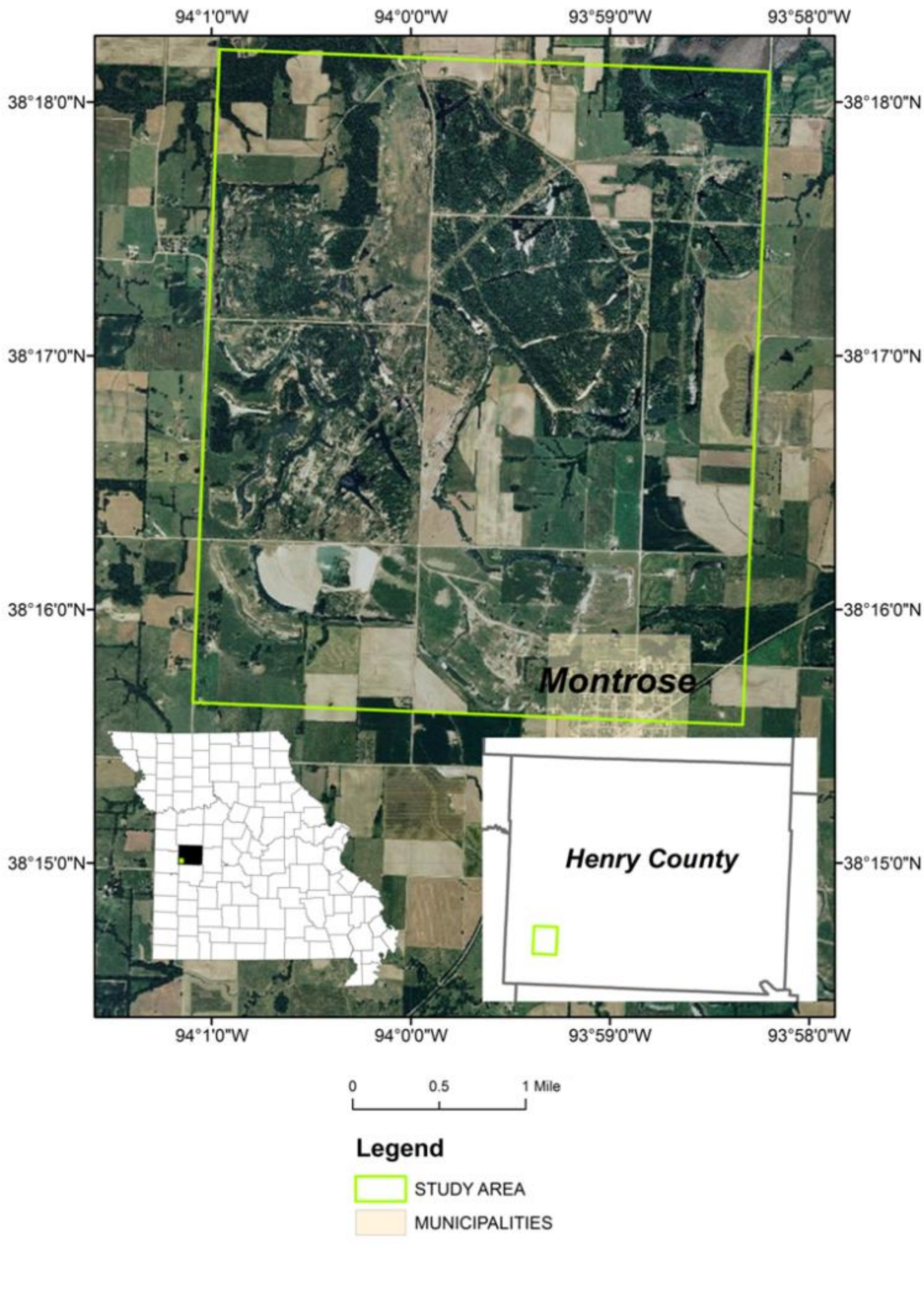

Figure 1 – Study Area

Figure 2 – Aerial photo of a portion of the study area prior to reclamation (Missouri Department of Natural Resources 2001)

Figure 3 – Photo of the Noah Reclamation Project after grading and revegetation (Missouri Department of Natural Resources 2003)

II. LITERATURE REVIEW

2.1 History and effect of coal mining in Henry County, Missouri

Commercial coal mining in the State of Missouri began in the 1840s, with the majority of mining occurring underground. In the 1930s, coal mining shifted from underground to the surface where approximately 67,000 acres were affected before the enactment of SMCRA in 1977 (Office of Surface Mining Reclamation and Enforcement, 2013). Surface coal mining in Missouri within this time period generally utilized strip mining methods for extraction of the commodity. Strip mining can be described as removing overlying geological substrates (overburden) from a linear section of the mine site, excavating the commodity, and then repeating the process in the linear section directly adjacent until all material has been removed. This method of mining creates multiple piles of overburden throughout the mine site that are considered spoil material and often consist of substrates that can chemically react with the surface environment to form acid mine drainage that can adversely affect water quality. Due to the chemical composition of the spoil material, vegetation is not easily established and remains barren for long periods of time.

Southwest Henry County, Missouri has been affected by surface coal mining since the 1950s. Reclamation of the surface mines began in 1972, but as of 1987, the majority of the land was still unreclaimed (Blevins, 1991). Since most of the land was mined pre-SMCRA, there were no laws in place to require the reclamation of the land prior to 1977. SMCRA was written to address the problems associated with previously mined land as well as land that would be mined in the future. After the enactment of SMCRA, land affected by surface mining was required to be permitted and bonded in order to “assure that adequate procedures are undertaken to reclaim surface areas as contemporaneously as possible …” (Surface Mining Control and Reclamation Act, 1977). SMCRA also provided for the reclamation of “pre-law” surface mined lands, and established a fund to perform such work.

The study area selected for this research was chosen partially due to the fact that it has previously been studied extensively by Blevins (1991) of the United States Geological Survey (USGS). A Water-Resources Investigations Report (90-4047) was published in cooperation with the MDNR, Land Reclamation Commission in 1991 (Blevins, 1991). The report described the impacts of surface coal mining on water resources and related poor water quality and hydrological conditions to unreclaimed mine spoil. Since the study area is nearly identical for both studies, some comparisons can be made.

Blevins (1991) reported that after 1987, there were approximately 1,200 acres of barren spoil, 100 lakes and several streams, many of which were acidic. The chemical reactions that take place when surface runoff and groundwater interact with exposed spoil material are the source of the acidic conditions. The pH of runoff from barren, unreclaimed spoils were between 3.2 and 3.5. The lakes he described consisted primarily of last-cut depressions and haul roads that have filled with water after the cessation of mining. Fifty-five lakes were sampled for water quality analysis, and 60% were found to be slightly acidic to extremely acidic.

In addition to barren spoil, Blevins (1991) described rough, ungraded spoil that was forested. This vegetative cover was not the result of reclamation, but rather natural forest succession. By 1987, there was also some acreage which had been reclaimed, which consisted of graded spoil that was partially capped with topsoil, and covered with grass. Many of these areas were, and are still, being used as pasture for cattle. The landcover as described by Blevins (1991) includes four major classes: barren spoil, vegetated spoil, pasture and water. The distribution of these classes within the study area can be assessed using remotely sensed data.

2.2 Using remote sensing for mine land assessment

Although the use of remotely sensed images has not been a major influence on the work done by the MDNR AML section thus far, their use in the assessment of mined lands is not uncommon elsewhere. In fact, remote sensing for surface mine inventorying has been utilized since the 1970s (Anderson 1977). Since then, there have been other diverse applications of remotely sensed imagery to assess the affects of both surface and underground mines around the world. The successes of these studies can be incorporated into a methodology for assessing the effectiveness of coal mine reclamation in the State of Missouri.

Remote sensing has been used in a wide variety of applications for assessing mine land. Remotely sensed imagery has been used to classify single classes of mine-related features, such as exposed coal (Kuenzer et al. 2008, Repic et al. 1991). Classification of multiple mine-related features within an image, such as spoil, reclaimed land and water has also been performend using a variety of source data (Bonfazi et al. 2010, Charou et al. 2010, Schmidt and Glaesser 1998, Demirel et al. 2011, Prakash and Gupta 1998). NDVI analysis has also been performed using remotely sensed imagery for the purpose of mine land assessment (Latifovic et al. 2005, Yunxia et al. 2007, Salyer 2006).

A time series analysis was performed by Kuenzer et al. (2008) for a coal mining region using Landsat 5 and 7 images based on partial unmixing (aka mixture tuned matched filtering). This method was tested specifically to develop a method for quantitative monitoring of a single surface class (coal surfaces) to reduce analyst bias incurred using Maximum Likelihood Classification. The targeted surfaces included outcropping coal seams, coal storage piles, coal waste piles and coal washery discard. Two advantages of this approach are that only the spectral characteristics of the coal features must be known, and the coal material can occur with subpixel coverage. Some challenges of partial unmixing are that it requires thorough radiometric processing, and the accuracy of the representative input spectra must be well known. Subpixel percentages derived from partial unmixing should only be interpreted in a relative way. The methodology utilized for this study is somewhat unique in comparison to the majority of studies that utilize remote sensing to assess mine land in that it focuses on a single class of interest, coal surfaces.

Another study was done that focused on a single mine-related class by Repic et al. (1991). They used multispectral videography to detect mine water affected by acid mine drainage. Spectral characteristics of acid mine drainage affected water was correlated to chemical characteristics of water samples taken from the same locations. The resulting data was used to identify varying degrees of iron ion concentration and acidity.

Remote sensing and GIS were also used to identify multiple classes in order to describe the spatio-temporal effects of coal mining (Bonfazi et al. 2010). Specifically, three environmental cumulative effects were identified as: 1. persistence in the environment, 2. solid waste and wastewater, and 3. accumulation in the environment at a rate that is not sustainable. The study explored the use of satellite data with varying resolutions from multiple time periods. These included Landsat 5, SPOT 5, Ikonos, ASTER, Aerial Photos and IRS-P6. There were three study areas: Brajrajnagar coal mines complex (India), Mae Moh lignite mine (Thailand) and Fuxin coal waste dump (China). The authors were able to successfully classify land use changes between different time periods. They also identified some of the benefits of using geospatial classification tools as opposed to traditional approaches and some further studies that will be done to enhance their procedures.

Similarly, remote sensing was used by Charou et al. (2010) to identify, delineate and monitor pollution sources and affected land related to mining operations by generating multi-class images. Their study utilized Landsat 5, Landsat 7, SPOT Panchromatic and ASTER data. There were three study areas as follows: Lake Vegoritis and the Amynteon mine (both located in northern Greece) and the Lavrio mine area, in central Greece. The data was processed using TNT MIPS by Microimages. The assessment performed included a study of the environmentally critical areas of land degradation and water pollution, as well as changes in land use. The authors concluded that the use of multi-temporal ASTER, Landsat and SPOT images were inexpensive and effective tools for mapping large mining districts. They also determined that the higher resolution (15 m) ASTER images were the most preferred data for monitoring land cover changes associated with mining.

In another study that produced a multi-class analysis, three coal mining areas (two in reclamation and one active) were investigated by Schmidt and Glaesser (1998) based on digital analysis of several Landsat TM and ERS-1 data sets from between 1989 and

1994. Coal mine features such as waste, water bodies, change of land use, reclamation processes and estimation of vegetation cover were classified using the maximum likelihood classification. Bare soil areas were classified based on sediment type, vegetated areas were classified based on density and age of vegetation and water bodies were classified based on hydrochemical properties. The final classification algorithm was applied to multi-temporal data for change detection.

There are other researchers who have demonstrated the use of remotely sensed images for generating multi-class images. Demirel et al. (2011) used classified IKONOS and Quickbird images for change detection analysis to monitor land cover changes in surface coal mining areas in Goynuk, Turkey. They utilized the maximum likelihood classification algorithm for both types of images and were able to achieve classification accuracy sufficient to provide input for reclamation and closure activities.

Prakash and Gupta (1998) used Landsat images to define land cover classes and perform change detection analysis of the Jharia coalfield in India. Change was detected using image differencing, image ratioing, and differencing of NDVI images. They were able to infer how changes in land-use patterns within the study area have changed in response to the development of the coal mining industry.

NDVI analysis has been performed by others to assess mine land using remotely sensed imagery. Latifovic et al. (2005) used Landsat images to provide an initial assessment of using remote sensing to assess vegetation production trends in the Athabasca Oil Sands mining district in Alberta, Canada. They performed a primary landcover classification similarly to the studies discussed above. In addition, they also performed a secondary analysis to describe the vegetative health surrounding the mining district using NDVI change detection.

In situ analysis of coal waste, soil and vegetation was performed using a handheld spectroradiometer (ASD FieldSpec ProVNIR, Analytical Spectral Devices, Inc., USA) at the Haizhou coal mine in Fuxin City, China by Yunxia et al. (2007). The hyperspectral characteristics of the samples were used to calculate vegetation indices such as NDVI and difference vegetation index (DVI). A principal component analysis was performed. This data was then correlated to a "macro" remotely sensed image (merged panchromatic and multispectral SPOT 5). The authors concluded that the spatial resolution was improved by principal component analysis and that the merged image could be used to calculate NDVI.

