ESSE 4630: Research Project

Detecting Changes In the Clay Belt Area of Northern Ontario

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INTRODUCTION

This project will be addressing the environmental changes in Northern Ontario's Geography due to any transformations in soil carbon stock and greenhouse gas (GHG) emissions in this area. These changes are important to address because it is linked to climate change and detrimental agricultural practices. By identifying the magnitude of these impacts, we can provide reasoning to change agricultural practices to protect the environment as well as enhance sustainable growth farming. We will be working with our course teaching assistant, Ima Ituen, our project is based on her paper, and we shall be making use of her training data to perform our image classification.

Study Area and Data

Our study area will be a nearby area that Ima hasn't looked at yet. We will be looking at Cochrane in Northern Ontario and its surrounding area. The main industries in Cochrane are transportation, railway, tourism, and forestry where "marginal farming also exists though the soil is considered to be of good quality, the growing season is too short to have substantial crop production" [1].

We will be using Sentinel-2 MSI Level-2A satellite imagery to observe the following dates:

- 2016-1-1 to 2016-12-30
- 2017-1-1 to 2017-12-30
- 2018-1-1 to 2018-12-30
- 2019-1-1 to 2019-12-30
- 2016-5-23 to 2016-10-31, average growing season for 2016
- 2017-5-23 to 2017-10-31, average growing season for 2017
- 2018-5-23 to 2018-10-31, average growing season for 2018
- 2019-5-23 to 2019-10-31, average growing season for 2019

The growing season date is a season where crops grow optimally. We can compare this vegetation growth to see a difference between multiple years. We also got data of the year as a whole to find differences in snowfall as winter is a dominant season in Northern Ontario. Unfortunately, the imagery for years 2017 and 2019 were off in Sentinel and Landsat 8 (which we used as a check). This data was collected through Google Earth Engine. We were provided code by Ima to export an image from a polygon we created on Google Earth Engine. For reference, the coordinates of the polygon can be found in the code provided in the appendix. The polygon encompasses other nearby towns such as Frederickhouse, forests, and other bodies of water. Images of the years and growing season are provided in our files. Unfortunately, the satellite imagery for the 2017 and 2019 full years is of poor quality. Due to this, we have avoided creating classifications for these images.

We also have a shapefile (.shp) that contains the attributes of Northern Ontario's geographic features. We uploaded this shapefile to both ArcGIS (to determine where the land covers are) and to Catalyst to create the training data of the land covers using the shapefile as a guide. The land cover classes we created for supervised image classification were:

- Water (WAT)
- Forested Land Productive (FOR)
- Unclassified Land (UCL)
- Treed Muskeg (TMS)

- Open Muskeg (OMS)
- Grass and Meadow (GRS)
- Developed Agricultural Land (DAL)
- Brush and Alder (BRS)
- RIVER(RIV)*(used only in the growing season classifications)*

METHODOLOGY

As stated in Study Area and Data, we created our land covers based on the attributes and shapes from the shapefile. We were able to create the polygons accurately within the indicated lines to ensure that the data is mono-modal. The Maximum Likelihood algorithm was used for the classification.
The 2016- and 2018-year classification was created by Ryan while Nadine created the classifications for 2016, 2017, 2018, and 2019 growing seasons.

RESULTS AND DISCUSSION

The codes for the figures and tables are as follows: A – Appendix, B – Ryan, C – Nadine

ANALYZING DATA OF 2016 AND 2018 FULL YEARS BY RYAN

The data I will be analyzing are the 2016 and 2018 full years. Comparing the reports for the 2 years, the accuracy of 2018 is worse than 2016. The classification is prone to human error which has varying accuracies due to data being analyzed by different people. This is why the growing season and full year are respectively analyzed by Nadine and Ryan separately.

In the Appendix, we can look at the classification between the two years along with their respective reports. The overall accuracy has decreased from 77.61% to 65.64%. Accuracy and pixel count changes are tabulated:

Land Cover	2016 Accuracy (%)	Change in Accuracy(%)	2018 Accuracy (%)
WAT	97.45	-2.35	95.10
FOR	86.41	-19.37	67.04
UCL	70.37	-12.11	58.26
TMS	87.20	+4.69	91.89
OMS	60.71	-8.9	51.81
GRS	56.84	-28.22	28.62
DAL	86.14	-1.59	84.55
BSH	56.32	-40.24	16.08

Table B1: Changes in Accuracy between 2016 and 2018

Land Cover	2016 Pixels (% of image)	Change in Pixel Count (% of image)	2018 Pixels (% of image)
WAT	51666 (1.23)	+54451 (+1.3)	106117 (2.53)
FOR	1248157 (29.77)	+115679 (+2.75)	1363836 (32.52)
UCL	259474 (6.19)	-117140 (-2.8)	142334 (3.39)
TMS	183728 (4.38)	+272545 (+6.5)	456273 (10.88)
OMS	241779 (5.77)	+598276 (+14.26)	840055 (20.03)
GRS	688618 (16.42)	-349270 (-8.33)	339348 (8.09)
DAL	312989 (7.46)	+60.873 (+1.46)	373862 (8.92)
BSH	1206869 (28.78)	-635414 (-15.15)	571455 (13.63)
TOTAL	4193280		4193280

Table B2: Changes in Pixel Count between 2016 and 2018

Looking at the pixel count, it seems that TMS and OMS have increased and GRS and BSH decreased over the years. Although GRS and OMS have dropped significantly in accuracy, we can make some sort of inference.
An increase in TMS is an increase in stunted trees, meaning trees that can't grow to normal size. This shows an effect on the health of the trees within 2 years as trees planted now, will be unable to grow into bigger, healthier trees.
An increase in OMS is an increase in wet areas of mosses, sedges, and small herbaceous plants. Sedges are plants that grow near wide bodies of water which is excellent as sedges deal with water runoff [2]. However, this increase in sedges can also prevent water from reaching other vegetation which could explain the Grass and Meadow decrease.
Grass and Meadows is pasture vegetation for domesticated farm animals. This layer relates to the available forage for feeding a farm animal [3]. With a decrease in vegetation, there are limited opportunities for feeding cattle and can result in a decrease in the cattle population.
Brush and Alder's layer encompasses vegetation of non-commercial trees that often border streams and other bodies of water. Non-commercial trees are similar to stunted trees as they are both too small to be chopped for wood but can also mean non-targeted trees for deforestation. Regardless, they are somehow being decreased over the years. This is concerning because there is an increase in these small, unhealthy trees being grown, but are going to decrease rapidly as well as many of those trees cannot sustain in their environment.

Looking at the two classifications, we can see that the geographical polygons of the land covers have changed over the 2 years. Let's take a closer look at the image where we can see notable changes starting with the top left corner of the classification.

