Comparing aerial image analysis and ground-level monitoring of weed control strategies for Rakaia and Clarence River

A report prepared for

Environment Canterbury

M Saif I Khan

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Introduction

The combination of glacial or high precipitation mountainous catchments discharging through steep slopes and valleys while redistributing the alluvial loads carried from these catchments creates the unique braiding pattern of shifting water channels to form braided river ecosystems. The mountain range's proximity to the ocean and indigenous biodiversity make New Zealand braided rivers unique among these globally rare ecosystems.

Flora and fauna of braided rivers are well adapted to these ecosystems components and contribute to the functional integrity of New Zealand's braided river ecosystems (Gray, Scarsbrook & Harding, 2006). The vegetation regulates the water flow and alluvial distribution by facilitating the formation and sustenance of islands and gravel bars (Coulthard, 2005). Due to high precipitation events, recurrent flooding results in incessant alluvial reworking and eventually limits the unidirectional vegetation succession on any part of these riverbeds (Gray, 2010). The cyclical alluvial reworking, shifting channels and changes in vegetation keep the braided river ecosystem in a 'dynamic steady state', with a proportionate mix of channels, islands and vegetation across the braid plains (Gray, 2007). These ecosystem processes are under increasing threat due to anthropogenic interventions, such as hydroelectric projects, irrigation dams, flood protection infrastructures and introduced flora and fauna (Caruso, Edmondson & Pithie, 2013). Introduced pest species, both flora and fauna, often act contrary to the functional role played by their native counterparts, species that have evolved with the system.

Riverbed plants are pioneers able to cope with extreme, unstable environments. Many naturalised species are more efficient at exploiting this habitat than indigenous species. Classic riverbed native plant associations have largely disappeared from lowland environments and could be threatened in the high country unless weed control is initiated. The introduced flora such as willow (*Salix fragilis*), broom (*Cytisus scoparius*), gorse (*Ulex europaeus*) and lupins (*Lupinus sp.*) often develop very strong root systems to quickly stabilise the riverbed patches that they occupy. Once established, even major flood events are unable to rework these patches. This is a major concern to the alluvial re-distribution processes of the system resulting in the loss of braids and islands, effectively stopping the water channel shifting. Thus, the dynamic nature of the ecosystem gets heavily reduced, braid plains shrink and lose the unique characteristics of the braided river ecosystems.

It is critically important to be able to control weeds to sustain braided river systems. Government and non-government organisations have committed a significant amount of resources to limit the encroachment of weeds into the braided river system. Developing economic yet effective tools to detect and monitor weeds in braided river systems is highly desirable. Furthermore, the ability to detect weed encroachment early is crucial against the battle for controlling weeds.

Monitoring extensive braided river systems is very resource-intensive. However, regular monitoring is key to enabling early treatment of scattered weeds and facilitates strategic control of weeds at the landscape level. Among all other resources, time is the critical factor as weeds tend to grow exponentially with time and lapses in regular monitoring can create essentially irreversible changes to the ecosystem. Therefore, periodic monitoring is warranted. If the consistent application of standard monitoring techniques can be ensured, the changes in weed cover can be used to determine the effectiveness of weed management strategies over time (Brown *et al.*, 2011). While field data has traditionally been used in weed monitoring, ground-based monitoring is logistically challenging and difficult to replicate consistently due to resource limitations, including expertise.

Remote sensing has long been considered an alternative to ground surveys and can play an important role in establishing baselines and tracking subsequent changes in the size and condition of braided river vegetation (Nagendra *et al.*, 2013). The applicability and importance of remote sensing in conservation are well recognised, even with very coarse ground resolution (Turner *et al.*, 2003). The earlier uses were mostly at a landscape level for monitoring habitat conservation efforts (Nagendra *et al.*, 2013). For vegetation change monitoring, remote sensing – particularly aerial photography is most widely used in the forestry sector (Goodbody *et. al.*, 2019; Hall, 2012). Forest dynamics, including tree height measurement and tree volume analysis, were done through stereoscopic aerial images even before digital image processing had emerged (Spurr, 1948; Van Laar, 1963). However, the process was manual and the processing time was high for such analysis. Availability and affordability of diversified and high-resolution sensors such as RGB, infra-red, thermal and laser have increased the potential of using remote sensing in many other conservation efforts, including detection and counting of organisms and thereby population monitoring. The sensors can be mounted on satellites, manned aeroplanes and unmanned aerial vehicles (UAVs). The agricultural sector has widely adopted manned and UAVs aerial imaging-based weed detection techniques (Roslim *et. al.*, 2021). Satellite images, due to coarse resolution, is not suitable for weed detection in agricultural settings. Due to the commercial benefit of efficiently detecting weeds in smaller areas, many of the vegetation indices based on digital aerial images are initiated in the agricultural sector (Agapiou, 2020). As the technology evolves, a plethora of software for planning, acquiring and analysing remote sensing data has also emerged. All these technologies are improving fast and are likely to benefit weed control efforts in braided river ecosystems.

Objectives

In pursuit of having more effective tools for weed monitoring in the braided river systems, the current work compares the cost-effectiveness of ground surveys and aerial photogrammetry and explores the potential of using aerial photogrammetry for weed monitoring.

Methodology

Data collection

Aerial images were collected from a Cessna-180 with Aviatrix aerial photography system using a Canon EOS 5DS r with a Sigma 50 mm for a section of Waiau Toa/ Clarence River (3067 ha) and another section Rakaia River (8790 ha). The flight planning was done with the Flight Planner Pro software from Aeroscientific (Adelaide, Australia), licensed through the Department of Conservation. The image sizes were 8688 × 5792 pixels with 50% sidewise and 68% forward overlaps. The images were taken in January 2020 for the Rakaia River and in February 2020 for the Waiau Toa/ Clarence River. The acquired images have three visible bands, red, green and blue (in sRGB colour space). The planned ground resolution was 4.3 cm.

