

### **3 Policy Implications of Remote Sensing in Understanding Urban Environments: Developing a Wetlands Inventory for Community Decision-Making in Lucas County, Ohio**

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The growth in urbanized land has created a variety of impacts to natural areas. Urbanization has many effects on a wetland in terms of climate, air and water quality, hydrological changes, and boundaries and fragmentation of flora and fauna (Ehrenfeld, 2000). Wetlands must be valued as they provide many public amenities with long-term functions, which may be unrecoverable if the wetlands are lost through development, including drainage, water supply and natural habitat provisions (Mitsch et al, 2000). Because public policy supported the filling and destruction of wetlands for so long, land use planners are often reluctant or uninformed on how to integrate them into urban environments (Tilton, 1995).

The use of remote sensing technology for the identification, inventory, mapping, and classification of land wetlands has been a common application of satellite imagery (MacDonald, 1999; Lyon, 2001). Numerous studies have discussed the positive benefits and opportunities presented by the technology as well as the barriers and limitations (Hardisky et al, 1986; Johnston and Barson, 1993; Kindscher et al., 1998; Lunetta and Barlogh, 1999; Munyati, 1999; Schmidt and Skidmore, 2003, Shuman and Ambrose, 2003, Townsend and Walsh, 2001). With recent improvements in the methods, computing advances, and the easier access and availability of the satellite imagery and data, it has become more possible to consider further advancements in the use of remote sensing to specifically address issues associated with wetlands research and related policy implications. The results of such research have important applications in addressing wetland management issues – such as wetland loss, degradation, and potential for restoration and remediation – within urban centers where land use pressures have negative impacts on the existence and health of wetland ecosystems. For a comprehensive review of the issues regarding the use of satellite remote sensing for wetlands, the reader is referred to Ozesmi and Bauer (2002).

Beyond the methodological and technological advances – and remaining limitations – related to the use of remote sensing for wetlands inventories there are several other practical related issues in regards to how the results from such studies can be applied to address the management and decision-making at the community scale in urban areas. In addition to overcoming common barriers characteristic to the transfer of advanced computer technology - such as needs for software training, access to data sets, the availability of sufficient computer hardware requirements, and related cost issues – the use of remote sensing requires consideration of several other additional remaining issues. The application and transfer of remote sensing methods and technology for urban planning requires understanding of the complexity of wetland definitions and related management issues, acceptance of the level of accuracy obtained by the remote sensing technology, commitment for the support and funding necessary to continue and maintain inventories, databases, and for future updating of the wetland classification. The technical, educational, and decision-making issues regarding the development and utilization of remote sensing for a wetlands inventory for use in urban planning and decision-making will be examined in this paper.

### **3.1 Wetlands**

The U.S. Army Corps of Engineers and the U.S. Environmental Protection Agency define wetlands as those areas that are inundated or saturated by surface or groundwater at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions. Wetlands exhibit an incredible array of ecological benefits including holding storm water, allowing gradual recharge of groundwater, providing critical habitat for plants, fish and wildlife, controlling erosion, mitigating water pollution, providing food and recreational bases for people, and contributing to a healthy water cycle and lake levels (Tiner, 1999).

In the last 200 years over 90% of Ohio's wetlands have been destroyed due to installation of an extensive network of drainage ditches, filling for recreational, urban and rural uses, lowering of the groundwater table, pollution, and invasion by exotic species (Ohio Department of Natural Resources, 2003). The serious impact of wetland loss is felt across the U.S. and resulted in legislative protection under the Clean Water Act and a goal of "no net loss" of existing wetlands. Yet it is difficult to prevent the loss of wetlands since there is no accurate and up-to-date record of their location—especially on private lands where most loss takes place. Outdated and inaccurate maps from the National Wetland Inventory and a 1989 Ohio wetland inventory exist, but provide minimal useful information regarding the current location, type, and inventory of existing wetlands.

