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Wetland classification using Landsat-7 ETM+

Research Paper

Segmentation and object-oriented classification of wetlands in a karst Florida landscape using multi-season Landsat-7 ETM+ imagery

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Segmentation and object-oriented processing of single-season and multi-season Landsat-7 ETM+ data was utilized for the classification of wetlands in a 1560 km^2 study area of north central Florida. This segmentation and object-oriented classification outperformed the traditional maximum likelihood algorithm (MLC) in accurately mapping wetlands, with overall accuracies of 90.2% (single-season imagery) and 90.8% (multi-season imagery), compared to overall accuracies for the MLC classifiers of 78.4% and 79.0%, respectively. Kappa coefficients were over 1.5 times greater for the segmentation/object-oriented classifications than for the MLC classifications and producer and user accuracies were also higher. The producer accuracies of the segmentation/object-oriented classifications were 90.8% (single-season) and 91.6% (multi-season), compared to 70.6% and 74.4%, respectively, for the MLC classifications. User accuracies were 73.9% and 73.5% for the single-season and multi-season segmentation/object-oriented classifications, respectively, compared to 54.1% (single-season) and 55.0% (multi-season) for the MLC classifications. The use of multi-seasonal data resulted in only a slight increase in overall accuracy over the single-season imagery. This small increase was primarily due to better discrimination of riparian wetlands in the multi-season

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data. Segmentation and object-oriented processing provides a low-cost, high accuracy method for classification of wetlands on a local, regional, or national basis.

Keywords: Segmentation; Object-oriented classification; Wetlands; Landsat

1 Introduction

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 (Sugumaran *et al.* 2004). Wetlands are more economically and ecologically valuable than many other natural land cover types and provide numerous and unique ecosystem functions, including storing flood waters (Ozesmi and Bauer 2002, Li and Chen 2005, Toyra and Pietroniro 2005), minimizing sediment loss and controlling runoff volume (Tiner 2003), improving water quality (Ozesmi and Bauer 2002, Li and Chen 2005, Baker *et al.* 2006), and recharging groundwater aquifers (Ozesmi and Bauer 2002, Toyra and Pietroniro 2005, Baker *et al.* 2006). Wetlands also provide unique and critical habitat to rare and endangered flora and fauna, support biodiversity (Li and Chen 2005), protect shore and coastlines (Ozesmi and Bauer 2002), and play an important role in global carbon and methane cycles (Li and Chen 2005). In addition, the local economies of many countries depend on wetlands for fisheries, reed harvesting, grazing, and recreation (Ozesmi and Bauer 2002).

The continental USA once had an estimated 221 million acres (89.5 million hectares) of natural wetlands. Less than half of this original acreage remains today (Sugumaran *et al.* 2004). Extensive wetland loss is due to draining, dredging, filling, leveling, and flooding, especially in urban and agricultural areas where land use change is extensive (Sugumaran *et al.* 2004). There has also been extensive loss of wetlands in many other countries throughout the world (Mitsch and Gosselink 2000).

In order to prevent further loss of wetlands and conserve existing wetlands, it is important to inventory, map, and monitor them and their adjacent land use. Accurate wetland mapping is also important to understanding wetland functioning and monitoring wetland response to natural and anthropogenic change. In addition, wetland mapping can be used to evaluate land use decisions and monitor the effects of mitigating measures (Baker *et al.* 2006). There are three basic techniques for wetlands monitoring and mapping: (1) on-site evaluations, (2) airphoto interpretations, and (3) satellite remote sensing. On-site assessments provide detailed information about flora and fauna, water chemistry, and soil data (Baker *et al.* 2006). However, because of the high cost of equipment, personnel, and time, on-site evaluations are not feasible for wetland monitoring and mapping on a local or regional scale. In addition, wetlands are often located in remote areas, making access difficult. Aerial photos allow a more synoptic view of wetlands and can be used in mapping them at local and regional scales. However, airphoto interpretation is limited by the amount of time required to map wetlands over larger areas and the lack of continuous coverage needed to update wetland maps (Baker *et al.* 2006). Aerial photography is perhaps best used for assessing the accuracy of wetland maps, as opposed to creating and updating these maps. Satellite remote sensing is arguably the only practical method for accurately mapping and monitoring wetlands on a regional basis, in a timely manner. Satellite remote sensing provides synoptic views of wetlands consistently over time and at low cost.

