National SCIENCE Challenges

SUSTAINABLE SEAS

Ko ngā moana whakauka

Guidance for using drones to monitor coastal ecosystems

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Report

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About the Sustainable Seas National Science Challenge

Our vision is for Aotearoa New Zealand to have healthy marine ecosystems that provide value for all New Zealanders. We have 75 research projects that bring together around 250 scientists, social scientists, economists, and experts in mātauranga Māori and policy from across Aotearoa New Zealand. We are one of 11 National Science Challenges, funded by the Ministry of Business, Innovation & Employment.

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Cover image: Aerial image of rocky shore. Hamish Sutton [NIWA]

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Summary

Coastal rocky reef habitats support diverse and productive ecosystems, as well as valuable commercial, recreational, and customary fisheries. With increasing pressures on coastal areas from land-use, coastal development and climate change, there is a need to effectively monitor these environments at scales that can inform management strategies.

Traditional monitoring of coastal ecosystems includes a variety of data collection methods such as visual observations of community assemblages and water and sediment quality metrics. These on-ground survey methods have greatly assisted in understanding the health and community composition of surveyed areas, however, they are typically labour-intensive, are restricted to a small spatial footprint, and can bias results towards accessible areas. Gathering data at greater spatial scales reduces the inherent variability of results associated with small scale sub-sampling and increases our understanding of the whole ecosystem, including habitats and areas not accessible to traditional methods.

Remote sensing technologies can be used to increase both spatial and temporal monitoring of coastal ecosystems. These range from satellites to manned aircraft to unmanned aerial vehicles (UAV; i.e., drones). Remote sensing technologies have been applied to a wide range of environmental and ecological monitoring including coastal benthic habitat mapping (Ventura et al. 2023), water quality assessments (Gupana et al. 2021; Adjovu et al. 2023) and the presence of macroalgal blooms (Al-Shehhi and Abdul Samad 2022; Hu et al. 2023).

High resolution remote sensing (i.e., UAV multispectral imaging) can be particularly useful in accurately detecting and discriminating between marine vegetation, such as kelp and seaweed species, on account of specific reflection and absorption of light in the red and infrared regions (Chao Rodríguez et al. 2017; Tait et al. 2019). This characteristic has enabled broadscale mapping of these critical ecosystem components, and can be used to infer the health of coastal rocky reef ecosystems (Murfitt et al. 2017; Tait et al. 2019). For example, recent mass mortality events of nationally significant bull kelp has been documented by multispectral aerial drones and has enabled the identification of remnant populations in areas otherwise inaccessible to traditional methods (Tait et al. 2021b).

This document provides guidance on choosing a remote sensing platform and the use of UAVs for aerial monitoring of coastal rocky reef ecosystems.

Platform selection

Overview

Remote sensing of coastal ecosystems is possible from a variety of remote sensing platforms from earth-oriented satellites, manned aircraft, and unmanned 'drones'. Each remote sensing platform varies in its spatial coverage, resolution and cost (Table 1). Earth observation satellites have the greatest spatial and temporal coverage and are often freely available but are limited in their resolution and flexibility on when an image is captured. In comparison, a drone provides high pixel resolution and flexibility on the timing at which imagery is captured but is more expensive and has lower spatial coverage.

Table 1: Relative spatial coverage, pixel resolution, cost per unit time and cost per unit area of aerial imaging platforms. Note that actual costs and coverage depend on too many factors to provide definitive values, so assessments are provided over a broad relative scale.

	Drone*	Fixed-wing drone**	Manned helicopter	Manned fixed-wing	Earth observation satellites ***
Spatial coverage	Very low	Low	Moderate	Moderate	High
Pixel resolution	Very high	High	High	Moderate	Very low
Cost per time	Moderate	Moderate	Very high	High	Very low
Cost per unit area	Very high	High	Very high	Moderate	Very low
Flight time flexibility	Very flexible	Very flexible	Flexible	Moderately restricted	Highly restricted

* e.g., DJI M200 quadcopter. ** e.g., senseFly eBee. *** e.g., Sentinel-2A constellation (European Space Agency)

Choosing the most suitable platform depends on the requirements of the proposed monitoring programme and typically involves a trade-off between spatial resolution (pixel size) and spatial coverage. The higher the spatial resolution, the smaller the area covered. Key considerations include:

1. What is my feature of interest (FOI)? How big is it, how rare or abundant is it?

2. What level of taxonomic resolution do I require?

3. How big is my area or region of interest (ROI)?

If the FOI occurs at large spatial scales, passive remote monitoring by freely available satellites or manned aerial aircrafts can provide imagery of high enough resolution for broad habitat classification (Figure 1; Bell et al. 2018). For example, earth observation satellites with a pixel size of 10–30m have been used for the remote imaging of giant kelp (*Macrocystis pyrifera*) and relates well to *in situ* observations (Cavanaugh et al. 2011; Bell et al. 2015; Bell et al. 2018). These procedures can be run over very large scales and provide frequent observations through time. These types of timeseries are critical for understanding the influence of climate oscillations and long-term trends while also reducing monitoring costs (Tait et al. 2021b).

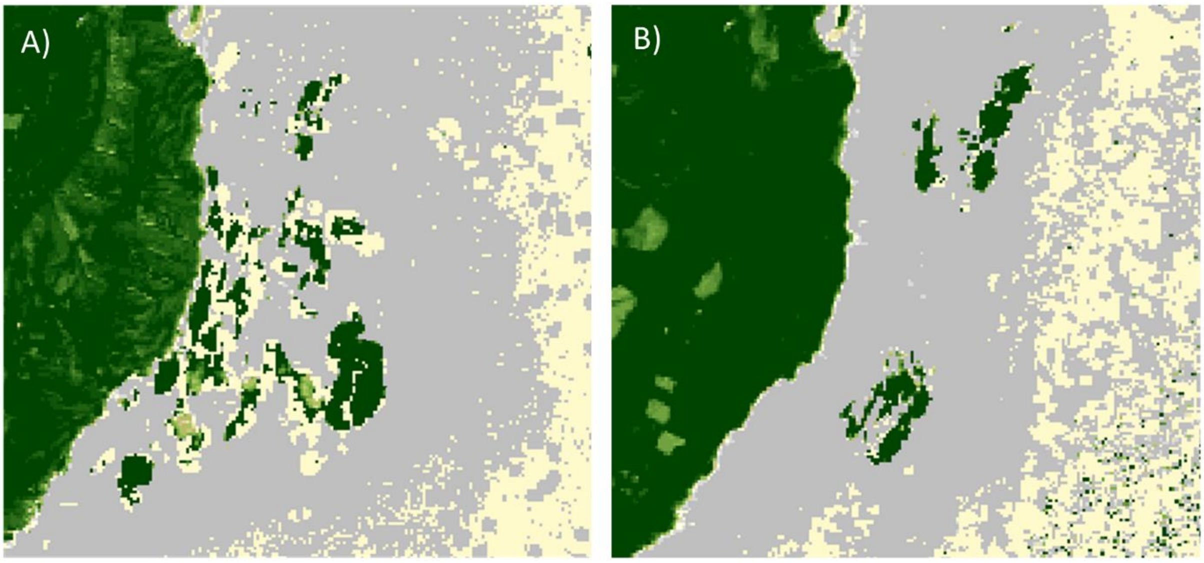

*Figure 1: Example use of satellite imagery (Sentinel-2 false colour to enhance vegetation signals) for detecting and mapping beds of giant kelp (*Macrocystis pyrifera*). Map shows coastal kelp beds in Otago in A) July 2020 and B) July 2021.*

If the FOI is smaller than can be observed with earth observation satellites but spatial and temporal coverage is a priority, then higher resolution imagery can be collected by tasked satellites (where imagery is taken on request at a chosen location e.g., SkySat), or through manned aircraft. These platforms provide varying pixel resolutions (ca. >1m) over reasonable areas, but can be costly and restricted in their deployment around ideal oceanographic and meteorological conditions.