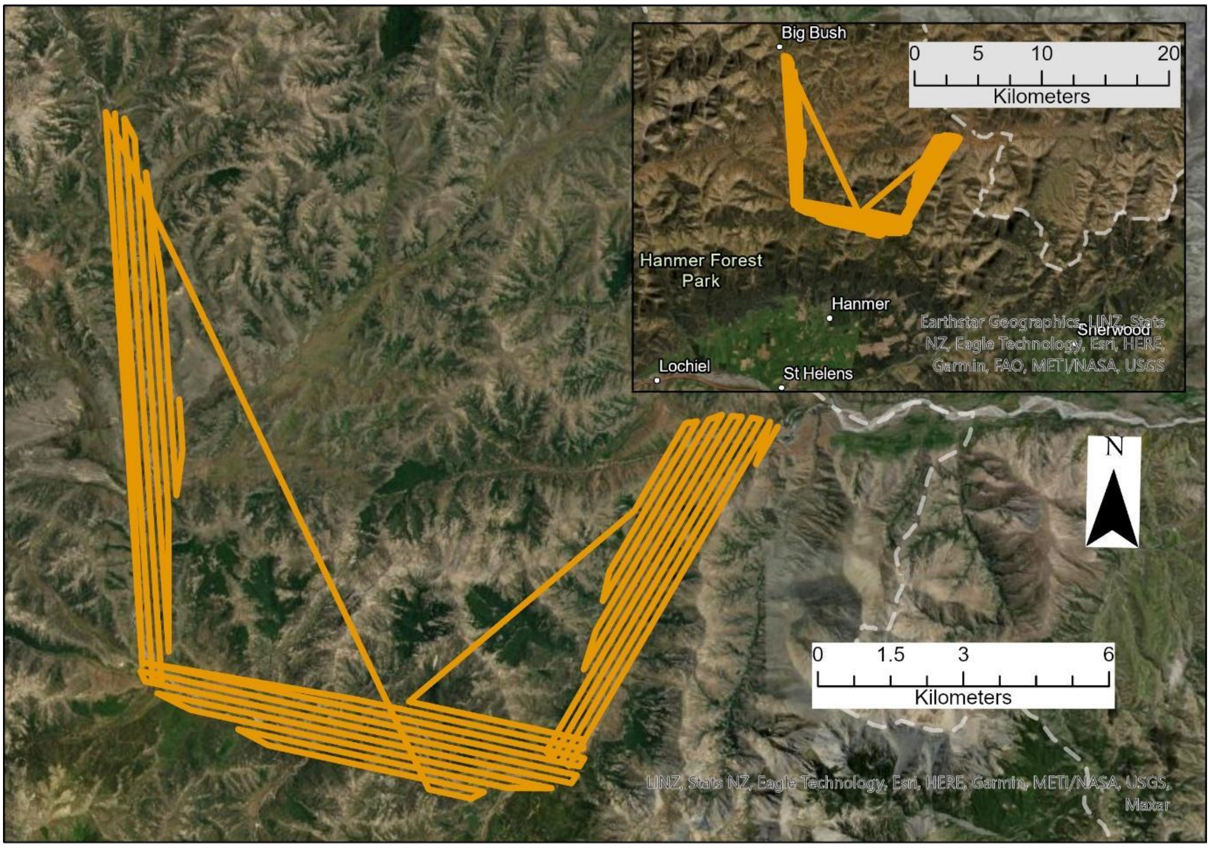

Figure 1: Flight path and location of aerial image acquisition for a section of the Waiau Toa/ Clarence River

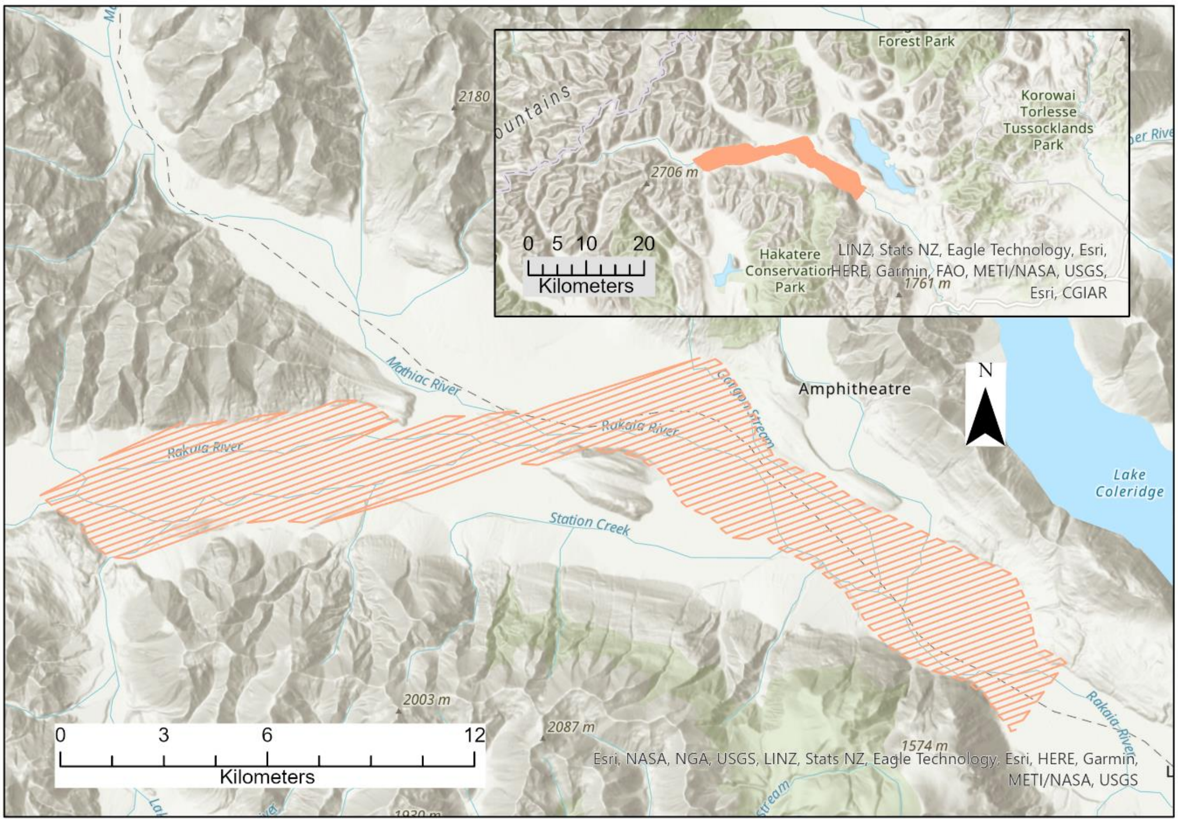

Figure 2: Flight path and location of aerial image acquisition for a section of the Rakaia River

Creating mosaics and tiling for each of the river sites

Image geotags were updated using ExifTool software (Kingston, ON, Canada) by syncing with the aviatrix trigger time log. Image mosaicking was carried out in ESRI ArcGIS Pro v.2.5-2.8.

Due to the large size of high-resolution images, images were split into smaller sections. There were three sections for the Clarence site and four sections for the Rakaia site. Split section mosaics were used to create mosaics for the whole area for each of the river sites separately. Final mosaics were still very large to handle. Therefore, mosaics were systematically tiled into roughly 1km X 1km tiles. There were 75 tiles for the Waiau Toa/ Clarence River site (Figure 3) and 141 for the Rakaia River site (Figure 4) with aerial image coverage.

Vegetation classification

Vegetation classification was Pixel-based supervised classification using a machine-learning approach of support vector machine (SVM) and was carried out with ArcGIS pro v. 10.8. SVM was preferred over other classifications for its efficiency in handling unequal training samples for classification modelling training (Greene *et al.*, 2020). The training samples were spread all across the river site and the trained model was saved. Two separate models for the Waiau Toa/ Clarence and Rakaia River were developed. The model was deployed separately for classifying image mosaic tiles of the corresponding site.

