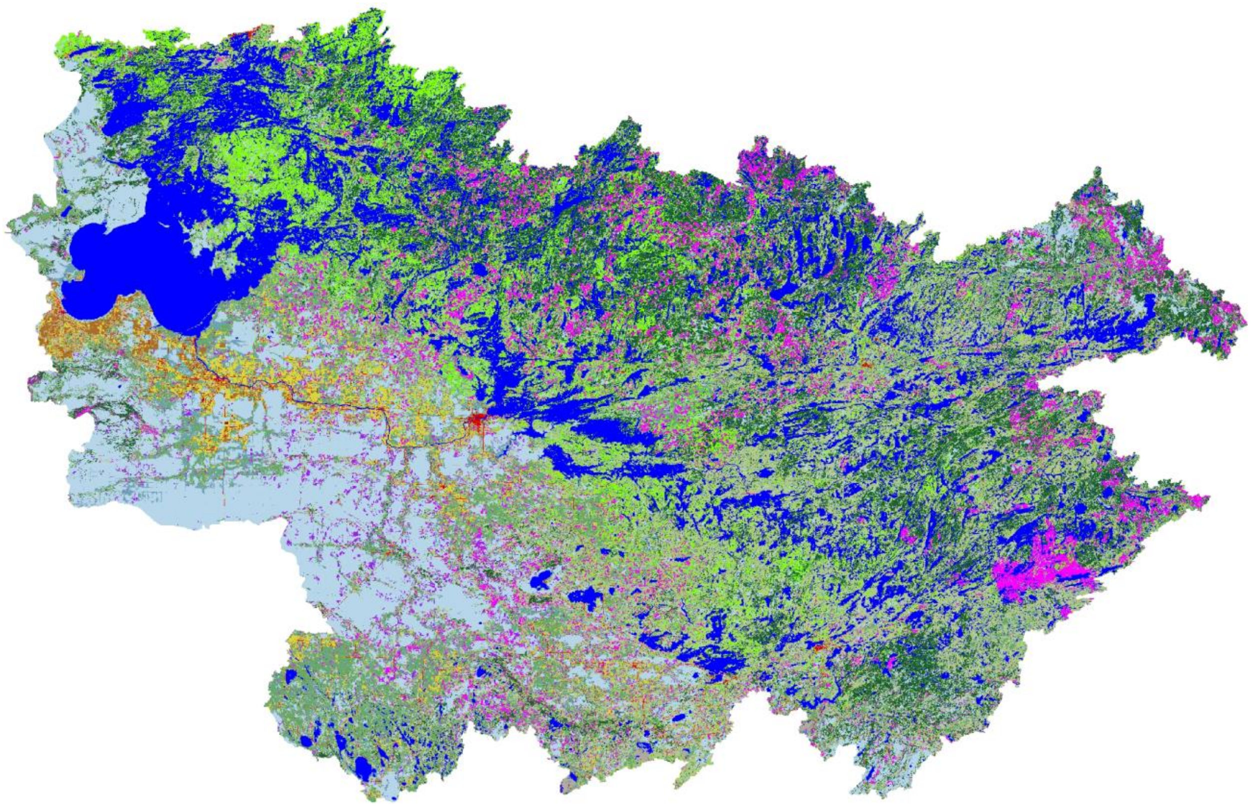
Lake of the Woods/Rainy River Basin Land Cover 1990 and 2010



FINAL REPORT to Minnesota Pollution Control Agency from University of Minnesota
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Lake of the Woods/Rainy River Basin Land Cover 1990 and 2010

Leif Olmanson and Marvin Bauer

Rationale and Background

With a perceived increase in the frequency and intensity of cyanobacterial algal blooms in Lake of the Woods (LOW), there has been an increased effort to collect information about the nature of algal blooms, nutrient concentrations and sources of nutrients to the LOW. As part of this effort, land cover maps of the LOW Watershed are needed as inputs to hydrology models and analyses of land use and land use change.

Historically, remote sensing in the form of aerial photography has been an important source of land use-land cover information. However, the cost of aerial photography acquisition and interpretation and subsequent digitization of cover types is prohibitively expensive for large geographic areas. An alternative is to acquire the needed information from digital satellite imagery such as from the Landsat Thematic Mapper (TM). This approach has several advantages: (1) the synoptic view of the sensor provides coverage of large geographic areas (e.g. an individual image covers 100 x 100 miles), (2) the digital form of the data lends itself to more efficient analysis, (3) the classified data are compatible with geographic information systems, and (4) land cover maps can be generated at considerable less cost than by other methods (albeit at 30-meter spatial resolution).

This project for the Minnesota Pollution Control Agency used a combination of multitemporal Landsat imagery, lidar data (Minnesota) and object-based image analysis to cover the entire extend of the Lake of the Woods/Rainy River Basin using a uniform method for the ~1990 and ~2010 time periods so that land cover and changes over that time period can be quantified and used for hydrologic modeling.

Methods

1. Landsat Data Acquisition and Processing

To complete the land cover classification for 1990 and 2010 time periods for the entire 70,000 km^2 Lake of the Woods/Rainy River Basin forty-four Landsat images were utilized. These images included Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) images from paths 26, 27, 28 and 29 and rows 25, 26 and 27 from different seasons and vegetation development stages to distinguish different kinds of vegetation and other cover types (Figure 1 and 2). Imagery dates include: Path 26 (April 19, 1990, August 28, 1991, March 25, 2010, May 15, 2011, June 26, 2009 and September 30, 2009); Path 27 (May 12, 1990, July 31, 1990, April 17, 2010 and September 16, 2013) Path 28 (April 20, 1991, September 5, 1989, August 24, 2008, April 8, 2010 and August 17, 2011) Path 29 (April 24, 1990, August 30, 1990, May 27, 2008, September 19, 2009, July 31, 2014 and October 19, 2014). Further information about Landsat is available at http://landsat.usgs.gov/.

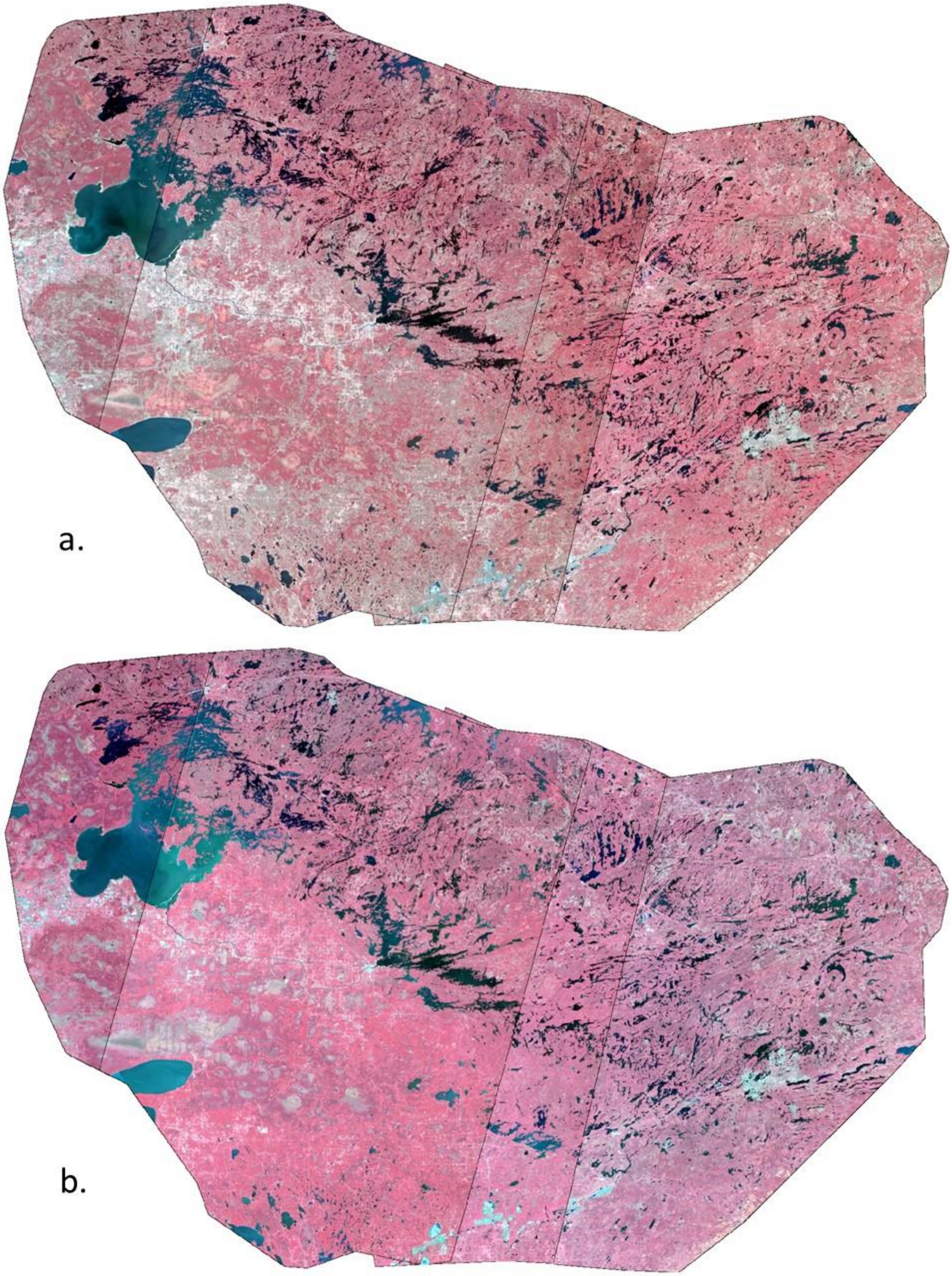


Figure 1. Landsat image mosaic (3-band false color composite) a. spring, b. summer.

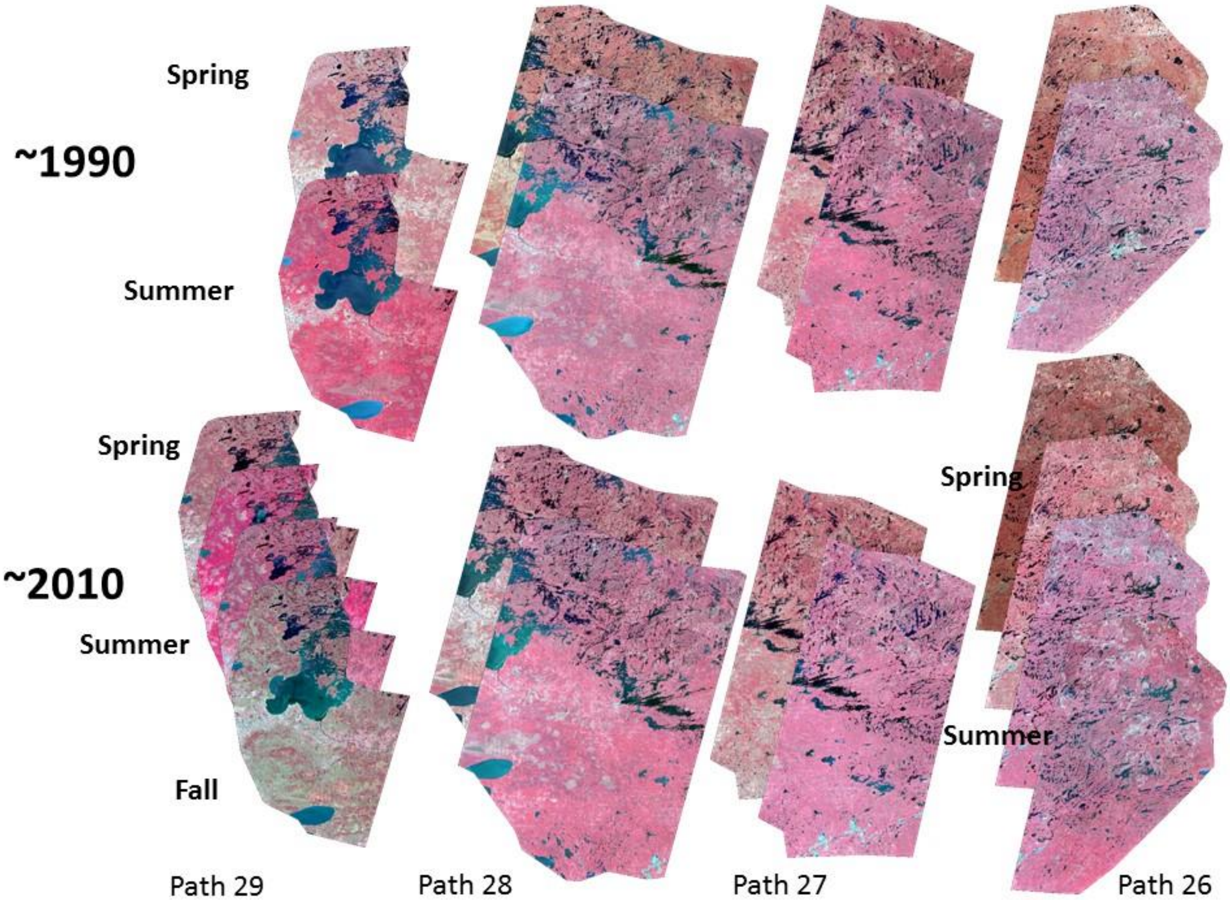


Figure 2. Multitemporal Landsat paths of images (3-band false color composite) used for land cover classification.

With multiple dates of imagery per Landsat path (Figure 2), each with seven to ten spectral bands it is useful to compress the images using the principal components. Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Eight to 10 independent principal components were derived for each path of imagery. The first four are shown in Figure 3 along with a composite image of the first three in Figure 4. The composite image clearly shows separability of major cover type classes.

Additional transformations of the Landsat data used were the "tasseled cap transformation," principal components like transformation. The first component is brightness which is related to the amplitude of responses. The second, orthogonal to brightness, is known as greenness because of its sensitivity to the amount of green vegetation. The third, called wetness, is related to moisture content. An example, showing the differences in the three components is shown in Figure 5.

