ABSTRACT

In 2006, several agencies from the state of Minnesota along with federal agencies collaboratively developed a comprehensive wetland assessment, monitoring, and mapping strategy for Minnesota. One of the key components to this strategy is to update the National Wetland Inventory Data for Minnesota using the best available data and techniques. Planning and pilot testing for the NWI update was initiated in 2008 and production level mapping efforts began in 2010. Methods employ a combination of object oriented image analysis, RandomForest™ algorithm based classification, and manual photo-interpretation. Image segmentation of high resolution color IR aerial photography from both spring and summer was used to extract wetland and upland feature boundaries. The geometry and spectral characteristics from the extracted features were combined with additional data including PALSAR satellite RADAR, airborne LiDAR derived DEMs, and soils data to train a RandomForest algorithm to classify wetland types. The segmentation based geometry and RandomForest classification results are then integrated into a photo-interpretation workflow to create the final updated wetland inventory.

KEYWORDS: NWI, OBIA, eCognition, RandomForest, Wetland mapping, Data fusion

INTRODUCTION

Wetland inventories are an essential tool for effective wetland management, protection, and restoration. Such inventories provide baseline information for assessing the effectiveness of wetland policies and management actions. Wetland inventory data is used at all levels of government, as well as by private industry and non-profit organizations for wetland regulation and management, land use and conservation planning, environmental impact assessment, and natural resource inventories. In Minnesota, as with other states, the National Wetland Inventory (NWI) is the only spatially comprehensive wetland inventory available. However, the original NWI database for Minnesota is between 20 to 30 years out of date. Many changes in wetland extent and type have occurred since the original inventory was completed. Changes in the extent of agricultural and urban development have resulted in loss of wetlands creating inaccuracies when out-of-date wetland inventory maps are used to support current decision making. Changes in wetland policies and programs have also resulted in the creation of new wetlands since the
original MN NWI was completed. The lack of an up-to-date wetland inventory will also make it more difficult to track or model future impacts to wetlands in Minnesota.

When the original NWI was compiled for Minnesota, the available technology, methodology and source data were limited in comparison to current standards. Experience using the original NWI for Minnesota shows that very small wetlands and forested wetlands are under-represented in the data. Wetland inventory maps based on the 1:80,000 scale, black and white imagery collected on some parts of Minnesota can be particularly problematic as they tend to omit many forested and emergent wetlands without significant visible standing water (LMIC 2007). A comparison of the original NWI data and new wetland data which was remapped in 2006 (for 1802 random plots) shows that for some wetland categories, such as deepwater habitat, there is substantial agreement between the older and newer data (Kloiber 2010). However, for other wetland types, such as forested and emergent classes, there is considerable discrepancy between the older and newer data. The observed differences are usually the result of land-use change or due to methodological differences in the mapping process.

In 2006, an inter-agency partnership developed a comprehensive strategy for monitoring, assessing, and mapping wetlands in Minnesota. The update of the NWI for Minnesota was one of three key recommendations of this strategy document (Gernes and Norris 2006).

Project Area

The project area consists of 13 counties in east-central Minnesota including: Anoka, Carver, Chisago, Dakota, Goodhue, Hennepin, Isanti, Ramsey, Rice, Scott, Sherburne, Washington, and Wright Counties (Figure 1). This area is 6,328 square miles, but the updated wetland inventory will include complete coverage for all USGS quarter quadrangles that intersect any of these counties (about 7,150 square mile).

Figure 1. Project area - counties and quarter quadrangles covered.
Process Overview

**METHODS**

**Image Data Preparation**

The primary image data set for the East Central MN Phase II NWI update is 2010/11 4-band (RGB+CIR), digital orthophoto quarter quads of spring leaf-off aerial imagery collected by SURDEX. The imagery was collected for eleven of the thirteen counties in 2010, with Rice and Goodhue imagery collected in 2011. Four counties (Wright, Sherburne, Isanti, and Chisago) were collected with an image spatial resolution of 50 cm. Seven counties (Carver, Scott, Dakota, Hennepin, Ramsey, Anoka, and Washington) were imaged with a spatial resolution of 30 cm. For the image segmentation process, the 30cm data was resampled to 50cm resolution using a bilinear interpolation algorithm. The resampled data allowed for a single set of processing algorithms to be developed for the entire project area. The original 30cm imagery was used for photo-interpretation where available.

