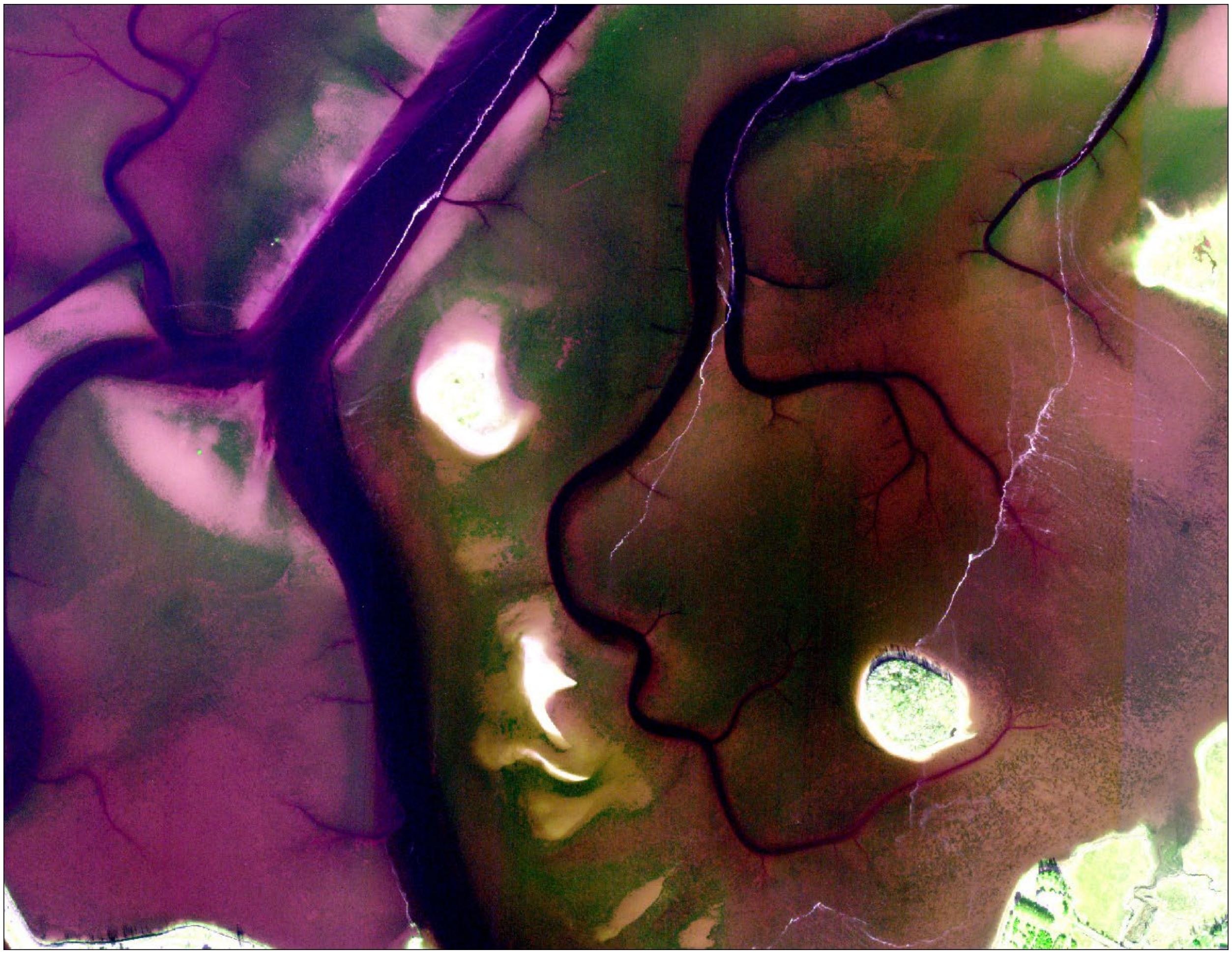

PROJECT REPORT

Validating remote sensing tools to identify effective management measures to protect eelgrass

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How to Cite This Work and Report:

Applied Geomatics Research Group. 2023. Project Report: Validating remote sensing tools to identify effective management measures to protect eelgrass. Applied Geomatics Research Group, NSCC Middleton, NS.

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Executive Summary

The Nova Scotia Community College – Applied Geomatics Research Group (NSCC-AGRG) utilized a support vector machine (SVM) classifier to determine the presence of eelgrass in 14 bays along the Gulf of St. Lawrence. The SVM process was chosen due to its fast processing time and accurate results compared to other classification methods. The classification was conducted on 2022 imagery for seven sites in New Brunswick, six sites in Prince Edward Island, and one in Nova Scotia. The accuracy of the classification was limited by the quality of the imagery and was challenged by sun glint and vertical banding as a result of the sensor collection. Although there was a lack of synchronous and high spatial precision ground truth data, the accuracy assessment reports of the SVM classification demonstrated a generally high detection rate of eelgrass in the bays. Single beam data collected using a BioSonics MX echosounder was processed to analyze plant canopy and bathymetry and provide a secondary form of validation of the SVM classification.

Introduction

Eelgrass plays an essential role in the Gulf of St. Lawrence's ecosystem, serving as a critical habitat for many species and contributing to water quality (Schein et al., 2012). The Department of Fisheries and Oceans (DFO) – Gulf Region recognizes the importance of identifying and mapping eelgrass habitats accurately to develop effective conservation strategies. DFO partnered with the Nova Scotia Community College - Applied Geomatics Research Group (NSCC-AGRG) to carry out this project.

In recent years, satellite imagery has emerged as a promising tool for mapping and monitoring eelgrass habitats. A study conducted by Forsey et al. (2020) showed that satellite imagery can be an effective resource for eelgrass classification in the Gulf region. Building on this knowledge, DFO procured high-resolution WorldView 2 satellite imagery, which was shared with NSCC-AGRG.

To identify the best approach for classifying eelgrass habitats, NSCC-AGRG conducted a comprehensive analysis of three software packages and two machine learning classification algorithms. The software packages evaluated were Esri ArcGIS Pro, Trimble eCognition, and PCI Geomatics CATALYST. The machine learning algorithms tested were the random trees and support-vector machine (SVM), both accessible through all the software packages evaluated. Ultimately, the pixel-based SVM classification technique was selected due to its high quality and efficiency in classifying a large number of images.

DFO provided raw single beam sounding data which were processed using the Visual Aquatic software to generate a secondary reference dataset for detecting submerged vegetation in several areas of interest, independent of the SVM classification. This dataset provided an estimation of submerged plant height, plant coverage, and depth.

Methods

Study Area

This project focused on 14 bays located along the Gulf of St. Lawrence. These bays included seven sites in New Brunswick, six sites in Prince Edward Island, and one site in Nova Scotia (Figure 1).

Figure 1 Map of reference showing the areas of interest classified using satellite images from 2022.

Image Pre-processing

NSCC-AGRG carried out top of atmosphere and atmospheric (TOA and ATCOR) corrections on the satellite imagery in CATALYST prior to conducting any classification analysis. A land mask was applied to the imagery to limit the analysis to only submerged areas.

The TOA computation converted pixel values to reflectance values that represent the amount of solar energy reflected by the Earth's surface, as measured above the atmosphere. This normalization process accounted for varying solar illumination conditions at different acquisition times and helped to validate the calibration coefficients of the image. Inaccurate calibration coefficients were identified by a high percentage of pixels in the image with TOA values over 100.

ATCOR is a tool designed to correct satellite images for atmospheric conditions, making them suitable for various types of analysis such as GCP collection, segmentation, classification, or extraction of vegetation indices. To perform this correction, ATCOR required a haze-free image generated by HAZEREM, or a raw or orthorectified image that did not have any haze. Additionally, a terrain file from TERSETUP was also necessary for the correction process. Once these inputs were provided, ATCOR generated a ground-reflectance image that was corrected for atmospheric and terrain effects. The output from ATCOR included two files: the corrected image and an optional visibility map for the scene. By adopting this approach, the analysis precision was enhanced by focusing solely on the eelgrass present in the different bays. A visual comparison of the ATCOR process is shown in Figure 2.

Figure 2 Example of image's conditions before and after atmospheric corrections. To the left image unprocessed, in the middle with TOA correction and to the right image with ATCOR correction.

NSCC-AGRG utilized an SVM algorithm in ArcGIS Pro for eelgrass classification. To eliminate any land from the images, an image mask was computed using NIR 1 (Band 7). This was achieved by selecting a threshold, and any pixels holding values equal to or less than the threshold were considered water, while those above the threshold were considered land.

The NIR 1 band in the satellite imagery produced a response that indicated that water areas had pixel values below 1500, while dry land had much higher pixel values. To generate a mask that separates water from land, a Con statement was applied to the raster, assigning a value of 1 to pixels with values between 0 and 1500, and 0 to those above 1500. The resulting raster mask was converted to polygons, and the bay area was extracted from it. The atmospherically corrected image was then clipped using the Extract by Mask process, resulting in a multispectral image of only the submerged area, which was used for eelgrass classification. The final product is presented in Figure 3. This approach improved the precision of the eelgrass classification by enabling a focus on the specific areas of interest in the bays.

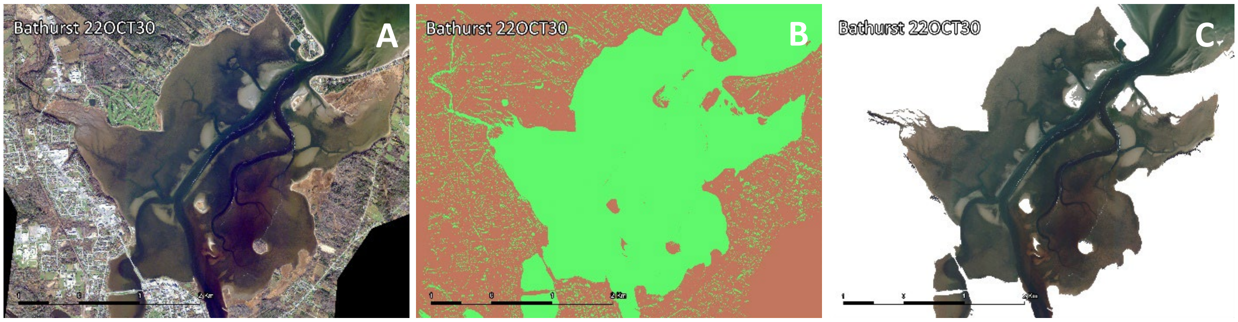


Figure 3 Comparison showing the process of masking and subsequent clipping of the area submerged in water using the ArcGIS Pro processes: Extract Band, Con, Raster to Polygon, and Extract by Mask.