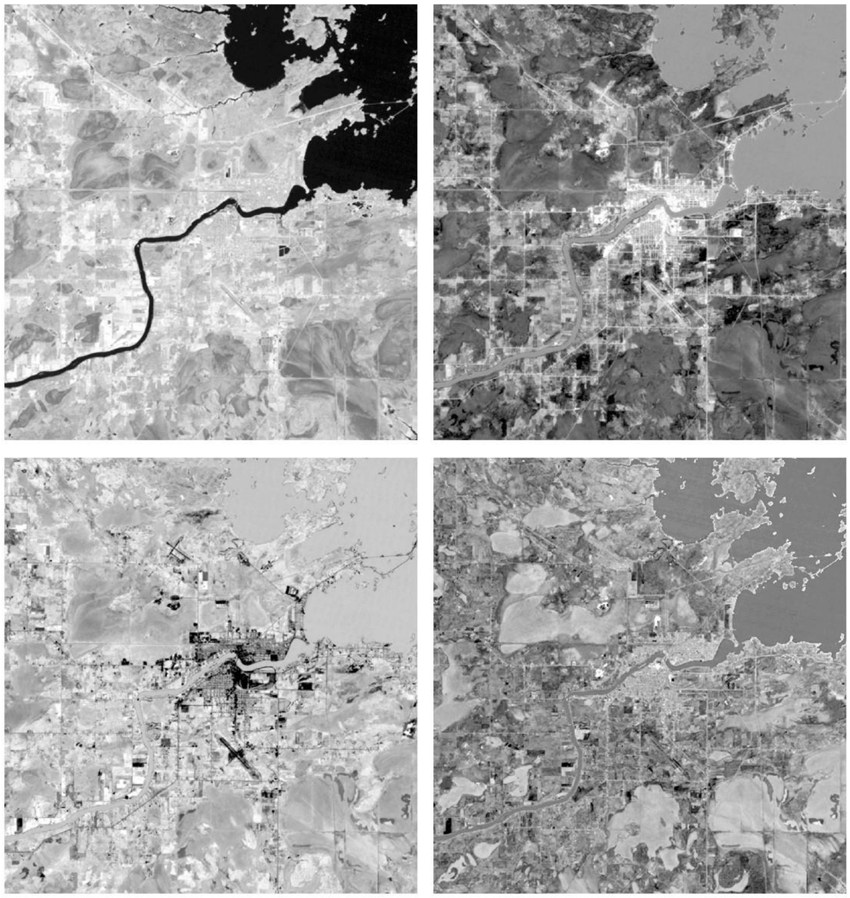


Figure 3. Principal components 1 – 4 of the International Falls/Fort Frances area.

Figure 4. Composite image of first three principal components of the International Falls/Fort Frances area.

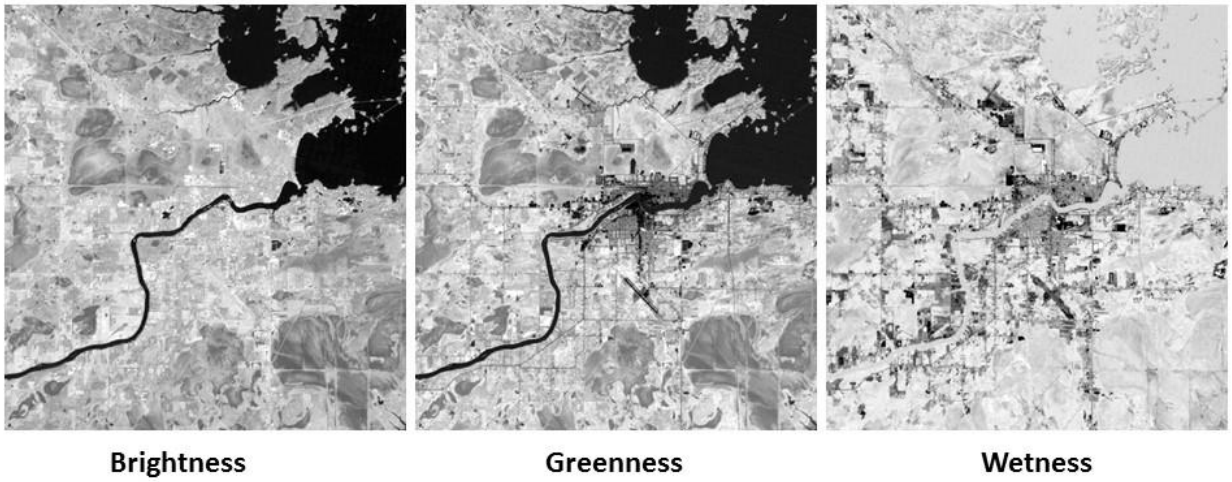


Figure 5. Tasseled cap components for International Falls/Fort Frances area summer 2010 image.

Another useful and frequently used transformation is the normalized difference vegetation index (NDVI) which is the ratio of the difference to the sum of the near infrared and red spectral band responses (Figure 6).

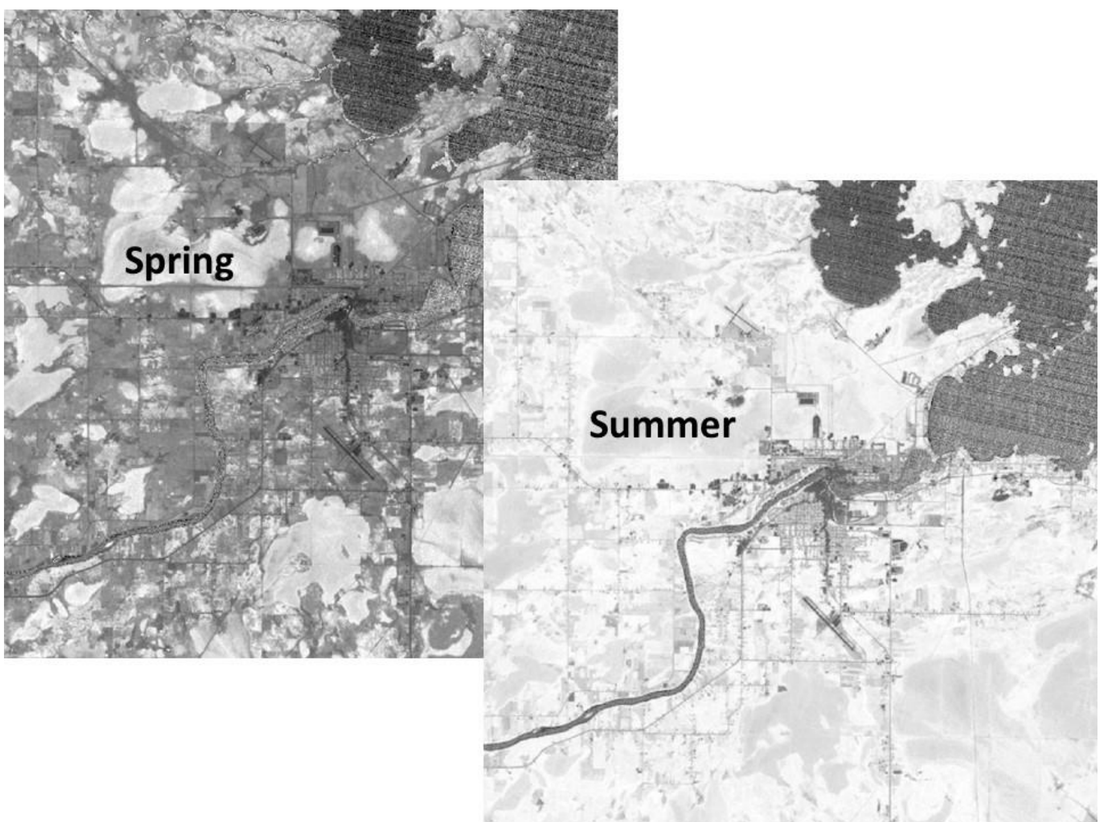


Figure 6. Examples of NDVI images for International Falls/Fort Frances area.

2. Lidar Data Acquisition and Processing

Lidar data acquired provides additional information on height and elevation. Lidar LAS files were acquired from the Minnesota DNR for the tiles within the areas covering the Minnesota portion of the Lake of the Woods/Rainy River Basin. The LAS tiles were used to generate mean and maximum vegetation height rasters at 20-meter spatial resolution (Figure 7). The DNR-provided 1-meter bare earth DEM was also used to create additional lidar-derivative layers at 10-meter spatial resolution, such as Compound Topographic Index (CTI), slope, and dissection. These DEM derived variables are especially useful for wetland identification. More information about the lidar data are available at: http://www.mngeo.state.mn.us/chouse/elevation/Lidar.html

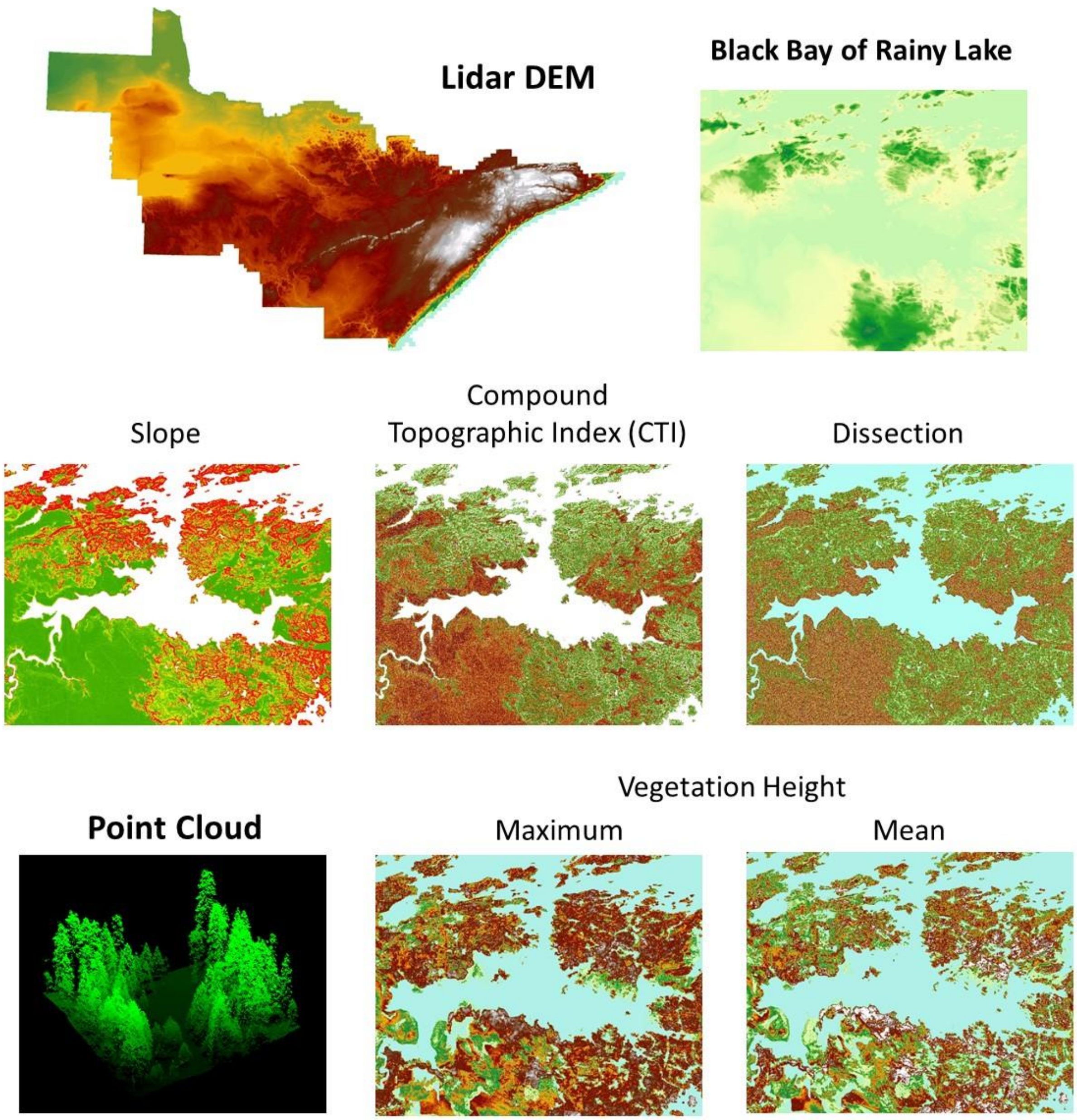


Figure 7. Lidar derived variables.

3. Additional GIS Maps and Data

Additional GIS layers were used for image segmentation included major roads, other roads and railroads were acquired from the Minnesota Department of Transportation, Ontario Ministry of Natural Resources and Forestry and Manitoba Infrastructure and Transportation. Once the classification was finalized and accuracies were calculated these layers were also overlain on the maps so that roads narrower than the 60 m Landsat data could be included in the 2010 map. For the 1990 map an edited version of the roads layer was used which excluded roads that were identified as being built since 1990.

4. Classification Scheme and Reference Data

A critical element of any image classification project is the classification scheme, a systematic listing of the classes of interest. It should be exhaustive (there is a class for everything), mutually exclusive (each cover type is a member of only one class) and hierarchical (so that more detailed classes (e.g., Level 2) can be collapsed into more general classes (e.g., Level 1). The classes are similar to those used for previous classifications in Minnesota, although modified to take advantage of the unique characteristics of the Lake of the Woods/Rainy River Basin.

Table 1. Classification scheme with Level 1 and 2 classes.

