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SOIL SURVEY ENHANCEMENT OF LANDSAT THEMATIC
MAPPER DELINEATION OF WETLANDS: A CASE
STUDY OF BARRY COUNTY, MICHIGAN

by

Rosemary Ann Anger

A Thesis
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Department of Geography

Western Michigan University
Kalamazoo, Michigan
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A SOIL SURVEY ENHANCEMENT OF LANDSAT THEMATIC
MAPPER DELINEATION OF WETLANDS: A CASE
STUDY OF BARRY COUNTY, MICHIGAN

Rosemary Ann Anger, M.A.

Western Michigan University, 2003

The Landsat Thematic Mapper Satellite system has provided a unique platform for the study of natural and man-made features since 1972. This suite of sensors has become an important tool in assessing vegetation type and health over large areas of the earth. This paper reviews the Landsat Thematic Mapper's ability to categorize wetlands using an unsupervised classification scheme. A preliminary exploration of an unsupervised classification of wetlands using soil engineering characteristics from the Natural Resource Conservation Service's soil survey as a pseudo bandwidth is described. The result of this project suggests that when compared to the National Wetlands Inventory, an enhancement of the delineation by soil characteristics is a measurable improvement. It is argued that soil characteristics, if added as a pseudo bandwidth, are appropriate in the classification of wetlands.

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CHAPTER 1

INTRODUCTION

Imagery as a Source of Land Cover Information

Wetland delineation in land use and land cover surveys has always been problematic. "When human beings visually interpret remotely sensed imagery, they systematically take into account the following characteristics of the data: (1) context, (2) edges, (3) texture, and (4) tonal variation in color" (Jensen, 1986, 169). To fully take advantage of human interpretative abilities requires well-trained operators using time intensive manual or capital expensive automated techniques. It would also be resource consuming and labor intensive. It is then wise to concentrate the effort on "problem" areas. By performing the simplest of classifications by automated techniques, the human labor and expertise is directed where most needed. However, satellite data sets alone are not sufficient for accurate interpretation of wetland sub-classes.

Kramer (1994) indicates these varied applications of Landsat Data: (a) land use, (b) agriculture, (c) forestry, (d) geology, (e) water resources, (f) standing vegetation biomass, (g) biological productivity, (h) ecosystem boundaries, and (i) mapping. Applications of space remote sensing have been created to answer many social and environmental questions. Wetlands are entirely different biological and

land cover units, distinct from upland land cover and subject to specific environmental laws and regulations. With such a narrow aerial extent within a land use classification, wetlands are not adequately addressed by applications that focus on all upland land use classes.

It is necessary to include secondary data to discriminate problem classes. The earliest application of secondary data to satellite classification can be seen in “trained” classifications of imagery where the operator programs the computer to look for certain characteristics derived from secondary data sources. This is accomplished by finding examples within the imagery that fit the secondary data and then asking the computer to find all similar areas. "There is ample evidence that many tree species cannot be discriminated in TM imagery unless additional ecological information such as topography and soils are used as prior evidence" (Strahler, 1980, 136). Since individual trees fall below the minimum mapping unit of the sensors, secondary information is necessary to make use of the satellite data. Ancillary data sources can offer the unique ability of human observation in aid of the raw calculating efficiency of the computer.

For this exact reason it is wise to find a data source to complement the satellite data. Understanding that comprehensive field samples cannot be practically obtained, comprehensive soil surveys prove very important in determining potential sites for wetlands. Wetland soils are clearly demarked on soil surveys as areas of little or no slope, seasonal standing water, and hydric indicators in the engineering characteristics. Additionally, soil information is available over a large area with a two

hectare sampling size similar to the pixel size of a Landsat TM image. Therefore, wetland information from the soil survey would be considered a likely candidate for inclusion in an *a priori* automated classification of wetlands.

An Introduction to Wetlands in Remote Sensing

Definition of Wetlands

Wetland science from a geographer's point of view incorporates the study of surface and sub-surface water features at local, regional, and global scale.

Recognizing the connection of these features is the unique challenge of geography, which unlike other disciplines, is not limited by feature which must occur above or below the surface of the ground or in relation to biological or legal definitions of wetlands.

To find wetlands we must state the legal definitions:

The Michigan regulatory definition states:

"'Wetland' means land characterized by the presence of water at a frequency and duration sufficient to support and that under normal circumstances does support wetland vegetation or aquatic life and is commonly referred to as a bog, swamp, or marsh..." (P.A. 203, sec. 281.702 (g))

The U.S government regulatory definition states:

"Those areas that are inundated or saturated by surface of ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted of life in saturated soil conditions. Wetlands generally include swamps, marshes, bogs and similar areas." (Environmental Laboratory, 1987, 13)

The difference between the Michigan definition and the Federal definition of wetlands is the existence of the qualifiers of "prevalence" and "typical" in the federal

definition and the inclusion of aquatic life in the Michigan definition. In federal definition the prevalence of wetland vegetation is subject to human interpretation and atypical situations are not addressed like they are for the Michigan delineation manual.

Satellite Applications to Wetlands

As ecotones, some wetlands exhibit the same spectral characteristics as non-wetland vegetation on aerial photography and in most satellite bands. (Fornshell, 1992) In the visible spectrum, imagery and aerial photography delineations are limited by this similarity. The expanded infrared capabilities of the Landsat Thematic Mapper (TM) bands four and five can pick out wetland areas from the similar upland vegetation. The sophisticated and powerful processing ability of modern computers make an automated assessment of wetlands efficient and more feasible than a manual assessment.

A simple manual assessment would rely on an operator's knowledge of wetland types to outline each individual wetland. In fact, one of the largest initiatives to map wetlands on a national scale is the National Wetlands Inventory. Using false color infrared color film flown at a scale of 1:52,000 individual operators outline individual wetlands on topographic maps.

An automated satellite delineation of wetlands differs from the manual approach in that there is a reliance on an algorithm to break the image up into classes

that have similar spectral characteristics. The operator then chooses the categories that the spectral cluster represents. The computer delineation itself takes less than five minutes for seven bands and fifty clusters which may cover hundreds of miles. The class assignment itself may take a day to prepare, but any subsequent classification of the image would employ the same assignments. The manual technique may require hours to produce and code if the delineation is done in the most efficient way by screen digitizing.

The reasons outlined above support the choice for creating an automatic delineation of wetlands over large areas. This purpose of this research is directed to find an appropriate delineation scheme for an unsupervised classification of wetlands in the study area and to improve upon this scheme by the use of soil characteristics used as *a priori* information. There are a number of wetland classes that are difficult to interpret on both an automatic delineation and a manual photo-interpretation delineation.

Any wetland class that is actively farmed, drained or seasonally flooded can be difficult to classify. These wetlands are mistaken for their upland cousins. Another problem class is wetlands that have a high percentage of detritious materials. Dead trees, reed grasses and sedges will increase the spectral value in many of the classes.

It is suggested by Brady and Flather (1994) that the loss of forested wetland in the past was five times the loss of any other wetland type. This is due directly to timber production from wetland areas and clearing for agricultural purposes. In Michigan, these losses may exceed this prediction due the extensive clearing of

forests in Lower Michigan to build local villages and meet the demand for cut lumber from growing out-of-state cities. This is also exacerbated by losses of wetlands due to sedimentation from clear cutting of upland areas leading to eutrophication of low lying wetlands and changes in flow of surface water.

Problems created by wetland loss are: (a) flooding, (b) saltwater intrusion, (c) improper filtration of surface contaminant, (d) loss of wildlife, (e) loss of waterfowl, (f) loss of vegetation and (g) loss of important fisheries. These problems have spawned many initiatives to protect wetlands, creating an interesting mix of legal issues.

Delineation and the Legal Environment of Wetlands

Michigan is the only state outside the northeastern states that has been granted regulatory control over its own wetlands. As part of the Goermare-Anderson Wetland Protection Act of 1979 and subsequent regulations, Michigan has employed a point delineation scheme. The directives of this methodology are more specific than national standards establishing wetland in this priority: 1) the presence of water at a frequency and depth sufficient to support wetland vegetation or aquatic life, 2) a predominance of wetland (hydrophytic vegetation) or aquatic life.

Approaching wetlands geographically presents a problem in the definition and scope of traditional map making. Wetlands boundaries are not definite, interior of areas are non-continuous, and wetland vegetation types change with water level.

Wetlands hydrology incorporates aspects of hydrogeology, fluvial morphology, and

atmospheric science; the difficulty is recognizing that each is a contributor to the study of wetland and not an exclusive answer to wetland science unto itself. When an atypical situation arises the federal definition cannot possibly account for the classification of the area. This may arise in local vegetation adaptation, unique hydrologic situations and wetland that are influenced by pollution. An atypical situation can be found in many farm ponds, detainment ponds, drained wetlands, and sewage lagoons.

In the permit process for any property changes to a water body or wetland adjacent property in the State of Michigan, a site visit is required. A conventional delineation of wetlands by MDNR standards would incorporate the National Wetlands Inventory (NWI) Map designation and a soils map from the USDA Soil Conservation Service (SCS). Both the SCS and NWI maps are produced from air-photos and field survey. If a site is located in hydric soil from the official state hydric soil list or is listed as a NWI wetland during research for a preliminary permit application, there is a legal requirement for an on-site visit by an environmental technician to delineate the area and assess the impacts of the proposed project. "The determination of wetland boundaries to within a tolerance of less than a meter for regulatory purpose will probably always require on-site evaluation." (Mitsch 1993, 642)

Exact wetland delineation has been problematic in the United States. The legal battle which rages over the wetland definition for use in field delineation removes the very privilege of scientific etymology from the hands of wetland scientists and places

it into the hands of bureaucrats and policy makers. Although there has been a temporary consensus reached on the definition of wetlands, delineation is still subject to individual interpretation and is highly dependent on landowner initiative. For example according to Kusler (1992), ninety percent of the permit applications are approved and the only true hurdles to wetland alteration are paperwork and fees.

In previous years remote sensing was almost exclusively a governmental research tool used at a very coarse scale. As small units of government are able to make use of satellite data with the increase in affordable computer software and hardware processing power, the study areas are shrinking and the mappable units are getting smaller. As applications of remote sensing grow, the new question in the practical application of this technology is the comparison of different classification schemes and their accuracy.

Satellite data uses the reflectance in seven bands whereas the color infrared film used for the National Wetlands Inventory (NWI) maps uses a single composite IR picture and combined with the interpreter's unique human ability to interpret pattern, tone, texture, shadow, site, shape, size and association. If we are to compare the classifications produced by each method, the satellite data will prove inferior because the computer can only distinguish color, tone, and continuity.

Statement of Problem

The Landsat VII Thematic Mapper sensor has the capability to detect vegetation and moisture of 30m x 30m pixels from space. "Satellite data, when used

in conjunction with other databases such as hydric soils maps, have provided a useful approach for inventorying wetlands in large areas. The state of Ohio, for example, has adopted that approach to inventorying their 107,000 km² state" (Mitsch 1993, 639). Under various classification schemes that are employed by remote sensing analysts, wetlands can be delineated with varying degrees of accuracy. Satellite data offers convenient assimilation and analysis.

An unsupervised classification of land cover types within the study area will be compared to the National Wetlands Inventory classification of wetlands to measure accuracy of wetland classification without *a priori* information. After this classification is established the same methodology will be employed using two separate soil engineering characteristic from the soil survey as an secondary data set. These classifications will then be compared to the National Wetlands Inventory to assess if *a priori* information increases the classification accuracy.

Statement of Hypothesis

Hypothesis 1: The satellite classification of wetlands is no different than the classification from the National Wetland Inventory classification maps.

Hypothesis 2: The satellite classification with soil organic content as a "pseudo band width" is no different than the classification from the National Wetland Inventory classification maps.

Hypothesis 3: The satellite classification with soil water capacity is no different than the classification from the National Wetland Inventory classification maps.

Hypothesis 4: The satellite classification with soil organic content as a pseudo band width better represents the National Wetland Inventory classification than an unmodified satellite classification at $\alpha = 0.05$.

Hypothesis 5: The satellite classification with soil water capacity as a pseudo band width better represents the National Wetland Inventory classification than an unmodified satellite classification at $\alpha = 0.05$.

Wetland Specific Problems

Wetlands are delineated under assumed normal circumstances, but just what are these "normal" circumstances? Can it be assumed that normal circumstances are evenly distributed over the wetland and over time or does each wetland have a period of normalcy and period of abnormality. It is important then to tie wetlands to a more stabilized data set that is not subject to seasonal variation. "The proposed 1991 [federal] manual, however, disallows the use of vegetation and soil indicators to prove hydrology and thus removes the most reliable indicators available." (Kusler, 1992, 34)

Determining hydrology as the deciding factor for wetland delineation is much more costly than using soils and vegetation. Hydrology is directly dependent on atmospheric conditions that are seasonal and subject to climate variation like drought,

flooding and global effects such as El Nino – La Nina and global climate change. Lee (1994) states that wetlands are difficult to map because of the following reasons: (a) water levels fluctuate, (b) there is a difference in wetland types, (c) there are accessibility problems for ground control, and (d) there are hydrologic induced changes in boundaries within natural cycles.

There is limited urban development to interfere with delineation in the study area. The northern portion of Orangeville Township is included in the Yankee Springs Recreation Area and large tracts of Hope and Barry Townships, excluding the Upper Crooked Lake area, are devoted to agriculture. Fortunately, most of the lakes and smaller water bodies are located in this portion of the county. Part of the reason for finding a heavily wetland area is to permit more accurate statistical analysis. This quarter of the county is further subsetted to represent the boundaries of the image and the extent of the data layers available. A 0.5% sample of wetland sites from the computerized delineation to a field survey is suggested by Jensen (1986). This amounts to just under ten thousand pixels in a quarter scene.

These sample areas can be keyed out in the field using the standard MDNR delineation 1987 draft manual with limited equipment outlays. Material requirements: a vegetation identification manual, soil bore or shovel, Munsel soil chart and waders. "The aerial limits of a wetland are the result of dynamic hydrologic, biologic and climatic processes. These naturally occurring changes, which are gradual, cannot be predicted and neither can a future natural location of a wetland boundary" (Pearsell

and Mulamootil, 1994, 867). This problem in the scientific definition of a wetland is translated into an equally ambivalent legal definition.

In review of the literature there are a number of techniques employed to find land use / land cover features from satellite imagery. Frequently, the accuracy of these delineations are not assessed. Wetlands are an involved, field intensive and theory intensive delineation. It would be helpful if there was a nice, simple, non-invasive technique to delineate and estimate the area of wetlands on a local scale without extensive field work. A consistent delineation methodology can assist in assessing the viability of wetlands over weeks or years, and an accurate technique would also prove useful for change detection studies.

There should be a logical agreement between the placements of wetland pixels and the coexistence of hydric soil or point wetland. "In contrast to agricultural systems, wetland soils are inundated regularly; the vegetation does not grow in rows, there is a frequently a large dead biomass component" (Gross 1989, 474). In Berta's delineation of wetlands in Lake County, Illinois her result showed an 86% accuracy in the wetland classification on the basis of field survey results (1994). To approach that accuracy and be able to make a meaningful comparison between a hydric soil assisted delineation of wetlands, NWI classification, and field conditions is the test of the viability of the classifications.

CHAPTER 2

DESCRIPTION OF THE STUDY AREA

History of Barry County

Settlement of Barry County

Barry County was organized on April 29, 1829, named for Postmaster General William T. Barry. (Figure 1) Early European settlers easily settled the oak savanna areas of the western portion of the county near what is now Yankee Springs, taking advantage of native prairies and the fertile soils. Currently the county is a major agricultural area and a bed-room community with over 327 named lakes that attract seasonal residents.

The first Europeans in Barry County were the French fur traders. Although no written history of the indigenous peoples remains, it is known the Potawatomi Indians lived in the prairies in the southwestern portion of the county. Their principal industry was reed gathering and basket production, which produced an active barter between settlers for foodstuffs. The wall in Wall Lake was an artificial pond to which natives in canoes would herd fish for netting in the shallows.

The first federal government surveyors arrived in the early 1800s under the Public Land Survey Act of 1785. They were disappointed to report back that all of

Lower Michigan was nothing but swamp land. In fact approximately one-third of the area was swamps and marshes. They subdivided the territory into one-mile sections for later settlement and further subdivision.



Figure 1. Location of Barry County

Native American's of the Potawatomi Band taught the first settlers survival techniques in the wilderness. Natural medications and food sources were all the

settlers had to rely on so far from their homelands. The Potawatomi tree markings led settlers to safe drinking water, passable trails and good homestead sites. Many of the Native Americans renounced their heritage and became landholders in 1840 when federal law forced all "Indians" across the Mississippi, yet many of the landmarks like Chief Noonday Lake bear the names of native leaders.

The principal occupation of the settlers was farming. They cultivated the open prairie in the summer and cleared the surrounding forest in the winters. Most of the wood was burned due to the low value of timber prior to 1840 and a haze of wood smoke descended on the county. Orchard fruit became an export industry with peaches being shipped to Kalamazoo and then on to Chicago. The Chicago, Kalamazoo & Saginaw (CK&S) railroad extended from Kalamazoo to Richland, Delton, Cloverdale, and Hastings. Six trains ran per day bringing vacationers up from Kalamazoo and students to the high school in Hastings.

The area was full of game. The French and British fur traders had long hunted out the beaver, which was an important component in the creation of stream bed wetlands. Log cabins were eventually replaced by the finer plank board housing that still stands today. A remnant of the early days the last log cabin in Barry County collapsed into shamble on the north side of Shallow Lake in 1987.

The earliest recollection of the area for European settlers was daunting. Large tracks of land were either water or wetlands (Figure 2) "The first time Mr. Peake went to Hastings it took him an entire day to get one mile from his home, as he has to cut

his way through the woods and around lakes and marshes." (Bicentennial Hope Twp, 1976, 156)

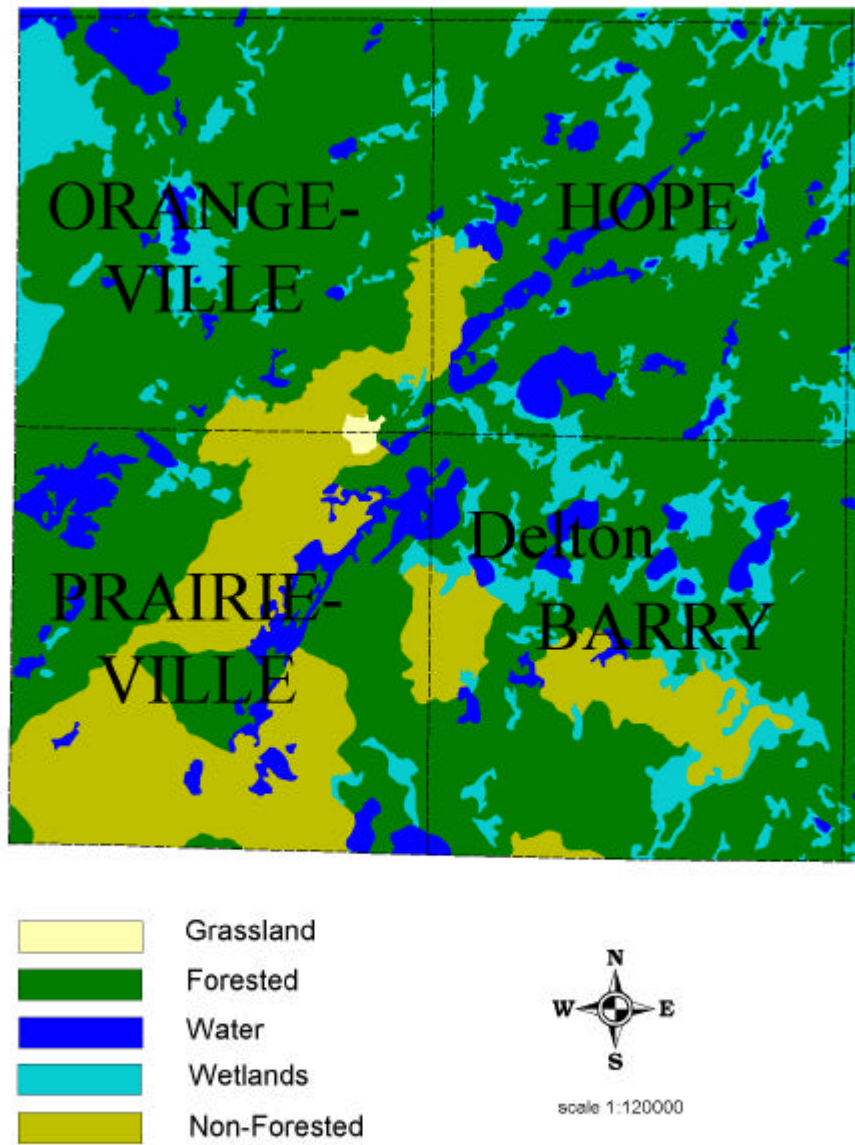


Figure 2. Pre-settlement Vegetation of Southwest Barry County

Source: Michigan Center for Geographic Information, Office of Information Technology, Spatial Data Library 2002. Permission for use granted in W3C policy page 1.