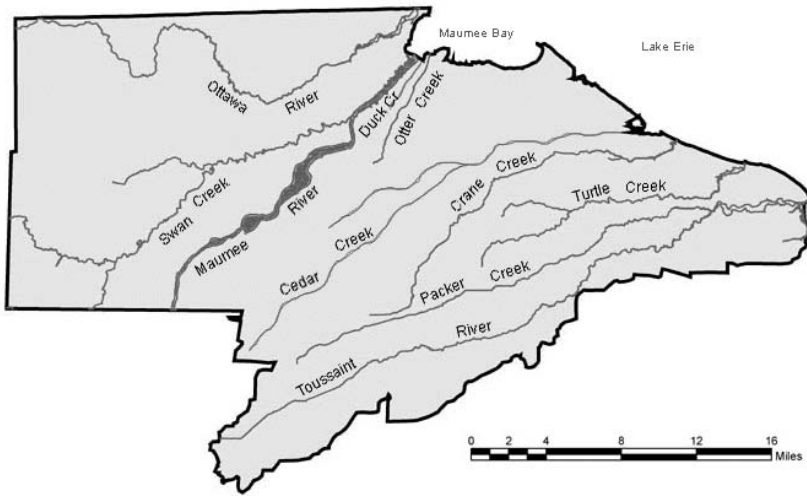
The Ohio Wetland Inventory shows areas of shallow marsh (emergent vegetation in water three feet or less), scrub shrub wetland (emergent woody vegetation three

feet or less), forested wetland (mature woods with hydric soils), wet meadow (wet grass areas in water less than six inches on hydric soils) and farmed wetland (wet meadow in agriculture areas on hydric soils). The Ohio Wetlands Inventory is based on analysis of satellite data and is intended solely as an indicator of wetland sites for which field review should be conducted (Yi et al., 1994). The satellite data reflect conditions during the specific year and season the data was acquired, therefore all wetlands present in an area may not be indicated. Statistics generated from the inventory are intended solely as an approximation. The wetlands inventory for the State of Ohio was produced by the digital image processing of Landsat Thematic Mapper Data. The Thematic Mapper is a multi-spectral scanner that collects electromagnetic radiation reflected from the earth's surface in the visible, near infrared and mid infrared wavelength bands. The resolution of the Thematic Mapper data is a 30 meter by 30 meter cell (Schaal, 1995).

### 3.2 Study Area

Improved information on wetlands in the Lower Maumee River watershed within Lucas County, Ohio is needed to help stop the loss of existing wetlands in this region. Urbanization continues to expand causing alteration of natural waterways, increased water pollution, and destruction of wildlife habitat. Wetland mitigation funding generated from building projects in the Maumee River watershed has been used to protect wetlands in other areas outside the watershed. Wetlands within the Maumee River watershed that function to reduce runoff, minimize flooding, filter pollutants, control erosion and sedimentation, and provide wildlife habitat are disappearing. This loss of wetlands not only affects the urban area economically, it affects the quality of life and environmental health within this region.

The Maumee River begins in Ft. Wayne, Indiana, and travels more than 130 river miles, 105 miles of which are located in Ohio. The boundaries of the Maumee Area of Concern (AOC) were initially defined as the area from the Bowling Green water intake (River Mile 22.8) downstream to Maumee Bay and Lake Erie, including Duck Creek, Otter Creek, Cedar Creek, Grassy Creek, Crane Creek, Swan Creek and the Ottawa River (Figure 1). In 1992, the AOC was expanded to include Packer Creek, Turtle Creek, Rusha Creek and the Toussaint River. The drainage area for the AOC covers all of Lucas County and parts of Wood, Ottawa and Sandusky counties. The Maumee has the largest drainage area of any river in the Great Lakes with 3,942 stream miles draining into the Maumee River (Maumee RAP, 1997). The Maumee Remedial Action Plan (RAP) is striving for abundant open space and a high quality natural environment; adequate floodwater storage capacities and flourishing wildlife; citizens who take local ownership in their resources, and rivers, streams, and lakes that are clean, clear, and safe for recreational use.



**Fig. 1.** Maumee Area of Concern

The Open Space and Wetlands Action Group of the Maumee RAP has been developing a revised wetlands classification and inventory for the Lower Maumee watershed in Lucas County, Ohio through a grant from the Ohio Environmental Protection Agency, the Maumee River Watershed Wetlands Protection and Enhancement Planning Project. The issues the project addresses include:

It identifies and evaluates existing wetlands and potential mitigation sites in the watershed.

It provides information to local planners, government officials, environmental consultants, and conservation agencies about local wetland locations, quality, and importance.

It creates an up-to-date, accessible GIS-based map of wetlands and potential wetlands in the Lower Maumee River watershed.

