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SATELLITE REMOTE SENSING OF ISOLATED WETLANDS USING OBJECT-ORIENTED CLASSIFICATION OF LANDSAT-7 DATA

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Abstract: There has been an increasing interest in characterizing and mapping isolated depressional wetlands due to a 2001 U.S. Supreme Court decision that effectively removed their protected status. Our objective was to determine the utility of satellite remote sensing to accurately detect isolated wetlands. Image segmentation and object-oriented analysis were applied to Landsat-7 imagery from January and October 2000 to map isolated wetlands in the St. Johns River Water Management District of Alachua County, Florida. Accuracy for individual isolated wetlands was determined based on the intersection of reference and remotely sensed polygons. The January data yielded producer and user accuracies of 88% and 89%, respectively, for isolated wetlands larger than 0.5 acres (0.20 ha). Producer and user accuracies increased to 97% and 95%, respectively, for isolated wetlands larger than 2 acres (0.81 ha). Recently, the Federal Geographic Data Committee recommended that all U.S. wetlands 0.5 acres (0.20 ha) or larger should be mapped using 1-m aerial photography with an accuracy of 98%. That accuracy was nearly achieved in this study using a spatial resolution that is 900 times coarser. Satellite remote sensing provides an accurate, relatively inexpensive, and timely means for classifying isolated depressional wetlands on a regional or national basis.

Key Words: detection, imagery, mapping, segmentation

INTRODUCTION

Geographically isolated wetlands are a unique and significant part of the nation's wetlands resources and provide vital habitats for fish and wildlife (Tiner et al. 2002, 2003a). Isolated wetlands have received increasing attention due to the 2001 *Solid Waste Agency of Northern Cook County (SWANCC) vs. U.S. Army Corp of Engineers* Supreme Court ruling [531 U.S. 159 (2001)] that isolated, intrastate non-navigable wetlands could not be protected under the Clean Water Act (CWA) based solely on the presence of migratory birds (Downing et al. 2003). Because isolated wetlands have no apparent surface connections to navigable waters, their protection status under the CWA was effectively removed as a result of this ruling.

Wetlands are defined as areas that are transitional between terrestrial and aquatic systems, where the water table is usually at or near the surface or the land is covered by shallow water. Traditionally, isolated wetlands have not been consistently defined, however (Leibowitz 2003, Leibowitz and Nadeau 2003). The National Research Council (1995) defined an isolated wetland as a wetland not adjacent to a water body. Tiner et al. (2002) defined isolated wetlands, in terms of their relationship to surface waters, as wetlands with no apparent surface water connection to perennial rivers and streams, estuaries, or the ocean. Isolated wetlands can actually be defined from a number of hydrologic, ecologic, geographic, or other perspectives (Tiner 2003b). For example, ecologists have referred to them as rare and highly dispersed habitats (Pearson 1994) and as islands in a terrestrial landscape (Edwards and Sharitz 2000). Tiner (2003b) maintains that geographic isolation is the easiest way to determine isolation, because it defines the position of the wetland on the landscape, and defines an isolated wetland as a wetland that is completely surrounded by uplands. For the purposes of this paper, we define geographically isolated wetlands as wetlands that are completely surrounded by uplands, with no apparent connections to perennial surface waters. This definition does not require complete hydrologic isolation of the wetland; thus, these wetlands may or may not be connected to other waters through ground water (Gibbons 2003, Leibowitz 2003, Tiner 2003b, Winter and LaBaugh 2003). In addition, isolated wetlands may also have occasional surface-water connections during very wet conditions through overland flow (Leibowitz and Nadeau 2003).

Isolated wetlands are important ecological systems that support high levels of biodiversity, including significant numbers of rare and endangered plant and animal species (Semlitsch and Bodie 1998). A total of 86 plant and animal species listed as threatened or endangered under the Endangered Species Act are supported by isolated wetlands, and more than half of these species are completely dependent on isolated wetland habitat (Comer et al. 2005). In addition, Comer et al. found a total of 274 at-risk plant and animal species are supported by isolated wetlands, 35% of which are restricted to isolated wetland habitat. Also, isolated wetlands play an important role in the aquatic ecosystem by contributing habitat, water quality improvements, flood reduction, and aquatic productivity (Downing et al. 2003). Moreover, most of the ecological functions attributed to non-isolated wetlands are also provided by isolated wetlands (Tiner 2003a).

There has been an ever increasing interest in assessing and mapping isolated wetlands since the 2001 U.S. Supreme Court decision in the *SWANCC vs. U.S. Army Corps of Engineers* case. Although there have been a number of studies that have used geographic information systems (GIS) to map isolated wetlands, the national extent of isolated wetlands is still unknown (Tiner et al. 2002). Tiner (2003b) used GIS analysis of the U.S. Fish and Wildlife Service (USFWS) National Wetlands Inventory (NWI) data and the United States Geological Survey (USGS) digital line graphs (DLG) to estimate the extent of isolated wetlands for 72 study sites in 44 states. Nearly 70% of the 72 study areas had more than half of their wetlands designated as geographically isolated; nine of the 72 study sites had more than 90% of their wetlands classified as isolated (Tiner et al. 2002). At least four states have produced estimates of isolated wetlands: Nebraska, Wisconsin, Indiana, and Illinois (Tiner 2003b). For example, McCauley and Jenkins (2005) estimated isolated wetlands for Illinois using a GIS model based on USGS digital raster graphic (DRG) and digital elevation model (DEM) data.

There are several limitations, however, with many of the studies that have used GIS analysis of existing datasets to estimate isolated wetlands. First, isolated wetlands are very dynamic ecosystems and their wetted area, size, and shape, can change from year to year with hydrologic inputs. Isolated wetlands are also affected by changes in land use. The data used in the aforementioned studies is, in most cases, dated and thus, may not reflect the current landscape with respect to isolated wetlands. Furthermore, datasets such as the NWI are incomplete and do not cover all areas of the United States. One of the major considerations in mapping isolated wetlands is often to determine the change in their extent over time; these changes cannot be assessed using GIS analysis of existing USGS and USFWS datasets.