Early settlers perceived wetlands as a nuisance. Marshes made roads impassible and the mosquitoes spread Ague and “malarial” fever. There was the "Dead Sea" of Cloverdale that was known to engulf any attempt to build a road across it. Located on the north side of Little Cedar Lake in Hope Township, the wetland was known to consume plank roads within twenty-four hours of placement.

Another notorious sink in the area was the marsh in the back of Hind School that would “eat” poles sunk into it for the purpose of gauging depth. It took several tries before the sink was finally filled. The variability of the area's wetlands took many of the settlers by surprise. "Shallow Lake has gone through four cycles since the 1890's with wet and dry eras. In 1890 for instance, water holes were dug for the cows to drink from. In the early 1900's water was high enough for good fishing. 1929-30 found the lake covered with a vegetable garden full of melons and sweet corn. It remain miry until about 1960, becoming a lake again." (Bicentennial Hope Twp, 1976, 46) Shallow Lake’s water level varied as much as three feet from 1994 to 1995.

Modern Barry County

Barry County now supports one city and four incorporated villages. Hastings, the county seat, is located northeast of the county center and serves as a junction of four major state and county maintained highways. The industrial base of the county is located in this area while the rest of the county is local commerce, lake and highway residential corridors, and agriculture. The major extractive industry of the county is

sand, gravel, and marl production from the glacial moraines and petroleum extraction in Hope Township.

Aside from state and federal laws protecting wetlands, the concern of the local planners is sanitation on the larger lakes. The primary concern is sewage and the secondary concern is drinking water supply. In July of 1990 the residents of Fine Lake, Wall Lake, Crooked Lake, Pine Lake and the Delton business district formed the Southwest Barry County Sewage Disposal System. As of December of 1991 \$447,950 was expended in planning and construction of a sewer and wastewater treatment facility for the area.

By 1955 wetlands in Lower Michigan decreased from 33% of the landscape to 10%. With the support of Public Act 1921 as amended, the powers of counties and minor units of government were extended from simple zoning to comprehensive planning. In 1974 Barry County completed its first Master Plan. The plans for the lake areas include the promotion of medium density lakeshore development with minimum degradation of shoreline and water quality. Major river areas were designated floodplain with limited uses pursuant to DNR and FEMA directives. Additions to the plan prohibit “key-holing” on water bodies, which is the practice of making an shared access point for multiple back lot owners which is less than the required minimum front for a single lake front owner.

The townships in the study area (Figure 3) were each allowed to set their individual goals for the future: (a) Hope - encourage as much residential development as possible, (b) Barry - encourage the development of Delton and the surrounding

lake areas, (c) Prairieville - continued emphasis on agriculture with medium density development of the lake areas, and (d) Orangeville - maintain the status quo with development only on Gull Lake.

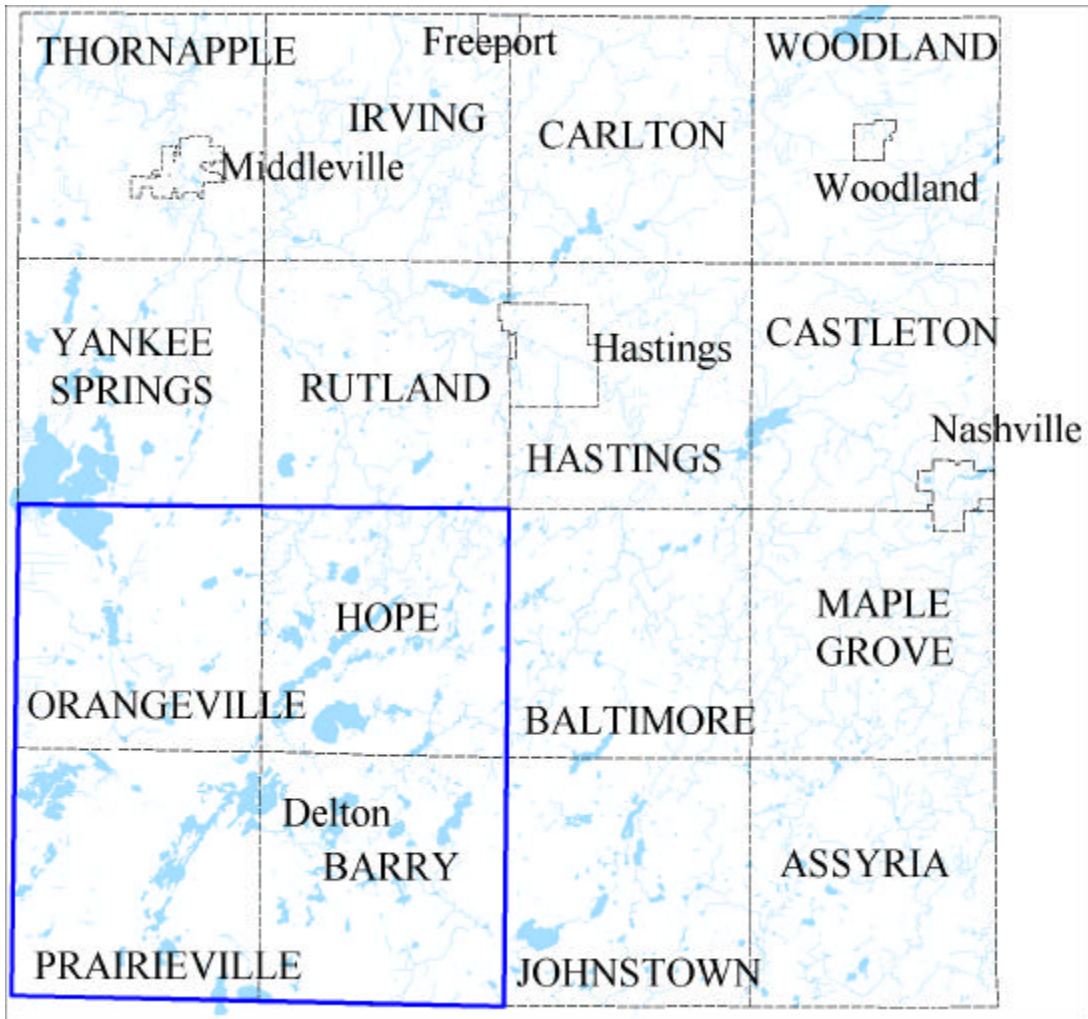


Figure 3. Outline of Study Area

The lake areas soon became a magnet for commuters to Kalamazoo. The hope for a resort-like lake development did not occur and the area became a "bedroom" community. In a trend that matches the rest of Michigan, lake housing was becoming more attractive for occupancy year round. Residents often converted simple cottages

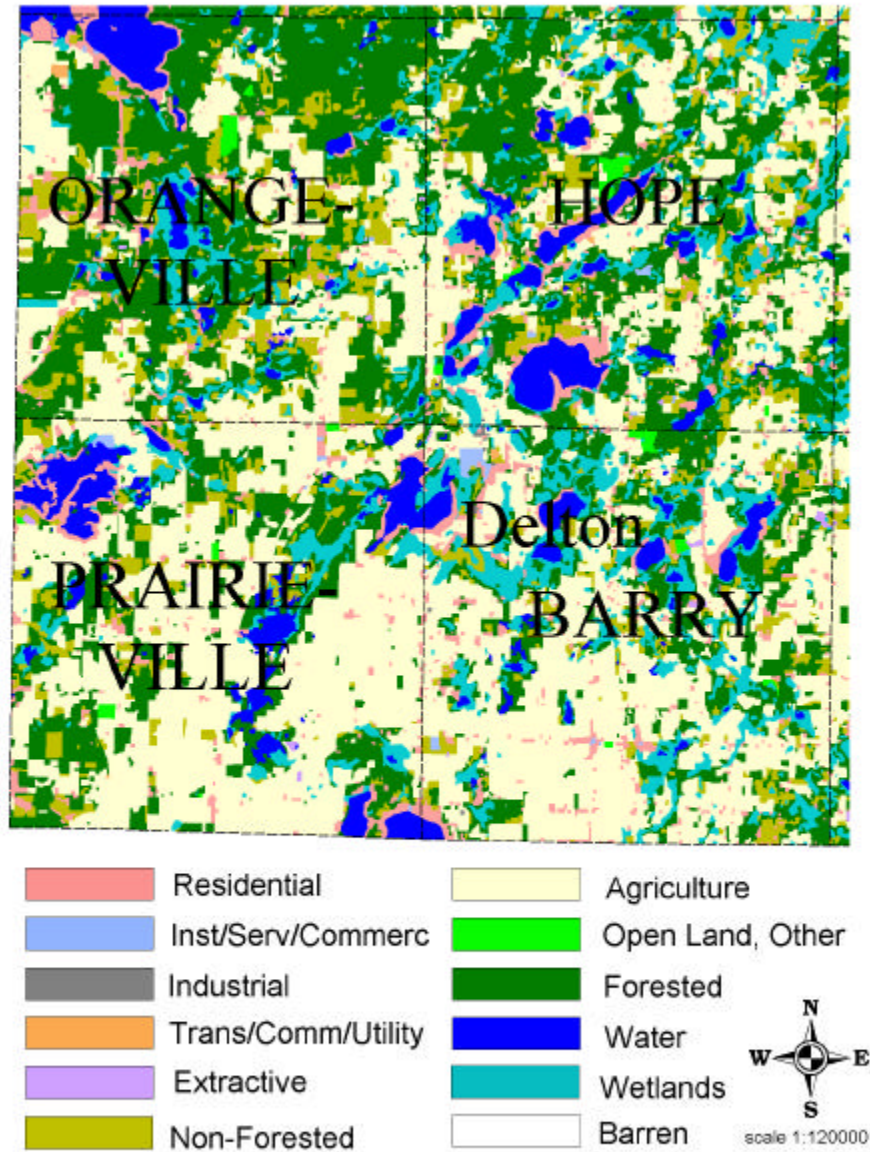


Figure 4. Barry County Land Use and Land Cover 1994

Data Source: Barry County Planning and Zoning 1996. Permission for use granted by J. McManus, director, 1996.

into year round housing; thereby, driving lake front land values up and contributing toward more permanent residences.

The 1997 land use plan goal is to support the establishment of natural land trusts and to "preserve the quality of the surface and ground water of Barry County by promoting the development of public sewers in major lake area and discouraging development in wetland areas or in areas where ground water is likely to be contaminated." (Barry County Land Use Plan, 1996, 5) Some other goals include limited development around landfills, and air quality emissions standards. Lake side areas are prioritized for development with off lake access properties by special permit only.

Table 1

Land Use in Barry, Hope, Prairieville, and Orangeville Townships

Land Use Class	~1800	1978	1994
	% of area	% of area	% of area
Residential	--	3.34	5.65
Commercial	--	0.18	0.24
Industrial	--	0.04	0.06
Trans / Utility	--	0.07	0.08
Extractive	--	0.20	0.11
Open Land / Recreation	--	0.30	0.45
Agricultural	--	41.55	39.56
Non-forested	16.85	9.53	8.77
Forested	64.2	28.47	28.23
Water	7.94	6.33	6.30
Wetlands	11.01	9.43	9.58

Source: Barry County Land Use Plan, 1996.

Land use has been compiled for the area to represent the trends in land development that have affected wetlands in the last 150 years. (Table 1) The pre-settlement land use is important as a reference layer (Figure 2) to compare to the most recent land use land cover layer compiled in 1994 (Figure 4). The sample size for pre-settlement vegetation with land cover determined from original surveyor's notes is smaller than the later land use classification that used aerial photo slides to create land use groups.

Physiography of Southwest Barry County

There are 577 square miles in Barry County. The study area is underlain by sandstone and shale (in SW corner) from shallow sea deposits from the Ordovician. The Coldwater Shale formation is under a small portion of the study area. This formation has poor permeability and is a poor aquifer. A large band of the Marshall sandstone formation is under the study area. This sandstone is highly permeable and is a good aquifer. The Michigan formation is a clay formation with limestone and gypsum inclusions. This again is impermeable and a poor aquifer.

All known surface deposits are of Wisconsin age in the Pleistocene. Potter (1912) describes the area between the Kalamazoo and Thornapple River valleys as the Barry Summit. This summit is actually the corner area of the Michigan and Saginaw lobes of the Kalamazoo Moraine. The high point is a place referred to as Mount Hope in Hope Township. The hills form a corner that is described by Thomas Straw as the "crotch" of two moraines separated by a narrow band of pitted out wash.

The terrain is "hummocky" with areas of high topographic variability interspersed with flat outwashes.

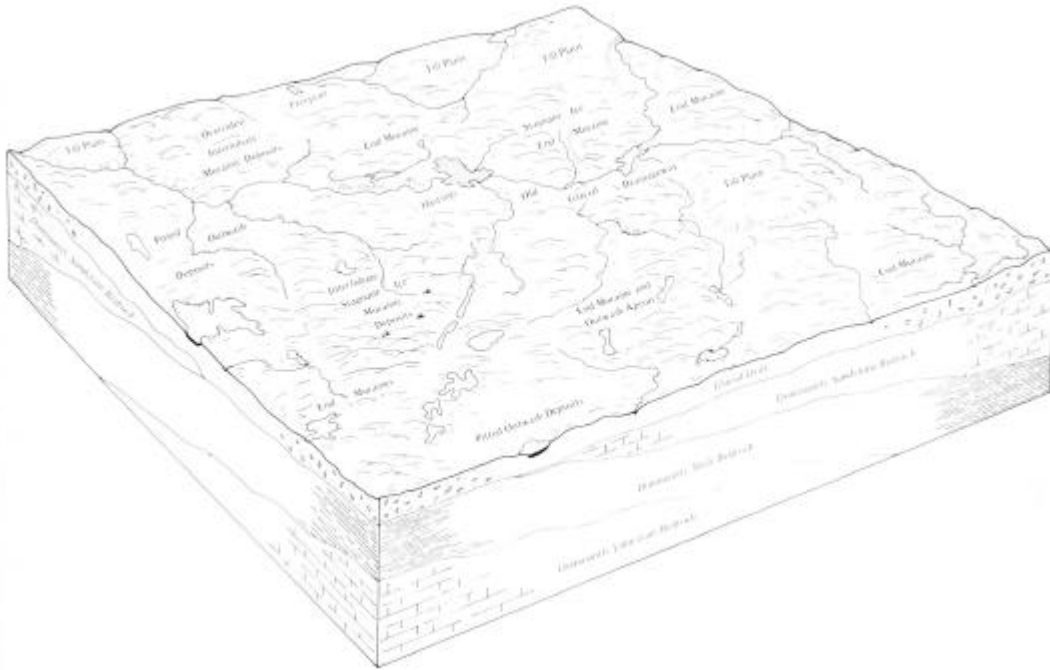


Figure 5 Physiography of Barry County Michigan
Source: United States Department of Agriculture, 1990, pg 3.

The morainal deposits host a number of lakes and wetlands in the topographic lowlands. The glacial moraines have many kettle lakes. With the combination of topographic lakes and glacial kettles, the wetland's characteristics are a combination of factors. There are thirty-four lakes greater than seventy-five acres. Of these thirty-four half are in this study area and four of the largest six are in Prairieville township.

Hydrology and Climate of Southwest Michigan

The study area is highly influenced by the lake effect on temperature and precipitation. The closer to the lake, the higher the average temperature for the winter and lower the average temperature for the summer. The lake effect prevents an early warm up that may lead to premature budding of trees. This reduces the risk for an early fatal frost. This natural insulation is taken advantage of by orchard growers.

The average winter temperature in Barry County is 24.6F and the average summer temperature is 69.5. These temperatures show great day-to-day variability due to the temperate influences of the air masses from the Gulf of Mexico and the colder continental air masses out of Canada. "A large part of Michigan has not yet developed an integrated drainage system due to the youthfulness of the glacial deposits. As a result shallow lakes, swamps and marshes are common as well as streams with many lakes along their courses. All these features are characteristic of an immature drainage system" (Squire, 1972, 3).

CHAPTER 3

Discussion of Raw Data

Three major sources of data were obtained for this study. The first being the acquisition of the satellite imagery; the second being the acquisition and creation of the soil data for use as *a priori* data and the National Wetlands Inventory as reference information. Also a township framework of section lines and corners was used to register the imagery. The major sources of data are discussed below.

National Wetlands Inventory

As required by the National Wetlands Inventory Act, the United States Department of Agriculture conducts a survey of wetlands of the conterminous United States at the scale of 1:24000. Attempts at delineating wetlands on the large scale were limited prior to the 1970's. Tested delineation methods have been standardized and the legal definition of wetlands was settled after the George H.W. Bush Administration-Congressional conflict.

The National Wetlands Inventory maps are produced by visual interpretation of high altitude color infrared photography (1:58,000). The scale of 1:24,000 makes the generalization of wetlands more specific due to total reliance on the image, the

soil survey is tied to samples and air-photo imagery only give limited clues to soil type.

The formulation of classes for the National Wetlands Inventory follows closely Cowardin's classification of wetlands for the state of Wisconsin. The exact definitions are laid out in United States Fish and Wildlife Service "Classification of Wetlands and Deepwater Habitats of the United States". Each wetland polygon or linear feature has at least three codes that indicate regional system, vegetation, and inundation. Each of these codes represent the presence of one or two individual factors, sub classifications and special modifiers.

Table 2

National Wetlands Inventory
System and Subsystem Codes
for the Study Area

Code	Name	Sub Code	Description
P	Palustrine		
L	Lacustrine	1	Limnetic
		2	Littoral
R	Riverine	2	Lower Perennial
		3	Upper Perennial
		4	Intermittant

The highest layer of the classification is the system that indicates a commonality in hydrology, chemistry, biology, and morphology. This code represents

the geographic placement of the wetland in relation to upland and ocean water bodies. This also indicates the wetlands approach to base level. Base level is the concept of placement of the water from the high land source to the final ocean destination. As demonstrated in Table 2, only three systems are present in the NWI classifications of wetlands in the study area. The relative distribution of National Wetlands Inventory wetlands located within the study area are demonstrated in Figure 6.