It identifies watershed restoration needs and action strategies.

It provides for advisory and implementation groups to facilitate the success of the project.

The ultimate goal of this wetlands planning and mapping project is to protect existing wetlands, increase the number of wetland enhancement projects, and reduce non-point source pollution in the lower Maumee River watershed.

The project was undertaken through cooperation between the RAP members and local university researchers and volunteers to develop and field test a protocol for producing an accurate wetland GIS map. Once produced and verified, this map will be made available to AOC planners, consultants, and elected officials to aid in their efforts to protect and plan around existing wetlands. It is also proposed to identify potential wetland mitigation sites to increase these important habitat types in the AOC.

The project objectives are:

Complete development of Wetlands Classification and Inventory Mapping by use of ERDAS Knowledge Engineer and integrate into GIS model product.

Organize and host a set of Professional Training Workshops to display mapping products and facilitate feedback and discussions in regards to the accuracy and utility of the wetlands classification inventory methods and results.

Convert all the mapping products and related wetlands information into a web based format by use of Arc IMS to be hosted by the UT GISAG lab.

Present the project results to related Maumee RAP groups and community organizations and partners.

Under this project, current Landsat satellite imagery from the OhioView Remote Sensing Consortium was utilized within ERDAS Imagine software to inventory wetlands in the AOC identifying the main wetland classes and their distribution. The product of the project is intended to be a map of existing wetlands that would identify potential high quality wetland sites to be utilized by local planning authorities, cities, townships and conservation agencies involved with wetland preservation and mitigation. The protocol would then be able to be re-applied to subsequent Landsat images in future years to allow for the continued evaluation of wetland areas. A series of workshops and education outreach programs were to be implemented to highlight the wetlands map and increase awareness of wetland issues.

### **3.3 Background**

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

vegetation, hydric soil and wetland hydrology) (Levine and Roten, 2001). The researchers first gathered SSURGO-based soils information and USGS digital elevation models, as well as orthophotos, surface hydrology maps (streams and ponds), Current Agricultural Use Value (CAUV) parcel data to locate cultivated land and general parcel and road information from the Lucas County Auditor's Office (AREIS). Levine and Roten created a mosaic from several Landsat 7 images: Band 8 from the Panchromatic, Band 6a and 6b from the Thermal image, and all other bands (1-5 and 7) from the Multispectral image. They did this for four dates representing the major seasons within 1999/2000: November 1999, March 2000, July 2000 and September 2000.

Unsupervised classifications of the Full Year, Panchromatic and Thermal images resulted in general classifications. Knowledge Engineer and supervised classification further refined the protocol to identify five varieties of wetlands in the AOC: coastal, prairie, riverine, forested wetlands, as well as open water habitat (Levine and Roten, 2001). Field verification of the resulting wetland map showed that there was a high degree of error: particularly in identifying wooded, prairie and riverine wetlands. In addition, farm fields and commercial rooftops were identified as open water habitat.

At this point, an undergraduate student, Sarah Fuller, was supported by an NSF Research Experience for Undergraduates (REU) at the University of Toledo's Lake Erie Center helped to refine mapping of prairie wetlands by identifying known wetlands at Kitty Todd and Irwin Prairie. Imagery was obtained for time periods covering each of the four main seasons in order to examine temporal changes in wetland conditions that could be determined by analysis of the Landsat 7 data. It was found that imagery from March had the most potential for identifying prairie wetlands due to wetter soil conditions and vegetation cover types. Within ERDAS a classifying module/knowledge engineer was used to specify prairie wetlands as a single classification. Key factors contributing to the application of remote sensing imagery for wetland classification included knowledge of the area of study, application of the ERDAS Knowledge Engineer, and the use of a GPS unit for proper wetland delineation. Although this was an improvement over the past wetland maps, there were still large areas associated with this classification.

Two of the Maumee RAP Open Space and Wetland Action Group project leaders, Michelle Grigore from the Natural Area Stewardship and Matthew Horvat from the Toledo Metropolitan Area Council of Governments (TMACOG), took a remote sensing class from the University of Toledo in hopes to gain enough remote sensing knowledge to improve the wetlands classification. They used the newly available spring and summer 2001 images and eliminated slope from the identification process (which tended to result in overly conservative estimates of wooded wetland), increase the buffer along the stream maps to better identify riverine wetlands, corrected an error in the formula for identifying open water habitat to re-

move wet fields from the finished map, and used supervised classification for wet prairie and emergent wetlands (Lawrence et al., 2003). The accuracy of the unsupervised classification was improved upon by utilizing 75 classes and 10 iterations (congruence = .949) rather than the ten class method from Levine and Roten (2001).

