# A Review, Enhancement, and Accuracy Assessment of Wetland Features within the eFRI

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#### **A Review, Enhancement, and Accuracy Assessment of Wetland Features within the eFRI\***

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### <span id="page-2-0"></span>Executive Summary

The Ontario forest inventory system identifies wetland areas based on the Ecological Landscape Classification (ELC) system. However, a limitation of the inventory process is that wetlands within waterbodies and small islands are classified as water.

Our project used the ADS40 imagery to identify wetland areas missing from the original forest inventory for Quetico Provincial Park. The review resulted in the addition of 1,886 new wetland polygons classified into six different ecosites for a total area of 2,607.6 hectares. Most of the delineated wetlands were identified as either Organic Shallow Marsh (ecosite 149, 54.3%) or Open Water Marsh: Organic (ecosite 152, 28.2%). Secondary ecosites were applied to 494 polygons (36% of all new polygons) that were formerly classified as water, indicating that these areas consist of more than one ecosite which are too small or interspersed to map independently. Approximately 7% of all areas classified as islands in the original inventory were fully or partial wetland ecosites. Nearly 9% of all waterbodies were found to have contain at least one wetland.

Field validation work was conducted on 167 plots during 2018 and 2019 to allow for an accuracy comparison of the digitization process. Ecosite specific accuracy was low largely due to the inability to determine substrate type (organic vs mineral) from the aerial imagery. Broader categories of classification such as shallow marshes had fairly good agreement with the digitized polygons (71% correct) as did digitized open water marshes in comparison to the field data (77% correct). Of the 116 field sites that were classed as open water, 72 (62%) were in polygons that had open water marsh as either the primary or secondary ecosite. These results illustrate the advantageous use of primary and secondary calls in complex areas.

Ducks Unlimited Canada helps further enhance the utility of wetland classes in the eFRI through the application of a cross-walk of DUC's Enhanced Wetland Classification (EWC).

Lastly, the project investigated the of convolutional neural networks to automate the classification of wetland areas within waterbodies and islands. The model was able to classify the broad classes of water, land and wetlands with accuracies of 95%, 97% and 98% respectively. Model accuracy was lower in specific ecosites (e.g. 135 and 144), but ecosite149 was predicted with good accuracy (90%) as were overall marsh classes (combined ecosite 149 and 152 was 90%).

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## <span id="page-4-0"></span>1 Project Rationale and Overview

Wetlands provide a wide range of biological, social, and hydrological functions. Accurate wetland inventories and an enhanced understanding of wetland habitat supply is increasingly important in meeting the growing requirements of fish and wildlife management, the Species at Risk and Migratory Birds Acts, and forest certification standards. An accurate wetland inventory for Quetico Provincial Park will also assist in the development of a fisheries and aquatic ecosystem plan, and First Nations have identified wetlands as an important ecosystem component (Brian Jackson, pers. comm.).

While detailed wetland inventories are not available for most areas in Ontario, the eFRI process does classify forest polygons, including most wetland areas, into ecosites based on the Ecological Landscape Classification (ELC) system.

The eFRI system includes 35 potential wetland ecosites, but the inventory process omits most wetlands lying within the boundary of waterbody and island polygons (i.e. small island polygons less than 8 ha are not assigned an ecosite). For example, the Quetico inventory has little area (< 500 ha) in ecosite 147 (shrub shore fen), and no area in either ecosites 149 (organic shallow marsh) or 152 (open water marsh: organic). Field and mapping work by Quetico staff suggests extensive open water wetlands have not been identified in the FRI (Brian Jackson, pers. comm.).

The omission of some wetland ecosites from traditional forest inventories was quantified by the project team during the completion of a wetland inventory project on the adjacent Dog River-Matawin (Dog-Mat) Forest in 2017. While this prior project resulted in the addition of over 5,000 new wetland polygons (over 2,100 hectares) to the inventory on that forest, it was completed solely through photointerpretation with no field verification.

This current project for Quetico expands on our previous methodologies by including field verification as a critical piece of the wetland evaluation process. This project will assess the ability to identify wetland ecosites missing from the eFRI, quantify the amount of wetland area that can be added to the inventory through such a process, and determine the accuracy in doing so using field validation work.