The first of these is the Palustrine system. Palustrine wetlands are the example of most inland wetlands. Wetlands of this type can be characterized as temporary in a geologic sense. They may be the end result of an eulogotropic lake system, a detainment area for seasonal flooding, areas of low permeability, or shallow areas intersecting the current ground water table. Commonly know as fens, bogs, marshes, swamps, wet prairie and ponds, these areas are the most susceptible to engineering activities because they are easiest to dredge, fill, or drain.

The Riverine system acts as a convenience for water and flora and fauna. Streams and rivers drain Palustrine wetlands either through surface flows of subsurface contributions. Some Riverine systems do not qualify as wetlands because their condition cannot satisfy the requirement for vegetation and/or hydrology. Since water is moving in these systems the gradient and intermittence of the system may not support typical wetland characteristics.

The Riverine system is divided into four subsystems, three are represented in the study area. The intermittent subsystem includes all wetlands that are not fed from

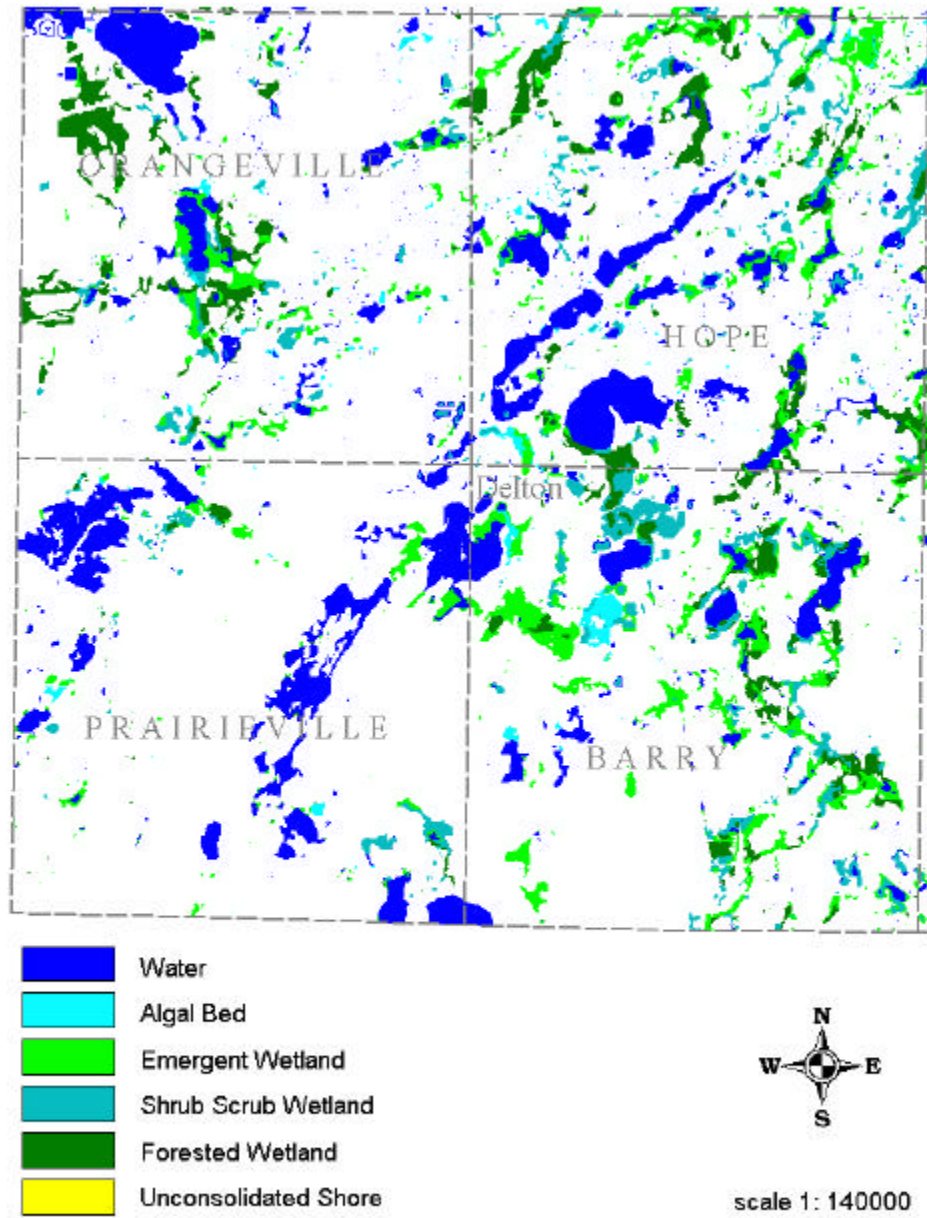


Figure 6. National Wetlands Inventory Classification in Southwest Barry County

a base flow. The upper perennial subsystem is high gradient high-energy conduits with high oxygen saturation and little plant life. In contrast, the lower perennial subsystem that represents low velocity streams with a high sediment load, plant-life and well-developed flood plain. The tidal system is absent from the study area but includes all tidally influenced systems and is very similar to the lower perennial subsystem.

The third system is the Lacustrine system. It may be said that water entering this system has attained a temporary base level. These wetlands are a standing water habitat, which are more difficult to alter than a Palustrine wetland. The vegetation may be limited due to deeper waters and these areas are commonly found in lakes and they're near shore areas. They are classified as wetlands because even deep-water habitats may support the vegetative (floating vascular and algal) and aquatic life to qualify as a wetland.

There are two subsystems in the Lacustrine system. The first is the Limnetic subsystem. These areas have deepwater deposition of planktonic life and an established wave system. The Littoral lakes are shallow having no wave systems and inclusions of Palustrine wetlands within the boundaries of the lake.

The last two systems are not included in the study area. The Estuarine system is the coastal system that supports saltwater and freshwater wetlands. Commonly known as the buffer zone between open ocean and uplands these wetlands are important fisheries and weather abatement areas. The Estuarine system has two subsystem, the permanently flooded inter-tidal and the intermittently flooded sub-

Table 3

National Wetlands Inventory Substrate and Vegetative Classes for
Southwest Barry County, Michigan

Code	Name	Description	Vegetation
FO	Forested Wetland	Full growth trees with specific adaptive strategies for life in saturated soils. Forested wetlands are the least dependant on constant soil moisture	Tamarack, White Oak, Willow, Cherry
SS	Shrub-Scrub	Wetland populated by shrubs and immature trees in near shore areas. Shrub-Scrub wetlands create an uneven mat of vegetation and may represent transitional areas	Buttonbushes, Cottonwood, Cherry, Willow, and immature Sassafras
EM	Emergents	Emergent wetlands contain upright, rooted, water tolerant plants which are present annually	Dock, cattails, sedges and grasses
AB	Aquatic Bed	Rooted and un-rooted floating plants on still water. Aquatic Beds may become mud flats in years of extreme drought	Duckweed, algae, water lilies, water lettuce, and water ferns
UB	Unconsolidated Bottom	Small open-water areas with shifting beds which do not allow the rooting of permanent plant life	
OW	Open Water	Larger, standing water habitats with deepwater deposition of planktonic life, with and without established wave systems	

Source: Cowardin, 1979.

tidal. The Marine system is almost entirely saltwater and is a high-energy system with salinities exceeding 30%. The Marine subsystems are identical to the Estuarine system.

The second level of classification is the vegetation and substrate codes as listed in Table 3. This is rather simply arranged from the plant life that is most water dependent (obligate) and the plant life and water beds that are least water dependent (facultative). The vegetation-substrate code typically represents one family of plant life or bottom type, but some of the wetlands may have a dominant and secondary wetland type. These two signatures may coexist or may be seasonally dominant over each other.

The vegetation family least dependent on a constant water level is the Forested wetland (FO). With the exception of Mangrove areas in estuarine systems most full growth trees cannot be supported by saturated soils. Roots suffocate in water without specific adaptive strategies. These wetlands are frequently inundated outside of the forest-growing season such that some of the trees may actually be upland trees.

The Scrub-shrub class (SS) is more dependent on water. Small shrubs and immature trees pioneer the near shore areas that suffer saturated soils that make it difficult for trees to mature. Buttonbushes, cottonwood, and willow create an uneven mat of vegetation that may be representative of a stable community or may be transitional to a forested wetland.

Emergent wetlands (EM) are populated with upright, rooted, water tolerant plants that are present annually. They include dock, cattails, sedges, and grasses. The wetlands are most usually considered permanent, but due to extreme water table fluctuations and ice flows the emergent wetland may be non-persistent.

Aquatic Bed wetlands (AB) represent the rooted and uprooted floating and surface plants which occupy still water areas of wetlands. Notable vegetation types are duckweed, algae, water lilies, water lettuce, water ferns, short grasses, and subsurface plant life. Aquatic Bed wetlands may latter become mud flats in response to loss of water table and evaporation.

The substrate classes are used to describe the saturated soils and water boundaries that are mostly unvegetated due to the high level of activities from water flow, waves and tides. Unconsolidated Bottom (UB) represents most of the open water areas in post-glacial wetlands. The particles in an unconsolidated bottom are shifting and do not allow the rooting of plant life. The Unconsolidated Shore (US) represents saturated soils which do not support vegetation due to their constant erosion and deposition. The Rock Bottom class does not appear in this study area.

The third level of classification indicated the presence of water in the wetland area, and whether or not it is artificially or seasonally dependant. The classes proceed from the driest wetland (A) that are artificially flooded to open water habitats that never dry (H) as indicated in Table 4.

Table 4

Water Regime Modifiers Indicative of Inundation

Class Name and Code	Description
Permanently Flooded (H)	Water covers the land surface throughout the year in all years.
Intermittently Exposed (G)	Surface water is present throughout the year except in years of extreme drought.
Semipermanently Flooded (F)	Surface water persists throughout the growing season in most years.
Seasonally Flooded (E)	Surface water is present for extended periods especially early in the growing season, but is absent by the end of the season in most years.
Saturated (D)	The substrate is saturated to the surface for extended periods during the growing season, but surface water is seldom present
Temporarily Flooded (C)	Surface water is present for brief periods during the growing season, but the water table is usually well below the soil surface.
Intermittently Flooded (B)	The substrate is usually exposed, but surface water is present for variable periods without detectable seasonal periodicity.
Artificially Flooded (A)	The amount and duration of flooding is controlled artificially.

Source: Cowardin, 1979.

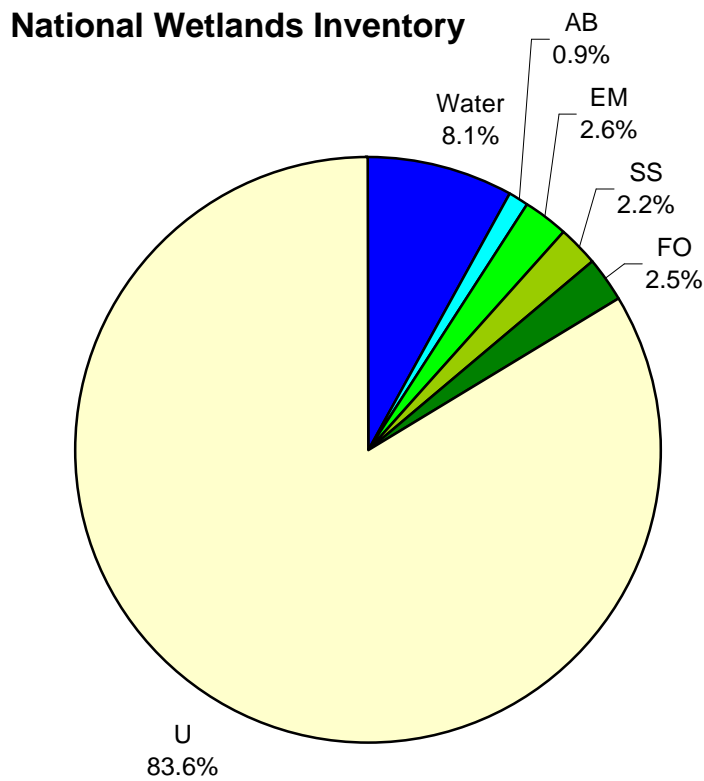


Figure 7. Distribution of Wetland Types as Classified by the National Wetlands Inventory

Calculation of wetland area within the study area finds 8.1% water and 8.3% wetland. Wetland groups are subdivided according to Figure 7. The NWI maps cannot be relied upon to find transitional bands in wetlands because the scale is too large to map a three meter wide strip of shrubs, therefore only the largest expanses of wetland type can be mapped accurately. The classification scheme is very specific, possibly leading to a false sense of accuracy, but on the small scale where wetlands need to be detected and monitored, rather than classified, the maps appear to be accurate in intent.

Soil Survey

To assist in agricultural stabilization, the United States Department of Agriculture for years has produced a soil survey of agricultural counties in the United States. These are produced from field surveys. Soil scientists walk the landscape, demarking approximate boundaries and taking soil samples for every two hectares. This point field data and the boundary approximations are then used to impose classification polygons on aerial photographs.

The aerial photographs are mosaiced and combined to equal size part sheets of the county. Problems arise in the mosiacing of four to six individual photographs onto a single sheet. Match lines are influenced by the location of section line roads that appear on the survey, and other man-made boundaries.

The soil classification system has an advanced taxonomic structure that allows for exact physical descriptions of the soil in addition to characteristics of sub-surface hydraulics, engineering properties, and vegetation. The physical descriptions on the surface describe the aggregate of conditions and variation within the soil survey is to be expected. "On the landscape, soils are natural objects. In common with other natural objects, they have characteristic variability in their properties. Thus, the range of some observed properties might extend beyond the limits defined for a taxonomic class." (United States Department of Agriculture, 1990, 5)

Most inclusions are non-conflicting (very similar) to the taxonomic class. It is assumed that a mapped boundary is the best guess from observed surface characteristics, but the boundary may only represent a transition zone and

subsequently cannot be taken as an exact measure of where one soil ends and another begins.

"Hydric soils have a reducing regime that is virtually free of dissolved oxygen because the soil is saturated by ground water or by water of the capillary fringe" (Michigan Department of Natural Resources, 1989, 13). Most wetland soils are included in the typical hydric subgroups and the aquic suborders in non-hydric subgroups. All histosols except folist are considered hydric. Poorly drained soils are excluded from the hydric soils list, but the inclusion of hydric areas is frequent and demarked on the surveys as individual marsh symbols.

Hydric soils have reducing conditions during a significant portion of the growing season. Indicators of hydric soils are as follows (Environmental Laboratory 1987): (a) water table within six inches of the surface, (b) water table within twelve inches of the surface in areas with a permeability greater than six inches per hour, (c) twenty percent organic material in less than twenty percent clay soils, (d) thirty percent organic material in greater than sixty percent clay soils, (e) sulfide or rotten egg smell, (f) iron/magnesium nodes, (g) gleying and (h) mottling.

The soil survey is being used in this study to identify surface areas that have a higher probability of wetland characteristics. The soil survey does not directly indicate the presence of wetlands in that the scope of the survey is not the delineation of vegetation. There are, of course, natural inclusions of wetlands in what would otherwise be upland areas, but these are small natural variations in soils. What must

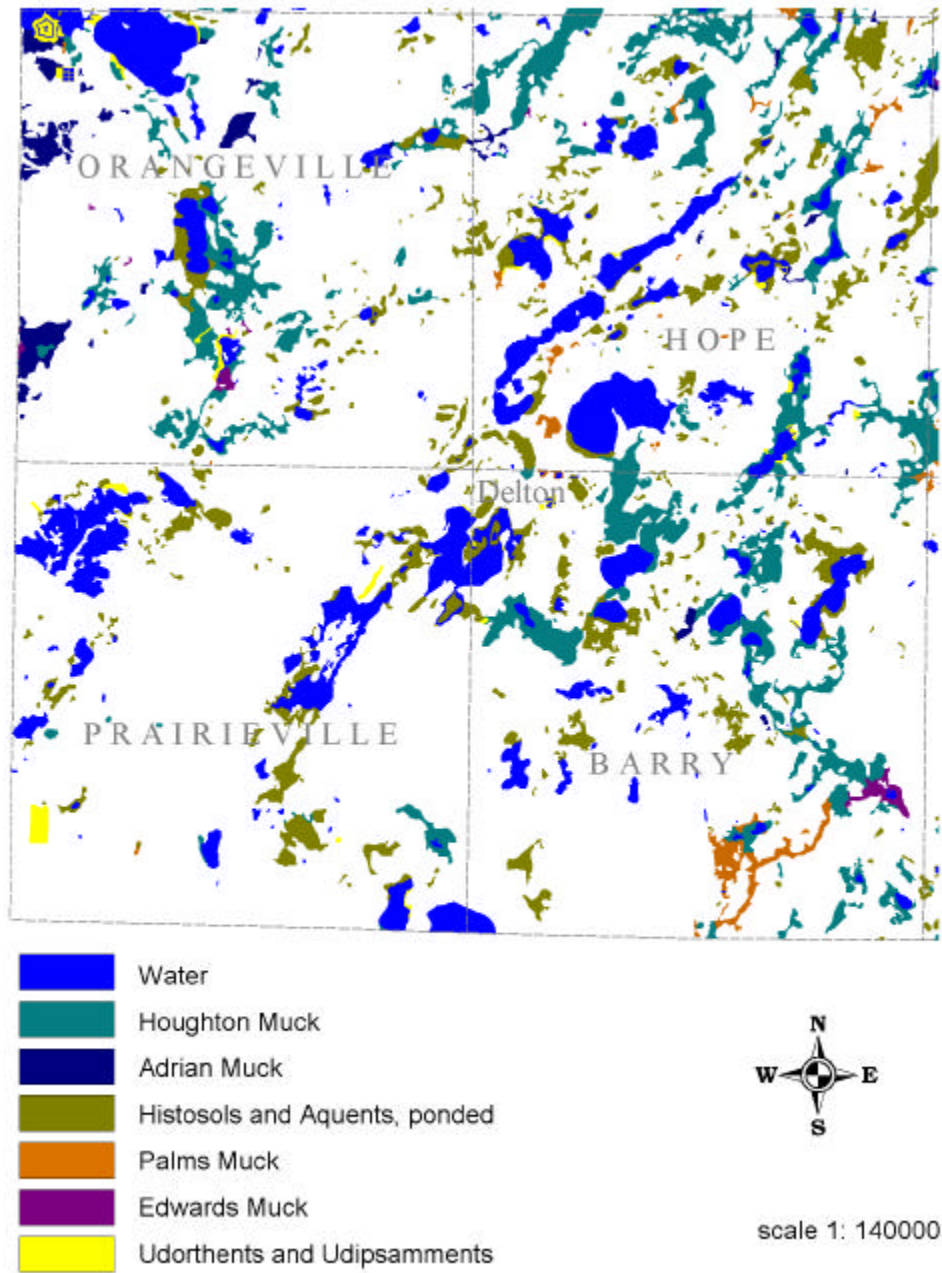


Figure 8. Hydric Soils in Southwest Barry County

be separated for specific study are the large areas of wetland soils as classified by the soil survey.

Histosols and Aquents are the general classification of wetland supporting soils; they are saturated for a frequency and duration that would support wetland vegetation under normal conditions. Histosols contain an organic composition consistent with the decay of plant materials under reducing conditions. Aquents are immature wetland soils that do not contain an organic layer below the layer of surface litter. General descriptions of the individual wetland soils can be found in the each soil survey.