Accuracy Assessment

To evaluate the accuracy of the SVM classification, 30 sampling points were chosen randomly from the satellite image, comprising both the presence and absence of eelgrass, with 15 points assigned to each category. The accuracy assessment process involved extracting pixel values from the raster based on the coordinates of the evaluation points. The comparison of these values was used to determine the accuracy of the SVM classification, which was expressed as a percentage. This was calculated by determining the proportion of matching values between the evaluation points and the raster.

Sounding Data

Single beam data collected from a BioSonics MX echosounder were processed using the Visual Aquatic software, which provided a range of tools and algorithms to estimate submerged aquatic vegetation and bathymetry quickly and accurately. A Time Varied Gain (TVG) was applied to the echogram and a Rising Edge threshold was used alongside manual editing for detecting bathymetry. Similar methods were used for analyzing the plant canopy in which the Plant Detection threshold (dB) was adjusted for varying degrees of plant density.

Results

SVM Classification

Cocagne

The Cocagne region was classified using imagery captured on two different dates in June and August 2022 (Figure 4). The June imagery had a significant amount of sun glint in the central part, likely caused by windy conditions and boat traffic in the bay at the time, which posed challenges for the classification and identification of eelgrass in Cocagne for that month. In contrast, the August imagery had much less sun glint, but it showed banding and lacked clarity in regions with deep bathymetry. Both images were accurately classified, with the August image better identifying the presence of eelgrass (Table 1; Table 2).

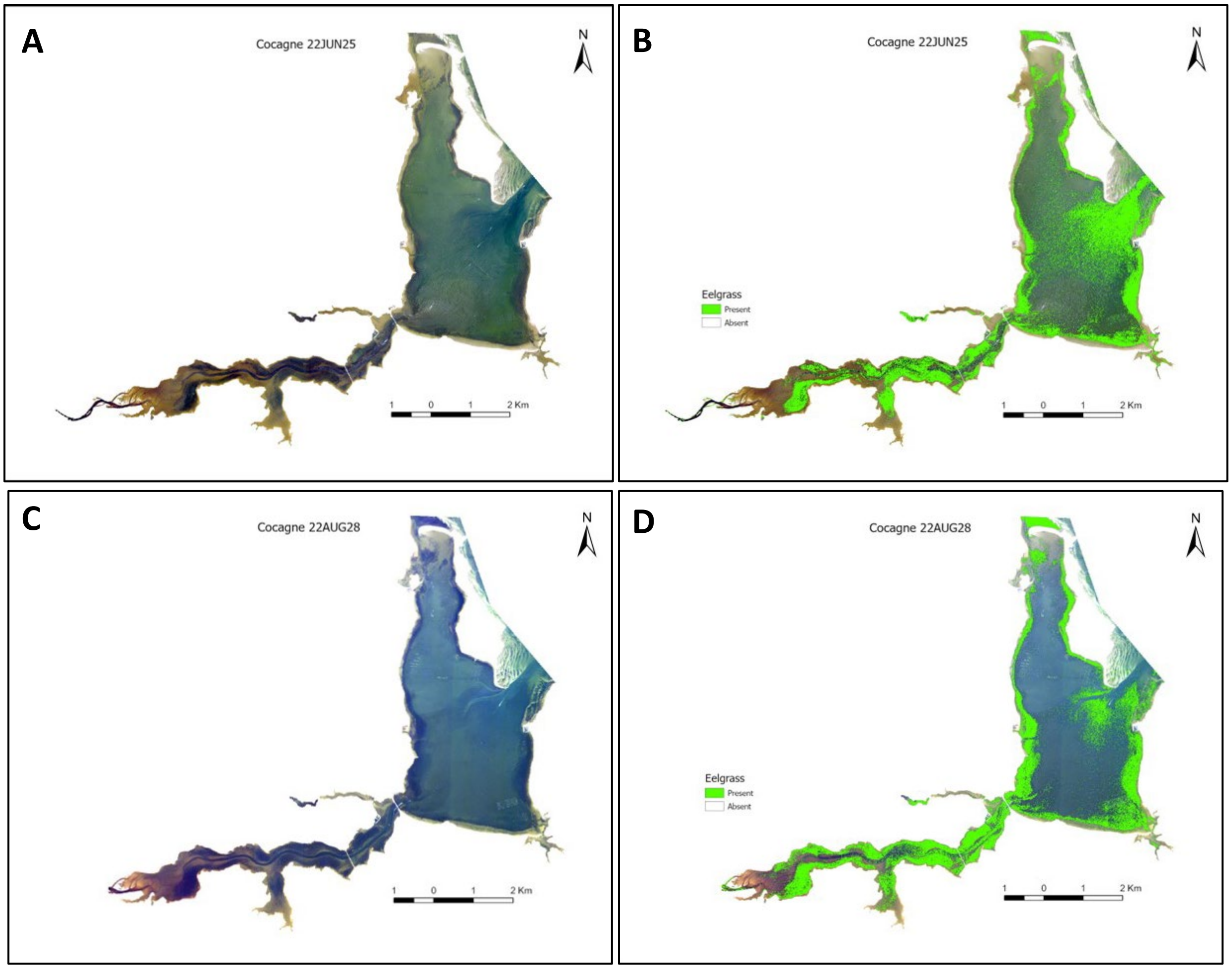


Figure 4 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Two different WorldView 2 images of the Cocagne Bay were used, one collected on June 25th, 2022, and the other on August 28th, 2022.

Table 1 Classification accuracy assessment of the Cocagne region on June 25th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

June 25th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	13	2	15	0
Accuracy	87%	13%	100%	0%

Table 2 Classification accuracy assessment of the Cocagne region on August 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

August 28th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	13	2	15	0
Accuracy	87%	13%	100%	0%

Kouchibouguac

The bay of Kouchibouguac was divided into six sections and classified individually to achieve better accuracy. Despite some sun glint in the central region, the overall quality of the image was good (Figure 5). The bay was segmented into zones, including the long and shallow rivers, the deep central area, the shallower northern region, and the ocean area. The classifications of these zones were then combined and assessed together (Table 3).

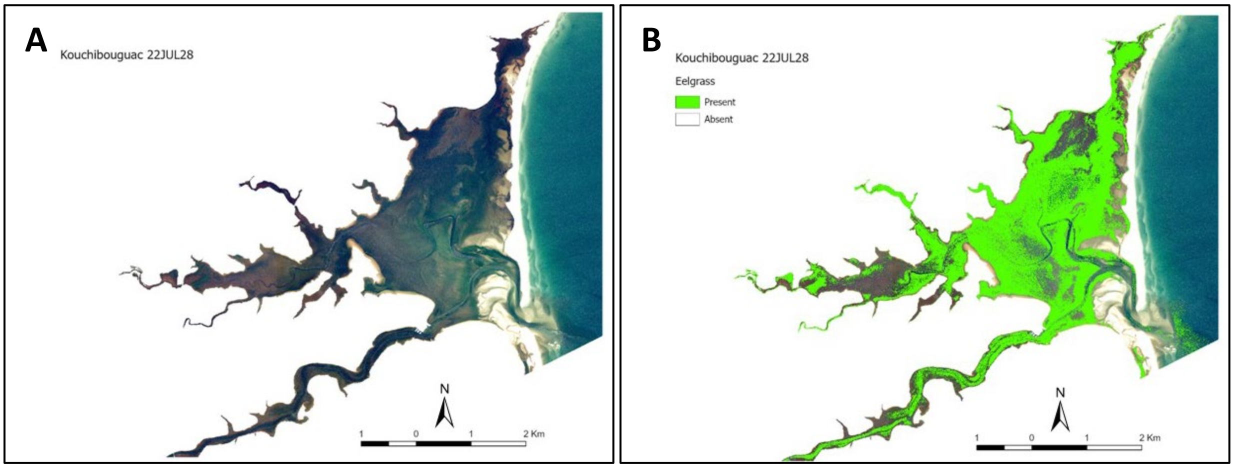


Figure 5 Eelgrass presence/absence in Kouchibouguac Bay, classification done on WorldView 2 imagery collected on July 28th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 3 Classification accuracy assessment of the Kouchibouguac region on July 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 28th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	14	1	15	0
Accuracy	93%	7%	100%	0%

Grande-Digue

Grande-Digue imagery was collected twice in June and August 2022, as shown in Figure 6. The image quality was high for both dates, resulting in accurate classification. The June image, however, had some glare in the river channel and part of the bay channel, caused by waves and the position of the sun during the image capture. In contrast, the August image had better quality and sharpness, resulting in improved classification. Table 4 and 5 provide an assessment of the classification results.