**RADAR Data Preparation**

PALSAR L-band RADAR data was acquired through a data grant from the Alaska Satellite Facility (ASF) DAAC and AADN data pool. Thirteen single date scenes were acquired to cover the east-central Minnesota project area. The scenes available were a combination of single and dual polarization during a leaf-off seasonal window (Figure 3).
ASF MapReady Remote Sensing Tool Kit (ASF, 2011) was used for terrain correction, geocoding, and exporting to geo-tiff file format. After terrain correction was applied the pre-processed PALSAR scenes still contained some distortion within the project area so further geo-rectification was performed in ArcGIS using selected control points from the aerial imagery. The RADAR processing extension in Opticks (Opticks, 2011) was used to reduce speckle in the PALSAR data.

A 10 class maximum-likelihood clustering routine implemented in ERDAS Imagine software (ERDAS, 2008) was used to produce an unsupervised classification of the PALSAR data. Clusters visually identified as being associated with “wet forest” were assigned that classification value. Analysts noted some confusion between wet deciduous forest and pine plantations, some agricultural areas and urban areas. This confusion was remedied during subsequent image segmentation and classification steps. The final product from the PALSAR analysis was a binary 1/0 raster layer representing likely wet areas within deciduous forests. This layer was integrated into the overall wetland mapping process by incorporating it into the image segmentation process and as an additional ancillary data layer available to the photo-interpretation team.

Soils Data Preparation
The Natural Resources Conservation Service (NRCS) digital Soil Survey Geographic (SSURGO) layers were available for the entire east-central Minnesota project area (NRCS 2010). Two SSURGO based derived raster products were produced to serve as inputs in the National Wetland Inventory update for Minnesota; (1) a categorical map based on the predominant soil water regime, and (2) a continuous variable representing the percentage of the SSURGO unit (by area) meeting the hydric soil criterion. The hydric soil criterion variables included in the analysis are those most likely to be related to NWI definitions of wetland water regime (e.g. drainage class, flood frequency for April, pond frequency for April, and pond frequency for August).
Elevation Data Preparation

In the East-Central project area, DEMs were derived from two different datasets. LiDAR based DEMs (3 meter) were not available for the entire project area at the time of the analysis so where necessary, the National Elevation Dataset DEM (10 meter) was used as an alternative.

Several DEM based derived layers were produced in an effort to provide additional predictors that would potentially be useful in the Random Forest classification phase of the process. The NED 10 meter DEM was resampled to 3 meter resolution after the derived products were created. These derived layers include three variations on topographic curvature (Simple Curvature, Planform Curvature and Profile Curvature) which were calculated using functions found in ArcGIS Spatial Analyst (ESRI 2011).

The Topographic Position Index (TPI) developed by Weiss (2001) was calculated using a custom model developed with ArcGIS model builder software. TPI for each pixel is calculated by subtracting the mean elevation of its neighborhood from its own elevation value. A positive score indicates the pixel is higher than its neighbors, while a negative score indicates it is lower. This simple classification is a useful means of mapping topographic depressions. Groups of pixels with negative TPI scores represent such depressions, and are possible wetland locations. Selection of appropriate neighborhood settings is an important part of the TPI development process. Selecting too small of a neighborhood will result in very fine resolution which is not adequate for detecting topographic depressions over large areas. Selecting too large of a neighborhood will result in depressions which may encompass upland areas as well. For the east-central project area, a circular neighborhood with radius of 15 and 20 were selected.

The Compound Topographic Index (CTI) (Moore 1991) was calculated using sinkless versions of the 3m spatial resolution LiDAR derived DEMs. A slope grid and flow direction grid were calculated using the D-Infinity Flow Directions tool implemented in TauDEM software (Tarboton 2003). The contributing area surface was then derived from the flow direction layers. The slope grid and contributing area layers were used to initialize a python script written for a batch spatial calculation of the CTI equations.

All of the layers described above were formatted for input to the eCognition segmentation process by clipping them to the image boundary of the relevant quarter quad and stacking the clipped layers with ERDAS Imagine software (ERDAS 2008) to create a single multi-layer *.tif file subsequently referred to here as the layer-stack. The spring 2010 aerial imagery was kept in its original separate files.

Field Data Collection

The reference data field collection for the east-central project area served three purposes: 1) to provide localized wetland identification and classification experience for the photo-interpretation team, 2) to gather in-situ ground photography for use in the creation of a project-specific wetland photo interpretation guidebook, and 3) to collect training data for the classification of potential wetlands using a RandomForest algorithm. A set of 12 representative quadrangles were selected for field verification in order to capture representative data for the wetland types found throughout the project. These quads included urban, residential, and rural areas.

