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Mapping wetlands and potential wetland restoration areas in Black Hawk County, Iowa using object-oriented classification and a GIS-based model

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MAPPING WETLANDS AND POTENTIAL WETLAND RESTORATION AREAS

IN BLACK HAWK COUNTY, IOWA USING

OBJECT-ORIENTED CLASSIFICATION

AND A GIS-BASED MODEL

An Abstract of a Thesis

Submitted

In Partial Fulfillment

of the Requirements for the Degree

Master of Arts

James Harken

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ABSTRACT

Wetlands are transitional lands between terrestrial and aquatic systems that provide many benefits, including: floodwater retention, non-point pollution treatment, wildlife habitat, and soil-erosion control. Wetlands in Iowa have decreased over 95% in the last 200 years. Therefore, there is a need to map and monitor these resources, as well as to determine potential sites for wetland restoration. In Black Hawk County, wetland maps are outdated, and ground surveys have proved to be too time-consuming and expensive. Traditional pixel-based automated classifiers of remotely-sensed imagery have also proven to be inaccurate in classifying wetlands because of spectral confusion. This study tests multispectral data, hybrid data, hyperspectral data, a seasonal matrix, and a new object-oriented classifier. These are tested against traditional multispectral, pixel-based (ISODATA and Maximum-Likelihood) classifiers both to see if wetland classification accuracies from remotely-sensed imagery can be increased and to produce an updated wetlands map for Black Hawk County. A hyperspectral image of Eddyville, Iowa is tested to evaluate how well wetlands are classified when a hyperspectral image is used with an object-oriented classifier and a hyperspectral pixel-based (Spectral Angle Mapper or SAM) classifier. A GIS-based wetland restoration model is developed to identify potential wetland restoration sites in Black Hawk County.

This study shows that the object-oriented classifier is more accurate in identifying wetlands and overall land-cover than pixel-based ones (ISODATA, Maximum-Likelihood, SAM) in both multispectral, hybrid-multispectral, and hyperspectral imagery. The summer/fall seasonal matrix produced unacceptable accuracies. Wetlands in Black

Hawk County decreased by 1500 acres (plus or minus an error margin of 375 acres) from 1983 to 2003. The restoration model identified 2,971 acres in Black Hawk County as being highly suitable, 34,307 acres as being moderately suitable, and 121,271 acres as having low suitability for wetland restoration. The results are available at http://gisrl-9.geog.uni.edu/wetland.

Limitations of the study include file size when using the object-oriented classifier, image availability for the seasonal matrix, and the number of variables employed in the GIS-based restoration model. The future direction of the study lies in obtaining hyperspectral data for Black Hawk County, more current Landsat multispectral imagery for the seasonal matrix, and testing of more non-parametric classifiers, such as the CART algorithm.

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CHAPTER 1

INTRODUCTION

Wetlands are an important ecosystem. Cowardin, Carter, Golet, and LaRoe (1979) provide the official federal definition of wetlands: "Wetlands are lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water" (p.1). Other definitions include "Wetlands are a mix of characteristics from terrestrial or upland areas and the characteristics of aquatic or water environments" (Lyon, 1993, p. 7), "...places where plants and animals live amid standing water or saturated soils, also called swamps, sloughs, marshes, bogs, fens, seeps, oxbows, shallow ponds, or wet meadows" (Cohen, 2001, p. 1), and the US Army Corp of Engineers Wetlands Delineation manual: "Those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions" (Environmental Laboratory, 1987, p. 9).

There are several wetland classifications available in the literature. One of the most important is defined by the U.S. Fish and Wildlife Service which classifies wetlands into five types: Palustrine (non-tidal freshwater habitats and open water less than 20 acres), Estuarine (deepwater tidal habitats), Marine, Lacustrine (open water greater than 20 acres), and Riverine, defined as freshwater rivers and streams; (Dahl, 2000). All of these wetland categories must have one or more of the following three attributes: (a) at least periodically, the land supports predominately hydrophytes; (b) the substrate is predominantly undrained and hydric (soil that has developed anaerobic conditions); and (c) the substrate is nonsoil and is saturated with water or covered by shallow water at some time during the growing season of each year. A pictorial representation of two typical freshwater inland wetlands is given in Figure 1.

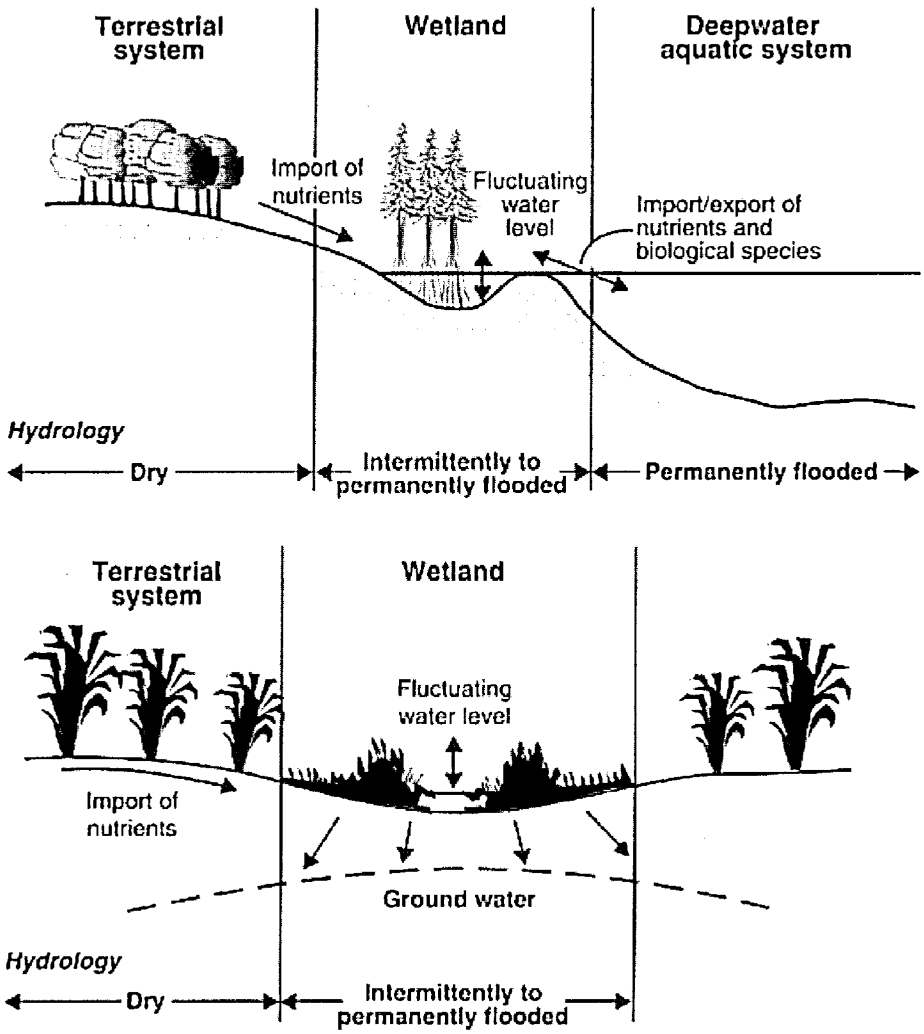


Figure 1. Ecology of Wetland Systems.
(Source: Mitsch & Gosselink, 2000)

The Importance and Status of Wetlands

Wetlands compromise only 3 to 6% of the earth's land surface area, but they provide human populations with a host of goods and services, including food storage, water quality maintenance, agricultural production, fisheries, and recreation (Acreman & Hollis, 1996). They are critical to flood protection, and act like sponges to soak up water and release it slowly. Although most wetlands store an average of approximately three feet of water, a single acre of wetland can store up to five feet, or 1.66 million gallons of flood water (Sierra Club, 2000). Wetlands are also believed to play a significant role in global climate change by acting as a source of atmospheric greenhouse gases such as methane and a sink for both carbon (wetlands contain 15-22% of the world's soil carbon pool), nitrogen, and methane (Takeuchi, Tamura, & Yasuoka, 2003; Trettin, Song, Jurgensen, & Li, 2001). Global biodiversity is also enhanced by wetlands because they are vital for the survival of a disproportionately large number of threatened and endangered species (Mitch & Gosselink, 2000). Wetlands have become a popular way for treating contaminated surface and wastewaters, and are particularly suited for treating non-point pollution, such as agricultural and urban runoff (Dierberg, DeBusk, Jackson, Chimeny, & Pietro, 2002). They can also lessen soil erosion, and moderate stream temperature (critical for certain species survival like trout, Budlong, 2002). Lastly, wetlands have been found to preserve archeological remains (Chapman & Cheetham, 2002).

Despite these proven advantages, wetland conversion to other land uses has been a problem historically and continues to the present day. However, the last few decades have witnessed an enormous rise in awareness of the importance of wetlands. Nationally, at the time of European settlement, the continental United States contained an estimated 221 million acres (89.5 million hectares) of wetlands, or 9% of the total surface area. Over time, wetlands have been drained, dredged, filled, leveled, and flooded to the extent that less than half of the original acreage remains (Dahl, 1990; Whittecar & Daniels, 1999).

Within the state of Iowa, wetlands were viewed as a hindrance to land development and agriculture. In less than 150 years, these rich resources were drained, filled, or otherwise altered, drastically changing the face of Iowa's land. Similar percentages are given concerning the amount of wetland losses in Iowa. One study places the loss at 95% (Arbuckle & Pease, 1999) and another 90%-95% (Cohen, 2001). In a mandated report to Congress by the U.S. Fish and Wildlife Service, only two other states showed higher wetlands losses than Iowa: California and Ohio (Dahl, 1990). According to the Iowa Department of Land Stewardship [IDALS] (1998), the amount of wetlands six years ago covered only 1.2% of Iowa's surface area, compared to 11% two-hundred years ago (Figure 2).

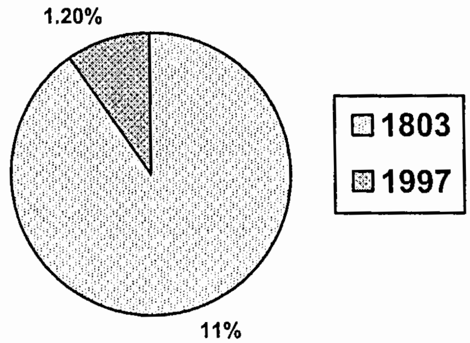


Figure 2. Iowa Surface Area Covered By Wetlands.

This is a loss of approximately 3.5 million acres, or an area approximately the size of the state of Connecticut. The reduction of wetlands in Iowa has also contributed to the fact that Black Hawk, Hamilton, Johnson, Linn, Story, and Tama counties were designated federal (flood) disaster areas five times from 1989-1998 (Sierra Club, 2000) and all of Iowa's 99 counties were designated federal (flood) disaster areas at least once during that time.

The loss of these critical resources (wetlands) in Iowa with some 92% of the land being used for agriculture (Dung, 2003), and their documented value, shows an urgent need to monitor these resources, measure their changes, and provide a method for identifying potential wetland restoration areas. Traditionally, wetlands are delineated using ground surveys. However, these surveys are difficult and time-consuming (Lyon, 1993; Yasuoka et al., 1995). Geospatial technologies, such as remote sensing, Geographical Information Systems (GIS), and Global Positioning Systems (GPS) can provide an alternative and possibly better solution to mitigate the before-mentioned problems (Goldberg, 1998). In addition, remote sensing data can be used for the following: (a) to determine the extent of wetlands, (b) to identify the type of wetland resource, (c) to characterize the general wetland land cover type, (d) to identify submergent and emergent wetlands, and (e) to supply details about the resource (Lyon & McCarthy, 1995). Geographical Information Systems and GPS can be used effectively for natural resource management, conservation, and restoration (Konecny, 2003). This includes inventorying and updating wetlands (Houhoulis & Michener, 2000). The need to update the last wetlands survey undertaken for Black Hawk County (completed by the National Wetland Inventory and Iowa Department of Natural Resources and based upon aerial photos taken in 1983 and 1984), is the justification for this research.

According to the Iowa Department of Natural Resources (2004), "Wetlands are one of the easiest and most quickly restored elements of natural landscape, and they can provide nearly instantaneous wildlife habitat. The Wildlife Bureau offers technical assistance to landowners interested in restoring wetlands on their properties." The Iowa Natural Resource Conservation Service (NRCS) administers the Wetland Reserve Program aimed at returning former wetland areas that have been cropped. The Emergency Wetland Reserve Program also works to place permanent easements on land that has a flood history, returning it to wetland conditions. Wetland determination and mitigation assistance is provided for United States Department of Agriculture wetland compliance programs.

Goal and Objectives

The main research goal is to map and identify potential wetland restoration areas in Black Hawk County, Iowa using remote sensing and GIS technologies. To achieve this goal, the following four objectives are presented:

1. Extract up-to-date and accurate wetland areas from multispectral and hyperspectral images;

2. Evaluate different image classifiers, specifically object-oriented, Maximum-Likelihood, ISODATA, and Spectral Angle Mapper (SAM);

3. Analyze different GIS wetland restoration models from the literature and create such a model for use in Black Hawk County;

4. Disseminate the final results through the Internet via Arc Internet Map Server (ArcIMS).

Research Questions

On the basis of the goal and objectives of the study, the research questions are as follows:

1. How well does the object-oriented classifier perform in comparison to traditional ones, such as Maximum-Likelihood and ISODATA, for the delineation of wetlands using multispectral imagery in Black Hawk County?;

2. Can data fusion, specifically between Landsat Enhanced Thematic Mapper (ETM) multispectral and ETM panchromatic images, improve wetland classification?

3. Is the object-oriented classifier more accurate than SAM in high resolution hyperspectral image classification of wetlands?

4. What role does summer and fall seasonality play in wetland classification when using remote sensing data?

5. What are the most important factors in a GIS-based wetland restoration model for Black Hawk County?

CHAPTER 2

LITERATURE REVIEW

The value of wetlands and their contributions to a healthy ecosystem have been gaining increasing recognition over the past few decades as have the spectral and spatial resolution of remote-sensing satellites since Landsat was first launched in 1972. Along with the increased power of geographical information systems, mapping and monitoring wetlands and other ecosystems with remotely-sensed imagery is proving to be an indispensable tool for understanding these valuable resources and keeping wetland inventories current. In Iowa 92% of the land is in agricultural use (the highest in the nation) and Iowa ranks in the top three states in wetland losses (Dahl, 1990). Therefore, there is a need to update decades-old inventories and research potential wetland restoration areas.

The literature compiled for this study is broken down into classification techniques of wetlands from remotely-sensed imagery and GIS-based wetland restoration models. The review is based on the most current studies published. Although the literature gives an excellent, solid foundation in multispectral assessment of wetlands, recent software introductions (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004) and availability of hyperspectral data give the chance to further research methods of wetland classification. Lastly, wetland restoration models are reviewed to develop a model that can be applied to the landforms of the study area.

Traditional Multispectral Classification of Wetlands

Traditionally, Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and the French Système Pour l'Observation de la Terre (SPOT) satellite systems have been used to study wetlands (Lunetta & Balogh, 1999; Shaikh, Green, & Cross, 2001; Shepard, Wilkinson, & Thompson, 2000; Töyrä, Pietroniro, & Martz, 2000). Other studies have included the moderate-resolution remote-sensing platforms of the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR), the Indian Remote Sensing Program (IRS), the Japanese Earth Resources Satellite (JERS-1), the European Remote-Sensing Satellite (ERS-1), the Shuttle Imaging Radar (SIR-C), and lastly, the Canadian Radio Detection and Ranging Satellite, RADARSAT (Alsdorf, Smith, & Melack, 2001; Bourgeau-Chavez et al., 2001; Chopra, Verma, & Sharma, 2001). Some of the earliest work included visual interpretation of aerial photographs. Unsupervised classification or clustering is the most commonly used classification to map wetlands and maximum-likelihood is the most common supervised method (Özemi, 2000). To aid in the low wetland accuracy percentages that usually accompany these classification methods (30 – 60% accuracies), multi-temporal and ancillary data are often used along with various models to improve classification accuracies. Ancillary data provide a practical solution to help solve the problem of distinguishing among spectral similarities in wetlands, agricultural fields, and forests (Houhoulis & Michener, 2000).

However, there are limitations in delineating wetlands using traditional, optical, multispectral techniques. One limitation on the use of optical data for wetland mapping is their inability to penetrate vegetation canopies, and thus their inability to remotely sense flooding beneath a closed canopy (Bourgeau-Chavez et al., 2001). There has been some research done on wetlands using radar data (Alsdorf et al., 2001; Bourgeau-Chavez et al., 2001; Rio & Lozano-García, 2000) as well as LIDAR (MacKinnon, 2001), but the majority has been concentrated on Landsat TM, MSS, SPOT, and airborne Color Infrared (CIR) photos.

Previous studies for classification of wetlands using rule-based classifiers have shown mixed results. Jenssen and Middelkoop (1992) showed improvements of six to twenty percent accuracies for crop cover classification of Landsat TM images over the maximum-likelihood classifier. Halid (1997) had a decrease in accuracy of land cover changes using a knowledge-based classifier compared to a maximum-likelihood one (78% overall accuracy decreasing to 44%). However, he noted that rule-based classification had the advantages of being quicker and requiring less field work. Sader, Ahl, and Liou (1995) reported overall accuracies of 80% and 82% for wetlands in Maine (in Orono and Acadia National Parks, respectively). Wetland producers accuracy in Acadia National Park was determined to be 77% and wetlands users accuracy 62%. In Orono National Park, wetlands producers accuracy was determined to be 66% and wetland users accuracy 82%. Forested wetlands were emphasized in the study. Özemi (2000) noted that rule-based classifiers generally provide more accurate classification results than the traditional maximum-likelihood method, but not always. In addition, she noted that classification accuracies were much greater using two dates of imagery for Landsat TM (leaf-on and leaf-off). This indicates that seasonal comparison of images for wetland classification is probably needed. Hodgson, Jensen, Mackey, and Coulter (1987) also indicated wetlands could be better defined on imagery acquired in spring when the water table was high.

Houhoulis and Michener (2000) created a rule-based method of wetland change detection using National Wetlands Inventory and SPOT data for a study area in the Flint River Basin in south-west Georgia. Their utilization of the modulus to reduce data volume and provide spectral variability was added to the attribute table of the wetland polygons along with majority land-cover attributes to determine the change criteria (within one standard deviation). They also used a custom Arc Macro Language (AML) script to determine thresholds and provided an accuracy assessment of over 10% of the 12,000 wetland polygons used in the study. The overall accuracy of the study was an impressive 96%, with 90% accuracy for changed wetlands and 8% of the wetlands showing a conversion to other land uses. The reasoning behind the study was that the National Wetland Inventory (NWI) coverages were two decades old and needed to be updated. Limitations of the study include the fact that since only previously surveyed wetlands were monitored for change, the accuracies were artificially high compared to wetlands delineation from scratch. Also, no ground-truthing was performed, accuracy was limited to the 20-meter resolution of the SPOT data, and no allowance was made for created or mitigated wetlands that could have been created within the past twenty years. Other work has been done using multi-sensor assessment (Töyrä et al., 2001) and neural networks (Han, Cheng, & Meng, 2003; Özemi, 2000).

Hyperspectral Classification of Wetlands

Hyperspectral classification of wetlands is relatively new and the literature not yet fully developed. Recently, only a few researchers have reported the use of hyperspectral images for wetland mapping. Relevant studies include Anderson, Garono, and Robinson (2003), Bakker and Schmidt (2002), Carter, Wells, and Lewis (2004), Juan, Jordan, and Tan (2000), and Schmidt and Skidmore (2002). This dearth of studies exists perhaps because hyperspectral imagery requires more complex software and more powerful computers for processing than multispectral imagery. It is also more expensive, but according to the following research, has yielded more accurate results than traditional multispectral imagery classification. The following sections provide a brief background and summarize the available literature.

Studies using pixel classifiers, such as SAM, Minimum Noise Fraction, and Matched Filter, in conjunction with hyperspectral imagery include Marcus, Legleiter, Aspinall, Boardman, and Crabtree (2003), Salem and Kafatos (2001), and Underwood, Ustin, and DiPietro (2003).