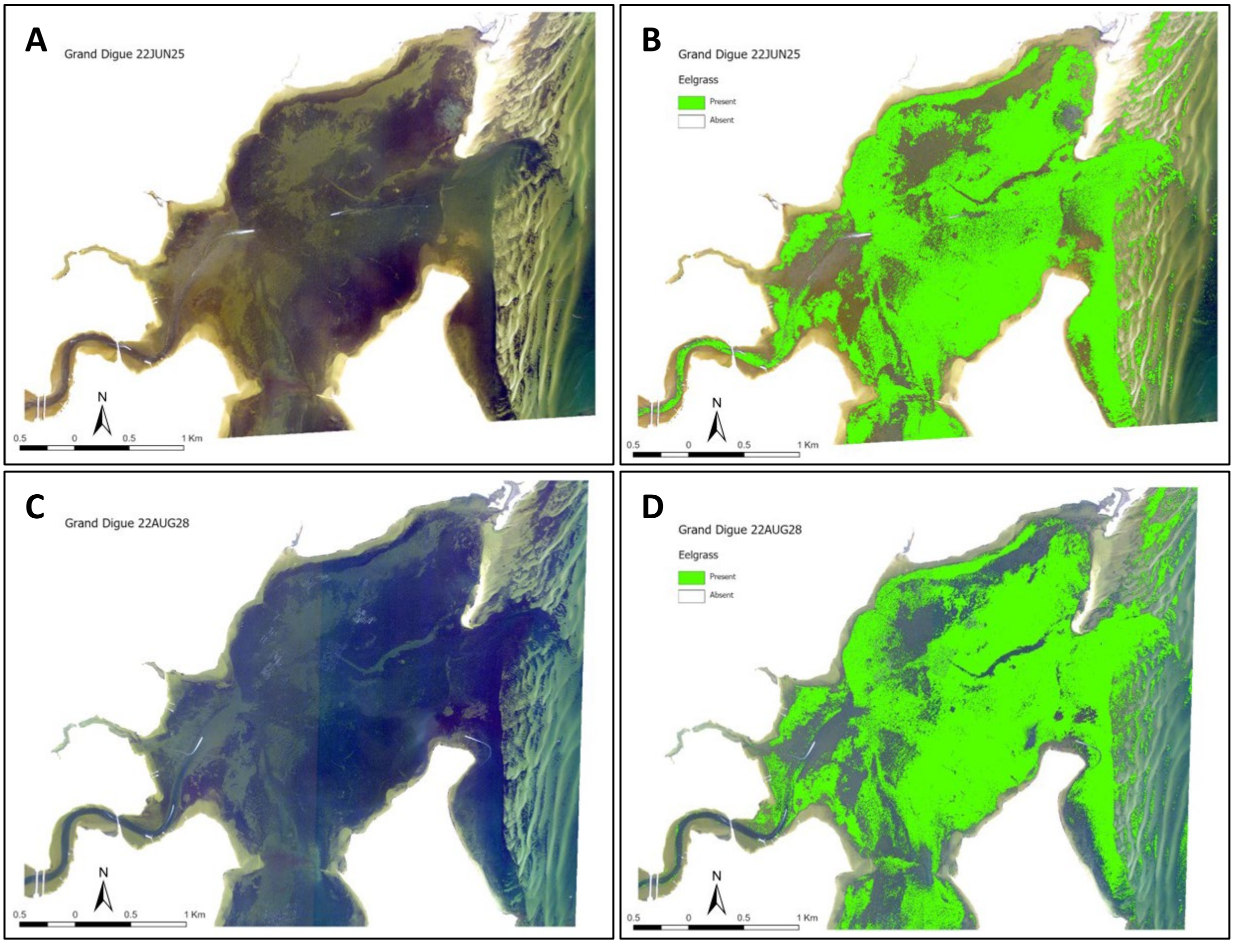


Figure 6 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Two different WorldView 2 images of the Grand Digue Bay were used, one collected on June 25th, 2022, and the other on August 28th, 2022.

Table 4 Classification accuracy assessment of the Grande-Digue region on June 25th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

June 25th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	15	0
Accuracy	100%	0%	100%	0%

Table 5 Accuracy assessment of classification on the Grande-Digue region on August 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

August 22nd, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	15	0
Accuracy	100%	0%	100%	0%

Tabusintac

The image quality in the Tabusintac region was generally high, although there was some banding in the center of the image. This banding made it challenging to accurately identify eelgrass in this area due to the heterogeneity between the two bands (Figure 7). The overall classification accuracy was favourable, particularly in the northern, eastern, and southern regions of the image (Table 6).

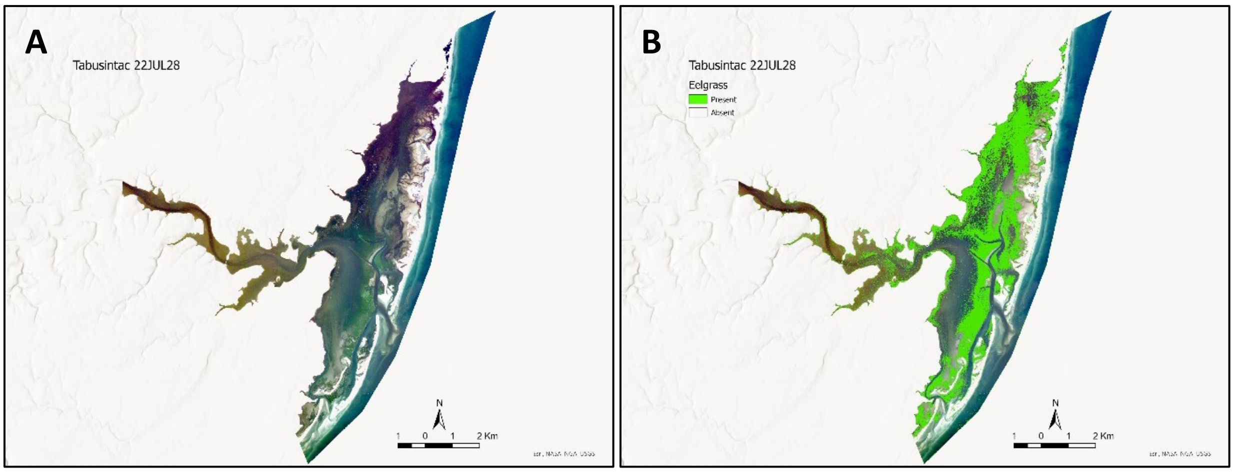


Figure 7 Eelgrass presence in Tabusintac, classification done using WorldView 2 imagery collected on July 28th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 6 Classification accuracy assessment of the Tabusintac region on July 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 28th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	12	3	15	0
Accuracy	80%	20%	100%	0%

Saint-Simon (North and South)

The classification process of the Saint-Simon region utilized a single image for both bays. The image quality and clarity were satisfactory, however, there was a notable presence of suspended sediment in the water that occasionally interfered with the identification algorithm. This interference affected the accuracy assessment of the eelgrass, particularly in the eastern region of the North Bay, as shown in Figure 8 and described in Table 7.

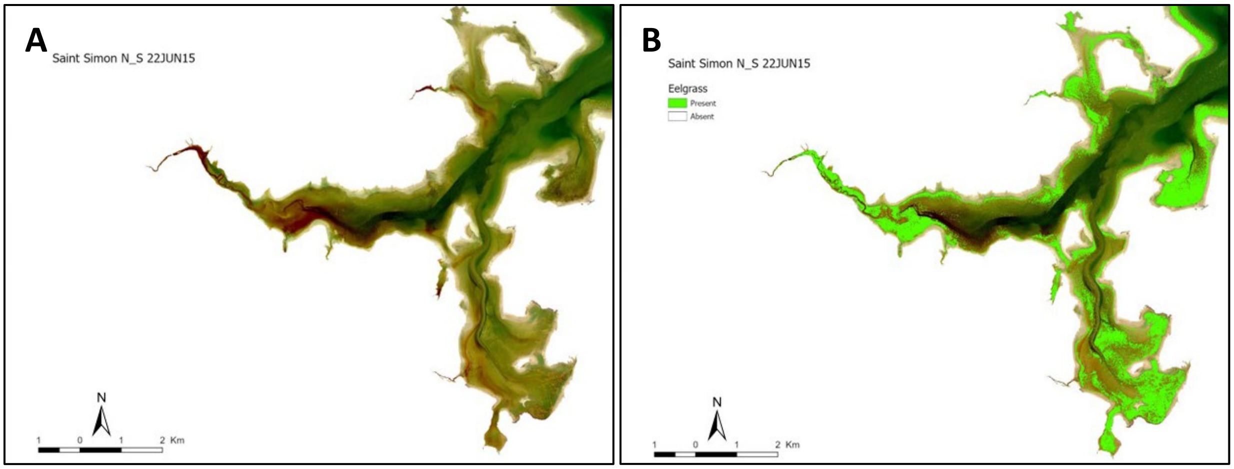


Figure 8 Eelgrass presence in Saint Simon Bay North and South, classification done using WorldView 2 imagery collected on June 15th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 7 Classification accuracy assessment of the north and south region of Saint-Simon on June 15th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

June 15th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	12	3	15	0
Accuracy	80%	20%	100%	0%

Tracadie

Tracadie Bay was classified using two sets of imagery captured in June and August (Figure 9). The clear and high-quality images enabled accurate classification. Although some changes were evident between the two months, they were minimal and mainly related to the natural dynamics of the ecosystem. The assessment of the classification can be seen in Table 8 and Table 9.

