PROJECT REPORT

Eelgrass Classifications in the Gulf of Saint Lawrence

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Introduction

The Department of Fisheries and Ocean - Gulf Region (DFO) has a need to classify eelgrass habitat in the bays of the Gulf of Saint Lawrence. They contracted the Applied Geomatics Research Group – Nova Scotia Community College (AGRG) to study the available methods for classifying satellite imagery, choose one, and carry out the classifications.

Academic studies have shown that satellite imagery is a viable resource for classifying eelgrass in the Gulf region (Forsey et al. 2020). DFO purchased WorldView 2 satellite imagery for this project and they were shared with AGRG. DFO Gulf Region scientists shared a few recommendations about how the classifications could be carried out based on prior research conducted. These include a pixel-based approach with the random forest classification algorithm as this has been shown to be successful (Forsey et al. 2020).

AGRG compared three software packages during this project and two different machine learning classification algorithms to determine which options would provide the highest quality classifications. The software packages were Esri ArcGIS Pro, Trimble eCognition, and PCI Geomatica (now known as Catalyst).

The machine learning algorithms tested were the random trees (RT) and support-vector machine (SVM), accessible through all the software packages tested. The random trees algorithm had to be used instead of the recommended random forest due to availability, it uses the same method to calculate decision trees that the pixels in the image can then be analyzed using, but it calculates less of these trees and therefore the results are more prone to overfitting and results are usually less accurate. The support vector machine plots the pixels in feature space and then draws a line to separate classes from one another. There was also some testing done with the other algorithms such as the Maximum likelihood classifier that was quickly ruled out as it did not perform well.

Object based image analysis (OBIA) techniques were tested as they can be superior to pixel-based approaches, especially when satellite imagery resolution allows for the objects being classified to be made up of groups of pixels (Blaschke).

After testing all software and classifier combinations, and analyzing the results to determine the best method, other factors such as the processing time and number of licenses available to use at AGRG came into account because the main goal was to classify as many images to high quality as possible. Therefore, the pixel-based SVM classification technique was selected to carry out the classifications.

Methods

All the methods explored in this project fall into the category of supervised classifications, where a user selects and labels training areas in the satellite image that are representative of features they would like to classify. Then a classification algorithm is trained using information from these inputs and it is applied to the rest of the image.

Pixel Based Classification

A pixel-based classification works by analyzing the spectral signatures of pixels in labeled training areas selected by a user. A trained image classifier can determine which class each pixel belongs to based solely on the different reflectance values of the different bands of light collected by the satellite.

ArcGIS Pro

ArcGIS Pro was the only software package tested that allowed for pixel-based machine learning classifications. It is accessed through their Image Analyst or Spatial Analyst extensions, and using the classification wizard, any GIS technician can easily preform this analysis. Unfortunately, you only have access to the spectral information from the three bands you are displaying on the map, limiting the amount of information available to the machine learning classifiers. The three bands used to classify the image were the red, green, and blue wavelengths. These bands penetrate the water column and are reflected of the sea floor, providing information on the benthic environment.

Object Based Classification

Object-based classifications are like pixel-based classifications but vary in a few ways. An extra preprocessing step called image segmentation is run to group collections of pixels with similar spectral signatures and distribution into what are known as image objects. These image objects are then classified by a classification algorithm using information such as their spectral signature and the object shape.

ArcGIS Pro

This software package allows for object-based classifications as well as pixel-based classifications. They are very similar to use and other than the extra step of running a segmentation analysis they are identical. The biggest downside to using ArcGIS for this type of analysis is that they only allow for 3 bands to be used at any time for the segmentation and classification. The classifications were able to be completed quickly with minimal knowledge of image classifications.

eCognition

This in an object-based classification software package that gives access to many different parameters while conducting a classification. All image bands can be used when running the segmentation and classification algorithms, thus not limiting the amount of information like ArcGIS Pro, there can even be new bands computed in the software for use. This software offers the most flexibility of all the packages tested. The classifications were slow to set up and a high level of knowledge of image classifications is recommended.

PCI Geomatica

This software package was deemed inadequate due to the poor segmentation algorithms that it uses. The minimum segment size was far too large to be useful in the classifications. It did allow for many spectral bands to be used in the machine learning classifiers, but it did not allow for the machine learning classifications to be done at the pixel level.

Image Pre-processing

The images delivered were often much larger than the extent of the bays being classified, therefore subsets were extracted to be analyzed. Another reason for subsetting an image was to minimize the effects that banding artifacts were having on the classifications. To compute more accurate classifications in large bays with a lot of banding present, were split along some of the lines and classified separately (Figure 1; Figure 3).

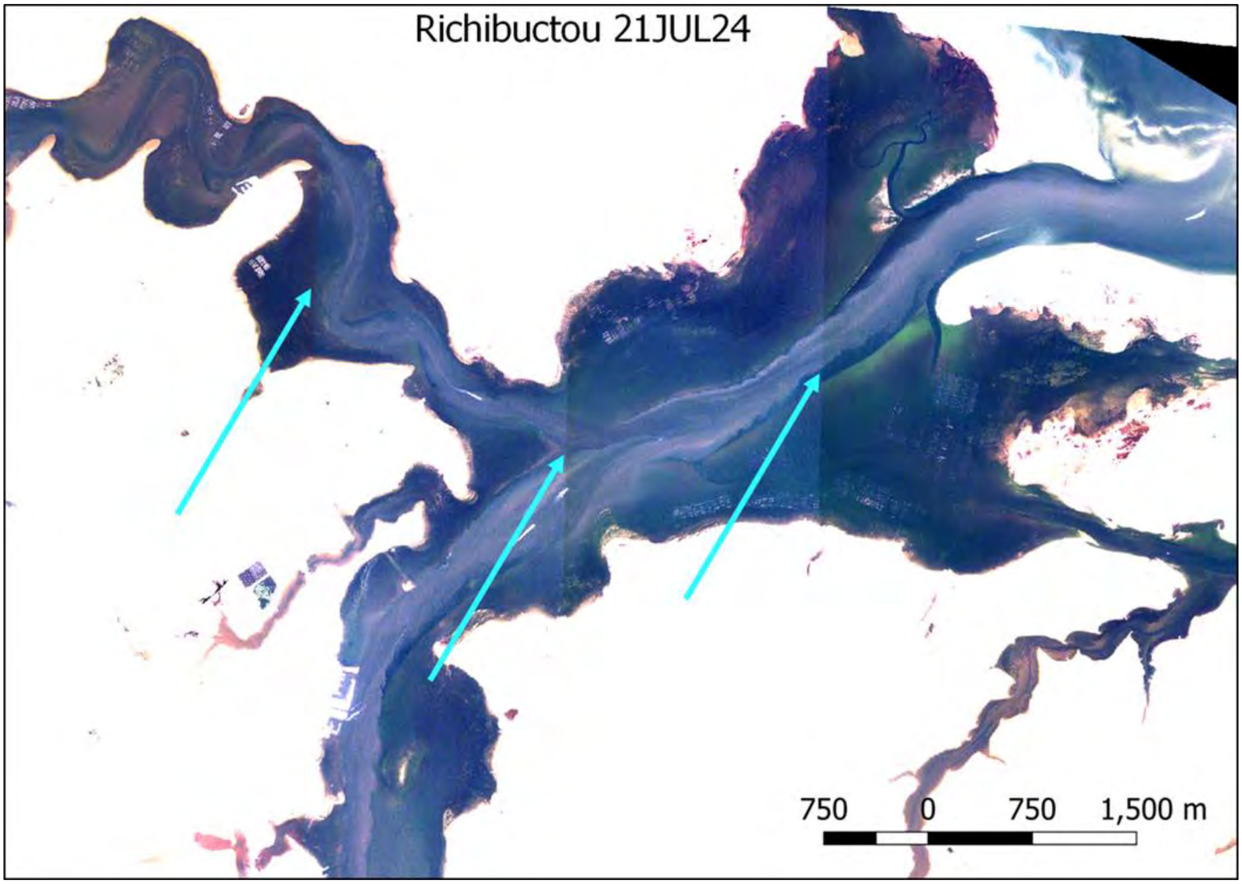

Figure 1 Example of image banding artifact seen in some of the imagery. Cyan arrows point to some of the extreme examples seen in the Richibucto Bay July 24th, 2021, image. The image displayed has a custom enhancement to help display these effects that are not as obvious when viewing under normal renderings, this is causing the land to appear as bright white.

Some areas were not fully covered by a single image but were present in multiple collections from the same day, in these cases the images were classified separately but then their results were mosaiced together to create one classification result. Due to the WorldView sensor movement between the collections the bay exhibits different light level in the scenes (Figure 2).

To remove any land in the images an image mask was calculated using NIR 1 (Band 7). To do this a threshold was chosen and any pixels holding this value or less counted as water and any above counted as land (Figure 3).

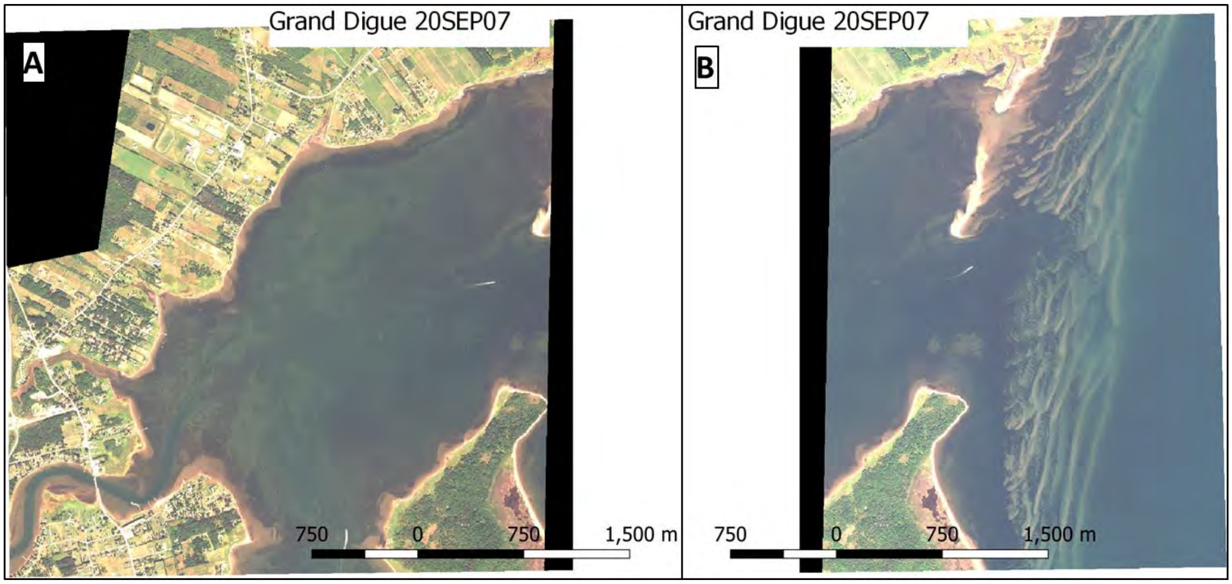

Figure 2 Example of a bay covered during two separate collections on the same day. The movement of the satellite between collection causes the light levels to be different but the conditions remain the same. Scale bar placement doesn't change between the frames showing there is significant overlap.

