



# Multi-temporal Sub-pixel Landsat ETM+ Classification of Isolated Wetlands in Cuyahoga County, Ohio, USA

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**Abstract** The goal of this research was to determine the utility of subpixel processing of multi-temporal Landsat Enhanced Thematic Mapper Plus (ETM+) data for the identification and mapping of isolated wetlands  $\geq 0.20$  ha (0.50 acres) in Cuyahoga County, Ohio. Segmentation and object-oriented analysis of Landsat ETM+ was used to map forested and emergent marsh isolated wetlands in Alachua County, Florida, previously; however, the isolated wetlands in our study area lacked the well-defined, high-contrast boundaries between wetland and surrounding upland needed to make this method successful. We developed a new methodology that incorporated Landsat ETM+; a Normalized Difference Vegetation Index mask; and subpixel matched filtering—which determines the apparent abundance of wetlands at subpixel levels in the presence of spectrally-mixed, unknown background through a partial unmixing algorithm—to map  $> 43$  km<sup>2</sup> (16 mi<sup>2</sup>) of isolated wetlands in our 1,189 km<sup>2</sup> (459 mi<sup>2</sup>) study area. The final overall accuracy of the classification was 92.8%, with a Kappa coefficient of

0.86; producer accuracy for isolated wetlands was 87.9% (omission error 12.1%) and user accuracy was 97.4% (commission error 2.6%). The subpixel matched filtering method used in this research appears to provide an effective means for mapping isolated wetlands  $\geq 0.20$  ha, especially those with boundaries that are not easily identified.

**Keywords** Detection · Imagery · Mapping · Matched filtering

## 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 (Mitsch and Gosselink 2000). Geographically isolated wetlands are wetlands that are completely surrounded by uplands, with no apparent surface water connections to perennial waters (Tiner 2003a). Research on isolated wetlands has increased in recent years due to the 2001 *Solid Waste Agency of Northern Cook County (SWANCC) vs. U.S. Army Corps of Engineers* U.S. Supreme Court ruling [531 U.S. 159 (2001)], which effectively removed federal protection status for isolated wetlands under the Clean Water Act using the Migratory Bird Rule, thereby limiting their protection (Downing et al. 2003).

While federal protection of isolated wetlands is now limited, these systems nevertheless perform many important ecological and hydrological functions, such as ground water recharge (Leibowitz 2003), floodwater retention and maintenance of lotic system base flow (Whigham and Jordan 2003; Lane and D'Amico 2010), and biogeochemical cycling of nutrients (Tiner 2003b; Whigham and Jordan 2003). In addition, although typically smaller than non-isolated

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Dr. Robert Frohn passed away on October 16, 2010.

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wetlands, isolated wetlands are locally quite numerous (Tiner 2003a) and are important in wetland metapopulation dynamics (Semlitsch and Bodie 1998). Isolated wetlands also provide habitat for unique endemic species and often have high species diversity and richness (Semlitsch and Bodie 1998; McKinney and Charpentier 2009). A recent study by Comer et al. (2005) found that at least 86 plant and animal species listed as threatened or endangered are supported by isolated wetlands, and more than half of those taxa are completely dependent on isolated wetland habitat.

Isolated wetlands are distributed throughout the United States and include playas, prairie potholes, pocosins, woodland and California vernal pools, wet dune swales, sinkhole wetlands, desert springs, kettle hole bogs, and fens (Tiner et al. 2002). Comer et al. (2005) determined that of the 276 types of wetlands described for the United States, 29% (81) are defined as geographically isolated; most of these types of isolated wetlands are located in depressions on the landscape (Leibowitz 2003). A number of factors contribute to the formation of these natural isolated wetlands, including climate, topography, surficial geology, glacial history, and tectonics (Tiner 2003b).

Unfortunately, the vast majority of geographically isolated wetlands have not been identified or mapped. McKinney and Charpentier (2009) maintained that the first step in the conservation of geographically isolated wetlands was to identify their frequency, distribution, size, and type. There is a pressing need for an accurate and reliable assessment of the number and area of isolated wetlands to monitor their loss, understand their ecological importance, and address mitigation measures (Munoz et al. 2009).

Satellite remote sensing analysis has had a long and successful history in accurately mapping wetlands (e.g., Hutton and Dincer 1979; Jensen et al. 1984; Ozesmi and Bauer 2002; Töyrä and Pietroniro 2005; Frohn et al. 2011). Ozesmi and Bauer (2002) provided an excellent review on satellite remote sensing of wetlands and detailed successful mapping techniques. There are many advantages for using satellite imagery to map isolated wetlands, including repeated coverage, mapping of multi-temporal and multi-seasonal changes, multispectral data layers, and ease of integration in a geographic information system (Ozesmi and Bauer 2002; Frohn et al. 2009). Despite these advantages, very few studies use satellite remote sensing for mapping isolated wetlands (e.g., Frohn et al. 2009; Reif et al. 2009), possibly due to the limited availability of data sets that identify isolated wetland systems (see Burne 2001; Lathrop et al. 2005).

