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Improved Wetlands Mapping Methods: A Summary Report

Midwest Wetlands Assessment and Advanced Wetlands Mapping Support for USFWS Region 3 Ecological Services

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I. Introduction

It is important to have up-to-date information on wetland distribution to allow effective conservation and management of wetland resources. Research studies concerning wetland sites and vegetation are critical because wetlands are good indicators of changes occurring on the surrounding landscape. Whether the changes include growth of an invasive species, reduction in size of the wetland, effects of a changing climate, or changes due to chemical/mineral deprivation, each can indicate that there may be harmful changes taking place in a wetland system (Adam, 2010; Govender, 2008). Over time, there have been many studies designed to increase the efficiency by which wetland researchers collect data on their location and type. Early on, data collection was a labor intensive process including, but not limited to, field work identifying different species and visual estimations of percent coverage, among other time consuming analyses, which typically resulted in small areas of concentration (Adam, 2010).

There are many possible ways to identify, classify, and characterize wetland systems. Wetland classification systems often are driven by the needs of the organization classifying and mapping the wetlands. This paper outlines and reviews six wetland classification programs and methodologies that are currently active:

- The Canadian Wetlands Classification System (includes Ontario Ministry of Natural Resources (MNR) Inventory)
- Ducks Unlimited/Equinox Analytics/Minnesota Department of Natural Resources (MNDNR) Wetlands Mapping
- Hyperspectral Wetlands Mapping Methods
- The Wisconsin Wetlands Mapping Program
- Electro-Optical Radar Fusion Methods (Bourgeau-Chavez)
- United States Geological Survey (USGS) Potential Wetlands Index Program.

Michigan Tech Research Institute (MTRI) has entered into a Cooperative Agreement with the US Fish and Wildlife Service (USFWS) to perform this methodology review report as well as an accuracy and agreement assessment on a classification of wetlands in Iowa. In addition, there are numerous wetland inventories at local and county regional levels across the basin not reviewed in this summary report. Trying to address all inventories would have been cost prohibitive.

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II. The Canadian Wetlands Classification System

I. Ontario Wetland Evaluation System

The Ontario Wetland Evaluation System (OWES) is defined by the Ontario Ministry of Natural Resources (MNR) as “a science-based system that is used to evaluate and rank the relative value of wetlands” (OWES Executive Summary, 2011). The OWES manuals are technical guidance documents that use scientific criteria to quantify wetland values and allow comparisons between wetlands. Ontario acknowledges differing conditions between southern regions of the province (near the Great Lakes) and the northern regions of the province by publishing a Southern and Northern manual. The Ontario Wetland Evaluation System Southern Manual is used to evaluate wetlands located in Ecoregions 6 and 7, generally the areas around southern Lake Huron, and along the north shores of Lakes Erie and Ontario. The Ontario Wetland Evaluation System Northern Manual is used to evaluate all wetlands located in Ecoregions 2, 3, 4, and 5 which covers the balance of the province (Figure 1).

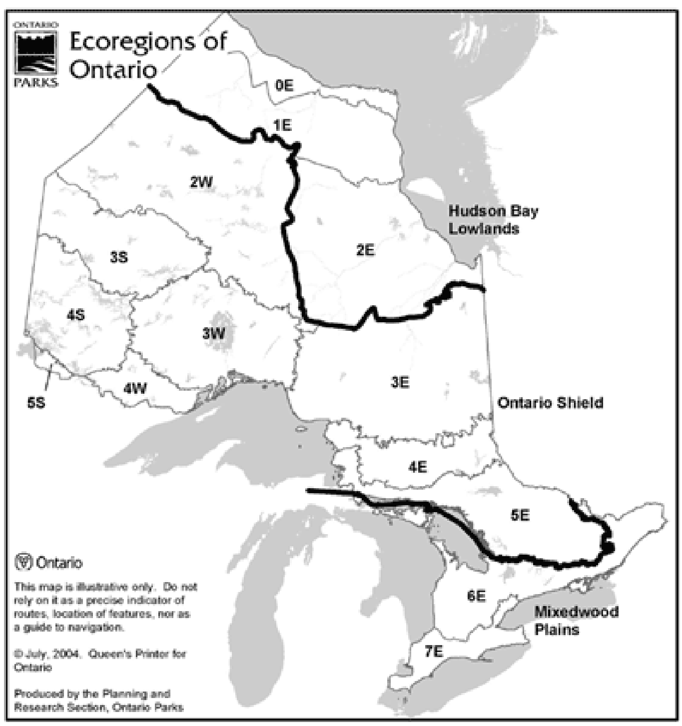

Figure 1. Generalized map of Ecoregions of Ontario. The southern dark black line is the boundary for application of Southern and Northern OWES Manuals.
(http://www.ontarioparks.com/english/today_protected.html)

The OWES wetland evaluation process involves definition, identification and measurement of wetland functions and values, a very different approach from the Canadian Wetland Classification System. In the Ontario system, “wetlands are assessed based on the perceived values of characteristics, activities or expressions of the wetland or its parts that act to maintain ecosystem processes (ecosystem values), or have some utility or amenity value to a segment of society (human utility values)" (OWES Executive Summary, 2011). The OWES defines ecosystem values as "primary production, watershed protection, conservation of biological diversity, and maintenance of natural bio-geochemical cycles. Human utility values include flood attenuation, recreation, production of harvestable products, water quality improvements, and research and education. The OWES groups wetland functions and values into four main categories or components: Biological, Social, Hydrological and Special Features.

This report was written using information contained in the 2002 revision to the third edition of the OWES, published in March, 1993. A December 2011 draft update to the OWES is posted at the Ontario Ministry of Natural Resources website. As of this writing (January, 2013), the December 2011 draft of the Northern and Southern Manuals of the OWES is up for public review and comment.

The December 2011 draft of the Southern Manual is available at http://www.mnr.gov.on.ca/stdprodcontrib/groups/lr/@mnr/@fw/documents/document/stdprod_092362.pdf, the December 2011 Northern Manual draft is available at http://www.mnr.gov.on.ca/stdprodcontrib/groups/lr/@mnr/@fw/documents/document/stdprod_092363.pdf.

II. Canadian Wetland Classification System

People look at wetlands through the lens of their needs. A wildlife biologist will typically look at the same wetland differently than a farmer, hydrologist, botanist or civil engineer. The perceptions of users of wetland classification system can be dramatically different based on the needs and perceptions of the user group. The goal of the Canadian Wetland Classification System (CWCS) is to provide a "common platform that allows the exchange of data and results between different groups or disciplines, using a common language" (Zoltai and Vitt, 1995). The CWCS defines a wetland as "land that is saturated with water long enough to promote wetland or aquatic processes…" (Zoltai and Vitt, 1995). Five wetland classes are recognized by the CWCS: bogs, fens, swamps, marshes and shallow open waters. Within the CWCS, these classes are broken down into wetland forms (which can be subdivided into subforms) and wetland types. The CWCS is described by the National Wetlands Working Group as an "expert system" where the user is "expected to have a general knowledge of wetland processes and associated characteristics" (Warner and Rubec, 1997).

The current (second) edition of the Canadian Wetlands Classification System (CWCS) (1997) is a refinement of a provisional first edition, released in 1987. The first edition of the CWCS evolved from work done in 1973 by the National Committee on Forest Lands to develop an organic terrain classification system. Stephen Zoltai followed in 1975 with a proposed four level hierarchical, ecologically based system. This system eventually formed the basis of a comprehensive wetland classification system. About the same time, different regional systems were developed by Ontario and the Prairie provinces. These classifications were developed with the needs of wildlife biologists and engineers in mind, as well as an organic soil classification developed by the Canada Soil Survey Committee. Each classification was done with the needs of a particular user group in mind, resulting in classification systems that had little usefulness to users other than those for which the classification was intended.

The CWCS methodology differs from the Cowardin classification methodology used in the United States. Different conditions exist in the Precambrian Canadian shield than in southern Ontario and the United States. Much of the Precambrian Canadian Shield, which makes up a large part of Canada, are peatlands. As a result, Canada has less wetland variety than in the United States. According to Zoltai (1988), a large proportion (96%) of Canadian wetlands would be classified in the Palustrine system using the Cowardin wetland classification system, highlighting the need for a wetland classification system that can differentiate between all the classes present in the Canadian landscape. The status of Canadian Wetland Inventory is displayed in Figure 2.

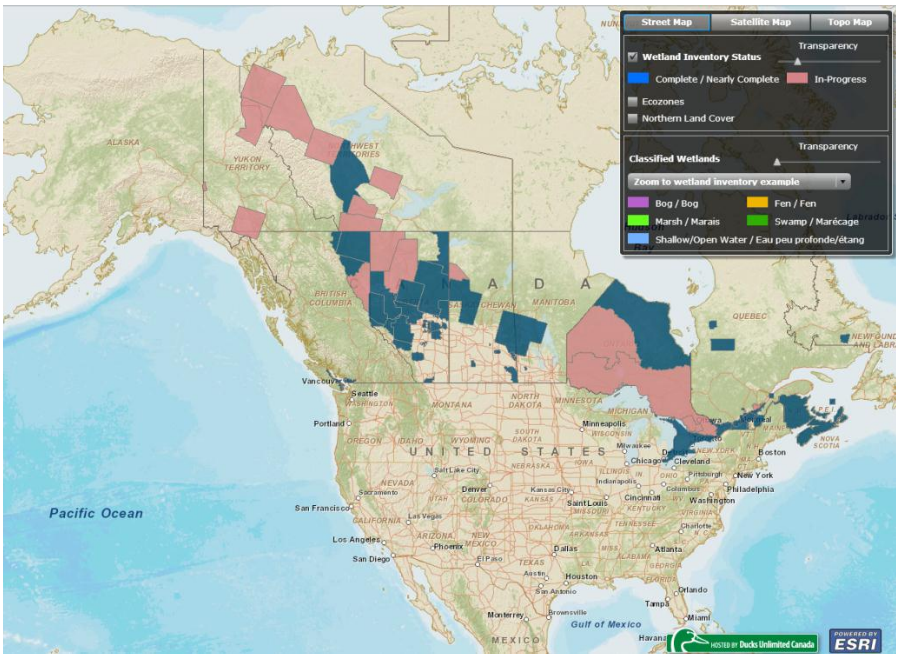

Figure 2. The current status of wetland mapping within the Canadian Wetland Inventory (Ducks Unlimited Canada, http://maps.ducks.ca/cwi/).

The National Wetlands Working Group (NWWG) defines a wetland as "land that is saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment" (Warner and Rubec, 1997). In the Canadian system, wetlands are then divided into two categories – *organic wetlands,* more commonly referred to as peatlands and *mineral wetlands* found where excess water collects on the surface but for various reasons little to no peat is produced.

The five CWCS classes are (Warner and Rubec, 1997):

a. Bog Wetland Class:

"A *bog* is a peat landform which is characterized by a variety of shapes and sizes. The bog surface, which is raised or level with the surrounding terrain, is virtually unaffected by runoff waters or groundwaters from the surrounding mineral soils. Generally the water table is at or slightly below the bog surface. Bogs may be treed or treeless, and they are usually covered with *Sphagnum* spp. and ericaceous shrubs. The driest bogs, especially in permafrost terrain may be covered in dwarf shrubs and lichens."

The primary characteristics of bogs are:
(1) an accumulation of peat;
(2) surface raised or level with surrounding terrain;
(3) water table at or slightly below the surface and raised above the surrounding terrain;
(4) ombrogenous;
(5) moderately decomposed *Sphagnum* peat with woody remains of shrubs; and
(6) most frequently dominated by *Sphagnum* mosses with tree, shrub or treeless vegetation cover. (Warner and Rubec, p.19)

b. Fen Wetland Class

A *fen* is a peatland with a fluctuating water table. The waters in fens are rich in dissolved minerals and, therefore, are minerotrophic. Groundwater and surface water movement is a common characteristic of fens. Surface flow may be directed through channels, pools, and other open water bodies that can form characteristic surface patterns. The dominant materials are moderately decomposed sedge and brown moss peats of variable thickness.

The primary characteristics of fens are:
(1) an accumulation of peat;
(2) surface is level with the water table, with water flow on the surface and through the subsurface;
(3) fluctuating water table which may be at, or a few centimeters above or below, the surface;
(4) minerogenous;
(5) decomposed sedge or brown moss peat; and
(6) graminoids (grasses) and shrubs characterize the vegetation cover.
(Warner and Rubec, p. 28)

c. Swamp Wetland Class

The term *swamp* has been used in Canada to refer to forested or wooded wetlands and peatlands. The treed swamps have also been called *swamp forest* or *forested wetland*. A swamp can be defined as a treed or tall shrub (also called *thicket*) dominated wetland that is influenced by minerotrophic groundwater, either on mineral or organic soils. The essential features of the swamp class are the dominance of tall woody vegetation, generally over 30% cover, and the wood-rich peat laid down by this vegetation.