Satellite remote sensing analysis has had a long and successful history in accurately mapping wetlands (Hutton and Dincer 1979, Jensen *et al.* 1984, Palylyk *et al.* 1987, Sader *et al.* 1995, Ozesmi and Bauer 2002, Hess *et al.* 2003, Toyra and Pietroniro 2005, Li and Chen 2005, Baker *et al.* 2006, Shanmugam *et al.* 2006). Nearly all types of wetlands have been studied with satellite remote sensing using a wide variety of sensors, including Landsat Multispectral Scanner (MSS; Palylyk *et al.* 1987), Landsat Thematic Mapper (TM; Sader *et al.* 1995, Shanmugam *et al.* 2006), Landsat-7 Enhanced Thematic Mapper Plus (ETM+; Baker *et al.* 2006), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER, Kato *et al.* 2001), Systeme Probatoire d'Observation de la Terre (SPOT; Jensen *et al.* 1993), Advanced Very High Resolution Radiometer (AVHRR; Ramsey *et al.* 1997), the Indian Remote Sensing Satellite (IRS-1B; Chopra *et al.* 2001), the Japanese Earth Resources Satellite (JERS-1; Hess *et al.* 2003), the European Remote Sensing Satellite (ERS-1; Kushwaha *et al.* 2000), and Canada's Radar Remote Sensing Satellite (RADARSAT; Li and Chen 2005, Toyra and Pietroniro 2005). Several wetland studies have suggested that Landsat-based classifications provide greater overall accuracies than other space-borne studies (Civco 1993, Bolstad and Lillesand 1992, Baker *et al.* 2006). Landsat TM and ETM+ data are ideal for wetland mapping, because these data have a middle-infrared (IR) band that is sensitive to wetness (band 5), and red (band 3) and near-IR (band 4) bands, which are sensitive to vegetation. In addition, Landsat data provide continuous coverage every 16 days and the Landsat TM data dates back to 1984. Many studies have been successful in utilizing Landsat TM and ETM+ data for wetland mapping (Jensen *et al.* 1993, Sader *et al.* 1995, Sugumaran *et al.* 2004, Li and Chen 2005, Baker *et al.* 2006, Shanmugam *et al.* 2006).

Various types of classification algorithms have been applied to Landsat data for mapping wetlands, including unsupervised clustering, maximum likelihood, hybrid classifiers, regression analysis, fuzzy classifiers, linear mixture modelling, subpixel estimators, rule-based classifiers, and decision trees (Ozesmi and Bauer 2002). The traditional maximum likelihood classifier, used in such studies as Palylyk *et al.* (1987) and Shanmugam *et al.* (2006), is by far the most commonly used classification technique in wetlands mapping. However, fuzzy classifications, subpixel classifications, and spectral mixture estimates appear to provide more detailed information on wetlands, and rule-based and hybrid classifiers may give more accurate results than traditional classifiers (Ozesmi and Bauer 2002). One relatively new classification technique that has not been used extensively in wetlands mapping, but shows great promise, is segmentation and object-oriented processing.

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 (Benz *et al.* 2004). Image segmentation/

object-oriented processing has a number of advantages over conventional per-pixel spectral classifiers, including the ability to: (1) incorporate spectral, textural, contextual, and shape information (Shackelford and Davis 2003), (2) provide classification results with higher accuracy (Stuckens *et al.* 2000, Geneletti and Gorte 2003), (3) reduce local spectral variation (Hill 1999), (4) provide classification results in a form that is immediately useable in a geographic information system (GIS; Geneletti and Gorte 2003), (5) reduce occurrence of smaller mapping units, resulting in a more attractive classification map (Stuckens *et al.* 2000), (6) create objects from segmentation that are more visually recognizable than pixels, and (7) ecologically speaking, provide image objects that are more similar to landscape patches than are pixels (Laliberte *et al.* 2004).

Segmentation/object-oriented processing has shown excellent potential for land cover mapping, and may be particularly useful in classifying wetland land cover, yet few studies have used it in wetlands mapping (e.g., Costa *et al.* 2002, Atunes *et al.* 2003, Burnett *et al.* 2003, Hess *et al.* 2003, Stankiewicz *et al.* 2003, Sugumaran *et al.* 2004, Hurd *et al.* 2006). Hess *et al.* (2003) used segmentation of JERS-1 radar data to delineate wetland extent in the central Amazon basin with 95.0% accuracy. Costa *et al.* (2002) used segmentation to map Amazon floodplain communities with RADARSAT and JERS-1 data. Antunes *et al.* (2003) used segmentation on IKONOS® imagery to identify riparian areas in Parana, Brazil. Burnett *et al.* (2003) used a segmentation/object-based analysis of color-infrared aerial photography for mapping a bog in Estonia. Stankiewicz *et al.* (2003) used object-oriented classification of optical and microwave satellite images to map vegetation in a wetland ecosystem in the northeast part of Poland. In a technical report to the Iowa Space Grant, Sugumaran *et al.* (2004) found that segmentation and object-oriented processing of Landsat-7 ETM+ data had much higher accuracies for wetland classification (90.7%) than maximum likelihood classification (64.0%) and ISODATA clustering (59.7%). More recently, Hurd *et al.* (2006) reported at the American Society of Photogrammetry and Remote Sensing (ASPRS) Annual Conference on the use of segmentation and object-based classification of Landsat data to classify tidal wetlands throughout Long Island Sound. We have found no published studies in refereed journals that have applied segmentation and object-oriented processing to Landsat data for the classification of wetlands.

