SPECTRAL DETAIL VERSUS SPATIAL DETAIL: A LAND COVER CLASSIFICATION FOR NORTHEASTERN GEORGIAN BAY USING SENTINEL-2 MULTISPECTRAL IMAGERY

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ABSTRACT

Northern Georgian Bay, Ontario presents an extremely complex landscape composed of a wide variety of land covers ranging from diverse forests to lakes and wetlands, including many preserved natural ecosystems. A land cover classification is important for this area because of potential climate change risks to the region that could displace and disrupt the lifestyle of the region's Indigenous communities such as the Shawanaga. The European Space Agency's Sentinel-2 mission gathers global satellite imagery with a five-day revisit. A land cover analysis was conducted using Sentinel-2 image composites at 10- and 20-metre resolutions to compare the benefits of both spectral and spatial detail for this complex region. The methods and results explored throughout the project aim to help develop a foundation for producing regularly-updated land cover maps to help improve management of the region's ecosystems and preserve Indigenous practices. Spectral detail was found to be valuable for identifying spectrally similar land cover types such as the many forest species in Georgian Bay, with an overall classification accuracy of 80%. Alternatively, higher spatial detail appeared to be beneficial in differentiating between unique classes such as roads, water, and urban areas with a 78% overall accuracy. Conclusions were made that future land cover classification projects using Sentinel-2 should consider using a larger quantity of spectral bands as it produces more accurate overall classification results, but spatial detail should not be entirely overlooked.

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INTRODUCTION

Georgian Bay is a vast region in Ontario home to a variety of Indigenous communities including the Shawanaga First Nation. This region, as well as much of northern Ontario, primarily consists of forest cover and wetlands, therefore the area appears relatively uniform when examining a satellite image over the region with one's eyes. However, with growing concerns of climate change and damage to the Earth's natural world, it is likely that Georgian Bay is at risk for land cover changes such deforestation and reduced wetland cover (Weller & Chow-Fraser 2019). These types of general land cover changes could greatly impact traditional Indigenous hunting and fishing practices, through affecting faunal migratory patterns (McLean 2012).

With urbanization and land management of the territory, new infrastructures have been built on or close to the First Nation reserve, and further urbanization could result in significant impacts to the surrounding environment (Shawanaga 2021). Indigenous groups like the Shawanaga (2021) are highly dependent on the natural environment for many resources such as fish, wildlife, and plants. Land cover changes in the past, present, and future may impact Indigenous accessibility to natural resources due to complex interactions in the region's ecosystems (Murray & King 2012).

The Shawanaga community along with other Indigenous groups are interested in visualizing the land cover within their territory and surrounding areas through investigating land cover on a regular basis across First Nation reserves. Land cover can change for several reasons and is often due to a variety of factors including both anthropogenic and biophysical processes (Brown 2010). The ability to visualize and measure land cover in Georgian Bay would aid in monitoring pressures and stresses put on ecosystems, biodiversity loss, and informing land use plans for the Shawanaga and other communities in the region (OECD 2018).

Annually producing classification maps for areas susceptible to land cover changes can also help with detecting changes in these regions as well as predicting future risks to the landscape. Most land cover-related data available for northern Georgian Bay are static sources that are not regularly updated due to financial and technical requirements. Analyzing land cover changes requires the ability to produce regularly updated land cover classifications for the Georgian Bay region; something that has not been done before.

By producing successful land cover classification maps, organizations can replicate the methods on a regular basis, thereby enabling the ability to detect the land cover change by comparing classifications from different times. Image quality is an important factor that greatly impacts the classification accuracy (Park and Lee 2016). High resolution images contain more spatial detail than low resolution images, thus a lower-resolution image can lead to over-, and underestimation compared to a high-resolution image (Park and Lee 2016). Another factor that may impact the classification accuracy is the number of spectral bands in the image, known as spectral resolution. Spectral bands are the reflectance from the Earth's surface, and images containing more bands contain larger quantities of valuable information that can help result in a more accurate classification (Fauvel et al. 2012).

Through developing methods that can be repeated regularly, annual land cover maps can be created and used to predict changes to the landscape, thus developing better management plans to conserve the region's many ecosystems (Murray & King 2012). The Sentinel-2 project launched by the European Space Agency collects multispectral satellite imagery over the entire globe every five days (The European Space Agency 2020). Using both static land cover data and Sentinel-2 imagery, it is possible to develop methods to generate land cover maps for northern Georgian Bay that can be regularly updated.

This study is important because there is an interest to visualize land cover changes in Indigenous territories across Canada, and this will help to facilitate other research such as how biodiversity, wildlife abundance, and other changes relate to the region's land cover (OECD 2018). Through understanding the land cover present within the study area, the appropriate authorities within Indigenous communities may replicate the methods provided to expand the work completed in this classification project.

Trade-off between spatial resolution and spectral detail is a common phenomenon in remote sensing image analyses (Price 1997). Higher spectral detail comes at a cost of reduced spatial resolution in Sentinel-2's case, but a great amount of ground detail means losing valuable spectral information from the additional spectral bands.

The purpose of this study is to develop a series classified maps for the land cover in northern Georgian Bay using Sentinel-2 image composites and compare the classification accuracy between spatial and spectral detail to determine if one is more beneficial than the other.

RESEARCH OBJECTIVES

The classification project was met initially with determining five primary objectives, beginning most importantly with determining a classification schema adequate for the Sentinel-2 image composites covering the Georgian Bay region. No prior knowledge of the region's land cover was known, so it was crucial to learn what land cover types were to be identified. The

Sentinel-2 images also needed to be pre-processed to ensure we were working with a high-quality image containing limited obstacles.

Objective three took place after the methods themselves, producing a series of classified rasters and quantifying the accuracy of the 10-metre and 20-metre classifications. The strengths and weaknesses of the land cover classification were also discussed, comparing spatial and spectral detail with regards to identifying different land cover types. Lastly, there was a desire to investigate the spectral differences between the identified land classes based on the final classified images.

STUDY AREA

The study area being examined is located near Georgian Bay in the southeast of Ontario, Canada (Figure 1). The study covers an area of 1314 km^2 focusing on the Shawanaga First Nation Territory and surrounding areas reaching from the Magnetawan River to Parry Sound. The Indigenous community that inhabits the Shawanaga reserve live and manage the land themselves and continue to uphold their traditional practices (Shawanaga 2021). The surrounding land in the study area appears very similar to the Shawanaga territory itself and is closely connected to the people who live in the area and their daily activities, primarily composed of forests and wetlands (Shawanaga 2021).

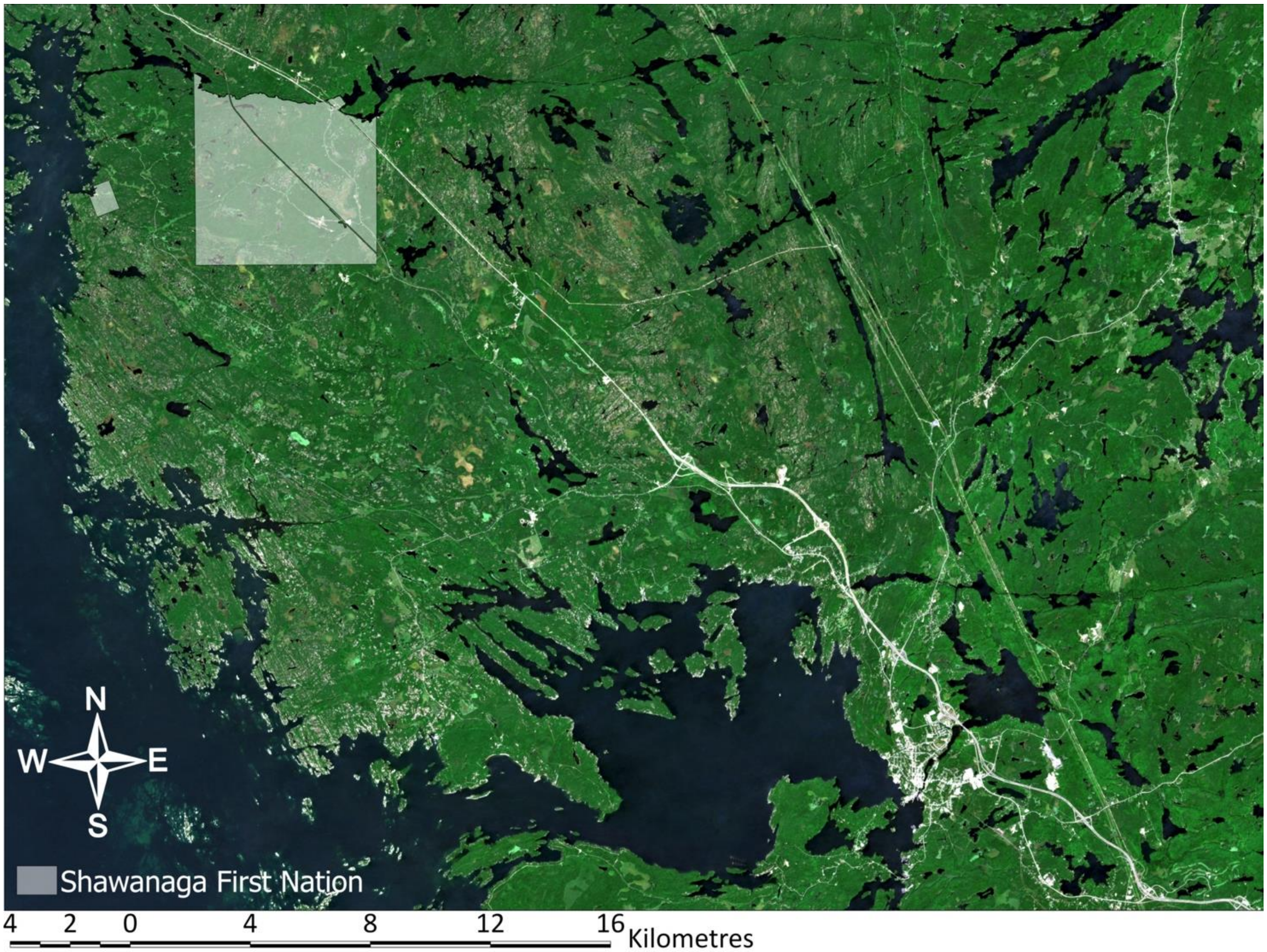


Figure 1 A snapshot of the study area in Northern Georgian Bay, Ontario. Displayed is a 20-metre resolution median composite Sentinel-2 image produced from the Google Earth Engine Code Editor. The Shawanaga First Nation Territory is highlighted in the northwest portion of the image, and Parry Sound can be seen in the southeast.

METHODS & DATA

Prior to conducting the land cover classification, we first had to decide on the specific classification method. Image classification itself, according to Environmental Systems Research Institute, or ESRI (2021e), is a means of extracting information from a raster image, such as land cover classes through various steps from pre-processing to the actual classification. A pixel-based classification was selected for the Georgian Bay project (Figure 2). The nature of a pixel-based classification involves assigning each individual pixel in an image a land cover class based on its spectral characteristics (ESRI 2021e). In many cases, the characteristics of adjacent pixels are not considered in pixel-based classifications (ESRI 2021e).

Figure 2 A workflow of the classification project methods, for more detail see Appendix C.

The satellite images used in this project are Sentinel-2 multispectral image composites produced from the Google Earth Engine containing median spectral reflectance values. The image composites used were produced from a combination of images acquired by Sentinel-2 over time, created by computing the median surface reflectance for each pixel in the image. Every pixel in the image has a median spectral reflectance value across all Sentinel-2 images taken between the months of May and September, as to avoid Winter and Autumn differences.

