Wetland Mapping Methods for the Arrowhead Region of Minnesota

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Contents

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1. Introduction

1.1. Objectives

This document is a report to the Minnesota Department of Natural Resources (MNDNR) that provides a review of research conducted on wetland mapping methods for the Arrowhead, or boreal forest, region of Minnesota (the counties of Carlton, Cook, Itasca, Koochiching, Lake, and St. Louis). This report is intended as a companion to the report, "Wetland Mapping Methods for the Twin Cities Metropolitan Area," which was submitted to MNDNR in June of 2009. Given herein are recommendations for wetland mapping methods appropriate for the ongoing National Wetlands Inventory update in Minnesota. This document is provided to MNDNR by the University of Minnesota's Remote Sensing and Geospatial Analysis Lab (RSGAL) in partial fulfillment of a contractual agreement between the two parties. The structure of this report is as follows: 1) detailed summaries of the research undertaken by RSGAL under this agreement, 2) Recommendations and a suggested protocol for wetland mapping in the Arrowhead.

1.2. Background

For background information on wetland mapping we respectfully refer the reader to the report "Wetland Mapping Methods for the Twin Cities Metropolitan Area," which was submitted to MNDNR in June of 2009. This report should be viewed as an addendum to the previous work.

Wetlands are jointly defined by the U.S. Army Corps of Engineers (USACE) and the U.S. Environmental Protection Agency (EPA) 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, 1982; Federal Register, 1980). Wetlands are a valuable natural resource as they play a crucial role in the ecology of a landscape. Wetlands function as a buffer to open water bodies and provide important ecosystem functions by maintaining water quality by filtering nutrients and pollutants, storing floodwater and mitigating its effects on water bodies, and also providing habitat to a variety of wildlife that have adapted to life in saturated environments. Wetlands also play a role in the global carbon cycle, acting as both carbon sources and sinks.

Wetland loss has occurred at an alarming rate. In a 200 year period between colonization and the 1980's, the lower 48 states lost an estimated 53% wetland acreage due to a variety of human activities such as agriculture, urbanization and development, and pollution (Dahl, 1990; Johnston, 1989). Over 50% of Minnesota's 3.6 million hectares(ha) of wetlands have been lost. The concentration of wetland loss is greatest, over 80%, in southern Minnesota and the Red River Valley where wetlands were drained for agriculture. Urbanization causes small wetland area losses, but significantly alters a wetland's physical, biological, and chemical properties (Johnston, 1989). The loss of wetlands continues, but trends appear to be that wetland loss is slowing (Dahl and Johnson, 1991). Accurate mapping of the spatial distribution of wetlands is an important tool for understanding the effects of wetland loss, and may contribute to policy decisions influencing land use (Baker, et al. 2006).

2. Methods/Results

2.1. Wetland Mapping using Decision Trees

2.1.1. Decision Trees Introduction

Mapping wetlands can be achieved through a variety of methodologies ranging from field investigation to remote wetland assessment. Remote sensing has been used as a wetland mapping tool since the 1960's (Cowardin and Myers, 1974) but early assessments were not accurate enough for many practical applications. However, with recent advances in remote sensing technologies, it may be possible to map wetlands in a large geographic area with sufficient accuracy in an efficient and cost-effective manner. The following study is a survey of the usefulness of various geospatial data types in wetland mapping using decision tree classifiers (e.g. RandomForests™, CART™, etc.).

2.1.2. Decision Trees Methods

2.1.2.1. Pilot Study Areas

Two areas, one located in the St. Paul – Minneapolis metropolitan area and one located in the northern forested region of Minnesota, were selected as pilot areas for the study. Pilot areas were selected to be areas in which high quality geospatial datasets were available. In addition, local government agencies in both areas had recently performed wetland inventories. The GIS datasets and wetlands inventories were excellent tools to study automated wetland classification. The location of the two pilot study areas is shown in Figure 1, below.

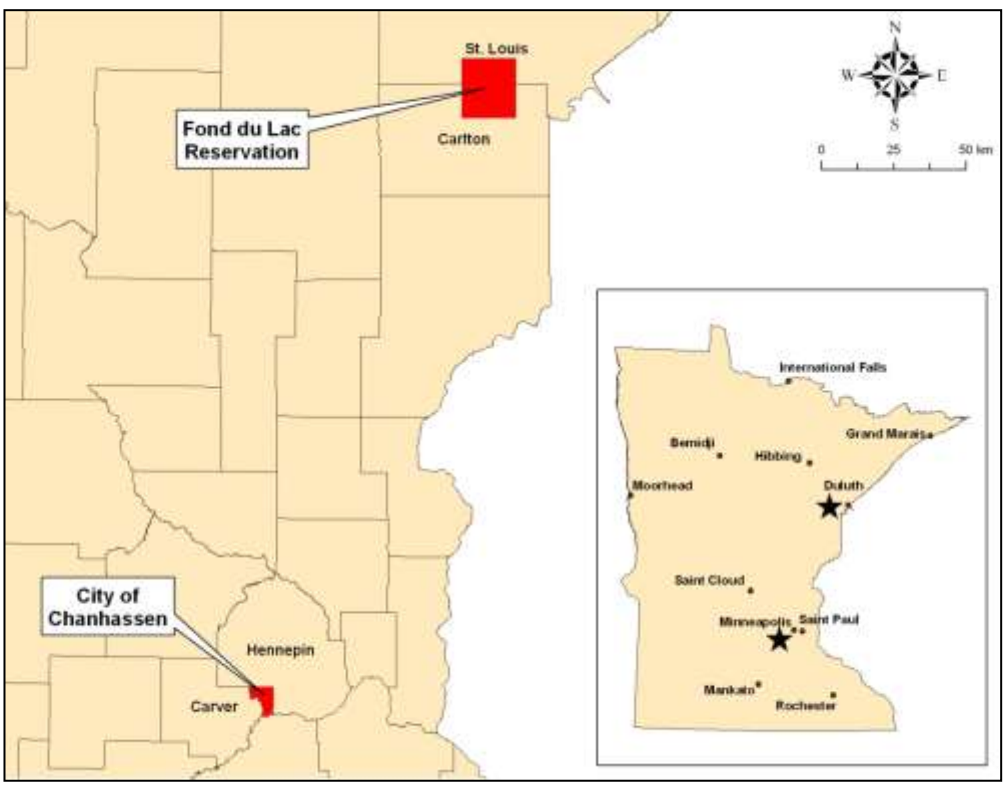

FIGURE 1 – LOCATION OF PILOT STUDY AREAS

City of Chanhassen, Minnesota

The metro study area is located within the limits of the City of Chanhassen, Carver County, Minnesota, a southwestern suburb of Minneapolis with an area of approximately 22.9 mi^2. Land use within the city is primarily medium density residential housing with some areas of industrial and dedicated open space. Wetlands, lakes, ponds, and rivers account for approximately 26% of the city's surface area (City of Chanhassen, 2006). The City of Chanhassen completed an update to its Surface Water Management Plan (SWMP) in 2006. Wetlands and water features throughout the city were identified and observed in the field, and mapping of features throughout the city was completed using a combination of GPS delineation and image interpretation. Further methodology is described in the City of City of Chanhassen SWMP (2006).

In addition to the wetland mapping conducted as a part of the Chanhassen SWMP, high resolution LiDAR elevation data was available for Carver County. The LiDAR data was acquired as a digital elevation model (DEM) with 3m horizontal spatial resolution.

Fond du Lac Reservation, Minnesota

The Fond du Lac Reservation, located northwest of the City of Cloquet, Minnesota, was selected as the pilot area for the northern forested area. The Fond du Lac Reservation has an area of approximately 150 mi^2. Land cover is primarily dominated by both deciduous and evergreen forests and low density residential housing. Wetlands and water bodies account for approximately 38% of the Reservation's surface area. The Fond du Lac Reservation completed a reservation wide wetland inventory in 2008. The wetland inventory was completed primarily by manual photo interpretation, and was used along with other ancillary data sets as a guide in development of training areas for wetland classification.

In addition to the reservation wide wetland inventory, radar imagery and spring leaf off imagery were also acquired for the area. The Radar data acquired for the Fond du Lac Reservation were collected on June 15, 2009 from RADARSAT-2, co-operated by the Canadian Space Agency (CSA) and MacDonald Dettwiler and Associates Ltd. (MDA). The data acquired were Fine Quad-Polarization, C-band (5.6 cm wavelength) imagery with WGS 84 geographic projection and 4.73m pixel spacing. Four polarizations are available from RADARSAT-2 data, horizontal-horizontal (HH), horizontal-vertical (HV), vertical-vertical (VV), and vertical-horizontal (VH). Each pixel in each polarization is represented by a real and imaginary 16-bit unsigned integer, and as a result, Radar images do not look like a typical optical image. The real values describe the mean magnitude, or backscattering, of the reflected target whereas the imaginary values describe the complex behavior of the scattering mechanisms of the target (Raney, 1998). Reflectivity values of Radar imagery typically have a wide range in value that can span several factors of ten; thus, Radar imagery is converted to a logarithmic form using decibel values (Frulla, 1998). After converting to decibel values, the imagery used in this study was georectified using 30 ground control points with a root mean square error (RMSE) of 1.5m and resampled to 3m pixels using the nearest neighbor resampling technique. Leaf off aerial imagery was acquired for the several counties in northeastern Minnesota during the spring of 2009. The imagery contained four spectral bands (color and infrared) and had a horizontal spatial resolution of 0.5m.

2.1.2.2. Field Data Collection

Field validation data was necessary to assess the accuracy of the wetland classification to be performed in the Fond du Lac pilot area. A field study was conducted July 13-17, 2009 by researchers from the University of Minnesota, including one MN Certified Wetland Delineator. A stratified random sampling scheme was used within wetland types to generate a sample of 250 wetland points. An additional 150 points were randomly generated within uplands. All points were generated within areas of public or reservation owned land throughout the study area. The points were loaded into Trimble GeoXT and GeoXH handheld GPS units, which are sub-meter accurate under optimal conditions. A minimum of 50 positions were collected for each GPS point collected during the field study. Data were post processed and corrected using Pathfinder Office. Due to time restraints, and in order to maximize the wetland data points collected per wetland class, some points were collected on the fly. A total of 195 points were collected during the week of field work. The initial data collection was focused on shrub and forested wetlands. The small number of validation points, as well as oversampling of shrub and forested wetland classes, may adversely affect overall accuracy assessments when considering all wetland types within Fond du Lac Reservation. Additional field validation data will be collected during the summer of 2010 in order to provide a more robust validation sample to be used in accuracy assessment.

2.1.2.3. Automated Wetland Classification

Wetlands were classified to the Cowardin class level (Table 1) and a simplified plant community classification developed by the Minnesota DNR. This modified wetland type classification was developed specifically for the remote sensing-based update of the NWI.

Table 1 – Cowardin Wetland Classes

Cowardin Code[1]	Description
PEM	Palustrine Emergent
PSS	Palustrine Scrub Shrub
PFO	Palustrine Forested
L	Lacustrine
PUB	Palustrine Unconsolidated Bottom

[1] Cowardin codes are taken from Cowardin et al. (1974).

Table 2 and Table 3 show the wetland composition in Chanhassen and Fond du Lac by Cowardin classes and DNR modified wetland types, respectively. Wetland data for the City of Chanhassen were collected during the 2006 SWMP update and data for Fond du Lac are derived from the 2008 wetland inventory.

TABLE 2 – Summary of WetlAnd Types by Cowardin Class

	Chanhassen			Fond du Lac		
Class	Count	Acres	% of Total	Count	Acres	% of Total
PEM	305	2304	58.4%	826	4311	11.8%
PFO	40	19	0.5%	1797	15776	43.1%
PSS	3	1	0.02%	2334	13584	37.1%
W[1]	189	1621	41.1%	309	2949	8.1%
Total Features	**537**	**3944**	**100.0%**	**5266**	**36619**	**100.0%**
Study Area		**14515**	**27.2%**		**96119**	**38.1%**

[1] Water class includes Lacustrine and PUB wetlands as well as non-vegetated stormwater detention basins.

TABLE 3 – Summary of Wetland Types by DNR Simplified Plant Communities

	Chanhassen			Fond du Lac		
Class	Count	Acres	% of Total	Count	Acres	% of Total
Coniferous Wetland	0	0	0.0%	883	9743	26.6%
Deep Marsh	52	228	5.8%	148	1045	2.9%
Hardwood Wetland	47	25	0.6%	914	6033	16.5%
Seasonally Flooded	10	5	0.1%	0	0	0.0%
Shallow Marsh	132	1410	35.8%	270	2013	5.5%
Shrub Wetland	3	1	0.02%	2334	13584	37.1%
Water[1]	191	1635	41.5%	309	2949	8.1%
Wet Meadow	102	641	16.2%	408	1253	3.4%
Total Features	**537**	**3944**	**100.0%**	**5266**	**36619**	**100.0%**
Study Area		**14515**	**27.2%**		**96119**	**38.1%**

[1] Water class includes Lacustrine and PUB wetlands as well as non-vegetated stormwater detention basins.

2.1.2.4. Decision Tree Classification

Automated wetland classification was done using decision tree classification, a type of expert classification. The decision tree classifier was developed using See5 software package developed by Rulequest, Inc. (http://rulequest.com) and the NLCD Mapping Tool, developed by MDA Ltd. Three steps are involved in decision tree classification: data sampling, data mining and decision tree creation, and classification. A detailed, stepwise, guide to the processes used throughout wetland classification can be found in Appendix E.