Ducks Unlimited Canada (DUC) helps further enhance the utility of wetland classes in the eFRI through the application of a cross-walk of DUC's Enhanced Wetland Classification (EWC).

Lastly, the project investigates the potential of using deep learning techniques to automate the classification of wetland areas within waterbodies and islands.

### <span id="page-5-0"></span>2 Field Wetland Identification

### <span id="page-5-1"></span>2.1 Overview

FRI photo-interpretation calibration and verification plot data are not frequently collected for wetland ecosite types, and thus a significant gap exists in our knowledge of how well our wetland identification system is working in the FRI process. A field accuracy assessment program was conducted in 2018 and 2019 to determine ground-truth ecosite classification and collect additional attributes to help with subsequent aerial photo interpretation.

### <span id="page-5-2"></span>2.2 Methods

Wetlands for field validation were delineated from eFRI imagery prior to fieldwork. Study areas were chosen based on accessibility from designated canoe routes and proximity to large numbers of wetland polygons.

Vegetation data were collected in accordance with Ontario's Ecological Land Classification standards. Plant species cover was estimated in a 5 m X 5 m quadrat. All vascular plant species and macroalgae (no bryophytes or lichens were observed) occurring in the quadrat were recorded and the percent cover for each species was estimated. Each species was assigned to one of the following physiognomic layers from (species in layers  $1 - 5$  did not occur in any quadrats) in [Table 1.](#page-5-4)

#### <span id="page-5-4"></span>**Table 1. Species layer assignments in field validation qudrats.**



The taxonomic authority was VASCAN (Brouillet et al. 2010+). The total cover of all species in each physiognomic layer was also estimated.

Surface water and substrate pH and conductivity were recorded from three samples at each site using a handheld Oakton multi-meter. Water depth was measured near the centre of each quadrat. The dominant substrate type (humic organic, sand, silt, clay, rock) was recorded. At each plot the ecosite (Banton et al. 2011) and w-type (Harris et al. 1996) were recorded and photographs were taken. Fetch distance (m) and direction (degrees) were estimated following the field work using a Geographical Information System.

### <span id="page-5-3"></span>2.3 Results and Discussion

In 2018 field verification data were collected from 75 wetland polygons delineated during air photo interpretation. Fieldwork was completed on August 19 to 24 by Allan Harris and Brian Ratcliff. Polygons were accessed by canoe and quadrat locations were recorded with a GPS. An additional 10 sites were sampled by Brian Jackson (Quetico Park Biologist), to bring the total samples to 85 for the 2018 season.

In 2019 field verification data were collected from 82 wetland polygons delineated during air photo interpretation. Fieldwork was completed on August 12 (Al Harris and Seba Belmar) and August 22 to 26 (Al Harris and Brian Ratcliff). Polygons were accessed by canoe and quadrat locations were recorded with a GPS. [Figure 1s](#page-6-0)hows the locations of field sites during both seasons.

Site and vegetation data for both seasons are included in Appendices  $1 - 4$ .



<span id="page-6-0"></span>**Figure 1. Location of field sample sites in 2018 (Red) and 2019 (Blue).**

A full comparison of field data and the ecosites from digitized polygons is discussed in Section 3.

## <span id="page-7-0"></span>3 Wetland Digitizing

### <span id="page-7-1"></span>3.1 Overview

The main component of the project was to review all waterbody and islands using digital aerial imagery (ADS40) to identify wetland ecosites omitted during the initial eFRI creation for the entire Quetico Park area. New wetland polygons were digitized and added to the inventory during this process. An accuracy comparison was made between interpreted ecosites and field verification data.

### <span id="page-7-2"></span>3.2 Methods

Within waterbodies, all wetlands larger than 0.05 ha (500 m<sup>2</sup>) and not included in the eFRI dataset were delineated into new polygons. This was considered the minimum practical polygon size given the resolution of the imagery and is also the smallest wetland size delineated in other wetland inventory projects (e.g. Lane and D'Amico 2016). In addition, all island polygons ( $N = 6.953$ ) were reviewed to evaluate if they were fully or partially wetlands. For the reclassification of island polygons, the minimum size of 500  $m<sup>2</sup>$ was removed as many islands ( $N = 496$ ) were smaller than this size [\(Figure 2\)](#page-7-3).