Two additional bands including a Normalized Difference Vegetation Index (NDVI) and a Mean Normalized Difference Water Index (MNDWI) were added to the image for a total of 11 spectral bands in the 20-metre resolution image (Appendix B); the 10-metre image contained six spectral bands. The NDVI is calculated using the following equation: NDVI = NIR - Red / NIR + Red, where NIR refers to the Near-Infrared band (Tucker 1979). The MNDWI is calculated with a separate equation: MNDWI = Green - SWIR / Green + SWIR, where SWIR stands for the Short-Wave Infrared band (Xu 2006).

Before a supervised land cover classification can be conducted, an adequate land cover classification schema, or land use index must be determined to know exactly what land classes should be identified. According to LaGro (2005), a high interpretation accuracy is needed for the land cover categories being established, while also being suitable for remote sensing data collected over a broad timescale and outside of the study area. Level I classification, also called family classes, contains the general land cover or land use such as urban, agricultural, forests, water, or wetlands (LaGro 2005). The second level of the classification system further breaks up land categories for a deeper analysis that can be applied to larger-scale study areas (LaGro 2005).

With limited prior knowledge of the study area, different datasets (Table 1) from other sources were used to help identify and build the training samples by overlaying these datasets with the Sentienl-2 images. The Ontario Geohub contains a wide variety of data ranging from forest cover for all of Ontario, to layers depicting the Province’s lakes and rivers. The European

Space Agency's Sentinel-2 images for the region contain four bands at 10-metre resolution and nine bands at 20-metre resolution (The European Space Agency 2020). The forest dataset used contains eight dominant species within the study area, illustrated in Appendix A (Ministry of Natural Resources 2016).

Table 1: All the datasets used in the classification that were acquired from outside sources including the Sentinel-2 imagery and Forest Inventory data for Ontario. Each dataset includes the source, publication year, and a brief description of each source and why we used it.

Dataset	Source	Year	Description
Sentinel-2	European Space Agency https://earthexplorer.usgs.gov/https://code.earthengine.google.com/d41280d1ff16593055f07d856b9d2a6a	2020	Satellite image covers the study area with 10-metre & 20-metre resolution.
Google Maps Satellite View	Google Maps https://www.google.com/maps	2021	Better resolution used as a reference for creating Training Data.
Forest Inventory	Ontario Ministry of Natural Resources http://geo1.scholarsportal.info/#r/details/_uri@=831693057	2016	The Forest Inventory data consists of eight major tree species within the study area.
Road Network	Statistics Canada http://geo.scholarsportal.info/#r/details/_uri@=4291084613&_add:true_nozoom:true	2016	Helps in creating the road Training Samples.
Ontario Integrated Hydrology (OIH)	Ontario Ministry of Natural Resources https://geohub.lio.gov.on.ca/datasets/dc6da6816e2446279210668718af91c9	2020	Helps in creating the agriculture Training Samples.

Dataset	Source	Year	Description
Annual Crop Inventory 2019	AAFC – Agriculture and Agri-Food Canada https://open.canada.ca/data/en/dataset/d90a56e8-de27-4354-b8ee-33e08546b4fc	2019	Helps in creating the agriculture Training Samples.
Agriculture and Agri-Food Canada – Land Use 1990, 2000, 2010	AAFC – Agriculture and Agri-Food Canada http://www.agr.gc.ca/atlas/landu	2010	Provides cropland information within the study area to aid classification.

In addition to forests, wetlands are also very prominent in the northern Georgian Bay area, so further research into Ontario's wetland ecosystems was conducted to help with the classification schema. We determined that there are two primary types of wetlands in the region, including open wetlands and treed wetlands. Exploring both the Sentinel-2 images and using Google Earth's satellite view at a higher resolution helped to identify other important land cover classes within the study area which are all included in Table 2.

Table 2: A list of the finalized classification schema used in the classification analysis. Each class listed on the left of the table represents a parent class, and with it their class value. Some parent classes such as Forest and Developed contain subclasses which are also listed, while classes without subclasses are listed as N/A. The class values represent numbers to associate each class with, we based these numbers on the ArcGIS Pro default schema numbers, with parent classes increasing by increments of ten.

Parent Class Name	Parent Class Value	Subclass Name	Subclass Value
Agriculture	70	N/A	N/A
Developed	20	Roads	22
Developed	20	Urban Areas	21
Forest	40	Deciduous Forest	41
Forest	40	Poplar	48
Forest	40	Tolerant Hardwoods	44

Parent Class Name	Parent Class Value	Subclass Name	Subclass Value
Forest	40	White Birch	46
Forest	40	Coniferous Forest	42
Forest	40	Jack Pine	401
Forest	40	Lowland Conifers	47
Forest	40	Red/White Pine	45
Forest	40	Upland Conifers	49
Forest	40	Mixed Forest	43
Grassland	60	N/A	N/A
Rock	30	N/A	N/A
Shrubland	50	N/A	N/A
Soil	100	N/A	N/A
Water	10	N/A	N/A
Wetlands	80	Open Wetland	81
Wetlands	80	Treed Wetland	82

Training samples were produced to train the classifier based on the 20-metre resolution image composite. Only three spectral bands could be displayed at the same time, so different band combinations were explored to help better interpret the training data, but all existing spectral bands were used in the final classification (Table 3).

Table 3: A documentation of the various spectral band combinations used in interpreting the training samples. The table states what land cover the band combination best displayed, with the band numbers used in an RGB format. Please see Appendix B for definitions of each band number.

Image Resolution	Land Class Identified	Band Combination (RGB)
20m	Wetland	B08, B05, MNDWI
	Wetland	B11, B05, B02
	Urban Areas & Rock	B12, B04, MNDWI
	Forest (Various Species)	B08, B04, B03
	Forest (Various Species)	NDVI, B08, B03
10m	All	B04, B03, B02

The training samples in ArcGIS Pro were produced as circle polygon features (Figure 3), coloured according to their land cover class in the schema and given class values based on the typology. Each circle feature representing the training data were created with varying sizes, simply based on the size of pixel clusters that specific samples encompassed, so many of the water samples were much larger than other land covers.

The training samples were created iteratively by testing and refining consecutively larger quantities of training data. We documented our process throughout the training data in order to note where we had to make improvements to our collection of samples. Over 3000 final training samples were produced and manually placed to train the classifier, with at least 40-50 samples for most classes (Table 4). Additionally, not all parent classes were represented in the final training samples, as the purpose was to classify the subclasses.

During the classification processes, individual samples containing varying amounts of pixels each held different weights in training the classifier based on the amount of samples, and amount of pixels contained within the circles.

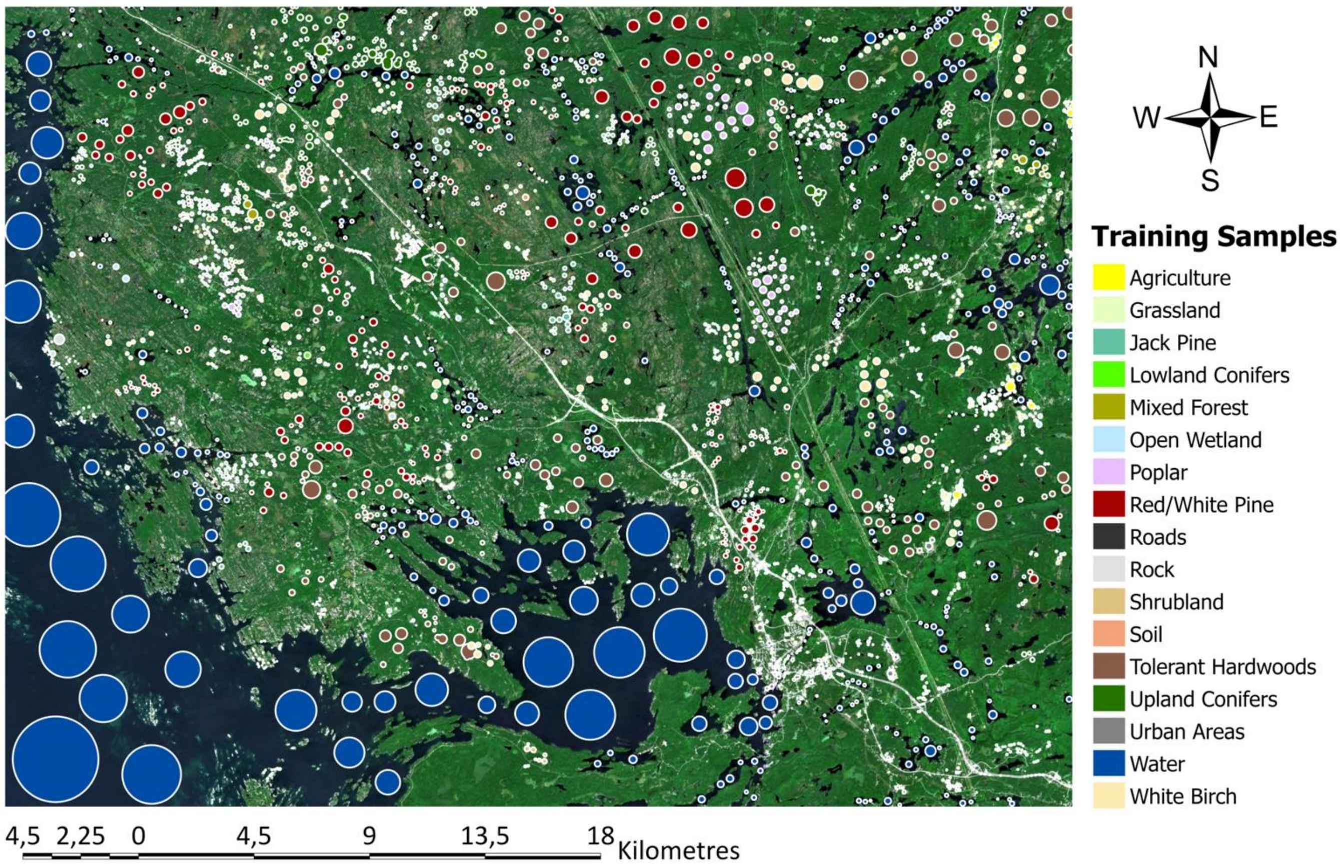


Figure 3 A snapshot map showing the Sentinel-2 image with a 20-metre resolution, depicting a true colour composite band combination. Overlayed on the image are the final set of training samples used for the classification displayed as circle polygon features, coloured based on what land cover class they are associate.

Figure 3:

Table 4: Each class represented by our final set of training samples, with the number of samples created per class, varying in size, as well as the pixel percentage of each class's training samples. Classes with a higher pixel percentage and higher number of training samples were predicted to be classified with better accuracy.

Class Name	Number of Samples	Pixel Percentage
Agriculture	188	1.17%
Grassland	262	0.78%
Shrubland	43	0.40%
Soil	95	0.40%
Rock	165	0.35%

Class Name	Number of Samples	Pixel Percentage
Open Wetland	380	1.70%
Roads	257	0.31%
Urban Areas	186	0.79%
Poplar	233	2.78%
Tolerant Hardwoods	253	11.64%
White Birch	158	3.85%
Jack Pine	105	1.13%
Lowland Conifers	48	0.29%
Red/White Pine	419	10.44%
Upland Conifers	230	2.69%
Mixed Forest	64	0.86%
Water	601	60.42%
Total Number of Training Samples	3687	100%

The classification wizard in ArcGIS Pro combines various individual functions in the program so they can be executed in a user-friendly manner to produce a classified raster output, producing the following overall workflow: Configure >> Train Classifier >> Classify Raster >> Merge Classes >> Reclass Errors (ESRI 2021e).

We used Maximum-Likelihood to classify the satellite images as this method determines the likelihood of what land cover class certain pixels belong to, based on their neighbouring pixels. Prior to finalizing the output, the reclassification tool in the wizard was used to reclassify any misclassified areas of the preview raster, as well as regions where there appeared to be random pixel noise.

The software used throughout this study was ArcGIS Pro by the Environmental Systems Research Institute (ESRI), along with image modification using Google Earth Engine's code editor.