Finally, Salyer (2006) utilized Landsat images covering a study area in Wise County, Virginia to assess changes in vegetation as a result of coal mining. Vegetative state of the study area was described in terms of changes in the percentage of healthy vegetation based on the Normalized Difference Vegetation Index (NDVI).

These studies can all be used as indicators that the classification of remotely sensed imagery and subsequent change detection can be successfully used to assess the condition of abandoned mine land. As an additional measure of the condition of the land, NDVI has also been successfully used to evaluate the vegetative vigor of landcover associated with mine lands. The combination of these analyses can provide an effective means to describe the effects of mining within the study area.

III. CONCEPTUAL FRAMEWORK AND METHODOLOGY

The methods for this study are, in general, to use image classification, change detection and the Normalized Difference Vegetation Index (NDVI) to quantitatively assess abandoned coal mine lands. These analyses were performed on remotely sensed images of the study area.

3.1 Data Source

The type of remotely sensed data selected for this study was Landsat TM imagery (Bands 1-7). The reason that this type of imagery was chosen was that it is easily accessible via the United States Geological Survey's Earth Explorer website (www.earthexplorer.usgs.gov). Also, the spectral and spatial resolution of this imagery is beneficial to the analysis. Other remotely sensed imagery with greater spatial and spectral resolution was also considered; however none was freely accessible.

The images were selected from spring growing seasons during 1984 and 2011. The exact dates of the images are April 18, 1984 and April 29, 2011. These images give the most useful information related to vegetative cover, vegetative vigor and change in land cover types over time. The images were downloaded directly from the Earth Explorer website, which delivers the imagery as seven different TIFF Images, one for each band. The TIFF Images were stacked into a single image file. The two images were then be clipped to include only the study area. The areas of interest were selected using the spatial extent of the study area to ensure all subsets are of the same coverage.

3.2 Image Classification

For both images, supervised image classification was used to create land cover classes that represent four land cover types: barren spoil, vegetated spoil, pasture and water. The barren spoil class represents areas where mining has occurred, spoil material is exposed and there is no vegetation. The vegetated spoil class also represents areas where mining has occurred, but the spoil material is not exposed. Vegetation in these areas are generally forested, as pasture and other grasses do not readily grow on un-reclaimed spoil material. The pasture class consists of grass covered areas where either no mining has ever occurred, or reclamation has been completed. The water class represents water bodies, most of which have been created by mining activities. The spectral display appearance (RGB 4/3/2) of the four classes are summarized in Table 1. The spectral profiles of all seven bands for each class are displayed in Figures 4 and 5.

Table 1 – Spectral display appearance of the four classes used in image classification

Class	**RGB 4/3/2 Display Appearance**
Barren Spoil	White to Light Blue
Vegetated Spoil	Light Blue to Light Pink
Pasture	Bright Red to Light Pink
Water	Dark Blue to Black

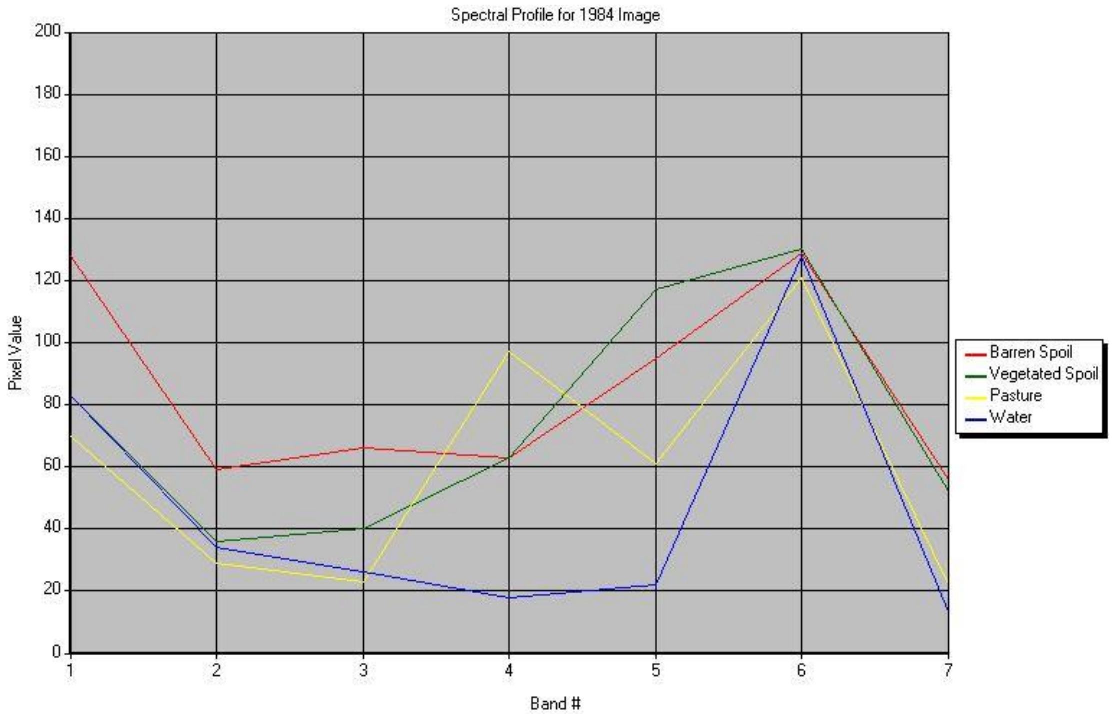

Figure 4 – Spectral profile of the 1984 image

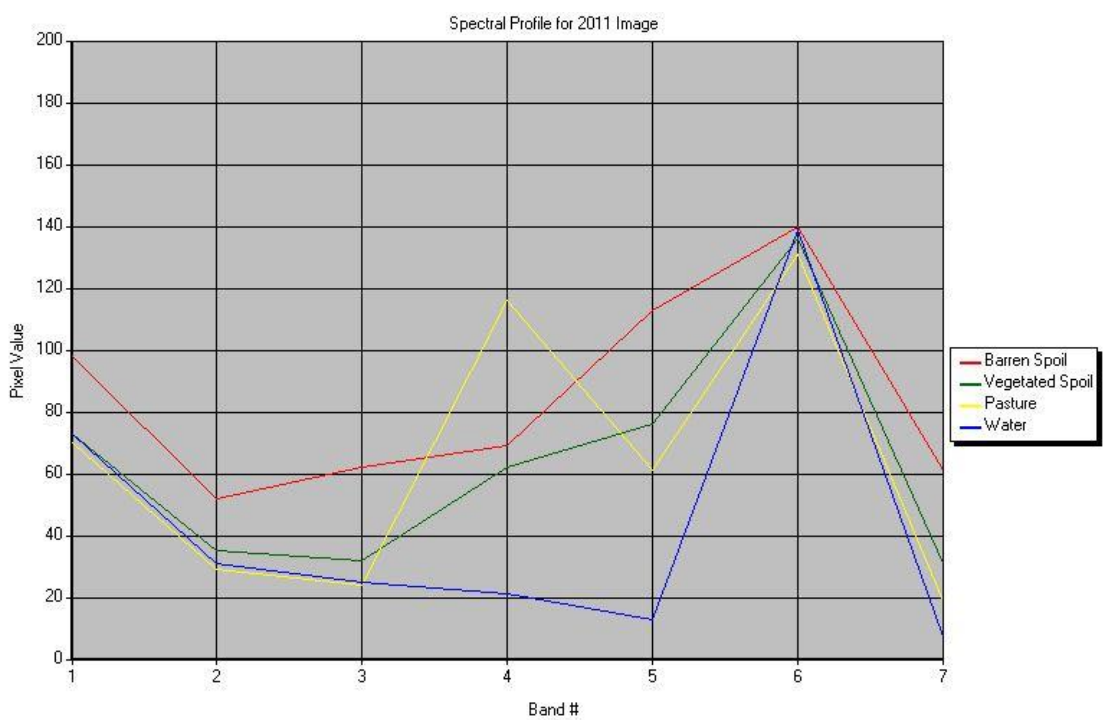

Figure 5 - Spectral Profile of the 2011 image

Development and forest land cover types were not present in sufficient proportions to justify their use in the classification. Vegetated spoil generally has a similar plant community to forested areas, as most pioneer species in these areas are trees. Additional classes were also considered to differentiate between AMD affected and unaffected water; however, there were no AMD affected waters that were able to be identified at the 30 meter resolution Landsat TM imagery. It is possible that there were AMD affected waters at the time of image collection that are smaller than the 900 square meter pixel coverage area, or that were not actively producing iron precipitates that would make the areas easily identifiable. Training sites were selected for the four classes listed in Table 1.

Following the selection of the training sites, three different classification algorithms were applied to assign each pixel to a class. The three algorithms were parallelepiped, minimum distance and maximum likelihood. The parallelepiped algorithm produces some unknown pixels if their brightness value does not fall within the thresholds defined by the training sites. This results in some pixels being placed into an unclassified group. Similarly, the minimum distance to means algorithm assigns pixels to classes based on thresholds defined by the training sites; however, it classifies pixels outside of the thresholds by applying a distance calculation. The unknown pixel is then assigned to the class that is the shortest distance to the mean of all classes. The maximum likelihood classification algorithm assigns unknown pixels to classes based on the probability that it belongs to that class. (Jensen, 2005). The accuracy of each classification algorithm was assessed by generating 120 random checkpoints within the study area (Figure 6) and comparing the land cover class to the other imagery collected

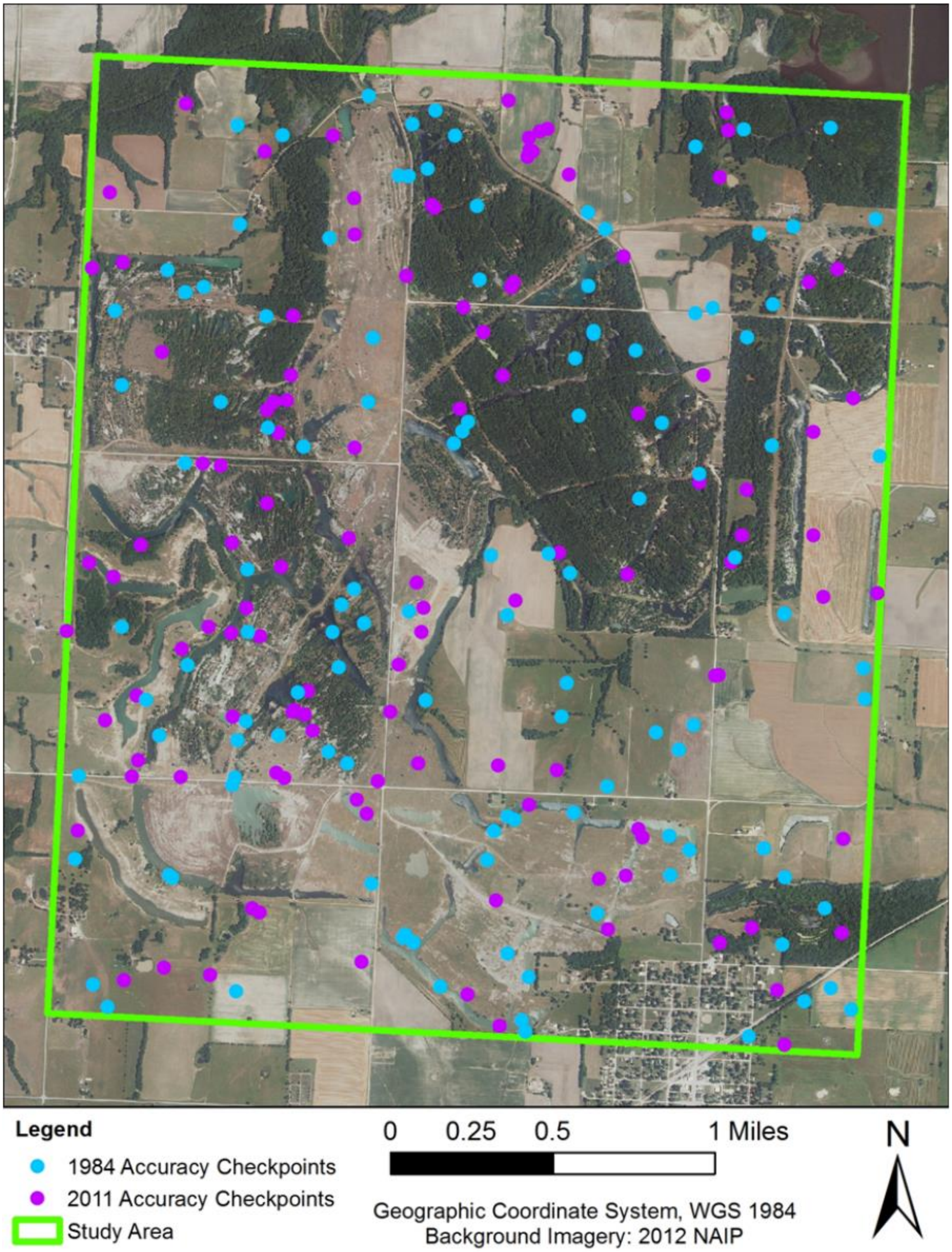

Figure 6 – Distribution of 30 random checkpoints within the study area used to assess classification accuracy of three algorithms

within the same year. The Landsat image from 1984 was compared to an aerial photograph obtained from the USDA Farm Service Agency and the image from 2011 was compared to NAIP imagery, downloaded from the Missouri Spatial Data Information Service (MSDIS). The algorithm with the highest percentage of correct classifications was used for change detection analysis.