Within the Barry County soil survey, there are four identifiable, mature wetland soils and two immature soil groups. (Figure 8) Hydraulic and engineering conditions are established for the mature soils and the immature soil classifications are dependent on site considerations and frequently do not contain descriptions.

By itself, the soils layer is not a reliable indicator of wetlands. There are man-made alterations such as drainage, dredging, and filling which can affect the local hydrology of soils. There are also natural climate and seasonal changes to be considered. The deciding factor in wetland delineation in the State of Michigan is the presence of hydric indicators in the soil in addition to vegetative or hydrologic indicators. The Army Corps of Engineers delineations omit all areas with hydric soils unless both hydrologic and vegetative specifications are met.

The soils have already been scanned and digitized and exist as a labeled polygon file in both C-Map and ARC-Info formats. The "spot wetland" sites have yet

to be entered as a point data file that will be converted to pixels (or buffered if a vector overlay is employed) and added to the soils layer. Although Soil Conservation Service soil types are sometimes generalized over large areas, the spatial accuracy of the satellite data is only thirty meters by thirty meters and the allowable rectification error of the soils layer is thirty feet, still less than the satellite's thirty meter spatial resolution.

Landsat Thematic Mapper

The advantage of satellite imagery is the near simultaneous sampling of a large portion of the earth's surface. Landsat imagery is available as full scene as 100x100 nautical mile (87x87 statute miles) windows. A standard Michigan county is 24x24 statute miles, so a county size study area will fit into a single image unless the county falls on the lower or upper boundaries of the image. Sometimes multiple images may be considered to obtain cloud free imagery and some scenes may have perturbations that make them unusable. There is little preprocessing involved in cleaning the good data sets before they are usable in the study area because topographic variation is not a concern with less than one hundred feet of real elevation change. Radiometric and atmospheric corrections are made by the unsupervised classification when the individual bands are redistributed while processed.

Spatial resolution is a limitation to classification of ground data. With a spatial resolution of 54 feet by 54 feet the smallest mappable object would be the size of a

small house. By sampling slices of the electromagnetic spectrum the spectral resolution is reduced, and each image is only representative of the season and year of sample. Any increase in resolution, whether spatial, spectral or temporal, results in an increase in data file size.

Table 5

Characteristic of Thematic Mapper Spectral Bands

Band 1: 0.45 – 0.52 μm (blue). Provides increased penetration of water bodies as well as supporting analyses of land use, soil, and vegetation characteristics.

Band 2: 0.52-0.60 μm (green). This band spans the region between the blue and red chlorophyll absorption bands and therefore corresponds to the green reflectance of healthy vegetation.

Band 3: 0.63-0.69 μm (red). This is the red chlorophyll absorption band of healthy green vegetation. It is also useful for soil-boundary and geological boundary delineations.

Band 4: 0.76-0.90 μm (reflective-infrared) This band is especially responsive to the amount of vegetation biomass present in a scene. It emphasizes soil-crop and land-water contrasts.

Band 5: 1.55-1.75 μm (mid-infrared) This band is sensitive to turgidity and amount of water in plants.

Band 6: 2.08-2.35 μm (mid-infrared) This is an important band for the discrimination of rock formations.

Band 7: 10.4-12.5 μm (thermal infrared) The band is useful for location geothermal activity, vegetation classification, vegetation stress analysis and soil moisture studies.

Source: Jensen 1986

With Thematic Mapper data we are certain about one point per pixel. A feature must comprise at least one half of the pixel to be reliably classified. One thing we know is that "liquid water in leaves absorbs solar radiation in Mid-IR. An

increase in the soil moisture decreases its relative refractive index between the soil grains and the spaces between them, and thus increases the forward scattering by grains and the ability to trap light.” (Kaufman, 1994, 673) It is then of great importance to include this information in a classification.

The same liquid water absorbs the radiation to 3.75 μm and thus reduces the reflectivity of most soils. Band 5 on the Thematic Mapper which is mid-infrared is less sensitive to aerosol effects than the red band used in greenness and brightness classifications. The band which displays 3.75 μm does not show the seasonal variation in the vegetation of the open field that is observed by 0.64 μm (Table 5)

"Even though plant species and soil types and characteristic are generally used as criteria for identifying wetland, the dominant feature is the presence of excess water either on the surface or underground." (M. Demissie, 1989, 1) When a pixel has a high reflectance in the near infrared and green band the spectral signature may "yell" plant, but there needs to be a noticeable decline in Mid-IR spectral reflectance to accurately assume the presence of water on the surface or in the soil substrate.

It is important to note that vegetation moisture ranges from 1.67 to 1.77 μm and soil moisture ranges from 8 to 14 μm . This is particularly helpful in discrimination between highly vegetated and poorly vegetated wet areas. An un-vegetated wet area could be a prairie pothole, farmed wetland, or a recently modified wetland by draining, flooding or dredging.

The entire county is small enough (36 x 36 miles) to fit in a partial Landsat TM image without overtaxing the ability to process overlays (~2 million pixels). The

lower corner of the county is subsetted from the entire county for the project because it has a completed soil layer and NWI layer unlike the rest of the county.

Furthermore, a serious problem with this satellite imagery is the timing of the data collection.

The imagery needs to be chosen to maximize accuracy in delineation. In early June, the hardwood wetland scrubs, buttonbushes-*Cephalanthus occidentalis* and pale dogwood-*Cornus obliqua*, have just begun to leaf out in the open water and near shore areas. The evapo-transpirative capabilities of the sedges and grasses will not start until the temperature rises in late June so there is still much free standing surface water in early June without the full vegetative cover from nearby shrubs.

One way to accommodate fluctuations from year to year is to incorporate imagery from multiple years on or near anniversary dates (Berta, Kettler and Gress 1994). Variation within the scene itself could be minimized by incorporating multiple images from a short time period such as the sixteen day repeat cycle of the satellite, but the chances of two cloud free days in the sixteen day cycle would be slim. Either way, the likelihood of anomalous inclusions is decreased with more than one day of imagery.

Imagery was available through the Western Michigan University Department of Geography for July 1987; this was stored on nine 9-track magnetic tapes at a data density of 1600 bits per inch. A second quarter image of Kalamazoo County available from the Department of Geology for one 9-track magnetic tape at 6250 bits per inch was available for early June 1986.

The second image is ideal in that it falls in the first week of June during the early vegetation and wet substrate season, but the scene has a few small clouds in the area and uneven aerial haze which make it very difficult to derive a reliable classification. Therefore, the July 1987 image is qualified for further processing, but by no means is the June 1986 disqualified. In assigning categories to the July 1987 image the June 1986 image can further differentiate vegetative classes which are spectrally discernible but not visible to the naked eye.

Band 5 is notable for its ability to pick up rock faults by differences in moisture. Band 4 detects live vegetation, the characteristic red color of vegetation in infrared photography. Since there is generally over two hundred feet of unconsolidated material to bedrock in southern Lower Michigan, band 5 is relatively fault "noise" free.

The goal is to identify those areas with low reflectance in band 5 (wet) and a high reflectance in band 4 (vegetated) and to assess the accuracy of this relationship to known wetlands. This is accomplished by assigning band five to blue color values and band 4 to red color values for a visual determination. Similar to Jansen's search for the magenta (red-flus) areas of cattails in the inland Florida wetlands (1995), Michigan wetlands reflect a unique color in this assignment. This purely visible technique allows for the classification of cluster means and the establishment of classification seeds for maximum likelihood or nearest neighbor classifications.

One must keep in mind that raster data are point data with a specific aerial extent. The pixel borders do not indicate the exact physical boundaries; furthermore,

the pixel itself may represent the boundary or transition zone such as a road, fencerow, coast or river. These objects may be too narrow to have their own detectable class or simply not discernible with the available sensor.

Digital Conversion Methodology

The Landsat satellite image from June 8th, 1986 was downloaded from 8-bit magnetic tape. The original data was in band sequential format. The format was imported into ERDAS where the image information was made readable in the standard ERDAS LAN format. The LAN format is importable by TNTmips for georeference, resampling, and classification.

Once into TNTmips the image was georeferenced using the coordinates obtained for section corners from MIRIS information in the state plane coordinate system. Errors less than twenty feet were considered acceptable. The image was resampled using a binomial resample with pixels the same size as the original and nearest neighbor resampling.

Data that are available for use as a GIS data layer frequently are a digital version of a paper map. Hardcopy maps, no matter how bulky, frequently are more visually pleasing and easier to interpret as single entities, but when it is necessary to overlay maps to extract information, the computer is invaluable. At best a visual overlay would convert the layers to equal scales and at most allow the overlay of two or three maps at a time. What distinguished the GIS on the computer is the ability of the operator to query the database and create a geographic representation.

A GIS data layer is the converted form of this map, be it point, line or polygons with one or limitless attributes. The main function of the GIS is to overlay, combine, extract, and derive data from one or many layers in respect to their real-world geographic positions.

"The errors introduced by digitizing categorical data using the polygon data model are generally small compared with the uncertainties present in the source document and passed intact into the spatial database." (Goodchild et al, 1992, 89) Assuming a one percent error due to mislabels, a one percent error due to lineage, and a one percent error due to missing labels or omitted data, a similar error in the data entry is a fraction of the total error.

Sources of error in hardcopy NWI maps can be defined as errors in label placement, errors in scale, errors of commission and omission, and finally errors in attribute accuracy. It is difficult to show accuracy of less than 0.5mm; therefore, on a map of 1:24000, showing a feature less than ten meters in size is impossible to represent with any accuracy. Line and polygon labels may be mislabeled and sometimes a label is missing or duplicated.

Line and polygon labels are not differentiated by size or color, this makes for interpretation errors when polygon have line attributes. Some line features have no distinct end point. To further complicate the accuracy, some of the polygons fall below the minimum mapping unit and operator visibility. Gross errors sometimes appear on the map. For example, within the State forest is a 100 feet wide "PUSG"

(Palustrine Unconsolidated Shore permanently flooded) polygon which in lake areas is commonly referred to as a beach.

Only four georeference points are available on mylars, but the vector and raster files line up very well with composite maps due to the original georeference to USGS topographic quadrangles. Less than 1% of area is field checked in the 33 quads processed. Wetness varies in frequency, duration, depth, depth of inundation, and water quality. The NWI maps clearly state that boundaries will vary and must be determined on site. Inclusions on the wetland map may be less than one hectare. Flooding and severe weather can significantly alter the wetland hydrology or vegetation.

The classification employed by the Fish and Wildlife service is modeled after the classification scheme developed by Cowardin. The taxonomic structure is exhaustive. With separated levels of association one could separate wetlands by frequency of inundation, structure-hydrology, vegetation, and special wetland characteristics such as salinity, fauna, and specific hydrology, beaver ponds etc.

There are issues with positional accuracy due the fact that the photography is not orthogonal. Since most of the survey work is completed from field notes, the boundaries that are actually scribed onto the map may be misinterpreted to correspond to a distorted base image. This has been improved on in recent years, the surveys are now into their second generation with a increase in samples and better mapping standard. Line widths vary from soil survey to soil survey and with a scale of 1:15600, the line width plays an important role in visual accuracy.

There are certain errors inherent in the United States Public Land Survey's Township and Range boundary system that translate into sliver errors in some coverages. A road which jogs around a wetland or other obstruction will be included in one survey but not the sheet mate, thus producing a gap where the road deviates from a straight line. Most notably there are road jogs along larger divided roads that run with section lines resulting in polygons which appear on two sheets with different classes.

There are missing polygon labels, some of which can be inferred by adjacent polygons, others are totally unknown. Section corners can be obscured due to an increase in line heaviness due to roads; therefore, positional accuracy is sacrificed. Some of the soil polygons have artificially imposed boundaries due to road cuts and fills that force polygon line to cross roadbeds perpendicular to the road. A lesser problem is that the labeling and classification scheme is not consistent from county to county and in some cases the physical characteristics of a soil are vastly different from the physical characteristics of a soil of the same class in an adjacent county. Lines are only an approximation of true boundaries and are more representative of transitions zone the hard boundaries.

Errors in classification differing from NWI maps are not strictly Boolean. Because there are multiple levels of classification for the NWI maps, the priority is first whether they were classified as a wetland. That compromises at least one half of the accuracy. A wetland classified as LFO1C only differs for PFO1C in one degree and from PFO2C in two.

By far the most important level of the classification for a single data image is the initial determination of wetland vegetation classification. Frequency of inundation is second on a single date image and class is final and most unreliable due to its direct connection to subsurface hydrology, seasonality and date.

Error in the soft copy maps are created when computer line width is less than hard copy line width; therefore, polygon junctions frequently lose their smooth appearance. The heavier the original map line width, the more roughness in the lines within the computer. Node and vertices less than the computer minimum are automatically snapped together, this usually does not represent a problem. An artificial frame is imposed on the map that causes boundaries to snap to the frame that frequently pulls the node perpendicular to the line.

CHAPTER IV

DESIGN AND METHODOLOGY

Creation of Uniform Classification

Before the creation of any classification scheme, a common ground must be established to ensure the further processing potential of the data set. The creation of a uniform classification must be applied to the experimental classification and outside sample classifications. It is also important to construct a consistent etymology of terms. For the sake of further discussion the unmodified classification of the satellite image is the control classification.

To assess the accuracy of the classification to the NWI classification and to each other the following table illustrates the simplified classification used by both the satellite and NWI maps to compare and contrast the accuracy of subsequent classifications. Please note that no saturation modifiers were considered in the creation of NWI assignments.

Wherever possible it is wise to consolidate classes into larger groups. Since it is not feasible to retain all classes when using two totally separate sources, combining those two sources for a common classification is reasonable. (Table 6)

If there is already a reputable classification system for the phenomenon we are interested in, it is foolish to start anew, reinventing another system which will probably only be used by ourselves. It is better to adopt or modify existing nationally recognized classification systems. This allows us to interpret the

significance out of classification results in light of other studies and makes it easier to share data. (Rhine and Hudson, 1980, 185)

Table 6

Uniform Classification

Unified Class	Satellite Classes	NWI classes
1- upland	agriculture Herbaceous open land Forest Urban	U
2-dry-end wetlands	forested wetland Farmed wetland	PFO1* PFO2* PFO3* PFO1/SS* PFO2/SS* PFO3/SS* PSS*
3 - mid range wetlands	shrub-carr Forested wetland dead	PFO5* PSS*/FO* PFO5/SS* PFO*/EM* PSS*/EM*
4 - wet end wetlands	emergents	PEM* PEM*/AB PEM*/SS* R*EM*
5 - algal beds	algal beds	PAB PAB/EM* PAB/UB PEM*/UB L*EM* L*AB R*AB
6 - water	water	L*UB PUB R*UB

The problem is to increase the accuracy of a Landsat Thematic Mapper delineation of wetlands by efficient application of secondary data and to better train the computer and the human user for automated delineations. Numerous secondary data sources can be used to increase the accuracy of Landsat classifications. In tropical areas, Kaufman (1994) used rainfall data to distinguish tree canopy thickness. Williams (1992) used digital elevation model to increase the delineation of forest types in Alberta, Canada by nearly 10.81 to 72.77%.

Ancillary Data Ordering

Each category has its own spectral uniqueness and can fall into many classic land use / land cover classifications, meaning that agricultural wetlands could be classified either as wetlands or agriculture on a traditional land use survey. With the focus on only wetlands, care has to be taken to be inclusive of all wetland types, whether or not they are a different land use. Williams (1992) points out that it is wise to also include an unclassifiable class in early analysis.

The computerized delineations of the wetlands must be compared to the standard distribution of wetlands from maps and in the field. To do this one must incorporate the wetland map and soil survey into computerized formats and scale them appropriately to the problem. The current soils and wetlands layers as available from the government are in standardized vector formats. Usually on such a small scale it would not be necessary to rasterize the data, but it would cause difficulties to process vector polygon overlays. With satellite data, raster comparisons are easier to

process because of the possibility of individual pixel-sized polygons, as commonly is the case.

To efficiently address the use of Thematic Mapper (raster) data and vectorized map data layers, the differences must be consolidated into a single font, scale, sample size. The methodology employed in the study of wetlands in Barry County follows closely with methods layered out by Fornshell delineation of wetlands in Mississippi. The unsupervised classification of the satellite image was best subdivided with a thirty class, simple-pass classification with a minimum cluster distance of twenty. With any more classes or a smaller cluster distance clusters that are spectrally close are divided into many small classes. At a cluster distance of ten, one-third of the classes contain less than one percent of the pixels.

The clouds and their shadows are eliminated from the classification with a binary mask of the affected areas. This same binary mask is combined via a union function with wetland potential binary masks to produce sub-images for classification. The sub-images are classified with the same classification parameters receiving the same number of clusters and being interpreted by their adjacency to the previous wetlands classes.

In the first classification, of the thirty classes nearly half of the clusters represent pixels that fall in the farmed hydric soils in the upper left-hand corner of the image. The spectral signatures of these classes were noted and the minimum distance to means was increased to 20 to force grouping. They are all classes that are small in extent with pixel values that are very similar with the exception of extreme

highs or extreme lows in one of the seven bands. It is also interesting to note that these classes are not particularly homogenous.

There were two classes that were labeled as water areas. Group eight was obvious and group nine more represented cloudy algal waters. In the wetlands, the groups formed roughly linear features and it was very difficult to determine wetland type from the satellite image. The rare find in the wetland classes was the distinctiveness of the cluster that had dead forest or shrub material. This is commonly referred to as a class "5" in the wetlands maps and is spectrally between the ranges for agricultural fields and vegetated wetlands.

There are very few detectable residential classes. These were confined to two classes that occurred primarily in the village of Delton and on the northern shore of Pine Lake. The agricultural classes make up a majority of the image with a very fine spectral line separating them from the herbaceous open-lands. Forests were relatively easy to determine from the visual relation of these classes to the actual image.

Questions which need to be addressed in any classification: What are the uncertainties involved at each stage of image classification, how is this quantified, and what is the degree of uncertainty of the quantification? Maps from imagery have to be considered generalizations. "Since generalization involves subjective judgment, selection and simplification, the generalized objects are unlikely to be well defined and will probably be fuzzy." (Wang, 1994, 29)

To give no indication of inaccuracy is to assume perfection. "A classification is not complete until it has been assessed. Then and only then can the decision made

based on the information have any validity." (Congalton 1991, 45) It is then important to completely document the properties of data layers. Combining data with varying scales can cause serious problems that will compound with each addition data layer.

"A picture is worth a thousand words and unless GIS users are careful, those thousand words can be the wrong words and can be seriously misinterpreted."

(Hlinka, 1989, 1) A data lineage should include any consideration that may affect the level of detail at which that data can be used with confidence and should consider limitations to its use. This will include: (a) scale conversions, (b) georeferencing, (c) treatments of sliver polygons, (d) minimum mapping unit, and (e) spatial averaging.

Samples should reflect importance of the classification data. A finite population sample is best served by an equal sized finite classification. Therefore, if the sampling size of soils is one per two acres, then a polygon could not possible be smaller than two acres. The aerial photographs used to classify the National Wetlands Inventory maps are flown at a scale of 1:53,000. The ground resolution distance (GRD) therefore is about 45 feet, therefore a classification could not use pixels less than 45 feet by 45 feet.

The notable problem is that the polygon interiors are not the area of highest inaccuracy, the lines of the polygons are themselves the worst culprits of inaccuracy. A polygon line in the soil survey is about 1/75 inch, smaller than the 1/30 allowable for maps under 1:20,000, but this width jumps considerably along roadbeds and map edges. This may seem insignificant but these edges polygon can account for up to 60% of the coverage.