The goal of this project was to apply segmentation and object-oriented processing to Landsat ETM+ imagery for the classification of wetlands in Alachua County, a 2510 km^2 area in north-central Florida, USA. Two objectives for this project were (1) to determine the accuracy of segmentation and object-oriented classification of wetlands compared to that of the traditional maximum likelihood algorithm, and (2) to determine if classification of multi-season Landsat imagery provided higher accuracies than that of a single-season Landsat image.

2 Methodology

2.1 *Study area and data acquisition*

The study area covers the eastern portion of Alachua County, Florida, USA, that lies within the St. Johns River Water Management District (SJRWMD) and occupies an area of approximately 1560 km^2 (figure 1). Wetlands are abundant in this area and consist of at least 17 different wetland types, including cypress domes, sinkhole wetlands, pond pines, freshwater marshes, wet prairies, and wetland hardwoods. The SJRWDM has detailed land use and land cover data (including wetland types) digitized from colour-IR aerial photos from 2000 for this area; these data were acquired through the SJRWMD website (http://sjr.state.fl.us/gisdevelopment/docs/themes.html, accessed 10/06) and used for training and accuracy assessment. The wettest and driest Landsat-7 (Level 1G) images for the year, based on an analysis of band 5, were acquired from the University of Florida Map and Imagery Library (Path 17 and Row 39). The wettest scene was a January 2, 2000 image and the driest scene was an April 7, 2000 image (figure 2). Each scene also corresponds to leaf-off and leaf-on data, respectively, for deciduous vegetation. The Landsat-7 (UTM) data were geo-registered to the SJRWMD land cover data using 10–15 ground control points and simple rotation, translation, and scaling. The Landsat data values were unchanged by the georegistration process. Two raw datasets were created from the imagery. First, a single-season 6-band dataset was created using bands 1–5, and band 7 from the January 2000 Landsat-7 image. The second dataset consisted of a 12-band multi-season dataset consisting of bands 1–5, and band 7 of both the January and April scenes.

2.2 *Landsat-7 image transformations*

Three different data transformations were applied to each georegistered dataset to improve the potential classification of wetlands. These include (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-meter spectral data with the 15-meter panchromatic (pan)-band of Landsat-7 ETM+.

The MNF was used to determine the inherent dimensionality of the data, to segregate noise in the data, and to reduce the complexity of the data. This transform, modified by Green *et al.* (1988), is essentially two cascaded principal components transformations. The first transformation, based on an estimated noise covariance matrix, decorrelated and rescaled the noise data. The 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.

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 neighbouring pixel values. The average of these four measures was calculated as the texture value for the pixel under consideration. The textural information significantly improved the general discrimination ability of wetlands.

In order to merge the 30-meter spectral data with the 15-meter panchromatic data of Landsat-7 ETM+, a Gram-Schmidt sharpening algorithm (Research Systems, Inc 2005) 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-meter spectral bands. The simulated panchromatic band became the first band of the new dataset. Then the 15-meter Landsat-7 panchromatic band was substituted for the first Gram-Schmidt band. The inverse Gram-Schmidt transform was then applied to the entire dataset, resulting in a 15-meter spectrally-merged dataset. For the multi-season dataset, the spectral bands were pan-merged to the 15-meter panchromatic band of the January data.

2.3 *Segmentation and object-oriented classification*

The classification scheme consisted of two classes: (1) wetlands and (2) non-wetlands. Wetlands were defined as areas transitional between terrestrial and aquatic systems, where the water table was at or near the surface or the land was covered by shallow water. All other areas were considered non-wetlands. The single-season January 2000 georegistered dataset was an eight-band, 15-meter pan-merged image consisting of Landsat spectral bands 1–5 and 7, the first MNF band, and the co-occurrence texture of band 5. The eight-band dataset was converted to a GeoTiff for segmentation and object-oriented processing. The multi-season georegistered dataset consisted of a 16-band, 15-meter pan-merged image with Landsat spectral bands 1–5 and 7, the first two MNF bands of the combined January–April dataset, and the co-occurrence texture of band 5 from both the January 2000 and April 2000 imagery.

The segmentation and object-oriented classification was divided into two steps: (1) segmentation to create image objects at multiple scales, and (2) classification of the image objects as either 'wetland'" or 'non-wetland'. All segmentation and object-based classification was performed using eCognition software (Definiens Imaging, München, Germany, version 4.0). All other image processing was performed using ENVI and IDL 4.2 software (ITT Corporation, Boulder, CO, USA).

