Wetland Mapping in the Upper Midwest United States: An Object-Based Approach Integrating Lidar and Imagery Data

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Abstract
This study investigated the effectiveness of using high resolution data to map wetlands in three ecoregions in Minnesota. High resolution data included multispectral leaf-off aerial imagery and lidar elevation data. These data were integrated using an Object-Based Image Analysis (OBIA) approach. Results for each study area were compared against field and image interpreted reference data using error matrices, accuracy estimates, and the kappa statistic. Producer's and user's accuracies were in the range of 92 to 96 percent and 91 to 96 percent, respectively, and overall accuracies ranged from 96-98 percent for wetlands larger than 0.20 ha (0.5 acres). The results of this study may allow for increased accuracy of mapping wetlands efforts over traditional remote sensing methods.

Introduction
Wetlands are naturally dynamic systems of important value to the environment and society. The US Army Corps of Engineers (USACE) in cooperation with the US Environmental Protection Agency (EPA) have defined wetlands, incorporating technical and policy considerations, as "…those areas that are inundated or saturated by surface or ground water at a frequency and duration to support and under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions" (Federal Register, 1980 and 1982). Wetlands can reduce some of the negative effects of flooding and recharge groundwater by gradually releasing flood water and snow melt. Wetlands offer habitat that supports wildlife and fishing activities. Wetlands also provide ecosystem services, including educational, aesthetic, and economic opportunities. For example, intact freshwater marshes in Canada have a total economic value of approximately 5,800 USD per hectare compared to 2,400 USD when those lands are drained and used for agriculture (Millennium Ecosystem Assessment, 2005; Turner *et al.*, 2000).

Due to wetland loss and degradation, many of the preceding benefits have been reduced and are increasingly impacted. About 215 million acres of wetlands existed in the United States at the time of European settlement. However, by the mid-1970s, only 99 million acres of the original wetlands remained. Many of the lost wetlands were drained and are currently used for agriculture, resource extraction, urbanization, and other commercial purposes (Dahl and Johnson, 1991; Frayer *et al.*, 1983; Stedman and Dahl, 2008). Minnesota is not an exception to this large national wetland loss. Nearly half of Minnesota's original wetlands were lost due to extensive agricultural drainage and urban development. According to the Minnesota Pollution Control Agency (MPCA) (2006), many original natural wetlands were changed into local storm-water ponds to make additional land available for urban development.

Currently in Minnesota only a few cities have updated wetland inventories. For the rest of Minnesota the only wetland inventory available is the National Wetlands Inventory (NWI). The Minnesota NWI maps were completed in the late 1980s using aerial photos (some black and white) collected between 1979 and 1988 (LMIC, 2007). Several 7.5' quadrangles in northwestern Minnesota and a much larger area in northeastern Minnesota were mapped based on 1970s 1:80 000 scale black-and-white photos (MPCA, 2006). Changes in the landscape have occurred which limit the use of the NWI maps due to the outdated data and techniques used to create them. Thus, there is a need to update wetland inventories with accurate boundaries and improved delineation of smaller wetlands. An updated wetland inventory would provide information that could be used to make accurate decisions for the conservation, protection, and restoration of wetlands. Although a Minnesota statewide update is underway, it is a heavily image interpretation-based project that is not expected to be completed until 2020. Thus, more automated techniques may be useful in the near term.

A fast and effective method to identify accurate wetland boundaries involves the use of remote sensing data and techniques (Butera, 1983; Corcoran *et al.*, 2011; Knight *et al.*, 2013). To the present time, the majority of wetland mapping efforts using remote sensing data and techniques has been focused on evaluating traditional pixel-methods with medium to coarse resolution data. In many cases, the use of remote sensing for wetland mapping has resulted in low accuracy estimates, often due to mixed pixels and insufficient spectral resolution (Grenier *et al.*, 2007; Fournier *et al.*, 2007; Lunetta and Balogh, 1999; Ozesmi and Bauer, 2002). Integration of high resolution optical and elevation data has been shown to reduce the mixed pixel problem (Frohn *et al.*, 2009; Maxa and Bolstad, 2009). Some studies have integrated optical and elevation data to map wetlands using traditional pixel-based methods. However, their accuracy results were low for wetland classification due to the use of low to medium spatial resolution data and pixel-based techniques (Baker *et al.*, 2006; Ozesmi and Bauer, 2002).

An object-based approach may be a better option to integrate high resolution data and overcome some limitations, including the mixed pixel problem and salt-and-pepper effect of traditional pixel-based techniques (Myint *et al.*, 2011; Zhou

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Photogrammetric Engineering & Remote Sensing
Vol. 80, No. 5, May 2014, pp. 439–449.
0099-1112/14/8005–439

doi: 10.14358/PERS.80.5.439

and Troy, 2008). Object Based Image Analysis (OBIA) segmentation and classification techniques have been considered as an alternative to pixel-based methods since the late-1990s because of their ability to include contextual information, human knowledge, and experience to interpret the objects of interest (Baatz *et al*., 2008; Blaschke, 2003; Blaschke, 2010). The foundation of the OBIA approach is an initial image segmentation that uses pixel-based features to create statistically homogeneous image objects (Benz *et al*., 2004; Fournier *et al*., 2007). These homogenous objects, also called geo-objects or segments, can be classified into land-cover classes using attributes of the objects such as spectral, textural, contextual and shape characteristics (Burnett and Blaschke, 2003; Bruzzone and Carlin, 2006; Hay and Castilla, 2008). The OBIA approach can be used to generate vector polygons from the classification and directly incorporate them into a geographic information system (GIS) (Castilla, *et al*., 2008; O'Neil-Dunne *et al*., 2012).

The aim of this research was to investigate the effectiveness of using high resolution leaf-off aerial imagery and lidar data to map wetlands in three different ecoregion study areas in Minnesota.

Study Area and Data

Study Area Description

Due to the complexity and variety of wetlands in Minnesota, we selected three study areas to evaluate the OBIA approach to map wetlands. The first study area was the Minnesota River Headwaters watershed located in the Northern Glaciated Plains ecoregion and within Big Stone, Traverse, and Stevens counties (Figure 1). This watershed is 717 km² in size and the main land use is agriculture. A large portion of the watershed is characterized by a rolling prairie of till plain, clay loam soils and a combination of poorly and well drained soils (Minnesota Department of Natural Resources, 2006). The average precipitation is 640 mm/year and 360 mm during the growing season (May to September). Many shallow lakes and wetlands are common features of the landscape in this watershed. These lakes and wetlands are perfect settings to support and nurture wildlife habitat and viewing opportunities for a variety of bird and duck species (Midwest Community Planning LLC, 2012).

The second study area was the Swan Lake watershed located in the Western Corn Belt Plains ecoregion and within Nicollet County (Figure 1). It has an area of 204 km², and the main land use is agriculture. A large portion of the watershed consists of glacial till plain with level to gently rolling prairie uplands. This area is characterized by clay loam soils and fertile deep soils with a high level of organic matter (Minnesota Department of Natural Resources, 2006). The average precipitation is 740 mm/year and 460 mm during the growing season (May to September). This watershed has one of the biggest prairie pothole marshes in the United States, providing habitat for different species, storm water retention and education opportunities (Nicollet County, 2008).

The third study area is the Thompson Reservoir St. Louis River watershed located in the Northern Lakes and Forest, between St. Louis and Carlton counties (Figure 1). It is 53 km² in size and the main land use is forested land. A large portion of the watershed is characterized by drumlins covered with forest, poorly drained wetland depressions, and fine sandy loam soils. The average precipitation is 710 mm/year and 440 mm during the growing season (May to September).