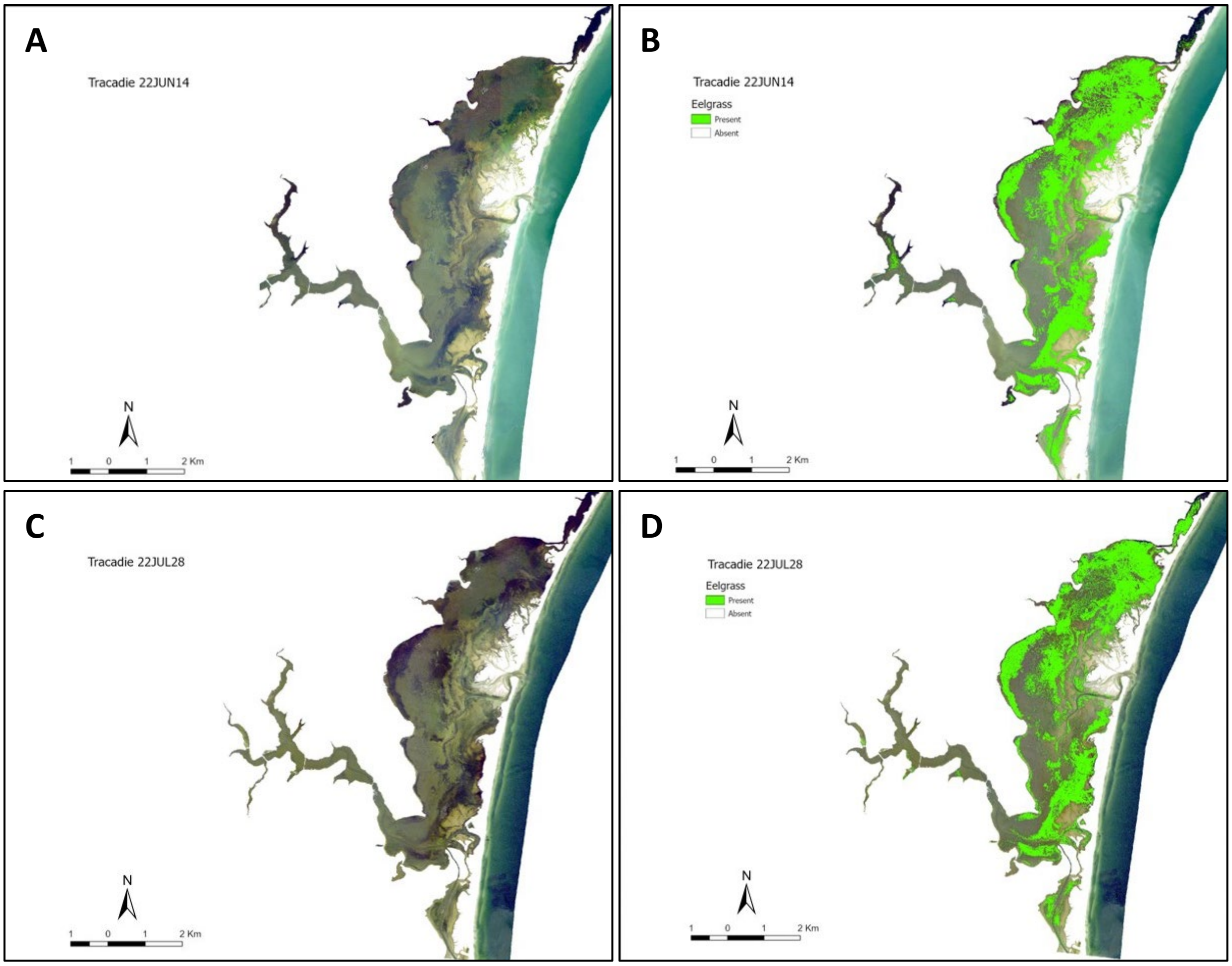


Figure 9 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Two different WorldView 2 images of the Tracadie Bay were used, one collected on June 15th, 2022, and the other on July 28th, 2022.

Table 8 Classification accuracy assessment of the Tracadie region on June 15th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

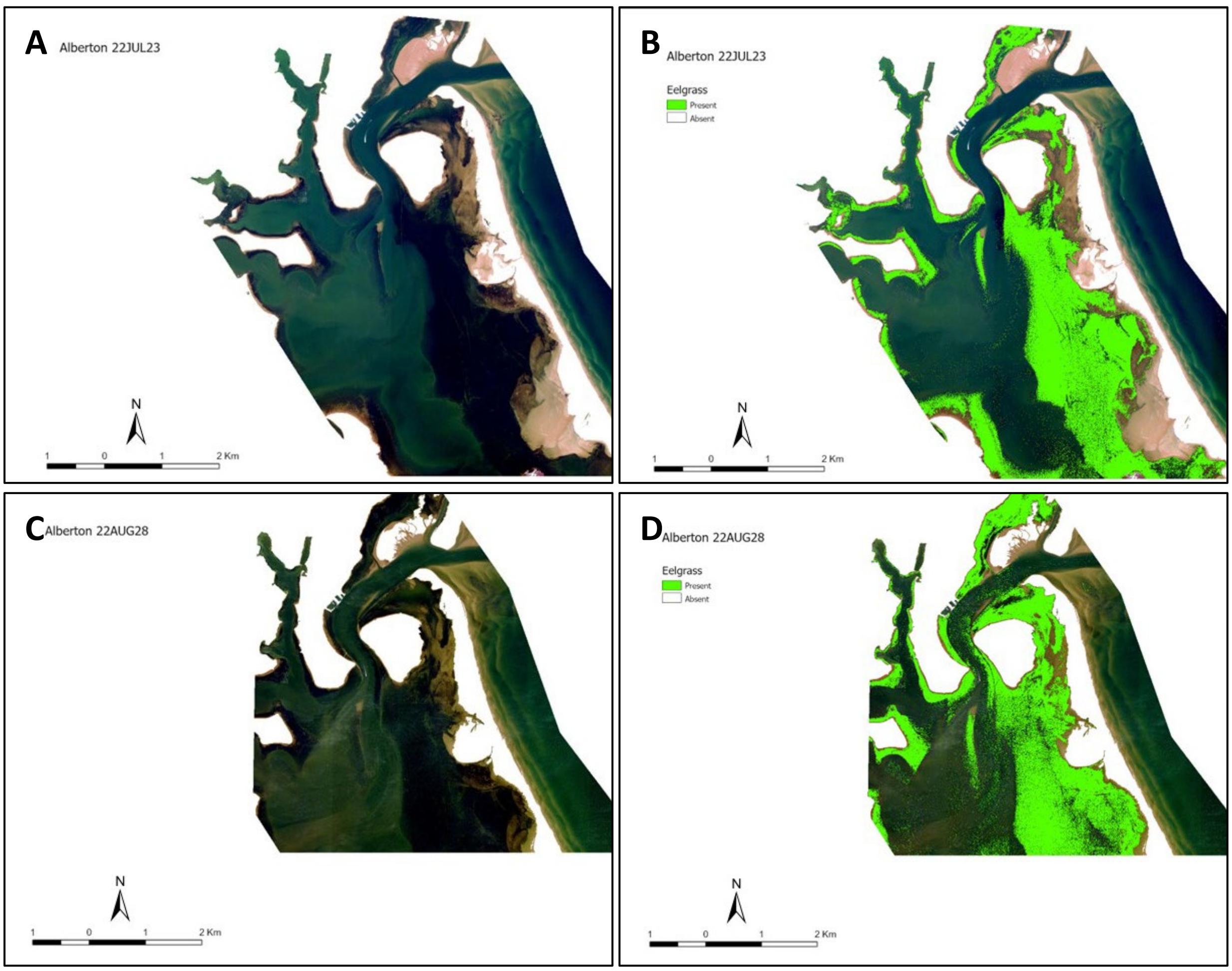
June 15th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	14	1
Accuracy	100%	0%	93%	7%

Table 9 Classification accuracy assessment of the Tracadie region on July 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 28th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	15	0
Accuracy	100%	0%	100%	0%

Dock River (Alberton)

The classification of imagery for the Alberton area of the Dock River was conducted three times in July, August, and October (Figure 10). All three images are of good quality and cover the area of interest. The July imagery, however, was affected by turbidity in the central waters, making it challenging to accurately identify the eelgrass. This issue was particularly problematic in the deeper waters, further complicating classification in this area. In August, the imagery presented a glare in the central and southern parts, as well as slight cloudiness in the central region, leading to difficulties in classification. The October imagery was of the highest quality and clarity, resulting in optimal classification results. The three classifications were complementary, especially in the provided AOI. The results of the accuracy assessment are listed in Table 10 through Table 12.



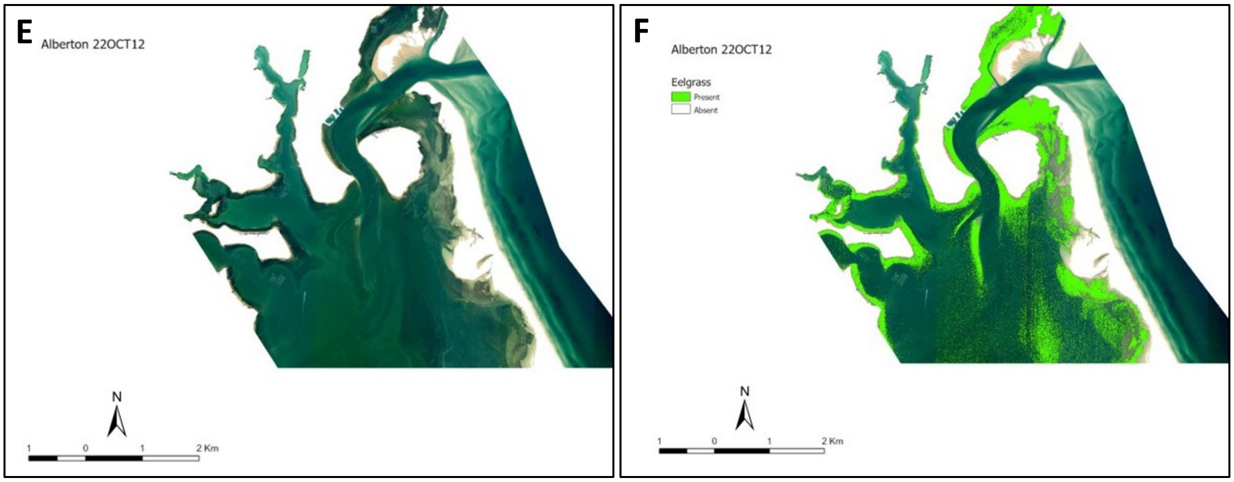


Figure 10 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Three different WorldView 2 images of the Alberton Bay were used, one collected on July 23rd, 2022, one on August 28th, 2022, and the other on October 12th, 2022.

Table 10 Classification accuracy assessment of the Alberton region on July 23rd, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 23rd, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	14	1	15	0
Accuracy	93%	7%	100%	0%

Table 11 Classification accuracy assessment of the Alberton region on August 28th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

August 28th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	14	1
Accuracy	100%	0%	93%	7%

Table 12 Classification accuracy assessment of the Alberton region on October 12th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 12th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	12	3	15	0
Accuracy	80%	20%	100%	0%

Lennox Island

Imagery of Lennox Island was captured on three separate occasions: July, September, and October (Figure 11). While the July and October imagery fully cover the areas of interest, the September imagery only partially covers them. The July imagery shows slight turbidity in the waters of the southern area of interest, and there are banding artifacts, but they did not significantly affect the classification (Table 13 and 14). The eastern part of the image is the clearest and of best quality. The September imagery is of high quality and allowed for adequate accuracy in the classification, but as previously mentioned, it covers only a part of the areas of interest. The October imagery is of high quality and sharpness, despite having slight banding, and allowed for a highly robust classification (Table 15).