Level 1	Level 2	Code	Description
Urban / Developed	High density	11	Commercial building and parking lots
	Medium density	12	Residential areas
	Low density	13	Rural development e.g. shoreline, farmsteads
	Managed Grass	14	Golf courses, parks
	Roads	15	Highways, other roads and railways
Extraction	Extraction	21	Quarries
Agriculture	Row Crops & Small Grains	31	Corn, soybean, wheat, oats and barley
	Hay & Pasture	32	Alfalfa and other hay and pasture
Forest	Coniferous Forest	41	White and red pine
	Deciduous Forest	42	Oak, Maple, Aspen, and other hardwoods
	Mixed Forest	43	Mixtures of conifer and deciduous
	Sparse Forest	44	Forested with bedrock outcrops
	Regenerating Forest	45	Harvested or burned forest
Open water	Lakes & Ponds	51	Open water
Wetlands	Herbaceous Wetlands	61	Herbaceous Wetlands
	Woody Wetlands	62	Forested and scrub shrub wetlands
	Regenerating Forested wetland	63	Harvested forested wetlands
	Wetland/Sandbar	64	Transitional barrier islands and shoreline

A second critical aspect of successfully classifying remote sensing data is the availability of accurate reference data that can be used to associate land cover/land use classes with the spectral-radiometric-temporal classes from the imagery and for accuracy assessment. Reference data used for classifier training and accuracy assessment were created by identifying objects of representative land cover types using the Landsat imagery and derivatives, lidar derivatives and high-resolution aerial photos available through Google Earth, Bing Maps and for the Minnesota portion the MnGeo Geospatial Image Service (http://www.mngeo.state.mn.us/chouse/wms/geo_image_server.html) which distributes ortho-rectified aerial digital imagery, particularly from the USDA National Agricultural Program Imagery (NAIP) 3-band, 1-meter natural color summer imagery and 4-band (including near infrared) spring leaf-off imagery. An example of NAIP imagery with examples of different level 1 cover type classes is shown in Figure 8. For classes, such as agriculture and wetlands, ancillary datasets were used to identify characteristic areas for training.

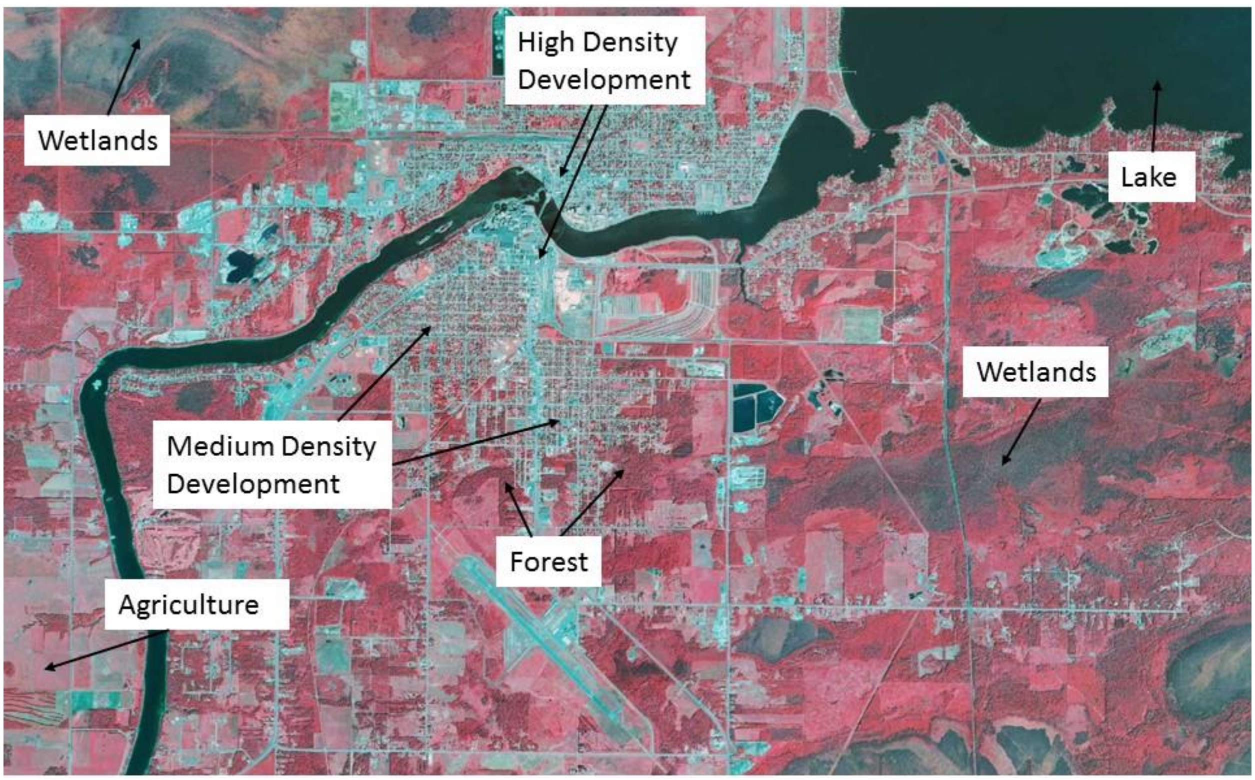


Figure 8. NAIP image with examples of cover type classes.

5. Image Classification

Some previous Minnesota land cover classifications used the maximum likelihood classifier based on the spectral responses of individual pixels (Yuan et al. 2005a, b). Although multispectral and temporal information was integrated by including two or three image dates, spatial information is not included with pixel level classifications. More recently object-based image analysis (OBIA) (Blaschke, 2010; Platt and Rapoza, 2008) has become the standard method for classification of high resolution imagery, but it can also be effectively used for moderate resolution data such as Landsat (Bauer et al. 2013). There is much more information available when the spatial information in imagery is considered and it generally increases the classification accuracy. Objects include more information than individual pixels, enabling the ability to take advantage of all the elements of image interpretation, particularly spatial information, including shape, size, pattern, texture, and context. Context is especially useful. Humans intuitively integrate "pixels" into objects and use contextual relationships to interpret images and draw intelligent inferences from them.

The OBIA approach using eCognition, the leading OBIA software system, included three main steps: (1) segmentation of the image into objects, (2) extraction of the object features, and (3) classification of the objects.

Segmentation: The imagery is first segmented into objects with similar pixels based on the spatial, as well as the spectral-radiometric (color) attributes. Segmentation primarily uses spectral information about individual pixels in the imagery to combine them into larger image objects or segments. As an example, individual pixels which comprise a crop field with similar spectral response values are combined to form an image object that represents the field. Other scaling information can be specified to regulate the size range of the desired objects. The goal of segmentation is to minimize within object heterogeneity and maximize the variance among objects, subject to user defined parameters. A scale parameter is specified to control the size of objects and there can be a nested hierarchy of objects with bigger objects containing smaller objects. Examples of segmentation results are shown in Figures 9 and 10.

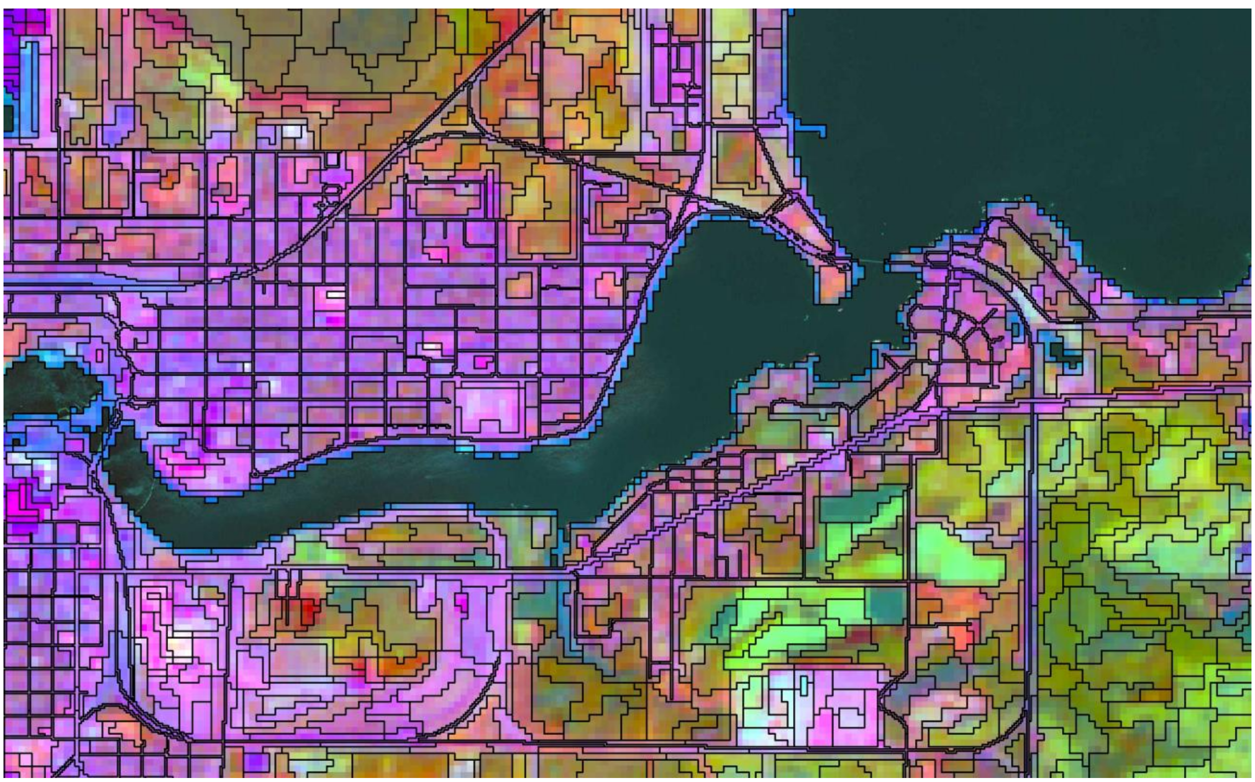


Figure 9. Segmentation objects of uplands and wetlands using principal components and major roads.

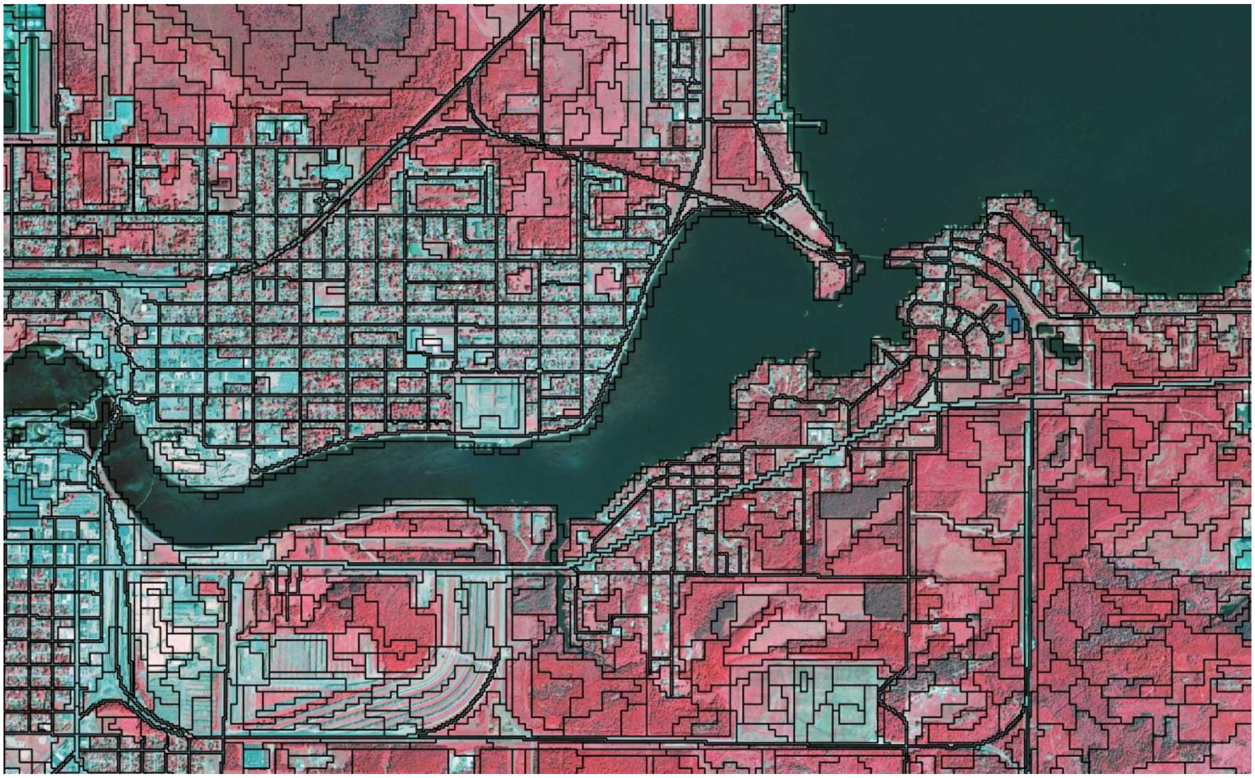


Figure 10. Objects over 2008 NAIP false color imagery for the same area as in Figure 9.

Since we wanted to utilize the same segmentations for 1990 and 2010 we determined that using the concentrated spectral data in the PCA image for each Landsat path along with the roads and railway layer produced the best segmentations. These segmentations were suitable for both time periods and could be used to classify change between 1990 and 2010.

Extraction of Object Features: Once image objects were created, a large number (>200) of features could be derived and potentially used for classification. The primary features, summarized in Table 2, included: spectral data, including means, modes, quantiles and standard deviations of individual bands and several transformations; geometry, including asymmetry, compactness, density, rectangular fit, roundness and shape index; texture, including, homogeneity and dissimilarity.

Table 2. Features calculated from objects.

