Memo

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To	Phoenix Hale Freshwater Technical Advisor – Biosecurity Department of Conservation Te Papa Atawhai
CC	Nigel Binks Freshwater Science Advisor Department of Conservation Te Papa Atawhai
Date	12 June 2023
Subject	Invasive macrophyte remote detection research - 2022/23

1. Introduction

NIWA is seeking to develop a remote detection and mapping system for submerged invasive species within a multi-year research project (Clements and Bulleid 2023). Development has initially focused on detecting the invasive submerged weed lagarosiphon (*Lagarosiphon major*) (Bulleid and Clements 2021). Department of Conservation Te Papa Atawhai (DOC) contributed funding to the project in 2021/22 and initial field testing of NIWA's prototype detection module targeting lagarosiphon in Lake Wakatipu and the Kawarau River was conducted. We demonstrated that automated 'detection-to-map' is practical and achievable, the prototype equipment generally worked as expected during field testing. Identified improvements included the need to focus on increasing detection precision, developing field-based algorithms and evaluating detection rates.

DOC want to progress the automated detection research and develop a detection system for another high-risk submerged aquatic weed, hornwort (*Ceratophyllum demersum*), with an end goal (beyond this project) of being able to detect and differentiate between multiple submerged species in the future. In 2021/22, NIWA also collected and collated video data associated with hornwort infested lakes (Clements and Bulleid 2022). In 2022/23 DOC provided additional funding and sought to initiate development of the hornwort detection system.

There are two parts to the research project that DOC sought to progress in 2022/23 outlined in this NIWA memo report:

i. Collection of further training video imagery of hornwort from Lake Rototoa (Auckland region) to use in the development of a hornwort detection algorithm.

ii. Develop and test an initial detection algorithm for hornwort from databased imagery.

2. Methods

2.1 Collection of further video training imagery of hornwort.

Video imagery of hornwort was collected from Lake Rototoa (Auckland region) on the 29-30th November 2022 and 17-18th May 2023 to use in the development of an initial hornwort detection algorithm.

Video imagery of hornwort was collected using underwater cameras (i.e., GoPro's with specific video technical characteristics, described in Table 1) at five sites distributed around the lake (Table 2). 71GB and

46GB of imagery was recorded from Lake Rototoa in November 2022 and May 2023, respectively. Control works using the herbicide diquat dibromide had been carried out by Auckland Council at four of the sites prior to each imagery collection, however some healthy hornwort was present at all five sites following treatment. At each site a georeferenced waypoint was taken at the main hornwort infested area and video imagery collected by divers of the lakebed and the submerged vegetation community present in each area.

Table 1: Submerged video camera technical characteristics used to collect hornwort imagery at Lake Rototoa in 2022/23.

Make and model	GoPro Hero 7 and 9 Black (GoPro Inc., San Mateo, CA)
Video resolution (pixels)	2.7 K
Frames per second	60 FPS
Field of view	Wide
Screen resolution (pixels)	2704 x 1520
Aspect ratio	16 : 9
HyperSmooth video stabilisation	Turned on

Table 2: Locations where video imagery of hornwort was collected in Lake Rototoa in 2022/23.

Site number	Grid reference
1	36° 31.029'S, 174° 14.475'E
2	36° 30.891'S; 174° 14.609'E
3	36° 30.823'S, 174° 13.972'E
4	36° 30.605'S, 174° 13.983'E
5	36° 30.117'S, 174° 14.186'E

2.2 Initial detection algorithm development for hornwort.

Collation of hornwort training data

For training the detection algorithm, we considered using only hornwort video imagery collected at sites not treated with herbicide and hence likely to display good plant health.

We used two different methods (Method 1 and Method 2, described below) for collating imagery training data for development of the initial hornwort detection algorithm. This is the first time a detection algorithm for hornwort using underwater imagery has been attempted by NIWA.

Method 1 - Dense hornwort training data preparation

We trialled a novel method (Method 1) to capture training data. The need for this method reflected the tendency for November 2020 and November 2022 video imagery collected from Lake Rototoa to consist mainly of dense hornwort weed beds. This made it difficult to extract imagery data of individual apical growing shoots (which has been the current method used to develop the lagarosiphon detection algorithm in South Island lakes). While the automated detection tool is being developed to detect early incursions or re/emergence of individual shoots following control works, nearly all the selected videos showed dense patches of hornwort where it was difficult to separate out individual shoots (See Appendix 1 for example imagery collected from Lake Rototoa). Here we extracted images from selected videos (shown in bold below) that NIWA collected during the two surveys. From each of these extractions, selected images were considered suitable for use as training images.

- NIWA project file (November 2020): DOC22213>RawData>Task 3-Hornwort video-collation of previous imagery by lake>1. Lake Rototoa_GoPro Footage_17-18-19.11.2020:

GH011164.MP4, **GH011165.MP4**, **GH011166.MP4**, **GH011167.MP4**, GH011168.MP4, GH011169.MP4, GH011170.MP4, GH011177.MP4, GH011178.MP4, **GH011179.MP4**, GH011181.MP4, **GH011182.MP4**, GH011183.MP4, GH011185.MP4, GH011186.MP4, GH011187.MP4, GH011188.MP4, GH011189.MP4, GH011190.MP4, GH011206.MP4, GH011220.MP4, GH011221.MP4, GH011223.MP4, GH011237.MP4, GH011259.MP4, GH011271.MP4, GH011272.MP4, GH011308.MP4, GH011309.MP4

- NIWA project file (November 2022): DOC22213>RawData>Task 4-Lake Rototoa hornwort imagery collection-Nov 2022>2. GP9-Site 2 only - Untreated Site:

GH013466.MP4, GH013467.MP4, **GH013468.MP4**, **GH013469.MP4**, **GH013470.MP4**, **GH013471.MP4**, GH013472.MP4, GH023440.MP4, GH023441.MP4, GH023467.MP4, **GH023471.MP4**, GH033441.MP4.

To develop a model trained on individual shoots rather than dense patches of hornwort, we extracted clear images of individual shoots from dense hornwort growths, as lack of visual clarity confuses model development, reducing detection efficiency (as we have learned in the development of the lagarosiphon detection algorithm). We created and tested composite images, made up from cropping individual hornwort shoots that were of reasonable visual clarity and representative of the target.

Our justification for this approach is that to detect patches of dense hornwort you do not need to detect every hornwort shoot, you need to detect a percentage of them to be confident a larger incursion has been detected. Further, detection of early-stage incursions, of individual shoots in amongst other diverse submerged plant communities, is the ultimate outcome.

We created Model 1A using 40 images from the 2020 dataset and Model 1B using 48 images extracted from both the 2020 and 2022 datasets. Each image contained an average of 10 shoots of hornwort. We manually annotated instances of hornwort shoots on a white background (Figure 1).

Figure 1: An example of a composite image created and used in training for Method 1.