If the FOI is rare in space and occurs in patches less than 1–2m^2, higher resolution data are required. This can be provided by drones which over a reduced area can provide stable, low elevation flights of higher pixel resolution (to a few cm) which enable species level or functional group classifications of coastal ecosystems (Figure 2; Murfitt et al. 2017; Tait et al. 2019).

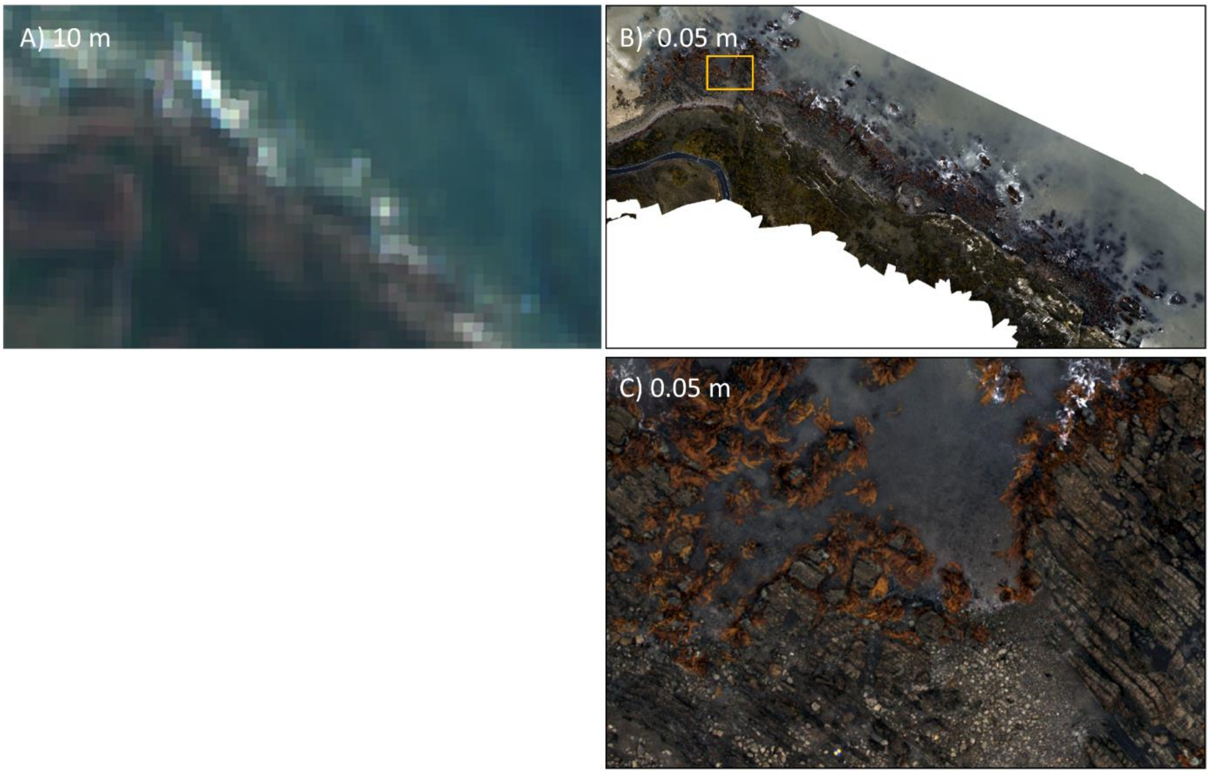

Figure 2: A comparison of kelp forest imagery acquired from difference platforms. A) Sentinel-2 imagery of a rocky reef with a 10m pixel size, B) a drone image of the same rocky reef with a 0.05m pixel size, and C) a zoomed in drone image with a 0.05m pixel size.

Spectral resolution: RGB versus multispectral imaging

Spectral resolution describes the number and width of spectral bands within the sensor. Visible light imagery, or RGB, includes three bands of data representing the intensities of the red, green and blue wavelengths of each pixel. This imagery is the same as a standard digital camera used for photography. Multispectral imagery includes additional bands outside of the visible light spectrum such as those in the ultra-blue, near infrared (NIR) and short-wave infrared wavelengths. This is particularly important when distinguishing vegetation because of the dissipation of infrared wavelengths during active photosynthesis. The reflection of electromagnetic radiation in specific wavelengths differs between species making it possible to distinguish species or higher functional groups in multispectral imaging. The combination of richer data (e.g., more bands) and specific spectral properties of different biogenic habitats in the NIR range provides a powerful tool for accurate identification of a greater range of species (Figure 3).

Freely available earth observation satellites regularly use multispectral imaging, such as the Sentinel-2A constellation (European space Agency: 13 bands between 443–2190nm) and Landsat-8 (U.S. Geological Survey: 9 bands between 430–1380nm) where the pixel resolution varies between bands. Fixed-wing or drones can be fitted with either RBG or multispectral cameras depending on resource availability.

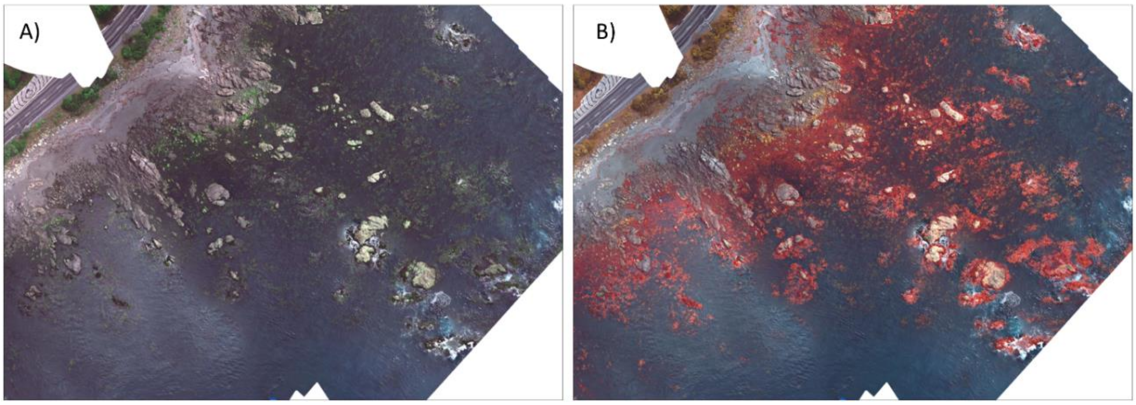

Figure 3: Drone imagery show in A) RGB and B) false colour to highlight photosynthetic pigments (red).