Layer Values	Geometry	Texture
Brightness	Asymmetry	Homogeneity
Maximum difference	Compactness	Dissimilarity
Mean (all layers)	Density	
Standard Deviation (all layers)	Rectangular fit	
Modes (all layers)	Roundness	
Quantiles (all layers)	Shape index	

Classification. To decrease the error between the 1990 and 2010 classification we classified both time periods together and added classes at Level 3 to identify change. These included areas that were developed, changes in agriculture, barrier and shore land areas that eroded away or were created, and forested areas that were harvested or regenerated. Since we had four Landsat paths of imagery each had to be classified separately since images from different dates would have different vegetation phenology which would increase classification error. Also to take advantage of the lidar data that was available in Minnesota, but not Ontario or Manitoba, the Minnesota sections of each Landsat path were classified separately. Therefore to cover the entire Lake of the Woods/Rainy River Basin using the best available data sources eight separate classifications were completed and mosaicked to create the final land cover maps and change maps.

Random forest, a state-of-the-art approach which could handle and take advantage of the large number of features, was used for the classification of the objects. It is an ensemble learning method for classification that operates by constructing multiple decision trees. Each tree is grown by growing each tree on different random subsamples of the training data and during the split selection process by using a subsample of the available features. It allows for the use of a large number of features or variables and identifies the important predictors. Examples of binary decision trees and key variable for classification are shown in Figures 11 and 12.

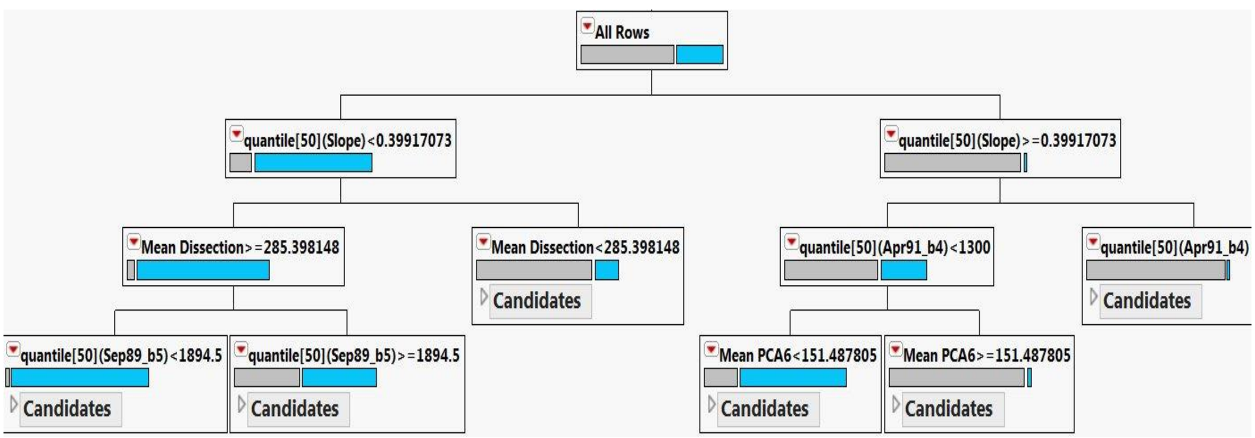


Figure 11. Example of binary decision trees for wetland vs. non-wetland.

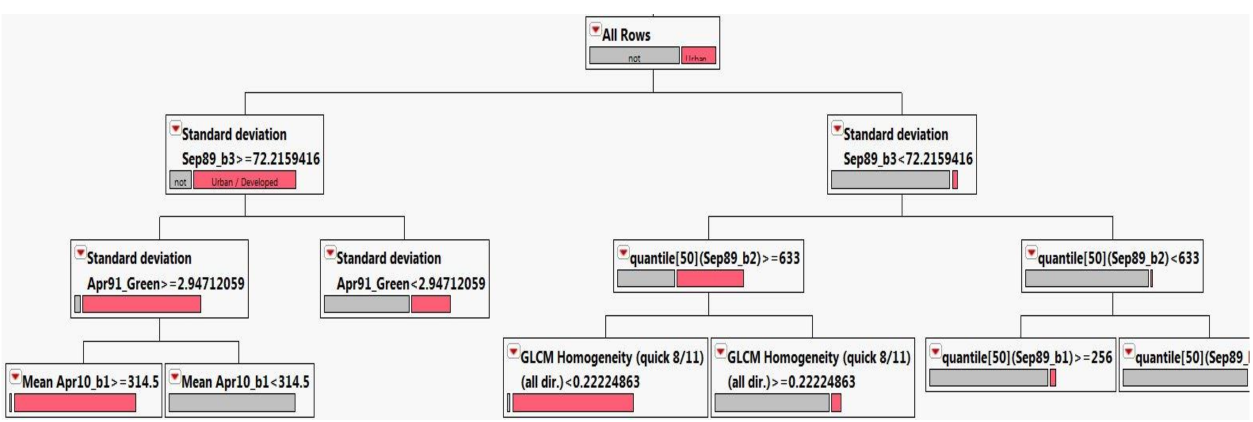
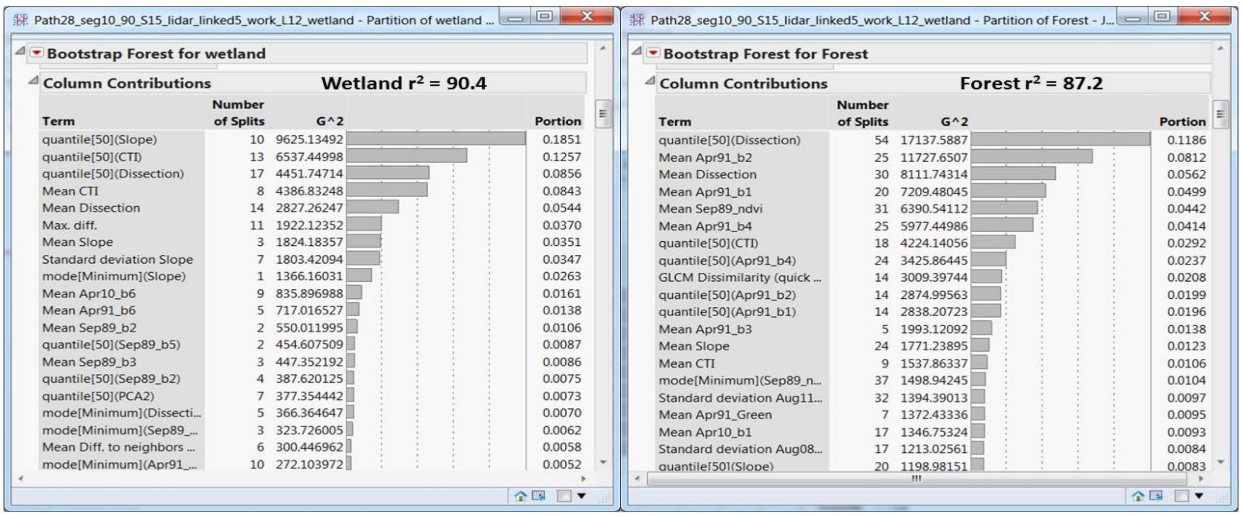


Figure 12. Example of binary decision trees for developed vs. non-developed.

The Gini index, a measure of entropy, was used to compute how often a particular variable is used and how “early” it is used in the trees in the forest. A higher Gini score indicates a more influential variable. The contributions of the most important variables to the classification of wetlands, forest, developed and agriculture utilizing lidar data and without are shown in Figure 13 through 16. The utilization of the lidar data substantially improved classification of wetlands and forest which is potentially due to the improved separation of forested wetlands from upland forest and since forested wetlands and forest cover a large percentage of the Lake of the Woods/Rainy River Basin. The utilization of the lidar data also improved the classification of agricultural areas somewhat potentially due to artificial drainage and farming of wetland areas or improved separation of wetlands from grasslands. The lidar data did not improve the separation of developed areas from other classes. Utilizing building footprints which were created from the lidar point cloud could improve separation and were utilized in Bauer et al. 2013, however were deemed to be of inconsistent quality over this region and thus were not used.



Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of wetland ...

Bootstrap Forest for wetland

Column Contributions — Wetland r^2 = 90.4

Term	Number of Splits	G^2	Portion
quantile[50](Slope)	10	9625.13492	0.1851
quantile[50](CTI)	13	6537.44998	0.1257
quantile[50](Dissection)	17	4451.74714	0.0856
Mean CTI	8	4386.83248	0.0843
Mean Dissection	14	2827.26247	0.0544
Max. diff.	11	1922.12352	0.0370
Mean Slope	3	1824.18357	0.0351
Standard deviation Slope	7	1803.42094	0.0347
mode[Minimum](Slope)	1	1366.16031	0.0263
Mean Apr10_b6	9	835.896988	0.0161
Mean Apr91_b6	5	717.016527	0.0138
Mean Sep89_b2	2	550.011995	0.0106
quantile[50](Sep89_b5)	2	454.607509	0.0087
Mean Sep89_b3	3	447.352192	0.0086
quantile[50](Sep89_b2)	4	387.620125	0.0075
quantile[50](PCA2)	7	377.354442	0.0073
mode[Minimum](Dissecti...	5	366.364647	0.0070
mode[Minimum](Sep89_...	3	323.726005	0.0062
Mean Diff. to neighbors ...	6	300.446962	0.0058
mode[Minimum](Apr91_...	10	272.103972	0.0052

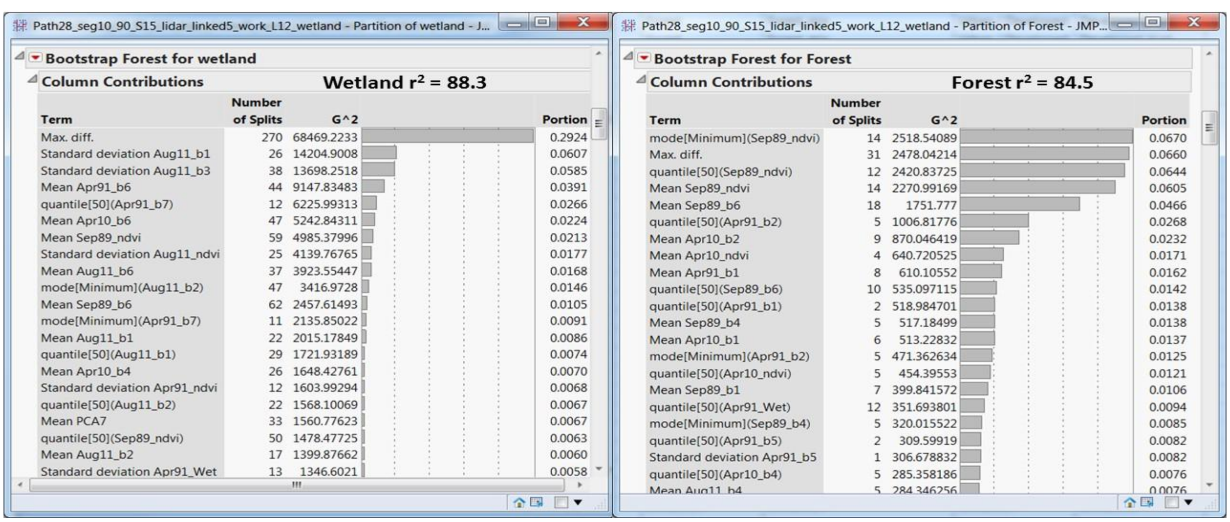
Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Forest - J...

Bootstrap Forest for Forest

Column Contributions — Forest r^2 = 87.2

Term	Number of Splits	G^2	Portion
quantile[50](Dissection)	54	17137.5887	0.1186
Mean Apr91_b2	25	11727.6507	0.0812
Mean Dissection	30	8111.74314	0.0562
Mean Apr91_b1	20	7209.48045	0.0499
Mean Sep89_ndvi	31	6390.54112	0.0442
Mean Apr91_b4	25	5977.44986	0.0414
quantile[50](CTI)	18	4224.14056	0.0292
quantile[50](Apr91_b4)	24	3425.86445	0.0237
GLCM Dissimilarity (quick ...	14	3009.39744	0.0208
quantile[50](Apr91_b2)	14	2874.99563	0.0199
quantile[50](Apr91_b1)	14	2838.20723	0.0196
Mean Apr91_b3	5	1993.12092	0.0138
Mean Slope	24	1771.23895	0.0123
Mean CTI	9	1537.86337	0.0106
mode[Minimum](Sep89_n...	37	1498.94245	0.0104
Standard deviation Aug11...	32	1394.39013	0.0097
Mean Apr91_Green	7	1372.43336	0.0095
Mean Apr10_b1	17	1346.75324	0.0093
Standard deviation Aug08...	17	1213.02561	0.0084
quantile[50](Slope)	20	1198.98151	0.0083

Figure 13. Contributions of variables to the classifications of wetland and forest using lidar data.



Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of wetland - J...