Method 2 – Sparse hornwort training data preparation

We used video imagery collected in May 2023 from Lake Rototoa, as the imagery was suited to developing the detection algorithm for sparse hornwort or individual hornwort shoots. We extracted images selected from videos (shown in bold below) that NIWA divers collected during the survey:

- NIWA project file (May 2023): DOC23204 > RawData> 5. Lake Rototoa hornwort imagery collection - May 2023

GP7 Day 1

GH012803.MP4, GH012804.MP4, GH012805.MP4, GH012806.MP4, GH012807.MP4, GH012808.MP4, **GH012809.MP4**, **GH012810.MP4**, GH012811.MP4, GH012812.MP4, GH012813.MP4, GH012814.MP4, GH012815.MP4, GH012816.MP4, **GH012817.MP4**, GH012818.MP4, GH012819.MP4, GH012821.MP4, GH012822.MP4, GH012823.MP4, **GH012824.MP4**, **GH012825.MP4**, GH012826.MP4.

GP7 Day 2

GH012827.MP4, GH012828.MP4, GH012829.MP4, **GH012830.MP4**, **GH012831.MP4**, **GH012832.MP4**, **GH012833.MP4**.

GP9 Day 1

GH013797.MP4, **GH013798.MP4**, **GH013799.MP4**, **GH013802.MP4**, **GH013803.MP4**.

GP9 Day 2

GH013804.MP4, GH013805.MP4, GH013806.MP4, GH013807.MP4, GH013808.MP4, GH013809.MP4, **GH013810.MP4**, GH023805.MP4, GH023809.MP4.

We created Model 2 using 76 images from the May 2023 dataset. We manually annotated instances of hornwort shoots in-situ, with the natural background present (in contrast to Method 1 above).

3. Results

3.1 Method 1 - Dense hornwort training process and results

We uploaded the annotated images and labels to the NeSI High Performance Computing Facility (HPC) and ran the training process. We found that longer training time improved detection accuracy, so we successively increased the number of times we passed the dataset through the neural network. As we increased the training time, the HPC returned accuracy figures of 33%, 76%, 92% and 97% (Figure 2), though when accuracy gets this high (97%) it is likely ‘overfitting’ the data. So, while the results look good here, we would not expect good detection results when exposed to a more diverse selection of hornwort images. The training and testing datasets were separated, so have some independency, but a more robust test would be a completely blind test using imagery from different years, seasons and water bodies.

HPC Training Log

Date	Model	Target	Labels	Trained on	Model	Loc P:\	In Size	Imgs, Trn, Tst	Batch	Ep/best	Thresh	Output file	AP C.d_f	Config	run Kmeans	HPC
8/05/2023	1a	HW	C.d_f	CVAT/HPC	Resnet_18	Source 1	1024x576	40/27/13	35412503	500/476	0.8	yolov3_resnet18_epoch_476_best.etlt	24%	en_qat true, reg L4	yes	hgx
8/05/2023	1a	HW	C.d_f	CVAT/HPC	Resnet_18	Source 1	1024x576	40/27/13	35423248	500/499	0.8	yolov3_resnet18_epoch_499_best.etlt	37%	en_qat true, reg L3	yes	hgx
17/05/2023	1b	HW	C.d_f	CVAT/HPC	Resnet_18	Source2	1024x576	48/30/18	35819480	500/481	0.8	yolov3_resnet18_epoch_481_best.etlt	33%	en_qat true, reg L2	yes	hgx
17/05/2023	1b	HW	C.d_f	CVAT/HPC	Resnet_18	Source2	1024x576	48/30/18	35821277	1000/769	0.6	yolov3_resnet18_epoch_769_best.etlt	76%	en_qat true, reg L1	yes	hgx
17/05/2023	1b	HW	C.d_f	CVAT/HPC	Resnet_18	Source2	1024x576	48/30/18	35837498	2000/1541	0.8	yolov3_resnet18_epoch_1541_best.etlt	92%	en_qat true, reg L0	yes	hgx
17/05/2023	1b	HW	C.d_f	CVAT/HPC	Resnet_18	Source2	1024x576	48/30/18	35845816	3000/2992	0.8	yolov3_resnet18_epoch_2992_best.etlt	97%	en_qat true, reg L1	yes	hgx
2/06/2023	2	HW	C,d	CVAT/HPC	Resnet_18	Source3	1024x576	76/51/25	36154812	3000/1596	0.8	yolov3_resnet18_epoch_1596_best.etlt	43%	en_qat true, reg L1	yes	hgx

Figure 2: The training log shows the average precision (AP) and best-trained output file from each training session. In the Imgs (images), Trn (training), Tst (test) column, e.g. in Model 1b, 48/30/18 refers to 48 images split into 30 for training and 18 retained for testing. The database used was not extensive enough to develop a robust model at this stage of development.

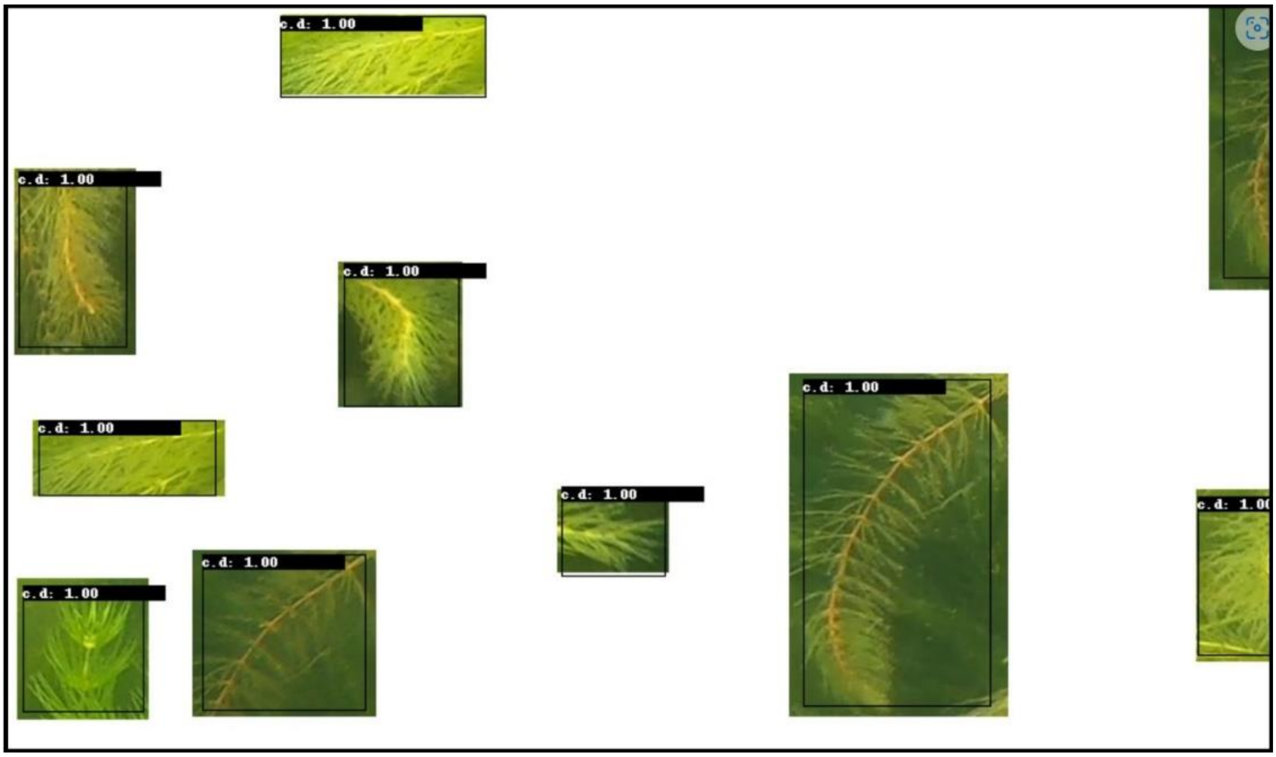


Figure 3: An example of the HPC checking detections predicted by Model 1B.