Within the 12 sample quadrangles individual wetlands were selected for field sampling using a stratified random sampling approach with strata proportioned according to the frequency of that wetland class across all 12 quads. Rarely occurring wetland types were all flagged for field sampling. During the four day sampling campaign period, 503 sites were visited. An additional seven were visited at an earlier date, for a total of 510 field sites. The field training data geodatabase (points, attributes and site photos) will be delivered to the MN DNR and U.S. Fish and Wildlife Service with the final project delivery and will be archived with the official NWI database for future reference.

All field data collected and subsequent mapping products were categorized according to the Cowardin classification system (Cowardin et al. 1979), which is a hierarchical system developed to standardize the classification of wetlands and deepwater habitats of the United States. At the highest level are five systems: marine, estuarine, riverine, lacustrine, and palustrine. Only three of these systems are relevant to the inland wetlands found in Minnesota: riverine, lacustrine, and palustrine. Santos and Gauster (1993) included a list of valid Cowardin wetland types for Minnesota in their regional user’s guide to the National Wetland Inventory Maps. Within the riverine and lacustrine systems, there are subsystems. Minnesota has lower perennial rivers, upper perennial rivers, and intermittent streams for riverine subsystems. There are no tidal riverine systems. There are also two lacustrine subsystems, limnetic and littoral. The palustrine system has no subsystems. Within each of these systems and subsystems there are several classes that are defined either on the dominant vegetation (e.g. scrub-shrub and forested) or the dominant substrate (e.g. unconsolidated bottom). Additional details of the classification system
including the definition of each system, subsystem, class, and subclass can be found in Cowardin et al. (1979) and Dahl et al. (2009).

**Image Segmentation**

The NWI classification process for east-central Minnesota consists of three basic steps: 1) creation of image segments (polygons), 2) random forest classification of the segments, and 3) photo interpretation and editing of the classified image segments. The spring 4-band imagery and layer-stack files were imported into eCognition software (Trimble 2010) to create the image segmentation files. The eCognition processing rule-set developed for this project contains a sequence of over 250 separate operations. These operations include:

1. Initial quad-tree based image segmentation
2. Sub-processes to manage edge matching between adjacent quads
3. A multi-resolution image segmentation sequence
4. Hierarchical image object aggregation by spectral, topographic, and classification based characteristics
5. Segmentation based re-scaling of the 25m spatial resolution PALSAR layer to make it visually compatible when vectored and merged with vectors derived from the 0.5m base imagery
6. Derivation of contour lines within forested areas based on the DEM layer
7. Smoothing of all image object boundaries
8. Elimination of image objects smaller than the specified minimum mapping unit
9. Export of a final shape file for each quarter-quad

Improvements to the ruleset and process development were conducted by creating prototype segmentations for the photo-interpretation team to review. Suggestions and requests to improve the properties of the segmentation were made by the photo interpretation team and incorporated into subsequent versions of the segmentation process. The ultimate goal is to develop eCognition based segmentation and feature extraction processes (Figure 4) that support and complement the work done by the photo interpretation team rather than to try to replace human photo-interpretation entirely.

![Figure 4. The unedited image segmentation results (red) with two wetland polygons selected (blue) displayed over the IR band of the primary 50cm resolution CIR imagery collected for this project](image)

We considered the image segmentation effort to be successful when we reached a point it took less time for an interpreter to edit an eCognition derived segmentation shape file for a quarter-quad than it would have taken for that interpreter to manually digitize all of the features in that quarter-quad. The photo-interpretation team now spends
the vast majority of its time interpreting wetland classes that are difficult to categorize when looking at the imagery. Most of the delineation is based on making minor edits to existing polygons rather than on manually creating new polygons for each feature. All subsequent segmentation process development efforts were directed toward improving the efficiency of the overall workflow in order to further reduce the amount of time required to complete the inventory within each quarter-quad.

An online tracking system was implemented where the photo-interpretation team could request processing of specific quarter-quads or suggest improvements to the segmentation process. Overall efficiency was also improved by optimizing the rule set for efficient batch processing using the production oriented functions provided by eCognition Server software. All image segmentation based polygons were assigned a unique identification number for tracking and to facilitate automated classification of the wetland characteristics with a RandomForest algorithm implemented in the R open-source statistical analysis environment (R Development Core Team 2011). Additional fields (attribute, comments, field verified) are added to the image segment attribute table to assist in the photo interpretation process.