RESEARCH RESULTS

The final outputs of the pixel-based classification were four output rasters: two classified rasters for the 10-metre image, and two for the 20-metre image. Each Sentinel-2 image composite produced a classified land cover raster containing all our land covers, aside from Treed Wetlands due to an inability to identify this class in the training sample process. Additionally, two classified rasters with merged forest classes were created with Deciduous and Coniferous Forest species merged into their respective parent class.

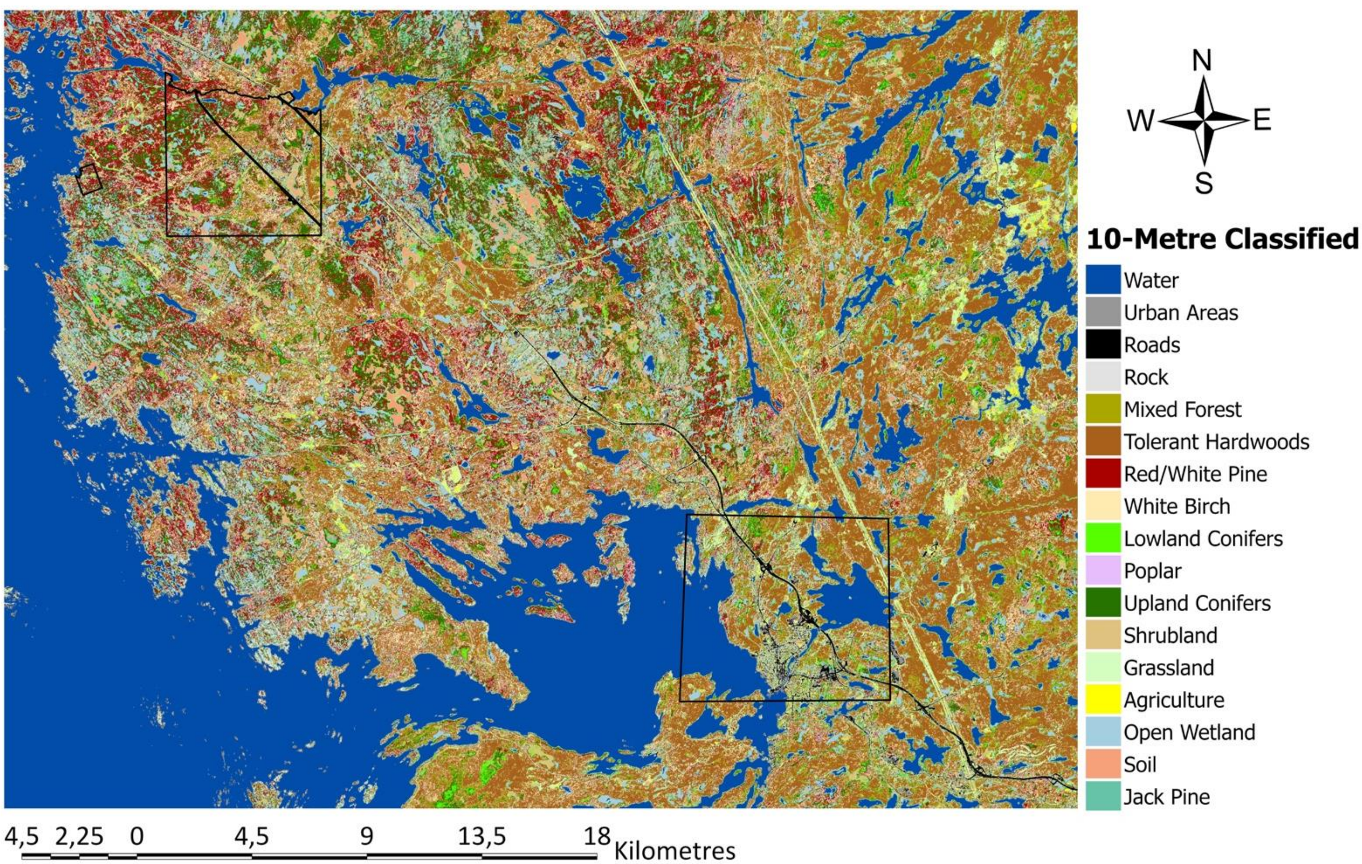


Figure 4 The final classification output raster for the 10-metre resolution Sentinel-2 image with all 17 land cover classes. Overlayed is a layer showing the Shawanaga First Nation Territory as well as a box around Parry Sound showing where we have zoomed into the image.

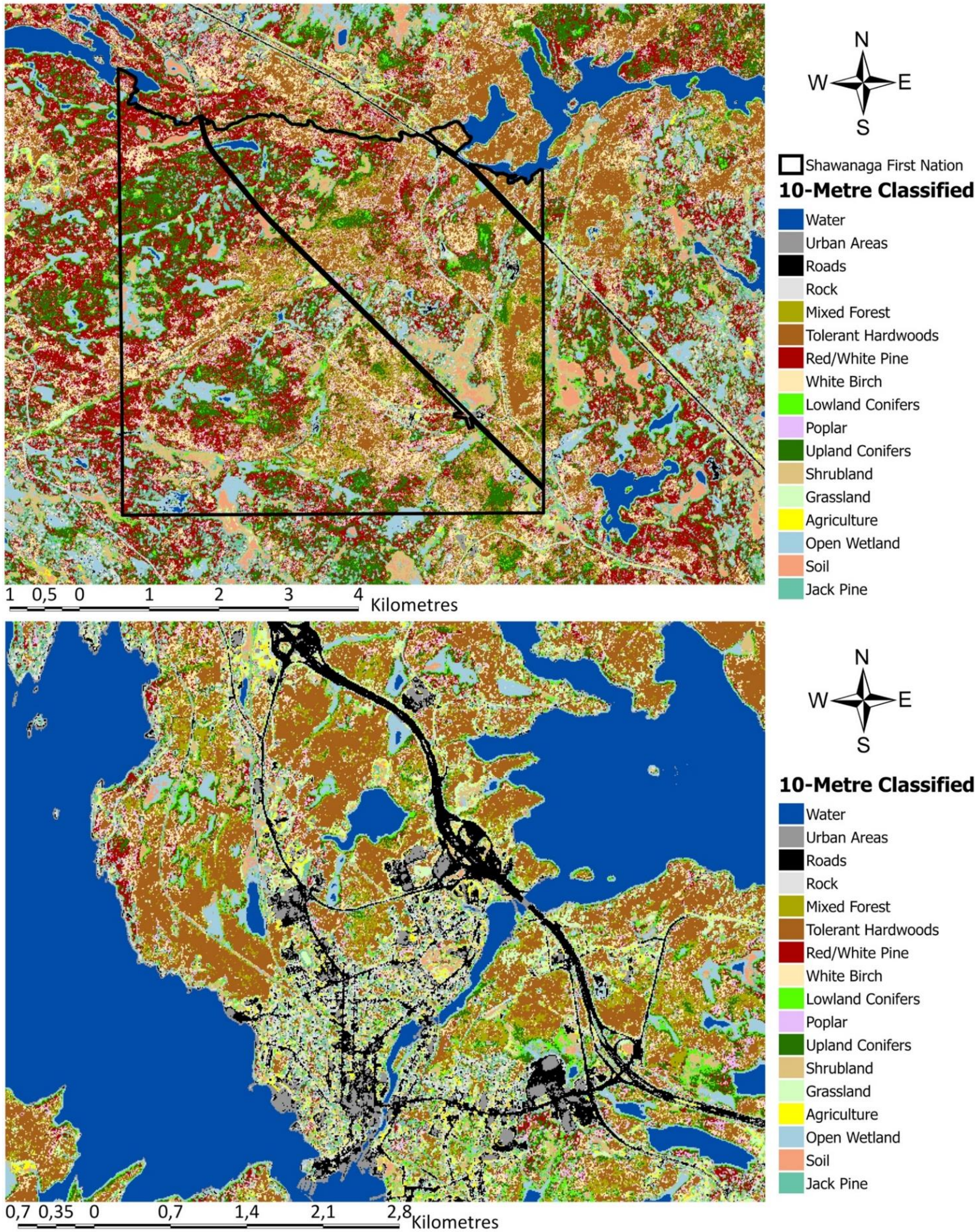


Figure 5 Zoomed in snapshots of the 10-metre resolution classified raster. The top image is focused on the Shawanaga territory and the bottom image is zoomed into the city of Parry Sound.

Based on Figure 5, there appear to be many wetlands present in the Shawanaga Territory, but the road that passes through the east portion of the area was misclassified in the 10-metre image. The bottom image in Figure 5 is zoomed into Parry Sound where we noticed a large amount of random pixel noise, with many different classes being identified in an otherwise mostly urban and road-dominated area of the image.

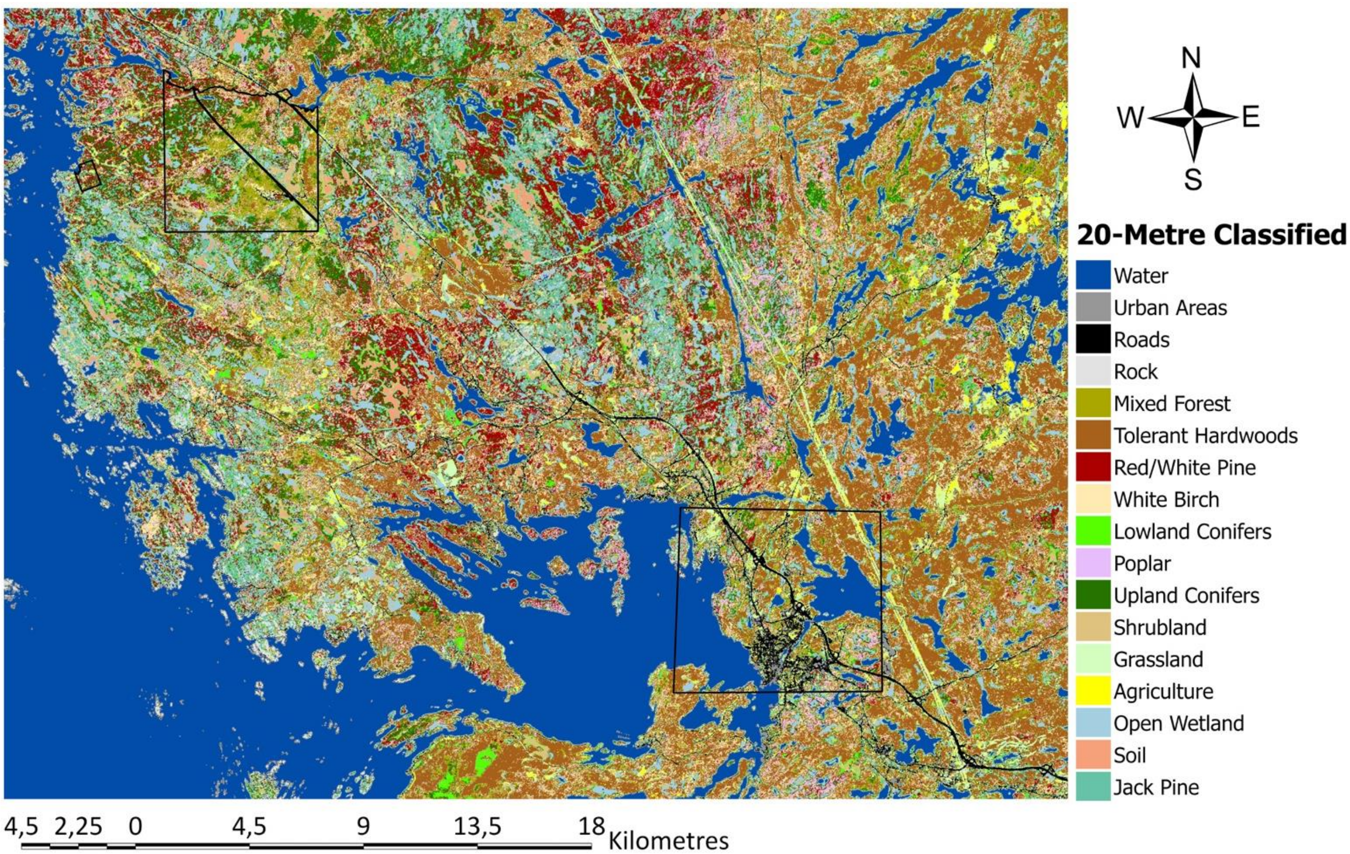


Figure 6 The 20-metre resolution Sentinel-2 classified raster output with all 17 land cover classes. Overlayed is a layer showing the Shawanaga First Nation Territory as well as a box around Parry Sound showing where we have zoomed into the image.