The next steps were to create prairie, shrub/scrub and emergent wetland signature files to use in Supervised classification of the 2001 spring and summer images. CAUV parcels were also identified and spring/winter images used to remove agricultural fields from the wooded wetland category. Knowledge Engineer allowed for the seaming of all wetland images together into a final map. The ERDAS Imagine Expert Classifier has two main elements; the Knowledge Engineer and the Knowledge Classifier. The Knowledge Engineer provides methodology for users with advanced information and experience to define variables, rules, and classifying interests to design a hierarchical decision tree and knowledge database. The Knowledge Classifier provides methodology to utilize the knowledge database created by the user and Engineer.

Previous attempts at classifying wetland types provides confirmed accurate training sites that can be utilized. Using the inquirer cursor function and signatures editor precise pixel values and signatures can be extracted for an AOI. With the hierarchical decision tree a hypothesis can be created with rules defining variables. The Knowledge Engineer feature allows the user to define nearly every aspect of the image. An example includes the first hypothesis created to identify coastal wetlands. The range of possible pixel values from the signature files for the training site is studied. A coastal buffer has been applied to restrict distance from shore. Currently each ETM Band has a given relationship for a defined variable and acceptable confidence levels. Additional techniques and constraints such as GIS techniques, signatures from multi-temporal stack images, and different input coverages can all be applied to a single database to produce a map.

A variety of methods and techniques were undertaken, including various supervised and unsupervised classifications of available Landsat imagery from 1999 and 2000 with selected images from spring, summer and fall seasons. The Knowledge Engineer function within ERDAS Imagine was used to develop a set of steps to select individual Landsat images or components of the reflected energy signal to identify specific wetland characteristics including water, vegetation and soil conditions and weigh these factors in developing a wetland classification. The initial results produced a preliminary wetlands inventory map that was then ground truthed by examining the location and occurrence of known wetlands within the study area.

A primary goal of this project is to detect existing locations of wetlands and develop a systematic methodology for future wetlands monitoring and investigation. Advances in Geographic Information Systems (GIS) and remote sensing provide sophisticated methodologies for data integration and analysis. A variety of tech-

niques can be applied to data for optimal processing and exploitation depending on specific goals and project objectives. Image enhancement algorithms are applied to remotely sensed data to improve the appearance of an image for human visual analysis or for subsequent machine analysis (Jensen 1996).

### **3.4 Analysis**

A primary goal of this project is to detect existing locations of wetlands and develop a systematic methodology for future wetlands monitoring and investigation. Three primary wetland types of concern were identified in this study including forest, coastal, and prairie wetlands. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery, which is available from the OhioView Remote Sensing Consortium, was used in this study and is available at <http://www.ohioview.org>. ERDAS Imagine and Environmental Systems Research Institute (ESRI) software was utilized. A hybrid method integrating both geo-technologies was used in this study.

#### **3.4.1 Data Preprocessing**

The Landsat 7 ETM+ sensor is a nadir-viewing, eight-band multispectral scanning radiometer that detects spectrally filtered radiation while orbiting the Earth in a sun-synchronous orbit at an altitude of 705 kilometers. Landsat 7 images used in this study provide 16-day overpass repeat intervals with recorded spectral reflectance ranging in the electromagnetic spectrum. Bands range from 15 meter spatial resolution for the panchromatic band 8, 30 meters for the visible, near infrared and mid infrared bands 1-5 and 7 and 60 meters for the thermal infrared band, 6 (Goward et al. 2001). Multitemporal images were used to take advantage of phenological cycle changes observable in vegetation over the growing season. Scenes from 2000 to 2002 for path 20 row 31 which cover the entirety of Lucas County were examined for vegetation changes, cloud coverage, and overall image quality. Seasonal scenes were selected and stacked using ERDAS Imagine Model Maker to create stacked multitemporal images.