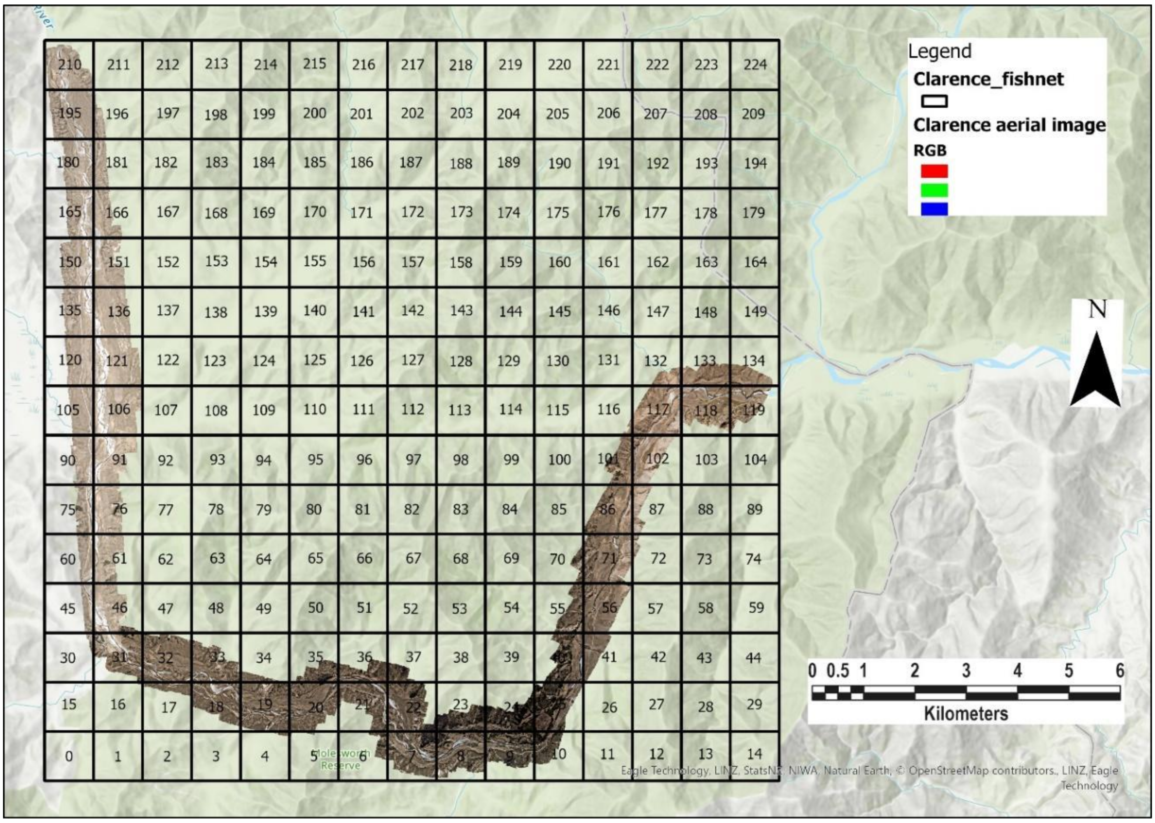

Figure 3: Aerial image mosaic of the Waiau Toa/ Clarence River site and corresponding tiling scheme. There are 75 tiles with aerial image coverage for the Clarence site.

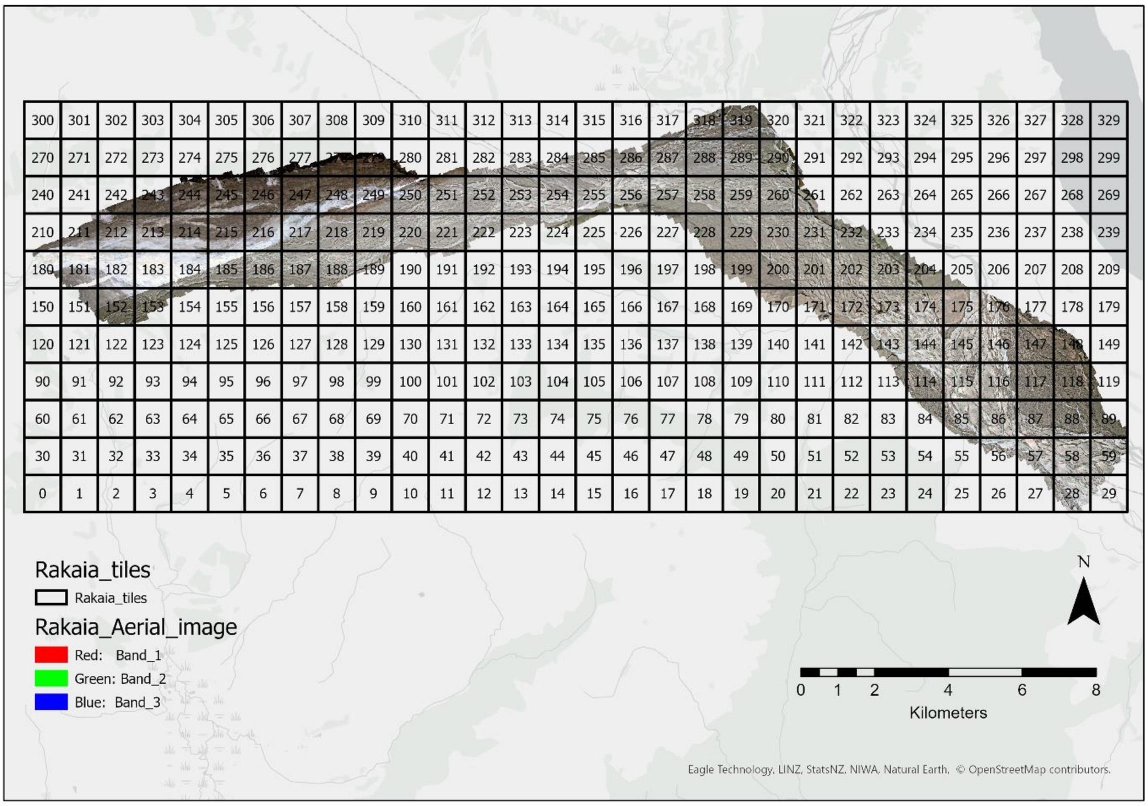

Figure 4: Aerial image mosaic of the Rakaia River site and corresponding tiling scheme. There are 141 tiles with aerial image coverage for the Rakaia site.

Comparing vegetation classification with existing weed information

The existing area of different weed species was delineated as GIS shapefiles. These shapefiles are accessible through Environment Canterbury's website and based on weed strategy work for the Waiau Toa/ Clarence (approx. 50000 ha.) and Rakaia (approx. 42000 ha.) rivers and adjacent areas. The delineated species polygons are based on ground observations with optical aid. Weed species abundance was also based on ground observations. At the species level, the abundance estimation was mutually exclusive. However, there are overlaps among species, meaning the same area could be designated as scarce of gorse and frequent of willow or sporadic of grass. Some species/tree locations were incorporated as points, especially for treated or dead individuals.

The existing weed shape files cover a larger area for both the Waiau Toa/ Clarence and Rakaia sites. As a first step, the shapefiles were clipped with the boundary of the mosaicked aerial images. Only weed shapefiles (both polygons and points) that were within aerial image coverage were retained. The polygons of each individual species merged into one containing areas with different abundances of the species. The polygons were rasterised to produce a raster for each individual species, with raster cells categorised according to the abundance of the species designated in the existing data. The resolution of the species raster was 5m X 5m. The lower or coarser resolution was used to reduce computational limitations of handling large data for species covering a very large area, such as willow (*Salix sp.*) or gorse (*Ulex sp.*; Figure 5, 6). The coarser resolution did not affect the comparison to a significant level, as only the area coverage of the species abundance categories was used in later analysis.