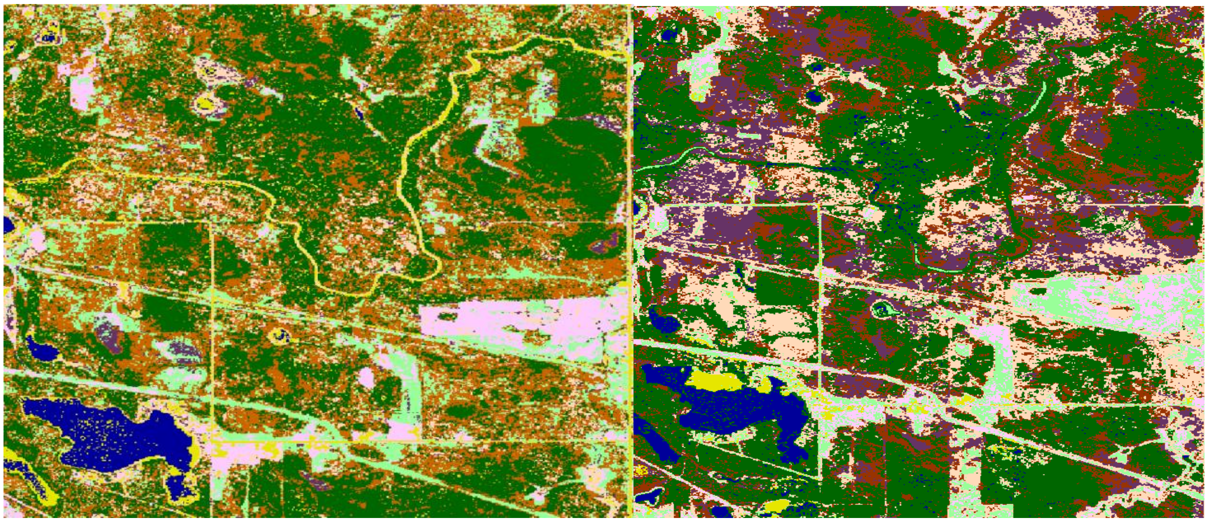

Figure B1: Top Left Corner of the Classification (Left Image is 2016, Right Image is 2018)

ID	Value	Name	Color	Threshold	Bias	Imported Sig	Description
1	1	WAT		3.00	1.00		
2	2	FOR		3.00	1.00		
3	3	UCL		3.00	1.00		
4	4	TMS		3.00	1.00		
5	5	OMS		3.00	1.00		
6	6	GRS		3.00	1.00		
7	7	DAL		3.00	1.00		
8	8	BSH		3.00	1.00		

Figure B1a: Legend of Land Covers

We can see here that the Brush and Alder (BRH) has been replaced by Treed Muskeg (TMS) and that the Developed Agriculture Land (DAL) has decreased in Grass and Meadows (GRS). This is what we expected for BRH and TMS as they decreased and increased respectively over the 2 years. But the results could be inaccurate due to the massive accuracy drop in BRH (56.32% → 16.08%) where TMS is actually the most correlated pixel in its code of 2018 with 30.55% (vs. 16.08%!). I would define this as a misconception between BRH and TMS.

DAL and GRS are more interesting as though DAL decreased and GRS increased in this image timespan, the report says the opposite of both especially GRS with an 8.33% decrease over 2 years. Although GRS has a horrible accuracy with 28.8%, and DAL being its next correlated pixel with 24.7%. DAL and GRS are correlated as we can see DAL has an accuracy of 84.55% with GRS being the next runner up in correlation with 10.08%. The data is showing that land crop increased and grass has decreased, but the image shows the opposite. These ambiguous results are diluted as both land covers are correlated with each other. But, based on the report and trusting more into the DAL results, there has been an increase in cropland which could have an influence on the remaining grass fields as there is a drastic drop in GRS with a minor increase in DAL.

Let's look at the actual town of Cochrane.

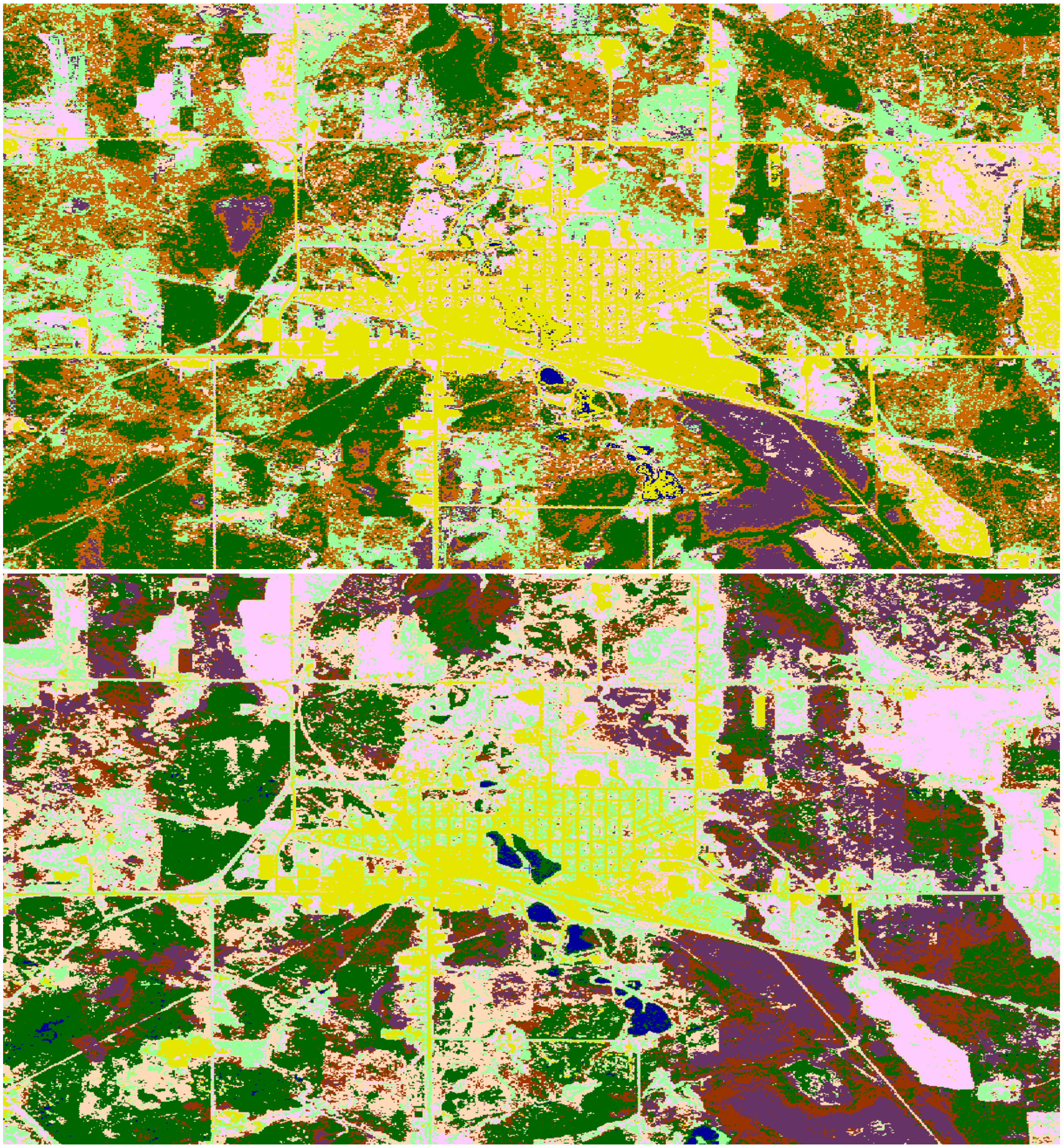

Figure B2: Cochrane Town of Classification (Top Image is 2016, Bottom Image is 2018)

Here, we can see an increase in DAL and GRS in the town of Cochrane. Again, this could be a misconception of DAL as it is also more prominent in 2018. We also see the same effect of TMS and BSH as TMS is encompassing more of BSH like the previous figure.

This next image is between the top left corner and the town of Cochrane which seems to be a river.