Data Acquisition

We used two data sources to investigate the effectiveness of integrating multiple datasets to map wetlands in the three study areas. These sources included lidar data and orthorectified digital aerial photography (0.5 m). The half-meter orthorectified imagery used for Swan Lake and the Minnesota River

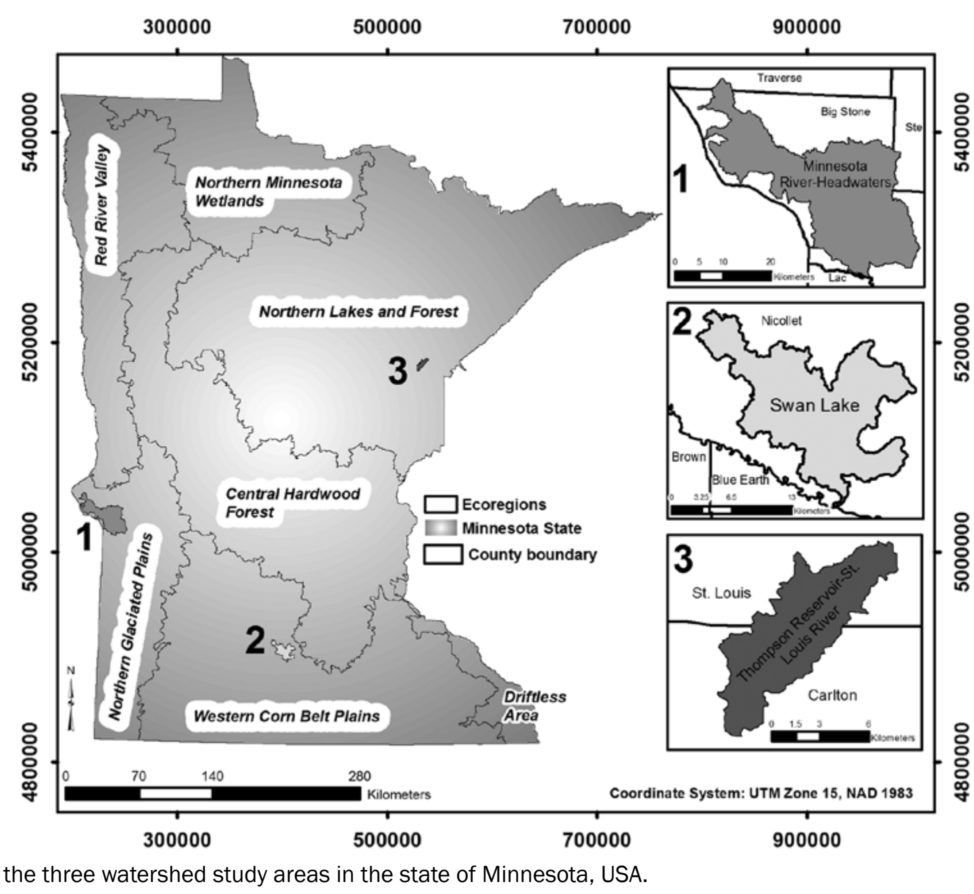

Figure 1. Location of the three watershed study areas in the state of Minnesota, USA.

Headwaters was collected by Surdex Corporation between 12 April 2011 and 16 May 2011. This imagery was provided by the vendor to the Minnesota Department of Natural Resources (MDNR) as a radiometric/orthorectified ready product. The Minnesota Department of Transportation (MnDOT) separately tested the horizontal positional accuracy of this imagery and obtained a root mean square error (RMSE) of 0.819 m with an NSSDA of 1.418 m (95 percent confidence level). This imagery was acquired with an Intergraph DMC® (digital mapping camera) from an altitude of about 3,000 m, capturing four multispectral bands (red, green, blue, and near infrared). The half-meter orthorectified imagery used for the Thompson Reservoir St. Louis River watershed was collected by Keystone Aerial Surveys, Inc. in May 2009. This imagery was provided by the vendor to the DNR as a radiometric/orthorectified ready product. The DNR separately tested the horizontal positional accuracy of this imagery and obtained an RMSE of 2 m with an NSSDA of 3.5 m (95 percent confidence level). This imagery was acquired with a Vexcel UltraCamX® camera from an altitude of about 7,300 m, capturing four multispectral bands (red, green, blue, and near infrared).

The lidar data (point cloud data, lidar DEM, and lidar hybrid intensity) used for the Minnesota River Headwaters study area was obtained through the International Water Institute (IWI) lidar download portal. The lidar data for the Minnesota River Headwaters was collected in the spring of 2010 during leaf-off conditions by Fugro Horizons, Inc. The data were collected with a Leica sensor ALS50-II MPiA® (Multiple Pulses in Air), at an altitude of 2,400 m above mean terrain (AMT), and with an average post spacing of 1.35m. The horizontal accuracy for these data was of ±1 m (95 percent confidence level), and a vertical accuracy RMSE of 15.0 cm. For this study area, we used the 1 m DEM and hybrid intensity images provided by the IWI. The DEM was produced by interpolating the bare earth LAS files delivered by the vendor using the "Raster to ASCII" command in ArcGIS® 10.1. The hybrid intensity layers were created from lidar intensity and raw lidar/hillshade by the vendor. Hybrid intensity images were created by interpolating the infrared reflectance value attributed for each point. The lidar data (point cloud data, lidar DEM and lidar intensity) used for Swan Lake and Thompson Reservoir St. Louis River watershed were acquired from the Minnesota Geospatial Information Office (MnGeo) FTP site.

The lidar data for the Swan Lake study area was collected between 26 April and 28 April 2010 by AeroMetric, Inc. The data were collected using a multiple fixed wing aircraft lidar system at an altitude of 1,700 m AMT, and an average post spacing of 1.3 m. The horizontal accuracy for these data was of ±0.3 m (95 percent confidence level), and a vertical accuracy RMSE of 10.0 cm**.** The lidar data collected for the Thompson Reservoir St. Louis River study area was collected between 03 May and 05 May 2011 by Woolpert, Inc. The data were collected at an altitude of about 2,400 m AMT with an average post spacing of 1.5 m. The horizontal accuracy for these data was ±1.2 m (95 percent confidence level), and vertical accuracy RMSE was 5 cm. In this study we used the 1 m DEM provided by the Minnesota DNR, which produced the DEM by extracting bare earth points from the point cloud data. The DEM was also hydro flattened using the edge of the water breaklines.

Methods

We mapped wetlands by using an OBIA approach through the creation of rule sets for each study area. We used the Cognition Network Language (CNL) within the software package Definiens eCognition® Developer version 8.8.0 to develop the three rule sets. The eCognition Server 64-bit package was used to execute in a batch mode all the tile stacks for each study area. The first subsection of the methods used in this study describes the data preparation performed for each study area. The next subsection explains the design of the rule set created for each study area. Finally, the last subsection addresses the accuracy assessment procedures used to evaluate results in each study area.

Data Preparation

Before the creation of the three rule set, we performed four data preparation steps needed prior to develop the OBIA approach. First, we generated several raster layers from the lidar point cloud data and DEM. The raster layers included: a digital surface model (DSM), a lidar intensity layer, the compound topographic index (CTI). These raster layers were chosen because of their topographic information, which is useful to differentiate wetland from other cover classes. We used Quick Terrain (QT) Modeler® version 7.1.6 to generate the 3 m DSM raster layer using the point cloud data for each study area. The natural-neighbor interpolation algorithm method, the maximum Z value of the first return for all the classes were used to create the DSM layer. We exported the DSM into a raster GeoTIFF file with 3 m spatial resolution.