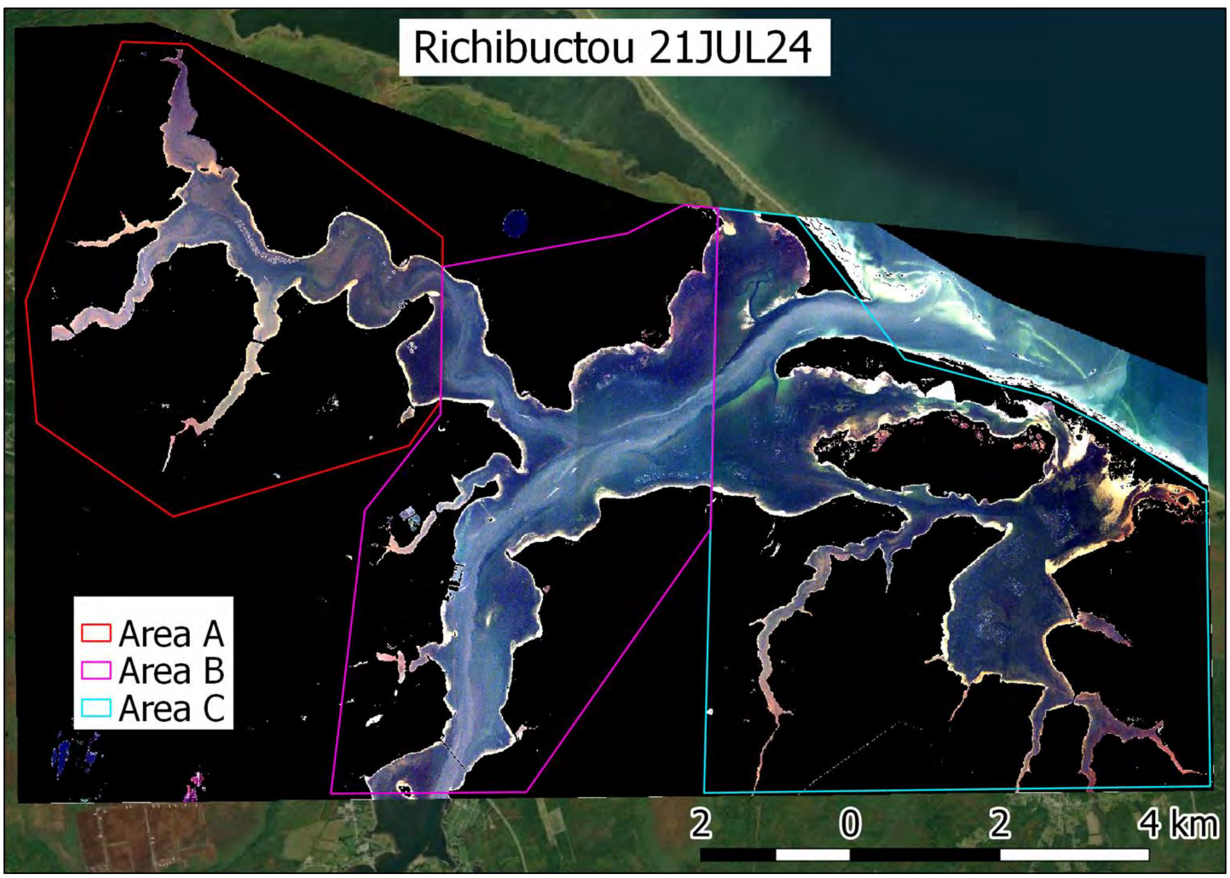

Figure 3 Example of how large bays with banding artifacts are split to calculate more accurate classifications. Blacked out area is an example of how the NIR1 band is used to mask out the land in these images.

Training

Training areas were manually selected by AGRG staff and consisted of circular samples of various sizes placed in areas of very high certainty (Figure 4). These areas were saved as a shapefile and used to train the classifier, representing examples of the pixels in each class. It was important to select high-quality examples of each class to ensure that the classifier was not trained on any incorrect data.

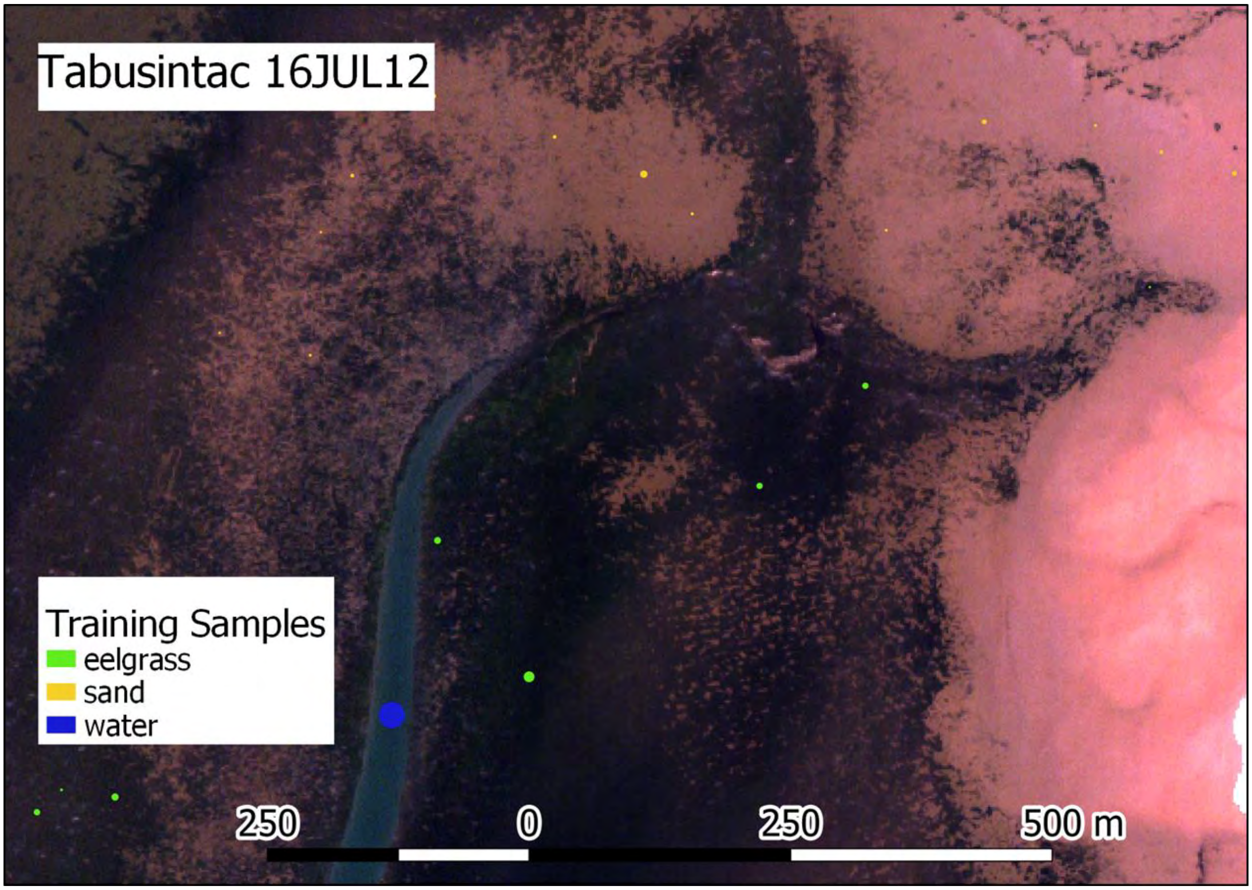

Figure 4 Sample of the training samples used in the classifications. Water samples represent deep water where the benthic habitat cannot be observed.

Accuracy Assessments

The accuracy assessments were tested first using ground truth data from DFO collected using a single beam echosounder but due to a GPS error (Figure 5) the DFO advised us to not use it. Therefore, another approach was developed where a set of ground truth points was picked out of each image (Figure 6) by a user to assess the classification. These points were independent from the training samples used to train the classifier.

Figure 5 Inaccurate biosonics data collected in 2020 overlaid on a WorldView 2 image collected July 24th, 2021. The cyan circle outlines a few of these incorrect points, they are labeled as vegetation absent while located on top of eelgrass.

