Introduction

Coral ecosystems are worth up to $172b in value per year for the world economy [1]. However, they are under considerable threat from global factors such as climate change and acidification, but also local factors such as destructive fishing practices, tourism and other pollutants. Coral surveys are vital to measure impacts and help advise governments and conservationists on management.

This introduction will give a brief insight to these threats and introduce various methods currently employed to measure the impact.

Understanding coral and their differences

It’s possible to split coral into two types, warm and cold water (or mesophotic) coral with the currently known locations shown in fig.1. Reef ecosystems in warmer waters photosynthesise using algae in temperatures ranging between 22-29°C. Whereas colder water corals grow much slower (5-25mm a year) and use larger polyps to catch food particles in the surrounding water. Reefs in cold water tend to have far fewer fish species in comparison with tropical reefs, but can have just as many invertebrate species.

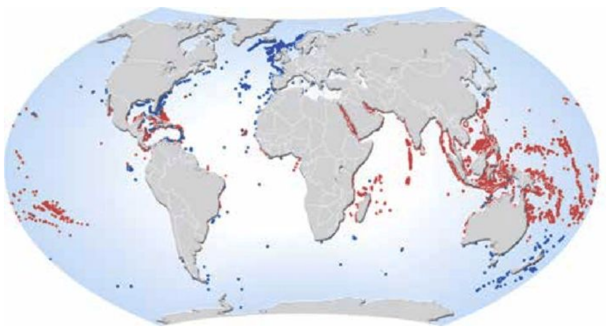

Fig.1: Cold water (blue) and tropical coral reef locations (red),Hugo Ahlenius.[2]

Reef health and actionability for government and conservationists

Both tropical and colder water coral are heavily impacted by temperature increases and ocean acidification from climate change, while the impacts of tourism are most obvious in shallow, tropical reefs.

One obvious sign of impact from climate change is coral bleaching where an extra few degrees cause coral to release the algae they use to cover sunlight for food, leaving a bright white skeleton. In addition, when typical reef areas are dominated by algae [3].

For governments and conservationists, the benefits of measuring tropical reef health can have significant natural and economic benefits.

Fig.2: Coral and reef builders vs. Algae [3]

One of the most high profile examples being the closure of Phi Phi Leh Island, Thailand, and within months of it’s closure in 2018, the ecosystem had already seen a return of reef sharks. On the other hand, Raja Ampat in Indonesia has seen a protected area set up around it’s islands, allowing locals to manage the reefs while benefiting from sustainable fishing and tourism. Know when and how to act is largely down to the success of marine surveys.

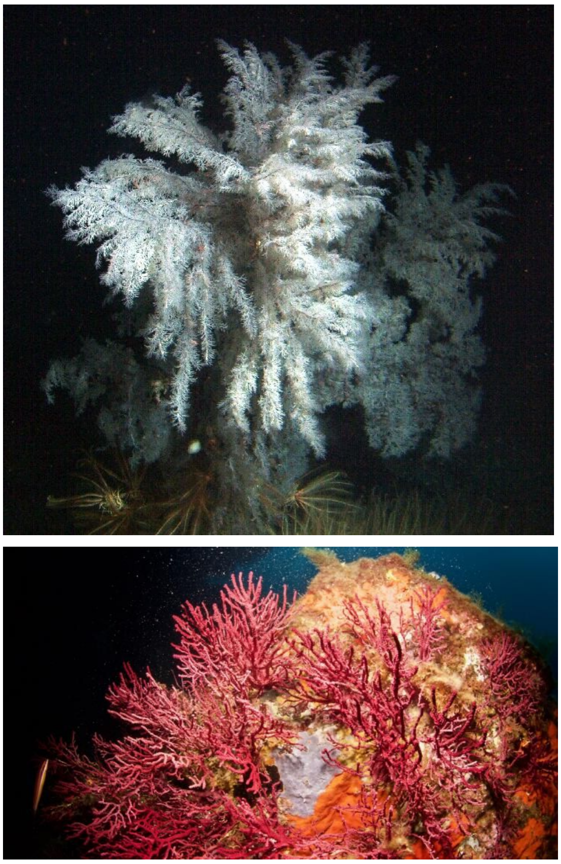

Fig.3: above: Antipathes dendrochristos, Mark Amend [4]. below: Thesea dalio, fotolia

Exploration

Exploration is also an important aspect of monitoring these environments, with less than 0.05% of the global seabed mapped by sonar [5], and far less using cameras. Unsurprisingly, new coral species are being discovered regularly, for example the cold water Antipathes dendrochristos in 1995, with description published in 2013 [4] and Theresea Talio off the coast of Panama in 2018 [4b] (fig.3).