The lidar intensity images for Swan Lake and the Thompson Reservoir St. Louis River study areas were also generated in QT Modeler with the grid statistic tool, using the mean intensity values of all the lidar returns. We exported the intensity grid layer into a raster GeoTIFF file with 3 m spatial resolution. The lidar intensity image for the Minnesota River Headwaters study area was obtained directly from the IWI download website.

The CTI layers for each study area were created using the DEM layer for each study area. We used the following formula to compute the CTI given by Beven and Kirkby (1979) study: CTI = $\ln [(\alpha)/ (\tan (\beta)]$. In this equation α represents the local upslope area draining through each cell, and β represents the local slope gradient. The CTI represents the potential distribution of the water movement and water accumulation across the landscape (Moore *et al.*, 1991). The CTI is used to identify parts of the landscape where sufficient wetness could allow for the formation of wetlands (Rodhe and Seibert, 1999).

Figure 2 shows a map of the Minnesota River-Headwaters study area representing CTI values, where higher CTI values represent water accumulation (potential wetland formation), and lower CTI values represent dryness or steep places where water would not likely accumulate based on topography. The choice of the flow direction algorithm used to calculate α (local upslope area) can affect the accuracy of the CTI. For example, single flow direction algorithms allow flow to pass only to one neighboring downslope cell while multiple flow direction algorithms allow water to flow into multiple neighboring cells. This multidirectional flow effect creates more realistic water flow patterns in different topographic settings, including convex and concave hillslopes (Erskine *et al.*, 2006; Gruber and Peckham, 2008; Wilson *et al.*, 2008). Thus, in this study we used the triangular multiple flow direction algorithm proposed by Seibert and McGlynn (2007) to compute the local upslope area. We used the Whitebox open-source software version 1.0.7 to calculate the contributing area (local upslope area) and local slope layers needed for the CTI. The slope layer was modified by adding a minimum value of 0.0001 to avoid division by zero for CTI calculations.

It is important to clarify that the DEM for the Swan Lake and Thompson Reservoir St. Louis River areas was obtained directly as a raster layer, already mosaicked, from the MnGeo FTP site. However, for the Minnesota River Headwaters areas, we had to mosaic each DEM and hybrid intensity tile contained within this area. Mosaicking was necessary because these data were provided by the IWI in raster tiles of 2,000 m by 2,000 m. We used ERDAS Image® 2011 to mosaic and exported the DEM and intensity layers as GeoTIFF files. We also

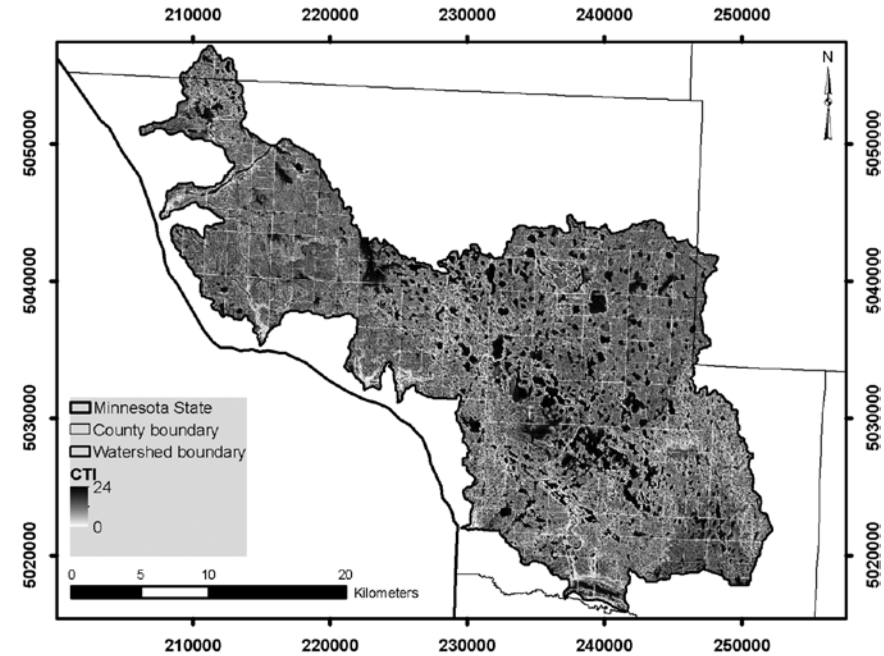

Figure 2. CTI index for Minnesota River-Headwaters study area.

exported the DEM for the Swan Lakes and the Thompson Reservoir St. Louis River study areas to GeoTIFF format.

Second, after calculating all the lidar layers, we used the MosaicPro tool from the ERDAS Image 2011 software to mosaic the orthorectified aerial imagery for each study area.

Third, once all the previous lidar and imagery layers were prepared, we used a watershed boundary shapefile layer for each study area to subset all the raster layers in ERDAS Image version 2011. The watershed boundaries were obtained from the Minnesota Department of Natural Resources (DNR). Finally, we produced a tile generation for each study area. The tile generation was carried out in ERDAS Image version 2011, using the Dice tool with the following parameters: tile size of 3,000 m × 3,000 m and an overlap of 300 m between adjacent tiles on all four sides. Each study area had a tile stack of four lidar product layers (DEM, DSM, CTI, and Intensity) and four bands of imagery layers (Figure 3). The following tile stacks were created: 224 for the Minnesota River Headwaters, 49 for Swan Lake, and 20 for the Thompson Reservoir St. Louis River.

Rule set Creation and Classification

Before the creation of rule sets for each study area, we developed a customized import routine in eCognition developer software to import all the tile stacks of layers for each study area. Each rule set was developed through a trial and error process using small subset areas (500 × 500 pixels). We used a *divide and conquer* approach (Quinlan, 1990; O'Neil-Dunne *et al.*, 2012), which is a multiscale iterative method where objects vary in size, shape, and spectral attributes. While the two major steps performed in the rule set development were the creation of objects and the classification of those objects, further steps were required for the classification of each object to be assigned to the class of interest (wetland class versus non-wetland class). Each rule set consisted of four main components: (a) image processing, (b) segmentation and classification, (c) export operation, and (d) cleanup operation.

In the image processing phase, we carried out the following tasks: calculation of the normalized Digital Surface Model (nDSM) = DSM – DEM, and application of a median filter to the nDSM and intensity layers, and computation of the Green Ratio Vegetation Index (GRVI) using the eCognition developer software tools for object features. The GRVI was computed using the NIR and green bands of the aerial imagery as the ratio of the NIR divided by the green band (Sripada *et al.*, 2006).

This index was chosen for two reasons: first, it is known that vegetation indices such as the Normalized Difference Vegetation Index (NDVI) can be useful for discriminating wetlands from other upland classes (Hodgson *et al.*, 1987, Wright and Gallant, 2007). Second, after testing several vegetation indices including the NDVI, the Green Normalized Difference Vegetation Index (GNDVI), the Difference Vegetation Index (DVI), and the GRVI to determine which index would be more helpful in differentiating wetland features from non-wetland features. Our unpublished results indicated that the GRVI was more accurate than the other indices to differentiate and exclude areas that were topographically suitable for wetlands but contain impervious cover (non-vegetated).

In the segmentation and classification phase, we performed the following tasks: we created preliminary objects using the multi-resolution segmentation algorithm (Baatz and Schape, 2000) with the following parameter values: scale 30, shape 0.3, and compactness 0.5. A weight value of 1 was given to the three visible optical bands and a weight value of 2 to the NIR band. The scale value of 30 was chosen because we wanted medium size preliminary objects. The shape value of 0.3 was chosen because more weight was given to the influence of color on the segmentation process. The NIR band was given a higher weight value because of its ability to spectrally separate potential non-water objects from water objects.