This training was conducted to simply test the new method, the model produced would not be expected to be particularly accurate or robust. We did not try this model (Method 1) in the prototype detection module (Clements and Bulleid 2022) but ‘parked it’ and proceeded with the more conventional method that we thought might be more appropriate for detecting sparse hornwort (Method 2 below).

3.2 Method 2 - Sparse hornwort training process and results

We passed the input data through the neural network 3000 times, achieving 43% accuracy (Figure 2) with the HPC image test set. This seemed a reasonable result given the small amount of initial training data used, so we proceeded to convert the HPC output file into a hornwort detector engine that would reside on NIWA’s prototype detector module. We tested the detector by feeding it with videos previously collected at Lake Rototoa as post-processing (i.e., not in live field trials).

Examples taken from output videos are shown in Figure 4. The labels are annotated with CD (*Ceratophyllum demersum*) with the detector’s confidence level (between 0 and 1) that the prediction is correct. The detection threshold was set at 0.7. If the model predicted an instance of hornwort with a confidence level of 0.7 or greater, i.e. is 70% sure that it is hornwort (CD), then it declares that a detection has occurred. The results were ‘as expected’, considering the minimal level of training provided at this stage in the detection algorithm development process (Figure 4).

The model will need to be further developed to enable it to differentiate between different species, such as native charophyte and Potamogeton species present at Lake Rototoa. With a plain background and no other species present, the initial detection model performed relatively well (Figure 4A and 4B). If the background was more diverse, we would expect to see false positive detections. The training dataset will need to be extended to achieve detections for targets that are further away from the camera. At present, detection range appears optimal at about one meter away from the camera lens (Figure 4C).

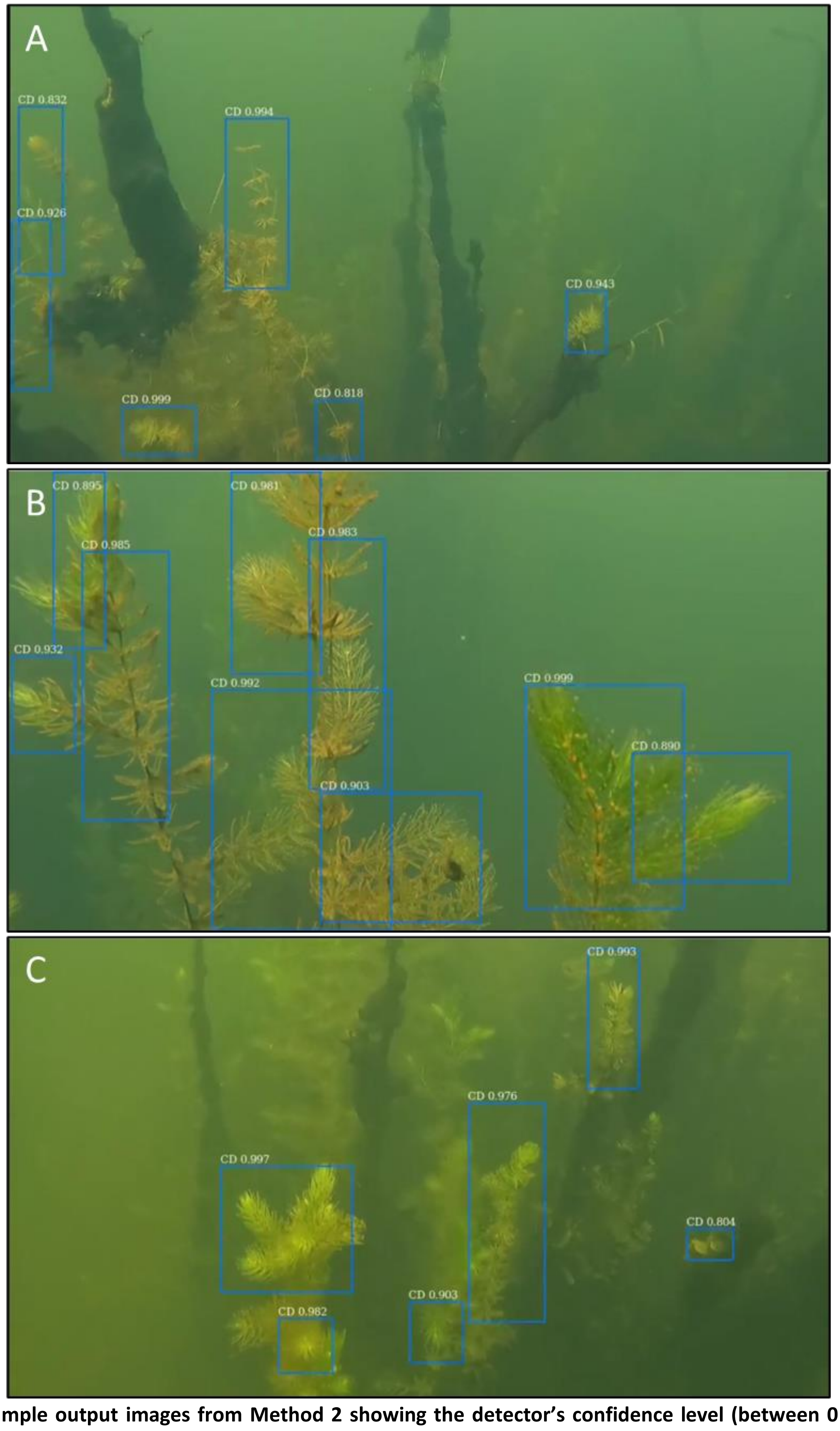


Figure 4: Example output images from Method 2 showing the detector's confidence level (between 0 and 1) that hornwort (*Ceratophyllum demersum*, CD) has been detected.

4. Discussion

To develop a robust detection system for hornwort, we need to increase the image training datasets used in algorithm development, and the images used need to be good quality for accurate target detections. Obtaining and preparing images for training detection models takes a significant amount of time currently, however over time increasing the amount of imagery used in training will improve detection accuracy.

If the requirement is to detect new incursions (or sparse regrowth), such as individual shoots of hornwort, then we should train a detection model on images that are most representative to differentiate the target from non-target background vegetation (Appendix 1). If the requirement is to detect dense growth, then, while a 'detection model' (detection of individual stems within an image) might be adequate in some cases, it may be a better option to develop a 'classification model' (classifying whole images). While we have not tried this for use in the current prototype detection module (currently developed to detect lagarosiphon apical shoots), both models could be run simultaneously on the module and fed from one or multiple cameras. This may make data preparation more efficient and improve detection/identification efficacy. To do this, we would need to make changes to the script on the HPC facility to enable us to train a 'classification model' rather than a 'detection model'. We would also need to make some changes to the module software to accommodate different model inputs.