### Random Forest Classification of Image Objects

The Random Forest classification algorithm is described in detail in Brieman (2001). The random forest classification process requires training data as input for the classification process. The initial training data for the east-central project area was aggregated from on-the-ground field work and ancillary data. In total, 3350 points were used in the initial training data set. The breakdown by system and subsystem is shown in Table 1, with a breakdown by full code in 510 sites were visited during field work, 1967 were chosen from ancillary datasets, and an additional 873 were identified by DU staff from aerial imagery.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Palustrine:</strong></td>
<td></td>
</tr>
<tr>
<td>Forested</td>
<td>359</td>
</tr>
<tr>
<td>Scrub-Shrub</td>
<td>103</td>
</tr>
<tr>
<td>Emergent</td>
<td>1029</td>
</tr>
<tr>
<td>Aquatic Bed</td>
<td>311</td>
</tr>
<tr>
<td>Unconsolidated Bed</td>
<td>547</td>
</tr>
<tr>
<td><strong>Lacustrine:</strong></td>
<td></td>
</tr>
<tr>
<td>Aquatic Bed</td>
<td>18</td>
</tr>
<tr>
<td>Unconsolidated Bed</td>
<td>39</td>
</tr>
<tr>
<td><strong>Riverine:</strong></td>
<td></td>
</tr>
<tr>
<td>Unconsolidated Bed</td>
<td>22</td>
</tr>
<tr>
<td><strong>Upland:</strong></td>
<td>796</td>
</tr>
</tbody>
</table>

As each quarter quad is updated, additional training data will be merged with the initial training data to create a more robust training data set. The predictor variable set included the spectral, DEM, PALSAR and soil map derived features that describe each image object polygon. Initial results indicate that the segmentation based Random Forest wetland classification separates wetlands from uplands with an overall (bootstrapped) accuracy rate of 92.2% and assigns wetland class with an overall (bootstrapped) accuracy rate of 66.87%. These accuracy values should be treated as an index only. Whenever the segmentation process is modified based on feedback from the photo-interpretation team the current Random Forest classification model becomes obsolete. The algorithm is automatically re-run whenever new segmentation files become available which means that classification accuracy values (including those reported here) are only useful as transient indices of the utility of the automated classification process. The formal accuracy assessment, designed to evaluate data that is ready to submit to the NWI, takes place only after the photo-interpretation and QA/QC processes are complete.

### The Photo Interpretation Process

After the segmentation and classification steps are completed, the photo interpretation process begins. Interpreters view the classified image segmentation shape file superimposed over the spring 2010 imagery in order to identify and categorize wetlands. The interpreters have the option to either use the segmentation derived boundary without modification, to manually edit or adjust the polygon boundary, or to discard the segmentation based
boundary to manually digitize a new boundary. Adjacent wetland polygons of the same class are merged. The photo interpreters have access to all available ancillary data including the PALSAR, SSURGO and DEM layers used in the segmentation process as well as the summer leaf-on NAIP imagery to assist them in assigning the correct NWI code. All automated wetland classification values must be either confirmed or manually reclassified by a human interpreter. The RandomForest classification is provided to the interpreters in two formats including a categorical wetland classification value and a continuous probability estimate of membership to each wetland class. The probability estimates are particularly useful in situations where the assignment of a wetland is ambiguous to a human interpreter as it can provides an objective data resource to help make difficult interpretation decisions.

Quality Control and Quality Assurance

Quality control and quality assurance (QA/QC) programs have been written to automatically check for topological and attribute errors within the classification after the photo interpretation process is complete. Once a quarter-quad is completed, the interpreter executes the QA/QC program and corrects any identified errors before moving on to another quarter-quad. After successful execution of the QA/QC process by the interpreter, a second interpreter inspects 10% of the wetland classification to ensure consistency and accuracy of the wetland classification between individual interpreters. After the second review, the NWI QA/QC analyst reviews the overall classification for that quarter-quad and executes a second series of automated QA/QC procedures provided by the USFWS.

The draft version of the NWI classification for the quarter quad is then sent to the Minnesota Department of Natural Resources for review. Once the review is completed, the quarter quad is merged into a seamless state-wide layer. Final accuracy of the NWI update will be calculated by a third party organization (The University of Minnesota) not directly involved in the mapping process. The formal accuracy assessment is based on comparing updated NWI polygons to a field reference data source that was created and maintained separately from the reference data sources used in the production mapping process. The final NWI layer for the east-central project area will be projected to Albers equal area projection and delivered to the U.S. Fish and Wildlife Service for incorporation into the National NWI database.

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