A Thesis entitled

The Utilization of Remote Sensing and Geographic Information System (GIS) for the Development of a Wetlands Classification and Inventory for the Lower Maumee River Watershed, Lucas County, Ohio

By
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Submitted as partial fulfillment of the requirements for the Master of Arts Degree

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The Ohio Environmental Protection Agency (EPA) and the Maumee Remedial Action Plan (RAP) groups identified the need for a revised wetland classification and inventory as a priority. A comprehensive geographic spatially explicit wetlands data model could add significant advances for addressing wetland projects in Lucas County. The objective of this study was to create a systematic methodology to identify wetlands using remote sensing and GIS (Geographic Information System) techniques. The resulting wetlands inventory and classification advanced the wetlands project mapping needs. The model identified four primary wetlands of interest; prairie, coastal, forest, and riparian. The overall accuracy of the classification was 94.5%.
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1.0 Introduction

The Ohio EPA and the Maumee Remedial Action Pan (RAP), Natural Areas Stewardship, Inc., and RAP Open Space and Wetlands Action Group are focusing efforts to address water quality. The Maumee River watershed was recognized as an Area Of Concern (AOC) under the 1987 Great Lakes Water Quality Agreement due to declining water quality conditions. In order to make decisions and shape policies to address water quality issues, improved information on wetlands in the watershed is needed. This study is part of a larger ongoing wetlands project intended to explore and provide wetlands information that is currently lacking in the Lower Maumee River AOC.

Wetlands provide a range of environmental and socio-economic benefits. These benefits range from their ability to store floodwaters and improve water quality to providing habitats for wildlife to support biodiversity and aesthetic values (Daily 1997, Mitsch and Bouchard 1998, Sexton and Szaro 1998, Acharya 2000, Mitsch and Gosselink 2000, Soderqvist et al 2000, Ozesmi and Bauer 2002). The loss of wetlands has gained considerable attention over the past few decades. The effects of urbanization, sprawl, and land cover changes have been recognized as contributing to altering these valuable ecosystems. New policies
and regulations require improved wetlands management practices and wetlands information to promote wetland systems.

The utilization of satellite remote sensing and GIS technology for inventorying and identifying wetlands has proven to be a useful and frequent application (Hardinsky et al 1996, Kindscher et al 1998, Lunetta and Balogh 1999, Ozemsi and Bauer 2002). Remote sensing techniques are often less costly and time-consuming for large geographic areas compared to conventional field mapping methods. Satellite data provides regular overpass intervals that enable the monitoring of wetland changes seasonally and over longer time periods. Advances in technology and computer capabilities allow for optimal integration of remotely sensed data and geospatial datasets within a GIS.

Many of these studies discuss the limitations of the technology. Resolutions of the satellite-derived data are the foremost factor in limiting the ability to obtain high precision and accuracy mapping on a detailed level (Ozemsi and Bauer 2002). Delineation of boundaries of patched landscapes, such as wetlands, is difficult and largely based on spatial resolutions (Fortin et al 2000, Frazier and Page 2000). Additionally, spectral and radiometric resolutions are a prohibiting component regarding land cover separability of detailed level land cover types (Hoffer and Johannsen 1969, Vogelman et al 2001, Ozesmi and Bauer 2002).

A hybrid model was created in an attempt to improve wetlands information in the study area. A GIS rule-based decision tree algorithm was designed to classify four primary wetland types of interest: forest, prairie, riparian, and coastal
wetlands. Hybrid models integrating remote sensed data with GIS ancillary information has been advantageous for improving wetlands classification as shown in numerous studies (Bolstad et al 1992, Sader et al 1995, Smith 1997, Cedfeldt et al 2000, Chapman and Cheetham 2002, Ozesmi and Bauer 2002, Wolfson et al 2002). The models showed several advantages and were successful at advancing the wetlands mapping goals. However, the complexity of wetlands and the model have limitations in the application and ease of use.

Problem Statement. An improved and updated wetlands inventory is needed to provide decision makers with information to support and promote wetlands in Lucas County, Ohio.

Objective. The central project objective is to design a systematic methodology for using GIS and satellite data to advance the development of wetlands classification and inventorying mapping for Lucas County, Ohio.

1.1 Study site.

Lucas County, Ohio, covers approximately 225,000 acres within Maumee River and Lake Erie watersheds in NW Ohio (Figure 1). Lucas County, with a population of approximately half million (U.S. Census 2000), contains a mix of land uses including agriculture, industry, residential, forest and parks, and urban systems. The City of Toledo, with a population approximately 330,000, is located
at the mouth of the Maumee River, which flows into Maumee Bay of the Western Basin of Lake Erie.

Figure 1. Maumee Area Of Concern in yellow polygon. Striped pattern reflects Lucas County coverage within the watershed.

Lucas County has an important relationship with the Maumee River and the Maumee River watershed which covers 6,555² miles (ODNR 2002). The Maumee River begins in Ft. Wayne, Indiana, and travels more than 130 river miles, 105 miles of which are located in Ohio. In 1987 the boundaries of the Maumee AOC were initially defined as the area from the Bowling Green water intake downstream to the Maumee Bay and Lake Erie, including Duck Creek, Otter Creek, Cedar Creek, Grassy Creek, Crane Creek, Swan Creek and the Ottawa River. In 1992, the AOC was expanded to include Packer Creek, Turtle
Creek, Rusha Creek and the Toussaint River. The drainage area for the AOC covers all of Lucas County and parts of Wood, Ottawa and Sandusky counties. The Maumee has the largest drainage area of any Great Lakes river with 3,942 stream miles draining into the Maumee River (Maumee RAP 2004).

1.2 Project History

In the spring of 2000, the Maumee RAP Open Space and Wetlands Action Group received a 319 grant from the Ohio EPA to conduct wetlands mapping research. The Natural Area Stewardship Inc. was the lead organization on the grant. Dr. Norman Levine and graduate student Holly Rotten from Bowling Green State University were initially contracted to develop the protocol for the Maumee RAP Open Space and Wetlands Action Group to identify wetlands using ERDAS Imagine software and the U.S. Army Corps of Engineer requirements for jurisdictional wetlands (Levine and Rotten, 2001).

The researchers first gathered Soils Survey Geographic Database (SSURGO) -based soils information and USGS digital elevation models, as well and orthophotos, surface hydrology maps (streams and ponds), Current Agricultural Use Value (CAUV) parcel data to locate cultivated land and general parcel and road information from the Lucas County Auditor’s Office (AREIS). Levine and Rotten created a mosaic from several Landsat 7 images. They did this for four dates representing the major seasons within 1999/2000: November 1999, March 2000, July 2000 and September 2000.
Unsupervised classifications techniques provided inaccurate quality map results. Knowledge Engineer and supervised classification further refined the protocol to identify five varieties of wetlands in the AOC: coastal, prairie, riverine, forested wetlands, as well as open water habitat (Levine and Rotten, 2001). Field verification of the resulting wetland map showed that there was a high degree of error: particularly in identifying wooded, prairie and riverine wetlands. In addition, farm fields and commercial rooftops were identified as open water habitat (Lawrence et al. 2003).

In the summer of 2002, an undergraduate student, Sarah Fuller, who was supported by an NSF Research Experience for Undergraduates (REU) at the University of Toledo’s Lake Erie Center, helped to refine mapping of prairie wetlands by identifying known wetlands at Kitty Todd and Irwin Prairie. Imagery was obtained for time periods covering each of the four main seasons in order to examine temporal changes in wetland conditions that could be determined by analysis of the Landsat 7 data. It was found that imagery from March had the most potential for identifying prairie wetlands due to wetter soil conditions and vegetation cover types.

Within ERDAS a classifying module, Knowledge Engineer, was used to specify prairie wetlands as a single classification. Key factors contributing to the application of remote sensing imagery for wetland classification included knowledge of the area of study, application of the ERDAS Knowledge Engineer, and the use of a Global Positioning System (GPS) unit for proper wetland delineation. Although this was an improvement over the past wetland maps,
there were still large areas associated with this classification as well as no statistically significant accuracy assessment.