<span id="page-7-3"></span>**Figure 2. Example of a small island polygon (red outline, left image), within a water polygon (blue outline) in the original inventory. The image on the right shows both original polygons have been reclassified as wetland (Ecosite 144).** 

Wetlands separated by less than 5 m were delineated as a single polygon, whereas those separated by greater than 5 m were treated as separated polygons [\(Figure 3\)](#page-8-0). Newly digitized wetlands were identified in areas of waterbody or island polygons in the existing inventory (i.e. forested areas already assigned ecosites were not reviewed). Polygons that were already classified as forest or wetland areas were not altered in shape or existing ecosite class). Where applicable, wetland boundaries were created to share edges of existing polygons to allow for easy incorporation of these polygons into the existing inventory without creating polygon overlap or slivers.



**Figure 3. Example Delineation of New Wetland Polygon. blue outline represents original waterbody polygon and red outline illustrates newly delineated wetland area (Ecosite 149).**

<span id="page-8-0"></span>Digitized wetlands were classified into ecosites following the criteria in Key 10 "Permanently Flooded or Hydric Ecosites" of the ELC guidelines (OMNR 2009). A number of hydric ecosites are defined by whether the substrate is mineral or organic which cannot be assessed using the FRI imagery. In these cases, default decisions were used to assign ecosites to the newly created polygons [\(Table 2\)](#page-8-1). The defaults were to organic rather than mineral or rock substrate and to open water marsh rather than floating leaved marsh. The difficulty in discerning some of these ecosites from each other using aerial imagery is illustrated in [Figure 4](#page-9-0) .



#### <span id="page-8-1"></span>**Table 2. Default Ecosite Decision Rules.**



**Figure 4. Field photos from plot 38 (ecosite 148, left image) and plot 57 (ecosite 149, right image) from 2018. The similarity in vegetation appearance and coverage makes the determination of ecosite from aerial imagery very difficult.**

<span id="page-9-0"></span>The mapping of wetland areas is highly dependent on scale. Wetland vegetation communities often occur in patterns that are highly variable, and thus at times are not independently mappable at a scale useful for most inventory purposes. A primary and secondary ecosite labeling approached was used during delineation to avoid numerous small polygons and produce a more efficient workflow and final inventory product. In situations where more than one wetland ecosite occurred in a complex area, both ecosites were used to label a single polygon where the most common or dominant ecosite is listed first. Common examples include recurring patterns of meadow marsh and thicket swamp on a stream floodplain or a mosaic of emergent vegetation cover percentages along a shoreline [\(Figure 5\)](#page-9-1). In these cases, we annotated the polygon with both a primary and secondary ecosite, consistent with FRI standards (OMNR 2009; OMNR 2010).

<span id="page-9-1"></span>

**Figure 5. Example of a complex wetland polygon containing a mix shallow marsh (149, primary Ecosite) and open water marsh (152, secondary Ecosite).**

Field data from the 2018 and 2019 season was then compared to the newly created wetlands to assess the accuracy of interpreted ecosite labels.

#### <span id="page-10-0"></span>3.3 Results and Discussion

The Quetico forest inventory contains 7,209 water polygons (108,437 ha) and 6,953 island polygons (2,148 ha) which were reviewed for unidentified wetland ecosites. The review resulted in the addition of 1,886 new wetland polygons classified into six different ecosites for a total area of 2,607.6 hectares [\(Table 3\)](#page-10-1). Most of the delineated wetlands corresponded to two ecosites: Organic Shallow Marsh (149, 54.3%), and Open Water Marsh: Organic (152, 28.2%). Secondary ecosites were applied to 494 (36%) of the polygons that were formerly water, indicating that a these areas have a complex ecosite composition.