2.3.1 Image segmentation. There are many types of segmentation algorithms that can be applied to remotely sensed imagery, including measurement-space guided spectral clustering, hybrid linkage region growing, centroid linkage region growing, split and merge methods, and area and edge-based methods (Laliberte *et al.* 2004). In general, segmentation algorithms can be divided into two types: (1) global, behaviour-based, and (2) local, behaviour-based (Kartikeyan *et al.* 1998). Global methods are based on an analysis of data in feature space; the objective is to identify clusters in the histogram of the data and form segments from these clusters. Local based methods are more common and focus on the variation of tone or colour in a small neighbourhood (Kartikeyan *et al.* 1998). There are two types of local behaviour-based segmentation methods: (1) edge-detection and (2) region growing methods. Edge-based methods find boundaries between pixels by detecting edges; image regions completely surrounded by edge pixels become segments. Thus, pixels either belong to an edge to form a boundary or belong to a segment (Geneletti and Gorte 2003). One disadvantage of edge-based methods is that small terrain objects are completely obscured by boundary pixels (Geneletti and Gorte 2003). In region growing segmentation a small neighbourhood of pixels is tested for homogeneity criteria. Neighbouring pixels that have similar properties are merged to form a larger segment. A split and merge technique can be used to create regions of constant tone. Regions can also be grown from seed pixels (Kartikeyan *et al.* 1998, Makela and Pekkarinen 2001, Geneletti and Gorte 2003). One disadvantage of region-growing methods is that results can be affected depending on the order the image is processed (Geneletti and Gorte 2003). The choice between segmentation methods depends on the application, and hybrids of these methods can been used (Kartikeyan *et al.* 1998).

The segmentation method chosen in this study was a bottom-up region-merging approach starting with single pixel objects. In an optimization pair-wise clustering process, smaller objects were merged into larger objects based on heterogeneity criteria of colour 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 colour, defined in equation (2), and h_{shape} is the heterogeneity criterion for shape, defined in equation (3). The user-defined weight parameter w was set to 0.9, a conservative value that decreases the influence of colour, which can vary phenotypically within taxa, and increases the influence of shape.

The heterogeneity criterion for colour (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, 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 t 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 described below. 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 is defined in the segmentation process to set a threshold for the maximum increase in heterogeneity of two merging segments. When this parameter is reached, the segmentation process ends. The larger the scale parameter, the larger the segmented objects grow (Baatz and Schape 2000, Benz *et al.* 2004). Both datasets in this study were segmented at three different scale parameters (50, 10, and 7), chosen to provide a range of classification scales for iterative accuracy assessment. For the single-season data, a scale parameter of 50 yielded 2875 objects, a scale parameter of 10 yielded 63 874 objects, and a scale parameter of 7 resulted in 133 884 image objects. A comparison of two scale parameters is shown in figure 3. For the multi-season dataset, a scale parameter of 50 yielded 3872 objects, a scale parameter of 10 yielded 93 647 objects, and a scale parameter of 7 resulted in 192 666 image objects. The coarser scale parameter (50) was used primarily for data masking, while the finer scale parameters of 10 and 7 were used for direct classification of objects.

2.3.2 Object-oriented classification. The segmented image objects were classified at three different scales as either (1) wetland or (2) non-wetland. For the single-season data, all eight 15-meter pan-merged bands were used in the classification. For the multi-season data, all sixteen 15-meter 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 parameters was found to produce an acceptable accuracy. 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 parameters, 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.

2.4 *Maximum likelihood classification*

The maximum likelihood classifier (MLC) is the most widely used method for the classification of land cover (Ediriwickrema and Khorram 1997, Jensen 2005). This spectral classifier has been used by numerous researchers as a benchmark from which to compare the performance of other classifiers (Bastin 1997, Ediriwickrema and Khorram 1997, Stuckens *et al.* 2000, Hunter and Power 2002, Liu *et al.* 2002, Emrahoglu *et al.* 2003, Erbeck *et al.* 2004, Lo and Choi 2004, South *et al.* 2004). Several factors have contributed to the perceived high standard of MLC (Ediriwickrema and Khorram 1997), including the number, size, and location of training sites, the nature of discriminant variables, and the meaningful evaluation of the classification method (Foody 1992). MLC has been recognized as a stable, robust, and accurate method in standard digital image processing software systems (Ediriwickrema and Khorram 1997).

MLC incorporates both the variance and covariance matrix of the dataset into the classification decision rule. To accurately estimate the covariance matrix, a sufficient number of training samples must be selected and each training class assumed to be normally distributed. With this assumption, the statistical probability of a pixel being a member of a given training class can be computed from the mean vector and the covariance matrix, using a probability density function (Lillesand *et al.* 2004). The assumption of normality is often violated in multispectral datasets, however (South *et al.* 2004). Even minor deviations from normality can severely disrupt the classification (Foody 1992). Land cover categories with multi-modal histograms should have multiple, individual training samples for each mode to fulfil the normal distribution requirement (Jensen 2005).

MLC was applied to both the 30-meter data and the 15-meter pan-merged data. It was determined from initial accuracy assessments that the MLC performed better for the 15-meter pan-merged data than the 30-meter non-merged data; therefore, only the single-season and multi-season 15-meter results are presented in this paper and used as reference for comparison to the segmentation-based classifications.