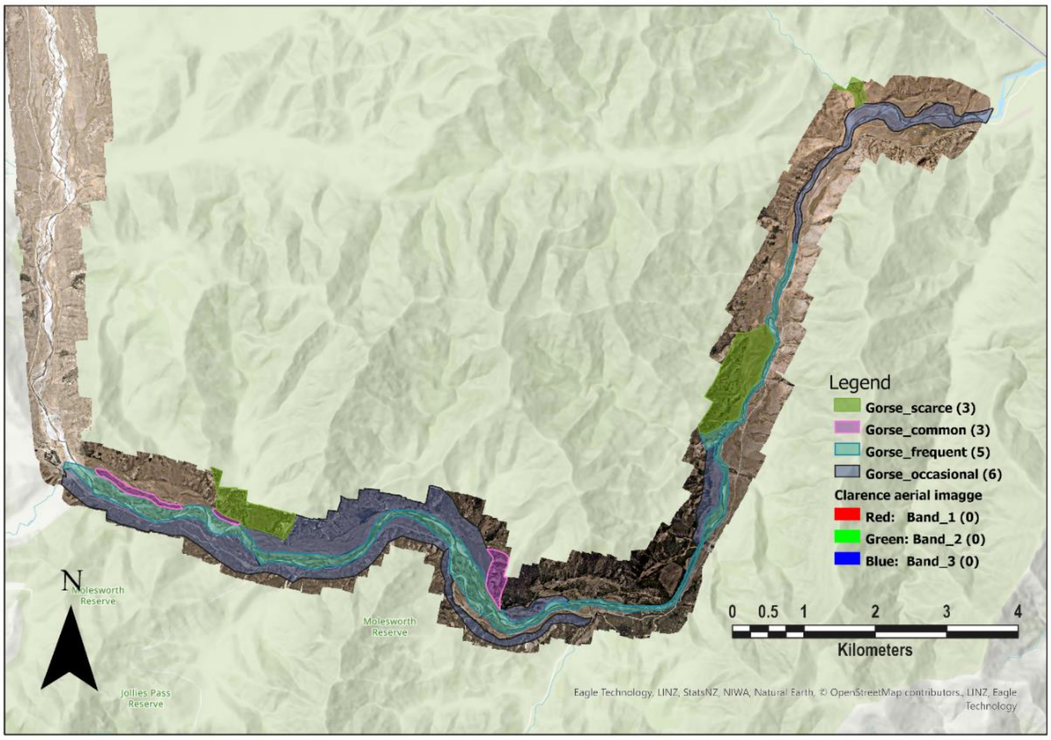

Figure 5: Aerial image mosaic of Waiau Toa/ Clarence River and areas classified with a different abundance of Gorse (Ulex europaeus) in the existing weed database

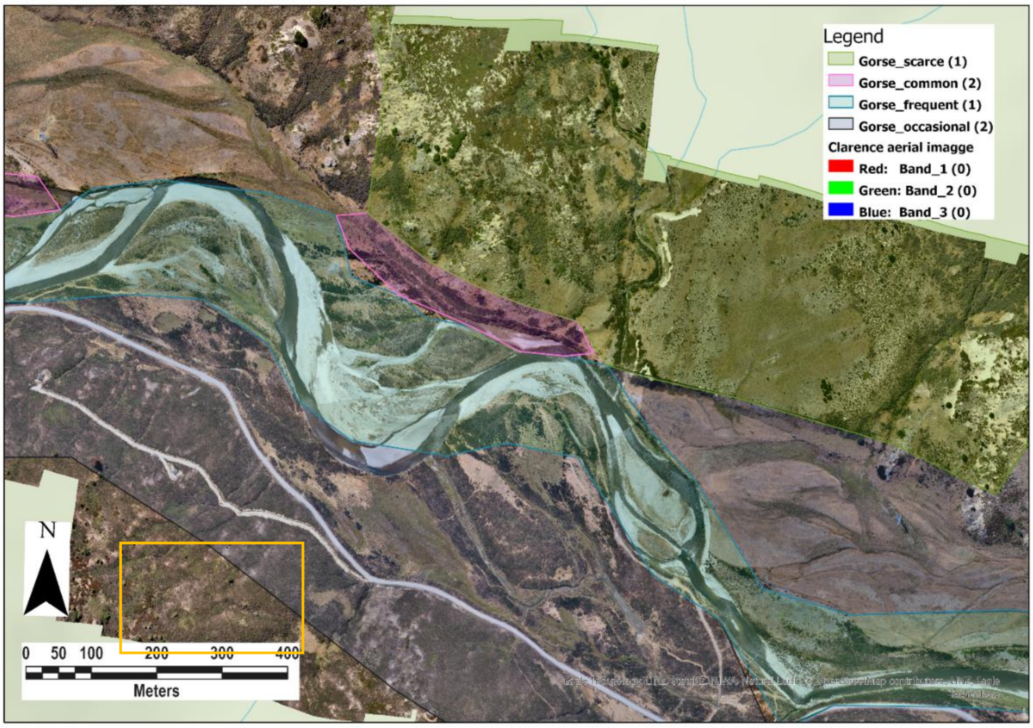

Figure 6: A close-up view of a section of aerial image mosaic of the Waiau Toa/ Clarence River overlaid with areas classified with a different abundance of Gorse (Ulex europaeus) in the existing weed database

Zonal statistics analysis in ArcGIS Pro was carried out to measure how much of each habitat class was within the existing species abundance categories. The percentage of different land classes within the species-area provides some comparable statistics to cross-examine the species abundance classification through ground observation and land cover classification through aerial image analysis.

Vegetation indices

In the absence of infrared bands, several vegetation indices based on RGB bands were explored. Among them, the following two, RGBVI and VVI, were promising. RGBVI is used widely in agricultural settings with drones (Agapiou, 2020), while VVI was developed to monitor global scale vegetation change analysis from satellite images (PHL, 2015). The indices were calculated using the raster function' band arithmetic' with ArcGIS Pro v. 2.8.

Red-Green-Blue (RGB) based vegetation index (RGBVI)

$$RGBVI = \frac{G^2 - (R * B)}{G^2 + (R * B)}$$

where R is red, G is green and B is blue band values in RGB images (Agapiou, 2020).

Visible vegetation index (VVI)

$$VVI = [\left(1 - \left|\frac{R - R_0}{R + R_0}\right|\right)\left(1 - \left|\frac{G - G_0}{G + G_0}\right|\right)\left(1 - \left|\frac{B - B_0}{B + B_0 + 1}\right|\right)]^{\frac{1}{w}}$$

where R, G and B are the red, green and blue band values, while R_o, $G_{o\ \text{and}}$ B_o is the vector for the reference green colour and *w* is a weight to adjust the sensitivity of the scale. R_o, G_o, B_o is 30, 50, 0 respectively for image band values saved with 256 channel values and w = 1. 1 is added to B_o in the denominator to avoid a division by zero in the equation, (PHL, 2015).

Canopy height layer

Along with image mosaic, a digital surface model (DSM) was developed for each site using ArcGIS Pro. The digital elevation model (DEM) for the sites was available through Toitū Te Whenua Land Information New Zealand (LINZ) 's data sharing website (https://www.linz.govt.nz/data/linz-data-service). The DEM tiles were resampled to the corresponding resolution of the image mosaic. The difference between the DSM and resampled DEM was considered the canopy height of the corresponding pixel. For pairwise batch processing of deducting resampled DEM tiles from DSM, ArcMap v. 10.7 was used.

Findings

The aerial image mosaics were of very high resolution with many features, including different types of vegetation being clearly visible (Figure 7). For demonstration, Clarence tile 210 is presented as a sample for the analytics of the aerial images.

The image mosaic tiles were classified at the pixel level and the classification schema had 12 land classes, including water channels, pervious roads, infrastructure, beach, bare soil, dead and crack willow, mixed forest, gorse, broom, grass and other herbs (Figure 6). Though classification was generally successful, some parts of the riverbed were misclassified as impervious roads due to spectral similarity. As aquatic vegetation was visible through clear river water, some parts of the river channel have also been classified as vegetation categories.