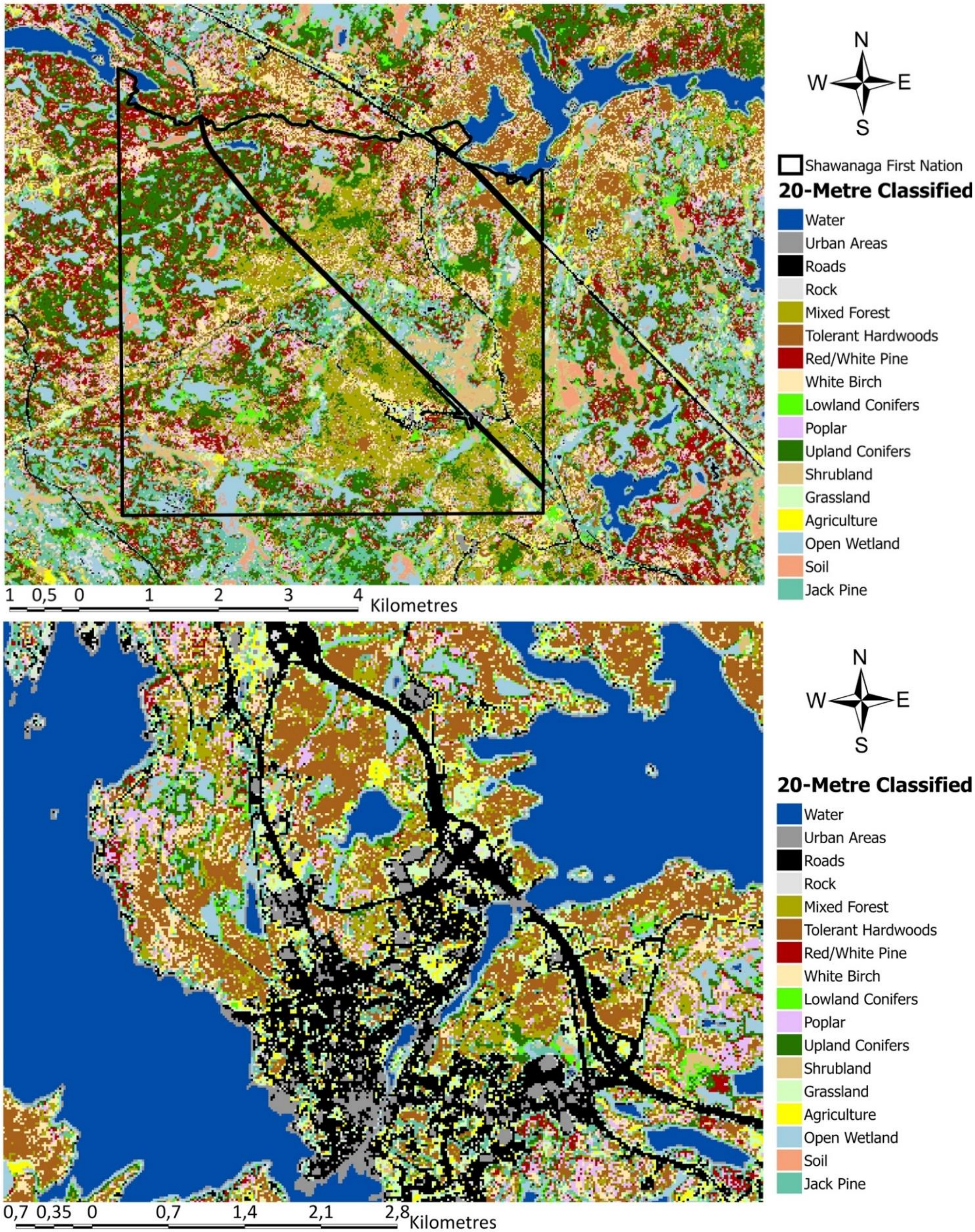


Figure 7 Two snapshots taken at significant regions of the 20-metre resolution classified raster. The two maps represent the same areas as Figure 5, with several noticeable differences between the classifications.

Overall, there appears to be less pixel noise in the 20-metre classified image due to a smaller quantity of pixels at a lower spatial resolution. In the Shawanaga Territory, there are still many wetlands classified within the area, and the road passing through the territory is classified to a better degree than the 10-metre image. Parry Sound is also classified with far less variety of classes in the 20-metre image, with more of the area being identified as urban and roads.

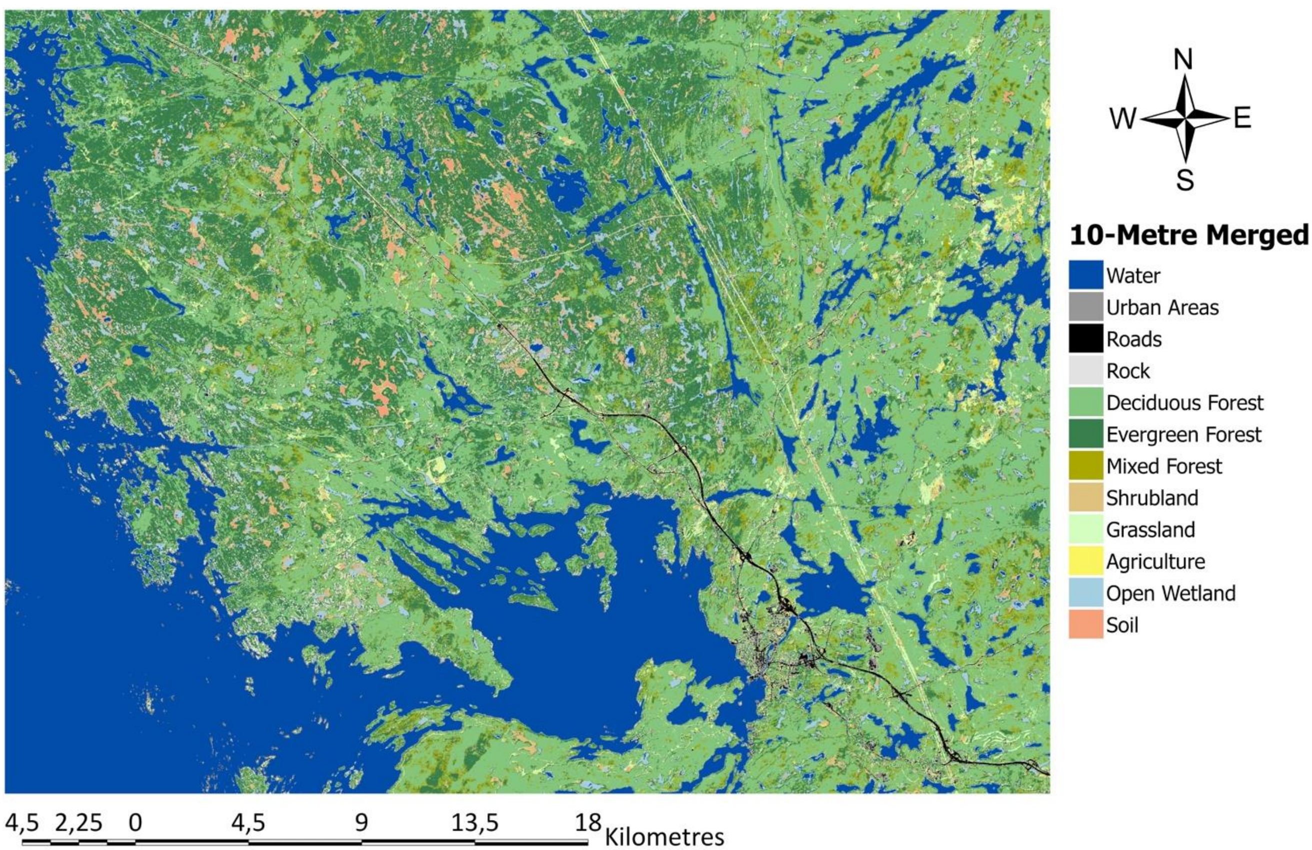


Figure 8 The classified 10-metre raster with all forest classes merged into their respected parent classes, meaning all deciduous species such as Tolerant Hardwoods, Poplar, and White Birch are merged into the Deciduous class, while all conifers and pine species merged into the Coniferous forest class.

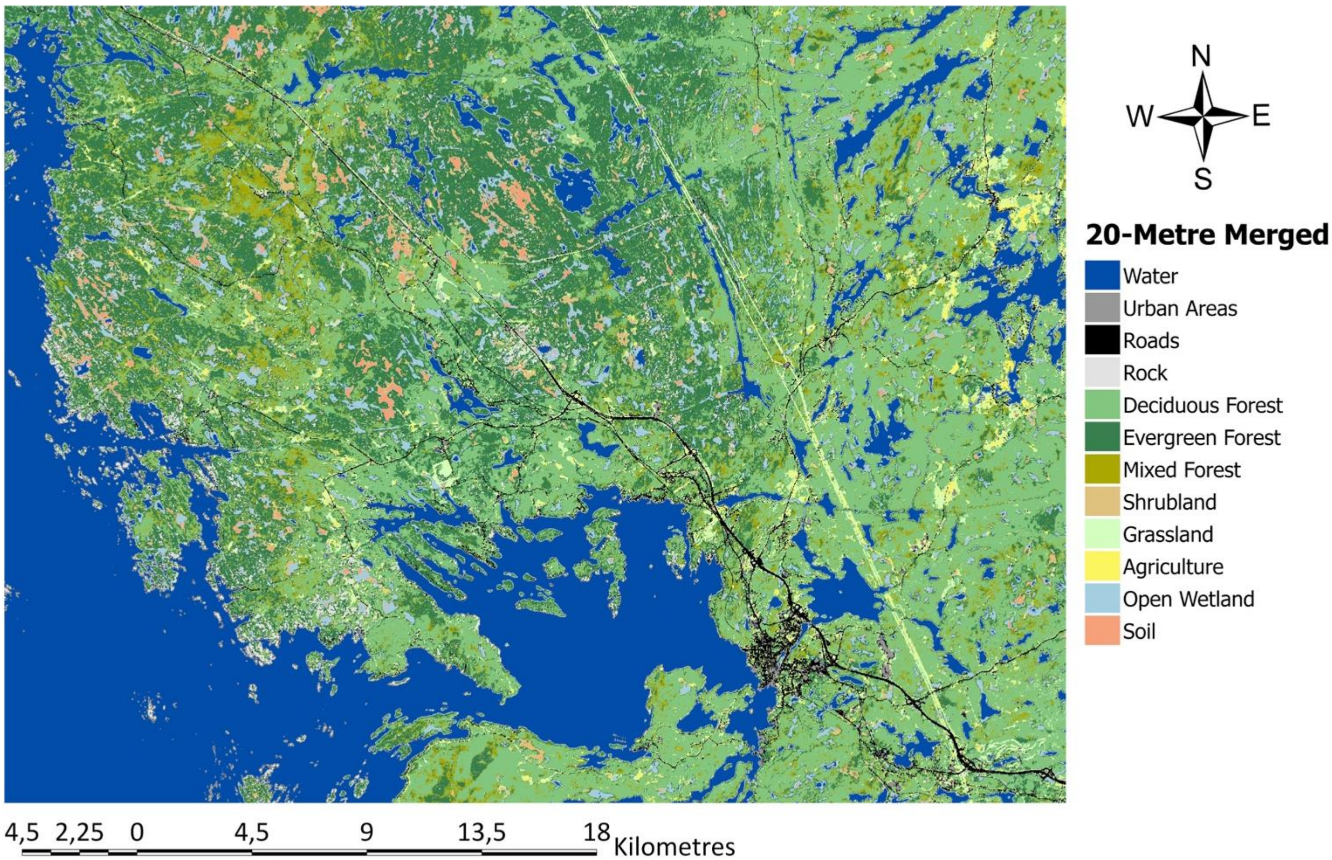


Figure 9 The classified 20-metre raster with all forest classes merged into their respected parent classes, meaning all coniferous species such as Jack Pine, Upland/Lowland Conifers, and Red/White Pine are merged into the Coniferous class, while all deciduous trees are merged into the Deciduous forest class.