In the NWI topographic quadrangles the line widths are dependent upon the individual scribing techniques of the cartographer, with a range of 1/100 to 1/40 on single maps. The labeling style indicates multiple cartographers on single maps and multiple interpreters in a single series. Certain wetlands are scanned from the topographic quadrangles that are 8/400 of an inch on the exterior of the circle and so small that no interior is created by the pen. Assuming the wetland is well represented by one-half the diameter of the dot, the wetland would be 1/100th of an inch, well below the minimum mappable feature.

The area of measurement and unit of measurement will play a role in the accuracy of the resulting statistics. One cannot solve a spatial problem without regarding the tendency of the data to be related and the size of the sample will increase or reduce the inter-correlation of the data values of a pixel with its neighbors. At some point a threshold is met in reducing pixel size when the neighboring pixels will be identical and interfere with the assumption of independence. Conversely, if pixels are grouped into too large of an area, accuracy is lost in the spatial definition of the data set.

Accuracy Assessment

The classifications of pixels has been extensively covered in the past paragraphs, but what about the grouping of similar pixels into larger classification polygons. Polygons are never truly homogeneous. A polygon is a spatial average of an aggregate. Assignment to a less thorough classification throws away inherent in-

class variation but makes it difficult for user interpretation. Misclassification probability increases as the spectral distance decreases. The problem is: can this be quantified? A standard maximum likelihood classification assumes that all classes have an equal probability, but with wetlands there is no equal probability

It is important to conduct an error assessment on the first classification iteration, this identifies possible problem classifications. These problem classifications can be more heavily attended to in further iterations of the classification. This is used in conjunction with the "unknown categories." Misclassifications are hardly continuous throughout the classification. Frequently misclassifications follow topographic liniments with errors of omission and commission in slivers along polygon borders. A inherent error in imputing remotely sensed imagery into a GIS is that there is no measure of accuracies of the boundaries created by the classifications.

Missed classifications are non-continuous and totally dependent on human error. In the soil surveys it is nearly impossible to guess at the probable classification of an unlabeled polygon, but in the NWI map it is probable to a high degree of accuracy that the missing label is probably started with palustrine.

Sometimes the subcategories can be determined through polygon identities across linear features or adjacent polygon wetness categories. Edge problems created by roads withstanding, it is at least probable to select through careful estimation at least one feature of a unlabeled polygon. It some cases even the producing agency could not identify a subclass of problem polygons.

Just because a class is assigned that disagrees with the Thematic Mapper classification really does not mean the classification is incorrect. Other factors play a role in the spectral response of a wetland. Roadside polygons and very small polygons are frequently misclassified because they represent transitional areas. Poorly drained fields may be misclassified as wetlands because they have the hydrology and soils of wetlands and vegetation. How can areas of poor drainage be separated from wetlands, and are the poorly drained areas actually not wetlands, or are they wetlands not under normal circumstances? With an underlying aerial photograph, the interpreter can see the texture of tractor plowing.

The current statistical models used to describe categorical data sets have been outgrown in the GIS environment. With newer technologies alternatives to the traditional approaches in classifying data must be developed to account for the contiguity and natural auto correlation of spatial data. Applications that are usable with the current limited Boolean processing of computers are massive, intense, and still only in their development stages. This has much to do with the nature of the data that geographers have traditionally handled.

Most categorical maps produced by geographers deal with bivariate or univariate data sets. The level of complication is limited to an ordinal scale with a few brave "mapmaticians" experimenting with classless maps. When we start using a categorical analysis in development of categories in a multivariate set, especially remotely sensed data, we use simple linear and Boolean relationship to describe a relationship on which the base map foundation itself is three dimensional.

The measures available to describe the behavior of multivariate data were developed by mathematicians to accommodate data in a cognitive univariate-bivariate environment with the initial assumption of normalness and independence. If anything can be noted directly from satellite data, it is that it is infrequently normal and never independent. The sampling of the data is regular across an image that may have classification regimes that are many times the area of the sample.

In converting a multivariate data set to categories without the use of GIS technology, classifications are exhausting, labor intensive, and rife with human error. In classifications that employ the available software, valuable data are lost in the computer assumptions of normalcy, independence and automated border creation. Neither can be completely quantified, but the computer-assisted classification is frequently seen as the easier.

The role of visual interpretation is vital in making the decisions that statistics, no matter how extensive, cannot perform. Unfortunately, in dealing with multiple layers that may be categorical or raw values, the human analyst is quickly overwhelmed by the complexity of the resulting data and must rely on artificial display tools such as computers. The highest hurdle in using multivariate data is that the methods to check the accuracy of the classifications are best at the ratio level and degrade to the nominal level of classifications.

In this study, statistics can be used to compare the correlation between the NWI map and the automated delineation; the NWI map classifications can be broken down into greater groups of similar classes and compared to the spectral classes

derived from the hydric assisted supervised classification, or they may retain their complexity in classification types with the resultant loss of mechanical processability. Instinctively, we can process the complex relationships between the classes, but the current emphasis on numeric results hinder the greater insights to be gained from a firm grasp of the raw data.

Foody (1994) performed a simple ordinal classification of woodland type, deciduous to coniferous, on which the ordinal statistical measures were a viable option for analysis. Wetland areas can be ordinalized according to degree of wetness from open water to upland with wetland classes classified between the two extremes. The least wet would be the forested wetlands followed by shrub scrub, emergent, aquatic bed, the open water unconsolidated bottom as the wettest.

Unfortunately, many of the classes overlap or switch rankings throughout the changing of the seasons. Forested wetlands and bare histosols can provide a challenge in their exact placement on a scale from driest to wettest because they exist on the extremes of the vegetation range.

A pixel that creates error in the classification might only be expressing the intermediary attribute of the pixel and its nearest neighbors. To find the pixel in error or omission to assess the adjacency to the target area, Jansen suggests a 0.5% sample per class. Within a full scene this could amount over 30,000 pixels (1986). Methods of analysis include the gamma (γ , nominal-ordinal) and λ (λ , ordinal-ordinal) coefficients. This is assuming data sets with more than three classes. These measures

are derived from the production of an error matrix and table, counting the number of errors versus the number of correct classifications.

Problems that are encountered with any classification scheme are the tendency towards auto-correlation or random agreement. To reduce this, Naeset (1995) suggests calculating the marginal agreement after the first unsupervised classification. With the results, heavily auto-correlated classes can be resampled to reduce random agreement. A second unsupervised classification derived from the corrected classes samples the wetland areas in greater detail if open water and upland areas are eliminated from the second classification.

The rather simple statistical measures of accuracy and correlation (gamma and lambda) can give an indication of the rough agreement, but errors and omissions must be measured by using modified Kappa (K) and Tau (T) and represented in table format (Zhenkui, 1995). Tau, like the marginal homogeneity Naeset (1995) calculates, is an a posteriori measure of probability. Modified Kappa is more useful if there is an equal chance of error across the data sets, but since wetlands delineation is a single land cover type delineation, ignoring urban, agricultural and other land uses, there will probably be unequal probability of error in the data sets.

A satellite delineation is compared to another remotely sensed classification to see if the classification are from the same data set. The threshold of relationship has been established by Jenson as 85% to prove correlation to the reference set and an minimum 5% improvement reduces the probability of chance agreement. It is the goal

of this study to produce a reasonable amount of change in the classification accuracy while still maintaining continuity between classifications.

Traditional accuracy assessment ignores the fact that the sample data and the population data are frequently at different scales and the classification involves uncertainties that means one cannot assume accuracy due to the ambiguity of the classes themselves. "There is no uniform error concept, no standard techniques to measure error and no methodology for assessing their significance." (Wang, 1994, 1)

CHAPTER V

RESULTS AND DISCUSSION

Simple Classification of Imagery

The simple classification of wetlands by means of clustering similar spectral pixels employs all seven bands. With an unsupervised classification of wetlands, Berta (1989) chooses a 200 spectral class sample per image. This, of course, assumes an area that is an entire Landsat image and a varied landscape. Experimentation with the data set produced indicated that a classification with fifty bins was the ideal classification size producing approximately four bins per class in this study.

Another consideration in constructing the control classification is the minimum distances to means. The means are the average values of each of the seven bands for a given cluster. By increasing the minimum distance to means, the tendency to have redundant information between the classes is reduced, but as the distance increases the tendency for class members to become unrelated also increases. For this classification, a minimum cluster distance of twenty was chosen. This may not have been ideal, but at values less than twenty there is a tendency for the wet soil region in the upper corner of the map to account for more than half of the clusters in the classification.

The third consideration is the redistribution, if any, of the input data. Limitations in the program require the same type of redistribution to be used on all seven bands, and in further classifications, on the normalized soil data. Without specific information on the sensor's characteristics in certain spectral ranges, one cannot construct a piecewise or polynomial stretching without jeopardizing the value of the minimum distances to means ability to separate redundant clusters. Therefore, no input redistribution was used on any of the image bands.

For the sake of clarity, clouds and their shadows are clipped from the classification and analysis groups. Clouds are confused with urban and agricultural land and frequently shadows fall into wetland and water categories. A simple view of the resulting classification indicates that most classes are well delineated by the automatic classification, but the error created by the inclusion of clouds give false wetlands. Since the purpose of the paper is to increase the accuracy of wetland delineation it is not in the best interest of the paper to include cloud related pixels.

After the classification, it is important to choose a clustering algorithm to make sense of individual pixels. "Given modern spatial technologies, there is no longer any justification for the loss of information that occurs when 0.15 acre pixels are aggregated to forty, ten, or even five acre pixels." (Fisher, 1991, 200) The closer to the original sample size the pixels are, the less inaccuracy in the classification of polygons. After the final classification, pixels can be aggregated and averaged to represent the highest level of accuracy obtainable at the scale of map production.

The TM pixels typically represent 54 square feet; therefore, a feature must comprise one half of the pixel to be classified as a single class dependably rather than the one fourth required for cartography. In some cases, no particular attribute compromises one half of the pixel. The controlled classification of wetlands in the study area which is compared to the National Wetlands Inventory classification of wetlands in the study area is the baseline to which measurement of the enhanced classifications are made. As Jensen suggested, the 85% threshold is the desired match between satellite classification and reference material. Any increase in this accuracy can be seen as a movement in the direction of mapping “truth”.

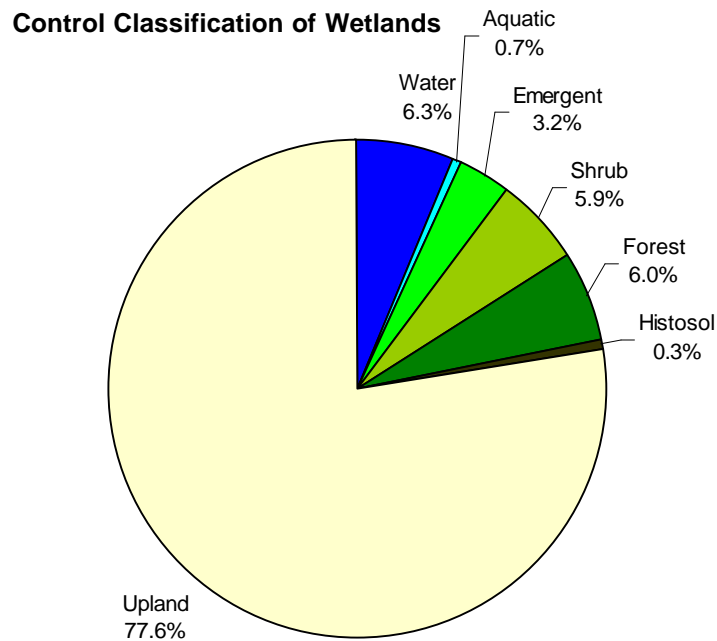


Figure 9. Resultant Class Percentages in the Control Classification of Wetlands

The spectral signatures of certain land cover types are quite distinctive. In creating a classification, pixels with similar spectral signatures are grouped into bins. These bins are then assigned a class. Similar bins are assigned to the same class (Figure 9). Using a fifty bin automated classification with a minimum mean tolerance of twenty, we can map spectral means on a scatter-plot to group families of related bins by comparing selected pixels with the visible bands and proximity to known classes.

Table 7

Omission and Co-Omission between Control Classification of Landsat TM Bands 1-7 and National Wetlands Inventory by Land Cover Group

	Control	NWI	Difference	Omissions	Omissions %	Co-Omissions	% Co-Omissions
Water	32395	41763	22.43%	11478	27.48%	2110	-5.05%
Wetland	81169	42635	-90.38%	26719	62.67%	65253	-153.05%
Upland	401225	430391	6.78%	57152	13.28%	27986	-6.50%
Total Error, Omissions plus Co-Omissions				37.04%			

Assessing the map “truth” is accomplished by using simple measures of agreement. The first degree of measurement is a visual inspection of the wetland area detected the by the unsupervised classification versus the wetland area classified by the National Wetlands Inventory. The National Wetlands Inventory classifies 83.6% of the study area as upland, 8.1% of the area as open water and the remaining 8.3% as wetlands. Table 7 demonstrates the rates of error of Omission and Co-Omission.

Table 8

Omissions and Co-Omissions between Control Classification
of Landsat TM Bands 1-7 and National Wetlands Inventory
for All Classes

	Control	NWI	% Omissions Difference		% Omissions	Co- Omissions	% Co- Omissions
Water	32395	41763	22.43%	11478	27.48%	2110	-5.05%
Aquatic Bed	3390	4883	30.58%	4836	99.04%	3343	-68.46%
Emergents	16657	13603	-22.45%	11851	87.12%	14905	-109.57%
Shrub- Scrub	30399	11117	-173.45%	8320	74.84%	27602	-248.29%
Forested Wetland	30723	13032	-135.75%	11636	89.29%	29327	-225.04%
Upland	401225	430391	6.78%	57152	13.28%	27986	-6.50%
Total Error, Omissions plus Co-Omissions 40.9%							

The first analysis of the control classification finds that the control classification seems to over classify wetland areas by removing area from both the water and upland components of the NWI classification. The control classification finds 77.6% as “true” uplands with 0.3% histosols and 6.3% open water. It would be erroneous to assume that the change from water to wetland represents a true error on the classification scheme. The relationship between open water and wetlands is long established and both are dynamic systems. Since open water is so dramatically different, spectrally, from other land cover types and no apparent turbidity or algae was detectable, the assumption is that the water classification is correct and the

difference may be due to a variation in season between the satellite image and NWI high altitude photography.

Simple classification ratios do not give the correct picture of how well the classification fares against the control map statistically. There are two different types of error. Error of omission and error of co-omission, summed, give total error. For the control classification, the sum of total error is 37.04% for simplified water, wetland and upland groups. On the first pass of analysis, this classification does not approach the 85% threshold necessary to establish a positive relationship between the satellite data and reference information.

Table 9

Omissions and Co-Omissions between Control Classification
of Landsat TM Bands 1-7 and National Wetlands Inventory
Allowing One Level of Error

	Control	NWI	Omissions	% Omissions	Co- Omissions	% Co- Omissions	% Difference
Water	32395	41763	9397	22.50%	1963	-4.70%	17.80%
Aquatic Bed	3390	4883	4520	92.57%	985	-20.17%	72.39%
Emergents	16657	13603	8937	65.70%	13568	-99.74%	-34.04%
Shrub- Scrub	30399	11117	5756	51.78%	24042	-216.26%	-164.49%
Forested Wetland	30723	13032	234	1.80%	2804	-21.52%	-19.72%
Upland	401225	430391	32180	7.48%	17507	-4.07%	3.41%
Total Error, Omissions plus Co-Omissions 23.68%							

The second line of inquiry is to measure the level of accuracy when all the wetlands types from the control classification are measured to the NWI inventory. Again it is assumed that the classes are arranged from wet end classes to dry end classes. The order from wettest to driest classes is water: (1) algal wetlands, (2) emergent wetlands, (3) shrub wetlands, (4) forest wetlands, (5) histosols, (6) upland. The total errors of omission and commission jump to 40.9% as demonstrated in Table 8. The most dramatic difference are in the shrub-scrub & forested wetland groups which are over-classified as compared to the National Wetland Inventory reference layer. Because of the variability of wetlands, it is not prudent to assume that near misses are always errors in classification. Allowing that pixels classified in the nearest adjacent class are not considered error of omission or commission the total error drops to 23.68% as demonstrated in Table 9.

This simple measure leads to the consideration of κ which, using a matrix, calculates the marginal homogeneity of the classification. The design of the matrix gives credit to near classifications. For example, the control classification clusters a pixel as “forested wetland” and the NWI classifies it as “P1SS01/FO1E” which is a shrub dominated, forested secondary wetland. In calculating errors of omission and commission this is an error which carries the same weight as a water classified as upland. The measure of κ is the sum of concordant matrix values minus the sum of the discordant matrix values.

In measure, the matrix of agreement and disagreement using six classes for the control classification (water, aquatic, emergent, shrub, forest & upland) and the

Table 10

Confusion Matrix for Control Classification of Landsat TM Bands 1-7
Versus National Wetlands Inventory Classification

		Landsat Thematic Mapper Classes							
		Water	Aquatic	Emergent	Shrub	Forest	Histosol	Upland	TOTAL
National Wetlands Inventory Classes	L	28147	1485	3068	576	174	3	758	34211
	UB	1137	253	896	313	139	1	502	3241
	L-AB	492	105	416	225	42	0	147	1427
	UB-AB	0	0	8	2	2	0	15	27
	L-EM	418	207	1007	284	37	0	374	2327
	UB-EM	91	31	93	70	20	0	164	469
	UB-SS	0	0	22	18	7	0	14	61
	AB-UB	0	1	9	6	16	0	14	46
	AB	147	45	302	482	260	0	3449	4685
	AB-EM	0	1	13	24	23	0	80	141
	AB-SS	0	0	0	0	1	0	10	11
	EM-UB	0	0	6	6	9	0	85	106
	EM-AB	15	5	44	38	16	0	37	155
	EM	184	236	1524	2164	1595	0	5062	10765
	EM-SS	9	35	160	307	352	0	1281	2144
	EM-FO	2	1	18	122	111	0	179	433
	SS-UB	0	3	7	9	10	0	12	41
	SS-AB	1	6	25	77	74	0	273	456
	SS-EM	290	37	135	131	145	0	1363	2101
	SS	46	40	845	2579	1317	0	3518	8345
	SS-FO	0	1	1	1	5	0	166	174
	FO-AB	0	0	0	4	10	0	19	33
	FO-EM	2	0	7	34	27	0	26	96
	FO-SS	4	1	25	100	179	0	2279	2588
	FO	11	31	153	785	1180	0	8155	10315
	U	1399	866	7873	22042	24972	1565	371674	430391
	TOTALS	32395	3390	16657	30399	30723	1569	399656	514789

* Diagonal values in bold type

same six groups for the NWI groups, we find a calculation of ? at 79.55%. Because of the agility of the NWI classification, the classes can be ordinalized using not only

primary wetland characteristics but also primary and secondary wetland characteristics. Therefore, a forested wetland is considered a drier class than a forested primary – emergents secondary wetland.

It is important to determine the diagonal values for the calculation of κ . In the final measure of agreement, the diagonal values for the seven-group classification are chosen from the primary characteristics of the twenty-six-group classification used for NWI. The measure of agreement is then calculated using these matrix cell values as the designated diagonal.