After creating the preliminary objects, the second step was to refine those objects by applying a spectral difference segmentation algorithm, based on a maximum spectral difference value. The spectral difference algorithm merges neighboring objects based on a maximum spectral difference value parameter (Definiens Imaging, 2009). A value of 14 was chosen as the maximum spectral difference parameter for this difference segmentation. This value was chosen after visually assessing different values.

The third step was to classify the preliminary objects into temporary classes, including wet versus dry, bright versus dark, and short versus tall. We used the following attributes of each dataset to create the temporary classes: min, max, and mean threshold values of the CTI, nDSM, intensity, NIR band, imagery brightness, and GRVI.

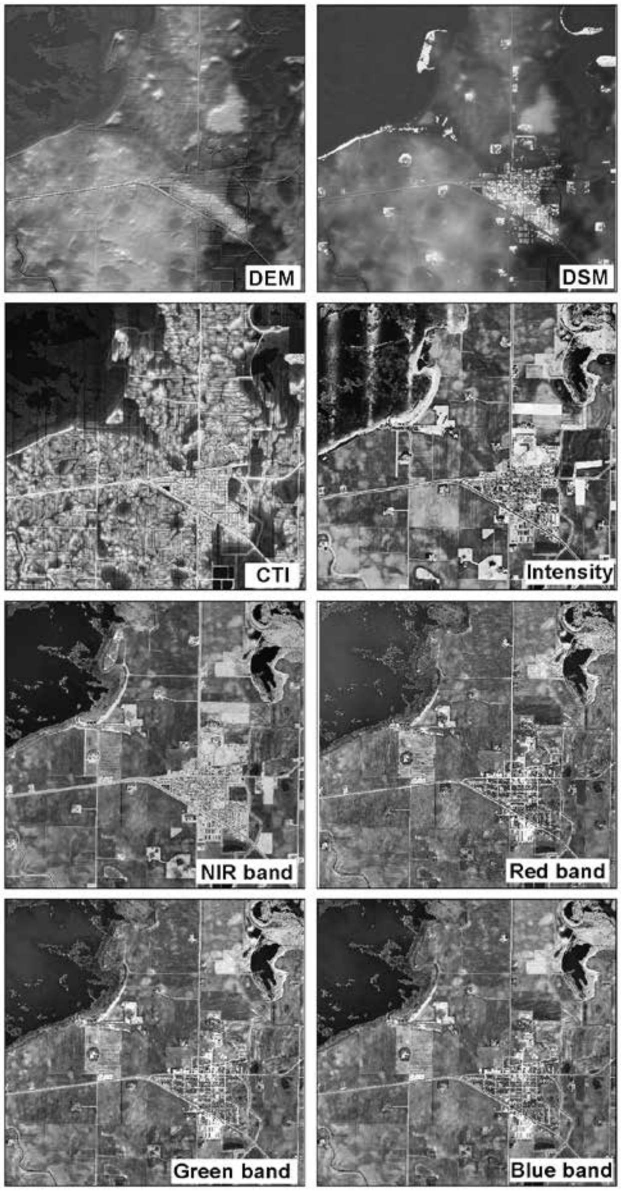

Figure 3. Tile stack of the dataset used for the OBIA approach.

The CTI, GRVI, and NIR layers were specifically used to separate wet versus dry classes with the following threshold values: NIR ≤45, GRVI ≤0.9, and CTI ≥10.78. These threshold parameters were determined through a series of trial-and-error efforts in combination with photo-interpretation to determine whether different "wet classes" (potential wetland classes) across the three different ecoregions were sufficiently separated from dry classes (potential non-wetland classes). The threshold of 10.78 resulted after testing several threshold values at different DEM resolutions including 3 m lidar data. Our unpublished results indicated that the most accurate CTI threshold values to separate wetness (potential wetland) from dryness (upland) was the mean plus one-half standard deviation of the CTI range of values. Also, this CTI threshold value of 10.78 agrees with the value that Galzki *et al.*, (2008) found in their study based on field work.

The imagery brightness, intensity, and GRVI layer were used to classify bright versus dark objects using the spectral difference segmentation algorithm with a maximum spectral difference parameter of 12. The nDSM layer was used to separate short versus tall objects using the contrast split segmentation algorithm with the following parameters: a minimum threshold value of 2, a max threshold value of 5, and a step size of 1. Previous parameters were determined after several trial-and-error experiments and a detailed visual assessment for separating bright versus dark classes and short versus tall classes.

Finally, we used contextual information from the different temporary classes to achieve the final desired classes. Final classes included wetlands, agriculture, forest, and urban classes. These classes were chosen to allow for easier discrimination between wetland boundaries and upland boundaries due to the spectral, contextual, and shape differences between classes. The contextual information was based on the spatial relationships of an individual object to neighboring objects. For example, small bright objects located in the middle of agriculture fields (unlikely to be impervious surfaces) were reclassified as agriculture classes based on contextual information (neighboring relationship).

In the export operation phase, we exported the final classes into raster and vector formats. In addition, we improved the wetland polygon's appearance by applying the smoothing and generalizing tools from the advanced editing toolbar in the ArcGIS software.

Accuracy Assessment

We assessed the classification results for the three study areas using a single pixel based approach based on the analysis of the error matrix (Congalton and Green, 2009). The following accuracy assessment estimators were computed in ERDAS Imagine for each study area: overall accuracies, producer's accuracy, user's accuracy, and kappa coefficient.

The classification results were evaluated using independent stratified randomly generated points for each study area. Each sample point was interpreted by a trained analyst, who gave the point a value of forest, agriculture, impervious, or wetland. The analyst used aerial photos and field data. In the summer of 2009 and 2011, a team from the Remote Sensing and Geospatial Analysis Laboratory at the University of Minnesota collected field reference data of independent randomly selected points of wetland/upland from different parts of Minnesota including the three study areas used in this study. The field data collected contained the following information: Plant type and percent coverage, land-cover/land-use type, UTM coordinates, five to six photos of the area, and Cowardin wetland type (Cowardin *et al.*, 1974). Upland types included crop fields, other agriculture, forests, grasslands, urban areas, construction areas, bare areas, and others. We generated 289 reference data points for the Minnesota River Headwaters: 118 for Swan Lake and 117 for the Thompson Reservoir St. Louis River study areas.

Results

Results for the three study areas are summarized in Tables 1 through 5, Plate 1, and Figure 4. Overall accuracy results for the OBIA classification were consistently high (90 to 93 percent), throughout the three study areas, with little confusion between the four classes. Within the classification scheme of the four classes, we obtained producer and user accuracies of 92 to 96 percent respectively for the wetland class that included wetlands larger than 0.20 ha (0.5 acres) across the three ecoregions. In addition to the OBIA accuracy assessment classification, a comparison assessment was performed to compare the accuracy of the original NWI and the OBIA classification using only two classes (wetland/upland) for the same study areas. It is important to acknowledge that this comparison of the NWI results and our OBIA results is not a direct and fair comparison. The temporal and methodological differences between the two datasets are significant. Thus, our main objective was to offer an alternative method (OBIA) that will allow for improvements to the accuracy of wetland