In land cover classification mapping, the spectral signals are often assumed to possess a level of separability or variation that noise and environmental effects can be ignored. In this investigation, the detection of wetland classes was difficult because the spectral reflectivity of the vegetation cover in each class is similar. Therefore, radiometric enhancements were performed to correct for atmospheric attenuation so that as much separation between the classes could be made. A Tasseled Cap transformation, which yields a component that correlates with haze, was performed. The haze component was removed from the imagery and it was transformed back into RGB space (ERDAS 2001). Examination of band histograms showed that enhancements increased band spectral ranges leading to increased classification accuracy.



Developing a detailed Area Of Interest (AOI) was a central step in the investigation. A highly developed AOI reduces computer storage needs, increases processing speeds, and was found to decrease map inaccuracy. Recognized jurisdictional wetlands normally require three characteristics, hydrophilic vegetation, hydric soils, and hydrological cycle requirements that vary by region (Tiner 1999). Integrating Geographic Information System (GIS) components and data to develop an AOI will increase map usability and decrease possible misclassifications. First a subset of the entire AOI is taken from the 185 X 185 km ETM+ scene in Path-Row 20-31 of the global notation Worldwide Reference System (WRS). The United States Department of Agriculture (USDA), Ohio Department of Natural Resources (ODNR), and the Soil Conservation Service (SCS) provide detailed information on soil coverage for the study area (USDA 1980). Using ArcGIS 8 all hydric soils were queried within the study area forming an advanced AOI. This reduced the initial AOI by approximately 50% to a total of 103, 017 acres. The regional governments in NW Ohio have spatial data on agriculture in the study area. The Current Agricultural Use Valuation (CAUV) program is an incentive taxed based program where registered landowners pay taxes on current agricultural use instead of its developed potential (AREIS 2003). For the purpose of this study, any land registered as an agricultural parcel, which is 82,727 acres in Lucas County Ohio, was eliminated from the AOI. By necessity, this eliminates wet agricultural fields as potential wetlands although most of the agricultural fields in Lucas County were once part of the Black Swamp before the land was drained.

### 3.4.2 Classification

A series of classification methods and attempts were performed in this investigation. Initial efforts began with simple AOI requirements and unsupervised classifications. Overall this returned an inaccurate product that was not usable. An advanced classification technique was determined to be required for the study. The ERDAS Imagine Expert Classifier was selected which has two main elements; the Knowledge Engineer and the Knowledge Classifier. The Knowledge Engineer provides methodology for users with advanced information and experience to define variables, rules, and classifying interests to design a hierarchical decision tree and knowledge database. The Knowledge Classifier provides methodology to utilize the knowledge database created by the user and Engineer (ERDAS 2001). An advantage of the Expert Classifier Knowledge Engineer is that the user can place different confidence levels on different classes and produce combination output products if desired.

Most land classification studies stop short of complete analysis due to time and cost constraints. Decision tree classification algorithms have significant potential for land cover mapping problems and have not been tested in detail by the remote sensing community relative to more conventional pattern recognition such as maximum likelihood classification (Friedl 1997). Previous attempts at classifying

wetland types provides confirmed accurate training sites that can be utilized. Using the inquirer cursor function and signatures editor precise pixel values and signatures can be extracted for the AOI. With the hierarchical decision tree a hypothesis was created with rules defining variables. The Knowledge Engineer feature allows the user to define nearly every aspect of the image. An example includes the first hypothesis created to identify coastal wetlands. The range of possible pixel values from the signature files for the training site is studied. A 2 km coastal buffer was applied to restrict distance from shore. Each ETM+ band has a given relationship for a defined variable and acceptable confidence levels for the AOI. The Knowledge Engineer allows for different input coverages with varied constraints and confidence iterations to produce single thematic outputs.

### **3.4.3 Results**

Several confidence iterations and variations of the knowledge database were run and analyzed. Accuracy assessments on optimal output products were conducted. A stratified random sampling scheme with 50 points per class was determined adequate were used to validate the classified image. The accuracy points were checked using aerial photography, expert assessments, and field ground-truthing. Site description, land cover, vegetation communities, GPS locations, digital pictures, soil type, and associated variables were collected for each point.