Two of the Maumee RAP Open Space and Wetland Action Group project leaders, Michelle Grigore from the Natural Area Stewardship and Matthew Horvat from the Toledo Metropolitan Area Council of Governments (TMACOG), took a remote sensing class from the University of Toledo in hopes to gain enough remote sensing knowledge to improve the wetlands classification. They used the newly available spring and summer 2001 images and eliminated slope from the identification process (which tended to result in overly conservative estimates of wooded wetland), increased the buffer along the stream maps to better identify riverine wetlands, corrected an error in the formula for identifying open water habitat to remove wet fields from the finished map, and used supervised classification for wet prairie and emergent wetlands (Lawrence et al., 2003). The accuracy of the unsupervised classification was improved upon by utilizing 75 classes and 10 iterations (congruence= .949) rather than the ten class method from Levine and Rotten [2001] (Appendix A). General assessments determined many misclassifications still existed provided severe limitations in map usability (Lawrence et al 2003) (See Appendix A).
2.0 Wetlands

Wetlands, wetland, wetland ecosystems, are all variations of the same definition of a set of natural features that have undergone a series of changing descriptions within the last century (Tiner 1999). For a variety of reasons, numerous related terms have been developed for wetland types including; marsh, swamp, bog, mire, pothole, alkali meadow, lowland, river bottom, floodplain, tidal flat, fen, and salt marsh to name a few. For over a century a common complaint in the science community is the usage of the word wetland having too many loose terms (Lefor and Kennard 1977). Wetlands are natural ecosystems subject to permanent or periodic inundation or prolonged soils saturation sufficient for the establishment of hydrophytes and/or the development of hydric soils or substrates unless the environmental conditions are such that they prevent them from forming (Tiner 1999, Lewis 2001). Hydrophytes are individual plants that are periodically subject to anaerobic conditions due to wetness, while hydric soils refer to saturation at or near the surface periodically.

Historically, prior to the 1970s, wetland ecosystems have been considered a nuisance land cover providing little or no environmental, economic or social benefits (Tiner 1999, Adger et. al. 2000, Turner et. al. 2000, USFWS 2000).
Wetlands were, and still continue to be, drained, filled, polluted, and cleared due to human usage and urbanization. A variety of factors contribute to reducing wetland areas nationally including agricultural, suburbination/urbanization, preference and land value beliefs, species eradication, landfill location, and natural resource economics.

Today, pressures of human settlement and urbanization on wetland ecosystems are being recognized and continue to be addressed. Within the past four decades, science has shown that wetland ecosystems provide a range of environmental and socio-economic benefits (Daily 1997, Turner et. al. 2000, Mitsch et. al. 2000). These include holding storm water, erosion and agricultural run off control, mitigating water pollution, contributing to a healthy water cycle, recreation, and providing wildlife habitat. Many studies detail the relationship between environmental and socio-economic benefits and the value of incorporating pro-wetlands management into policies, plans, and management practices (Hodge et al 2000, Burgress et al 2000, Primavera 2000, USFWS 2000).

Nationally, a recent comprehensive report by the Department of Interior United States Fish and Wildlife Service (USFWS), states that wetlands loss has decreased 80% in the last ten years across the US (USFWS 2000). A second ‘scientific-survey’ conducted by the US Department of Agriculture’s (USDA) Natural Resources Conservation Service (NRCS) National Resources Inventory (NRI) group found that significant reductions in wetlands loss occurred between 1992-1997 (NRCS 2004). The USFWS service stated that forest, coastal, and
fresh water wetlands suffer the most lost. In 1997 a total of 105 million acres of wetlands were estimated to exist of which 95% is fresh water. In 2000, the authors testified before Congress that 58,500 acres were lost annually in the early 1990s, which is actually an 80% decrease from the previous decade. They noted that while fewer wetlands are being lost nationwide recently, selected types of wetlands in specific locales remain vulnerable to loss and degradation. The analysis during this study period attributed causes of wetland losses nationally to the following uses: Urban Development (30%), Agriculture (26%), Silviculture (23%), and Rural Development (21%) (USFWS 2000).

2.1 Defining Wetlands.

Wetland related issues built momentum throughout the latter half of the 20th century. Legal issues began to fill the courts across the country. Development questions arose throughout local and state agencies, environmental organizations drew growing attention, and ecological confusion existed between groups. This caused the US House of Representatives to formally ask the Environmental Protection Agency to contract the National Academy of Sciences to develop a comprehensive report on all specific wetland related issues and questions.

Formally defining wetlands became a primary component. During the 1990s the National Research Council (NRC) distinguished seven different wetland definitions of significance. Although it appears repetitive, each definition is uniquely important depending on its particular focus especially in regards to
classifying and mapping research. All seven definitions contain two basic parts: first, a summary definition of what is a wetland usually containing a reference to water, and second a series of examples of a wetland often containing several example wetland names.

Early modern day US definitions of wetlands were developed primarily by the US Fish and Wildlife Service to conduct wetlands assessments. A well known circular in the wetlands professional community known as Circular (39) termed “wetlands” as referring to ‘lowlands covered with shallow and sometimes temporary or intermittent waters. They are referred to by such names as marshes, swamps, bogs, wet meadows, potholes, sloughs, and river-overflow lands. Shallow lakes and ponds, usually having emergent vegetation as a conspicuous feature, are included in the definition, but the permanent waters of streams, reservoirs, and deep lakes are not included. Neither are water areas that are so temporary as to have little or no effect on the development of moist-soil vegetation’ (Shaw and Fredine 1956). Shaw and Fredine’s wetlands classification contained more than 20 types of wetlands. This circular and classification system continues to be one of the most significant inventories to date. The system provides a base on which nearly all-modern day wetland definitions are built upon.

Many legal definitions exist at different levels. The US Army Corps of Engineers (COE), required by the Clean Water Act, defines wetlands as ‘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. Wetlands generally include swamps, marshes, bogs, and similar areas (Environmental Laboratory 1987).

A second modified US Fish and Wildlife Service definition was noted after the government began updating wetland inventories during the 1970s. The FWS scientific definition created in the late 1970s defines ‘wetlands as the 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. Wetlands must have one or more of the following three attributes. 1.) at least periodically the land supports predominantly hydrophytes, 2.) the substrate is predominantly undrained hydric soil, and 3.) 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 Canadian wetland definition was cited in the NRC’s report. Northern wetlands have proven to be an area of controversy due to the climate. According to Zoltai, a Canadian scientist, a ‘wetland is defined as land having the water table at, near, or above the land surface or which is saturated for a long enough period to promote wetland or aquatic processes as indicated by hydric soils, hydrophilic vegetation, and various kinds of biological activity which are adapted to the wet environment (Zoltai and Tarnocai 1981).

An international definition was included from the Ramsar Convention on Wetlands. In Ramsar, Iran in 1971 the Convention on Wetlands met and created an international treaty designed to provide the framework for national action and
international organization for wetlands conservation and research (Ramsar 2004). Over 100 million hectares are detailed under the Ramsar List and it is considered one of the most important global wetlands organizations. This international definition details wetlands as ‘areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish, or salt including areas of marine water, the depth of which at low tide does not exceed 6 meters. This may incorporate riparian and coastal zones adjacent to the wetlands and island or bodies of marine water deeper than 6 meters at low tide lying within the wetlands’.

The Natural Resource Conservation Service developed a definition during the Food Security Act of 1985 (FSA 1985). The ‘term wetland except when such term is part of the term “converted wetland” means land that 1.)it has a predominance of hydric soils; 2.) is inundated or saturated by surface or ground water at a frequency and duration sufficient to support a prevalence of hydrophytic vegetation typically adapted for life in saturated soil conditions; and 3.) under normal circumstances does support a prevalence of such vegetation’. The NRCS, including the SCS, is essentially the governing body of hydric soil parameters and regulations.