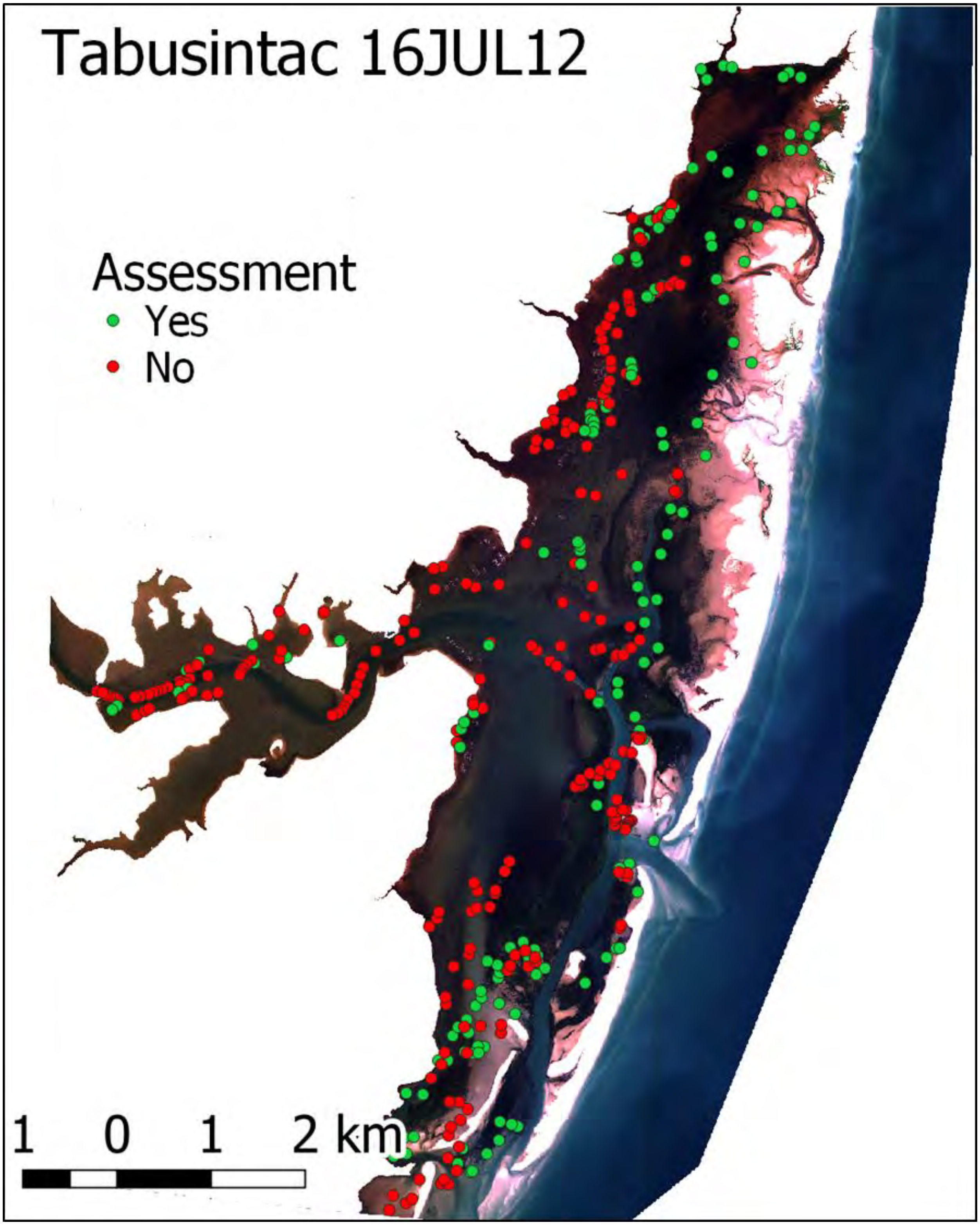

Figure 6 Manually selected assessment samples for the July 12th, 2016, collection. Points shown denote the presence or absence of eelgrass, yes referring to eelgrass present and no referring to eelgrass absent.

Results

The classification results were heavily dependent on the quality of the image used to produce them. All images were able to be classified and omission of eelgrass was mainly found in darker areas where deep eelgrass, deep water, and deep sand, all had a similar appearance. Commission of eelgrass was mostly seen in the deep water where sun glint on the water surface was present, this led to a speckling effect seen throughout many of the classifications.

Tabusintac Bay was the only location classified in two separate years, highlighting some of the changes in eelgrass distribution between the collections (Figure 7). Image quality was high in both collections however water clarity was quite different in the north-eastern section of the bay, with the 2021 collection having much darker water (Figure 8). Both images were accurately classified (Table 1)

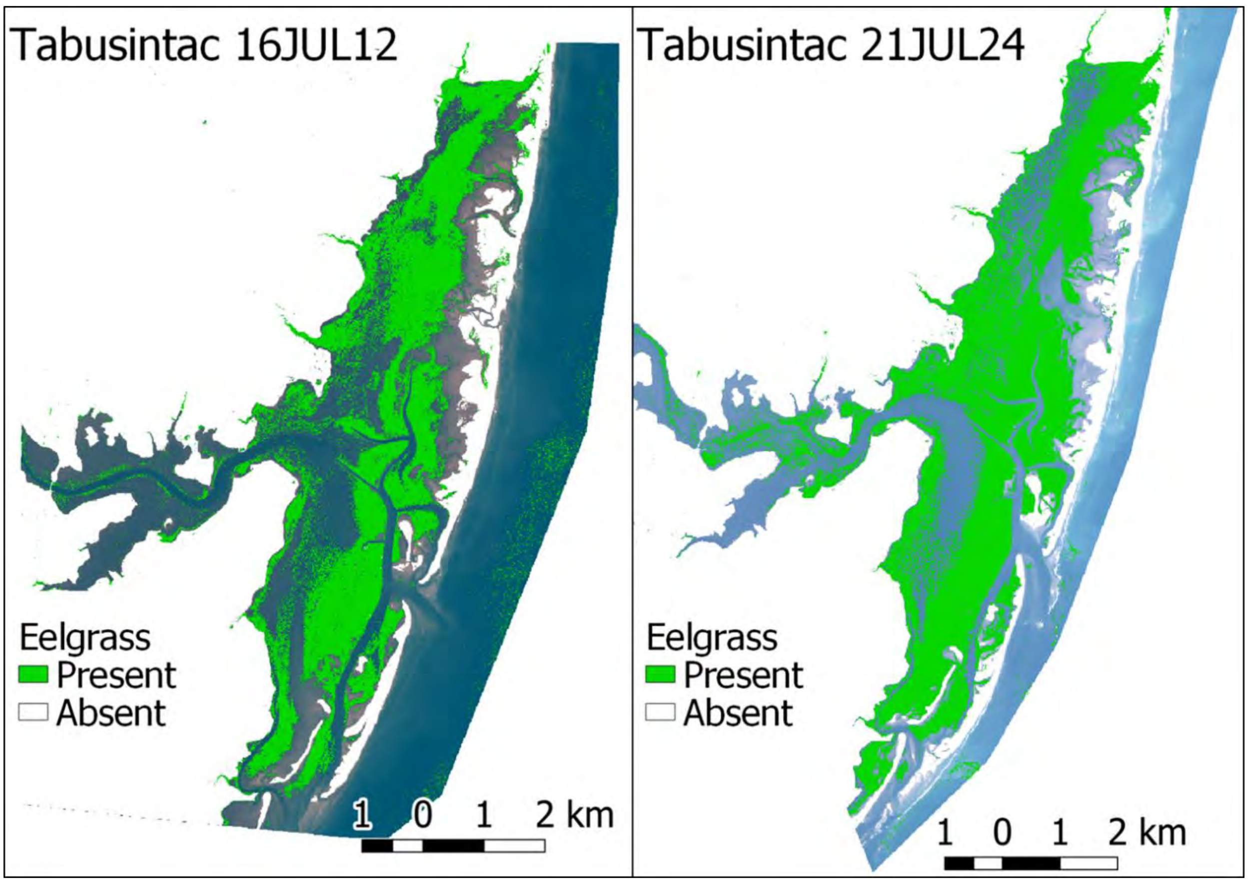

Figure 7 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Two different WorldView 2 images of the Tabusintac Bay were used, one collected on July 12th, 2016, and the other on July 21st, 2021.

Table 1 A) Tabusintac July 21st, 2021, B) Tabusintac July 12th, 2016 - accuracy assessments calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

A 21JUL24	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	22	1	15	3
Accuracy	0.96	0.04	0.83	0.17

B 16JUL12	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	151	6	232	3
Accuracy	0.96	0.04	0.99	0.01

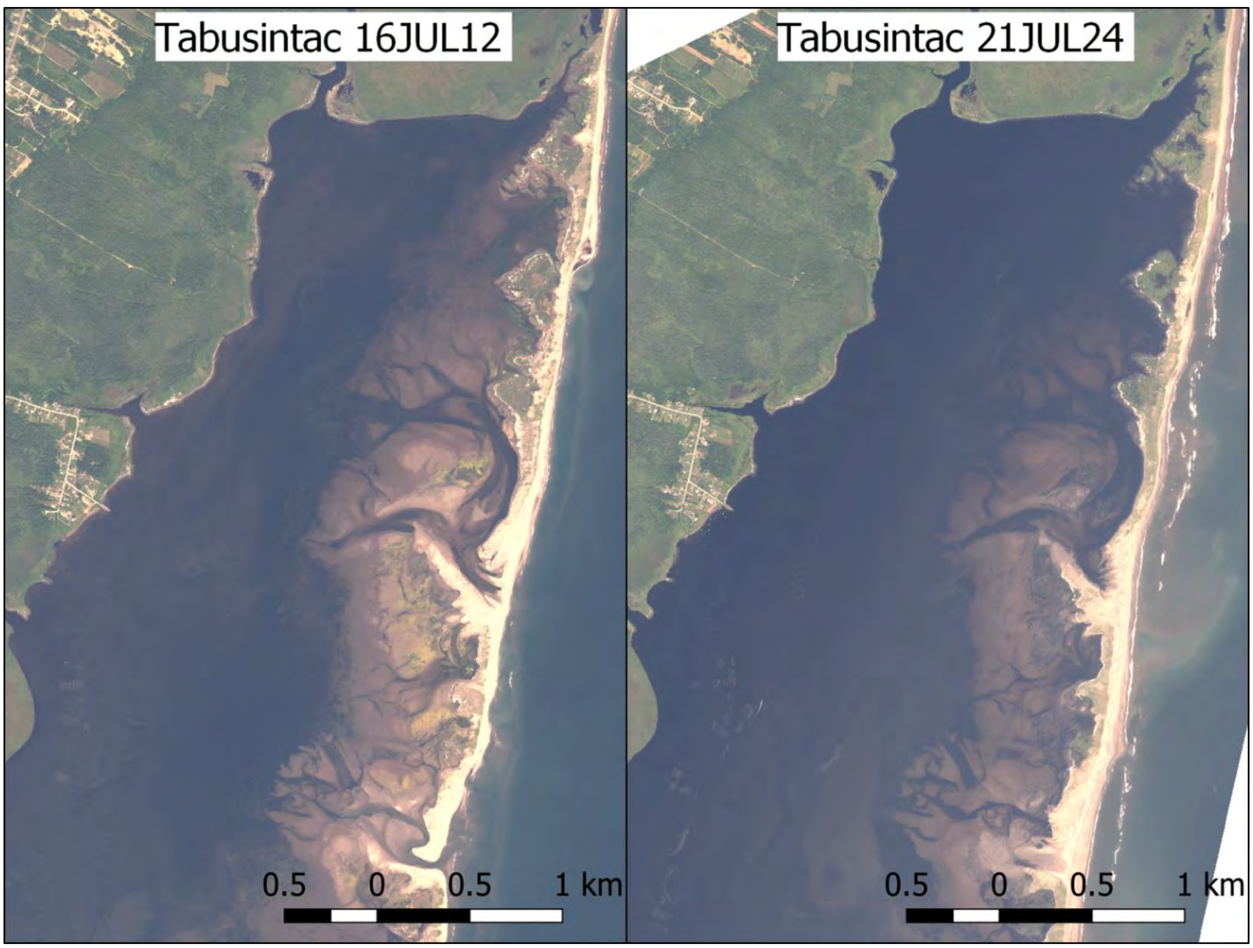

Figure 8 Comparison between the July 12th, 2016 and the July 24th, 2021 collections captured of Tabusintac bay. The benthic habitat is more visible in 2016 compared to 2021.