Tidal influences

When choosing a suitable imaging platform, a key consideration is the relative influence of the tide on the FOI. Intertidal areas, for example, are less amenable to observations with satellite imagery[1] for several reasons:

1. Satellites may not pass during desired tidal phases (e.g., over low or high tide).
2. Meteorologically and oceanographic conditions can obscure intertidal and shallow subtidal habitats.
3. Dominant species (or functional groups) form patchy mosaics.
4. Intertidal systems can be highly complex and composed of diverse mixtures of red, green and brown algae, as well as varied geological substrates and invertebrate communities.

Increases in water column depth within intertidal and shallow subtidal areas also depresses the spectral signatures of your FOI. This limits the use of all aerial monitoring at increasing depths, with water clarity further affecting the returning spectral signature of habitat classes.

[1] Note: some new datasets at resolutions of 80 cm may be useful. However, they must be purchased, and they have fewer spectral bands than widely available satellites such as Sentinel-2 and Landsat-8.

Summary

A summary of the recommendations for choosing the appropriate imaging platform is given in the flowchart below (Figure 4).

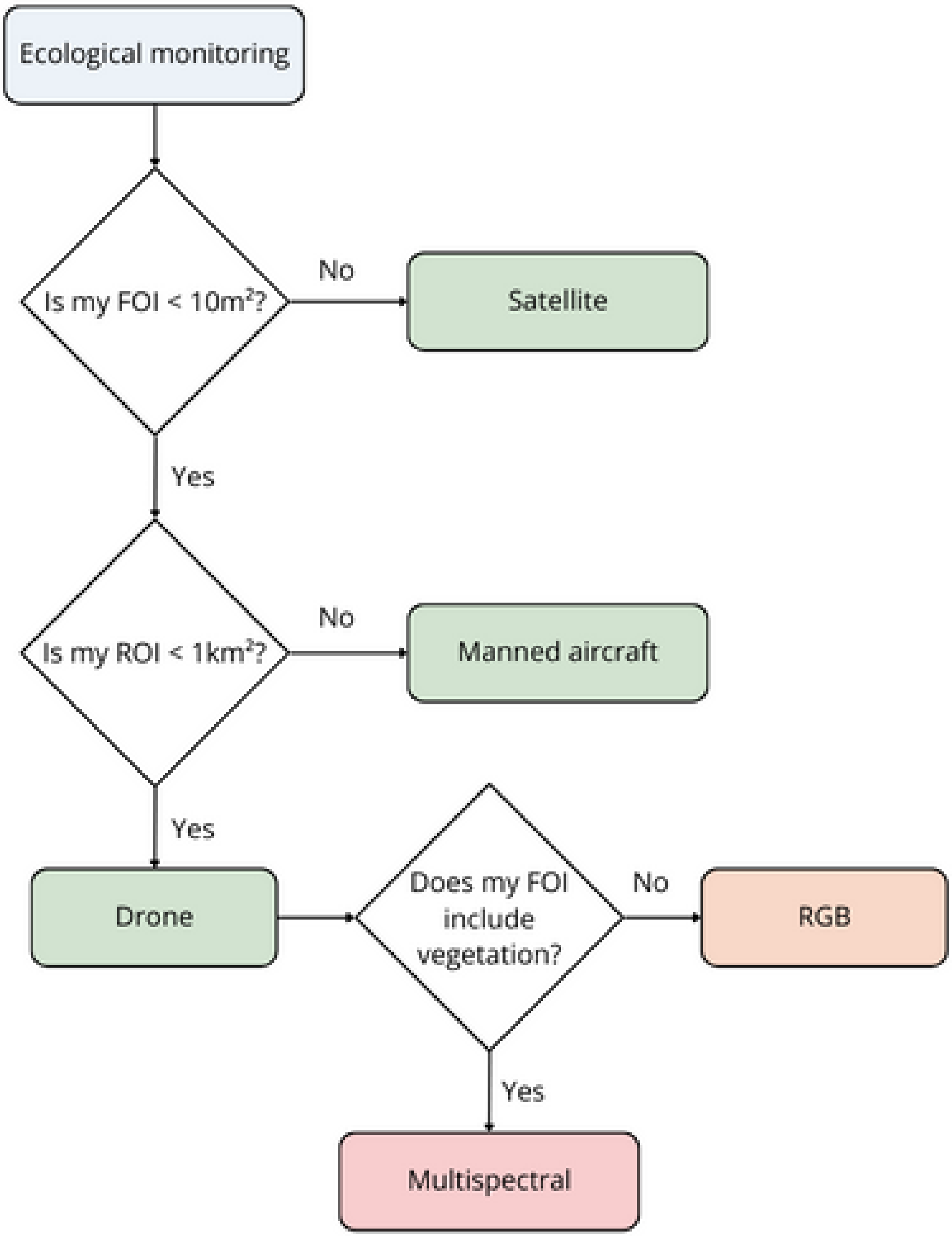

Figure 4: Flowchart decision tree for selecting appropriate imaging platform and camera type. FOI = feature of interest. RGB = red, green, blue camera.

The remainder of this document focuses on the use of drones for environmental and ecological monitoring.

Aerial monitoring using UAVs

Aerial drones are increasingly being applied to a range of environmental and ecological monitoring campaigns (Koh and Wich 2012; Chirayath and Earle 2016; Ventura et al. 2023), and in a number of ecosystem types such as rocky reefs and estuaries. In particular, drones are suitable for examining the spatio-temporal distribution of key biogenic features, or functional groups. As mentioned above, within some functional groups of vegetation it is possible to accurately separate to species/genus level, however, achieving this requires multispectral imagery (not RGB) and the integration of *in situ* sampling. *In situ* sampling provides validation of remote detection and allows robust estimates of uncertainty in analyses. Overall, the deployment of imaging sensors on UAVs has some advantages (as well as disadvantages) over other manned and unmanned platforms.

Key advantages include:

- High control over timing of imagery capture allows the alignment of optimal conditions for intertidal and shallow subtidal habitats.
- High pixel resolution allows smaller features, or patches to be identified.
- High pixel resolution imagery enables object-based recognition analyses, whereas coarse imagery (e.g., satellites) rely on spectral variation in pixels.
- Can enable scale matching between passive remote methods and *in situ* inventory surveys, e.g., typical *in situ* surveys monitor at samples of $1m^2$, which is difficult to align with $10m^2$ satellite pixels. However, $1\ m^2$ *in situ* quadrats can be matched to drone imagery (over 100’s–1000’s of metres squared), which can then be matched to satellites.