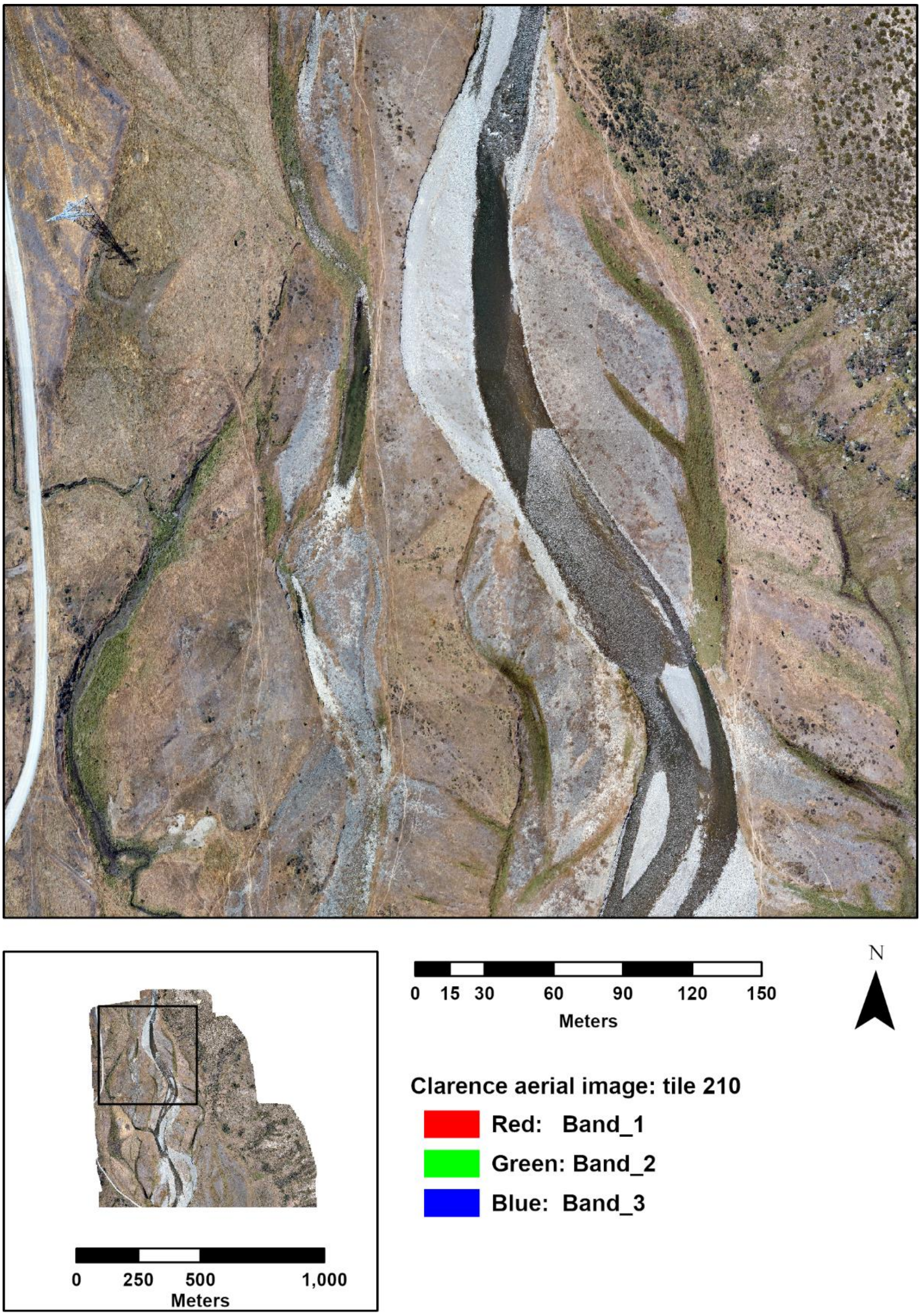

Figure 7: A tile of aerial image mosaic of the Waiau Toa / Clarence River site with a close-up view of a section showing different habitat features including river channels, sandy beaches, grasses, roads, vegetation.

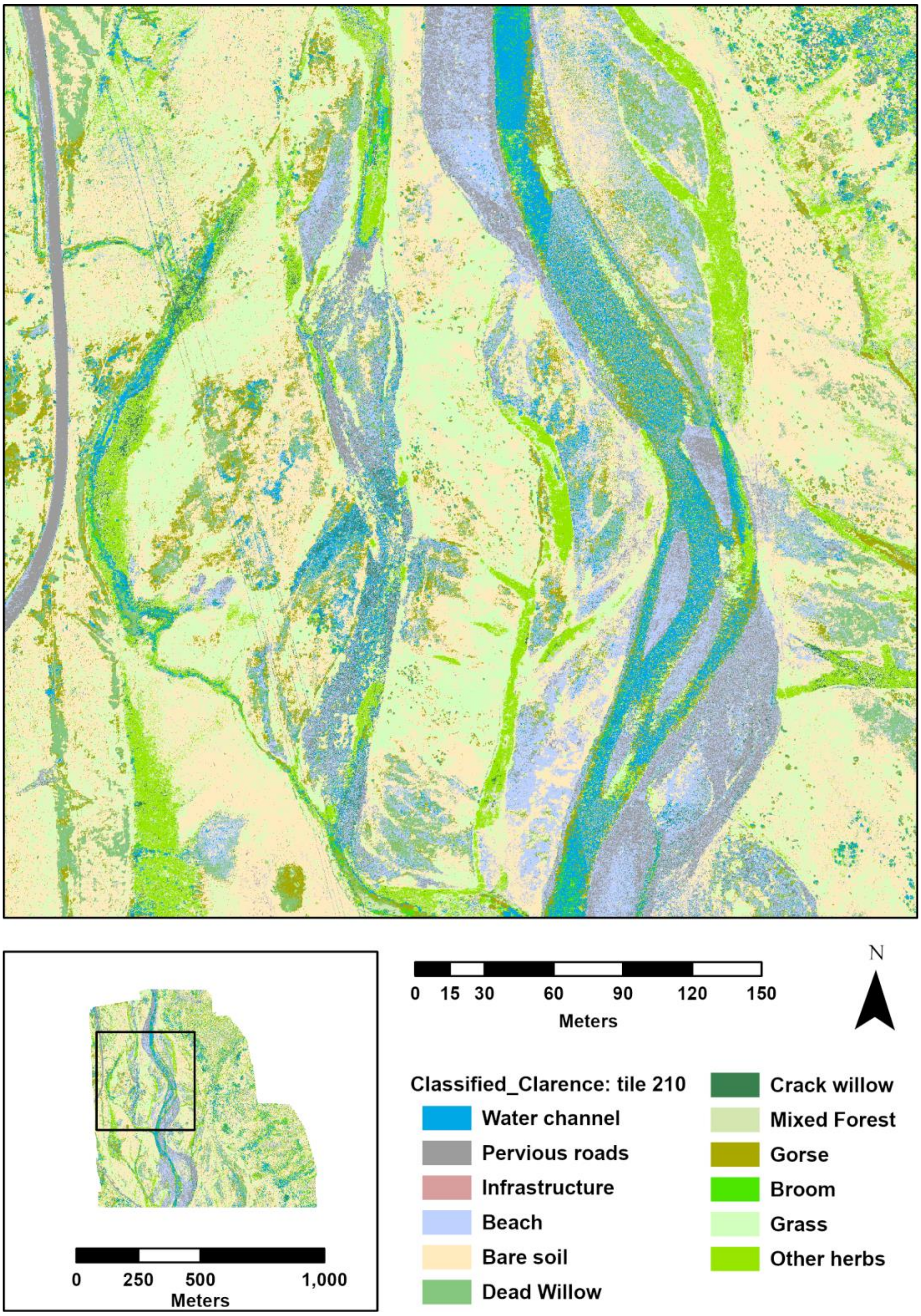

Figure 8: Land classes of a tile of aerial image mosaic of the Waiau Toa/ Clarence River site

The classification of aerial image mosaic was not able to detect all the weed species data contained in ground observation-based coverage polygons. However, some key species, such as broom, gorse and willow were available to compare for both in aerial image classification and ground observation-based polygon (Table 1; thicker border cells). Though the definition of the abundance category of the ground-based data is not very explicit, it is encouraging to note that dominant and frequent broom categories have higher broom areas calculated through classification. However, there was no such clear indication for area coverage for willow and gorse. A similar analysis for the Rakaia River site is included in supplementary data.

Table 1: Area coverage (%) for different land classes based on aerial image versus areas designated under different abundance categories of different species delineated with ground observations.