The overwhelming majority of wetlands were found within waterbodies (97.6%), whereas only 2.4% of the area was reclassified from island polygons. While the amount of wetland area found within islands is small, it does represent 7.1% of all island polygons being reclassified, at least in part, as wetlands. The 1,390 wetland polygons were found in 645 unique waterbody polygons (i.e. 8.9% of waterbody polygons contained at least one wetland).



<span id="page-10-1"></span>**Table 3. Summary of Newly Digitized Wetland Areas from Prior Water and Island Polygons.**

In 2018, 14 areas were field sampled that did not fall within delineated wetland polygons. This was due to these areas being smaller than the minimum polygon size used. As a result, polygon-field data comparisons were available for 71 sites. For the 2019 field season the new wetland delineation was complete, and field sample areas were pre-selected to ensure the samples were contained within wetland polygons.

[Table 4](#page-11-0) shows a comparison between ecosite types that were determined in the field and those from the digitization process. The ecosite-to-ecosite comparison illustrates the challenges in making correct ecositespecific calls as it relates to these wetland types. As mentioned above, default classification rules were applied where ecosites are dependent on substrate type (e.g. 148 vs. 149, 151 vs. 152). In situations where this level of detail is important for habitat or ecosystem evaluation the use of ADS imagery alone may be insufficient. Alternatively, site specific default rules could be constructed based on local knowledge of wetland ecology.



<span id="page-11-0"></span>**Table 4. Comparison between field and digitized wetland ecosites.**

[Table 5](#page-11-1) represents a more generalized comparison between the field and digitization process with ecosites combined into their respective wetland types. Shallow marshes identified in the field had fairly good agreement with the digitized polygons (71% correct) as did digitized open water marshes in comparison to the field data (77% correct). However, results do show substantial differences between areas assessed as open water marshes in the field but labelled as shallow marshes from the imagery (i.e. 81 of 116 sites). This may be in part due plot versus polygon spatial scales and variation across polygons where the relatively small field sample areas are within a larger wetland complex (i.e. the comparisons in [Table 4](#page-11-0) and [Table 5](#page-11-1) are only using primary ecosite call). Of the 116 field sites that were classed as open water, 72 (62%) were in polygons that had open water marsh as either the primary or secondary ecosite. This again illustrates the advantageous use of primary and secondary calls in these complex areas (see example in [Figure 6\)](#page-12-0).



<span id="page-11-1"></span>



<span id="page-12-0"></span>**Figure 6. Example of field sites (blue dots) which were classed as open water marsh (152) within a complex wetland polygon (red outline). This polygon had a primary ecosite of shallow marsh (149) with a secondary ecosite of open water marsh (152).**

### <span id="page-13-0"></span>4 Ducks Unlimited Canada Crosswalk

### <span id="page-13-1"></span>4.1 Overview

To facilitate DUC's interpretation of the wetlands present in Quetico Provincial Park, in addition to developing more concise and user-friendly information for practitioners and forest managers, a crosswalk from OMNR's eFRI permanently flooded/Hydric ecosites to DUC's EWC (Smith et al., 2007; [Figure 7\)](#page-13-3) boreal wetland classes was completed.

### <span id="page-13-2"></span>4.2 Methods

The crosswalk (i.e. translation of classes from one system to another) is detailed in [Table 6.](#page-14-0) 14 EWC classes were identified from this crosswalk exercise. The translation of classes from one classification system to another was completed by analyzing the species composition (i.e. presence), heights, and coverage for each code/class as described in their classification system documentation.



<span id="page-13-3"></span>**Figure 7. Ducks Unlimited Canada's Enhanced Wetland Classification (EWC) data model, consisting of 19 distinct minor wetland classes that conform to the five major classes of the Canadian Wetland Classification System (CWCS).**