Satellite monitoring

Measuring the risk of climate change, satellite imagery offers significant advantages in scale. For example, NOAA () predicts bleaching risk globally through sea temperatures [6], but breakthroughs in analysis have allowed reefs to be mapped through Dove satellite image segmentation (example results shown in fig.3)[7] . Tracking color changes in images over time will provide general indication of coral health, whether live, bleaching or dead.

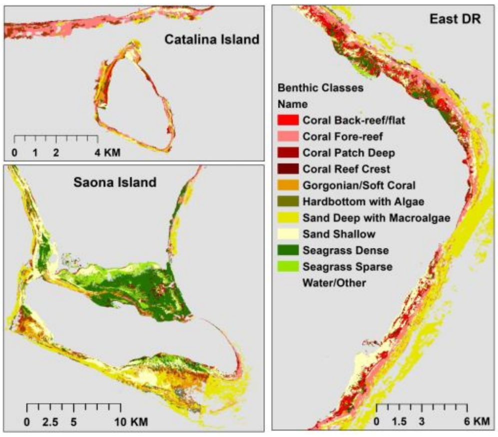

Fig.4: habitat classification results using satellite image segmentation [7]

‘Although the Dove imagery provides a 3.7m spatial resolution, it is sometimes not sufficient for detecting complex mixed benthic composition classes, such as gorgonian/soft coral habitats.’[7]. This issue is common for other satellite based solutions, such as Eomap with 2m resolution [8].

Camera based image capture

Photography captures benthic taxonomy more accurately than by satellite.

There have also been attempts at ‘multi-view’ reef imagery, captured by divers and result in 3D coral maps once stitched (fig.5). While offering unparalleled and unobstructed surface area, methods can require one man hour to collect images in a 10 x 10m area.

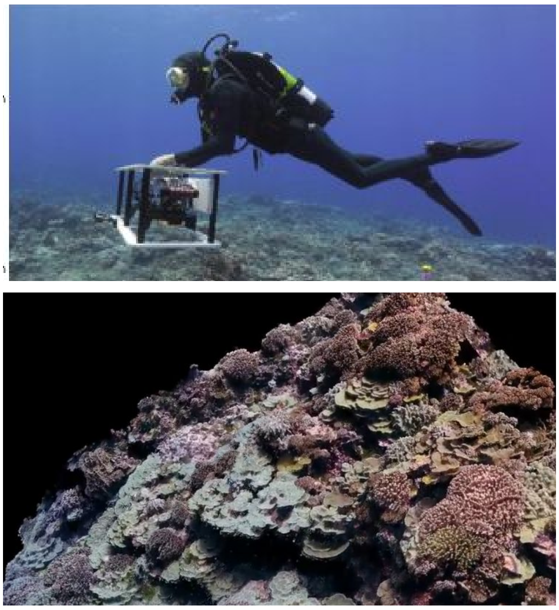

Fig 5: Top: diver captures images with dual-camera. Bottom: 3D point cloud map at Millennium Atoll, 2013 [9].

Autonomous underwater vehicles address this man hour challenge when it comes to data capture by taking thousands of images in a single mission, but are yet to use ‘multi-view’ cameras.