	Alder (Aln_glu)	Broom (Cyt_sco)						Heath (Eri_lus)	Crack willow (Sal_fra)		Gorse (Ule_eur)			
Row Labels	scarce	abundant	common	dominant	frequent	occasional	scarce	scarce	common	scarce	common	frequent	occasional	scarce
Bare soil	34.23%	11.08%	19.95%	5.55%	5.55%	23.94%	38.23%	24.50%	24.50%	23.20%	12.80%	9.35%	11.66%	15.81%
Beach	22.21%	5.97%	1.56%	5.48%	5.48%	4.39%	8.68%	20.40%	20.40%	15.51%	1.66%	8.95%	2.53%	0.84%
Broom	0.30%	9.60%	11.49%	19.91%	19.91%	2.88%	1.91%	2.09%	2.09%	4.49%	10.41%	11.15%	9.25%	4.33%
Dead willow	1.34%	1.00%	0.66%	2.69%	2.69%	1.11%	1.19%	1.39%	1.39%	2.25%	2.07%	2.47%	1.47%	0.60%
Crack Willow	5.00%	4.46%	5.67%	5.94%	5.94%	3.25%	4.29%	5.84%	5.84%	5.11%	8.43%	5.19%	4.26%	4.45%
Gorse	2.81%	24.17%	22.99%	22.36%	22.36%	17.80%	11.06%	8.37%	8.37%	11.35%	20.70%	22.12%	27.25%	30.05%
Grass	11.12%	19.89%	16.67%	8.18%	8.18%	27.89%	16.89%	14.12%	14.12%	15.34%	18.72%	15.17%	20.11%	24.10%
Infrastructure	0.52%	0.06%	0.08%	0.11%	0.11%	0.07%	0.28%	0.44%	0.44%	0.11%	0.24%	0.09%	0.02%	0.06%
Mixed Forest	2.38%	4.85%	7.39%	7.86%	7.86%	4.73%	4.95%	2.70%	2.70%	3.82%	8.05%	5.48%	7.00%	6.97%
Other herbs	3.17%	7.15%	6.90%	7.45%	7.45%	6.57%	4.73%	4.18%	4.18%	4.49%	10.26%	6.47%	8.52%	8.17%
Pervious roads	10.68%	2.63%	0.49%	2.32%	2.32%	1.81%	3.67%	7.15%	7.15%	6.97%	0.19%	3.42%	1.05%	0.24%
Water channel	6.23%	9.13%	6.16%	12.15%	12.15%	5.56%	4.11%	8.81%	8.81%	7.36%	6.46%	10.14%	6.88%	4.39%

The vegetation indices RGBVI (Figure 9) are oversensitive to the green band value on the images as revealed by aquatic vegetation visible through clear shallow water being miscategorised as vegetation in sections of the river channel. The VVI (Figure 10) is relatively less prone to classifying water areas as vegetation. Apart from this water channel-vegetation misclassification, vegetation indices work well to detect vegetation patches in terrestrial parts and are capable of detecting even quite small vegetated areas (Figure 11 and 12).

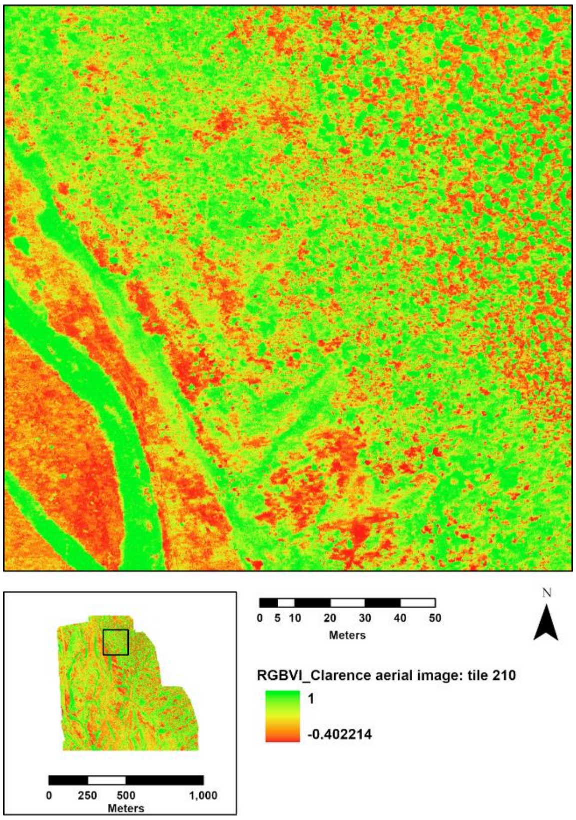

Figure 9: Red-Blue-Green (RGB) band-based vegetation index (RGBVI) of an aerial image mosaic tile from the Waiau Toa / Clarence River site

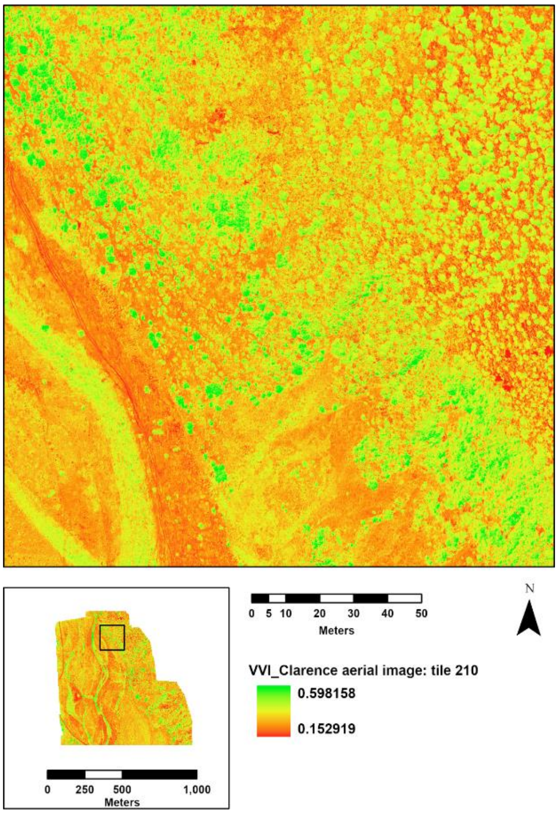

Figure 10: Visible band-based vegetation index (VVI) of an aerial image mosaic tile from the Waiau Toa / Clarence River site

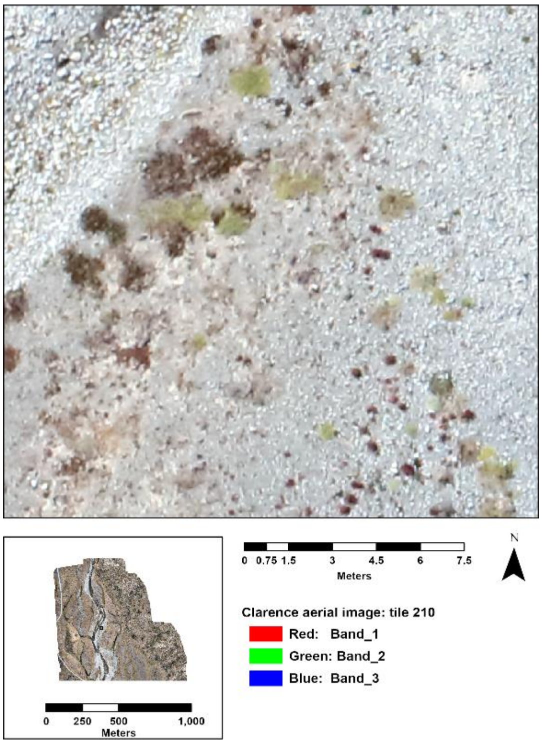

Figure 11: Close up view of aerial image mosaic from the Waiau Toa / Clarence River site