An alternative to using GIS analysis of existing datasets is to utilize remotely sensed satellite data for estimating the extent of isolated wetlands. Satellite imagery can provide the necessary temporal resolution and historical imagery for assessing the extent and distribution of isolated wetlands over time. Remotely sensed satellite data can also provide information about adjacent land cover, especially those areas that are potential threats to isolated wetlands. Satellite data are also relatively inexpensive compared to aerial photography and are easily integrated into a GIS (Ozesmi and Bauer 2002). Despite these advantages, satellite imagery has not been used for mapping isolated wetlands.

Image segmentation is a commonly applied technique in the fields of machine vision and pattern recognition (Pekkarinen 2002, Schiewe 2003) and is gaining popularity in the field of remote sensing. The basic processing units of object-oriented image analysis are objects, rather than individual pixels (Benz et al. 2004). Initial image segmentation uses low-level information (pixel-based features) to create higher-level contiguous regions or image objects. These higher-level objects have spectral, textural, contextual, and shape characteristics that can be used for classification.The goal of this project was to determine the utility of image segmentation and object-oriented processing of Landsat-7 imagery for detecting isolated wetlands in the St. Johns River Water Management District of Alachua County, Florida.

METHODS

Study Area and Data Acquisition

The study area for this research consisted of a 1560 km^2 area of the St. Johns River Water

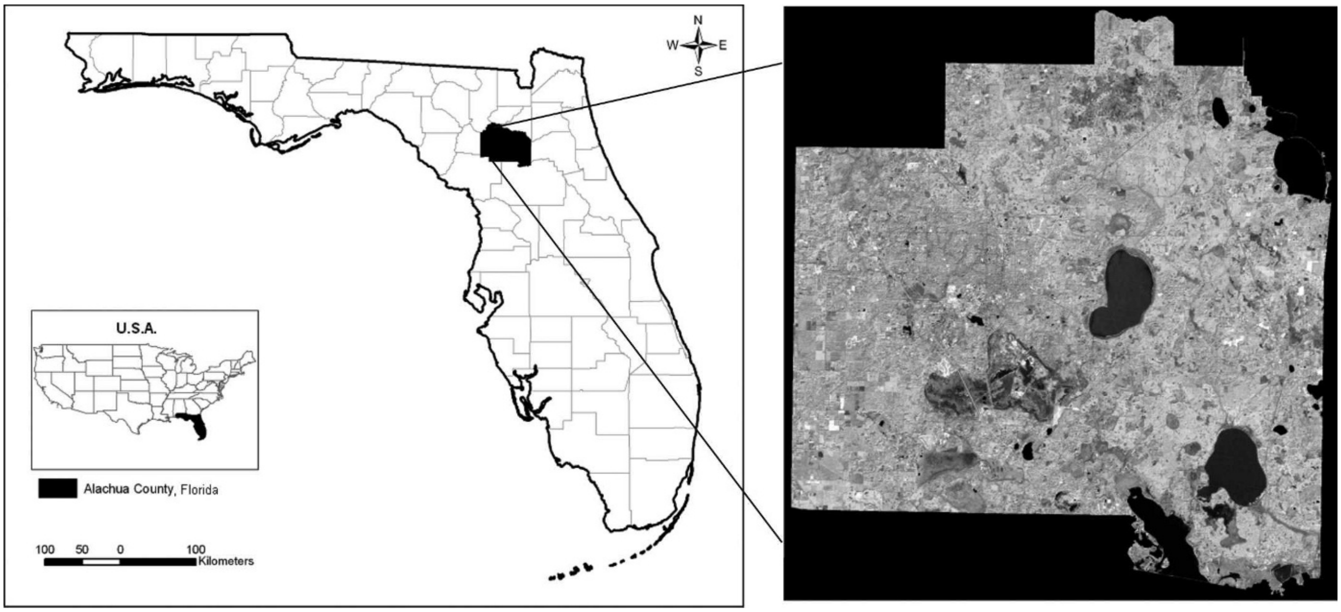


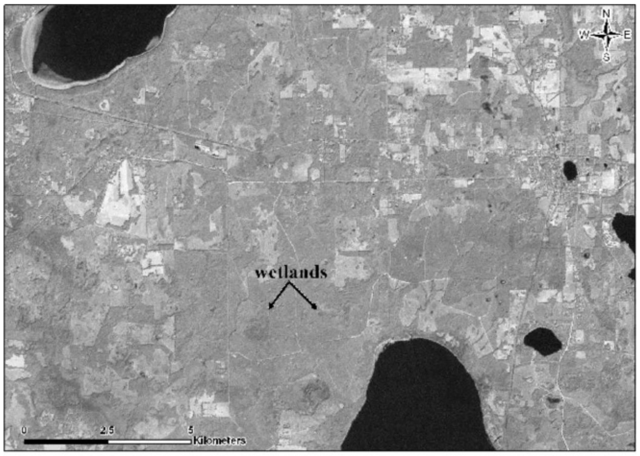
Figure 1. Landsat-7 scene clipped to the study area covering the St. Johns River Water Management District of Alachua County, Florida.

Management District (SJRWMD) located in Alachua County, Florida (Figure 1). The area was selected because of the high density of wetlands, the high diversity of mixed land cover, and the availability of GIS and remote sensing data products. The area geology is a mixture of clayey sands, medium to fine sands and silts, and limestone karst topography (Florida Department of Environmental Protection Environmental Geology data, http://www.dep.state.fl.us/gis/datadir.asp, accessed 01/09). Both isolated and non-isolated wetlands are abundant in this area and include over 17 wetland types, such as cypress domes, sinkhole wetlands, pond pines, freshwater marshes, wet prairies, and wetland hardwoods. The SJRWMD has detailed land use and land cover data (including wetland types) digitized from color-infrared (IR) aerial photos from 2000 for the study area; these data were acquired through the SJRWMD website (http://sjr.state.fl.us/gisdevelopment/docs/themes.html) and used for training and accuracy assessment in this research project.