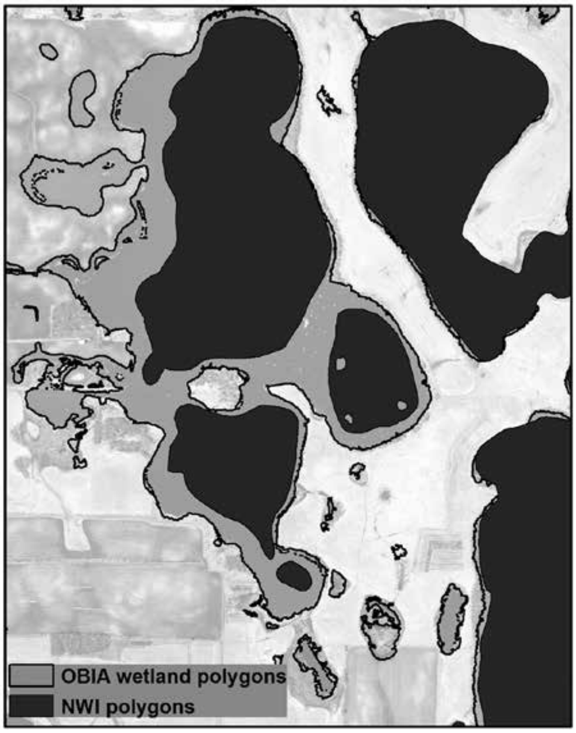

Figure 4. Comparison map of the original NWI polygons and OBIA polygons for a small portion of the Minnesota River-Headwaters with a background of an aerial image.

classification boundaries compared to current wetland boundaries. Updated accurate boundaries of wetlands are necessary, particularly for organizations that currently use older NWI maps as a tool to monitor and regulate wetland management and conservation.

The comparison assessment was done using the kappa-based Z-statistic test described in Congalton and Green (2009). Additionally, the overall accuracy, user's accuracy, and producer's accuracies for wetland and upland classes were computed for both classifications. These comparison results demonstrated that there was a statistically significant difference between the OBIA and the NWI classification at an alpha level of 0.05. For this classification scheme of two classes, the comparison results also indicated that the OBIA wetland class always had a higher user's accuracy (92 to 94 percent) and producer's accuracy (91 to 96 percent) across the three study areas compared to the NWI user's accuracy (56 to 71 percent) and producer's accuracy (57 to 79 percent) for the wetland class.

Table 1 shows a full error matrix and accuracy estimates of the four classes in the Minnesota River-Headwater study area using the OBIA method. The overall accuracy was 90 percent, with a kappa score of 0.84 and low errors of commission and omission. The wetland class was accurately identified with producer's and user's accuracies values at 92 percent. Plate 1a shows a final OBIA classification map with four classes for the Minnesota River-Headwater study area.

Table 2 shows a full error matrix and accuracy estimates of the four classes for the Swan Lake study area. The overall accuracy was 93 percent with a kappa score of 0.90, and with low errors of commission and omissions for the majority of the classes. Plate 1c displays a final OBIA classification map with four classes for this study area. The wetland class in this study area was the least confused compared to other classes (Table 2). Overall, the most confused class pair was agriculture and urban because these classes can be relatively similar spectrally and spatially close in proximity to each other (e.g., an unpaved road bordering or in the middle of an agricultural field).

Table 1. OBIA Classification Error Matrix for Minnesota River-Headwater Study Area

		Reference Data					
		Wetlands	Agriculture	Forest	Urban	Row Total	User's Accuracy
Map data	Wetlands	**47**	4	0	0	51	92%
	Agriculture	2	**148**	1	5	156	95%
	Forest	1	10	**31**	0	42	74%
	Urban	1	5	0	**34**	40	85%
	Column Total	51	167	32	39	**289**	Overall Accuracy
	Producer's Accuracy	92%	89%	97%	87%		**90 %**

Overall Kappa Statistic: 0.84

Table 2. OBIA Classification Error Matrix for Swan Lake Study Area

		Reference Data					
		Wetlands	Agriculture	Forest	Urban	Row Total	User's Accuracy
Map data	Wetlands	**27**	1	0	0	28	96%
	Agriculture	1	**46**	0	0	47	98%
	Forest	0	0	**23**	0	23	100%
	Urban	0	5	1	**14**	20	70%
	Column Total	28	52	24	14	**118**	Overall Accuracy
	Producer's Accuracy	96%	88%	96%	100%		93%

Overall Kappa Statistic: 0.90

Table 3. OBIA Classification Error Matrix for Thompson Reservoir St. Louis River Study Area

		Reference Data					
		Wetlands	Agriculture	Forest	Urban	Row Total	User's Accuracy
Map data	Wetlands	**32**	0	2	0	34	94
	Agriculture	1	**20**	3	0	24	83
	Forest	2	0	**37**	0	39	95
	Urban	0	2	1	**17**	20	85
	Column Total	35	22	43	17	**117**	Overall Accuracy
	Producer's Accuracy	91%	92%	86%	100%		91%

Overall Kappa Statistic: 0.87

Table 3 shows a full error matrix and accuracy estimates of the four classes for the Thompson Reservoir St. Louis River study area. The overall accuracy was 91 percent with a kappa value of 0.87, and with low errors of commission and omissions for all the classes. Plate 1b displays a final OBIA classification map with four classes for the third study area.

Table 4 shows accuracy estimators of the NWI classification and OBIA classification with two classes (upland versus wetland) for the three study areas, indicating a higher overall accuracy for the OBIA classifications (97 to 98 percent) compared to the NWI classification (74 to 85 percent). In addition, the total amount (hectares) of wetlands for the Minnesota River-Headwaters area, revealed an underestimation of wetlands within the NWI classification. This underestimation also is confirmed by the wetland omission error (43 percent) and low wetland producer's accuracy (57 percent) obtained for the NWI

Table 4. Overall Accuracy and Wetland User's and Producer's Accuracy for Two Mapping Classification Results (Classification Scheme: Wetland/Upland)

Land cover classification	Overall accuracy	Wetland user's accuracy	Wetland producer's accuracy	Total area for wetlands in ha
OBIA-Minnesota River-Headwaters	97%	92%	92%	7,620.90
NWI-Minnesota River-Headwaters	88%	71%	57%	6,526.38
OBIA-Swan Lake	98%	96%	96%	4,794.52
NWI-Swan Lake	85%	65%	79%	5,812.04
OBIA- Thompson Reservoir St. Louis River	96%	94%	91%	1,927.29
NWI-Thompson Reservoir St. Louis River	74%	56%	66%	2,233.42