Based on the two merged forest class rasters in Figures 8 and 9, and after overlaying the forest inventory data as a reference, it appears as though the classifier accurately differentiated between deciduous and coniferous forest types, even if some individual species were misclassified.

Four spectral profile charts were also created for the 10-metre and 20-metre Sentinel-2 images using the training samples to visualize the spectral information for every band used in either image (ESRI 2021d). These charts (Figure 10 & 11) helped us to justify our use of band combinations in the training data process, as well as review the value and importance of spectral information with regards to land cover classification (ESRI 2021d).

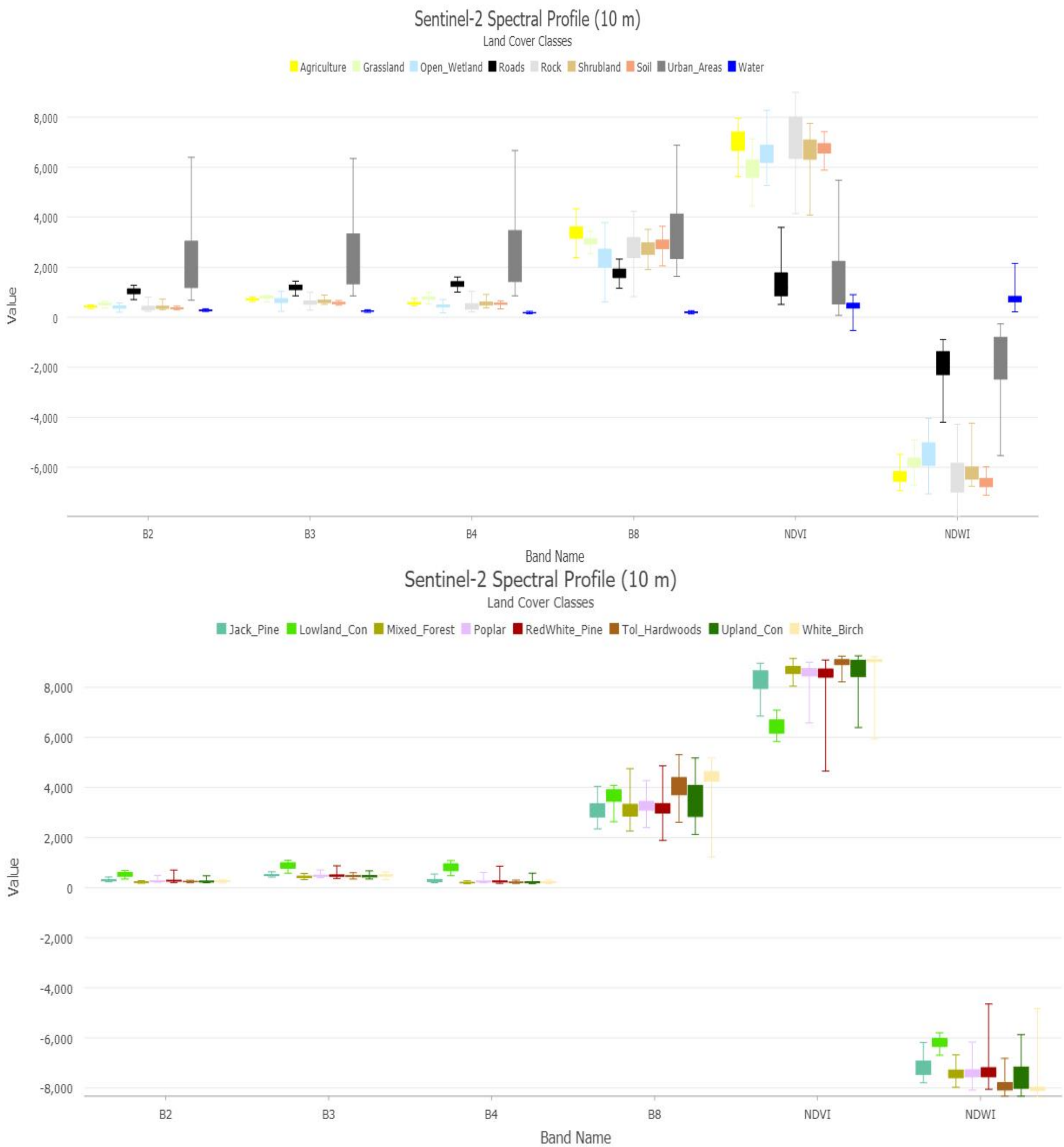
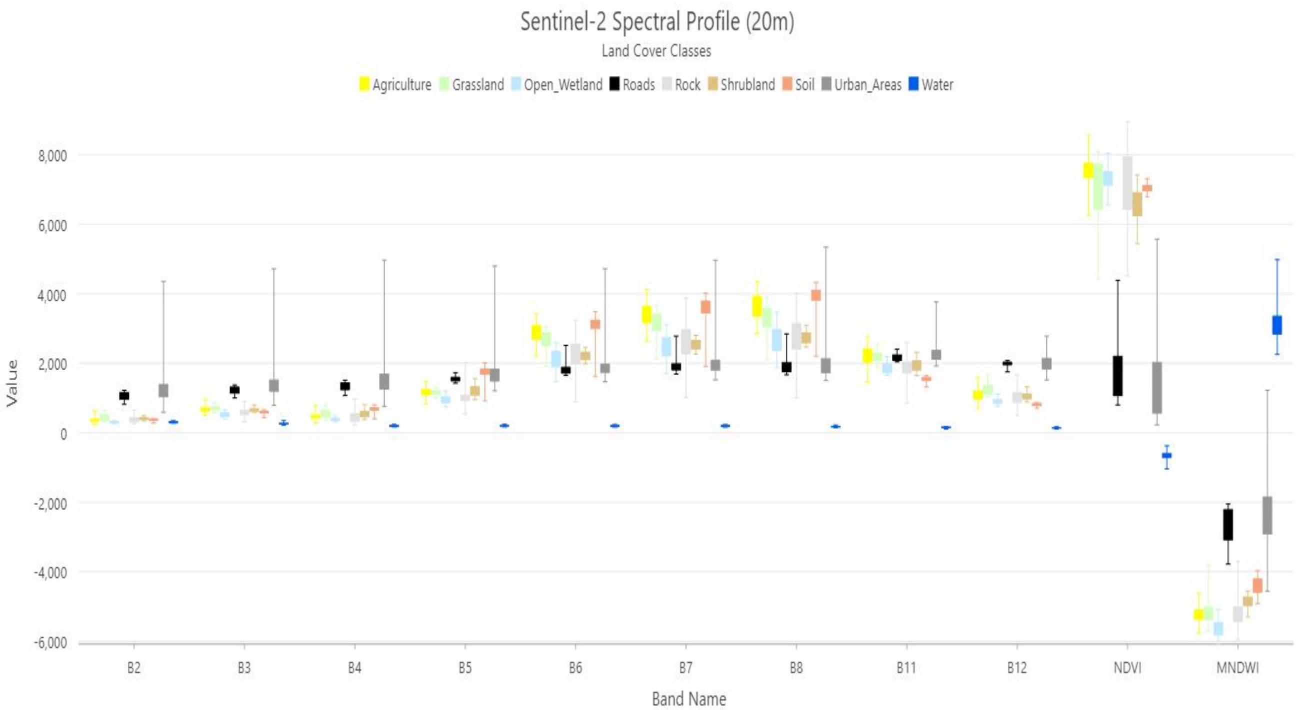


Figure 10 Two charts representing the spectral profile of the 10-metre spectral bands and training samples. The top figure contains all non-forest classes, and the bottom image displays all forest classes.



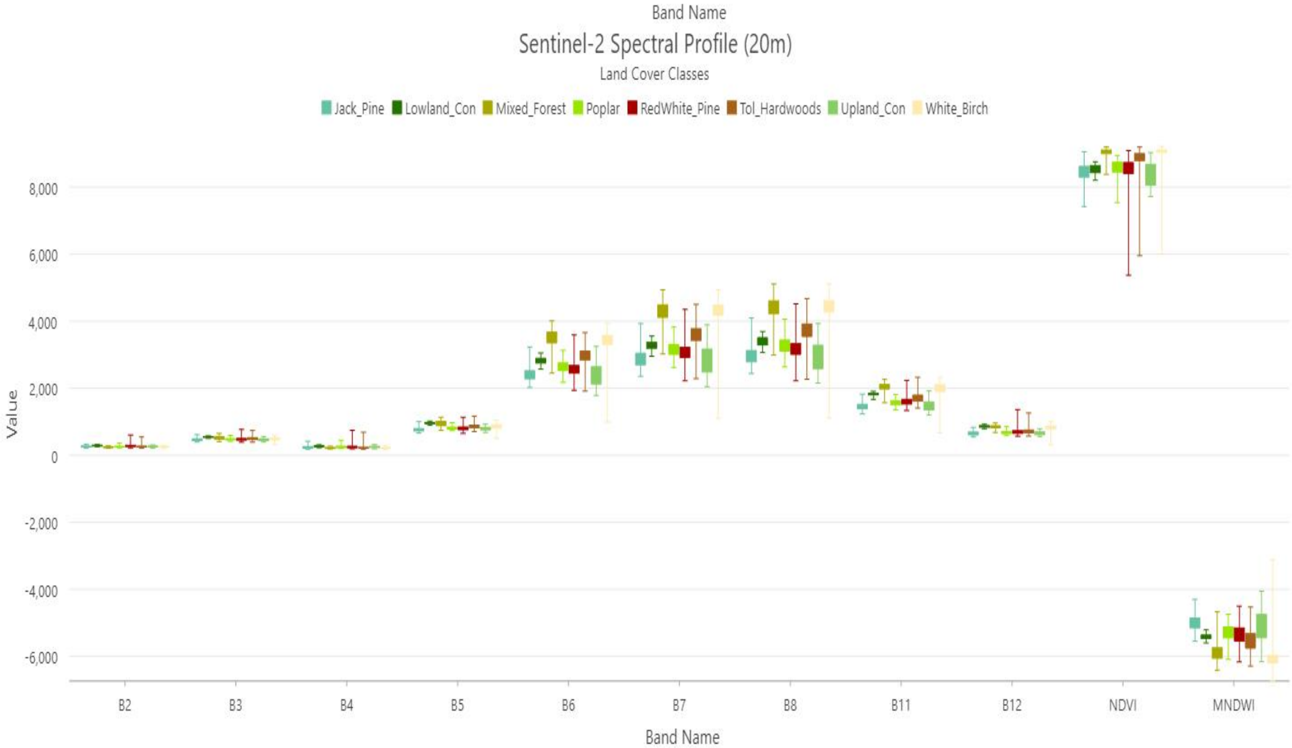


Figure 11 Two charts representing the spectral profile of the 20-metre spectral bands and training samples. The top image contains all non-forest classes, while the bottom image displays all forest classes.