Table 11

Summary of Error Measures for Control Classification of Landsat Bands 1-7 and National Wetlands Inventory

Statistical Measure	
Simple Agreement	79.6% (64.3% excluding upland class)
Simple Error	20.4%
Errors of Omission and Co-Omission	40.9%
Errors of Omission and Co-Omission With one level of allowed error	23.7%
Measure of Agreement	84.3% (84.9% with simplified classes)

When using the full classification of NWI ordinalized for primary and secondary wetland characteristics, it becomes clear that the agreement is much higher than the accumulated error of omission and co-omission would indicate. κ for a six by six class matrix was 79.55%; κ for a seven by twenty-six class matrix is calculated to be 84.27%. This approaches the 85% agreement needed to prove a positive

correlation between satellite classification and NWI classification assumed to be map “truth” as summarized in Table 11.

Classification with Organic Material as Pseudo-Bandwidth

The addition of soil characteristics to the information process is intended to push the measure of agreement above the needed 85%. In the classification of satellite images by an unsupervised classification by cluster analysis, each band is used to produce categories that represent distinct clusters of related data. The bands individually are normalized and clusters are derived from sample means. By adding the soils layer as an addition band, it may be possible to "trick" the computer into believing that it has another band of information to draw upon. When calculating the clusters for classification, the system automatically adjusts the percent of soil organics to a soil organic component expressed as a value from 0 to 255.

The spectral signatures of certain land cover types are quite distinctive. In creating a classification, pixels with similar spectral signature are grouped into bins. These bins are then assigned a class. Similar bins are assigned to the same class. Using a fifty bin automated classification with a minimum mean tolerance of twenty, we can map spectral means on a scatter-plot to group families of related bins by comparing selected pixels with the visible bands and proximity to known classes. These similar classes are derived from the control classification unless they are on the edge of established scatter plot regions.

Classification of Wetlands with Soil Organics Enhancement

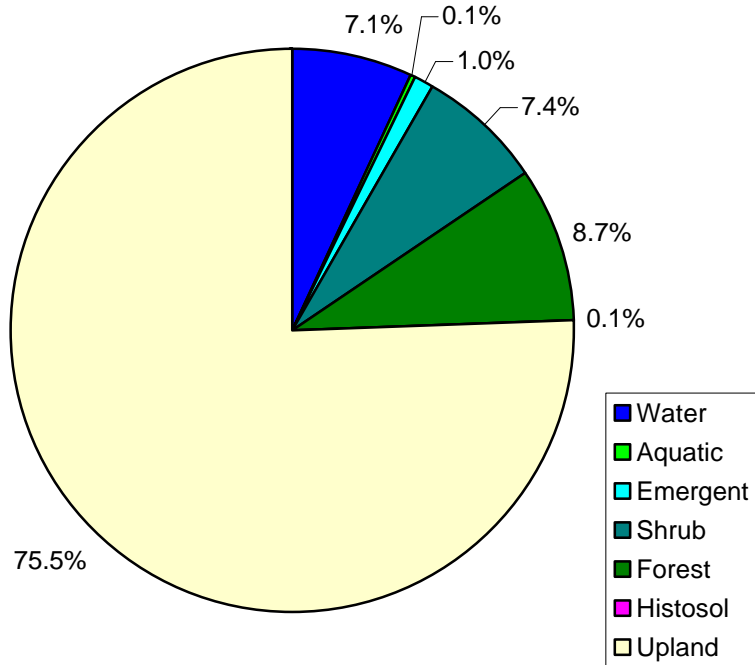


Figure 10. Resultant Class Percentages in the Soil Organics Enhancement Classification of Wetlands

Assessing the map “truth” is accomplished by using simple measures of agreement. The first degree of measurement is to inspect the wetland area detected the classification versus the wetland area classified by the National Wetlands Inventory. The National Wetlands Inventory classifies 83.6% of the study area as

upland, 8.1% of the area as open water and the remaining 8.3% as wetlands. The control classification finds 77.6% as “true” uplands with 0.3% histosols, 15.8% wetland and 6.3% open water. The classification with soil organic modification finds an upland class of 75.5% with histosols at 0.1%, 7.1% water and 16.3% wetland as demonstrated in Figure 10 and Table 12. This is an improvement over the control classification.

Table 12

Omissions and Co-Omissions between Classification of Landsat TM Bands 1-7 with Enhancement from Soil Organic Characteristics and National Wetlands Inventory by Land Cover Group

	Organics	NWI	% Omissions Difference		% Omissions	Co-Omissions	% Co-Omissions
Water	36138	41650	13.23%	9408	22.59%	3896	-9.35%
Wetland	88675	42062	-110.82%	10278	24.44%	56891	-135.26%
Upland	387649	428750	9.59%	50555	11.79%	9454	-2.21%

Total Error, Omissions plus Co-Omissions 27.4%

The first analysis of the classification modified by soil moisture characteristics finds that the classification seems to still over classify wetland areas by removing area from both the water and upland components of the NWI classification in the same way the control classification over-classified wetlands. The soil moisture classification finds 75.5% as “true” uplands with 0.1% histosols, 8.7% forested wetlands, 7.4% shrub wetlands, 1.0% emergent wetlands, 0.1% aquatic bed wetlands

and 7.1% open water. The forested wetlands and shrub-scrub classes increase their share of the classification and the wetter classes are reduced to less than their NWI anticipated percentages.

Using the same statistic measure as employed for the control classification we find that the sum of total error is 27.4% for simplified water, wetland and upland groups. On the first pass of analysis, this classification does not approach the 85% threshold necessary to establish a positive relationship between the satellite data and reference information, but it is an almost 10% increase from the 37.04% error for the control classification.

Table 13

Omissions and Co-Omissions between Classification of Landsat TM Bands 1-7 with Enhancement from Soil Organic Characteristics and National Wetlands Inventory for All Classes

	Organic	NWI	% Omissions Difference	% Omissions	% Omissions	Co- Omissions	% Co- Omissions
Water	36138	41650	13.23%	9408	22.59%	3896	-9.35%
Aquatic Bed	722	4804	84.97%	4788	99.67%	706	-14.70%
Emergents	5328	13386	60.20%	13231	98.84%	5173	-38.64%
Shrub- Scrub	37917	10925	-247.07%	5615	51.40%	32607	-298.46%
Forested Wetland	44708	12947	-245.32%	6358	49.11%	38119	-294.42%
Upland	387649	428750	9.59%	50555	11.79%	9454	-2.21%
Total Error, Omissions plus Co-Omissions 35.1%							

The level of accuracy when all the wetlands types from the soil moisture classification are measured to the NWI inventory, again assuming that the classes are arranged from wet end classes to dry end classes, the total errors of omission and commission jump to 35.1% as demonstrated in Table 13. The most dramatic differences are in the shrub-scrub & forested wetland groups which are over-classified as compared to the National Wetland Inventory reference layer

Table 14

Omissions and Co-Omissions between Classification of Landsat TM Bands 1-7 with Enhancement from Soil Organic Characteristics and National Wetlands Inventory Allowing One Level of Error

	Organic s	NWI	Omissions	% Omissions	Co- Omissions	% Co- Omissions	% Difference
Water	36138	41650	9139	21.94%	3711	-8.91%	13.03%
Aquatic Bed	722	4804	4676	97.34%	431	-8.97%	88.36%
Emergents	5328	13386	7009	52.36%	4972	-37.14%	15.22%
Shrub- Scrub	37917	10925	1283	11.74%	23962	-219.33%	-207.59%
Forested Wetland	44708	12947	106	0.82%	6827	-52.73%	-51.91%
Upland	387649	42875	23512	5.48%	5631	-1.31%	4.17%
		0					

Total Error, Omissions plus Co-Omissions 17.8%

Because of the variability of wetlands, it is not prudent to assume that near misses are always errors in classification. Allowing that pixels classified in the

nearest adjacent class are not considered error of omission or commission the total error drops to 17.8% as demonstrated in Table 14.

This simple measure leads to the consideration of ϕ which, using a matrix, calculates the marginal homogeneity of the classification. The design of the matrix gives credit to near classifications. For example, the control classification clusters a pixel as “forested wetland” and the NWI classifies it as “P1SS01/FO1E” which is a shrub dominated, forested secondary wetland. In calculating errors of omission and commission this is an error which carries the same weight as a water classified as upland. The measure of ϕ is the sum of concordant matrix values minus the sum of the discordant matrix values.

In measuring the matrix of agreement and disagreement using six classes for the control classification (water, aquatic, emergent, shrub, forest & upland) and the same six groups for the NWI groups, we find a calculation of ϕ at 82.5% as demonstrated in Table 15. Because of the agility of the NWI classification the classes can be ordinalized using not only primary wetland characteristic but also primary and secondary wetland characteristics. Therefore, a forested wetland is considered a drier class than a forested primary – emergents secondary wetland.

It is important to determine the diagonal values for the calculation of ϕ . In the final measure of agreement, the diagonal values for the seven-group classification are chosen from the primary characteristic of the twenty-six group classification used for NWI. The measure of agreement is then calculated using these matrix cell values as the designated diagonal as demonstrated in Table 16.

Table 15

Confusion Matrix for Classification of Landsat TM Bands 1-7 with
Enhancement from Soil Organic Characteristics Versus
National Wetlands Inventory Classification

		Landsat Thematic Mapper Classes							
		Water	Aquatic	Emergent	Shrub	Forest	Histosol	Upland	TOTAL
National Wetlands Inventory Classes	VALUE								
	L	29401	213	592	3049	299	0	191	33745
	UB	1359	49	138	1194	268	0	105	3113
	L-AB	612	6	28	688	30	0	31	1395
	UB-AB	0	0	4	7	6	0	8	25
	L-EM	738	1	49	1617	404	0	49	2858
	UB-EM	132	0	7	253	48	0	15	455
	UB-SS	0	0	5	52	2	0	0	59
	AB-UB	1	0	1	29	7	0	5	43
	AB	183	16	115	689	705	0	2906	4614
	AB-EM	1	0	2	62	65	0	6	136
	AB-SS	0	0	0	1	9	0	1	11
	EM-UB	0	0	0	25	58	0	18	101
	EM-AB	22	0	0	87	27	0	17	153
	EM	453	6	143	5069	3776	0	1142	10589
	EM-SS	48	0	8	789	994	0	273	2112
	EM-FO	3	0	4	246	129	0	49	431
	SS-UB	3	0	1	22	5	0	6	37
	SS-AB	5	2	5	182	208	0	48	450
	SS-EM	346	0	7	386	1117	0	214	2070
	SS	108	3	70	4713	2786	0	516	8196
	SS-FO	1	0	0	7	133	0	31	172
	FO-AB	0	0	0	13	11	0	9	33
	FO-EM	2	0	3	61	26	0	2	94
	FO-SS	5	0	27	221	1416	0	893	2562
	FO	42	5	22	2134	5136	0	2919	10258
	U	2673	421	4097	16321	27043	626	377569	428750
	TOTAL	36138	722	5328	37917	44708	626	387023	512462

* Diagonal values in bold type

Table 16

Simplified Confusion Matrix for Classification of Landsat TM Bands 1-7
with Enhancement from Soil Organic Characteristics
Versus National Wetlands Inventory Classification

		Landsat Thematic Mapper Classes						
VALUE		Water	Aquatic	Emergent	Shrub	Forest	Upland	TOTAL
National Wetlands Inventory Classes	W	32242	269	823	6860	1057	399	41650
	AB	185	16	118	781	786	2918	4804
	EM	526	6	155	6216	4984	1499	13386
	SS	463	5	83	5310	4249	815	10925
	FO	49	5	52	2429	6589	3823	12947
	U	2673	421	4097	16321	27043	378195	428750
	TOTAL	36138	722	5328	37917	44708	387649	512462

* Diagonal values in bold type

When using the full classification of NWI ordinalized for primary and secondary wetland characteristics, it becomes clear that the agreement is much higher than the accumulated error of omission and co-omission would indicate. Lambda for a six by six class matrix was 82.5%; κ for a seven by twenty-six class matrix is calculated to be 92.0%. This exceeds the 85% agreement needed to prove a positive correlation between satellite classification and NWI classification assumed to be map “truth”.

Table 17

Summary of Error Measures for Classification of Landsat TM Bands 1-7
with Enhancement from Soil Organic Characteristics and
National Wetlands Inventory

Statistical Measure	
Simple Agreement	82.5%
Simple Error	17.5%
Errors of Omission and Co-Omission	35.1%
Errors of Omission and Co-Omission With one level of allowed error	17.8%
Measure of Agreement	92.0%

Classification with Water Capacity as Pseudo-Bandwidth

The second reliable indicator of wetland soils is the soil water capacity expressed as percentage of soil moisture. By adding this information it may be possible to push the agreement above the require 85%. The soil moisture is distributed to the same numeric range of the satellite data (0 to 255) and clusters are derived from sample means. By making this addition to the satellite data it is possible to add another data source to for cluster means. This is accomplished by assigning soil polygons numeric ranks. The ranks are devised by directly imputing the soil characteristics as derived from the soil survey map. When calculating the clusters for classification the system automatically adjusts the of soil moisture expressed as a percentage to soil moisture expressed as a value from 0 to 255.

Classification of Wetlands Enhanced by Soil Water Capacity

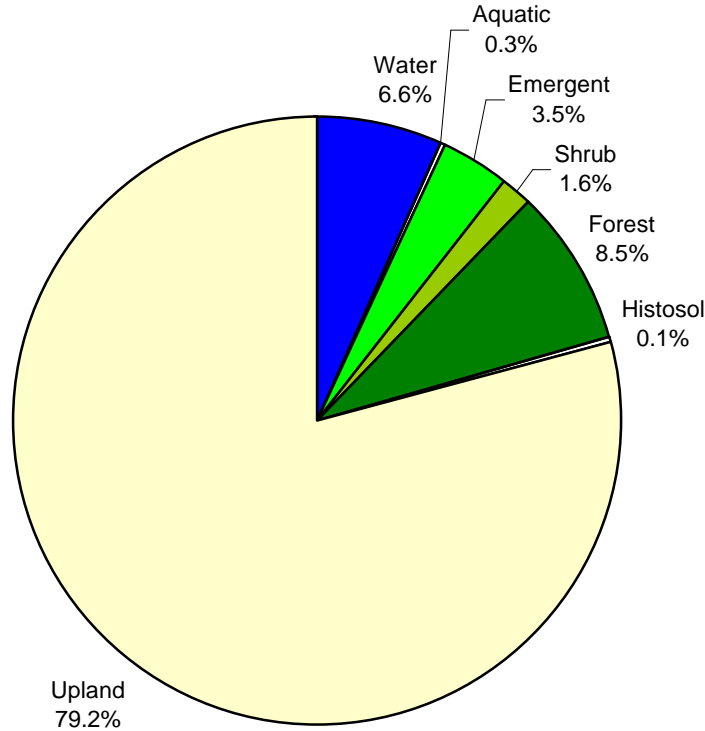


Figure 11. Resultant Class Percentages in the Soil Moisture Enhancement Classification of Wetlands

The spectral signatures of certain land cover types are quite distinctive. In creating a classification pixels, with similar spectral signature are grouped into bins. These bins are then assigned a class. Similar bins are assigned to the same class. Using a fifty bin automated classification with a minimum mean tolerance of twenty; we can map spectral means on a scatter-plot to group families of related bins by comparing selected pixels with the visible bands and proximity to known classes.

These similar classes are derived from the control classification unless they are on the edge of established scatter plot regions.

Assessing the map “truth” is accomplished by using simple measures of agreement. The National Wetlands Inventory classifies 83.6% of the study area as upland, 8.1% of the area as open water and the remaining 8.3% as wetlands. The control classification finds 77.6% as “true” uplands with 0.3% histosols, 15.8% wetland and 6.3% open water. The classification with soil moisture modification finds an upland class of 79.2% with histosols at 0.1%, 6.6% water and 13.1% wetland.

Table 18

Omission and Co-Omission between Classification of
Landsat TM Bands 1-7 with Enhancement
from Soil Moisture and National Wetlands
Inventory by Land Cover Group

	Water Capacity	NWI	% Omissions Difference	% Omissions	% Omissions	Co- Omissions	% Co- Omissions
Water	33824	41808	19.10%	11303	27.04%	3319	-7.94%
Wetland	71915	41874	-71.74%	10460	24.98%	40501	-96.72%
Upland	406508	428565	5.15%	32193	7.51%	10136	-2.37%
Total Error, Omissions plus Co-Omissions 21.1%							

The first analysis of the classification modified by soil moisture characteristics finds that the classification seems to still over classify wetland areas by removing

area from both the water and upland components of the NWI classification. The soil moisture classification finds 79.2% as “true” uplands with 0.1% histosols, 8.5% forested wetlands, 1.6% shrub wetlands, 3.5% emergent wetlands, 0.3% aquatic bed wetlands and 6.6% open water. The forested wetlands class makes a big increase and the wetter classes are reduced closer to their NWI anticipated percentages.

Simple classification ratios do not give the correct picture of how well the classification fares against control map. There are two different types of error. Error of omission and error of co-omission, summed give total error. For the soil moisture classification the sum of total error is 21.1% for simplified water, wetland and upland groups. On the first pass of analysis, this classification does not approach the 85% threshold necessary to establish a positive relationship between the satellite data and reference information, but it is a almost 15% increase from the 37.04% error for the control classification.

The second line of inquiry is to measure the level of accuracy when all the wetlands types from the soil moisture classification are measured to the NWI inventory. Again it is assumed that the classes are arranged from wet end classes to dry end classes. From the wet-end classes, water, algal wetlands, emergent wetlands, shrub wetlands, forest wetlands, & histosols/uplands to on the dry end. The total errors of omission and commission jump to 29% as demonstrated in Table 19. The most dramatic differences are in the forested wetland groups which is over-classified as compared to the National Wetland Inventory reference layer.

Table 19

Omissions and Co-Omissions between Classification of Landsat TM Bands 1-7
with Enhancement from Soil Moisture and National Wetlands Inventory
for All Classes

	Water Capacity	NWI	% Omissions Difference	% Omissions	% Omissions	Co- Omissions	% Co- Omissions
Water	33824	41808	19.10%	11303	27.04%	3319	-7.94%
Aquatic Bed	1722	4798	64.11%	4750	99.00%	1674	-34.89%
Emergent	18062	13345	-35.35%	10754	80.58%	15471	-115.93%
Shrub- Scrub	8413	10884	22.70%	10743	98.70%	8272	-76.00%
Forested Wetland	43718	12847	-240.30%	4507	35.08%	35378	-275.38%
Upland	406508	428565	5.15%	32193	7.51%	10136	-2.37%
Total Error, Omissions plus Co-Omissions 29.0%							

Because of the variability of wetlands, it is not prudent to assume that near misses are always errors in classification. Allowing that pixels classified in the nearest adjacent class are not considered error of omission or commission the total error drops to 17.3% as demonstrated in Table 20. This simple measure leads to the consideration of ? which, using a matrix, calculates the marginal homogeneity of the classification. The design of the matrix gives credit to near classifications. For example the control classification clusters a pixel as “forested wetland” and the NWI classifies it as “P1SS01/FO1E” which is a shrub dominated, forested secondary wetland. In calculating errors of omission and commission this is an error which

carries the same weight as a water classified as upland. The measure of κ is the sum of concordant matrix values minus the sum of the discordant matrix values.