The National Research Council Committee itself created the final wetland definition. A ‘wetland is an ecosystem that depends on contrast or recurrent, shallow inundation or saturation near the surface of the substrate. The minimum essential characteristics of a wetland are recurrent, sustained inundation or saturation at or near the surface and the presence of physical, chemical, or
biological features reflective of recurrent, sustained inundation or saturation. Common diagnostic features of wetlands are hydric soils and hydrophytic vegetation. These features will be present except where specific physiochemical, biotic, or anthropogenic factors have removed them or prevented their development’ (NAP 1995).

2.2 Wetland Policies.

The history of federal involvement in wetlands is extensive and contradicting at times. Two original historical Acts are of critical importance in wetlands regulations (Dennison 1993, Davis 1998). The first noteworthy piece of legislation came in 1849 with the Swamp Lands Act. This Act came into effect to aid the State of Louisiana in constructing necessary levees and drains to reclaim and/or control the swamps and overflow. The Swamp Lands Act affected much of the Mississippi River Valley. In 1850 the Swamp Land Act extended to Alabama, Arkansas, California, Florida, Indiana, Ohio, Iowa, Michigan, Mississippi, and Missouri. In 1860 Minnesota and Oregon were added to the Act. In total the Act gave rights to approximately 65 million acres (NRC 1995).

The second critical piece legislation that still has a large impact on today’s delineations is the Rivers and Harbors Act of 1899. This gave the Corps of Engineers responsibility for regulating dredging and filling of navigable waters. This Act not only gave responsibility but also in effect gave control of regulation. The Act formed the foundation of today’s water pollution laws created in the 1970s such as the Clean Water Act (Lewis 2001).
More recently a series of legislative documents came to be during the green movement of the 1960s and 1970s. In 1972 and 1977 amendments to the Federal Water Pollution Control Act (FWPCA) of 1956, gave birth to the modern term “wetlands’. The FWPCA became known as the Clean Water Act. At the same time the formal creation of the Environmental Protection Agency was occurring. Much debate relating to wetlands and what agency should officially oversee the regulation of wetlands arose. The prominent Senator from Maine, Sen. Muskie, led the argument. The core of this debate was attempting to shift the COE dredge and fill permitting to the EPA. This debate continues today with the principal dispute being that the mission of the COE is to protect navigable waters, not protect the environment. This led to the House creating Section 404 of the Clean Water Act, which set up cooperation between the COE and EPA. Section 404 is today’s highest governing legislation on wetlands (Environmental Law Institute 1993). Summarizing, the COE and the Rivers and Harbors Act deals with navigation and disposal of dredged material and construction of potential hazards to navigation, while the EPA and the Clean Water Act is more geographic and concerned with the health of waters of the US. The Corps provides permits with the EPA giving oversight (Dennison 1993).

In 1975 the US federal district court of D.C. tried a case that forced the courts to broaden its role and again modify its definition of wetlands. The Natural Resource Defense Council vs. Calloway [392 F. Supp. 685, 5 ELR 20285] argued that wetlands were included in “waters of the United States” and thus subject to dredging regulations within Section 404. This decision increased the
amount of wetlands by 85% (Want 1992). This changed the definition of wetlands to ‘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 soils’. Two years later a Presidential Executive Order strengthen many courts decisions by requiring all Federal agencies to take action necessary to protect wetlands under the federal jurisdiction.

This modified wetland definition contains a few key components. It requires that certain types of vegetation, hydrophytics, be capable of growing in the area. Prior to 1989, the land use was considered to be ‘normal circumstances’ when examining wetlands. Therefore if a land area was “left unattended for a sufficient period of time, the land would revert to having wetland plant communities through the devices of nature”. As a result farmlands were left outside the definitions and regulations (Zirschky 1996).

In 1985-88 the Food Security Act, 16 U.S.C. 3801-3862, was enacted and manuals published for distribution. This act directly and indirectly affects wetlands and specifically addresses wetlands destruction. A provision known as ‘Swamp-buster’ was written into the legislation. Part 512 of the Act declared that persons converting wetlands to agriculture would be denied agricultural loans, payments and benefits (US FWS 1992).

During this same period (1987) the birth of all modern guides for jurisdictional wetland delineations was written by the COE. Even with regional and local guideline manuals, this manual continues to go through many
adjustments, but is essentially the single governing document for wetland delineations in the US (See Appendix B). One year later the SCS, EPA, COE, and FWS wrote a second wetland delineation manual. Four main manuals exist with the COE being the most noteworthy. The summary of these manuals was very similar. Three main characteristics were/are required for a wetland delineation. A) predominance of hydric soils, B) inundation or saturation by surface or groundwater at a frequency and duration sufficient to support a prevalence of hydrophytic vegetation typically adapted for life in saturated soil conditions, C) under normal circumstances does support a prevalence of such vegetation.

2.3 Ohio Wetlands.

The state of Ohio has a wetlands history similar to national trends. In the past 200 years over 90% of Ohio’s wetlands have been destroyed as a result of human impacts (GLC 2002). The Great Lakes Basin watershed once was dominated by a variety of wetland ecosystems (Figure 2). 150 years ago in northwest Ohio, the Great Black Swamp covered 1500² miles and the Lake Erie Marsh stretched from Sandusky Bay to Maumee Bay (Gordon 1969). This significant wetland area dominated watershed is now a patched network of shrinking wetland landscapes.
On the geologic time scale NW Ohio was once a vast sea. During the last glacial maximum the Wisconsin glacier formed many distinctive features regionally. The glacial lakes are considered instrumental for the creation of three main features; the Great Black Swamp, Oak Openings, and the Lake Erie and Sandusky Bay marshes (Lafferty 1979). Today Oak Openings is a unique system of land uses. Oak Openings is a broad ridge of fine yellow quartz sand that extends from Liberty Center northeast towards Detroit. It covers parts of Henry, Fulton, and Lucas counties. The sand based soil lies upon clay type soils creating a matrix of ecosystem networks. The sand came from Michigan over thousands of years. Ancient glacial lake wave currents carried sand along the edges as lateral moraines. The lakes dropped and wind began to slope sand
dunes. These dunes have up to 35 feet in topography and can be from 3.5 to 7 miles in width with depth 15 – 50 feet. The drainage below the sand layer is very poor and water lies within three feet of the surface in many areas. These rare combinations created many of the wetlands in the region.

The ‘Great Black Swamp’ was once dominated NW Ohio. This tract nearly equaled the size of Connecticut being 120 miles in length by 40 miles in width. It contained a diverse plant community including birch, ash, elm, oak, cottonwood, poplar with maples, basswood, hickories shagbark, and shellbark (Gordon 1969). The population of Ohio grew rapidly which caused major alterations of the land uses. NW Ohio populations nearly doubled every 10 years during the latter half of the 19th century (OHS 1997). During the 1860s in Ohio the railways used 1 million cords of wood annually for fuel alone. Intense logging between 1860 – 1885 occurred in the Black Swamp region of NW Ohio to supply the growing demand of rich agricultural lands, industry, and transportation (Lafferty).

Ditches across the landscape began to drain the natural wet meadows and prairies (Gordon 1969, Jaeger 2001). One natural meadow was six miles long, and 2 miles wide adjoined the town of Circleville. During the 1820s ditches started to eradicate prairies for farmland purposes. Hardin County alone contained 25,000 acres of marshlands before the mass growth of Ohio. Within Lucas County, vast areas along the lakeshore began to be diked and pumped to take advantage of the rich farmland (Jaeger 2001). By the mid 1900s Lucas County had been largely reclaimed for agricultural purposes. It is estimated that small ditches dug over several years totaled over 150 miles (Bednarik 1984).
Remote Sensing

Remote sensing of land cover types has been an early application of satellite imagery. Since launching the Earth Resource Technology Satellite 1 (ERTS) on July 23, 1972, today commonly known as Landsat 1, the Landsat program has been the longest continuously running satellite data provider (Jensen 2000). The aim of Landsat 1 was to conduct basic mapping of geology, crops, and pollution events (Goward and Masek 2001b). The launch of Landsat 7 ETM+ on April 15, 1999 from Vandenberg Air Force Base, California, is beyond the aspirations of the original program engineers of the 1950s and 1960s. Although historically driven much by politics rather than science, Landsat 7 continues to provide the most advanced data available in the Landsat Data Continuity Mission archives (Arvidson et al 2001). The underlying goal of the Landsat 7 mission is to explore global change research and terrestrial land research. Goward et al [2001b] provide a review of the Landsat 7 mission and future directions.
Remote sensing exclusively for surface hydrology and wetlands mapping has become a 'regular' application of satellite imagery. Nearly ever sensor has been tested for wetlands identification and wetlands related research (Smith 1997, Frazier and Page 2000, Ozesmi and Bauer 2002). Each sensor has advantages and limitations often related to their associated resolutions. The key determinate factor often corresponds to the scale of the project. The explicit design and goal of the study usual dictates the choice of sensor. Smaller scaled local or county level studies require more detailed resolutions, while larger scaled studies are well suited for coarser scaled sensors. Other factors determining sensor choice, related to scale and sensor resolution, are cost and availability.
The temporal resolution and cost become a fundamental component of sensor choice.