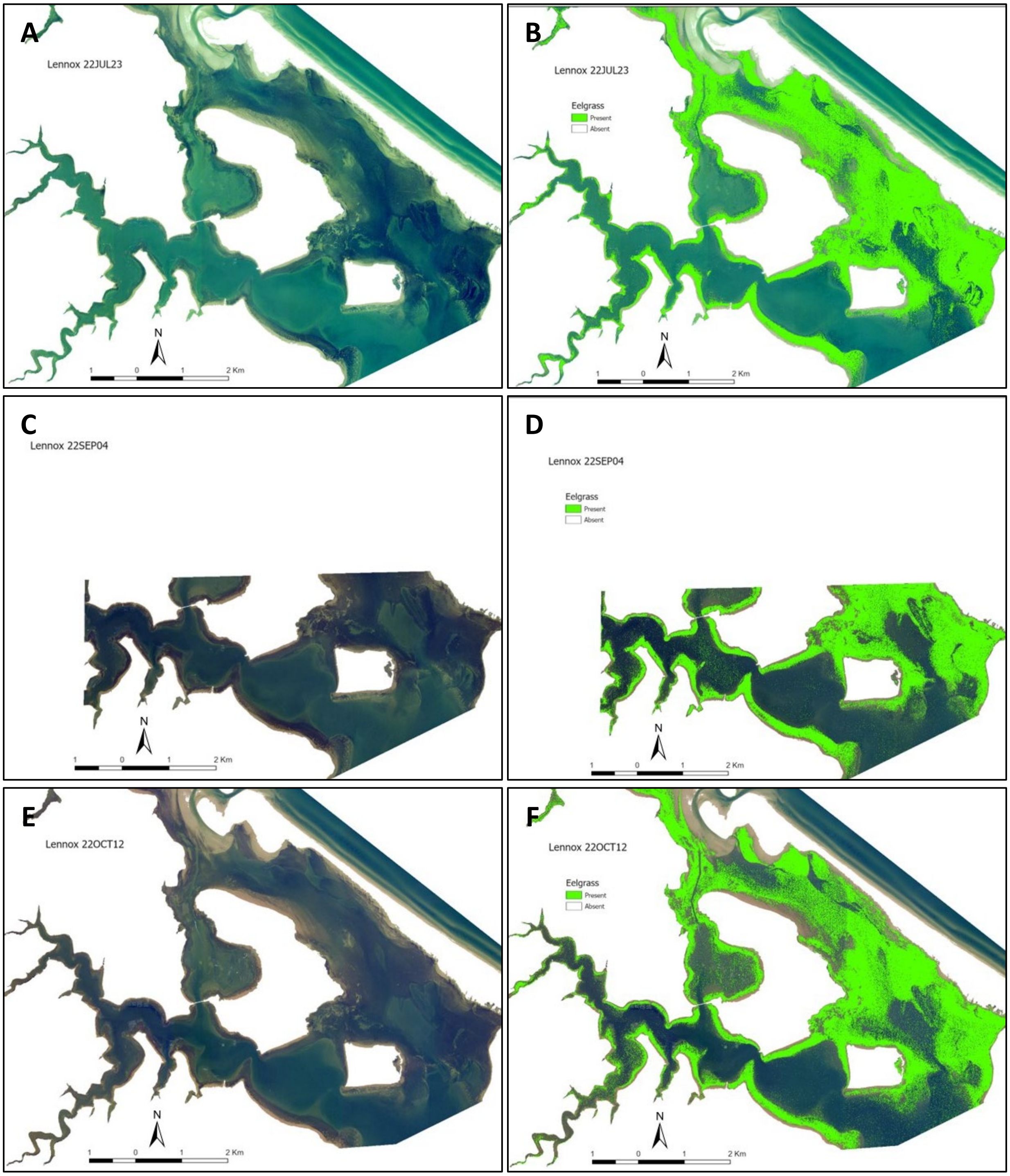


Figure 11 Side by side comparison of classification results from the SVM classifier in ArcGIS Pro. Three different WorldView 2 images of the Lennox Bay were used: July 23rd, September 4th, and October 12th, 2022.

Table 13 Classification accuracy assessment of the Lennox region on July 23rd, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 23rd, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	13	2	15	0
Accuracy	87%	13%	100%	0%

Table 14 Classification accuracy assessment of the Lennox region on September 4th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

September 4th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	15	0
Accuracy	100%	0%	100%	0%

Table 15 Classification accuracy assessment of the Lennox region on October 12th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 12th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	14	1	15	0
Accuracy	93%	7%	100%	0%

Percival River (North and South) and Enmore

A single image from the month of July 2022 was used to classify the north and south portion of the Percival River as well as the Enmore region (Figure 12). The image quality is of high quality, with no banding or sun glare issues, leading to a highly accurate classification (Table 16).

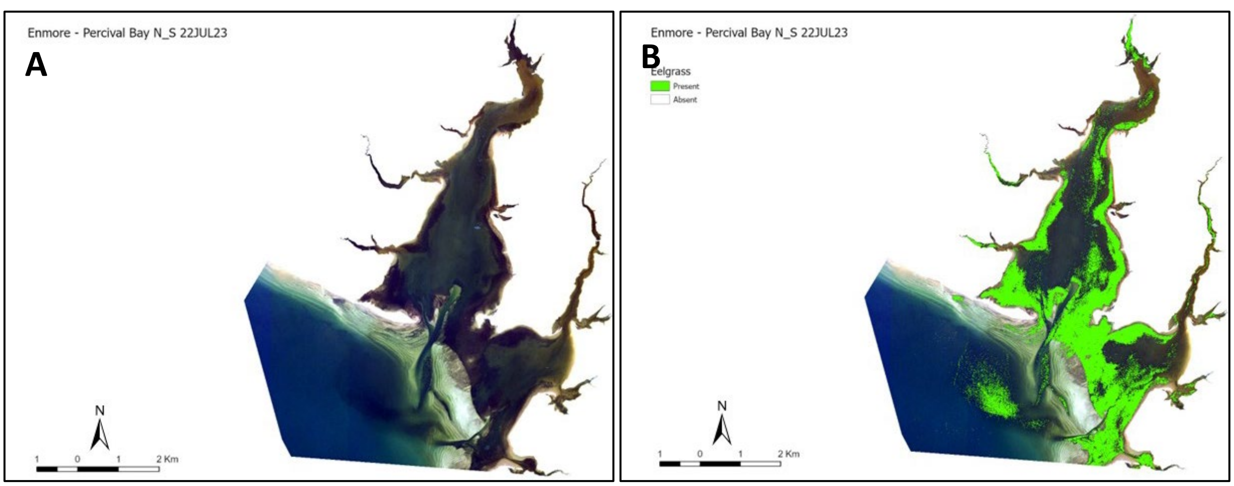


Figure 12 Eelgrass presence/absence in Enmore-Percival Bay (North and South), classification done on WorldView 2 imagery collected on July 23rd, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 16 Classification accuracy assessment of the Enmore-Percival Bay region on July 23rd, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

July 23rd, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	14	1
Accuracy	100%	0%	93%	7%

Bathurst

The Bathurst region was captured with high-quality imagery, and was free of glare, turbidity, or banding issues. This image provided the best conditions of all analyzed images, resulting in a highly accurate classification (Table 17). The classification highlights the presence of an underwater dendritic network surrounded by eelgrass. The accuracy of the classification may have been limited by the depth of these channels (Figure 13).

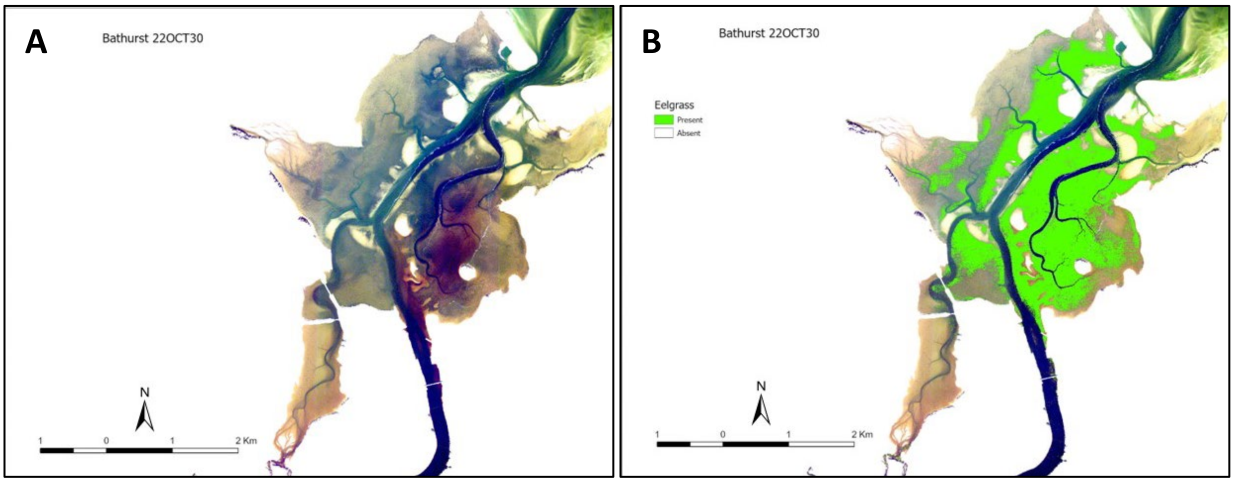


Figure 13 Eelgrass presence/absence in Bathurst Bay, classification done on WorldView 2 imagery collected on October 30th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 17 Classification accuracy assessment of the Bathurst region on October 30th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 30th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	14	1	15	0
Accuracy	93%	7%	100%	0%

Morel

The Morel region exhibited several unfavorable characteristics that hindered an accurate classification. The presence of sun glint caused by waves, likely produced by wind, coupled with depth and banding artifacts made it challenging to classify the central part of the bay (Table 18). The coastal areas of the bay were less problematic and allowed for easier identification (Figure 14).