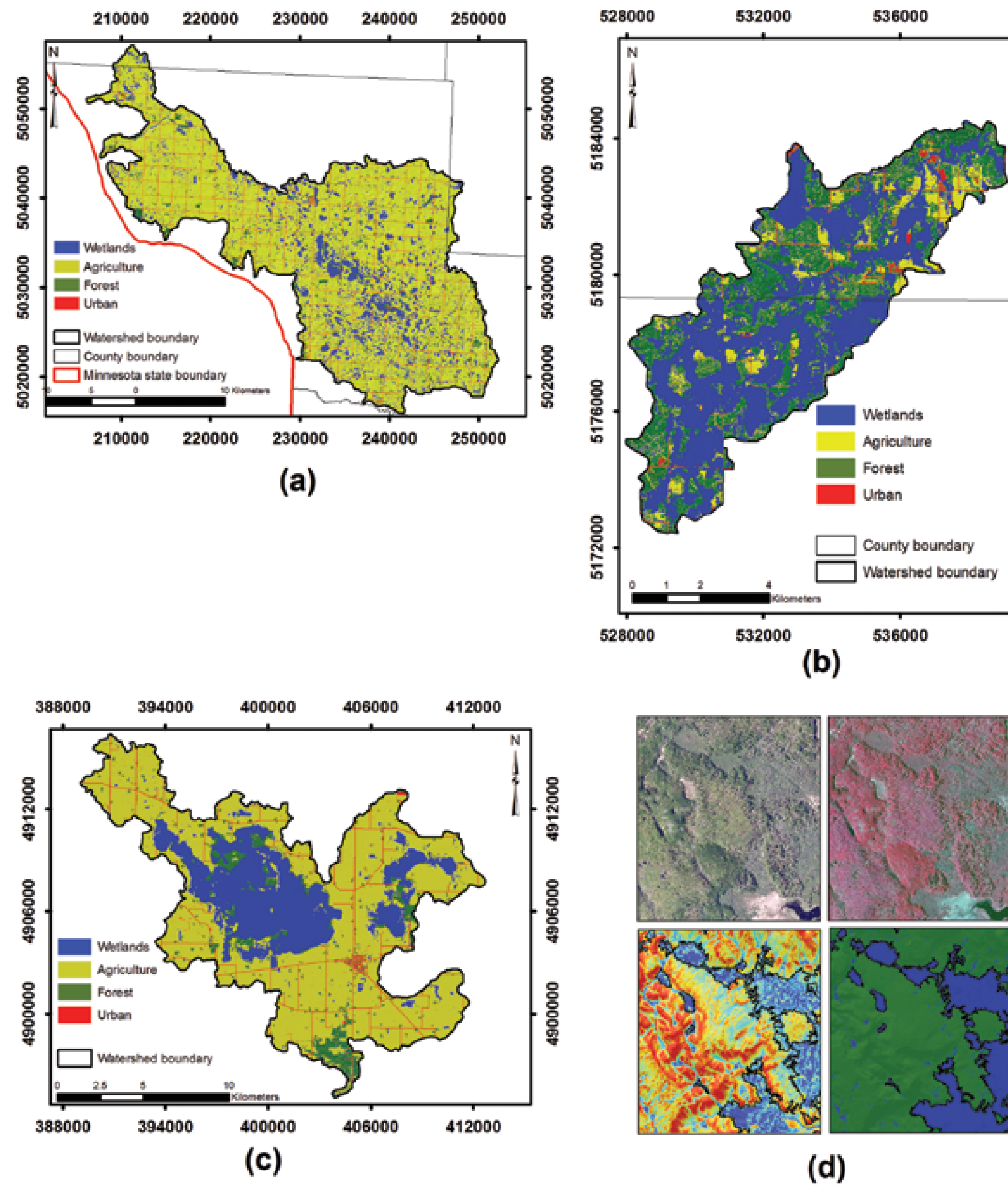

Plate 1. OBIA classification maps for (a) Minnesota River-Headwaters, (b) Thompson Reservoir St. Louis River, and (c) Swan Lake. Comparison of layers for a small portion of the Thompson Reservoir St Louis River study area, top left visible bands, top right NIR band, bottom left CTI, and (d) bottom right OBIA classes (wetland/upland).

Table 5. Significance Test (Z-test) for Comparing Two Mapping Classification Scheme (Wetland/Upland) Using the Same Independent Reference Data Points for Each Study Area

Land cover classification	Kappa1 versus Kappa2	Z-Value
OBIA versus NWI for Minnesota River-Headwaters	0.91 versus 0.56	4.61*
OBIA versus NWI for Swan Lake	0.98 versus 0.61	3.88*
OBIA versus NWI for Thompson Reservoir St. Louis River	0.90 versus 0.42	4.83*

* A Z-value over 1.96 indicates that there is a significant difference at 95% confidence level.

wetland class in this area. The total amount (hectares) of wetlands for the Swan Lake and Thompson Reservoir St. Louis River areas exposed an overestimation of the current amount of wetlands compared to the total area amount of wetlands within the NWI classification. This overestimation also is confirmed by the wetland commission error (35 to 44 percent) and low wetland user's accuracy (56 to 65 percent) estimators obtained for the NWI wetland class in these areas.

Table 5 shows the significance test (Z-test) comparison of the two classification methods for each study area; the results were found to be statistically different in each study area at a 95 percent confidence level. Figure 4 shows a comparison of the NWI polygons and OBIA polygons for a small portion of the Minnesota River-Headwaters area. This figure exposes significant differences between NWI and OBIA wetland boundaries, revealing greater amount of wetland omission area for the NWI classification. Although this comparison may be unfair between the NWI and our OBIA results, this comparison confirms the assumption that NWI maps are of limited utility due to their inaccuracy in wetlands versus upland boundaries.

Discussion and Conclusions

In this study, we have evaluated an OBIA approach to map and differentiate wetlands from other classes through the design of a rule set for each study area. The OBIA approach used in this study, across three different ecoregions, provided an adequate platform to integrate different types of high resolution data for accurately detecting wetlands that were greater than 0.20 ha (0.5 acres). OBIA classification maps corresponded well with the reference data for each study area, obtaining high overall accuracy percentages between 90 to 93 percent for the four classes. The results of this study reinforced previous findings regarding the value and importance of high resolution data to improve wetland classification accuracy. Previous studies have concluded that high resolution data including lidar, aerial, and satellite imagery are very advantageous to distinguish between wetlands and non-wetlands classes. These studies have found less confusion between wetlands and upland classes due to the reduction in mixed pixels and addition of high resolution elevation data to separate wetlands from uplands (Everitt *et al.*, 2004; Huan and Zhang 2008; Laba *et al.*, 2008).

The integration of high resolution imagery and lidar data helped to improve classification of wetlands in two ways. First, the use of high resolution data including optical and lidar through an OBIA approach helped to improve the accuracy of wetland classification over traditional pixel-based techniques. For example, Corcoran *et al.* (2011) integrated high resolution imagery with coarse topographic data using a decision-tree classifier to map wetlands, in a similar area to our third study area in the Northern lakes and forest ecoregion area in Minnesota. The Corcoran *et al.* (2011) results were lower in overall accuracy (72 percent) for wetland/upland classification compared to our OBIA results for wetland/upland classification (96 percent). Sader *et al.*, (1995) compared four satellite image classification methods, including a GIS rule-based model to delineate forest wetlands and other wetlands in Maine. Their results were lower in overall accuracy, ranging from 72 percent to 82 percent for their two study areas. Similarly, other studies have used coarse resolution imagery data including satellite data to map wetlands, but obtained low accuracy estimates for wetland classification because of mixed pixels with similar spectral reflectance (Jensen *et al.*, 1993; Lunetta and Balogh, 1999).

Our study demonstrated that an OBIA approach is more suitable than traditional pixel-based methods to take advantage of the high resolution data available to map wetlands (Dechka *et al.*, 2002; Halabisky *et al.*, 2011; Knight *et al.*, 2013; Maxa and Bolstad, 2009). The OBIA approach used in this study incorporated contextual, spectral, and shape information that came from homogenous objects instead of pixel units. It is important to note that all the high resolution data used in this study were available to the public free of charge. This free high resolution data can be advantageous to many governmental and non-governmental organizations interested in wetland conservation and protection.

Second, the integration of high resolution imagery and lidar data helped to improve classification of wetlands because of the use of high resolution lidar to calculate derivatives such as the CTI. In a qualitative visual assessment of all the data layer inputs, the CTI layer provided additional discrimination between wetland and other non-wetland classes because of its ability to separate low terrain areas from steep terrain areas based on topography (Figure 4). For example, forested vegetation in local low areas were often confused spectrally with forested vegetation in upland areas, but were easier to separate with the addition of the CTI data layer. Other studies have shown similar results when adding topographic data and optical data, resulting in a greater improvement of the wetland accuracy classification. For example, in a study by Knight *et al.* (2013), in an area similar to our third study area, different input datasets including optical and topographic data were evaluated to determine if the addition of different data types would improve the accuracy of wetland classification. The Knight *et al.* (2013), results indicated that topographic data and derivatives including the CTI helped to significantly improve the accuracy of wetland/upland classification compared to other data type scenarios including radar and optical data. That and other similar studies (e.g., Baker *et al.*, 2006; Murphy *et al.*, 2007) reinforce our results regarding the value of using topographic data, which can be categorized as one of the major factors to determine and accurately predict the potential location of wetlands across different ecoregions settings.