Table 20

Omissions and Co-Omissions between Classification of Landsat TM Bands 1-7 with Enhancement from Soil Moisture Characteristics and National Wetlands Inventory Allowing One Level of Error

	Water Capacity	NWI Omissions		% Omissions	Co-Omissions	% Co-Omissions	% Difference
Water	33824	41808	10735	25.68%	3181	-7.61%	18.07%
Aquatic Bed	1722	4798	4431	92.35%	1081	-22.53%	69.82%
Emergent	18062	13345	10618	79.57%	13042	-97.73%	-18.16%
Shrub-Scrub	8413	10884	1316	12.09%	8124	-74.64%	-62.55%
Forested Wetland	43718	12847	392	3.05%	12717	-98.99%	-95.94%
Upland	406508	428565	16852	3.93%	6058	-1.41%	2.52%
Total Error, Omissions plus Co-Omissions 17.3%							

In measuring the matrix of agreement and disagreement using six classes for the control classification (water, aquatic, emergent, shrub, forest & upland) and the same six groups for the NWI groups, we find a calculation of κ at 85.5% as displayed in Table 21. Because of the agility of the NWI classification the classes can be ordinalized using not only primary wetland characteristic but also primary and secondary wetland characteristics. Therefore, a forested wetland is considered a drier class than a forested primary – emergents secondary wetland.

Table 21

Simplified Confusion Matrix for Classification of Landsat TM Bands 1-7
with Enhancement from Soil Moisture Characteristics
Versus National Wetlands Inventory Classification

		Landsat Thematic Mapper Classes							
		VALUE	Water	Aquatic	Emergent	Shrub	Forest	Upland	TOTAL
National Wetlands Inventory Classes	W	30505	568	7060	301	2907	467	41808	
	AB	138	48	322	179	964	3147	4798	
	EM	277	25	2591	111	8846	1495	13345	
	SS	356	11	2107	141	7320	949	10884	
	FO	20	5	367	37	8340	4078	12847	
	U	2528	1065	5615	7644	15341	396372	428565	
	TOTAL	33824	1722	18062	8413	43718	406508	512247	

* Diagonal values in bold type

It is important to determine the diagonal values for the calculation of κ . In the final measure of agreement, the diagonal values for the seven-group classification are chosen from the primary characteristic of the twenty-six-group classification used for NWI. The measure of agreement is then calculated using these matrix cell values as the designated diagonal as demonstrated in Table 22.

Table 22

Confusion Matrix for Classification of Landsat TM Bands 1-7 with
Enhancement from Soil Moisture Versus
National Wetlands Inventory Classification

VALUE	Water	Aquatic	Emergent	Shrub	Forest	Histosol	Upland	TOTAL
L	28281	462	3860	177	826	0	236	33842
UB	1161	88	1082	56	648	4	109	3148
L-AB	512	6	622	15	213	0	39	1407
UB-AB	0	0	7	1	10	0	7	25
L-EM	449	9	1316	38	993	0	60	2865
UB-EM	102	1	138	11	197	0	12	461
UB-SS	0	2	35	3	20	0	0	60
AB-UB	0	0	13	2	22	0	8	45
AB	138	48	289	175	825	0	3130	4605
AB-EM	0	0	20	2	107	0	8	137
AB-SS	0	0	0	0	10	0	1	11
EM-UB	0	0	7	2	74	0	20	103
EM-AB	17	0	61	1	50	0	26	155
EM	237	23	2247	103	6842	0	1103	10555
EM-SS	21	2	245	5	1544	0	289	2106
EM-FO	2	0	31	0	336	0	57	426
SS-UB	0	0	12	3	17	0	9	41
SS-AB	4	0	41	10	346	0	51	452
SS-EM	295	2	183	25	1300	0	242	2047
SS	57	9	1869	103	5526	1	609	8174
SS-FO	0	0	2	0	131	0	37	170
FO-AB	0	0	0	0	21	0	12	33
FO-EM	2	0	9	2	78	0	2	93
FO-SS	4	0	44	3	1543	0	942	2536
FO	14	5	314	32	6698	0	3122	10185
U	2528	1065	5615	7644	15341	745	395627	428565
TOTAL	33824	1722	18062	8413	43718	750	405758	512247

* Diagonal values in bold type

Table 23

Summary of Error Measures for Classification of Landsat TM Bands 1-7
with Enhancement from Soil Moisture Characteristics and
National Wetlands Inventory

Statistical Measure	
Simple Agreement	85.5%
Simple Error	14.5%
Errors of Omission and Co-Omission	29.0%
Errors of Omission and Co-Omission With one level of allowed error	17.3%
Measure of Agreement	93.3 %

When using the full classification of NWI ordinalized for primary and secondary wetland characteristics, it becomes clear that the agreement is much higher than the accumulated error of omission and co-omission would indicate. Lambda for a six by six class matrix was 85.5%; λ for a seven by twenty-six class matrix is calculated to be 93.3%. This exceeds the 85% agreement needed to prove a positive correlation between satellite classification and NWI classification assumed to be map “truth” as demonstrated in Table 23.

CHAPTER VI

CONCLUSION

Re-statement of Problem

Satellite data offers convenient assimilation and analysis of land cover data. An unsupervised classification of land cover types within the study area has been compared to the National Wetlands Inventory classification of wetlands to measure accuracy of wetland classification without *a priori* information. The same methodology was employed using two separate soil engineering characteristic from the soil survey as an *a priori* data set. These classifications were then compared to the National Wetlands Inventory to assess if soil engineering characteristics increases the classification accuracy.

Hypothesis Testing

An untrained classification of wetland from Landsat TM data was not successful in obtaining the 85% match necessary to prove that the control classification is a classification of the same dataset as the National Wetlands Inventory. Including ground-based data from soil surveys assists in classifying satellite information for wetlands. Simple agreement alone is a rather dismal indicator of the performance of the classifications as demonstrated by Table 24.

Table 24

Summary of Error Measures for Classifications of Landsat TM
and National Wetlands Inventory

Statistical Measure	Control	Soil Organics	Soil Moisture
Simple Agreement	79.6%	82.5%	85.5%
Simple Error	20.4%	17.5%	14.5%
Errors of Omission and Co-Omission	37.04%	35.1%	29.0%
Errors of Omission and Co-Omission With one level of error	23.68%	17.8%	17.3%
Measure of Agreement	84.3%	92.0%	93.3 %

The final test of significance of findings eliminates the possibility that the correlation between the control classification and the enhanced classifications are due to chance agreement. If a classification change represented by an increase or decrease of 5% or less is observed between the control classification and the classifications with soil characteristics, then the change is not considered significant. If the change exceeds 5%, then the increase or decrease in classification accuracy can be attributed to the addition of the soil characteristics as a pseudo band width.

Hypothesis 1: The control satellite classification does not meet the 85% level of agreement necessary to prove the hypothesis. The control satellite classification only has a $\alpha = 84.3\%$ level of agreement.

Hypothesis 2: The satellite classification with soil moisture as a “pseudo band width” does meet the 85% level of agreement necessary to prove the hypothesis. The satellite classification with soil moisture has a $\alpha = 92\%$ level of agreement.

Hypothesis 3: The satellite classification with soil organics as a “pseudo band width” does meet the 85% level of agreement necessary to prove the hypothesis. The satellite classification with soil moisture has a $\kappa = 93.3\%$ level of agreement.

Hypothesis 4: The satellite classification with soil organics does not better represent the National Wetlands Inventory than result obtainable by chance. The satellite classification with soil organics has a $t = 0.0483$, below the test threshold to find the change not due to chance.

Hypothesis 5: The satellite classification with soil organics better represents the National Wetlands Inventory than result obtainable by chance. The satellite classification with soil organics has a $t = 0.0523$, below the test threshold to find the change not due to chance.

Suggestions for Further Study

As suggested by the findings, there is room for improvement in the classification of wetlands using satellite data. Using soil information as a pseudo band width is only one of many ways satellite data can be augmented. Other methods may include using soil masks to classify wetlands broken up by an ordinal data set, a use of a secondary index of forest types may help discriminate the problems in forested wetlands. Hydrologic and topographic properties may also be incorporated using surface and ground water flow modeling.

The classification of wetlands by use of soil masks only varies from using soil characteristic as a pseudo band-width in the soil polygons are used to break up the

classification into subsets of the image. Each of these subsets is then processed individually for classes that are indicative of their wetland capabilities. This follows a similar procedure used by Dillworth (1992) in her classification of upland and floodplain land use.

The vertical structure of forested wetlands inhibits delineation; a use of a second index is suggested in poorly defined areas. A second classification of a single problem class may uncover subtle hints on the frequency and duration of inundation and by incipient soil moisture. By sub-setting the wetland areas, can more attention be paid to soils in the good wetland potential and less be spent in the very poor wetland potential areas.

The most promising new data set is contour information, obtained by either LIDAR or digital elevation modeling. By modeling surface and ground water flow, the potential groundwater discharge and surface water collection areas can be identified to further train an unsupervised classification. These data sets are raster based and require no format conversion, vector to raster, to use.

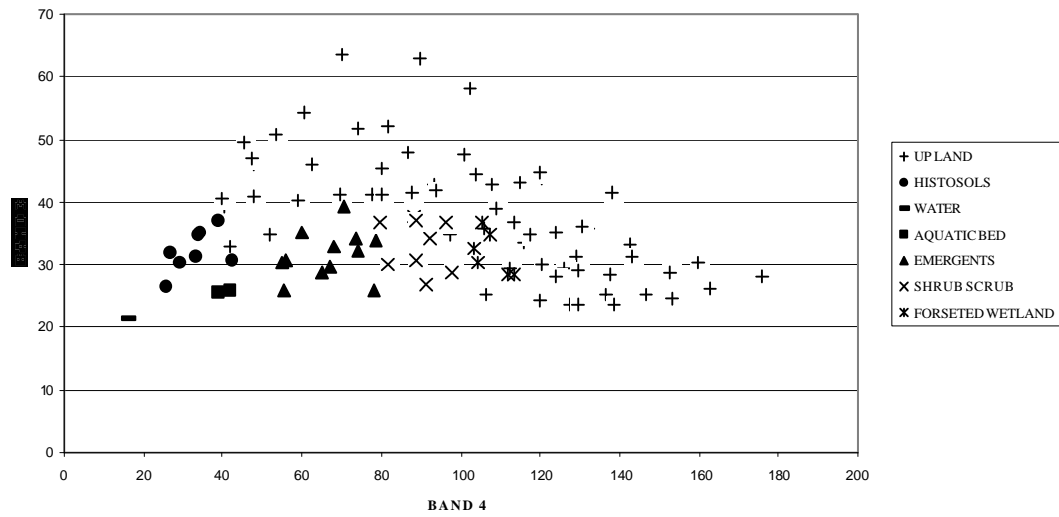
Wetlands are used for flood storage and conveyance, wave attenuation, pollution control, sediment control, food chain support, ground water replenishment, habitat for waterfowl and endangered species. Because of wetland loss, much attention has be paid to creating artificial wetlands. Kusler (1992), indicated that artificial, altered, and drained wetlands serve more functions than equilibrium wetlands, but land use planners must balance time, cost, and legality of wetland

creation and alteration. Using satellite data to assist in wetland creation and site selection may provide a reasonable tool within a region for environmental planning.