Frohn et al. (2009) developed a method for satellite remote sensing and mapping of isolated wetlands in Alachua County, Florida, USA, using segmentation and object-oriented analysis of Landsat-7 Enhanced Thematic Mapper Plus (ETM+) data to identify isolated wetlands  $> 0.20$  ha (0.50

acres) with an accuracy of 89%. While Frohn et al. (2009) were successful in identifying wetlands with a significantly different vegetation structure than their surrounding uplands (e.g., graminoid marshes or *Taxodium ascendens* Brongn.-dominated forested wetlands embedded in *Pinus* spp. flatwoods of Florida, USA), not all isolated wetlands fall neatly into this category, such as isolated wetlands with a mixed wetland/upland canopy and small, ephemeral wetland features in upland settings, such as woodland vernal pools (Colburn 2004; Calhoun and deMaynadier 2008). Initial analyses in more temperate ecoregions (Frohn, unpublished results) found poor segmentation and object-oriented analysis results in areas without such well-defined, high-contrast boundaries between wetland and surrounding upland. For these types of isolated wetlands, a new methodology needed to be developed. Because these types of wetlands are small and have mixed vegetation and soil wetness within a single pixel, an approach coupling subpixel processing of remotely sensed data with Normalized Difference Vegetation Index (NDVI) masking was explored.

The NDVI is a useful transformation of satellite data for wetland analysis to enhance the wetland/upland boundary and mask out non-wetland areas and has been widely used in satellite remote sensing of wetlands (Tucker 1979; Narumalani et al. 1997; Hui et al. 2009). Hui et al. (2009) used NDVI in a decision tree classification scheme with Landsat TM data to map wetland paddies and lakes. Melesse et al. (2001) also used NDVI with multi-temporal Landsat TM data to help delineate the boundary between wetlands and water and wetlands and uplands. Because of its sensitivity to vegetation spectral response, NDVI has been found beneficial for wetland mapping even with coarse spatial resolution sensors such as MODIS (Zhao et al. 2009) and AVHRR (Tamura et al. 1998).

A number of subpixel processing methods have been developed in remote sensing for the classification of various land use and land cover types with mixed pixels. These include fuzzy classifications (Stankiewicz et al. 2003), linear spectral unmixing (Shanmugam et al. 2006), and direct subpixel techniques (Huguenin et al. 1997; Ozesmi and Bauer 2002). Subpixel processing is defined as the search for a specific material of interest within a mixed pixels composition (Ozesmi and Bauer 2002). Several researchers have been successful in applying these techniques for the classification of wetlands. Shanmugam et al. (2006) compared linear spectral unmixing with traditional classifiers in southern India and determined that subpixel methods outperformed traditional methods for the classification of wetlands. Oki et al. (2002) also used linear unmixing on multi-temporal Landsat Thematic Mapper (TM) imagery to map Kushiro mire wetlands in Japan, and their method outperformed traditional maximum likelihood classifications. Wang and Lang (2009) recently used linear

unmixing to classify cypress (*Taxodium*) canopies in the Florida Panhandle with multi-temporal Landsat ETM+ data at an accuracy of 88%. Huguenin et al. (1997) used a direct subpixel processing technique to classify bald cypress (*Taxodium distichum* Brongn.) and tupelo gum (*Nyssa* spp.) wetlands with Landsat TM at an accuracy of 89% and 91%, respectively.

Subpixel classification can be achieved using spectral unmixing methods, including full unmixing and partial unmixing methods (Boardman et al. 1995; Nielsen 2001; Mundt et al. 2007). Linear spectral unmixing (Hu et al. 1999; Heinz and Chang 2001) is the standard full unmixing method that has been used for subpixel remote sensing classification of wetlands (Oki et al. 2002; Shanmugam et al. 2006). Linear spectral unmixing assumes a linear combination of reflectance of all classes of spectrally pure materials within a mixed pixel. These spectrally pure materials are known as endmembers in spectral unmixing processing. To use full unmixing methods, like standard linear spectral unmixing, all endmembers (or classes) must be accounted for within the pixel. The spectral signatures for all endmembers must be known, and the number of endmembers in the model cannot exceed the number of bands in the dataset (Nielsen 2001). The full unmixing methods produce the fractional abundance estimates for all endmembers within a pixel. Partial unmixing methods (Mundt et al. 2007), however, do not model all endmembers; instead, they only detect one or a few target endmembers of interest and estimate the subpixel abundance of these target endmembers in each pixel, ignoring other endmembers that are not related to the specific goal of the detection problem. Since a priori knowledge of spectral signatures for many unimportant endmembers in the background is not required, the difficulty and cost associated with the identification of a complete set of endmembers and acquisition of spectra for all endmembers are dramatically reduced in partial unmixing methods (Settle 2002; Kuenzer et al. 2008). Recently, a number of partial unmixing methods have been developed, including matched filtering (Boardman et al. 1995), constrained energy minimization (CEM; Settle 2002), and orthogonal subspace projections (OSP; Harsanyi and Chang 1994).

