

An aerial photograph of a river winding through a vast, dense forest in British Columbia, Canada. The river is the central focus, meandering through the green landscape. The forest is a mix of various shades of green, suggesting different types of trees and vegetation. The overall scene is a natural, undisturbed wilderness.

AN ENHANCED WETLANDS CLASSIFICATION USING OBJECT-ORIENTED CLASSIFICATION METHODOLOGY: AN EXAMPLE FROM BRITISH COLUMBIA, CANADA.

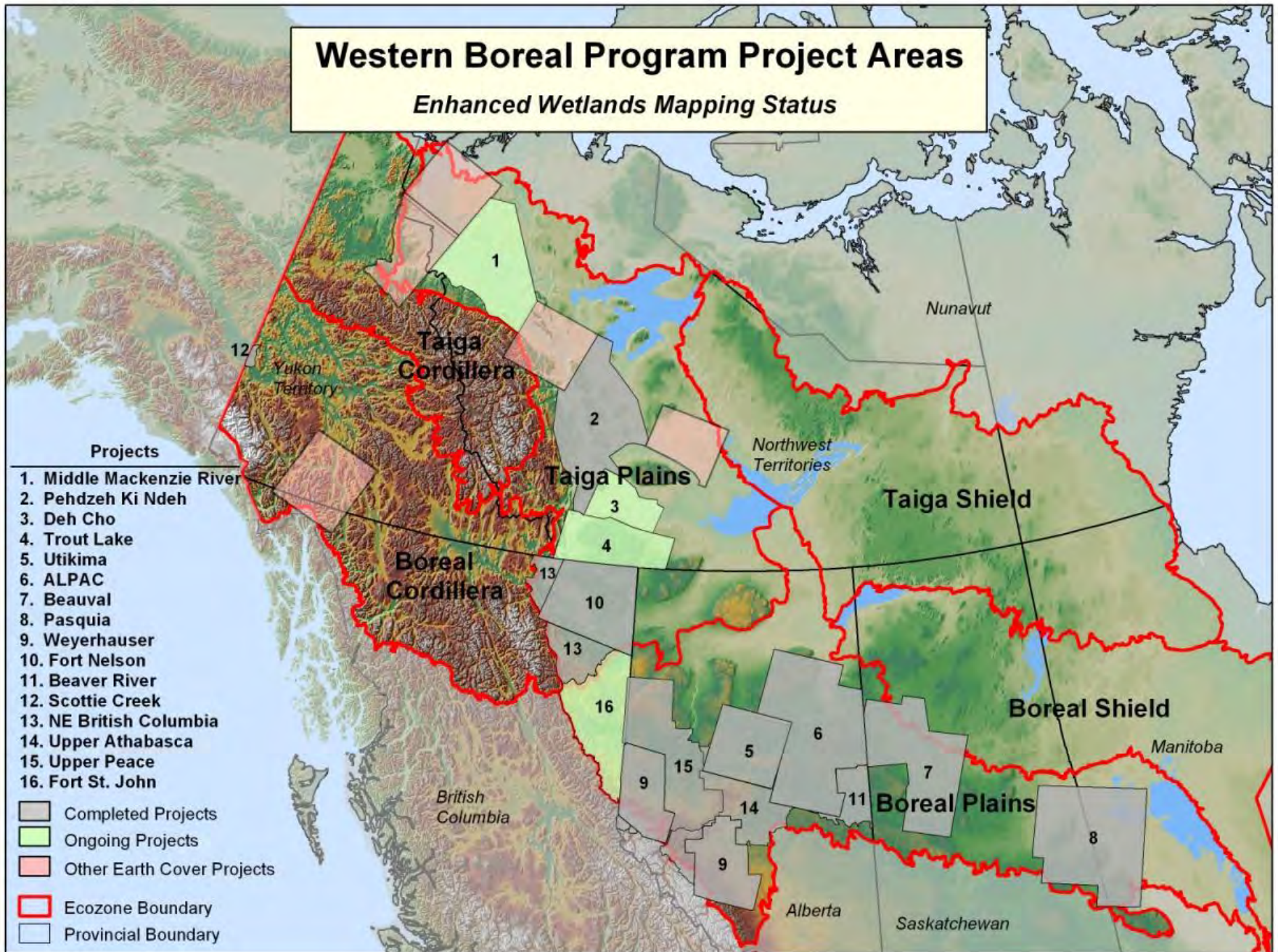
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² Ducks Unlimited Canada – Western Boreal Program

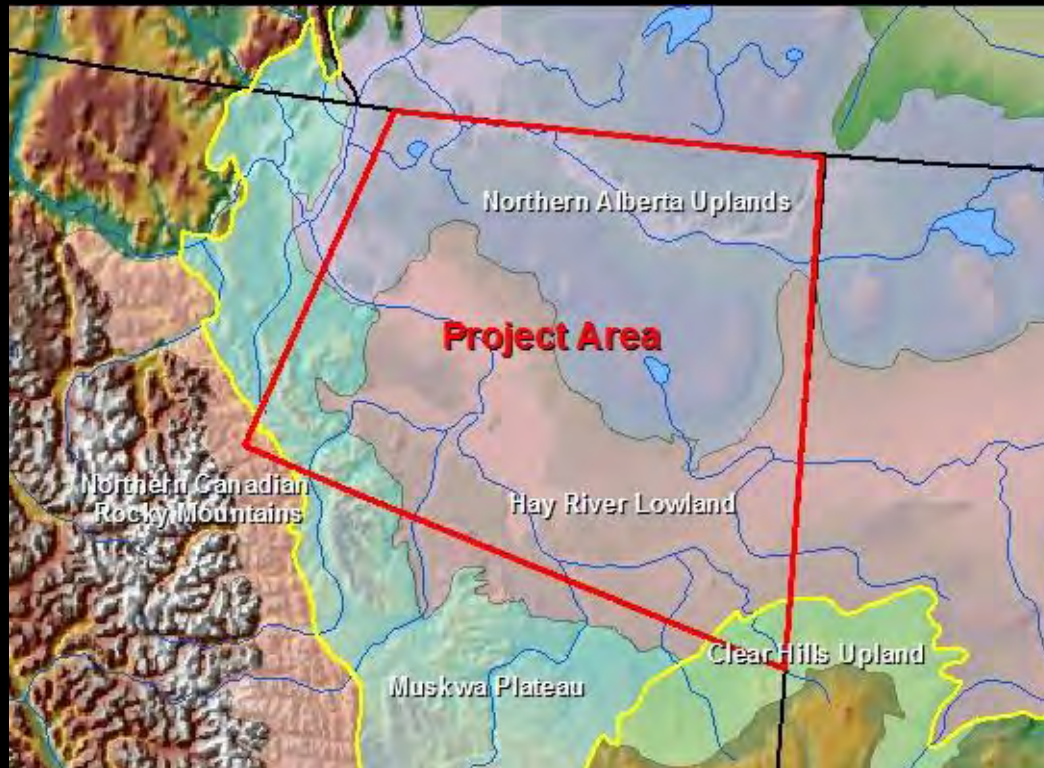
Western Boreal Program Project Areas

Enhanced Wetlands Mapping Status



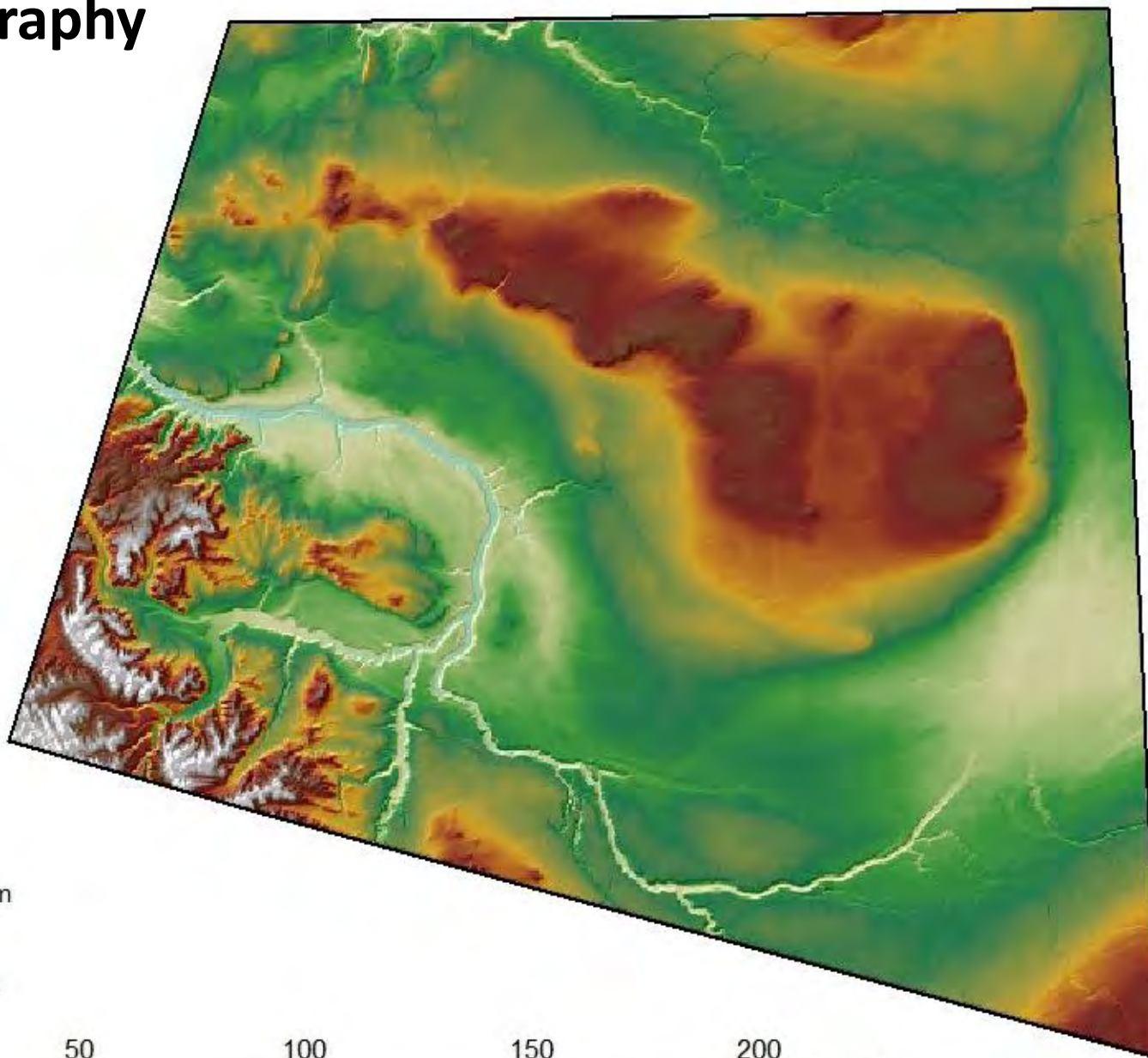


Fort Nelson project in relation to Ecozones.