Key disadvantages include:

- Can realistically only cover small areas (e.g., $<1km^2$ within the windows that tides allow).
- Require field teams deployed to within 100–300m of study site.
- Depending on the camera used, the taxonomic resolution can be limited to functional groups.

Resources required

The primary tool for aerial monitoring is a drone. While there are many options for drones, there are a few minimum capabilities that should be considered for monitoring of coastal ecosystems.

1. Drones should be capable of flight times >15 minutes (ideally >20 minutes).
2. Camera should be at least 20 megapixels.
3. The data should be GPS integrated (and tagged into image EXIF files).

DJI© drones are becoming an industry standard across Aotearoa New Zealand because of their availability (including parts), reliability, battery life, security, and flight software. The exact choice of drone will depend mainly on the camera payload, with bigger cameras (e.g., multispectral cameras) requiring larger gimbals and stronger lift capacity. Other suggested equipment includes (see methodology for descriptions):

1. Real Time-Kinetic (RTK) -GPS system.
2. Large ground control points (GCPs, c. $1m^2$).
3. Point and shoot camera to record photos of "point samples".

Compiling imagery into a final orthomosaic of the survey area requires image stitching software. There are several options for stitching together imagery datasets and it is not the intention of this document to be prescriptive about the exact software that should be used. However, there are several considerations for choosing an appropriate software application:

1. Software should have capabilities for adding GCPs.
2. When using multispectral imaging, availability of camera specific plugins for various software platforms (or proprietary software specific to the camera) must be considered. Increasingly, key image stitching software can process multiband imagery.

Data storage also needs to be considered as the collections of aerial imagery products can produce very large datasets, especially when collecting multispectral imagery. Once processed the individual images can be converted into a large "orthomosaic" (i.e., a large image of the whole survey area) which maintains the pixel resolution of individual images but discards overlapping pixels occurring in multiple images. Retaining both datasets (individual images and combined orthomosaics) will require significant storage capacity. For example, unprocessed RGB and multispectral imagery from a single location $<1km^2$ = 60GB, with orthomosaics ranging from 80MB to 2GB.

Methodology

Aerial monitoring can be roughly divided into two sections:

1. Data capture and image pre-processing, and
2. Analysis and interpretation.

Data capture and image pre-processing

Data capture typically requires two people: a drone pilot and an experienced operator of a high-precision GPS system (e.g., RTK (Real Time-Kinetic)). Drone pilots must be certified to Civil Aviation Authority (CAA) level 1.01. Pilots will ideally have a good understanding of camera settings, particularly for optimising image exposure in order to deal with the range of lighting scenarios occurring in the field.

Suitable conditions for imagery capture

For all aerial platforms, mapping of coastal areas is best achieved by aligning a range of environmental and oceanographic variables, including:

- zero cloud cover, consistent high cloud cover or less desirable consistent cloud coverage
- sufficient light intensity to avoid slow shutter speeds or high ISO (i.e., blur)
- low tides and ideally spring low tides
- calm wave conditions to better observe the benthos
- clear water (i.e., not after storms/rainfall) to increase the depth penetration of imagery
- low wind speeds (<15 knots).

Aligning all these variables is extremely challenging and greatly limits the windows available for drone flying. However, UAV platforms are more flexible than other platforms (e.g., manned aircraft) which can be difficult to mobilise at short notice to make the most of ideal conditions.

Site setup

Before the flights commence, it is important to:

1. Select a suitable launching platform where the drone will be visible over the entire ROI.
2. Set up of RTK-GPS system if in use.
3. Place GCPs.
4. For multispectral imaging, install reference surface for camera calibration. This is typically a 2 x 2m white/grey reference mat captured within the sampling area.

The use of an RTK-GPS system, while not mandatory, increases geospatial accuracy, identifies FOIs, and allows the production of accurate digital elevation models (DEM, using photogrammetry); therefore, should be incorporated wherever possible. Position accuracy is critical if surveys will be repeated for change detection, comparisons of FOI are made at a per-pixel basis or if imagery is integrated with other geospatial data sources.

The RTK-GPS system often consists of a base station and a rover (Figure 5). The base station is a highly precise Global Navigation Satellite System (GNSS) receiver that provides real-time differential corrections that generates centimetre-level positioning data, while the rover is used to take high-resolution positioning data of specific points across the survey area.

Figure 5: A) A base station set up on a levelled surveying tripod, B) base station and rover on 2m survey staff and C) personnel taking the GPS coordinates of the GCP.

To accurately georeference your imagery, GCPs are used. A GCP is a point on the ground with known coordinates within the survey area. A GCP determines the relationship between the raw drone imagery and the point on the ground, geo-rectifying the raw positioning of the drone imagery. Omitting GCPs will result in your final image having an incorrect scale, orientation or absolute position. GCPs are usually at least 0.5m x 0.5m and are composed of at least two contrasting colours to ensure visibility within the drone imagery (Figure 6).

Figure 6: Examples of Ground Control Point (GCP) targets used during aerial drone mapping.

The number of GCPs required will depend on the survey area and the drone equipment being used, but generally between 8–16 across the survey area is sufficient. If the drone is RTK equipped then fewer GCPs will be needed (<8). Ideally, they will be placed evenly across the full survey area (Figure 7A), however in coastal environments this configuration is often impracticable so they should be placed where possible (Figure 7B), maximising a spread across any changes in elevation. The position of the middle of each GCP is recorded using high-precision GPS (cm accuracy) which is used during image pre-processing.

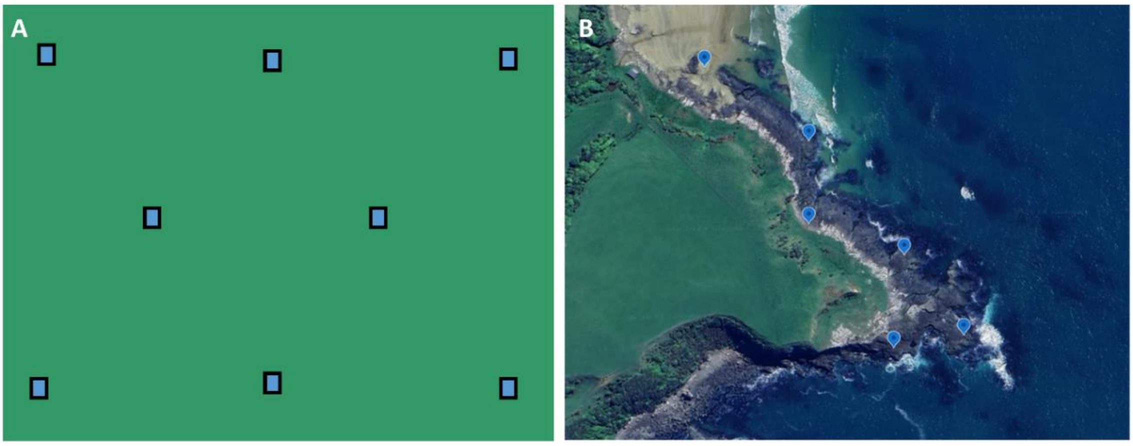

Figure 7: A) An example of ideal GCP configuration across a survey area and B) example of possible GCP locations on a small, narrow rocky reef.