3.3 Change Detection

The image produced using the most accurate classification algorithm was used to create change detection matrices to evaluate changes in land cover among images. An image and associated attribute table were generated from which the 4-by-4 change detection matrices were created. The 4-by-4 change detection matrices were then analyzed to determine how landcover has changed between 1984 and 2011. Changes were grouped into categories that helped to distinguish areas that were improved (such as from barren spoil to pasture) or that may be areas of concern (such as pasture to vegetated spoil). The major trends were identified and conclusions were drawn about the effectiveness of reclamation efforts and other changes taking place within this time period.

In addition to the change detection analysis performed on the classified images, an image was also created to compare NDVI images produced using the methods described in the following section. This image was used to demonstrate the change in vegetative vigor within the study area between 1984 and 2011. This image was also used to identify persistent areas of poor areas of vegetative cover. The identification of these areas can be used to target areas that may have had exposed spoil material for long periods of time, and are potential sources of acid mine drainage.

3.4 Normalized Difference Vegetation Index

NDVI was calculated to assess vegetative cover and vigor during the times the images were acquired. The output rasters were stretched to unsigned 8 bit (pixel value range between 0 and 255). Low values indicate areas of unhealthy vegetation, while high values indicate vigorous growth. Areas with low NDVI values, especially in the 2011 image, can be targeted for assessment of future reclamation priority or maintenance. Of special interest is the comparison of NDVI values in mined areas pre- and post-reclamation.

Although NDVI is a ratio value, and cannot be used to quantitatively compare two images, qualitative interpretation was used to identify areas of healthy vegetative growth in both the 1984 and 2011 Landsat images. Creation of rasters, in which values less than 100 were symbolized differently from those with values greater than 100, facilitated comparisons between the images. The threshold between healthy and unhealthy vegetation was selected as 100 because most pixels within the areas that were classified as barren spoil were less than this value. The change detection image described in Section 3.3 was also used to interpret the NDVI images.

IV. ANALYSIS RESULTS AND DISCUSSION

The results of image classification provided six, four-class images with land cover classes of barren spoil, vegetated spoil, pasture and water (three classification algorithms for the years of 1984 and 2011). Change detection analysis provided a matrix union image and associated change detection matrix. NDVI analysis resulted in two raw NDVI images and two rasters used to symbolize areas of high and low pixel values. A change detection image was also created to demonstrate differences between the NDVI images.

4.1 Image Classification Results

Three supervised classification algorithms were generated and compared in order to select the most accurate classification image for change detection and NDVI analysis. The three algorithms, parallelepiped, minimum distance and maximum likelihood, produced distinct images. The most accurate classification was selected for further analysis by calculating a simple percentage of correctly classified pixels at 120 random checkpoints.

The classified image generated using the parallelepiped algorithm correctly classified pixels at 70 of 120 checkpoints, or 58.33% correct classification of the 1984 image. The 2011 image was correctly classified at 56 checkpoints, or 46.67% correct classification. The results of this classification are presented in Figures 7 and 8. Inherent to the parallelepiped classification algorithm, there are unclassified pixels present in the images. This, in addition to the low percentage of correctly classified pixels, made the images undesirable for further analysis.

The classified image generated using the minimum distance algorithm correctly classified pixels at 73 checkpoints, or 60.83% correct classification of the 1984 image.

The 2011 image was correctly classified at 66 checkpoints, or 55.00% correct classification. The results of this classification are presented in Figures 9 and 10. This algorithm assigns all pixels within the image to a class; however, the relatively low percentage of correctly classified pixels excluded them from further analysis.

The classified image generated using the maximum likelihood algorithm correctly classified pixels at 90 checkpoints, or 75.00% correct classification of the 1984 image. The 2011 image was correctly classified at 81 checkpoints, or 67.5% correct classification. The results of this classification are presented in Figures 11 and 12. This algorithm generated images with the highest percentages of correctly classified pixels which were selected for change detection and NDVI analysis.

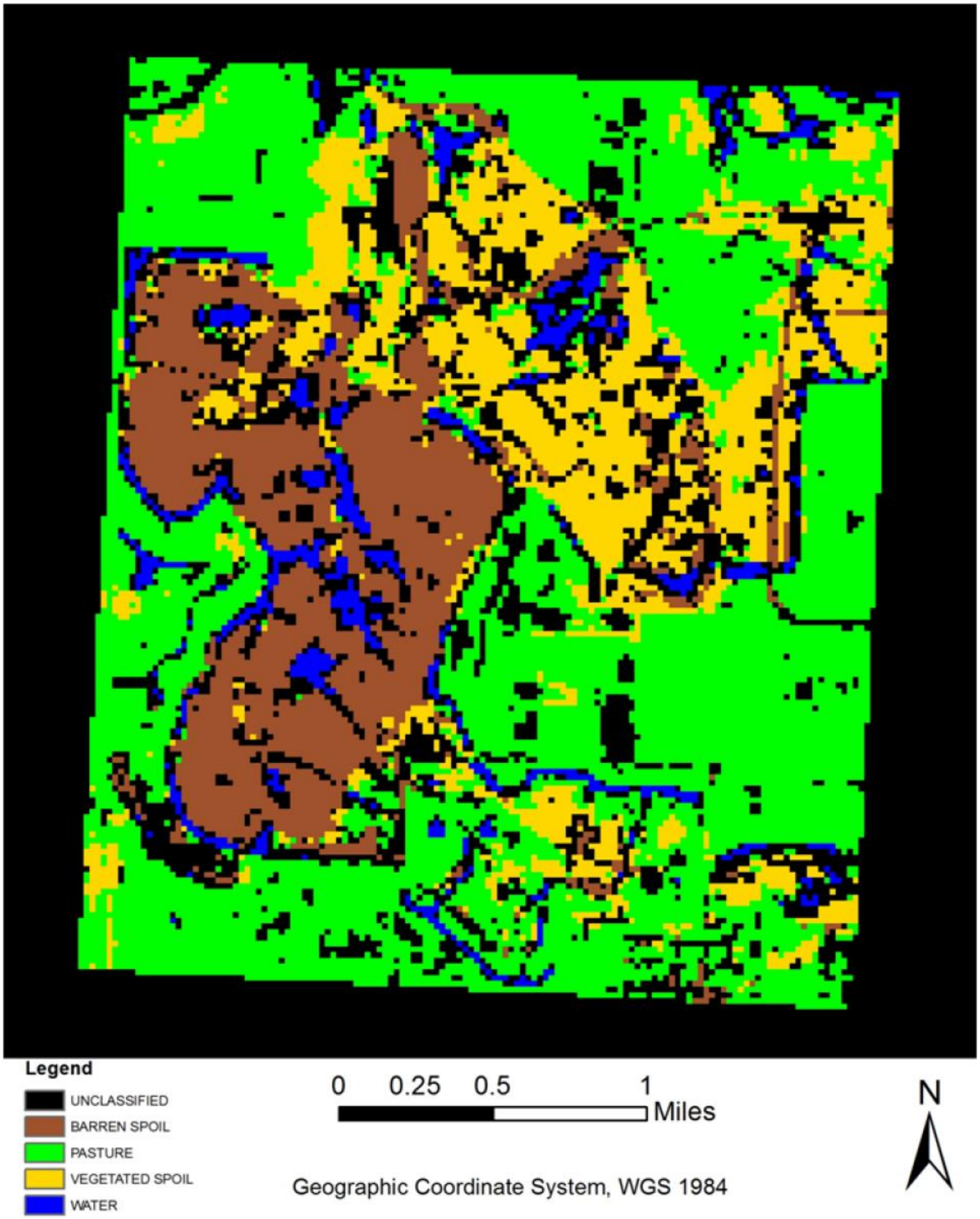

Figure 7 – Classified image of the study area in 1984 using the parallelepiped algorithm

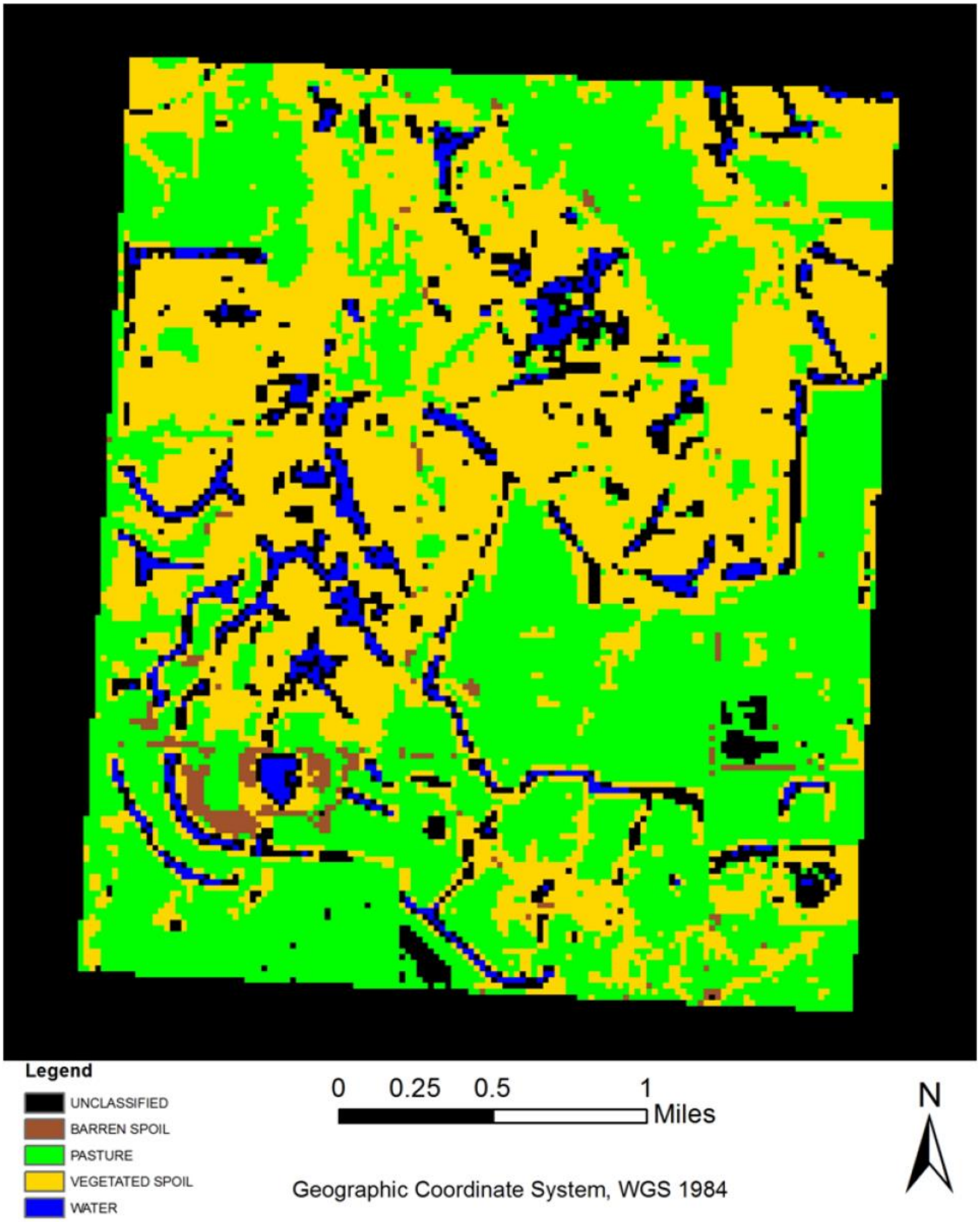

Figure 8 – Classified image of the study area in 2011 using the parallelepiped algorithm