3.1 Landsat 7 Enhanced Thematic Mapper Plus

For this study, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery was used as the primary remotely sensed data. The choice of using Landsat 7 imagery was two fold. First are the resolutions of Landsat 7 ETM+ (Table 1).

Table 1. Landsat 7 Enhanced Thematic mapper plus (ETM+) characteristics

<table>
<thead>
<tr>
<th>Bands</th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral range (µm)</td>
<td>.45 - .515</td>
<td>.525 - .605</td>
<td>.63 - .96</td>
<td>.75 - .90</td>
<td>1.55 - 1.75</td>
<td>10.4 - 12.5</td>
<td>2.09 - 2.35</td>
<td>.52 - .90</td>
</tr>
<tr>
<td>Spatial resolution (m)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>60</td>
<td>30</td>
<td>15</td>
</tr>
</tbody>
</table>

Landsat 7 ETM+ images used in this study provide 16 day overpass repeat intervals with recorded spectral reflectance ranging in the electromagnetic spectrum. Bands 1-5, and 7 have a spatial resolution of 30 meters, band 6 (thermal band) is 60 meters, band 8 (panchromatic) is 15 meters (Goward et al. 2001).

OhioView is a grassroots organization created in the mid 1990s by a consortium of eleven partners to make satellite imagery accessible. In essence OhioView distributes free data for the entire state of Ohio (OhioView 2004). This component was in fact a primary driving force behind the choice. In order to set up a monitoring or inventorying study longer term analysis is required compared to a one time baseline study. The future possibility of updating the data model with recent imagery was part of the study concept and model design.
3.2 Land Cover

Land cover separability plays an important role in classification methodology mapping. Sensor resolutions are the key determinate in the ability to define land cover types (Avery et al 1992, Green et al 1994, Ridley et al 1998, Smith et al 1998). Defining different wetland ecosystems are considered an advanced level of land cover type compared to defining a level 1 land cover such as residential, industrial, or commercial land cover (Anderson et al 1976). The USGS Land Cover scheme ‘Minimum Remote Sensing Resolutions’ required to obtain equivalent land cover data uses a temporal resolution <4 years, a spatial resolution of < 5 meters, and a spectral resolution of panchromatic - visible - near infrared - mid infrared (Anderson et al 1976, Jensen and Cowen 1999, Jensen 2000).

Spectral signatures are measurements of the spectral response of different features in the bands of the remote sensor (Jensen 2000, Ozesmi and Bauer 2002). Wetland spectral signatures have been studied and published extensively throughout the literature. Noteworthy research includes the Gluck et al [1996] finding it difficult to separate different wetland types from one another because of the overlap in their spectral signatures. Anderson and Perry [1996] measured differences in leaf spectral reflectance of red maple (Acer rubrum) on semi-permanently and temporarily flooded sites in Virginia. Pax-Lenney [2001] discuss the role of spectral manipulation for more favorable classification. Ozesmi and Bauer [2002] summarize that many wetlands types have similar reflectance responses making it difficult to separate into classes.
Figure 4. Selected land cover reflectance for Lucas County.

Land Cover Figure 4 displays spectral response from a Landsat 7 image from 11/9/01 of selected land cover types in Lucas County. The eight land covers are typical of NW Ohio and the study site. The pond represents a high absorption land cover while the building roof represents a high reflectance. Bands 1-3 generally have a small range of reflectance responses. The IR (infra-red) region, particularly the NIR (near infra-red) and MIR (mid infra-red) wavelengths between 740 – 2500 nm (nanometers), is considered a water discrimination region and a fundamental spectral region for water and water related land covers (Jensen 2000). In this region water absorbs incidence radiation appearing very dark and/or black. The pond pixel has the lowest response in Landsat band 4, while the land covers, such as agriculture and golf coarse, have higher reflectance responses. The Maumee River response, measured near downtown Toledo, has
a higher reflectance than the pond pixel. This is from elevated levels of sediment and turbidity.

Figure 5. Electromagnetic absorption and vegetation responses (Jensen 2000).

Figure 5 (Jensen 2000) illustrates spectral reflectance responses of healthy vegetation for the 0.4 – 2.6 \( \mu m \). Significant water absorption regions are depicted in the IR region of the spectrum. High reflectance recordings are located in the NIR region as well as a smaller rise in the green area of the visible spectrum. Chlorophyll absorption areas are pointed out over the visible spectrum.
3.2.1 Soils & Hydrology Reflectance

As indicated by the definitions of wetlands, subtle differences occur but all past studies discuss the importance of the relationship between soil conditions and hydrology. Soils and hydrology play a central role in wetlands land cover separability and classification. The uniqueness of that relationship in sense determines the ability of a sensor to delineate wetlands from other land covers (Fortin et al 2000). That relationship also in a sense determines the sensor to be used in a particular study depending on research objectives. The soil, soil hydrology, and soil moisture have an established relationship with satellite platform sensors throughout the literature (Kim et al 2002, Brad and Ramona 1988, Hummel et al 2001, Muller and Decamps 2001, Wigneron et al 1998, Kim and Barros 2002).

Soil moisture is a complex combination of chemical and physical attributes, composition, properties, climate, geography, and other factors (Childs et al 1986, White 1997, Weidong et al 2002). Each one of these factors alone can have significant contributions to the reflectance response observed by a sensor. As stated in section 4.2 Land Cover, absorption and reflectance of energy has different levels of sensitivity throughout the spectrum. A pond was discussed as having a dark object response. The same factors apply with soil moisture levels. Increased soil moisture will typically have a decreased reflectance response over the spectrum (Bowers and Hanks 1965, Hoffer and Johannsen 1969).
Figure 6 depicts the concept of soil moisture reflectance visually (Jensen 2000). The upper graphic (Figure 6a) details how incident energy reflects off a dry soil composition. The bottom graphic (Figure 6b) illustrates how energy is absorbed at a greater level with a moist soil and high water content of a wet soil. Figure 7 displays the reflectance of 5 soils with various physio-composition. Organic soils have the lowest response while soil types largely made of sand have significantly increased responses. Additionally noted is the general trend of increased response individually as the wavelengths increase as the spectrum approaches the NIR region of the sensor.

Ishiyama et al [1996] produced similar results from a study of ground cover reflectance that can be directly related to wetlands and soil moisture and difficulties in interpreting the data. First, they found the difference in spectral response of different soils is comparatively small. Second, there is a tendency that spectral reflectance of soils increases with increases in wavelength. Third, they found that reflectance of the soils decreases with increase of soil moisture content. The water absorption bands, particularly around 1450 and 1950 nm, are a distinctive region pertaining to soil moisture/water reflectance.
Figure 6. Specular reflectance of soil moisture regimes (Jensen 1996).
3.3 Multitemporal

Multitemporal techniques have been well established and accepted as a theory in land cover classifications particularly associated to wetlands related remote sensing (Jensen et al 1986, Johnston and Barson 1993, Gluck 1996, Smith et al 1998, Lunetta and Balogh 1999, Kushwaha et al 2000, Phinn et al 2000, Ozesmi and Bauer 2002, Brown de Colstoun et al 2003, Lunetta et al 2004). Changes in land cover types, such as wetlands, becomes an important
factor when applying classification models. The ability to use data capturing the changes in phenological cycles, seasonal weather patterns, and regional hydrological influences can potentially add to the classification advancement.