In order to analyze a scene from the same year as the SJRWMD land cover data, a search was conducted to acquire the wettest Landsat-7 scene for the year 2000. Daily rainfall records were examined for the county and a Landsat-7 October 16, 2000 scene [Path 17 (orbit), Row 39 (scene center)] was acquired from the University of Florida Map and Imagery Library. It was later determined that rainfall records were not necessarily a good indicator for overall scene wetness. Several other Landsat-7 scenes were acquired from the University of Florida Map and Imagery Library and band 5 (1.55–1.75 μm) of each scene analyzed for overall scene wetness. Band 5 of Landsat is very sensitive to water content in vegetation and soil (USGS 2003) and through analysis of this band, it was determined that a January 2, 2000 scene was the wettest scene for the year. The full January 2, 2000 scene (Path 17 and Row 39, Scene ID LE7017039000000250) was acquired from Global Observatory for Ecosystem Services, Michigan State University and used for classification of isolated wetlands in the project. In this paper, we present analysis of both the January 2000 and October 2000 scenes (Figure 2) for comparison. Differences in wetness and ease of wetland identification are obvious when comparing the two scenes. The Landsat-7 data, which feature a 15-m resolution panchromatic (pan) band and six, 30-m resolution multispectral bands, were georegistered to the SJRWMD land cover data using 10–15 ground control points and a first-order polynomial data transformation.

Data Transformations

Three different transformations were applied to the georegistered Landsat-7 ETM+ data to improve the potential classification of isolated wetlands. These included 1) a minimum noise fraction (MNF) transformation, 2) a texture transformation based on mean co-occurrence in band 5, and 3) a pan-merge transformation to merge the 30-m spectral data with the 15-m pan-band (band 8).



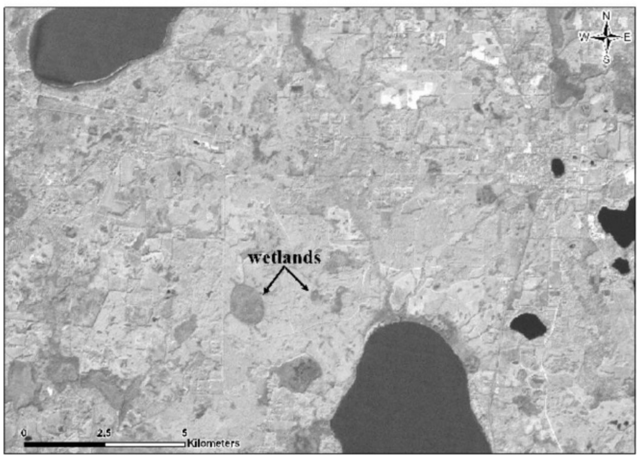


Figure 2. Comparison of the October 2000 (top) and January 2000 (bottom) Landsat-7 imagery. Wetted soils are visible as darker areas throughout the image; lakes are indicated in dark gray or black. Relative wetness of the two scenes can be seen in the wetlands indicated by arrows.

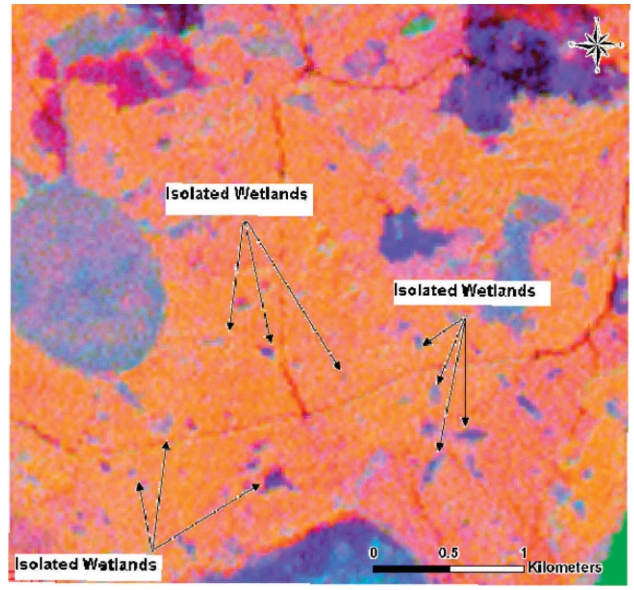


Figure 3. Minimum Noise Fraction Transformation (MNF) showing isolated wetlands in blue. Wetland areas are in blue tones and areas surrounding wetlands are in orange tones. The area in this figure is an inset of the lower center portion of Figure 2 and includes the wetlands indicated by arrows in that figure.

The MNF was used to determine the inherent dimensionality of the data, to segregate noise, and to reduce the complexity of the data. This transformation, modified by Green et al. (1988) and implemented in ENVI 4.2 (ITT Visual Information Solutions, Boulder, CO), is essentially two cascaded principal components transformations. The first transformation, based on an estimated noise covariance matrix, decorrelated and rescaled the noise data. This first step resulted in transformed data in which the noise had unit variance and no band-to-band correlations. The second step was a standard principal components transformation of the noise-whitened data. The inherent dimensionality of the data was determined by examination of the final eigenvalues and the associated images. Figure 3 shows the first three MNF bands of the January 2000 data in RGB; isolated wetlands are clearly visible in the MNF transformation.

Haralick (1986) proposed a variety of measures to extract useful textural information from co-occurrence matrices. In this study, the mean of the co-occurrence matrix, based on a 3-pixel by 3-pixel moving window of band 5, was used. During computation, four brightness value spatial-dependency matrices were derived for each pixel based on neighboring pixel values. The average of these four measures was output as the texture value for the pixel under consideration. The textural information significantly improved the general discrimination ability for wetlands.

In order to merge the 30-m spectral data with the 15-m panchromatic data of ETM+, a Gram-Schmidt sharpening algorithm (ITT Visual Information Solutions, Boulder, CO, USA) was utilized. First, a panchromatic band was simulated from the lower spatial resolution spectral bands. Then, the Gram-Schmidt algorithm was applied to the simulated panchromatic band and the rest of the 30-m spectral bands. The simulated panchromatic band became the first band of the new dataset, then the 15-m resolution Landsat-7 panchromatic band was substituted for the first Gram-Schmidt band, and the inverse Gram-Schmidt transform applied to the entire dataset. This pan-merge transformation resulted in a 15-m spectrally merged dataset.

Segmentation and Object-Oriented Analysis

Because isolated wetlands have boundaries that are highly contrasted to the surrounding uplands, we chose a segmentation and object-oriented approach for the final classification. The classification scheme consisted of two classes: isolated wetlands and other. The georegistered data consisted of an eight-band, 15-m pan-merged dataset with the following bands: 1) Landsat spectral bands 1–5, and 7 (6 bands total); 2) the first MNF band from the MNF transformation; and 3) a co-occurrence mean texture band calculated using Landsat spectral band 5. The eight-band dataset was input for segmentation and object-oriented processing. The segmentation and object-oriented classification was divided into two steps: segmentation to create image objects at multiple scales and classification of the image objects as either "isolated wetland" or "other." Segmentation and object-based classification was performed using eCognition software (Definiens Imaging, Munich, Germany, version 4.0); all other image processing was performed using ENVI and IDL 4.2 software (ITT Visual Information Solutions, Boulder, CO, USA).