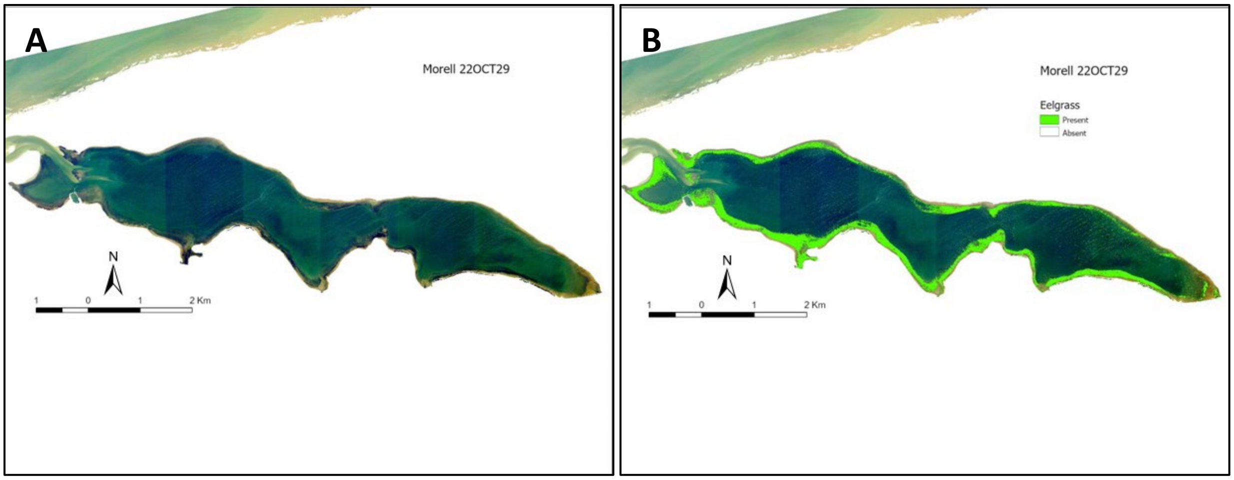


Figure 14 Eelgrass presence/ absence in Morell Bay, classification done on WorldView 2 imagery collected on October 29th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 18 Classification accuracy assessment of the Morrell region on October 29th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 29th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	13	2	15	0
Accuracy	87%	13%	100%	0%

Margaree

The smallest location analyzed was Margaree (Figure 15). The image had significant cloudiness, and although it was suggested to focus on the river, the eelgrass areas could not be fully identified due to the depth. The unobstructed and shallow areas in the image played a significant role in achieving an accurate classification, particularly in the vicinity of the river mouth (Table 19).

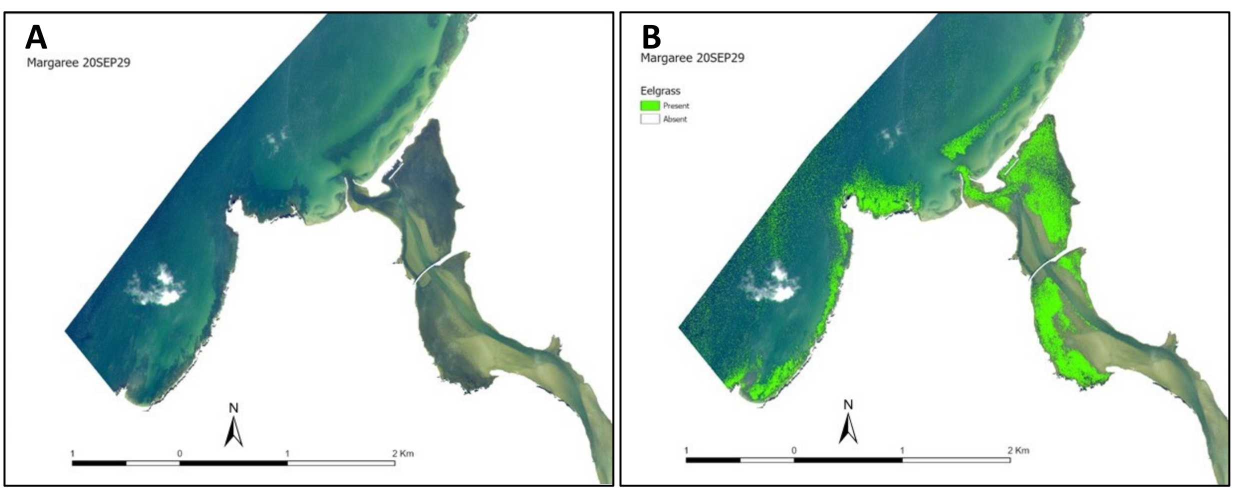


Figure 15 Eelgrass presence/ absence in Margaree Bay, classification done on WorldView 2 imagery collected on September 29th, 2020, classification completed in ArcGIS Pro using the SVM classifier.

Table 19 Classification accuracy assessment of the Margaree region on September 29th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

September 29th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	13	2	15	0
Accuracy	87%	13%	100%	0%

Murray River

The area of interest for the Murray River region was Mink River. The captured imagery was of good quality with minimal cloud cover which did not hinder the identification of eelgrass (Figure 16). The shallower areas and the edges of the river were easily distinguishable and identifiable (Table 20).

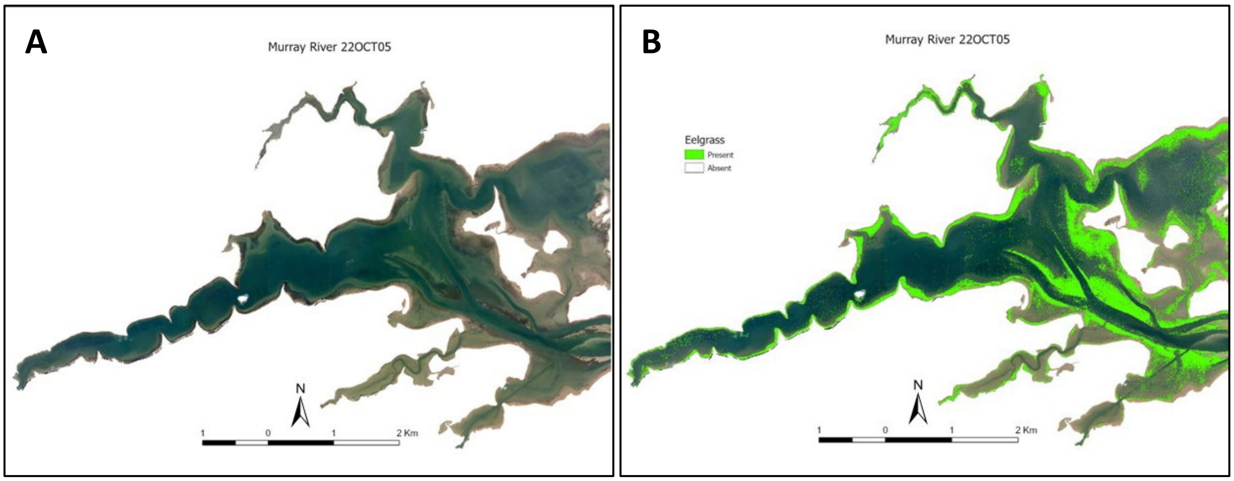


Figure 16 Eelgrass presence/ absence in Murray River, classification done on WorldView 2 imagery collected on October 5th, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 20 Classification accuracy assessment of the Murray River on October 5th, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 5th, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	15	0
Accuracy	100%	0%	100%	0%

New London Bay

The imagery for the New London Bay region was slightly obstructed with clouds. The classification was conducted by focusing on the cloud-free areas and the Bayview area of interest (Figure 17). Consequently, only the areas near the riverbanks and the bay were able to be classified, not the central and deepest parts of the bay (Table 21).

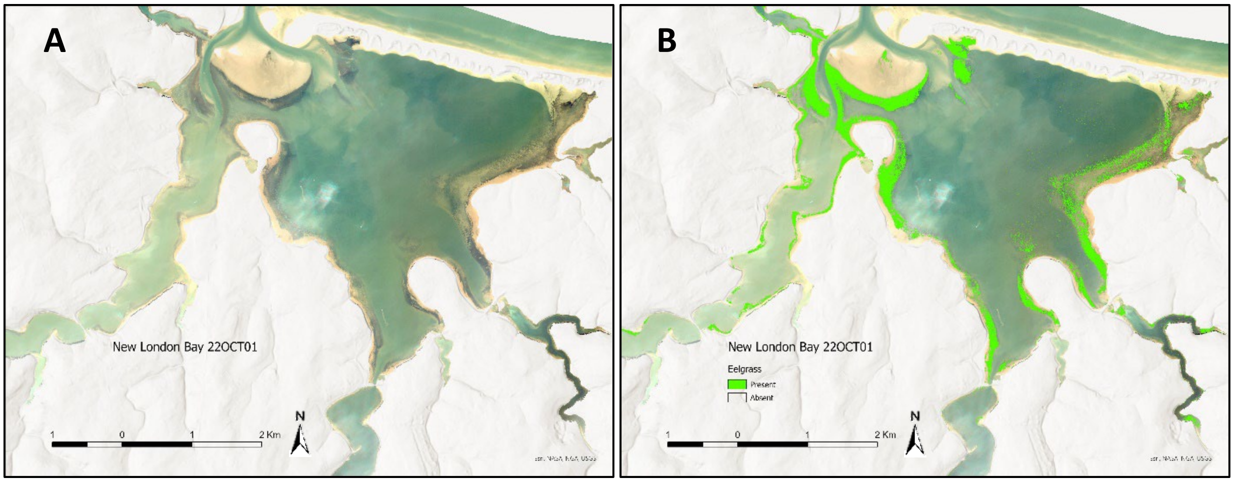


Figure 17 Eelgrass presence/ absence in New London Bay, classification done on WorldView 2 imagery collected on October 1st, 2022, classification completed in ArcGIS Pro using the SVM classifier.

Table 21 Classification accuracy assessment of the New London Bay region on October 1st, 2022, calculated using a set of samples independent of those used in the classification. Accuracy is reported as a percentage, number of samples reflects the manual selected values (eelgrass (EG) or not eelgrass (NG)) and if the classification agrees (correct (COR) or wrong (WRO)).

October 1st, 2022	EG_COR	EG_WRO	NG_COR	NG_WRO
Samples (n)	15	0	13	2
Accuracy	100%	0%	87%	13%

Sounding Data

Bottom elevation data was processed for 5 locations, of which 2 locations were further analyzed for plant canopy height detection and coverage (Table 22). The resulting files were used to generate shapefiles containing plant height and depth information. These shapefiles were used to compare with the SVM classification results at their respective locations. As requested, certain locations only required the bathymetry to be processed and therefore the plant detection was not conducted.

Table 22 Processed single beam echosounder dataset locations and respective features detected.