Brown de Colstoun et al [2003] found the usage of ETM+ scenes from multiple dates significantly improved classification accuracy for different ecosystem types. Fortin et al [2000] additional found that specific vegetation changes seasonally and that data can be exploited for detecting ecotones. Lunetta et al [2004] discuss the importance of remote sensor data temporal frequency for specific ecosystem regeneration rates. Ozesmi and Bauer [2002] address the fact that it is hard to detect wetland types with drier water regimes, such as forested wetlands, scrub-shrub, and emergent wetlands. And in order to separate wetlands it is usually advantageous to use satellite images from dates when the wetlands are at their highest water levels. Townsend and Walsh [2001] found using multitemporal imagery increased the accuracy and classification detail level of ecologically important vegetation types specifically forested wetlands.

Many of the multitemporal studies indicate that classifying detailed land covers, such as wetland types, potentially requires different and/or increased time series data input for optimal mapping. Multitemporal imagery often aids in the classification of wetlands and their separation from other land cover classes. These studies indicate the role of synthesizing together theories of land cover separability, soil moisture reflectance, and multitemporal imagery.
Lucas County, being largely agricultural, requires multitemporal techniques for advanced land cover separation in wetlands classifying. Figure 8 [Jensen 1996] displays hard red winter wheat phenology for a period of 1 year in the Great Plains. Plant growth initially begins in early spring around mid-March when temperatures warm the air and ground. It continues to grow and ‘green up’ throughout the summer months until harvest late summer. Often winter wheat can be left dormant year round if tillage is not performed. Figure 9 is a picture taken in western Lucas County on 7/9/03 and is a representative of a typical winter wheat field.

Figure 8. Winter wheat cycle (Jensen 2000).
Figure 9. Common Lucas County wheat crop.

Figure 10 [Jensen 2000] illustrates two other crops found extensively in Lucas County. Soybeans (Figure 10a) begin to sprout mid-May and have 50% coverage by mid-summer. The plants reach complete coverage throughout the summer months. Figure 10b displays the growth chart for corn. Greening periods occur during spring months, with full bloom during the summer and early fall time period. Harvesting late fall potentially reflects similar vegetation responses to cooling weather patterns.
Figure 10. Growth cycle of Lucas County crops (Jensen 2000).
Figure 11 exhibits the phenological cycle of a typical wetland species. Cattails (*Typha* spp) and water lilies (*Nymphaea* spp.) green up as air and water temperatures enable photosynthesis (Rickles 1983) during early spring through late summer.

Figure 11. Displays typical wetland plant growth cycles (Jensen 2000).

Figure 12 are pictures from 7/17/2003 at training sites in located in coastal wetland pools inside Ottawa National Wildlife Refuge. Water lilies are located throughout the coastal wetland ecosystem in Ottawa national Wildlife Refuge. By
late summer water lilies begin to peak in coverage and photosynthesis. Water lilies generally ‘green up’ slightly after cattails begin to emerge. They begin senescing in mid fall and disappear by November (Jensen 2000). These wetlands will have a slightly smaller growing season compared to the data from Par Pond South Carolina where the graphs illustrate growing seasons.

Figure 12. Coastal wetland ecosystem.
4.0 Methods

Advances in Geographic Information Systems (GIS) and remote sensing provide sophisticated methodologies for data integration and analysis (Demers 2000, Demers 2002). A hybrid assessment method integrating both geotechnologies was used in this study. Leica Geosystem's ERDAS Imagine 8.6 and Environmental Systems Research Institute's (ESRI) ArcView 3.2 and ArcGIS 8.3 are the chief software utilized for remote sensing and GIS applications respectively.

Users have defined integrated assessments or hybrid models in a variety of fashions depending on execution. Demers [2000] defines hybrid models as accommodating the linkage between spatial entities and their attributes. Others' have generally used the term hybrid models to reflect a series of steps utilizing traditionally different techniques or “rules” to classify data. Both definitions apply to the model built in this study, which uses data and system integration as well as rule-based classifiers. A decision tree methodology was executed to classify the remote sensor images.

Hybrid models using different data sources have increasingly expanded into the field do to the proliferation of imagery and digital data. Using satellite
imagery together with other data sources can improve on wetlands classifications (Ozemsi and Bauer 2002). Ozemsi and Bauer [2002] synthesize the literature indicating that generally multitemporal imagery and ancillary information such as soils, elevation, or other maps, improves wetlands classification. Bolstad and Lillesand [1992], Sader [1995], and Lunetta et al [1999] found that using wetlands related ancillary data, including field data collections, can significantly improve classifications. This study incorporated agricultural parcel, boundary, and soils spatial data as “rules” or restrictions to improve wetlands mapping within the AOC (Figure 13).

A decision tree classification algorithm was created as the main technique for using the satellite data. Most land classification studies stop short of complete analysis due to time and cost constraints (Friedl and Brodley 1997). Decision tree classification algorithms have significant potential for land cover mapping problems (Defries et al 1998, Hansen et al 2000) and have not been tested in detail by the remote sensing community relative to more conventional pattern recognition such as maximum likelihood classification (Friedl 1997). Decision trees have substantial advantages for remote sensing classifications problems because of their flexibility, intuitive simplicity and computational efficiency (Hansen et al 1996, Friedl et al 1999). Decision trees predict class membership by recursively partitioning a data set into more homogenous subsets (Defries and Chan 2000). A hierarchical decision tree hypothesis was created with rules defining the integrated GIS data for the wetlands classification model used in this study.
4.1 Precipitation

Wetlands and the COE guidelines require hydrological regimes that support these systems. In particular, studies have shown, it is hard to detect wetland types with drier water regimes, such as forested wetlands, scrub-shrub wetlands, and emergent wetlands, because they are easily confused with other vegetation. Additionally, in order to separate wetlands from uplands, it is usually advantageous to use satellite images from dates when the wetlands are at their highest water levels (Ozesmi and Bauer 2002).
The COE manual requires more specific criteria in the area of precipitation and water levels. An example relating to water levels and precipitation could include 1.) an area has wetland hydrology if it is inundated or saturated to the surface for at least 5% of the growing season in most years, a.) in northwest Ohio 14 consecutive days of saturation is required during the growing season, b.) “in most years” means at least 50 years out of 100, or 50% probability in any one year, c.) the growing season is defined as the portion of the year when soil temperature (measured 20 inches below the surface) is above biological zero (5 Celsius or 41 Fahrenheit) (Environmental Laboratory 1987).

Precipitation data for Toledo Express Airport was obtained from the National Oceanic and Atmospheric Administration’s (NOAA) National Weather Service Office in conjunction with the National Climatic Data Center (NCDC). Figure 14 displays monthly averages from 2000–2003 and a 30-year average beginning from 1971. Significantly dry or wet periods can effect spectral responses and alter data interpretation. Generally, in the past four years mid-late spring has had slightly increased precipitation levels as well as fall excluding 2002. Yearly averages reflect totals above the 30-year trend except for 2002, which total is 3 inches below the trend.
4.2 GIS Components

A series of vector shapefiles relating to the study site were created. Two main GIS data sources were used. The first being the Lucas County Auditor's Real Estate Information System (ARIES) CD. ARIES is a spatial database containing information relating to property ownership, transportation, census, and land cover information. One variable utilized from ARIES includes the Current Agricultural Use Valuation (CAUV) (Figure 15). The CAUV program is an
incentive taxed based program where registered landowners pay taxes on current agriculture use instead of its developed potential (AREIS 2003).

Figure 15. CAUV data coverage overlaying an image. The red parcels are enrolled parcels vs. the yellow represents non-CAUV land.
Figure 16. CAUV data breakdown.
The pie chart displays the CAUV data by area (Figure 16). Approximately 83% of the 82,000 acres are classified as tillable (orange color). Tillable parcels (blue color) makeup 30% of the entire county, both CAUV and nonCAUV data.