This study focused on Cuyahoga County, an area of the USA in the Erie Drift Plain ecoregion (Omernik 1987) and a focal area for recent wetland research (e.g., White and Fennessy 2005; Carrino-Kyker and Swanson 2007; Fennessy et al. 2007; Kettlewell et al. 2008). The study area has a relative abundance of scattered, dense patches of wetlands and isolated wetlands located in multimodality upland landscapes, often with full facultative and/or upland tree canopy closure (e.g., Burne and Lathrop 2008). Woodland vernal pools were initially targeted as they are temporarily to semi-permanently inundated wetland

features relatively common in the glaciated midwestern to northeastern North America (Colburn 2004; Calhoun and deMaynadier 2008). Numerous in certain landscapes—although difficult to identify—woodland vernal pools are important areas for pond-breeding amphibians, migratory passerine and waterfowl, and invertebrates (Colburn 2004). Like most isolated wetlands, they generally lack predatory fish species and are inhabited by characteristic taxa such as fairy shrimp (Order: Anostraca) and certain salamanders (e.g., *Ambystoma maculatum* Shaw, the spotted salamander), amongst other organisms (see Colburn et al. 2008; Cutko and Rawinski 2008; Semlitsch and Skelly 2008). However desirable, it was not possible to a priori identify and categorize these specific wetland types on the landscape; therefore, all wetlands defined herein as isolated (see [Methods](#)) were included. The goal of this research was to determine the utility of subpixel processing of multi-temporal Landsat ETM+ data for the mapping of isolated wetlands in Cuyahoga County, Ohio, USA, with potential application to other parts of North America.

## Methods

### Study Area and Data Acquisition

The study area for this research was Cuyahoga County, located in the Erie Drift Plains ecoregion (Omernik 1987) of the northeast corner of the state of Ohio. Cuyahoga County occupies an area of 1,189 km<sup>2</sup> (459 mi<sup>2</sup>) and is within the Cuyahoga River basin, which is apocryphally infamous for being an impetus for the modern Clean Water Act after catching fire in 1969 (Broderick 2005). The Cuyahoga basin has a long history of land use change, primarily due to industrialization dating back to the mid-1800s (Beach 1998). The county is dominated by developed (76%) and forested (19%) land uses ([www.mrlc.gov](http://www.mrlc.gov), accessed March 2010), and characterized by loamy soils with both perched and apparent water tables (Carrino-Kyker and Swanson 2007).

### GIS Reference Data

Two reference datasets were built and later combined to test the isolated wetland classification methods developed in this study. The first reference dataset consisted of a combination of three wetland datasets from local Cuyahoga sources—the Cuyahoga Remedial Action Plan (CuyRAP), the Davey Resource Group (DaRG), and the Cuyahoga Valley National Park (CVNP). The CuyRAP dataset was developed by the Davey Resource Group (2003) for the Cuyahoga River watershed in Cuyahoga County, Ohio using aerial photos from 1993, National Wetlands Inventory (NWI) data, and

soil survey maps. Emphasis was placed on identifying wetlands  $> 0.41$  ha (1.0 acre) in size, with a goal of mapping all wetlands in the study area; efforts were also made to field verify the wetlands in the CuyRAP dataset. The average wetland size in the CuyRAP dataset is 0.73 ha (1.8 acres), with size ranges from 0.01 ha (0.03 acres) to 19.95 ha (49.30 acres); 274 wetlands were  $< 0.20$  ha (0.50 acres). The Cuyahoga County portion of the Cuyahoga River watershed comprises the extent of the CuyRAP study area. DaRG wetland data was similarly developed by the Davey Resource Group (2006) and incorporates the CuyRAP dataset, but has a greater extent—the entirety of Cuyahoga County. The DaRG dataset was developed based on 2002 aerial photos and wetlands were field verified (Davey Resource Group 2006). The wetlands in the DaRG dataset range in size from  $< 0.01$  ha (0.01 acres) to 95.26 ha (235.40 acres), with an average size of 0.73 ha (1.8 acres). There are 2721 polygons in the DaRG dataset, 1153 of which are  $< 0.20$  ha (0.50 acres). The final component of this first reference dataset was data on wetlands within the Cuyahoga Valley National Park (CVNP), again identified by the Davey Resource Group (2001 [unpublished]; Skerl 2001). The CVNP dataset used 1:24,000 black and white orthophotography (date unknown) and other datasets to identify 1217 wetlands averaging 0.57 ha (1.4 acres) in size, with only 190 wetlands  $> 0.41$  ha (1.0 acre). Wetlands within the CVNP dataset were clipped to Cuyahoga County for use in this study. There was substantial overlap between the CVNP, DaRG, and CuyRAP datasets; these datasets were merged together, and when combined, provided for coverage of Cuyahoga County in its entirety. The 2752 wetland polygons in the merged Cuyahoga County dataset ranged in size from  $< 0.01$  ha ( $< 0.01$  acres) to 94.86 ha (234.40 acres), with an average wetland size of 0.81 ha (1.99 acres).