Richibucto Bay had good image quality with some sun glint present in the channel resulting in commission errors with eelgrass being classified where it cannot be seen (Figure 9). The area was quite large and was therefore split into three separate areas to be classified individually. The image was split along the scan line banding artifacts that are seen in some images. The classifications were then combined and assessed together (Table 2).

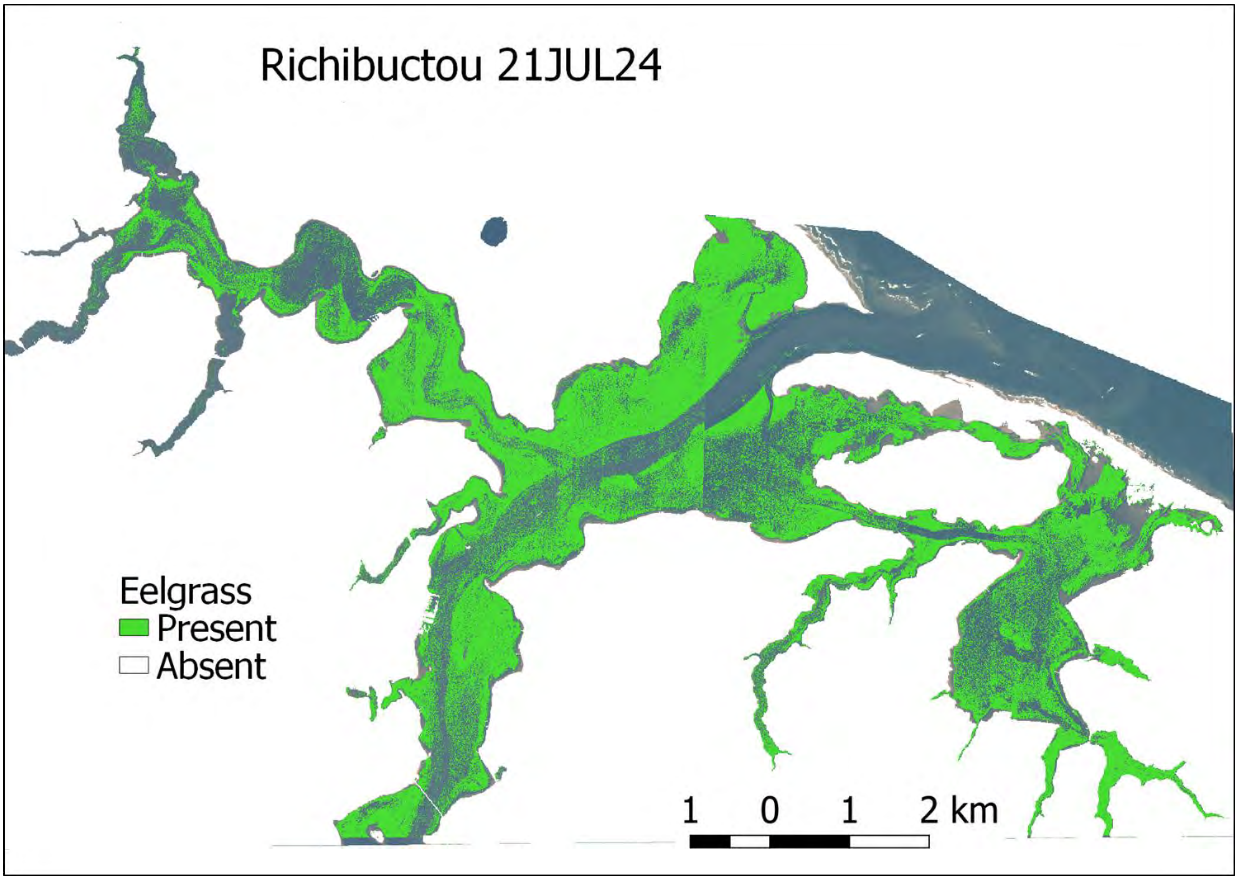

Figure 9 Eelgrass presence/ absence in Richibucto Bay, classification done on WorldView 2 imagery collected on July 24th, 2021, classification completed in ArcGIS Pro using the SVM classifier.

Table 2 Richibucto July 24th, 2021, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	35	10	43	5
Accuracy	0.78	0.22	0.90	0.10

Saint Simon North and South bays were classified from a single image, there were issues with sun glint in the image that led to commission errors in the classification with eelgrass being classified in areas that it cannot be seen (Figure 10). Deeper water in the north bay made this section more difficult to assess (Table 3).

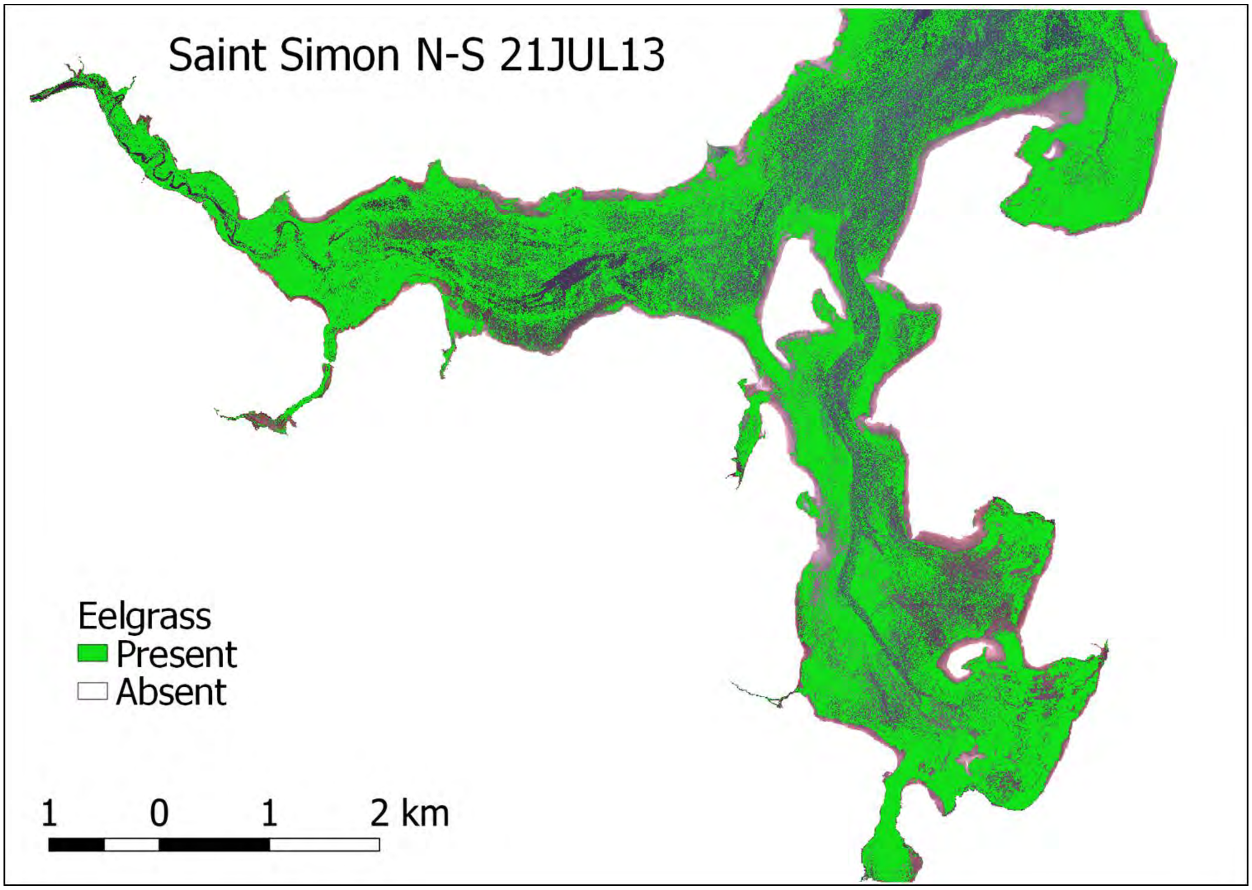

Figure 10 Eelgrass presence in Saint Simon North and South bays, classification done on WorldView 2 imagery collected on July 13th, 2021, classification completed in ArcGIS Pro using the SVM classifier.

Table 3 Saint Simon Nord and Sud July 13th, 2021, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	23	2	23	4
Accuracy	0.92	0.08	0.85	0.15

Neguac Bay classification was hampered by the sun glint from surface artifacts (Table 4), the classification though still shows the extent of large eelgrass beds on the eastern shore of the bay that disappear into deep water (Figure 11).