Image Segmentation

The segmentation was a bottom-up, region-merging approach that started with single pixel objects. In an optimization pair-wise clustering process, smaller objects were merged into larger objects based on heterogeneity criteria of color and shape (Benz et al. 2004):

$$f = w \cdot h_{color} + (1 - w) \cdot h_{shape} \tag{1}$$

where f is the threshold fusion value for merging segments, h_{color} is the heterogeneity criterion for color as defined in equation (2), and h_{shape} is the heterogeneity criterion for shape as defined in equation (3). The user defined weight parameter w was set to 0.9, a conservative value that decreases the influence of color, which can vary phenotypically within taxa, and increases the influence of shape.

The heterogeneity criterion for color (h_{color}) was calculated before and after potential merging of each adjacent object as:

$$h_{color} = \sum_c w_c \left(n_{Merge} \cdot \sigma_c^{Merge} - \left(n_{Obj1} \cdot \sigma_c^{Obj1} + n_{Obj2} \cdot \sigma_c^{Obj2} \right) \right) \tag{2}$$

where n_{merge} is the number of pixels within a merged object, n_{obj1} is the number of pixels in object 1, n_{obj2} is the number of pixels in object 2, and σ_c is the standard deviation within object of band c. Subscripts *merge* refer to merged objects and *obj1* and *obj2* refer to the objects prior to a merge.

The heterogeneity criteria for shape describe the improvement of shape with respect to smoothness and compactness:

$$h_{shape} = w_{cmpct} \cdot h_{cmpct} + \left(1 - w_{cmpct}\right) \cdot h_{smooth} \tag{3}$$

The user defined weight parameter w_{cmpct} was set to 0.5, the median value for integrating smoothness and compactness in determining heterogeneity criteria. The change in smoothness (h_{smooth}) and compactness (h_{cmpct}) were calculated before and after a potential merging of objects:

$$h_{smooth} = n_{Merge} \cdot \frac{l_{Merge}}{b_{Merge}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{b_{Obj1}} + n_{Obj2} \cdot \frac{l_{Obj2}}{b_{Obj2}} \right) \text{ and} \tag{4}$$

$$h_{cmpct} = n_{Merge} \cdot \frac{l_{Merge}}{\sqrt{n_{Merge}}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{\sqrt{n_{Obj1}}} + n_{Obj2} \cdot \frac{l_{Obj2}}{\sqrt{n_{Obj2}}} \right) \tag{5}$$

where n is the object size, l is the object perimeter, and b is the perimeter of a bounding rectangle.

With each iteration, the pair of adjacent objects with the smallest growth from the defined heterogeneity criteria was merged. The process stopped when the smallest growth for merging of adjacent objects exceeded a pre-defined scale parameter. This procedure simulated the simultaneous growth of segments during each step so that output objects were of comparable size and scale (Benz et al. 2004).

A scale parameter was defined in the segmentation process to set a threshold for the maximum increase in heterogeneity of two merging segments. When this parameter was reached, the segmentation process ended. The larger the scale parameter, the larger the segmented objects grow (Baatz and Schäpe 2000, Benz et al. 2004). The dataset in this study was segmented at five different scale parameters (100, 50, 10, 7, and 4), chosen to provide a range of classification scales for iterative accuracy assessment. These scale parameters resulted in 785, 2875, 63,874, 133,884, and 422,647 objects, respectively. The scale parameters of 100 and 50 were primarily used for data masking, while those of 10, 7, and 4 were used for direct classification of objects. A comparison of all five scale parameters is shown in Figure 4.

A variety of band combinations from the eight-band dataset were used in the optimization of the

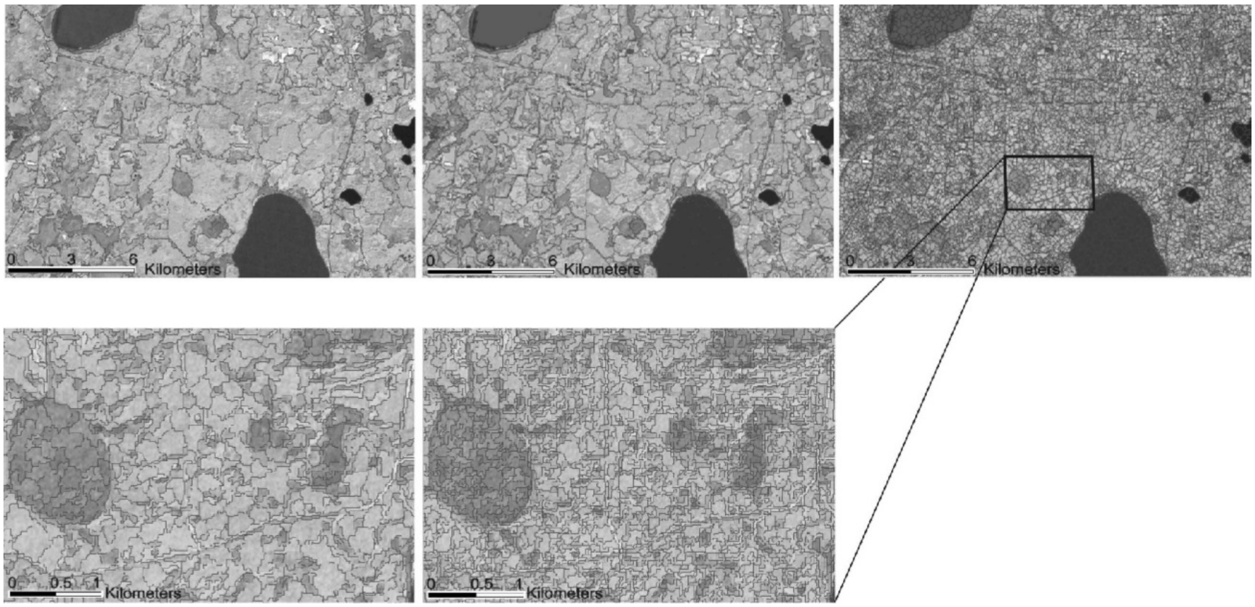


Figure 4. Comparison of the size and number of segments created using scale parameter 100 (top left), 50 (top middle), 10 (top right), 7 (bottom left), and 4 (bottom right). The area of the top three images is the same area depicted in Figure 2; the area of the bottom two images is an inset of the lower center portion of these images to show more detail.

segmentation process. Initial analyses based on iterative comparisons to the reference dataset, suggested that the band combination 5,4,3 RGB of the the pan-merged dataset produced superior results; thus, this was used for the segmentation of objects. This band combination produced superior results due to the sensitivity of bands 4 and 3 to vegetation cover and the senstivity of band 4 to water content.