Isolated wetlands for Cuyahoga County were determined using a buffer geoprocessing procedure. Any wetland in the combined Cuyahoga County wetland dataset that was  $> 10$ -m from a water feature identified on the USGS 1:24,000 National Hydrography Dataset (NHD; available from <http://nhd.usgs.gov/data.html>, accessed Fall 2008) was determined to be isolated (Reif et al. 2009). Water features included named lakes and ponds, as well as any linear feature within the NHD, with the exception of features that were obviously artificial, ditched channels, and/or disconnected streams. The combined Cuyahoga County wetland dataset was post-processed to remove all non-isolated wetlands (i.e., wetlands within the 10-m hydrology buffer).

Of the isolated wetlands remaining in the post-processed Cuyahoga County wetland dataset, those  $\geq 0.20$  ha (0.50 acres) in size (1088 polygons) were used as reference data. The 0.20 ha (0.50 acre) size cut off was established to allow comparisons between this area of study and that of Frohn et al. (2009); this size represents approximately two Landsat

ETM+ 30-m pixels, and encompasses 53% of all isolated wetlands in the post-NHD processed dataset. Of the 1088 polygons  $\geq 0.20$  ha (0.50 acres) in the Cuyahoga County reference dataset, the average isolated wetland size was 0.89 ha (2.19 acres), with a range from 0.20 ha (0.50 acres) to 44.95 ha (111.08 acres).

The second reference dataset was constructed from an updated National Wetland Inventory (NWI) dataset acquired from the Ducks Unlimited Great Lakes/Atlantic Region (<http://www.ducks.org/Conservation/GLARO/3822/GISNWIData.html#oh>, accessed 2009). The updated NWI dataset included 2250 polygons within the study area, ranging in size from 0.02 ha (0.05 acres) to a lacustrine area of 249.88 ha (617.46 acres), with an average wetland size of 1.18 ha (2.92 acres). Wetlands  $< 0.20$  ha (0.50 acres) represented 947 of the 2,250 polygons.

The updated NWI dataset was post-processed to remove all non-isolated wetlands using the NHD buffer procedure previously described. Only isolated wetlands  $\geq 0.20$  ha (0.50 acres)—47% of the post-processed NWI isolated wetlands dataset—were used as reference data. The resulting NWI reference dataset had 750 wetland polygons ranging in size from 0.20 ha (0.50 acres) to 28.92 ha (71.47 acres), with a mean of 0.82 ha (2.03 acres). The 145 polygons in the NWI reference dataset that overlapped with wetlands in the Cuyahoga County reference dataset (created from the DaRG, CuyRAP, and CVNP data) were not used. A final reference dataset of 1693 isolated wetland polygons was developed for method testing by combining the NWI and Cuyahoga County reference data. Table 1 shows the properties of the two sets of reference data combined to create the final reference dataset. It should be noted that the majority (98.9%) of the reference wetland polygons came from the DaRG dataset that was originally derived from 2002 aerial photographs and verified with field observations. Due to its high accuracy, high spatial resolution and approximate coincidence in time with the acquisitions of satellite data used in our analysis, the reference data are well qualified for training the classifiers and evaluating the wetland classification result.

#### Remote Sensing Data Acquisition and Merging

We acquired two Landsat-7 ETM+ scenes for our study area (Path 19, Row 31) from the U.S. Geological Survey (USGS) Global Visualization (GLOVIS) data server with dates from the time period coinciding with the DaRG study (2002–2003). These scenes consisted of a leaf-on July 16, 2002 image and a leaf-off April 14, 2003 image. The two image scenes were radiometrically corrected using the log residuals calibration method implemented in ENVI software package (Research Systems Inc. 2007). This method creates a pseudo reflectance image through dividing the input image



**Table 1** Properties of Cuyahoga County wetlands (source data) and isolated wetlands (reference data after post-processing with the National Hydrography Dataset [NHD])

	Source dataset – all wetlands			Reference dataset – isolated wetlands only				
	Minimum size	Maximum size	Average size	Count	Minimum size	Maximum size	Average size	Count
Combined Cuyahoga County Wetlands <sup>a</sup>	< 0.01 ha (< 0.01 ac)	94.86 ha (234.40 ac)	0.81 ha (1.99 ac)	2752	0.20 ha (0.50 ac)	44.95 ha (111.08 ac)	0.89 ha (2.19 ac)	1088
Updated NWI <sup>b</sup>	0.02 ha (0.05 ac)	249.88 ha (617.46 ac)	1.18 ha (2.92 ac)	2250	0.20 ha (0.50 ac)	28.92 ha (71.47 ac)	0.82 ha (2.03 ac)	750

<sup>a</sup> The combined Cuyahoga County wetlands dataset includes wetlands from the Cuyahoga Remedial Action Plan (CuyRAP), Davey Resource Group (DaRG), and Cuyahoga Valley National Park (CVNP)