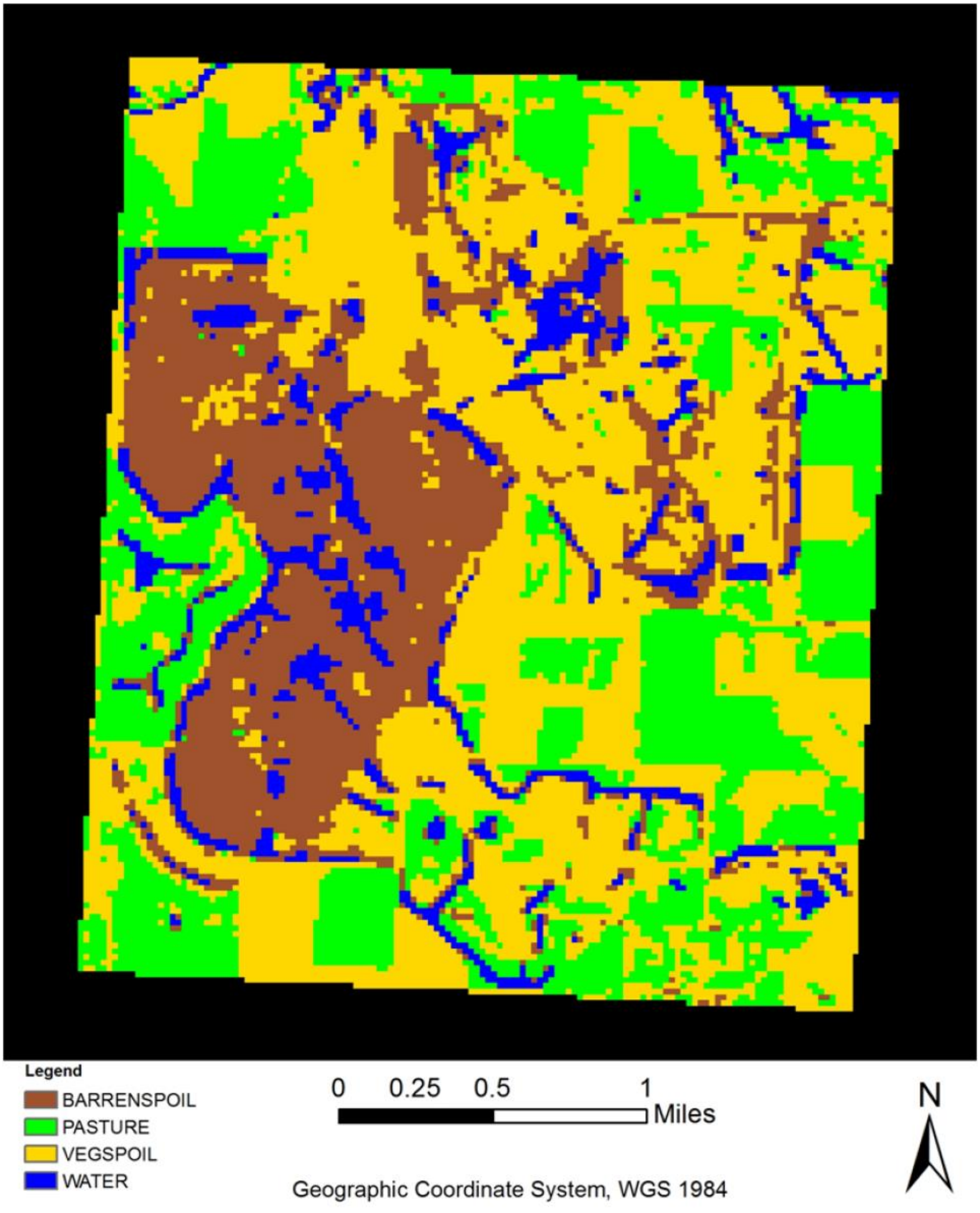

Figure 9 - Classified image of the study area in 1984 using the minimum distance algorithm

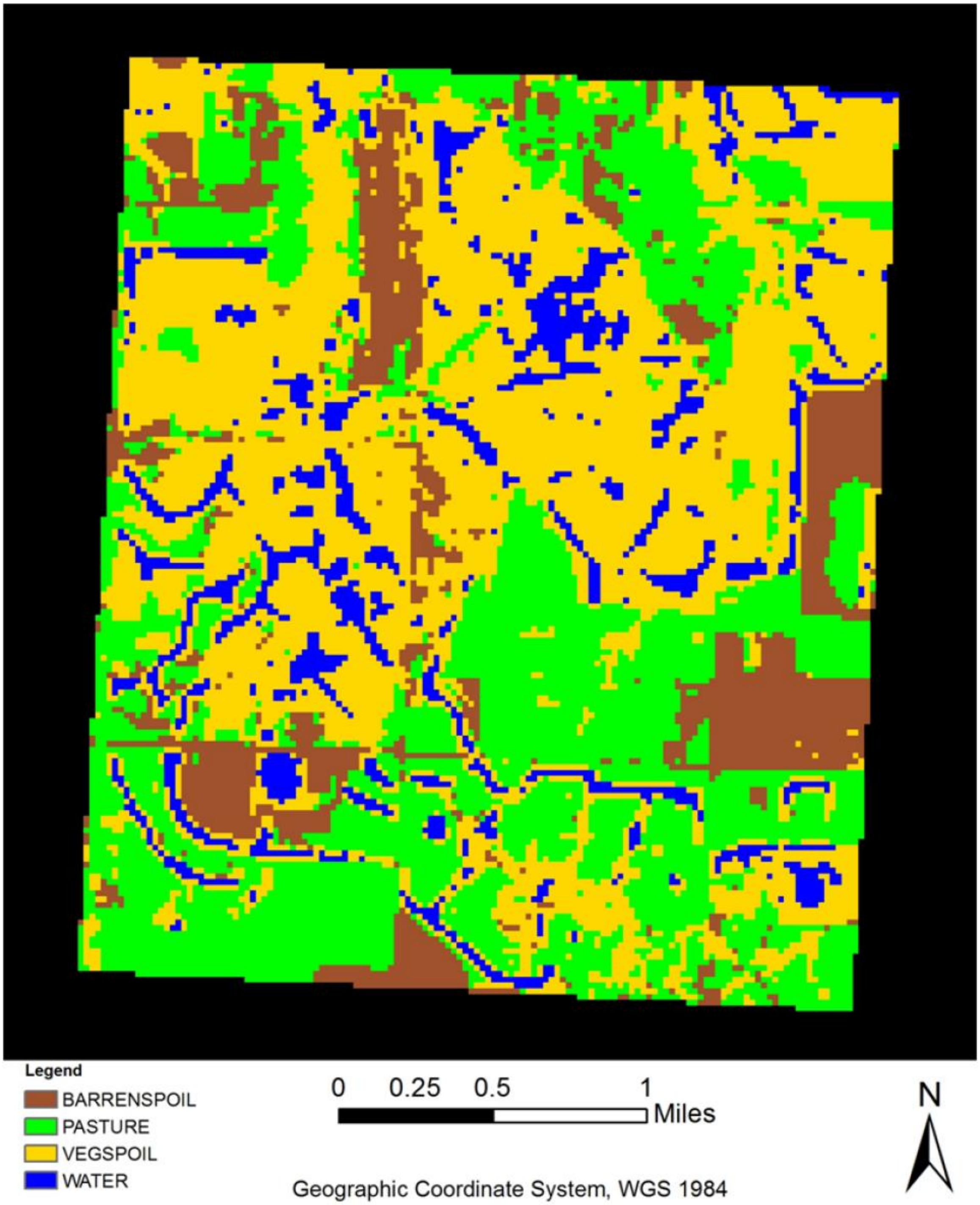

Figure 10 - Classified image of the study area in 2011 using the minimum distance algorithm

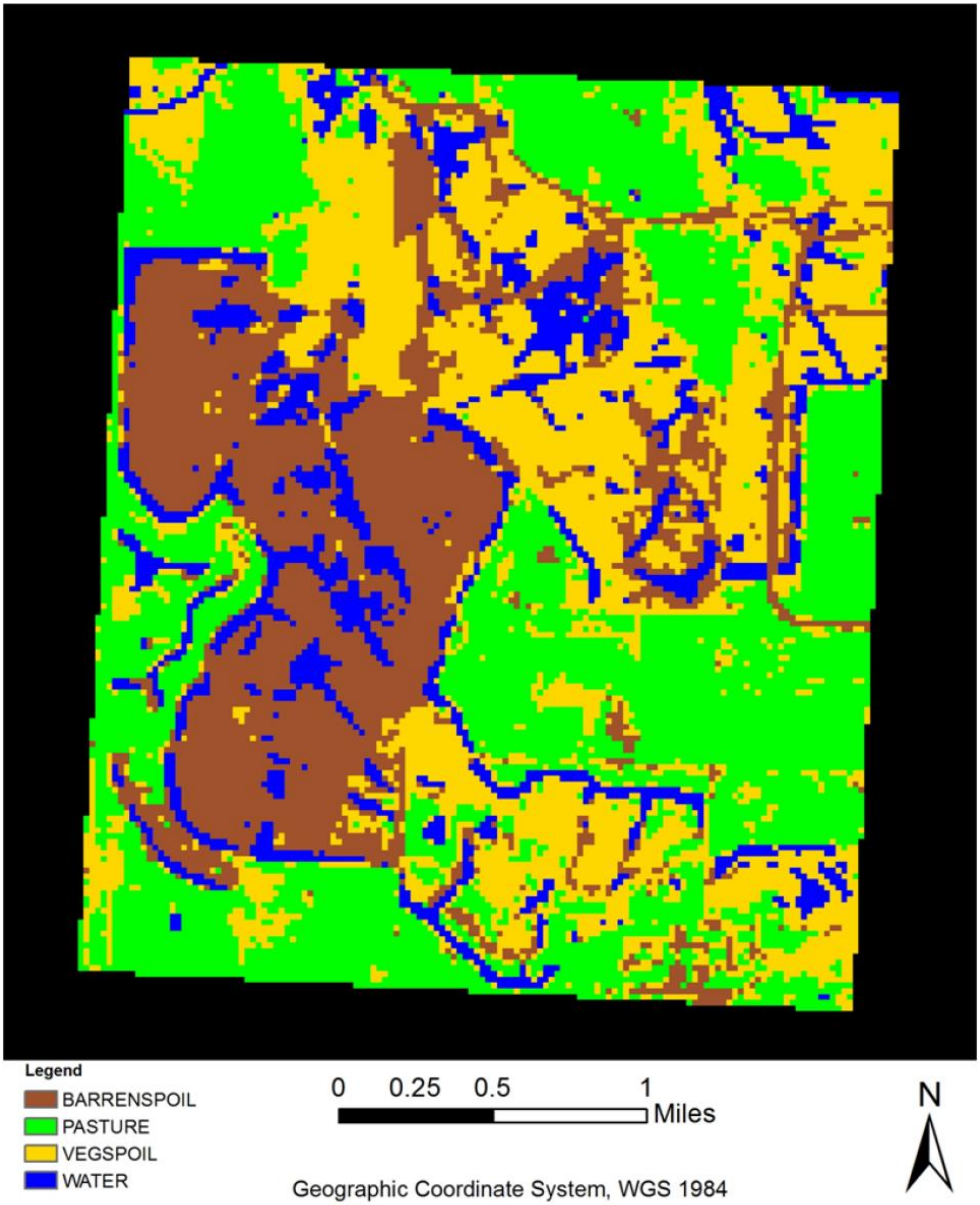

Figure 11 - Classified image of the study area in 1984 using the maximum likelihood algorithm

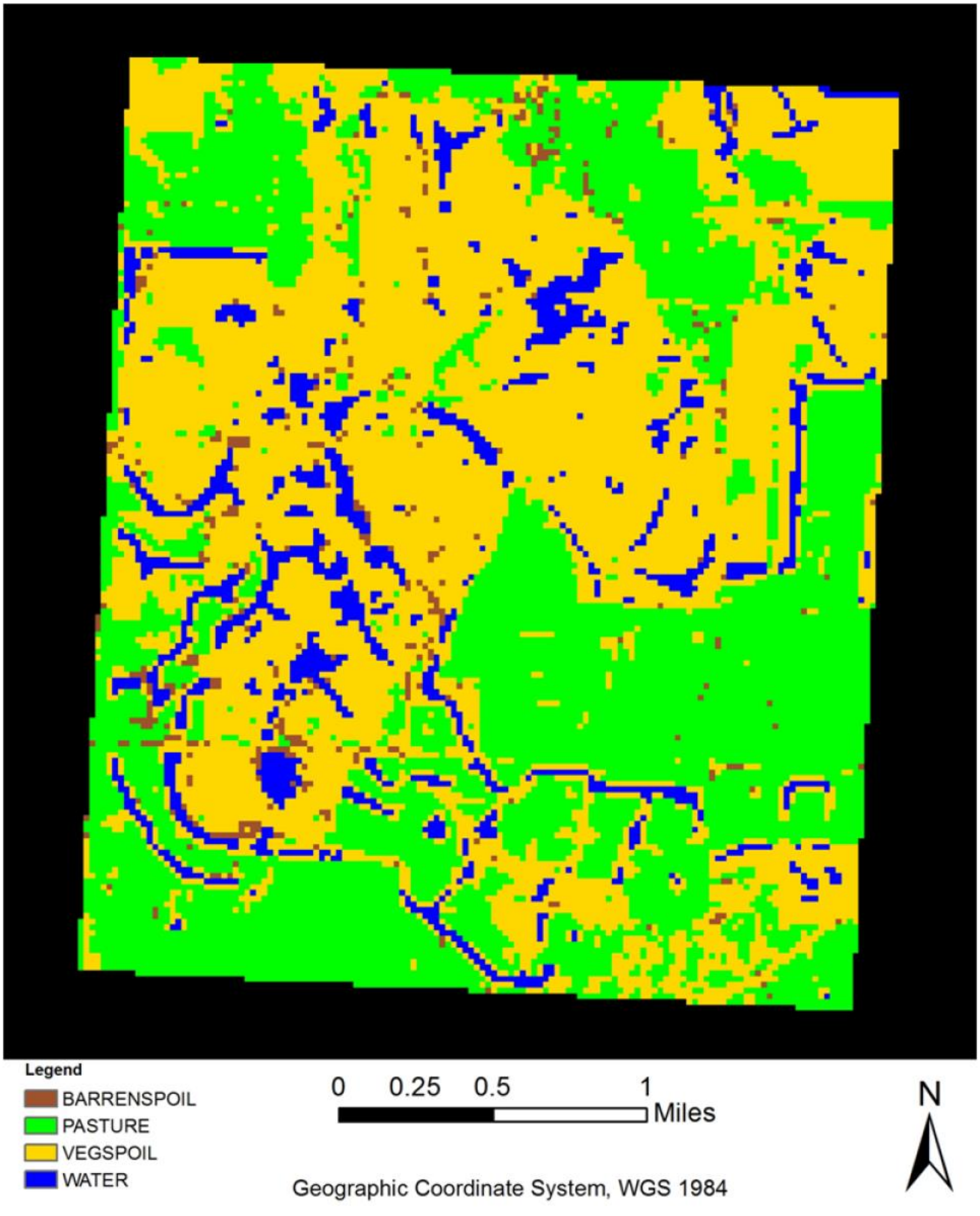

Figure 12 - Classified image of the study area in 2011 using the maximum likelihood algorithm

The accuracy of the images generated using the maximum likelihood algorithm was more thoroughly assessed by creating and analyzing an accuracy assessment error matrix. The accuracy was verified using the same random checkpoints and aerial photographs as were used for the simple percentage accuracy assessment. The accuracy of the maximum likelihood classification of the 1984 image is summarized in Table 2. The accuracy of the maximum likelihood classification of the 2011 image is summarized in Table 3.