The primary characteristics of swamps are:
(1) peatland and mineral wetland;
(2) water table at or below the surface;
(3) minerogenous;
(4) highly decomposed woody peat and organic material; and
(5) coniferous or deciduous trees, or tall shrub vegetation cover.
(Warner and Rubec, p. 37)

d. Marsh Wetland Class

A *marsh* is a wetland that has shallow water, and has levels that usually fluctuate daily, seasonally or annually due to tides, flooding, evapotranspiration, groundwater recharge, or seepage losses. Marshes may experience water level drawdowns which will result in portions drying up and exposing the sediments. Marshes receive their water from the surrounding catchment as surface runoff, stream inflow, precipitation, storm surges, groundwater discharge, longshore currents and tidal action. Marshes dependent upon surface runoff usually retain less permanent water than sites supplied by groundwater. The water table usually remains at or below the soil surface, but soil water remains within the rooting zone for most of the growing season, except in years of extreme drought.

The primary characteristics of marshes are:
(1) mineral wetlands;
(2) shallow surface water which fluctuates dramatically;
(3) minerogenous;
(4) little accumulation of organic material and peat of aquatic plants; and
(5) emergent aquatic macrophytes largely rushes, reeds, grasses, and sedges and some floating aquatic macrophytes.

e. Shallow Water Wetland Class

Shallow water wetlands are distinct wetlands transitional between those wetlands that are saturated or seasonally wet (i.e. bog, fen, marsh or swamp) and permanent, deep water bodies (i.e. lakes) usually with a developed profundal zone. Shallow waters are subject to aquatic processes typical of upper limnetic or infralittoral lake zones, such as nutrient and gaseous exchange, oxidation and decomposition.

Shallow water wetlands have standing or flowing water less than 2 m deep in mid-summer. Water levels are seasonally stable, permanently flooded, or intermittently exposed during droughts, low flows or intertidal periods. Open shallow water must occupy more than 75% of the surface area of a confined basin or saturated zone, inclusive of adjoining wetlands. Shallow water wetlands may also occupy bays and margins of profundal zones of lakes (Figures 3 and 4).

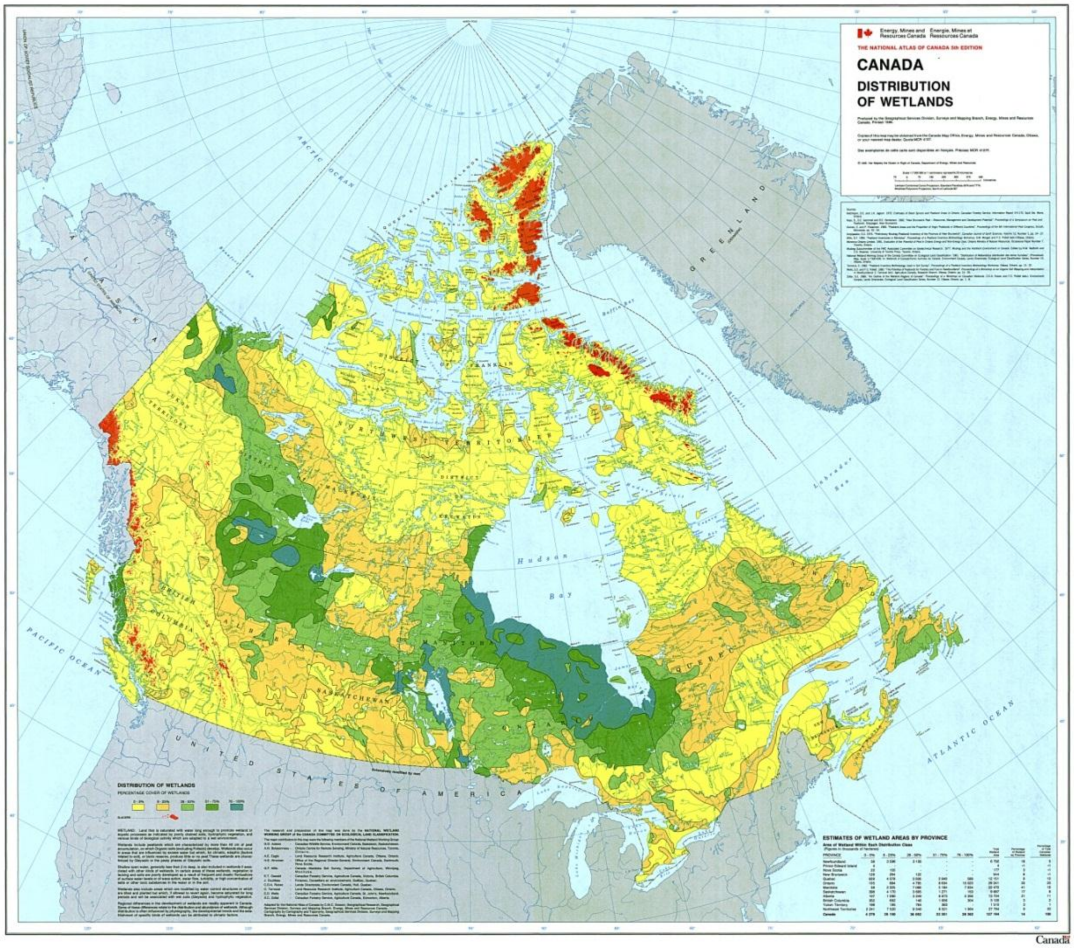

Figure 3. Distribution of Canadian wetlands map
Source:
http://atlas.nrcan.gc.ca/site/english/maps/archives/5thedition/environment/ecology/mcr4107

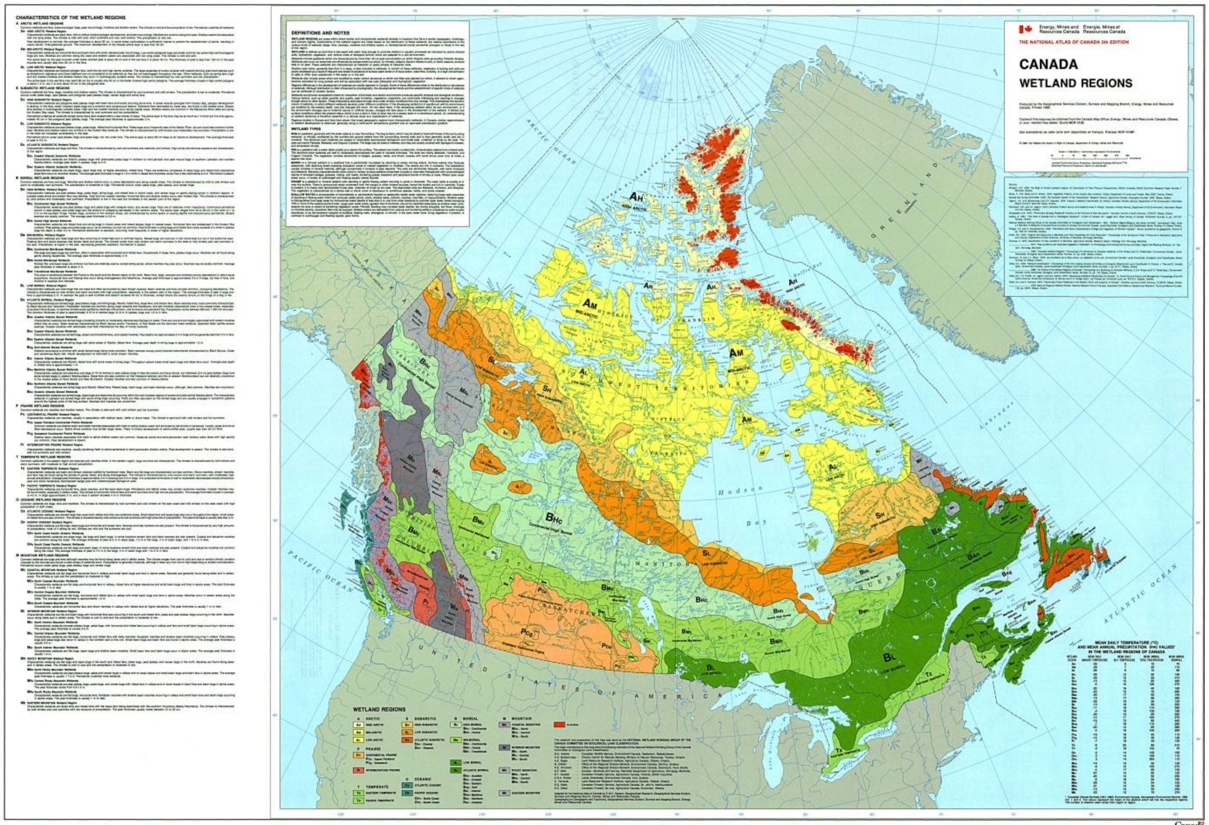

Figure 4. Canadian Wetland Regions map
Source:
http://atlas.nrcan.gc.ca/site/english/maps/archives/5thedition/environment/ecology/mcr4108

Each of the classes outlined above have forms and subforms associated with them. The details are too much information for this report, classification details can be found in the CWCS manual.

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III. Wetlands Mapping for the Ducks Unlimited, Equinox Analytics, and Minnesota Department of Natural Resources Collaborative Effort

I. Introduction

Wetland inventories are a critical tool for wetland management, protection and restoration. An accurate inventory of wetlands that includes their location and classification is important for effective management and policymaking. The National Wetlands Inventory (NWI) is a comprehensive wetland inventory that includes the state of Minnesota. However, the NWI has several significant challenges. In many areas, the data in the NWI have not been updated in 25 – 30 years and limitations in the original source data, technology and methods appear to have under-represented some wetland classes (Tiner, 2009). These and other issues provided motivation to update the existing NWI data in Minnesota.

Recent efforts by Ducks Unlimited and Equinox Analytics, Inc. have yielded an improved method for rapidly and effectively assessing and mapping wetlands. This effort was focused on the inventory of restorable wetlands (see http://www.fws.gov/midwest/hapet/RWI.html). The following is a brief review of this effort (Smith, et al. 2012). Principals include Robb Macleod (Ducks Unlimited) and Aaron Smith (Equinox Analytics, Inc.). Going forward, this consortium will be referred to as "DU/EA". Sponsors for this effort included the Legislative-Citizen Commission on Minnesota Resources (LCCMR) and the USFWS. The goal of this effort has been to provide a robust, semi-automated method to update NWI data. For this project Minnesota was the focus; the project area consisted of 13 counties located in east central Minnesota (see Figure 5). The NWI data for much of Minnesota was last updated in the 1980s (some areas were updated in the 1990s). Significant changes to the wetlands landscape have occurred over this twenty to thirty year period. Forested wetlands and emergent wetlands have been historically under-assessed due to technological limitations or subjective interpretation. A State of Minnesota inter-agency partnership has identified improving the classification of under-represented wetland classes such as forested wetlands as a key recommendation/motivation for the updating of NWI data. To that end, an improved methodology has been developed by the MNDNR and DU/EA to improve the identification/classification and mapping of wetlands. The effort by the DU/EA consortium effectively addresses the shortcomings of the existing wetlands inventory through the development of the improved classification methodology described below.