Bootstrap Forest for wetland

Column Contributions — Wetland r^2 = 88.3

Term	Number of Splits	G^2	Portion
Max. diff.	270	68469.2233	0.2924
Standard deviation Aug11_b1	26	14204.9008	0.0607
Standard deviation Aug11_b3	38	13698.2518	0.0585
Mean Apr91_b6	44	9147.83483	0.0391
quantile[50](Apr91_b7)	12	6225.99313	0.0266
Mean Apr10_b6	47	5242.84311	0.0224
Mean Sep89_ndvi	59	4985.37996	0.0213
Standard deviation Aug11_ndvi	25	4139.76765	0.0177
Mean Aug11_b6	37	3923.55447	0.0168
mode[Minimum](Aug11_b2)	47	3416.9728	0.0146
Mean Sep89_b6	62	2457.61493	0.0105
mode[Minimum](Apr91_b7)	11	2135.85022	0.0091
Mean Aug11_b1	22	2015.17849	0.0086
quantile[50](Aug11_b1)	29	1721.93189	0.0074
Mean Apr10_b4	26	1648.42761	0.0070
Standard deviation Apr91_ndvi	12	1603.99294	0.0068
quantile[50](Aug11_b2)	22	1568.10069	0.0067
Mean PCA7	33	1560.77623	0.0067
quantile[50](Sep89_ndvi)	50	1478.47725	0.0063
Mean Aug11_b2	17	1399.87662	0.0060
Standard deviation Apr91_Wet	13	1346.6021	0.0058

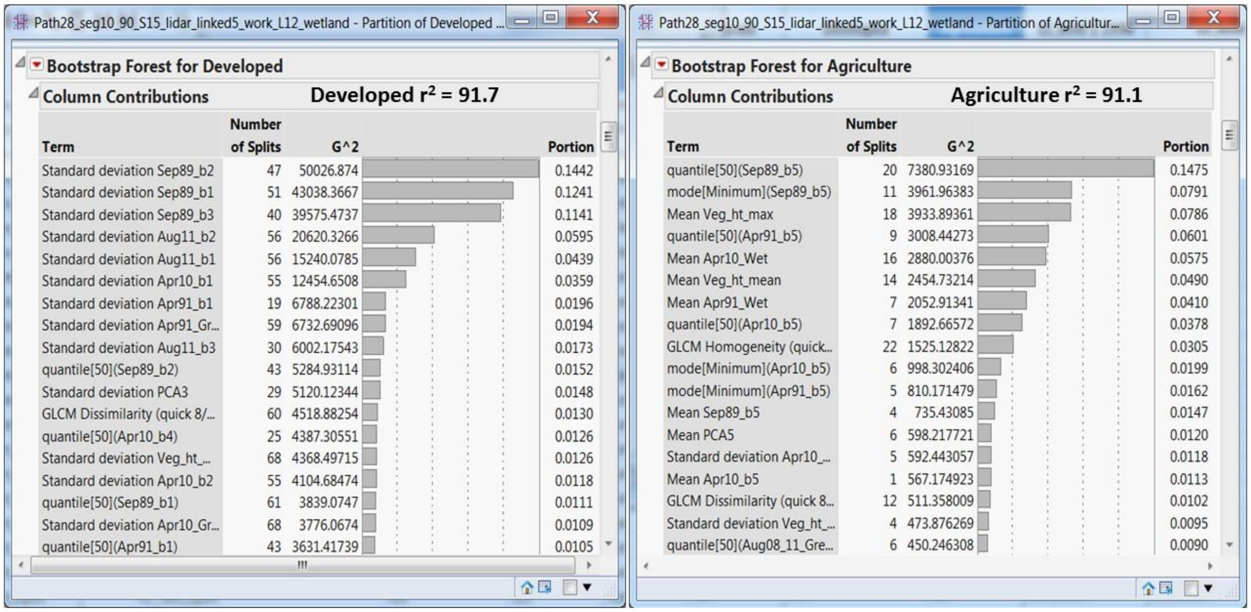
Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Forest - JMP...

Bootstrap Forest for Forest

Column Contributions — Forest r^2 = 84.5

Term	Number of Splits	G^2	Portion
mode[Minimum](Sep89_ndvi)	14	2518.54089	0.0670
Max. diff.	31	2478.04214	0.0660
quantile[50](Sep89_ndvi)	12	2420.83725	0.0644
Mean Sep89_ndvi	14	2270.99169	0.0605
Mean Sep89_b6	18	1751.777	0.0466
quantile[50](Apr91_b2)	5	1006.81776	0.0268
Mean Apr10_b2	9	870.046419	0.0232
Mean Apr10_ndvi	4	640.720525	0.0171
Mean Apr91_b1	8	610.10552	0.0162
quantile[50](Sep89_b6)	10	535.097115	0.0142
quantile[50](Apr91_b1)	2	518.984701	0.0138
Mean Sep89_b4	5	517.18499	0.0138
Mean Apr10_b1	6	513.22832	0.0137
mode[Minimum](Apr91_b2)	5	471.362634	0.0125
quantile[50](Apr10_ndvi)	5	454.39553	0.0121
Mean Sep89_b1	7	399.841572	0.0106
quantile[50](Apr91_Wet)	12	351.693801	0.0094
mode[Minimum](Sep89_b4)	5	320.015522	0.0085
quantile[50](Apr91_b5)	2	309.59919	0.0082
Standard deviation Apr91_b5	1	306.678832	0.0082
quantile[50](Apr10_b4)	5	285.358186	0.0076
Mean Aug11_b4	5	284.346256	0.0076

Figure 14. Contributions of variables to the classifications of wetland and forest w/o lidar data.



Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Developed ...

Bootstrap Forest for Developed

Column Contributions — Developed r^2 = 91.7

Term	Number of Splits	G^2	Portion
Standard deviation Sep89_b2	47	50026.874	0.1442
Standard deviation Sep89_b1	51	43038.3667	0.1241
Standard deviation Sep89_b3	40	39575.4737	0.1141
Standard deviation Aug11_b2	56	20620.3266	0.0595
Standard deviation Aug11_b1	56	15240.0785	0.0439
Standard deviation Apr10_b1	55	12454.6508	0.0359
Standard deviation Apr91_b1	19	6788.22301	0.0196
Standard deviation Apr91_Gr...	59	6732.69096	0.0194
Standard deviation Aug11_b3	30	6002.17543	0.0173
quantile[50](Sep89_b2)	43	5284.93114	0.0152
Standard deviation PCA3	29	5120.12344	0.0148
GLCM Dissimilarity (quick 8/...	60	4518.88254	0.0130
quantile[50](Apr10_b4)	25	4387.30551	0.0126
Standard deviation Veg_ht_...	68	4368.49715	0.0126
Standard deviation Apr10_b2	55	4104.68474	0.0118
quantile[50](Sep89_b1)	61	3839.0747	0.0111
Standard deviation Apr10_Gr...	68	3776.0674	0.0109
quantile[50](Apr91_b1)	43	3631.41739	0.0105

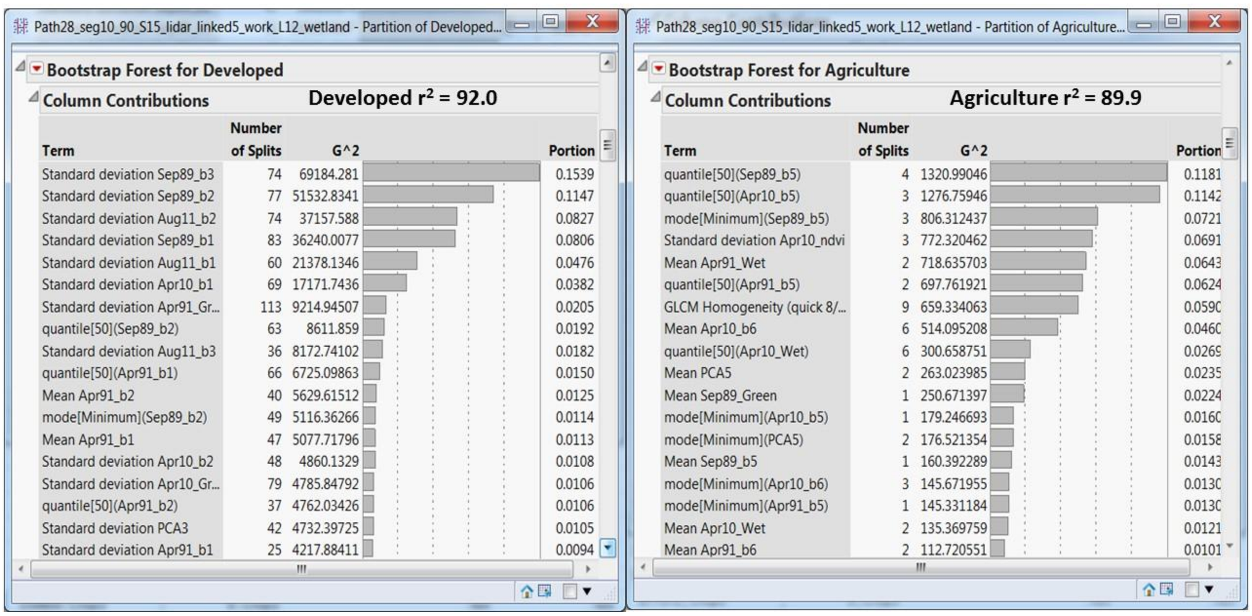
Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Agricultur...

Bootstrap Forest for Agriculture

Column Contributions — Agriculture r^2 = 91.1

Term	Number of Splits	G^2	Portion
quantile[50](Sep89_b5)	20	7380.93169	0.1475
mode[Minimum](Sep89_b5)	11	3961.96383	0.0791
Mean Veg_ht_max	18	3933.89361	0.0786
quantile[50](Apr91_b5)	9	3008.44273	0.0601
Mean Apr10_Wet	16	2880.00376	0.0575
Mean Veg_ht_mean	14	2454.73214	0.0490
Mean Apr91_Wet	7	2052.91341	0.0410
quantile[50](Apr10_b5)	7	1892.66572	0.0378
GLCM Homogeneity (quick...	22	1525.12822	0.0305
mode[Minimum](Apr10_b5)	6	998.302406	0.0199
mode[Minimum](Apr91_b5)	5	810.171479	0.0162
Mean Sep89_b5	4	735.43085	0.0147
Mean PCA5	6	598.217721	0.0120
Standard deviation Apr10_...	5	592.443057	0.0118
Mean Apr10_b5	1	567.174923	0.0113
GLCM Dissimilarity (quick 8...	12	511.358009	0.0102
Standard deviation Veg_ht_...	4	473.876269	0.0095
quantile[50](Aug08_11_Gre...	6	450.246308	0.0090

Figure 15. Contributions of variables to the classifications of developed and agriculture utilizing lidar data.



Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Developed...

Bootstrap Forest for Developed

Column Contributions — Developed r^2 = 92.0

Term	Number of Splits	G^2	Portion
Standard deviation Sep89_b3	74	69184.281	0.1539
Standard deviation Sep89_b2	77	51532.8341	0.1147
Standard deviation Aug11_b2	74	37157.588	0.0827
Standard deviation Sep89_b1	83	36240.0077	0.0806
Standard deviation Aug11_b1	60	21378.1346	0.0476
Standard deviation Apr10_b1	69	17171.7436	0.0382
Standard deviation Apr91_Gr...	113	9214.94507	0.0205
quantile[50](Sep89_b2)	63	8611.859	0.0192
Standard deviation Aug11_b3	36	8172.74102	0.0182
quantile[50](Apr91_b1)	66	6725.09863	0.0150
Mean Apr91_b2	40	5629.61512	0.0125
mode[Minimum](Sep89_b2)	49	5116.36266	0.0114
Mean Apr91_b1	47	5077.71796	0.0113
Standard deviation Apr10_b2	48	4860.1329	0.0108
Standard deviation Apr10_Gr...	79	4785.84792	0.0106
quantile[50](Apr91_b2)	37	4762.03426	0.0106
Standard deviation PCA3	42	4732.39725	0.0105
Standard deviation Apr91_b1	25	4217.88411	0.0094

Path28_seg10_90_S15_lidar_linked5_work_L12_wetland - Partition of Agriculture...

Bootstrap Forest for Agriculture

Column Contributions — Agriculture r^2 = 89.9

Term	Number of Splits	G^2	Portion
quantile[50](Sep89_b5)	4	1320.99046	0.1181
quantile[50](Apr10_b5)	3	1276.75946	0.1142
mode[Minimum](Sep89_b5)	3	806.312437	0.0721
Standard deviation Apr10_ndvi	3	772.320462	0.0691
Mean Apr91_Wet	2	718.635703	0.0643
quantile[50](Apr91_b5)	2	697.761921	0.0624
GLCM Homogeneity (quick 8/...	9	659.334063	0.0590
Mean Apr10_b6	6	514.095208	0.0460
quantile[50](Apr10_Wet)	6	300.658751	0.0269
Mean PCA5	2	263.023985	0.0235
Mean Sep89_Green	1	250.671397	0.0224
mode[Minimum](Apr10_b5)	1	179.246693	0.0160
mode[Minimum](PCA5)	2	176.521354	0.0158
Mean Sep89_b5	1	160.392289	0.0143
mode[Minimum](Apr10_b6)	3	145.671955	0.0130
mode[Minimum](Apr91_b5)	1	145.331184	0.0130
Mean Apr10_Wet	2	135.369759	0.0121
Mean Apr91_b6	2	112.720551	0.0101

Figure 16. Contributions of variables to the classifications of developed and agriculture without lidar data.

6. Accuracy Assessment

A key part of the project is accuracy assessment. We evaluated classification accuracy by comparing the classification results to an independent stratified (by class) random reference sample of 6,610 objects (20 percent of the reference data that were withheld from classifier training) and reporting the error matrix and statistics derived from it including overall accuracy and user and producer accuracies (Conglaton, 1991; Foody, 2002).

7. Generation of Output Products

The primary output of the project is the maps and statistics of land cover and land cover change in an ArcGIS database. Maps and statistics summarizing the classifications by sub-watershed will be added to our online database available at http://land.umn.edu. Maps and statistics can also be generated for user defined areas. The classification data and metadata have been provided to the Minnesota Pollution Control Agency.

Results

The overall classification legend of the Lake of the Woods/Rainy River Basin for 1990 and 2010 is shown in Figure 17 and the 1990 and 2010 level 2 classifications in Figure 18, with an enlargement of the International Falls/Fort Frances area in Figure 19 and 20.

Figure 17. Lake of the Woods/Rainy River Basin level 2 land cover classification legend.