2.1.2.5. Data Sampling

The first step involves assembling training data points and data sets to be sampled. Training data for the Chanhassen classification were derived from the city's 2006 SWMP data. Wetland polygons were edited in GIS to correct for subsequent wetland loss and creation as a part of the Highway 212 construction project. Five thousand random points were generated throughout the City in both known wetland and known upland areas for a total of 10,000 sample points.

Training data for Fond du Lac were created using a combination of techniques because, unlike Chanhassen, the Reservation's wetland assessment did not include field data verification. Training polygons were developed in geographically similar locations to the field collected data points in areas that shared like spectral characteristics. In an effort to obtain a large enough number of sample data points in each training polygon, and at the same time capture spectral variety within wetland types, a segmentation was created using 2008 NAIP and the 2009 spring leaf off imagery in Definiens' eCognition (http://www.ecognition.com). Five random sample points were generated within each eCognition segment for a total of 5,412 sample points.

The NLCD Sampling Tool v2.0, a utility included in the NLCD Mapping Tool, was used to create an input data file for use in See5. The NLCD Sampling Tool extracts values for each input raster file at each sampling point of known wetland type. This generates a tabular data file which contains a row for each sampling point with comma separated values for each input raster file. Table 4 shows the data that were available for use in classification in both the Chanhassen and Fond du Lac study areas.

TABLE 4 – Data Available for Wetland Classification

Data Layer	Fond du Lac	Chanhassen
Aerial Imagery		
2008 NAIP Leaf On Imagery (R,G,B,IR)	X	X
2009 Spring Leaf Off Imagery (R,G,B,IR)	X	
Radar Imagery (Quad Pol)	X	
Aerial Imagery – Derived		
2008 NAIP NDVI	X	X
2009 Leaf Off NDVI	X	
NDVI Difference	X	
Topography		
10m NED DEM	X	
2-ft Hi-Res LiDAR Based DEM		X
Topography Derivations		
CTI (3m LiDAR derived)		X
CTI (10m NED derived)	X	
CTI (24m LiDAR degrade derived)		X
Slope (3m LiDAR derived)		X
Slope (10m NED derived)	X	
Curvature (3m LiDAR derived)		X
Curvature (10m NED derived)	X	
Other Data		
SSURGO (Drainage Class)	X	X

2.1.2.6. Data Mining

The second step involves data mining algorithms developed by Rulequest, Inc. as a part of their See5 software package. See5 mines for patterns within the data tables created using the NLCD Sampling Tool. The boost, fuzzy thresholds, and global pruning options were enabled for classifier construction. The result of the data mining process is a decision tree that is used to produce a classification. Decision trees were constructed to perform wetland/upland classification, wetland classification to the Cowardin class level, and wetland classification using the DNR simplified plant communities. The output file also includes an accuracy assessment done using all of the input sampling points as a measure of error inherent in the resultant decision tree. The cross-validation option was also enabled to provide an estimated accuracy assessment of sampling data withheld from several extra iterations of decision tree generation. These options are described further in Appendix E.

2.1.2.7. Classification

The final step is to produce a classification. The outcome classes are the same as those from the training data and the area classified is the geometric intersection of all input raster datasets. The classification was performed using the See5 Classifier Tool, a part of the NLCD Mapping Tool. The additional option to produce a classification confidence image was also selected. A wetland/upland classification was performed on the entire study area. Wetland type classifications were performed only on those areas classified as wetlands with at least 70% confidence in the initial wetland/upland classification. Even though the 70% wetland mask was applied, uplands remained a potential output class in the wetland type classifications. A small percentage of pixels initially classified as wetlands were subsequently classified as uplands and were considered as such in the final classifications and accuracy assessments.

Several wetland classifications were performed in an effort to determine the effects of various datasets on the classification accuracy. Classifications for both Chanhassen and Fond du Lac were performed using the best available data, shown in Table 4, the best available data without topography, and only the NAIP imagery. Additional classifications in Chanhassen were performed to compare differences between high resolution (2-ft) and low resolution (10m) topography data as well as differences in the Compound Topographic Index (CTI) and the surface curvature topographic derivations. Additional classifications in Fond du Lac were performed to determine effect of Radar data and leaf-off imagery on the classification accuracy. Table 5 shows which data were used for each classification.

TABLE 5 – Data Used for Wetland Classification

	Classification Scenario														
	Chanhassen								Fond du Lac						
Data Layer	All Data	HR – CTI	HR – Curve	NED Data	NED – CTI	NED – Curve	No Topo	NAIP Only	All Data	No Radar	No Leaf Off	No Topo	Aerials Only	NAIP Only
Aerial Imagery														
2008 NAIP Leaf On Imagery (R,G,B,IR)	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2009 Spring Leaf Off Imagery (R,G,B,IR)									X	X		X	X	
Radar Imagery (Quad Pol)									X		X	X		
Aerial Imagery – Derived														

2008 NAIP NDVI	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2009 Leaf Off NDVI									X	X		X	X	
NDVI Difference									X	X		X	X	
Topography														
10m NED DEM				X	X	X			X	X	X			
2-ft Hi-Res LiDAR Based DEM	X	X	X											
Topography Derivations														
CTI (3m LiDAR derived)	X	X												
CTI (10m NED derived)				X	X				X	X	X			
CTI (24m LiDAR degrade derived)	X	X												
Slope (3m LiDAR derived)	X	X	X											
Slope (10m NED derived)				X	X	X			X	X	X			
Curvature (3m LiDAR derived)	X		X											
Curvature (10m NED derived)				X		X			X	X	X			
Other Data														
SSURGO (Drainage Class)	X	X	X	X	X		X		X	X	X	X		

2.1.2.8. Other Classifications

Traditional unsupervised and supervised classifications were performed in Imagine 2010, developed by Erdas, Inc. (http://www.erdas.com) for both pilot study areas in addition to the decision tree classification. Unsupervised classification was performed using the ISODATA algorithm and 20 classes. Classes were reclassified based on summary statistics of areas of known wetland types and visual inspection of the classification. Supervised classification was performed using the same training locations as were used for decision tree classification.

2.1.3. Decision Trees Accuracy Assessment

The accuracy of each classification performed was assessed using field validated points. Randomly generated training data included some wetland classes comprising a very small portion of the total wetland area within the study area. While wetland classifications were performed for all wetland types present in the training sample, accuracy assessments were performed for wetland types with more than 10 field validation points. However, because the dominant wetland classes could be misclassified as the less dominant wetland classes, all wetland types were reported in error matrices. Error matrices were calculated using RS Accuracy (Joe Knight, http://knightlab.org) and formatted as described in Congalton and Green (1999).

2.1.3.1. Chanhassen Accuracy Assessment Methodology

In Chanhassen, a random sample of 10,000 points was generated throughout the city. Wetland classes were extracted from the SWMP for each point. Single wetland polygons in the SWMP with two or more wetland types noted were considered to be the more dominant wetland type. The sampling scheme was not stratified so the total reference set consisted of 7343 upland points and 2657 wetland points. The greater number of upland points would bias the accuracy assessment, so upland reference data were removed when calculating accuracy for wetland types.

Wet features in Chanhassen mostly consisted of water and emergent wetlands, as shown in Table 1 and Table 2 Wetland type classification by Cowardin class included water (L, PUB, PAB), emergent (PEM), scrub shrub (PSS), and forested (PFO) wetlands. Scrub shrub comprised a very small area of the wetland cover in the city and contained only five field validation points, and was therefore removed from the accuracy assessment. Wetland type classification by DNR simplified plant communities included water, wet meadow, shallow marsh, deep marsh, shrub wetland, seasonally flooded, hardwood wetland classes. Seasonally flooded and shrub wetlands each had less than 10 field validation points and were removed from the accuracy assessment.

2.1.3.2. Fond du Lac Accuracy Assessment Methodology

The 195 field collected data points were used as validation data in the accuracy assessment for the Fond du Lac study area. These reference data are independent of the training polygons used in decision tree development. The initial goal of the study was to concentrate on classifying forested wetland types and therefore most field collected points consisted of scrub shrub and forested wetlands. Additional field work in 2010 will supplement the existing field validation data in order to provide for a more robust sample across all wetland types.

Wet features in Fond du Lac consisted mostly of forested and scrub shrub type wetlands. Wetland type classification by Cowardin class included water (L, PUB, PAB), emergent (PEM), scrub shrub (PSS), and forested (PFO) wetlands. Most of the field validation points were scrub shrub and forested wetlands, so emergent wetlands were not included in the accuracy assessment. Wetland type classification by DNR simplified plant communities included water, wet meadow, shallow marsh, deep marsh, shrub wetland, hardwood wetland, and coniferous wetland. The wet meadow, shallow marsh, and deep marsh classes each had less than 10 field validation points and were removed from the accuracy assessment.

2.1.4. Decision Trees Results

Numerous iterations of the NLCD Sampling Tool and See5 were performed using a variety of combinations of datasets in an effort to determine the effect of each of these datasets on the accuracy of the resulting wetland classification. The results for wetland/upland, Cowardin class, and simplified plant community classifications are presented below.

2.1.4.1. City of Chanhassen Results

The following sections present the results of wetland classifications for the City of Chanhassen. For comparison purposes, the 2008 NAIP aerial photograph is provided at a city scale in Figure A.1 and at a local scale in Figure A.2 to show the land cover in the area. Chanhassen SWMP wetlands are shown by Cowardin class at city and local scales in Figure A.3 and Figure A.4, respectively, and by DNR simplified plant community type at city and local scales in Figure A.5 and Figure A.6, respectively. Additional figures showing each classification described at both large and small scales can also be found in Appendix A. Full error matrices for each classification can be found in Appendix C.

Best Performing Classification Scenario

The best performing classification for the City of Chanhassen used as many data sets as were available for the area, including NAIP Imagery, a high resolution LiDAR-based DEM, the Soil Survey Geodatabase

(SSURGO) drainage class, and a several imagery and topography derivations as shown in Table 5. The wetland/upland accuracy for the best performing classification, *Hi-Res Topo (All Data)*, was 93.1%, as shown in Table 6. Cowardin class accuracy was 85.7% (Table 7), and DNR simplified plant community type accuracy was 76.5% (Table 8).
Figure **2** and
Figure **3** show the best classification for simplified plant community type at a city and local scale, respectively, with the SWMP wetlands shown for comparison purposes. Figure A.7 and Figure A.8 show the *Hi-Res Topo (All Data)* classification for Cowardin class at city and local scales, respectively.

TABLE 6 – HI-RES TOPO (ALL DATA) – W/U ERROR MATRIX

Reference Data

Map Data	Upland	Wetland	Map Total
Upland	6945	296	7241
Wetland	398	2361	2759
Ref. Total	7343	2657	10000

Producer's Accuracy

Reference	Percent
Upland	94.6
Wetland	88.9

User's Accuracy

Map	Percent
Upland	95.9
Wetland	85.6

OVERALL ACCURACY = 9306 / 10000 = **93.1%**

TABLE 7 – HI-RES TOPO (ALL DATA) – COWARDIN CLASS ERROR MATRIX

Reference Data

Map Data	UPL	PEM	W	PFO	PSS	Map Total
UPL	0	230	34	11	0	276
PEM	0	1262	53	8	0	1323
W	0	41	1013	0	0	1054
PFO	0	1	0	2	0	3
PSS	0	0	0	0	0	0

Ref. Total	0	1534	1101	21	0	2656
	Total N does not include reference uplands or wetland classes with less than 10 reference data points. See Section 2.4 for details.					

Producer's Accuracy

Reference	Percent
UPL	0
PEM	95
W	96
PFO	67
PSS	0

User's Accuracy

Map	Percent
UPL	0
PEM	82
W	92
PFO	10
PSS	0

OVERALL ACCURACY = 2275 / 2656 = **85.7%**

OVERALL ACCURACY (upland errors removed) = 2275 / 2380 = **95.6%**

TABLE 8 – HI-RES TOPO (ALL DATA) – SIMPLIFIED TYPES ERROR MATRIX

Reference Data

Map Data	Upland	Shallow Marsh	Water	Wet Meadow	Deep Marsh	Hardwood Wetland	Seasonally Flooded	Shrub Wetland	Map Total
Upland	0	126	42	104	37	12	0	0	321
Shallow Marsh	0	743	23	64	30	2	0	0	862
Water	0	22	1005	11	39	0	0	0	1077
Wet Meadow	0	37	14	251	14	3	0	0	319
Deep Marsh	0	9	17	7	31	2	0	0	68
Hardwood Wetland	0	2	0	2	0	2	0	0	6
Seasonally Flooded	0	0	0	1	0	0	0	0	1

Shrub Wetland	0	0	0	0	1	0	0	0	1
Ref. Total	0	939	1101	442	152	21	0	0	2655
	Total N does not include reference uplands or wetland classes with less than 10 reference data points. See Section 2.4 for details.								