The Spectral Angle Mapper (SAM) algorithm is a physically-based spectral classifier that uses an n-dimensional angle to match pixels to reference spectra (ENVI, 2002). The mathematical formula for SAM is as follows:

$$\alpha = \cos^{-1} \frac{\Sigma XY}{\sqrt{\Sigma(X)^2 \Sigma(Y)^2}} \qquad (1)$$

Where in Equation 1;

α = angle formed between reference spectrum and image spectrum
X = image spectrum
Y = reference spectrum

The advantage of the Spectral Angle Mapper technique over traditional Maximum-Likelihood and ISODATA techniques is that the illumination differences across landscapes (e.g., different aspects) do not create false differences between pixels of the same composition (ERDAS, 2002). For a detailed description of the SAM technique see Salem and Kafatos (2001) and ENVI (2002).

Carter, Wells, and Lewis (2004) evaluated the potential of ITD VNIR 10E (a type of sensor) hyperspectral imagery to detect invasive wetland plant species in northern Mobile Bay, Alabama, in September of 2003. Ground resolution was one meter, and the wavelengths captured were in the 400 to 1000 nm range. They were successful in detecting Chinese tallow tree (*Tridica sebifera*), and water hyacinth (*Eichhornia crassipes*), as well as mapping native wetland plants. The researchers continue to evaluate different algorithms for use in coastal wetlands.

Schmidt and Skidmore (2003) studied 27 salt marsh vegetation types in a coastal Dutch wetland and concluded that statistical variation of wetland vegetation reflectance spectra is possible in the visible to short-wave range. They used a three step analysis to test difference between type classes, used continuum removal as a normalization technique in the visible range (although it failed in the infrared range), and measured the distance of the vegetation types in spectral space using the Bhattacharyya and Jeffries-Matusita distance measures. S-Plus software was used to process the 579 bands between 400 and 2500 nm with a gap between 1820 to 1940 nm for atmospheric water absorption. A GER spectrometer was used to measure the in situ reflectance on 132 vegetation plots. The bands found to be the most useful for discriminating wetland vegetation types were between 740-1820 nm in the shortwave infrared and between 400 to 700 nm in the visible spectrum. Six wavelength bands were then selected out of the above mentioned bands based on their higher frequency of statistically different median reflectance and their more-or-less spacing across the whole spectrum. Those bands are: 404, 628, 771, 1398, 1803, and 2183 nm. This study provides a foundation for other researchers wishing to test those specific bands for their own wetland study areas.

Bakker and Schmidt (2003) concentrate on edge filtering for hyperspectral images in agriculture and salt marsh test areas. They conclude that hyperspectral edge filters can assist in image interpretations. Lastly, Juan et al. (2000) flew a hyperspectral mission over Fort Drum Marsh in Florida using an unspecified hyperspectral sensor that collected 64 wavebands in the 399.2 to 920.5 nm range. They were successful in delineating the wetland species from the airborne hyperspectral imagery, but did not release what wavebands were most sensitive for different plant species.

Anderson, Garono, and Robinson (2003) used Compact Airborne Spectrographic Imager (CASI) Imagery along with Landsat 7 ETM+ images to map wetlands along the Columbia River. They originally wanted to map the entire area with CASI, but ran into time and budget issues. Their configuration for the CASI imagery was 19 bands from 459.3 nm to 819.8 nm, and 1.5 meter spatial resolution. They masked out the urban areas and used National Wetland Inventory maps along with ground truthing to create the classification. They were able to determine over 80 different classes with the CASI imagery, 20 of which were purely spectrally determined. They also used ERDAS Imagine software and the ISODATA unsupervised classification algorithm, where 6-7 major habitat types were identified and then continuously cut from the originally 19-band mosaic until all spectral classes fit their criteria of narrowness. Their accuracy assessment has still not been completed.

Lastly, Underwood et al. (2003) mapped iceplant (*Carpobrotus edulis*) successfully in a southern California coastal habitat using the Minimum Noise Fraction algorithm and band-ratio indices. Salem and Kafatos (2001) used the SAM algorithm along with hyperspectral imagery to detect oil spills in Chesapeake Bay, and concluded such a method minimized the limitations of conventional remote-sensing techniques (i.e., multispectral and aerial photographs). Marcus et al. (2003) evaluated one meter, 128 band hyperspectral imagery for mapping in-stream habitats, depths, and woody debris in Yellowstone National Park. They concluded that clear water was necessary to measure depth, and that tree canopy cover was also a problem. They accomplished high overall accuracies ranging from 69 to 99%. One method (classifier) not seen in the hyperspectral and wetlands literature is the object-oriented one, discussed in the next section.

Object-Oriented Classification of Wetlands

Object-oriented classification is relatively new to the field of remote sensing and most of the studies completed have taken advantage of high-resolution imagery (IKONOS, QuickBird, etc.) for land-cover classification. Of particular interest to many researchers is urban area classification due to the functions associated with eCognition software. However, other research has focused on natural resource and wetland classification, as shown by many studies (Antunes, Lingnau, & Da Silva, 2003; Civco, Hurd, Wilson, Song, & Zhang, 2002; Gomes & Marcal, 2003; Ivits & Koch, 2002; Kaya, Pultz, Mbogo, Beier, & Mushinzimana, 2002; van der Sande, de Jong, & de Roo, 2004).

van der Sande et al. (2004) divided one meter, four-band IKONOS-2 imagery into different land cover segments with an overall accuracy of 74%, and then used that thematic map as an input for a flood-simulation model. They were able to then successfully estimate flood damage for local land-use planners and insurance companies.

Gomes and Marcal (2003) used 9-band 15-meter Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery to revise a 1995 land-cover data set for the Vale do Sousa region in northwest Portugal. Their overall accuracy was 71.5%; forested areas, which were emphasized in the study, had an average accuracy of 46.3%.

Antunes et al. (2003) segmented a 4 band IKONOS image to identify riparian areas that could not be spectrally differentiated in the northern part of the state of Parana in southern Brazil. They needed to map declining wetland areas for resource management because of increased agricultural activities. Their accuracies were 75.4% for riparian vegetation and 78.6% for swamp vegetation. They also ran a Bayesian Maximum Likelihood classifier for the same areas and came up with 56.0% for riparian areas and 45.3% for swamp vegetation. Although they showed promising results, there was a disappointing lack of detail in their exact pre-processing and methodology steps.

Civco et al. (2002) compared knowledge-based and object-oriented techniques (among others) for land cover change detection in the Stony Brook Millstone River watershed in New Jersey using Landsat ETM+ data. They concluded that no single method was superior for their study data and area. However, they admitted "The image segmentation and object-oriented classification holds much promise." and "The image segmentation and object-oriented classification and change detection appeared to have produced better overall results, especially in terms not only detecting and characterizing the nature of change, but also in minimizing the *salt-and-pepper* effect caused by isolated and non-contiguous pixels" (p. 8). Ivits and Koch (2002) used six European test sites and IRS panchromatic and Landsat ETM imagery along with object-oriented classification to develop a preliminary landscape habitat ecological analysis.

Kaya et al. (2002) acquired RADARSAT-1 data to map wetlands and other land cover types in coastal Kenya to assess malarial risk. Their object-oriented approach resulted in 85.5% overall accuracy and 65.3% accuracy for wetlands. They tested Synthetic Aperture Radar (SAR) data because of lack of availability of multi-spectral cloud free images for coastal, tropical regions. Some problems they encountered with the data included backscattering returns being classified as wetlands, as well as certain forest types (mangrove) also being wrongly classified as wetlands. Harken and Sugumaran (2004) found that an object-oriented classifier had a high degree of accuracy in classifying freshwater wetlands using 60 cm CASI hyperspectral imagery in a study area in Eddyville, Iowa.

Wetland Restoration Models Using GIS

As Hey and Philippi (1999) note, wetlands can be restored to provide functions that have been lost. They also note that wetland restorations are most effective when they currently occupy less than 10% of the area to be restored. There are no standard models for restoring wetlands as there are for determining and mapping wetlands (which in itself is a complex, time-consuming procedure). However, there have been five studies completed where remotely-sensed / GIS-based wetland restoration models have been created and implemented. Berman, Rudnicky, Berquist, and Hershner (2002) worked in Virginia and the Lower Mississippi River Conservation Committee (2001) completed a study in the Mississippi Alluvial Valley in Missouri. Sader et al. (1995) worked in Maine, Braster and Hadish (1996) in western Iowa, and Riverlink (2000) in North Carolina.

Other useful studies include wetland hydrological modeling (Brown, Johnston, & Cahow, 2003; Loiselle, Bracchini, Bonechi, & Rossi, 2001; Tsihrintzis, John, & Tremblay, 1998; Whittecar & Daniels, 1999) as well as wetland nutrient modeling (Wang & Mitsch, 2000), wetland soil carbon modeling (Trettin, Song, Jurgensen, & Li, 2001), wetland habitat modeling (Wakeley, 1988) and wetland buffer modeling (Budlong, 2002). The end product of the Lower Mississippi River Conservation Committee (2001) model is a raster map, where each 30-meter cell has a arbitrary weighted value of 7 to 75, which is to be interpreted as an indicator of relative probability of a given grid cell to deliver water quality benefits if restored. The model's purpose was to prioritize areas for forested wetland areas on private land next to the Mississippi River in south-east Missouri. They used ARC/INFO and ArcView Grid Analyst software, as well as State Soil Geographic Database (STATSGO) soil coverages, a Digital Elevation Model (DEM), and geomorphology coverages. Hydrology (flooding, topography) was given

73.33% of the total model weight, and reforestation (soils) 26.67%. The reasoning behind the weighting was not given.

Riverlink (2000) developed three disparate mountain wetland restoration models; one for a general need assessment that identified 94 watersheds, a second to identify high-probability wetland restoration areas that identified 140,000 acres of land, and a third to identify large parcels of land, 25 acres or more, that identified 477 potential sites, and 78 high potential sites. Hydrologic units were determined to have too coarse a resolution for the study needs so small management units were created in ArcView based on a flow accumulation of 5,000 grid cells or approximately 1,148 acres. Grid cells in each layer of the model (wetlands, building starts, agriculture, roads, elevation, sewer, and conservation/natural resource areas) were ranked on their presence or absence, their linear distance from each other, and what percent of the grid cell they covered. The cells were then scored and regrouped into three natural break categories of restoration potential, high need, medium need, and low need. They also used another natural break (Jenks) regrouping based on final parcel size; i.e., their need was to develop wetland restoration areas in the largest tracts possible.

Budlong (2002) used three factors in determining potential riparian habitat buffers in the Whitewater River Watershed in south-eastern Minnesota. They were: proximity of row crops to streams and rivers, slope, and proximity of feedlots to rivers and streams of the watershed. It should be noted that in most of the restoration models reviewed, proximity to a hydrological feature (usually a river or stream) and slope were always used as model factors. Hydric soils were also found to be important in ranking potential wetland restoration areas, and these areas were always preferred to be agricultural. Budlong's ranking system divided subwatersheds into high, moderate-high, moderate, or low restoration potential. To achieve this goal of ranking, percentages were used for land-cover types within the 50-meter stream buffer (>65% row crop area meant high potential, etc.), mean slope value within 300 meters of all hydrological features, and total areas of feedlots within the 50-meter stream buffers. The final equation was: (x = row crop land-cover %, y = slope, and z = feedlot areas) RESTORATION POTENTIAL = (x * 0.65) + (y * 0.25) + (z * 0.10). One of the most important conclusions from this study was that riparian stream buffers should be adjacent to the headwater streams of a watershed for maximum ecological effect.

Berman et al. (2002) used ARC/INFO software, a land-cover layer derived from 30-meter Landsat United States Geological Survey (USGS) imagery, a digital Soil Survey Geographic Database (SSURGO) layer, a hydrology layer, a National Wetlands Inventory (NWI) layer, and conservation-area layers. They based their analysis on wetland functions. Polygons were ranked as good, high, or excellent according to water quality, flood control, sediment control, erosion control, and wildlife habitat. Landscape position and surrounding land-cover was also used to assign rankings. Agricultural areas were again favored in the ranking schema.

Lastly, Braster and Hadish (1996) wanted to identify current land uses and offer alternatives to land managers of floodplain areas. They wanted to do this by using GIS, strengthening relationships with local organizations and landowners, and providing informed development strategies. Chi-square values were developed for the variables of depth of water table, number of NWI wetlands, presence of NWI wetlands, position of soil mapping units, corn-suitability ratings, presence of hydric and non-hydric soils, and proximity to levees. Logit modeling was used and weights and ratings for the variables were based on the chi-square for the first model (Model 1) and field experience for the second model (Model 2). The formula for the composite score was = $(W^1 * R^1) + (W^2 * R^2) + \ldots + (W^\wedge 7 * R^\wedge 7)$ where W^1 is the weight for the variable mapped data layer 1 and R^1 was the rating assigned to the category on data layer 1. Weightings were based on a GIS map arithmetic approach, after Anderson (1992). After applying the models to the 312 selected study sites frequency statistics were generated. Both models showed a high improvement over chance (83.0 and 82.1% respectively) in predicting high-probability locations of wetland restorations.

All of these studies in both wetland classification and restoration methods have been important in the fields of wetland delineation and restoration research. Their limitations include not bringing together updated wetland classification and restoration models and unacceptable accuracies. This study will attempt to address some of those issues through the use of a new classifier (object-oriented), up-to-date data sets, and a unique site context (the Iowan Surface and Southern Iowa Drift Plain landforms, more specifically Black Hawk County and Eddyville) in which to apply the methods and potential wetland area restoration model. Also, in the literature the majority of hyperspectral mapping of wetlands has been concentrated in coastal and estuarine areas, and not in freshwater inland areas.

CHAPTER 3

METHODS

Study Area

Two study areas were used in this research: Black Hawk County, located in the northeastern part of the state and encompassing 567 square miles, and 50 acres near Eddyville, in south-east Iowa. The imagery used included 30-m Landsat ETM+ for Black Hawk County and 60 cm CASI for Eddyville, discussed further in the next section. The two study areas were chosen for the following reasons: (a) Black Hawk County because imagery was available at no cost, and local experts could critique the methodology along the way; and (b) Eddyville because it is the only portion of the state with a hyperspectral dataset where wetlands are present.

Data Used

Black Hawk County Multispectral Images

Black Hawk County, Iowa is the fourth most populous county in the state and is located at 42.491N Latitude and 92.367W Longitude. The multispectral imagery used for classification is as follows: An April 2002, 1-meter resolution Color Infrared Photo mosaic (Figure 3, left), obtained from the Iowa Geographic Image Server, a September 2000, 30-m Landsat ETM+, and a July 1999, 30-m Landsat ETM+ obtained from the University of Northern Iowa's STORM Project (Figure 3, right). Two hybrid data sets were created by pan-sharpening the Landsat images with their 15-m panchromatic band, Principal Components Analysis and a Matrix of the two seasonal Landsat images. The choice of the data sets was based on their no cost availability and their temporal applicability (all three within the last four years). This is pertinent because one of the project goals was to create an updated wetlands map for the county using the most up-to-date imagery available. As stated previously, the current wetlands map, created by the Iowa Department of Natural Resources (IDNR) and the NWI, is based on aerial photograph interpretation and field surveys done almost twenty years ago. The vector ancillary data used for cross checking the multispectral imagery, classification accuracy assessments, and as direct inputs into the restoration model (wetland areas, hydrology, soils, and conservation areas) were obtained from various sources, including the USGS, NRCS, IDNR, NWI, and Iowa Geographic Map Server. Additionally, data were acquired from the Black Hawk County GIS office. The software used with the multispectral imagery was ERDAS Imagine 8.6, eCognition 3.0, and ArcGIS 8.2.

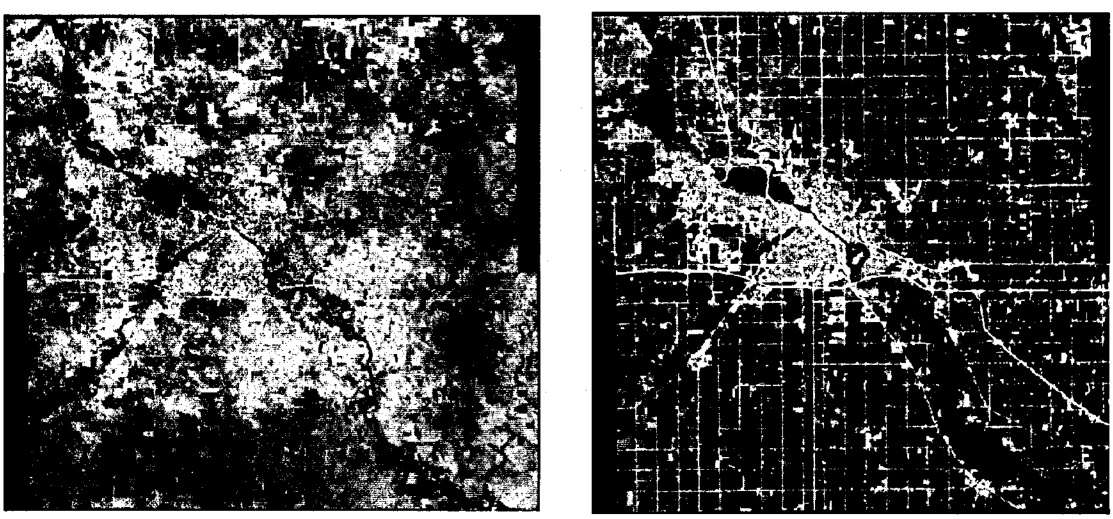


Figure 3. Black Hawk County, Iowa. One meter CIR image (left) and 15 m Landsat ETM image (right).

Eddyville Hyperspectral Image

Eddyville, Iowa is a small town located in the south-central part of the state along the Des Moines River at 41.160N Latitude and 92.631W Longitude. The hyperspectral image used for classification was flown with the CASI sensor in July of 2001 for a Iowa Department of Transportation & National Consortium on Remote Sensing in Transportation – Environmental Group project (Iowa Department of Transportation & National Consortium on Remote Sensing in Transportation – Environmental Group [NCRST-E], 2002). The 2001 image is a mosaic of seven flight lines and has a spatial resolution of 60 cm with 25 contiguous spectral bands, each of which is approximately 0.018 micrometers with a range of 350 to approximately 2500 nanometers (Figure 2). In addition, a 1-meter Color Infrared Image from the IDNR, SSURGO maps and NWI data were used for training and accuracy assessment. The software used to process and classify the hyperspectral image was ENVI 3.6 and eCognition 3.0.

The 60-centimeter 2001 Eddyville image encompasses approximately 969 acres and contains unique ecological habitats. The Iowa Department of Transportation discovered this when they planned a highway bypass northeast of the city and citizens informed the IDOT of the protected species and habitats (NCRST-E, 2002). However, only a 50-acre test portion of the study area was classified in this research (See Figure 4). Wetland vascular plant species in the area include such species as: *Festuca rubra L.* (red fescue), *Pycnanthemum tenuifolium* (Slender mountain mint), *Polygonum persicaria* (Spotted ladysthumb), *Conyza sp., Phalaris arundinacea* (Reed canarygrass), *Galium aparine* (Goose-grass), *Utica dioica* (nettles), *and Morus alba* (White mulberry). All of the before mentioned species occur on the 1996 National List of Vascular Plant Species that Occur in Wetlands, published by the U.S. Fish and Wildlife Service (United States Fish and Wildlife Service, 1996).