Object-Based Classification

The segmented image objects were classified at five different scales as either isolated wetland or other. All eight 15-m pan-merged bands were used in the classification. The classification of individual objects was based on a number of decision rules determined according to feature attributes of the objects. These attributes were determined through a process of trial and error, until a combination of feature values was found to produce the best output. In this study, the mean values in bands 4 and 5, the mean values of MNF band 1, the ratio of band 4 to the overall brightness, shape and size values, and texture calculations were all feature attributes used in the classification of isolated wetland objects.

Each decision rule was determined from a fuzzy set consisting of membership functions of the object features. A membership function ranged from 0 to 1 for each object's feature values with respect to its membership to an assigned class. The output classification was determined by assigning each object to the class with the highest degree of membership, based on all membership features used. A classification-based segmentation was performed to fuse all adjacent objects that were assigned the same land cover category.

Use of GIS Ancillary Data

GIS data layers of buffered hydrology and lakes were also used in the classification process. These were used to mask data where potential wetlands intersected stream, river, and lake buffers, to prevent these data from being classified as isolated wetlands. The segmentation/object-oriented classification was also compared to a "potential isolated wetlands" GIS data layer, as described below, and the classification parameters were iteratively adjusted, based on errors found, until the classification process was completed.

USGS high resolution (1:24,000 scale) National Hydrography Dataset (NHD) line and polygon data (http://nhd.usgs.gov) were clipped to the study extent and used to identify surface water features and determine the relative isolation of wetland systems. Because the goal of the study was to map isolated wetlands and we were using the NHD to identify and exclude non-isolated wetlands, features attributed in the NHD as swamps or marshes were removed from the buffer mask, as they themselves could be isolated wetlands. Upon further evaluation of the NHD polygon data, it was discovered that many of the small lake and pond features could not be found on recent aerial photography (http://www.

labins.org) or conflicted with the NWI classification of palustrine wetlands. In order to be as inclusive as possible, the small lake and pond features were removed from the buffer mask as well, so as not to exclude potential isolated wetlands from being identified. In the end, 30 large lake and pond features were included for use in the buffer delineation. In addition to the polygon features, linear features were also edited to exclude surface water features that were obvious artificial or ditched channels or streams, disconnected streams, or other stream features that could not be seen on recent aerial photography (http://www.labins.org). The resultant lentic and lotic features were buffered using a 10-m buffer width to exclude non-isolated wetlands from the study. This was a more inclusive and conservative buffer width than the 12-m buffer proposed for use with 1:24,000 scale hydrology data by the Association of State Wetland Managers (2001).

Post-GIS processing of the segmentation/object-oriented classification was used to eliminate any wetlands that intersected the stream and lake buffers. Although most of these wetlands were masked from the data during the classification process, there were still a small number that needed to be eliminated through GIS post-processing.

Accuracy Assessment

To assess the accuracy of the remote sensing analyses, a dataset was developed using five USGS 7.5-minute quarter-quadrangles (quarter-quads) within the study area. These five quads were randomly selected using a stratified sampling approach (Figure 5). Color infrared, digital aerial photographs (years 1999–2004) obtained from the Land Boundary Information System (http://www.labins.org) were photointerpreted, and isolated wetlands within the selected quarter-quads were heads-up digitized using ArcGIS software [Environmental Systems Research Institute (ESRI), Redlands, CA, versions 9.0 and 9.2]. In addition to the aerial photographs, ancillary data sources, such as the NWI, NHD, DRGs, and the SJRWMD land use and land cover data, were sometimes used to aid in the photointerpretation process.

Accuracy for individual isolated wetlands was determined based on the intersection of reference and remotely sensed polygons. In order to account for wetland size in our accuracy assessment, the accuracy dataset was subdivided into five isolated wetland size classes: 1) $>$ 4.13 acres (1.67 ha; the mean size of all isolated wetland polygons, 2) $>$ 2.0 acres (0.81 ha), 3) $>$ 1.5 acres (0.61 ha), 4) $>$ 1.0 acre (0.40 ha), and 5) $>$ 0.5 acres (0.20 ha). In

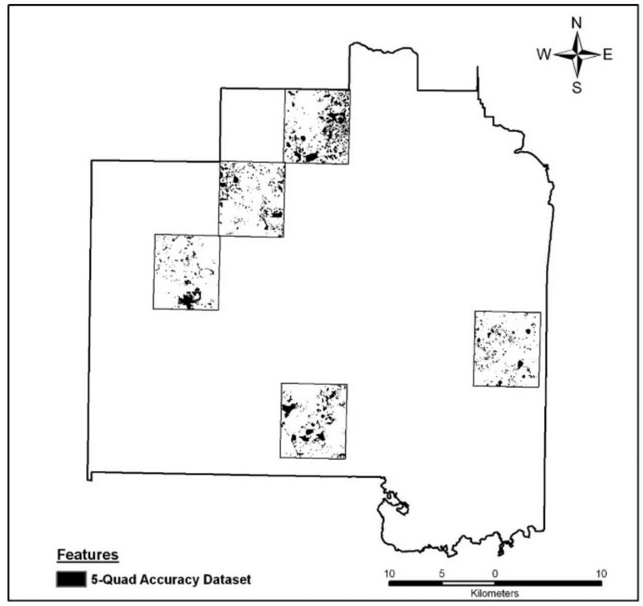


Figure 5. Accuracy assessment dataset created by photo-interpreting five color-IR quarter quads. For the accuracy assessment, the study area was divided into five rows and one quad was randomly selected in each row for a total of five quads. Wetlands are depicted in black.

general, if a reference isolated wetland polygon (of a selected size-class) "intersected" any size mapped isolated wetland polygon, then the mapped isolated wetland polygon was considered to be a positive match and accurate (no matter if the size or shape were the same). This method of accuracy assessment was chosen because our goal was to determine if the approximate location of an actual isolated wetland was mapped or not; we were not interested in mapping the actual photointerpreted shape or boundary of the isolated wetland. A contingency matrix was constructed to compare the reference data to both the January and October 2000 isolated wetland classifications. Accuracy was determined by evaluating correctly classified polygons with respect to the total number of polygons in the error matrix. Individual class user and producer accuracies were also calculated for each of the five size classes, following Story and Congalton (1986). Producer accuracy represents the probability of a reference polygon being correctly classified as an isolated wetland and is a measure of omission error. User accuracy is the probability that a polygon classified as an isolated wetland actually represents that category in the reference data and is a measure of commission error.