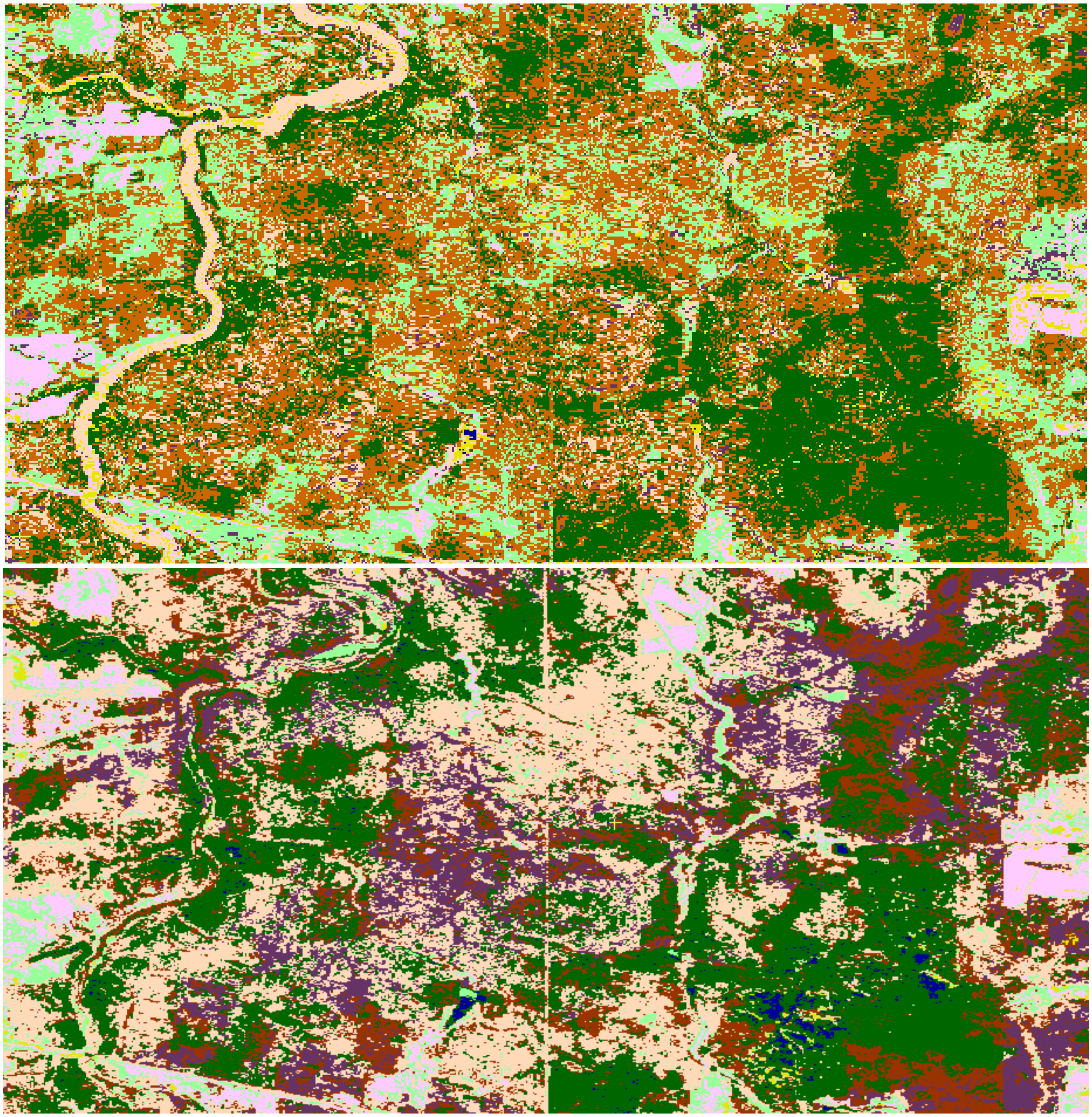

Figure B3: River Image of Classification (Top is 2016, Bottom is 2018)

There seems to be an error where there is a thick stream of Open Muskeg (OMS) when it is actually supposed to be Water (WAT). Although Open Muskeg is interspersed with water, water should be the dominating pixel in that area. This stream disappears over the years but increases and encompasses the BRH layer. According to the report, OMS has had a significant increase in pixel count. This image illustrates the increase in Open Muskeg as well as its interspersion with water.

ANALYZING THE GROWING SEASONS OF 2016, 2017, 2018 AND 2019 BY NADINE

The software used to analyze the raster files were ArcGIS, CATALYST and Google Earth Pro. The Cochrane shapefile was used as a general guide when selecting the shapefiles, however, the shapefile was created in 2014 so it isn't up to date. Hence, Google Earth Pro was also used as a reference especially when it came to selecting agricultural land and urban areas, as some expansion may have taken place over the years. Since classes like OMS and TMS are usually located next to water bodies, especially OMS, special care was taken to not include water when selecting the training data.

There seems to have been some technical issue when it came to data collection in year 2017 as is evidenced by the color distortions in the raster file. Please refer to the data folder to see the acquired raster files. These areas were generally avoided during the selection process. Some of these areas mostly fell under the UCL and DAL classes. Since UCL included urban areas, it wasn't surprising that it had a higher reflectance than other classes, however, some areas defined as DAL also had very high reflectance. So, these areas were avoided when selecting training data for DAL. It is most likely that the agricultural land was converted to something else, or plants weren't grown in that portion of land at the time of collection. The 2017 raster file also had somewhat of a blue haze covering the water bodies, this may also affect the results. Samples were collected from water bodies with the blue haze and water bodies that were completely dark as expected.

It is also good to note that for each growing season a median of all the raster files is estimated and those median raster files are used in the analysis process. A new class was added to the existing ones for this classification process, the new class represents one of the main rivers in the raster file. The river was classified as water in the Cochrane shapefile; however, it has a different reflectance value compared to all the other water bodies so it was given its own class.
The main statistics used to analyze the quality of the classification would be the confusion matrix and the separability matrix.

Year	2016	2017	2018	2019
Accuracy	66.73%	76.43%	84.59%	65.45%
Minimum Separability	(FOR, BSH)	(FOR, BSH)	(FOR, BSH)	(FOR, BSH)

Table C1: Accuracy of the classifications and the classes that was difficult to differentiate.

Land Cover	2016	Change	2017	Change	2018	Change	2019
WAT	97.26	*-1.69*	95.57	*1.91*	97.48	*0.12*	97.6
FOR	52.48	*16.56*	69.04	*13.63*	82.67	*-27.26*	55.41
BSH	59.13	*18.2*	77.33	*1.3*	78.63	*-4.44*	74.19
GRS	38.43	*43.66*	82.09	*-1.79*	80.3	*-16.77*	63.53
UCL	83.62	*12.4*	96.02	*-26.68*	69.34	*7.61*	76.95
DAL	70.88	*-6.99*	63.89	*25.95*	89.84	*-38.15*	51.69
OMS	48.96	*-15.39*	33.57	*28.14*	61.71	*-29.32*	32.39
TMS	50.01	*18.31*	68.32	*26.4*	94.72	*-12.71*	82.01
RIV	97.36	*-2.73*	94.63	*-4.89*	89.74	*0.7*	90.44

Table C2: Accuracy of each class within each year and the changes between each year