Table 2 – Accuracy of the maximum likelihood classification of the 1984 image

	Pasture	Barren Spoil	Water	Vegetated Spoil	Total	User's
Pasture	**27**	0	0	3	30	90.00%
Barren Spoil	0	**27**	3	0	30	90.00%
Water	1	6	**16**	7	30	53.33%
Vegetated Spoil	9	1	0	**20**	30	66.67%
Total	37	34	19	30	90	
Producer's	72.97%	79.41%	84.21%	66.67%		

Total Accuracy = 75.00%

Kappa Coefficient = 0.67

Table 3 – Accuracy of the maximum likelihood classification of the 2011 image

	Pasture	Barren Spoil	Water	Vegetated Spoil	Total	User's
Pasture	**28**	0	0	2	30	93.33%
Barren Spoil	10	**8**	0	12	30	26.67%
Water	0	1	**22**	7	30	73.33%
Vegetated Spoil	6	1	0	**23**	30	76.67%
Total	44	10	22	44	81	
Producer's	63.64%	80.00%	100.00%	52.27%		

Total Accuracy = 67.50%

Kappa Coefficient = 0.57

In the 1984 classified image produced using the maximum likelihood algorithm, 37 pixels at random checkpoints were supposed to be classified as pasture, but only 27 were. There were ten errors of omission, and a producer's accuracy of 72.97%. Nine of the incorrectly classified pixels were classified as vegetated spoil instead of pasture. One of the incorrectly classified pixels was classified as water instead of pasture. There should have been 34 pixels classified as barren spoil, but only 27 were resulting in a producer's accuracy of 79.41%. The errors of omission were six classifications as water and one classification as vegetated spoil rather than barren spoil. There were 16 pixels correctly classified as water, and three errors of omission resulting in a producer's accuracy of 84.21%. The incorrectly classified pixels were classified as barren spoil rather than water. There were 30 pixels that should have been classified as vegetated spoil, but only 20 were. The producer's accuracy is 66.67%. Three of the incorrectly classified pixels were classified as pasture and seven were classified as water rather than vegetated spoil.

Also, in the 1984 classified image, there were 27 pixels correctly classified as pasture, and three pixels misclassified as pasture, resulting in a user's accuracy of 90.00%. The misclassified pixels should have been classified as vegetated spoil rather than pasture, errors of commission. There were 27 pixels correctly classified as barren spoil, and three pixels misclassified as barren spoil, also resulting in a user's accuracy of 90.00%. The three misclassified pixels should have been classified as water rather than barren spoil. Sixteen pixels were correctly classified as water. Fourteen pixels were misclassified resulting in a user's accuracy of 53.33%. There was one pixel that should have been classified as pasture, six pixels that should have been classified as barren spoil and seven pixels that should have been classified as vegetated spoil. There were 20 pixels correctly classified as vegetated spoil and 10 errors of commission, resulting in a user's accuracy of 66.67%. Nine of the misclassified pixels should have been classified as pasture, and one should have been classified as barren spoil. The total accuracy of the 1984 classified image is 75.00%, with a kappa coefficient of 67.67%. This is an acceptable accuracy level for the desired uses.

In the 2011 classified image produced using the maximum likelihood algorithm, 44 pixels at random checkpoints were supposed to be classified as pasture, but only 28 were. There were 16 errors of omission, and a producer's accuracy of 63.64%. Ten of the 16 pixels were incorrectly classified as barren spoil instead of pasture. Six of the 16 pixels were classified as vegetated spoil instead of pasture. There were supposed to be 10 pixels classified as barren spoil, but only eight were. There were two errors of omission. One pixel that was supposed to be classified as barren spoil but was classified as water and one pixel was classified as vegetated spoil; therefore, the producer's accuracy for barren spoil is 80.00%. The low number of pixels classified as barren spoil in the 2011 image was to be expected, due to the reclamation of barren spoil within the 27 years between image collection dates. Subsequently, random checkpoints within this classification were also few. There were 22 pixels at random checkpoints that were supposed to be classified as water and 22 were, resulting in a producer's accuracy of 100.00% for this class. There were 44 pixels at random checkpoints that were supposed to be classified as vegetated spoil but only 23 were, resulting in a producer's accuracy of 52.27%. There were two pixels that were classified as pasture, 12 pixels that were classified as barren spoil and seven pixels that were classified as water instead of vegetated spoil.

Also, in the 2011 classified image, there were 28 pixels correctly classified as pasture, and two pixels misclassified as pasture, resulting in a user's accuracy of 93.33%. The misclassified pixels should have been classified as vegetated spoil rather than pasture, errors of commission. There were eight pixels correctly classified as barren spoil, and 22 pixels misclassified as barren spoil. There were 10 pixels that were misclassified as barren spoil that should have been classified as pasture, and 12 pixels that should have been classified as vegetated spoil. This resulted in a user's accuracy of 26.67%. Again, this is influenced by the low frequency of landcover classified as barren spoil in the 2011 image. There were 22 pixels correctly classified as water, and eight pixels that were misclassified resulting in a user's accuracy of 73.33%. One of the pixels was misclassified pixels was classified as barren spoil and seven pixels were classified as vegetated spoil. There were 23 pixels correctly classified as vegetated spoil, and seven pixels that were misclassified resulting in a user's accuracy of 76.67%. Six of the misclassified pixels were classified as pasture and one was classified as barren spoil.

The 2011 classified image has a total accuracy of 67.50% and a kappa coefficient of 56.67%. Although it is somewhat lower than the preferred value, the classification still sufficient for the purposes of distinguishing areas affected by mining from those that are not, assessing the success of reclamation efforts and monitoring previously reclaimed land. The classified image provides a generalized depiction of the four landcover types, and is acceptable for the desired uses.

For both the 1984 and 2011 images, issues with classification accuracy can be attributed to the similar spectral reflectance of some classes during the times of image collections. For example, confusion of pasture for vegetated spoil, and vice versa, is likely due to the similar spectral reflectance of the vegetation growing on the spoil areas and in pastures in early spring. The water class in both images was also difficult to accurately classify due to the narrow width of the waterbodies. This, combined with the 30 meter spatial resolution of the image, could easily result in the lack of precise pixel classification within and directly adjacent to waterbodies.

4.2 Change Detection Results

Changes in landcover between 1984 and 2011 analyzed by creating a matrix image and associated change detection matrix. Change detection matrices are provided that describe the changes in term of pixels (Table 4) and in terms of acres (Table 5).

Using the matrices, the changes can be described based on a class by class basis in order to thoroughly assess the dynamics within each landcover type.

4.2.1 Pasture

The pasture landcover class had a total of 6,321 pixels (1,405.8 acres) that did not change between 1984 and 2011. There were 127 pixels (28.2 acres) that changed from pasture to barren spoil, 23 pixels (5.1 acres) that changed from pasture to water and 971 pixels (215.9 acres) that changed from pasture to vegetated spoil. This represents a total loss of pasture of 1,121 pixels (249.2 acres) between 1984 and 2011. This could be due to the erosion of pasture land to expose barren spoil, the creation of new or the expansion of existing waterbodies or natural forest succession on land previously reclaimed to pasture.

Table 4 – Change Detection Matrix (Pixels)

		2011			
		Pasture	Barren Spoil	Water	Vegetated Spoil
	Pasture	**6321**	127	23	971
1984	Barren Spoil	557	**210**	193	4176
	Water	15	30	**1443**	933
	Vegetated Spoil	1705	52	56	**4695**

Table 5 – Change Detection Matrix (Acres)

		2011			
		Pasture	Barren Spoil	Water	Vegetated Spoil
	Pasture	**1405.8**	28.2	5.1	215.9
1984	Barren Spoil	123.9	**46.7**	42.9	928.7
	Water	3.3	6.7	**320.9**	207.5
	Vegetated Spoil	379.2	11.6	12.5	**1044.1**

There were also changes within the time period that represent conversion of other land cover classes to pasture. There were 557 pixels (123.9 acres) that changed from barren spoil to pasture, 15 pixels (3.3 acres) that changed from water to pasture and 1,705 pixels (379.2 acres) that changed from vegetated spoil to pasture. This represents a total gain in pasture of 2,277 (506.4 acres). This change is most likely due completely to reclamation efforts within the study area since natural change from barren spoil, water or vegetated spoil is highly unlikely.

4.2.2 Barren Spoil

The barren spoil landcover class had a total of 210 pixels (46.7 acres) that did not change between 1984 and 2011. There were 557 pixels (123.9 acres) that changed from barren spoil to pasture, 193 pixels (42.9 acres) that changed from barren spoil to water and 4,176 pixels (928.7 acres) that changed from barren spoil to vegetated spoil. This represents a total reduction in barren spoil of 4,926 pixels (1,095.5 acres) between 1984 and 2011. The change from barren spoil to pasture, as previously mentioned, is most likely the result of reclamation efforts within this time period. The change from barren spoil to water is also most likely related to reclamation work. The change from barren spoil to vegetated spoil could be the result of reclamation work, or simply the result of natural forest succession on relatively less acidic spoil material.

Increases in barren spoil were also observed within the study area between 1984 and 2011. There were 127 pixels (28.2 acres) that changed from pasture to barren spoil, 30 pixels (6.7 acres) that changed from water to barren spoil and 52 pixels (11.6 acres) that changed from vegetated spoil to vegetated spoil. Changes from pasture and vegetated spoil to barren spoil could be the result of erosion that exposed spoil material.

Change from water to barren spoil most likely represents a change in the water level of a waterbody that exposed underlying spoil material.

4.2.3 Water

The water landcover class also experienced changes within the study time period, although the majority of waterbodies did not change (1,443 pixels or 320.9 acres). There were 15 pixels (3.3 acres) that changed from water to pasture, 30 pixels (6.7 acres) that changed from water to barren spoil and 933 pixels (207.5 acres) that changed from water to vegetated spoil. This is a total change of 978 pixels (217.5 acres) from water to another class. As described previously, the changes from water to pasture or barren spoil are most likely due to either reclamation efforts or changes in water levels that expose spoil materials. Changes from water to vegetated spoil are not as easily explained, but could also be the result of changes in water levels within waterbodies. If waterbody levels decreased over time, and trees were able to grow in the shallow water or newly exposed substrate this could explain the change. When the 2011 NAIP imagery was examined within these areas, this did appear to be the case.

Changes from other classes to water were as follows: there were 23 pixels (5.1 acres) that changed from pasture to water, 193 pixels (42.9 acres) that changed from barren spoil to water and 56 pixels (12.5 acres) that changed from vegetated spoil to water. This represents an overall increase in water of 272 pixels (60.5 acres). As discussed in previous sections this change is attributable to the creation of new waterbodies as a part of reclamation work, or the raising of some water levels that result in the increase of the surface area of the waterbodies.

4.2.4 Vegetated Spoil

The vegetated spoil landcover class had a total of 4,695 pixels (1,044 acres) that did not change between 1984 and 2011. There were 1,705 pixels (379.2 acres) that changed from vegetated spoil to pasture, 52 pixels (11.6 acres) that changed from vegetated spoil to barren spoil and 56 pixels (12.5 acres) that changed from vegetated spoil to water. This represents an overall decrease in vegetated spoil of 1,813 pixels (403.3 acres). Again, the change in vegetated spoil to pasture is most likely the result of reclamation work, the change from vegetated spoil to barren spoil is most likely the result of erosion and the change from vegetated spoil to water is most likely the result of the creation or expansion of waterbodies.

Increases in vegetated spoil landcover were also observed. There were 971 pixels (215.9 acres) that changed from pasture to vegetated spoil, as a result of natural forest succession within previously reclaimed areas. There were 4,176 pixels (928.7 acres) that changed from barren spoil to vegetated spoil as a result of natural forest succession or reclamation work within previously unreclaimed areas. There were 933 pixels (207.5 acres) that changed from water to vegetated spoil as a result of lower water levels and subsequent tree growth. There was an overall increase in vegetated spoil of 6080 pixels (1,352.1 acres).