Producer's Accuracy

Reference	Percent
Upland	0
Shallow Marsh	79
Water	91
Wet Meadow	57
Deep Marsh	20
Hardwood Wetland	10
Seasonally Flooded	0
Shrub Wetland	0

User's Accuracy

Map	Percent
Upland	0
Shallow Marsh	86
Water	93
Wet Meadow	79
Deep Marsh	46
Hardwood Wetland	33
Seasonally Flooded	0
Shrub Wetland	0

OVERALL ACCURACY = 2032 / 2655 = **76.5%**

OVERALL ACCURACY (upland errors removed) = 2032 / 2334 = **87.1%**

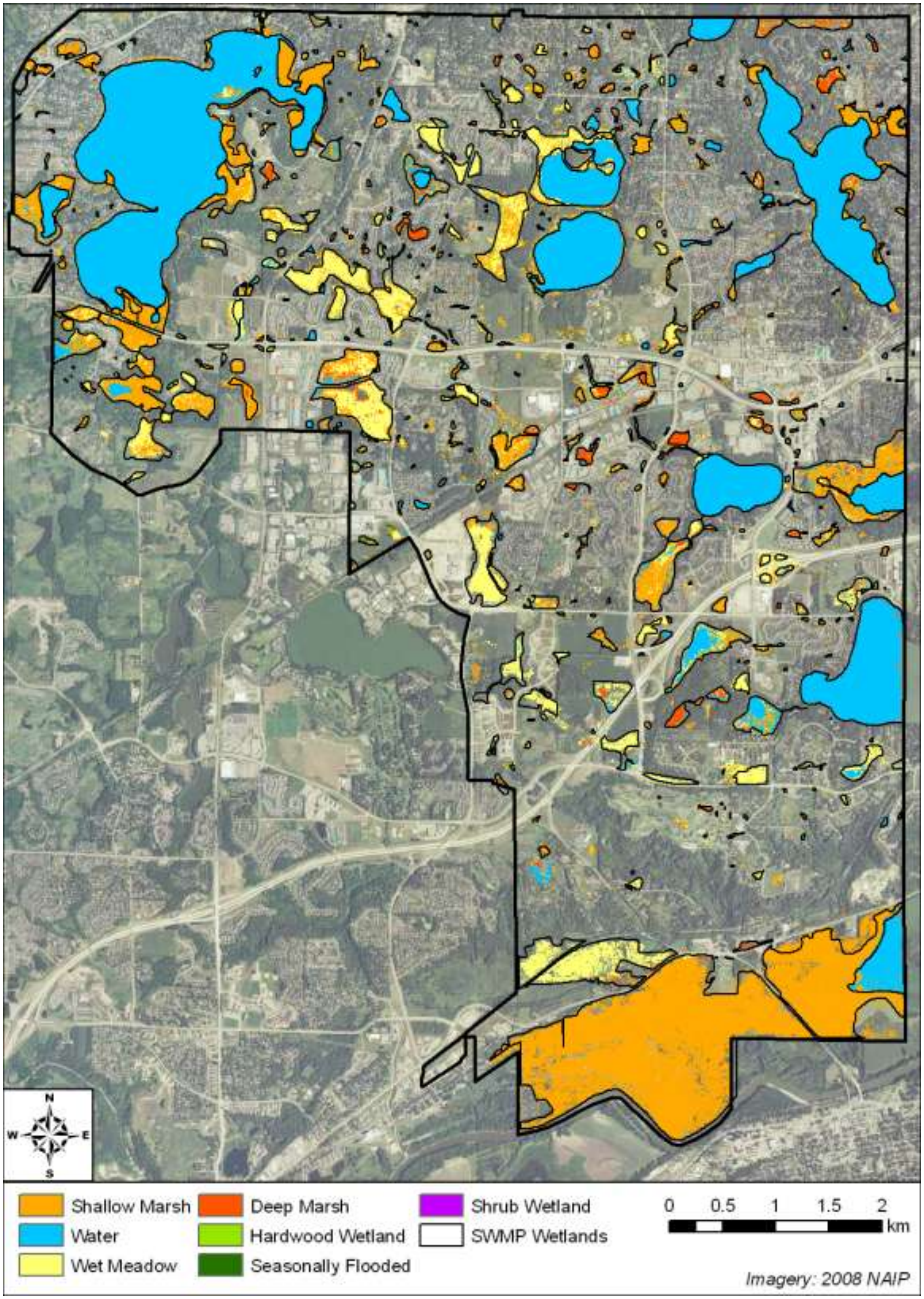

Figure 2 – Hi-Res Topo (All Data) – Simplified type – city view (with SWMP wetlands)

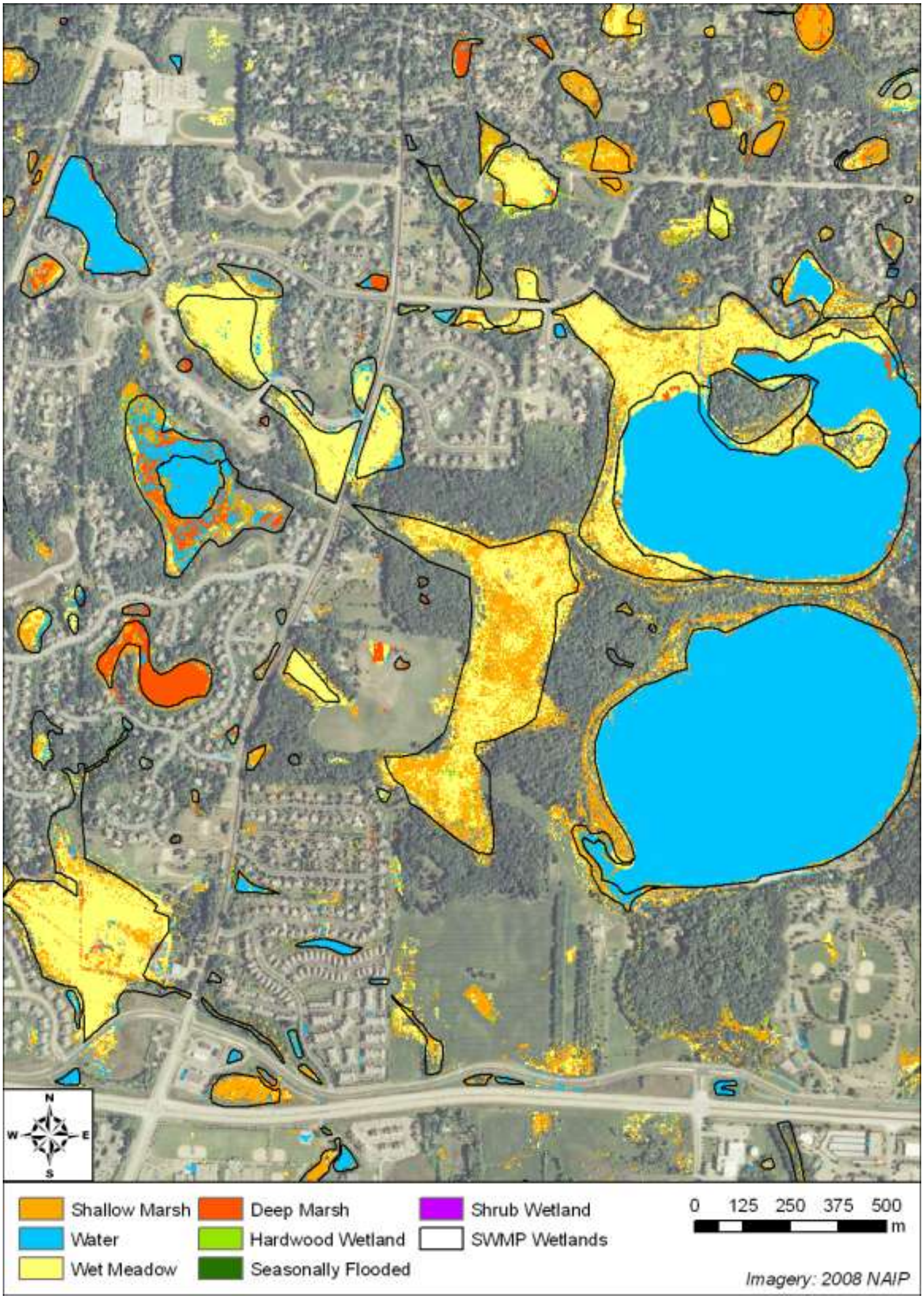

Figure 3 – Hi-Res Topo (All Data) – Simplified type – local view (with SWMP wetlands)

NED and No Topography Scenario

The best performing classification scenario, *Hi-Res Topo (All Data)*, was performed using a 3m resolution LiDAR based DEM. Additional classifications were performed using the U.S. Geological Survey's (USGS) National Elevation Dataset (NED) with a spatial resolution of approximately 10m. Classifications were also performed without topography or topographic derivates as input datasets.

Effects of Resolution

The wetland/upland accuracy for the classification *NED Topo (All Data)* was 91.6%, as shown in Table C.1. Cowardin class accuracy was 84.4% (Table C.2), and DNR simplified plant community type accuracy was 76.2% (Table C.3). Figure A.9 and Figure A.10 show the *NED Topo (All Data)* classification for Cowardin class at city and local scales, respectively. Figure A.11 and Figure A.12 show the classification for DNR simplified plant community type at city and local scales, respectively.

The wetland/upland accuracy for the classification *No Topo* was 88.7%, as shown in Table C.4. Cowardin class accuracy was 79.8% (Table C.5), and DNR simplified plant community type accuracy was 60.6% (Table C.6). Figure A.13 and Figure A.14 show the *No Topo* classification for Cowardin class at city and local scales, respectively. Figure A.15 and Figure A.16 show the classification for DNR simplified plant community type at city and local scales, respectively.

Effects of Topographic Derivations

The best performing classification scenario, *Hi-Res Topo (All Data)*, was performed using several topographic derivations including the compound topographic index (CTI), slope, and surface curvature. Slope was included in all topographic classifications, but additional classifications were performed without curvature and without the CTI as input datasets. Such classifications were performed for both high resolution and NED data.

Compound Topographic Index

The wetland/upland accuracy for the classification *Hi-Res Topo (CTI)* was 92.4%, as shown in Table C.7. Cowardin class accuracy was 84.1% (Table C.8), and DNR simplified plant community type accuracy was 75.1% (Table C.9). Figure A.17 and Figure A.18 show the *Hi-Res Topo (CTI)* classification for Cowardin class at city and local scales, respectively. Figure A.19 and Figure A.20 show the classification for DNR simplified plant community type at city and local scales, respectively.

The wetland/upland accuracy for the classification *NED Topo (CTI)* was 91.4% (Table C.10). Cowardin class accuracy was 84.8% (Table C.11), and DNR simplified plant community type accuracy was 76.6% (Table C.12). Figure A.21 and Figure A.22 show the *NED Topo (CTI)* classification for Cowardin class at city and local scales, respectively. Figure A.23 and Figure A.24 show the classification for DNR simplified plant community type at city and local scales, respectively.

Curvature

The wetland/upland accuracy for the classification *Hi-Res Topo (Curvature)* was 92.5%, as shown in Table C.13. Cowardin class accuracy was 84.2% (Table C.14), and DNR simplified plant community type accuracy was 75.7% (Table C.15). Figure A.25 and Figure A.26 show the *Hi-Res Topo (Curvature)* classification for Cowardin class at city and local scales, respectively. Figure A.27 and Figure A.28 show the classification for DNR simplified plant community type at city and local scales, respectively.

The wetland/upland accuracy for the classification *NED Topo (Curvature)* was 91.3% (Table C.16). Cowardin class accuracy was 84.0% (Table C.17), and DNR simplified plant community type accuracy was

76.2% (Table C.18). Figure A.29 and Figure A.30 show the *NED Topo (Curvature)* classification for Cowardin class at city and local scales, respectively. Figure A.31 and Figure A.32 show the classification for DNR simplified plant community type at city and local scales, respectively.

Other Classification Scenarios

Several other classifications were performed in addition to those described above for comparison purposes. A classification using only the NAIP imagery was performed, as well as traditional unsupervised and supervised classifications.

Imagery Only

The wetland/upland accuracy for the classification *NAIP Only* was 78.3%, as shown in Table C.19. Cowardin class accuracy was 54.7% (Table C.20), and DNR simplified plant community type accuracy was 60.6% (Table C.21). Figure A.33 and Figure A.34 show the *NAIP Only* classification for Cowardin class at city and local scales, respectively. Figure A.35 and Figure A.36 show the classification for DNR simplified plant community type at city and local scales, respectively.

Unsupervised Classification

The wetland/upland accuracy for the unsupervised classification was 52.5%, as shown in Table C.22. Cowardin class accuracy was 61.4% (Table C.23). Figure A.37 and Figure A.38 show the unsupervised classification for Cowardin class at city and local scales, respectively. No unsupervised classification was performed for the DNR simplified plant community types.

Supervised Classification

The wetland/upland accuracy for the supervised classification was 53.3%, as shown in Table C.24. Cowardin class accuracy was 57.8% (Table C.25). Figure A.39 and Figure A.40 show the supervised classification for Cowardin class at city and local scales, respectively. No supervised classification was performed for the DNR simplified plant community types.

See5 Cross-Validation Accuracy

See5 produces a measure of accuracy during its optional cross validation step. Table 9 and Table 10 show a comparison between the accuracy assessment using reference points and the See5 cross validation accuracy.