<sup>b</sup> An updated National Wetlands Inventory (NWI) dataset was acquired from the Ducks Unlimited Great Lakes/Atlantic Region for analysis

data values by the spectral geometric mean and then by the spatial geometric mean. Since the atmospheric transmittance and other effects are considered multiplicative, logarithm transform of the data values were performed. The use of the spectral mean of all bands for each pixel removed topographic effects. The use of spatial mean of all pixels for each band accounted for the effects of solar irradiance, atmospheric transmittance, and instrument gain from radiance data. The radiometrically corrected images were then co-registered to one another, and georeferenced to UTM Zone 17 N projection with reference to WGS84 ellipsoid. Initial experiments had been performed by applying various classification methods to the leaf-on image acquired in July, 2002, including Maximum Likelihood Classification (MLC), minimum distance classification, Mahalanobis distance classification, and Spectral Angle Mapper (SAM). Applying these classification methods to the single leaf-on image resulted in low overall classification accuracy, ranging from 65 to 79%. Inspired by the idea that the combination of leaf-on and leaf-off imagery may capture the unique phenology characteristics of wetland vegetation, we used a multi-temporal satellite dataset for better wetland classification in this study. The six sharpened spectral bands from each of two images scenes (leaf-on and leaf-off) were stacked to form a multi-temporal dataset with 12 data layers. Thermal bands (i.e., band 6) were not used in the analysis due to their coarse (60-m) spatial resolution. To merge the 30-m spectral data with the 15-m panchromatic data of Landsat-7 ETM+, a Gram-Schmidt sharpening algorithm (Laben and Brower 2000; Research Systems Inc. 2007) was utilized. First, a low resolution (30-m) panchromatic band was simulated from the lower spatial resolution spectral bands of Landsat ETM+ imagery using a specific weighting scheme for Landsat ETM+. 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 actual high resolution (15-m) Landsat-7 panchromatic band was used to substitute for the first Gram-Schmidt band. The inverse Gram-Schmidt transform was applied to the entire dataset, resulting in a 15-m sharpened dataset.

#### NDVI Mask

This study used the Normalized Difference Vegetation Index (NDVI) mask to enhance the wetland/upland boundary, mask out non-wetland areas, and help to eliminate false positives (i.e., commission errors). A NDVI was calculated using the July 2002 Landsat ETM+ data and Eq. 1:

$$NDVI = \frac{(ETMBand4 - ETMBand3)}{(ETMBand4 + ETMBand3)} \quad (1)$$

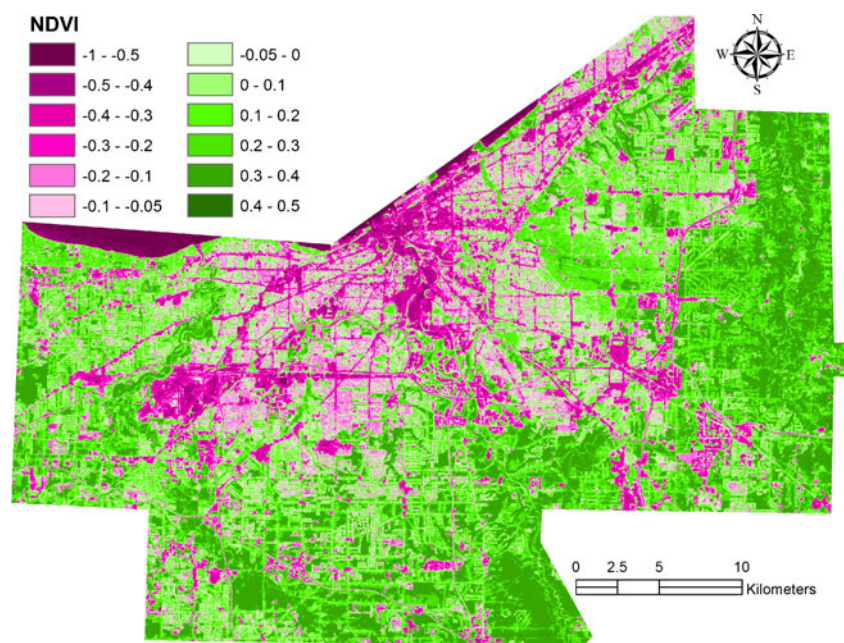
NDVI values range from  $-1.00$  to  $+1.00$ . Figure 1 shows the NDVI image of the leaf-on July 2002 Cuyahoga County data, which had NDVI values ranging from  $-1.00$  to  $+0.46$ . A subset of the 1693 polygons in the final reference dataset was used as training data. A NDVI mask was created for the study area with a NDVI threshold value of  $-0.05$ , which is determined by the mean NDVI of the training data (i.e.,  $+0.25$ ) minus one standard deviation ( $0.30$ ). Inside the mask, the features with a NDVI value lower than  $-0.05$  were considered to have a low likelihood of isolated wetland presence. The NDVI mask was applied to the 12-band multi-temporal Landsat dataset and the unmasked data were then used in subpixel processing for classification of wetlands. As shown in Fig. 1, the features masked out mainly correspond to buildings, pavements, parking lots, roads, and open waters.