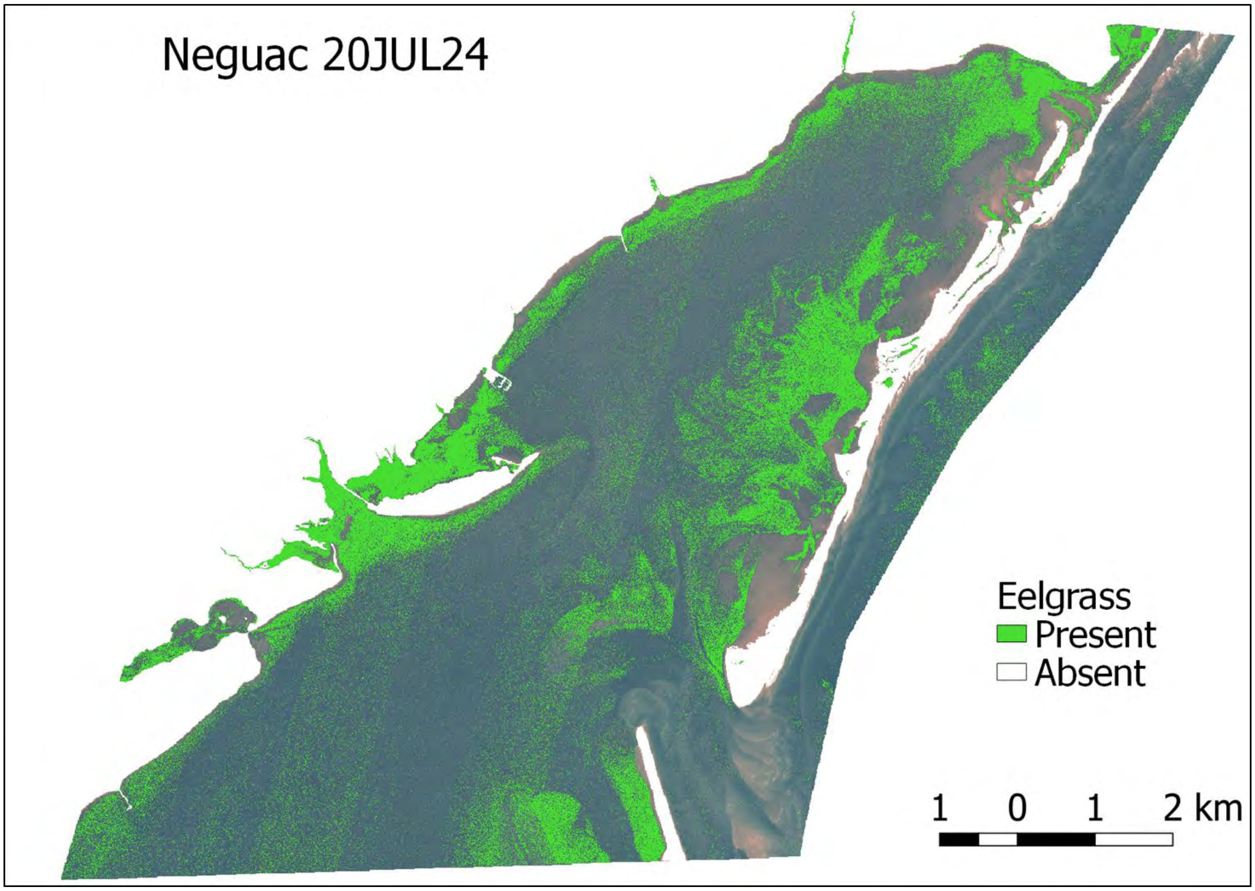

Figure 11 Eelgrass presence in Neguac Bay, classification done on WorldView 2 imagery collected on July 24th, 2021, classification completed in ArcGIS Pro using the SVM classifier.

Table 4 Neguac July 24th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	18	8	34	0
Accuracy	0.69	0.31	1.00	0.00

The Caraquet Bay classification was affected by the scan line banding artifacts but only minimally. The image was high quality in terms of water clarity and surface artifacts (sun glint); it produced one of the better results (Table 5) (Figure 12). Deep water in the middle of the bay limited the detection of eelgrass in this area.

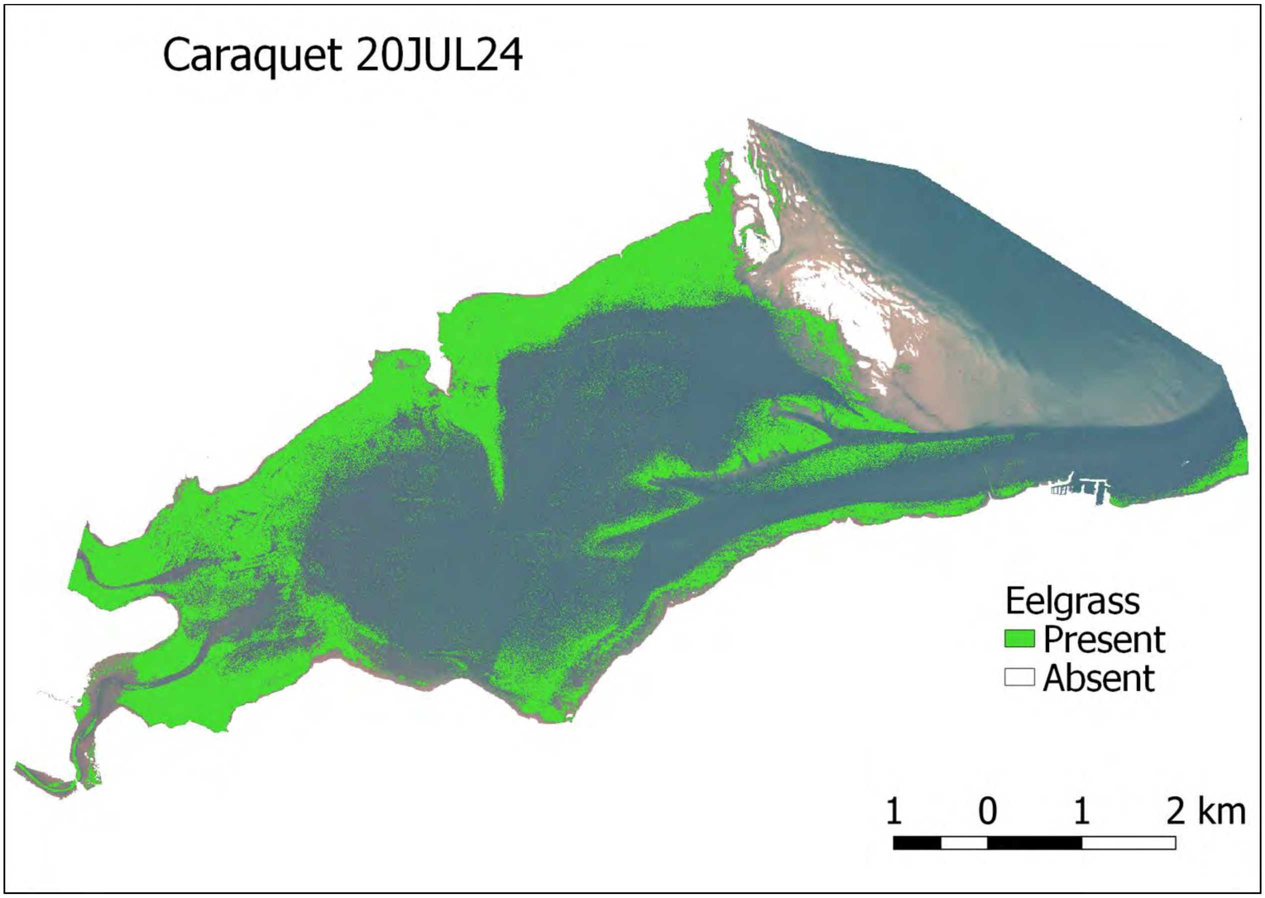

Figure 12 Eelgrass presence in Caraquet Bay, classification done using WorldView 2 imagery collected on July 24th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 5 Caraquet July 20th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	27	6	25	2
Accuracy	0.82	0.18	0.93	0.07

Grand Digue Bay was classified in two parts and then merged as consequence of how the data were collected by the satellite. Both images were collected at virtually the same time, and they were of very high quality and produced and excellent classification (Figure 13). One image covered the western edge and most of the inner bay and the other covered the eastern side and outer bay area. The classifications were combined and assessed together (Table 6)

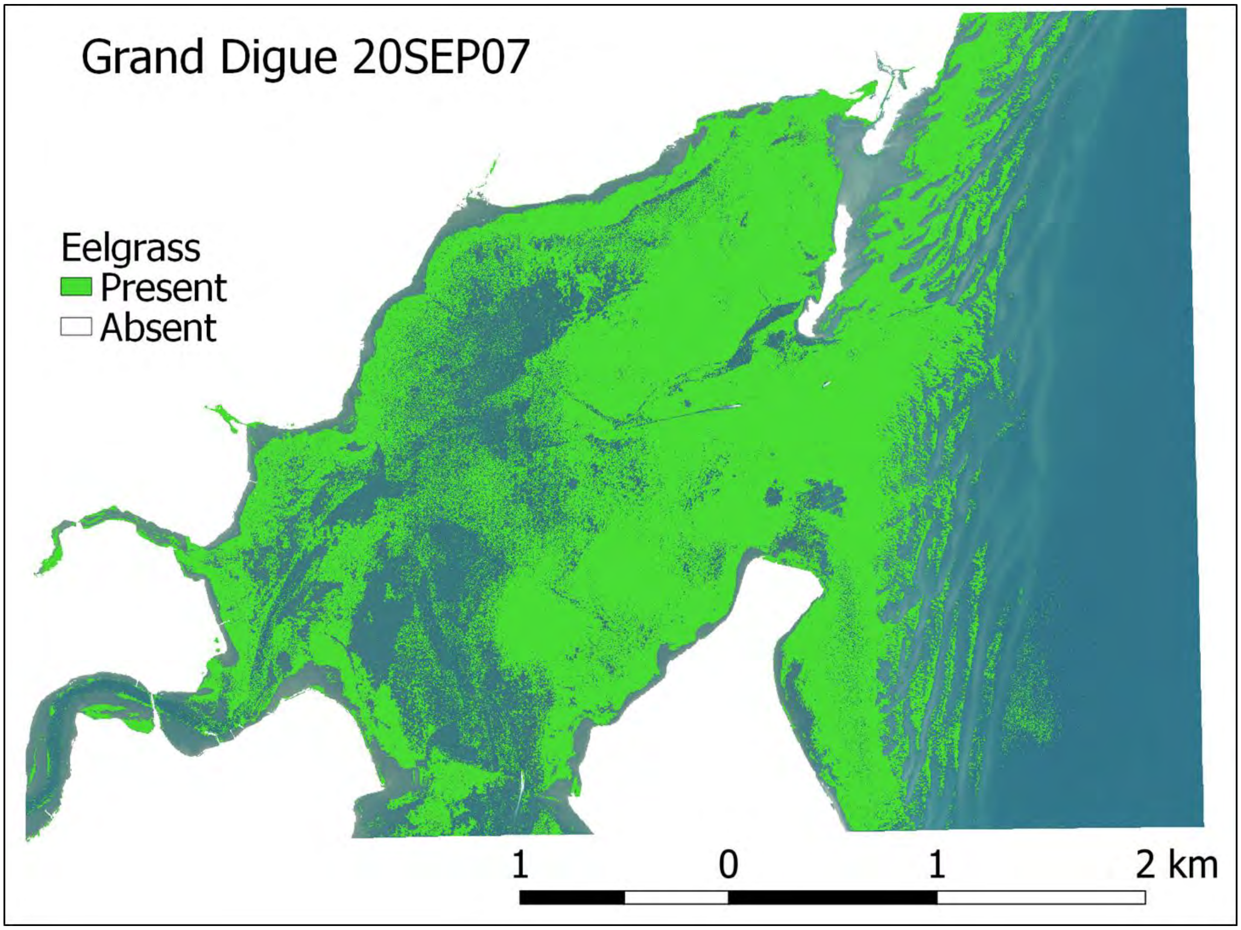

Figure 13 Eelgrass presence in Grand Digue, classification done using WorldView 2 imagery collected on September 7th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 6 Grand Digue September 7th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	29	1	28	2
Accuracy	0.97	0.03	0.93	0.07

Cocagne Bay was classified successfully with some sun glint commission errors seen, classifying eelgrass where it cannot be seen. Deep water in the middle of the bay kept this area from full examination (Figure 14). The image quality is good, there is a shadow from a cloud present in the tidal part of the river near the small south reaching bay, this led to some potentially inaccurate results in this area. The assessment of the classification can be seen in Table 7.