<b>ELC</b> <b>Key</b>	<b>ELC Ecosite</b>	<b>CWCS Major Class</b>	<b>EWC Minor Class</b>
<b>B126</b>	<b>Treed Bog</b>	Bog	<b>Treed Bog</b>
<b>B137</b>	<b>Sparse Treed Bog</b>	Bog	Shrubby Bog
<b>B138</b>	Open Bog	Bog	Open Bog
<b>B139</b>	Poor Fen	Fen	Graminoid Poor Fen
<b>B136</b>	<b>Sparse Treed Fen</b>	Fen	<b>Treed Poor Fen</b>
<b>B140</b>	Open Moderately Rich Fen	Fen	Graminoid Rich Fen
<b>B141</b>	Open Extremely Rich Fen	Fen	Graminoid Rich Fen
<b>B146</b>	Open Shore Fen	Fen	Graminoid Rich Fen
<b>B147</b>	Shrub Shore Fen	Fen	Shrubby Rich Fen
<b>B130</b>	Intolerant Hardwood Swamp	Swamp	Hardwood Swamp
<b>B131</b>	Maple Hardwood Swamp	Swamp	<b>Hardwood Swamp</b>
<b>B132</b>	Oak Hardwood Swamp	Swamp	Hardwood Swamp
<b>B133</b>	<b>Hardwood Swamp</b>	Swamp	<b>Hardwood Swamp</b>
<b>B134</b>	<b>Mineral Thicket Swamp</b>	Swamp	Shrub Swamp
<b>B135</b>	<b>Organic Thicket Swamp</b>	Swamp	Shrub Swamp
<b>B127</b>	Poor Conifer Swamp	Swamp	Conifer Swamp
<b>B128</b>	Intermediate Conifer Swamp	Swamp	<b>Conifer Swamp</b>
<b>B129</b>	<b>Rich Conifer Swamp</b>	Swamp	Conifer Swamp
<b>B222</b>	Mineral Poor Conifer Swamp	Swamp	<b>Conifer Swamp</b>
<b>B223</b>	Mineral Intermediate Conifer Swamp	Swamp	Conifer Swamp
<b>B224</b>	Mineral Rich Conifer Swamp	Swamp	<b>Conifer Swamp</b>
<b>B142</b>	<b>Mineral Meadow Marsh</b>	Marsh	<b>Meadow Marsh</b>
<b>B143</b>	<b>Rock Meadow Marsh</b>	Marsh	<b>Meadow Marsh</b>
<b>B144</b>	<b>Organic Meadow Marsh</b>	Marsh	<b>Meadow Marsh</b>
<b>B145</b>	<b>Floating Marsh</b>	Marsh	<b>Emergent Marsh</b>
<b>B148</b>	<b>Mineral Shallow Marsh</b>	Marsh	<b>Emergent Marsh</b>
<b>B149</b>	<b>Organic Shallow Marsh</b>	Marsh	<b>Emergent Marsh</b>
<b>B150</b>	Open Water Marsh: Floating- Leaved	<b>Shallow Open Water</b>	<b>Aquatic Bed</b>
<b>B151</b>	Open Water Marsh: Mineral	<b>Shallow Open Water</b>	<b>Aquatic Bed</b>
<b>B152</b>	Open Water Marsh: Organic	<b>Shallow Open Water</b>	<b>Aquatic Bed</b>
<b>B154</b>	<b>Active Limnetic Rock</b>	<b>Shallow Open Water</b>	Open Water
<b>B155</b>	Active Limnetic Mineral	<b>Shallow Open Water</b>	Open Water
<b>B156</b>	Active Limnetic Organic	<b>Shallow Open Water</b>	Open Water

<span id="page-14-0"></span>**Table 6. OMNR ELC ecosite crosswalk (i.e. translation) to CWCS and EWC wetland classes.**

### <span id="page-15-0"></span>4.3 Results and Discussion

The eFRI to EWC crosswalk process described in the previous section was spatially applied to the improved Quetico Provincial Park wetland inventory using ArcGIS 10.7 software. This GIS task was applied on the primary ecosite codes assigned in the inventory. [Figure 8](#page-16-0) displays the final, EWC inventory of Quetico Provincial Park.

A total of 14 EWC classes were identified in Quetico Provincial Park after cross-walking the new eFRI data. Table 7illustrates that the upland class (i.e. non-wetland areas) occupies the largest percentage of the park at 66.67%. Open water (22.02%, which is separate from aquatic bed, and includes both deep and shallow systems) is the most extensive EWC wetland class across the park, followed by conifer swamp (6.35%), meadow marsh (2.06%), and treed poor fen (1.35%). The more rare EWC classes include treed, shrubby and open bogs, and graminoid poor fens (all four classes occupy <1% of the park).