Percentage of Image								
Land Cover	2016	Change	2017	Change	2018	Change	2019	Change between 2019 and 2016.
WAT	1.7	*-0.2*	1.5	*0.09*	1.59	*0.09*	1.68	*-0.02*
FOR	45.1	*-23.16*	21.94	*10.33*	32.27	*-4.54*	27.73	*-17.37*
BSH	23.85	*4.58*	28.43	*1.31*	29.74	*1.52*	31.26	*7.41*
GRS	6.55	*13.65*	20.2	*-1.26*	18.94	*-4.23*	14.71	*8.16*
UCL	7.34	*2.24*	9.58	*-5.91*	3.67	*3.14*	6.81	*-0.53*
DAL	7.39	*-3.48*	3.91	*0.92*	4.83	*2.17*	7	*-0.39*
OMS	3.45	*1.03*	4.48	*1.65*	6.13	*-0.79*	5.34	*1.89*
TMS	4.34	*5.23*	9.57	*-7.24*	2.33	*2.55*	4.88	*0.54*
RIV	0.29	*0.09*	0.38	*0.1*	0.48	*0.11*	0.59	*0.3*

Table C3: Percentages of each class in an image for each year and the changes between each year

From Table C1 we can see that the year 2018 had the highest accuracy, followed by 2017, 2016 and lastly 2019. Ideally, it would be preferred if the accuracy was in the 90s, but we do have to consider the terrain that is being analyzed. As can be noted in the same table, the forest and brushes were very similar and therefore hard to distinguish within all four years this may have also led to the low accuracies. At this point I'd also like to recall that the shapefile being used is from 2014 and a lot of changes may have occurred within this time period that could affect the analysis.

When looking at the individual classes, water and river had the highest accuracies as expected. This is mostly due to the fact that the water and river are distinguishable from the rest. Water appears dark in the sentinel images so there was no hesitation when it came to classifying it.

The forest and the brushes, however, were quite difficult to distinguish. Of course, the shapefile was a guide, but changes could have occurred during this time, so some slight interpolations had to be made. As mentioned earlier, it was also quite difficult to accept that some of the land stated as agricultural land was in fact true, since it had a high reflectance like UCL.

Between 2016 and 2019 there seems to have been a significant decrease in forestation and an increase in brush and grass. Due to the separability issue, it may just be a case of miss classification and some forest pixels were misclassified as brush and grass. There was also a significant increase in OMS when compared to TMS. The values themselves might be small, however, it is still important to note. The OMS was usually located next to water bodies, and we do see a slight decrease in water, this could lead to an increase in OMS with the new acquired space. This finding does support my colleague's results stating that there was an increase in OMS.

In year 2017, the classification map shows a huge section with Grass, this is a misclassification caused by the ill quality of that raster file. So, the results of 2017 will be ignored at this juncture. The images below show the increase in OMS. As stated earlier there was an increase in the brushes too but this might just be due to human error, misclassification, and the usage of an old shape file. Please refer to the appendix and the data folder for all the classified images and quality reports.

ID	Value	Name	Color	Threshold	Bias	Imported Sig	Description
1	1	WAT		3.00	1.00		Water
2	2	FOR		3.00	1.00		Forested
3	3	BSH		3.00	1.00		Brush and alder
4	4	GRS		3.00	1.00		Grass and meadow
5	5	UCL		3.00	1.00		Unclassified land like roads, rail lines etc
6	6	DAL		3.00	1.00		Develoved agricultural land.
7	7	OMS		3.00	1.00		Open muskeg and with no trees
8	8	TMS		3.00	1.00		Trees, Muskeg,Scattered stunted trees
9	9	RIV		3.00	1.00		RIVER

Figure C1: Legend of Land Covers

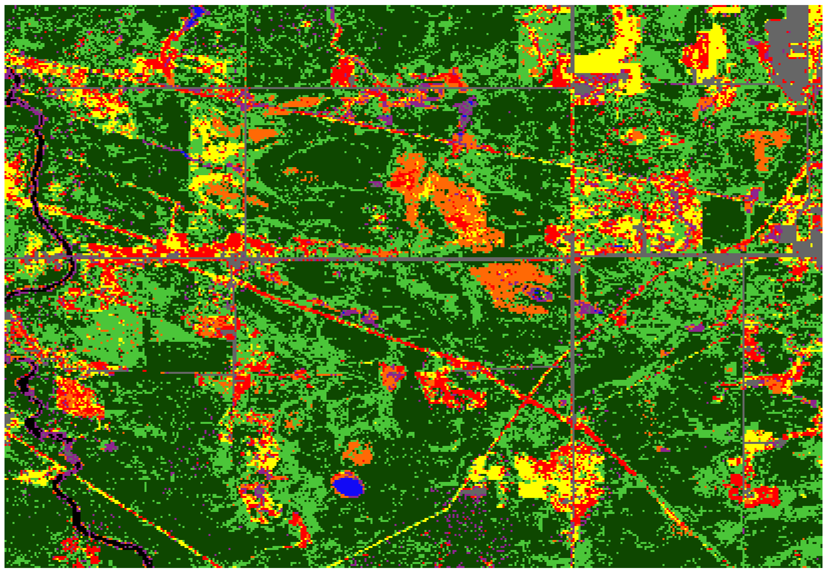

Figure C2: CLIP of 2016 CLASSIFICATION MAP

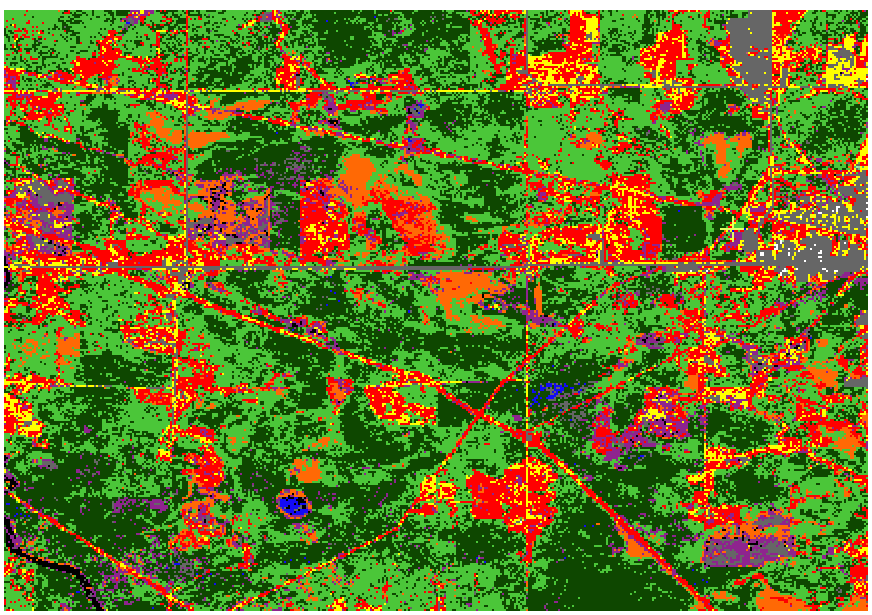

Figure C3: CLIP of 2019 CLASSIFICATION MAP

The clip shown in figure C2 and C3 were taken at the same location, and we can see an increase in OMS (refer to figure C1 for the legend).

CONCLUSION

There are various reasons as to why there might be an increase in OMS. Since the OMS Layers are next to water bodies, a decrease in the water level or a slight deviation from its natural path may create the right environment for OMS to flourish. We also noticed a decrease in the forest population but a lot more research would have to be done. For this to be an accepted conclusion. At this point the best reason we can give for the differences would be due to misclassification.