TABLE 9 – CHANHASSEN COMPARISON – SEE5 CROSS VALIDATION VS. ACCURACY ASSESSMENT

	Hi-Res Topo		NED Topo		No Topo		NAIP Only	
	X-Val	Assess	X-Val	Assess	X-Val	Assess	See5	Assess
Wetland/Upland	89.9	93.1	86.2	91.6	81.8	88.7	68.5	78.3
Cowardin Class	85.0	85.7	81.8	84.4	77.4	79.8	64.2	54.7
Simplified Type	81.3	76.5	76.6	76.2	67.2	60.6	59.7	43.4

TABLE 10 – CHANHASSEN COMPARISON – SEE5 CROSS VALIDATION VS. ACCURACY ASSESSMENT (CONT'D)

	Hi-Res Topo Curvature Only		NED Topo Curvature Only		Hi-Res Topo CTI Only		NED Topo CTI Only	
	X-Val	Assess	X-Val	Assess	X-Val	Assess	X-Val	Assess
Wetland/Upland	85.7	92.5	85.1	91.4	89.6	92.4	86.0	91.4
Cowardin Class	81.1	84.2	80.7	84.0	84.6	84.1	81.7	84.8
Simplified Type	77.1	75.7	76.0	76.6	79.4	75.1	77.0	76.6

2.1.4.2. Fond du Lac Reservation Results

The following sections present the results of wetland classifications for the Fond du Lac Reservation. For comparison purposes, the 2008 NAIP aerial photograph is provided at a city scale in Figure B.1 and at a local scale in Figure B.2 to show the land cover in the area. Additional figures showing each classification described at both large and small scales can be found in Appendix B. Full error matrices for each classification can be found in Appendix D.

Best Performing Classification Scenario

The best performing classification for the Fond du Lac Reservation used the highest quality datasets available for the area, including NAIP imagery, leaf-off imagery, Radar imagery, NED, SSURGO drainage class, and several imagery and topography derivations as shown in Table 5. The wetland/upland accuracy for the best classification, *All Data*, was 79.0% (Table 11). Cowardin class accuracy was 58.2% (Table 12), and DNR simplified plant community type accuracy was 55.7% (Table 13). Figure 4 and Figure 5 show the best classification for the simplified plant community type at reservation and local scales, respectively. Figure B.3 and Figure B.4 show the *All Data* classification for Cowardin class at reservation and local scales, respectively.

TABLE 11 – FOND DU LAC ALL DATA CLASSIFICATION – W/U ERROR MATRIX

Map Data		Reference Data: Upland	Reference Data: Wetland	Map Total
	Upland	27	37	64
	Wetland	4	127	131
	Ref. Total	31	164	195

Producer's Accuracy			User's Accuracy	
Reference	Percent		Map	Percent
Upland	87		Upland	42
Wetland	77		Wetland	97

OVERALL ACCURACY = 154 / 195 = **79.0%**

TABLE 12 – FOND DU LAC ALL DATA CLASSIFICATION – COWARDIN CLASS ERROR MATRIX

Reference Data

Map Data	PSS	UPL	PFO	PEM	W	Map Total
PSS	31	0	14	0	0	45
UPL	14	0	20	0	1	35
PFO	8	0	47	0	0	55
PEM	8	0	1	0	0	9
W	0	0	0	0	14	14
Ref. Total	61	0	82	0	15	158

Total N does not include reference uplands or wetland classes with less than 10 reference data points. See Section 2.4 for details.

Producer's Accuracy			User's Accuracy	
Reference	Percent		Map	Percent
PSS	69		PSS	51
UPL	0		UPL	0
PFO	85		PFO	57
PEM	18		PEM	0
W	100		W	93

OVERALL ACCURACY = 92 / 158 = **58.2%**

OVERALL ACCURACY (upland errors removed) = 92 / 123 = **74.8%**

Table 13 – Fond du Lac All Data Classification – Simplified Type Error Matrix

Reference Data

Map Data	Shrub Wetland	Upland	Coniferous Wetland	Shallow Marsh	Water	Hardwood Wetland	Deep Marsh	Wet Meadow	Map Total
Shrub Wetland	34	0	11	0	0	6	0	0	51
Upland	13	0	7	0	1	12	0	0	33
Coniferous Wetland	3	0	25	0	0	2	0	0	30
Shallow Marsh	8	0	1	0	0	1	0	0	10
Water	0	0	0	0	14	0	0	0	14
Hardwood Wetland	2	0	2	0	0	15	0	0	19
Deep Marsh	0	0	0	0	0	0	0	0	0
Wet Meadow	1	0	0	0	0	0	0	0	1
Ref. Total	61	0	46	0	15	36	0	0	158

Total N does not include reference uplands or wetland classes with less than 10 reference data points. See Section 2.4 for details.

Producer's Accuracy

Reference	Percent
Shrub Wetland	56
Upland	0
Coniferous Wetland	54
Shallow Marsh	0
Water	93
Hardwood Wetland	42
Deep Marsh	0
Wet Meadow	0

User's Accuracy

Map	Percent
Shrub Wetland	67
Upland	0
Coniferous Wetland	83
Shallow Marsh	0
Water	100
Hardwood Wetland	79
Deep Marsh	0
Wet Meadow	0

OVERALL ACCURACY = 88 / 158 = **55.7%**

OVERALL ACCURACY (upland errors removed) = 88 / 125 = **70.4%**

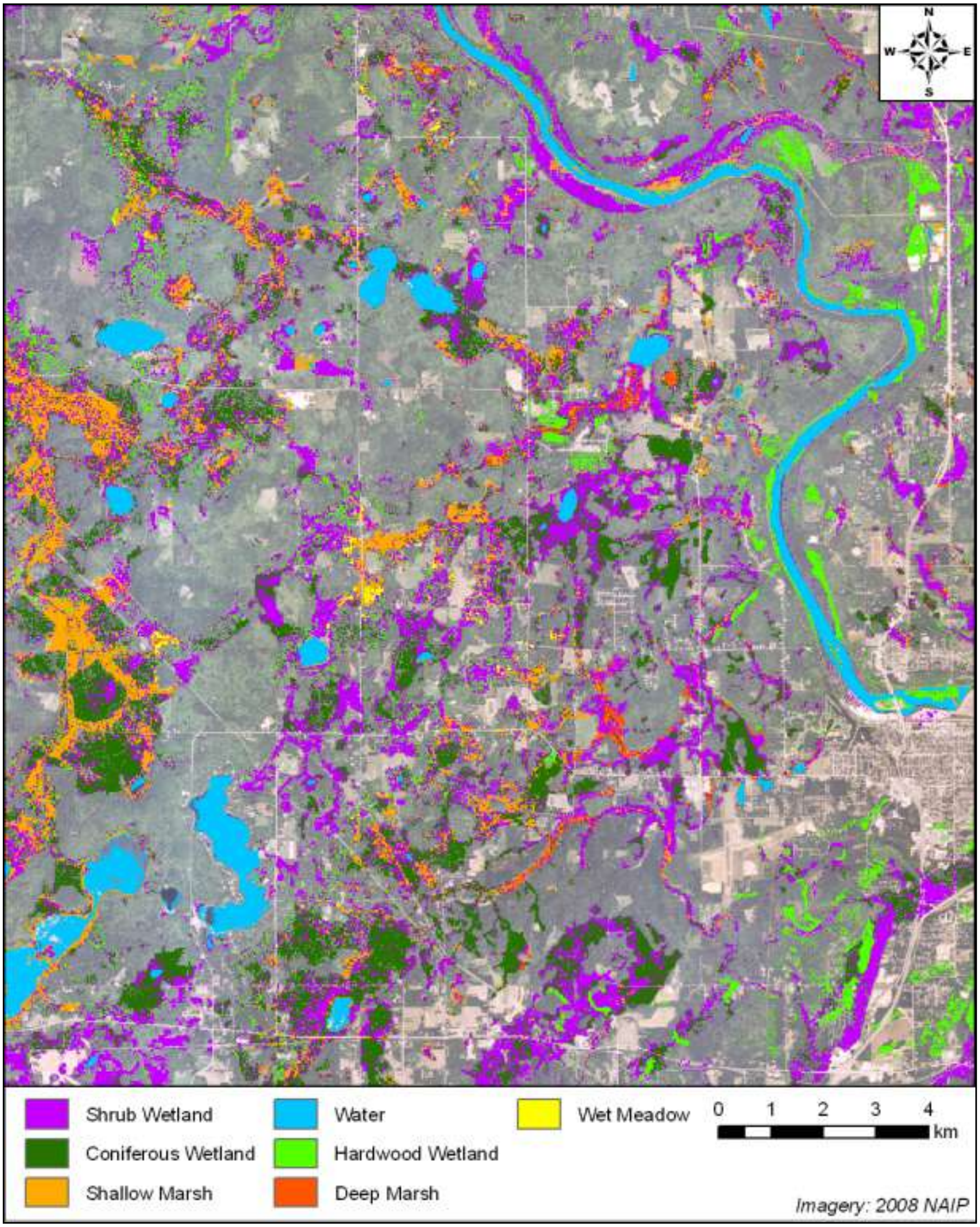

FIGURE 4 – FOND DU LAC ALL DATA CLASSIFICATION – SIMPLIFIED TYPE – RESERVATION VIEW

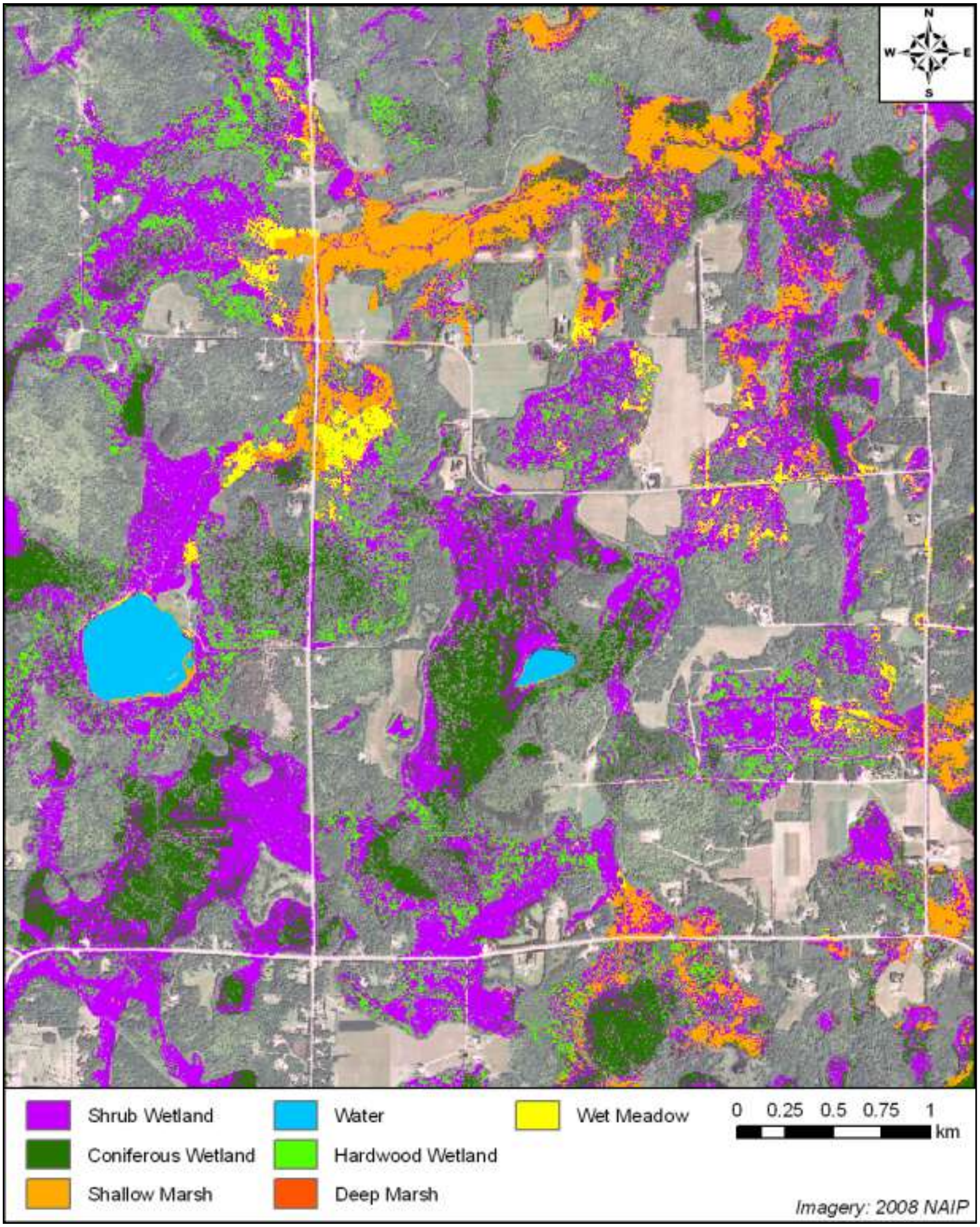

FIGURE 5 – FOND DU LAC ALL DATA CLASSIFICATION – SIMPLIFIED TYPE – LOCAL VIEW

Effects of Types of Imagery

The best performing classification scenario, *Fond du Lac All Data,* was performed using several types of aerial and satellite imagery including the 2008 NAIP imagery, 2009 leaf-off imagery, and Radar imagery. Additional classifications were performed without each of these data sets in an effort to determine their effect on classification accuracy.

Radar Imagery

The wetland/upland accuracy for the classification *No radar* was 77.9%, as shown in Table D.1. Cowardin class accuracy was 53.8% (Table D.2), and DNR simplified plant community type accuracy was 53.2% (Table D.3). Figure B.5 and Figure B.6 show the *No radar* classification for Cowardin class at reservation and local scales, respectively. Figure B.7 and Figure B.8 show the classification for DNR simplified plant community type at reservation and local scales, respectively.