The second GIS data source is the Ohio Department of Natural Resources (ODNR) Geographic Information Management System (GIMS). GIMS is a term used by ODNR to describe a collection of related technologies used to manage spatial data. These technologies include GIS, computer-aided design systems, automated and desktop mapping systems, remote sensing and image analysis systems, and their related database management systems. The goal of the GIMS program is to provide natural resource information to the public in a more efficient and effective manner (ODNR GIMS). GIMS provides digital soils information for the study site.

The USDA, ODNR, and the Soil Conservation Service (SCS) provide detailed information on soil coverage for the study area (USDA 1980). GIMS supplies self-extracting zip files in .e00 format requiring the use of the ESRI ArcView Import 71 function. ODNR uses a different projection system compared to the AREIS data. The soils data was reprojected using the ArcToolbox function. Reprojection information was executed as Lambert Conformal Conic State Plane NAD 83 Ohio North FIPS 3401 Feet with modified parameters. This reprojection matched the AREIS metadata including the Mr.Sid format aerial photos.
The NRCS criterion for hydric soil determination was used for defining soil types in the study site (See Appendix C). Hydric soils are determined by

1. All Histosols, except Folists, or
2. Soils in Aquic suborders, great groups, or subgroups, Albolls suborder, Aquisalids Pachic subgroups, or Cumulic subgroups are:
   a. somewhat poorly drained with a water table equal to 0.0 ft from the surface during the growing season, or
   b. poorly drained or very poorly drained and have either:
      (1) water table equal to 0.0 ft during growing season if textures are coarse sand, sand or fine sand in all layers within 20 inches or
      (2) water table at \( \leq 0.5 \) ft from the surface during the growing season if permeability is \( \geq 6.0 \) in/hour in all layers within 20 in or
      (3) water table is at \( \leq 1.0 \) ft from the surface during the growing season if permeability is \( \leq 6.0 \) in/hr in any day within 20 in or
3. Soils that are frequently ponded for long duration or very long duration during the growing season or
4. Soils that are frequently flooded for long duration or very long duration during the growing season.

Figure 17. Hydric soils coverage.
Figure 17 represents the extent of the hydric soil coverage for Lucas County using the Natural Resource Conservation Service (NRCS) guidelines. Red represents hydric soils. This example does not include non-hydric soils with hydric inclusions in the county. Nearly 50% of the county, or 102,973 acres, is considered hydric. This equates to more than half the county potentially possessing the soil requirements for wetlands to exist.

Figure 18. Lucas County soils data breakdown.

![Hydric Soils Chart](chart.png)

Figure 18 details the hydric soil type data makeup for the entire county. As illustrated in the chart, three soil types, Granby Loamy Fine Sand, Latty Silty Clay,
and Hoytville Clay Loam, makeup more than 50% of the hydric soil types in the county by the current NRCS classification regime. See Appendix C for a complete listing of soil names and codes.

Using ArcGIS Geo-processing functions the hydric soils coverages were manipulated for wetlands data extraction. All hydric soils were queried within the study area forming an advanced Area of interest (AOI). This reduced the initial study site AOI by approximately 50%. This method or modeling technique is a common practice to help specifically define a study area often referred to as constraint mapping (Demers 2002). For the purpose of this study, any land registered as an agricultural parcel, which is 82,727 acres in Lucas County Ohio, was eliminated from the AOI.

4.3 Satellite Imagery
4.3.1 Pre-Processing

Early steps in the project included general data conditioning and preparation. In preparing the satellite imagery, first a subset of the entire study site was taken from the 185 X 185 km ETM+ scenes. This was done with the Imagine Data Preparation function. An AOI incorporating the entire study site, Lucas County, was created using the AOI Tools function. This reduces data size and computer processing needs. Images from the past three years were examined for phenological cycle changes, cloud cover, and overall image quality. Several new data sets were next created. Using the Model Maker function a series of single temporal images were stacked to create multitemporal images.
The different wetland ecosystem types used different input data sets and parameters, which is discussed in greater detail under section 5.3.

4.3.2 Atmospheric Correction

A variety of techniques can be applied to satellite data for optimal processing and exploitation depending on specific goals and project objectives. Image enhancement algorithms are applied to remotely sensed data to improve the appearance of an image for human visual analysis or for subsequent machine analysis (Moran et al 1992, Jensen 1996, Ouaidrari and Vermote 1999, Song et al 2000). The image data, or digital number (dn), is a function of not only of plant and soil conditions, but also of the sensor calibration, solar zenith angle, sensor viewing angle, seasonal variability of Earth-sun distance, and diurnal variability atmospheric conditions (Smith et al 1999, Moran et al 2001). Atmospheric attenuation intervening between the terrain of interest and the remote sensing system can contribute significant noise to the data (Song et al 2000). In land cover classification mapping, the spectral signals are often assumed to possess a level of separability or variation that noise and environmental effects can be ignored (Jensen 1996). In this investigation the level of class detection is similar therefore radiometric enhancements were performed to correct for atmospheric attenuation.

Atmospheric corrections are often limited primarily to image-based methods that do not rely on concurrent collection of atmospheric parameters and imagery (Vogelmann et al 200, 1Pax-Lenney et al 2001). For multispectral
images a method based on a Tasseled Cap transformation, which yields a component that correlates with haze, was executed. This component is removed and the image is transformed back into RGB space (ERDAS 2001). The Tasseled Cap is a linear combination of spectral channels using sensor-specific response coefficients that transform the data into orthogonal axes that highlight specific surface properties (Crist and Kauth 1986). Histograms were produced evaluating spectral responses at all stages of data processing for examination. The enhancements applied to the remotely sensed data increased band spectral ranges and increased classification detail.

Figure 19. Histograms illustrating preprocessing techniques.

Figure 19 displays histograms of Landsat 7 ETM+ reflectance responses. The data represent the same pixel. The left graph displays single image before possessing. The right graph displays the spectral response of a multitemporal stacked image (14 data points) with the applied tassel capped based algorithm
for atmospheric haze enhancement. This radiometric enhancement is similar to a
dark object subtraction (Pax-Lenney et al 2001). The largest gains in data, or
greatest change in DN, occur in bands 4 and 5.

4.4 Classification Methods

4.4.1 Knowledge Engineer.

The earlier series of classification attempts performed in this investigation
provided the framework for future research. Overall, early products proved the
difficulty in classifying detailed level land covers such as wetland types. The
returned outputs were inaccurate products that were not usable. The project
managers determined that an advanced user intensive model would be needed
to increase map usability.

The ERDAS Imagine Expert Classifier was selected which has two main
elements; the Knowledge Engineer and the Knowledge Classifier. The
Knowledge Engineer provides methodology for users with advanced information
and experience to define variables, rules, and classifying interests to design a
hierarchical decision tree and knowledge database. The Knowledge Classifier
provides methodology to utilize the knowledge database created by the user and
Engineer (ERDAS 2001). The Knowledge Engineer feature allows the user to
define nearly every aspect of the image and data model.
4.4.2 Training Sites

Previous attempts at classifying wetland types provided information and confirmed training sites that were utilized. Three primary wetland types were initially focused on for training site development and mapping goals- forest, prairie, and coastal. Each potential wetland training site was visited and assessed. Assessments included: GPS readings for precise locations, soil core logs for examination, vegetation transect sampling, hydrologic examination, and digital picture catalogs were created at each site.

Figure 20 displays pictures of sampling soil cores taken for each training site. The top picture directly to the left shows complete saturation of soils in Irwin Prairie on 10/20/03, mid-fall. Using the NRCS data, Irwin Prairie contains Granby Loamy Fine Sand, coastal pool training sites contain primarily Latty Silty Clay & Toledo Silty Clay, and Kitty Todd proved to be Granby Loamy Fine Sand- all hydric soils. Field visit samples were cross-referenced using the COE guided Munsell charts. Soil chromas, hues, values, moisture levels were examined. Other soil characteristics such as redoxamorphic features, mottles, contrasts, textures, and general descriptors confirmed hydric qualifiers. Sample (Figure 20b) is coastal and illustrates a thick gleyed matrix with strong anaerobic smells, a wetland indicator (USDA 2002). Notice the water on the surface between the reeds.
Figure 20. Soil examination at training sites. Figure 20a shows Munsell chart.