We think with our findings of an increase of stunted trees and the decreasing lifespan of them, that there should be a revision of agricultural laws and farming practices. This is concerning as the health of the environment is deteriorating with the decrease of grass and meadows vegetation.

With the completion of this project, we have expanded our knowledge on various steps to take when performing image classification. It is essential to note the year the data was collected and the year of any reference files that may be used. These files can sometimes be outdated so it is crucial to always find up to date information and additional data to support any results that may be found.

REFERENCES

[1] Cochrane, Ontario. (2021, September 24). Retrieved December 8, 2021, from https://en.wikipedia.org/wiki/Cochrane,_Ontario

[2] Versatile Sedges for Lawn and Garden. (n.d.). Retrieved December 11, 2021, from https://nativeplantherald.prairienursery.com/2016/05/versatile-sedges-for-lawn-and-garden/

[3] Hearst & Cochrane files is the name of the dataset. Created by Ima Ituen, Nadine Norman, and Ryan Nguyen. The data has been collected and published over the span of 2014 to 2019 which has been commissioned by New Directions Research Program (NDRP), OMAFRA, and Baoxin Hu, York University. Sentinel-2 MSI Level-2A was used to capture the images.

APPENDIX

Link to Google Earth Engine code: https://code.earthengine.google.com/ba07aa88770fef7cb174fdabccf16e08

RYAN'S IMAGES

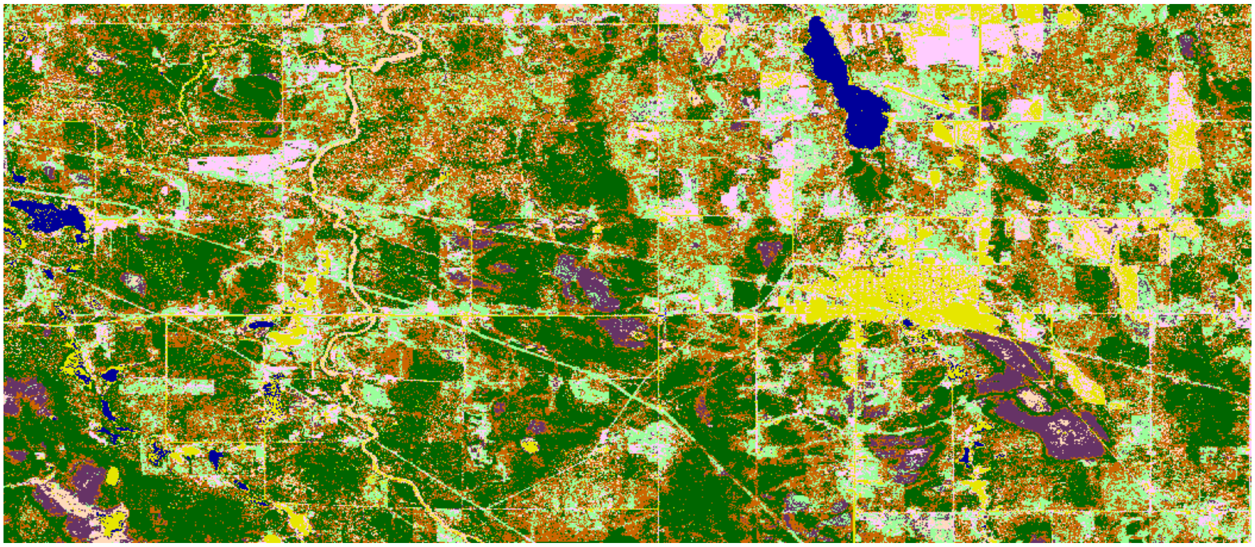

Figure A1: 2016 Year Classification

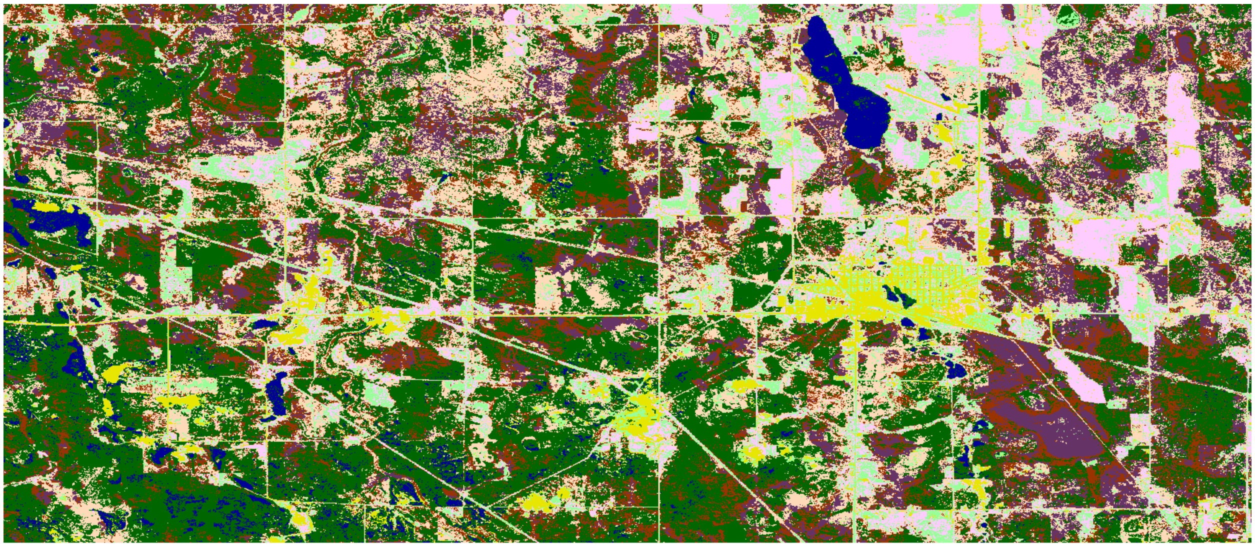

Figure A2: 2018 Year Classification

Name	Code	Pixels	%Image	Thres	Bias
WAT	1	51666	1.23	3.00	1.00
FOR	2	1248157	29.77	3.00	1.00
UCL	3	259474	6.19	3.00	1.00
TMS	4	183728	4.38	3.00	1.00
OMS	5	241779	5.77	3.00	1.00
GRS	6	688618	16.42	3.00	1.00
DAL	7	312989	7.46	3.00	1.00
BSH	8	1206869	28.78	3.00	1.00
NULL	0	0	0.00		
	Total	4193280	100.00		

CONFUSION MATRIX

_____Areas_____ ___Percent Pixels Classified by Code____

Name	Code	Pixels	1	2	3	4	5	6	7	8
WAT	1	25025	97.45	0.00	2.47	0.00	0.08	0.00	0.00	0.01
FOR	2	23783	0.00	86.41	0.29	0.67	0.27	0.30	0.00	12.05
UCL	3	64195	0.00	0.21	70.37	1.12	1.71	3.24	22.83	0.53
TMS	4	22015	0.00	0.50	0.45	87.20	8.24	0.93	0.01	2.67
OMS	5	12590	0.00	2.31	3.12	24.90	60.71	2.30	1.64	5.00
GRS	6	10727	0.00	3.58	0.24	1.50	1.87	56.84	6.66	29.31
DAL	7	12563	0.00	0.00	3.09	1.02	2.67	7.01	86.14	0.06
BSH	8	5760	0.00	24.31	0.33	1.08	3.59	13.35	1.02	56.32