2.5 ***Accuracy assessment***

To assess the accuracy of the remote sensing analyses, a dataset developed by the third author was used. Five 7.5-minute quarter-quadrangles (quarter-quads) within the study area were randomly selected using a stratified sampling approach (figure 4). Colour, infrared, digital aerial photographs (years 1999–2004) obtained from the Land Boundary Information System (http://www.labins.org, accessed 02/07) were photointerpreted, and heads-up digitized isolated wetlands within the selected quarter-quads 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 U.S. Fish and Wildlife Service National Wetlands Inventory (NWI), the U.S. Geological Survey (USGS) National Hydrography Dataset (NHD), the USGS Digital Raster Graphics (DRGs), and the St. Johns River Water Management District land use and land cover data, were sometimes used to aid in the photointerpretation process. A contingency matrix was constructed to compare the reference data to the land cover classification. Overall accuracy was calculated by dividing the total correct pixels by the total number of pixels in the error matrix. Individual class user accuracy (error of commission) and producer accuracy (error of omission) were calculated following Story and Congalton (1986). The Kappa coefficient was also calculated to compare the accuracy of the classification to that of a random classification (Congalton *et al.* 1983).

3 Results and discussion

The results of the segmentation/object-oriented classification accuracies are presented in table 1 for both the single- and multi-season datasets. Table 1 also compares the segmentation results to those for the traditional maximum likelihood classifications. The overall accuracies of the single-season and multi-season segmentation classifications were 90.2% and 90.8%, respectively. 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) or larger in the lower 48 states should be mapped using 1-meter 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.

The overall accuracies of the single-season and multi-season segmentation classifications are much higher than the overall accuracies for the maximum likelihood classifiers, which were 78.4% for the single-season dataset and 79.0% for the multi-season dataset. Kappa coefficients, which represent how well the classifications performed compared to that of a random classification, were also much higher for the segmentation classifications than for the maximum likelihood classifications. Kappa was 0.75 for both the single-season and multi-season segmentation classifications compared to only 0.47 (single-season) and 0.49 (multi-season) for the maximum likelihood classifications.

Producer and user accuracies were also calculated for all four classifications. The producer accuracy represents the probability of a reference pixel being correctly classified as a wetland and is a measure of omission error. User accuracy is the probability that a pixel classified as a wetland actually represents that category in the reference data and is a measure of commission error. For example, if the entire image were classified as wetlands then the producer accuracy would be 100% and the user accuracy would be 0%. However, if zero pixels in the image were classified as wetland then the producer accuracy would be 0% and the user accuracy would be 100%. The producer accuracies of the segmentation/object-oriented classifications were 90.8% and 91.6% for the single-season and multi-season datasets, respectively. These producer accuracies are much higher than those for the maximum likelihood classifications, which were only 70.6% (single-season) and 74.4% (multi-season). User accuracies for both classification methods were lower than producer accuracies, indicating that wetland areas were more likely overestimated than underestimated. User accuracies for the segmentation/object-oriented approach were 73.9% and 73.5% for the single-season and multi-season datasets, respectively. These accuracies were still much higher than those for the maximum likelihood classifications, which had user accuracies of 54.1% (single-season) and 55.0% (multi-season).

Figure 5 shows a direct overlay of the multi-season wetlands classification resulting from segmentation/object-oriented processing, with one of the photo-interpreted accuracy assessment quads. Areas in pink are agreements between the reference data and the classified data. Areas in white are wetlands that the classification missed, but are found in the reference data (errors of omission). Areas that are red are areas that were classified as wetlands, but not present in the reference data (errors of commission). Most of the commission errors are simply boundary mismatches between the reference data and classifications. Very few wetlands were missed in the classification and most of these consisted of small isolated wetlands. Figure 6 displays a side by side comparison of the segmentation multi-season classification and a photo-interpreted accuracy assessment quad. Overall the same pattern, shape, and size of wetlands are found in both the wetland classification and the reference data.

It is clear that the segmentation and object-oriented classifiers outperformed the traditional pixel-based spectral maximum likelihood classifier. There are several reasons that account for the superiority of the segmentation/object-oriented approach. First, the segmentation algorithm is capable of extracting the boundaries of wetlands from the adjacent upland areas. This allows the wetland areas to be processed as homogeneous objects, instead of individual pixels. The objects then have spectral, textural, spatial, and contextual patterns that can be used to aid in the classification. Pixels, on the other hand, are limited to the spectral characteristics alone. A pixel-based spectral approach can only classify the physical cover on the ground that creates the signature. Thus, it ignores the textural, contextual, and pattern components which are very important in distinguishing wetlands from the adjacent upland areas.