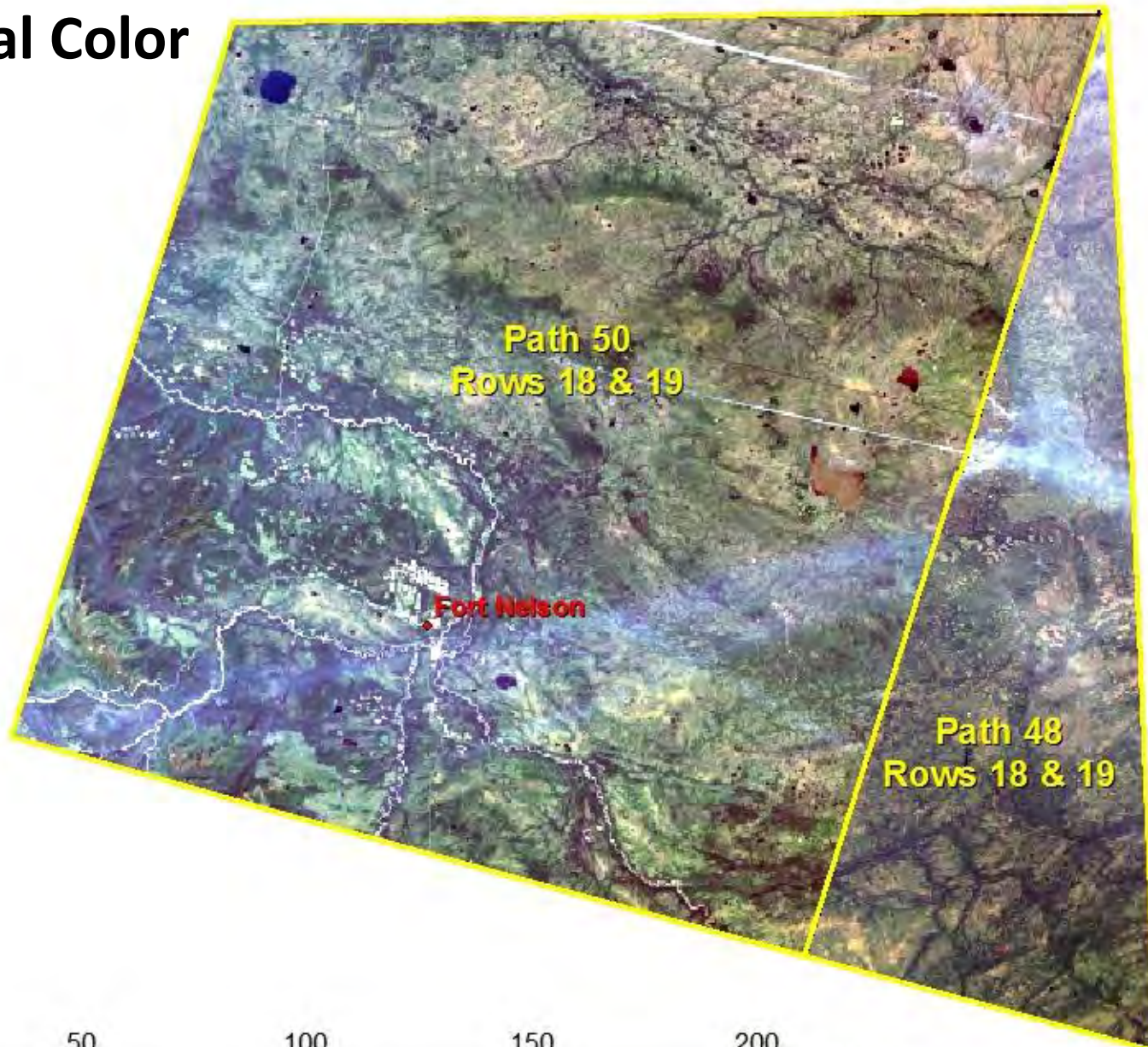


Ecoregions within the Fort Nelson project area.

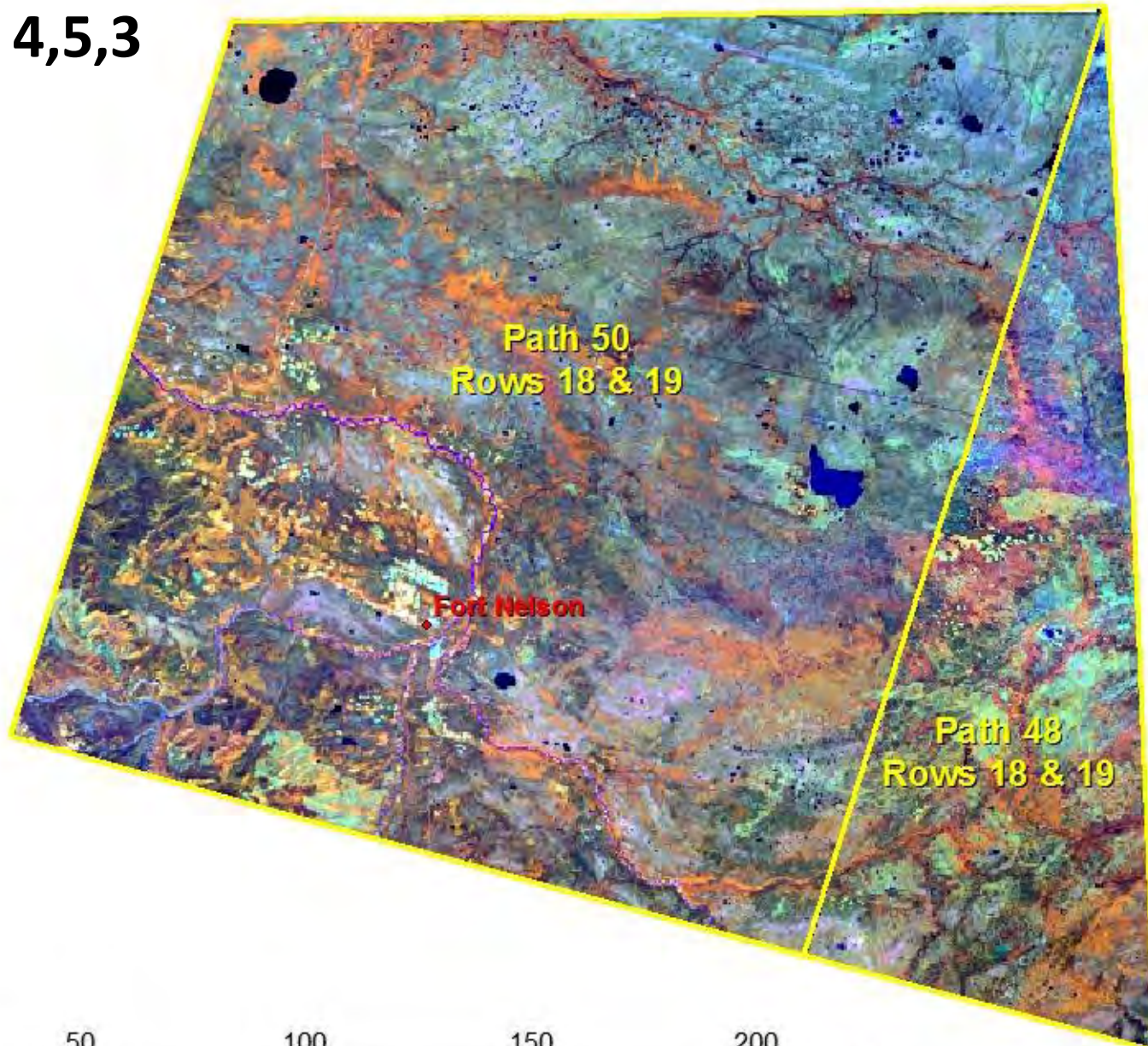
Topography



Natural Color

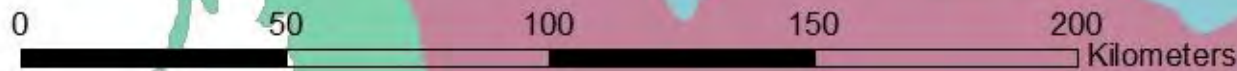
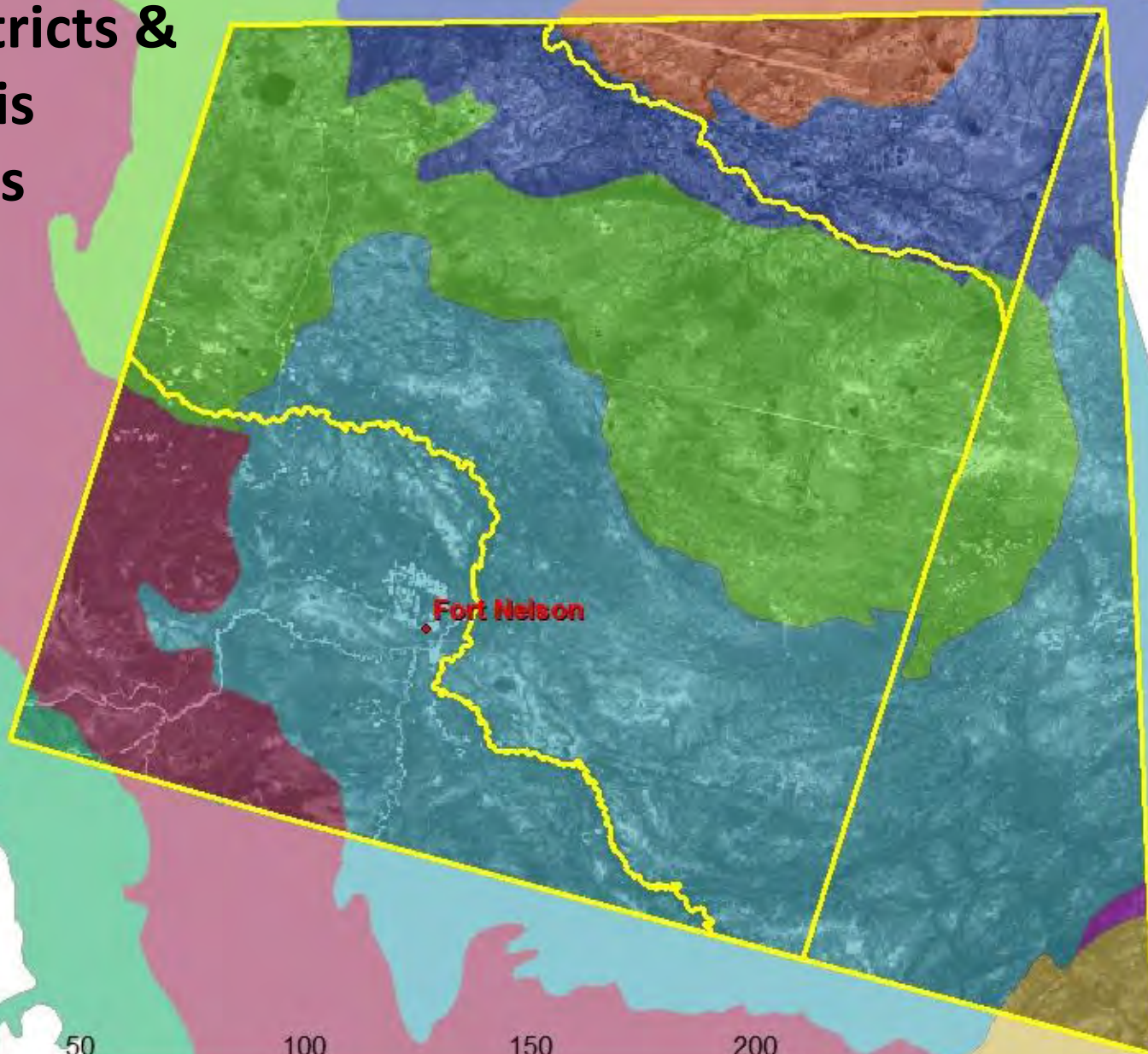