Average accuracy = 75.18 %
Overall accuracy = 77.61 %

Figure A3: 2016 Year Report

Name	Code	Pixels	%Image	Thres	Bias
WAT	1	106117	2.53	3.00	1.00
FOR	2	1363836	32.52	3.00	1.00
UCL	3	142334	3.39	3.00	1.00
TMS	4	456273	10.88	3.00	1.00
OMS	5	840055	20.03	3.00	1.00
GRS	6	339348	8.09	3.00	1.00
DAL	7	373862	8.92	3.00	1.00
BSH	8	571455	13.63	3.00	1.00
NULL	0	0	0.00		
	Total	4193280	100.00		

CONFUSION MATRIX

_____Areas_____ ___Percent Pixels Classified by Code____

Name	Code	Pixels	1	2	3	4	5	6	7	8
WAT	1	23666	95.10	4.74	0.04	0.00	0.05	0.06	0.00	0.01
FOR	2	40678	7.41	67.04	1.30	4.47	9.03	0.93	0.12	9.70
UCL	3	54015	0.00	0.18	58.26	0.08	5.84	25.04	10.40	0.20
TMS	4	16954	0.00	0.87	0.00	91.89	2.26	0.60	0.00	4.38
OMS	5	12408	0.02	15.67	0.16	15.97	51.81	4.01	1.29	11.08
GRS	6	10232	0.00	10.20	5.43	0.71	21.94	28.62	24.70	8.40
DAL	7	12988	0.00	0.07	1.74	0.02	2.56	10.08	84.55	0.98
BSH	8	10381	0.00	29.42	0.04	30.55	18.32	3.43	2.17	16.08

Average accuracy = 61.67 %
Overall accuracy = 65.54 %

Figure A4: 2018 Year Report

NADINE'S IMAGES

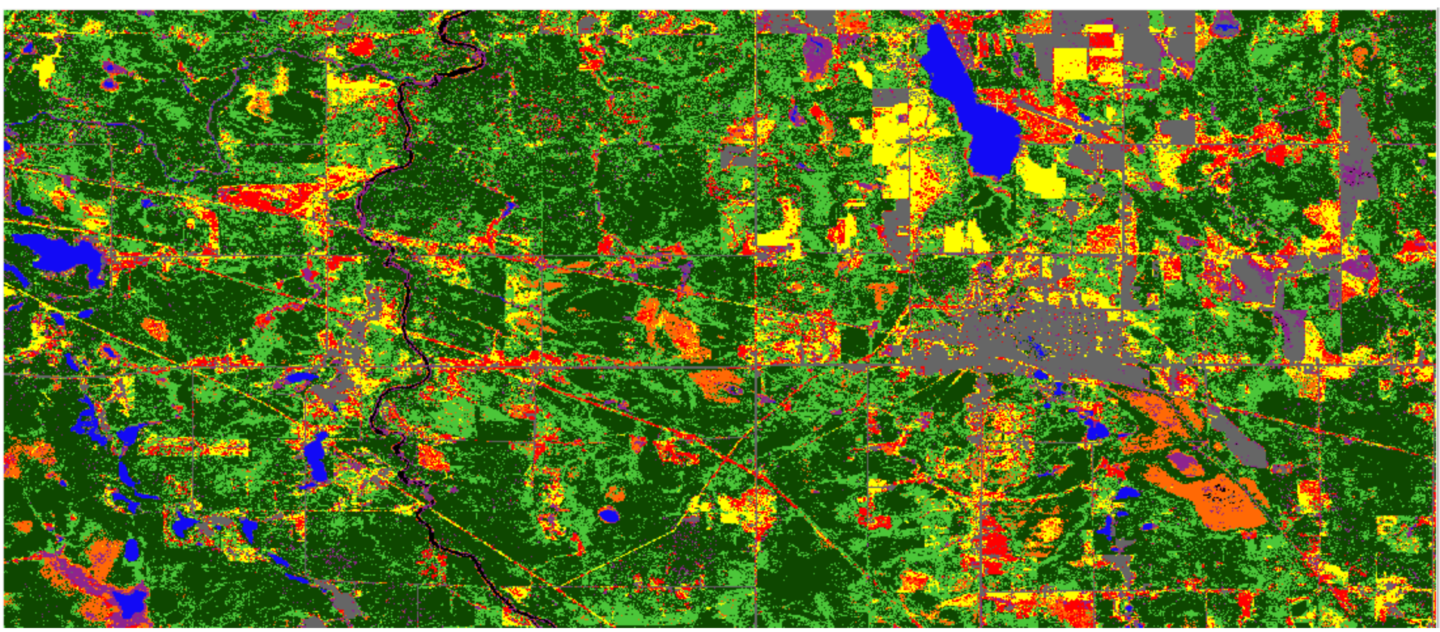

Figure A5: 2016 Classification Map

Areas			Percent Pixels Classified by Code								
Name	Code	Pixels	1	2	3	4	5	6	7	8	9
WAT	1	39759	97.26	0.03	2.41	0.00	0.30	0.00	0.00	0.00	0.00
FOR	2	35848	0.00	52.48	0.76	2.98	1.41	4.20	6.89	31.28	0.00
UCL	3	48602	0.00	0.78	83.62	0.82	3.02	4.51	6.79	0.46	0.00
TMS	4	32028	0.00	13.27	0.57	50.01	3.81	3.67	6.58	20.78	1.31
OMS	5	14758	0.00	5.90	2.33	23.41	48.96	6.79	0.39	12.19	0.03
GRS	6	30864	0.00	5.01	1.39	5.45	1.78	38.43	31.63	16.31	0.00
DAL	7	24515	0.00	0.52	0.95	6.80	0.30	16.12	70.88	4.44	0.00
BSH	8	9992	0.10	21.34	0.24	6.67	3.19	5.14	4.19	59.13	0.00
RIV	9	3938	0.00	0.00	0.13	0.43	2.08	0.00	0.00	0.00	97.36

Average accuracy = 66.46 %
Overall accuracy = 66.73 %

Figure A6: 2016 Confusion Matrix

Separability Measure: Transformed Divergence

Average separability: 1.588695
Minimum separability: 0.253341
Maximum separability: 2.000000
Signature pair with
Minimum separability: (FOR,BSH)

	WAT	FOR	UCL	TMS	OMS	GRS	DAL	BSH	RIV
FOR	1.999981								
UCL	2.000000	2.000000							
TMS	2.000000	1.238717	2.000000						
OMS	2.000000	1.562289	1.999873	0.763568					
GRS	2.000000	0.955291	2.000000	1.032589	1.057427				
DAL	2.000000	1.346067	2.000000	1.213713	1.463058	0.409251			
BSH	1.999999	0.253341	2.000000	0.696693	1.220202	0.790704	1.190253		
RIV	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000	