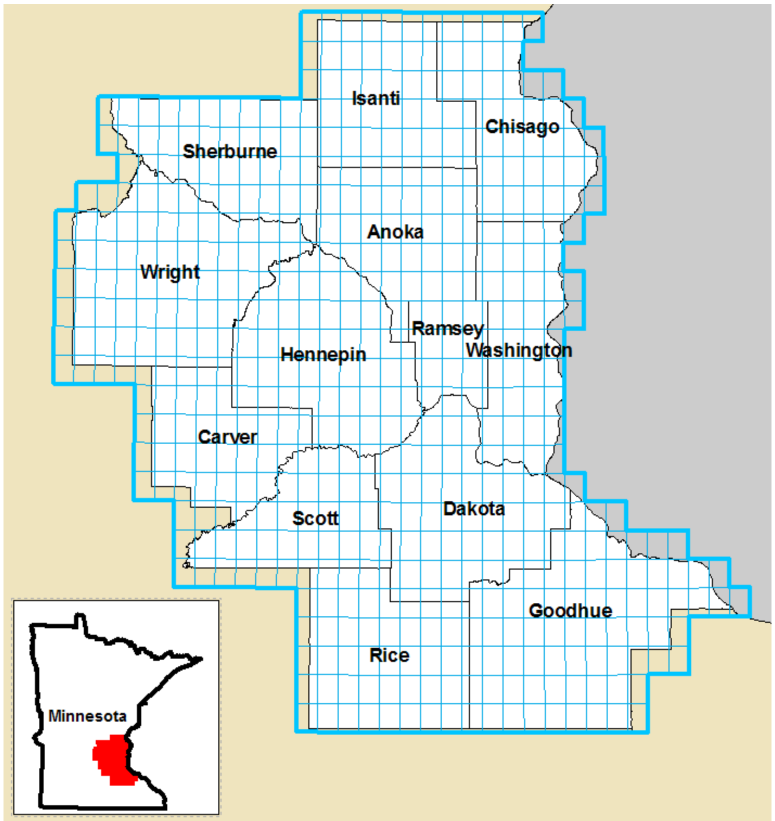

Figure 5. DU/EA Consortium Study Area, East Central Minnesota. (Smith, et al. 2012)

II. Data Sources and Software

Imagery, data sources and data processing techniques are available now that were not available when the original NWI was compiled. Radar derived data, light detection and ranging (LiDAR) derived digital elevation models (DEMs), high spatial resolution digital multi-band aerial photography and digital Soil Survey Geographic (SSURGO) data are some of the data sets useful when identifying and classifying wetlands. The data sources employed in this effort have been:

- Phased Array type L-band Synthetic Aperture Radar (PALSAR) radar Data
- High Resolution Color Infrared Imagery
- LiDAR DEMs
- SSURGO Soils Data
- Field Collected Data

Computer hardware has made quantum leaps in processing speed and storage capacity since the compilation of the original NWI. Current software has become increasingly capable of handling the sophisticated image and data processing tasks necessary to complete the classification process at a regional or statewide level. Image processing/mapping software used for the DU/EA project includes:

- ESRI ArcGIS Desktop
- ERDAS Imagine
- RandomForest™
- Trimble eCognition

- Alaska Satellite Facility (ASF) MapReady

III. Methodology

The update to the Minnesota NWI classifications was performed using the Cowardin (1979) wetland classification system. Some modifications to the classes were made to adapt the classes to prevailing conditions in the state. The pilot project area consisted of 13 counties in east-central Minnesota. Counties in the project area included Anoka, Carver, Chisago, Dakota, Goodhue, Hennepin, Isanti, Ramsey, Rice, Scott, Sherburne, Washington and Wright. The 6328 mi^2 project area was divided into cells using an overlay made up of USGS quarter quadrangles boundaries (Figure 5). If the county was partially included in a particular quad, the entire quarter quadrangle was included in the analysis.

The process flow is outlined in Figure 6. The primary processes are indicated as rectangles in the process flow chart, from left to right; Image Segmentation, Random Forest Classification, Photo Interpretation/Object Editing/Manual Delineation, and Quality Assurance/Quality Control (QA/QC) & Accuracy Assessment. Each of these primary processes are outlined below, with input/output indicated.

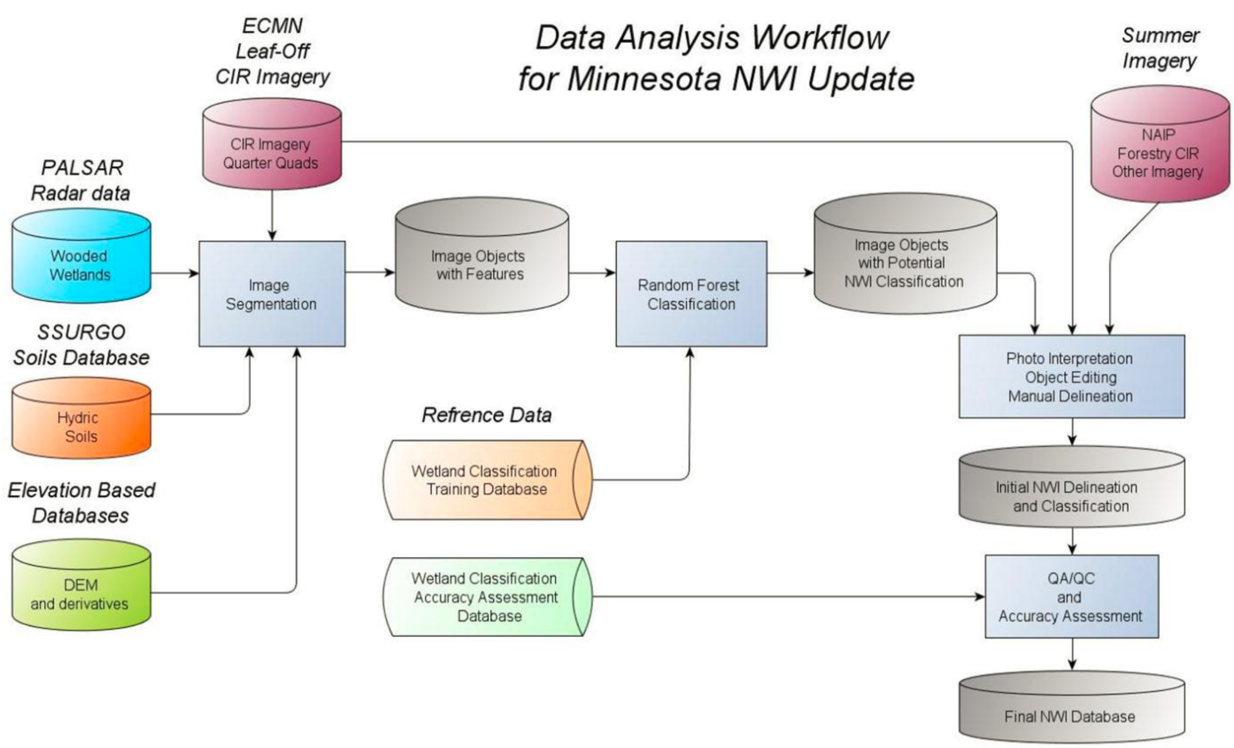

Figure 6. Process Flow Chart – Improved Wetlands Classification Methodology (Smith, et al. 2012)

a. Image Segmentation (using eCognition)

Inputs: Wooded Wetlands, Hydric Soils, DEM and Derivatives, Color Infrared (CIR) Imagery
Outputs: Image Objects with Features and a point file (represents centroids of polygons) with training data

The image segmentation process provides the foundation of the DU/EA NWI update process. This process uses the CIR aerial imagery, LiDAR derived DEMs, PALSAR Radar data and the SSURGO soils data to segment the image into polygons based upon detected boundaries. Trimble eCognition is the workhorse for this process, providing the output – a segmented image object file with feature polygons (Figure 7). The rule-set used for this processing includes over 250 operations, utilizing the data inputs outlined above. These inputs are described below in further detail.

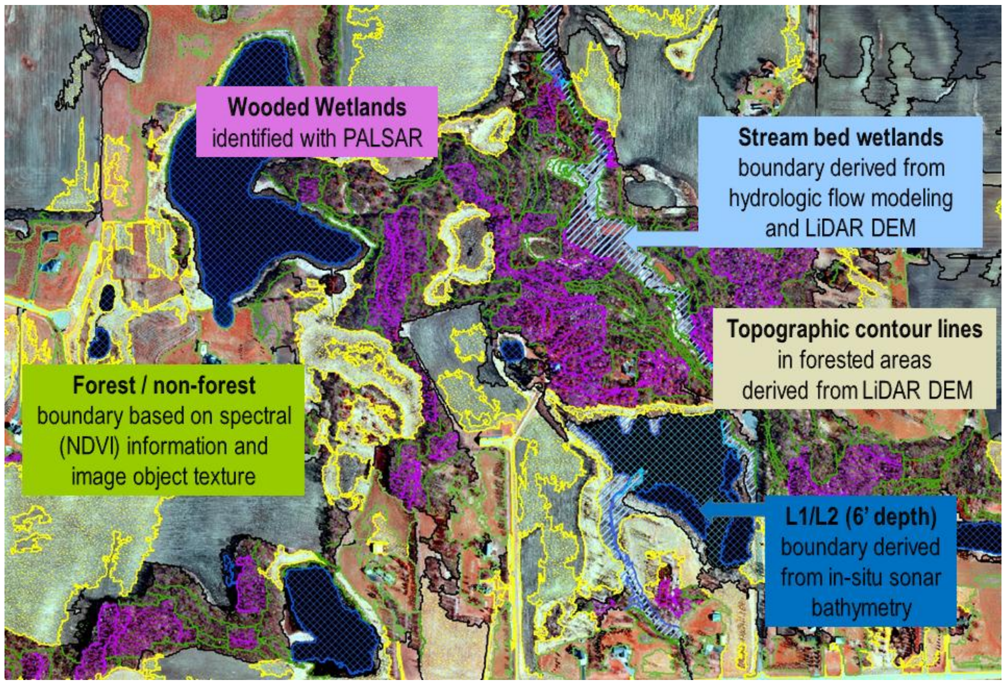

Figure 7. A polygon segmented image based on the multiple data sets listed below.

i. Wooded Wetlands

PALSAR L-band RADAR data was processed using ASF MapReady. MapReady produces a geotiff format file that is geocoded and terrain corrected. Additional post-processing image correction is accomplished using ArcGIS for geo-correction. A clustering routine is then implemented in ERDAS Imagine. The final output is a binary layer that identifies wooded wetlands which is utilized in the Image Segmentation process. This layer is also available to the image interpreter as a supporting data source for final classification.

ii. Hydric Soils

SSURGO data are available from the Natural Resources Conservation Service (NRCS). These layers were processed into a layer containing the predominant water regime and allow an estimation of the proportion and location of hydric soils in a cell.

iii. DEM and Derivatives

LiDAR DEMs were used for a majority of the area (3m per pixel spatial resolution). In areas where LiDAR was unavailable, the National Elevation Dataset (NED) DEM was used (10m per pixel spatial resolution). These elevation data are utilized in RandomForest. Additionally, a Topographic Position Index (TPI) (Weiss 2001) was calculated. The

Compound Topographic Index (CTI) (Moore, 1991) was also calculated. These Indices are utilized in the Image Segmentation process.

iv. CIR Imagery

CIR imagery was collected in 2010 – 2011 in spring leaf-off condition. The majority of the imagery was captured at 30cm per pixel spatial resolution, with the balance being captured at 50cm per pixel resolution. The higher resolution 30 cm per pixel data was resampled to 50cm per pixel resolution to provide a seamless dataset for ease of processing.

b. Field Training Data

A significant training dataset was utilized by the DU/EA group – 3350 validation points were included in the training data (Figure 8). Field data was collected by the project team in twelve representative quads, including urban, residential, and rural areas. Categorization was accomplished using the Cowardin classification system (Cowardin et al., 1979). The input datasets were detailed in the previous section. RandomForest provided a classification which was utilized by the Image Interpreter as an aide for areas not readily classified.

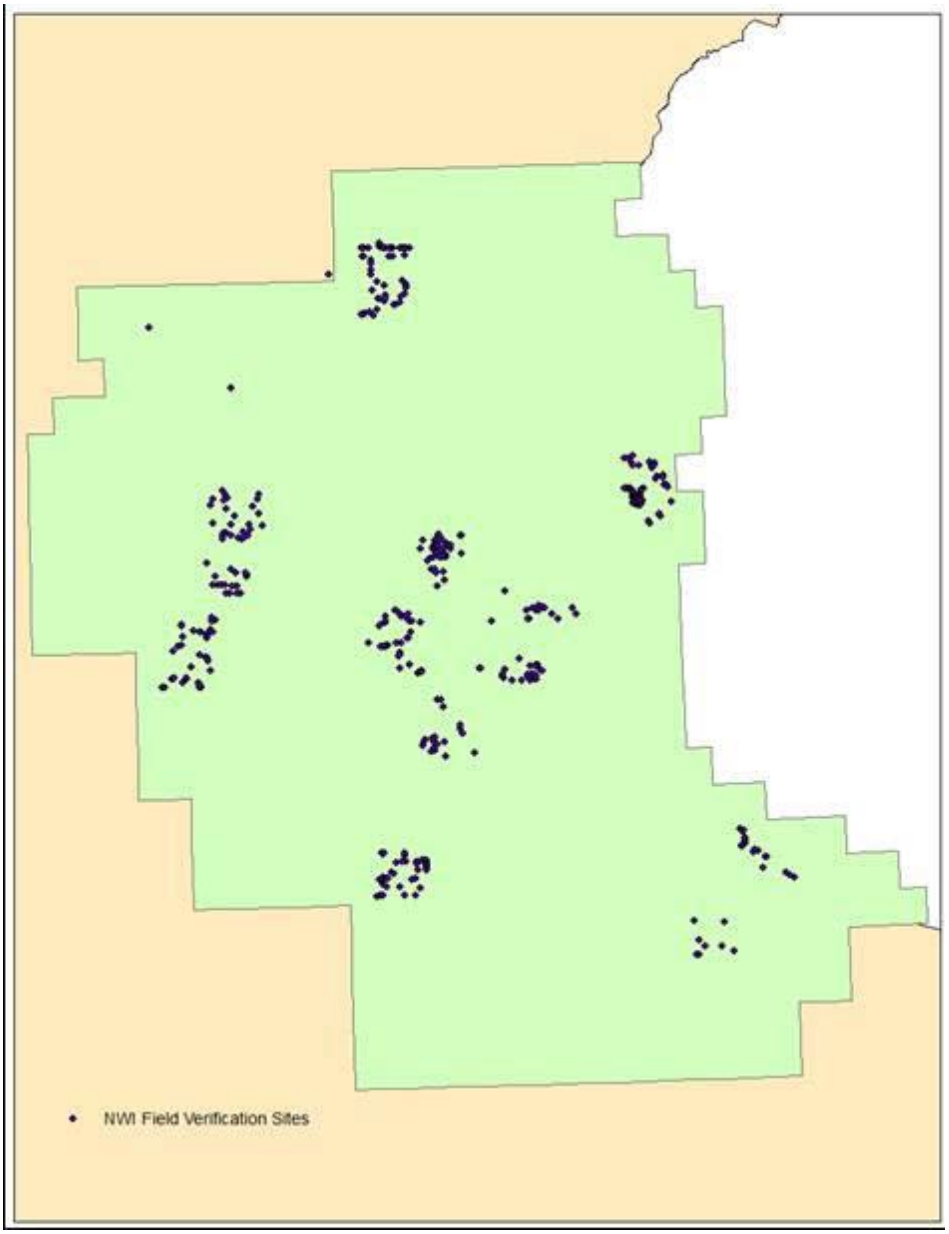

Figure 8. A map of the 510 field sites visited by DU/EA personnel for the Minnesota wetlands mapping project

c. The Classification Process

Inputs: Image Objects with Features from eCognition, Wetland Classification Database
Outputs: Image Objects with Potential NWI Classification attributes.