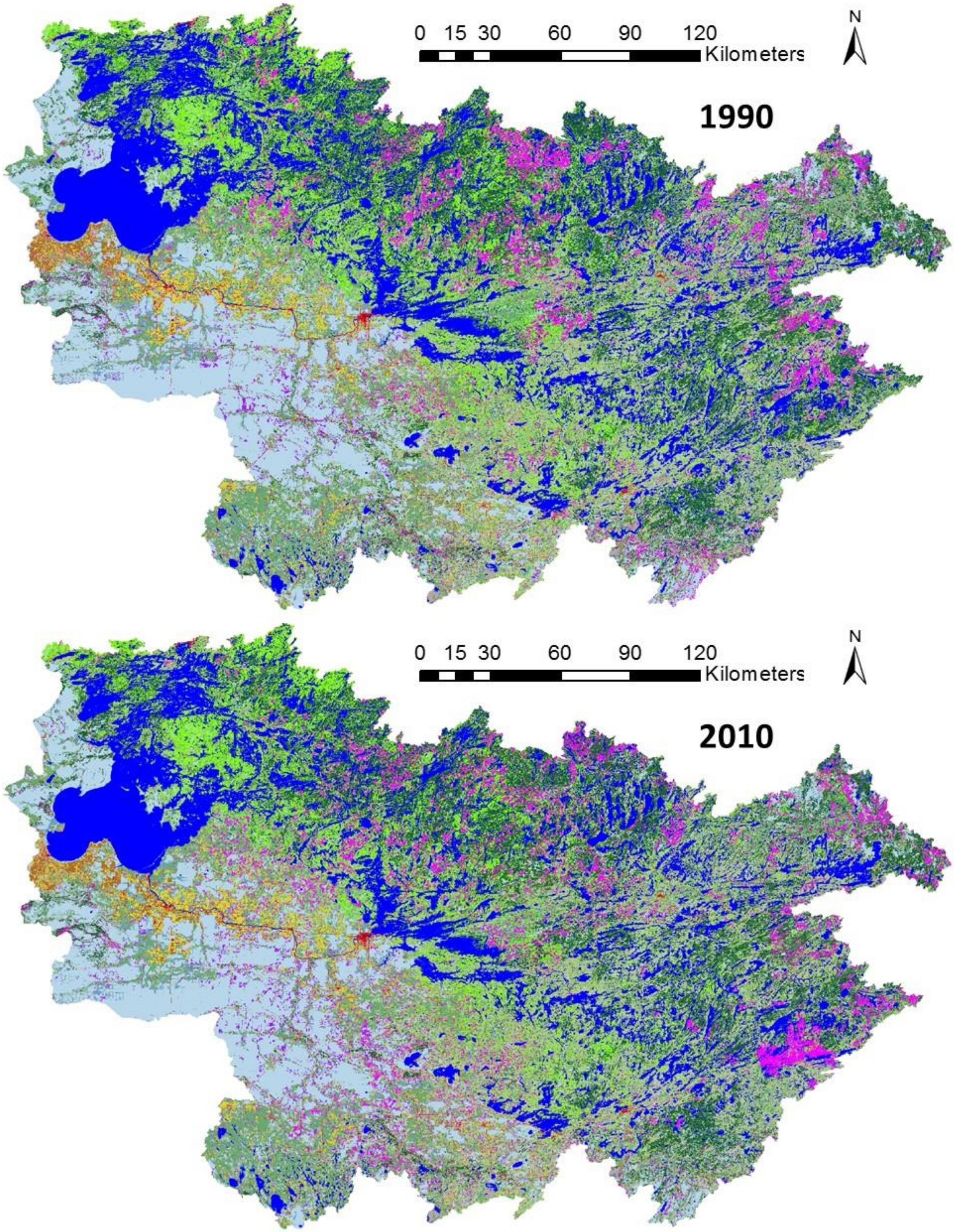


Figure 18. 1990 and 2010 Lake of the Woods/Rainy River Basin level 2 land cover classification.

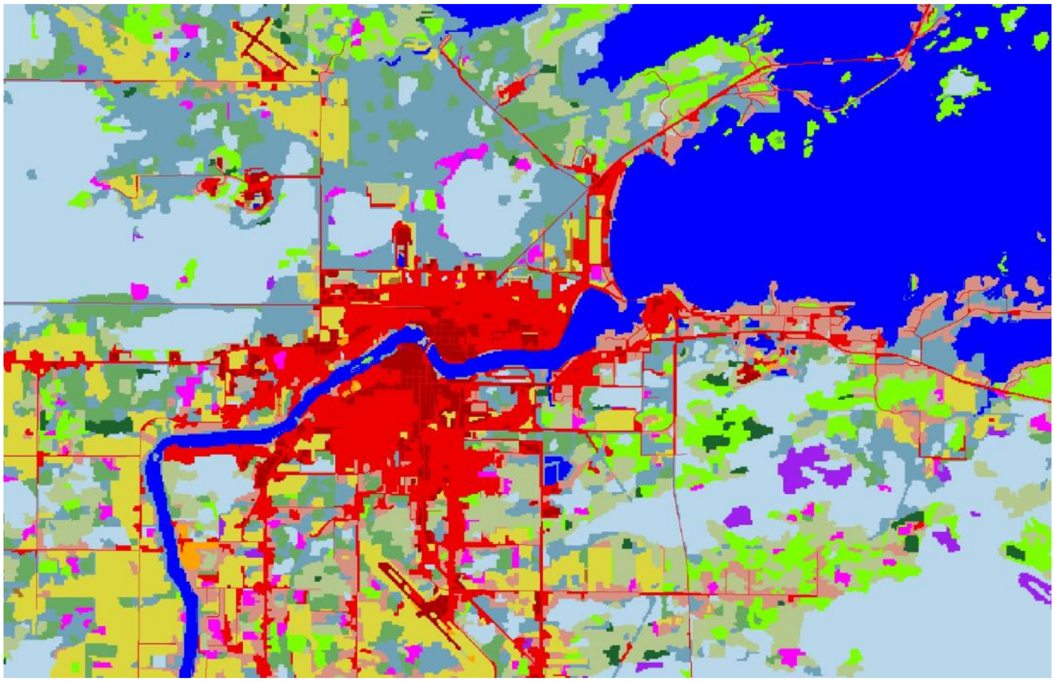


Figure 19. 1990 International Falls/Fort Frances area level 2 land cover classification. The legend is shown in figure 16.

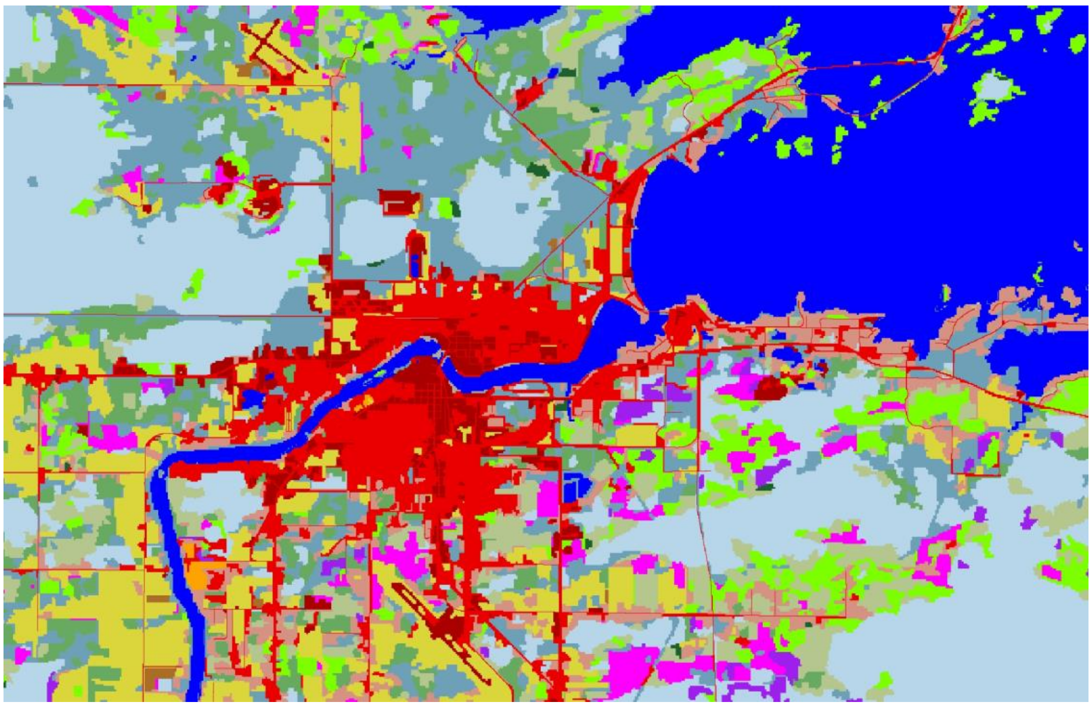


Figure 20. 2010 International Falls/Fort Frances area level 2 land cover classification. The legend is shown in figure 16.

Figure 21. Bing Maps high resolution color image of the International Falls/Fort Frances area for comparison to the classification.

Qualitatively, the Landsat/lidar classification (Figures 18, 19 and 20) compared to the high resolution image in Figure 21, shows a high correspondence between the two. Quantitative assessment of the classification accuracy for levels 1 and 2 with and without lidar data by Landsat path is shown in Table 3. Quantitative assessments of the classification accuracy for level 1 with and without lidar data for 1990 are shown in Tables 4 and 5, respectively, 2010 in Tables 6 and 7, and for level 2 1990 in Table 8 and 9, and 2010 Tables 10 and 11. On average both are greater than 90 percent accurate, with an expected higher accuracy for the fewer, more general level 1 classes. The difference, however, is smaller than our previous experience with per pixel maximum likelihood classifications. We attribute this to the use of the object-based classification, random forest classifier and the inclusion of lidar data features. Also the Minnesota classification using lidar data also had an expected higher accuracy.

Table 3. Overall accuracies (percent) for level 1 and 2 classifications and by Landsat path with and without lidar data.

	Class. Acc. with Lidar (%)				Class. Acc. without Lidar (%)			
	Level 1		Level 2		Level 1		Level 2	
Path	1990	2010	1990	2010	1990	2010	1990	2010
26	98.8	98.8	92.2	94.1	97.4	97.4	90.1	92.8
27	97.6	98.3	94.6	94.7	96.3	97.0	92.4	93.9
28	97.8	98.7	95.3	96.3	96.4	96.6	94.1	94.4
29	92.0	94.8	87.9	89.5	92.0	93.1	86.4	87.8
Mean	**96.5**	**97.7**	**92.5**	**93.6**	**95.5**	**96.0**	**90.7**	**92.2**

Table 4. Classification error matrix and accuracies (percent) for 1990 level 1 with lidar data.

	Objects Classified As						Ref.	
Ref. Class	Agriculture	Extraction	Forest	Open water	Developed	Wetlands	Total	Prod. Acc (%)
Agriculture	278	0	1	0	7	2	288	96.5
Extraction	1	43	1	0	1	0	46	93.5
Forest	4	0	1142	0	43	17	1206	94.7
Open water	0	0	1	182	0	0	183	99.5
Developed	8	0	12	0	1301	8	1329	97.9
Wetlands	2	0	18	1	1	1154	1176	98.1
Class. total	293	43	1175	183	1353	1181	4228	
User Acc. (%)	94.9	100.0	97.2	99.5	96.2	97.7		**97.0** Overall

Table 5. Classification error matrix and accuracies (percent) for 1990 level 1 without lidar data.

	Objects Classified As						Ref.	
Ref. Class	Agriculture	Extraction	Forest	Open water	Developed	Wetlands	Total	Prod. Acc (%)
Agriculture	354	2	5	0	19	7	387	91.5
Extraction	2	40	2	1	3	0	48	83.3
Forest	6	3	2139	1	30	43	2222	96.3
Open water	0	0	0	301	0	5	306	98.4
Developed	22	1	56	0	1608	17	1704	94.4
Wetlands	4	0	49	5	1	1884	1943	97.0
total	388	46	2251	308	1661	1956	6610	
User Acc. (%)	91.2	87.0	95.0	97.7	96.8	96.3		**95.7** Overall

Table 6. Classification error matrix and accuracies (percent) for 2010 level 1 with lidar data.

	Objects Classified As						Ref.	
Ref. Class	Agriculture	Extraction	Forest	Open water	Developed	Wetlands	Total	Prod. Acc. (%)
Agriculture	254	0	1	0	8	2	265	95.8
Extraction	2	88	0	0	6	0	96	91.7
Forest	1	0	1041	0	4	17	1063	97.9
Open water	0	0	0	199	0	0	199	100.0
Developed	10	1	3	0	1423	8	1445	98.5
Wetlands	2	0	19	0	1	1138	1160	98.1
total	269	89	1064	199	1442	1165	4228	
User Acc. (%)	94.4	98.9	97.8	100.0	98.7	97.7		**98.0** Overall

Table 7. Classification error matrix and accuracies for 2010 level 1 without lidar data.

	Objects Classified As						Ref.	
Ref. Class	Agriculture	Extraction	Forest	Open water	Developed	Wetlands	Total	Prod. Acc (%)
Agriculture	343	2	3	0	20	7	375	91.5
Extraction	3	90	1	1	6	0	101	89.1
Forest	2	0	2015	0	7	42	2066	97.5
Open water	0	0	0	343	0	3	346	99.1
Developed	25	4	54	0	1717	19	1819	94.4
Wetlands	4	0	49	3	1	1846	1903	97.0
total	377	96	2122	347	1751	1917	6610	
User Acc. (%)	91.0	93.8	95.0	98.8	98.1	96.3		**96.1** Overall

Table 8. Classification error matrix and accuracies (percent) for 1990 level 2 with lidar data.