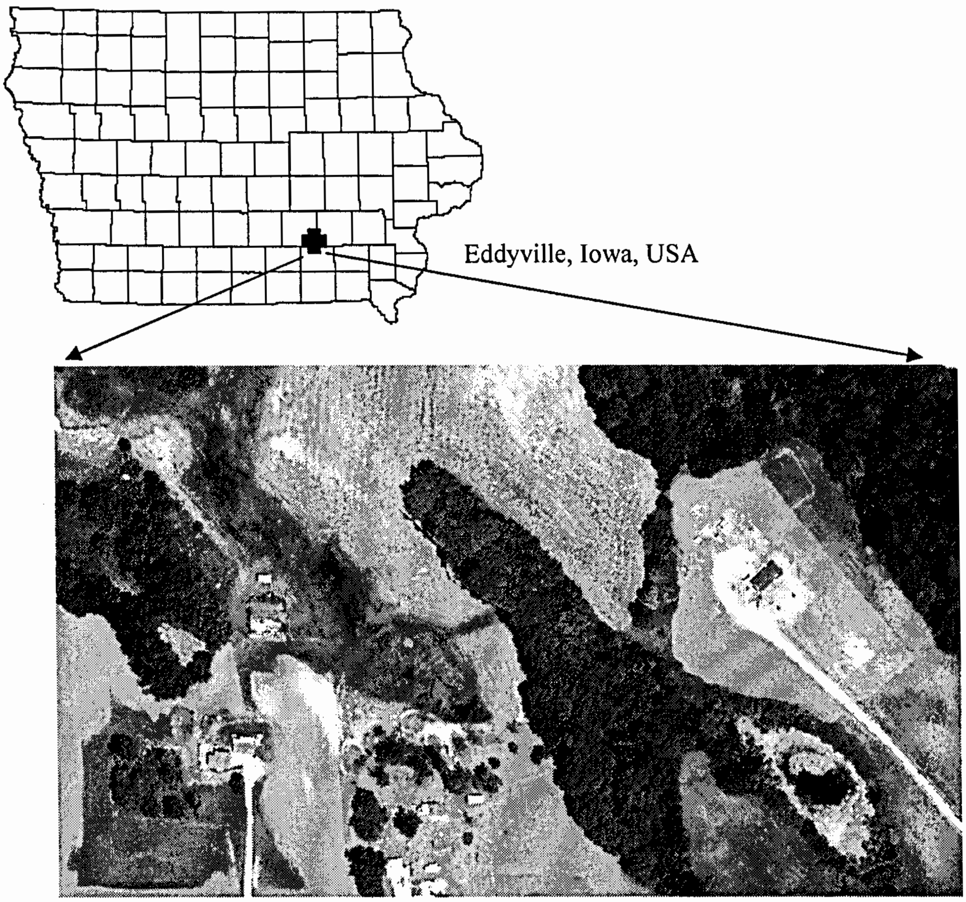


Figure 4. Hyperspectral Image 50 Acre Study Area.

Image Analysis and Classification

The following sections provide an overview of object-oriented classification and the processing behind the multispectral and hyperspectral images. Figures 5 and 6 demonstrate the overall flow of the multispectral and hyperspectral image analysis process.

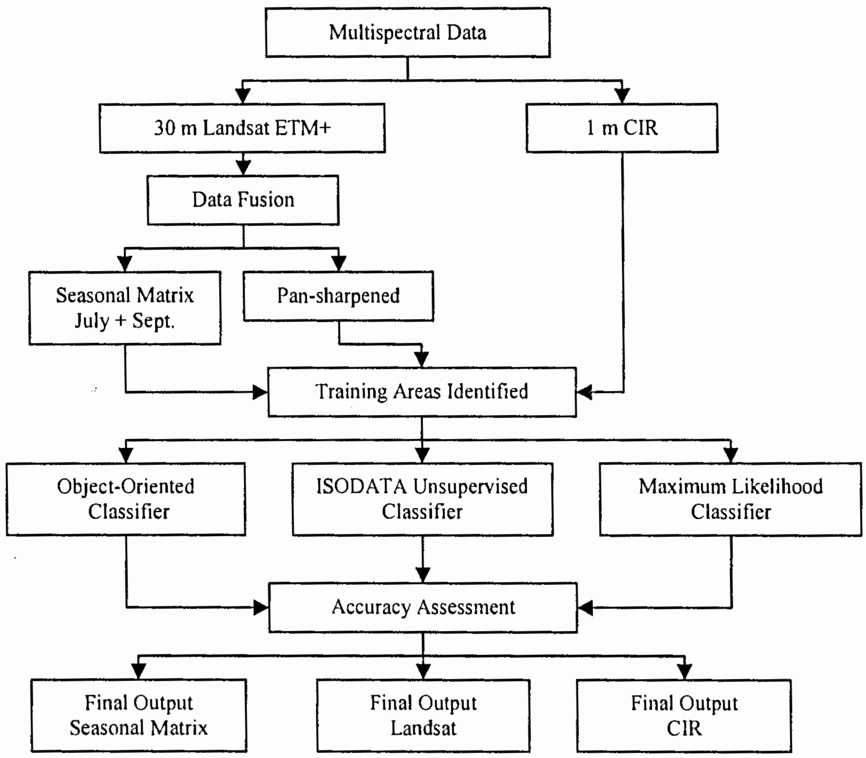


Figure 5. Multispectral Imagery Processing Flowchart.

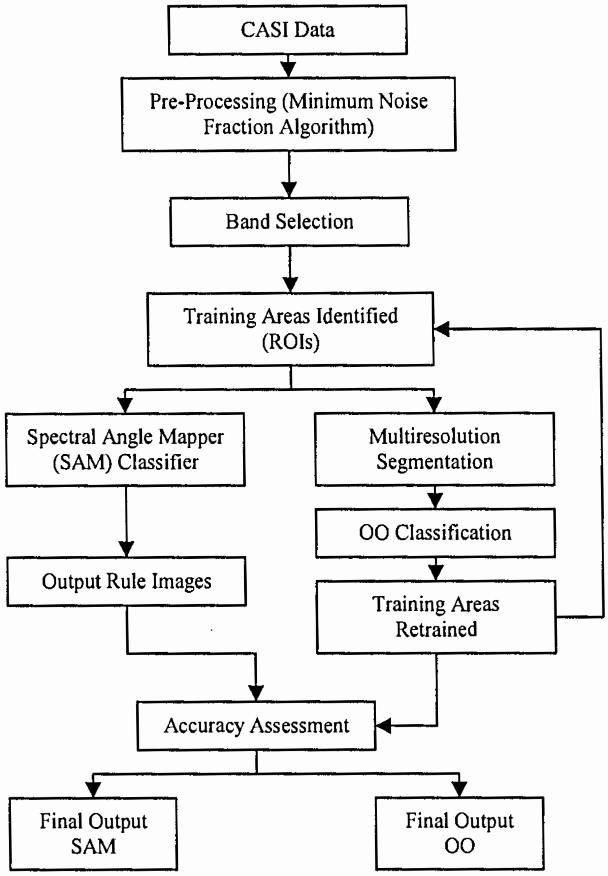


Figure 6. Hyperspectral Image Processing Flowchart.

Object-Oriented Classification

In contrast to traditional image-processing methods, the basic processing units of object-oriented analysis are image objects or segments, and not single pixels (Baatz & Schape, 2001). The reasoning behind this is the expected result of many image-analysis tasks is the extraction of real-world objects. Representation of image information is based on the networking of these image objects, which must be explicitly worked out in contrast to implicit neighbor objects on the pixel scale. Scale is an important consideration in object-oriented analysis because it determines the occurrence or nonoccurrence of a certain object class, i.e., a house or a subdivision, or a field or an ecosystem. This is achieved by a strict hierarchical structure that allows relations between objects and their sub-objects and super-objects. Single pixel objects represent the smallest possible processing scale. Other information used in object-oriented analysis includes tone, shape, texture, context, and information from other object layers.

The method of segmentation of the image objects is important, as there are an almost infinite number of solutions. They can be roughly grouped into two categories: knowledge-driven (top down) and data-driven (bottom up). Examples of data-driven segmentation include unsupervised spectral classification, region-growing algorithms from seed pixels, and texture-segmentation algorithms. According to the eCognition User Guide (Baatz & Schape, 2001), image segmentation in the eCognition software is essentially a heuristic optimization procedure which locally minimizes the average heterogeneity of image objects for a given resolution over the whole scene. The parameters that must be set for image segmentation in eCognition include: (a) aliases, (b) layer weights, (c) image-object level, (d) scale parameter, (e) segmentation mode, (f) composition of homogeneity criterion, and (g) type of neighborhood.

Classification is based on fuzzy systems which use a degree of probability to express an object's assignment to a class. Please refer to Figure 7 for a graphical example of a fuzzy function. The membership value lies between 1.0 and 0.0, where 1.0 expresses full membership/probability and 0.0 expresses absolute non-membership/improbability.

In eCognition, the software used for this project, supervised classification was used to create training areas to classify the data, and ultimately, to see how well wetlands were classified.

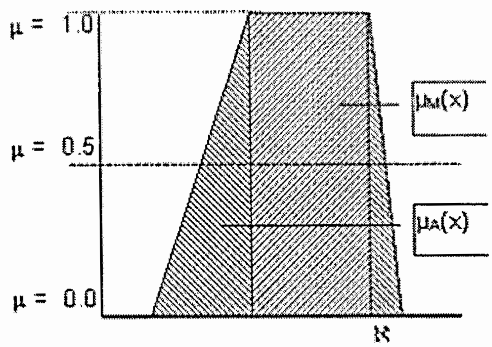


Figure 7. Example of a Fuzzy Function. A crisp set M (rectangle) and the fuzzy sets A and C (triangles) over a feature range X.

Multispectral CIR Image Classification

The unsupervised classification of the CIR 1-meter (4.6 GB file size) was completed using ERDAS Imagine's ISODATA algorithm with the following parameters: 120 classes with a convergence threshold of .95 and 30 maximum iterations. To identify separable clusters in the histogram, 120 classes were selected. Classes were then identified by visual interpretation based on the original false-color image and recoded (merged) into 6 general classes based on the Anderson, Hardy, Roach, and Witmer (1976) USGS classification system: Wetland (includes Woody and non-Woody Wetlands), Mixed Forest, Artificial Surface, Fallow/Bare Soil, Mixed Grasses (includes Mixed and Herbaceous Grasses), and Open Water. The supervised classification of the CIR was completed with ERDAS Imagine's Maximum-Likelihood Classifier, using a created signature file of polygon AOI's by visual interpretation and NWI ancillary data and grouped into the same six general classes used in the unsupervised classification: Wetland, Mixed Forest, Artificial Surface, Fallow/Bare Soil, Mixed Grasses, and Open Water. The accuracy assessment for the CIR was performed by generating 300 random stratified points or 50 points per class. The points were then visually interpreted on an unclassified 2002 CIR image.

For the object-oriented classification of the 1-m CIR image, a 2,881-acre subset was classified, due to file size restraints within the software. This specific limitation is discussed in greater detail in Chapters 4 and 5. Layer 3 of the CIR image was given a slightly higher weighting (1.0 versus 0.8 for layers 1 and 2) based on its proven vegetation sensitivity characteristics (Lillesand & Kiefer, 2000). For the accuracy assessment of the subset image, GPS ground truthing was performed for 35 areas during June of 2003.

Multispectral Landsat ETM Image Classification

The unsupervised classification of the Landsat ETM+ 15-m image of Black Hawk County was done using the same parameters as the other unsupervised classification (CIR) to insure statistically comparable results. The ISODATA algorithm was used to separate the image into 120 classes with a convergence of 0.95 and 20 maximum iterations. Classes were identified by visual interpretation, histogram separability, and ancillary data and then grouped into six classes. A Row Crop class was substituted for Fallow/Bare Soil for this classification because the image was captured in September and much more planted vegetation was present than in the April CIR. The other five classes remained the same. The supervised classification of the Landsat image was completed using the ERDAS' Maximum-Likelihood Classifier, using a created signature file of polygon AOI's based on visual interpretation and NWI ancillary data and grouped into the same six classes as the unsupervised Landsat classifications. The accuracy assessment was performed by generating 240-300 random stratified points or 40-50 points per class depending on pixels-per-class availability and visually interpreted using both an aerial photo and an unclassified TM image.

For the object-oriented classifier in eCognition, Layers 3, 4 and 5 on the Landsat Image as well as layer 3 (SWIR) on the CIR were given slightly higher weightings (1.0 compared to 0.8) during the initial segmentation based on their proven vegetation sensitivity characteristics. Each data set in eCognition was classified according to an average of 185 objects per class and 50 samples per class were tested (6 classes) for a total of 300 random sample points for the accuracy assessment (except for the Landsat ETM 30-m where lack of objects kept the points down to 20 per class). Objects generally ranged from 5-15 pixels in size for the CIR and 94-95 pixels for the Landsat image.

A seasonal matrix (Landsat summer/fall images) was created in ERDAS Imagine's interpreter function under GIS analysis to address the third research question and followed the same classification and accuracy assessment procedures as mentioned above. Figure 5 shows the overall multispectral processing flow for both the CIR and Landsat ETM+ data.

Hyperspectral Image Classification

The Spectral Angle Mapping Wizard was run in ENVI against the subset Eddyville hyperspectral image. The wizard is composed of 10 steps, however only 4 of the most pertinent steps are shown in the flowchart in Figure 6. The first step in the image analyses was to select suitable bands and to reduce noise. A Minimum Noise Fraction (MNF) algorithm was run to determine the inherent dimensionality of image data, segregate noise, and to reduce the computational requirements for subsequent processing (Boardman & Kruse, 1994). The MNF is a linear transformation that consists of two separate principle component analysis (PCA) rotations, separating noise from signal and compressing spectral information to a few bands (Green, Berman, Switzer, & Craig, 1988). Based on the MNF output graph of eigenvectors and by visually inspecting the new bands, 16 of the 25 bands were selected as inputs for the classification. The next step in the flow chart is the identification of training areas or ROI's (Regions of Interest), or supplying spectral endmembers as stated in the SAM wizard. Regions of Interest were selected from ground control points and augmented with visual interpretation. For the entire 969 acre image, 82 ground truth points were available, 41 of which were used to develop training areas and 41 of which were used to develop ROI's for accuracy assessment purposes. Training and accuracy areas were also grown from seed pixels and manually delineated into polygons based on visual interpretation of a 1-meter Color Infrared Image along with corresponding digital SSURGO soil maps and National Wetlands Inventory data. The Spectral Angle Classifier was then run using a maximum angle of 0.10. Output rule images were also generated to see if any of the classes were poorly identified. A comparison between the classified image and validation areas was generated using standard post-classification techniques, resulting in a confusion matrix (see Table 14). For more information on post-classification techniques using ENVI and hyperspectral images, refer to Underwood, Ustin and DiPietro (2003).

Nine classes were chosen to represent all wetland types present as well as additional aggregated land cover types. Wetland types were based on ground truth assessments and other land cover types were based on the Anderson Level classification (Anderson et al., 1976). The classes include three classes of wetland: Open Water, Aquatic Vegetation, and Flooded Forest, and the other land cover classes include: Floodplain Crop, Upland Crop, Artificial Surface, Herbaceous Cover, Shadow, and Mixed Forest. These are shown in the final output maps (Figure 10).

For the object-oriented classifier, the same procedures were followed for steps one through four of the flowchart shown in Figure 5. The same 16 bands used for the SAM classifier were exported to an ERDAS Imagine format (.img), and then subset into a smaller file size (because of eCognition's file size limitation), and lastly imported into eCognition. The hyperspectral image was segmented using the following parameters: 33-pixel average object-size (derived from a segmentation parameter of 10 pixels), equal weighting given to each of the 16 bands or layers, and standard nearest-neighbor relationship for the class hierarchy. For more information on object-oriented classification see Benz (2001), Baatz and Schape (1999), and Darwish, Leukert, and Reinhardt (2003).

A standard accuracy assessment was also run in eCognition, using ground truth points and visually interpreted areas, resulting in a confusion matrix output analogous to ENVI's: overall accuracy, wetland users accuracy, wetland producers accuracy, and the kappa statistic.

GIS-Based Restoration Model

A restoration model for Black Hawk County was developed to identify areas that cannot be defined as current legal wetlands, but due to their nature of soil properties, distance to surface hydrological features, and elevation, were most likely wetlands in the past. It was also created to reveal what areas that would provide the most benefit for the least cost and time when planning conservation within the county.

The model shown in Figure 8 is based on Berman et al. (2002), Braster and Hadish (1996), Budlong (2002), Cowardin et al. (1979), Lower Mississippi River Conservation Committee (2001), Riverlink (2000), Sader et al. (1995), and the US Army Corp of Engineers Wetland Delineation Manual (Environmental Laboratory, 1987). These authors found hydric soil, low slope, and distance to hydrological features and existing wetlands as the most important variables. Those variables were weighted in this model accordingly except for low slope, as the entire county study area is flat enough to disregard that as a factor. Other variables included in the literature but not deemed applicable to the study area of Black Hawk County were defining hydrological basins, distance to levees, and amount of forest cover. Since this study is focused on wetland restoration sites and not current delineation and mapping of wetlands, criteria one of the federal wetland definition (hydrophytic vegetation) was not used. Significant land cover changes (mostly conversion to agriculture) in the study area during the last 150 years have resulted in destruction of most hydrophytic vegetation.

Four data layers were incorporated into the model shown in Figure 8: (a) a SSURGO soil type layer from the NRCS, (b) a hydrology layer (rivers and streams) from the IDNR, (c) an existing wetlands layer from the NWI, and (d) a shapefile of Black Hawk County Conservation Areas obtained from the Black Hawk County GIS office. All shapefiles were converted into coverages in ArcGIS 8.2 to build topology and converted to the same projection, Universal Transverse Mercator Zone 15 North, North American Datum 27. The four coverages were then converted into raster (grid) format in ArcGIS Spatial Analyst to facilitate weighting and ensure uniform cell size between layers. A 30-meter cell size was chosen as this was the lowest resolution of confidence according to the accuracy assessments included in the layers' metadata. Also, a 1992 30-meter USGS Landcover map was used to initially mask out areas unsuitable for restoration (urban, bare rock and sand, open water, existing wetlands) and a 1996 county roads map from the IDNR was used to mask out a 30-m buffer along roadsides (see Berman et al., 2002).

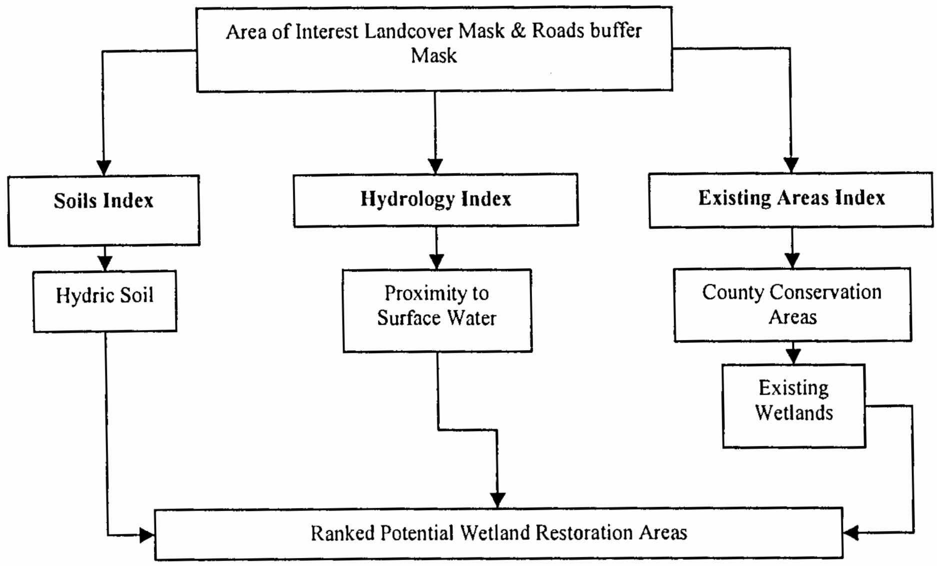


Figure 8. GIS-Based Wetland Restoration Model for Black Hawk County.