Spring Imagery

The wetland/upland accuracy for the classification *No Leaf-off* was 77.4%, as shown in Table D.4. Cowardin dass accuracy was 59.5% (Table D.5), and DNR simplified plant community type accuracy was 57.6% (Table D.6). Figure B.9 and Figure B.10 show *the No Leaf-off* classification for Cowardin class at reservation and local scales, respectively. Figure B.11 and Figure B.12 show the classification for DNR simplified plant community type at reservation and local scales, respectively.

Other Classification Scenarios

Several other classifications were performed in addition to those described above for comparison purposes. Classifications using the all data without topography, only NAIP and leaf-off imagery, only NAIP imagery, and traditional unsupervised and supervised classifications were performed.

No Topography

The wetland/upland accuracy for the classification *No Topo* was 71.3%, as shown in Table D.7. Cowardin dass accuracy was 44.3% (Table D.8), and DNR simplified plant community type accuracy was 43.0% (Table D.9). Figure B.13 and Figure B.14 show the *No Topo* classification for Cowardin class at reservation and local scales, respectively. Figure B.15 and Figure B.16 show the classification for DNR simplified plant community type at city and local scales, respectively.

Imagery Only

The wetland/upland accuracy for the classification *NAIP & Leaf-Off* was 50.3%, as shown in Table D.10. Cowardin class accuracy was 29.1% (Table D.11), and DNR simplified plant community type accuracy was 31.6% (Table D.12). Figure B.17 and Figure B.18 show the *NAIP & Leaf-Off* classification for Cowardin class at reservation and local scales, respectively. Figure B.19 and Figure B.20 show the classification for DNR simplified plant community type at reservation and local scales, respectively.

The wetland/upland accuracy for the classification *NAIP Only* was 41.5%, as shown in Table D.13. Cowardin class accuracy was 25.9% (Table D.14), and DNR simplified plant community type accuracy was 23.4% (Table D.15). Figure B.21 and Figure B.22 show the *NAIP Only* classification for Cowardin class at reservation and local scales, respectively. Figure B.23 and Figure B.24 show the classification for DNR simplified plant community type at reservation and local scales, respectively.

Unsupervised Classification

The wetland/upland accuracy for the unsupervised classification was 74.4%, as shown in Table D.16. Cowardin class accuracy was 32.9% (Table D.17). Figure B.25 and Figure B.26 show the unsupervised classification for Cowardin class at reservation and local scales, respectively. No unsupervised classification was performed for the DNR simplified plant community types.

Supervised Classification

The wetland/upland accuracy for the supervised classification was 80.5%, as shown in Table D.18. Cowardin class accuracy was 54.4% (Table D.19). Figure B.27 and Figure B.28 show the supervised classification for Cowardin class at reservation and local scales, respectively. No supervised classification was performed for the DNR simplified plant community types.

See5 Cross-Validation Accuracy

Table 14 and Table 15 show a comparison between the accuracy assessment using reference points and the See5 cross validation accuracy for the classifications performed in Fond du Lac Reservation.

TABLE 14 – FOND DU LAC COMPARISON – SEE5 CROSS VALIDATION VS. ACCURACY ASSESSMENT

	All Data		No Leaf Off		No Radar		No Topo	
	X-Val	Assess	X-Val	Assess	X-Val	Assess	X-Val	Assess
Wetland/Upland	96.1	79.0	95.8	77.4	95.6	77.9	92.3	71.3
Cowardin Class	93.0	58.2	93.2	59.5	93.2	53.8	86.9	44.3
Simplified Type	93.1	55.7	92.3	58.1	92.9	53.2	85.7	43.0

TABLE 15 – FOND DU LAC COMPARISON – SEE5 CROSS VALIDATION VS. ACCURACY ASSESSMENT (CONT'D)

	NAIP & LeafOff		NAIP Only	
	X-Val	Assess	X-Val	Assess
Wetland/Upland	84.0	50.3	76.4	41.5
Cowardin Class	79.6	29.1	72.9	25.9
Simplified Type	78.0	31.6	71.2	23.4

2.1.5. Decision Trees Discussion

2.1.5.1. See5 Cross-Validation

See5 cross-validation is a measure of accuracy done using training points as a part of the decision tree construction process. With the validation option enabled, See5 performs a user determined number of iterations of decision tree construction (i.e. folds) with a subset of the total training points and uses the remainder of the points for an accuracy assessment. In this study, a 10-fold cross validation was used. In this scheme, 10% of the training points were randomly set aside and the decision tree was constructed using the other 90% of points. Repeat iterations were performed with a different subset of points set aside such that after 10 iterations each point has been used in accuracy assessment once. Accuracy is reported for each fold and totaled for an estimate of overall classification accuracy.

The See5 cross-validation method is not a true assessment of accuracy because it uses training data employed in tree construction. However, it has been used as a preliminary surrogate for accuracy assessment when a formal independent accuracy assessment is yet to occur (Homer, 2007). In the Chanhassen study, cross-validation appeared to be a low estimate of accuracy for the wetland/upland classification and a high estimate for the simplified types when compared to the formal accuracy assessment. Table 9 and Table 10 compare the cross-validation accuracy with the formal accuracy assessment for each classification performed in Chanhassen. In the Fond du Lac study, cross validation appeared to be a high estimate for each classification. The reason for this is probably two-fold. First, the reference points used in the formal accuracy assessment are not a complete representation of the wetlands present, and accuracy within wetland types may be lower because of this. Second, training polygons were created in areas that were obvious representatives of target wetland classes. The training data used for cross-validation were spectrally similar and probably did not account for the diverse spectral difference inherent within wetland types. As a result, variation between natural wetlands may not have been adequately captured in the cross-validation accuracy. Table 14 and Table 15 show the comparison of cross-validation accuracy and formal accuracy assessment for classifications performed in Fond du Lac.

While not a statistically sound assessment of accuracy, the cross-validation process takes seconds to complete and does appear to show general trends. There may not be a strong, consistent relationship between the cross validation accuracy and the formal accuracy assessment, but the trend of increased or decreased accuracy across classifications as determined by See5 through cross validation may be valuable information if interpreted appropriately.

2.1.5.2. Comparison to Traditional Classifications

The decision tree method consistently proved to be superior to traditional unsupervised and supervised classification of wetlands for both wetland/upland and Cowardin class classifications. Wetland/upland classification accuracy for the unsupervised, supervised, decision tree with only NAIP imagery, and decision tree with all data classifications are shown in Table 16, below.

TABLE 16 – COMPARISON OF DECISION TREE AND TRADITIONAL CLASSIFICATION ACCURACY RESULTS

	Chanhassen				**Fond du Lac**			
	Sup	Unsup	DT w/ NAIP	DT w/ All Data	Sup	Unsup	DT w/ NAIP	DT w/ All Data

Wetland/Upland	53.3	52.5	78.3	93.1	74.4	80.5	76.4	79.0
Cowardin Class	57.8	61.4	54.7	85.7	54.9	34.8	72.9	57.3

The unsupervised and supervised classification accuracies were lower than reported in the literature. Ozesmi and Bauer (2002) report studies with accuracies of approximately 70%-80%, but these studies were accomplished using more sophisticated classification techniques such as cluster busting and hybrid approaches. Traditional classifications were not the primary focus of this study and were meant for comparison purposes only. Accuracy results for decision tree classifications performed with only the NAIP imagery are also presented in Table 16, also for comparison purposes. It is evident that the decision tree method outperforms traditional classifiers, but the results of various decision tree scenarios show that the type and quality of data used to construct the tree have an effect on the quality of the decision tree classification.

2.1.5.3. City of Chanhassen

The City of Chanhassen offered the best opportunity for testing because of the city-wide wetland inventory. An unlimited amount of data was available for training and validation purposes within the area which allowed for a strong and diverse training data set and a robust accuracy assessment. However, Chanhassen contains little wetland variety. Most of the wet features in Chanhassen are water bodies and emergent wetlands. While few scrub shrub and forested wetlands did exist, the opportunity to train a decision tree to discriminate these wetland types was limited.

Effects of Topography

Resolution

A LiDAR based DEM with a spatial resolution of 3m was used for topography and topographic derivations in the best classification scenario. However, LiDAR data is expensive to acquire and is not readily available for most areas. The U.S. Geological Survey (USGS) produces and continuously updates the NED, a seamless DEM for the United States that is public domain. The additional cost of using LiDAR data should be justified by directly correlating to higher classification accuracy. Table 17 compares the accuracy of classifications using high resolution LiDAR-based topography, NED topography, and no topography.

TABLE 17 – ACCURACY RESULTS FOR VARYING TOPOGRAPHIC RESOLUTION

	Hi-Res Topo	Z	NED Topo	Z	No Topo	Z
Wetland/Upland	93.1	**3.8**	91.6	**6.8**	88.7	**10.5**
Cowardin Class	85.7	1.1	84.4	**4.2**	79.8	**5.4**
Simplified Type	76.5	0.1	76.2	**13.9**	60.6	**13.9**
Z-statistic values in bold show a significant difference (Z>2) between classifications to the left and right. Z value at the far right is for differences between Hi-Res Topo and No Topo.						

As shown in Table 17, classification accuracy for wetland/upland decreases significantly between classifications using high resolution, NED topography, and no topography as input data. No significant difference between high resolution and NED topography existed for the Cowardin class and simplified type classifications, but decreases in accuracy were significant between the *NED Topo* classifications and the *No Topo* classifications. High resolution topography appears to be more useful in discriminating wetlands and uplands than it does in differentiating wetland types, however, a classification with no topography significantly decreases wetland type classification and should be avoided. As expected, a decrease in accuracy is evident as more classes are characterized. The decrease in accuracy seems to be consistent for each set of topography classifications.

Significant differences are present between classification accuracies using NED and high resolution topography data, however, the benefits of the increased classification accuracy come at a substantial financial cost. The goals of future classification should be carefully considered to determine if the cost for acquiring high resolution data is worth the increase in classification accuracy. The freely available NED topography data allows for 91.6% accuracy in upland/wetland discrimination, a result that should not be ignored and one that could prove beneficial given the correct circumstances.

Topography Derivations

The CTI and surface curvature were both used as input datasets for the best classification. The calculation of the CTI is both labor and time intensive and, for high resolution topography data, requires considerable computer resources. The surface curvature derivation is a one step calculation that can be done relatively easily with standard software packages. The accuracy of classifications performed with each of these topographic derivations was compared in order to determine their impact on wetland classification (Table 18).

TABLE 18 – ACCURACY RESULTS FOR VARYING TOPOGRAPHIC DERIVATIONS

High Resolution LiDAR Topography						
	CTI & Curvature	Z	CTI Only	Z	Curvature Only	Z
Wetland/Upland	93.1	1.9	92.4	0.4	92.5	1.5
Cowardin Class	85.7	1.5	84.1	0.1	84.2	1.4
Simplified Type	76.5	1.2	75.1	0.5	75.7	0.6
NED Topography						
Wetland/Upland	91.6	0.3	91.4	0.5	91.4	0.8
Cowardin Class	84.4	0.4	84.8	0.8	84.0	0.4
Simplified Type	76.2	0.4	76.6	0.3	76.2	0.04
Z-statistic values in bold show a significant difference (Z>2) between classifications to the left and right. Z value at the far right is for differences between CTI & Curvature and Curvature Only.						

There was a slight decrease in accuracy between the classifications using high resolution CTI and surface curvature in conjunction and using each derivation individually, but this change was not significant (Z<2). This slight decrease was present only with derivations calculated from high resolution topography and not with the NED data. No significant differences existed between wetland/upland, Cowardin class, or simplified types for any set of topographic derivation classifications.

Due to the lack of significant changes between the methods of topographic derivation, it appears that the curvature is an acceptable alternative to the labor intensive CTI. This could represent a large time and cost saving opportunity in future classification methods development.

2.1.5.4. Fond du Lac Reservation

The Fond du Lac Reservation offered an opportunity to investigate the effects of various types of imagery on classification accuracy. Unfortunately, only a partial set of field verified reference points was collected. Optimally, these points would be well distributed, representative of all wetland types present, and numerous enough to be used for both decision tree construction and a formal accuracy assessment. The original intended use of the reference data involved only scrub shrub and forested wetlands so a high percentage of the points collected represented these types.

Most of the wet features in the Fond du Lac Reservation are shrub and forested wetlands, but enough wetland diversity exists to train a decision tree classier for less dominant types given appropriate data. An additional field study in Fond du Lac will occur in summer 2010 to supplement the existing data and provide a complete reference data set. These data will be used in future studies to provide more spectrally diverse training data and a more robust accuracy assessment.

Effects of Imagery

Radar Imagery

Radar imagery was used in conjunction with other data sets in the best classification scenario. Radar data can be sensitive to soil moisture (Whitcomb et al., 2007; Henderson and Lewis, 2008) and may be a useful addition to wetland classifiers. However, radar data is expensive to acquire and is not readily available for use without appropriate licensing or ownership. The additional cost of using radar data should be justified by directly correlating to higher classification accuracy. Table 19 compares the accuracy of classifications with and without using radar data.

TABLE 19 – ACCURACY RESULTS FOR EFFECTS OF RADAR IMAGERY

	All Data	Z	No Radar
Wetland/Upland	79.0	0.2	77.9
Cowardin Class	58.2	0.6	53.8
Simplified Type	55.7	0.3	53.2
Z-statistic values in bold show a significant difference (Z>2) between classifications to the left and right.			