Bands 4,5,3

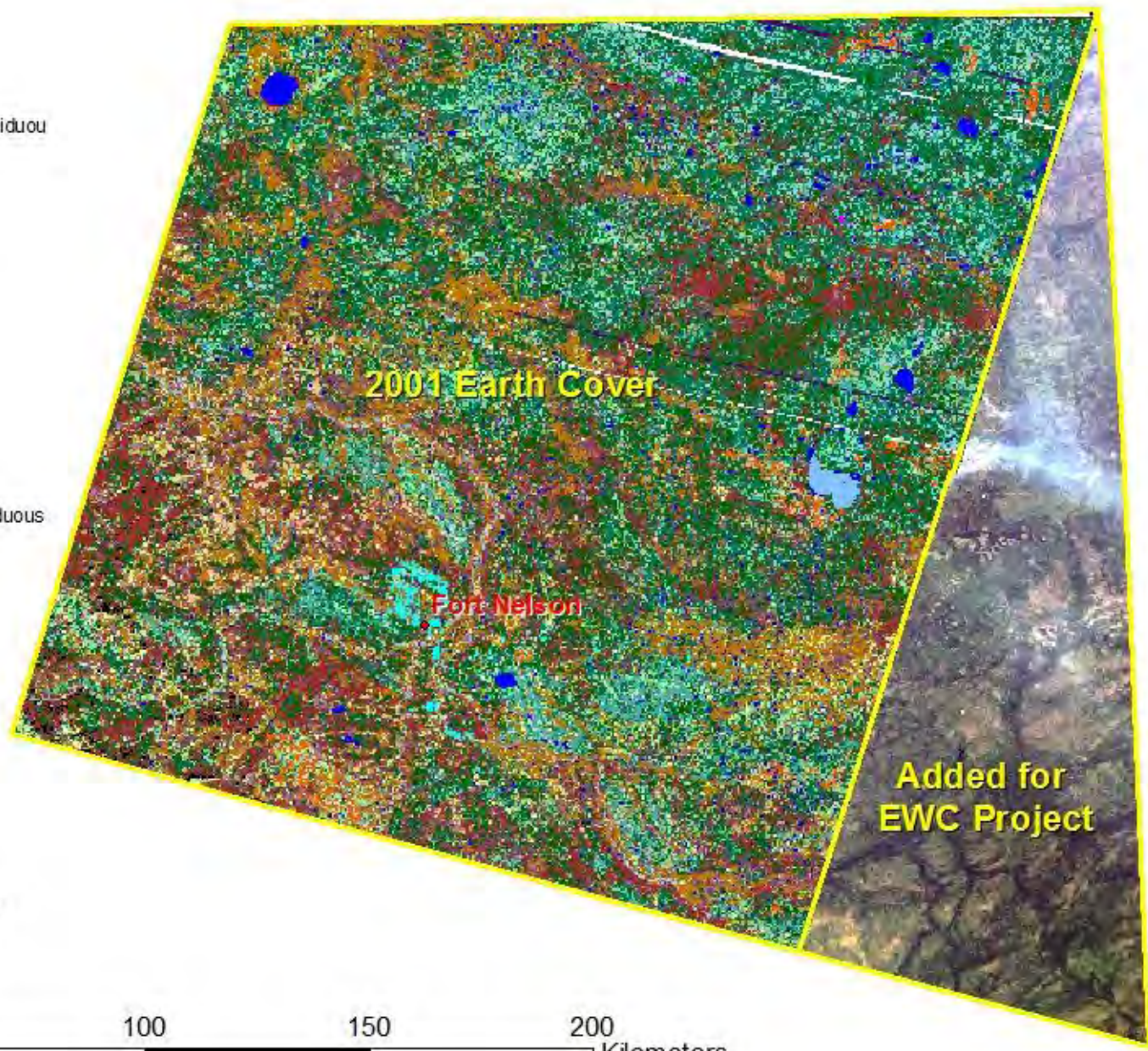


0 50 100 150 200 Kilometers

Ecodistricts & Analysis Regions



- Aquatic Bed
- Burn Veg. Regeneration
- Clear Water
- Closed Deciduous
- Closed Mixed Needleleaf/Deciduou
- Closed Needleleaf
- Cloud
- Cloud Shadow
- Cutblock-Forest Harvest
- Dwarf Shrub Moss
- Emergent Vegetation
- Low Shrub Other
- Moss
- Non-Vegetated Soil
- Open Deciduous
- Open Mixed Needleleaf/Deciduous
- Open Needleleaf-Moss
- Open Needleleaf-Other
- Other
- Rock/Gravel
- Sparse Vegetation
- Tall Shrub
- Terrain Shadow
- Turbid Water
- Urban
- Wet Graminoid
- Woodland Needleleaf-Lichen
- Woodland Needleleaf-Moss
- Woodland Needleleaf-Other



2001 Earth Cover

Fort Nelson

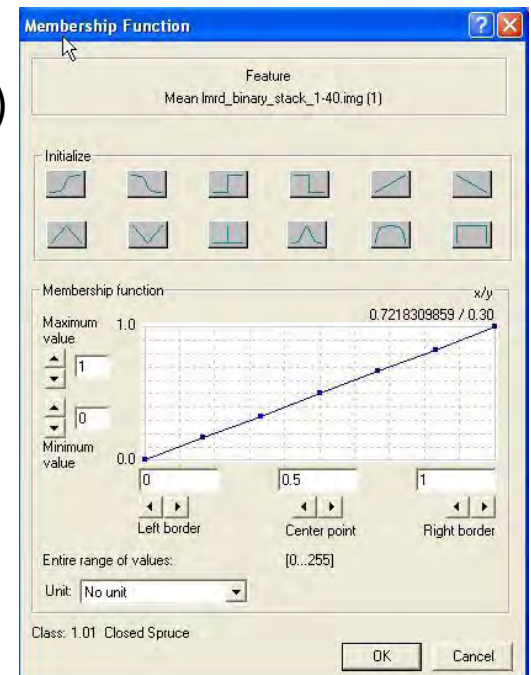
Added for
EWC Project



Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

Objective: To convert the Fort Nelson pixel-based classification created in Erdas Imagine to an object-based classification.

1. Convert the original pixel-based classification to a binary stack where each class is represented by a layer or band in the output image and each occurrence of the class within that layer is represented in binary format where 1 = presence of class X and 0 = not present.
2. In eCognition, segment on the TM image.
3. Add the binary stack to eCognition and set up a decision rule for each class where Class 1 = binary_stack.img (layer1) with a linear function.



Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

Method

Tried using the straight majority function to label the LMRD objects, but found instances where the majority class wasn't a good representative of the whole object. For example, consider an object with: 40% Closed Tall Shrub, 30% Open Spruce Lichen, 20% WNO, and 10% WNL. The straight majority is Closed Tall Shrub (40%), but 60% of the site is made up of forested classes.

To minimize this problem, a two-step method was developed in which each object was first given a majority general class label and then the majority earth cover class from among the assigned general class was applied as the final earth cover class label.

1. Converted `lmr_classification_recode1.img` to a 40 layer binary stack image using `7-2-07_new_model.gmd` (bands 1-20) and `7-2-07_new_model2.gmd` (bands 21-40). Appended the results to create `lmr_binary_stack1-40.img`
2. Recoded `lmr_classification_recode1.img` to general classes as follows to create `lmr_general2_classes.img`:

Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

Original Earth Cover Class	General Class
Closed Spruce Open Spruce Lichen Open Spruce Moss Open Spruce Other Closed Mixed Needleleaf Deciduous Open Mixed Needleleaf Deciduous Open Mixed Needeleaf Other Closed Birch Closed Poplar Woodland Needleleaf Lichen Woodland Needleleaf Moss Woodland Needleleaf Other	1. Forest
Closed Tall Shrub Open Tall Shrub Low Shrub Other Low Shrub Lichen Low Shrub / Alder Low Shrub Tussuck Tundra Dwarf Shrub Lichen Dwarf Shrub Other Tussock Tundra Tussock Tundra Lichen Lichen Mesic Dry Forb Mesic Dry Graminoid Meadow	2. Shrub/Herbaceous

Original Earth Cover Class	General Class
Wet Graminoid Wet Form Aquatic Bed Emergent Vegetation Clear Water Turbid Water	3. Water/Wetlands
Sparse Vegetation Rock Gravel Non-Vegetated Soil Urban Haze Snow Burn/ Regenerating Burn Other Shadow	4. Other

Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

3. Convert the recoded general map to a 4 band binary stack using 7-13-07_model_general2_class.gmd -> lmr_d_binary_stack_general2_class.img
4. Created new eCog project and segmented with the following parameters:
TM bands 3-6 (weight 1)
Scale 2.6 Color .9 Shape .1
Compactness .3 Smoothness .7
Save the eCog project as *area_base.dpr* – keep this base segmentation; will make copies of it to use for general and final majority classification, so all eCog projects for this area will have the same base segmentation.
5. Make a copy of *area_base.dpr* and save as *area_general2.dpr*.

Add the general binary stack (lmr_d_binary_stack_general2_class.img) to the eCognition project. This may take awhile.

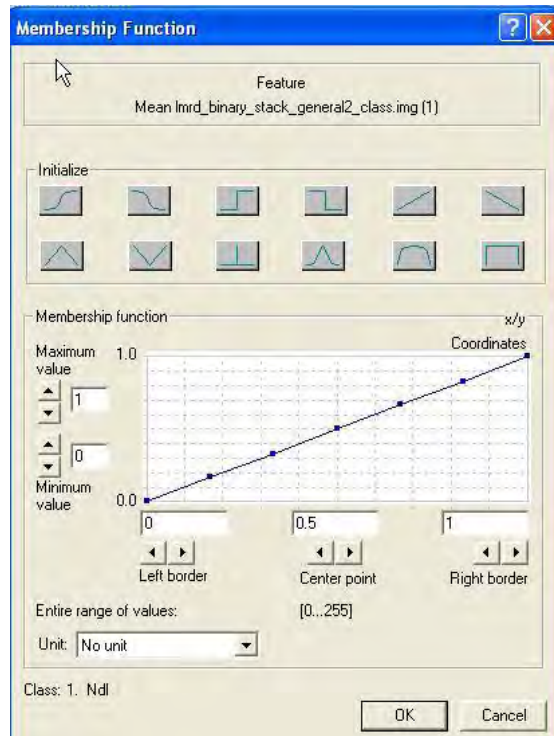
6. In *area_general2.dpr*, set up the class hierarchy (general2_class_hierarchy.dkb) as follows:



Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

Where:

1. Ndl = lmr_d_binary_stack_general2_classes.img (layer1) defined with a linear function as follows:



2. Shrub/Herbaceous = lmr_d_binary_stack_general2_classes.img (layer2), linear
3. Wet = lmr_d_binary_stack_general2_classes.img (layer3), linear
4. Other = lmr_d_binary_stack_general2_classes.img (layer4), linear

Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

7. Run the classification and export the results as a classification (Export -> Classification) -> *area_general2_classes.img*
Save and close *area_general2.dpr*
8. Make a copy of *area_base.dpr* and save it as *area_final2.dpr*
9. Open *area_final2.dpr* and import the general majority classification from step 7 (*area_general2_classes.img*).
Set up an alias for *area_general2_classes.img* called "general2_classes"
10. Add *lprd_binary_stack1-40.img* to *area_final2.dpr*. This will take quite some time.
11. Load the class hierarchy (*final2_hierarchy_alias.dkb*) or set it up as shown in Fig 3.
12. Run the classification. Export the results as image objects (if it's not too large) and as a classification. The image objects can be used to help identify and evaluate the objects that were unclassified. The classification will be stitched together with the final classifications from the other ecoregions to produce the final object-based map -> *lprd_earthcover_image_objects.img*

Fort Nelson Earth Cover Conversion from Pixel-based to Object-based

1. Ndl - mean general2_classes.img = 2
2. Shrub/Herb - general2_classes.img = 3
3. Wet - general2_classes.img = 4
4. Other - general2_classes.img = 5

Define each earth cover class as follows:

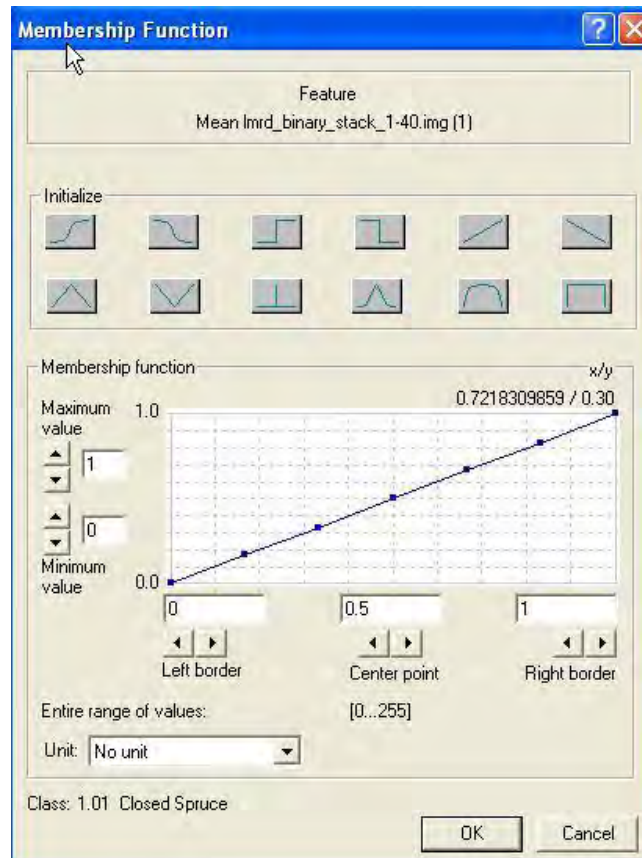
Ex: 1.01 Closed Spruce

Then add an Unclassified class to each general section where:

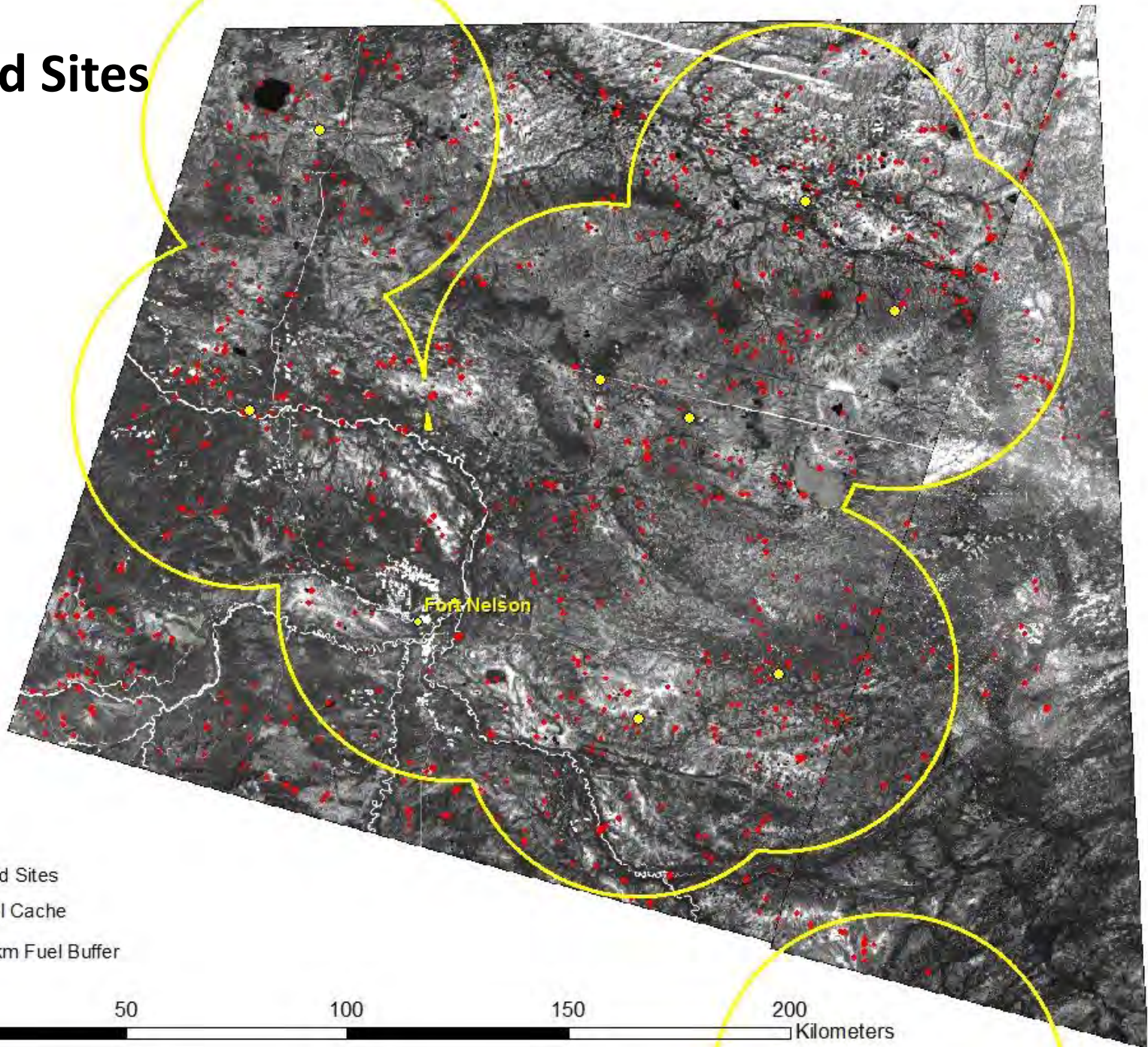
Unclassified = not classified as

1.01 Closed Spruce

And Not classified as 1.02 Open Spruce Lichen
Spruce Lichen
Etc.



Field Sites



■ Field Sites

◆ Fuel Cache

□ 40 km Fuel Buffer

0 50 100 150 200 Kilometers

Class	Count
Anthropogenic	4
Aquatic Bed	37
Burn	22
Conifer Swamp	45
Conifer Upland	104
Deciduous Upland	86
Emergent Marsh	43
Graminoid Poor Fen	25
Graminoid Rich Fen	26
Hardwood Swamp	48
Meadow Marsh	28
Mixedwood Swamp	25
Mixedwood Upland	61
Open Bog	8
Open Water	1
Shrubby Bog	23
Shrubby Poor Fen	3
Shrubby Rich Fen	43
Tamarack Swamp	1
Thicket Swamp	22
Treed Bog	62
Treed Poor Fen	70
Treed Rich Fen	10
Upland Other	7
TOTAL	804

General Classification

Three primary software packages were used for the image analysis:

1. Erdas **Imagine 2010** was used for the basic image processing tasks, such as subsetting and creating new data layers.
2. ESRI **ArcGIS 2010** was used to handle the GIS coverages and other ancillary datasets.
3. Object-oriented **eCognition** software was the primary image classifier. This software offers a number of advantages:
 - a) It allows for the processing of imagery datasets using a **region-based approach**;
 - b) It uses parameters such as **shape, color, texture, and contextual information** to aid in classification; and
 - c) It allows for the development of a **knowledge base** for the classification.

Due to the complexities of regional wetlands and imagery spectral response, several techniques were attempted, as no standardized technique would be applicable over the varying regions of the project. Therefore the classification methodology presented in the following sections is a generalized methodology. Individual processing areas had customized processing parameters and techniques.

General Classification

Generation of New Bands

The Landsat ETM+ imagery contained 8 bands of data: 1 panchromatic band, 3 visible bands, 1 near-infrared band, 2 mid-infrared bands, and 1 thermal band. The Landsat TM imagery has the same bands with the exception of the panchromatic band. The thermal band was not used in the classification, but several additional indices and transformations were used to help classify the imagery.

These included:

1. **Tasseled-cap** transformation,
2. Normalized Difference Vegetation Index (**NDVI**),
3. Normalized Difference Water Index (**NDWI**),
4. Enhanced Vegetation Index (**EVI**),
5. several **band ratios**, and
6. A six-band principal component analysis (**PCA**) of the Landsat imagery.

Segmentation

eCognition and object-oriented classification allows the analyst to create objects that:

1. have **inheritance** and **topology**,
2. capture features on the landscape while **minimizing noise-induced speckle**, and
3. provides a method for the semi-automated application of the analyst's **knowledge base**.

By using this object-oriented framework, the classification more accurately represents the analyst's interpretation of the imagery, which has been developed and supported through fieldwork.

Ultimately the classification is guided by the analyst, who has to be able to accurately interpret the imagery from his **knowledge base**. This knowledge is gained from

1. **experience** in the field,
2. the ability to **interpret** wetland signatures in satellite imagery,
3. a careful review of the **field site database**, and
4. an understanding of the **biogeochemical and ecological processes** (e.g. hydrology, geomorphology, climate, permafrost, nutrients, fire) that govern the formation of wetlands in the area.

Segmentation

The classification is built with:

1. **membership functions** designed to delineate general classes and
2. **interactive nearest neighbor** classification to fine tune separation between the detailed classes.
3. The final step in the classification is cleaning up missed areas through **manual classification**.

Throughout the segmentation and classification process this **knowledge base** is critical in determining objects of interest, guiding the classification, and manually editing for areas that spectral information alone could not separate wetland types.

The overall goal of the segmentation process is to create **image objects that are as large as possible but as small as necessary** to discriminate and map the enhanced wetland features.

The analyst guides the segmentation process using their **knowledge base** to maximize the **wetland class signal** from the imagery and **minimize the noise** caused by spectral variations in the imagery that do not correspond to different wetland classes.

Segmentation

For example, an **image object** needs to be **thin and narrow** to pull out a faint drainage feature from the imagery.

At the same time, **some image objects** also need to be **large and round** for homogenous areas.

Within the imagery, a **large area may be only one wetland class but it's spectrally signature will vary widely** based on slight variations in shrub understory, presence of water, or amount of litter present. This spectral variation that doesn't correspond to a change in wetland class is noise. In a **pixel-based process**, this noise can greatly affect the classification and **produce speckle** that does not correlate to wetland classes.

Segmentation

With object-based processing, the analyst uses spatial, spectral, and contextual information to derive the types of objects that will provide the building blocks for the classification. **The quality of these objects is very important for the classification.**

If the boundaries of the image objects are not representative of the shapes of the wetland areas (e.g. narrow drainage features), then classification of the wetland areas will in turn be difficult.

At the same time, objects need to be large in homogenous areas. The objects are able to filter out the spectral noise that doesn't correspond to change in wetland classes.

So the **image objects work to maximize the capture of the signal and reduce errors of omission and they work to minimize the noise of the imagery and reduce errors of commission.**

Segmentation

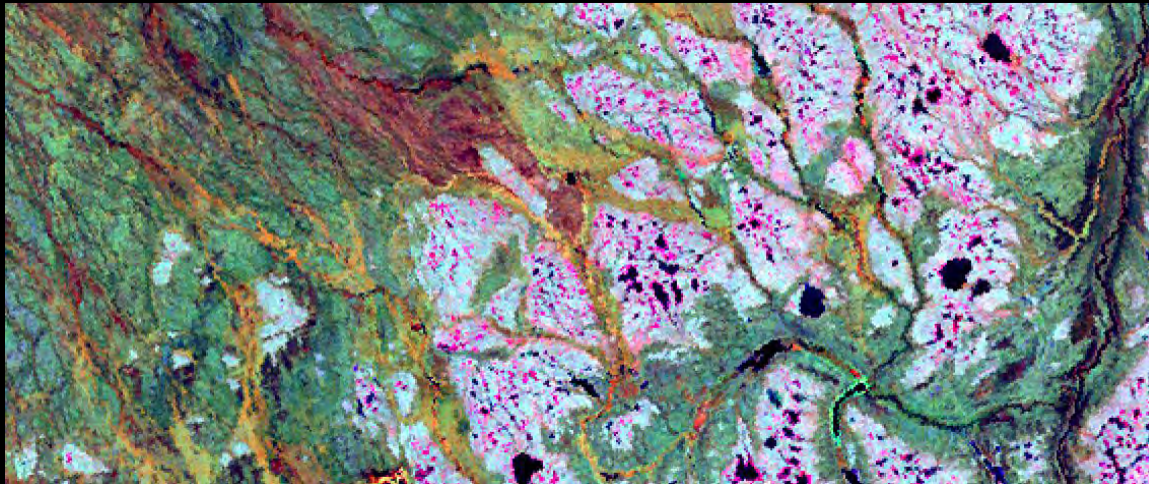
For each processing area,

1. the **six-band ETM+** image subset, excluding the panchromatic and thermal bands, was added to an eCognition project along with
2. the first three bands of the **principal components** image and
3. the **tasseled-cap** brightness/greenness/wetness image.