As the next phase of development for the hornwort detection system, we suggest enacting a process used recently in the related lagarosiphon detection project. To train an accurate model for detecting any target, with the image data available at any time, we adopted a model-rating benchmark assessment process. Here we create 100 representative test images (that include instances of the target species) as the benchmark. We then get an expert to count the number of targets visible in each image. We then run the benchmark images through the trained detector (as post-processing) and compare the two methods – 'man vs machine'. This enables us to determine how a model is performing as we increase the quantity, quality, and diversity of the database before we progress to trialling the detection system in live field trials.

Because of the large amount of computing capacity required to process large numbers of images to train the Deep Learning detection models, we use the NeSI High Performance Computing Facility (HPC) and a YOLOv3 model for training. The trained HPC output file is then exported to a miniature supercomputer in the deployable detection module where it is then converted into a trained detection engine adapted to the capabilities of this specific supercomputer. The detection module is then ready for use in the field (Appendix 2). We have ensured that our chosen technology has a clear path forward as we increase the 'detection load', such as simultaneously running different models and cameras, as well as increasing the number of different target species and enabling faster inference.

5. Conclusion

The concept of automated detection of invasive species has been successfully trialled, 'end-to-end', from invader to map (Clements and Bulleid 2022, Appendix 2). While accuracy depends on how well a detector module is trained, and this depends on the quality and quantity of available training data, we don't see any major impediments (technical or otherwise) to achieving scalable systems that would allow real time detection of target species in the field.

For hornwort, we need to:

- Increase the image training datasets used in algorithm development to achieve sufficient detection accuracy from previously databased imagery.
- Continue to collect hornwort field training datasets and use in detection algorithm training. Train models using good quality representative images that are likely to be encountered in the field.
- Carry out the model-rating benchmark assessment process on improved algorithms.
- Finalise detection module software and hardware and prepare for field test.

- Field test developed automated detection system.
- Explore a consortium funding approach from authorities responsible for freshwater biosecurity in New Zealand to enable this solution to be rapidly advanced and adopted.

6. Acknowledgements

Thanks to Aleki Taumoepeau, Inigo Zabarte-Maeztu, Svenja David, Richie Hughes (NIWA) and Nigel Binks (DOC) for their assistance in the field at Lake Rototoa in 2022/23.

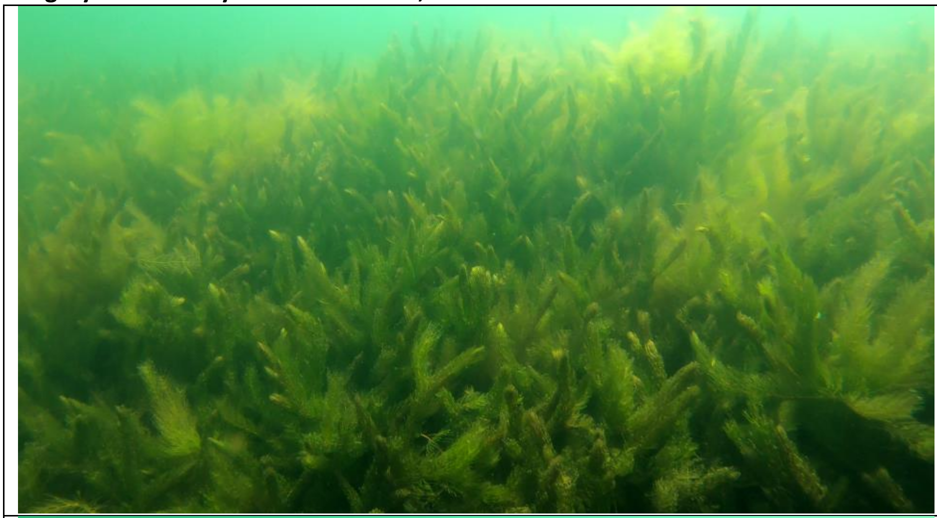
7. References

Bulleid, J., Clements, D. (2021) NIWA New Zealand freshwater researchers developing autonomous intel for war on waterway weeds. Australasian Hydrographer. September 2021: 15-19.

Clements, D., Bulleid, J. (2022) Invasive macrophyte remote detection research: Memo update June 2022. NIWA memo report to Department of Conservation Te Papa Atawhai.

Clements, D., Bulleid, J. (May 2023). Using artificial intelligence to detect submerged aquatic weeds to protect Aotearoa New Zealand's waterways - Freshwater Biosecurity. 4th International Congress on Biological Invasions-ICBI 2023. Proceedings, Pg. 58. Ōtautahi Christchurch, New Zealand, 1-4 May 2023.

Appendix 1: Lake Rototoa submerged vegetation species imagery examples - DOC23204. Invasive macrophyte remote detection research - development of an initial hornwort detection algorithm.
Imagery collected by Daniel Clements, NIWA.