Training samples

High-resolution GPS can be used to collect training and validation samples of relevant habitat types and/or taxa present within the survey area. Training data can be collected in several ways, with the methods of collection determining the robustness of machine learning results and accuracy estimates. Ideally, this would include haphazard collection of high accuracy GPS points across a range of FOI and associated habitats across or transect/quadrat inventories.

The collection of these training samples requires experience with Aotearoa New Zealand marine biodiversity, and ideally experience with the biodiversity of the study site. Once the species composition of a study site is well established, training data can be expanded by collection of sample polygons within GIS software.

Imaging

A full summary of camera settings is outside of the scope of this document and is highly subjective and condition dependent but broad guidance and key points related to camera and drone settings are outlined.

Camera settings are crucial to obtaining quality imagery. In particular, a fast shutter speed is critical for avoiding blurry imagery. Shutter priority mode is recommended, with 1/1000 shutter or faster (1/1600) in bright light conditions. Aperture, ISO and focus should be kept as auto (or infinity for focus). If lighting conditions are low or if the camera has a narrow aperture, both shutter speed and flight speed can be reduced.

Stop and shoot modes are not recommended as a way to reduce motion blur because drone flights are more stable when flying at a constant speed through clean air and become more unstable when hovering due to the creation of their own turbulence (Biggs 2020). A faster shutter speed helps to reduce or avoid motion blur whilst providing improved battery life and spatial coverage.

Both the ROI and FOI will determine lens selection (focal length). Many smaller amateur grade drones come with wide angle lens (between 8-24mm focal length). Increasing the focal length greatly increases pixel resolution at the ground, but reduces area covered.

When deciding on flight settings, it is important to have a minimum overlap of 60/80%. This means 60% overlap on the sides (i.e., from one flight line to the next) and 80% front to back (i.e., from one image to the next).

Flight altitude will be determined by the ROI and FOI, with a trade-off between pixel resolution and spatial coverage (flight time; Figure 8). For example, halving the altitude will increase the flight time by four. As a rule of thumb pixel size should be one half to one quarter the size of your FOI. It is also worth considering the homogeneity of the ROI and the challenges of featureless environments for image stitching. Such environments might require higher altitude flights to capture identifiable features across multiple frames.

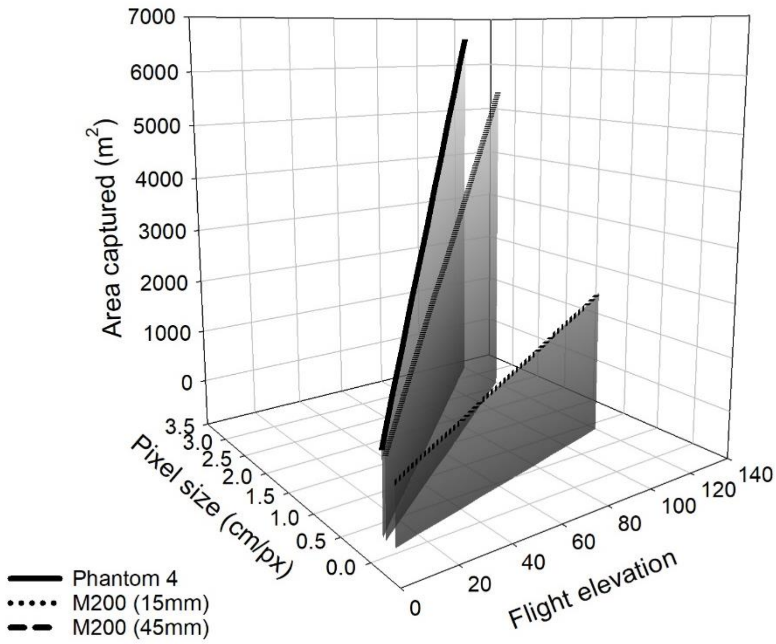

Figure 8: Visualisation of the influence of flight elevation on pixel size at the ground and area captured for three imaging systems with different camera focal lengths.

Image pre-processing

Once quality images have been collected, an image stitching programme is required to combine individual images into a single orthomosaic image covering the extent of the ROI. There are a number of software platforms that can be used, many of which can run with little intervention, but this will vary depending on whether RGB or multispectral imagery was collected. Inputting GCPs (curtesy of RTK positioning of GCPs) can require a greater understanding of these platforms and experience with these procedures is recommended. Pre-processing is completed over a number of steps:

For multispectral images:

>> Stitch images >> Georeference ground targets >> Mask or clip unwanted regions >> Calculate bands (e.g., DEM) >> Combine bands >> Export for classification.

For RGB images:

>> Stitch images >> Georeference ground targets >> Mask or clip unwanted regions >> Segment image >> Export for classification.

Post-processing: analysis, interpretation and reporting

Post-processing here refers to the manipulation of imagery products (i.e., orthomosaics produced during the “pre-processing” stage). Analysis of spatial datasets requires experience using GIS software such as Esri®ArcGIS™ Pro. Familiarity with procedures such as clipping, masking, compositing, geo-rectifying, confusion matrices, and classification features is recommended. The classification procedures will benefit from having people with experience in the broad habitat types and species present and their distribution (or experience implementing automated habitat classification for other ecosystems).

Data analysis

It is not the intention of this document to be prescriptive about the exact software applications required. Where possible techniques are described broadly and it should be noted there are many applications that can be used, some of which are open source. For transparency, the author has used Metashape (Agisoft) for pre-processing of RGB and multispectral images including identifying GCPs, image orthomosaic creation and DEM creation, and uses ArcGIS™ Pro (ESRI®) for post-processing and data analysis. Key points:

- Orthomosaics should be pre-processed to mask areas outside of the study zone.
- When importing from separate pre-processing software, ideally orthoimages should be in the geoTIFF format.
- Coordinate systems need to be uniform across all data types and sampling points. We recommend using New Zealand Transverse Mercator (NZTM2000) across software applications.

- Where possible orthomosaics should include other data such as elevation or relevant indices (e.g., normalised difference vegetation index (NDVI) and Normalised Difference Water Index (NDWI)).

- User defined training samples should be saved in a “shape” file format (“.shp”).

- For object-based classification procedures, image segmentation is required.

- Validation samples can be imported as GPS points labelled with habitat classes (typically imported as CSV file).

- Training samples are used for training machine learning algorithms such as random trees, and support vector machines (SVM). For every pixel (multispectral) or segment (RGB) these algorithms will decide the most likely class based on spectral signatures (multispectral) and segment attributes (size, shape).

It is often necessary to run multiple iterations of classification to determine if all distinct features within the area of interest are captured. It can be necessary to use one or more ambiguous habitat classes that describe, for example, vegetation covered by varying depths of overlying water, or habitats obscured by shadows (Figure 9). The relative accuracy of multiple iterations can be assessed using the testing samples and the production of confusion matrices and “Cohens Kappa” values. More detail is available in the open-source, peer reviewed manuscript by Tait et al. (2019).