According to the accuracy assessment performed for this study, adding radar data to a wetland/upland, Cowardin class, or simplified wetland type classier does not have a significant effect on the accuracy of the resulting classification. Previous studies (Arzandeh and Wang, 2003; Costa, 2004) prove the benefit of radar data in wetland classification. These results are believed to be biased and not valid because of poor quality of the reference data set. The classification and accuracy assessment will be revisited when a robust reference data set is collected.

Spring Imagery

Leaf-off imagery was used in conjunction with other data sets in the best classification scenario. Leaf-off imagery, when used in addition to summer leaf-on data, provides multi-temporal data that show vegetative characteristics throughout the growing season. Aerial imagery is not typically flown in the spring prior to leaf out, so additional aerial photography must be completed to acquire such data. Table 20, below, compares the accuracy of classifications with and without spring leaf-off imagery.

TABLE 20 – ACCURACY RESULTS FOR EFFECTS OF LEAF-OFF IMAGERY

	All Data	Z	No Leaf-off
Wetland/Upland	79.0	0.6	77.4
Cowardin Class	58.2	0.2	59.5
Simplified Type	55.7	0.4	57.6
Z-statistic values in bold show a significant difference (Z>2) between classifications to the left and right.			

According to the accuracy assessment performed for this study, adding leaf-off imagery to a wetland/upland, Cowardin class, or simplified wetland type classier does not have a significant effect on the accuracy of the resulting classification. Many studies (Ozesmi and Bauer, 2002; Lunetta and Balogh, 1999) document the increased accuracy, especially in forested areas, of adding multi-temporal imagery to a wetland classification. Because of poor quality of the reference data set, these results are believed to be biased and not valid. The classification and accuracy assessment will be revisited when a robust reference data set is collected.

2.1.6. Decision Trees Conclusions

The results presented in this research prove that decision tree classifiers outperform traditional classification methods when discriminating wetlands from uplands and when classifying wetland types. The See5 software package used in conjunction with the NLCD Mapping Tool performed above expectations in the streamlined ease and efficiency of use. The cross-validation tool in See5 was a valuable, albeit not statistically sound, surrogate for a formal accuracy assessment and may be used to quickly compare results in a qualitative manner. Achieving high accuracy when performing automated classification of wetland types, while using limited data, is a positive outcome. With the addition of other relevant data into the decision tree classifier, the potential for increases in wetland classification accuracy beyond those presented herein certainly exists.

Several conclusions can also be made regarding the usefulness of topography data in decision tree development. Topography data is an essential element in decision tree construction, but high resolution topography data may not guarantee higher classification accuracy. In this study, the use of high resolution topography yielded a significant increase in classification accuracy compared to the NED topography only for the wetland/upland determination. Topographic derivatives are also a necessary input data source, but the use of the CTI as an input dataset did not outperform the simply calculated curvature model. The goals of future research projects should be carefully considered when choosing input types and quality of input data. High resolution topography data and complex topographic derivative calculations may not be necessary in order to achieve adequate wetland classification accuracy.

While there were several informative outcomes from this study in the Chanhassen study area, the results of classifications from the Fond du Lac study area conflict with several literature sources which indicates a flawed methodology. The primary flaw in the Fond du Lac portion of the study involves inadequate reference data, and is discussed further below.

2.1.7. Decision Trees Future Directions

The results of this study highlighted several items that should be revisited in the future. First and foremost, adequate reference data must be collected for the Fond du Lac study area. Unfortunately, the reference data set for the Fond du Lac area available at the time of this study did not include a large enough sample size. In addition, the reference samples that were available were not distributed evenly across wetland types. A field data collection will occur during the summer of 2010 in an effort to obtain a more robust reference data set for the Fond du Lac Reservation. With a larger reference data set it is hoped that more samples of each wetland class will allow for greater differentiation of classes during classification, higher spectral variability within classes will be represented in the decision tree model, and a large enough sample size will remain available for an unbiased accuracy assessment.

Additional work can also be done with radar data. Only radar reflectivity values were used in decision tree construction for this study. Unfortunately, due to the inadequate Fond du Lac reference data, radar reflectivity data were unable to be assessed for its effects on wetland classification accuracy in this study. A variety of other radar products in addition to reflectivity values may also be derived, particularly those utilizing the imaginary backscatter mechanism data unique to radar. Further exploration of these complex radar derivatives may prove beneficial to future wetland classification efforts.

2.2. Wetland Mapping using Radar Image data

2.2.1. Radar Mapping Introduction

Most of the focus of remote sensing of wetlands has been put on sensors operating in the optical and infrared range of the electromagnetic spectrum, the limitations of which have been noted (Ozesmi and Bauer, 2002). Unlike optical sensors, radar sensors are unique in that they operate in the microwave portion of the electromagnetic spectrum and are insensitive to atmospheric conditions (e.g. cloud cover) and low light conditions and can therefore offer more consistent multi-temporal images. radar backscatter is sensitive to soil and vegetation moisture properties and can, to some degree, penetrate the forest canopy and provide sub-canopy vegetation and soil saturation information (Whitcomb et al., 2007; Henderson and Lewis, 2008). Because radar is sensitive to moisture, techniques using inferometric analysis of radar data can identify changes in water levels down to the centimeter (Wdowinski, 2007).

Radar antennas can transmit radar waves of varying wavelengths. Common radar bands are C-band, L-band, and P-band, in order of increasing wavelength. Longer wavelengths tend to penetrate much farther into the forest canopy, thus providing a backscatter signal that conveys information about sub-canopy vegetation and moisture conditions (Whitcomb et al., 2007). Woody wetlands have high backscatter and appear white, and are often confused with urban areas, while herbaceous wetlands have less backscatter and appear darker (Wdowinski, 2007). Wang (1995) used C-band, L-band, and P-band radar and found that high leaf area indices had an effect on C-band radar only, not L-band or P-band. Thus, L-band radar is significantly better at detecting flooded forests with intact canopy cover than C-band (Kasischke, 1997; Rosenqvist et al., 2004; Hess et al., 2003). Conversely, C-band radar is better at identifying herbaceous wetlands (Henderson and Lewis, 2008).

Radar waves can be sent and received at similar or dissimilar polarizations. Similar polarizations (HH, VV) are reported as useful in discriminating forested wetland/non-wetland by providing better image contrast than cross-polarization (HV), whereas cross-polarization was preferable when distinguishing between forested swamps and herbaceous marshes (Hess et al., 1990; Hess et al., 1995).

Multiple studies report that a combination of C-band and L-band radar, as well as mixed polarizations, significantly increased accuracy of wetland/non-wetland discrimination and wetland vegetation classification (Hess et al., 1990; Hess et al., 1995; Dobson, 1995; Whitcomb et al., 2007; Henderson and Lewis, 2008). Henderson and Lewis (2008) wrote that cross-polarized imagery can be as valuable as single-polarized, multitemporal imagery. Studies also found that vegetation information is enhanced by using multitemporal and cross-polarized imagery and reported land cover accuracies above 90% when using SAR imagery (Kasischke, 1997; Dobson, 1995). Lozano-Garcia and Hoffer (1993) reported increased accuracy in land cover classification when they combined SIR-B data with Landsat TM data.

Whitcomb et al. (2007) used JERS to collect two seasons of L-band SAR imagery to produce a wetland map throughout the state of Alaska. Ancillary data sets including DEM (66m spatial resolution), map of open water, and latitude were included in the classification model. The Random Forests decision tree algorithm (Breiman, 2001) was used as a classifier. Nine wetland classes were aggregated which roughly correlated to the Circular 39 (FWS citation here) wetland classifications. They reported accuracies ranging from 69.5% to 95%, depending on wetland class, with an overall accuracy of 89.5%. The NWI map for Alaska was used as test data set in the accuracy assessment. The authors suggest L-band in combination with C-band SAR will better distinguish between emergent wetland types (Whitcomb et al. 2007).

Henderson and Lewis (2008) provide the most recent review of usage of radar data to detect and classify wetlands. They reported that distinguishing wetlands and non-wetlands is consistently done with higher accuracy than discriminating wetland vegetative species. However, they noted that when mapping wetland species, most of the confusion is between wetland types and not between wetland and non-wetland vegetation. (Henderson and Lewis, 2008).

2.2.2. Radar Mapping Methods

This preliminary study examines the usefulness of radar-derived products for wetland mapping using decision trees. The radar data used consists of two RADARSAT-2 fine mode (10 m spatial resolution), quad polarized (HH, HV, VV, VH) images acquired on June 15 and September 19, 2009. The data were processed to represent constant beta intensity in decibels. Three polarimetric decompositions were then applied to both images. These decompositions were “van Zyl” (vZ), “Freeman-Durden” (F-D), and “Cloude-Pottier” (C-P). The vZ decomposition estimates three parameters of a radar image: odd bounce, even bounce, and diffuse scattering. vZ works on the theory that scattering objects on the ground create a number of bounces or reflections that then create recognizable phase differences between the HH and VV channels. The F-D decomposition estimates three paramaters: surface/single bounce, double bounce, and volume scattering. F-D is based on a physical model that separates the scattering mechanisms of the target and computes a percentage of each type of scatterer in each pixel. The C-P decomposition computes entropy, alpha angle, and anisotropy from the eigenvalues and eigenvectors of the image’s correlation matrix. Entropy is the randomness of scattering (low values indicate a single scattering mechanism and high values indicate a random mixture). Alpha angle is indicative of the average or dominant scattering mechanism (low angles indicate surface scattering, mid-angles indicate dipole scattering, and high values indicate multiple scattering). Anisotropy indicates multiple scatterers. The three decompositions were combined with additional data in a decision tree classification algorithm (described below).

Additional geospatial data used included color infra-red (CIR) aerial images of leaf-on (summer 2008) and leaf-off (spring 2009) conditions and a USGS National Elevation Data (NED) 10 m Digital Elevation Model (DEM), from which elevation and slope were derived and used as inputs to the classifier.

A decision tree classifier is a rule-based algorithm that uses training data. The algorithm is designed to reduce intra- and inter-class variability through binary splitting of training values. The result of this splitting is a branching dichotomous key in which the various decision points are based on the variables that are found to be most significant in explaining the variation in the training data. The trained decision tree is then applied to a data set to classify it into the applicable categories. The decision tree classifier used in this project was the Random Forest algorithm (described alternately as Random Forest***s***). Random Forest (RF) generates an ensemble of decision trees that use different combinations of the training data. Each tree is given a "vote" as to which best discriminates the desired classes. The RF algorithm then chooses the tree with the most votes – i.e. the best performance in using the training data to classify the same training data. RF uses "out of bag" (OOB) sampling of roughly 1/3 of the input data to compute an unbiased estimate of the error in the classification trees and to estimate the importance of the input variables. The outputs of the algorithm are the best performing decision tree, the Gini Index of the importance of each input variable, the cross validation accuracy of the classifier derived from OOB sampling, a classification map of all pixels in the input layer, and a confidence map showing the relative classification confidence for each image pixel. The input data were 158 Fond du Lac field verified wetland type points described above. The classes of interest were Open Water, Emergent Wetland, Forested Wetland, Scrub Wetland, and Upland. The study area was the Fond du Lac portion of Carlton County described above.

2.2.3. Radar Mapping Results

The three decomposition layers are shown in Figures 7, 8, and 9. The vZ decomposition, with its dependence on bounce type and diffuse scattering, appears to perform reasonably well in discriminating open water from forested areas. It also is highly sensitive to water level, as shown in the difference in the value of the decomposition between the June and September dates. The F-D decomposition (Figure 8) is similar to the vZ decomposition in that it is highly dependent on bounce type; however F-D emphasizes the number of bounces rather than whether that number is odd or even. It also uses the volume scattering parameter rather than diffuse scattering, which increases its water and vegetation type discrimination potential. In this study F-D was able to discriminate forest versus scrub vegetation and areas where vegetation bordered water due to the strong double bounce effect at water-vegetation boundaries. The C-P decomposition (Figure 9) is the most difficult of the three to interpret visually. There layers of the decomposition represent the various combinations of entropy, scattering, and anisotropy, as summarized in Table 21. In general, the C-P decomposition was not effective in discriminating vegetation type or water-land boundaries. Most of the variability in C-P values was found within open water areas, making it less than suitable for wetland type mapping.