Figure A7: 2016 Separability Matrix

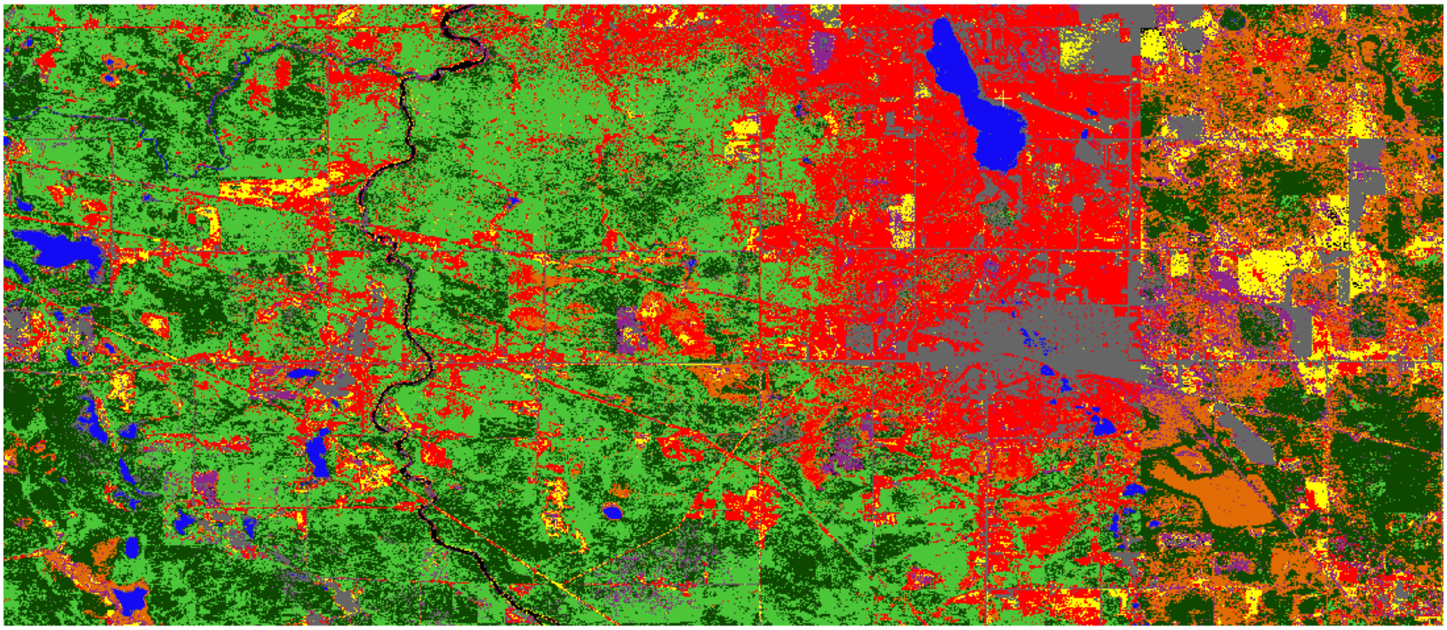

Figure A8: 2017 Classification Map

CONFUSION MATRIX

Areas			Percent Pixels Classified by Code								
Name	Code	Pixels	1	2	3	4	5	6	7	8	9
Wat	1	30977	95.57	0.08	0.00	0.00	4.24	0.00	0.10	0.01	0.00
FOR	2	72075	0.01	69.04	23.93	0.56	0.50	0.11	1.38	4.46	0.00
BSH	3	10321	0.00	18.88	77.33	2.33	0.20	0.23	0.24	0.78	0.00
GRS	4	10978	0.00	0.29	8.73	82.09	0.91	7.35	0.23	0.40	0.00
UCL	5	18951	0.00	0.00	0.00	3.52	96.02	0.06	0.40	0.00	0.00
DAL	6	14849	0.00	0.01	0.26	20.43	2.31	63.89	9.75	1.06	2.28
OMS	7	5808	0.00	0.86	3.22	9.09	1.24	10.16	33.57	39.65	2.20
TMS	8	14980	0.00	1.58	20.57	0.81	0.20	2.66	5.86	68.32	0.00
RIV	9	2963	0.00	0.00	0.00	0.00	3.34	1.15	0.88	0.00	94.63

Average accuracy = 75.61 %
Overall accuracy = 76.43 %

Figure A9: 2017 Confusion Matrix

Separability Measure: Transformed Divergence

Average separability: 1.857263
Minimum separability: 0.589908
Maximum separability: 2.000000
Signature pair with
Minimum separability: (OMS,TMS)

	Wat	FOR	BSH	GRS	UCL	DAL	OMS	TMS	RIV
FOR	1.999887								
BSH	2.000000	0.697561							
GRS	2.000000	1.969234	1.991782						
UCL	2.000000	2.000000	2.000000	1.999995					
DAL	2.000000	1.995808	2.000000	1.587041	1.999970				
OMS	2.000000	1.974137	1.999992	1.832352	1.999319	0.775031			
TMS	2.000000	1.963027	1.999974	1.955795	2.000000	1.531453	0.589908		
RIV	2.000000	2.000000	2.000000	2.000000	2.000000	1.999900	1.999364	1.999942	