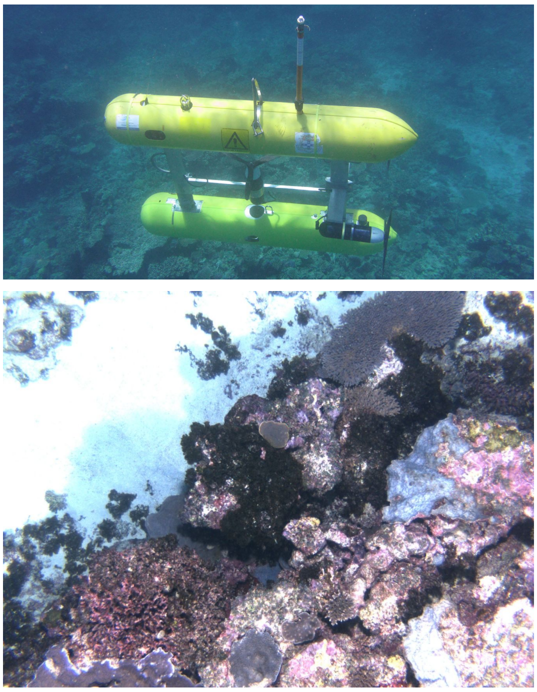

Fig 6: Top: AUV on survey mission. Bottom: Example AUV benthic image taken in Australia.

Image annotation challenges

Efficient annotation of images is crucial for analysing coral at scale and much is dependent on image quality. There are a number of factors which can affect the ease in which this can be done, for example, lighting, distance, turbidity and class overlapping. For captures with an AUV there is also risk of motion blur. 3D maps partly solve some of these difficulties but require up to 60 man hours for a 10 x 10m area [10].

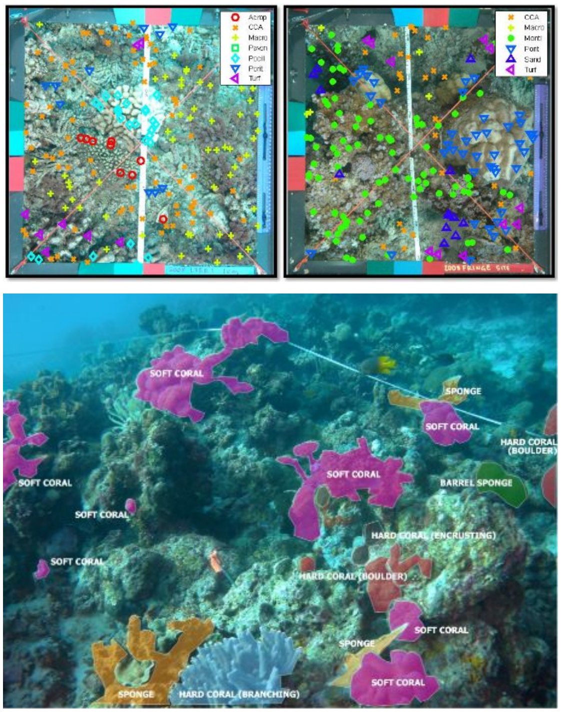

Fig 7: Top: example of point annotated images from UCSD's MLC dataset [sparse]. Bottom: segmentation based manual annotation type example [pix][11].

Feature maps and augmentation

Data augmentation such as flipping and mirroring has limited benefit when using small patches [12].

Pattern or texture recognition is a key objective because of the diversity in coral appearance and class overlap. A combination of HSV colours and a Local Binary Pattern feature map achieves better results than on their own [13].

RGB colour alone is not good enough for underwater imagery, and LAB colour space is more effective than both RGB and HSV [15].

Deep convolutional neural nets have been shown to capture better detail than using hand-crafted image features [16], examples in fig.8.

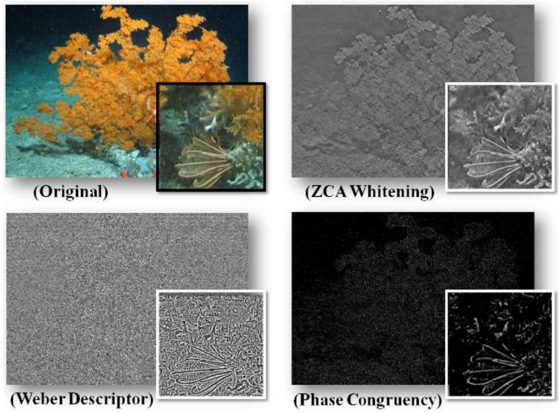

Fig 8: Examples of hand-crafted image features [14].