The knowledge engineer output database produced 1200 acres of wet prairie, 3200 acres of wet forest, and 1000 acres of coastal wetlands (Table 1) The overall classification accuracy was 94.5%, with an overall Kappa statistic of 0.91. Kappa analysis is a discrete multivariate technique of use in accuracy assessment that is a measure of agreement (Jensen 1996, Carletta 1996). Wetland prairies proved to be the most difficult to accurately classify with a users accuracy of 83.33%. The User's Accuracy, or commission errors are pixels whose land cover is different than what the satellite classification produced. This indicates for the user of the map the probability that a pixel classified on the map actually represents that category on the ground (Congalton 2002). Figure 2 illustrates a sample coverage of the wetlands inventory for the Kitty Todd Nature Preserve located within the Lucas County portion of the Maumee AOC.



**Fig. 2.** Sample image of the wetlands inventory showing wet forests and prairie wetlands in the vicinity of the Kitty Todd Nature Preserve within Lucas County, Ohio.

Table 1. Accuracy Results

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Coastal Wetland	49	49	49	100.00%	100.00%
Wet Forest	58	56	55	94.83%	98.21%
Wet Prairie	35	42	35	100.00%	83.33%

Overall Classification Accuracy = 94.56%

*KAPPA (K^)* STATISTICS

Overall Kappa Statistics = 0.9188

Conditional Kappa for each Category.

Category	Kappa
Coastal Wetland	1
Wet Forest	0.9705
Wet Prairie	0.7813

### 3.5 Conclusions

The use of remote sensing as applied in this study have contributed to an improved classification, identification, and inventory of main wetland types and sites within northwest Ohio. The ability to prepare a revised wetlands map with a high degree of accuracy has several important implications for urban land use planning and decision-making. The results provide for a greatly improved understanding of the types and distribution of wetlands in this region, which is undergoing rapid urbanization. The resulting development is placing increased pressures on existing wetland features and other areas where wetland restoration would be possible, but difficult due to conflicting land uses and traditionally a lack of knowledge, information, awareness and appreciation of wetlands.

An important aspect of this project has been to consider the means by which the study results, methods and technology would be readily understood and accessible to community planning agencies, government authorities and citizens with responsibilities, mandates, authority, or interest related to wetland conservation with the communities in northwest Ohio. A fundamental challenge with the use of remote sensing in understanding urban environments is the need to overcome barriers associated with the inability of the potential users of the technology and products derived from it. Traditionally these barriers have included cost, lack of adequate computer hardware and software, access to the data and satellite imagery, and limited expertise and knowledge to understand and make use of the resulting data and related products, such as the wetlands mapping as developed within this study.

The establishment of OhioView (<http://www.ohioview.org/>) has provided many opportunities to overcome these barriers and allowed for improved abilities of the university and research groups to engage in direct project development and applications with community partners with the intention of facilitating technology transfer. This project is an example of how removing those barriers although possible – and successful – can assist but not completely overcome remaining challenges. Although it has been possible from a technical aspect to make great strides in producing a more accurate wetlands maps by applying more advanced methods and the most recent data, the project has also revealed a need to consider the best means and approaches to transfer the knowledge, methods and science to the agencies and individuals in the community who are in the position to use it in the planning and management of land uses, development and related wetland areas and impacts. The ability to succeed in applying the results of the use of remote

sensing technology for wetland identification to addressing and solving wetland management issues and concerns with the Maumee Area of Concern will be the true test of using the method and technology successfully in such a manner that the utility is fully realized.

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### References

- Anderson, J.E. and J. E. Perry. 1996. Characterization of Wetland Plant Stress Using Leaf Spectral Reflectance: Implications for Wetland Remote Sensing. *Wetlands* 16:477-487.
- Barrett, E.C. and L.F. Curtis. 1992. *Introduction to Environmental Remote Sensing*, 3rd ed. London: Chapman & Hall.
- Carletta, J. 1996. Assessing agreement on classification tasks: the kappa statistic. *Computational Linguistics*. 22:249-254.
- Ehrenfeld, J.G. 2000. Evaluating wetlands within an urban context. *Ecological Engineering* 15: 253-265.
- Friedl, M., Brodley, C. 1997. Decision Tree Classification of Land Cover from Remotely Sensed Data. *Remote Sensing of Environment*. 61:399-409.
- Goward, S., Masek, J., Williams, D., Irons, J., Thompson, R. 2001. the Landsat 7 mission: Terrestrial research and applications for the 21st century. *Remote Sensing of Environment*. 78:3-12.
- Hardisky, M.A., M.F. Gross, and V. Klemas. 1986. Remote Sensing of Coastal Wetlands. *Bioscience* 36:453-460.
- Jensen, J. 1996. *Introductory Digital Image Processing: a Remote Sensing Perspective*. New Jersey: Prentice Hall.
- Johnston R.M., Barson M.M. 1993. Remote Sensing of Australian Wetlands: An Evaluation of Landsat TM Data for Inventory and Classification. *Australian Journal of Marine and Freshwater Resources*. 44:235-252.
- Kindscher, K., Fraser, A., Jakubauskas, M.E., and Debinski, D.M. 1998. Identifying wetland meadows in Grand Teton National Park using remote sensing and average wetland values. *Wetlands Ecology and Management*. 5:265-273.
- Lawrence, P.L., Horvat, M., Grigore, M., Czajkowski, K. and Torbick, N. (2003). *Challenges and Limitations Using Remote Sensing to Delineate Wetlands in Northwest*