	Objects Classified As																	
Ref. Class	Dev_grass	Dev_high	Dev_low	Dev_med	Dev_road	Extraction	Forest_con	Forest_dec	Forest_mix	Hay/pasture	Open water	Reg/Forest	Reg/For/wet	Row crop	Sand bar	Wet_herb	Wet_woody	Total	Prod. Acc. (%)
Dev_grass	94	1	8	2	0	0	0	0	8	4	0	0	0	0	0	0	0	117	80.3
Dev_high	0	22	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	27	81.5
Dev_low	2	0	624	8	4	0	0	0	2	2	0	0	0	0	0	0	2	644	96.9
Dev_med	1	5	10	175	1	0	0	0	0	0	0	0	0	0	0	1	0	193	90.7
Dev_road	0	0	4	0	334	0	0	0	1	1	0	1	0	0	0	5	0	346	96.5
Extraction	0	0	0	1	0	43	0	0	1	1	0	0	0	0	0	0	0	46	93.5
Forest_con	0	0	0	0	0	0	210	0	18	0	0	0	0	0	0	0	7	235	89.4
Forest_dec	0	0	0	0	0	0	0	146	5	1	0	5	0	0	0	1	0	158	92.4
Forest_mix	1	1	36	3	0	0	28	6	549	1	0	1	0	2	0	2	2	632	86.9
Hay/pasture	1	0	6	0	0	0	0	0	0	205	0	0	0	11	0	1	0	224	91.5
Open water	0	0	0	0	0	0	1	0	0	0	182	0	0	0	0	0	0	183	99.5
Reg/Forest	0	0	2	0	0	0	4	6	1	0	0	163	4	0	0	0	1	181	90.1
Reg/For/wet	0	0	0	0	0	0	1	0	1	0	0	2	116	0	0	0	4	124	93.5
Row crop	0	0	0	0	0	0	0	0	1	8	0	0	0	54	0	0	1	64	84.4
Sand bar	0	0	0	0	0	0	0	0	0	0	1	0	0	0	18	0	0	19	94.7
Wet_herb	0	0	0	1	0	0	0	1	2	2	0	1	0	0	0	272	6	285	95.4
Wet_woody	0	0	0	0	0	0	5	0	5	0	0	0	0	0	0	4	734	748	98.1
Total	99	29	690	195	339	43	249	159	594	225	183	173	120	67	18	286	757	4226	
User Acc. (%)	94.9	75.9	90.4	89.7	98.5	100.0	84.3	91.8	92.4	91.1	99.5	94.2	96.7	80.6	100.0	95.1	97.0		**93.3**
																			Overall

Table 9. Classification error matrix and accuracies (percent) for 1990 level 2 without lidar data.

	Objects Classified As																	
level 2 1990	Dev_grass	Dev_high	Dev_low	Dev_med	Dev_road	Extraction	Forest_con	Forest_dec	Forest_mix	Hay/pasture	Open water	Reg/Forest	Reg/For/wet	Row crop	Sand bar	Wet_herb	Wet_woody	Total	Prod. Acc. (%)
Dev_grass	103	1	0	2	0	0	0	0	9	10	0	0	0	0	0	0	1	126	81.7
Dev_high	0	31	0	10	0	0	0	0	0	1	0	0	0	2	0	0	0	44	70.5
Dev_low	2	0	716	20	4	0	20	0	18	6	0	2	0	0	0	6	4	798	89.7
Dev_med	0	6	8	227	3	0	0	0	2	1	0	0	0	0	0	0	0	247	91.9
Dev_road	0	0	6	0	469	1	0	1	3	2	0	1	0	0	0	5	1	489	95.9
Extraction	1	1	0	1	0	40	0	0	2	2	1	0	0	0	0	0	0	48	83.3
Forest_con	0	0	0	0	0	0	624	2	33	0	0	4	0	0	0	0	12	675	92.4
Forest_dec	0	0	0	0	0	0	3	197	13	1	0	3	0	0	0	0	1	218	90.4
Forest_mix	1	0	20	7	0	3	77	15	800	2	1	4	0	3	0	7	15	955	83.8
Hay/pasture	3	0	14	0	1	1	0	0	2	269	0	2	0	9	0	4	1	306	87.9
Open water	0	0	0	0	0	0	0	0	0	0	301	0	0	0	2	3	0	306	98.4
Reg/Forest	0	0	2	0	0	0	4	3	4	0	0	353	5	0	0	1	2	374	94.4
Reg/For/wet	0	0	0	0	0	0	0	0	0	0	0	7	112	0	0	1	4	124	90.3
Row crop	0	0	0	1	0	1	1	0	0	8	0	0	0	68	0	1	1	81	84.0
Sand bar	0	0	0	0	0	0	0	0	0	0	2	0	0	0	70	0	0	72	97.2
Wet_herb	0	0	0	1	0	0	3	1	5	4	3	2	0	0	0	579	16	614	94.3
Wet_woody	0	0	0	0	0	0	19	1	10	0	0	1	2	0	0	13	1087	1133	95.9
Total	110	39	766	269	477	46	751	220	901	306	308	379	119	82	72	620	1145	6610	
User Acc. (%)	93.6	79.5	93.5	84.4	98.3	87.0	83.1	89.5	88.8	87.9	97.7	93.1	94.1	82.9	97.2	93.4	94.9		**91.5**
																			Overall

Table 10. Classification error matrix and accuracies (percent) for 2010 level 2 with lidar data.

	Objects Classified As																	
Ref. Class	Dev_grass	Dev_high	Dev_low	Dev_med	Dev_road	Extraction	Forest_con	Forest_dec	Forest_mix	Hay/pasture	Open water	Reg/Forest	Reg/For/wet	Row crop	Sand bar	Wet_herb	Wet_woody	Total	Prod. Acc.(%)
Dev_grass	87	0	6	1	0	0	0	0	0	4	0	0	0	0	0	0	0	98	88.8
Dev_high	0	76	4	9	0	0	0	0	0	1	0	0	0	1	0	0	0	91	83.5
Dev_low	2	0	657	9	4	0	0	0	1	3	0	0	0	0	0	0	2	678	96.9
Dev_med	1	8	23	193	1	1	0	0	0	0	0	0	0	0	0	1	0	228	84.6
Dev_road	0	1	4	0	337	0	1	0	1	1	0	0	0	0	0	5	0	350	96.3
Extraction	0	3	2	1	0	88	0	0	0	1	0	0	0	1	0	0	0	96	91.7
Forest_con	0	0	0	0	0	0	219	0	18	0	0	0	0	0	0	0	3	240	91.3
Forest_dec	0	0	0	0	0	0	0	124	6	0	0	1	0	0	0	0	1	132	93.9
Forest_mix	0	0	4	0	0	0	21	9	373	0	0	0	0	0	0	1	4	412	90.5
Hay/pasture	1	0	7	0	0	0	1	0	0	181	0	0	0	8	0	1	0	199	91.0
Open water	0	0	0	0	0	0	0	0	0	0	199	0	0	0	0	0	0	199	100.0
Reg/Forest	0	0	0	0	0	0	0	0	1	1	0	269	6	0	0	2	0	279	96.4
Reg/For/wet	0	0	0	0	0	0	0	0	0	0	0	6	293	0	0	0	4	303	96.7
Row crop	0	0	0	0	0	0	0	0	0	3	0	0	0	62	0	0	1	66	93.9
Sand bar	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	3	66.7
Wet_herb	0	0	0	1	0	0	0	2	2	2	0	0	1	0	0	272	5	285	95.4
Wet_woody	0	0	0	0	0	0	4	0	4	0	0	0	1	0	0	4	556	569	97.7
Total	91	88	707	214	342	89	246	135	406	197	199	277	301	72	2	286	576	4228	
User Acc. (%)	95.6	86.4	92.9	90.2	98.5	98.9	89.0	91.9	91.9	91.9	100.0	97.1	97.3	86.1	100.0	95.1	96.5		94.3

Table 11. Classification error matrix and accuracies (percent) for 2010 level 2 without lidar data.

	Objects Classified As																	
Ref. Class	Dev_grass	Dev_high	Dev_low	Dev_med	Dev_road	Extraction	Forest_con	Forest_dec	Forest_mix	Hay/pasture	Open water	Reg/Forest	Reg/For/wet	Row crop	Sand bar	Wet_herb	Wet_woody	Total	Prod. Acc. (%)
Dev_grass	97	0	0	2	0	0	0	0	0	9	0	0	0	0	0	0	1	109	89.0
Dev_high	0	85	0	16	0	3	0	0	0	2	0	0	0	2	1	0	0	109	78.0
Dev_low	2	0	734	21	4	0	24	0	20	9	0	3	0	0	0	6	5	828	88.6
Dev_med	0	9	12	252	3	0	0	0	1	1	0	1	0	0	0	0	0	279	90.3
Dev_road	0	1	6	0	473	1	0	1	3	2	0	1	0	0	0	5	1	494	95.7
Extraction	1	2	2	1	0	90	0	0	1	2	1	0	0	1	0	0	0	101	89.1
Forest_con	0	0	0	0	0	0	646	0	10	0	0	2	0	0	0	0	12	670	96.4
Forest_dec	0	0	0	0	0	0	4	164	10	1	0	0	0	0	0	1	1	181	90.6
Forest_mix	0	0	6	0	0	0	56	13	604	1	0	2	1	0	0	2	16	701	86.2
Hay/pasture	3	0	12	0	1	1	1	0	1	263	0	0	0	7	0	4	1	294	89.5
Open water	0	0	0	0	0	0	0	0	0	0	343	0	0	0	0	3	0	346	99.1
Reg/Forest	0	1	0	0	0	0	3	2	5	0	0	494	3	0	0	5	1	514	96.1
Reg/For/wet	0	0	0	0	0	0	0	0	0	0	0	9	288	0	0	1	3	301	95.7
Row crop	0	1	2	1	0	1	1	0	0	2	0	0	0	71	0	1	1	81	87.7
Sand bar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	32	100.0
Wet_herb	0	0	0	1	0	0	1	2	5	4	3	3	4	0	0	579	12	614	94.3
Wet_woody	0	0	0	0	0	0	16	3	8	0	0	2	2	0	0	13	912	956	95.4
Total	103	99	774	294	481	96	752	185	668	296	347	517	298	81	33	620	966	6610	
User Acc. (%)	94.2	85.9	94.8	85.7	98.3	93.8	85.9	88.6	90.4	88.9	98.8	95.6	96.6	87.7	97.0	93.4	94.4		92.7

Table 12. 1990 area (hectares) summary of Level 2 classes by sub-basin and total Lake of the Woods/Rainy River Basin.

Sub-basin	Big Fork River	Big Turtle River	Lake of the Woods	Little Fork River	Lower Rainy	Rainy Headwaters	Rainy Lake	Rapid River	Shoal Lake	Vermilion River	Basin Total Ha
Developed high density	98	17	333	148	693	122	493	185	9	39	2,137
Developed medium density	897	16	1,748	894	5,188	420	860	732	73	163	10,990
Developed low density	5,166	1,014	16,187	5,831	4,331	1,135	3,421	968	802	3,725	42,580
Developed managed Grass	103	1	62	199	274	205	91	15	42	120	1,114
Developed roads	5,145	1,485	4,245	5,253	4,908	4,426	4,268	973	221	2,453	33,377
Extraction	15	9	230	3,918	101	1,406	180	87	1	588	6,535
Row Crops & Small Grains	96	0	21,732	66	6,690	0	25	588	7	0	29,205
Hay & Pasture	15,006	78	18,431	17,086	63,350	710	4,665	8,029	21	2,303	129,678
Coniferous Forest	19,732	203,159	177,333	40,826	11,209	343,130	237,441	4,558	17,368	21,879	1,076,634
Deciduous Forest	120,818	4,526	58,527	72,208	43,440	40,705	58,438	20,573	411	15,778	435,424
Mixed Forest	59,435	88,002	74,056	116,746	23,315	555,906	279,511	4,308	6,085	94,941	1,302,306
Sparse Forest	5,553	95,608	236,567	12,446	8,489	118,915	151,783	605	18,795	31,695	680,455
Regenerating Forest	10,206	61,864	43,700	20,520	9,101	74,646	84,106	2,919	145	12,584	319,792
Lakes & Ponds	24,354	123,165	460,033	11,214	4,022	291,192	248,452	22	29,902	35,124	1,227,481
Herbaceous Wetlands	42,879	20,388	72,812	38,043	41,067	76,598	77,561	23,862	6,005	15,934	415,147
Woody Wetlands	208,212	44,708	184,469	131,979	165,094	123,233	121,506	168,398	28,042	29,504	1,205,146
Regenerating Forested Wetland	14,500	11	3,449	7,248	5,971	931	1,533	7,536	3	785	41,967
Wetland/Sandbar	1	13	1,957	308	23	4	35	7	174	0	2,523
Total Hectares	532,215	644,066	1,375,872	484,933	397,265	1,633,683	1,274,369	244,365	108,108	267,616	6,962,492

Table 13. 1990 summary of percentage of Level 2 classes by sub-basin and total Lake of the Woods/Rainy River Basin.

Sub-basin	Big Fork River	Big Turtle River	Lake of the Woods	Little Fork River	Lower Rainy	Rainy Headwaters	Rainy Lake	Rapid River	Shoal Lake	Vermilion River	Class Total
High density	0.02	0.00	0.02	0.03	0.17	0.01	0.04	0.08	0.01	0.01	0.03
Medium density	0.17	0.00	0.13	0.18	1.31	0.03	0.07	0.30	0.07	0.06	0.16
Low density	0.97	0.16	1.18	1.20	1.09	0.07	0.27	0.40	0.74	1.39	0.61
Managed Grass	0.02	0.00	0.00	0.04	0.07	0.01	0.01	0.01	0.04	0.05	0.02
Roads	0.97	0.23	0.31	1.08	1.24	0.27	0.33	0.40	0.20	0.92	0.48
Extraction	0.00	0.00	0.02	0.81	0.03	0.09	0.01	0.04	0.00	0.22	0.09
Row Crops & Small Grains	0.02	0.00	1.58	0.01	1.68	0.00	0.00	0.24	0.01	0.00	0.42
Hay & Pasture	2.82	0.01	1.34	3.52	15.95	0.04	0.37	3.29	0.02	0.86	1.86
Coniferous Forest	3.71	31.54	12.89	8.42	2.82	21.00	18.63	1.87	16.07	8.18	15.46
Deciduous Forest	22.70	0.70	4.25	14.89	10.93	2.49	4.59	8.42	0.38	5.90	6.25
Mixed Forest	11.17	13.66	5.38	24.07	5.87	34.03	21.93	1.76	5.63	35.48	18.70
Sparse Forest	1.04	14.84	17.19	2.57	2.14	7.28	11.91	0.25	17.39	11.84	9.77
Regenerating Forest	1.92	9.61	3.18	4.23	2.29	4.57	6.60	1.19	0.13	4.70	4.59
Lakes & Ponds	4.58	19.12	33.44	2.31	1.01	17.82	19.50	0.01	27.66	13.12	17.63
Herbaceous Wetlands	8.06	3.17	5.29	7.84	10.34	4.69	6.09	9.76	5.55	5.95	5.96
Woody Wetlands	39.12	6.94	13.41	27.22	41.56	7.54	9.53	68.91	25.94	11.02	17.31
Regenerating Forested Wetland	2.72	0.00	0.25	1.49	1.50	0.06	0.12	3.08	0.00	0.29	0.60
Wetland/Sandbar	0.00	0.00	0.14	0.06	0.01	0.00	0.00	0.00	0.16	0.00	0.04
Percentage of LOW basin	7.64	9.25	19.76	6.96	5.71	23.46	18.30	3.51	1.55	3.84	100.00

Table 14. 2010 area (hectares) summary of Level 2 classes by sub-basin and total Lake of the Woods/Rainy River Basin.