The spectral profiles informed us how well each spectral band displays most training samples; for example, the forest classes have a higher reflectance in the NDVI band, while the MNDWI represents water quite well but the forest classes poorly. In the 10-metre spectral profile it is apparent that roads and urban areas are differentiated better in an image with higher spatial detail. Of the four spectral profiles, two contain all non-forest classes while the other two display only the forest classes to help with clarity of the information in the charts.

After exploring the classified rasters and spectral profiles for the 10-metre and 20-metre Sentinel-2 composites, various accuracy assessments (Figures 5-9) were conducted to calculate the statistical producer's and user's accuracies of the classifications. A low producer's accuracy means a large amount of class 'X' samples have been misclassified as other classes (Comber 2016). A low user's accuracy refers to many other land covers were misclassified as class 'X' (Comber 2016).

Table 5: The accuracy assessment confusion matrix produced in ArcGIS Pro, depicting the User's and Producer's accuracy for the 10-metre classification. The 10-metre had a lower overall accuracy score, the full confusion matrix can be found in Appendix E.

Land Class Name	**Producer's Accuracy**	**User's Accuracy**
Agriculture	0.3349	0.5635
Grassland	0.4157	0.3520
Jack Pine	0.3	0.2357
Lowland Conifers	0.2203	0.0568
Mixed Forest	0.2383	0.0807
Open Wetland	0.4778	0.8557
Poplar	0.1691	0.2212
Red & White Pine	0.3672	0.6584
Roads	0.6122	0.2885
Rock	0.5156	0.3626
Shrubland	0.5789	0.1522
Soil	0.7037	0.38

Land Class Name	Producer's Accuracy	User's Accuracy
Tolerant Hardwoods	0.7150	0.6995
Upland Conifers	0.3986	0.2258
Urban Areas	0.4535	0.8478
Water	0.9992	1
White Birch	0.1812	0.2026
Overall Accuracy	0.7801	
Kappa Coefficient	0.6412	

Table 6: The accuracy assessment confusion matrix produced in ArcGIS Pro, depicting the User's and Producer's accuracy for the 20-metre classification. The 20-metre output had a higher overall accuracy, and the full confusion matrix can be found in Appendix E.

Land Class Name	Producer's Accuracy	User's Accuracy
Agriculture	0.5992	0.6893
Grassland	0.5786	0.4126
Jack Pine	0.3585	0.2209
Lowland Conifers	0.3731	0.1471
Mixed Forest	0.3892	0.0964
Open Wetland	0.5514	0.8578
Poplar	0.3152	0.3020
Red & White Pine	0.4041	0.7549
Roads	0.8194	0.5086
Rock	0.6875	0.625
Shrubland	0.7808	0.3353
Soil	0.7831	0.5118
Tolerant Hardwoods	0.6834	0.7442
Upland Conifers	0.5229	0.2924
Urban Areas	0.5556	0.8108
Water	0.9978	1
White Birch	0.2699	0.2949
Overall Accuracy	0.8022	
Kappa Coefficient	0.6783	

Table 7: The accuracy assessment confusion matrix depicting the User's and Producer's accuracy for the 10-metre merged classification. The 10-metre output had a lower overall accuracy, and the full confusion matrix can be found in Appendix E.

Land Class Name	**Producer's Accuracy**	**User's Accuracy**
Agriculture	0.2841	0.6111
Grassland	0.3987	0.3112
Mixed Forest	0.2824	0.0842
Open Wetland	0.4535	0.7761
Roads	0.5294	0.3495
Rock	0.4167	0.3333
Shrubland	0.6133	0.1592
Soil	0.8101	0.4267
Deciduous Forest	0.8137	0.8517
Coniferous Forest	0.7370	0.8068
Urban Areas	0.4710	0.7935
Water	0.9987	0.9999
Overall Accuracy	0.8872	
Kappa Coefficient	0.8071	

Table 8: The accuracy assessment confusion matrix depicting the User's and Producer's accuracy for the 20-metre merged classification. The 20-metre output had a higher overall accuracy, and the full confusion matrix can be found in Appendix E.

Land Class Name	**Producer's Accuracy**	**User's Accuracy**
Agriculture	0.5894	0.7005
Grassland	0.5674	0.3604
Mixed Forest	0.3514	0.0966
Open Wetland	0.5234	0.7920
Roads	0.8448	0.4153
Rock	0.6203	0.5568
Shrubland	0.6747	0.3294
Soil	0.7816	0.5354
Deciduous Forest	0.7996	0.8559
Coniferous Forest	0.7547	0.8387
Urban Areas	0.525	0.7568
Water	0.9975	1
Overall Accuracy	0.8960	
Kappa Coefficient	0.8225	

Table 9: The accuracy assessment confusion matrix produced in ArcGIS Pro, depicting the User's and Producer's accuracy for water classification compare to OIH dataset.

Water	10-Metre Resolution	20-Metre Resolution
Producer's Accuracy	0.7285	0.6163
User's Accuracy	0.7285	0.6163

Overall, upon classifying both 10-metre and 20-metre resolution Sentinel-2 image composites, the 20-metre image appears to have classified with a higher accuracy for most of the land cover classes. Through merging the forest classes, the overall accuracy for both images improved by about 10%. Lowland Conifers were poorly classified in both images, and Mixed Forests also had a low accuracy which was expected since it is composed of different tree species. Both image composites proved successful in classifying differences between deciduous and coniferous forests. Grassland and Agriculture were commonly confused with each other in both images, and many Urban Areas were misclassified as Roads. The accuracy test for Water shows that the 10m resolution classification has higher accuracy than the 20-metre, this may be due to water being relatively easy to identify under most of the spectral bands, and a higher spatial resolution better defines water body shorelines (Park and Lee, 2016).

Additionally, Sentinel-2 appears to be useful for identifying land cover classes over larger study areas, but a more accurate classification would require more human input, such as reclassifying areas that are misclassified. An example of this includes the lower number of Shrubland samples, meaning some areas were misclassified as Shrublands and had to be reclassed as Wetlands, Grasslands, or Soil cover. The only other major classes that ArcGIS Pro appeared to confuse were Roads and Urban Areas, especially in Parry Sound where parts of the city were initially classed entirely as a road layer, so these spots were reclassified in ArcGIS Pro's classification wizard (ESRI 2021e).

DISCUSSION

The classification of the northern Georgian Bay study area has given evidence that for areas of Northern Ontario where wetlands, forests, and water bodies dominate the landscape, Sentinel-2 imagery can provide insight into the land cover of these areas.

We would suggest that for future land cover classifications, 20-metre resolution imagery should be used for smaller-scale classifications, to maximize the use of information contained within the various spectral bands. However, it should be noted that for some more easily separable classes, such as urban areas and water bodies, spatial detail is more important.

Initially upon exploring the four classified rasters and comparing the 10-metre with the 20-metre, in combination with our reference datasets, we noted many strengths and weaknesses between the final classifications which can be seen in Table 10.

Table 10: The strengths and weaknesses for both the 10-metre and 20-metre land cover classifications. There are a number of strengths and weaknesses for both classifications.

Spatial Resolution	Spectral Bands	Strengths (both P and U accuracy >60%)	Weaknesses
10-Metre	4-Bands	• Water classified very well • Differs between Coniferous & Deciduous well	• Areas classified accurately in 20-metre are misclassified in 10-metre (Tolerant Hardwoods)

Spatial Resolution	**Spectral Bands**	**Strengths (both P and U accuracy >60%)**	**Weaknesses**
		• Tolerant Hardwoods classified well • More distinct reflectance differences between each class for the same band	• Inferior overall classification to 20 m • More random pixel noise than 20 m (expected) • Some Roads classified poorly • More areas misclassified as Agriculture
20-Metre	11-Bands	• Water classified very well • Differs between Coniferous & Deciduous well • Tolerant Hardwoods classified well • Classifies Rock well • Agriculture classified very well	• Some individual tree species (Jack Pine, Red/White Pine) are confused • Some confusion between Grassland & Agriculture (improvement to test trial) • Roads & Urban Areas confused in Parry Sound • Random pixel noise among tree classes (expected)

Additionally, the decision was made to include the merged forest class rasters to justify the belief that the classification differentiates well between Deciduous and Coniferous forests, even if some individual species were misclassified.

It should also be noted that the reference datasets used in this classification such as the Ontario Forest Inventory dataset were extremely crucial as a guideline for identifying what forest classes are present in the study area due to a lack of background knowledge. However, the forest map was produced in 2016 which may lead to some misclassification when overlayed with our image composites due to changes that could have taken place over the four-year period.

The true precision of our land classification may also be questionable since the accuracy of reference datasets themselves were not included in their metadata. As for the water accuracy assessment, it was identified that plants are growing along the lakeshore, so it was common for these areas to be classified as wetlands since the date range covered the growing season.

Classes that are more easily separable should be identified using a 10-metre resolution image to improve the accuracy of those classes. Water for example, was almost never confused with other land cover types, and the 10-metre image performed better with greater detail for shorelines. In future classifications, using both 10-metre and 20-metre resolution images, depending on the land cover type, may help improve the overall accuracy.

The number of training samples was also one of the most important factors that affected our classification, based on a trial classification conducted halfway through the training samples process (Appendix D). Agriculture continued to be misclassified in some areas of the final classification due to a lower number of samples, as well as the date range for the Sentinel-2 image composites was during growing season so many agricultural lands appeared similar to grasslands.

In addition to misclassifications, the nature of a Pixel-Based classification is that it assigns each individual pixel in an image with a land cover type, and we based our classification on Maximum-Likelihood (ESRI 2021f). However, due to such spectral similarities among forest species, pixel-based classification was the superior option to an object-based classification. The Maximum-Likelihood method also gave the pixel classification an element of the alternative through considering adjacent pixels when classifying the image (ESRI 2021e).

This product revealed many areas of forests with random pixel noise and outliers among our different forest classes. However, this was an expected result due to the nature of forests not being entirely uniform, and that the forest classes merely stated what species was dominant (Muskoka Watershed Council 2015).

CONCLUSION

The land cover classification analysis has given positive results for future land cover projects in Georgian Bay that may use Sentinel-2's multispectral imagery. The European Space Agency’s satellite imagery that is regularly collected and updated for regions all over the Earth has proven useful for a land cover analysis in a region of Ontario with very subtle differences in the present land cover.

It has been discovered throughout the Georgian Bay land cover analysis that spectral detail can be more valuable for image classifications involving forest cover where it is more difficult to differentiate between spectrally similar tree species (Wu 2019). Therefore, in future research it should be noted that the more spectral information that is used, the more promising the results can be (Wu 2019). Although, GIS image classification tools are unlikely to produce perfect results without some human correction, other types of classification tools not explored in this project could be explored in the future.

The future of land cover classifications for Canada’s many natural landscapes can potentially replicate the methods conducted in this study on a regular basis to produce updated land cover maps for the study area of interest. Additionally, regularly produced classified Sentinel-2 images can undergo change detection analyses to visualize land cover changes, predict future consequences, and help to inform land management and conservation efforts in vulnerable regions.

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APPENDIX A

FOREST INVENTORY CLASSES

Below is a table adapted from the Ontario Ministry of Natural Resources Forest Inventory dataset, depicting each forest class from the forest layer used as a reference, and the code associated with each class that can be found in the dataset's attribute table (Ontario Ministry of Natural Resources 2016).