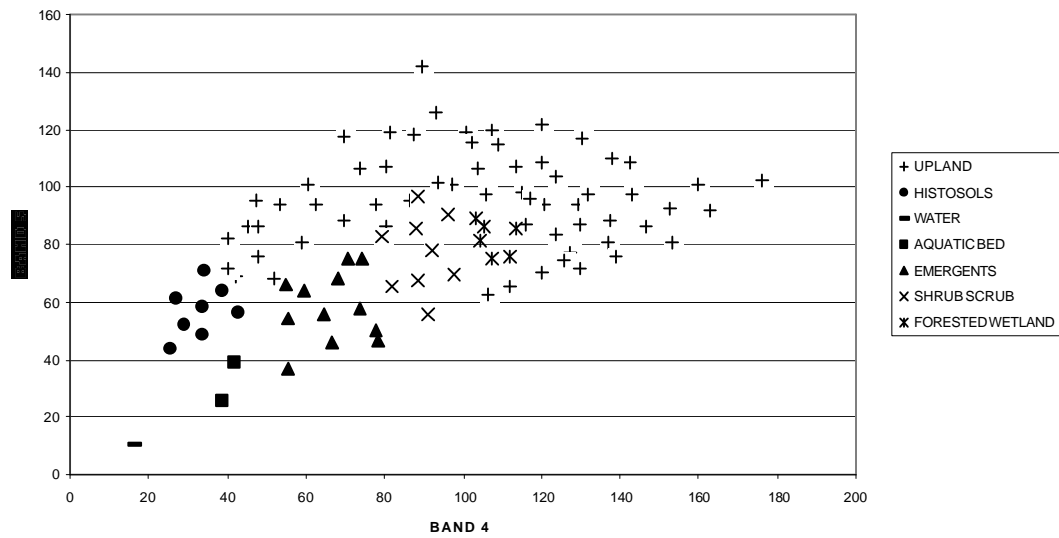
Appendix A

Scatter-plots of Cluster Means for Control Classification of Wetlands

**CONTROL CLASSIFICATION SCATTERPLOT
LANDSAT TMBANDS 4 & 3**

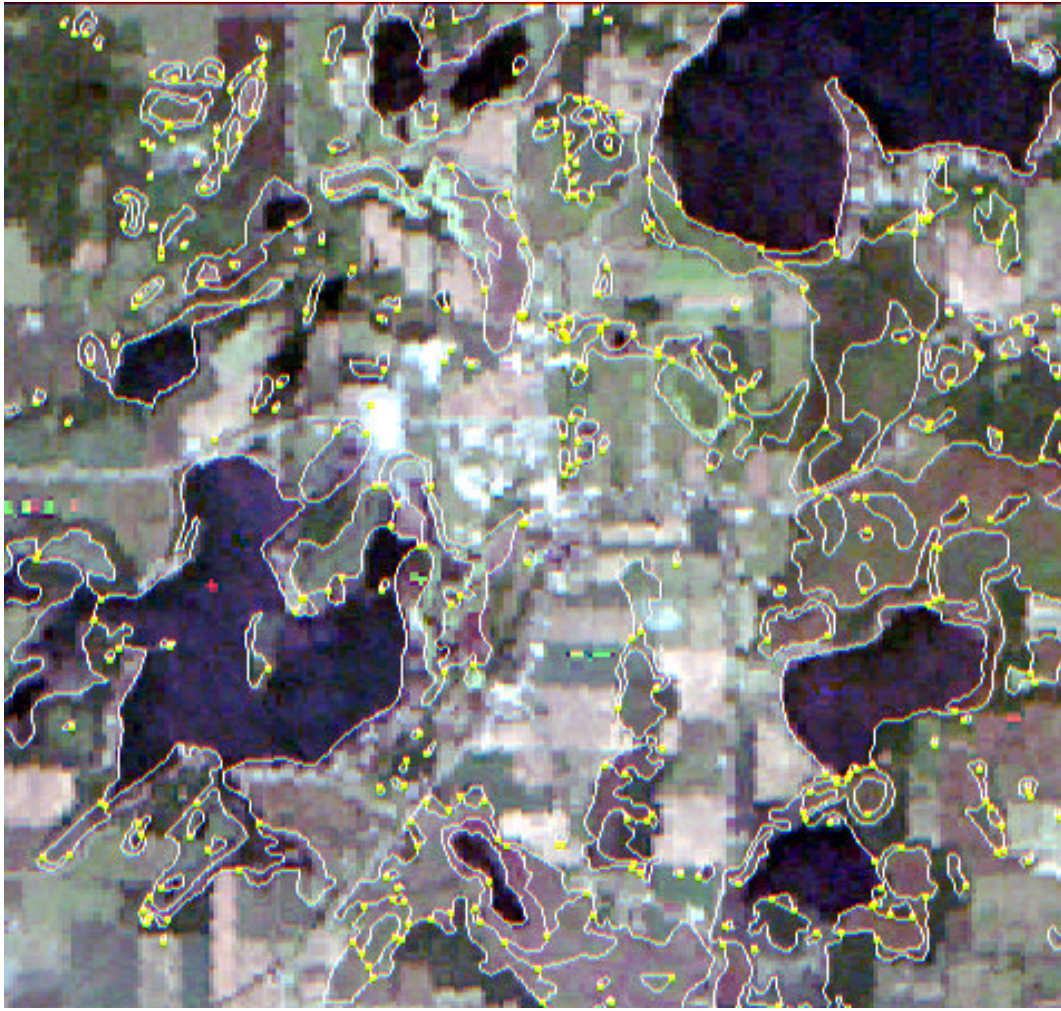


CONTROL CLASSIFICATION SCATTERPLOT LANDSAT TM BANDS 4 & 5



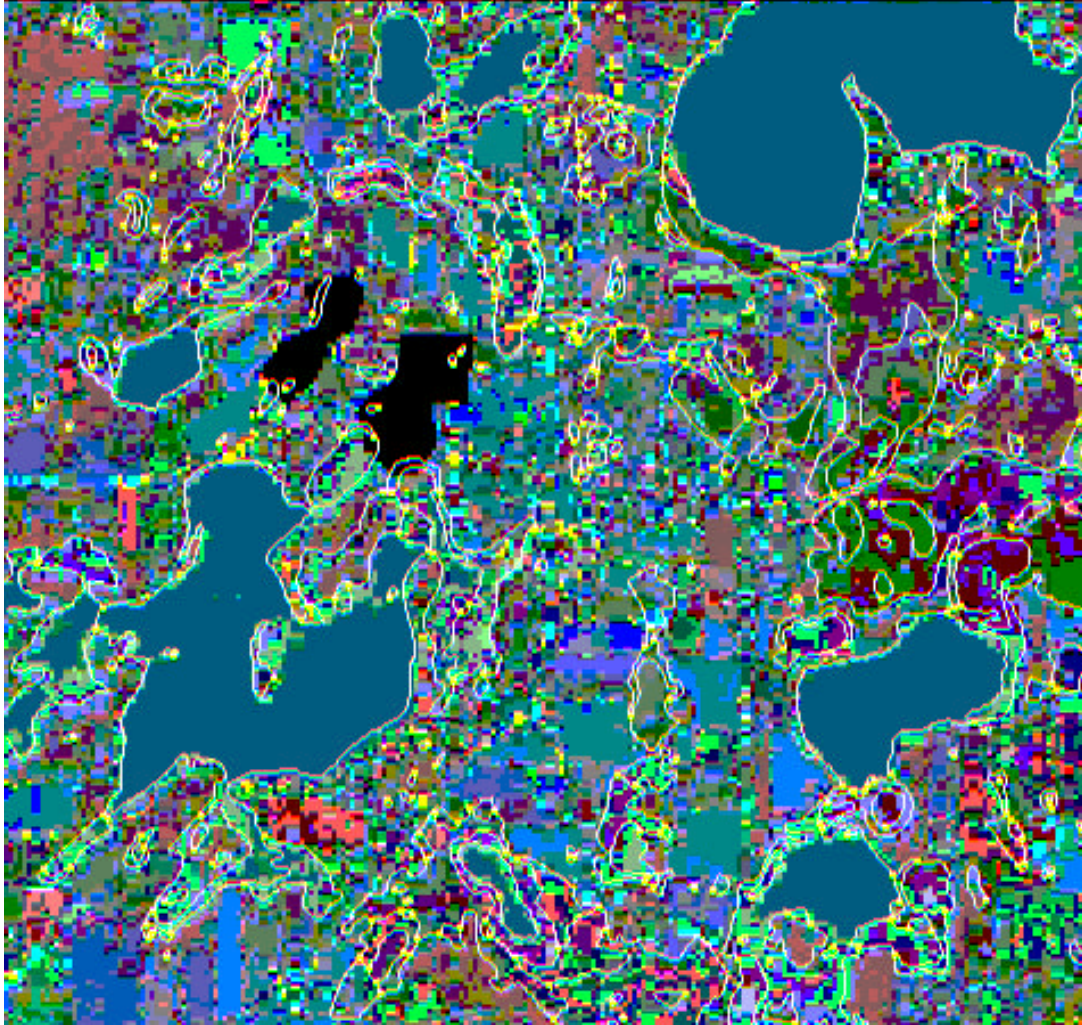
Appendix B

Screen Shots of Landsat Classifications



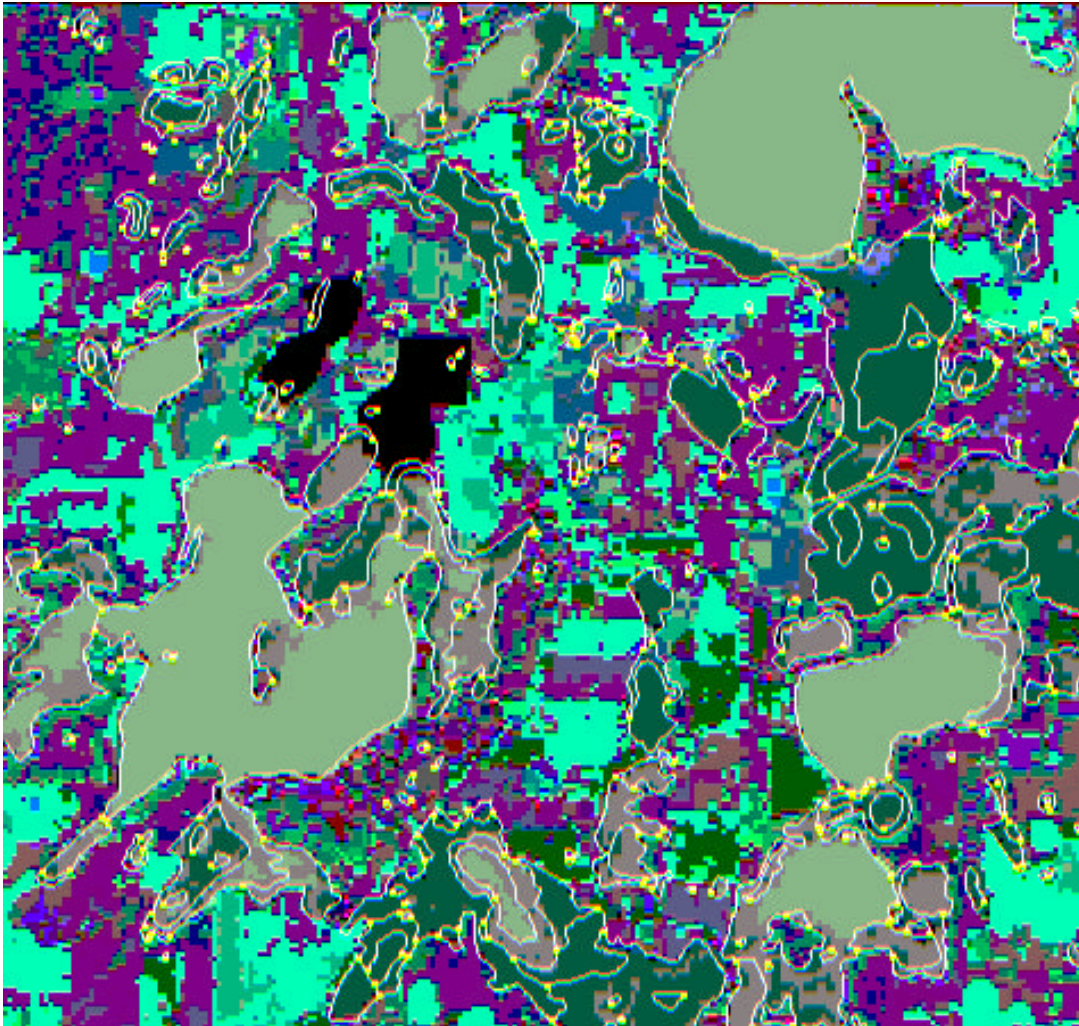
Community of Delton

Landsat Thematic Mapper Bands 4,3,2 with National Wetland Inventory Polygons.



Community of Delton

Landsat Thematic Mapper Unsupervised Classification with National Wetland Inventory Polygons. (Note: Black areas are clouds and cloud shadows removed from study.)



Community of Delton

Landsat Thematic Mapper Unsupervised Classification using soil water capacity as a pseudo band width with National Wetland Inventory Polygons. (Note: Black areas are clouds and cloud shadows removed from study.)

BIBLIOGRAPHY

- Arnoff, Stan. Geographic Information Systems: A Management Perspective. Ottawa: WDL Publications, 1993.
- Barry County Book Committee. Barry County Michigan 1985. Dallas, TX: Taylor Publishing, 1985.
- Barry County Land Use Plan Dec 1996. Barry County Planning, 1996
- Barry County Land Use Plan Feb 1974. Grand Rapids: Williams and Works, Inc., 1974.
- Baumgartner, D. W. and K. P. Price. "An Integrative Approach to Change Detection in An Agricultural Environment," In Looking to the Future with an Eye on the Past edited by A. J. Lewis. New Orleans: ASPRS/ACMS. 2 (1993): 2-10
- Beard, M. Kate and Barbera P. Butterfield. "Spatial, Statistical and Graphical Dimensions of Data Quality," Proceedings of Interface 92 College Station, EX: IEEE / American Statistical Association, March, 1992.
- Beard, M. Kate and William Mkaness. "Visual Access to Data Quality in Geographic Information Systems," Cartographica 30 (Summer/Autumn 1993) 37-45.
- Berta, Susanne M., D. J. Kettler, T. A. Gress. "SCS Wetland Recertification Using Satellite Data: Accounting for Regional Diversity," In Papers & Proceedings of Applied Geography Conferences by State University of New York. Binghamton, NY: State University of New York. 17 (1994): 25-29.
- Bicentennial Hope Twp. Bicentennial Hope Township Committee, 1976.
- Center for Remote Sensing and GIS. "Introduction to Aerial Photo Interpretation" Michigan State University (2002)
- Blazye, Christopher J. "An Assessment of Satellite Remote Sensing for Land Cover Classification,": Dissertation, University of Nottingham, United Kingdom, 1989.
- Brady, Stephen J. and Curtis H. Flather. "Changes in Wetland on Non-Federal Rural Land of the Conterminous United States from 1982 to 1987," Environmental Management 18 (1994) 693-705.

Bibliography – Continued

- Brockhaus, J. A. “An Assessment of Remotely Sensed Imagery for Use in Hardwood Stand Diversity Distribution Mapping in Central California,” In Technical Papers: Vol. 3 Remote Sensing by ASPRS/ACSM. Baltimore: ASPRS/ACSM, 1989, 109-117.
- Burrough, P. A. “Development of Intelligent Geographical Information Systems,” International Journal of Geographical Information Systems 6 (1992) 1:1-11.
- Butera, M. Kristine. “Remote Sensing of Wetlands,” IEEE Transactions on Geoscience and Remote Sensing. 21(July 1983)3:383-392.
- Carter, Virginia. “Wetland Classification and Mapping in Western Tennessee,” Photogrammetric Engineering & Remote Sensing. 45(March 1993)3:272-284.
- Cherril, A. “A Comparison of Three Landscape Classifications and Investigation of the Potential for Using Remotely Sensed Land Cover Data for Landscape Classification.” Journal of Rural Studies 10 (1994) 275-289.
- Chiou Chyi-Rong. “A Fuzzy Milticriteria Decision Process for Classification of Landsat TM Data of the Rocky Mountain National Park,” Dissertation, Colorado State University, 1994.
- Chou Yue Hong. “Map Resolution and Spatial Autocorrelation,” Geographical Analysis 23 (1991) 3:228-246.
- Chuvieco, Emilio, and Russel G. Congalton. “Application of Remote Sensing and Geographic Information Systems to Forest Fire Hazard Mapping,” Remote Sensing of the Environment. 29(1989) 147-159.
- Conese, Claudio, and Fabio Maselli. “Use of Error Matrices to Improve Area Estimates with Maximum Likelihood Classification Procedures,” Remote Sensing of the Environment. 40(1992)113-124.
- Congalton, Russel G. “A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data,” Remote Sensing of the Environment 37 (1991) 35-46.
- Congalton, Russel G., Richard G. Oderwald, and Roy A. Mead. “Assessing Landsat Classification Accuracy Using Discrete Mutlivariate Analysis Statistical Techniques,” Photogrammetric Engineering & Remote Sensing. 49(December 1983) 12:1671-1678.
- Czaplewski, Raymond L. “Misclassification Bias in Arial Estimates,” Photogrammetric Engineering & Remote Sensing 58 (1992) 2:189-192.

Bibliography – Continued

- Demissie, M. “Research in Wetland Hydrology and Hydraulics: Who’s going to use it and why?” Proceeding of the Annual Conference of the Illinois Section of the American Water Resources Association, October 2, 1989 USA: American Water Resources Association, Illinois Section, 1989.
- Dorgan, Michael, et al. “Delineation of U Ave & Oakland Drive Wetland, June 1993” Geology 614 final paper. Western Michigan University, Department of Geology, 1995.
- Environmental Laboratory. Corps of Engineers: Wetland Delineation Manual Technical Report Y-87-1, Vicksburg, MS: United States Army Corps of Engineers Waterway Experiment Station, 1987.
- Finn, John T. “Use of the Average Mutual Information Index in Evaluating Classification Error and Consistency,” International Journal of Geographical Information Systems 7(1993) 4:349-366.
- Fisher, Peter F. “Modeling Soil Map-Unit Inclusions by Monte Carlo Simulation.” International Journal of Geographical Information Systems 5 (1991) 2:193-208.
- Foody, Giles M. “Ordinal-Level Classifications of Sub-Pixel Tropical Forest Cover,” Photogrammetric Engineering & Remote Sensing 60 (January 1984) 1:61-65.
- Fornshell, Donna Jean. “Identification of Wetland in Noxubee County, Mississippi: A Hydroclimatologic, Thematic Mapper, and GIS Analysis,” Dissertation, Mississippi State University, 1992.
- Fotheringham, A. Stewart and Peter A. Rogerson. “GIS and Spatial Analytical Problems,” International Journal of Geographical Information Systems 7 (1993) 1:3-19.
- Gi-Chul Yi et al. “Development of Ohio’s GIS Based Wetland Inventory,” Journal of Soil and Water Conservation 49 (1994) 23-25.
- Goodchild, Michael F., Sun Guoqung, and Yang Shiren. “Development and Test of an Error Model for Categorical Data,” International Journal of Geographical Information Systems 6 (1992) 2:87-104.
- Goodchild, Michael F. et al. “Intergrating GIS and Spatial Data Analysis: Problems and Possibilities,” International Journal of Geographical Information Systems 6 (1992) 5:407-423.
- Grady, Richard K. “The Lineage of Data in Land and Geographic Information Systems (LIS/GIS),” URISA Journal 2 (1990) 2:2-6.

Bibliography – Continued

- Gross, Michael F., Michael A. Hardisky, and Vytantas Klemas. “Applications to Coastal Wetlands Vegetation.” In Theory and Applications of Optical Remote Sensing edited by Ghassen Asrar, New York: John Wiley & Sons, 1989.
- Heubelink, Gerard B. M. and Peter A. Burrough. “Error Propagation in Cartographic Modeling Using Boolean Logic and Continuous Classification,” International Journal of Geographical Information Systems 7 (1993) 3:231-246.
- Hinson, J. M., C. D. German, and W. Pulich Jr. “Accuracy Assessment and Validation of Classified Satellite Imagery of Texas Coastal Wetlands,” Marine Technology Society Journal 28 (1994) 4-9.
- Hlinka, Kenneth. “GIS Applications in Ground Water Data Management: The Problem of Scale.” Proceedings of the Annual Conference on the Illinois Section of the American Water Resources Association, October 2, 1989 USA: American Water Resources Association, Illinois Section, 1989.
- Hodgson, Michael E. et al. “Remote Sensing of Wetland Habitat: A Wood Stork Example,” Photogrammetric Engineering & Remote Sensing. 53(August 1987) 8:1075-1080.
- Janssen, Lucas L. and Frans J. M. van der Wel. “Accuracy Assessment of Satellite Derived Land-cover Data: A Review,” Photogrammetric Engineering & Remote Sensing. 60 (April 1994) 419-426.
- Jensen, John R. Introductory Digital Image Processing: A Remote Sensing Perspective. Eagle Cliffs, NJ: Prentice Hall, 1986.
- Jensen, John R., et al. “Inland Wetland Change Detection in Everglades Water Conservation Area 2A Using a Time Series of Normalized Remotely Sensed Data,” Photogrammetric Engineering & Remote Sensing 32 (1994) 672-683.
- Kaufman, Yoram J. and Lorraine A. Remer. “Detection of Forests Using Mid-IR Reflectance: An Application for Aerosol Studies,” IEEE Transactions on Geoscience and Remote Sensing 32 (1994) 672-683.
- Keane, R. E., P. Morgan and J. P. Menakis. “Landscape Assessment of the Decline of Whitebark Pine (*Pinus albicaulis*) in the Bob Marshall Wilderness Complex, Montana USA,” Northwest Science 68 (1994) 213-229.
- Kramer, Herbert. Observation of the Earth and Its Environment: Survey of Missions and Sensors. 2nd Edition. Berlin: Springer-Verlag, 1994.

Bibliography – Continued

- Kusler, Jon. “Wetlands Delineation: An Issue of Science or Politics?” Environment 34 (March 1992) 6-11,29-37.
- Lee, K. H. “Wetlands Detection Methods Investigation” EPA Project Summary, US Government Printing Office, August 1991. EPA/600/54-91/014.
- Michelson, Daniel B. “GIS Supports Wetland Landuse Analysis,” GIS World 6 (1993) 56-59.
- Michigan Department of Natural Resources. Manual for Wetland Evaluation Techniques, Operational Draft. Division of Land Resource Programs, Michigan Department of Natural Resources, 1989.
- Mishra, J. K., R. Aarathi, and M. D. Joshi. “Remote Sensing Quantification and Change Detection of Natural Resources over Delhi,” Atmospheric Environment 28 (1994) 3131-3137.
- Mitsch, William J. and James G. Gosselink. Wetlands, 2nd Edition. New York: VanNostrand Reinhold International Thompson Publishing Co., 1993.
- Naessett, Eric. “Testing for Marginal Homogeneity of Remote Sensing Classification Error Matrices with Ordered Categories,” ISPRS Journal of Remote Sensing 50 (April 1995) 30-36.
- National Center for Geographic Information and Analysis. Final Report of the Accuracy Assessment Task Force, California Assembly Bill AB1580 California Department of Forestry and Fire Protection Interagency Agreement, Santa Barbara: University of California, April, 1994.
- Pearsell, Grant and George Mulamoottil. “Wetland Boundary and Land-use Planning in Southern Ontario, Canada,” Environmental Management 18 (June 1994) 865-870.
- Pearson, Randall Scott. “Mapping 1985 Food Security Act Wetland Categories Using Landsat Thematic Mapper Digital Data and GIS Modeling,” Dissertation, Indian State University, 1993.
- Potter, William W. History of Barry County. Grand Rapids: Read Tander Co., 1912.
- Ramsey, Elijah W., Ruth E. Spell, and Richard H. Day. “Measuring and Monitoring of the Wetlands Response to Acute Stress by Remote Sensing Techniques,” In Proceedings of the 26th International Symposium on Remote Sensing and Global Environment Change: Tools for Sustainable Development. Graz, Austria, April 4-8, 1993. Ann Arbor: Environment Research Institute, 1993.

Bibliography – Continued

- Rosenfield, George H. “Analysis of Thematic Map Classification Error Matrices,” Photogrammetric Engineering & Remote Sensing 52 (May 1986) 5:681-686.
- Rosenfield, George H. and Katherine Fitzpatrick-Lins. “A Coefficient of Agreement as a Measure of Thematic Classification Accuracy,” Photogrammetric Engineering & Remote Sensing 52 (February 1986) 2:223-227.
- Satterwhite, Melvin, William Rice, and Jerome Shipman. “Using Landform and Vegetation Factors to Improve Interpretation of Landsat Imagery,” Photogrammetric Engineering & Remote Sensing 50 (January 1984) 1:83-91.
- Second Addition Hope Twp. Hope Township Bicentennial Book Group, 1978
- Shaffer, Robert W. 1991 Annual Report: Barry County’s Lakes and Streams Barry County Drain Commission, 1991.
- Sheffield, Charles. “Selecting Band Combinations from Multispectral Data,” Photogrammetric Engineering & Remote Sensing. 51 (June 1985) 6:681-687.
- Squire, Gregg R. A Field Guide to the Geology of Southwest Michigan. Kalamazoo: Western Michigan University, Department of Geology, 1972.
- State of Michigan. Goemare-Anderson Wetland Protection Act, P.A. 203, sec. 281.703 (g), 1979.
- Stehman, S. V. “Thematic Map Accuracy Assessment from the Perspective of Finite Population Sampling,” International Journal of Remote Sensing 16 (March 1995) 589-593.
- Story, Micheal and Russel G. Congalton. “Accuracy Assessment: A User’s Perspective,” Photogrammetric Engineering & Remote Sensing 52 (March 1986) 3:397-399.
- Strahler, Alan H. “The Use of Prior Probabilities in Maximum Likelihood Classification of Remotely Sensed Data,” Remote Sensing of the Environment. 10 (1980) 135-163.
- Thompson, M.M. Maps for America Washington D.C.: Superintendent of Documents, US Government Printing Office, 1979.
- Toll, David L. “Effect of Landsat Thematic Mapper Sensor Parameters on Land Cover Classification,” Remote Sensing of the Environment. 17(1985) 129-140.

Bibliography – Continued

United States Department of Agriculture, Soil Conservation Service. Soil Survey of Barry County, Michigan by Gregory F. Theon. Michigan Agricultural Experiment Station, Michigan Department of Agriculture, Michigan Technological University, October, 1990.

United States Environmental Protection Agency. Wetland Detection Methods Investigation: Project Summary by K. H. Lee. Las Vegas, NV: Environmental Monitoring System Laboratory, 1991. Item 0431-L-12 (microfiche).

Verbyla, D. L. and T. O. Hammond. “Conservative Bias in Classification Accuracy Assessment Due to Pixel-by-pixel Comparison of Classified Images with Reference Grids,” International Journal of Remote Sensing 16 (March 1995) 581-587.

Wang, Minhua. “Modeling Errors for Remote Sensing Image Classification,” Dissertation, University of Waterloo, Canada, 1994.

Williams, Joan Alexandra. “Vegetation Classification Using Landsat TM and Spot HRV Imagery in Mountainous Terrain, Kananaskis Country, Southwestern Alberta,” Thesis, University of Calgary, 1992.

Wolfaardt, P. J. “Assessment of the Spatial Accuracy of Classified Multispectral Digital Data,” In GIS '87. Proceedings of the 2nd International Conference, San Francisco, 1987. Volume 1 ASPRS/ACSM, 1987.

Zhenku Ma, and Roland L. Redmond. “Tau Coefficients for Accuracy Assessment of Classification of Remote Sensing Data,” Photogrammetric Engineering & Remote Sensing 60 (April 1995) 435-439.