<table>
<tr><td></td><td>Dense hornwort (Ceratophyllum demersum) - Nov 2020</td></tr>
<tr><td></td><td>Dense hornwort (Ceratophyllum demersum)
– With discoloration
– Nov 2020</td></tr>
<tr><td></td><td>Dense hornwort (Ceratophyllum demersum)
– With discoloration
– Nov 2020</td></tr>
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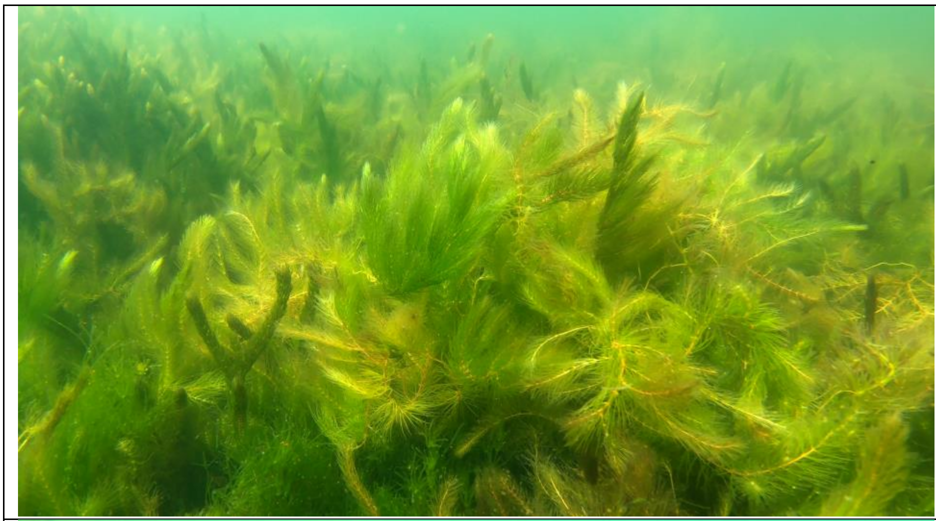
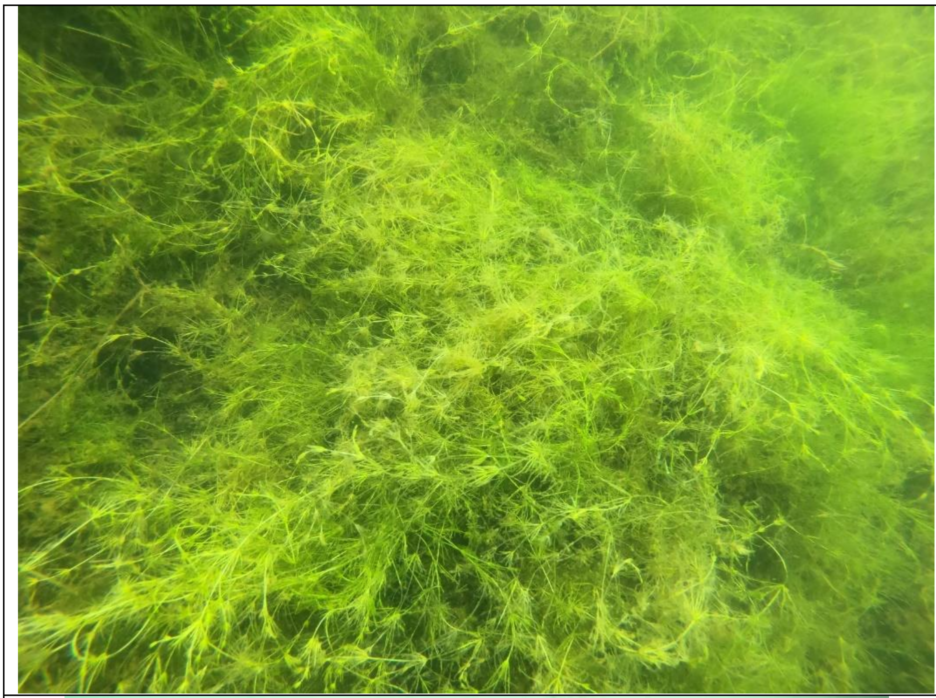
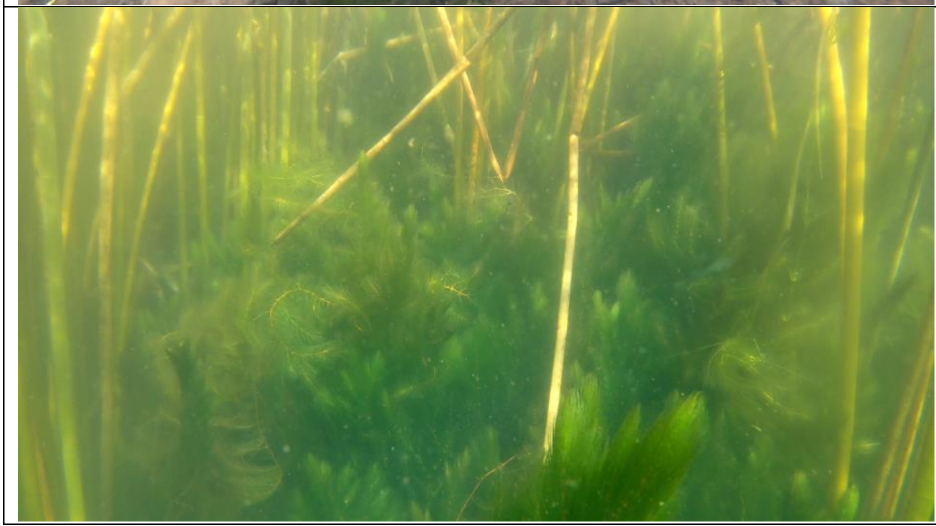
	Dense hornwort (*Ceratophyllum demersum*) – With discoloration – Nov 2020
	Native charophyte sp. in foreground – dense hornwort behind (*Ceratophyllum demersum*) – Nov 2020
	Native charophyte sp. - Nov 2020

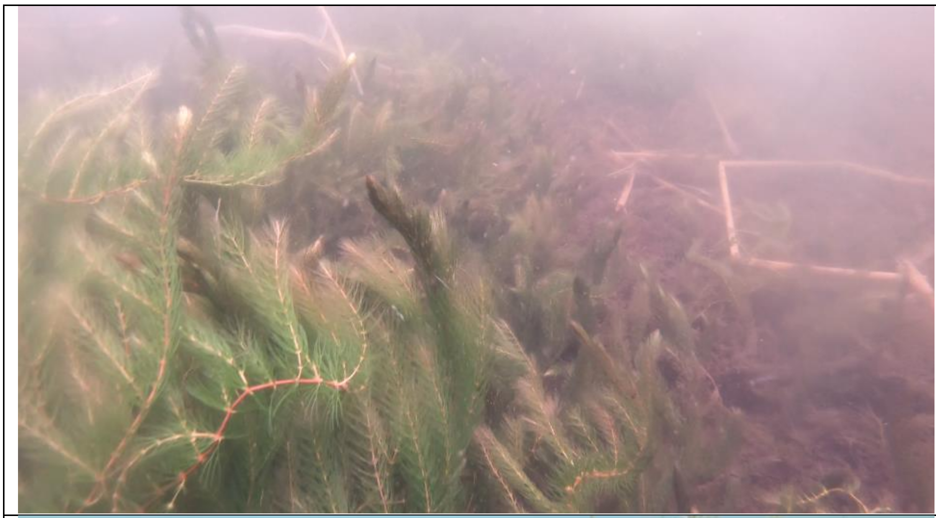
	Charophyte sp. Native – Nov 2020
	Hornwort (*Ceratophyllum demersum*) below *Eleocharis sphacelata* (reed) - Nov 2020

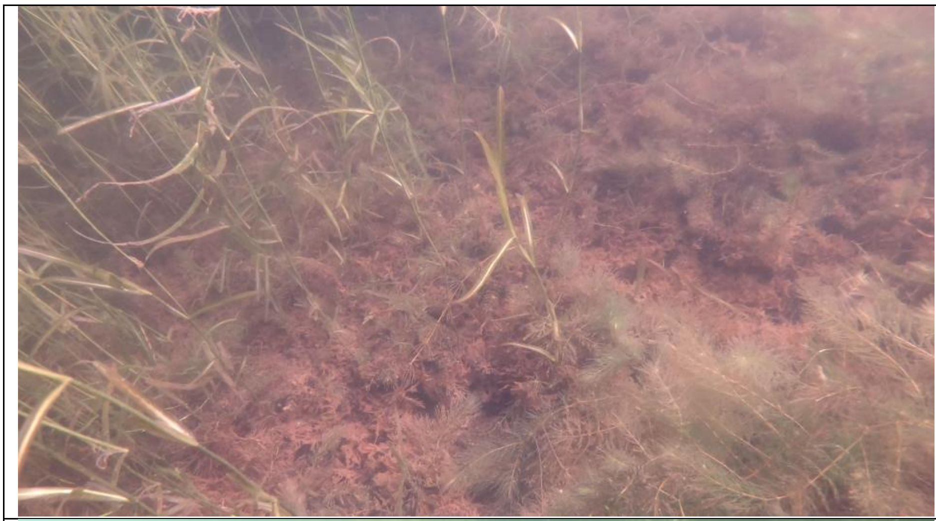
	*Utricularia gibba* Exotic - Nov 2020
	*Potamogeton ochreatus* Native - Nov 2020