The RandomForest classification utilizes the procedure described by Breiman (2001). Inputs to RandomForest are the point file and training data generated by eCognition in a previous step in the process. The RandomForest classification classifies each point in the input point file and assigns a confidence value to the classification. The unique identification shared by the point file and attributes and polygons generated by eCognition is used to join the image segments and the classification suggested by RandomForest. The classified image segments are used to enhance a traditional photointerpretation that ultimately decides the classification of a polygon.

d. Photo Interpretation – Object Editing/Manual Delineation

Inputs: Image Objects with Potential NWI Classification, CIR Imagery Quarter Quads, NAIP Forestry CIR Other Imagery
Output: Initial (draft) updates to NWI Delineation and Classification

The image interpretation step includes the primary human-interface portion of the process. Image interpreters work with the output of the Image Segmentation Process, which includes an initial classification. These initial boundaries are reviewed and adjusted or redrawn, if necessary. The initial classification is reviewed an accepted or altered. All input datasets are available to the interpreter as an aide to make the boundary and classification review. The output from the RandomForest algorithm is used as a secondary dataset for areas not readily classified. The NWI classification with boundary delineation is the output of this process. This is subject to a QA/QC review, outlined below.

e. QA/QC and Accuracy Assessment

Input: Initial draft NWI Delineation and Classification
Output: Final NWI Database

Upon completion of the Initial Delineation and Classification, the image interpreter runs an automated QA/QC protocol designed to identify topological errors and attribute inconsistencies. A second step of the QA/QC process includes a second interpreter evaluating 10% of the completed products to verify consistency between interpreters. This yields the final NWI product. This database is then assessed for accuracy by a third party, using an independent field reference source.

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IV. Hyperspectral Wetlands Mapping Methods

I. Background

With the advancement of remote sensing, studying wetlands has become more realistic through the use of hyperspectral imagery. Hyperspectral remote sensing collects data through the use of hundreds of spectral bands, producing much more detailed spectral datasets in one single acquisition (Govender, 2007). The increased spectral dimensionality of hyperspectral imagery allows for a more thorough spectral analysis than the traditional approach using multispectral or color-infrared imagery. Multispectral sensors traditionally collect data using three to eight spectral bands of varying bandwidths, which are located in the visible and near-infrared portions of the electromagnetic spectrum. Hyperspectral bands possess a wider range across the spectrum, and can consist of visible, near-infrared, mid-infrared, and thermal infrared portions (Govender, 2007). Due to the sensor's ability to collect a wider range of electromagnetic radiation, hyperspectral can be used when classifying types of hydrophytic vegetation within a wetland. This in turn, can help identify similar vegetation species, which may look similar in multispectral or visible sensor data but produce different spectral graphs when using hyperspectral data (Adam, 2010).

Many studies have focused on methods to help improve hyperspectral remote sensing and its ability to detect different wetland vegetation. Some studies were concerned with evaluating the limits of sensing technologies (Anderson 1970; Best et al. 1981), while others focused on determining the overall health of a wetland site (Underwood 2003; Lin 2006). Both groups, though studying different aspects of hyperspectral remote sensing, agree that hyperspectral remote sensing still has challenges and needs improvements, such as reducing sensor and data processing costs, as well a reduction in data volume (Govender, 2007; Becker, 2005). In 2007, Becker et al. worked on improving the utility of hyperspectral remote sensing using rigorous analysis. Becker argues that the operator must beforehand determine the specific spectral and spatial resolutions that will return the optimal results, therefore producing better classification accuracy for multiple vegetation species.

II. Becker et al. (2007) Methodology

Becker's study came to this conclusion after studying Lake Huron's Wildfowl Bay island complex, located in Saginaw Bay, Michigan (Figure 9). For this study, two sets of imagery were flown, collecting two hyperspectral datasets using the Compact Airborne Spectrographic Imager-II (CASI 2). The first consisted of 18 non-contiguous bands with 1-meter spatial resolution, and the second 46 contiguous bands with 4-meter spatial resolution. Both datasets were classified using ENVI's Spectral Angle Mapper (SAM) (Research Systems Inc.), which classified the vegetation based on 24 (1-meter imagery) and 21 (4-meter imagery) supervised training classes. The classification process was then repeated using varying bandsets from the original imagery to test the utility of the number of spectral bands used in the SAM classification routine. The classification process was highly reliant on the number of bands the algorithm took into account. Becker et al. (2007) found that if too few bands were used, subtle differences in spectral targets would be lost, while using too many bands caused a redundancy in input information.

Figure 9. An example of hyperspectral imagery in Wildfowl Bay, Michigan. Image provided by PhotoScience Inc. and Zach Raymer, formerly of Central Michigan University.

Spatially, hyperspectal data is limited when the resolution is greater than 5-meters, as determined by ITRES (2000). To test the validity of this, Becker et al.(2007) resampled the 1-meter hyperspectral imagery to 2-, 4-, and 8-meters. The resulting imagery was then processed through the SAM classification algorithm, which classified vegetation species based on the original supervised training sites. Results for each of the resampled resolutions were then compared to the evaluation standard via confusion matrices. In the confusion matrices, an evaluation standard was created by taking ground based spectral data (252 bands) collected in 2000 and 2001, using a Spectron Engineering (SE)-590 spectroradiometer at 24 sites within the study area, and processing it through the SAM algorithms. Any difference between the evaluation standard and resampled data was considered an effect from changing the pixel size. This is due to the imitated spatial degradation; pixels near the edges of the study sites have a potential to mix spectral radiances with neighboring vegetation.

Next, the necessity, or lack thereof, for increased spectral resolution when performing species level classification was tested using three different methodologies that would use an altering number of bands in the analysis. First, the study created two evaluation standards from the 4-meter imagery, both standards consisted of 112,500 benchmark pixels; however one standard used all 46 spectral bands, while the other used seven optimal bands previously identified by Becker et al. (2005). Three bandwidth selections/configurations were then applied to the hyperspectral images. These methods took into account derivative magnitudes (Table 1, Items 1-44), fixed intervals (Table 1, Items 46-55) and derivative histograms (Table 1, Items 56-65) when selecting bands. Confusion matrices were used to compare and contrast the results of each band selection method to the evaluation standards. In addition, statistical Z-scores were calculated to identify if any two vegetation classifications were significantly different at the predetermined confidence level of 95%.

Becker et al's (2005) study was concerned with identifying the fewest and most practical spectral bands that are able to optimally discern vegetation differences. The areas of concern were located in Prentiss Bay, Michigan, and as similar to the 2007 study, Wildfowl Bay, Michigan. In situ radiance measurements were collected during the 2000 and 2001 growing seasons, using a Spectron Engineering (SE)-590 spectroradiometer at 82 different sites. The radiance values were converted into percent reflectance measurements, which were then placed into seven categories based on the plant community and/or substrate type. Using 2nd-derivative approximations, the percent reflectance was analyzed to determine where abrupt slope changes occurred within the reflectance curves. This analysis took into account three bands per calculation, in order to guarantee that the generated values occurred only on the center band.

For each of the 82 pooled spectra, the top and bottom five magnitude values were ranked based on their values. From this list, eleven bands were identified as being unique and added to a list of an additional 37 bands that existed within the next four lower magnitude levels. These 48 bands (414.3 nm – 951.5 nm) were also placed into biophysical spectral zones, with each band within the zone sharing similar properties. By completing the analysis on the 82 pooled spectra in the Great Lakes region, Becker et al. (2005) indicated that the graph produced by the second-derivative values could identify wavelengths/bands that are optimally and botanically explanatory. In addition, the seven vegetation categories were also analyzed based on the second-derviative calculations and graphs. Based on in-depth analysis of the seven categories, seven bands appeared most relevant when studying the botanically diverse Great Lakes region: 425.4, 514.9, 560.1, 685.5, 731.5, 812.3, and 916.7 nm. Other studies also concur that there are several key bands that exist in vegetation studies, but are dependent on the study area.

III. Becker et al. (2007) Results

After the spatial resolution test was processed through the classification routine and analyzed using confusion matrices, the study found that species level classification of wetland vegetation was more accurate when using higher spatial resolution images, with the 2-meter image performing the best. Using the 2-meter image, a total of 77% of the pixels were classified similarly between both the evaluation standard and resampled image, while 65% of the pixels contained matching classifications for the 4-meter test, and only 50% were classified in the 8-meter test. These results reaffirm that classification accuracy is sensitive to pixel size.

The derivative magnitude band selection method produced 44 different classification configuration results. Each configuration had their kappa and resiliency values calculated. The results are near linear when comparing the kappa and resiliency values to the number of bands utilized and contain the highest values when the greatest number of bands is included. However, the two values cross a threshold once the number of bands is reduced to a total of five or less. Another outcome of this method of band reduction is evident when the study became concerned with a resilient percentage of 85%. Tests indicated that to maintain this percentage, reduction of bands cannot go below 21. This is despite what classification results from the other two methods indicated, which showed that that an 85% residual could be reached with fewer than 21 bands (Figure 10).

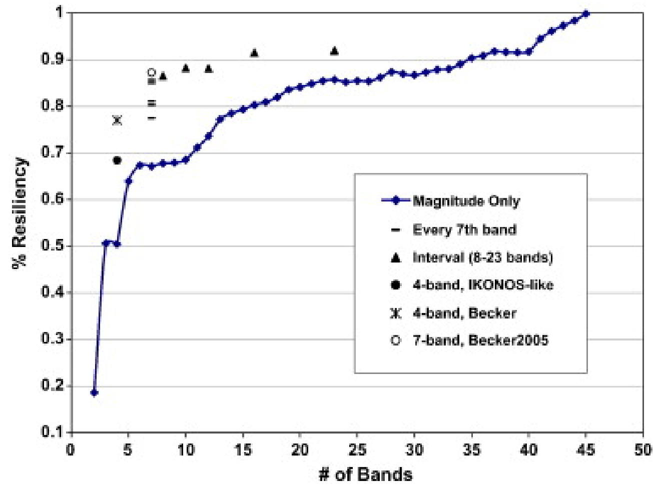


Figure 10. Percent resiliency for each band configuration described in Table 1.

During the fixed interval band selection process the classification accuracy results decreased as the number of bands included in the classification routine decreased. Interestingly, all of the six configurations had better results than the derivative magnitude band selection process when using a similar number of bands. The best results were found when classifications were based on 7, 8, and 10 bands. Becker et al. (2007) states that this is because the bands are more evenly distributed across the spectral field of the imagery, rather than concentrated in wavelengths that always produce high derivative values. In an additional four test, a total of seven bands were used per configuration, but starting points of band selection were varied. Resiliency values began to decline the further away the starting band was from the first band, 425.4 nm. This led the authors to believe that classification results can be altered by starting locations of band configurations.