Weighting was accomplished by evaluating which criteria were the most important for the study area of Black Hawk County. The Existing Areas Index was evaluated to be the most important, with areas adjacent or contained in an existing county conservation area ranked as a one (on a scale of one through four, one being the highest), and the adjacent to existing wetlands factor ranked as a three. The reasoning behind this is that wetlands have a greater chance of being restored and are easier to manage if they are to be located in land already owned or adjacent to county conservation land (S. Finegan, personal communication, May, 2003). The Soils Index was ranked as the next in importance, because to meet the federal definition of a wetland, the wetland must contain hydric soil (Cowardin et al., 1979). Therefore poorly-drained, hydric soil was given a ranking of two. Lastly, proximity next to a surface hydrological feature was ranked at four, because of the importance given this variable in previous studies

(Budlong, 2002). All cells in each layer were reclassified using Spatial Analyst's Reclassify function by adding a column in the attribute table (RANK) and providing a score. The final equation, adapted from Budlong (2002), was: (x = existing area index total, y = soil index total, z = hydrology index total) RESTORATION POTENTIAL = [(x * 0.85) + (y * 0.65) + (z * 0.40)].

CHAPTER 4

RESULTS AND DISCUSSION

The classification results can be thought of as a binary tree, as shown in Figure 8. Multispectral classification results for Black Hawk County include three classifiers for the CIR imagery, and three classifiers for the Landsat ETM imagery. Hyperspectral classification results for Eddyville include two classifiers for the CASI imagery.

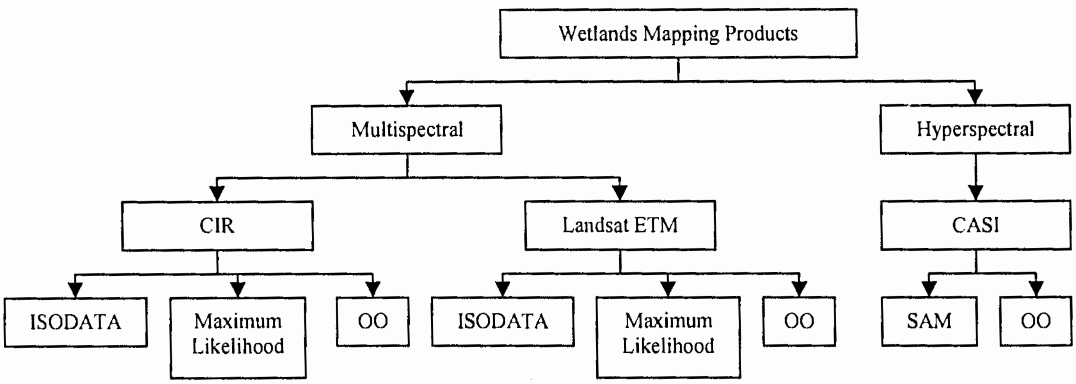
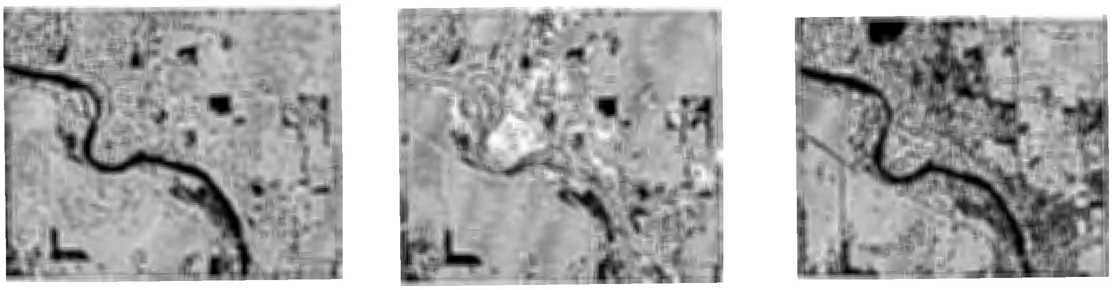


Figure 9. Research mapping results.

Multispectral CIR Image Classification

Figure 9 depicts the CIR image classification with three classifiers: ISODATA, supervised Maximum-Likelihood, and Object-Oriented. In Figure 8, light/white areas represent wetlands, black, water, and gray tones other land-cover classes. For full-color results of the CIR classification, see Appendix: Maps 1 through 3.



CIR – ISODATA classified image | CIR - ML classified image | CIR - OO image classified image

Figure 10. Results from Multispectral One Meter CIR Image Classification.

The object-oriented method gave the highest overall accuracy when classifying the CIR (73.2%) while the Maximum-Likelihood classifier gave the highest wetland producers accuracy (75.0%) while the object-oriented classifier gave the best wetland users accuracy (50%; see Table 13). The object-oriented classifier in general performed worse than expected, and in contrast to previous studies in which high-resolution imagery (four meter IKONOS) had been used to identify wetlands (Antunes et al., 2003). Two possible reasons include incorrect scale parameters used in the segmentation step and poor spectral resolution. The eCognition (object-oriented) software consistently performed better the more layers present there were to segment (see Table 6, 12, and 17). However, the one-meter CIR was very useful as an ancillary data source and wetlands could be manually (visually) delineated. Thus, CIR imagery is a cost-effective solution to agencies seeking to define wetlands from remotely-sensed imagery. Also, the entire county was not classified with the object-oriented classifier and the CIR image, because of file limitations in the eCognition software, a problem that also surfaced with the Eddyville hyperspectral image. For more information, refer to Chapter 5, Conclusion.

The ISODATA unsupervised algorithm differentiated artificial surfaces, tree canopies and wetland areas better than the Maximum-Likelihood supervised method; it was also slightly more accurate overall. Strangely, the supervised method identified the open-water class more effectively.

Table 1 provides the error matrix for the CIR Maximum-Likelihood supervised classification, and Table 2 shows the various accuracy percentages for different types of land-cover classes. Similarly, Table 3 displays the error (or confusion) matrix for the CIR unsupervised ISODATA algorithm classification, and Table 4 lists the class accuracy percentages for the before mentioned method. Lastly, Table 5 represents the confusion matrix for the object-oriented classification method, again using the 2002 Color Infrared one meter aerial photo. Table 6 illustrates the class accuracy percentages for the CIR object-oriented method. One random point for the CIR supervised classification accuracy assessment had to be discarded since it fell out of range of the image; similarly 16 points had to be discarded for the unsupervised classification accuracy assessment.

Table 1

Error Matrix CIR Supervised Classification

Class	Artificial Surface	Open Water	Fallow/Bare Soil	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	11	3	34	2	0	0	50
Open Water	1	49	0	0	0	0	50
Fallow/Bare Soil	1	0	48	0	1	0	50
Mixed Grasses	1	0	0	45	3	1	50
Wetland	4	0	7	12	18	9	50
Mixed Forest	1	1	43	0	2	2	49
Total	19	53	132	59	24	12	299

Table 2

Accuracy Percentages CIR Supervised Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	57.89	22.00	0.1671
Open Water	92.45	98.00	0.9757
Fallow/Bare Soil	36.36	96.00	0.9284
Mixed Grasses	76.27	90.00	0.8754
Wetland	75.00	36.00	0.3041
Mixed Forest	16.67	4.08	0.0007

Note. Overall Accuracy 57.86%, Overall Kappa 0.4941.

Table 3

Error Matrix CIR Unsupervised Classification

Class	Artificial Surface	Open Water	Fallow/Bare Soil	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	36	1	12	1	0	0	50
Open Water	7	12	25	0	2	4	50
Fallow/Bare Soil	1	0	48	0	1	0	50
Mixed Grasses	0	0	0	50	0	0	50
Wetland	2	0	30	2	11	5	50
Mixed Forest	1	0	5	16	6	22	50
Total	47	13	120	69	20	31	300

Table 4

Accuracy Percentages CIR Unsupervised Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	76.70%	72.00%	0.6457
Open Water	92.31%	24.00%	0.2056
Fallow/Bare Soil	40.00%	96.00%	0.9333
Mixed Grasses	72.46%	100.00%	1.0000
Wetland	55.00%	22.00%	0.1643
Mixed Forest	70.97%	44.00%	0.3755

Note. Overall Accuracy: 59.67%, Overall Kappa: 0.5160.

Table 5

Error Matrix CIR Object Oriented Classification (GPS ground truth points)

Class	Artificial Surface	Open Water	Fallow/Bare Soil	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	4	0	0	0	0	0	4
Open Water	1	5	0	0	0	0	6
Fallow/Bare Soil	0	0	4	0	0	0	4
Mixed Grasses	0	0	1	5	2	0	8
Wetland	0	0	0	0	6	4	10
Mixed Forest	0	0	0	0	2	1	3
Total	5	5	5	5	10	5	35

Table 6

Accuracy Percentages CIR Object Oriented Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	100.0	80.0	0.778
Open Water	83.3	100.0	1.00
Fallow/Bare Soil	100.0	80.0	0.778
Mixed Grasses	62.5	100.0	1.00
Wetland	68.75	50.0	0.517
Mixed Forest	33.3	20.0	0.135

Note. Overall Accuracy: 73.2%, Overall Kappa: 0.701.

Multispectral Landsat ETM Image Classification

The object-oriented classifier outperformed the pixel-based methods (ISODATA & ML) when classifying the September 2000 Landsat imagery. Overall accuracy was higher in both the 30 m (73.9%) and 15 m (90.7%) images (Table 13). However, wetland identification accuracy was only better than the pixel-based methods when spatial resolution was increased (73.7% producers accuracy, 66.7% users accuracy). Segmentation parameters were taken from previous studies (Antunes et al., 2003; Fisher, Gustafson, & Redmond, 2002; Gomes & Marcal, 2003; Meinel, Neubert, & Reder, 2001; Schiewe, 2001) who also used multispectral satellite imagery and reported generally similar accuracies for different land cover types using the object-oriented classifier. In Figure 11, the results of the Landsat ETM image classification are shown side by side for comparison. For full color maps of the classifications refer to Appendix: Maps.

ETM – ISODATA classified image

ETM - ML classified image

ETM - OO image classified image

Figure 11. Results from Multispectral 15 Meter Landsat ETM Image Classification.

In Figure 11, light areas represent wetlands, black, water, and gray tones other land cover types. Table 7 illustrates the confusion matrix for the pan-sharpened Landsat and Maximum-Likelihood supervised classification. Table 8 then gives the accuracy percentages for the before mentioned method according to class. Similarly, Table 9 represents the error matrix for the ISODATA unsupervised classification of the Landsat image in ERDAS Imagine and Table 10 explains the class producer and users accuracy for the ISODATA method. Lastly, Table 10 shows the object-oriented classification error matrix for the classified Landsat ETM+ and Table 11 the object-oriented class producer and user accuracies.

Table 7

Error Matrix Landsat ETM 15 m Supervised Classification

Class	Artificial Surface	Open Water	Row Crop	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	51	3	42	30	3	9	138
Open Water	0	15	0	0	0	0	15
Row Crop	0	0	39	0	0	0	39
Mixed Grasses	0	0	0	60	0	0	60
Wetland	0	3	0	6	21	3	33
Mixed Forest	0	0	0	3	6	6	15
Total	51	21	81	99	30	18	300

Table 8

Accuracy Percentages Landsat ETM 15 m Supervised Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	100.00	36.96	0.2404
Open Water	71.43	100.00	1.0000
Row Crop	48.15	100.00	1.0000
Mixed Grasses	60.61	100.00	1.0000
Wetland	70.00	63.64	0.5960
Mixed Forest	33.33	40.00	0.3617

Note. Overall Accuracy: 64.0%, Overall Kappa: 0.552.

Table 9

Error Matrix Landsat ETM 15 m Unsupervised Classification

Class	Artificial Surface	Open Water	Row Crop	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	38	0	0	2	0	0	40
Open Water	0	38	0	2	0	0	40
Row Crop	0	0	38	0	2	0	40
Mixed Grasses	0	0	0	40	0	0	40
Wetland	0	0	6	12	16	6	40
Mixed Forest	0	0	8	2	10	20	40
Total	38	38	52	58	28	26	240

Table 10

Accuracy Percentages Landsat ETM 15 m Unsupervised Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	100.00	95.00	0.9406
Open Water	100.00	95.00	0.9406
Row Crop	73.08	95.00	0.9362
Mixed Grasses	68.97	100.00	1.000
Wetland	57.14	40.00	0.3208
Mixed Forest	76.92	50.00	0.4393

Note. Overall Accuracy: 79.17%, Overall Kappa: 0.75.

Table 11

Error Matrix Landsat ETM 15 m Object Oriented Classification

Class	Artificial Surface	Open Water	Row Crop	Mixed Grasses	Wetland	Mixed Forest	Total
Artificial Surface	19	0	0	0	0	0	19
Open Water	0	20	0	0	0	0	20
Row Crop	0	0	23	0	0	0	23
Mixed Grasses	0	0	1	33	2	0	36
Wetland	1	2	0	0	14	2	19
Mixed Forest	0	0	0	0	5	18	23
Total	20	22	24	33	21	20	140

Table 12

Accuracy Percentages Landsat ETM 15 m Object Oriented Classification

Class	Producers Accuracy	Users Accuracy	Kappa
Artificial Surface	100.0	95.0	0.942
Open Water	100.0	90.9	0.894
Row Crop	100.0	95.8	0.95
Mixed Grasses	91.7	100.0	1.0
Wetland	73.7	66.7	0.614
Mixed Forest	78.3	90.0	0.837

Note. Overall Accuracy: 90.7%, Overall Kappa: 0.888.

For the Landsat imagery, the ISODATA classifier performed as well as the object-oriented one for classifying land-cover types other than Wetland and Mixed Forest types. Overall accuracy for the unsupervised classifier was superior to the supervised classifier in both the Landsat and CIR imagery, suggesting that a "cluster-busting" method of determining land-cover classes is more accurate than traditional Maximum-Likelihood classification. Also, the above results (Tables 7 through 12) and the overall Landsat results (in Table 17) are based on classification of a partial September 2000 Landsat ETM+ image. A full scene for Black Hawk County was available for July of

1999, and was used for the seasonal matrix and used for the final Black Hawk County wetlands map (see Appendix A: Map 7), but not for classifier comparison due to the large amount of flooding present on the Landsat ETM+ July 1999 image.

Hyperspectral CASI Classification

Figure 11 and Tables 13 through 16 show the classified outputs and accuracy assessment for the object-oriented and SAM classifiers for the CASI image. Average wetland producers accuracy for the Spectral Angle Mapper classifier was 79.3%, somewhat higher than in other comparable studies, such as Garono, Schooler, and Robinson (2003). They achieved 74% accuracy with the ERDAS ISODATA unsupervised algorithm to map tidal wetlands along the lower Columbia River with CASI imagery. The greatest confusion between wetland classes for the SAM classifier was between the flooded forest and mixed (upland forest) categories, and also with the emergent (herbaceous) land cover class. This has also been found in many other studies, due to the inability of the wavelengths to penetrate the vegetation canopies. Possible solutions to this problem include RADAR (Bourgeau-Chavez et al., 2001) and LIDAR (MacKinnon, 2001) to penetrate dense vegetation canopies. Confusion between emergent herbaceous vegetative cover and wetland classes is also fairly well documented (Özemi, 2000). A workable solution to this problem is the extraction of individual plant species from the hyperspectral imagery, which was not completed in this study due to time constraints.

In the object-oriented classification, average wetland producers accuracy for the object-oriented classifier was 97.6%. Object-oriented classifiers have been shown to increase accuracy of wetland classification in multispectral imagery (Antunes et al., 2003). The results of this classification appear to be valid also for hyperspectral imagery. Wetland users accuracy for the object-oriented classifier (86.7%) was lower than producers accuracy, mirroring the SAM classifier. Confusion between classes was mainly limited to forested wetland and forested upland, which was also a problem with the SAM classifier. The accuracy assessment is based on the 50-acre study area. The comparison between these two classifiers revealed some interesting results. The object-oriented classifier produced better overall accuracy (92.3% vs. 68.2%) and better wetland class accuracy (97.6% vs. 79.3%) than the SAM classifier. Wetland Users Accuracy was lower than Producers Accuracy in both classifiers, suggesting that these two methods are more suited to detecting wetlands than for managing them from a users standpoint.

The last wetlands survey completed for Mahaska, Wapello, and Monroe counties was conducted by the Iowa Department of Natural Resources in 1996 and is based upon National High Altitude Program Color Infrared Photographs taken in 1983 and 1984. The total wetland acreage for the *entire* hyperspectral image area according to that information is 53 acres. For the 50-acre study area that was classified in this research, 2.6 acres of wetlands were identified from the last wetlands survey. Comparison of the 1996 wetlands survey against the 2002 1-m CIR aerial photo clearly shows that many wetland areas have been developed or farmed or have shifted, necessitating an updated survey. The SAM classifier for the 50-acre study area identified 4.1 wetland acres, 0.2 of which were Open Water, 0.6 acres of Aquatic Vegetation, and approximately 3.3 acres of Flooded Forest. The object-oriented classifier for this study identified 3.9 acres, 0.3 of which were Open Water, 0.6 acres of Aquatic Vegetation, and approximately 3 acres of Flooded Forest.

There are also issues with these two classifiers for wetland classification. Known sources of bias include the fact that pixel-based classifiers such as SAM in hyperspectral imagery tend to perform best when extracting individual spectra of individual plant species (ERDAS, 2002; ENVI, 2002) and this study grouped different species of wetland vegetation into generic land-cover classes, a fact that might have favored the object-oriented classifier, which inherently classifies such object-based primitives. Other studies have shown higher accuracies using hyperspectral imagery and pixel-based methods (such as MNF, ration indices, etc.) to extract individual plant species spectra (Garono et al., 2003; Underwood, 2003). File size in eCognition is also another limitation. The version of eCognition that was used, 3.0, was unable to segment and classify files larger than 100 MB, which in this study represented 15-20 acres of the total 969 acre image. Therefore, the CASI image had to be divided into 60 different tiles. Definiens Imaging, the parent of eCognition software, has told the researchers that this file size limitation will be corrected in the release of eCognition 4.0. In Figure 12, the results of the hyperspectral classification are shown.

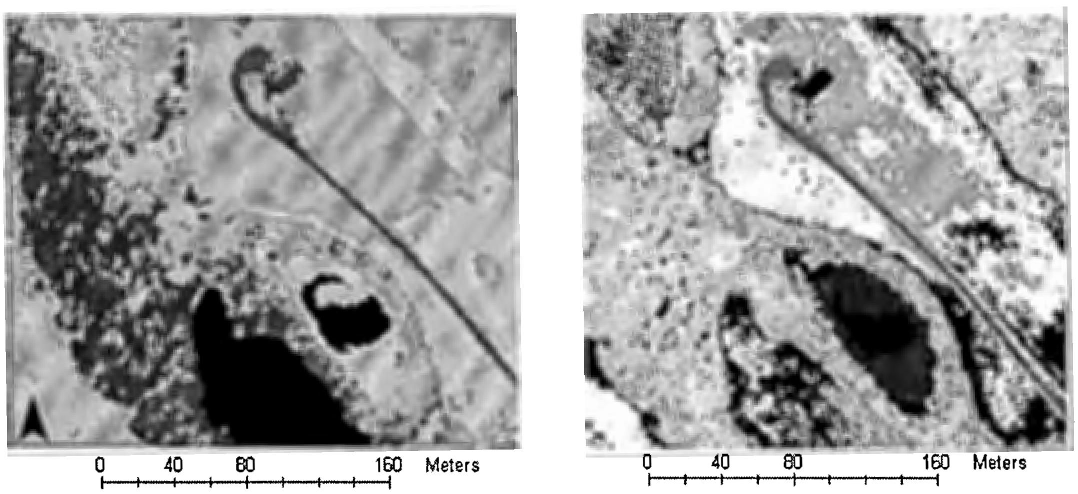


Figure 12. Results from CASI Hyperspectral Image Classification. The left-hand image was classified using the eCognition Object-Oriented Classifier and the right-hand image, the ENVI Spectral Angle Mapper classifier. In the left-hand (object-oriented classification) image, the dark tones represent open water, saturated soil, and upland (non-wetland) forest. The lighter areas are aquatic vegetation and herbaceous cover. The gray-tone classes represent dry bare soil and flooded (wetland) forest. On the right-hand side image (Spectral Angle Mapper classification), dark tones represent open water, saturated soil, and aquatic vegetation. Lighter areas represent upland and flooded forests, and gray-tones herbaceous cover and dry bare soil.