Forest Type	Forest Code
White Birch	BWT
Lowland Conifers	MCL
Upland Conifers	MCU
Mixedwoods	MIX
Jack Pine	PJK
Poplar	POP
Red & White Pine	PWR
Tolerant Hardwoods	TOL

APPENDIX B

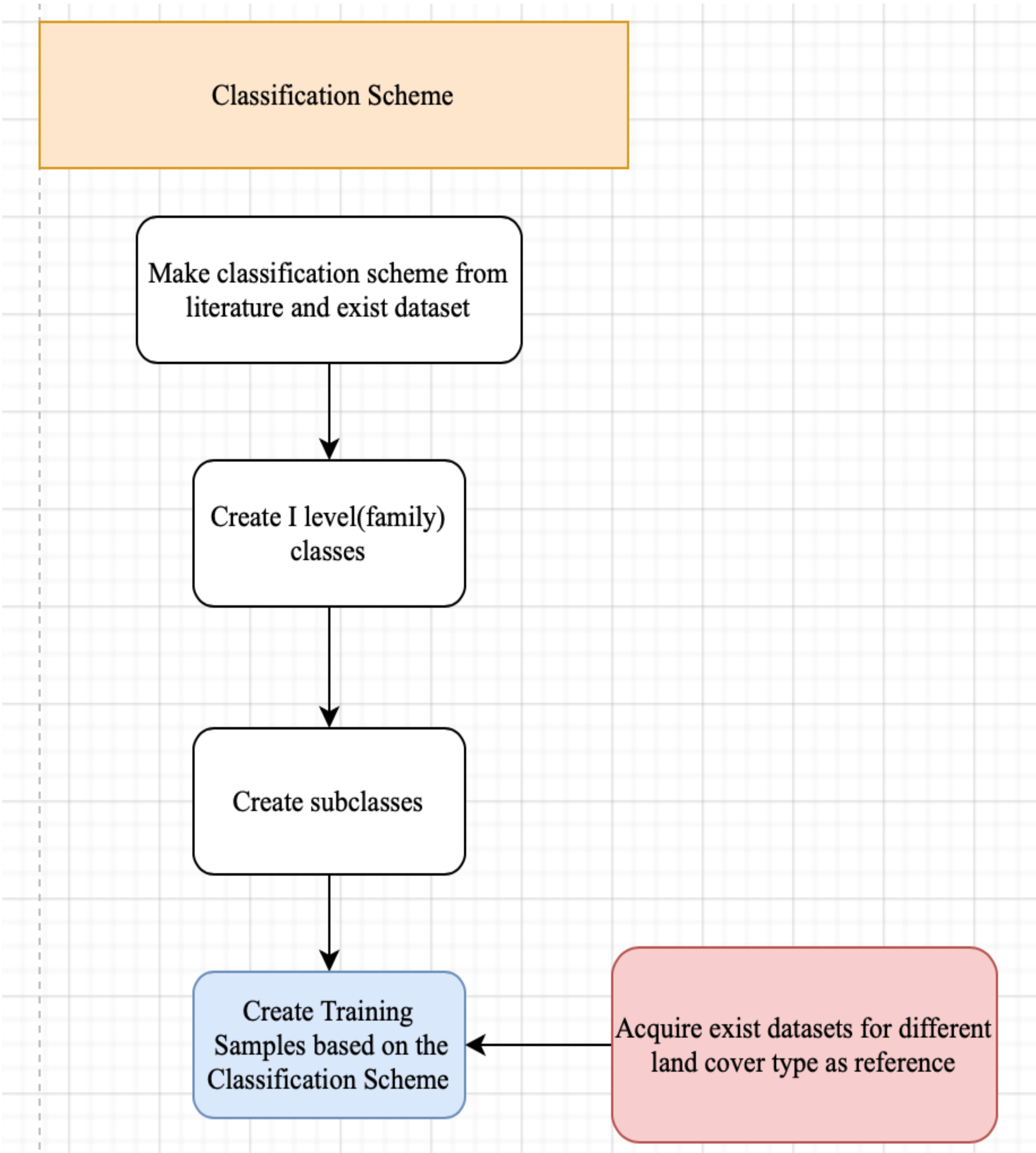
BAND INFORMATION

The table representing all the spectral bands present in the Sentinel-2 images. Note that in the 20-metre resolution image, all bands listed were present and used throughout the training samples process and classification, however for the 10-metre resolution image, only B02, B03, B04, and B08 are available at 10-metre resolution, so the higher spatial detailed Sentinel-2 image contains only four of the listed bands.

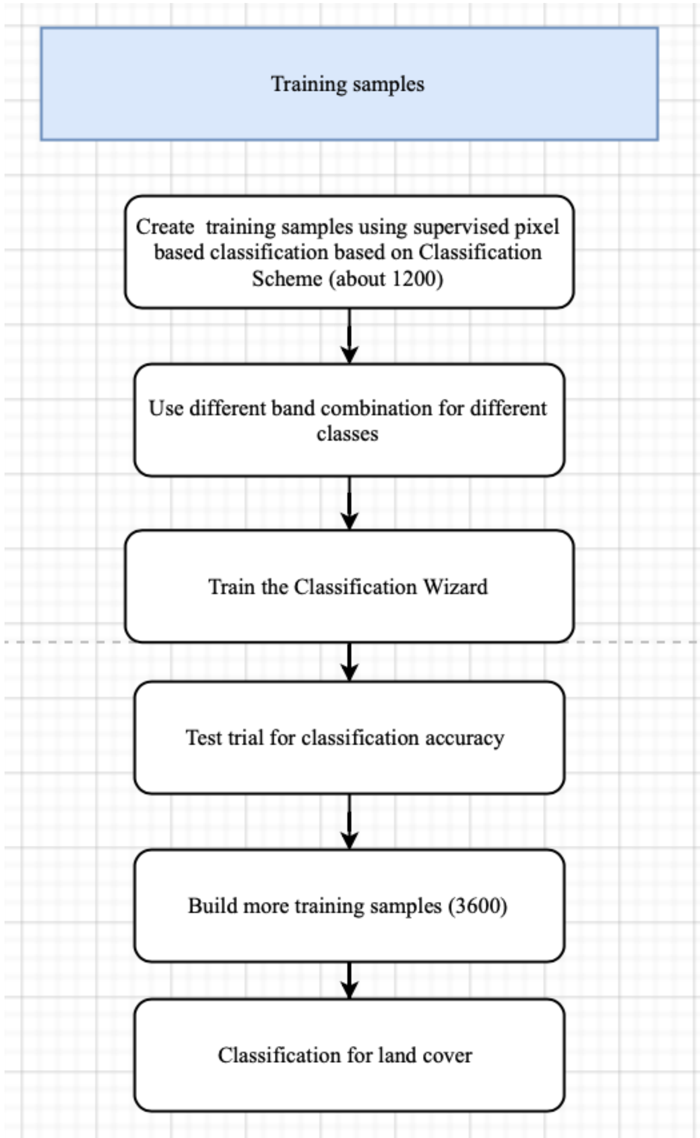
Band Number	Band Name	Wavelength	Default Resolution
B02	Blue	490nm	10-metre & 20-metre
B03	Green	560nm	10-metre & 20-metre
B04	Red	665nm	10-metre & 20-metre
B05	Red Edge 1	705nm	20-metre
B06	Red Edge 2	740nm	20-metre
B07	Red Edge 3	783nm	20-metre
B08	Near-Infrared (NIR)	842nm	10-metre & 20-metre
B11	Short-Wave Infrared 1 (SWIR-1)	1610nm	20-metre
B12	Short-Wave Infrared 2 (SWIR-2)	2190nm	20-metre
NDVI	Normalized Difference Vegetation Index	N/A	N/A
MNDWI	Mean Normalized Difference Water Index	N/A	N/A

APPENDIX C

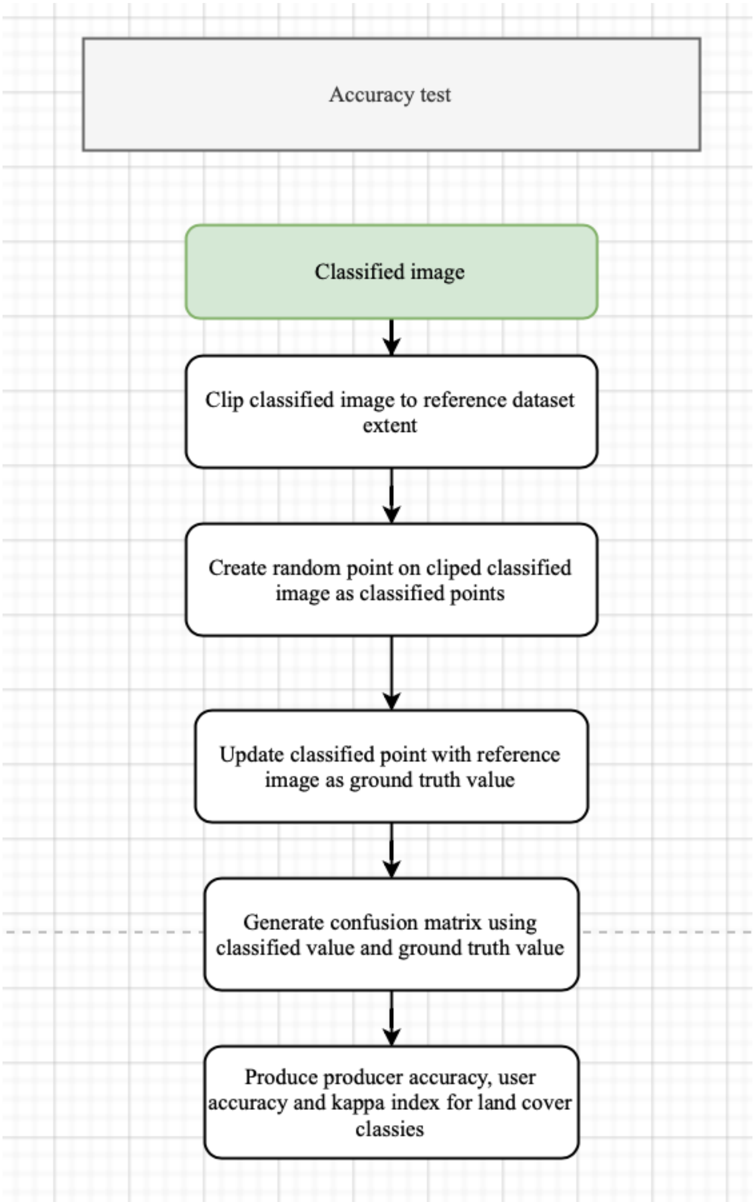
FLOWCHARTS



The flowchart above represents the methods undertaken to build the classification schema.



Above is the workflow for the training samples step of the methods, one of the longest portions of the project.