The derivative histogram band selection was based on the Becker et al. (2005) paper that identified seven optimal bands. Resulting in 86.3% classification accuracy, this configuration was used as the evaluation standard in the 2007 study. In this study, the 7 band configuration was changed by starting each configuration with a different bandwidth, to see what affect it would have on the classification outcomes. This resulted in classification resiliencies that were not much different from each other. However, other configuration tests indicated that even though there was not much of a difference between the six derivative histogram tests, bands should not necessarily be interchanged due to their narrow specific natures. In addition, two other 4-band configurations were tested. The first test used four bands that imitated the band centers of three well known sensors. Compared to the evaluation standard, over 70% of the cells were correctly classified. As for the second 4-band test, which used bands that performed the best from Becker et al. (2005), the resiliency value was 77%. Both tests indicated that when it comes to classifying vegetation with 4-meter imagery, the band configuration of current sensors do not perform as well as the four band configuration determined by using derivative processing of in-situ data during pre-maturity and late growing season (Becker et al. 2007) (Figure 10).

IV. Discussion

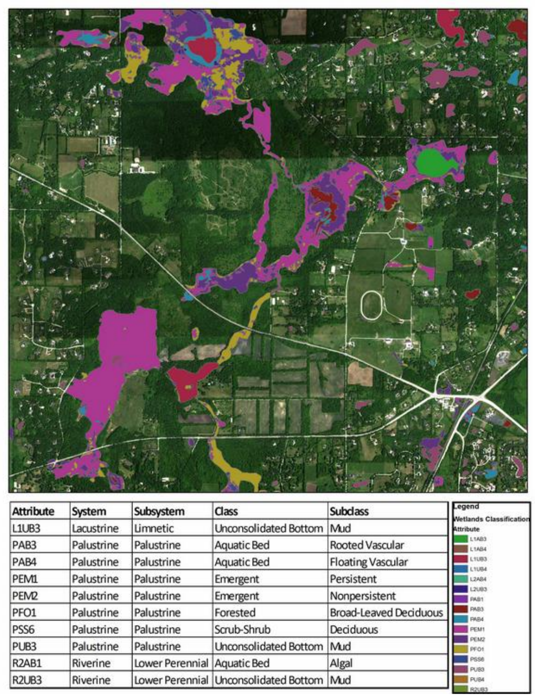
For future uses of hyperspectral imagery, Becker et al. (2007) makes a few recommendations based on their findings. As stated earlier, ITRES (2000) published a report stating that imagery with a spatial resolution of 5-meters or less should be suitable for wetland classifications. Becker et al. (2007) however argues that after the 2-, 4-, and 8-meter tests, not even the 2-meter resolution is reliable enough to make species classifications, due to only a 77% similar comparison. In addition, Becker et al. (2007) suggest using hyperspectral imagery with a spatial resolution of 1-meter or less for in-depth species level analysis. On the other hand, ITRES suggested that resolutions up to 4-meters could be used for areas of study that possess greater homogeneity.

For each of the three band reducing configuration methods, the study indicates whether using a reduced bandset is feasible. The derivative magnitude was determined to be unreliable. This is due to the test result stating that at least 21 bands must be used for classifications, even though other configurations with far fewer bands still produced desirable results. Because of this, Becker et al. (2007) do not suggest using derivative magnitudes as a method for band reduction. As the fixed interval method was heavily influenced by where the starting band was located, suggestions made by the authors state that there is an ideal band configuration and starting location, which would produce optimal classification accuracy. This in turn led the study to suggest that it also is not the best band selection methodology, due to its reliance on starting band locations. The derivative histogram methodology, based on the Becker et al. (2005) paper, which combined both derivative magnitude and frequency of occurrence proved to classify wetland species quite accurately. With the additional band configuration tests applied to it, it became apparent that classification results can be altered by regrouping the species that were not accurately named. Therefore, to reduce errors, it is recommended that more than the seven optimal bands are used for wetlands with greater diversity.

The study highlights that in order to classify wetland species using hyperspectral imagery, the best method of band selection is through derivative histogram. It has the ability to make classifications using the fewest number of bands, while experiencing the least degradation compared to the evaluation standard. In addition, the study also suggests that only imagery with a spatial resolution of 1-meter or better should be used when classifying vegetation at a species level. Using this recommendation will lower the likelihood of spectral radiance interference from neighboring vegetation. Unfortunately, it is pointed out that only airborne imaging systems are capable of producing products with these spatial and (hyper)spectral resolutions, while generating species level identification with high accuracy. One of the most striking points that Becker et al. (2007) concludes with is that current sensors, such as IKONOS and Quickbird, cannot outperform the four band configuration produced by the derivative processing of in-situ data shown in Becker et al. (2005) in mapping Great Lakes coastal wetlands during the pre- and late growing season.

Other studies include similar findings in the use of hyperspectral sensors in wetland mapping. Govender et al. (2007) and Govender et al. (2008) also suggest that seasonal variances in a target’s spectral reflectance and band selection can affect the overall classification accuracy in at least multispectral sensors. By using statistical classification approaches, Govender et al.’s 2008 study found that multispectral imagery can only classify vegetation to the genus level, while hyperspectral imagery is able to classify up to the species level. This concurs with Becker et al. (2007) that for a finer spectral resolution, an optimal and unique set of bands must be determined. In addition, Govender et al. (2008) suggest that future remote sensing technologies should take into account these findings.

An additional hyperspectral study is currently being conducted by the Forest Preserve District, the Department of Geographic Information Systems of the Cook County Bureau of Technology, and the USFWS. Aiming to identify and define the boundaries of each wetland located within the Forest Preserve District property at one meter resolution, the study is using the AISA Eagle hyperspectral sensor, which operates across the visible and near-infrared portion of the electromagnetic spectrum (Galileo Group Inc, 2007; Forest Preserve District of Cook County, 2012) (Figure 11) . In-situ data with known spectral signatures are providing the basis on which the hyperspectral imagery are being compared and classified to (Forest Preserve District of Cook County, 2012) (Figure 11). This wetland mapping and analysis is scheduled to be complete by the end of the summer 2013.



Attribute	System	Subsystem	Class	Subclass
L1UB3	Lacustrine	Limnetic	Unconsolidated Bottom	Mud
PAB3	Palustrine	Palustrine	Aquatic Bed	Rooted Vascular
PAB4	Palustrine	Palustrine	Aquatic Bed	Floating Vascular
PEM1	Palustrine	Palustrine	Emergent	Persistent
PEM2	Palustrine	Palustrine	Emergent	Nonpersistent
PFO1	Palustrine	Palustrine	Forested	Broad-Leaved Deciduous
PSS6	Palustrine	Palustrine	Scrub-Shrub	Deciduous
PUB3	Palustrine	Palustrine	Unconsolidated Bottom	Mud
R2AB1	Riverine	Lower Perennial	Aquatic Bed	Algal
R2UB3	Riverine	Lower Perennial	Unconsolidated Bottom	Mud

Figure 11. An AISA Eagle hyperspectral sensor (left) and example of the product produced by the Forest Preserve District (right).

Ultimately, it is believed that by following these recommendations, the current shortcomings with hyperspectral imagery can be solved. Such issues such as large data volumes and expensive technology may be overcome by using an optimal bandset in accordance with the sensing target, coupled with an optimal spatial resolution, thus reducing the amount of data collected and reducing imagery costs.

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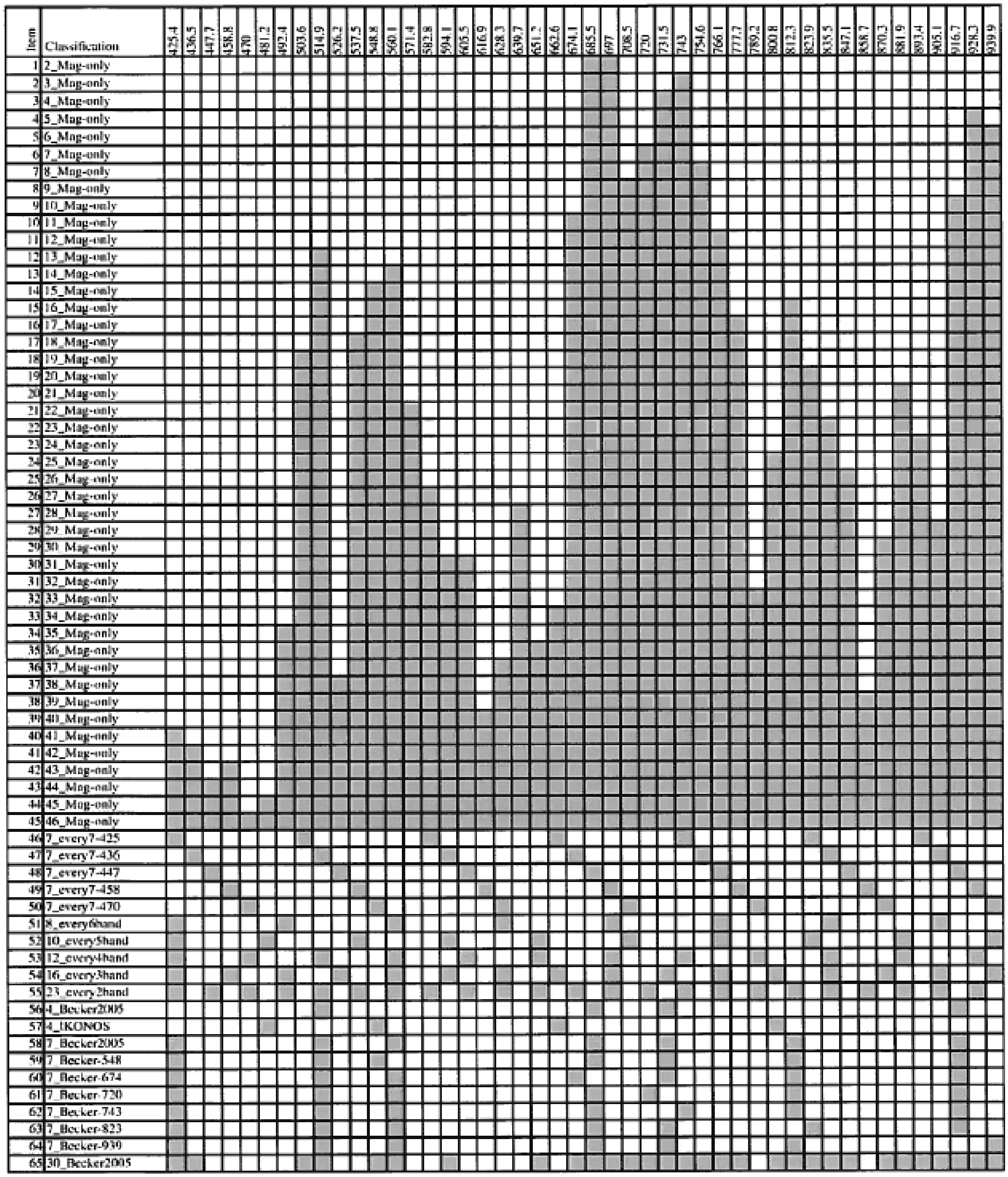

Table 1: Band location for 65 classifications (4-meter imagery); from Becker et al. (2007)

V. The Wisconsin Wetlands Mapping Program

I. History of Wisconsin Wetlands Inventory

The Wisconsin Department of Natural Resources (DNR) set out to create a wetlands inventory for the state in 1977. Aerial photo collection was set to begin in 1978 and the inventory was to be completed by 1983. This was done independently from the USFWS NWI. Although there was concern about bringing the Wisconsin effort together with the NWI, a meeting in 1978 between the Wisconsin DNR and USFWS resulted in Wisconsin continuing with their initial inventory plans. By 1980 the USFWS evaluated the Wisconsin Wetlands Inventory (WWI) and determined it to be better than what was being accomplished for the NWI. The USFWS decided to adopt the WWI as the official wetlands inventory for the state on condition that that the Wisconsin DNR provide the derived products to the USFWS.

This agreement was not finalized, as there were growing concerns within USFWS because the WWI did not exactly follow the Cowardin classification system, used different hydrologic modifiers, did not map deep water habitat and used different numeric coding for vegetative classes. Despite these issues the USFWS entered into a cooperative agreement with Wisconsin DNR in 1982. This agreement outlined that the USFWS would provide $50,000 to the Wisconsin DNR to finish digitizing their wetlands inventory in return for map products and summaries.

II. Original Methods

The original methods of the WWI were developed in the late 1970s when the Wisconsin DNR started to conduct their first inventory. First the Wisconsin DNR commissioned aerial black and white infrared imagery. This imagery was flown at a 1:20,000 scale and it was analyzed by technicians using stereoscopes to delineate the wetland boundaries by hand. For classifying the wetlands Wisconsin DNR mostly used the classification scheme outlined in Cowardin et al. 1977.