Table 13

Confusion Matrix for SAM Classification (Ground Validation Pixels)

Class	Open Water	Aquatic Vegetation	Flooded Forest	Artificial Surface	Upland Crop	Flooded Crop	Herbaceous Cover	Mixed Forest	Shadow	Total
Unclassified	13	0	32	22	0	5	3	17	6	98
Open Water	230	0	0	192	0	0	0	0	0	422
Aquatic Vegetation	0	318	0	0	0	0	0	0	0	318
Flooded Forest	0	0	191	0	0	0	38	86	3	496
Artificial Surface	0	0	0	496	0	1	0	0	0	319
Upland Crop	0	0	0	35	516	62	0	0	0	613
Flooded Crop	0	0	0	0	0	2	0	0	0	280
Herbaceous Cover	0	0	84	0	0	3	141	49	4	561
Mixed Forest	0	0	125	0	199	188	0	421	12	387
Shadow	0	0	11	0	0	13	0	181	71	276
Total	243	318	443	745	715	274	182	754	96	3770

Table 14

Accuracy Percentages CASI SAM Classification

Class	Prod. acc. (%)	User acc. (%)
Open Water	94.65	54.5
Aquatic Vegetation	100.00	100.00
Flooded Forest	43.12	59.87
Artificial Surface	66.58	100.00
Upland Crop	72.17	84.18
Flooded Crop	68.61	45.58
Herbaceous Cover	77.47	50.36
Mixed Forest	55.84	75.04
Shadow	73.96	25.72
Wetland Avg. (3 classes)	79.3	71.5

Note. Overall Accuracy: 68.22%, Overall Kappa: 0.6373.

Table 15

Confusion Matrix for Object-Oriented Classification (Ground Validation Objects)

Class	Open Water	Aquatic Vegetation	Flooded Forest	Artificial Surface	Upland Crop	Flooded Crop	Herbaceous Cover	Mixed Forest	Shadow	Total
Unclassified	0	0	0	0	0	0	0	0	0	0
Open Water	5	0	0	0	0	0	0	0	0	5
Aquatic Vegetation	0	19	0	0	0	0	0	0	0	19
Flooded Forest	0	0	13	0	0	0	1	0	0	14
Artificial Surface	0	0	0	10	0	0	0	0	0	10
Upland Crop	0	0	0	0	20	0	0	0	0	20
Flooded Crop	0	0	0	0	0	20	0	0	2	22
Herbaceous Cover	0	0	0	0	0	0	19	0	0	19
Mixed Forest	0	1	7	0	0	0	0	20	0	28
Shadow	0	0	0	0	0	0	0	0	6	6
Total	5	20	20	10	20	20	20	20	8	143

Table 16

Accuracy Percentage Classifications CASI Object-Oriented Classification

Class	Prod. acc. (%)	User acc. (%)
Open Water	100.0	100.0
Aquatic Vegetation	100.0	95.0
Flooded Forest	92.9	65.0
Artificial Surface	100.0	100.0
Upland Crop	100.0	100.0
Flooded Crop	90.9	100.0
Herbaceous Cover	100.0	95.0
Mixed Forest	71.4	100.0
Shadow	100.0	75.0
Wetland Avg. (3 classes)	97.6	86.7

Note. Overall Accuracy: 92.3%, Overall Kappa: 0.912.

Overall Classifier Comparison

The overall classification accuracy for different classifiers is provided in Table 17. Accuracy comparisons between the classifiers were completed using the same areas; for example, county-wide stratified random points for the CIR and Landsat images, and the same 50-acre subset for the hyperspectral Eddyville image. Accuracies increased (both for the wetland class and the overall average) when spatial resolution of the Landsat imagery was sharpened with the panchromatic band; also, the unsupervised ISODATA algorithm performed better for overall accuracy than the supervised Maximum-Likelihood classifier. This is consistent with the results of other studies (Özemi, 2000). The object-oriented classifier increased overall accuracy with the Landsat imagery over the traditional pixel-based classifiers, but did not increase wetland-identification accuracy until the spatial resolution was increased (see Table 13). The CIR imagery in general performed poorly with all automated classifiers, suggesting that even though the spatial resolution was very sharp, either more bands such as Landsat 4 & 5, (see Chen 2002), are needed to detect vegetation, or seasonality played a role because the imagery was flown in late April/early May of 2002 before the growing period of many wetland vascular plants in the northeastern part of the state. The most accurate results came from the hyperspectral object-oriented approach and the pan-sharpened Landsat object-oriented approach.

The seasonal matrix of the pan-sharpened Landsat images produced lower accuracies than anticipated, especially for identifying wetland areas. It did, however, increase accuracies for row-crop cover and herbaceous cover. This may be due to the large amount of flooding present in the July 1999 Landsat image. Landsat imagery remains a valid choice for large-scale wetlands mapping projects, especially with the added capability of the panchromatic band.

Table 17

Overall Classification Accuracy for Different Classifiers

	CIR 1 m O-O	CIR 1 m ISO-DATA	CIR 1 m Max-Like	LSAT 15 m ISO-DATA	LSAT 15 m Max-Like	LSAT 15 m Pan O-O	LSAT 15 m Seasonal Matrix	LSAT 30 m O-O	HYPER-SPECTRAL CASI 60 cm O-O	HYPER-SPECTRAL CASI 60 cm S.A.M.
Overall Accuracy	73.2	59.7	57.9	79.17	64.0	90.7	67.3	73.9	91.7	68.2
Wetland Producers Accuracy	68.8	55.0	75.0	57.14	70.0	73.7	77.78	58.8	94.6	79.3
Wetland Users Accuracy	50.0	22.0	36.0	40.0	63.6	66.7	46.67	50.0	86.7	71.5
Kappa	0.701	0.52	0.49	0.75	0.552	0.888	0.622	0.667	0.904	0.637

Note. O-O: Object-Oriented Classifier, ISODATA: Unsupervised Classification, 120 Initial Classes Max-Like: Maximum Likelihood Algorithm, S.A.M.: Spectral Angle Mapper Algorithm.

GIS-Based Restoration Model Results

The results of the wetland restoration model are as follows. Black Hawk County, Iowa encompasses an area of 567 square miles, or 362,880 acres. From that initial acreage, 56,729 acres were masked out as unsuitable based on the USGS Landcover raster layer of the following classes: (a) Low Intensity Residential, (b) High Intensity Residential, (c) Commercial/Industrial/Transportation, (d) Bare Rock/Sand/Clay, (e) Quarries/Strip Mines/Gravel Pits, (f) Urban/Recreation Grasses, (g) Open Water, (h) Woody Wetlands, and (i) Emergent Herbaceous Wetlands. The accuracy assessment for that 1992 data set was made publicly available on March 17, 2004 (United States

Geological Survey, 2004). The overall accuracy for Black Hawk County was only 53%, but for the classes masked out the accuracy was 60.4%. Urban areas were chosen as unsuitable restoration areas as well as bare areas and existing wetlands. Landcover classes left as suitable for restoration included: (a) Deciduous Forest, (b) Mixed Forest, (c) Grasslands/Herbaceous, (d) Pasture/Hay, (e) Row Crops, and (f) Small Grains.

From the remaining 306,151 acres, 93.4 acres in 10 parcels were also masked out as they are recognized as wetland parcels by the county assessor's office. Non-urban county roads along with a 30-meter buffer totaling 24,724 acres were also masked out to eliminate right-of-way areas owned by the Iowa Department of Transportation (see Berman et al., 2002). That left 281,334 acres or 440 square miles for wetland restoration consideration. Based on the flow chart in Figure 8 on page 36, cells classified as having soil that was hydric with poor drainage were given a score of 4 in the SSURGO soil data layer. Cells that did not meet this criterion were eliminated from consideration, as according to the federal definition of a wetland (see page one) a wetland must contain hydric soil, hydrophytic vegetation, or be in an area where the water table saturates a non-soil substrate or covers the area with shallow water periodically. As hydrophytic vegetation would not necessarily be present in a disturbed land-cover area (such as an agriculturally based one) and water table depth information was not available, the hydric soil criterion was chosen as the ranking factor or Step 2 in the flowchart. Eliminating cells that were not hydric resulted in narrowing the suitability area down to 121,271 acres. The next step was determining if the potential wetland restoration area was within a buffer of 20 meters for a hydrological feature (stream) or 50 meters of the Cedar River, as wetland areas are proven floodwater storage areas (Sierra Club, 2000) and wetlands restored adjacent to hydrological features moderate stream temperature and reduce erosion (Budlong, 2002). These cells were given a score of 1, and totaled 17,491 acres. Step 4 included identifying cells that were adjacent to existing wetlands. For the wetland areas, a 1996 Iowa Department of Natural Resources wetlands layer was used (based on 1983/84 aerial photos) instead of the updated Black Hawk County wetlands map produced earlier in the research as the wetland producer and user accuracies were lower (73.7 and 66.7% respectively) in the updated wetlands map. However, the model was run using the updated wetlands map and produced results less than one standard deviation from the mean as compared with using the older wetlands data, indicating no dramatic shifts in wetland areas or total acreage, a fact also shown by the Black Hawk County Wetlands timeline in Figure 13 on page 57. Cells that were adjacent to existing wetlands were given a score of 2 (see also Hey & Philippi, 1999).

Lastly, cells that were adjacent to or contained within county conservation areas were given a score of 3. The reasoning behind this is that wetlands have a greater chance of being restored and are easier to manage if they are to be located in land already owned or adjacent to county conservation land (S. Finegan, personal communication, May, 2003). The final equation from the methodology section was: (x = existing area index total, y = soil index total, z = hydrology index total) RESTORATION POTENTIAL = [(x * 0.85) + (y * 0.65) + (z* 0.40)]. Cell scores were computed using ArcGIS Spatial Analyst raster calculator according to the above equation (for example, if a cell had a perfect ranking, meeting all desirable criteria, [((3+2)*0.85) + (4*0.65) + (3*0.40)], it would have a score of 8.05.

Three categories were then defined using a Jenks Natural Breaks method: Cells with scores of 3.9 through 8.05 were ranked as most suitable areas, cells with scores of 2.7 through 3.8 were given a ranking of medium suitability, and cells with scores of 2.6 were given a ranking of low suitability. Cells with scores lower than 2.6 were deemed as unsuitable or unclassified. For a map of these areas, refer to Map 9 in Appendix A. There were not too many surprises in the results of the model, as all areas were close to surface hydrological features and generally were in areas where wetlands were present historically. The topography of the county does not vary greatly, and some areas have been known to county conservation officials for some time as highly-suitable areas for wetland restoration, such as the Crane Creek watershed and areas in the southeastern part of the county along the Cedar River. What this study contributes, through the use of GIS, is to demonstrate where restoration of wetlands could and should take place if county or state resources become available. Table 18 displays a numerical summary of the restoration model. Figure 13 references a timeline for wetland changes in Black Hawk County.

Table 18

Results from GIS-Based Restoration Model

Cell Type	Cell Total Area (acres)
Black Hawk County	362,880
Highest Suitability	2,971
Medium Suitability	34,307
Lowest Suitability	121,271
Unsuitable	204,331
USGS Landcover Mask	56,729
Wetland Parcel Mask	93.4
County Roads Buffer Mask	24,724
Hydric Poorly Drained Soil	121,271
Adjacent to Hydrology	17,491
Adjacent to Wetlands	30,590
Adjacent or Contained in County Conservation Area	7,170

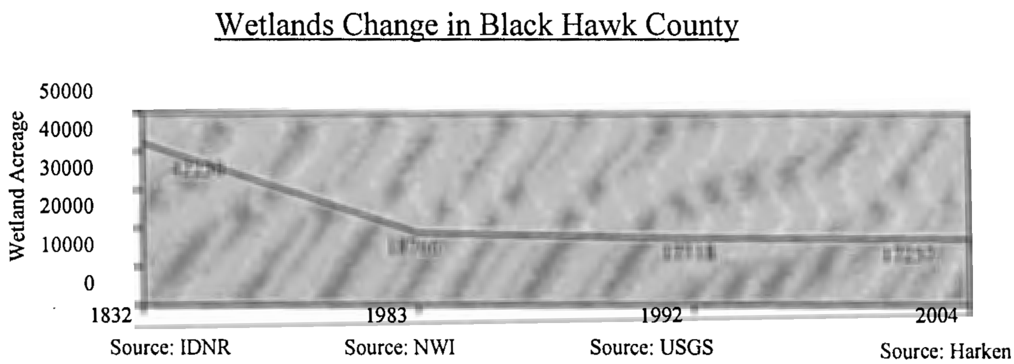


Figure 13. Black Hawk County Wetlands Timeline.

As shown by the above timeline, Figure 13, wetlands have decreased in the past twenty years in Black Hawk County. This is possibly due to natural variations in the hydrological cycle, agricultural practices, or image bias. While the acreage amount of decrease is not great, it still shows a need for restoration planning and implementation. As Hey and Philippi (1999) note, wetlands can be restored to provide ecological benefits (wildlife habitat, non-point pollution treatment, flood water storage) that have been lost. They also noted that wetland restorations are most effective when the wetlands occupy less than 10% of the area to be restored, as is the case in Black Hawk County where wetlands currently account for only 5% of the county's surface area.

Web-Based Data Dissemination

The Black Hawk County wetland project homepage is available to the general public at http://gisrl-9.geog.uni.edu/wetland/ (Figure 14). The homepage explains the goals and objectives and also methodologies and protocols developed in this project. It also provides a summary of results, links to other wetland sites, and a comprehensive list of references. Also available on the website is a technical report published for the Iowa Space Grant Consortium in January 2003.

Figure 15 shows a screen shot of the ArcIMS viewer. An ArcIMS-based web page was created so stakeholders in the project as well as the general public could access the results and use them for their own needs. According to ESRI (2003), ArcIMS is software specifically designed to serve geographic data on the Internet, and to develop Web pages that communicate with maps. Potential uses of the website include: (a) landowners identifying parcels of land that would be highly suitable to restore wetlands, (b) corroborating evidence for local government officials for conservation planning, and (c) general information on wetlands in Black Hawk County for the public. Users of the website can select different layers to display, as well as use built-in functions such as a measuring, querying, and buffering tools.

Figure 14. Screen Shot of Homepage

Figure 15. Screen Shot of Web-Based Data Interface

CHAPTER 5

CONCLUSION

In this study multispectral (CIR; ETM) and hyperspectral (CASI) images were tested for wetland classification using different classifiers (Maximum-Likelihood, ISODATA, Object-Oriented and Spectral Angle Mapper). The object-oriented classifier produced superior results over traditional pixel-based classifiers (ISODATA; Maximum-Likelihood) in multispectral imagery (73.7% vs. 57.14%; 70.0%) when mapping wetlands but *only* when spectral resolution was increased (i.e., 15-m 6-band Landsat imagery achieved superior results over 1-m 3-band Color Infrared Aerial photography) *and* the spatial resolution of the Landsat imagery was increased (Pan-sharpened from 30-m to 15-m).

The results for Eddyville also clearly showed that hyperspectral images enabled more accurate wetland mapping than multispectral datasets when using the object-oriented classifier (94.6%) and the SAM classifier (79.3%). The object-oriented classifier in this case also performed better than the pixel-based (SAM) classifier. A seasonal comparison of Landsat imagery to identify wetlands did not produce accurate results, perhaps due to extensive flooding present in the summer (July) imagery.

The answers to the research questions from Chapter 1, Page 7, are as follows:

1. The Object-Oriented classifier was superior and more accurate in comparison to the pixel-based Maximum-Likelihood and ISODATA for the delineation of wetlands using multispectral imagery in Black Hawk County.

2. Data fusion between a Landsat ETM multispectral and ETM panchromatic band increased the accuracy of wetland classification in Black Hawk County.

3. The Object-Oriented Classifier was more accurate than the SAM classifier for identifying wetlands in the Eddyville hyperspectral (CASI) image.

4. Seasonality may play a significant role in classifying wetlands from remotely-sensed imagery; however this study did not yield anticipated higher wetland detection accuracies.

5. The most important variables for a GIS-based wetland restoration model in Black Hawk County were: (a) hydric soil; (b) proximity to surface hydrological features; (c) proximity to existing wetlands; and (d) proximity to existing conservation areas owned by the county.

The results of the GIS-based model used in this study for wetland restoration in Black Hawk County identified far more acres than initially believed were suitable for such purposes (56% of county land area deemed unsuitable, 33% low suitability, 10% medium suitability, 1% highly suitable). Two highly-suitable identified areas had already been previously targeted by conservation officials for wetland easements or restorations should funding become available.

Known sources of error include the fact that any wetland identified through remotely-sensed imagery must be field-checked by a qualified ecologist or biologist in order to qualify for legal status or protection. Wetlands in Black Hawk County showed a slight decrease of roughly 1500 acres (+/- an error margin of 375 acres) from 1983-2003. A web site with an ArcIMS viewer was created in order to disseminate information to the stakeholders involved in the study, as well as the general public. Information available on the website include: a summary of findings, maps of classification results, wetland links, a comprehensive bibliography, as well as a technical report published for the Iowa Space Grant Consortium. Available on the ArcIMS site is the ability to arrange different layers, as well as measurement, buffer, and query tools.

In conclusion, it is the findings of this research that wetland classification from multispectral imagery in the study area can be accurately completed if spatial resolution is increased by data fusion, but not at the cost of spectral resolution. A non-parametric object-oriented classifier can also identify freshwater inland wetlands for the study areas of Black Hawk County and Eddyville more accurately than traditional pixel-based (ISODATA, Maximum-Likelihood) ones. Hyperspectral imagery is preferable to multispectral imagery in identifying freshwater inland wetlands because of increased spectral resolution. The object-oriented classifier also identifies wetlands more accurately using hyperspectral imagery, but has limitations for large file sizes.

Limitations of the research include: (a) image availability for the seasonal matrix, (b) classifying only a subset of the multispectral and hyperspectral imagery with the object-oriented classifier, and (c) a limited number of variables used in the GIS-based restoration model.

Recommendations for Future Research

The future direction of this study lies in testing more non-parametric classifying methods, such as a CART (classification and regression tree) algorithm since other studies have shown it to be more accurate than a purely spectral based classifier (Sugumaran, Pavuluri, & Zerr, 2003). In addition, greater long-term seasonality will also be addressed, as other studies have stressed the importance of multi-seasonal variation in detecting wetlands via remote-sensing imagery (Özemi, 2000; Houhoulis & Michener, 2000). Future efforts for the restoration model include adding more variables, such as land ownership, as well as field testing of high potential sites for evidence of hydrophytic vegetation and confirmation of hydric soils.