### Subpixel Classification Based on Spectral Unmixing

This study aimed to map the subpixel abundance of a single land cover class (isolated wetlands); other land cover classes surrounding the wetlands were treated as spectrally-mixed composite background. We identified the wetlands as isolated based on a masked constraint and the reference dataset. This basically reduced the classification problem to a two-component unmixing algorithm: the abundance of one known endmember (isolated wetlands) against an unknown composite background of all other land cover classes. The partial unmixing method used in this research was the matched filtering algorithm implemented in the ENVI software package (Research Systems Inc. 2007). Matched filtering was originally developed for use in electrical and

signal processing (Turin 2002); the algorithm is designed to filter and project the input data to maximize the response of the known target endmember, while suppressing the response (variance) of the unknown composite background endmember of all other land cover materials (Boardman et al. 1995; Mundt et al. 2007). The matched filtering algorithm was applied to the masked 12-band dataset. The reference dataset (consisting of post-processed isolated wetlands from the updated NWI, CuyRAP, DaRG, and CVNP) was used as the training dataset to obtain the spectral signature of the target endmember—isolated wetlands. The computation result was the matched filtering score image, representing the relative match degree (similarity) of the pixel spectra to the reference isolated wetland spectra (Williams and Hunt 2002; Harris et al. 2005; Mitchell and Glenn 2009). A matched filtering score of 1.0 is a perfect match to the target endmember, and a zero value represents the background (no target endmember material). The matched filtering score can be interpreted as the estimate for the relative fractional abundance of the target endmember (i.e., isolated wetlands) within each image pixel of the study area. In order to create the final classification, the matched filtering scores were compared with a threshold value. Those image pixels with a matched score larger than the threshold value were classified as isolated wetlands, and all other pixels were classified as the composite background. The threshold value was selected as the mean matched filtering score minus one standard deviation ( $\bar{x} - 1SD$ ) of the pixels in the reference isolated wetland polygons of the training dataset. The final classified isolated wetland map was then post-processed to clump and merge adjacent pixels, in which the adjacency is defined by four neighbors. The post-classification

**Fig. 1** Normalized Difference Vegetation Index (NDVI) image of the July 2002 leaf-on Landsat-7 ETM+ data. Areas in green have higher NDVI values, while magenta areas have lower NDVI values; NDVI values of the image ranged from  $-1.00$  to  $+0.46$



processing produces a cleaner version of the isolated wetlands map for the subsequent analyses.

### Accuracy Assessment

The final classification map of isolated wetlands was assessed for accuracy using a dataset that consisted of 5,000 randomly selected data points extracted from the reference wetland dataset for verification. A contingency matrix was constructed to compare classified data with the reference data, and overall accuracy, producer accuracy, user accuracy, and Kappa statistic were calculated. Overall accuracy was calculated by dividing the total correct pixels by the total number of pixels in the error matrix. Individual class producer accuracy (error of omission) and user accuracy (error of commission) were calculated following Story and Congalton (1986). The Kappa coefficient was calculated to compare the accuracy of the classification to that of a random classification (Congalton et al. 1983). The Kappa coefficient is a measure of the agreement between the remote sensing classification and the reference data determined both from the major diagonal of the confusion matrix and the chance agreement calculated from the non-diagonal rows and columns (Jensen 2004).