Location	Date	Feature Detected
Dock River (Alberton)	July 2022	Bathymetry, plant height, plant coverage
Inner Tabusintac	August 2022	Bathymetry, plant height, plant coverage
Barachois	August 2022	Bathymetry
Lennox Island	July, September 2022	Bathymetry
Pokemouche	August, 2022	Bathymetry

Submerged Vegetation

The analysis of sounding data revealed the presence of submerged vegetation in the majority of the Alberton study area, with an average plant height of 0.28 +/- 0.17 m (Figure 18). The average height of the submerged vegetation in the Tabusintac region was 0.09 +/- 0.11 m (Figure 19). The SVM classifier and the Visual Aquatic plant detection both show a correlation in detecting vegetation presence in the shallower coastal region. However, it is important to note that SVM classification was unable to pick eelgrass presence in the deeper parts of the region where the Visual Aquatic analysis suggested the presence of short, submerged vegetation.

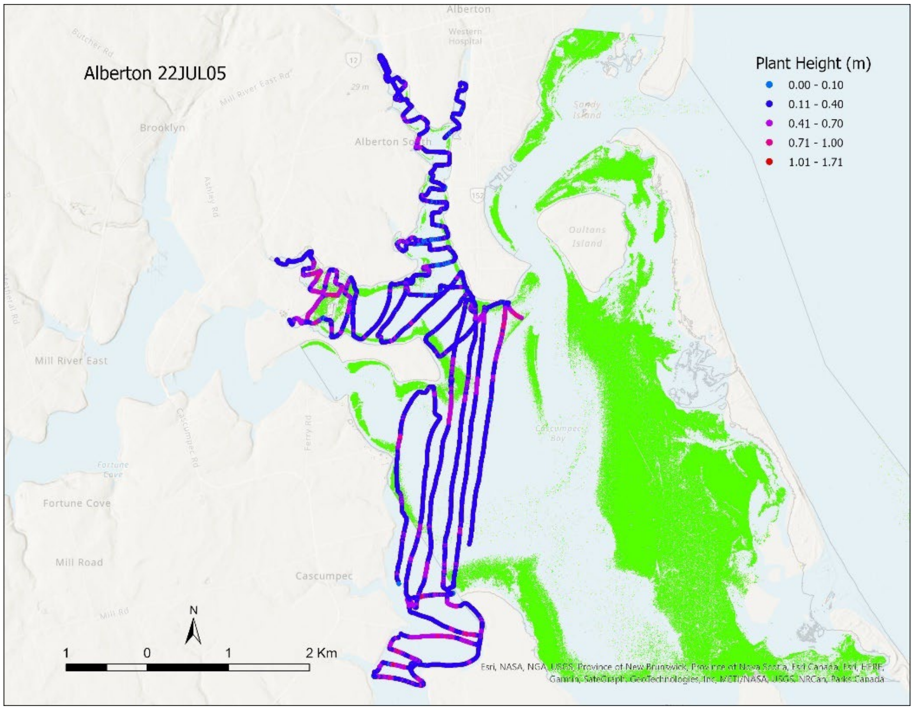


Figure 18 Plant canopy detection in Alberton using single beam echosounder data collected on July 5th and 14th, 2022 overlayed on the SVM classification of July 22nd, 2022 imagery.

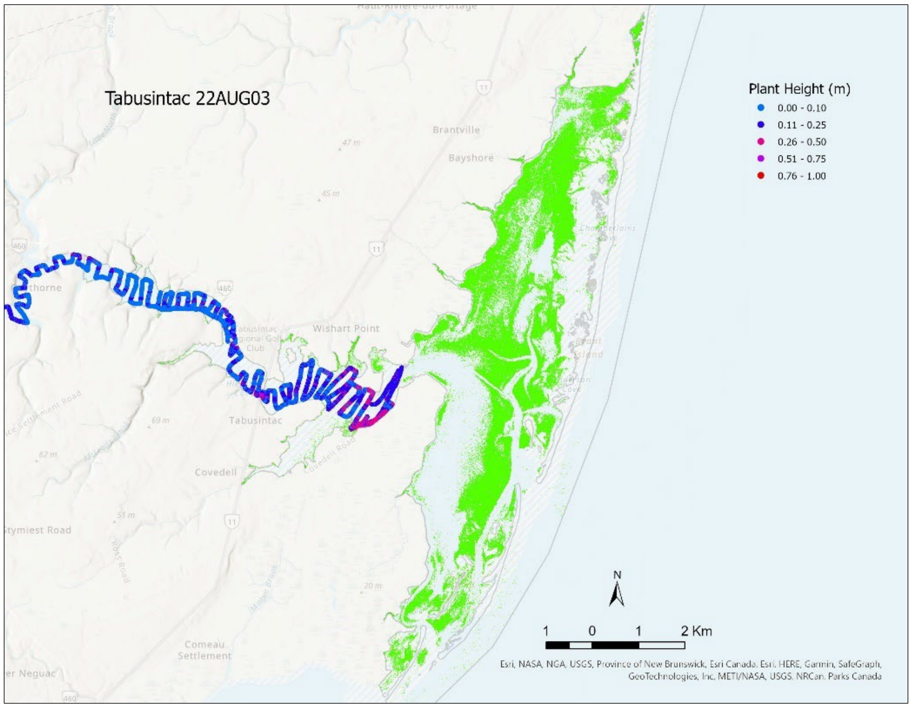


Figure 19 Plant canopy detection in Tabusintac using single beam echosounder data collected on August 3rd and 4th, 2022 overlayed on the SVM classification of July 28th, 2022 imagery.

Bottom Elevation

Bottom elevation for the Dock River (Alberton) region ranged from -0.82 to -13.55 m (Figure 20). The Tabusintac region had a bottom elevation range of -0.78 to -9.59 m, while in the Barachois region, it ranged -0.78 to -4.62 m (Figure 21; Figure 22). In the Lennox Island region, the values ranged from -0.79 to -12.60 m, and for the Pokemouche region, the range was -0.77 to -3.80 m (Figure 23; Figure 24).

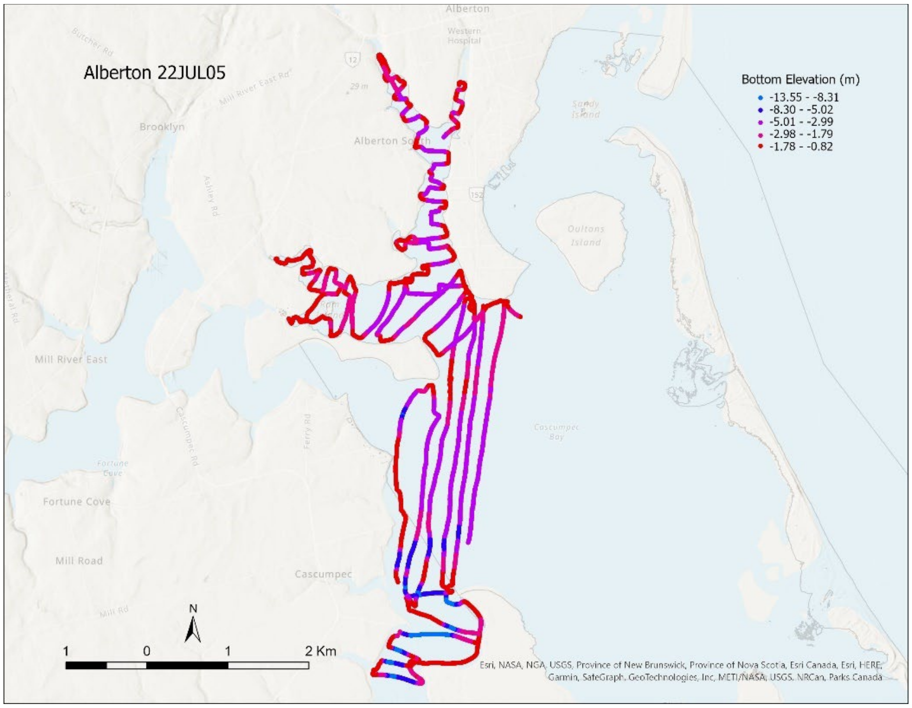


Figure 20 Bottom elevation detection in Alberton using single beam echosounder data collected on July 5th and 14th, 2022.

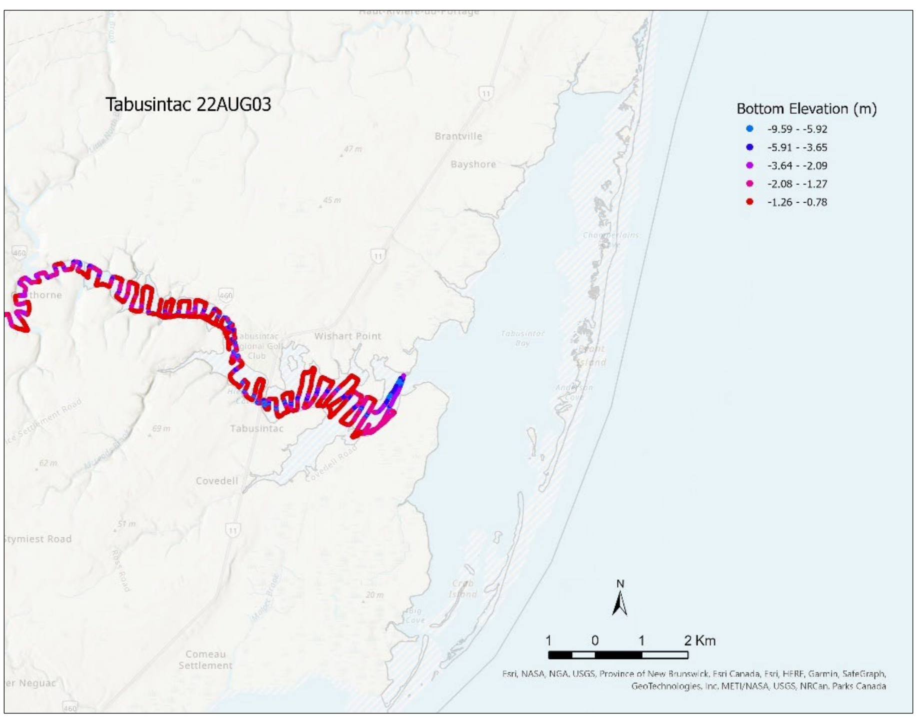


Figure 21 Bottom elevation detection in Tabusintac using single beam echosounder data collected on August 3rd and 4th, 2022.