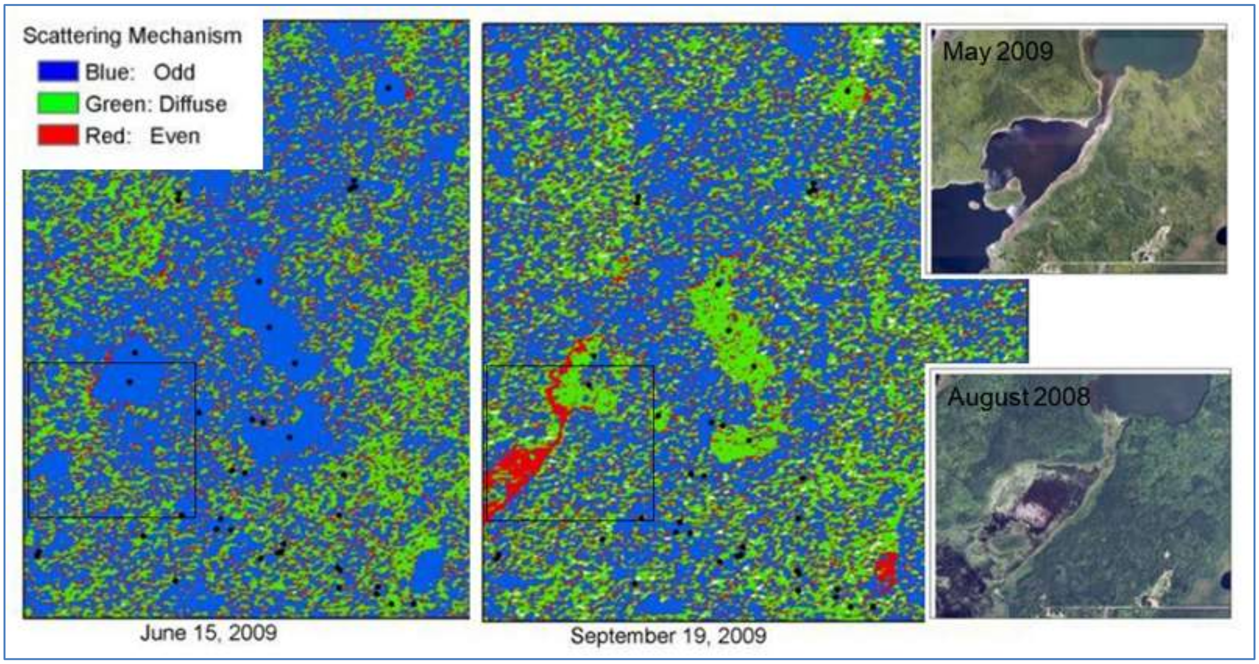

Figure 7. The van Zyl (vZ) decomposition layer with seasonally contemporaneous aerial images for comparison.

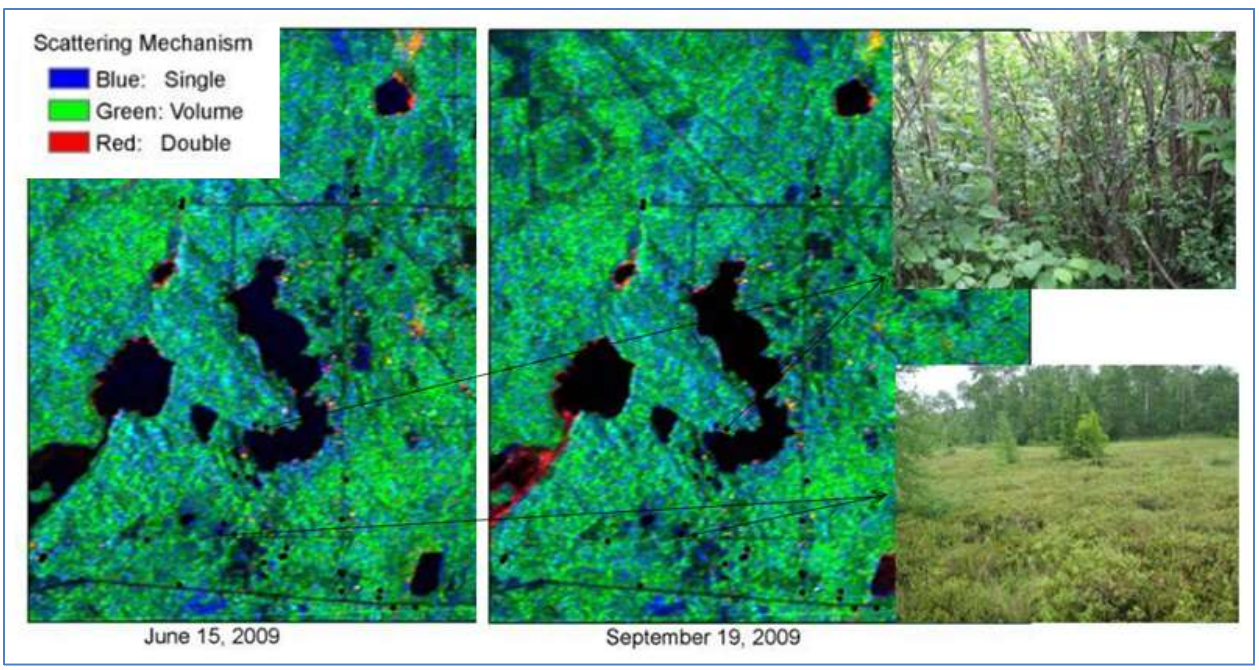

Figure 8. The Freeman-Durden (F-D) decomposition layer with field photos for comparison.

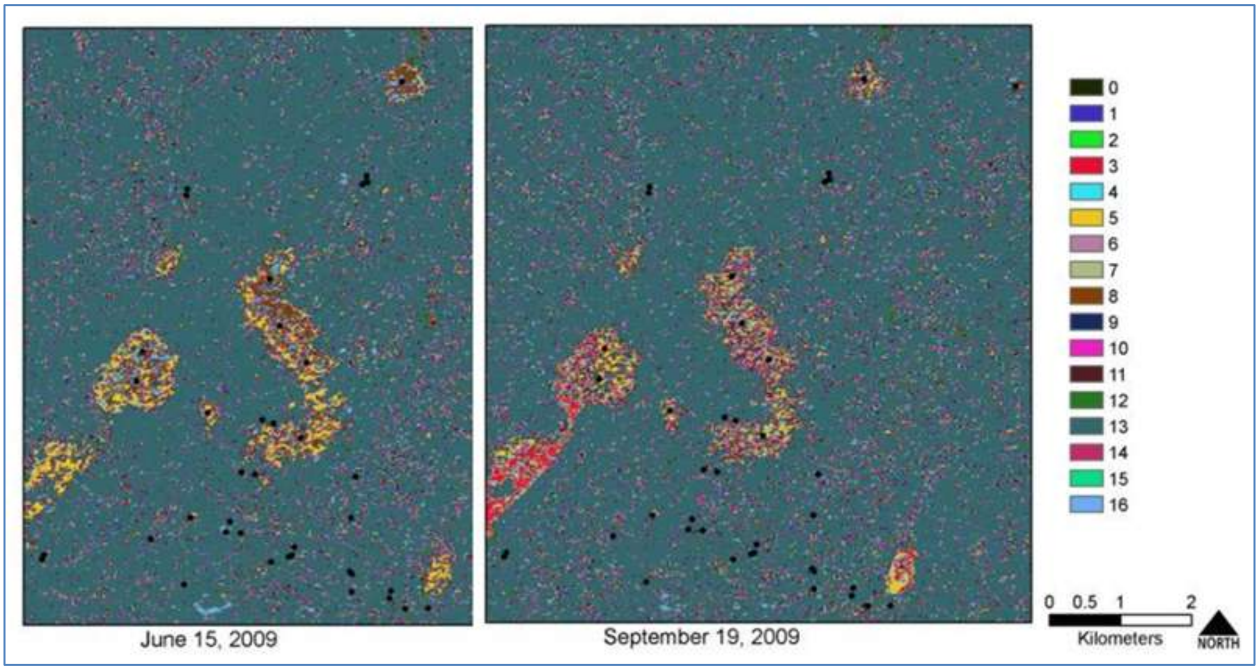

Figure 10. The Cloude-Pottier (C-P) decomposition layer. The class numbers represent the various combinations of entropy, scattering, and anisotropy, as summarized in Table 21.

Table 21. List of C-P decomposition layers

Classes 0–7 have low anisotrophy, 8–15 have high anisotropy
0 & 8: High entropy double bounce scattering
1 & 9: High entropy multiple scattering
2 & 10: Medium entropy multiple scattering
3 & 11: Medium entropy dipole scattering
4 & 12: Medium entropy surface scattering
5 & 13: Low entropy multiple scattering
6 & 14: Low entropy dipole scattering
7 & 15: Low entropy surface scattering
Class 16 is high entropy surface scattering, which is considered not a feasible region in entropy/alpha space

Figures 11, 12, and 13 give the results of the RF decision tree classification. Figure 11 shows the Gini Index values for the input data sets. Higher values of the Gini Index mean that the data set was more useful in discriminating the classes of interest. Interestingly, the most useful variables were the raw image bands themselves – particularly the infra-red leaf-on and leaf-off aerial image bands and the raw quad polarization radar bands. Closely following in Gini values were the terrain-derived variables of slope and elevation. The radar decomposition values were not highly useful in the decision tree. We attribute this result partially to the timing of the radar data collects (we did not capture a transition from wet to dry) and partially to the composition of the field data (most of the points were in forested wetlands). Figure 12 shows the current, outdated NWI along with a recent aerial photo. In this case, the NWI layer appears to reasonably accurately identify the wetlands in the frame. Figure 13 shows the same NWI layer along with the output of the RF classifer. The broad wetland patterns match well with the NWI. The RF does persistently underestimate the amount of upland in the frame. We attribute this again to the training data. Since few of the 158 training points fell in upland areas – and very few in what would be termed urban areas – the classifier likely could not adequately discriminate those areas. The overall computed RF cross-validation accuracy resulting from the OOB sampling was 74.5%, which we suggest is reasonable for a limited training set. Several hundred new points collected during the 2010 field season are expected to remedy these training data related problems.

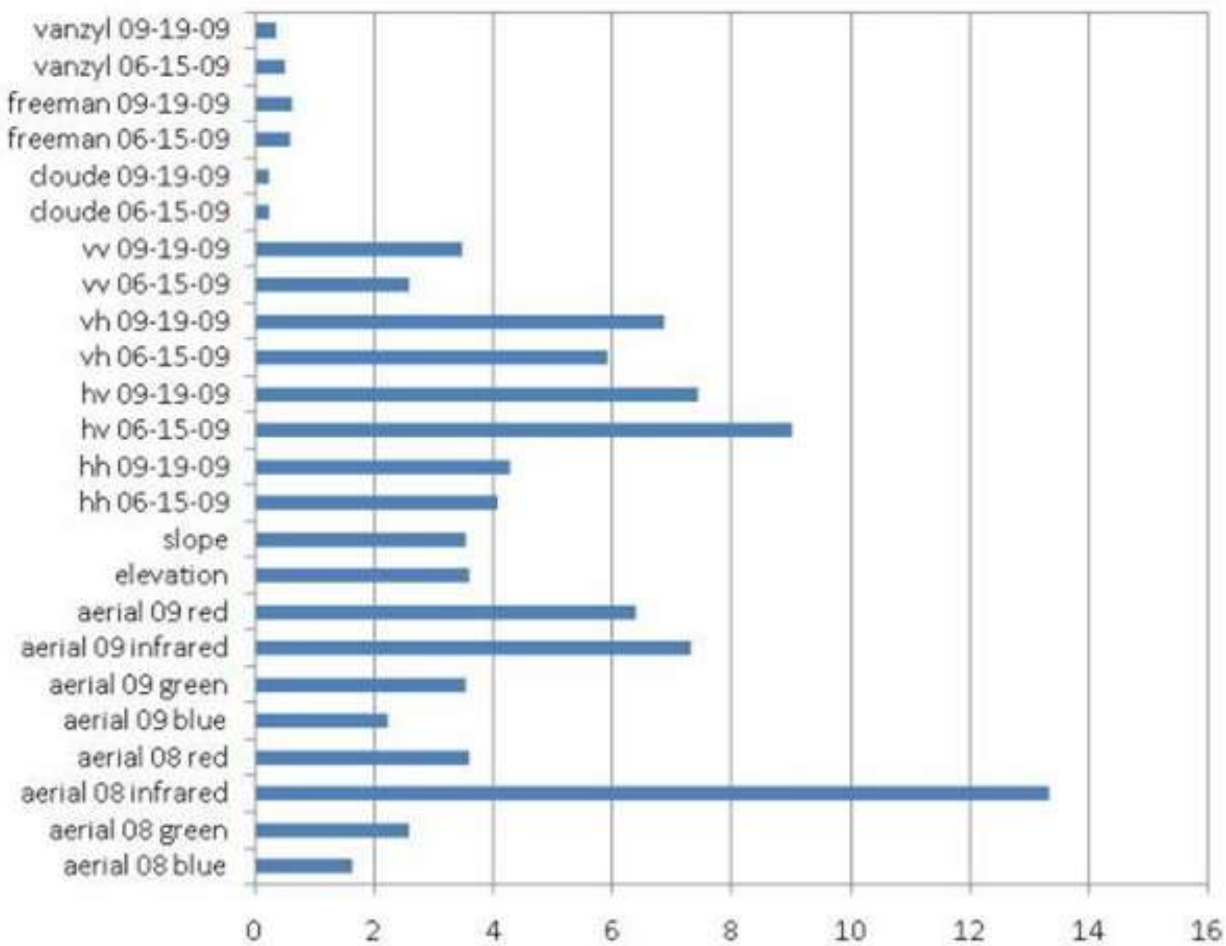

Figure 11. The Gini index for each variable in the decision tree classifier. Higher values indicate that the variable had a greater value in correct determination of wetland areas.