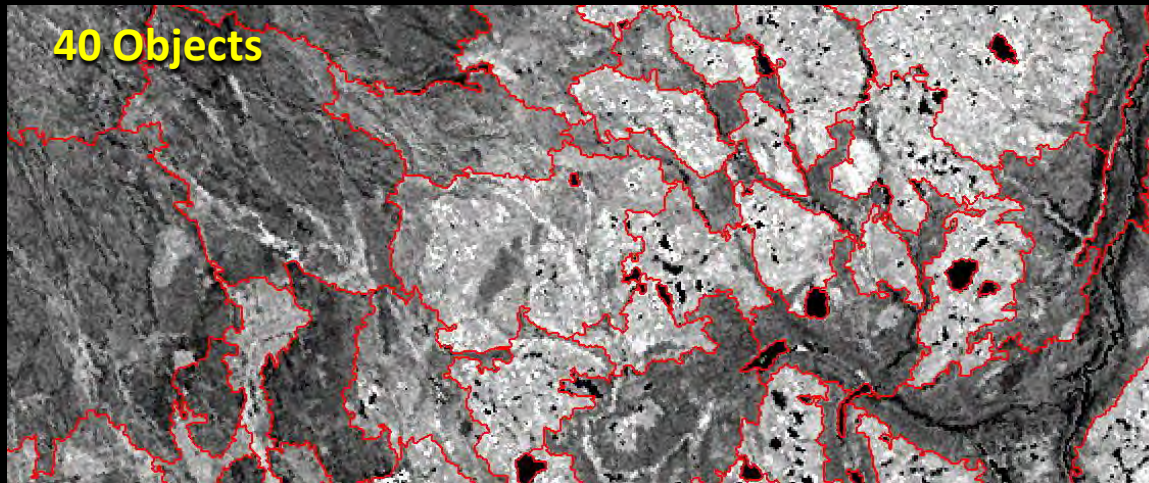
The imagery was then segmented at **scale 2.25**. Scale 2.25 was chosen because the resulting image objects provided good discrimination of spectral differences between and within enhanced wetland types, yet was not so fine as to result in a high proportion of single pixel objects. Scale 2.25 has been used in other DU projects when only TM imagery was available.

Segmentation

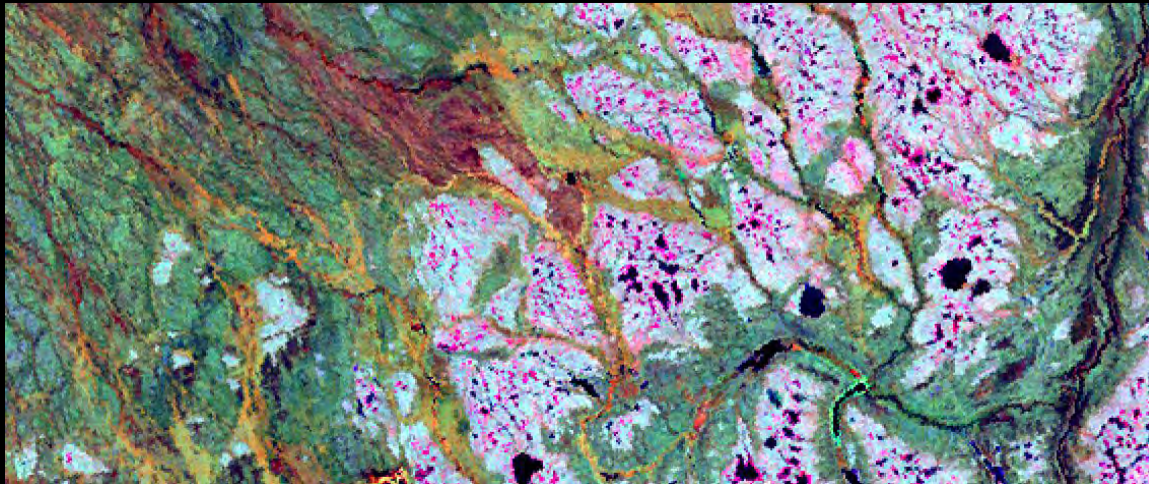
1. Input bands for the segmentation included the six bands of the ETM+ imagery and additional bands that showed clear separation of the objects being classified in the imagery.
2. In the Taiga Plains where the spectral separation between wetland classes is very subtle, **introducing additional bands** helps to more accurately delineate the image objects along wetland boundaries.
3. The characteristics of the input bands greatly affect both the **image objects size and shape**.
4. The following graphic shows an example of the same area segmented with the same segmentation parameters at a scale of 50. For illustrative purposes, one is segmented using only the near-infrared band as input and the other is segmented using only the PCA band 1. The PCA band 1 segmentation produced smaller objects that delineated the boundaries of the peatland with finer detail. Emphasizing band 4 for peatland delineation would not effectively extract the general peatland class from the surrounding landcover.
5. **Different input bands and weights** were used specific to the wetland being extracted from the imagery in order to obtain the ideal image object size and shape.



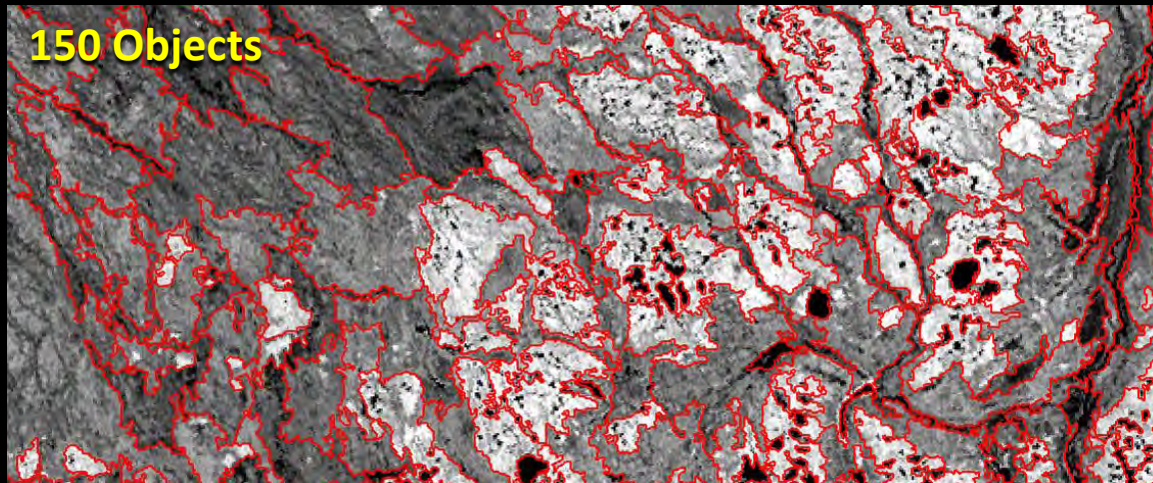
Band 453 – Lichen dominated Peatlands in white.



Band 4 – Near Infrared



Band 453 – Lichen dominated Peatlands in white.



PCA Band 1 – Brightness

Segmentation

Image Layers	Weight	Scale: 2.25 Shape: 0.1 Compactness: 0.9 Smoothness: 0.1
ETM+ / TM Band 1 - Blue	1	
ETM+/ TM Band 2 - Green	1	
ETM+/ TM Band 3 - Red	2	
ETM+/ TM Band 4 - Near-Infrared	2	
ETM+/ TM Band 5 - Mid-Infrared 1	2	
ETM+/ TM Band 7 - Mid-Infrared 2	1	
Principle Component 1	Input bands used for specific classes.	
Principle Component 2		
Principle Component 3		
Tasseled Cap Brightness		
Tasseled Cap Greenness		
Tasseled Cap Wetness		

The above table lists the **most common weights and parameters** used for most classes. The majority of the spectral variation was contained in bands 3, 4, and 5. Band 3 consistently highlighted distinctions between certain wetland types. The majority of the project was segmented at **scale 2.25**.

Additional segmentations, not listed in table 5, were performed at higher scales (scales 22 & 50) to classify clouds and cloud shadows and to create super-object masks for refining the classification of the general classes at scale 2.25. For example, **segmentation at scale 22** was used to map **peatland areas** or areas dominated by **deciduous uplands**. The attributes of these classes were then passed down to the scale 2.25 level.

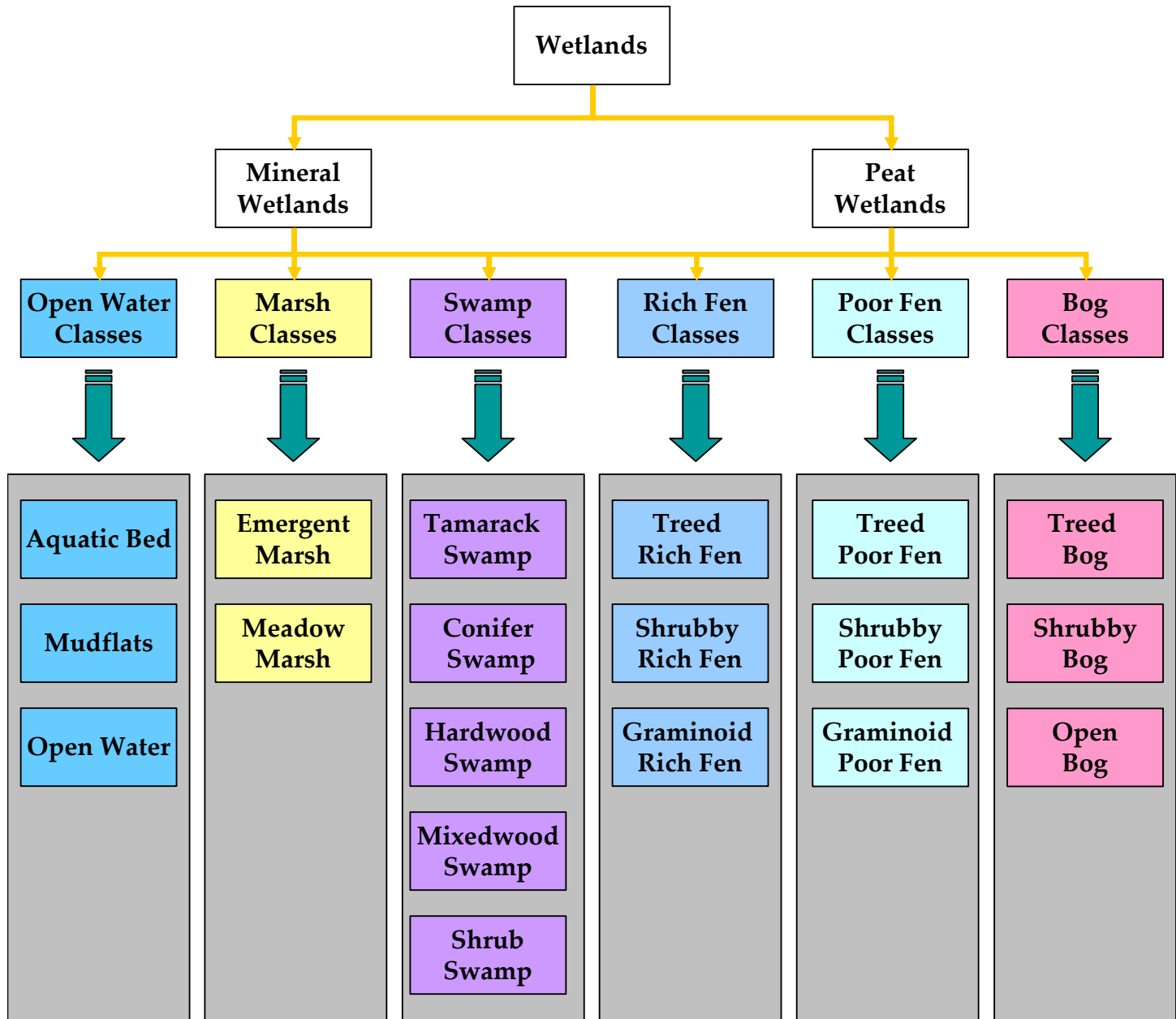
Classification

The classification scheme is based on the “**Enhanced Wetland Classification for the Boreal Plains**” (Smith et al., 2007). For an example of its application see “A User’s Guide to the Enhanced Wetland Classification for the Al-Pac Boreal Conservation Project” (Smith 2006).