The final EWC inventory of Quetico Provincial Park is made available as a feature class stored in geodatabase (GDB) format. A layer (.lyr) symbology file has also been prepared, according the EWC color scheme (as seen in [Figure 7\)](#page-13-3) developed by Ducks Unlimited Canada (Smith et al., 2007).

The EWC is a user friendly classification system that profiles the wetland types existing on the landscape, however there are several value added inferred products that can be derived from the EWC classes. Wetlands develop in response to numerous variables such as geology, hydrology, and climate, which dictate wetland vegetation, species diversity and underlying characteristics. Ducks Unlimited Canada has inferred several of these underlying characteristics from our EWC including water flow, soil moisture content, and relative nutrient status (Ducks Unlimited Canada, 2011;Table 8). These inferred products, which allow the mapping of these variables across the landscape, enhance the knowledge of wetland functions and provide useful recommendations to help conserve the boreal. Further, value added information can aid in the development and implementation of best management practices (BMP) around activities associated with development, such as road building, and can also help assist in meeting various provincial/federal regulatory requirements, including Species at Risk and Migratory birds Convention Acts, and forest certification standards (e.g. SFI, FSC, CSA).



<span id="page-16-0"></span>**Figure 8. EWC map of Quetico Provincial Park. Image subsets are of high-density wetland regions.**



**Table 7. Total park area by EWC wetland class.**

**Table 8. EWC wetland classes and their associated inferred classifications according to Ducks Unlimited Canada.**



[Figure 9](#page-18-0) displays the inferred products derived from the EWC for Quetico Provincial Park. This inferred information is contained within the attribute table of the EWC feature class, and each inferred product has an accompanied layer (.lyr) symbology file as a deliverable with this project.



<span id="page-18-0"></span>**Figure 9. Inferred products derived from the Quetico Provincial Park EWC. a) hydrodynamics, b) nutrient regime, and c) soil moisture.**

## <span id="page-19-0"></span>5 Wetland Deep Learning Identification

### <span id="page-19-1"></span>5.1 Overview

The original project proposal did not include a deep learning (convolutional neural network) component, however the authors wished to quickly examine the possibility of using the created wetland polygons in this manner. Thus, it is important to note that this investigation was not intended to be a complete analysis of what is possible, but rather a brief exploration as a 'value added' part of the project. As the previous sections of the report illustrate, the manual identification and delineation of wetland ecosites within waterbodies is feasible. However, the exercise is labour intensive and methods to automate the task should be investigated. Studies suggest deep learning methods may outperform other methods of classification (e.g. random forest) (Amani et. al. 2018, Mahdianpari, et. al. 2018). A number of studies have investigated the use of convolutional neural networks and satellite imagery to identify wetlands in Canada at large spatial scales (Amani et. al. 2019, Pouliot et. al. 2019), but, to our knowledge, few studies have leveraged fine resolution imagery (Du et. al. 2020) and scales as described below.

### <span id="page-19-2"></span>5.2 Methods

Image chips of 32 x 32 pixels were extracted from each of six different classes: water, terrestrial island (i.e. true island), ecosite 135, ecosite 144, ecosite 149 and ecosite 152. Wetland ecosite 146 was not included in the deep learning exercise as there were only two polygons in this class within the study area. This image size was selected as it represented a reasonably fine level of feature identification (e.g.  $\sim$ 13m length, or  $\sim$ 164m<sup>2</sup>) and is an image size used in other deep learning training sets (e.g. CIFAR) which would allow some advantage if transfer learning were to be investigated.

Image chip locations were manually selected within areas to ensure the sample area represented the class and were not overlapping boundaries of other classes. Preliminary random chip extraction within polygons illustrated this to be a problem. For example, a number of wetland polygons frequently encompassed areas of open water and it would create a false training set to have labelled images from these locations (see [Figure 10\)](#page-20-0). In addition, care was taken to include a diversity of conditions for water (i.e. deep, shallow, waves, and turbulent outfalls of river)s and land (i.e. variety of tree cover conditions, rocky outcrops, etc.).