The main difference is that Wisconsin does not classify deep water lakes as they believe that these are already well defined in other datasets. These unclassified lakes have a depth greater than six feet and are not manmade waste ponds/lagoons or pits. But within the lakes classification, lakes that are smaller than 20 acres are considered "standing water, palustrine" and designated with an "H" while lakes greater than 20 acres are considered "standing water, lake" and are designated with an "L". Figure 12 shows a flow chart that was used for the original WWI.

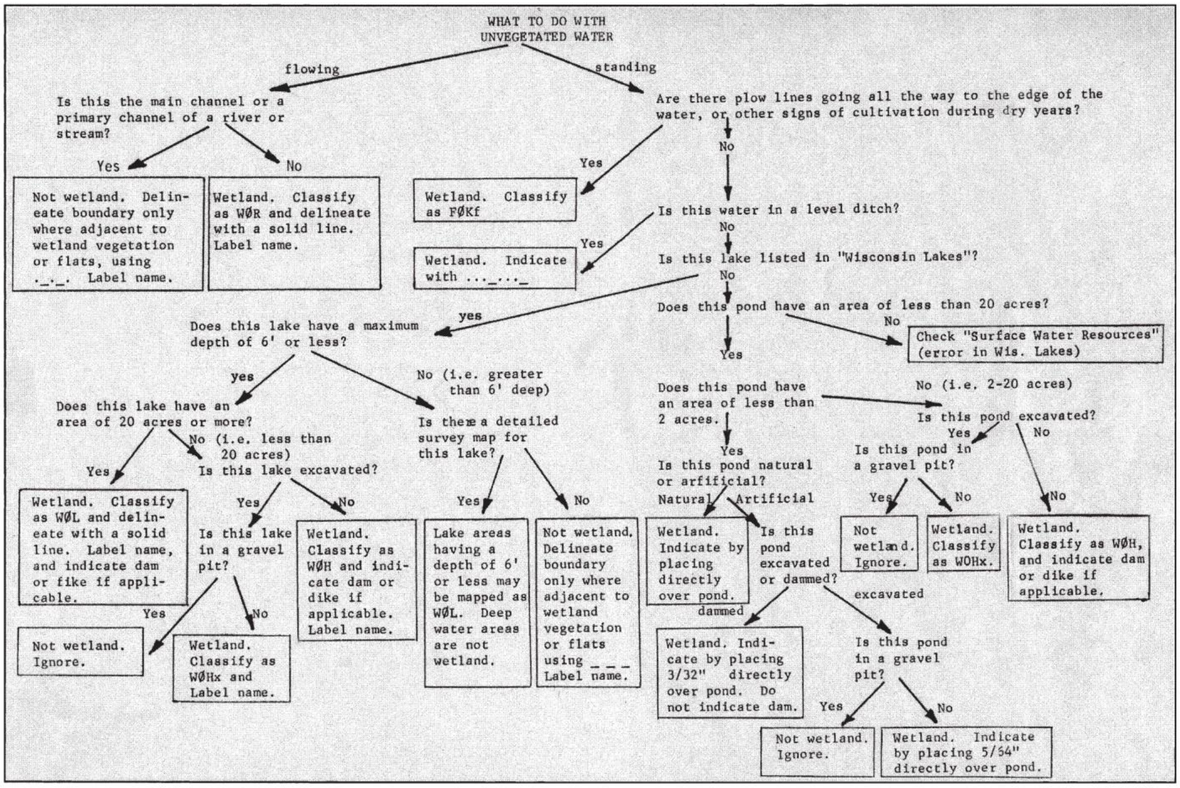

Figure 12. Flow chart for classifying lakes from the initial WWI (Johnston and Meysembourg 2002)

Once the photos were interpreted, the wetland delineations were transferred to either township centered photographic enlargements or orthophotoquads. The orthophotoquads were preferred but were only available for about 15% of Wisconsin (Johnston and Meysembourg 2002) (Figure 13).

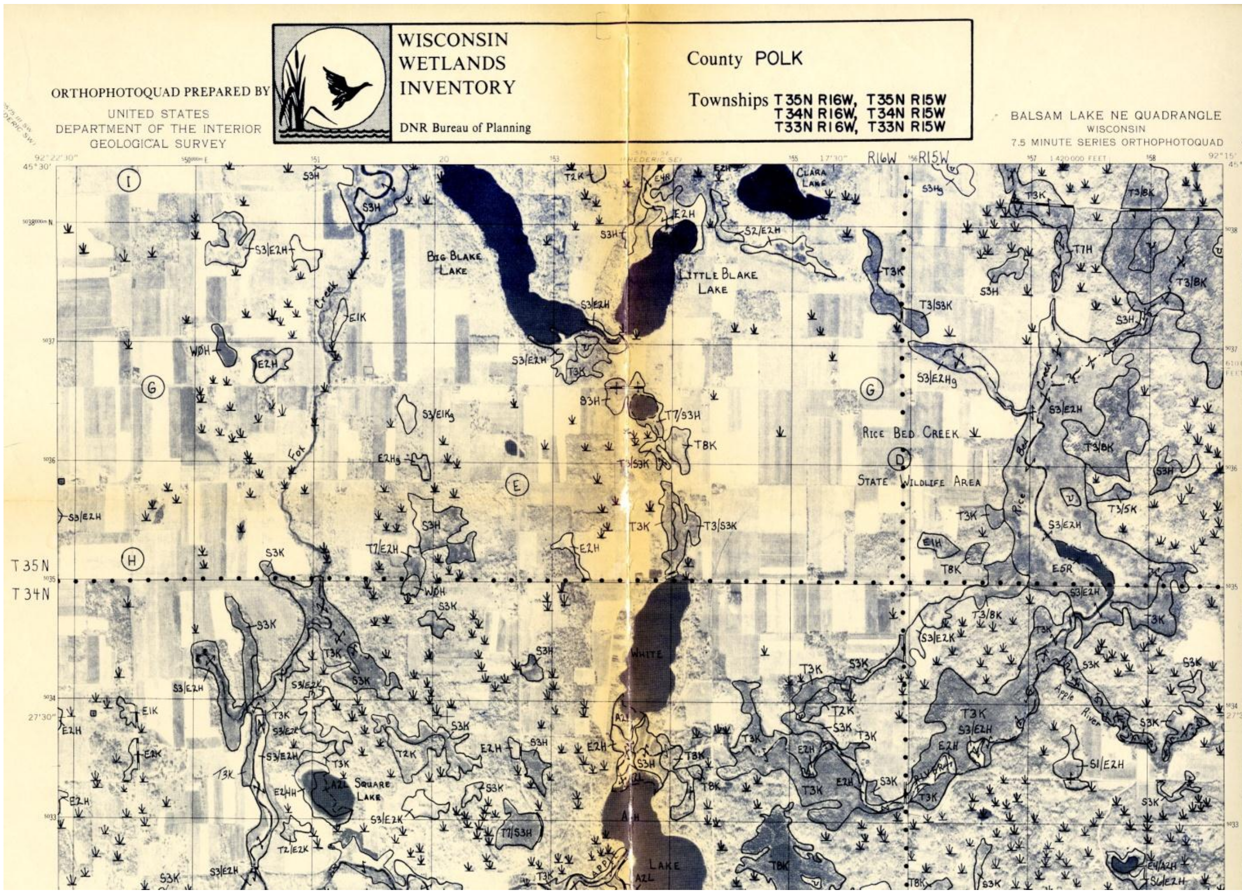

Figure 13. Part of the USGS Balsam Lake NE orthophotoquad showing the first WWI delineated from photos taken in 1978.

III. Differences Between NWI and WWI

The main difference between the two wetland inventories is that while the WWI used black and white infrared aerial imagery flown at 1:20,000 scale, the NWI initially used black and white imagery flown at 1:80,000 scale. This is because NWI used National Aeronautics and Space Administration (NASA) or USGS imagery that was already available while Wisconsin DNR commissioned to have their own imagery flown. This photo scale difference did not affect the minimum mapping unit for wetlands, though. The WWI has a smaller minimum mapping area of only 2 acres or 5 acres depending on the county, while the NWI is 3 acres. WWI mapped smaller wetlands with symbol designations, instead of outlining their shapes. Also since NWI used the Cowardin system and WWI used a variation of that system, there are differences in classification. As pointed out earlier, WWI does not map deep water lakes and used different modifiers for the same wetland system (Figure 14).

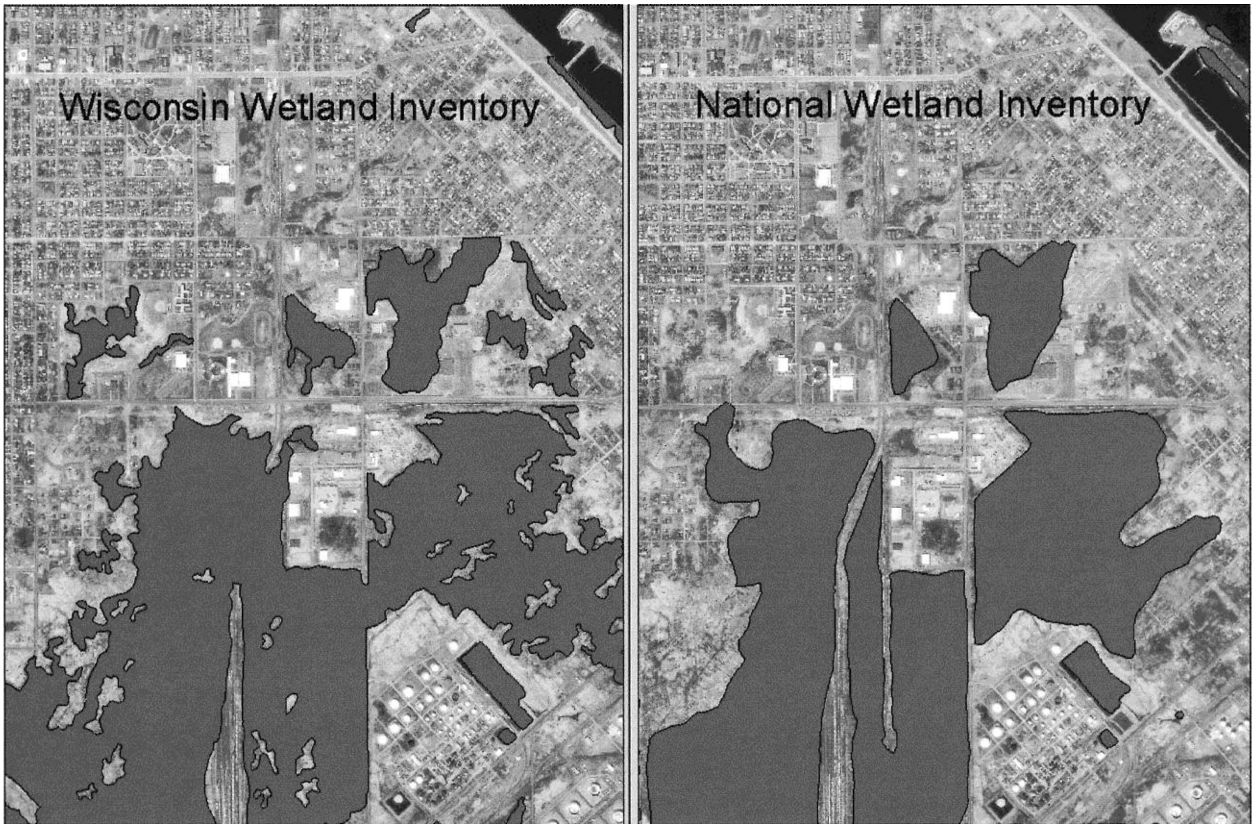

Figure 14. Comparison of the WWI and NWI for a section of Superior USGS quadrangle. The shaded areas depict areas classified as palustrine (Johnston and Meysembourg 2002)

IV. Current Methods

Lois Simon, who is the Wetlands Inventory Coordinator for the WWI, was contacted on December 17, 2012 to confirm their current wetland mapping methods. From that conversation it was confirmed that Wisconsin DNR uses color infrared photography that is flown over three counties per year. Wetlands are then delineated using stereoscopes and then transferred to orthophotoquads. The final product is then given to Saint Mary's University to digitize the boundaries. The WWI classification system has also been merged with the Cowardin system used in the NWI. Once digitized, the WWI is displayed online at the Wisconsin DNR's surface water data viewer and is also converted to the Cowardin system and sent to be made available on the NWI website. Figure 15 shows the status of inventory production based on county.