Figure A10: 2017 Separability Matrix

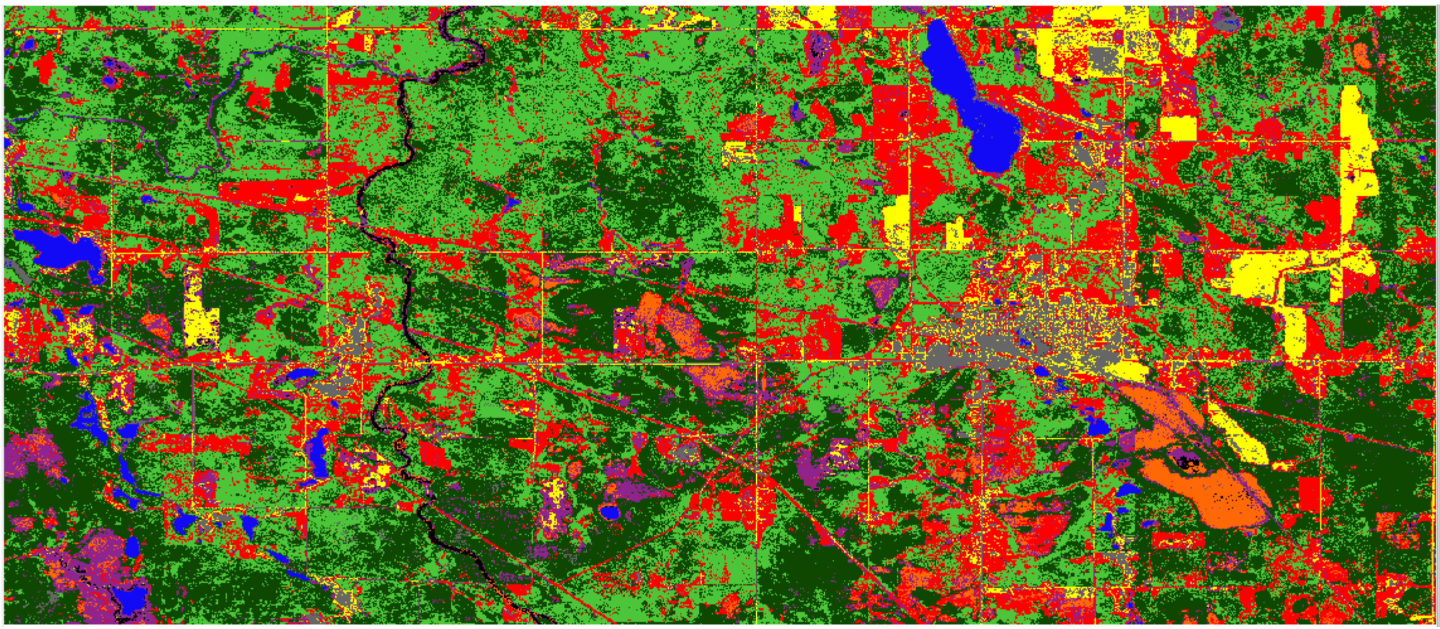

Figure A11: 2018 Classification Map

CONFUSION MATRIX

_____Areas_____ ___Percent Pixels Classified by Code____

Name	Code	Pixels	1	2	3	4	5	6	7	8	9
WAT	1	26821	97.48	0.00	0.00	0.00	2.14	0.00	0.37	0.00	0.00
FOR	2	54211	0.00	82.67	14.15	1.21	0.88	0.00	1.02	0.06	0.00
BSH	3	10357	0.00	17.79	78.63	3.13	0.20	0.00	0.12	0.14	0.00
GRS	4	11609	0.00	1.63	10.84	80.30	0.08	1.30	4.92	0.94	0.00
UCL	5	15315	0.00	0.01	0.02	6.95	69.34	18.50	5.15	0.03	0.00
DAL	6	14781	0.00	0.00	0.00	1.68	5.03	89.84	1.36	2.08	0.00
OMS	7	5062	0.00	0.41	1.60	9.92	1.21	0.75	61.71	6.62	17.78
TMS	8	13488	0.00	0.07	0.04	0.47	0.50	0.00	2.49	94.72	1.71
RIV	9	1082	0.00	0.00	0.00	0.00	1.11	0.00	7.58	1.57	89.74

Average accuracy = 82.72 %
Overall accuracy = 84.59 %

Figure A12: 2018 Confusion Matrix

Separability Measure: Transformed Divergence

Average separability: 1.899836
Minimum separability: 0.735558
Maximum separability: 2.000000
Signature pair with
Minimum separability: (FOR,BSH)

	WAT	FOR	BSH	GRS	UCL	DAL	OMS	TMS	RIV
FOR	1.999944								
BSH	1.999999	0.735558							
GRS	2.000000	1.977722	1.990927						
UCL	2.000000	2.000000	2.000000	1.999932					
DAL	2.000000	2.000000	2.000000	1.824190	1.580951				
OMS	2.000000	1.992412	1.999707	1.531035	1.999853	1.911811			
TMS	2.000000	1.999960	1.999999	1.932326	2.000000	2.000000	1.825004		
RIV	2.000000	1.999940	2.000000	1.997971	2.000000	1.999995	1.328174	1.766680	

Figure A13: 2018 Separability Matrix

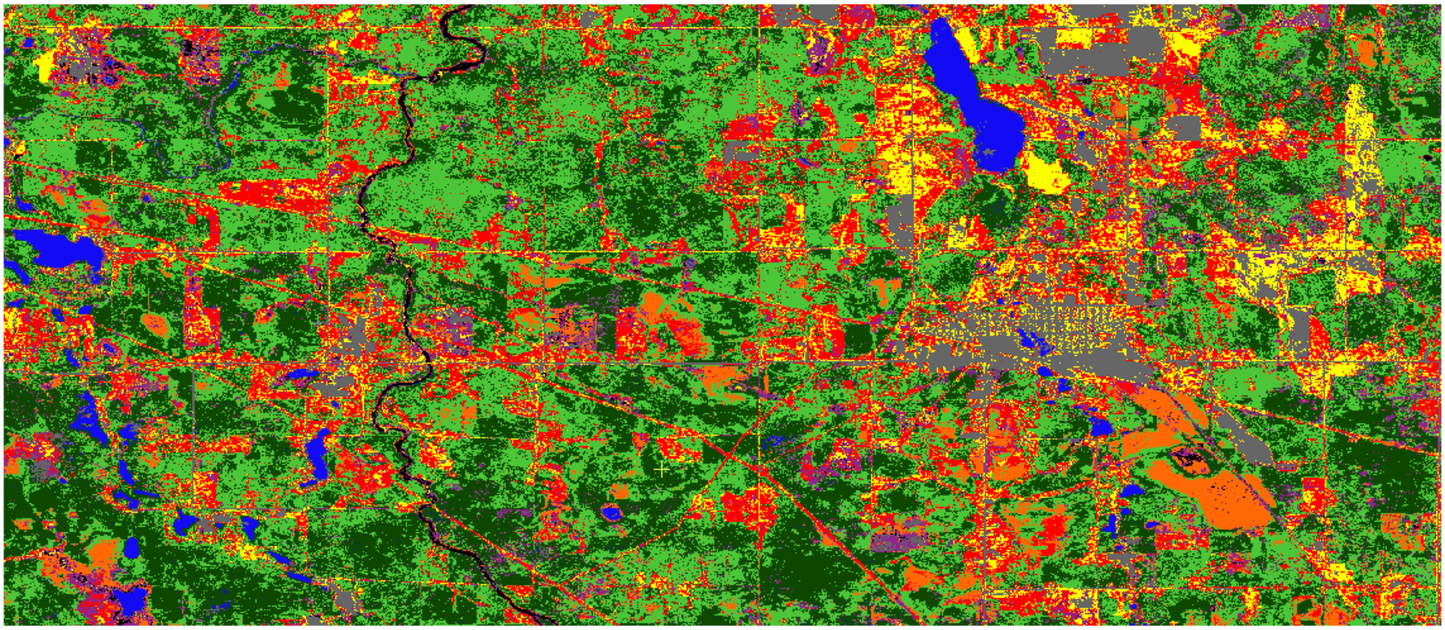

Figure A14: 2019 Classification Map

CONFUSION MATRIX

_____Areas_____ ___Percent Pixels Classified by Code____

Name	Code	Pixels	1	2	3	4	5	6	7	8	9
WAT	1	31343	97.60	0.28	0.00	0.00	2.12	0.00	0.01	0.00	0.00
FOR	2	93257	0.45	55.41	39.72	2.47	0.63	0.19	0.68	0.46	0.00
BSH	3	13357	0.00	21.60	74.19	2.74	0.09	0.11	0.38	0.88	0.00
GRS	4	15085	0.00	2.43	10.62	63.53	0.31	19.76	2.65	0.63	0.06
UCL	5	17198	0.00	0.00	0.05	3.90	76.95	16.11	2.81	0.06	0.13
DAL	6	30458	0.00	0.05	0.05	38.02	4.71	51.69	5.13	0.26	0.09
OMS	7	7311	0.00	0.07	3.17	7.32	0.66	12.35	32.39	27.11	16.93
TMS	8	15111	0.00	0.75	9.03	3.75	0.05	0.03	3.06	82.01	1.30
RIV	9	2123	0.00	0.00	0.00	0.00	0.47	0.57	3.67	4.85	90.44

Average accuracy = 69.36 %
Overall accuracy = 65.45 %

Figure A15: 2019 Confusion Matrix

Separability Measure: Transformed Divergence

Average separability: 1.836648
Minimum separability: 0.202369
Maximum separability: 2.000000
Signature pair with
Minimum separability: (FOR,BSH)

	WAT	FOR	BSH	GRS	UCL	DAL	OMS	TMS	RIV
FOR	1.960056								
BSH	1.993646	0.202369							
GRS	2.000000	1.994944	1.987172						
UCL	2.000000	2.000000	2.000000	1.999969					
DAL	2.000000	1.999493	1.998829	0.553530	1.998403				
OMS	2.000000	1.999699	1.998843	1.344088	1.997348	1.254120			
TMS	2.000000	1.999677	1.998439	1.920462	2.000000	1.961515	1.321715		
RIV	2.000000	1.999999	1.999999	1.999761	2.000000	1.999914	1.713396	1.921911	

Figure A16: 2019 Separability Matrix