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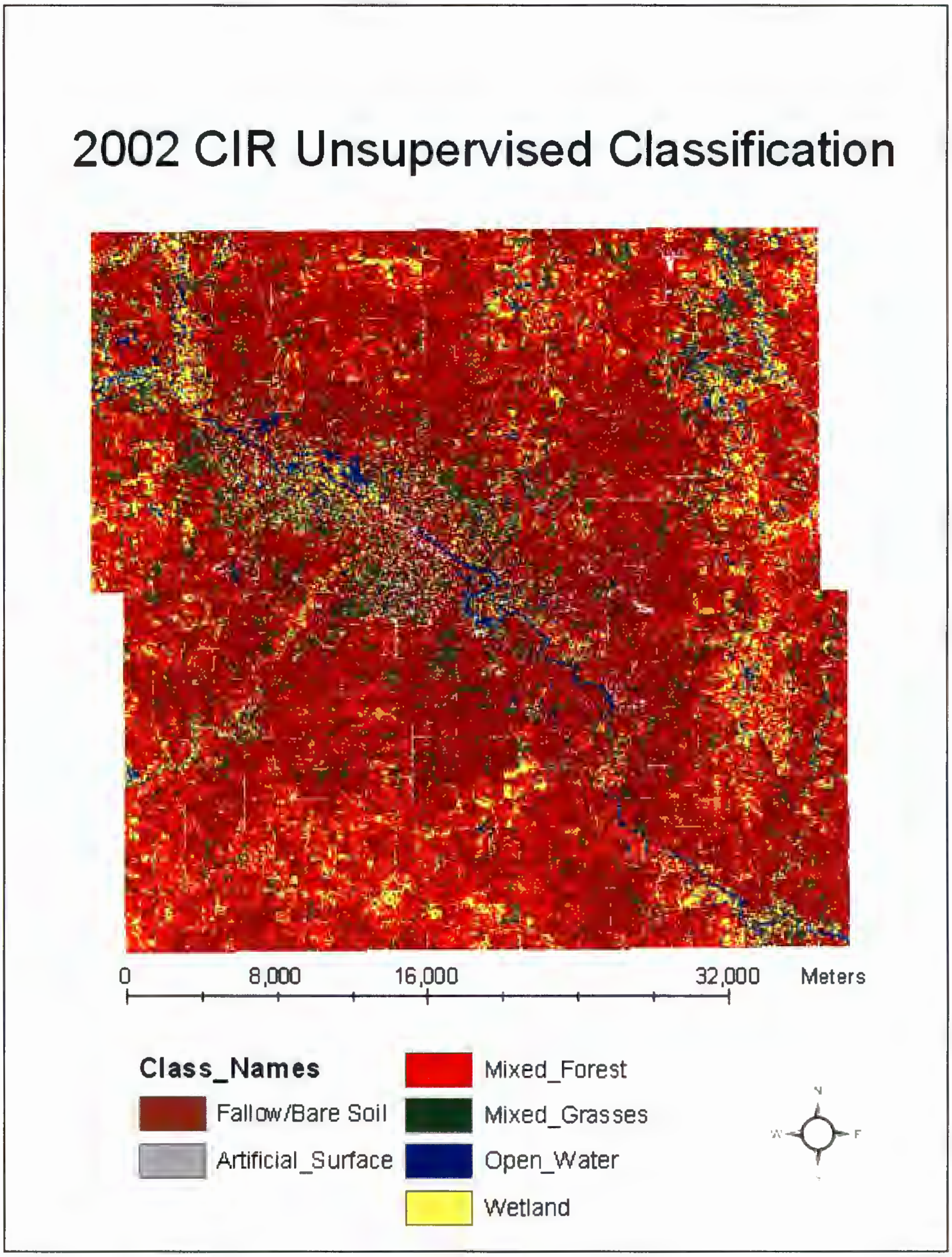
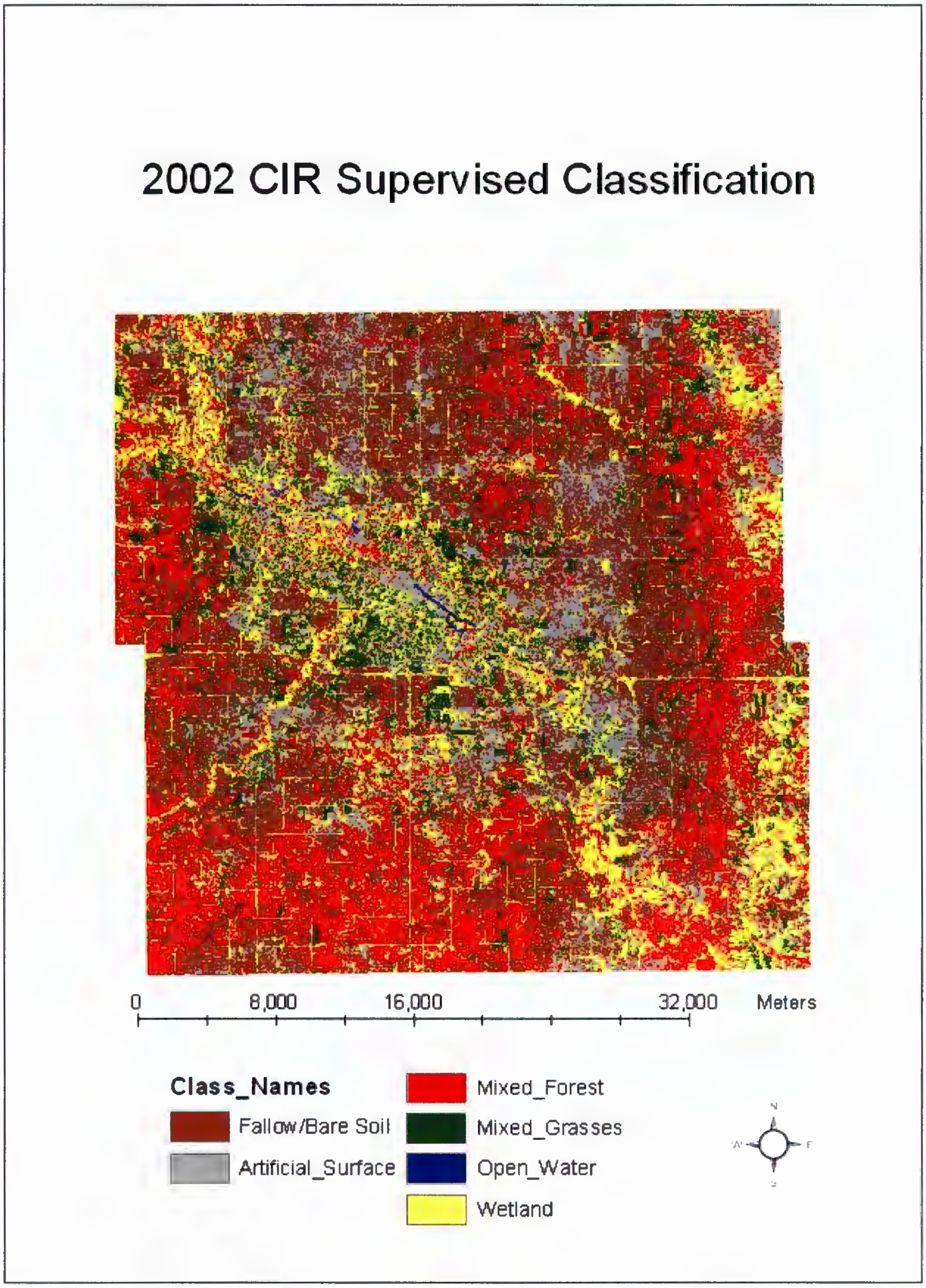
APPENDIX

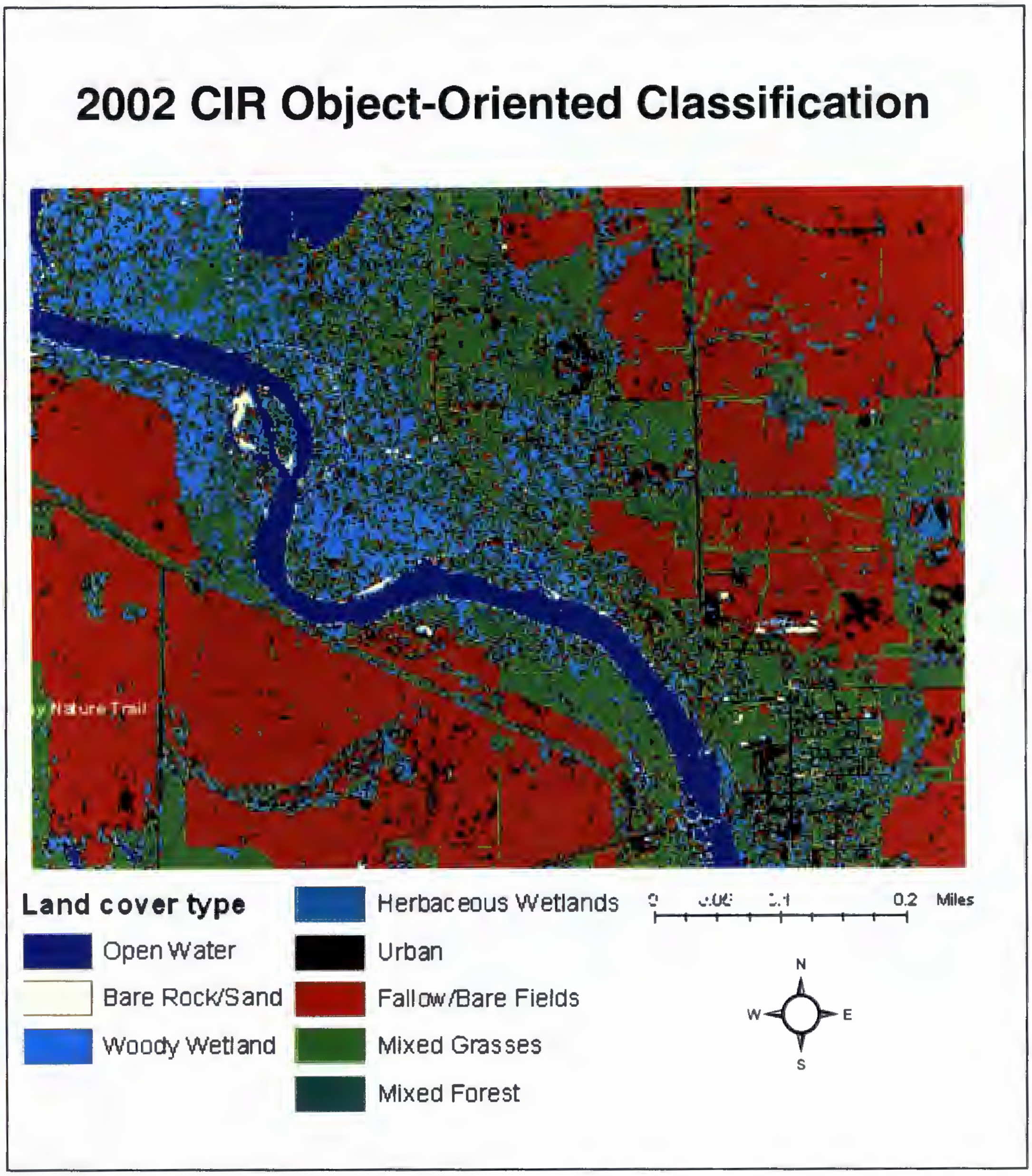
MAPS



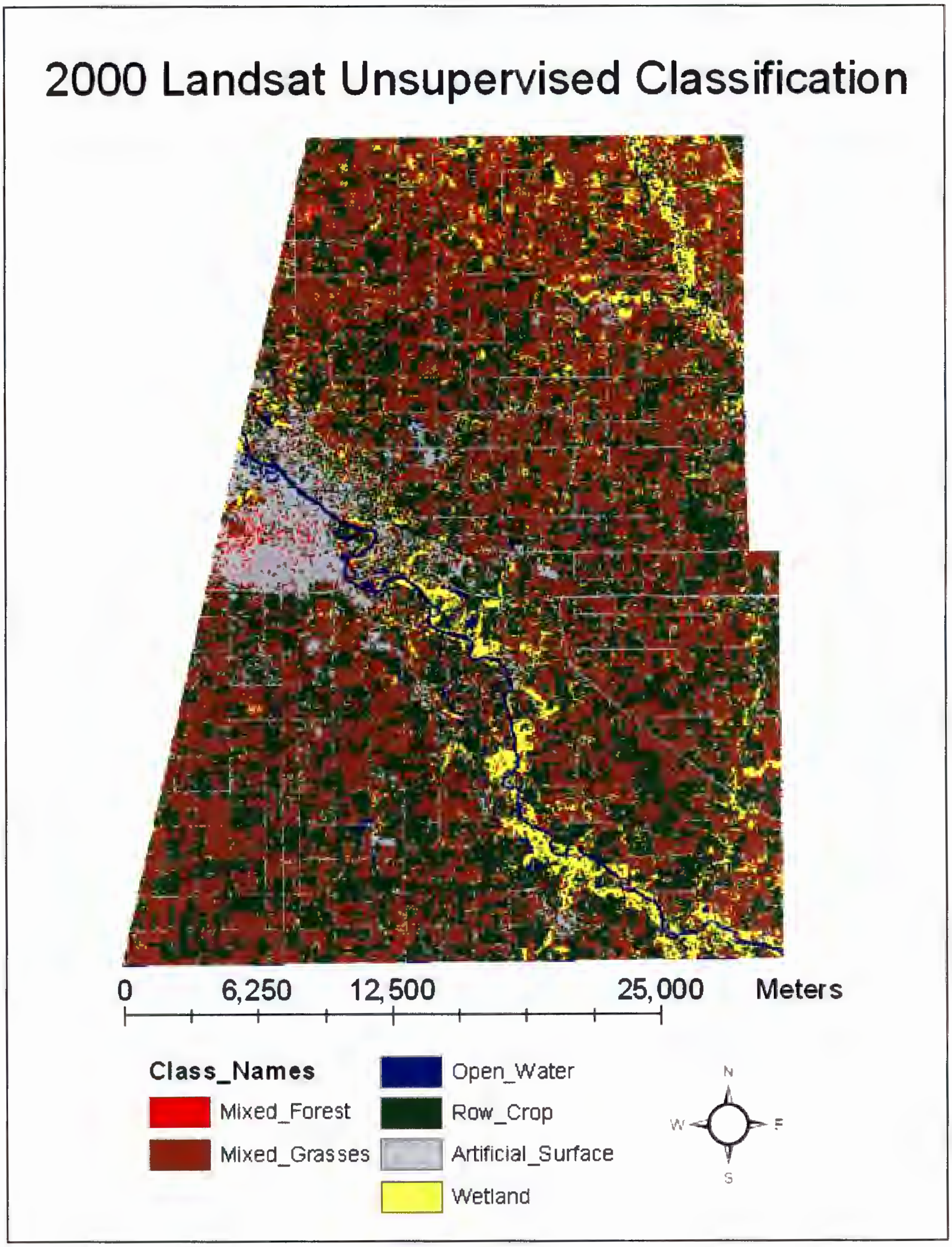
Map 1: 2002 CIR Unsupervised Classification, Black Hawk County



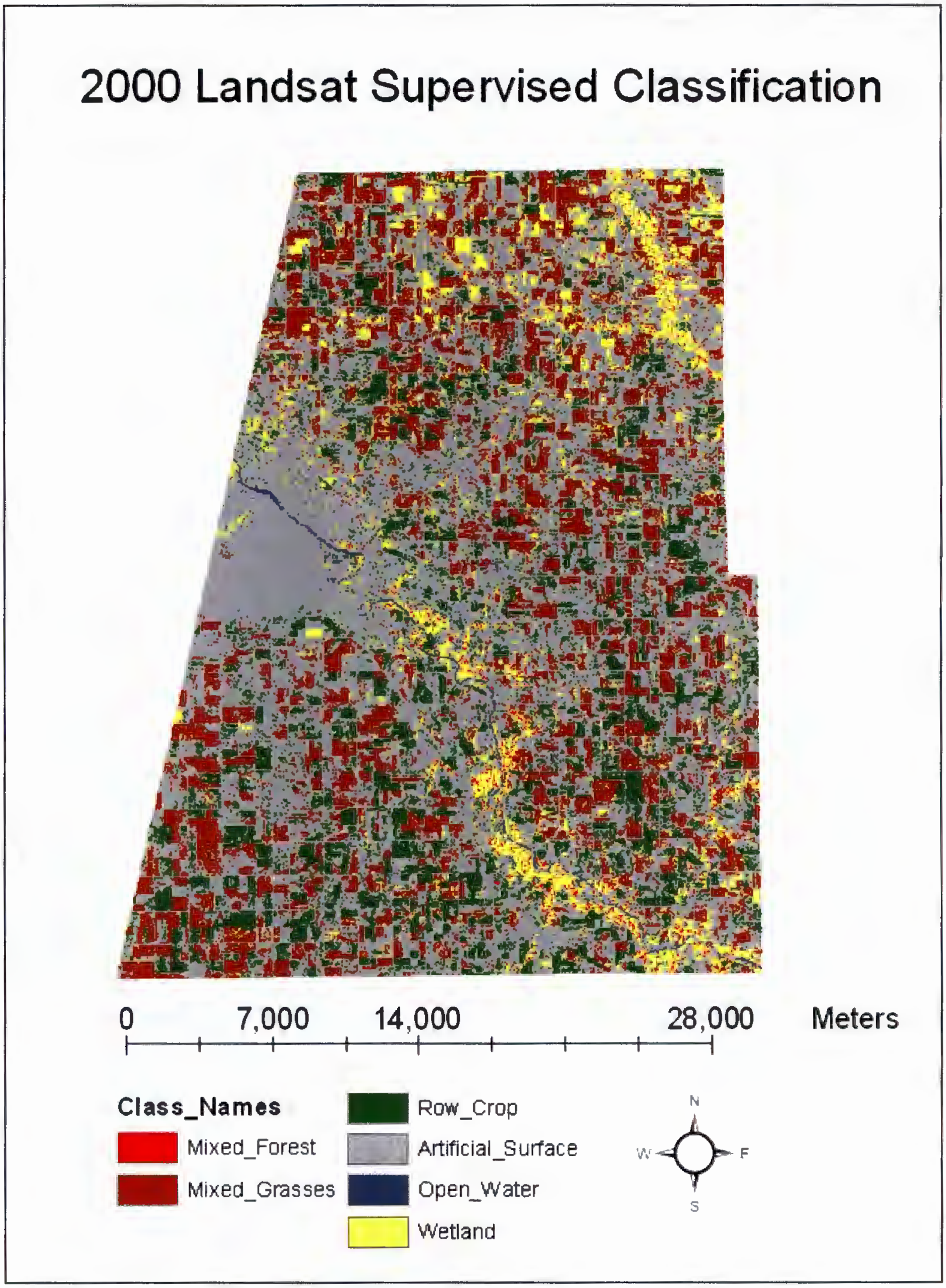
Map 2: 2002 CIR Supervised Classification, Black Hawk County



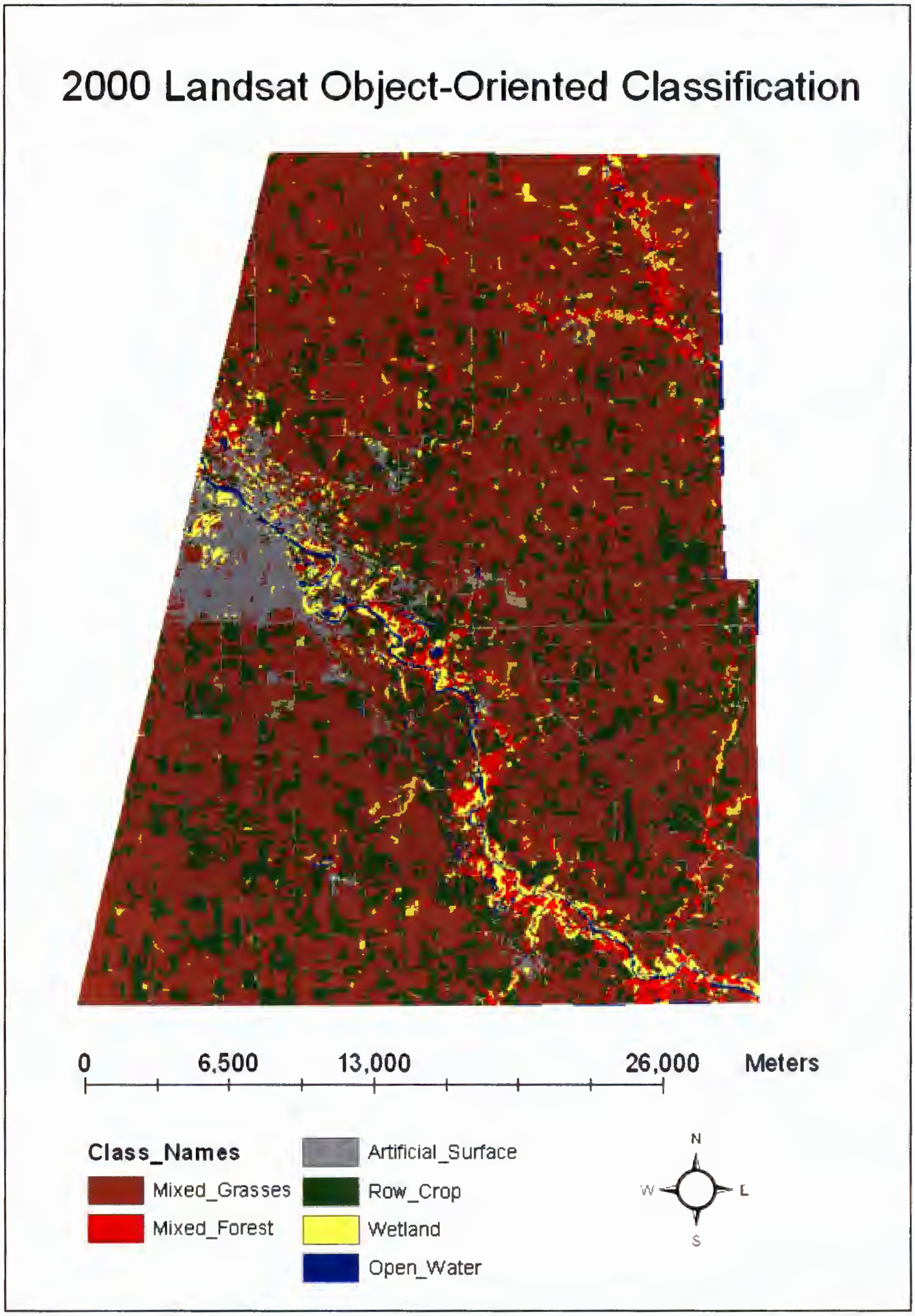
Map 3: 2002 CIR Object-Oriented Classification, Black Hawk County
(Subset image, near Gilbertville)