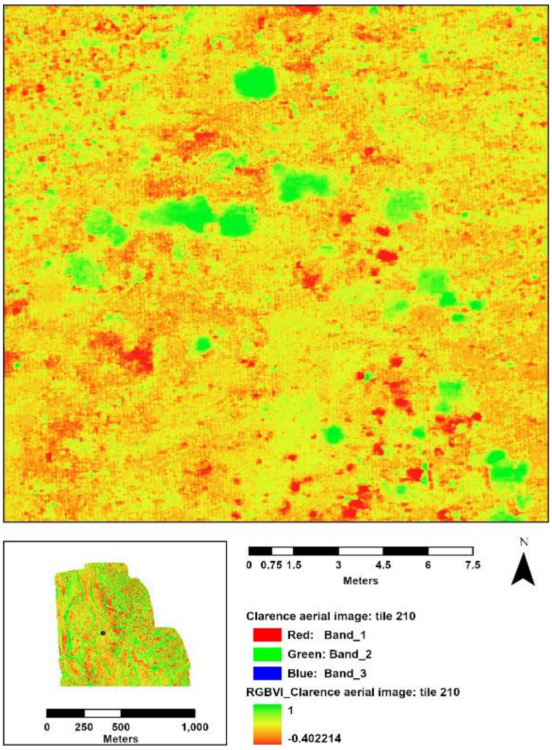

Figure 12: RGBVI index of close-up view of the aerial image mosaic from the Waiau Toa / Clarence River site

The canopy height layer (Figure 13) is an added information to help assess the weed condition of the area in consideration.

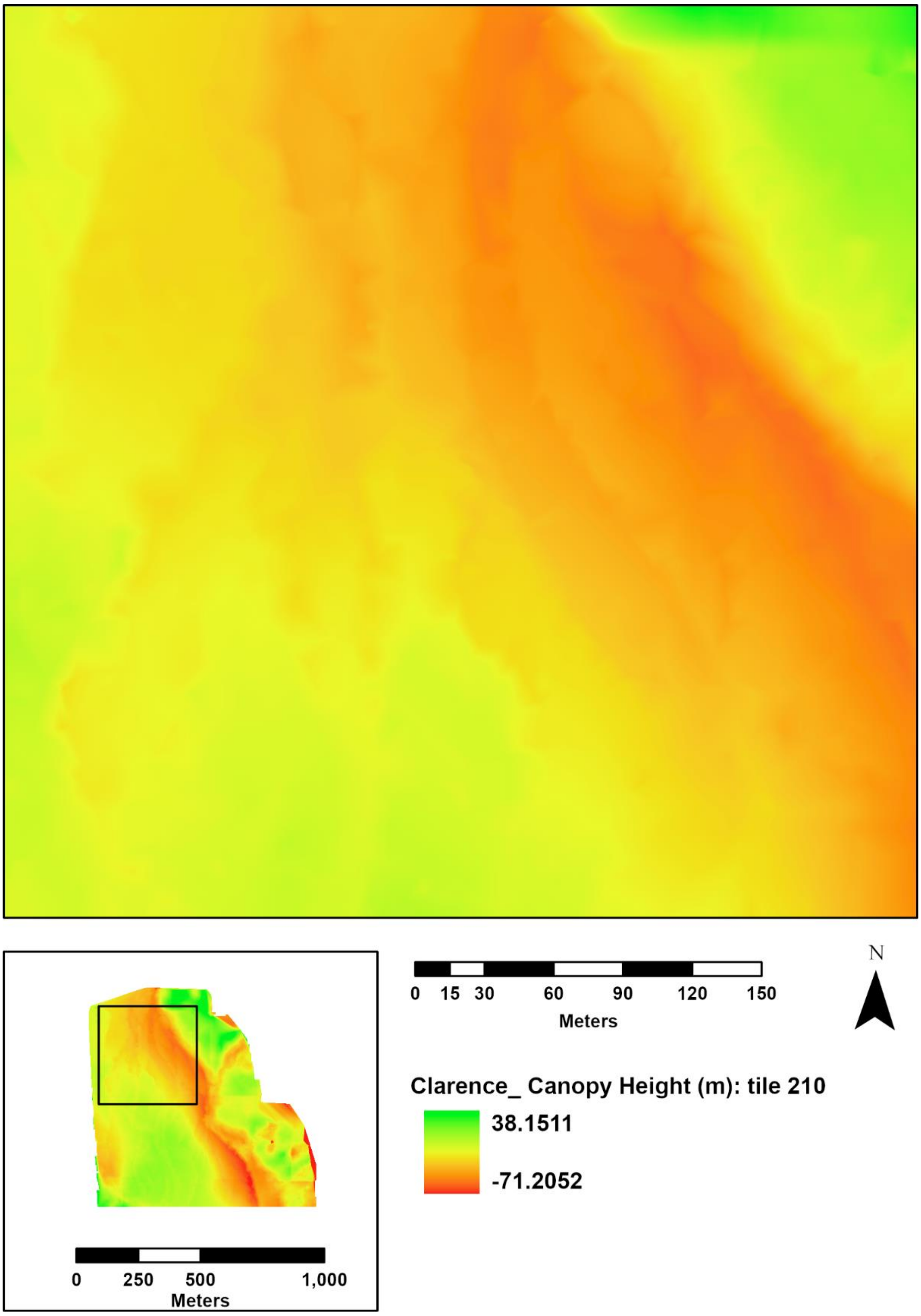

Figure 13: Canopy height representation of a section of the Waiau Toa / Clarence River site.

Discussion

Potential use of the high-resolution aerial images

Tiled image mosaics can be used for planning ground operations to control weeds. The images are capable of detecting vegetation occurrence at a very high ground resolution, where even single seedlings or grass tuffs are visible. This can be done through manual scanning currently and also by using vegetation indices, which helps to segregate vegetated and non-vegetated patches. Though species-level identification may not yet be possible in many cases, manual identification of such encroaching patches into riverbeds can be identified on the image. With monitoring protocols in place with imaging at a justifiable interval, the rate of vegetation encroachment and spread can be measured and weed control strategies can be prioritised accordingly.

The canopy height layer can add to the identification of species and also assess the urgency of weed control needs. The canopy height data can also be helpful for operational planning and assessing resource needs for weed control on the ground.

The high-resolution images can provide a detailed 3D view of the sites with local scene mapping through ArcGIS Pro (Figure 14, 15). This can provide a lot of context to the data and allow for repeated observations by one or more experts, which is not feasible with ground survey only.

Figure 14: 3D view of the Waiau Toa/ Clarence River site with aerial image coverage

Figure 15: A close-up and ground level view of the 3D scene for the Waiau Toa/ Clarence River site.

Cost-effectiveness of aerial imaging for weed monitoring

The total cost of collecting data across about 12,000 ha of the Clarence and Rakaia rivers was around USD 15,000. About USD 7,000 was the cost of the two flights to collect aerial images and the rest is attributed to image processing, data analysis and associated administrative costs.

In comparison, for ground data collection over about 90,000 ha across the two river sites and a small amount of associated weed control (for scattered remote plants), the costs were about USD 68,000. Based on these figures, aerial imagery costs are 1.65 times higher per unit area (USD 0.75/ha for the ground survey and USD 1.25/ha for aerial images, including processing). However, the cost of only acquiring aerial images was about USD 0.58/ha, which is lower than the ground survey. With a larger area, the cost for imaging would be less (Khan *et al.*, 2021). It should also be noted that the actual ground survey physically covered a portion of the 90,000 ha and mapping was aided by available satellite image base maps. Also, the data analysis carried out with aerial images was not replicable with ground survey data. However, as a new tool to adopt, aerial imagery and associated analytics would have some associated investment costs, including computational hardware, image storage, software licensing and skilled human resources. Nonetheless, for the adoption of new technology, the cost-benefit analysis should go beyond financial costs and include other associated costs and benefits.