It is a bit surprising that the use of multi-season data had a minimal increase in the accuracy of the wetlands classification. Other researchers have found greater increases in accuracy when using multi-season versus single-season data for wetlands classification (Ozesmi and Bauer 2002). For example, Lunetta and Balogh (1999) found that classification accuracy increased from 69% to 88% when using multi-date imagery instead of single-date imagery. Two reasons may account for the relatively small increase in accuracy from single-season to multi-season data in this study. First, the January scene was the wettest scene for the year; wetlands could be clearly delineated using this image, thus, a second scene wasn’t necessary to help delineate the wetlands. Also, with an already high accuracy of approximately 90% using the segmentation/object-oriented method, there is little room for improvement. Upon visual inspection of the two datasets, it was noticed that the multi-season data distinguishes riparian wetlands more clearly than the single-season data. Figure 7 shows a comparison between the multi-season and single-season data for an area of the image that has numerous riparian wetlands. It is obvious by comparing the two images that the riparian wetlands are better distinguished in the multi-season data than in the single-season data. Despite the slight increase in detecting riparian wetlands using the multi-season data, it may not be worth the added cost to use multiple seasons for wetland classifications, especially on a regional basis. The best approach for classifying wetlands is to acquire the wettest scene for a particular year and use segmentation and object-oriented processing for classifying wetlands in that scene.

4 Summary and conclusion

The goal of this project was to apply segmentation and object-oriented processing to Landsat-7 ETM+ imagery for the classification of wetlands in Alachua County, Florida. Two objectives were met: (1) to determine the accuracy of segmentation and object-oriented classification of wetlands compared to that for the traditional maximum likelihood algorithm, and (2) to determine if classification of multi-season Landsat-7 imagery provided higher accuracies than that for a single-season Landsat-7 scene. The segmentation/object-oriented classifiers outperformed the traditional maximum likelihood classifiers for mapping wetlands. The overall accuracy of the single-season and multi-season segmentation classifications was 90.2% and 90.8%, respectively. These accuracies were much higher than the overall accuracies for the maximum likelihood classifiers which were 78.4% for the single-season dataset and 79.0% for the multi-season datasets. Producer and user accuracies and Kappa coefficients were also much higher for the segmentation/object-oriented approach than for the maximum likelihood classifiers. Several conclusions with regard to remote sensing of wetlands can be made from the results of this study:

(1) Segmentation and object-oriented processing outperformed the maximum likelihood classifier for satellite classification of wetlands;

(2) Segmentation and object-oriented methods provided high classification accuracies in mapping wetlands due to their ability to delineate wetland boundaries and incorporate spectral, textural, contextual, and pattern information in the classification process;

(3) Wetland classification accuracies were higher when the wettest scenes for a particular time period were used in the classification process; and

(4) The use of multi-season data improved the classification of riparian wetlands, but overall resulted in only slight increases in wetland classification accuracy and may not be worth the added cost.

This research is one of the first to apply segmentation and object-oriented methods to Landsat imagery for the classification of wetlands. With the high accuracies produced by segmentation and object-oriented processing, it is recommended that these methods be used on a regional or national basis for low-cost, high accuracy classification of all wetlands in the future.

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References

ANTUNES, A.F.B, LINGNAU, C. and DA SILVA, J.C., 2003, Object-oriented analysis and semantic network for high resolution image classification. *Anais XI SBSR*, Belo Horizonte, Brasil, INPE, 273–279.

BAATZ, M. and SCHAPE A., 2000, Multiresolution segmentation-an optimization approach for high quality multi-scale image segmentation. In *Angewandte Geographische Informations-Verarbeitung XII,* J. Strobl, T. Blaschke, and G. Gresebner. (eds), pp. 12–23 (Heidelberg, Germany: Wichmann-Verlag).

BAKER, C., LAWRENCE, R., MONTAGNE, C. and PATTEN, D., 2006, Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models. *Wetlands* **26,** 465–474.

BASTIN, L., 1997, Comparison of fuzzy c-means classification, linear mixture modeling and MLC probabilities as tools for unmixing coarse pixels. *International Journal of Remote Sensing*, **18,** 3629–3648.

BENZ, U.C., HOFMANN, P., WILLHAUCK, G., LINGENFELDER, I. and HEYNEN, M., 2004, Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, **58,** 239–258.

BOLSTAD, P.V. and LILLESAND, T.M., 1992, Rapid maximum likelihood classification. *Photogrammetric Engineering & Remote Sensing*, **57,** 64–74.

BURNETT, C., AAVIKSOO, K., LANG, S., LANGANKE, T., and BLASCHKE, T., 2003, An object-based methodology for mapping mires using high resolution imagery. In *Ecohydrological Processes in Northern Wetlands*, A. Järvet and E. Lode. (eds), pp. 239–244 (Tallinn, Estonia: Tartu University Press).

CONGALTON, R.G., ODERWALD, R.G. and MEAD, R.A., 1983, Assessing Landsat classification accuracy using discrete multivariate statistical techniques. *Photogrammetric Engineering & Remote Sensing*, **49,** 1671–1678.

CHOPRA, R., VERMA, V.K. and SHARMA, P.K., 2001, Mapping, monitoring and conservation of Harike wetland ecosystem, Punjab, India, through remote sensing. *International Journal of Remote Sensing*, **22,** 89–98.