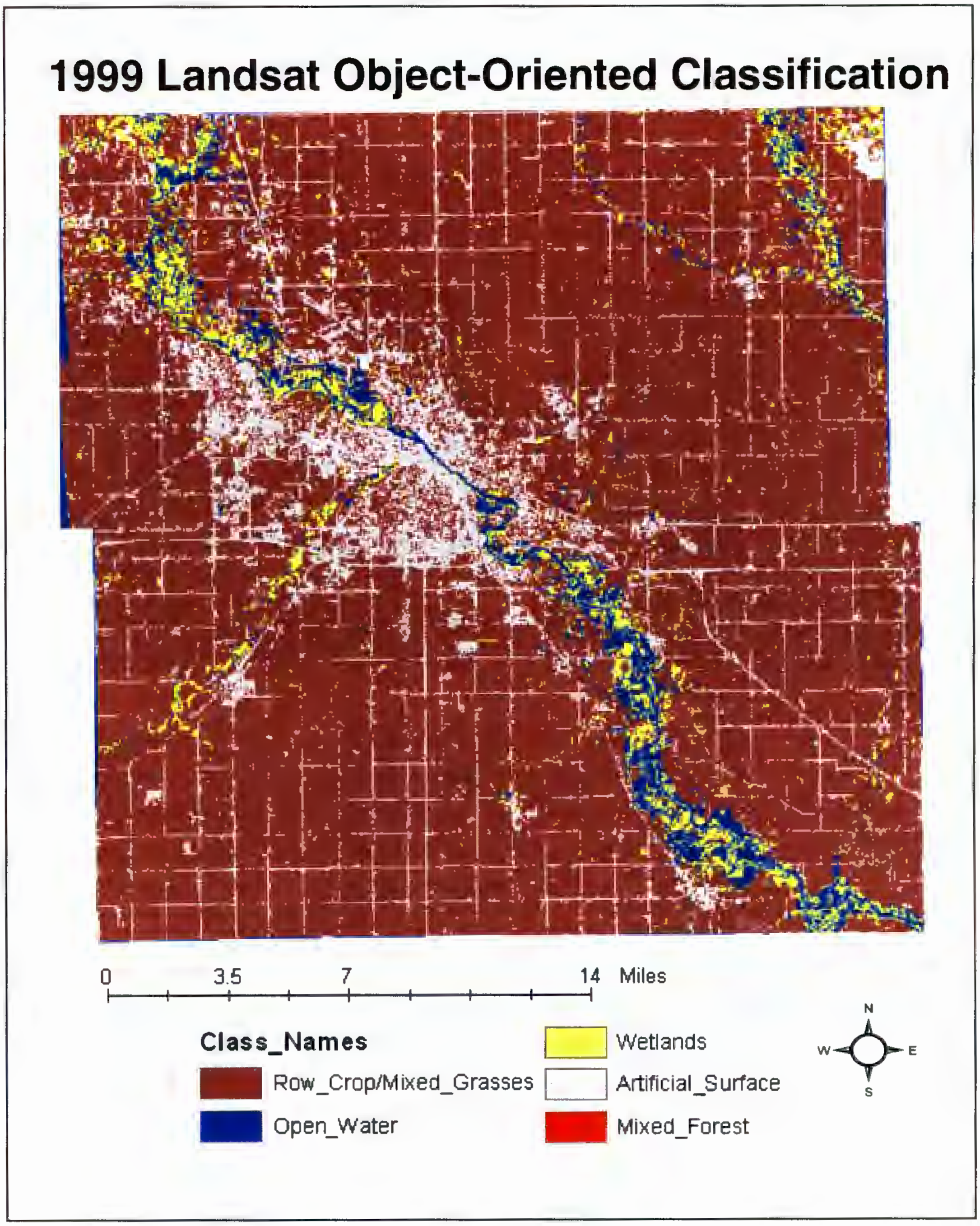
Map 4: 2000 Landsat Unsupervised Classification, Black Hawk County



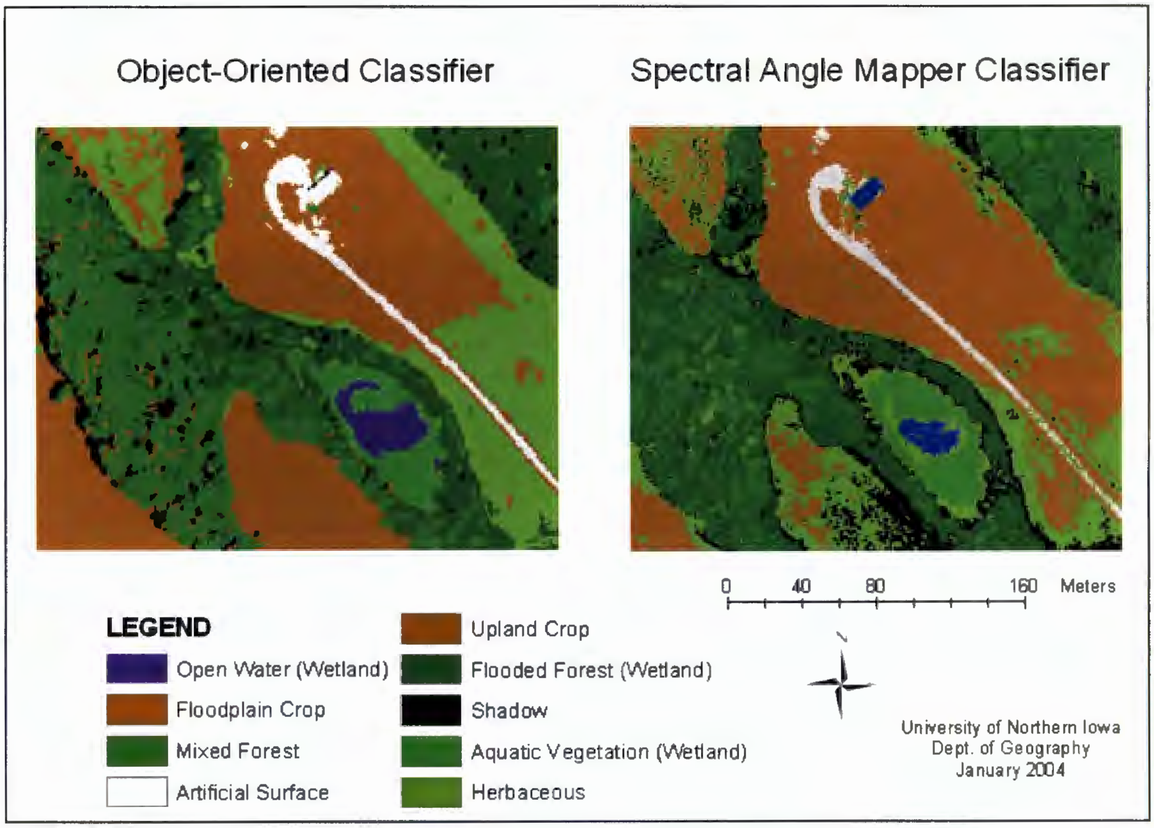
Map 5: 2000 Landsat Supervised Classification, Black Hawk County



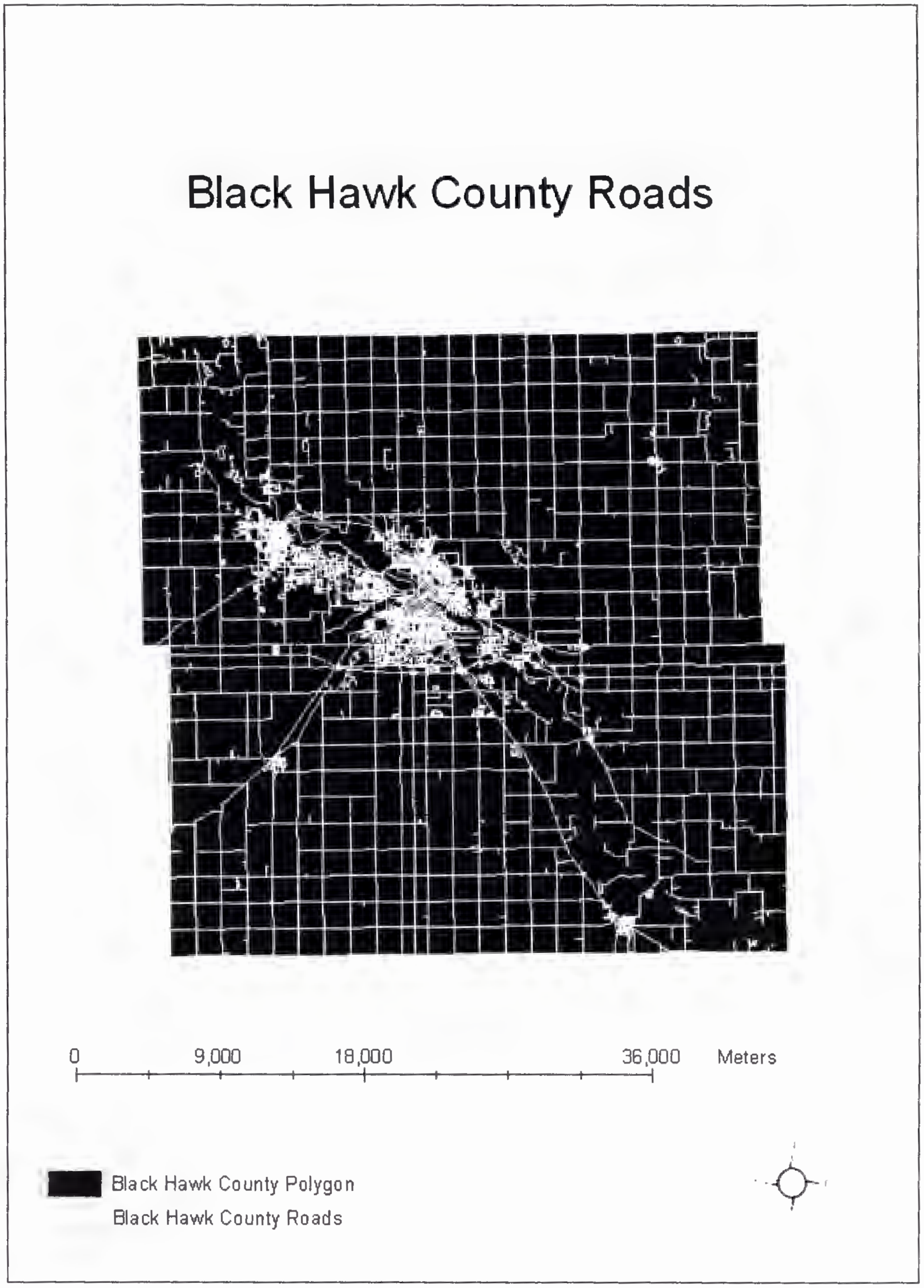
Map 6: 2000 Landsat Object-Oriented Classification, Black Hawk County



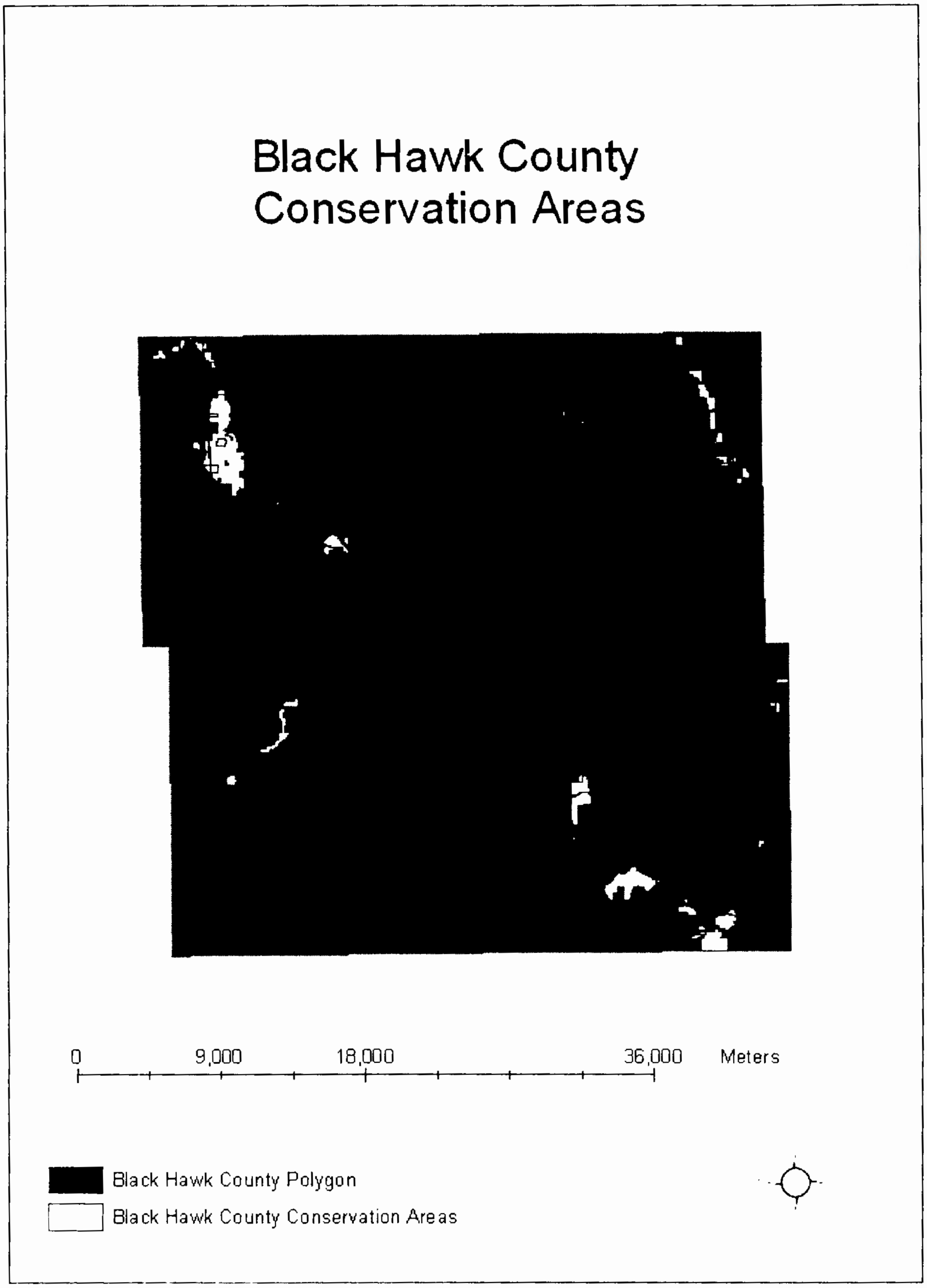
Map 7: 1999 Landsat Object-Oriented Classification, Black Hawk County



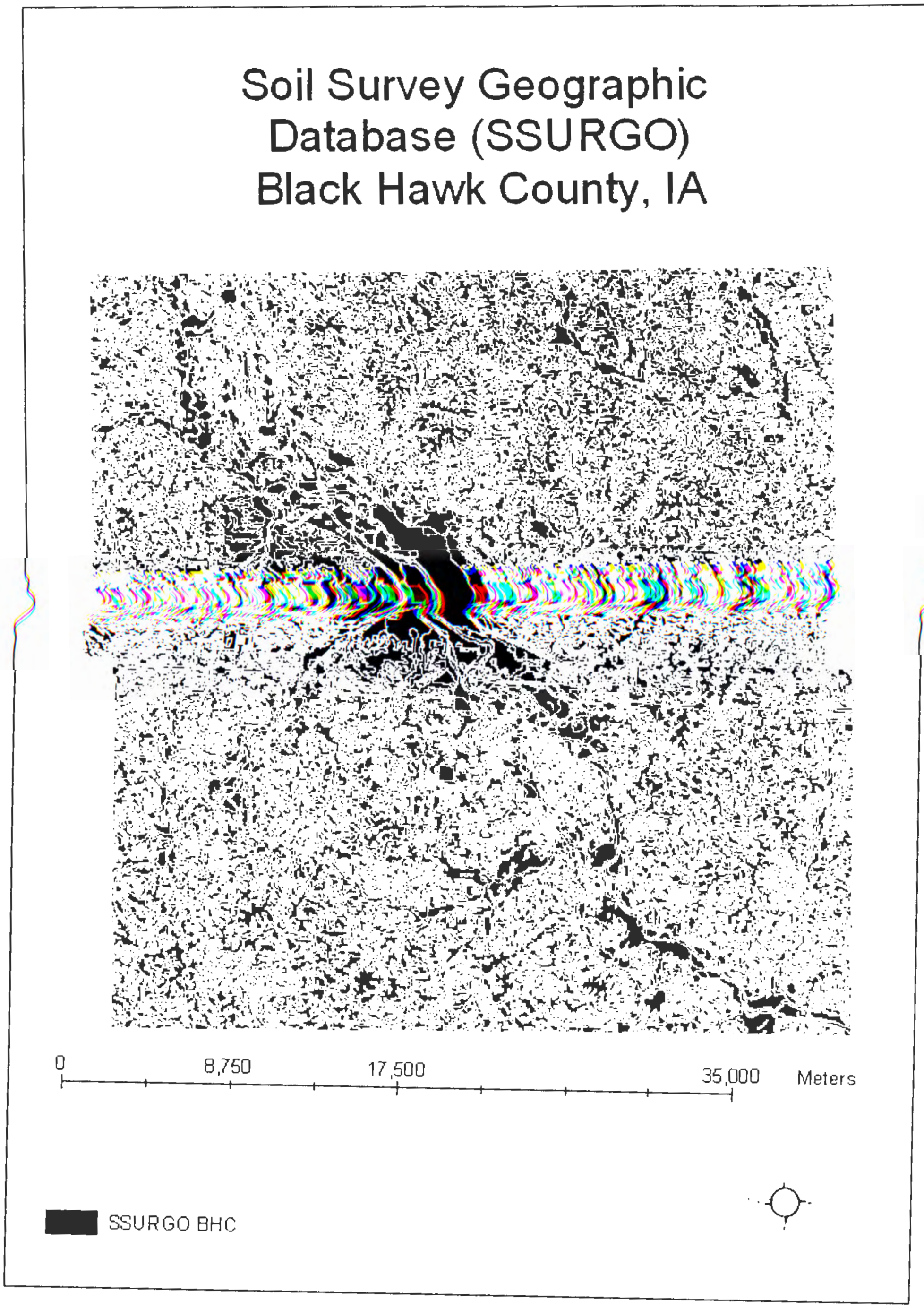
Map 8: 2001 CASI Object-Oriented Classification (left), Eddyville, IA
2001 CASI Spectral Angle Mapper Classification (right), Eddyville, IA
(16 acre subset of 50 acres)