For the ground survey of the Rakaia and Clarence sites, preparation and administration needed 13 person-days, the ground survey required 74 person-days, mapping needed 14 person-days and the report preparation required 13 person-days . In total, 114 person-days were required for the ground survey of the Clarence and Rakaia sites. Among 74 field-based person-days, 44 person-days were by an ecologist. For aerial imaging, the flight planning preparation for two sites was eight person-days, flying was over two person-days, 45 days were for mapping and analysis, while 20 days were allotted for report writing – totalling 75 person-days. However, with now standardised workflow, the image analysis would require less time in future and also, the computational power is ever-improving to accelerate the analysis further.

Table 2: Comparing resource requirements for ground survey and aerial image-based analysis for weed detection for Rakaia River and the Waiau Toa/ Clarence River sites

Ground survey		Aerial imaging	
Time required	Days		Days
Prep/ admin	13	Flight planning	8
Ground survey	74	Flying	2
Mapping	14	Mapping and analysis	45
Report preparation	13	Report writing	20
Total	**114**	**Total**	**75**
Expertise required*			
Ecologist	44	Ecologist	5
Geo-spatial/ Image processing technologist	4	Geo-spatial/ Image processing technologist	20
Field support staff	38	Field support staff	None used
Financial cost	USD		USD
Area: 90,000 ha.	68,000	Area: 12,000 ha	15,000

* Expertise is estimated as man-days. The expertise required for aerial image capturing is outsourced and included in the financial cost.

The ground survey is hard to repeat as it is dependent on availability of required expertise to be physically on the ground. Without a well-documented and detailed protocol of the ground survey methodology, it is also hard for point-to-point comparison for monitoring the weed coverage of weed expansion or assess effectiveness of the weed control strategies over time. Ground surveys also have limitations in terms of scalability – as the ground survey cannot be expanded for greater coverage in a particular field season due to human resource and logistics.

With aerial imagery, the ecological expertise can be made flexible to work around the year as data analysis can also go beyond the ideal field season once the images are captured at a desired time. The image processing and analysis do require expertise in image processing and geospatial analysis. However, a significant portion of the time required for image processing is actually computational time when the machine automation takes care of the repeated tasks on the batches of image tiles. For Rakaia and Clarence images, about two-thirds of the time required for image analysis was computational time only. Once a standard image processing protocol is established for monitoring weed status for a site, the required engagement of image and geospatial analysts will be even less and the process can be scaled up by using more working stations for parallel computation of image processing.

The required engagement of geospatial technologists would be higher for newer sites as flight planning may be more involving and flights across different seasons may be required for species-level identification of weeds. Once a weed baseline is established for a site, subsequent monitoring flights and image processing will require rather limited engagement from the geospatial technologists. The logistical challenge of aerial image-based monitoring would be organising flights on cloud-free days as pilots and specialised planes for image capturing remain in very high demand over several assignments.

For recurring monitoring of weed coverage, an ideal workflow can be to capture images in the late summer or fall, analyse them over the winter and be prepared with weed control plans for next spring and summer. The timing of the image capturing is proposed to capture the resultant effect of weed control or weed expansion after the vegetation growing season. With such possibilities, the potential for effective monitoring is very high with aerial imagery.

Limitations of image classification for weed detection

Species-level identification of the weed species is challenging through automated or computer-aided classification. It is even more challenging to classify images with only visible RGB bands. It is also important to note that information on identification features of weed species on aerial images is very limited or non-existent. Nevertheless, the classification of aerial mosaic can be revisited with an improved species-level vegetation classification schema and validated by inputs from vegetation experts.

The high-resolution images, even with only 3-bands, are data-intensive and require significant time to process. For this project, there were many exploratory attempts to find solutions to minimise processing times and organise a reasonable workflow. As more and more projects incorporate aerial imaging and analysis, image processing should improve.

Suggested improvements for data collection and analysis

Use of precise GPS data logger alongside camera GPS

The in-built camera GPS is often slower than its image clicking rate and logs several images with the same GPS tags. For this project, the GPS tags were updated using image sequence number and timestamp in coordination with the Aviatrix system log, which triggered each image capture.

However, there is a lot of manual effort involved in the process and it is also reliant on the notes maintained by the pilot for any variation of flight plans. This is time-consuming for a large dataset with several long flight lines. The height data is even more critical to rectify, especially for areas with high variation in elevation within a short distance. An improved GNS unit with known distance and direction from the camera would be helpful in rectifying this issue.

Use of the infrared band

It is challenging to have a reliable vegetation index from only visible bands, especially for vegetation that is not green. Also, if only visible bands for vegetation detection are used, green aquatic plants visible through clear waters of the braided rivers may lead to the misclassification of water channels as vegetated patches. Corresponding infrared image/data would enable the calculation of the widely used Normalised Difference Vegetation Index (NDVI), which would lessen the possibility of such misclassification.

Use of digital elevation model in flight planning for aerial image collection

The elevation is critical for ensuring the quality of digital surface models generated through overlapping aerial images, especially in areas where elevation changes are sharp and frequent. Therefore, the use of a digital elevation model in flight planning is essential for ensuring enough forward and side overlaps for creating orthomosaics and, more crucially, for the 3D scenes for the site.

Combining ground information

Identifying vegetation patches to species level is critical to developing a weed baseline for a particular site. The visibility of features traditionally used to identify individual weed species is limited in aerial images. Therefore, phenological vegetation features (e.g., flowers and leaf shedding), which are relatively easily detectable from aerial images, can be used instead to identify target weed species. Combining phenological information of weed species when the aerial image is acquired will further strengthen the classification modelling. For example, it would be easier to distinguish weeds with yellow flowers (gorse/broom) from other green vegetation if aerial images are acquired in the corresponding season when these species are in bloom. Once the species is identified with its geospatial location on the images, the patches can be monitored in other seasons as well.

Deep-learning based image classification for weed detection

Deep-learning based image classification has been used to identify individual species on aerial images. Detection models can be developed for each target weed species for braided river ecosystems in New Zealand as well. There will be an initial investment required for this, but once developed, this will be a solution to many of the classification issues mentioned in this report. The image classification models will be knowledge-transferable, i.e. could be used independently on different sites, with the possibility of gradually updating the model with new information on context and variety.

Conclusion

This project has incorporated potential analysis of aerial images with only RGB bands, which yielded some helpful results and showed promising signs for the detection and monitoring of weeds within braided river ecosystems. However, there remain many areas that could be improved for RGB based aerial imagery being used for weed monitoring. The classification models can be improved with a higher number of weed species areas incorporated as separate classes. As ground-truthing data is often scarce for remote sites, weed experts can identify weed species on the images and help improve the quality of training sample input for the models. The RGB based vegetation indices and canopy height layers can help detect and monitor vegetation encroachment. However, deep-learning-based image classification is the potential way forward for more automated monitoring of the weed species. Even without automation, high-resolution aerial imagery can be an effective tool to aid ground-based weed control operations. A complementary combination of ground surveys and aerial imagery would be the most effective strategy for monitoring weeds of the braided river ecosystems.

Associated data

	Data types	Clarence	Rakaia
1	Raw images (.CR2)	1929 images (121 GB)	6118 images (441 GB)
2	Geotagged updated images (JPEG)	72 GB	263 GB
3	Image mosaic workspaces	170 GB	976 GB
4	Land classification model	.ecd format (ESRI)	.ecd format (ESRI)
5	Image mosaic tiles	75 tiles	141 tiles
6	Vegetation indices (RGBVI, VVI)	Raster functions (band arithmetic) associated with mosaic tiles	Raster functions (band arithmetic) associated with mosaic tiles
7	Canopy height tiles (including DSM, DEM tiles)	300 GB	1200 GB

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