This Enhanced Wetland Classification in **the Taiga Plains is a modification of the Boreal Plains classification scheme**. The Taiga Plains in general has **lower nutrient levels** and more **open canopies**. The same wetland classes in the Boreal Plains will be expressed differently in the Taiga Plains.

For example, *Larix laricina* (**Tamarack**) is a primary wetland indicator tree species found in fens and swamps of the Boreal Plains ecozone, but it is not a dominant species in fens and swamps of the Taiga Plains.

Climate-driven processes such as **permafrost** formation also changes the expression of the wetland types and their position in the landscape.



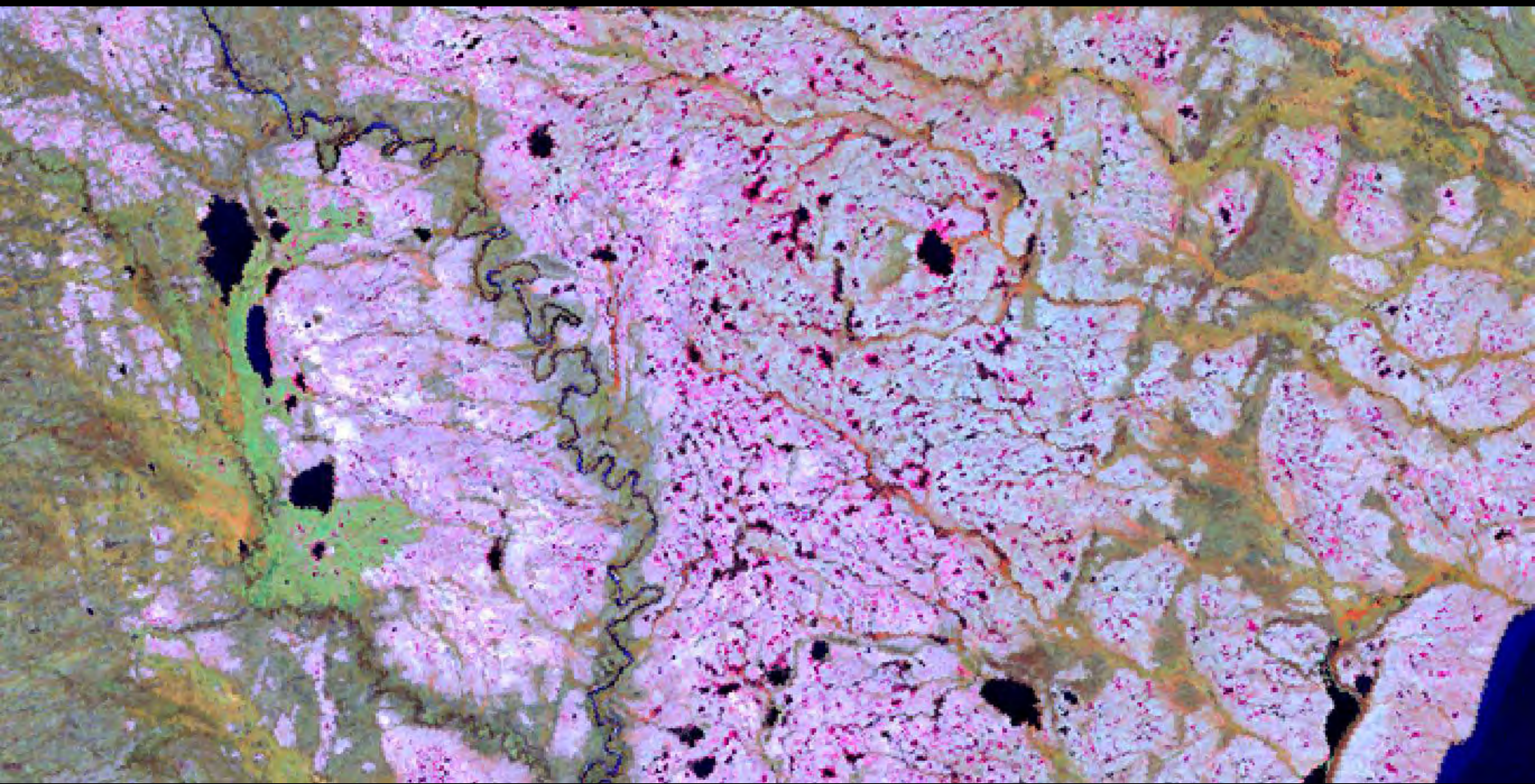
Classification

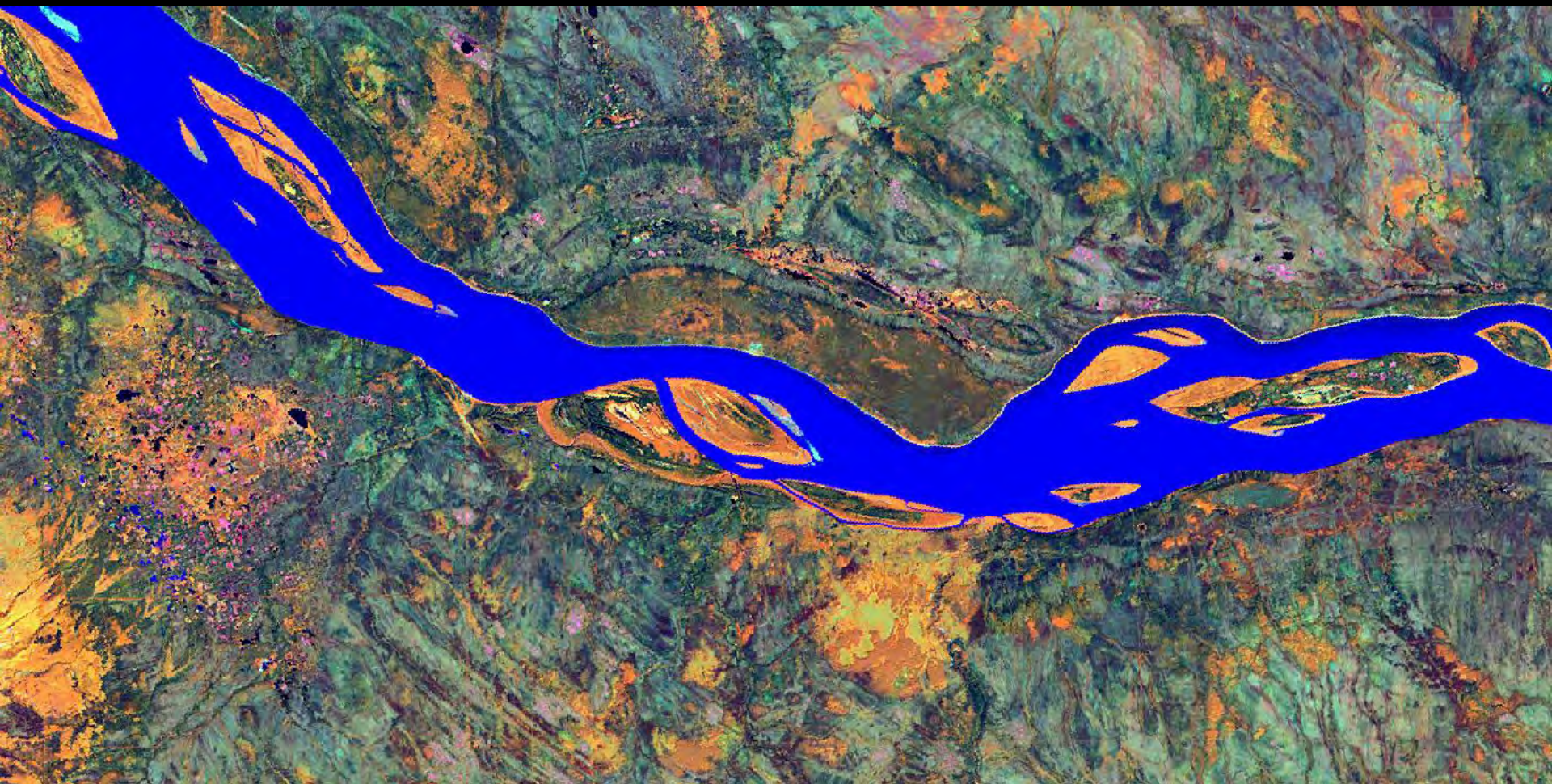
The first step in the classification procedure is an **initial segmentation** that aims to delineate general wetland classes from the imagery.

The **Basin general class** is usually the first class that is delineated. The Basin general class contains the detailed classes of Open Water, Aquatic Bed, and Emergent Marsh. This segmentation is designed to separate the Basin class from the rest of the imagery, because of the large amount of spectral overlaps between wetland signatures and many upland signatures in the imagery.

An initial classification is performed with **membership functions**, which can be as simple as a threshold placed on a single band or it can be very complicated with many thresholds and conditional statements joined in a logical structure. Membership functions are also used to access the object's topology and inheritance. The **initial classification highlights weak areas in the initial segmentation** where features were not adequately captured.

The **project is resegmented** with parameters adjusted to capture features that were initially missed in the first segmentation. The image objects are then classified using membership functions with a secondary classification.





Classification

Once the general classes are defined, the underlying detailed classes were separated using an **interactive nearest neighbor** classification.

The **segmentation parameters** are designed now to separate **within-class subtle variations** associated with changes in the detailed classes.

Field sites are initially used in the nearest neighbor classification. But the analyst guides the overall classification by selecting **visually interpreted training sites** to augment the process. By visual interpretation, the analyst can shape the classification in a semi-automated fashion.

Membership functions are also used within the nearest neighbor classification but are primarily used to **spatially limit the application of different training sites** on the image.

Classification

The development of the Enhanced Wetland Classification is a combination of elements used in **the earth cover classification and then the splitting of the final detailed earth cover classes into their wetland subclasses** (following table). The Basin general class is used in dividing different earth cover classes into their respective wetland subclasses. The final detailed classes are segmented to separate each of the wetland classes held within each of the earth cover class.

Although parts of the earth cover classification are reused in the enhanced wetland class, the majority of the processing for the enhanced wetlands classification is taking the earth cover classes and breaking them into their corresponding wetland subclasses (following table). **27 earth cover classes were split into as many as 4 wetland classes each, totaling 60 classes.** The techniques for each of these splits were unique to the wetland classification and required application of the analyst's knowledge base via membership functions. Not only was spectral information used but also features such as standard deviation of superobjects, relative distance, position in the landscape, and membership to an ecodistrict. **These 60 classes were then grouped into 26 classes for the Enhanced Wetlands classification.** The Enhanced Wetlands Classes were then grouped together to form the CWS classes. A general upland and wetland class were also studied for landscape position and accuracy assessment since this can be the most difficult distinction to make.