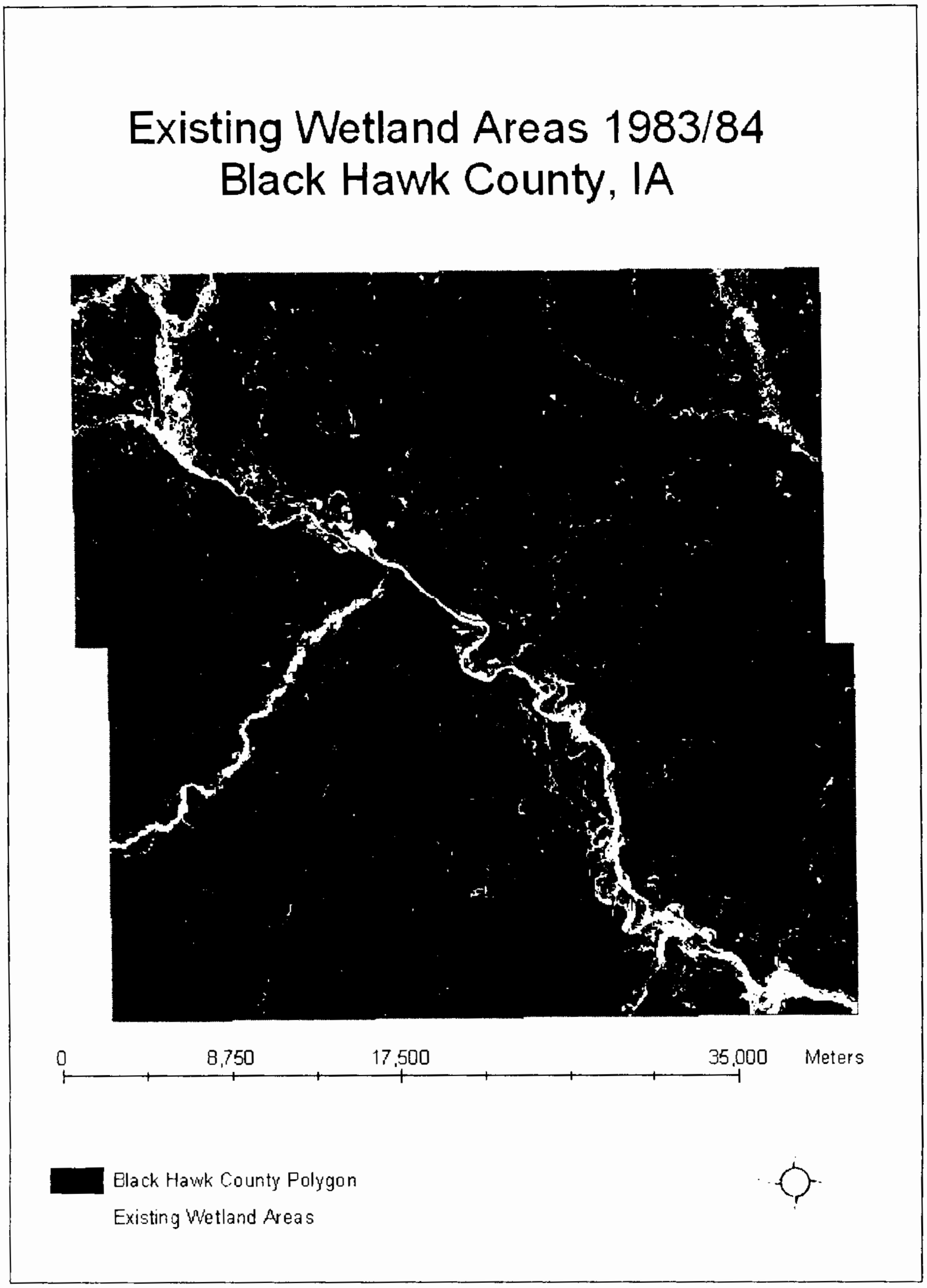
Map 9: Black Hawk County Roads Layer Used in GIS-Based Model



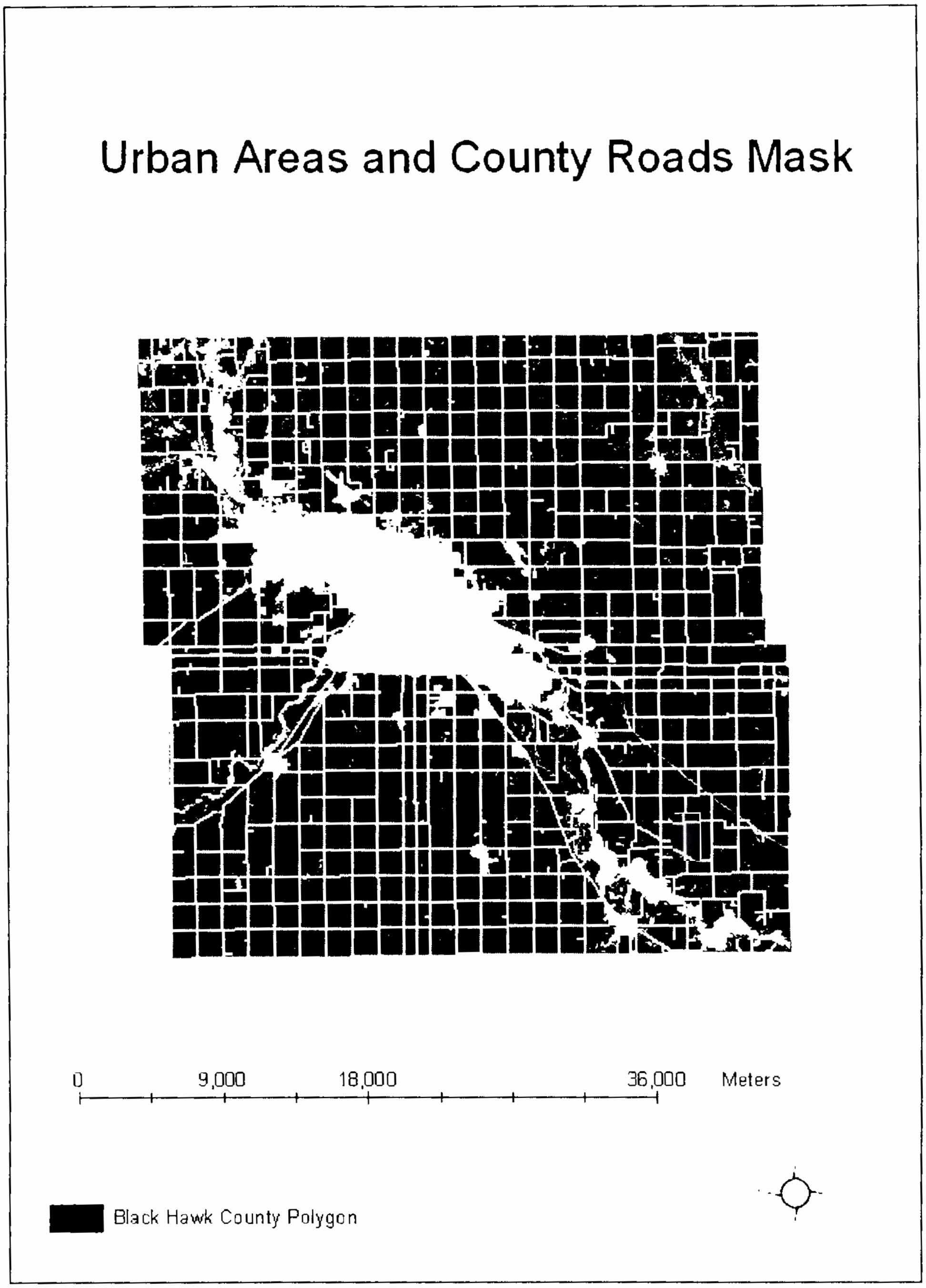
Map 10: Black Hawk County Conservation Areas Layer Used in GIS-Based Model



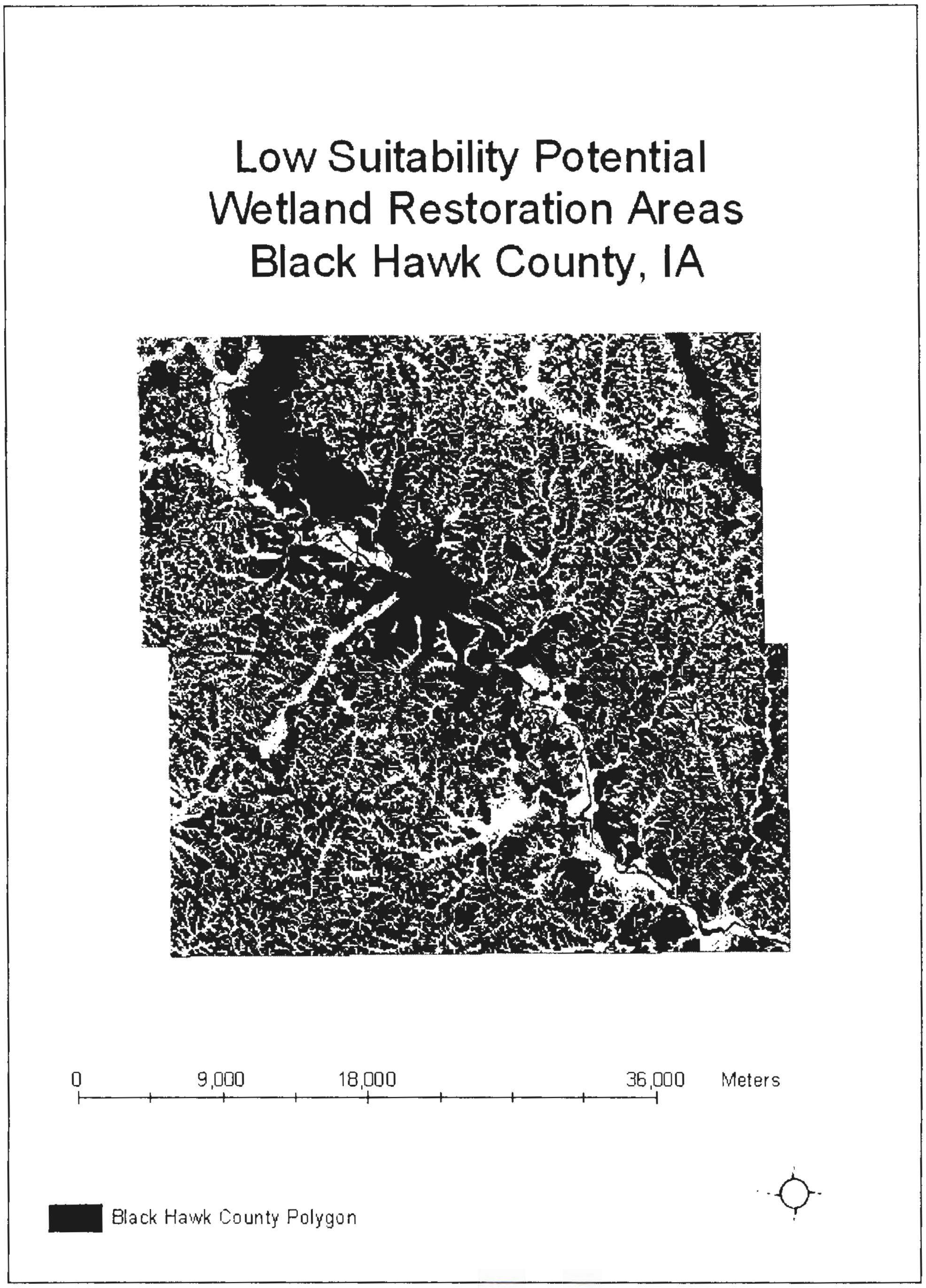
Map 11: SSURGO Soil Coverage Layer Used in GIS-Based Model



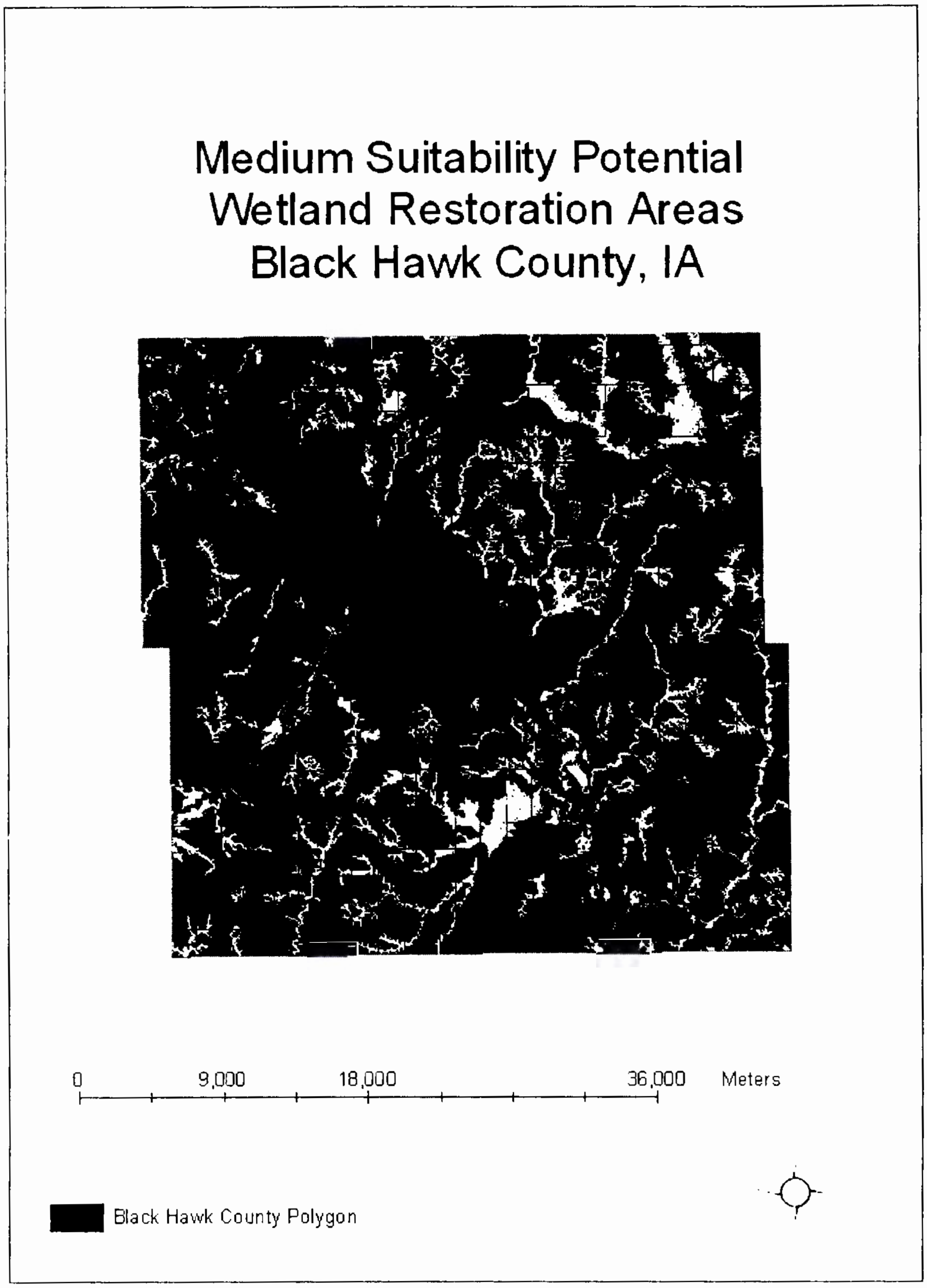
Map 12: NWI Wetland Areas Layer Used in GIS-Based Restoration Model



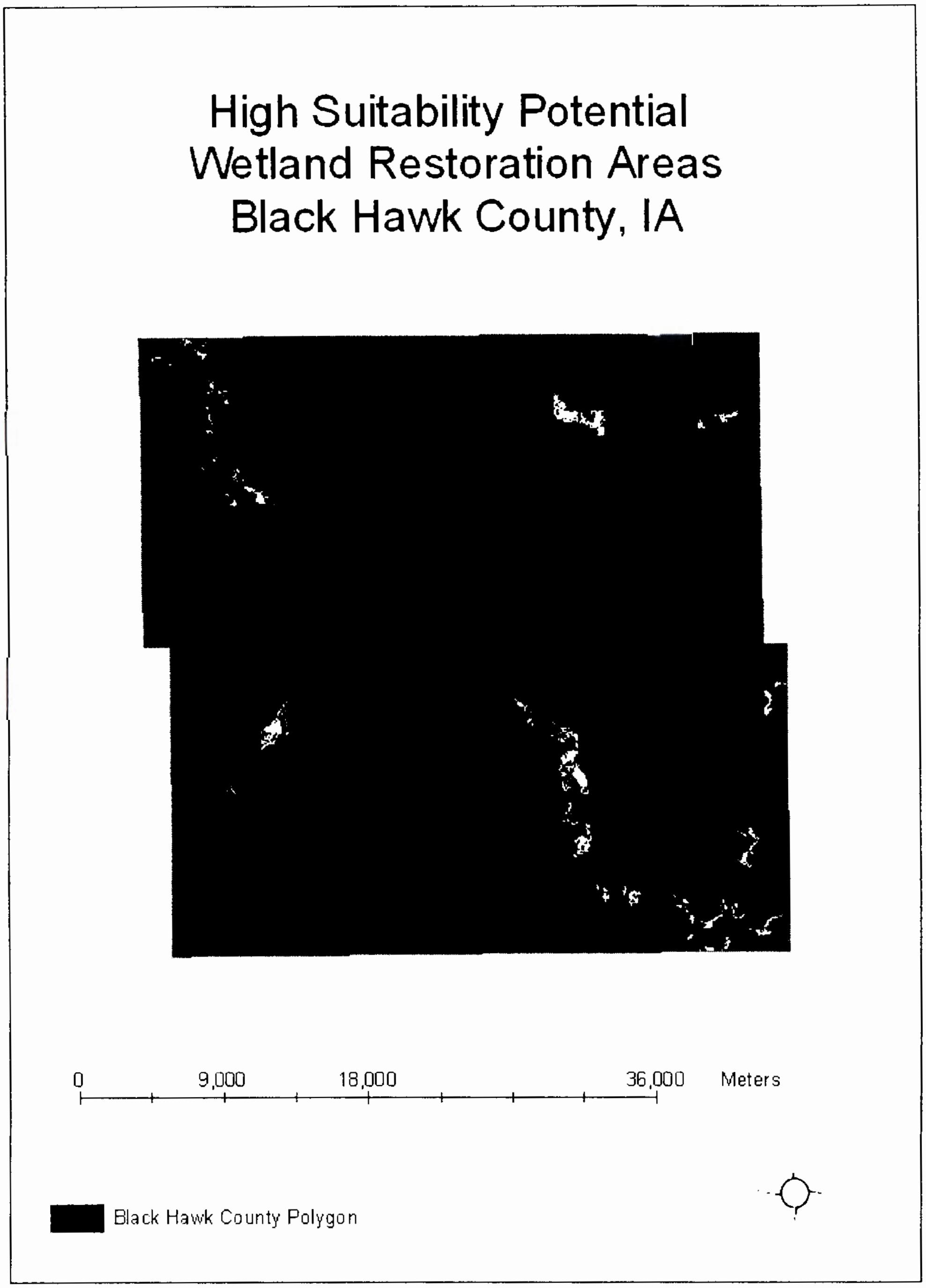
Map 13: Landcover and Roads Buffer Mask Layer Used in GIS-Based Restoration Model



Map 14: Low Suitability Potential Wetland Restoration Areas identified by GIS-Based Model



Map 15: Medium Suitability Potential Wetland Restoration Areas identified by GIS-Based Model



Map 16: High Suitability Potential Wetland Restoration Areas identified by GIS-Based Model