Figure 20b. Soil core in coastal pool.
Figure 21a. Wetland delineation and GPS point data collection.

Figure 21b. GPS collected points in Irwin Prairie.

Figure 21a shows recording of GPS location of standing water in a manage corridor near the Kitty Todd region of Oak Openings. Figure 21b depicts location of training points along a transect through Irwin Prairie.
Figures 22a and 22b are pictures of coastal wetland pools used for coastal wetlands training data.

Figure 22a. Ottawa National Wildlife Refuge pool.

Figure 22b. Managed coastal wetlands pool.
Figure 23a and 23b are pictures taken in Kitty Todd Nature Preserve.

Figure 23 are pictures taken from Kitty Todd, the forest wetland training site just north of Toledo Express Airport. These forest wetland images were taken 4/5/2003. It is a leaf off situation with vegetation buds rapidly emerging. The forest floor was completely saturated with standing surface water and other wetland indicators located throughout the landscape.
Figure 24 are pictures of Irwin Prairie. These photos capture management practices incorporated by the USFWS and ODNR for preserving these valuable landscapes. The left picture (Figure 23a) reflects a meadow burning regime, while the right photo (Figure 23b) shows mowing practices performed. Figure 23c taken on 3/31/2003 shows a typical scene of unique prairie grasses and sedges located in the region.
After training site data collection the decision tree with class signatures were developed within the Knowledge Engineer framework. Using the inquirer cursor function and signature editor, precise pixel values and signatures were examined and extracted from the training site AOIs. Figure 25 displays a screen capture of signature development and wetlands classification difficulty. AOIs were drawn around four separate coastal pools for coastal wetlands class signatures. The histogram insert shows the variability between the different AOIs within the same class.
Bands 4 and 5 (infrared water/moisture absorption region) have the greatest range of data. Due to the fact that wetlands types are a unique patched landscape within the study site, limited pixels could be examined to formulate the signatures. One advantage to using the decision tree method within the knowledge engineer is the acceptability of nonparametric data (Friedl et al 1999). This process was repeated for each wetland class of interest. More detailed statistics were investigated but were later determined to be beyond the necessary scope of this methodology.

Figure 26 visually displays the conceptual framework interface of the decision tree. The hypothesis represents a class that is the goal of that particular ‘branch’. The rule would then represent a defining parameter to be investigated.
The variable here is the specific parameter data that is being defined to create the class. This example shows that a possible ETM+ pixel reflectance data is given an allowable data range for each possible data point, or band.

Figure 26. Knowledge Engineer conceptual model framework.
The different wetland types required different inputs into the knowledge engineer model to be classified. To improve coastal wetlands, a two-kilometer (km) buffer zone was applied. Using ESRI Geo-possessing techniques the 2 km buffer was created along the coastal line for the entire county. This new buffer shapefile was imported into the Knowledge Engineer model to restrict possible coastal classifications to within 2 km of the shoreline (Figure 27).

Figure 27. Lucas County coastline.
5.0 Results

Different iterations, or “model runs”, were executed. This can be a time and machine consuming process depending on user changes. The level and specific inputs were altered several times for optimal mapping classifications.

5.1 Model Scenario

This project used a single spring scene (3/14/01) with the 2-km buffer for coastal wetlands. Forest wetlands scenes utilized 1 additional late summer/early fall scenes (8/21/01) for a total of 14 data point ranges. Prairie wetlands also used the two season multitemporal radiometrically enhanced ETM+ imagery used in the forest classification for iteration1. The detailed AOIs were incorporated in the knowledge engineer model limiting possible classifications to non-tillable-CAUV land with hydric soils. Iteration 1 produced approximately 500 acres of wet prairie, 2200 acres of wet forest, and 1000 acres of coastal wetlands.
Figure 28 is an early output iteration to show the thematic output the knowledge engineer model. This area includes portions of the Kitty Todd region just north of Toledo Express Airport. The green indicates forested wetlands scattered throughout the region. The yellow pixels represent prairie wetlands that are scattered throughout the area.

Figure 29 is a more detailed representation of the model. The map is a zoomed in view of the Kitty Todd area just north of Toledo Express. The transparent red is hydric soils, streets provide reference, the striped areas are tillable CAUV parcels, while the green is forested wetlands.
Figure 29. Kitty Todd region classification model output.
Figure 30. Coastal region model output.

Figure 30 is of the Maumee Bay state park - Cedar Point coastal area. The bright red color signifies coastal wetlands, transparent red showing hydric soils, and striped patterned area represents tillable CAUV parcels. Much of the coastal areas of Lucas County possess hydric soils. Behind the GIS data layers is an aerial photo overlaid on a Landsat image for reference. A second less conservative iteration was executed with the knowledge database.

5.2 Accuracy Assessment.

The industry standard for accuracy assessment in remote sensing is the error matrix table (Congalton 1999). This table is a count of correct and incorrect classifications of the classified image providing several statistics. Essentially it is a discrete multivariate test with errors of omission and commission, similar to
type 1 and type 2 statistical responses. Several confidence iterations and variations of the knowledge database were run and analyzed. Statistically significant accuracy assessments on selected optimal output products were conducted using ERDAS accuracy assessment tools. A stratified random sampling scheme with 50 points per class was determined adequate (Plourde and Congalton 1999, Congalton 2002). Figure 31 displays an array of accuracy assessment points scattered throughout the Toledo Express, Oak Openings Metropark, and Kitty Todd region.

Figure 31. Point data locations of assessment around Toledo Express Airport.

The accuracy points were checked using a variety of techniques. Initially all points were produced over the satellite imagery and knowledge engineer
outputs. Approximately two-thirds of the points were able to be determined on class accuracy. Remaining points were reprojected into the GIS and converted in decimal degrees for further investigation. Aerial photography and field ground-truthing of the remaining locations provided a comprehensive database detailing vegetation communities, site description, GPS locations, digital pictures, soil type, and associated variables at each point.

Table 2. ACCURACY REPORT

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
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</thead>
<tbody>
<tr>
<td>Coastal Wetland</td>
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<td>49</td>
<td>49</td>
<td>100.00%</td>
<td>100.00%</td>
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<tr>
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<td>98.21%</td>
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<tr>
<td>Wet Prairie</td>
<td>35</td>
<td>42</td>
<td>35</td>
<td>100.00%</td>
<td>83.33%</td>
</tr>
</tbody>
</table>

Overall Classification Accuracy = 94.56%

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.9188

Conditional Kappa for each Category.

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<th>Kappa</th>
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</tr>
<tr>
<td>Wet Forest</td>
<td>0.9705</td>
</tr>
<tr>
<td>Wet Prairie</td>
<td>0.7813</td>
</tr>
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</table>

Table 2 displays an error matrix table for Iteration 1 of the knowledge engineer thematic output. The overall classification accuracy was 94.5%, with an overall Kappa statistic of .91. Wetland prairies proved to be the most difficult to accurately classify with a users accuracy of 83.33%. The User’s Accuracy, or
commissions errors, indicates for the user of the map the probability that a pixel
classified on the map actually represents that category on the ground.

Figure 32. Coastal assessment illustration.
Figure 32 illustrates a coastal accuracy assessment scenario. Bottom right is stratified random points over aerial sid photo. Bottom left is knowledge engineer output converted into a shapefile. Top is image of coastal pool looking west from point #20.

A second statistically significant accuracy assessment was performed on a second less conservative iteration. Iteration 2 produced 2300 hundred acres of coastal wetlands, 3900 acres of forest wetlands, and 1900 acres of wet prairie (Table 3). The less conservative iteration run was conducted in similar fashion. The largest difference is the drop in wet prairie users accuracy. An overall accuracy of 84.17% is considered an acceptable classification accuracy level (Jensen), but wet prairie dropped below usable levels to approximately 50% (Table 4).

Table 3. Iteration acreage totals.