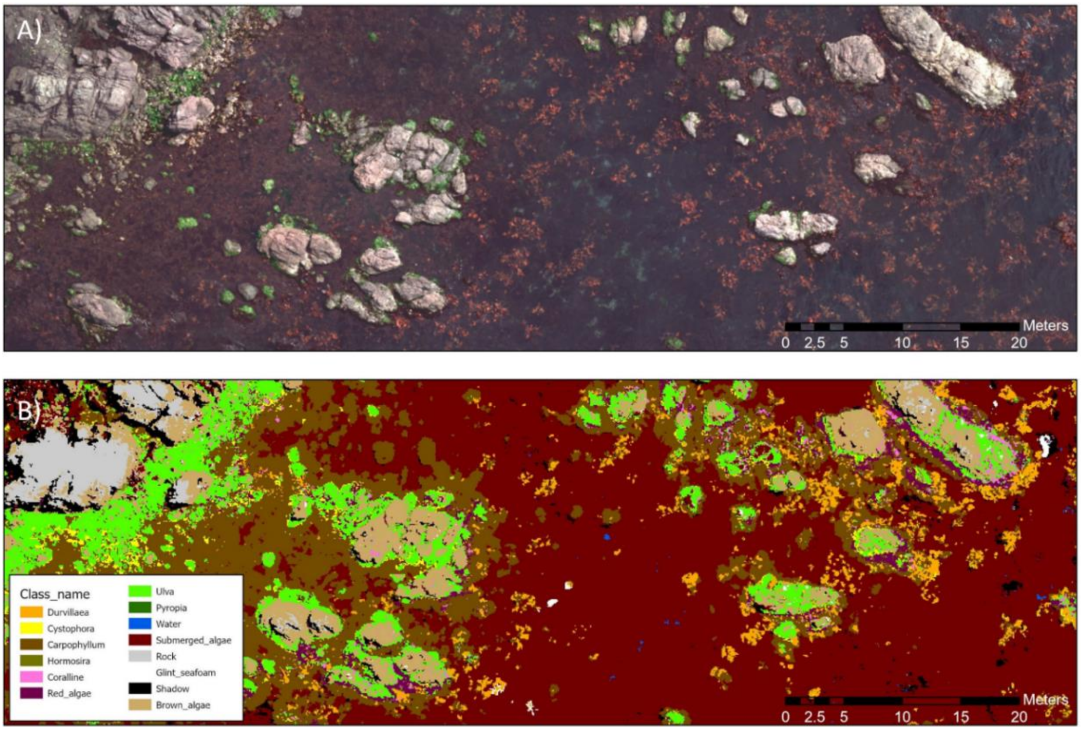

Figure 8: An example of A) multispectral imagery of a rocky shore, and B) the classification of multispectral imagery.

Data interpretation

The key value for interpreting the outcomes of habitat classification procedures is the Cohens Kappa, produced by confusion matrices. A value >0.85 is widely recognised as an acceptable degree of accuracy for automated classification of habitat types.

Calculation of confusion matrices requires two inputs, the classified image, and the testing dataset. These indices determine the proportion of pixels/segments classified correctly, but also identifies the classes where incorrect pixels/segments were identified. High rates of misclassification may require similar classes to be combined.

Reporting

Following classification procedures, it is possible to extract each habitat class and provide an estimate of coverage. Changes in coverage through time can be sub-sampled within replicate clips of the wider orthomosaic and reported as time-series trends. More sophisticated spatial analysis of patch dynamics is outside the scope of this document.

Summary of workflow

An overview of the proposed workflow for planning UAV surveys, key *in situ* datasets to be collected and the steps for analysis and accuracy assessment of classified outputs is given in Figure 10.