4.2.5 Improvements and Concerns

In order to further analyze the landcover trends between 1984 and 2011, the changes were grouped into five major categories (Tables 6 and 7). These include: 1. No negative change, 2. Areas of improvement, 3. Areas of concern, 4. New waterbodies, and 5. Former waterbodies (Figure 13). This analysis reveals that there were notable

Table 6 – Five major landcover trends between 1984 and 2011

Category	Classified as in 1984	Classified as in 2011
No negative change	Pasture	Pasture
	Vegetated Spoil	Vegetated Spoil
	Water	Water
	Pasture	Vegetated Spoil
Areas of improvement	Barren Spoil	Vegetated Spoil
	Barren Spoil	Pasture
	Vegetated Spoil	Pasture
Areas of concern	Barren Spoil	Barren Spoil
	Pasture	Barren Spoil
	Vegetated Spoil	Barren Spoil
New waterbodies	Pasture	Water
	Vegetated Spoil	Water
	Barren Spoil	Water
Former waterbodies	Water	Pasture
	Water	Vegetated Spoil
	Water	Barren Spoil

Table 7 – Summary of five major land cover trends between 1984 and 2011

		2011			
		Pasture	**Vegetated Spoil**	**Barren Spoil**	**Water**
1984	**Pasture**	No Negative	No Negative	Concern	New Water
	Vegetated Spoil	Improvement	No Negative	Concern	New Water
	Barren Spoil	Improvement	Improvement	Concern	New Water
	Water	Former Water	Former Water	Former Water	No Negative

improvements to large areas within the study area. It also reveals that there were areas of no negative changes and there may be some areas of concern. Areas of "no negative change" are distinguished from simply areas of "no change" in that they are areas in which the landcover was not persistently barren spoil. Areas that were barren spoil both in 1984 and 2011 would be considered an area of concern. These categories also can

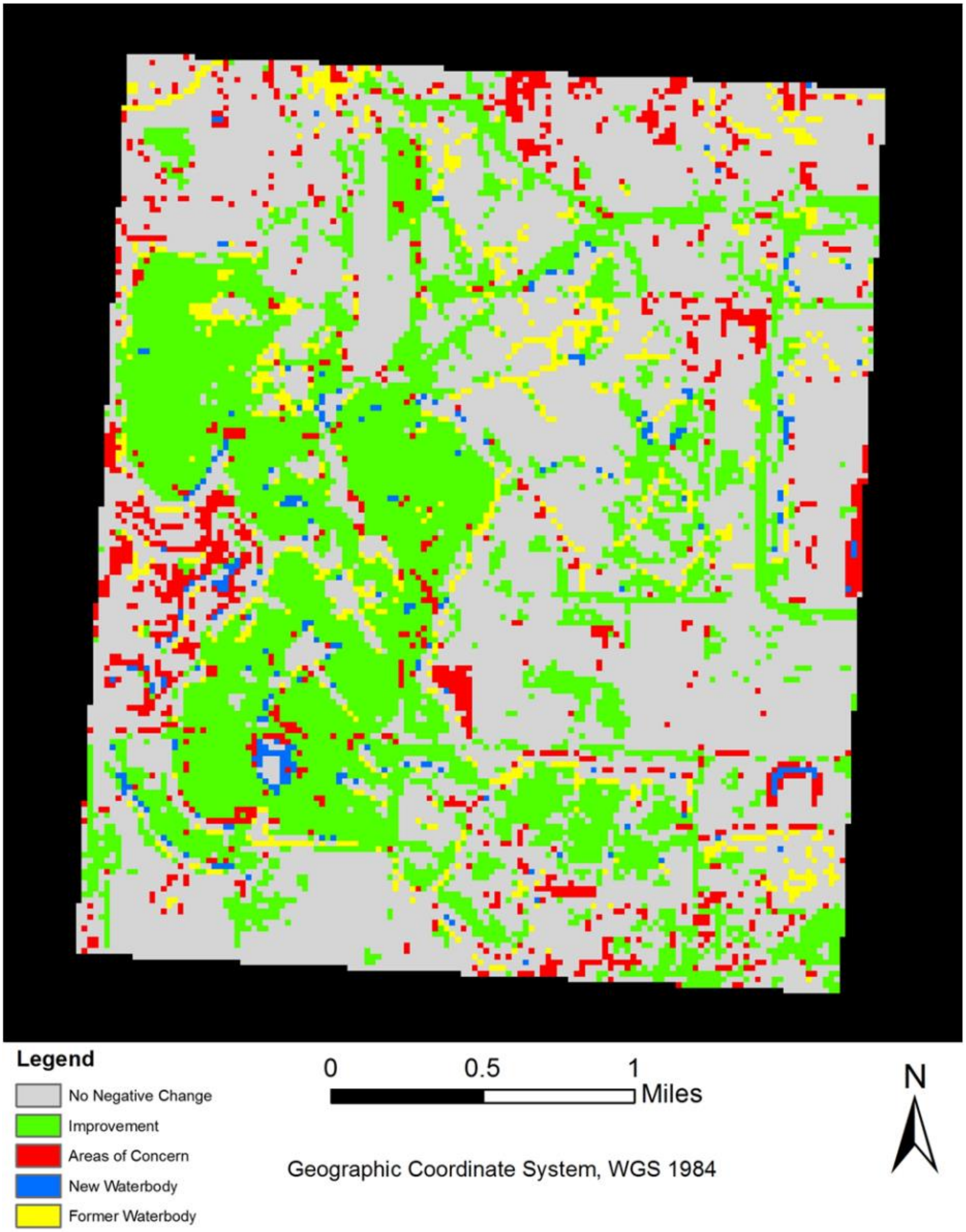

Figure 13 – Matrix image symbolized by categories of no negative change, areas that improved, areas of concern, new waterbodies and former waterbodies

help to easily identify where there may be potential problems that need to be addressed through reclamation work.

There were a total of 2,770.8 acres that did not change, or did not change to a less desirable landcover, and would not be considered an area of immediate concern for this reason. In other words, landcover classified as pasture, vegetated spoil and water in 1984 and stayed the same in 2011are considered no negative change. Further, land that changed from pasture to vegetated spoil was not considered a negative change. This change most likely reflects a pasture that has naturally overgrown. There were also 46.7 acres that did not change, but that would be an area of concern. Land that was classified as barren spoil both in 1984 and 2011 would fall into this category. Also in this category would be land that was classified as pasture, water or vegetated spoil and changed to barren spoil. There were 1,431.8 acres where there was a change from a less desirable landcover type to a more desirable landcover type. These include changes from barren spoil to vegetated spoil or pasture, and from vegetated spoil to pasture. There were 48.0 acres that, according to the change detection matrices, appear to be newly created waterbodies. Several of these pixels are most likely classification errors; however, there are at least two actual waterbodies that were either newly created or expanded in area (Figure 14). Finally, there were 217.5 acres that were formerly waterbodies. These areas represent acreage where water has been eliminated during reclamation or water levels have receded between image collection dates.

In general, the trend of changes is from mine affected land to reclaimed land. Much of this change is due to active reclamation by MDNR and private landowners, such as the changes from barren spoil to pasture. Some of the change is due to natural

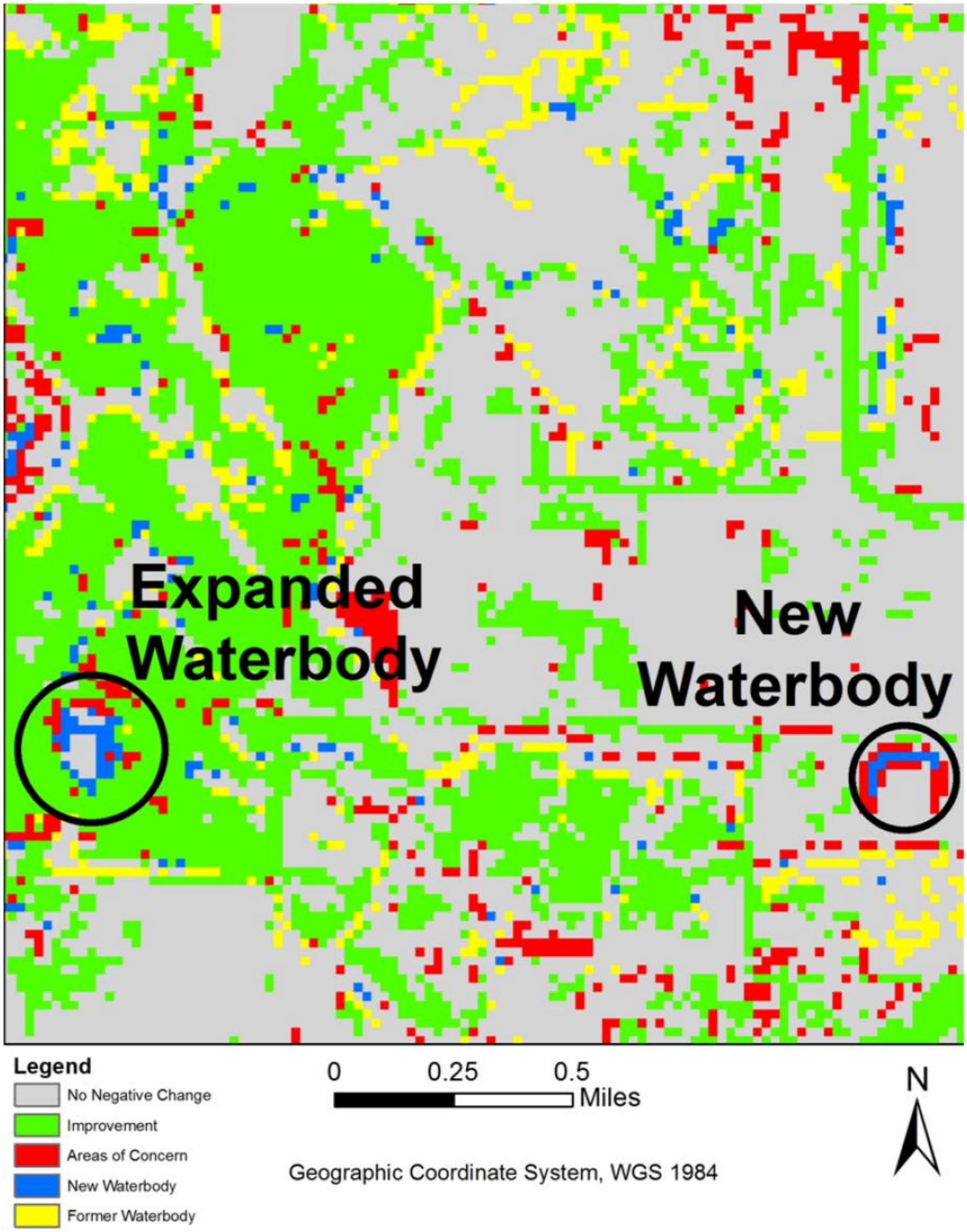

Figure 14 – Change detection of new or expanded waterbodies

attenuation of mine spoil, such as the change from barren spoil to vegetated spoil. Change from various land cover classes to water may be directly related to mine reclamation, as is the case with the expanded waterbody identified in Figure 14. Some of the change from water to other land cover types may be related to filling-in of hazardous water-bodies, especially those that are along or near public roadways. Within the study area, change detection analysis indicates that 29.93% of the land within the study area has improved between 1984 and 2011.

Since one of the possible uses of the classified images is the identification of areas where reclamation is needed or completed reclamation work is in need of maintenance, the change detection category of “Areas of Concern” were examined in greater detail. Concentrated areas of this type were visually identified and compared to the 2011 NAIP imagery used for accuracy analysis. Figure 15 demonstrates an area of concern that was identified using the matrix image beside the NAIP imagery. It is apparent from the imagery that this area is not adequately vegetated and erosion features are present. Figure 16 depicts a similar situation.

Figure 17 depicts a concentration of “Area of Concern” pixels, but is not actually a mine feature in need of reclamation. This area is the City of Montrose. Since impervious surface is not a major landcover class within the study area, it was not included in the classification. The spectral reflectance of barren spoil most closely approximates that of impervious surface. For this reason, the city was identified as an area of concern. Future classifications used on a larger scale, and that include more impervious surface landcover would benefit from an additional “Development” class to prevent this from occurring.