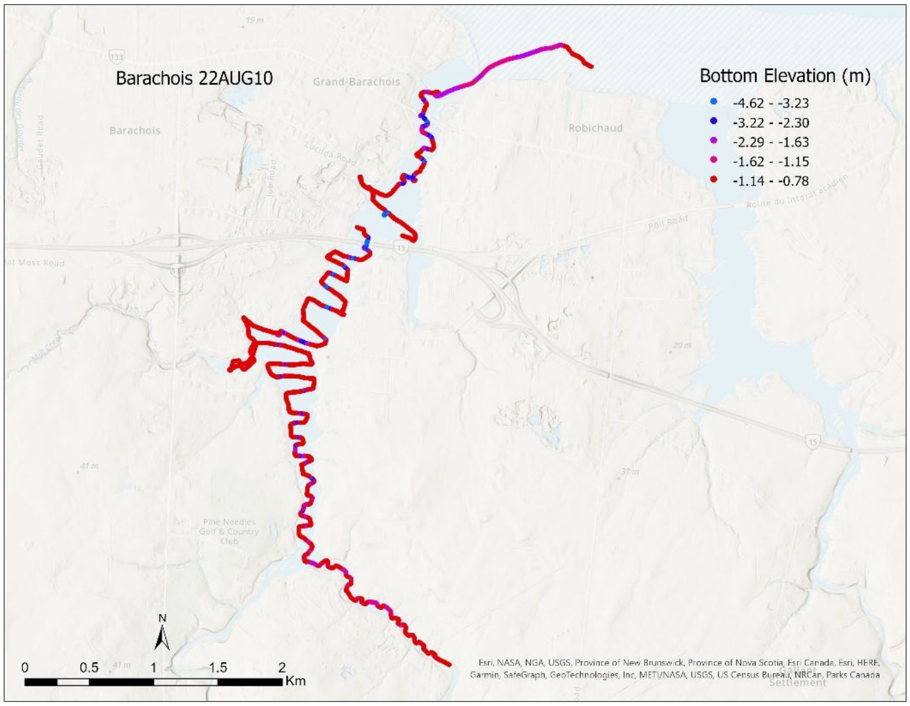


Figure 22 Bottom elevation detection in Barachois using single beam echosounder data collected on August 10th, 2022.

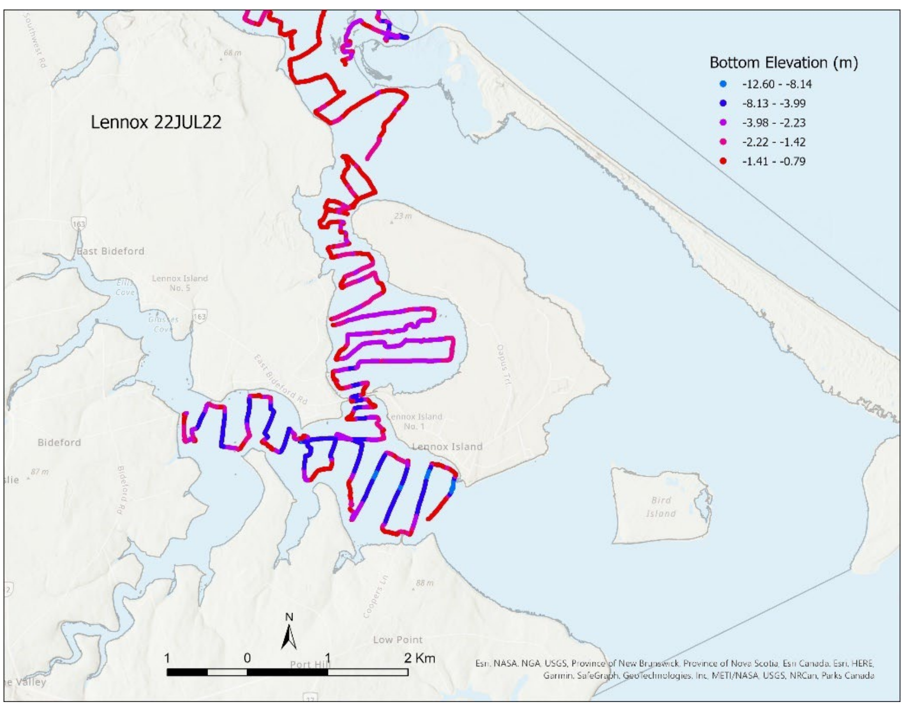


Figure 23 Bottom elevation detection near Lennox Island using single beam echosounder data collected on July 22nd, September 10th, and September 11th, 2022.

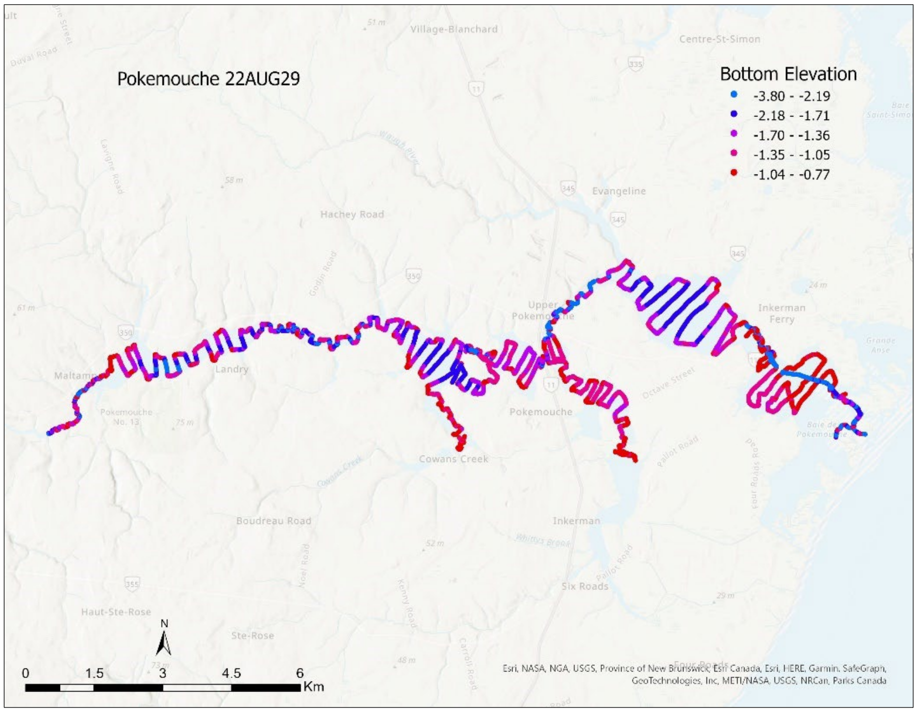


Figure 24 Bottom elevation detection in Pokemouche using single beam echosounder data collected on August 29th and 30th, 2022.

Discussion

The accuracy of the eelgrass classification was significantly influenced by the quality of the input images. Although all images were successfully classified, errors in classification were predominantly observed in darker regions where deep eelgrass, deep water, and deep sand shared similar spectral characteristics. The eelgrass was primarily distributed in the deep-water areas, where the presence of sun glint on the water surface caused speckling artifacts that were evident across several classification outputs.

The SVM classifier showed a strong correlation with eelgrass presence in the shallow coastal region but was unable to detect eelgrass in deeper areas where the sounding data detected short, submerged vegetation. Furthermore, when bottom elevation data captured by the single beam echosounder was taken into account, the accuracy of the SVM classification was found to degrade at bottom depths greater than 3 m. Similar results were obtained for the Tabusintac region, where the SVM classification was found to have a good correlation with submerged vegetation presence in shallow regions. These findings suggest that the SVM classification method was effective at detecting eelgrass but was challenged by the limitations posed by degraded image quality as bottom depth increased.

Compared to previously explored methods in eelgrass classification (Webster & Ferris, 2022), atmospherically corrected images performed better overall in SAV detection. The application of masking and atmospheric correction (ATCOR) techniques used in this year's analysis played a crucial role in improving the accuracy of our results. By reducing the negative effects of clouds and atmospheric conditions on the imagery, while also masking land cover. We focused on the areas with the highest quality imagery, resulting in more overall accurate classification results in this year's study. It is possible that previous potential biases, which could have arisen from only assessing pixels with a high degree of certainty, have been mitigated. With highly accurate methods in place, future projects can focus on SAV change detection.

The processing of data from the single beam echosounder required significant manual intervention for the classification of bathymetry and plant height. Due to project time constraints, only certain datasets were processed, indicating that the analysis could benefit from incorporating additional data sources to improve classification accuracy or validation.

Conclusion

The results of this study demonstrate the effectiveness of combining satellite imagery with machine learning algorithms to predict the distribution of eelgrass meadows in shallow coastal areas. The use of masking and ATCOR techniques helped to mitigate the impact of clouds and other atmospheric conditions on the accuracy of our predictions. These findings suggest that deep learning models have great potential for enhancing our understanding of the seafloor landscape and its features, which can have important implications for ocean exploration, resource management, and environmental monitoring.

The use of single beam sounding data processed with the Visual Aquatic software provided a valuable secondary reference dataset for detecting submerged vegetation in several areas of interest. This dataset provided an estimation of submerged plant height, plant height, and depth and allowed for comparison with the SVM classification results at their respective locations. While this method required significant manual classification efforts, future projects would benefit from incorporating more single beam sounding data as a source of classification accuracy assessment or as a secondary source of validation.

Overall, this study highlights the potential of machine learning approaches to support eelgrass conservation efforts by providing accurate and efficient tools for mapping and monitoring these critical ecosystems. By using these techniques, we can better understand and protect these important habitats for the benefit of marine life.

References

Forsey, D., Leblon, B., LaRocque, A., Skinner, M., and Douglas, A. 2020. Eelgrass mapping in Atlantic Canada using worldview-2 imagery. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLIII-B2-2020, 2020XXIV ISPRS Congress (2020 edition). pp. 685-692.

Schein, A., S.C. Courtenay, C.S. Crane, K.L. Teather, and M.R. van den Heuvel. 2012. The role of submerged aquatic vegetation in structuring the nearshore fish community within an estuary of the southern Gulf of St. Lawrence. Estuaries and Coasts 35:799–810.

Webster, T., Ferris, K. 2022. Project Report: Eelgrass classifications in the Gulf of Saint Lawrence. Applied Geomatics Research Group, NSCC Middleton, NS.