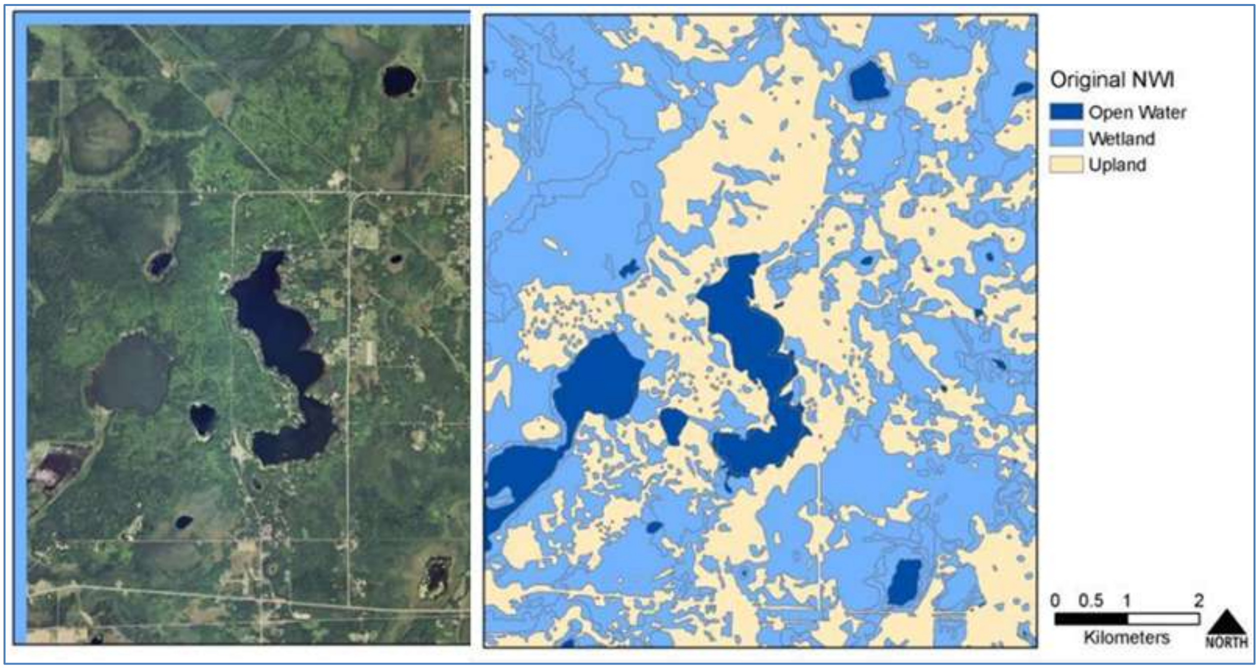

Figure 12. The current NWI layer as compared with a recent aerial image.

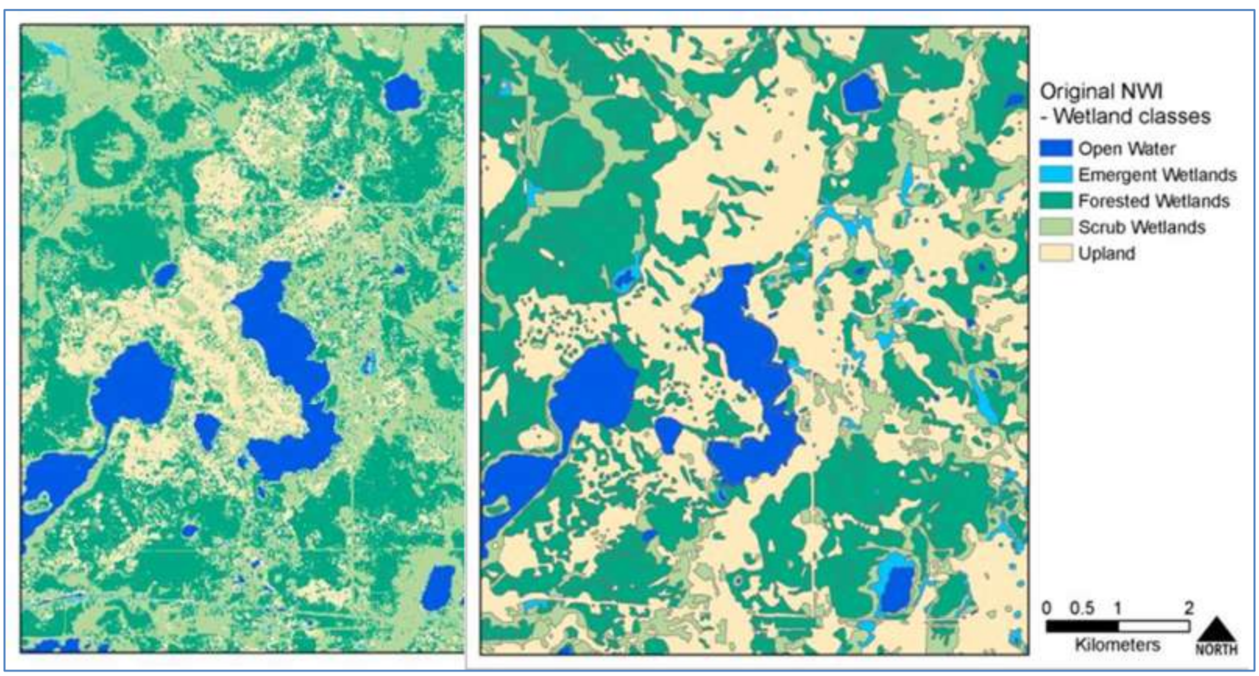

Figure 13. The current NWI (right) as compared with the output of the decision tree classifier.

2.2.4. Radar Mapping Conclusions

In this study decompositions derived from radar data did not significantly impact classification results. However, while products derived from radar were not deemed useful, the raw quad polarized radar bands were significant variables. The June 2009 HV polarization was the second most useful input variable as measured by the Gini Index. We are continuing to work with radar data. We expect that improved field data will make the limited conclusions we've drawn from this study more comprehensive and robust.

2.3. The Importance of Leaf-off Imagery

The results of this study indicate that leaf-off images are very important for accurate wetland mapping. In both See5 and RF decision tree studies, the spring leaf-off image bands were significant contributors to the overall accuracy of the results. In the See5 study the accuracy of the output maps decreased when leaf-off images were removed from consideration. In the RF study, the leaf-off infra-red band was the third most significant variable. Therefore, for the creation of the ancillary data layers we recommend that the wetland mapping workers use to assist in their efforts (e.g. the "likely wetland" layers), leaf-off images are vital.

In addition, the temporal difference in ground conditions between the spring leaf-off and summer leaf-on images is significant. In forested areas, the tree canopy matures quickly in the spring and will obscure wetland features. In regions dominated by agriculture wet soil conditions will not be captured by summer imagery because of both the common drying of soil from spring through summer and the growth of crop canopies, which obscure remaining wet features. Therefore we strongly recommend that leaf-off images be collected statewide for use in the MN NWI update.

3. Recommendations and Protocol for Wetland Mapping in the Arrowhead

3.1. General Recommendations

The results presented above suggest that an ideal geospatial dataset for wetland mapping, whether for automated analysis or interpretation by analysts, would include recent high resolution color infra-red images in both leaf-on and leaf-off conditions, high resolution LIDAR data providing both a bare earth DEM and vegetation height information, RADAR image data for several dates in spring and summer, and comprehensive soil type data for the study area. The limited geospatial data available for the Arrowhead is not sufficient to create such an idea dataset. Thus, a wetland mapping approach for the Arrowhead must identify the most useful of the available data types and analysis approaches. The following are general recommendations for conducting an NWI update in the Arrowhead:

- *Base image data for interpretation*: 2009 leaf-off 1 meter color infra-red imagery.
- *Ancillary image data*: 2008/2009 NAIP. NAIP imagery was collected in Minnesota in 2009 but it does not have a color infra-red band. An important characteristic of infra-red images is that water and saturated areas appear significantly darker than non-wet areas because of the absorption of infra-red wavelengths by water. Thus, while the 2009 NAIP images are newer and will provide a more recent wetland map, the spectral information present in the 2008 images is likely to be more advantageous in both manual interpretation and image segmentation. The new NAIP could be viewed side-by-side with the 2008 and leaf-off images, providing improved spectral and temporal information.

- *Elevation data*: LIDAR DEMs where available (soon to be statewide), National Elevation Data in LIDAR coverage gaps. Elevation data are critical for identifying depressional areas that may not be readily visible on optical imagery.
- *Soils data*: NRCS SSURGO layers. The SSURGO database, while limited in availability in the Arrowhead (notably absent in St. Louis County), and at relatively coarse spatial resolution, provides useful information about the general soil characteristics of an area. Parameters drawn from the database, such as hydric and poorly-drained designations and soil acidity data, can be used to distinguish some commonly confused wetland types – particularly in the Eggers and Reed classification system.
- *Image preprocessing*: The base image data should be segmented using an object oriented algorithm prior to interpretation. While very time consuming initially, creating image segments will substantially reduce manual interpretation time and subjectivity in drawing wetland polygon boundaries.
- *Classification system*: The Cowardin classification system should be the main wetland typing method used; however, the Eggers and Reed type for each wetland should be identified during the interpretation process. Increasing nationwide adoption of the Eggers and Reed indicates that failing to collect such data would be a substantial oversight – particularly given the difficulty of developing a robust crosswalk between Cowardin and Eggers and Reed.

3.2. Mapping Protocol

The following is a set of detailed guidelines and protocol steps for mapping wetlands in the Arrowhead. The project steps are presented in order: data acquisition, pre-interpretation data processing, data display and interpretation, post processing, delivery, and quality control.

3.2.1 Data Types and Software

The following data types should be acquired for use in this project:

- 2009 Spring leaf-off images for the study area
- 2008 National Agriculture Imaging Program (NAIP) images for the study area
- 2009 National Agriculture Imaging Program (NAIP) images for the study area
- USDA NRCS Soil Survey Geographic (SSURGO) soils data
- High resolution LiDAR DEMs where available
- National Elevation Data at 10 meter spatial resolution
- MN DNR hydrology dataset (rivers, lakes, etc.)
- USGS quarter quadrangle tile index from MN DNR
- Minnesota ecoregions layer from MN DNR

Software:

- ESRI ArcGIS
- Definiens Server 7 (or later)
- Python GDAL library
- TauDEM hydrology extension for ArcGIS
- The R statistical package with decision tree module (Random Forest)

3.2.2 Preprocessing

- Prepare the 2009 leaf-off images (all four bands) for image segmentation by subsetting them into quarter quadrangle tiles using the tile index. This can be automated using Python and the GDAL library.
- Use the batch feature in Definiens to automate segmentation of the NAIP tiles using the following parameters:
  - Color/shape: 0.5 each
  - Scale 50-70 (lower for smaller wetlands)
- Generalize segment boundaries by a reasonable amount to reduce the number of vertices. This will make subsequent editing of segment boundaries much easier and will not significantly affect the segments shapes.
- Export segments from Definiens as ArcGIS Shapefiles. Ensure they are exported with projection/coordinate information.
- Create a Normalized Difference Vegetation Index layer from the NAIP infra-red and red bands
- Threshold the NDVI layer to include only pixels with values greater than 0.2
- Use the LiDAR or NED elevation layers to create a Compound Topographic Index layer using the d-infinity water flow algorithm in TauDEM
- Compute a "likely wetland" map by using the data types described above as inputs to the Random Forest decision tree algorithm in combination with valid training data (either collected by the mapping contractor or provided by DNR or others). The output of the RF algorithm will be a layer showing the wetland presence/absence as well as type attributes for the study area, along with a confidence map depicting the statistical certainty of the classification result for each pixel.

3.2.3 Data display and Interpretation

- We recommend against viewing the old NWI polygons at any point in this procedure so as not to bias the results. The old NWI could perhaps be used after the initial interpretation as a comparison.
- A dual monitor setup is recommended if possible.
- Display in ArcGIS or other appropriate software the leaf-off tile of interest, the wetland likelihood map, a topography layer (LiDAR, NED), and the image segments.
- Display leaf-off images and segments for each adjacent image tile so that local context can be used to inform the interpretation process at the edges of the tile of interest.
- For each segment:
  - Determine whether it is wetland or upland using the interpreter's best professional judgment.
  - If the segment is wetland, record the Cowardin and Eggers & Reed (E&R) types in the ArcGIS table associated with the segment layer. We recommend this be done using a constrained attribute domain to minimize data entry errors.
  - Edit the boundaries of the segment using the ArcGIS feature editing tools so that the boundaries correspond to the natural wetland edges.

3.2.4 Data Post-processing and Delivery

- Dissolve (merge) adjacent segments that have the same wetland type. This operation should not be done if the E&R types are different.
- Delete upland segments from the segment layer.

- Deliver final segment layer as NWI wetland map. The map should be delivered at a scale desired by MN DNR, either at the quarter quad, full quad, or county, and in a GIS format such asgeodatabase.
- The product should be fully compliant with all USFWS requirements so that it is ready for upload to the main NWI.

3.2.5 Quality Assurance / Quality Control

- The mapping contractor should perform comprehensive in-house validation of the data products both during and subsequent to interpretation work. These should include positional and thematic accuracy assessments.
- If a free text data entry approach is used (e.g. the interpreters type in rather than select Cowardin codes for wetland segments), attribute validity checks should be used to ensure consistency.

4. Conclusions

The research presented in this document is an in-depth analysis of selected wetland mapping techniques for the Arrowhead. While some work remains to be completed, such as the wetland typing using radar images approach, the results are sufficient to draw conclusions and to make recommendations for the optimal approach to accomplishing the objectives of the Minnesota NWI update. The protocol provided above is expected to be suitable for meeting or exceeding the FGDC wetland mapping standard and thus allowing for the inclusion of Minnesota's updated wetland maps in the USFWS National Wetland Inventory.

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