**Figure 10. Example of image chip locations (orange squares) extracted from a wetland feature. White arrows indicate areas of intermixed open water which were avoided.**

<span id="page-20-0"></span>Image chips were created for both 3 band RGB and a 3 band false-colour combination of NIR, red and green as these wavelengths are known to have strong predictive value for wetlands (Amani et. al. 2018). The two training sets (true colour and NIR) allowed deep learning models to be tested against each set to evaluate if different band combinations had an impact on model performance.

For testing and validation, one thousand image chips were created per category for a total of 6,000 images in both the true colour and NIR training sets. While more image samples could be easily collected from some of classes (e.g. water and common ecosites like 149), it was important to keep the number of samples even between classes to provide a better deep learning environment. An additional 600 samples (100 per class) were created for independent testing so the models could be evaluated against an image set not previously seen. To facilitate this, the north-west corner of the park was selected as the area for testing image locations as it has a relatively high density of wetlands as well as field sample data from 2019 [\(Figure 11\)](#page-21-1).

All models were created in Tensorflow 2.1.0 (www.tensorflow.org).



<span id="page-21-1"></span>**Figure 11. Image sample locations.**

### <span id="page-21-0"></span>5.3 Results and Discussion

Preliminary models (convolutional neural networks) were created to test for the differences between optimizers (stochastic gradient descent and 'adam'), impacts of drop-out and regularization to prevent overfitting, the differences between true colour and NIR datasets in their predictive ability, and to find model(s) that had a structure suitable for further investigation.

Nine preliminary models were run using a training/validation split of 80/20 (i.e. 4,800 images for testing and 1,200 images for validation) and run for 100 epochs.

Given the relatively few training images (1,000 per class), many models commonly showed signs of overfitting (i.e. increases in validation loss and no improvement in validation accuracy compared to training data) within 20 epochs [\(Figure 12\)](#page-22-0). Increasing the split between training and validation typically resulted in unstable and poor overall model performance.



<span id="page-22-0"></span>**Figure 12. Example training and validation loss and accuracy (model 3, NIR)**

The final training and validation accuracy for the nine preliminary models is shown in [Table 9,](#page-22-1) and highlight that a number of models had developed overfitting by 50 epochs with generally poor validation accuracy. It is noteworthy that the RGB data was more susceptible to overfitting than the NIR data. This suggests that, for the model configurations reviewed here, the NIR data was more appropriate to identify general wetland features.

	<b>RGB</b>	<b>NIR</b>
	(Training Accuracy/Validation Accuracy)	(Training Accuracy/Validation Accuracy)
Model 1	94.0/65.4	90.9 / 69.8
Model 2	84.6/64.1	88.6 $/72.3$
Model 3	79.3/59.5	82.2 / 73.7
Model 4	64.2/61.2	74.2 / 73.3
Model 5	78.2/60.3	82.2 / 72.8
Model 6	65.7/65.3	72.6/70.8
Model 7	76.8/64.3	84.9 / 70.9
Model 8	85.4/66.5	84.8 / 73.6
Model 9	91.4/65.9	87.2 / 71.0

<span id="page-22-1"></span>**Table 9. Training and Validation Results for Preliminary Models Using RGB and NIR Datasets at 50 Epochs.**

While Model 4 and 6 in the above table had relatively low training accuracies at 50 epochs, the models did not show signs of overfitting. These models were then further investigated with changes to improve accuracy and run for more epochs. The final model was also only investigated with the NIR dataset as preliminary results showed slightly better performance than with the true colour images.

The final model architecture is shown in [Figure 13.](#page-23-0) The model was run with a training/validation split of 80/20, a batch size of 32, and run for 125 epochs. The optimizer was stochastic gradient decent with a set learning rate of 0.01.



<span id="page-23-0"></span>**Figure 13. Model Architecture. Blue = convolution layers with same padding, Green = MaxPooling, Red = Dropout. All activations are ReLu except the final Softmax layer.**

The model produced a training and validation accuracy of 90.7% and 82.7% respectively at the end of 125 epochs.