<table>
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<th>Iteration 2</th>
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<tr>
<td>Prairie</td>
<td>500</td>
<td>1900</td>
</tr>
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<td>Forest</td>
<td>2200</td>
<td>3900</td>
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Table 4. ACCURACY REPORT 2

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<th>Class Name</th>
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<th>Users Accuracy</th>
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<td>48</td>
<td>97.96%</td>
<td>96.00%</td>
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<tr>
<td>Wet Forest</td>
<td>61</td>
<td>50</td>
<td>47</td>
<td>77.05%</td>
<td>94.00%</td>
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<tr>
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<td>22</td>
<td>39</td>
<td>22</td>
<td>100.00%</td>
<td>56.41%</td>
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Overall Classification Accuracy = 84.17%

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.7641

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<td>Prairie</td>
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6.0 Discussion.

The industry standard error matrix accuracy assessment performed very well in this case. The entire assessment process proved to be time consuming and often more difficult than a simple correct/incorrect classification. In a single day between 6 and 12 sites can be investigated. The stratified random points can fall on private property, remote locations, or areas difficult to place into a mutually exclusive category.

Two main related reasons contributed to general misclassifications. First is the nature of the data itself. Wetlands ecosystems in the study site create an extremely patched network across the landscape; subpixel heterogeneity is high. Figure 33 shows an area just west of Toledo Express. The area is a mixture of vegetation covers that push the limits of Landsat 7 resolutions to accurately classify the area.
Figure 33. Landscape and resolutions influence illustration.
The second related general misclassification is due to the difficulty in determining categories. Figure 34, just outside Maumee Bay state park, has wet prairie, forest wetlands, and coastal wetlands all in the same landscape region.

Figure 34. Patched landscape illustration.
Figure 35. Both photos were taken of the kitty Todd forest wetlands training area. Bottom photo is from spring (4/5/2003). The top photo was taken during the summer (7/15/2003). The hydrological and vegetation changes further created accuracy assessment problems.
Figure 36. Wet prairies proved to be the most challenging class. The picture on top shows a typical correct classification. This one is located between the Maumee River and Anthony Wayne Trail.

Figure 36. Wet meadow parcel.
Figure 37 is an example of wet prairie misclassification. Bottom photo is field located in a resident’s backyard in NW Lucas. Top photo (7/9/2003) shows the property is a dormant hydric field next to wheat crop.
7.0 Conclusions

Overall this study shows that advanced remote sensing and GIS modeling techniques can provide valuable wetlands information with limitations. Obtaining detailed level ecosystem land cover classification requires more advanced sensor resolutions and/or expert level knowledge for optimal output products. The result of the analysis is a product within an acceptable accuracy to provide some information. Further the knowledge engineer extended the project significantly. The decision tree and GIS rule based hybrid algorithm within the engineer framework proved to be a valuable tool for land cover classification and modeling. The ability to utilize different data sources and inputs for different classes was the single most advantageous component of the entire model. This was the reason the mapping products were able to advance to their current status.

The complexity of wetlands continues to be the most challenging aspect of the project. Having a clear concise project goal and approach assisted in focusing the project and model. Yet many different users, project contributors, and study personnel each have different ideas or angles on the project. These ranged from planning to ecological to geographical to institutional. This is where
the knowledge engineer structure is beneficial. Each variable can be adjusted, tweaked, or shifted to attempt to run different iterations for each approach or interest.

Increased classes and/or scenes could have potentially improved the wet prairie class and overall precision of the classification. The accuracy was relatively high, while the precision was very pixilated. Generally a wetland ecosystem will follow the landscape or topography of the area. With 30-meter pixels the exact wetland delineations were irregular. The best use of the current data is more in the sense of an additional support layer to make wetland related decisions. It should not be used alone to supplemental a wetland delineation, rather give a general idea and provide insight on possible locations and conditions of wetlands in a given area. Increased classes or categories could have improved this component of the study. A scrub-shrub class could potentially help further define the wetlands inventory and provide higher wetland prairie accuracies.

A second increase in data could pertain to other sensors. The underlying idea of this study was to create a machine-learning algorithm that could be executed in the future with free Landsat images provided from OhioView. Incorporating radar technologies could significantly increase soil moisture data. Hyperspectral data sets could add to the land cover separability complexity. While, LiDAR data for the county could add significant topographical and slope data input for the model. Having increased resolutions could potentially boost the
machine’s ability to develop more specific classes with higher precision and accuracy.

The wetlands study has progressed significantly from the initial proposal in 2000. A relatively accurate usable series of maps and data layers provides a variety of wetlands information (Figure 38), surface hydrology, soils, and land cover data to users. The project has built many relationships and currently involves several user groups from non-profit organizations to regional conservation groups to county agencies to academic departments. The wetlands project has provided a solid foundation for generating and directing future wetlands information and issues in the region. Several spin-off projects (See Appendix D for GIS Model) have begun generation and surrounding areas have been showing interest in wetlands mapping and inventory updating. A series of seminars, public outreach and education, and training workshops have taken place to promote wetlands and the mapping research. An ArcIMS and project website is in formulation that will continue to provide wetlands information to all users. The wetlands mapping project has reached a final stage, while providing future avenues for research and investigations.
Figure 38. Lucas County wetlands model output.
8.0 References


Lafferty, M. 1979. Ohio’s Natural Heritage. The Ohio Academy of Science. Columbus, Ohio.


Tiner, R. Wetland indicators: a guide to wetland identification, classification, and mapping. Lewis Publishers.


Appendix A. Earlier Wetland Maps.
Appendix A. Continued.
Appendix B. Common Wetlands Delineation Forms.

DATA FORM
ROUTINE WETLAND DETERMINATION
(1987 COE Wetlands Delineation Manual)

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<td>County:</td>
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<td>Investigator:</td>
<td>State:</td>
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<td>Is the area a potential Problem Area?</td>
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(If needed, explain on reverse.)

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VEGETATION

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Percent of Dominant Species that are OBL, FACW or FAC (excluding FAC). 

Remarks:

HYDROLOGY

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<td>Depth to Saturated Soil:</td>
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Wetland Hydrology Indicators:

Primary Indicators:

- Inundated
- Saturated in Upper 12 Inches
- Water Marks
- Drift Lines
- Sediment Deposits
- Drainage Patterns in Wetlands

Secondary Indicators (2 or more required):

- Oxidized Root Channels in Upper 12 Inches
- Water-Stained Leaves
- Local Soil Survey Data
- FAC-Neutral Test
- Other (Explain in Remarks)

Remarks:
### SOILS

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### Appendix C. NRCS Soil Names and Criteria Rankings.

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**Lucas County, Ohio**

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Hydric soils list for Lucas County

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**TOLEDO SILTY CLAY**

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**TOLEDO MUCK**

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**SIOUX EARTH OCCASIONAL FLOODPLAIN**

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**NASHUA TERRA FIRMräume**

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FOOTNOTE: There may be small areas of included soils or miscellaneous areas that are significant to use and management of the soil, yet are too small to delineate on the soil map at the map's original scale. These may be designated as spot symbols and are defined in the published Soil Survey Report of the USDA-WCS Technical Guide, Part II.

SYMBIC SOILS CRITERIA CODES AND DEFINITIONS

1. All Stillingas, except Polista, or
2. Soils in Aquic suborders, great groups, or subgroups, Allobols suborder, Aqualsids, Peptic subgroups, or Cumellic subgroups are:
   a. Somewhat poorly drained with a water table equal to 0.0 feet (ft) from the surface during the growing season, or
   b. Poorly drained or very poorly drained and have either:
      1. Water table equal to 0.8 ft during the growing season if textures are coarse sand, sand, or fine sand in all layers within 20 inches (in), or for other soils
      2. Water table at less than or equal to 0.2 ft from the surface during the growing season if permeability is equal to or less than 1.0 in/hour (in/hr) in all layers within 20 in, or
      3. Water table at less than or equal to 1.2 ft from the surface during the growing season if permeability is less than 6.0 in/hr in any layer within 20 in, or
3. Soils that are frequently ponded for long duration or very long duration during the growing season, or
4. Soils that are frequently flooded for long duration or very long duration during the growing season.