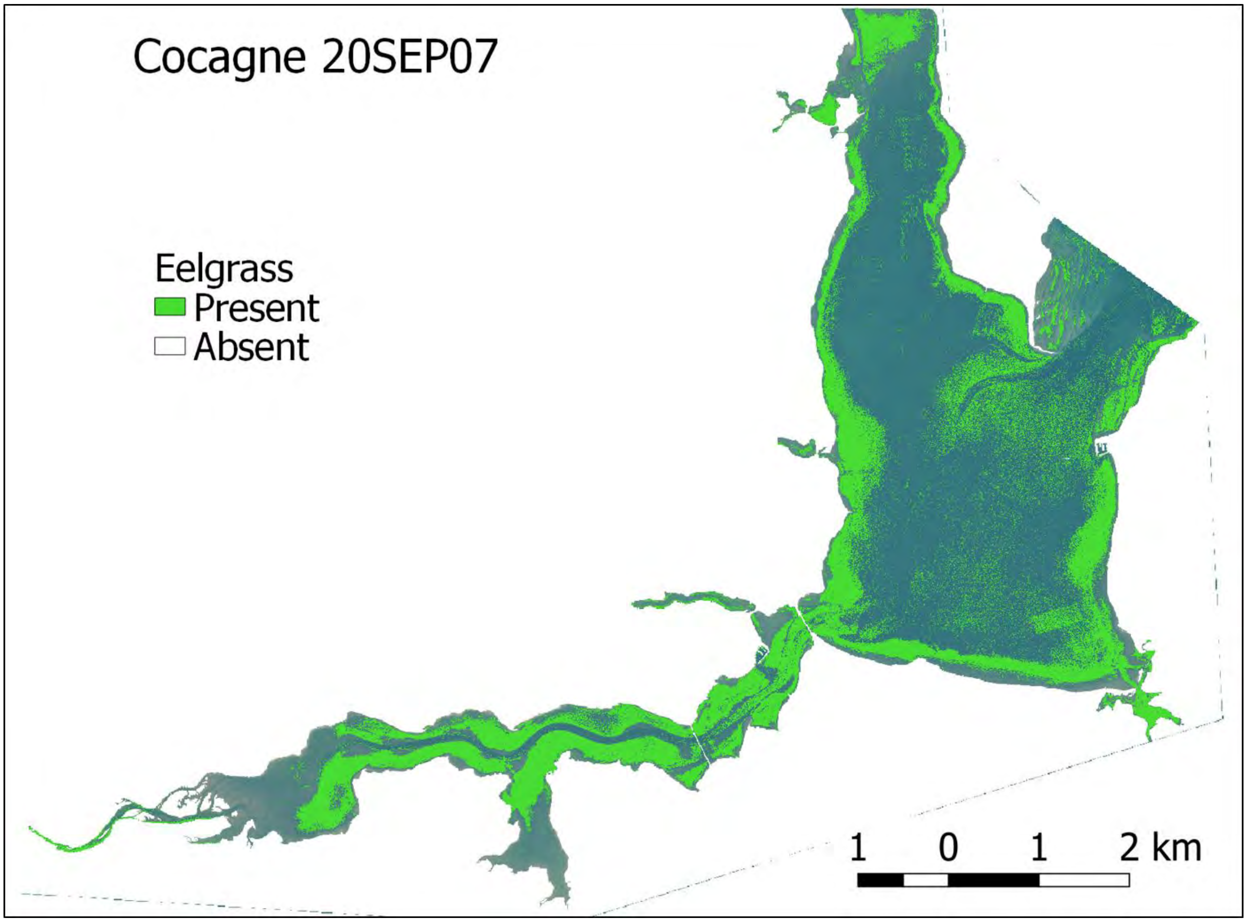

Figure 14 Eelgrass presence in Cocagne Bay, classification done using WorldView 2 imagery collected on September 7th, 2020, classification completed in ArcGIS Pro using the support vector machine algorithm.

Table 7 Cocagne September 7th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	25	2	22	9
Accuracy	0.93	0.07	0.71	0.29

Bouctouche Bay was classified well but had many commission errors from sun glint (Figure 15), the large eelgrass beds that are found in the eastern side of the bay can still be delineated and overall the accuracy of the classification wasn't significantly impacted (Table 8).

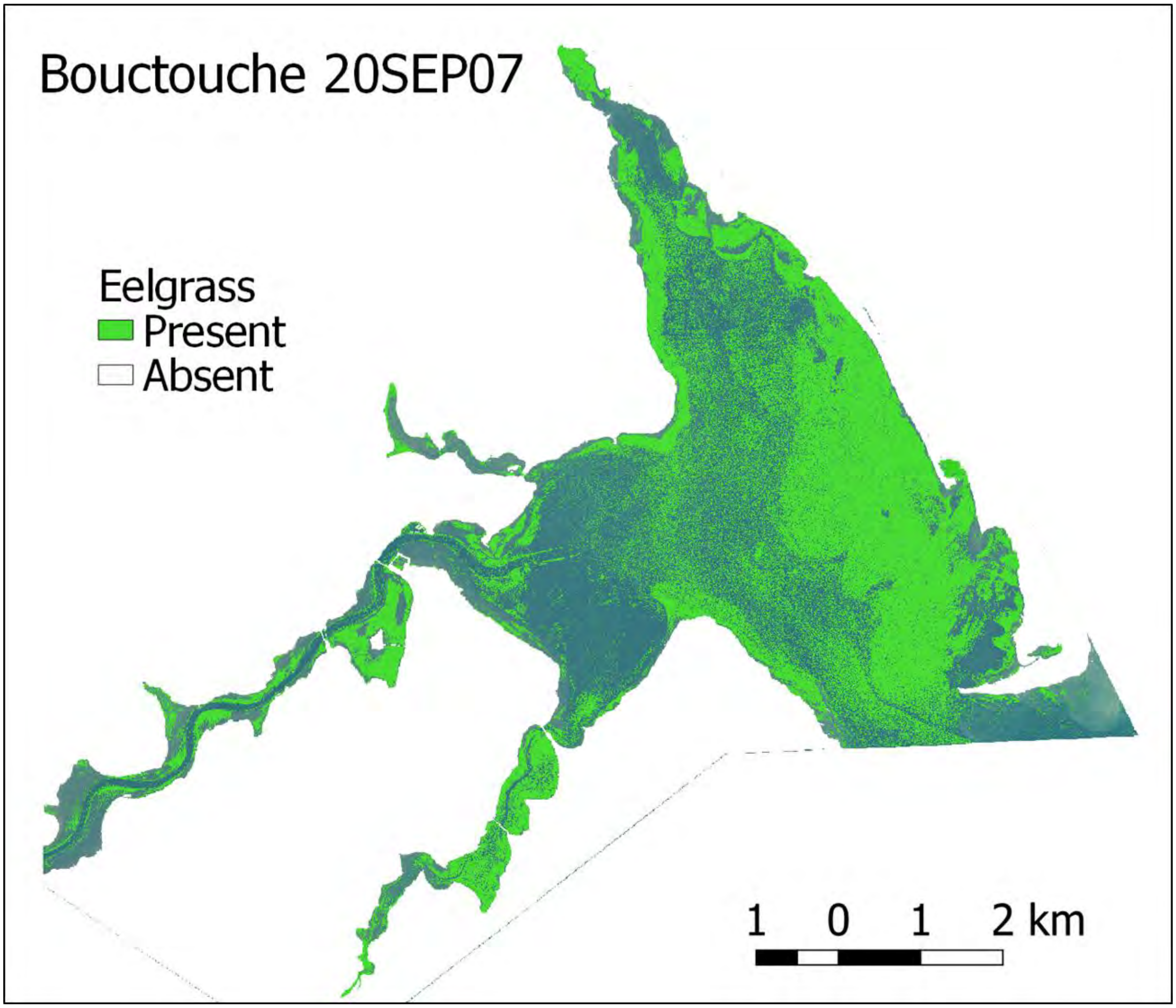

Figure 15 Eelgrass presence in Bouctouche, classification done using WorldView 2 imagery collected on September 7th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 8 Bouctouche September 7th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	33	2	24	1
Accuracy	0.94	0.06	0.96	0.04

Kouchibouguac and Kouchibouguacis bays were both classified using the same collection and are geographically located next to one another so their classifications can be addressed together. The image quality was very good, some sun glint was seen but the shallow bays allowed for the underlying benthic material to be seen throughout (Figure 16; Figure 17). The classifications were accurate (Table 9; Table 10) and the full coverage of the bays made them an excellent example of how well the SVM can work under ideal conditions.