The model was then used to predict the 600 test images that were held back from both training and validation. The confusion matrix for these results is in [Figure 14.](#page-23-1) The model was able to classify the broad classes of water (label = 99), land (label = 100) and wetlands with accuracies of 95%, 97% and 98% (391 of 400 images) respectively.

The model was able to predict specific ecosites with less accuracy. It performed well on ecosite 149 (90%), but most frequently misclassified ecosites 135 (30% accuracy) and 144 (29% accuracy). With respect to ecosite 135, this may be in part due to the limited number of polygons from which to choose from for the training set. A substantial amount of overlap between image chips was required to achieve 1,000 training samples, and the model therefore had limited information from which to create generalized predictions.

If ecosite 152 (open water) was combined with 149 (shallow water), the model had a 90% accuracy in classifying these marsh types within the test data.



<span id="page-23-1"></span>**Figure 14. Confusion matrix for test images [99 = water, 100 = land, and all other labels are wetland ecosites].**

Given the diversity of how a single ecosite may look across an area, it may be that additional samples are required to create a more accurate model. Wetland polygons delineated in this study often contained a mix of vegetation conditions and it may be that the fine scale image size is too focused to provide the context need to properly identify the overall feature (e.g. the proximity to shores, broken nature of flakes or strings). It would be worthwhile to investigate the performance of larger initial chip sizes with multiscale cropping (e.g. Pouliot et. al. 2019).

## <span id="page-25-0"></span>6 Conclusions

This project has demonstrated that the eFRI dataset with enhancements to refine island and waterbody polygons can be effectively used to produce high-resolution wetland inventories, and that they are comparable to inventories generated using alternative methods of classification, such as the DUC Enhanced Wetland Classification System. While the overall wetland area added to the inventory  $($   $\sim$  2,600 ha) is small compared to the overall park size, it is important to note that much of this area is in ecosites that were completely omitted from the original inventory. These areas can therefore aid in fish and wildlife habitat planning as well as broader ecosystem plans.

Interpretation of wetlands from the imagery had accuracies of 62 – 77% to field data depending on wetland class. These results show that there is a reasonable ability to identify wetland classes from the ADS imagery, but that some caution is needed as ecosite-specific determination remains difficult. Depending on the end use of the wetland inventory (i.e. if specific ecosites are required, or if broader classifications are sufficient), this may or may not be a problem. The use of both primary and secondary ecosite labels in complex wetland areas is one way to improve the accuracy of delineated areas. It is possible that the new imagery with increased spatial resolution may also aid in accurate identification.

One limitation of the use of eFRI imagery for the development of wetland inventories is that the time when the images were captured does not necessarily represent the time of maximum vegetation growth. This can potentially lead to underestimating the total area of a wetland ecosite and/or to errors in the ecosite classification. Wetland vegetation is at its maximum cover from about late June to mid-September. Year to year variation in wetland vegetation cover due to water level fluctuations is another potential source of error. If eFRI imagery was acquired outside of this period, alternate data sources, such as Google Earth and Bing imageries, can be used to assist the delineation and classification process. High temporal resolution image sources such as Planet would also provide a high level of accuracy on the timing of vegetation emergence and may aid in ecosite assessment.

The results from modelling using convolution neural networks and imagery with the near-infrared band illustrates a promising area of investigation into automated wetland classification. The model was able to classify the broad classes of water, land and wetlands with accuracies of 95%, 97% and 98% respectively. Model accuracy was lower in specific ecosites, but some such as ecosite149 were predicted with good accuracy (90%) as were overall marsh classes (ecosite 149 and 152). An increase in sample sizes for training these models, investigating the use of other image chip sizes, and the higher resolution from new ADS imagery may help produce higher accuracy results.

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<span id="page-27-0"></span>

#### **Appendix 1. Quetico wetland site data (2018)**











#### **Appendix 2. Quetico wetland vegetation data (2018)**

<span id="page-33-0"></span>







































<span id="page-53-0"></span>

### **Appendix 3 Quetico wetland site data (2019)**







#### <span id="page-57-0"></span>**Appendix 4. Quetico wetland vegetation data (2019)**



