It is important to acknowledge that most existing research (e.g., Frohn *et al.*, 2009; Moffett and Gorelick, 2013) using an OBIA approach to classify wetlands and other land cover has focused more on segmentation techniques, while our study focused more on the development of a customized rule set appropriate to each specific ecoregion setting. The OBIA multiscale iterative approach used in this study involved the design of a customized rule set, allowing us the incorporation of contextual and expert knowledge information through the CNL in the eCognition Developer software. Rule sets can be complex and unique to each area; however, they are adaptable with newer data and transferable to similar areas. Despite the fact that traditional pixel-based techniques are often preferred to study wetlands because of the reduction in analyst time over the classification process, OBIA offers a way to combine the experience and knowledge of the analyst with computer assistance to classify wetlands more accurately in a semi-automated way. Experience and expert knowledge are critical for mapping wetlands, because these ecosystems tend to have a high variability of physical properties. In addition, this experience and knowledge were necessary in our study to obtain and develop crucial contextual information that was not available through traditional pixel-based techniques. In addition to the high accuracy of the results, the output maps were more aesthetically pleasing than pixel-based maps.

Our OBIA results were significantly improved over the original NWI for the three study areas, with lower rates of wetland omissions. Though it is not fair to make a direct comparison between the NWI and the OBIA results, the OBIA approach used in this study suggests an alternative technique to improve the accuracy of wetlands boundaries.

Results from this study included a land-cover classification map with four classes and wetlands polygons for each study area. Lidar data in combination with high resolution imagery significantly improved the accuracy of wetland classification across the three different ecoregions in Minnesota. Our results provide evidence that diverse ecosystems such as wetlands of different sizes can be identified and classified accurately using an OBIA approach with high resolution data across the three different ecoregions studied in this paper. These results are encouraging and useful as an initial classification of wetland habitats but further research is encouraged to classify wetland types, using recently acquired remote sensing data and OBIA rule sets techniques. The OBIA approach presented here to map wetlands offers an alternative, semi-automated and improved method over traditional pixel based techniques and the original NWI. Furthermore, this OBIA approach may be suitable for extension to a larger range of wetlands located in areas such as the ones used in this study, with similar land-use, topography and ecoregion.

Acknowledgments

This research was funded by the Minnesota Environment and Natural Resources Trust (ENRTF), the Minnesota Department of Natural Resources (MNDNR), and the United States Fish and Wildlife Services (USFWS: Award 30181AJ194).

References

Baatz, M., and A. Schäpe, 2000. Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation, Angewandte Geographische Informationsverarbeitung XII (J. Strobl and T. Blaschke, editors), Wichmann, Heidelberg, pp. 12–23.

Baatz, M., M. Hoffmann, and G. Willhauck, 2008. Progressing from object-based to object-oriented image analysis, *Object Based Image Analysis* (T. Blaschke, S. Lang, and G.J. Hay, editors), Springer, Heidelberg, Berlin, New York, pp. 12–23.

Baker, C., R. Lawrence, C. Montagne, and D. Patten, 2006. Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models, *Wetlands,* 26(2):465–474.

Beven, K.J., and M.J. Kirkby, 1979. A physically based, variable contributing area model of basin hydrology, *Hydrological Sciences Journal*, 24(1):43–69.

Benz, U., P. Hoffman, 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(3-4):239–258.

Burnett, C., and T. Blaschke, 2003. A multi-scale segmentation/object relationship modeling methodology for landscape analysis, *Ecological Modelling*, 168:233–249.

Butera, M., 1983. Remote sensing of wetlands, *IEEE Transactions on Geoscience and Remote Sensing,* 21(3):383–392.

Blaschke, T., 2003. Object-based contextual image classification built on image segmentation, *Proceedings of the 2003 IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data*, 27-28 October, Washington, D.C., pp. 113–119.

Blaschke, T., 2010. Object based image analysis for remote sensing, *ISPRS Journal of Photogrammetry and Remote Sensing*, 65(1):2–16.

Bruzzone, L., and L. Carlin, 2006. A multilevel context-based system for classification of very high spatial resolution images, *IEEE Transactions on Geoscience and Remote Sensing*, 44(9):2587–2600.

Castilla, G., G.J. Hay, and J.R. Ruiz-Gallardo, 2008. Size-constrained region merging (SCRM): An automated delineation tool for assisted photointerpretation, *Photogrammetric Engineering & Remote Sensing*, 74(4):409–419.

Congalton, R.G., and K. Green, 2009. *Assessing the Accuracy of Remotely Sensed Data*: *Principles and Practices*, Second edition, Boca Raton, Florida, CRC Press/Taylor and Francis.

Corcoran, J.M., J.F. Knight, B. Brisco, S. Kaya, A. Cull, and K. Murnaghan. 2011. The integration of optical, topographic, and radar data for wetland mapping in northern Minnesota, *Canadian Journal of Remote Sensing*, 37(5):564–582.

Cowardin, L.M., V. Carter, F.C. Golet, and E.T. LaRoe, 1974. *Classification of Wetlands and Deepwater Habitats of the United States*, U.S. Department of the Interior, Fish and Wildlife Service, Washington, D.C.

Dahl, T.E., and C.E. Johnson, 1991. Status and trends of wetlands in the conterminous United States, mid-1970's to mid-1980, U.S. Department of the Interior, Fish and Wildlife Service, Washington, D.C. 28 p.

Definiens Imaging, 2009. eCognition Imaging Developer, version 8, *ECognition User Guide*.

Dechka, J.A., S.E. Franklin, M.D. Watmough, R.P. Bennett, and D.W. Ingstrup, 2002. Classification of wetland habitat and vegetation communities using multi-temporal Ikonos imagery in southern Saskatchewan, *Canadian Journal of Remote Sensing*, 28(5):679–685.

Erskine, R.H., T.R. Green, J.A. Ramirez, and L.H. MacDonald, 2006. Comparison of grid-based algorithms for computing upslope contributing area, *Water Resources Research*, 42:W09416.

Everitt, J.H., C. Yang, R.S. Fletcher, M.R. Davis, and D.L. Drawe, 2004. Using aerial color infrared photography and QuickBird satellite imagery for mapping wetland vegetation, *Geocarto International,* 19(4):15–22.

Frayer, W.E., T.J. Monahan, D.C. Bowden, and F.A. Graybill, 1983. *Status and Trends of Wetlands and Deep-Water Habitats in the Conterminous United States, 1950's to 1970's*, Colorado State University, Fort Collins, Colorado.

Federal Register, 1980. 40 CFR part 230: Section 404b (1), *Guidelines for Specification of Disposal Sites for Dredged or Fill Material*, 45(249):85352-85353.

Federal Register, 1982. *Title 33: Navigation and Navigable Waters; Chapter II, Regulatory Programs of the Corps of Engineers*, 47(138):31810.

Fournier, R.A., M. Grenier, A. Lavoie, and R. Helie, 2007. Towards a strategy to implement the Canadian Wetland Inventory using satellite remote sensing, *Canadian Journal of Remote Sensing*, 33(S1):S1–S16

Frohn, R., M. Reif, C. Lane, and B. Autrey, 2009. Satellite remote sensing of isolated wetlands using object-oriented classification of LANDSAT-7 data, *Wetlands,* 29(3):931–941.