Sub-basin	Big Fork River	Big Turtle River	Lake of the Woods	Little Fork River	Lower Rainy	Rainy Headwaters	Rainy Lake	Rapid River	Shoal Lake	Vermilion River	Basin Total
Developed high density	259	69	537	510	1,058	150	704	215	16	287	3,804
Developed medium density	922	16	1,756	923	5,276	426	896	733	73	207	11,227
Developed low density	5,229	1,014	16,664	5,864	4,362	1,162	3,466	976	802	3,793	43,334
Developed managed Grass	95	0	50	155	219	205	84	5	42	149	1,004
Developed roads	5,145	1,483	4,240	5,305	4,908	4,430	4,269	973	221	2,504	33,479
Extraction	17	23	288	4,264	104	1,446	207	87	1	889	7,326
Row Crops & Small Grains	369	1	20,335	318	8,051	0	90	1,326	5	4	30,500
Hay & Pasture	14,733	77	18,696	16,834	61,982	710	4,601	7,285	23	2,292	127,231
Coniferous Forest	13,505	208,104	178,029	28,284	5,539	337,126	232,771	4,040	16,032	21,912	1,045,341
Deciduous Forest	120,270	4,055	57,751	72,283	42,326	43,086	55,386	21,337	292	14,593	431,379
Mixed Forest	58,204	78,253	78,313	110,755	20,307	547,205	269,006	4,327	6,076	92,439	1,264,885
Sparse Forest	5,553	95,608	236,574	12,446	8,489	118,914	151,782	605	18,795	31,673	680,439
Regenerating Forest	17,969	67,076	39,883	38,200	18,466	86,864	102,020	2,631	1,601	15,526	390,236
Lakes & Ponds	24,356	123,178	461,570	11,506	4,045	291,197	248,485	29	30,069	35,125	1,229,561
Herbaceous Wetlands	42,878	20,388	72812	38,042	41,067	76,597	77,560	23,862	6,005	15,934	415,144
Woody Wetlands	202,832	41,822	185,802	123,004	160,609	122,279	118,996	16,828	28,033	28582	1,181,787
Regenerating Forested Wetland	19,880	2,898	2,116	16,224	10,457	1,885	4,043	6,106	13	1,706	65,326
Wetland/Sandbar	1	0	458	18	0	1	5	0	7	0	489
Total Hectares	532,215	644,066	1,375,872	484,933	397,265	1,633,683	1,274,369	244,365	108,108	267,616	6,962,492

Table 15. 2010 summary of percentage of Level 2 classes by sub-basin and total Lake of the Woods/Rainy River Basin.

Sub-basin	Big Fork River	Big Turtle River	Lake of the Woods	Little Fork River	Lower Rainy	Rainy Headwaters	Rainy Lake	Rapid River	Shoal Lake	Vermilion River	Class Total
High density	0.05	0.01	0.04	0.11	0.27	0.01	0.06	0.09	0.02	0.11	0.05
Medium density	0.17	0.00	0.13	0.19	1.33	0.03	0.07	0.30	0.07	0.08	0.16
Low density	0.98	0.16	1.21	1.21	1.10	0.07	0.27	0.40	0.74	1.42	0.62
Managed Grass	0.02	0.00	0.00	0.03	0.06	0.01	0.01	0.00	0.04	0.06	0.01
Roads	0.97	0.23	0.31	1.09	1.24	0.27	0.34	0.40	0.20	0.94	0.48
Extraction	0.00	0.00	0.02	0.88	0.03	0.09	0.02	0.04	0.00	0.33	0.11
Row Crops & Small Grains	0.07	0.00	1.48	0.07	2.03	0.00	0.01	0.54	0.01	0.00	0.44
Hay & Pasture	2.77	0.01	1.36	3.47	15.60	0.04	0.36	2.98	0.02	0.86	1.83
Coniferous Forest	2.54	32.31	12.94	5.83	1.39	20.64	18.27	1.65	14.83	8.19	15.01
Deciduous Forest	22.60	0.63	4.20	14.91	10.65	2.64	4.35	8.73	0.27	5.45	6.20
Mixed Forest	10.94	12.15	5.69	22.84	5.11	33.50	21.11	1.77	5.62	34.54	18.17
Sparse Forest	1.04	14.84	17.19	2.57	2.14	7.28	11.91	0.25	17.39	11.84	9.77
Regenerating Forest	3.38	10.41	2.90	7.88	4.65	5.32	8.01	1.08	1.48	5.80	5.60
Lakes & Ponds	4.58	19.13	33.55	2.37	1.02	17.82	19.50	0.01	27.81	13.13	17.66
Herbaceous Wetlands	8.06	3.17	5.29	7.84	10.34	4.69	6.09	9.76	5.55	5.95	5.96
Woody Wetlands	38.11	6.49	13.50	25.37	40.43	7.48	9.34	69.50	25.93	10.68	16.97
Regenerating Forested Wetland	3.74	0.45	0.15	3.35	2.63	0.12	0.32	2.50	0.01	0.64	0.94
Wetland/Sandbar	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
Percentage of LOW basin	7.64	9.25	19.76	6.96	5.71	23.46	18.30	3.51	1.55	3.84	100.00

With the finalized maps we tabulated the area and calculated percent of area by class at the sub-basin and total Lake of the Woods/Rainy River Basin for 1990 (Table 12 and 13 respectively) and 2010 (Table 14 and 15 respectively). The Lake of the Woods/Rainy River Basin is dominated by forest, wetlands and lakes which comprises 96.3 percent of the basin. Developed areas increases in the basin from 1.295 percent in 1990 to 1.334 percent in 2010. The most obvious changes are due to forest harvesting which is most apparent on the land cover maps (Figure 18) or the land change map (Figure 22). There were no changes from 1990 to 2010 for around 88 percent of the basin. While forests that have been harvested move around between the time periods there was also an increase to 5.6 percent of the basin in 2010 from 4.6 percent in 1990 that was detected.

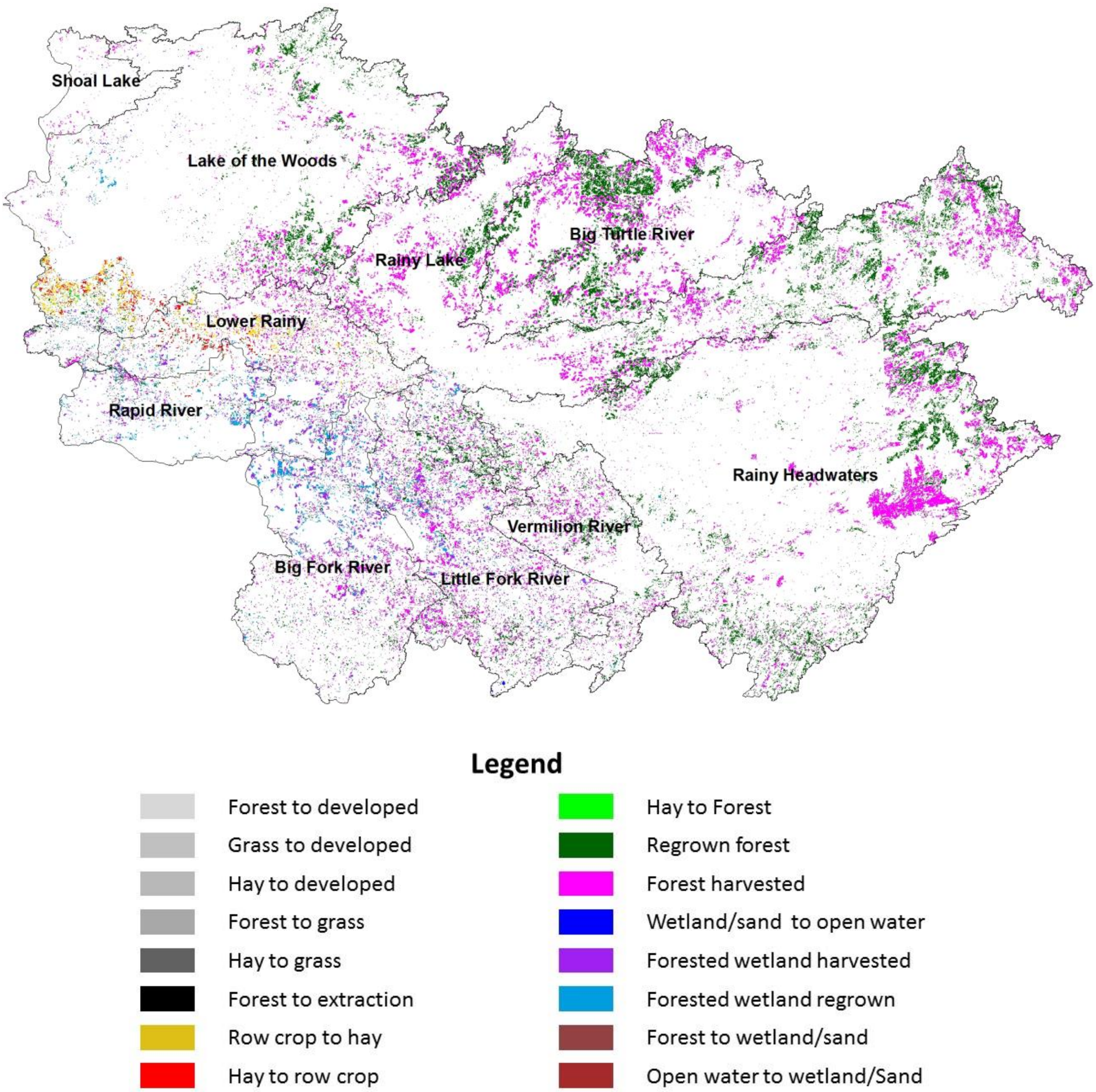


Figure 22. Land cover change from 1990 to 2010 for Lake of the Woods/Rainy River Basin the with sub-basin boundaries.

Table 16. Land cover change map 1990 to 2010 summary of percentage of change classes by sub-basin and total Lake of the Woods/Rainy River Basin.

Change	Code	Big Fork R.	Big Turtle R.	L. of the Woods	Little Fork R.	Lower Rainy	Rainy Head-waters	Rainy Lake	Rapid R.	Shoal Lake	Vermilion R.	Total
No change	0	88.15	79.52	92.21	82.76	86.52	89.93	84.92	91.79	98.21	88.28	87.80
Forest to developed	16	0.045	0.008	0.049	0.090	0.108	0.004	0.022	0.012	0.007	0.143	0.037
Grass to developed	17	0.001	0.000	0.001	0.009	0.014	0.000	0.001	0.004	0.000	0.010	0.002
Hay to developed	18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Forest to grass	19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.019	0.001
Hay to grass	20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Forest to extraction	29	0.000	0.002	0.004	0.071	0.001	0.002	0.002	0.000	0.000	0.112	0.011
Row crop to hay	38	0.000	0.000	0.567	0.001	0.964	0.000	0.001	0.016	0.001	0.000	0.168
Hay to row crop	39	0.051	0.000	0.466	0.053	1.307	0.000	0.006	0.318	0.000	0.002	0.187
Hay to Forest	47	0.000	0.000	0.082	0.000	0.002	0.000	0.000	0.002	0.000	0.000	0.016
Regrown forest	48	1.918	9.605	3.176	4.231	2.291	4.569	6.600	1.195	0.134	4.702	4.593
Forest harvested	49	3.376	10.414	2.899	7.877	4.648	5.317	8.006	1.077	1.481	5.802	5.605
Wetland/sand to open water	59	0.000	0.002	0.123	0.063	0.006	0.000	0.003	0.003	0.155	0.000	0.032
Forested wetland harvested	66	3.735	0.450	0.154	3.346	2.632	0.115	0.317	2.499	0.012	0.637	0.938
Forested wetland regrown	67	2.724	0.002	0.251	1.495	1.503	0.057	0.120	3.084	0.003	0.293	0.603
Forest to wetland/sand	68	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Open water to wetland/Sand	69	0.000	0.000	0.011	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.003

Summary

A combination of multitemporal Landsat data which providing synoptic views of the entire area and lidar data for the Minnesota portion along with object-based image analysis and the random forest classifier enabled accurate level 1 and 2 land cover classifications for the Lake of the Woods/Rainy River Basin for 1990 and 2010. The digital format of the classifications makes it possible to easily include them with other digital maps and data in a GIS for further analysis and modeling. The classification results have been provided to the Minnesota Pollution Control Agency as raster format tiff files and statistics. Maps and statistics in a web mapping application will also be available at http://land.umn.edu.

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