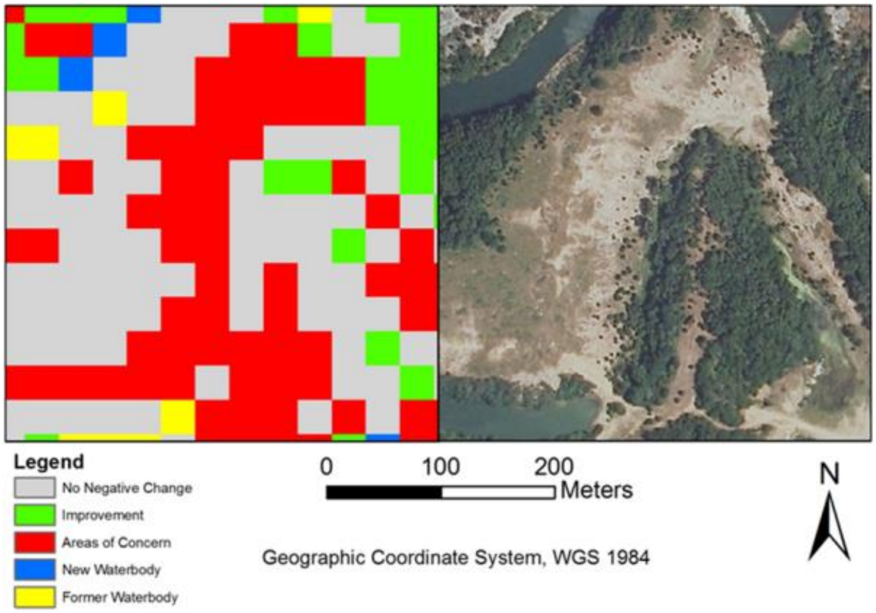

Figure 15 – Concentrated “Areas of Concern” and 2011 NAIP imagery of the same extent where reclamation may be necessary

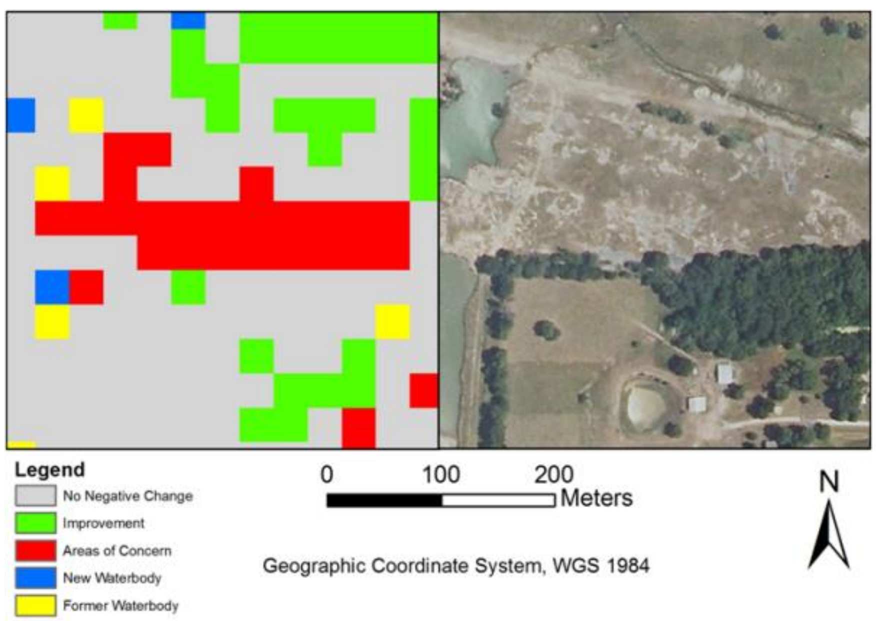

Figure 16 – Concentrated “Areas of Concern” and 2011 NAIP imagery of the same extent where reclamation may be necessary

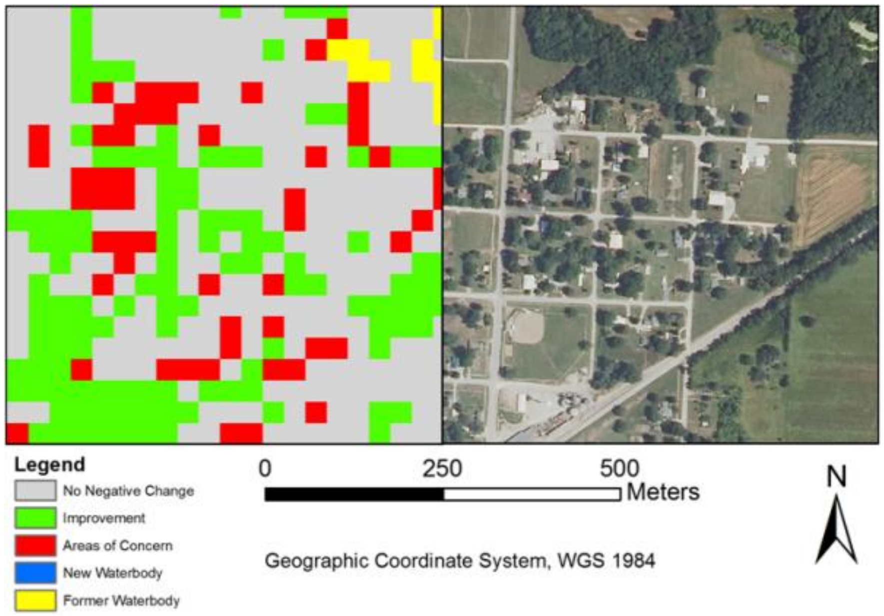

Figure 17 - Concentrated “Areas of Concern” and 2011 NAIP imagery of the same extent where reclamation is not needed

4.3 NDVI Results

Results of the NDVI analysis indicate that there are larger areas of unhealthy vegetation in the 1984 image compared to the 2011 image (Figures 18 and 19). This is apparent due to the larger areas of low-value pixels in the NDVI image from 1984 compared to the relatively smaller areas of low-value pixels in the 2011 NDVI image. The darkest areas of both images are waterbodies and were not considered when comparing the images. The relationship between the 1984 and 2011 NDVI images can be more clearly visualized when the images are symbolized by two categories. Figures 20 and 21 symbolize all NDVI values in two categories: less than 100 and greater than 100. This comparison indicates that the overall vegetative health within the study area has improved.

Unfortunately, these images did not provide a clear indication of specific areas that may be of concern. In fact, many of the areas in the 2011 NDVI image with pixel values just over 100 (in the range of 100-120) were identified as pasture in the classified image. The annual precipitation in Henry County in 1984 was 41.32 inches and 39.32 inches in 2011(National Oceanic and Atmospheric Administration, 2013), so growing conditions were similar for the two years. This is most likely more related to the fact that the Landsat TM image was collected during a time when the grasses in those particular fields were dormant. For example, the image was collected in the spring, and the pasture may consist of mostly warm season grasses that were not actively growing during this time. This would give the indication that the vegetative health of the pasture is not acceptable. If NDVI images are used to assess vegetative health, this must be taken into consideration.

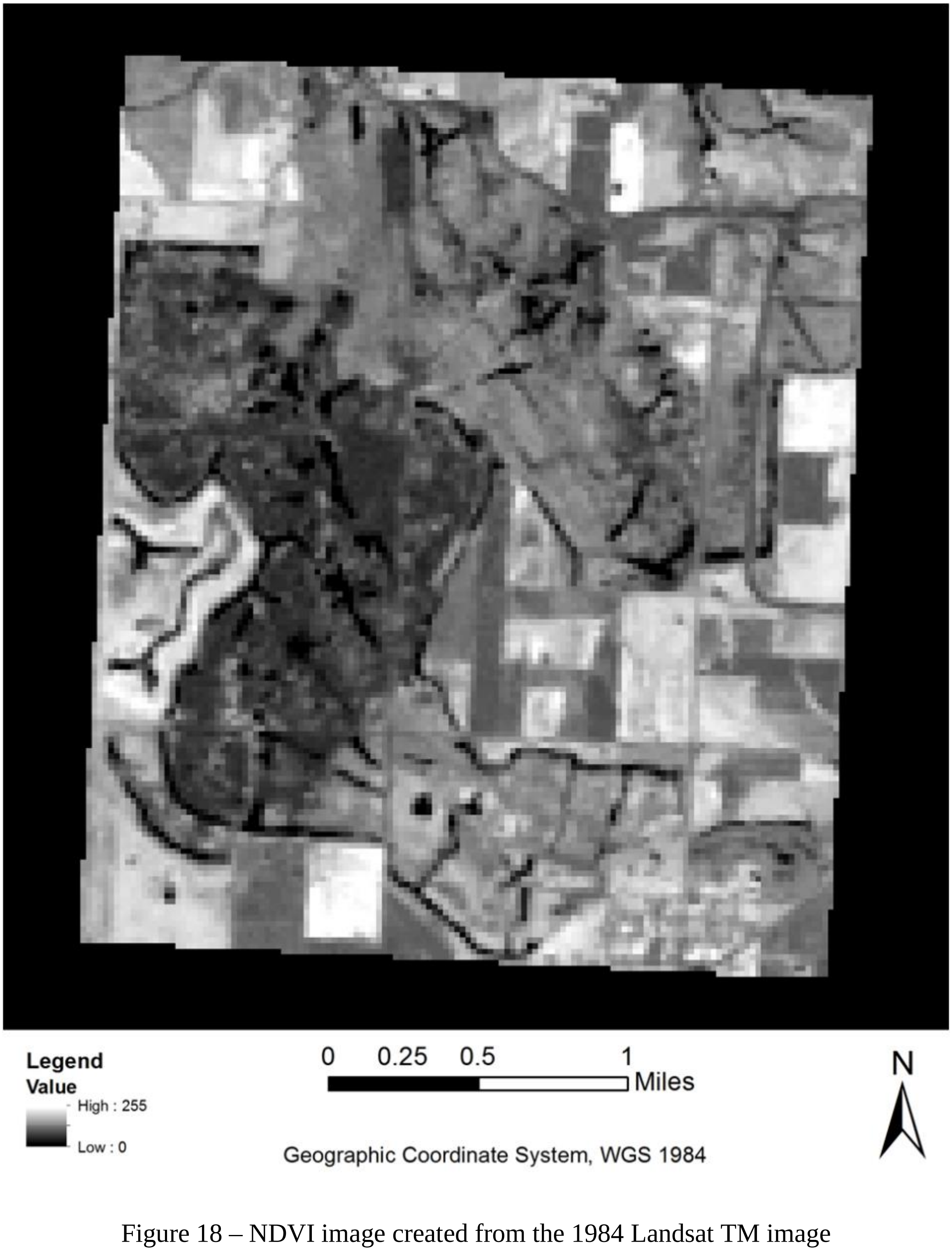

Figure 18 – NDVI image created from the 1984 Landsat TM image

Figure 19 – NDVI image created from the 2011 Landsat TM image

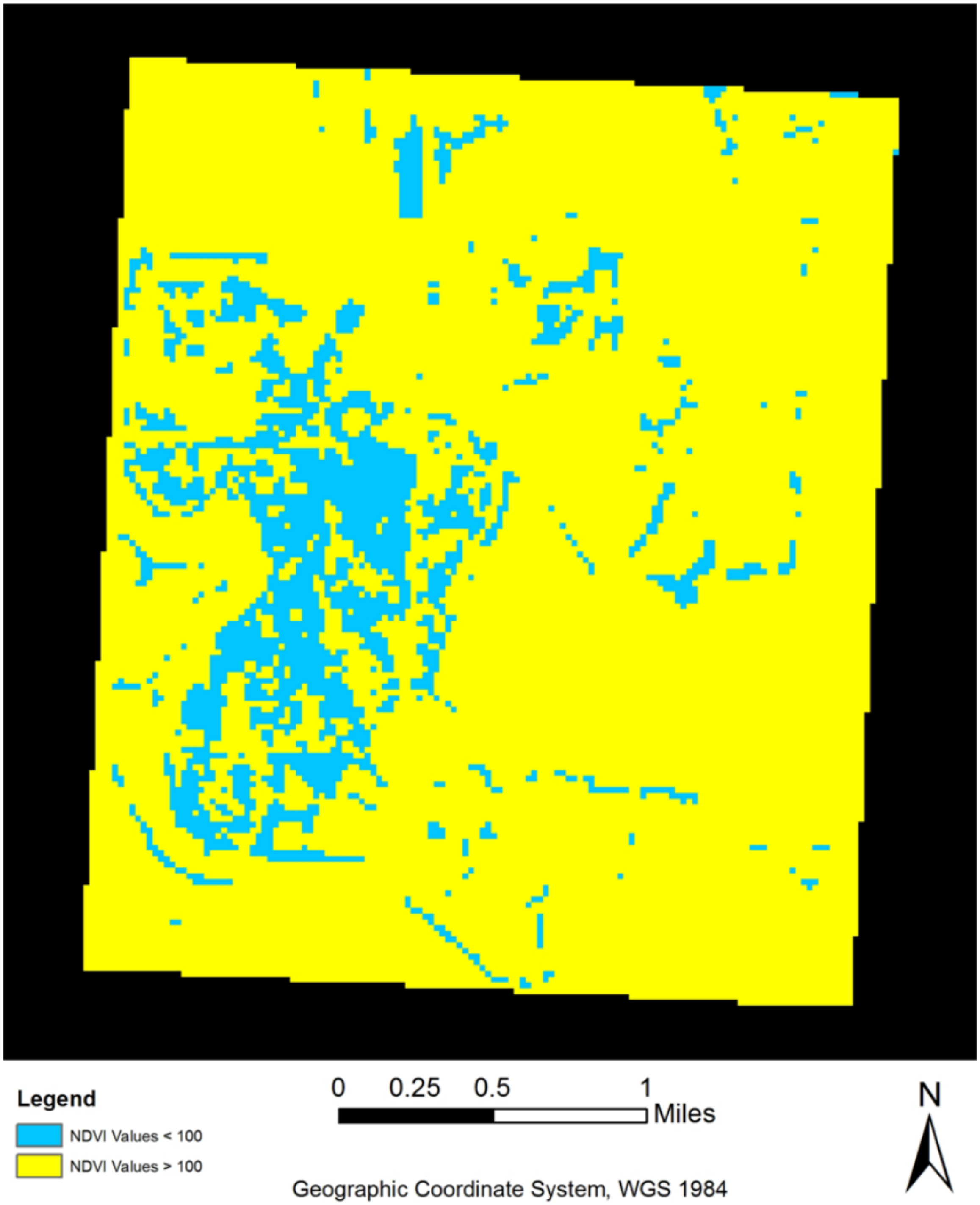

Figure 20 – Raster symbolizing high and low NDVI values derived from the 1984 Landsat Image