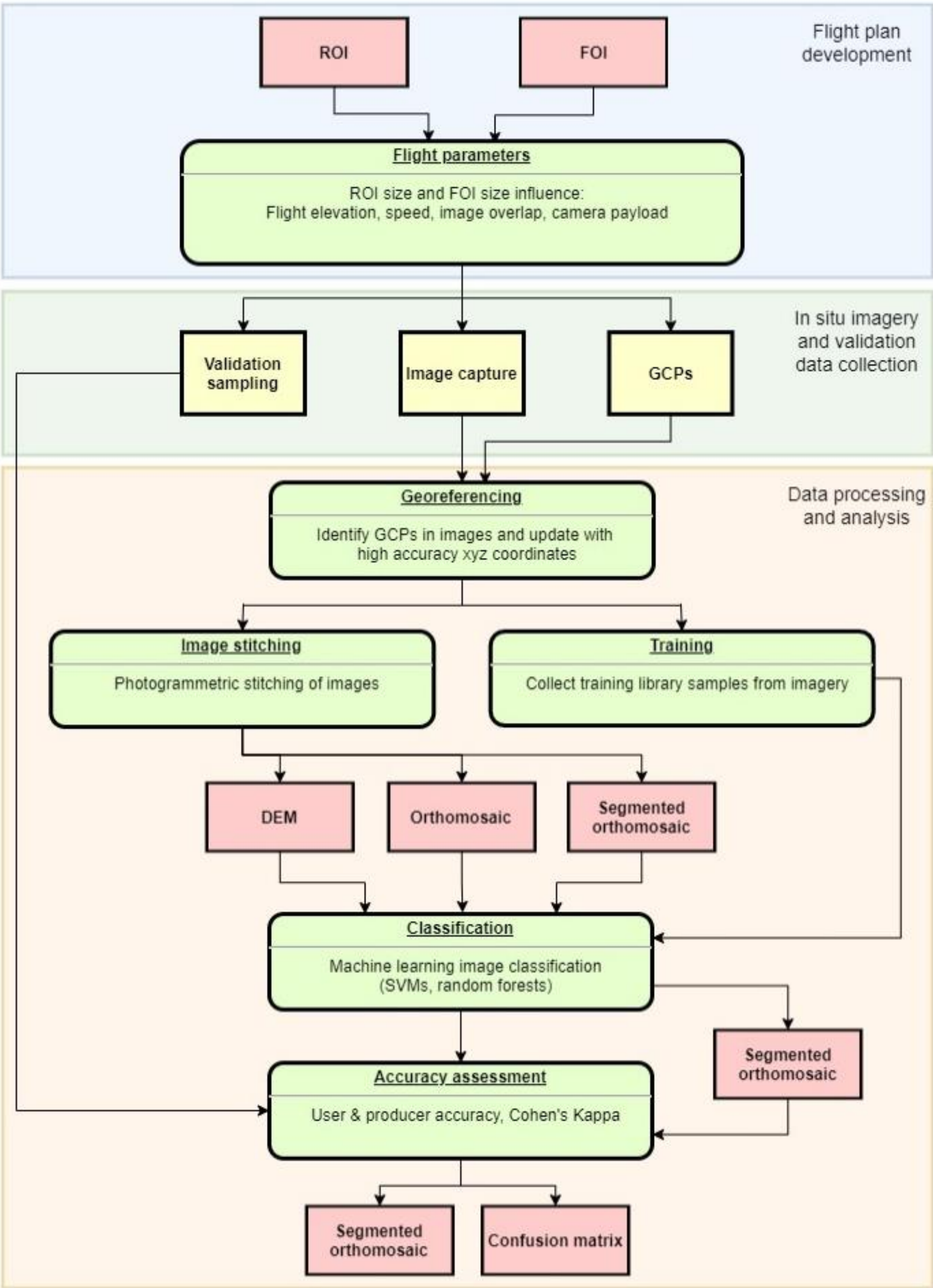

Figure 10: Proposed workflow for planning and undertaking UAV surveys and the steps for analysis. The size of the Region of Interest (ROI) and Features of Interest (FOI) are key in determining flight parameters, particularly the altitude of image capture. For example, a large ROI and very small FOI may be incompatible as the required ground pixel size would require low altitude mapping which can be difficult to achieve over large areas. GCP = Ground Control Points; DEM = Digital Elevation Model; SVM = Support Vector Machines.

Case study

Outline

Exposed rocky reef coastlines are some of the least accessible habitat types in the marine environment. These habitats have traditionally been sampled by field researchers using quadrats and transects, but sampling is often highly limited in spatial extent and is biased by accessibility. Aerial imaging via drones can enable very high coverage sampling of these reef platforms and can reduce the bias of accessibility by imaging rocky reef not accessible via land or sea. Here we detail an aerial imaging case study to assess the demographics of habitat-forming algae. The goal of these imaging campaigns was the identification of habitat-forming species to genus or functional group level across 10’s–100’s of hectares across multiple sites. We focused on the ecologically and culturally significant southern bull kelp (*Durvillaea* spp.) which has shown high vulnerability to marine heatwaves.

Methods

We mapped and sampled rocky reef areas using a combination of aerial imaging and *in situ* sampling with high accuracy GPS survey equipment.

Aerial imaging protocol

Flights were generally completed during the lowest tide series of the month and were completed within 30–60min each side of peak low tide. Marine conditions were typically limited to wave heights less than 1.0m and ideally coincided with light offshore wind conditions. This combination of conditions also needed to coincide with favourable sun angles (middle part of the day), resulting in a relatively specific set of operational parameters that directed the flight planning stage.

Multispectral imagery was captured on a DJI Matrice 600 (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with both an Airphen® (Hyphen, Avignon, France) six-band multispectral camera and RGB imagery on a Sony mirrorless RGB camera. The Airphen® multispectral camera has a focal length of 8 mm, a sensor resolution of 1280 × 960 pixels, and six synchronized global shutter sensors, centred at 530, 570, 630, 670, 710, and 750nm (band width 10nm). The three bands of the Sony® (Konan, Minato-ku, Tokyo, Japan) RGB camera span the visible wavelengths (400–700nm), with large overlap between blue and green and green and red, but little overlap between red and blue. The Sony camera was an A5100 with a 15mm Voitlander® (Braunschweig, Germany) rectilinear lens, providing final images of 6000 × 4000 pixels. Flights were at an elevation of 30m with 85% overlap and 80% sidelap to achieve a pixel resolution of 0.7cm.

To georeference the RGB and multispectral imagery, c. 16 GCPs were laid out evenly across the ROI and were surveyed using a high accuracy GPS system. During the drone flights, c. 200 surveyed “samples” of up to 16 dominant species (FOI) were collected across the ROI using the same RTK-GPS equipment. Tying these validated samples to the aerial imagery was achieved through precise identification of “targets” to the measured coordinates during both the image stitching phase and at the whole orthomosaic scale. The resulting dataset provided a foundation for accuracy assessments of habitat classification and provided even coverage of multiple habitat-types.

Imagery analysis

RGB imagery (8-bit) was stitched together using Agisoft Metashape™ (Agisoft LLC, St Petersburg, Russia) to create a 3-band orthomosaic image with a final pixel size of 1.25cm^2 per pixel. Multispectral images (32-bit) were stitched together using Agisoft Metashape to produce a 6-band orthomosaic with 2.5cm^2 pixels, a 3-band RGB orthomosaic, and a DEM. Reflectance was calibrated using a reference panel and the radiometric calibration tool in Agisoft Metashape™. A single-band NDVI orthoimage was calculated using the red, and NIR bands of the multispectral camera.

Habitat classification procedures were done on a per-pixel basis for multispectral imagery (6-bands + NDVI) using SVM, trained using 50 training samples per class (ArcGIS™ Pro, ESRI®, West Redlands, CA, USA). This analysis can be performed using the “Classification Wizard” or “Supervised classification” functions. For multispectral imagery “pixel-based” classification is ideal, however, RGB imagery should be segmented and classified using “object-based” classification.

RGB imagery was used to identify training samples within the multispectral image and provided an additional quality control layer to ensure alignment between validation samples, and the species/habitats they represented. Training samples were collected as polygons selected around habitat classes encompassing, in some cases, several hundred pixels. Determination of sample classes was established based on the species and taxonomic categories identified from *in situ* surveys. The *in situ* validation samples were retained for accuracy assessment to avoid overfitting. The assigned classes were: *Durvillaea* spp.; other brown algae (mostly *Carpophyllum maschalocarpum*, but also including the occasional *Cystophora* spp.); *Ulva* spp. (green algae, sea lettuce); red algae; coralline algae (including articulated and crustose coralline algae); a generic algal class not readily identifiable to species due to increasing water depth (but still identifiable as vegetation); bare rock; water (with no visible submerged vegetation); and shadow. User and producer accuracy were assessed by an equalised stratified random sampling procedure. Cohen’s Kappa of the combined agreement between the classified dataset and the validation sample was also computed.

Example of results

RGB and multispectral imagery produce differing imagery (Figure 11). The multispectral imagery can provide additional information, including a DEM and computation of vegetation indices (Figure 12). The presence of red-edge and NIR bands (Figure 12D) and the use of band arithmetic procedures (e.g., NDVI; Figure 12E) allowed the relative coverage of photosynthetic and heterotrophic habitat-formers to be assessed (e.g., algal beds and mussel beds). The incorporation of DEM layers (Figure 12C) enabled more refining of the ROI and incorporation of natural zonation patterns into classification routines. However, photogrammetric reconstruction of elevation performed poorly over water, particularly where breaking waves occur, and DEM estimates over water should be discarded.