RESULTS AND DISCUSSION

There were a total of 4388 isolated wetlands identified in the study area, covering a total area of

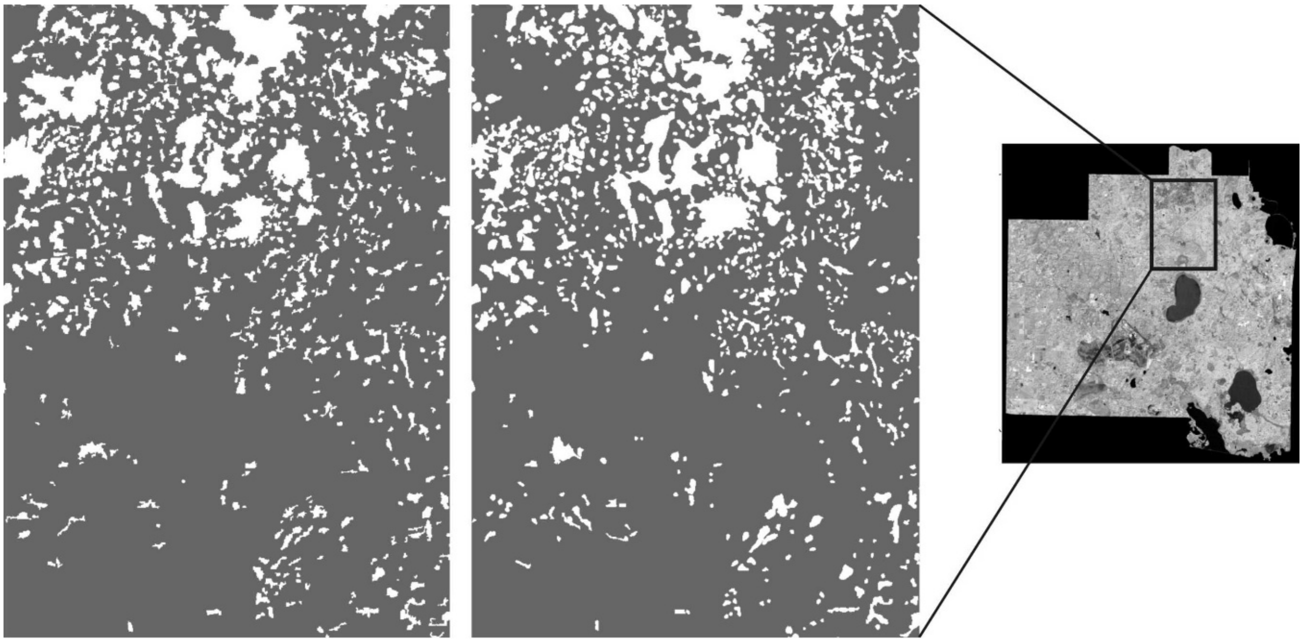


Figure 6. Comparison of isolated wetlands (in white) based on the St. Johns River Water Management District land use data (left) and the Landsat-7 January 2000 segmentation/object-oriented classification for the same area (right). The area depicted in these images is an inset of the top-center portion of the study area.

27.7 km^2. Figure 6 shows a comparison of a portion of the classified January 2000 image and the St. Johns River Water Management District land use data (post-processed for isolated wetlands) for the same area. Although the SJRWMD data is more detailed because it was based on photointerpretation of color-IR aerial photography, as compared to our classification, which was based on 15-m and 30-m pan-merged Landsat-7 data, the overall number, pattern, and shape of isolated wetlands is very similar in comparison. Figure 7 shows a direct overlay of the Landsat-7 January 2000 classification results and one of the photo-interpreted accuracy assessment quads for isolated wetlands. Overall, the visual overlay shows a very strong agreement between the accuracy data and the classification. The final January 2000 isolated wetland classification is shown in Figure 8, overlaid on the Landsat-7 imagery.

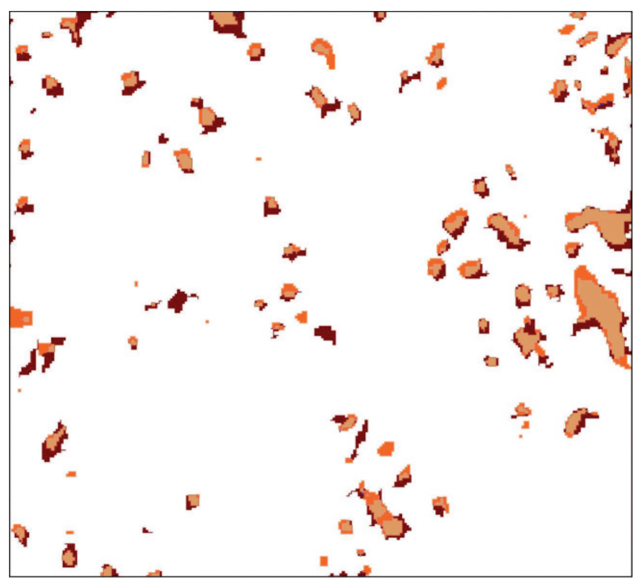


Figure 7. Direct overlay of the Landsat-7 January 2000 classification results and one of the photo-interpreted accuracy assessment quads for isolated wetlands. The background (white) is uplands or non-isolated-wetlands. The light brown areas are isolated wetlands that were classified in both the Landsat-7 imagery and in the photo-interpreted accuracy assessment quad. Maroon areas are isolated wetlands that were classified in the Landsat-7 imagery, but not in the accuracy assessment quad; and orange areas are isolated wetlands that were not classified in the Landsat-7 imagery, but were present in the accuracy assessment quad.