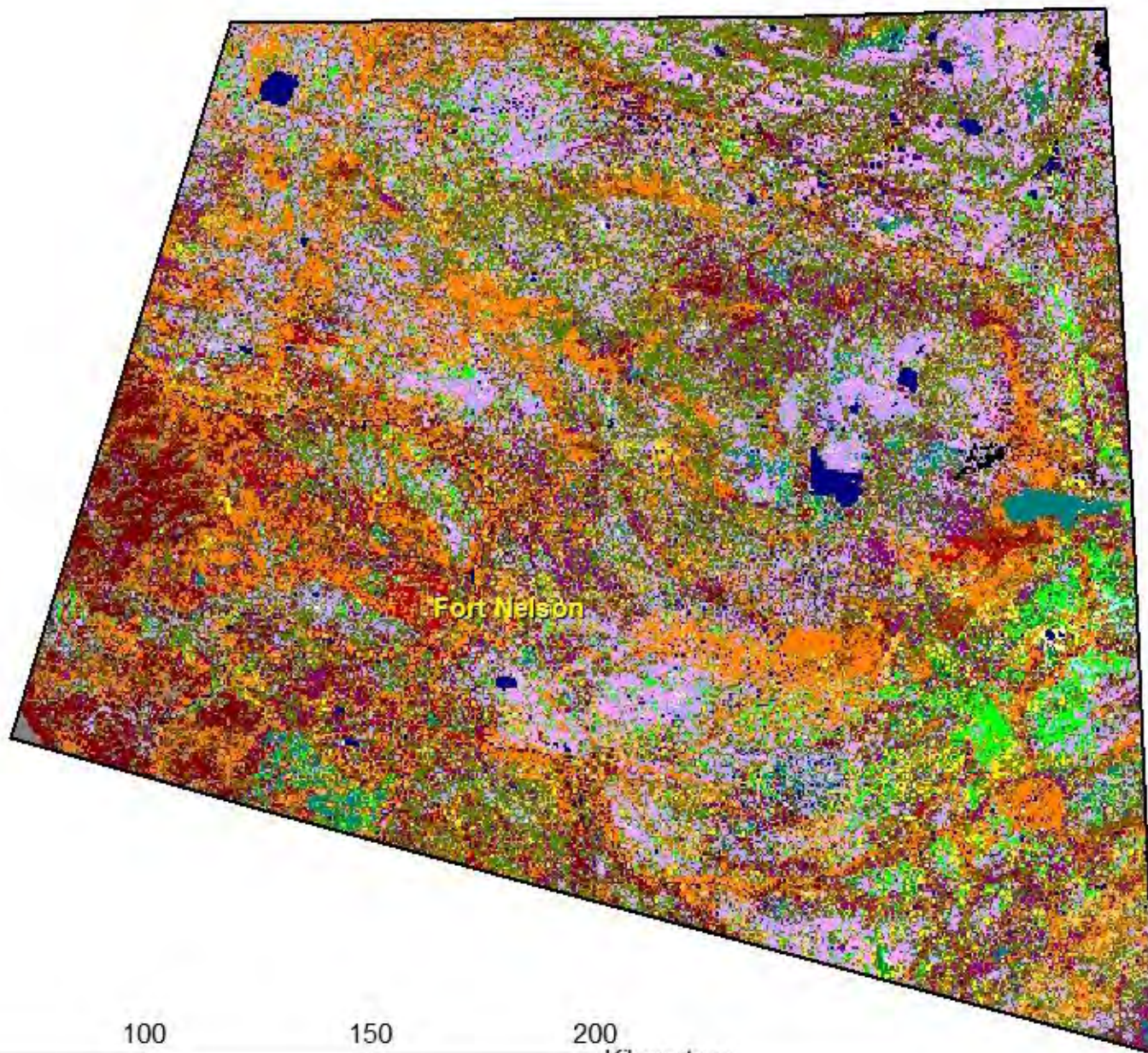
Earth Cover Class	Potential Wetland Class
Aquatic Bed	Aquatic Bed
Clear Water	Open Water
Closed Deciduous	Hardwood Swamp, Deciduous Upland
Closed Mixed Needleleaf	Treed Poor Fen, Conifer Swamp, Conifer Upland
Closed Mixed Needleleaf-Deciduous	Mixedwood Swamp, Mixedwood Upland
Closed Pine	Conifer Upland
Closed Spruce, >60%	Conifer Swamp, Conifer Upland
Closed Spruce, 40% - 60%	Treed Poor Fen, Treed Bog, Conifer Upland
Closed Tall Shrub	Shrubby Rich Fen, Thicket Swamp, Upland Other
Dwarf Shrub Lichen	Shrubby Bog, Upland Other
Emergent Vegetation	Emergent Marsh, Shrubby Rich Fen
Lichen	Open Bog, Upland Other
Low Shrub Lichen	Shrubby Bog, Upland Other
Low Shrub Other	Shrubby Rich Fen, Thicket Swamp , Upland Other, Burn
Mesic-Dry Graminoid	Meadow Marsh, Upland Other
Moss	Open Bog, Graminoid Rich Fen
Open Mixed Needleleaf Moss	Treed Poor Fen, Conifer Upland
Open Mixed Needleleaf Other	Treed Poor Fen, Conifer Upland, Burn
Open Spruce Lichen	Treed Bog
Open Spruce Moss	Treed Poor Fen, Treed Bog
Open Spruce Other	Treed Poor Fen, Treed Bog, Conifer Upland, Burn
Open Tall Shrub Other	Shrubby Rich Fen, Thicket Swamp , Upland Other, Burn
Sparse Vegetation	Upland Other, Burn
Turbid Water	Open Water
Wet Graminoid	Graminoid Rich Fen, Meadow Marsh, Open Bog
Woodland Needleleaf Lichen	Shrubby Bog, Open Bog
Woodland Needleleaf Other	Shrubby Rich Fen, Graminoid Rich Fen, Upland Other

Classification

Many attempts were made to use the DEM but the 30m resolution was too coarse to make any detailed analysis of wetlands. Wetlands often occur in flat areas, where subtle changes in elevation result in very different wetland types, and the vertical resolution of the DEM was not sufficient to discriminate wetland areas. **The DEM therefore was used only to make broad distinctions between mountains and plains.**

For this project, the final steps of the classification process were to edit the confused classes remaining after the classification process and to make final edits in areas that still had classification errors. Editing of classification errors was a process of comparing the classified image to the raw satellite image, field photos, and notes on field maps to identify errors remaining in the classification. **These errors were then corrected by manually changing the class value for the image objects that were classified in error to their correct class value.** This step is critical to the accurate mapping of wetland areas, which vary greatly across the study area, exhibit a wide range of spectral variation, and often occur in high percentages of the land area. Application of the analyst's knowledge base via manual editing is often necessary to accurately delineate the more challenging wetland types/areas.

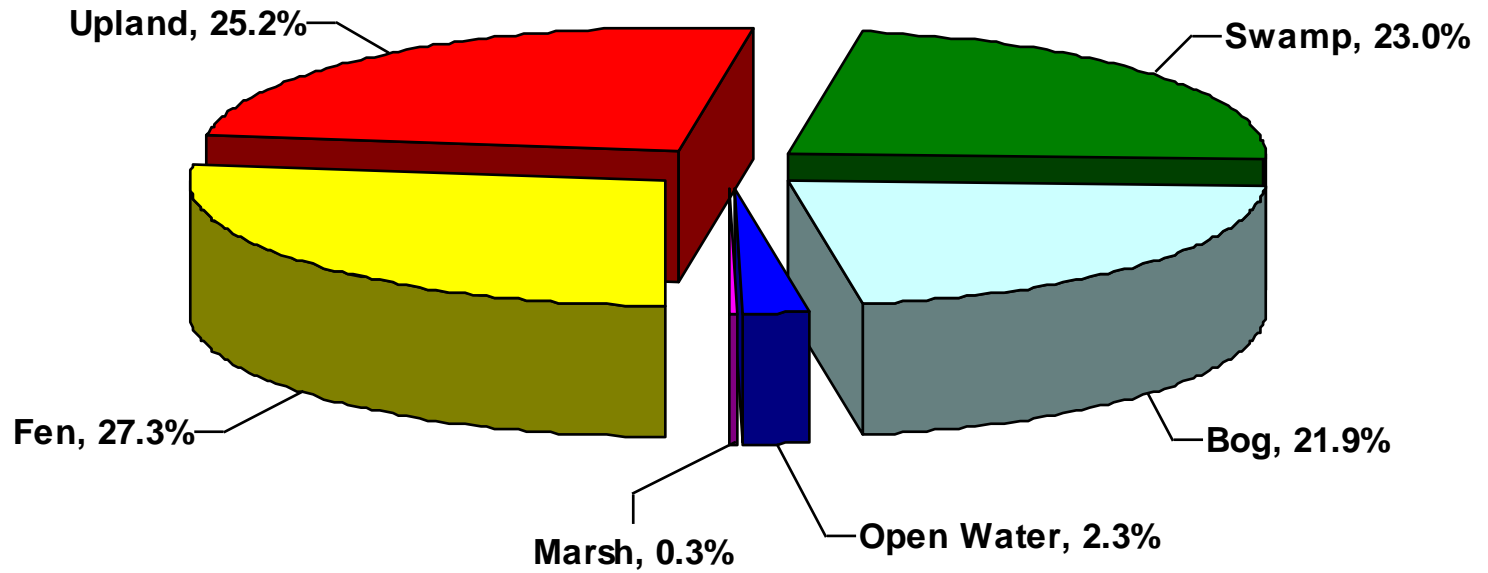
- Anthropogenic
- Aquatic Beds
- Burn
- Cloud/Cloud Shadow
- Conifer Swamp
- Emergent Marsh
- Graminoid Poor Fen
- Graminoid Rich Fen
- Hardwood Swamp
- Meadow Marsh
- Mixedwood Swamp
- Open Bog
- Sand / Gravelbar
- Shallow / Open Water
- Shrubby Bog
- Shrubby Poor Fen
- Shrubby Rich Fen
- Terrain Shadow
- Thicket Swamp
- Treed Bog
- Treed Poor Fen
- Treed Rich Fen
- Upland Conifer
- Upland Deciduous
- Upland Mixedwood
- Upland Other



0 50 100 150 200 Kilometers

Wetland Class	Hectares	Acres	Percent
Treed Poor Fen	948,283	2,343,258	21.12%
Treed Bog	732,295	1,809,539	16.31%
Upland Deciduous	490,602	1,212,303	10.93%
Conifer Swamp	379,631	938,088	8.45%
Upland Mixedwood	322,519	796,961	7.18%
Mixedwood Swamp	310,695	767,745	6.92%
Upland Conifer	242,765	599,885	5.41%
Shrubby Bog	218,140	539,035	4.86%
Hardwood Swamp	203,431	502,688	4.53%
Shrubby Rich Fen	167,403	413,663	3.73%
Thicket Swamp	106,311	262,700	2.37%
Shallow / Open Water	97,151	240,067	2.16%
Burn	55,684	137,599	1.24%
Anthropogenic	53,996	133,428	1.20%
Treed Rich Fen	40,295	99,572	0.90%
Upland Other	38,397	94,882	0.86%
Cloud/Cloud Shadow	26,182	64,696	0.58%
Graminoid Rich Fen	24,757	61,176	0.55%
Meadow Marsh	11,636	28,753	0.26%
Graminoid Poor Fen	5,958	14,723	0.13%
Sand / Gravelbar	4,365	10,786	0.10%
Terrain Shadow	3,560	8,796	0.079%
Open Bog	2,973	7,345	0.066%
Aquatic Beds	2,532	6,257	0.056%
Emergent Marsh	601	1,485	0.013%
Shrubby Poor Fen	142	351	0.003%
Total	4,490,303	11,095,780	

Wetlands Composition of Project Area



General (CWCS) Wetlands percent and area cover

Wetland Class	Hectares	Acres	Percent
Fen	1,186,839	2,932,743	27.31%
Upland	1,094,282	2,704,031	25.18%
Swamp	1,000,067	2,471,220	23.01%
Bog	953,407	2,355,920	21.93%
Open Water	99,684	246,324	2.29%
Marsh	12,237	30,238	0.28%