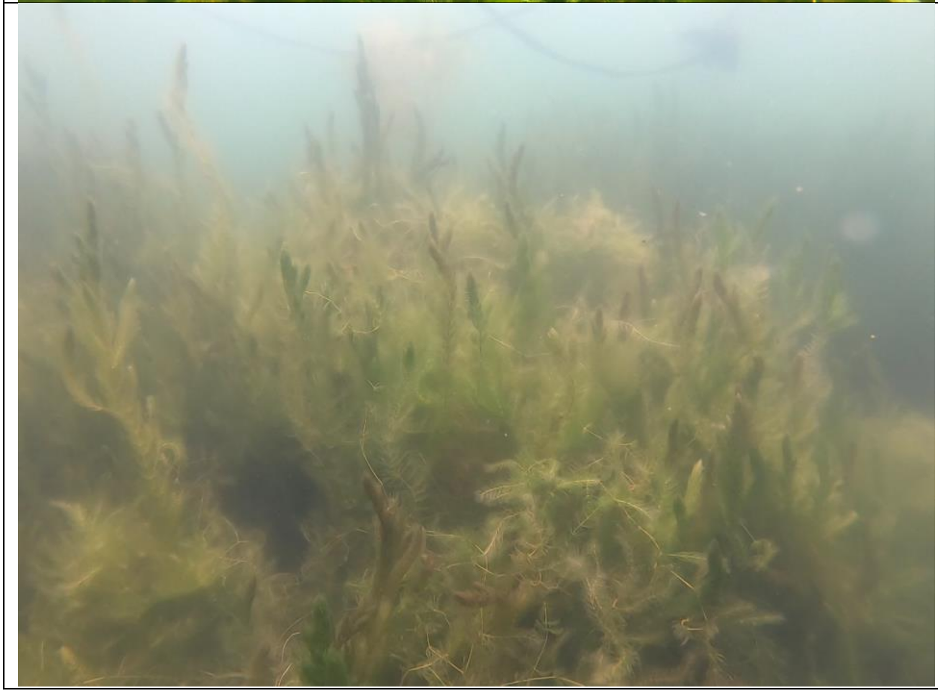
	*Potamogeton ochreatus* – Native - Nov 2020
	*Potamogeton cheesemanii* Native - Nov 2020
	*Potamogeton cheesemanii* Native - Nov 2020

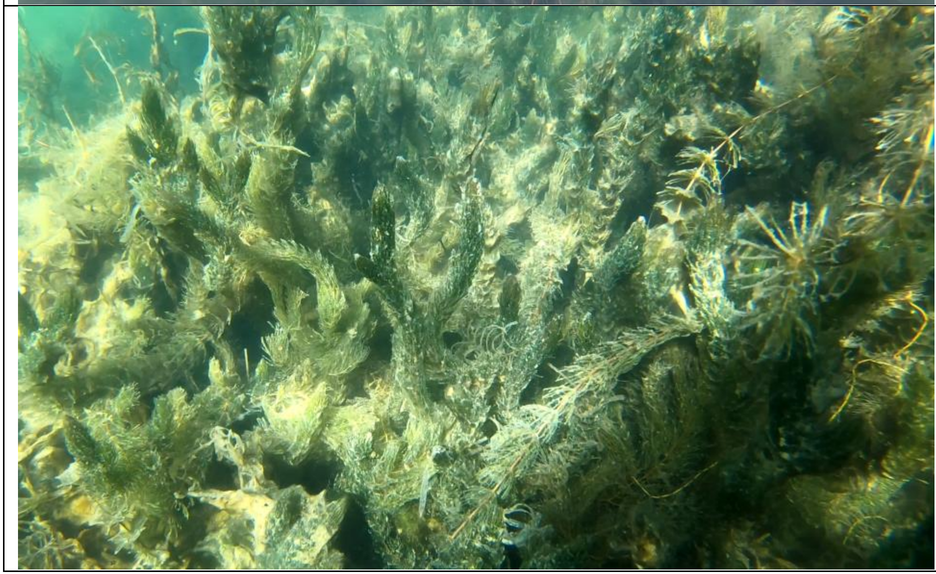
	Dense hornwort (*Ceratophyllum demersum*) – Nov 2020
	Dense hornwort (*Ceratophyllum demersum*) – Nov 2020
	*Potamogeton ochreatus* – Flowering - Native Nov 2020

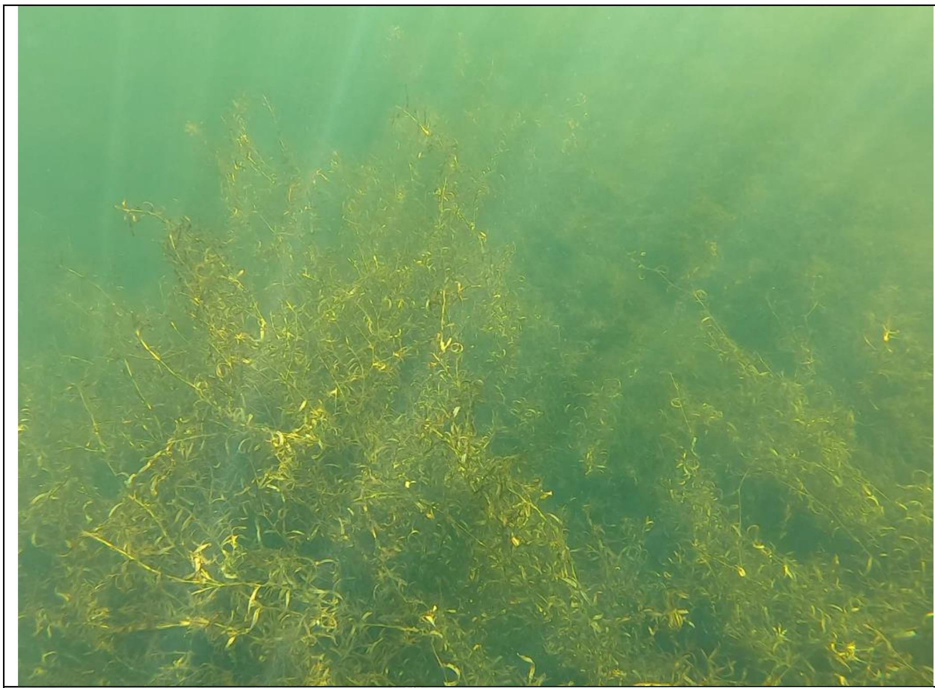
	Native sp. - Nov 2020 – Shallow water
	Hornwort (*Ceratophyllum demersum*) – Fragments Nov 2020
	Hornwort (*Ceratophyllum demersum*) amongst *Eleocharis sphacelata* (reed) - Nov 2020

	Hornwort (*Ceratophyllum demersum*) – low growing Nov 2020
	Native charophyte sp. - Nov 2020
	Hornwort (*Ceratophyllum demersum*) – stem fragments/detritus - Nov 2020

	Hornwort (*Ceratophyllum demersum*) (right) in amongst *Potamogeton ochreatus* (left) - Nov 2020
	Native charophyte sp. - Nov 2020
	Hornwort (*Ceratophyllum demersum*) – low growing – Nov 2020