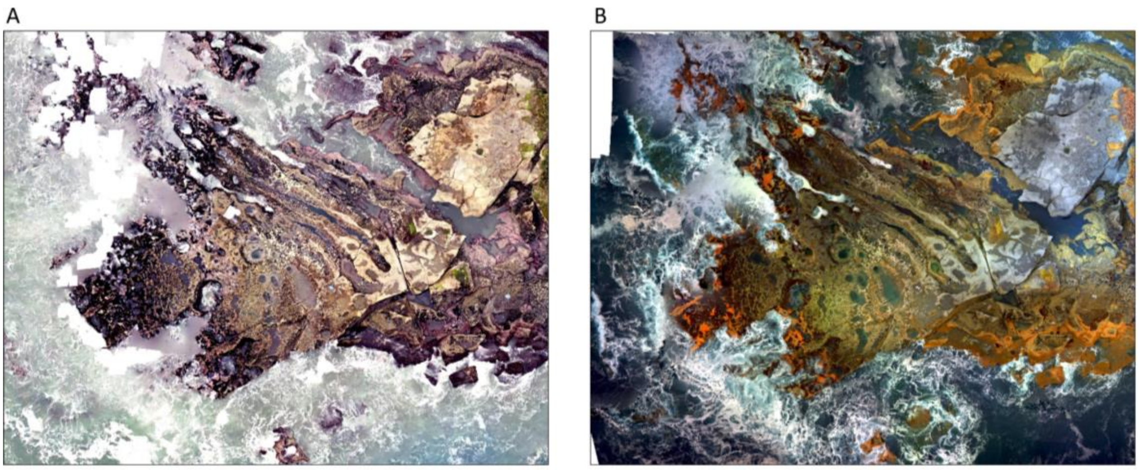

Figure 11: Raw imagery layers taken from (A) an RGB camera, and (B) a 6-band multispectral camera.

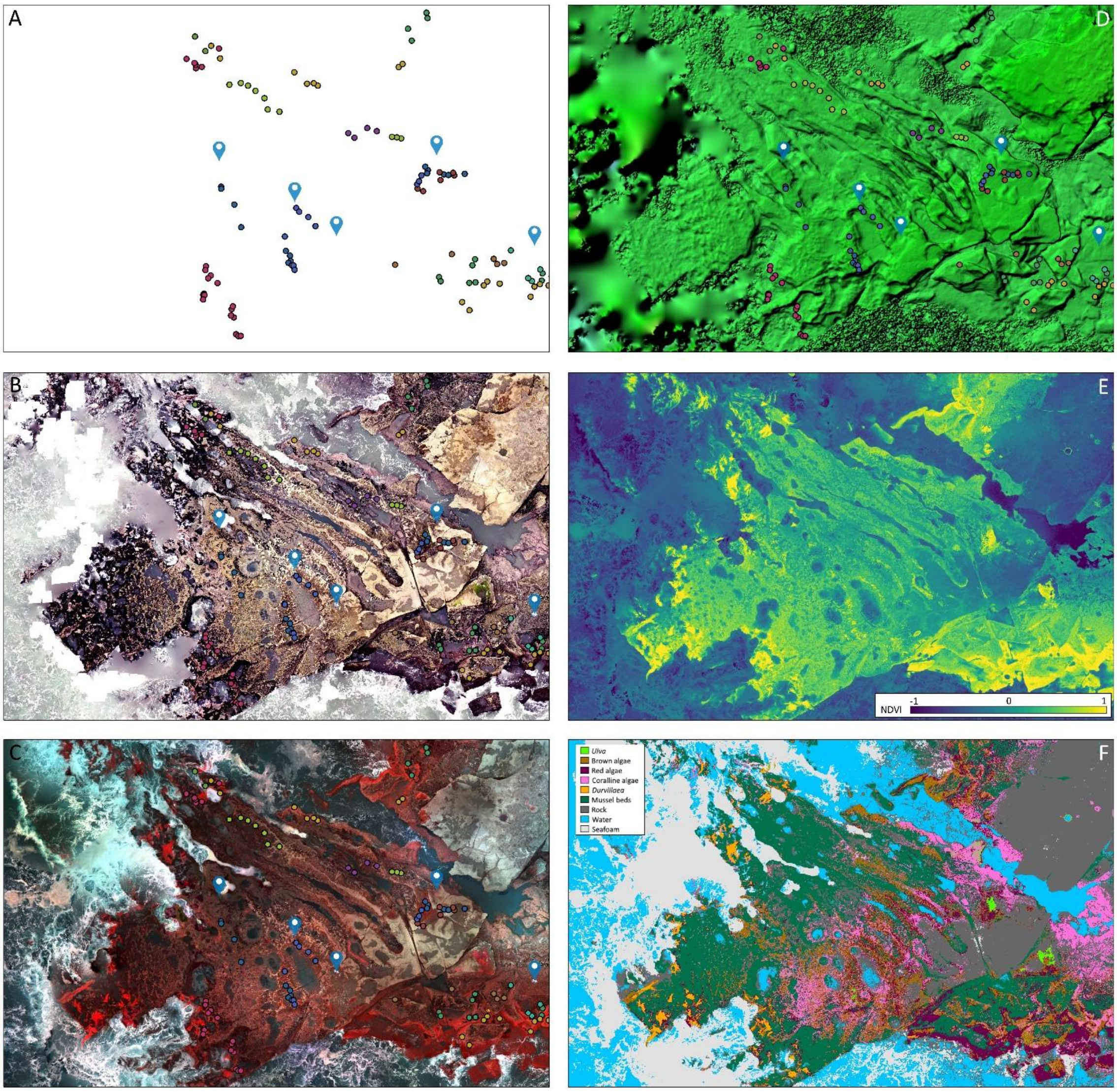

Figure 12: Layers of imagery and geospatial information of rocky reef ecosystems for performing and assessing habitat classification procedures.Layers show (A) locations of ground control points and in situ *validation samples for multiple habitat types; (B) RGB imagery; (C) photogrammetric construction of a digital elevation model; (D) 6-band multispectral imagery (false colour image showing NIR in "red" band); (E) normalised difference vegetation index; (F) classification results.*It is important to recognise that this imagery was captured under favourable conditions; consistent cloud cover (i.e., not changeable), very low tides, moderate sea conditions, and close to midday sun. The ability to take *in situ* measurements at depths greater than 1m is difficult, and deeper vegetation may have a unique spectral signature relative to bare substrate, but it is not possible to separate species.

The accuracy of machine learning habitat classification procedures showed overall high accuracy, with 94% of validation samples correctly classified (kappa value of 0.94.) All individual classes showed greater than 85% agreement with validation samples except for the user accuracy metric for *Ulva* spp. The high accuracy of species or functional group detection within high resolution multispectral imagery therefore provides a useful tool for monitoring diverse rocky reef ecosystems.

Details of the full study are available in an open-source, peer-reviewed manuscript by Tait et al. (2021a).

Glossary of abbreviations and terms

CAA	Civil Aviation Authority
DEM	Digital Elevation Model
FOI	Feature Of Interest
GCP	Ground Control Points
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
ISO	ISO is the sensitivity to light for camera sensors. The acronym stands for "International Organization for Standardization" but has little relevance for the use of this camera setting
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NIR	Near Infrared Radiation
Orthomosaic	An orthographic image produced by "stitching" many overlapping images together
RGB	Red Green Blue camera
ROI	Region Of Interest
RTK	Real Time-Kinetic
SVM	Support Vector Machines
UAV	Unmanned Aerial Vehicle

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