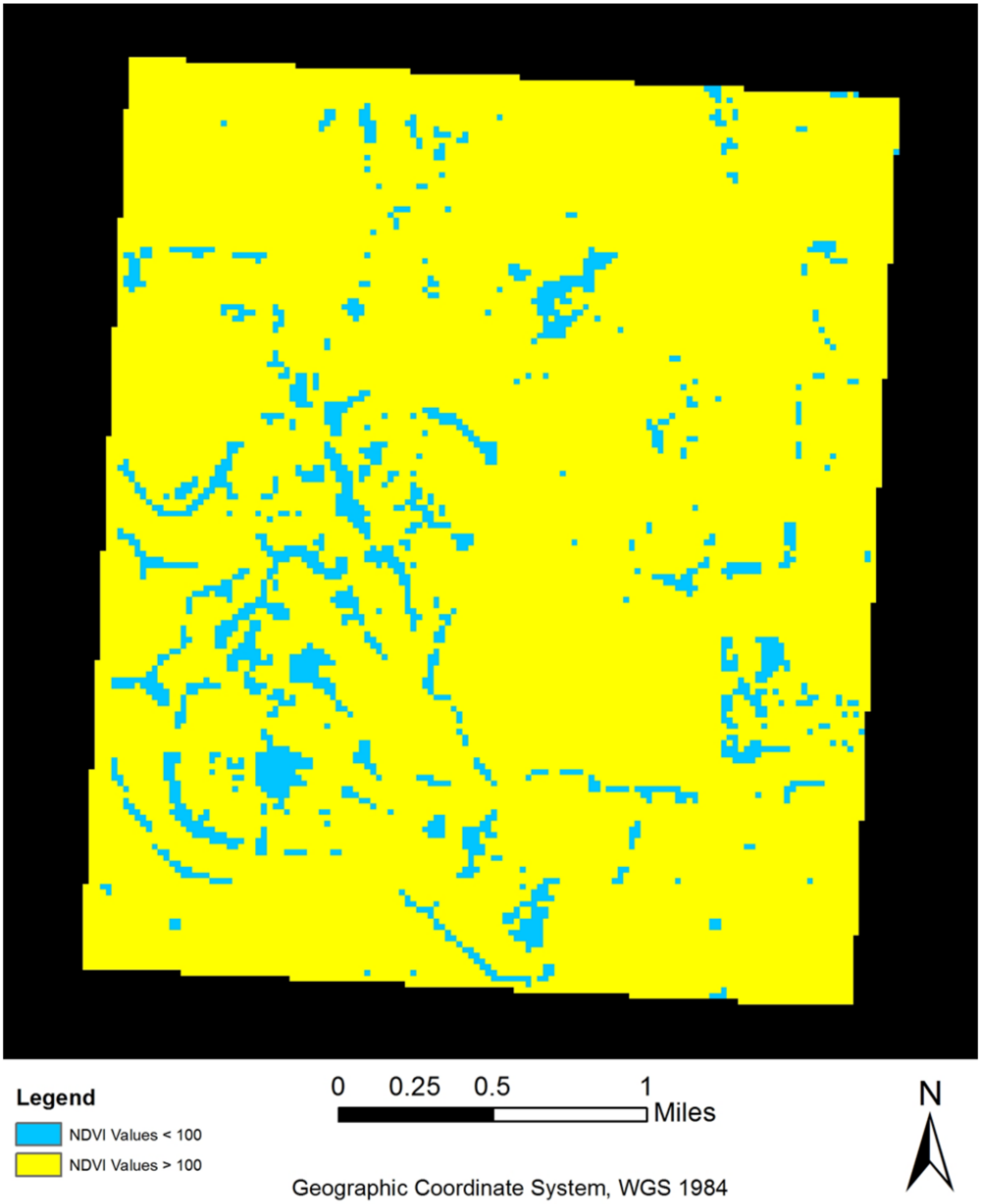

Figure 21 – Raster symbolizing high and low NDVI values derived from the 2011 Landsat Image

A difference raster was also created by subtracting the 1984 image pixel values from the 2011 image pixel values to demonstrate the change in NDVI from 1984 to 2011 (Figure 22). The image was symbolized to depict areas of strong negative change (a decrease in NDVI between -50 and -153, the global minimum of the difference raster), areas with relatively no change (a change in NDVI between -49 and 49) and areas of strong positive change (an increase in NDVI between 50 and 130, the global maximum of the difference raster). The thresholds between the categories were chosen manually to highlight only the areas that had strong negative or positive changes. The range of -49 to 49 was chosen as areas of no change in order to exclude changes that were minimal.

The areas of negative change indicate an area that has changed from an area with a relatively high NDVI to an area of relatively low NDVI. Similarly to other NDVI analysis, some of the more concentrated areas of negative change in NDVI are related to pastures that were most likely growing when the 1984 image was collected but not when the 2011 image was collected. The areas of no change indicate that there were no major improvements or reductions in vegetative vigor within them. The areas of positive change in NDVI indicate that there were relatively higher NDVI values in the 2011 image than the 1984 image. Conversely to the areas of negative change, the major changes here are most likely related to pastures that were actively growing when the 2011 image was collected but not when the 1984 image was collected.

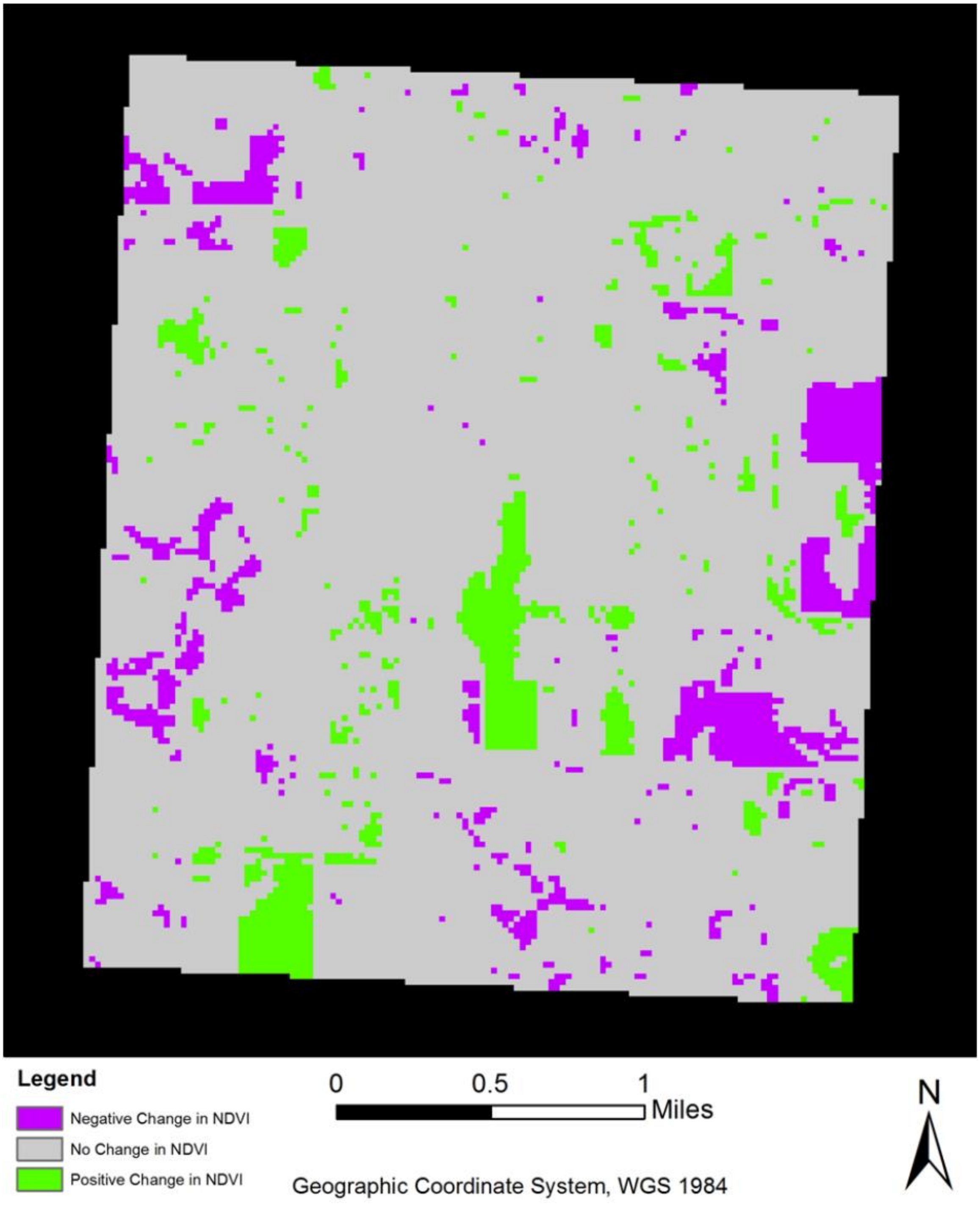

Figure 22 – Change in NDVI from 1984 to 2011

V. CONCLUSIONS

The classified images provided a good indication of land cover types as they relate to the reclamation of abandoned coal mines. They provided a classification scheme that can also be applied to other problem areas within the State of Missouri where reclamation has, or will, occur. They could also assist AML staff to identify features that need to be added to the inventory for future reclamation projects.

5.1 Research Limits and Further Improvements

One of the major limitations of this study was the resolution of the source data. The source data, Landast TM imagery, was selected for its spatial and spectral resolution. Also, its availability for the desired dates made it a preferred dataset. The 30 meter pixel spatial resolution was sufficient for classifying broad landcover types, but was not fine enough to identify small features such as acid mine drainage affected water bodies. Waterbodies in general were hard to identify due to their small size.

Other limitations included the low accuracy of the classifications and the lack of conclusive results of the NDVI analysis. The accuracy of the classification was not ideal, only reaching 75.00% for the 1984 maximum likelihood classification and 67.50% for the 2011 maximum likelihood classification. The small study area may have contributed to the difficulty encountered in creating a highly accurate classification due to the lack of suitable training sites. Additionally, the 30 meter spatial resolution of the images and the relatively small landcover features resulted in some pixels that represented more than one class. These mixed pixels are especially prevalent at the boundaries between two classes, and could help explain the low classification accuracy of some of the classes. The NDVI analysis also proved to be challenging due to the varied types of vegetation present within the study area. Pasture grasses that have active growth periods at different times of the year made it difficult to fully assess vegetative vigor at the time of imagery collections.

Future improvements could be made to address the issues encountered in the process of this study. First, higher resolution data sources could be identified to better identify small features within the study area. Although the availability of higher resolution datasets most likely will not be available that represent the early years of the desired timeframe, datasets from more recent years could provide valuable information about current reclamation needs. The accuracy of the classification could be increased by selecting a larger study area to include more possible training sites for the algorithm. A regional study area, all of Henry County, for example, may provide a better result. The classification accuracy could be further improved by applying spectral unmixing to the images; however, this can only be performed if the spectral signatures of the classes are well known. The NDVI analysis could possibly be improved by selecting imagery from later in the growing season, possibly from May or June, to get a more robust indication of vegetative vigor.

Other future work could be completed to establish an implementation strategy to apply these analyses during the regular workflow of the AML section. The benefits of using remotely sensed images to increase efficiency and success of reclamation activities should not be outweighed by lengthy and time intensive processes. Additionally, special training and resources should not be required in order to apply the analyses. These requirements necessitate the development of a system to assist the staff in their use.

This system could range from a simple guide detailing the steps of the process to a customized model and user interface that guides the production of the analysis outputs. The continued use of this research will be determined by the outcome of this implementation.

5.2 Summary

The change detection analysis provided a good indication of whether or not reclamation activities have been successful. The change detection analysis demonstrated a shift from mine related classes such as barren spoil to non-mine related features such as pasture. Areas where this change has occurred correlates with the areas where the AML section has completed reclamation work within the time between image acquisition dates. It also identified areas of concern where reclamation still needs to occur, or where completed reclamation is in need of maintenance.

NDVI analysis provided some useful information on the distribution and vigor of vegetation on abandoned mine lands both pre- and post-reclamation. The higher values derived from the analyses coincide with areas where either no mining has occurred, or reclamation has already taken place. NDVI images and derived rasters help to demonstrate the trend from barren land with no vegetation to land cover types of vegetated spoil or pasture.

These analyses have some potential benefits. Specifically, they can be used to identify abandoned mine features that are not currently in the program's inventory. They can also be used to assess the changes that occur as a result of reclamation work performed by the program. This can include both the calculation of mined land that has been successfully transformed from a mine affected land cover type to an unaffected land cover type as well as the assessment of vegetative cover and vigor. Overall, the utilization of remotely sensed images can be used to more effectively assess the progress that the AML section is making in reclaiming abandoned coal mines in the State of Missouri.

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