Galzki, J., J. Nelson, and D. Mulla. 2008. Identifying critical landscape areas for precision conservation in the Minnesota River Basin, *Proceedings of the 9th International Conference on Precision Agriculture* (R. Khosla, editor), Denver, Colorado.

Grenier, M., A.M. Demers, S. Labrecque, M. Benoit, R.A. Fournier, and B. Drolet, 2007. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: Test case on two sites in Quebec, Canada, *Canadian Journal of Remote Sensing*, 33(1):S28–S45

Gruber, S., and S. Peckham, 2008. Land-surface parameters and objects in hydrology, *Geomorphometry: Concepts, Software, Applications* (T. Hengl and H. Reuter, editors), Elsevier, Amsterdam, The Netherlands. pp. 171–194.

Halabisky, M., L.M. Moskal, and S.A. Hall, 2011. Object-based classification of semi-arid wetlands, *Journal of Applied Remote Sensing*, 5:053511–1–053511–13.

Hay, G.J., and G. Castilla, 2008. Geographic object-based image analysis (GEOBIA): A new name for a new discipline, *Object-based Image Analysis-Spatial Concepts for Knowledge-driven Remote Sensing Applications* (T. Blaschke, S. Lang, and G.J. Hay, editors), Springer-Verlag, Berlin, pp. 75–89.

Hodgson, M.E., J.R. Jensen, H.E. Mackey, and M.C. Coulter, 1987. Remote sensing of wetland habitat: A wood stork example, *Photogrammetric Engineering & Remote Sensing*, 53(8):1075–1080.

Huan, Y., and S. Zhang, 2008. Applications of high resolution satellite imagery for wetlands cover classification using object-oriented method, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37(B7):521–526.

Jensen J.R., D.J. Cowen, J.D. Althausen, S. Narumalani, and O. Weatherbee, 1993. The detection and prediction of sea level changes on coastal wetlands using satellite imagery and a geographic information system, *Geocarto International*, 4:87–98.

Knight, J.F., B.T. Tolcser, J.M. Corcoran, and L.P. Rampi, 2013. The effects of data selection and thematic detail on the accuracy of high spatial resolution wetland classifications, *Photogrammetric Engineering & Remote Sensing*, 79(7):613–623.

Laba, M., R. Downs, S. Smith, S. Welsh, C. Neider, S. White, M. Richmond, W. Philpot, and P. Baveye, 2008. Mapping invasive wetland plants in the Hudson River National Estuarine Research Reserve using QuickBird satellite imagery, *Remote Sensing of Environment*, 112:286–300.

Land Management Information Center (LMIC), 2007. *Metadata for the National Wetlands Inventory, Minnesota*.

Lunetta, R.S., and M.E. Balogh, 1999. Application of multi-temporal Landsat-5 TM imagery for wetland identification, *Photogrammetric Engineering & Remote Sensing*, 65(12):1303–1310.

Maxa, M., and P. Bolstad, 2009. Mapping northern wetlands with high resolution satellite imagery and lidar, *Wetlands*, 29(1):248–260.

Midwest Community Planning, LLC, 2012. Big Stone County Water Plan. URL: *http://www.bigstonecounty.org/environmental/water-planning/BigStoneCountyWaterPlan.pdf* (last date accessed: 04 March 2014).

Millennium Ecosystem Assessment, 2005. *Ecosystems and Human Well-Being: Wetlands and Water Synthesis*, World Resources Institute, Washington, D.C.

Minnesota Department of Natural Resources, 2006. *Tomorrow's Habitat for the Wild and Rare: An Action Plan for Minnesota Wildlife, Comprehensive Wildlife Conservation Strategy*, Division of Ecological Services, Minnesota Department of Natural Resources.

Moffett, K., and S. Gorelick, 2013. Distinguishing wetland vegetation and channel features with object-based image segmentation, *International Journal of Remote Sensing*, 34(4):1332–1354.

Moore, I.D., R.B. Grayson, and A.R. Ladson, 1991. Digital terrain modeling: a review of hydrological, geomorphological, and biological applications, *Hydrological Processes*, 5(1):3–30.

MPCA, 2006. A *Comprehensive Wetland Assessment, Monitoring and Mapping Strategy for Minnesota*, Saint Paul, Minnesota, Minnesota Pollution Control Agency.

Murphy, P.N.C., J. Ogilvie, K. Connor, and P.A. Arp, 2007. Mapping wetlands: A comparison of two different approaches for New Brunswick, Canada, *Wetlands*, 27(4):846–854.

Myint, S.W., P. Glober, A. Brazel, S. Grossman-Clarke, and Q. Weng, 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery, *Remote Sensing of Environment,* 115(5):1145–1161.

Nicollet County, 2008. Nicollet county local water management plan, URL: http://www.co.nicollet.mn.us/ (last date accessed: 04 March 2014).

O'Neil-Dunne, J.P.M., S.W. MacFaden, A.R. Royar, and K.C. Pelletier, 2012. An object-based system for LiDAR data fusion and feature extraction, *Geocarto International*, 10:1–16.

Ozesmi, S.L., and M.E. Bauer, 2002. Satellite remote sensing of wetlands, *Wetlands Ecology and Management,* 10(5):381–402.

Quinlan, J.R., 1990. Decision trees and decision-making, *IEEE Transactions on Systems, Man and Cybernetics,* 20(2):339–346.

Rodhe, A., and J. Seibert, 1999. Wetland occurrence in relation to topography: A test of topographic indices as moisture indicators, *Agricultural and Forest Meteorology*, 98-99:325–340.

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(3):133–44.

Seibert, J., and B. McGlynn, 2007. A new triangular multiple flow direction algorithm for computing upslope areas from gridded digital elevation models, *Water Resources Research*, 43(4):1–8.

Sripada, R.P., R.W. Heiniger, J.G. White, and A.D. Meijer, 2006. Aerial color infrared photography for determining early in-season nitrogen requirements in corn, *Agronomy Journal*, 98(4):968–977.

Stedman, S., and T.E. Dahl, 2008. *Status and Trends of Wetlands in the Coastal Watersheds of the Eastern United States 1998-2004*, National Oceanic and Atmospheric Administration, National Marine Fisheries Service and U.S. Department of the Interior, Fish and Wildlife Service, pp. 1–32.

Story, M., and R.G. Congalton, 1986. Accuracy assessment: A user's perspective, *Photogrammetric Engineering & Remote Sensing*, 52(3):397–399.

Turner, R.K., J.C.J.M. van den Bergh, T. Soderqvist, A. Barendregt, J. van der Straaten, E. Maltby, and E.C. van Ierland, 2000. Ecological-economic analysis of wetlands: scientific integration for management and policy, *Ecological Economics*, 35(1):7–23.

Wilson, J.P., G. Aggett, Y.X. Deng, and C.S. Lam, 2008.Water in the landscape: A review of contemporary flow routing algorithms, *Advances in Digital Terrain Analysis* (Q. Zhou, B. Lees, and G. Tang, editors). Springer, Berlin, pp. 213–236.

Wright, C., and A. Gallant, 2007. Improved wetland remote sensing in Yellowstone NationalbPark using classification trees to combine TM imagery and ancillary environmental data,b*Remote Sensing of Environment*, 107(4):582–605.

Zhou, W., and A. Troy, 2008. An object-oriented approach for analyzing and characterizingburban landscape at the parcel level, *International Journal of Remote Sensing*,b29(11):3119–3135.

(Received 14 June 2013; accepted 27 September 2013; final version 15 January 2014)