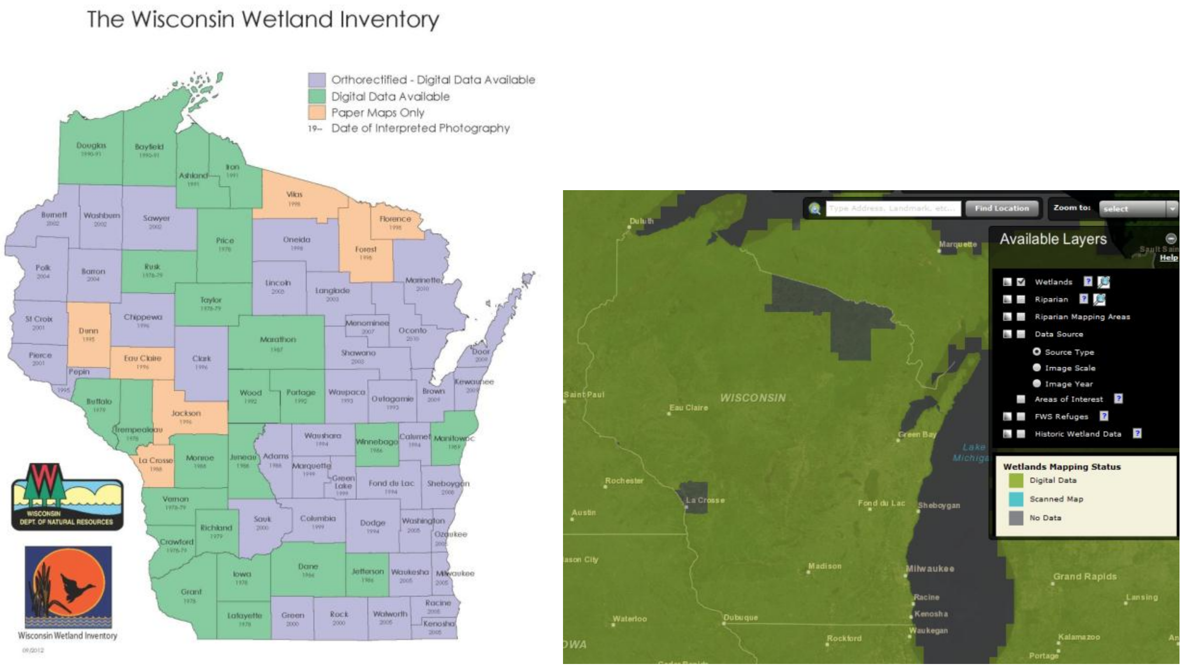

Figure 15. Wetland Inventory availability for Wisconsin in 2012 (Wisconsin DNR) (left) and NWI (National Wetlands Inventory Wetlands Mapper) (right).

Currently, the Wisconsin DNR is working on making the wetland updating process faster. They are working with local communities so that if wetland boundaries are changed, they are documented and sent to the DNR to update the inventory. This has mainly been true for when development has been done along a lake or river and a wetland is modified. This system is currently being expanded to include changes made to all wetland areas.

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VI. Electro-Optical Radar Fusion Methods

I. Introduction

Efforts are currently underway by the MTRI to map wetlands and adjacent land use for the entire coastal Great Lakes basin (an area of approximately 92,000 km^2 from the coast inland 10 km) with contemporary (2007 - 2011) satellite imagery of moderate resolution (10 – 30 m) from multiple sources following the recommended approach of the Great Lakes Coastal Wetlands Consortium (Bourgeau-Chavez 2008). This will be the first map of its type to include both the U.S. and the Canadian sides of the Great lakes. A hybrid classification of Anderson Level 1 classification in uplands and NWI class level classification in wetlands was developed to advance understanding of not only wetland habitats, but also surrounding uplands' influence on wetland ecosystems. The classification relies heavily on ground truth training data used as inputs into a random forests classifier.

II. Study Area

The study area consists of approximately 92,000 km^2 of vast, diverse cover types that introduce unique challenges to any type of land cover map. The Northern most wetlands of Lake Superior offer dense black spruce swamps as well as expansive peatlands, while the southernmost emergent wetlands of lakes Erie and Ontario are dominated by cattails and invasive *Phragmites*. The basin was divided by lake initially then broken up into areas of interest (AOIs) based on available imagery footprints. Processing began in Lake St. Clair and moved upwards across the basin.

III. Field Component

In spring of 2010, a large field campaign was initiated to collect information on wetland type and dominant cover at randomly selected locations within coastal emergent wetlands in the U.S. coastal Great Lakes basin. To match the minimum mapping unit (mmu) of the map product (0.2 ha; 0.5 acre), all sites were sampled in 0.2 ha increments. Both training data and validation data were collected from May to October of 2010 and 2011. This campaign has been continued to include the Canadian side of the basin through the summer of 2012 and will continue for one more field season. The most recent field campaign as well as future field campaigns will employ handheld Algiz rugged tablets for viewing georeferenced imagery in the field with GPS positional accuracy. This allows for delineation of areas directly observed in the field to be used as training data later. The original field campaign included 1158 field points across the U.S. side of the Great Lakes Basin. Data collected included GPS point, GPS photographs, water level, cover type, plant species, and hand drawn maps of the sample area. The latest field campaign was conducted by Michigan Natural Features Inventory and focused on Canadian wetlands. The additional 148 Canadian points allow for more accurate training and therefore more accurate results.

IV. Methods

a. Imagery

RandomForests software requires raster images, in our case a fusion of electro-optical (EO) and PALSAR images, as well as vector input data to create decision trees and ultimately classify the multiple images into one multisource land cover map.   Due to the variable image types employed in the random forests classification, pre-classification processing steps were dependent upon the type of imagery being prepared for classification. Cloud-free Landsat 5 EO data was downloaded from Earth Explorer and processed to top of the atmosphere reflectance (TOA). TOA is used to normalize values across multiple date input images and allows for easier change detection in areas with high seasonal variability. Normalized Difference Vegetation Index (NDVI) and temperature were also calculated from Landsat imagery by season and added as input layers for the classifier. Areas where cloud-free images could not be found were composited using multiple images to create a cloud-free image. Three season, fine beam dual (FBD) band, 20m resolution Advanced Land Observing Satellite (ALOS) PALSAR images were downloaded from the ASF and processed through MapReady for radiometric calibration. 10m resolution, publicly available DEMs were also downloaded and used for terrain correction. Once all layers have been pre-processed they are stacked in ENVI and clipped to their common boundary and assigned AOI names. AOIs are typically restricted in size to a 70km X 70km area due to the footprint of the smallest band in the stack (70km X 70km size of PALSAR images being used which have dramatically smaller footprints then Landsat images).

b. Classification Scheme

A hybrid classification scheme was developed by combining classes from multiple historical classifications, and where applicable classifying further. Anderson level 1 classes such as forest land, urban land, and barren land are broken down into more precise classes such as shrub, pine plantation, urban grass, urban road, light barren and dark barren. The hybrid classification also retains the top level Anderson class (i.e. Forest, urban) for areas that are too ecologically complex or simply out of the range of the sensors being used to be classified into the refined classes. Wetland classes were derived from the NWI's Wetlands and Deepwater Habitats Classification scheme. From there, top level classes were retained as they were broken down into more precise classes and in three cases (*Typha*, *Phragmites*, and *Schoenoplectus*) the hybrid classification scheme reached the species level (Figure 16).

Figure 16. Classes and species levels used in the classification of coastal wetlands surrounding the Great Lakes

c. Training Data

Vector Training data depicting positive identification of each class are created in house by trained Image interpreters that all have had field experience in the various class types. Their knowledge in conjunction with the extensive field data have proven more than effective at accurately identifying the diverse classes used in the classification. Multiple image interpreters meticulously analyze and draw shapes for each AOI from which some of the pixels are retained for validation at a later time. RandomForests ingests the vector training data as well as the large clipped imagery stack and creates a classified image to the best of its statistical ability (Figures 17 and 18).

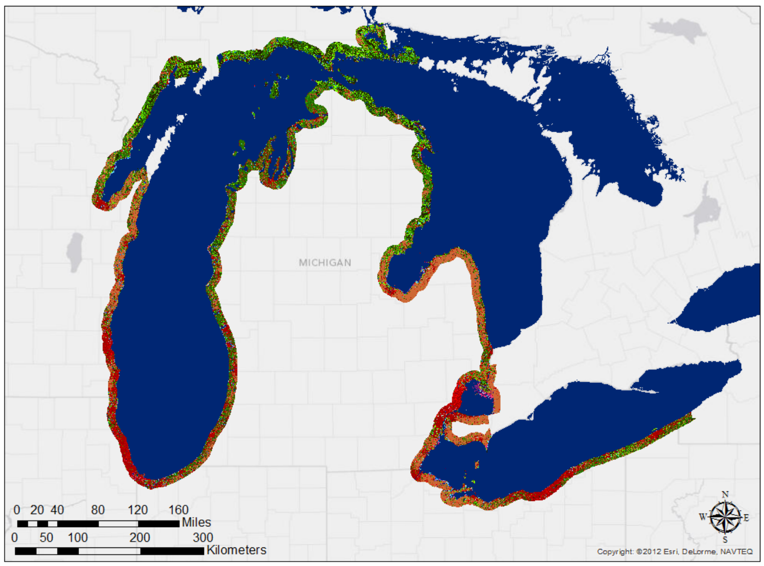

Figure 17. Land cover classification based on RandomForest analysis

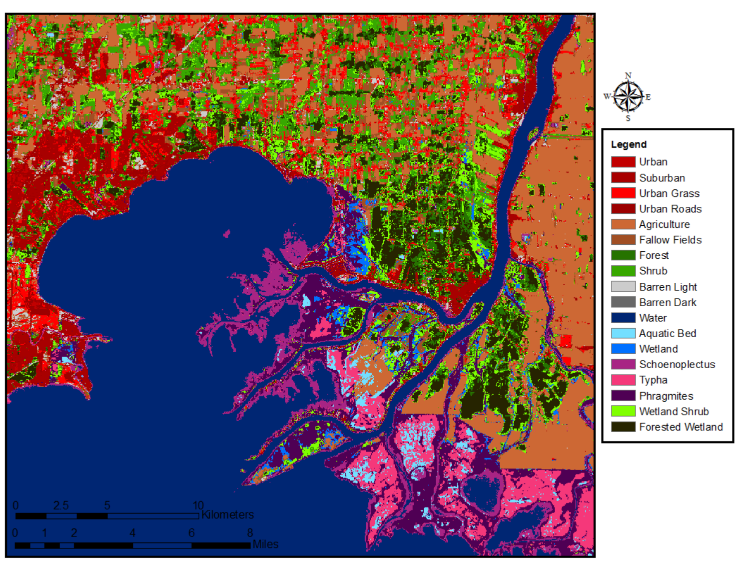

Figure 18. Land cover classification around northern Lake St. Clair

V. Results

Initial classification began on the US side of Lake Huron and is currently ongoing across the basin. Initial results have shown that due to the extreme biodiversity within the Great Lakes Basin many of the original 24 classes must be broken down further to prevent confusion with other classes.   Work is expected to be completed in 2014.

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VII. USGS Potential Wetlands Index Program

I. Introduction

The USGS and Multi-Resolution Land Characteristics Consortium (MRLC) are compiling comprehensive, up-to-date, and publically available information on the Nation's land cover for the National Land Cover Database (NLCD) 2011 data set. This soon to be released land cover product is slated to be available December 2013 and will include updates to the NLCD 2006 product (Fry et al., 2011). One of the many improvements includes a more in-depth analysis of wetlands. NCLD 2011 analyses will include the delineation of wetland classes through the combination of multiple data sets and the Potential Wetland Index (PWI) layer (Fry et al., 2011; MRLC, 2011).

The PWI will highlight areas that were previously wetlands which were removed, but have the potential to be restored to its original state (Ducks Unlimited, 2005). Wetlands are defined by their hydrology (dominant factor), undrained hydric soils, and hydrophytes (MRCL, 2011). Therefore, for the NLCD 2011, potential wetlands are determined by studying the relationship between three different data sets, the NWI, SSURGO database, and NLCD.

II. National Wetland Inventory

The NWI, established by the USFWS in 1974, is a nationwide database that provides information about wetland distribution and type. When the NWI was originally mapped, wetlands were delineated with relative high accuracy (MRLC, 2011). Errors were attributed to wetland conversions into other land types and/or one time aerial photography of land that was later converted into a wetland after the NWI data was collected (MRLC, 2011). Currently, the NWI is a mosaic of the best available data based on *Classification of Wetlands and Deepwater Habitats in the United States* (Cowardin et al., 1979), often referred to as the Cowardin Classification System. In addition, wetlands were originally mapped at small scales (1:125,000) and were manually digitized. Now-a-days, mapping takes place at larger scales (1:24,000) and are digitally digitized in geographic information systems (U.S. Fish and Wildlife Service, 2013 http://www.fws.gov/wetlands/NWI/Overview.html) (Figure 19).