Results comparing the segmentation and object-oriented classification accuracies for the January 2000 and the October 2000 classifications are shown in Table 1. Producer and user accuracies were very high for the January 2000 segmentation classification for all size classes $>$ 0.5 acres (0.20 ha). For isolated wetlands $>$ 4.13 acres (1.67 ha; the mean wetland size), the producer accuracy was 98% and user accuracy was 97%. When the size of the isolated wetlands decreased to $>$ 2 acres (0.81 ha), producer

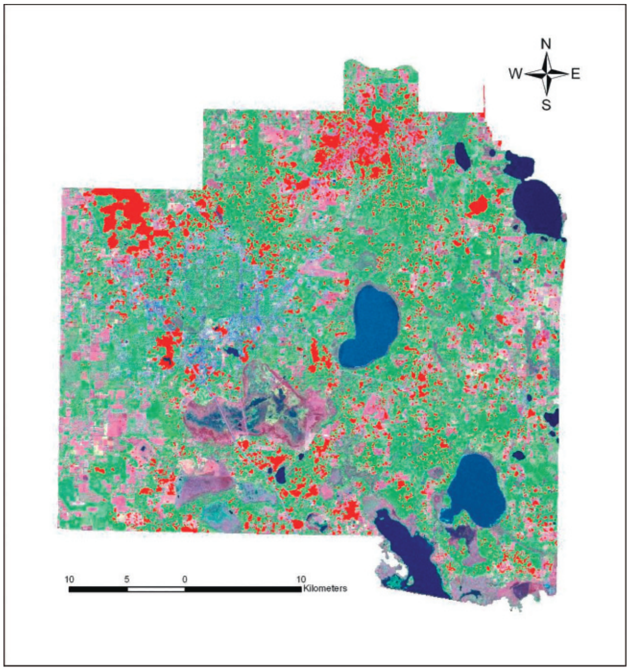


Figure 8. Final classification of isolated wetlands (red) overlaid on the Landsat-7 January 2000 image.

and user accuracies dropped only slightly, to 97% and 95%, respectively. Isolated wetlands of > 1 acre (0.40 ha) were mapped with a producer and user accuracy of 93%, and wetlands > 0.5 acres (0.20 ha) were mapped with producer and user accuracies of 88% and 89%, respectively. It should be noted that an isolated wetland of 0.5 acres (0.20 ha) is approximately two 30-m Landsat pixels. The accuracy is surprisingly high for objects two pixels or more in size and it is unrealistic to expect to map wetlands below this threshold with Landsat-7 data. It should also be noted that 98% of the wetlands in the study area are > 0.5 acres (0.20 ha); about 95% are ≥ 1 acre (0.40 ha) and 90% of the wetlands are ≥ 2 acres (0.81 ha). These accuracy numbers are very promising in light of a recent recommendation by the Federal Geographic Data Committee (FGDC) that all wetlands ≥ 0.5 acres (0.20 ha) in the lower 48 states should be mapped using 1-m aerial photography with an accuracy of 98% (Heber 2008). In this study, we have nearly achieved this accuracy using a spatial resolution that is 900 times coarser than that recommended by FGDC.

In comparing the January 2000 classification of isolated wetlands to that of October 2000 (Table 1), we can see that producer accuracy increased 21–29% and user accuracy increased 4–7%, for each size category using the January scene. This increase, especially in producer accuracy, is due primarily to the fact that the January 2000 scene was much wetter than the October scene, making the isolated wetlands much easier to detect. Band 5 of Landsat is very sensitive to water content in vegetation and soil. The lower the brightness values in band 5, the higher the amount of water in the scene. The mean brightness value of band 5 for the October 2000 data was 66, compared to only 45 for the January 2000 data, indicating that the January scene was much wetter than the October scene. Several researchers have found that wetland mapping using satellite imagery is more accurate when the water table is high (Hodgson et al. 1987, Sader et al. 1995). As a result, it was not unexpected that better results were obtained using the January 2000 scene.

SUMMARY AND CONCLUSIONS

This research represents the first attempt to map isolated wetlands using remotely sensed satellite data. The segmentation/object-oriented approach is ideal for classifying isolated wetlands because of the highly contrasted boundaries that these wetlands exhibit. Although segmentation and object-oriented analysis is a relatively new classification technique in remote sensing, compared to traditional spectral classifiers, it is surprising that there are very few studies that have used segmentation for classification of wetlands. Hess et al. (2003) used segmentation of JERS-1 radar data to delineate wetland extent in the central Amazon basin with 95% accuracy, and Costa et al. (2002) used segmentation to map Amazon floodplain communities with

Table 1. Isolated wetlands accuracy assessment comparing producer and user accuracies for multiple wetland size classes using Landsat-7 scenes of varying relative wetness.

	Oct. 2000 Classification		Jan. 2000 Classification	
Isolated Wetland Size Class	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
> mean (4.13 acres; 1.67 ha)	77%	93%	98%	97%
> 2 acres (0.81 ha)	72%	90%	97%	95%
>1.5 acres (0.61 ha)	70%	88%	96%	95%
>1 acre (0.40 ha)	65%	87%	93%	93%
>0.5 acres (0.20 ha)	59%	84%	88%	89%

RADARSAT and JERS-1 data. Likewise, Atunes et al. (2003) used segmentation on IKONOS imagery to identify riparian areas in Parana, Brazil. Segmentation is ideal for classifying any type of land cover that has highly contrasted boundaries, such as isolated wetlands. This research shows very encouraging results for the use of image segmentation and Landsat data for mapping both isolated and non-isolated wetlands.

Several conclusions and recommendations can be drawn from this research with respect to satellite mapping of isolated wetlands:

1) Landsat data provide the necessary temporal, spatial, and spectral resolutions for accurately detecting isolated wetlands that are $\geq$ 0.5 acres (0.20 ha);
2) Isolated wetlands can be mapped more accurately using the wettest scene of a particular year;
3) Rainfall data may not be the best indicator of the wetness within a scene. A better indicator is the mean value of a middle-IR band sensitive to wetness, such as band 5 of Landsat;
4) Object-oriented analysis is an ideal classification method for mapping isolated wetlands since they have highly-contrasted boundaries;
5) The use of data transformations, such as the minimum noise fraction transformation, texture analysis, and pan-merging techniques, are effective in improving the ability to classify isolated wetlands with remotely sensed satellite data; and
6) Satellite remote sensing provides an accurate, relatively inexpensive, and timely means for classifying isolated wetlands on a regional or even national basis.