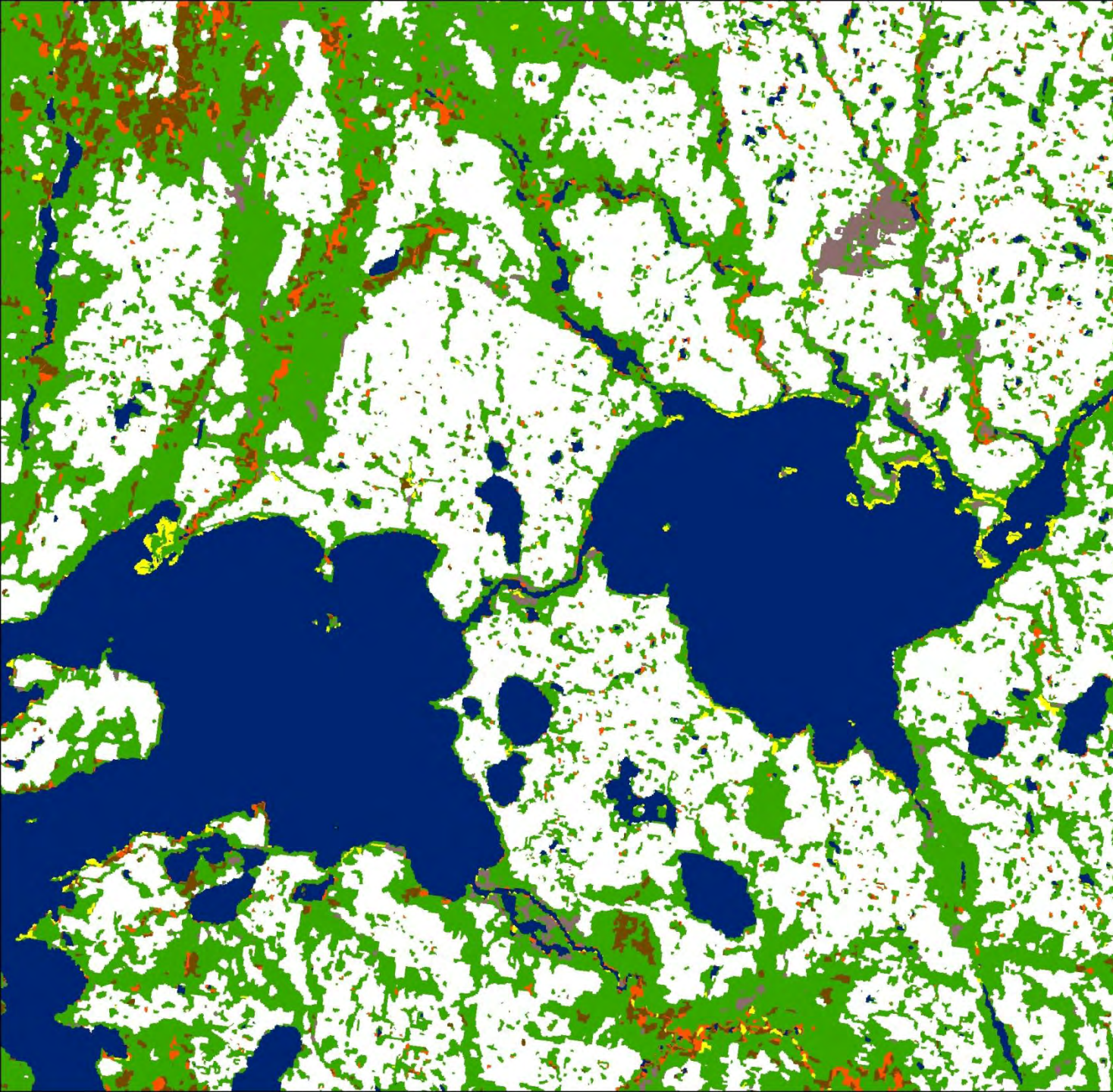
Shrubby Bog dominated by sphagnum moss.



A Thicket Swamp cutting through a peatland complex.

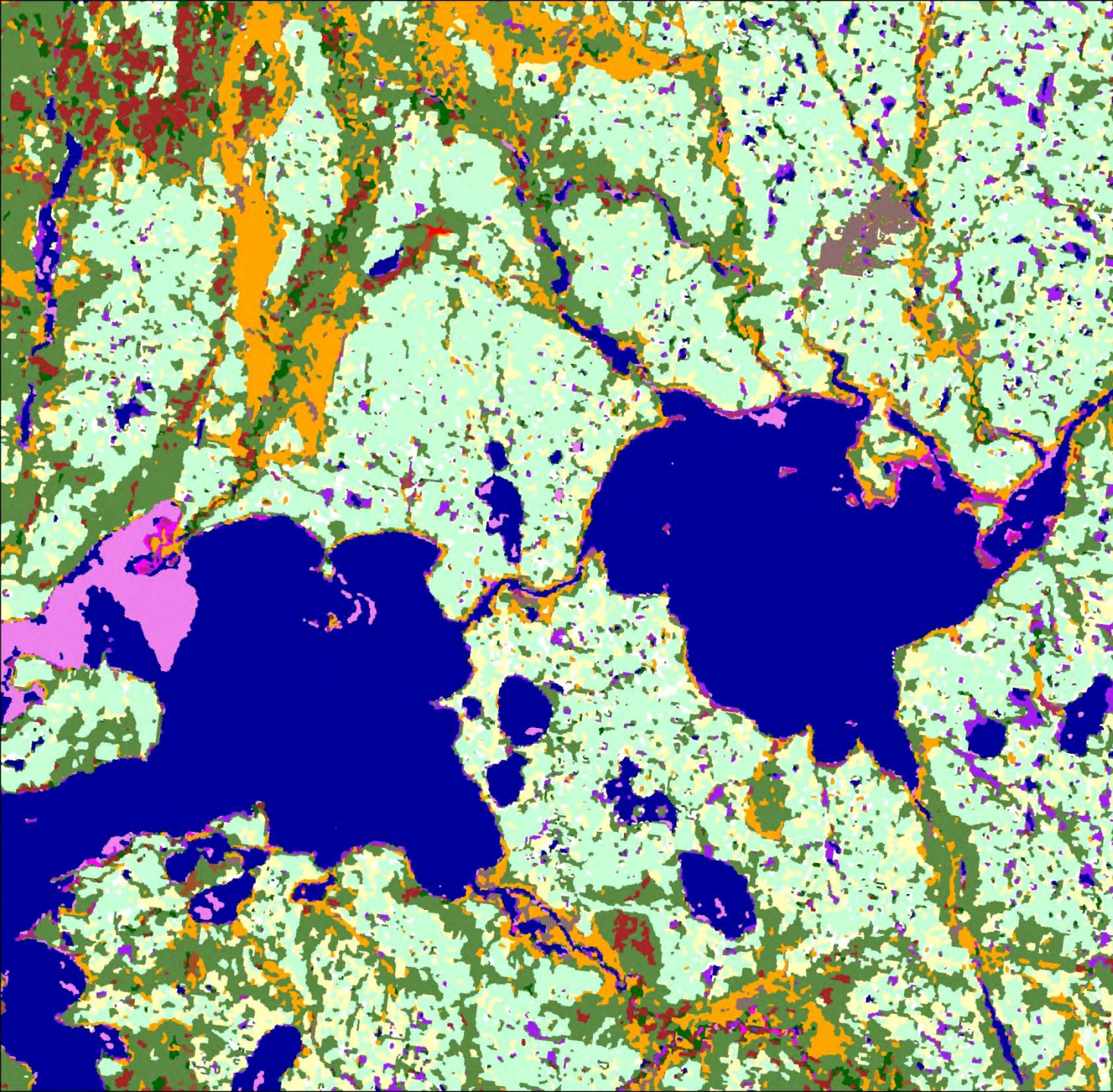


A mosaic of marshes and swamps along the flood areas of a meandering stream.



Legend

- Anthropogenic
- Bog
- Burn
- Cloud / Shadow
- Fen
- Marsh
- Open Water
- Swamp
- Upland



Legend

- Anthropogenic
- Aquatic Bed
- Burn
- Cloud / Shadow
- Conifer Swamp
- Conifer Upland
- Deciduous Upland
- Emergent Marsh
- Graminiod Rich Fen
- Hardwood Swamp
- Meadow Marsh
- Mixedwood Upland
- Open Bog
- Open Water
- Shrubby Bog
- Shrubby Rich Fen
- Swamp Thicket
- Treed Bog
- Treed Poor Fen
- Upland Other

Error matrix for the Enhanced Wetlands Classes.

Class	Up Con	Up Decid	Up Mix	TBOG	OBOG/SBOG	TrPF	GrPF/ShPF	ShRF	GrRF	AQBD	EMSH	MMSH	CSWP	HSWP	MSWP	TSWP	Total	User's
UpCon	19		1			1											21	90.5
UpDecid		26															26	100.0
UpMix	1		17														18	94.4
TBOG				14	1	2											17	82.4
OBOG/SBOG				2	9											1	12	75.0
TrPF	3			1		17							2				23	73.9
GrPF/ShPF							9		1								10	80.0
ShRF								11									11	100.0
GrRF									4								4	100.0
OWTR											5						5	0.0
AQBD										9							9	100.0
SBAR										1							1	0.0
EMSH											2						2	100.0
MMSH												6					6	100.0
CSWP	1												11				12	91.7
HSWP								1						15	1	1	18	83.3
MSWP															5	1	6	83.3
TSWP								1							3	4	8	50.0
Total	24	26	18	17	10	20	9	13	5	10	7	6	13	15	9	7	209	
Producer's	79.2	100.0	94.4	82.4	90.0	85.0	100.0	84.6	80.0	90.0	28.6	100.0	84.6	100.0	55.6	57.1		85.2

<u>Code</u>	<u>Enhanced Wetlands Class</u>	<u>Code</u>	<u>Enhanced Wetlands Class</u>
UpCon	Upland Conifer	OWTR	Shallow / Open Water
UpDecid	Upland Deciduous	AQBD	Aquatic Bed
UpMix	Upland Mixedwood	SBAR	Sand / Gravelbar
TBOG	Treed Bog	EMSH	Emergent Marsh
OBOG/SBOG	Open / Shrubby Bog	MMSH	Meadow Marsh
TrPF	Treed Poor Fen	CSWP	Conifer Swamp
GrPF/ShPF	Graminoid / Shrubby Poor Fen	HSWP	Hardwood Swamp
ShRF	Shrubby Rich Fen	MSWP	Mixedwood Swamp
GrRF	Graminoid Rich Fen	TSWP	Thicket Swamp

Accuracy Assessment

Error matrix for the Canadian Wetlands Classification System.

Class	Bog	Fen	Swamp	Marsh	Water	Upland	Total	User's
Bog	26	2	1				29	89.7
Fen	1	42	2			3	48	87.5
Swamp		2	41			1	44	93.2
Marsh				8			8	100.0
Water				5	10		15	66.7
Upland		1				64	65	98.5
Total	27	47	44	13	10	68	209	
Producer's	96.3	89.4	93.2	61.5	100.0	94.1		91.4

Error matrix for the Upland – Wetland delineation.

Class	Wetland	Upland	Total	User's
Wetland	140	4	144	97.2
Upland	1	64	65	98.5
Total	141	68	209	
Producer's	99.3	94.1		97.6

Summary

A satellite imagery-based enhanced wetland mapping project was completed for a 4.5 million hectare (11 million acres) area centered on Fort Nelson, BC in the northeastern portion of British Columbia. The imagery for the project was acquired during the summers of 1999 and 2004 and included imagery from two different paths. Field data was collected via helicopter at 804 sites from July 13 – July 24, 2001 and July 28 – August 1, 2008. Image segmentation, membership functions, and nearest-neighbor supervised classification techniques were applied to map 26 mapped features, of which 18 were wetland classes. The overall accuracy for the enhanced wetlands classification was 85.2% and for the CWCS wetlands classification was 91.4%. The accuracy between wetland and upland was 97.6%. Most of the error involved misclassification between related cover types, such as within fen types. The resulting wetland map indicates that the three most extensive enhanced wetland classes were Treed Poor Fen (21%), Treed Bog (16%), and Upland Deciduous (11%). From the general wetland classes, fens comprised 27.3% of the landscape, uplands were 25.2%, swamps were 23.0%, and bogs were 21.9%. The products from this project include a digital enhanced wetlands map, digital and hardcopy map products, a complete digital field database including field photographs, and a user's guide. These data will aid in the critical process of resource planning for this valuable and diverse area.

Partners



Questions ?