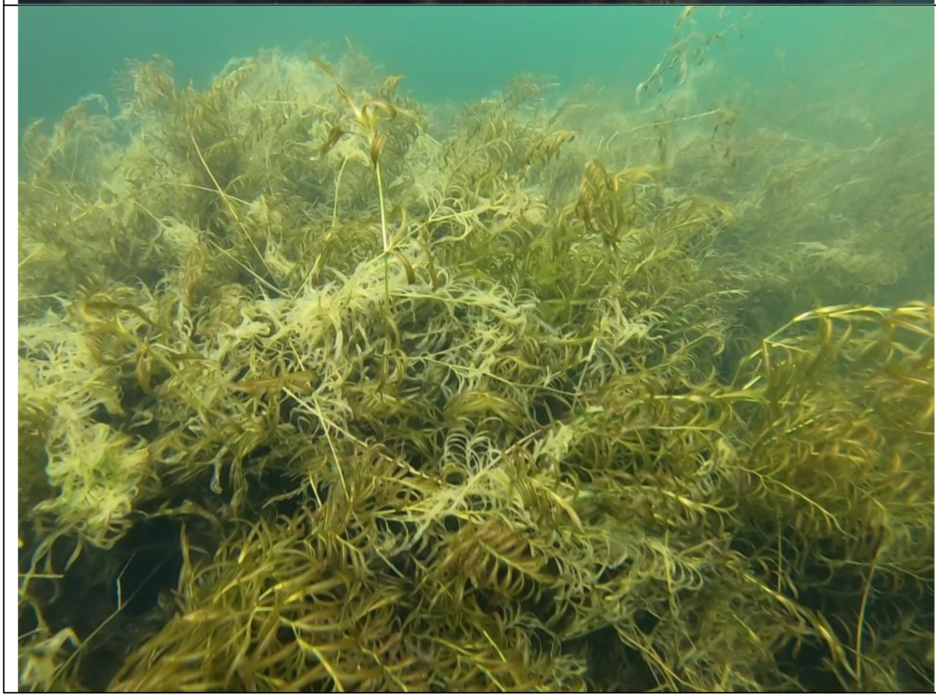
	Hornwort (*Ceratophyllum demersum*) – dense – Nov 2020
	Hornwort (*Ceratophyllum demersum*) – dense – Nov 2020
	Hornwort (*Ceratophyllum demersum*) – dense – Nov 2020

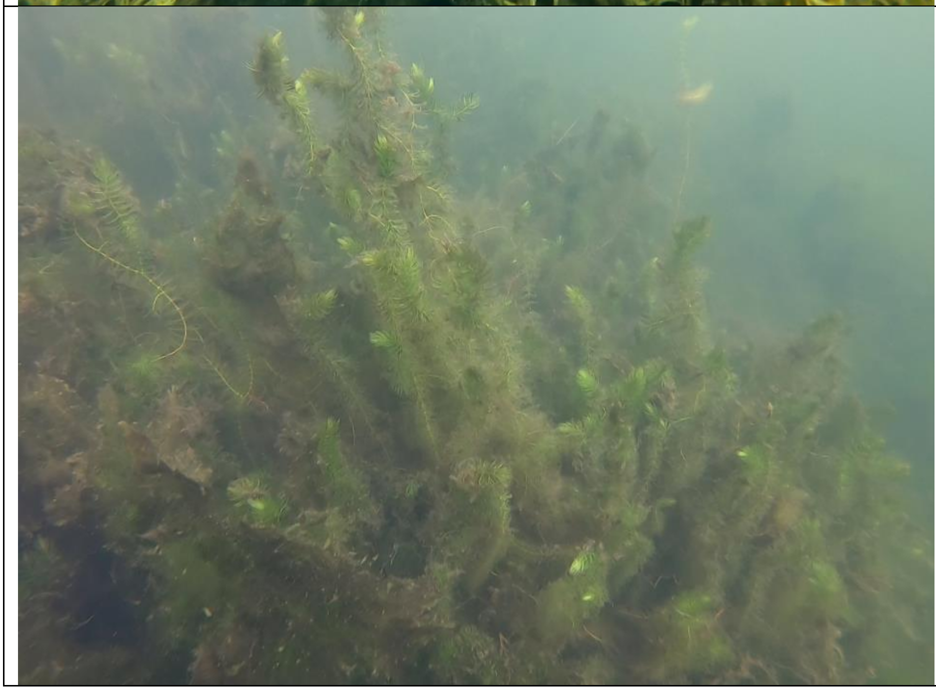
	Hornwort (*Ceratophyllum demersum*) – dense – Nov 2020
	Hornwort (*Ceratophyllum demersum*) – covered in algae – March 2022

	*Potamogeton cheesemanii* Native - July 2019
	Charophyte sp. Native – July 2019

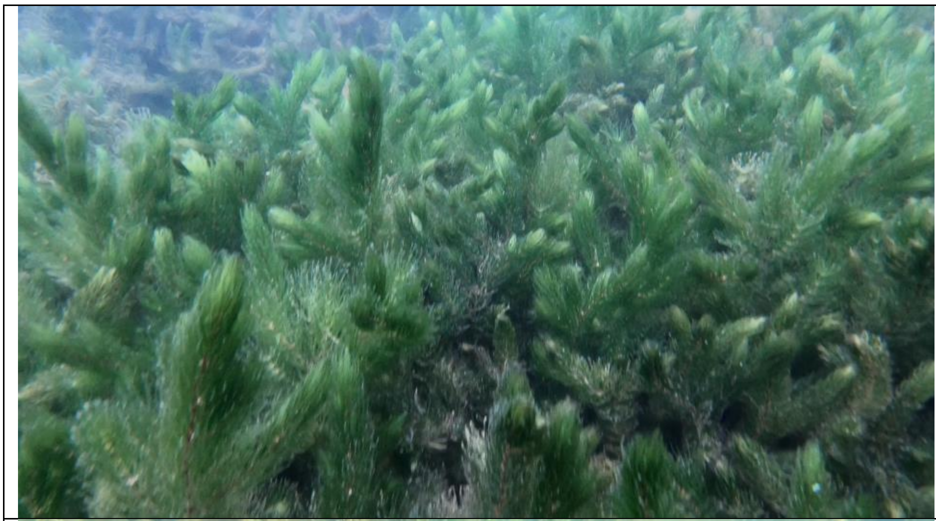
	Hornwort (*Ceratophyllum demersum*) – March 2022 – Site 1
	Hornwort (*Ceratophyllum demersum*) – March 2022 – Site 2
	Hornwort (*Ceratophyllum demersum*) (middle bottom) in amongst *Potamogeton ochreatus* (left) - March 2022 – Site 2

	Hornwort (*Ceratophyllum demersum*) with *Potamogeton ochreatus* (stem senescence) – March 2022 – Site 2
	*Potamogeton ochreatus* (native) covered in algae – March 2022 – Site 2
	Hornwort (*Ceratophyllum demersum*) individual apical shoot in amongst dense *Potamogeton ochreatus* (covered in algae) – March 2022 – Site 2