This research is important considering the unprotected status of most isolated wetlands due to the 2001 US Supreme Court decision in the *SWANCC vs. U.S. Army Corps of Engineers* case [531 U.S. 159 (2001)]. More studies, such as this, are needed so that the distribution and extent of these unique wetland ecosystems can be accurately mapped on a regional and national basis and strategies for their potential protection developed.

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LITERATURE CITED

Association of State Wetland Managers (ASWM). 2001. Consistent methods for identifying waters that may no longer be regulated under the Clean Water Act following the SWANCC decision. Association of State Wetland Managers, Berne, NY, USA.

Atunes, A. F. B., C. Lingnau, and J. C. Da Silva. 2003. Object-oriented analysis and semantic network for high resolution image classification. Anais XI SBSR, Belo Horizonte, Brasil. 05-10 Abril 2003, INPE, p. 273–79.

Baatz, M. and A. Schäpe. 2000. Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation. p. 12–23, *In* J. Strobl, T. Blaschke, and G. Griesebner (eds.) Angewandte Geographische Informations-Verbeitung XII. Wichmann Verlag, Karlsruhe, Germany.

Benz, U. C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing 58:239–58.

Comer, P., K. Goodin, A. Tomaino, G. Hammerson, G. Kittel, S. Menard, C. Nordman, M. Pyne, M. Reid, L. Sneddon, and K. Snow. 2005. Biodiversity values of geographically isolated wetlands in the United States. NatureServe, Arlington, VA, USA.

Costa, M. P. F., O. Niemann, E. Novo, and F. Ahern. 2002. Biophysical properties and mapping of aquatic vegetation during the hydrological cycle of the Amazon floodplain using JERS-1 and Radarsat. International Journal of Remote Sensing 23:1401–26.

Downing, D. M., C. Winer, and L. D. Wood. 2003. Navigating through the Clean Water Act jurisdiction: a legal review. Wetlands 23:475–93.

Edwards, A. L. and R. R. Sharitz. 2000. Population genetics of two rare perennials in isolated wetlands: *Sagittaria isoetiformis* and *S. teres* (Alismataceae). American Journal of Botany 87:1147–1158.

Gibbons, J. W. 2003. Terrestrial habitat: a vital component for herpetofauna of isolated wetlands. Wetlands 23:630–35.

Green, A. A., M. Berman, P. Switzer, and M. D. Craig. 1988. A transformation for ordering multispectral data in terms of image quality with implications for noise removal. IEEE Transactions on Geoscience and Remote Sensing 26:65–74.

Haralick, R. M. 1986. Statistical image texture analysis. p. 247–80, *In* T. Y. Young and K. S. Fu (eds.) Handbook of Pattern Recognition and Image Processing. Academic Press, New York, NY, USA.

Heber, M. 2008. FGDC *draft* wetland mapping standard. FGDC Wetland Subcommittee and Wetland Mapping Standard Workgroup. Environmental Protection Agency, Office of Water, Washington, DC, USA.

Hess, L. L., J. M. Melack, E. M. L. M. Novo, C. C. F. Barbosa, and M. Gastil. 2003. Dual-season mapping of wetland inundation and vegetation for the central Amazon basin. Remote Sensing of Environment 87:404–28.

Hodgson, M. E., J. R. Jensen, H. E. Mackey Jr, and M. C. Coulter. 1987. Remote sensing of wetland habitat: a wood stork example. Photogrammetric Engineering and Remote Sensing 53:1075–80.

Leibowitz, S. G. 2003. Isolated wetlands and their functions: an ecological perspective. Wetlands 23:517–31.

Leibowitz, S. G. and T.-L. Nadeau. 2003. Isolated wetlands: state-of-the-science and future directions. Wetlands 23: 663–84.

McCauley, L. A. and D. G. Jenkins. 2005. GIS-based estimates of former and current depressional wetlands in an agricultural landscape. Ecological Applications 15:1199–1208.

National Research Council (NRC). 1995. Wetlands: Characteristics and Boundaries. National Academy Press, Washington, DC, USA.

Ozesmi, S. L. and M. E. Bauer. 2002. Satellite remote sensing of wetlands. Wetlands Ecology and Management 10:381–402.

Pearson, S. M. 1994. Landscape-level processes and wetland conservation in the southern Appalachian mountains. Water, Air, and Soil Pollution 77:321–32.

Pekkarinen, A. 2002. A method for the segmentation of very high spatial resolution images of forested landscapes. International Journal of Remote Sensing 23:2817–36.

Sader, S. A., D. Ahl, and W.-S. Liou. 1995. Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. Remote Sensing of Environment 53:133–44.

Schiewe, J. 2003. Integration of multi-sensor data for landscape modeling using a region-based approach. ISPRS Journal of Photogrammetry and Remote Sensing 57:371–79.

Semlitsch, R. D. and J. R. Bodie. 1998. Are small, isolated wetlands expendable? Conservation Biology 12:1129–33.

Story, M. and R. Congalton. 1986. Accuracy assessment: a user's perspective. Photogrammetric Engineering and Remote Sensing 52:397–99.

Tiner, R. W. 2003a. Estimated extent of geographically isolated wetlands in selected areas of the United States. Wetlands 23:636–52.

Tiner, R. W. 2003b. Geographically isolated wetlands of the United States. Wetlands 23:494–516.

Tiner, R. W., H. C. Bergquist, G. P. DeAlessio, and M. J. Starr. 2002. Geographically isolated wetlands: a preliminary assessment of their characteristics and status in selected areas of the United States. U. S. Department of the Interior, Fish and Wildlife Service, Northeast Region, Hadley, MA, USA.

USGS. 2003. Landsat: a global land-observing program. U.S. Geological Survey, Reston, VA, USA. Fact Sheet 023-03.

Winter, T. C. and J. W. Labaugh. 2003. Hydrologic considerations in defining isolated wetlands. Wetlands 23:532–40.

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