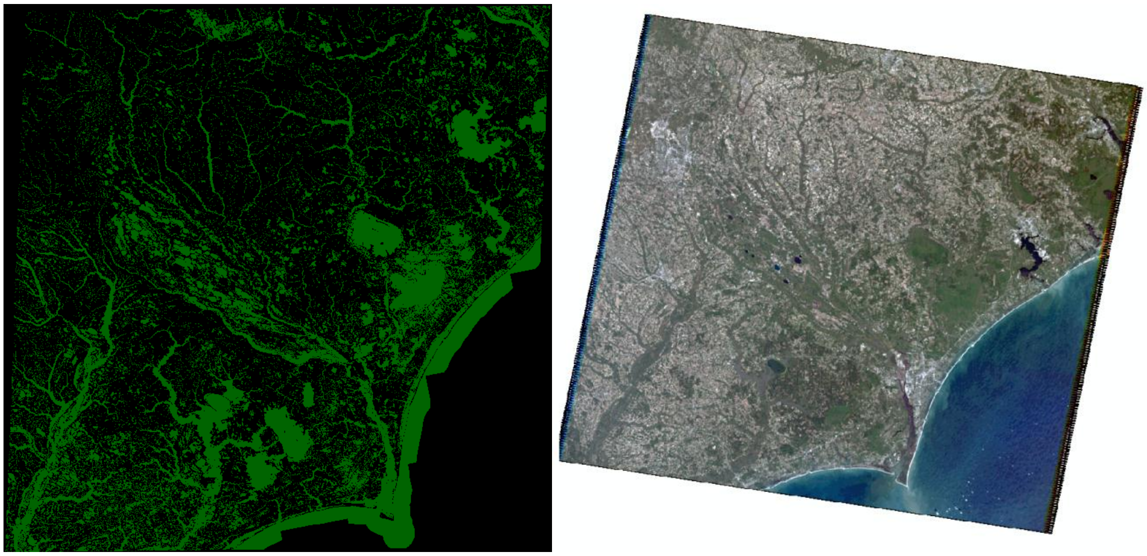

Figure 19. A) Wetland locations as indicated by the NWI. B) Area of study is within Landsat p15r36 (image from November 6, 2010), located over coastal North Carolina. NWI image provided by Limin Yang, USGS.

In order to identify potential wetlands, the NWI often serves as the starting point as it contains applicable data concerning wetland restorations. Specifically, it contains information relating to wetland filling, drainage and other modifications (U.S. Fish and Wildlife Service, 2013). While the NWI highlights previous wetland locations, it does not indicate if a historic wetland contains potential/restorable qualities and therefore cannot be the sole determining factor.

III. Soils-SSURGO

Hydric soils are defined as being sufficiently wet in the upper section and able to develop anaerobic conditions during the growing season (Natural Resource Conservation Service, http://soils.usda.gov/use/hydric/ntchs/tech_notes/note1.html). Such soils can often be identifiers of wetlands that are prominent in those areas due to their poorly drained and often flooded conditions (MRLC, 2011) (Figure 20). The presence of a poorly drained soil is the best indicator of a potential wetland landscape (Galbraith et al., undated).

As was the case with the NWI, selection of potential wetlands cannot solely be based on SSURGO data. Final decisions should be based on combinations of additional data that indicate former hydrological conditions, such as the previous presence of hydrophytes. Potential wetlands are more probable if a section of land contains hydric soil, previous indications of wetland-type vegetation, and lacks current NWI classification (Galbraith et al. undated). Older versions of the NLCD are used for determining previous vegetation types.

Figure 20. Wetland locations based on the hydric soil indicators. Image provided by Limin Yang, USGS.

IV. National Land Cover Database

Acting as the Landsat-based 30-meter resolution nationwide land cover database, the NLCD provides spatial and descriptive information of land surface characteristics (Figure 21). Initially, land cover products were to be released on a 10-year basis but with the release of NLCD 2006, the production cycle changed to five years to coordinate efforts with the Coastal Change Analysis Program (C-CAP) mapping program from the National Oceanic and Space Administration (NOAA). The C-CAP products are more detailed in the 'woody wetland' land cover category than the MRLC, but it is still at Landsat resolution. Three previous NLCD versions have been released (NLCD 1992, 2001, and 2006) with the next version scheduled for release in 2013 (NLCD 2011) (Homer et al., 2012). The latest version has been revised to include improved results for spectral change analysis and land cover classifications (Fry et al. 2011).

Some of the changes include using two, multi-temporal Landsat scene pairs to reduce error within change analysis, and using additional cultivated cropland information from the U.S. Department of Agriculture (USDA) National Agricultural Statistical Service (NASS) improving class distinctions. In addition, to improve wetland delineations the NLCD is combining with NWI and SSURGO data (Fry et al., 2011). This data set will serve as the basis for the PWI layer for the NLCD 2011.

Figure 21. Wetland locations based on NLCD (dark and light blue polygons). Image provided by Limin Yang, USGS.

V. Potential Wetland Index

The PWI was created by the MRLC to determine a ranking system for areas deemed to have wetland qualities by the three datasets mentioned above (Table 3). The scale ranges in values from two to eight. Areas of land in which the NWI, SSURGO, and NLCD indicate as having wetland qualities are highest ranked (rank 8) as potential wetlands. Conversely, areas in which only one dataset indicates wetland qualities are lowest ranked (ranks 2-4) and have the lowest potential of being a wetland. Intermediate rankings (ranks 5-7) are for those areas that are indicated as wetlands by two of three datasets (Figure 22).

Table 3. MRLC ranking system of potential wetlands.

Wetland Data Indicators	Ranking
Soils & NWI & NLCD	8
NWI & NLCD	7
Soil & NLCD	6
Soil & NWI	5
NLCD	4
NWI	3
Soil	2

While all three datasets must show indication of wetland qualities to have the highest potentiality, there are different weights between each dataset. Based on the PWI, the hydric soils layer provided by SSURGO is deemed to have the smallest amount of weight. This is evident when potential wetlands are only indicated by SSURGO data (rank 2). Additionally when SSURGO is paired with one of the other datasets, the pair receives the lowest of the intermediate rankings (ranks 5 and 6). On the other hand, the dataset with the greatest weight is the NLCD. When it is the only dataset to indicate a potential wetland it is given the highest of the lowest ranking (rank 4). As it is combined with an additional dataset, the pair is ranked with the two highest intermediate ranks (rank 6 and 7).

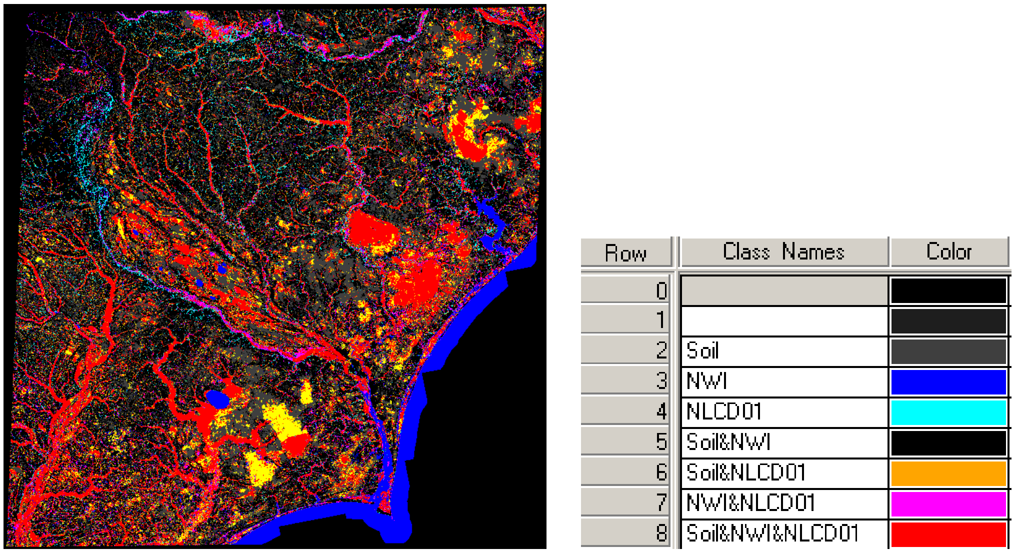

Figure 22. Potential wetland locations based on rankings. Image provided by Limin Yang, USGS.

VI. Additional Potential Wetland Research

Ducks Unlimited, Inc.

Ducks Unlimited, Inc.'s (DU) "Development of a Potential Wetland Restoration Layer for Research and Planning in the Great Lakes" details additional research, which created products similar to the PWI. DU developed the Great Lakes Potential Wetlands layer, which can identify areas that could potentially be restored as wetlands in the Great Lakes region (Ducks Unlimited, 2005). By using near and mid infrared bands from Landsat Enhanced Thematic Mapper satellite imagery, a soil moisture index (SMI) was created by measuring bare-earth surface moisture. This index ranked moisture into five classes ranging from very wet to very dry. The two wettest classes (very wet and wet) were used for further analysis. These efforts also inspired the work of Brooks et al. (2010) for a Wetlands Mitigation Site Suitability Index (WMSSI) created for the Michigan Department of Transportation.

In order to validate the results, the SMI was compared to SSURGO hydric soil data. There are many differences between the two data sets. For example, SSURGO identifies all hydric soils without consideration of environmental or human induced affects. Whereas the SMI will not identify drained areas and also detect wetlands where there are no hydric soils, possibly due to recent rain events.

Results from the SMI indicate that approximately 12.6 million acres of approximately 158.6 million acres, or about 8% of the study area falls within the "very wet" and "wet" classes and, are included within the potential wetland restoration layer (Figure 23). In addition, when compared to SSURGO data the overall agreement was 60%. However, the agreement was higher between the "dry" and "very dry" classes and SSURGO valued at 70%. This was determined to be due to the fact that it is easier to distinguish between dry (SMI) and non-hydric soils (SSURGO).

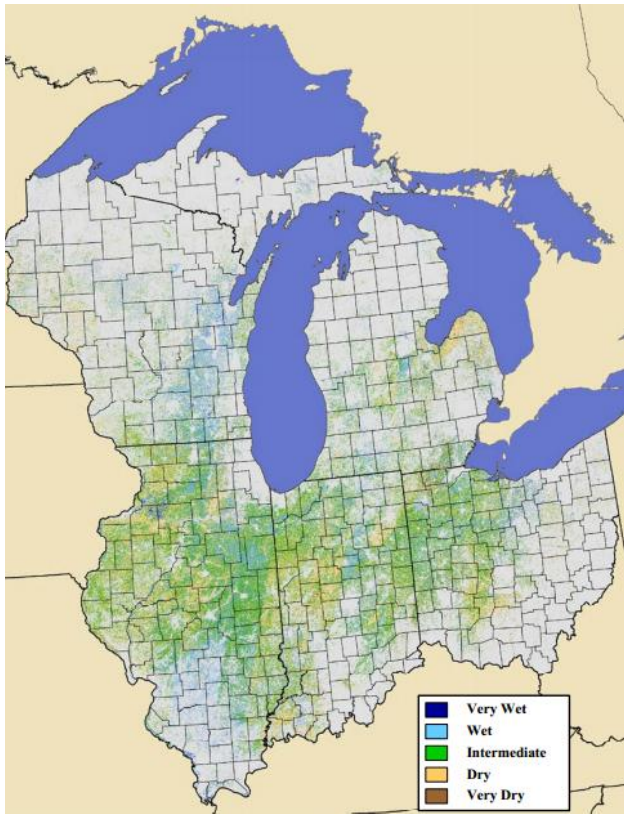

Figure 23. Results of the SMI in the Great Lakes region.

VII. Recommendations

With the addition of the PWI in the NLCD 2011, MRLC has recommended that multi-temporal Landsat imagery and the USDA's NASS be included in the analysis. This will assist in reducing error in spectral change analysis, which is caused by seasonally variable classes. In addition, it will also improve land cover classifications (Fry et al., 2011; MRLC, 2011). For inland water mapping, a more in-depth analysis will need to include regional differences in landscapes, wetland types, and land use/land cover changes that occur in wetland areas (MRLC, 2011).

There are supplementary data sets that may also aid in determining where potential wetlands can be classified. Such data sets include radar, elevation, and historic land cover. Radar data (e.g. PALSAR) can be used to detect forested wetlands. Specifically, longer wavelength L-band radar should be used as it is more advantageous for mapping forested and high biomass herbaceous wetlands than C-band or X-band (Bourgeau-Chavez et al. 2008). Elevation data (topographical wetness indices, DEMs, and LiDAR) could also prove useful for the PWI as each examine surface topography and/or potential effects on the spatial distribution of soil moisture, which often follows the surface topography. Lastly, historic land cover and existing farmed wetlands data could provide information concerning previously existing hydrophytes and wetlands within a specific location. Historic wetland data can be found in the Wetland Mapper, provided by the USFWS (http://www.fws.gov/wetlands/Wetlands-Mapper.html).

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