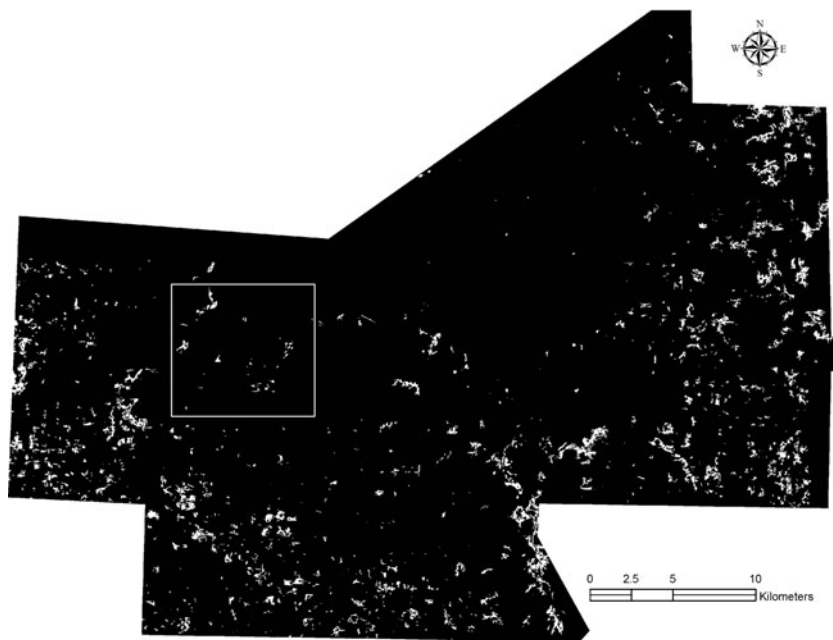
### Results and Discussion

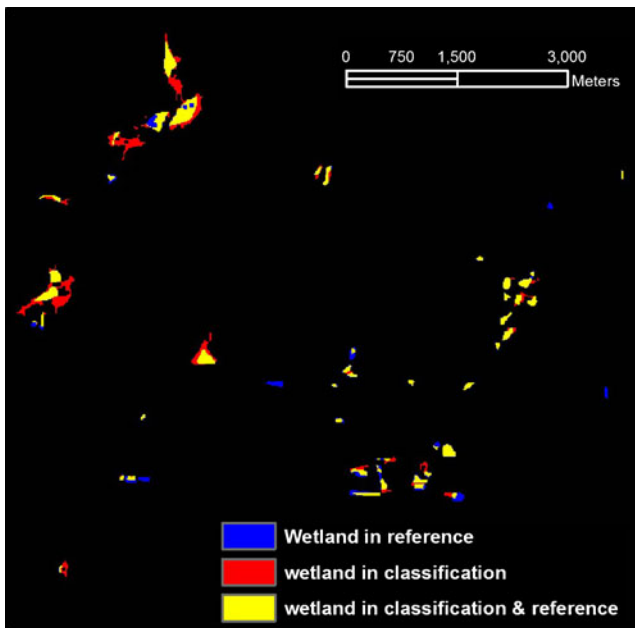
In this study, 328 potential isolated wetlands  $\geq 0.20$  ha (0.50 acres) in size—a total isolated wetland area of  $> 43$  km<sup>2</sup> (16 mi<sup>2</sup>)—were mapped in Cuyahoga County, Ohio, USA (Fig. 2). The NDVI mask was useful in masking out

impervious surfaces and open water bodies (see Fig. 1), avoiding possible misclassification of impervious surfaces and open waters to wetland occurrence and hence reducing the commission errors (false positives) in the classification process. The overall accuracy of the final classification of isolated wetlands was 92.79%, with a Kappa coefficient of 0.86; producer accuracy was 87.9% (omission error 12.1%) and user accuracy was 97.4% (commission error 2.6%). Figure 3 shows a comparison of the isolated wetlands mapped in this study and those in the reference isolated wetland dataset. The areas in yellow color shows the correct classification, which are wetlands indicated by both classification result and the reference data. The areas in red color show commission errors, which were classified as wetlands, but they are not in the reference data. The areas in blue color show omission errors, which are indicated as wetlands in the reference data, but they were not classified as wetlands. It is acknowledged that the wetlands determined to be isolated in this study were derived a priori from post-processed GIS layers; it may be that the wetlands are in fact connected to other systems, but our algorithms and GIS resolution were unable to identify those links.

As shown in Fig. 3, the classification performed well in identifying isolated wetlands  $\geq 0.20$  ha (0.50 acres), but tended to slightly overestimate the area of individual wetlands. This is understandable because the Landsat ETM+ imagery used in classification had a 30-m pixel size, resampled down to 15-m through Gram-Schmidt sharpening, and the reference isolated wetland dataset included only isolated wetlands  $\geq 0.20$  ha (0.50 acres) in size (i.e., approximately two 30-m pixels or eight 15-m pixels in size). In addition, the reference data was based on aerial photographs

**Fig. 2** Final classification of Cuyahoga County isolated wetlands (in white). The inset box is presented at a finer scale in Fig. 3





**Fig. 3** Color comparison of the isolated wetland identification results. The pixels in *yellow* color shows the correct classification, which are wetlands indicated by both classification result and the reference data. The pixels in *red* color show commission errors, which were classified as wetlands, but they are not in the reference data. *Blue* pixels color show omission errors, which are indicated as wetlands in the reference data, but they were not classified as wetlands

and site visits and was derived from a vector-based data layer.

Reif et al. (2009) used object-oriented classification with a similar pan-merged 15-m pixel size and were able to identify well-defined wetlands  $< 0.20$  ha (0.50 acres) in size, with an accuracy of up to 82%. However, isolated wetlands of the temperate Erie Plain ecoregion appeared to lack the well-defined spectral signature of flatwoods ponds and cypress domes required for object-oriented analyses, and poor results in initial analyses (not shown) limited our study to wetlands  $\geq 0.20$  ha. While smaller wetlands may on occasion, be identified with subpixel classification, it is not yet feasible to accurately map them as single pixels. Thus, depending on the landscape context and contrast, smaller isolated wetlands should be provisionally mapped with aerial photography or finer resolution satellite imagery (e.g., Burne 2001; Lathrop et al. 2005).