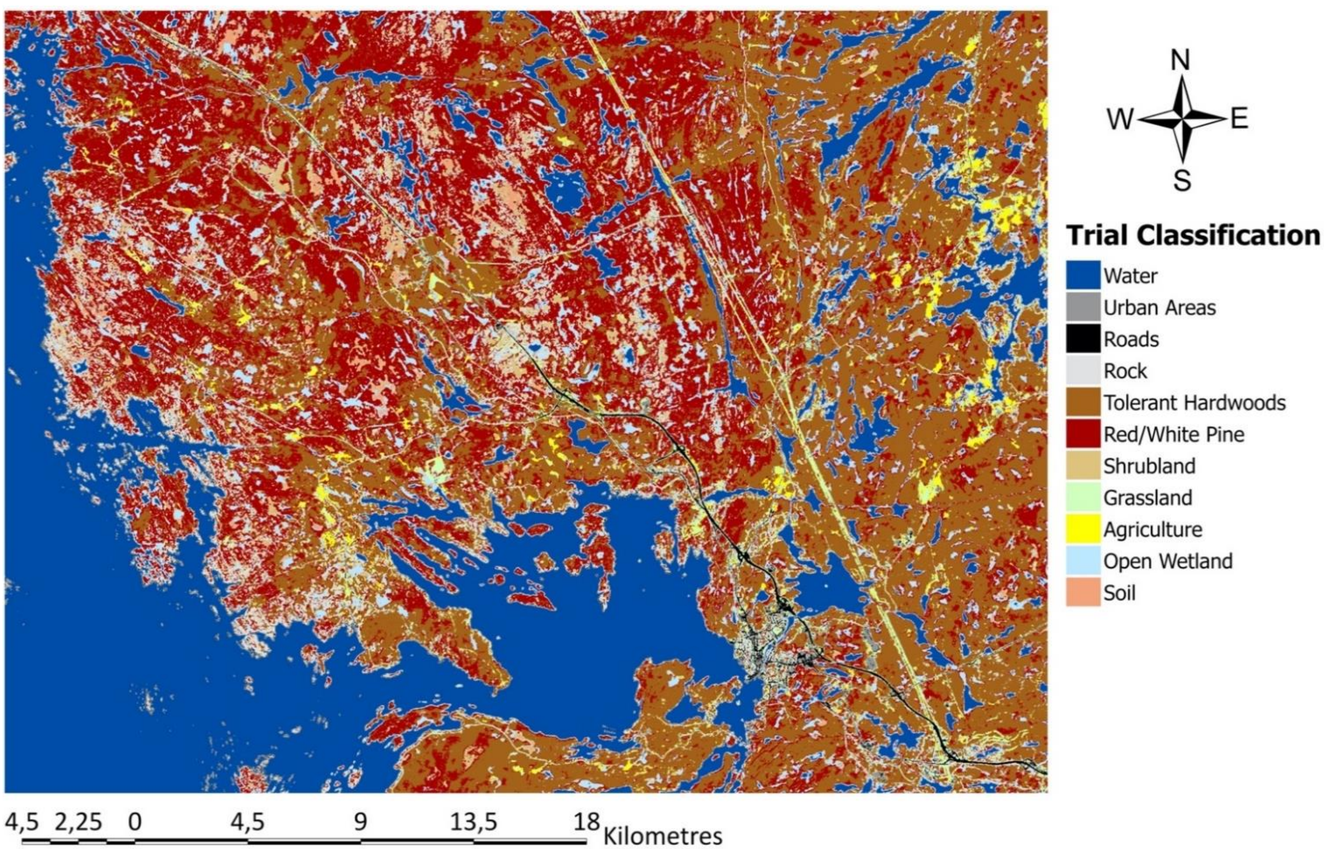


This is the workflow for the accuracy assessment completed after the final classifications were produced, to determine statistically how accurate the classification was by comparing the classified rasters to reference datasets.

APPENDIX D

TRIAL CLASSIFICATION

Below is a figure depicting a test trial classification that was conducted when 1200 training samples were produced – less than half of the total number of training samples used in the final classification. Not all of the land cover classes from the schema had been included in the training samples at this point in the methods, and many of the classes in the figure below were confused with other land types. Dozens of additional training samples were added for each existing class before the final classification to ensure maximum accuracy.



APPENDIX E

FULL CONFUSION MATRIX – 10-METRE & 20-METRE

Below are full tables for accuracy assessment includes Producer's accuracy and User's accuracy.

From the table we can see where each class is misidentified with other classes.

Accuracy assessment matrix for 10m resolution image with all classes.

OBJECTID *	ClassValue	C_10	C_21	C_22	C_30	C_43	C_44	C_45	C_46	C_47	C_48	C_49	C_50	C_60	C_70	C_81	C_100	C_401	Total	U_Accuracy	Kappa
1	C_10	12046	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12046	1	0
2	C_21	3	78	1	7	0	0	0	0	0	0	0	0	0	2	0	1	0	92	0.847826	0
3	C_22	1	62	30	5	0	0	0	0	0	0	0	0	0	2	4	0	0	104	0.288462	0
4	C_30	2	14	8	33	0	1	6	0	0	2	1	2	5	5	5	0	7	91	0.362637	0
5	C_43	0	0	0	0	46	140	157	58	4	93	54	0	0	1	1	0	16	570	0.080702	0
6	C_44	0	0	0	1	55	1648	84	447	0	82	25	0	3	1	2	0	8	2356	0.699491	0
7	C_45	0	1	1	3	29	42	773	41	6	101	128	0	1	0	1	0	47	1174	0.658433	0
8	C_46	0	0	0	1	17	323	109	139	2	69	23	0	1	0	0	0	2	686	0.202624	0
9	C_47	0	0	0	0	3	4	85	5	13	12	53	7	2	10	23	1	11	229	0.056769	0
10	C_48	0	0	0	3	15	82	145	45	6	94	19	0	0	1	2	0	13	425	0.221176	0
11	C_49	0	0	0	0	25	27	557	19	19	76	222	2	0	0	6	0	30	983	0.225839	0
12	C_50	0	2	2	4	0	3	56	3	3	5	10	44	38	31	57	19	12	289	0.152249	0
13	C_60	0	5	2	0	0	19	2	2	0	3	1	2	69	70	17	0	4	196	0.352041	0
14	C_70	0	9	1	0	0	4	3	2	2	0	0	0	25	71	7	1	1	126	0.563492	0
15	C_81	4	0	3	0	1	0	6	0	0	3	1	1	2	3	172	2	3	201	0.855721	0
16	C_100	0	1	0	0	0	1	2	0	2	0	1	11	15	7	53	57	0	150	0.38	0
17	C_401	0	0	1	7	2	11	120	6	2	16	19	7	5	8	10	0	66	280	0.235714	0
18	Total	12056	172	49	64	193	2305	2105	767	59	556	557	76	166	212	360	81	220	19998	0	0
19	P_Accuracy	0.999171	0.453488	0.612245	0.515625	0.238342	0.714967	0.367221	0.181226	0.220339	0.169065	0.398564	0.578947	0.415663	0.334906	0.477778	0.703704	0.3	0	0.780128	0
20	Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.641249

Accuracy assessment matrix for 20m resolution image with all classes.

OBJECTID *	ClassValue	C_10	C_21	C_22	C_30	C_43	C_44	C_45	C_46	C_47	C_48	C_49	C_50	C_60	C_70	C_81	C_100	C_401	Total	U_Accuracy	Kappa
1	C_10	12023	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12023	1	0
2	C_21	13	90	2	1	0	0	0	0	0	0	0	0	1	4	0	0	0	111	0.810811	0
3	C_22	0	42	59	3	0	0	2	0	0	0	0	0	4	3	2	0	1	116	0.508621	0
4	C_30	0	9	1	55	0	2	3	0	0	1	1	0	4	2	3	0	7	88	0.625	0
5	C_43	0	0	0	0	65	212	127	83	5	97	70	0	0	0	0	0	15	674	0.096439	0
6	C_44	0	0	0	0	34	1580	60	354	3	66	14	0	3	2	5	0	2	2123	0.74423	0
7	C_45	0	0	0	0	9	16	841	32	1	76	90	0	0	0	2	0	47	1114	0.754937	0
8	C_46	0	0	1	0	15	331	77	207	2	49	13	0	0	0	1	0	6	702	0.294872	0
9	C_47	0	0	0	2	4	11	55	1	25	16	20	6	3	0	11	1	15	170	0.147059	0
10	C_48	0	0	0	2	15	85	216	60	1	180	26	0	1	0	0	0	10	596	0.302013	0
11	C_49	0	0	0	1	22	26	524	13	22	56	286	0	0	0	2	0	26	978	0.292434	0
12	C_50	0	0	1	5	0	1	17	1	3	2	3	57	12	1	46	15	6	170	0.335294	0
13	C_60	0	11	1	0	1	19	1	1	0	2	0	1	92	76	18	0	0	223	0.412556	0
14	C_70	0	10	1	1	0	6	3	2	0	1	1	0	30	142	8	1	0	206	0.68932	0
15	C_81	14	0	3	0	0	0	4	0	0	4	0	0	1	4	193	1	1	225	0.857778	0
16	C_100	0	0	0	0	0	0	1	0	2	0	0	6	6	1	46	65	0	127	0.511811	0
17	C_401	0	0	3	10	2	23	150	13	3	21	23	3	2	2	13	0	76	344	0.22093	0
18	Total	12050	162	72	80	167	2312	2081	767	67	571	547	73	159	237	350	83	212	19990	0	0
19	P_Accuracy	0.997759	0.555556	0.819444	0.6875	0.389222	0.683391	0.404133	0.269883	0.373134	0.315236	0.522852	0.780822	0.578616	0.599156	0.551429	0.783133	0.358491	0	0.802201	0
20	Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.678261

Accuracy assessment matrix for 10m resolution image with merged forest classes. Class 41 is the deciduous forest and 42 is the coniferous forest.

OBJECTID *	ClassValue	C_10	C_21	C_22	C_30	C_41	C_42	C_43	C_50	C_60	C_70	C_81	C_100	Total	U_Accuracy	Kappa
1	C_10	12044	0	0	0	0	0	0	0	0	0	1	0	12045	0.999917	0
2	C_21	1	73	6	5	0	0	0	0	1	6	0	0	92	0.793478	0
3	C_22	0	49	36	7	0	0	0	0	3	5	3	0	103	0.349515	0
4	C_30	1	15	8	30	3	13	0	1	2	13	4	0	90	0.333333	0
5	C_41	0	0	0	5	2953	429	71	0	3	1	5	0	3467	0.851745	0
6	C_42	0	3	12	14	337	2152	51	19	12	22	45	0	2667	0.806899	0
7	C_43	0	0	0	0	293	229	48	0	0	0	0	0	570	0.084211	0
8	C_50	0	2	2	4	11	75	0	46	31	45	60	13	289	0.15917	0
9	C_60	0	4	0	2	19	6	0	1	61	83	19	1	196	0.311224	0
10	C_70	0	8	1	0	6	1	0	0	29	77	4	0	126	0.611111	0
11	C_81	14	0	2	3	6	12	0	1	1	5	156	1	201	0.776119	0
12	C_100	0	1	1	2	1	3	0	7	10	14	47	64	150	0.426667	0
13	Total	12060	155	68	72	3629	2920	170	75	153	271	344	79	19996	0	0
14	P_Accuracy	0.998673	0.470968	0.529412	0.416667	0.813723	0.736986	0.282353	0.613333	0.398693	0.284133	0.453488	0.810127	0	0.887177	0
15	Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.807149

Accuracy assessment matrix for 20m resolution image with merged forest classes.

OBJECTID *	ClassValue	C_10	C_21	C_22	C_30	C_41	C_42	C_43	C_50	C_60	C_70	C_81	C_100	Total	U_Accuracy	Kappa
1	C_10	12025	0	0	0	0	0	0	0	0	0	0	0	12025	1	0
2	C_21	12	84	1	2	1	0	0	0	2	9	0	0	111	0.756757	0
3	C_22	1	52	49	6	0	2	0	0	2	6	0	0	118	0.415254	0
4	C_30	0	9	1	49	5	13	1	2	0	3	5	0	88	0.556818	0
5	C_41	0	0	1	1	2928	409	71	0	4	2	5	0	3421	0.85589	0
6	C_42	0	0	1	10	317	2184	48	7	4	8	25	0	2604	0.83871	0
7	C_43	0	0	0	0	369	238	65	0	0	0	1	0	673	0.096582	0
8	C_50	0	0	1	8	1	24	0	56	14	0	49	17	170	0.329412	0
9	C_60	0	7	2	0	24	7	0	4	80	68	29	1	222	0.36036	0
10	C_70	0	7	0	0	11	1	0	1	31	145	11	0	207	0.700483	0
11	C_81	17	1	2	1	6	13	0	1	0	5	179	1	226	0.792035	0
12	C_100	0	0	0	2	0	3	0	12	4	0	38	68	127	0.535433	0
13	Total	12055	160	58	79	3662	2894	185	83	141	246	342	87	19992	0	0
14	P_Accuracy	0.997511	0.525	0.844828	0.620253	0.799563	0.754665	0.351351	0.674699	0.567376	0.589431	0.523392	0.781609	0	0.895958	0
15	Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.822532