- Ohio. Poster at Ohio Geospatial Technology Conference for Agriculture and Natural Resource Applications. Columbus, Ohio.
- Levine, N.S. and Roten, H.L. 2001. Wetlands Assessment and Identification using Remote Sensing and GIS Data within a Knowledge-Based Classifier. *Geological Association of America Annual Meeting 2001*. Paper 123-0.
- Lillesand, T.M. and R.W. Kiefer. 1994. *Remote Sensing and Photo Interpretation*, 3rd. ed. New York: John Wiley & Sons.
- Lunetta R.S., Barlogh M.E. 1999. Application of mult-temporal Landsat 5 TM imagery for wetland identification. *Photogrammetric Engineering and Remote Sensing*. 65:303-1310.
- Lyon J.G. 2001. *Wetland Landscape Characterization: GIS, Remote Sensing, and Image Analysis*. Sleeping Bear Press.
- MacDonald T.A. 1999. Wetland rehabilitation and remote sensing, in Streever E. (ed.), *An International Perspective on Wetlands Rehabilitation*. Boston: Kluwer Academic Publishers:251-264.
- Maumee RAP 1997. *Maumee River Remedial Action Plan: Strategic Plan*. Ohio EPA Northwest District Office, Bowling Green, OH. [www.maumeerap.org](http://www.maumeerap.org)
- Mitsch, J. and Gosselink, J.G. 2000. The value of wetlands: importance of scale and landscape setting. *Ecological Economics* 35: 25-33.
- Munyati, C. 1999. Wetland change detection on the Kafue Flats, Zambia by classification of a multitemporal remote sensing image dataset. *International Journal of Remote Sensing*. 21:1787-1806.
- Ohio Department of Natural Resources. 2003. *A History of Ohio Wetlands*. <http://www.dnr.state.oh.us/wetlands/history.htm>
- Ozesmi, S.L. and Bauer, M.E. 2002. Satellite remote sensing of wetlands. *Wetlands Ecology and Management*. 10:381-402.
- Sader, S.A., Ahl, D., and Wen-Shu, L. 1995. Accuracy of Landsat-TM and GIS Rule-Based Methods for Forest Wetland Classification in Maine. *Remote Sensing of the Environment*. 53:133-144.
- Schaal, G. 1995. *Methods used in the Ohio Wetland Inventory*. Columbus, Ohio: Ohio Department of Natural Resources.
- Schmidt, K.S. and Skidmore, A.K. 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment*. 85:92-108.
- Shuman, C.S. and Ambrose, R.F. 2003. A Comparison of Remote Sensing and Ground-Based Methods for Monitoring Wetland Restoration Success. *Restoration Ecology*. 11:325-333.
- Tilton, D. L. 1995. Integrating wetlands into planned landscapes. *Landscape and Urban Planning* 35: 205-209.
- Tiner, R. 1999. Wetland Indicators. *A Guide to Wetland Identification, Delineation, Classification, and Mapping*. New York: Lewis Publishers.
- Townsend, P. A., and Walsh, S. J. 2001. Remote sensing of forested wetlands: Application of multitemporal and multispectral satellite imagery to determine plant community composition and structure in southeastern USA. *Plant Ecology* 157:129-149.
- Yi, G.D., Risley, M., Koneff, M., and Davis, C. 1994. Development of Ohio's GIS-based wetlands inventory. *Journal of Soil and Water Conservation* 49:23-28.