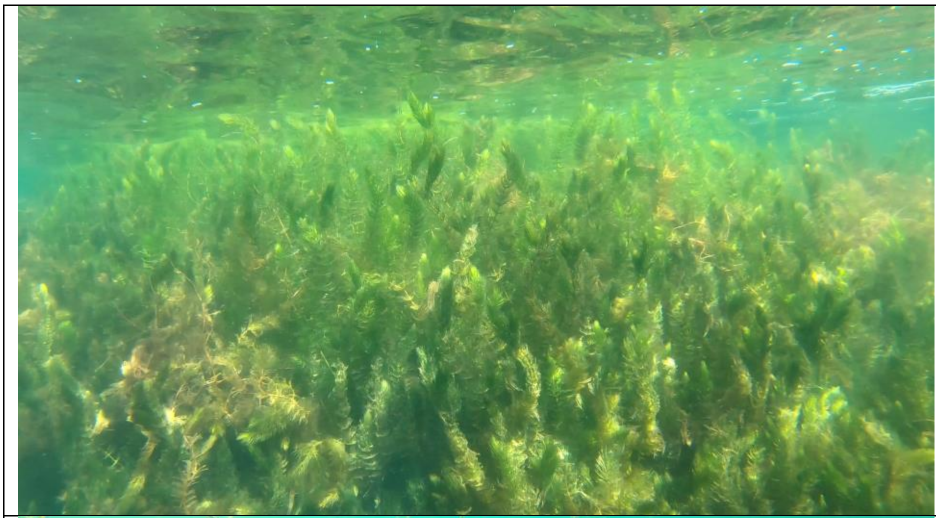
	Bombies of hornwort (*Ceratophyllum demersum*) covered in algae. – March 2022 – Site 2
	*Potamogeton ochreatus* (dense) – March 2022 – Site 2

	Shoots of hornwort (*Ceratophyllum demersum*) in amongst dense *Potamogeton ochreatus* - March 2022 – Site 2
	Hornwort (*Ceratophyllum demersum*) – March 2022 – Site 2

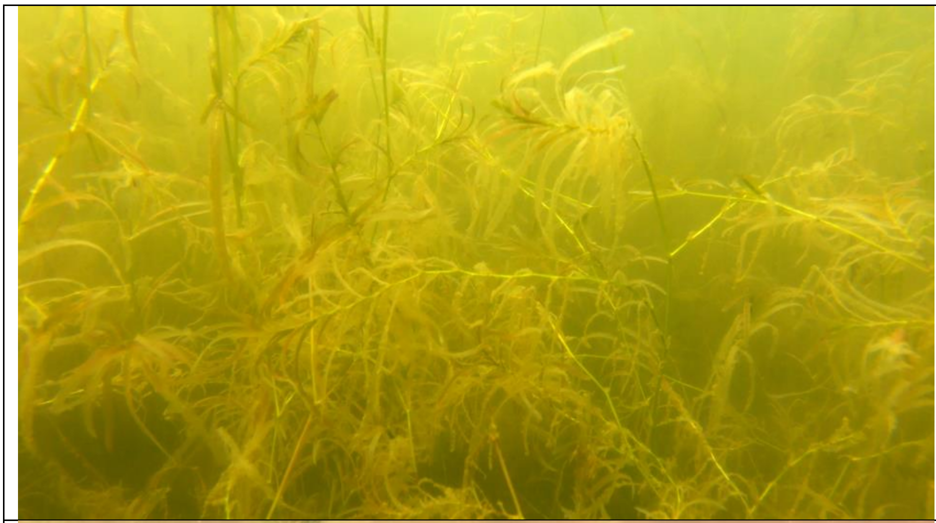
	Hornwort (*Ceratophyllum demersum*) covered in algae in amongst *Potamogeton ochreatus* – March 2022 – Site 3
	Hornwort (*Ceratophyllum demersum*) covered in algae – March 2022 – Site 3
	Hornwort (*Ceratophyllum demersum*) surface reaching – March 2022 – Site 3

	Hornwort (*Ceratophyllum demersum*) – March 2022 – Site 3
	Hornwort (*Ceratophyllum demersum*) in amongst *Potamogeton ochreatus* March 2022 – Site 3
	Hornwort (*Ceratophyllum demersum*) shoots in amongst *Eleocharis sphacelata* (reed) and low growing *Potamogeton ochreatus*. – March 2022 – Site 3

	Large surface reaching bed of hornwort (*Ceratophyllum demersum*) – March 2022 – Site 3
	Hornwort (*Ceratophyllum demersum*) covered in filamentous algae – March 2022 – Site 4
	Hornwort (*Ceratophyllum demersum*) covered in algae (left) with native charophyte sp. (right) – March 2022 – Site 4

	Hornwort (*Ceratophyllum demersum*) surface reaching – March 2022 – Site 4.
	Dense *Potamogeton ochreatus* (native) – March 2022 – Site 4
	Hornwort (*Ceratophyllum demersum*) in amongst *Potamogeton ochreatus* – March 2022 – Site 5

	Dense *Potamogeton ochreatus* with a few shoots of hornwort (*Ceratophyllum demersum*) below. – March 2022 – Site 5
	Hornwort (*Ceratophyllum demersum*) covered in algae. – March 2022 – Site 5
	Dense hornwort (*Ceratophyllum demersum*) – November 2022 – Site 2

	Dense *Potamogeton ochreatus* – November 2022 – Site 2
	Dense hornwort (*Ceratophyllum demersum*) – November 2022 – Site 2

Appendix 2: NIWA freshwater biosecurity update – Invasive species detection system – Second live trial: April 2023.

[Preston, G., Bulleid, J., (Christchurch), McDermott, H. (Twizel), David, S., Clements, D. (Hamilton)]

In May 2022, for the first time, we trialled NIWA's Invasive Species detection system in the field (in collaboration with Department of Conservation Te Papa Atawhai). The detection system features real-time 'edge computation' - deployment where the AI processing is implemented on-site, 'on-the-fly' in 'real-real-time', rather than centrally, in a cloud computing facility or data centre. Live data is streamed from a submerged video camera mounted on an autonomous or manned vessel and target detection locations are sent to a server as GPS references (and optional confirmatory images) so that management agencies can use the data in their on-ground invasive species management programmes.

We made some significant improvements since the initial field deployment in May 2022 and took an opportunity to carry out a second live trial on Lake Wakatipu and the Kawarau River, near Queenstown in April 2023, during a contracted (Land Information New Zealand – LINZ) diving inspection to locate incursions of lagarosiphon (a high-risk submerged weed). Improvements include the ability, via WiFi, for a user to view detections in real time on the detector's web page, and switch detection models and sensitivity thresholds remotely.

We trained the trial model with video databases from three previous field trips to Lake Wakatipu and the upper Kawarau River. This model has given the best results so far in desktop benchmarking and we used this to carry out live trials at the same locations. The equipment obtained good detection results, including the detection of new incursions of lagarosiphon around the Frankton Marina on Lake Wakatipu. This is a high-risk site, if lagarosiphon goes undetected, it can quickly grow upward towards the water surface and be spread by boats.

We anticipate proposing a plan to survey the whole marina by deploying an autonomous boat that, given GPS waypoints to follow, could map lagarosiphon incursions, with minimal need for divers for regular surveillance activities. The detection locations could be sent to lake managers who would then initiate eradication.

Figure: An example of recorded lagarosiphon detections in late April 2023 at Lake Wakatipu. Top left shows date/time, latitude/longitude. The detections are annotated with a blue box, species designation (LM) and prediction confidence range 0 (lowest) to 1 (highest).