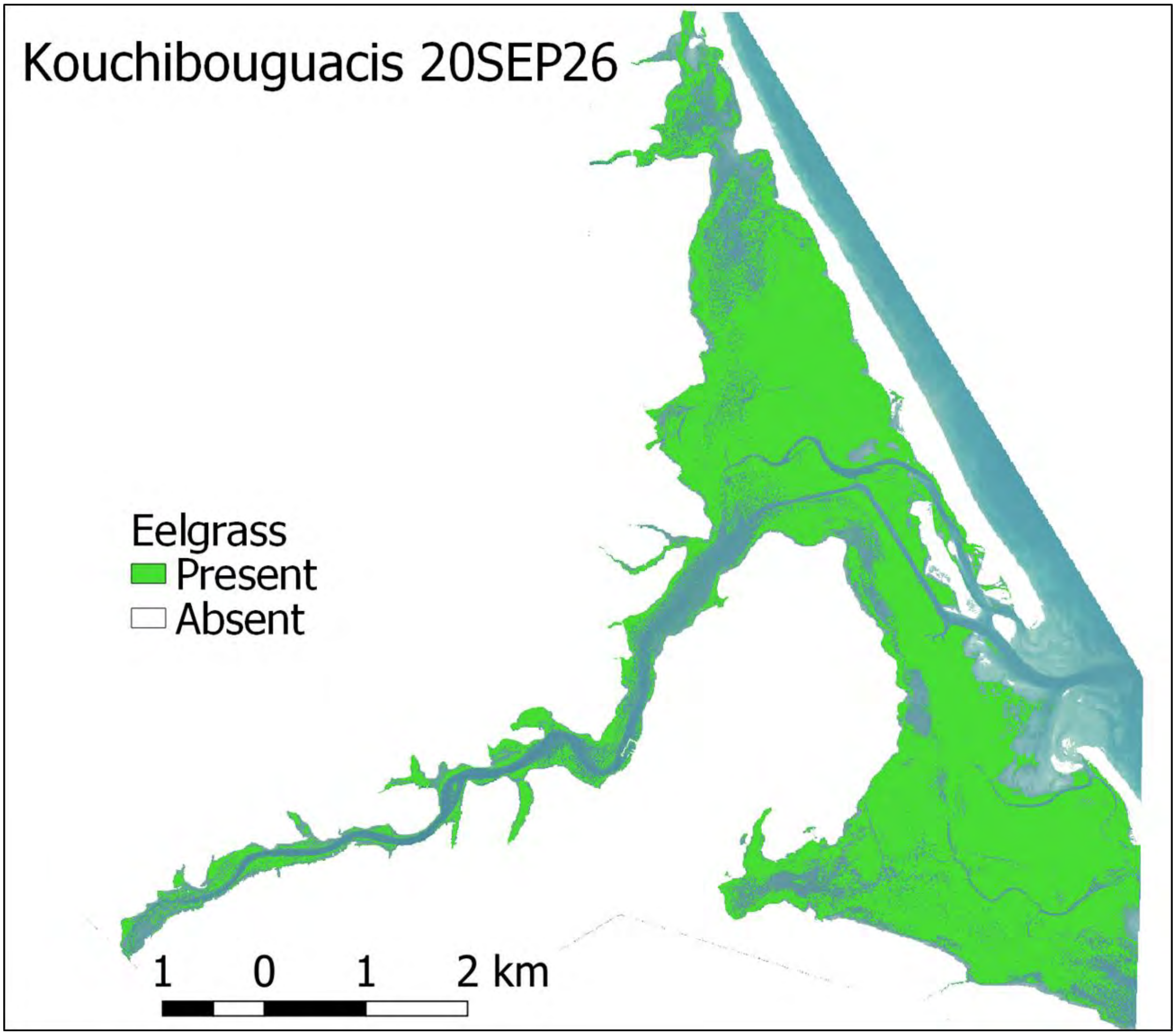

Figure 16 Eelgrass presence in Kouchibouguacis, classification done using WorldView 2 imagery collected on September 26th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 9 Kouchibouguacis September 26th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	25	1	33	1
Accuracy	0.96	0.04	0.97	0.03

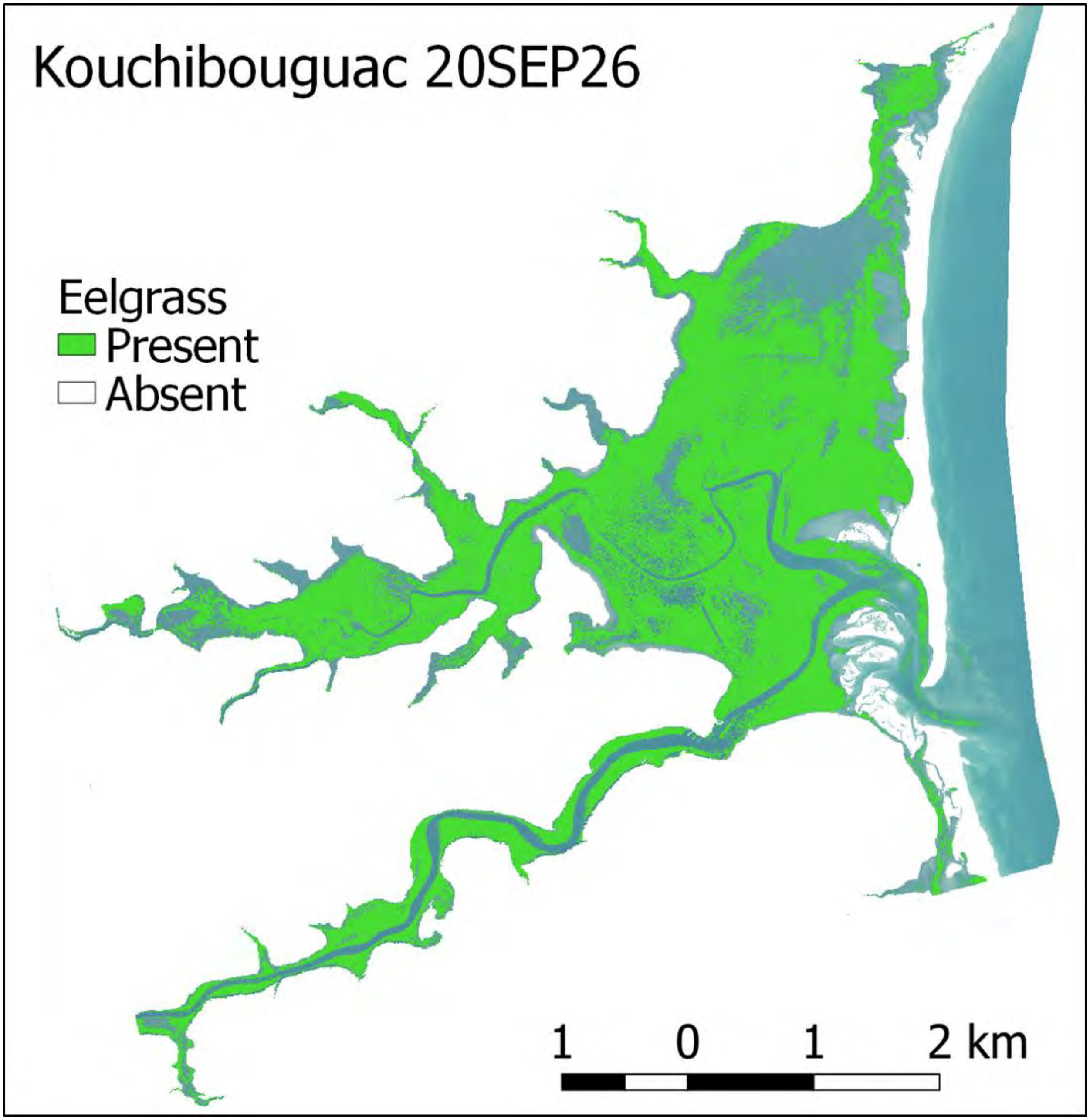

Figure 17 Eelgrass presence in Kouchibouguac, classification done using WorldView 2 imagery collected on September 26th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 10 Kouchibouguac September 26th, 2020, accuracy assessment calculated using a set of samples independent of those used in the classification. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

	EG_COR	EG_WRO	NG_COR	NG_WRO
# Samples	25	2	29	4
Accuracy	0.93	0.07	0.88	0.12

Discussion

The testing carried out during this project quickly narrowed down to two methods, the pixel-based SVM classification in ArcGIS Pro, and the object-based SVM classifier in eCognition. To test these methods against each other, an image of very high quality was selected and then both methods were used to classify the image using the same training areas. The results were very close (Table 11) but the object-based classification in eCognition did better, it also did not exhibit the same degree of speckling, resulting in a smoother classification. It was decided that because the results were so close and with the significant reduction in processing time (less than half as much) using ArcGIS Pro pixel-base classification that it was the right method to be used for the project.

The accuracy assessments unfortunately lacked real ground truth data. The areas not easily identifiable by AGRG staff could not be used in the assessments and therefore these ambiguous areas could not be accurately assessed. Only pixels with a very high degree of certainty were selected for assessment and the classifiers did not often struggle to classify these. It is possible this led to biased classification accuracies but a direct comparison between datasets can still give insight on which technique is classifying the image better.

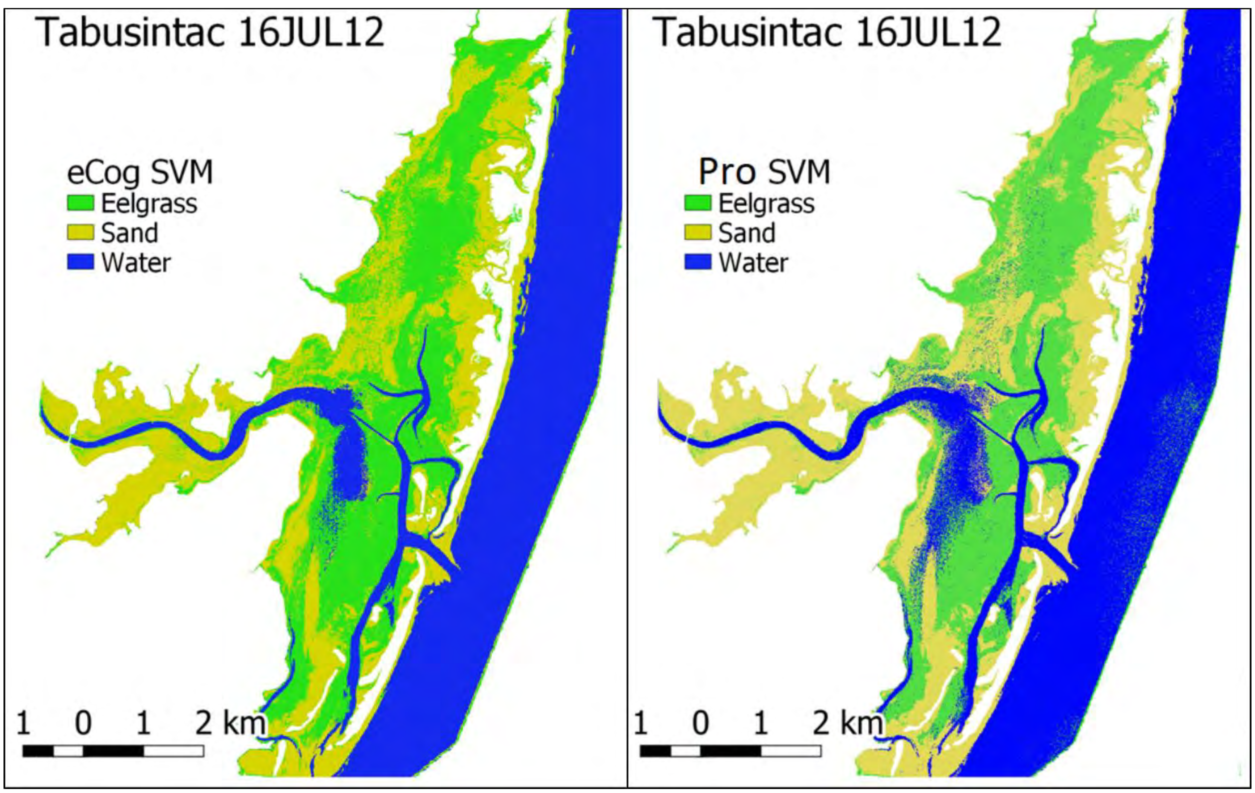

Figure 18 Side by side comparison of the SVM classification results from ArcGIS Pro and Trimble eCognition.