A number of other researchers have also found success using subpixel methods to classify wetlands. For example, Wei et al. (2008) mapped wetlands in the Yellow River Delta Area in China with an accuracy of 88.7% and Kappa coefficient of 0.86. Wang and Lang (2009) recently used a subpixel classification to identify cypress distribution in the Florida Panhandle with an accuracy of 88%. Because most of these studies used linear unmixing approaches, mapped different types of wetlands, and did not attempt to classify wetlands as isolated, it is difficult to directly compare their

results to the results found in this study. To our knowledge, this study has been the only attempt at using subpixel classification of multi-temporal satellite remote sensing data to map isolated wetlands.

The accuracy of isolated wetland mapping in this study is also similar to the accuracy of that in our previous study in Alachua County, Florida (Frohn et al. 2009). In that study, isolated wetlands  $> 0.20$  ha (0.50 acres) were mapped with a producer accuracy of 88% and user accuracy of 89%. As noted previously, the segmentation object-oriented approach used by Frohn et al. (2009) does, however, map the boundaries between wetland and upland much better than the subpixel approach used here. Therefore, in areas where there are high-contrast, well-defined boundaries between wetland and upland, the segmentation object-oriented methodology is preferred. On the other hand, when boundaries for wetlands are not easily detected, a subpixel method, such as the matched filtering algorithm described in this research, can provide mapping of isolated wetlands with high accuracy. It should be noted, however, that there are significant limitations on the size class currently detectable by Landsat ETM+ imagery. The minimum size of the isolated wetlands that can be identified largely depends on the spatial resolution of source satellite imagery. Although the multi-spectral bands of Landsat ETM+ imagery have been sharpened with the panchromatic band and although the subpixel method is utilized, we suggest that isolated wetlands with a width smaller than 30 m cannot be reliably identified using Landsat ETM+ imagery.

## Conclusion

This research is the first attempt at mapping potential isolated wetlands using subpixel analysis of multi-temporal satellite remote sensing data and a partial unmixing algorithm (matched filtering), which was applied to multi-temporal Landsat ETM+ data. This research demonstrates that matched filtering is efficient and powerful for identifying the subpixel presence of a single target land cover class— isolated wetlands— and estimating its relative fractional abundance. Its main advantage over multi-endmember full unmixing methods, like traditional linear spectral unmixing, is that only the spectral characteristics of the wetlands is required, and a priori knowledge of the spectral signatures of other land cover classes in surrounding uplands are not necessary. This method largely simplifies the classification problem and significantly reduces the operational difficulty and cost in identifying and acquiring the spectral characteristics (signatures) of the complete set of distinct land cover classes in uplands, as in linear spectral unmixing method. A NDVI mask was useful in masking out non-wetland areas such as urban impervious surfaces and hence reducing the



classification commission error (false positives) to 2.6%. Our preliminary experiments show low classification accuracy (65–79%) when a number of classification methods were applied to the single leaf-on image scene. In contrast, with the multi-temporal dataset our subpixel classification method achieved the overall accuracy of 92.8%, with producer accuracy of 87.9% and user accuracy of 97.4% respectively, for isolated wetlands  $\geq 0.20$  ha (0.50 acres). Smaller wetlands were not assessed due to the spatial resolution limitation of Landsat ETM+ data.

The following recommendations and conclusions were drawn from this research:

- (1) The subpixel matched filtering method in this research provided an effective means for mapping isolated wetlands, especially those with boundaries that are not easily identified.
- (2) Landsat data are useful and adequate for mapping isolated wetlands with a size of 0.20 ha (0.50 acres) or greater. For smaller isolated wetlands, either finer resolution satellite data or aerial photographs (or perhaps both) are necessary.
- (3) The NDVI can be a useful tool for enhancing the wetland/upland boundary for isolated wetlands; it is also effective in masking out various urban imperious surfaces (buildings, pavements, parking lots, and roads) and open waters and hence reducing commission errors.
- (4) A partial unmixing algorithm, such as matched filtering, is advantageous in that it allows the signature of the wetland to be identified without the need to model all other land cover classes within a mixed pixel (such as in linear spectral unmixing method).
- (5) The derivation of unique phenology characteristics of isolated wetlands from combining multi-temporal imagery (in this case, leaf-on and leaf-off imagery) allows for better mapping of isolated wetlands, in comparison with the use of only a single time image scene in classification.

More studies are needed to determine regional or national approaches for rapid, high-accuracy inventorying of isolated wetlands. It appears that no single method is superior to others for identifying and mapping isolated wetlands. Although this research shows that the subpixel matched filtering method is effective for isolated wetlands with fuzzy transitional boundaries, the segmentation object-oriented approach described by Frohn et al. (2009) is preferred for isolated wetlands that do have more easily identified boundaries. Multiple methods may be necessary for satellite remote sensing of isolated wetlands, depending on the location and type of wetlands that are being mapped. Furthermore, a hybrid classifier could be developed that takes into account the type and location of these wetlands, so that the highest accuracy of isolated wetland maps can be achieved. Additional efforts

should be directed towards identifying wetlands  $< 0.20$  ha (0.50 acres), which while small, remain important landscape components (Semlitsch and Bodie 1998; Creed et al. 2003; Yavitt 2010).

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