CIVCO, D.L., 1993, Artificial neural networks for land-cover classification and mapping. *International Journal of Geographical Information Systems*, **7,** 173–186.

COSTA, M.P.F., NIEMANN, O., NOVO, E., AND AHERN, F., 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,** 1401–1426.

EDIRIWICKREMA, J., 1997, Hierarchical maximum-likelihood classification for improved accuracies. *IEEE Transactions on Geoscience and Remote Sensing*, **35,** 810–816.

EMRAHOGLU, N., YEGINGIL, I., PESTEMALCI, V., SENKAL, O. and KANDIRMAZ, H.M., 2003, Comparison of a new algorithm with the supervised classifications. *International Journal of Remote Sensing*, **24,** 649–655.

ERBEK, F.S., OZKAN, C. and TABERNER, M., 2004, Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing,* **25,** 1733–1748.

FOODY, G.M., 1992, A fuzzy sets approach to the representation of vegetation continua from remotely sensed data: an example from lowland heath. *Photogrammetric Engineering & Remote Sensing*, **58**, 221–225.

GENELETTI, D. and GORTE, B.G.H., 2003, A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. *International Journal of Remote Sensing*, **24,** 1273–1286.

GREEN, A.A., BERMAN, M., SWITZER, P. and CRAIG, M.D., 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. In *Handbook of Pattern Recognition and Image Processing - Volume 1*, T.Y. Young and K.S. Fu (eds), pp. 247–280 (New York: Academic Press).

HEBER, M., 2008, *FGDC Draft Wetland Mapping Standard.* FGDC Wetland Subcommittee and Wetland Mapping Standard Workgroup, Environmental Protection Agency, Office of Water, Washington, D.C.

HESS, L.L., MELACK, J.M., NOVO, E.M.L.M., BARBOSA, C.C.F. and GASTIL, M., 2003, Dual season mapping of wetland inundation and vegetation for the central Amazon basin. *Remote Sensing of Environment*, **87,** 404–428.

HILL, R.A., 1999, Image segmentation for humid tropical forest classification in Landsat TM data. *International Journal of Remote Sensing,* **20,** 1039–1044.

HUNTER, E.L. and POWER, C.H., 2002, An assessment of two classification methods for mapping Thames Estuary intertidal habitats using CASI data. *International Journal of Remote Sensing*, **23,** 2989–3008.

HURD, J.D., CIVCO, D.L., GILMORE, M.S., PRISLOE, S. and WILSON, E.H., 2006, Tidal wetland classification from Landsat imagery using an integrated pixel-based and object-based classification approach. In *ASPRS 2006 Annual Conference Proceedings* (Maryland: American Society for Photogrammetry and Remote Sensing).

HUTTON, S.M. and T. DINCER, 1979, Using Landsat imagery to study the Okavango Swamp, Botswana. In *Fifth Annual William T. Pecora Memorial Symposium on Remote Sensing,* 10–15 June1979, Sioux Falls, SD, M. Deutsch, D.R. Wiesnet, and A. Rango (eds), pp. 512–519 (Middelburg, VA: American Water Resources Association).

JENSEN, J.R., CHRISTENSEN, E.J. and SHARITZ, R.R., 1984, Nontidal wetland mapping in South Carolina using airborne multispectral scanner data. *Remote Sensing of Environment* **16,** 1–12.

JENSEN, J.R., NARUMALANI, S., WEATHERBEE, O. and MACKEY, H.E., JR, 1993, Measurement of seasonal and yearly cattail and waterlily changes using multidate SPOT panchromatic data. *Photogrammetric Engineering and Remote Sensing,* **59,** 519–525.

JENSEN, R.J., 2005, *Introductory Digital Image Processing: A Remote Sensing Perspective* (Upper Saddle River, NJ: Prentice-Hall).

KARTIKEYAN, B., SARKAR, A. and MAJUMDAR, K.L., 1998, A segmentation approach to classification of remote sensing imagery. *International Journal of Remote Sensing*, **19,** 1695–1709.

KATO, M., SONOBE, T., OYANAGI, M., YASUOKA, Y., TAMURA, M.T. and HAYASHI, M., 2001, ASTER data utilization for wetland mapping and forest mapping. In *22nd Asian Conference on Remote Sensing*, 5–9 November 2001, *Singapore* (Centre for Remote Imaging, Sensing and Processing, national University of Singapore, Singapore Institute of Surveyors and Valuers, Asian Association on Remote Sensing).

KUSHWAHA, S.P.S, DWIVEDI, R.S. and RAO, B.R.M., 2000, Evaluation of various digital image processing techniques for detection of coastal wetlands using ERS-1 SAR data. *International Journal of Remote Sensing* **21,** 565–579.

LALIBERTE, A.S., RANGO, A., HAVSTED, K.M., PARIS, J.F., BECK, R.F., MCNEELY, R. and GONZALEZ, A.L., 2004, Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment*, **93**, 198–210.