Other model challenges

While Convolutional Neural Networks show the most promise in coral classification problems, most breakthroughs have come in bounding box methods such as Faster R-CNN or through the semantic segmentation of Mask R-CNN. However, annotations of underwater imagery are most often executed with random point annotations, which are necessary for time and reliability reasons. Therefore work arounds are needed such as using CNN feature maps as input to a more traditional classifiers [17].

For point cloud segmentation, while having less issue from class overlapping a key challenge is in recognising edges of a coral structure where texture may be inconsistent.

Many datasets contain class imbalance, which can have considerable impact on performance. Rather than over or undersampling, a cost learning layer was added before the soft-max [17]. [21] Shows an alternative solution.

It would also be important to note that most accurate CNN based models use transfer learning from widely used architectures such as ResNet and DenseNet pre-trained on ImageNet, for example [12].

Problem statement

Traditional solutions for reef surveys involve manual data collection by divers, which is expensive, time consuming and can't be scaled up easily, while satellite solutions have a wide scope but lack the capability to analyse deeper reefs or provide details of reef taxonomy. Therefore, in terms of exploring and measuring health of specific coral species, data collection via AUV provides the best opportunity to cover greater areas than traditional methods, and improved detail and depth over satellite imagery.

However, despite these advantages in terms of collection, the images captured need to be annotated before further analysis has been begun. This is not feasible through manual work if reefs are to be monitored regularly and en masse. In addition, thousands of AUV captured images are sitting unannotated due to time constraints of scientists. Therefore it can be difficult for conservationists and governments to understand imminent threats from local and global impacts.

Datasets and inputs

We have three available datasets which represent alternative input types useful to researchers.

The main dataset used in the project will be RSMAS, which contains 766 image patches of size 256x256 with 14 classes, collected by divers from the Rosenstiel School of Marine and Atmospheric Sciences of the University of Miami [18]. Photos were taken under different conditions and are zoomed in on sections of coral so each one contains just one class.

The first alternative dataset, out of the scope for this project would be the random point annotated AUV reef dataset, BENTHOZ-2015. With almost 10,000 images taken around Australia over different years and over 400,000 annotations [19].

However, the future of AUV coral reef data capture will likely be in 3D point cloud format, so a reef map from the 100 island challenge project by the Scripps Institute of Oceanography would fit that bill.

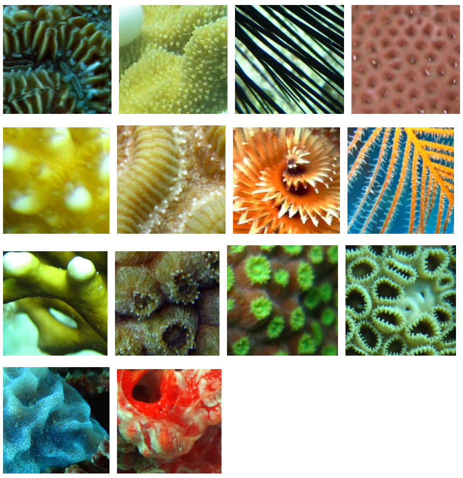

Fig 9: RSMAS [18] examples, classes left to right, row 1: Mmea, apal, dant, ssid. Row 2: Acer, cnat, dstr, gorg. Row 3: malc, mca, mont, paly. Row 4:spo, tuni.

Solution statement

Using the RSMAS dataset, preprocessing will involve color map modification to account for the lighting differences and highlight texture. Classification will be performed using a simple CNN on a ResNet150 architecture pre-trained on ImageNet, which showed the best results for this dataset [12].

The architecture will then deliver classifications via an api endpoint to a user who has uploaded reef patch photography.

Practically speaking, this tool will classify localised patches of a reef image, returning likelihood of certain corral types in the global space. However, this does not offer object localisation in the traditional sense.

Improvements to this tool could be possible by exploring unsupervised segmentation approaches on the BENTHOZ-2015 dataset, or semantic segmentation using the ‘100 Islands’ point cloud dataset.

Benchmark Model

The benchmark to be used will be using a vanilla CNN as opposed to a pre-trained network with colour map modifications.

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