Table 11 A) Results from the ArcGIS Pro classification, B) results from the eCognition classification, calculated using the assessment samples seen in Figure 6. Accuracy is reported as a ratio, number of samples reflects the manual selected values (eelgrass (YG) or not eelgrass (NG)) and if the classification agrees (correct or wrong).

A	YG_Correct	YG_Wrong	NG_Correct	NG_Wrong
# Samples	151	6	232	3
Accuracy %	96.18	3.82	98.72	1.28
B	YG_Correct	YG_Wrong	NG_Correct	NG_Wrong
# Samples	156	1	230	5
Accuracy %	99.36	0.64	97.87	2.13

There were some data quality issues in the WorldView imagery that caused some challenges when classifying the data. One problem seen in many of the images was sun glint at the water surface, artifacts from windy conditions during the time of collection produced inaccurate classification in these areas (Figure 19).

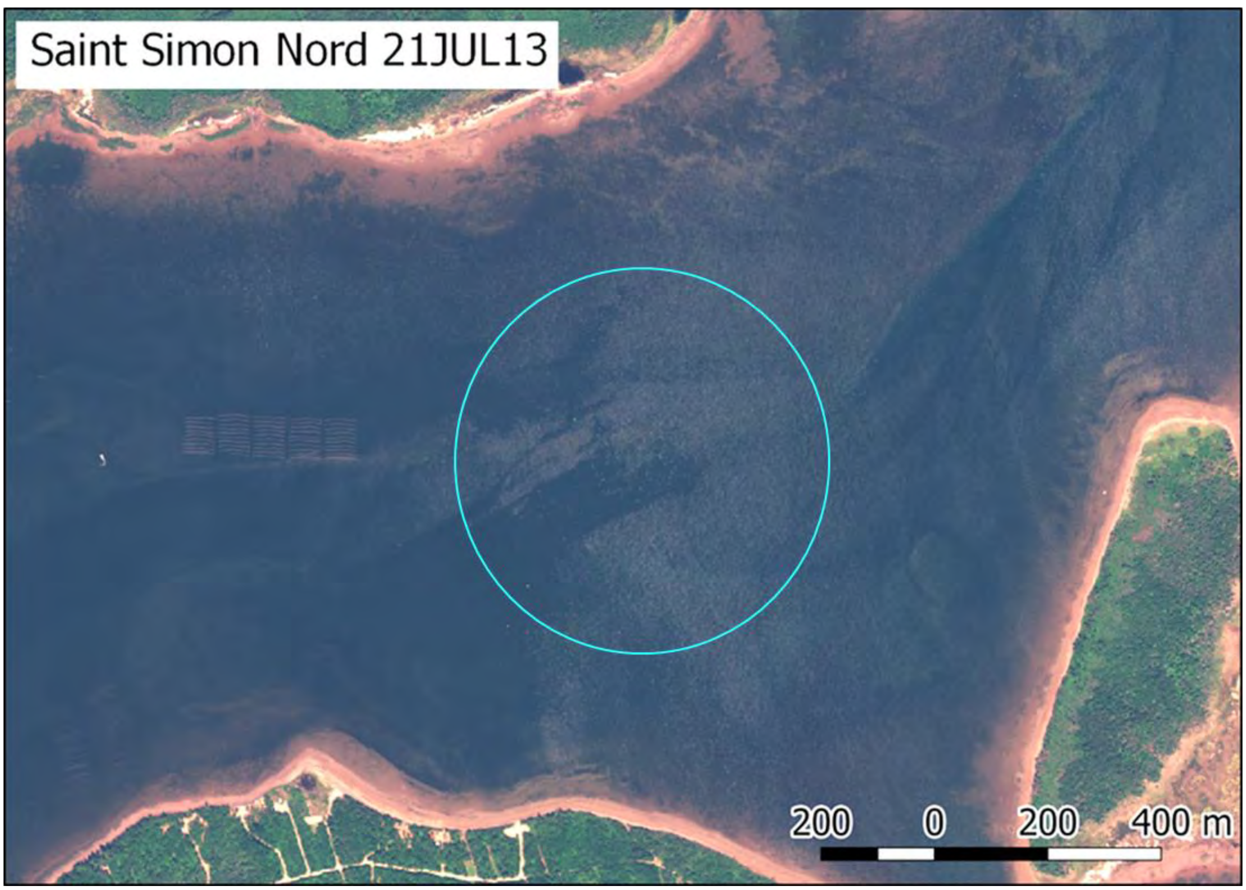

Figure 19 Sun glint on the water surface can be seen here in the middle-right of the frame, the cyan circle highlights an area partly filled with sun glint. Waves created by wind is causing roughness on the water surface made conditions for a mirror like reflection of the sun to the satellite, obscuring the seafloor.

Another artifact seen in many of the images were banding artifacts from the satellite sensor during collection (Figure 20). These artifacts caused single features to have a different appear different across the image and in some cases caused confusion between classes. For example, a section of eelgrass in one of these band artifacts may have a very similar spectral signature to deep water in another band.

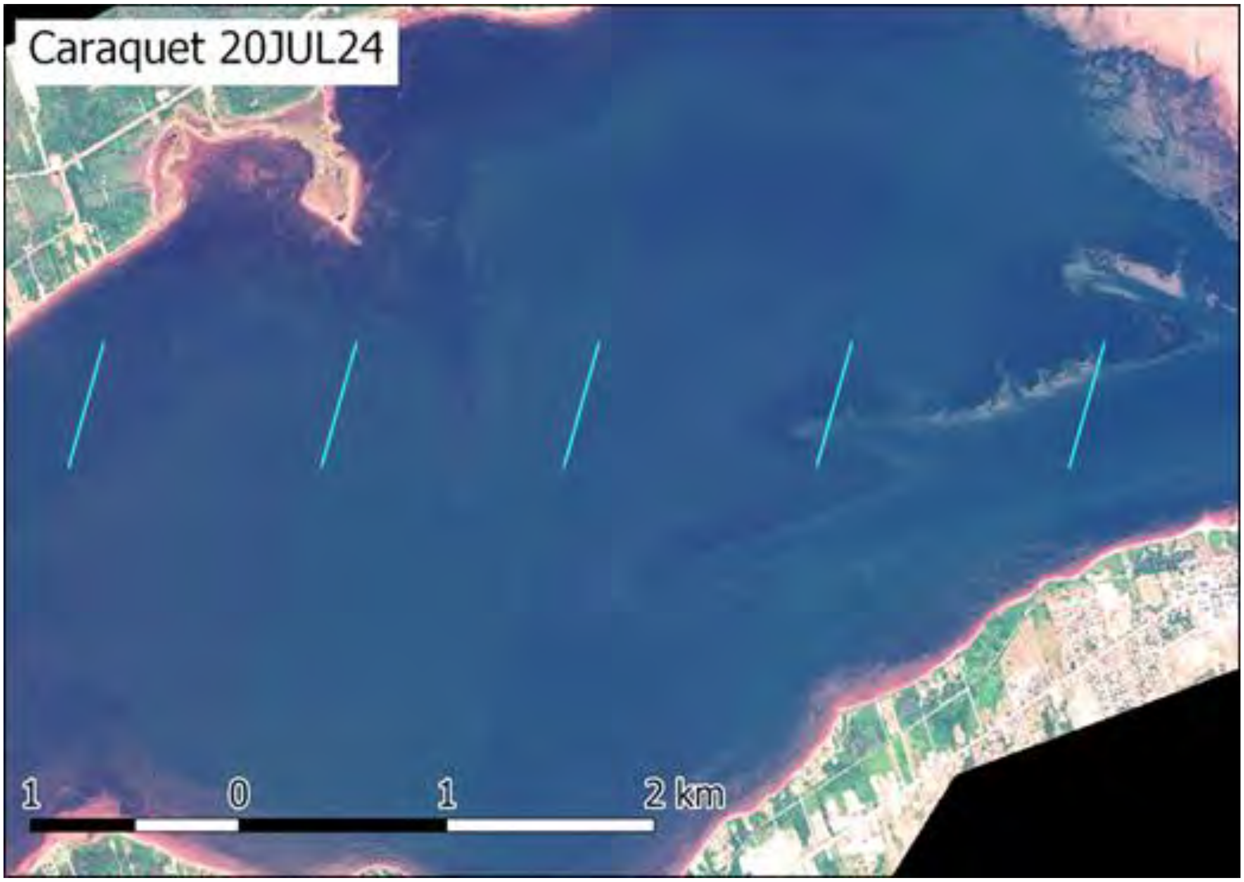

Figure 20 Vertical banding can be seen in the imagery, causing there to be lighter and darker areas in the image. The cyan lines are running partially along the boundaries of the banding artifacts and were added to help visualize their spacing.

Conclusions

The satellite classifications were successfully completed using the support vector machine classifier in ArcGIS Pro at the pixel level. This technique was quick, straight forward, and easy for someone with basic knowledge of GIS. Image artifacts like sun glint and banding from the sensor during collection contributed to inaccuracies in the classifications. The lack of synchronous and high spatial precision ground truth data for the bays led to problematic accuracy assessments but still provides good information about the classifications relative to one another.

Had there been more time for these classifications, better results were potentially attainable using Trimble eCognition and this software should always be considered when carrying out these types of classifications in the future.

The classifications provided could be improved by running a de-speckling algorithm or potentially with manual clean up. Most inaccuracies observed were a result from commission errors due to sun glint, where the random orientation of waves and resulting surface artifacts caused pixels of all range of colours to be displayed throughout the image and some were classified as eelgrass.

Moving forward there could be some pre-processing steps added into the classifications such as depth normalizing the values to help deeper objects appear more like those at shallow depths, atmospheric corrections, and glare reduction methods. Composite bands could also be calculated to help enhance the features trying to be classified. The better the image data are before training the classifiers, the better the classification results are, as seen with the images of higher quality in this study.

References

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