LI, J. and CHEN, W., 2005, A rule-based method for mapping Canada's wetlands using optical, radar and DEM data. *International Journal of Remote Sensing,* **26,** 5051–5069.

LILLESAND, T.M., KIEFER, R.W. and CHIPMAN, J.W., 2004, *Remote Sensing and Image Interpretation*, fifth edition (New York: John Wiley & Sons, Inc.).

LIU, X.-H., SKIDMORE, A.K. and VAN OOSTEN, H., 2002, Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry & Remote Sensing*, **56,** 257–268.

LO, C.P. and CHOI, J.M., 2004, A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images. *International Journal of Remote Sensing,* **25,** 2687–2700.

LUNETTA, R.S. and BALOGH, M.E., 1999, Application of multitemporal Landsat 5 TM imagery for wetland identification. *Photogrammetric Engineering & Remote Sensing*, **65,** 1303–1310.

MAKELA, H., and PEKKARINEN, A., 2001, Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. *Remote Sensing of Environment*, **77,** 66–75.

MITSCH, W.J. and GOSSELINK, J.G., 2000, *Wetlands*, third edition (New York: John Wiley & Sons, Inc.).

OZESMI, S.L. and BAUER., M.E., 2002, Satellite remote sensing of wetlands. *Wetlands Ecology and Management*, **10**, 381–402.

PALYLYK, C.L., CROWN, P.H. and TURCHENEK, L.W., 1987, Landsat MSS data for peatland inventory in Alberta. In *Symposium '87 Wetlands Peatlands,* 1987, Edmonton, Alberta, Canada, C.D.A. Rubec and R.P. Overend (eds), pp. 365–371 (Canadian Society of Wetlands and Peatlands and Canadian National Committee, International Peat Society).

PEKKARINEN, A., 2002, A method for the segmentation of very high spatial resolution images of forested landscapes. *International Journal of Remote Sensing*, **23,** 2817–2836.

RAMSEY, E.W. III, CHAPPELL, D.K. and BALDWIN, D.G., 1997, AVHRR imagery used to identify hurricane damage in a forested wetland of Louisiana. *Photogrammetric Engineering & Remote Sensing*, **63,** 293–297.

RESEARCH SYSTEMS, INC., 2005, *ENVI 4.2 User's Guide,* Volume 2 (Boulder, CO: Research Systems, Inc.).

SADER, S.A., AHL, D. and LIOU, W.S., 1995, Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. *Remote Sensing of Environment*, **53**, 133–144.

SCHIEWE, J., 2003, Integration of multi-sensor data for landscape modeling using a region-based approach. *ISPRS Journal of Photogrammetry & Remote Sensing*, **57,** 371–379.

SHANMUGAM, P., AHN, Y. and SANJEEVI, S., 2006, A comparison of the classification of wetland characteristics by linear spectral mixture modelling and traditional hard classifiers on multispectral remotely sensed imagery in southern India. *Ecological Modelling*, **194,** 379–394.

SHACKELFORD, A.K. and DAVIS, C.H., 2003, A combined fuzzy pixel-based and object–based approach for classification of high-resolution multispectral data over urban areas. *IEEE Transactions on Geoscience and Remote Sensing*, **41,** 2354–2363.

SOUTH, S., QI, J. and LUSCH, D.P., 2004, Optimal classification methods for mapping agricultural tillage practices. *Remote Sensing of Environment*, **91,** 90–97.

STORY, M. and CONGALTON, R.G., 1986, Accuracy assessment: a user's perspective. *Photogrammetric Engineering & Remote Sensing*, **52,** 397–399.

STANKIEWICZ, K., DABROWSKA-ZIELINSKA, K., GRUSZCZYNSKA, M., and HOSCILO, A., 2003, Mapping vegetation of a wetland ecosystem by fuzzy classification of optical and microwave satellite images supported by various ancillary data. In *Remote Sensing for Agriculture***,** *Ecosystems, and Hydrology IV*, Proceedings of SPIE Volume 4879, M. Owe, G. D'Urso and L. Toulios (eds), p.p. 352-361 (Bellingham, WA: International Society for Optical Engineering).

STUCKENS, J., COPPIN, P.R. and BAUER, M.E., 2000, Integrated contextual information with per pixel classified for improved land cover classification. *Remote Sensing of Environment*, **71,** 282–296.

SUGUMARAN, R., HARKIN, J., and GERJEVIC, J., 2004, Using remote sensing data to study wetland dynamics in Iowa. Iowa Space Grant Final Technical Report, University of Northern Iowa, pp. 1–17.

TINER, R.W., 2003, Geographically isolated wetlands of the United States. *Wetlands*, **23,** 494–516.

TOYRA, J. and PIETRONIRO, A., 2005, Towards operational monitoring of a northern wetland using geomatics-based techniques. *Remote Sensing of Environment*, **97,** 174–191.