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Comparative image analysis approaches to assess ecological effects of macroalgal removal on inshore reefs of Magnetic Island, Australia

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Abstract. Macroalgae removal is a proposed management option in the GBR to reverse declines in inshore coral reef health. Automated image analysis (AIA) is a valuable tool to assess benthic community assemblages. This study compared the accuracy of benthic community assemblages assessed through the AIA program CoralNet to manual image analysis. The ecological effect of macroalgae removal on benthic community composition was also investigated on established permanent quadrats (5x5 m) for reefs at Florence and Arthur Bay, Magnetic Island. Control and treatment quadrats (n=3 respectively) were photographed before and after macroalgae removal over 6 months. The results obtained by AIA and manual approaches were consistent, with macroalgae cover is approximately 77%-87% in all quadrats before macroalgal removal. Through the monitoring period, a small increase in coral cover in the macroalgal removal quadrats was observed in Florence and Arthur Bay (an increase of 1.8% and 0.1%, respectively). CoralNet was demonstrated to be robust for assessing reef benthic cover with no significant difference in recorded benthic categories when compared to the manual approach. CoralNet was accurate for identifying broad benthic categories, but less effective than manual image analyses for lower taxonomic categories (i.e., genus or species level).

Keywords: CoralNet, Macroalgae removal, Magnetic Island

1. Introduction

The Great Barrier Reef (GBR) is one of the most extensive and diverse coral reef ecosystems on the earth [1]. It supports important ecosystem services including maintaining marine genetic resources and providing ecological habitat for marine fauna, physical protection to coastal areas, and structural support for marine industries such as tourism and local fisheries [1]. However, multiple cumulative pressures are resulting in mass coral bleaching, overfishing, land-based sediment, pollution, nutrient run-off, and increased frequency and strength of tropical cyclones, all of which have impacted many areas of the GBR [2]. Recent studies have documented the loss of coral cover on the GBR over the past 40 years. For example, Death, Fabricius, Sweatman, and Puotinen [3] reported a significant decline in coral cover from 28% to 13.8% between 1985 to 2012. More recently, Hughes, Kerry, and Simpson [4] reported more than 60% corals loss due to back-to-back mass bleaching events in 2016 and 2017, with even remote and relatively pristine regions exhibiting high coral loss. Inshore reefs of the GBR are impacted not only by increasing seawater temperatures but also by declining water quality due to poor coastal land management.

Magnetic Island is situated in the central inshore region of the GBR and experiences multiple cumulative pressures which have contributed to reef degradation [5]. Elevated nutrients and sediments from marine dredging operations combined with water discharge and land-based sediments from coastal river systems have particularly impacted the water quality of fringing reefs around Magnetic Island [6-8], which have been categorized as “poor” to “very poor” condition [9, 10]. Over the past three decades, there has been a persistent shift from coral to macroalgae dominance [11]. Through visual census surveys, it has been observed that the coral cover on the inshore reefs of Magnetic Island has declined from 40-50% to 20-25% over the last 30-year period, while macroalgae cover remained relatively high (up to 40%) [9, 11]. The drivers of this shift can likely be attributed to changes in water quality, with extensive monitoring having documented high chlorophyll-*a* and phosphorus concentrations and high turbidity characteristic of degraded reefs [12]. High sediment and nutrient loading can inhibit coral recruitment, reduce the light available for photosynthesis, smother and kill coral tissue, and increase the incidence of coral diseases [13, 14]. Although sediments can also be stressful to macroalgae, algae are generally less impacted and exploit new areas rapidly. The observed benthic community shifts at Magnetic Island can be correlated with high turbidity levels derived from the Port of Townsville dredging activities and the Burdekin River discharge [8]. The combination of multiple pressures leading to effective replacement of one dominant benthic community by another, is known as a phase-shift [15].

The inshore reefs of Magnetic Island are structurally complex marine habitats. This three-dimensional habitat plays an essential role in ecosystem function and resilience, including providing shelter and refugia for benthic and pelagic organisms [16]. Diverse benthic assemblages have been documented on these reefs including a range of coral genera (e.g. *Acropora, Montipora, Porites, Favia,* and *Favites*) and macroalgae (e.g. *Sargassum, Padina, Lobophora,* and *Caulerpa*; [17, 18]. *Sargassum,* however, represents more than 85% of the total macroalgae biomass on the reefs at Magnetic Island [18]. Macroalgae is an important component of inshore reef ecosystems with canopy forming *Sargassum* establishing intermediary spaces in between, within, and underneath the alga, which provide refugia and particular environmental conditions that support other benthic and pelagic organisms [19]. However, in high abundance, macroalgae and especially *Sargassum*, can have negative effects on the benthic fauna underneath [20]. For example, macroalgae and coral species coexist in complex reef habitats and compete for space. Opportunistic macroalgae can grow rapidly; therefore, on degraded reefs, they can rapidly colonize bare substrate including dead corals, which inhibits coral community recovery through space exclusion [21, 22]. Once established, macroalgae can be persistent, leaving little chance for the reef to shift back to a coral-dominated state [23, 24]. Macroalgae-dominated habitats increase the mortality of adult corals through competition, reduce the production of coral gametes, decrease the growth and survival of coral juveniles and inhibit coral recruitment[25-28]. In addition, other negative effects of high macroalgal abundance include shading, pathogen transmission and allelopathy [5]. Chronic and persistent environmental pressures have resulted in the fringing reefs of Magnetic Island being dominated by *Sargassum* species [5] and this shifting baseline to macroalgal dominance has instigated research to develop effective interventions that enhance reef health.

Macroalgae removal has been proposed to improve the health status of reefs at Magnetic Island, by clearing benthic space to reduce competition and enhance the recruitment of corals. A range of pilot studies in various locations has examined the effects of removing macroalgae on coral health and ecosystem function. Tanner [29] studied macroalgae removal at Heron Island, in the southern GBR, and reported that the percent cover of *Acropora spp*. increased significantly in the macroalgae cleared area compared to the control areas over 18 months. Similarly, in French Polynesia, a macroalgae removal study found that the number of coral recruits in sites with macroalgae removed was approximately 5 times higher (10 recruits/m^2) than in control sites (2 recruits/m^2) and a macroalgae canopy removal only site (2 recruits/m^2) after 8 months [30]. In Fiji, growth rates of corals in contact with macroalgae were 62-90% lower than coral growth rates in non-contact areas [31]. A variety of removal methods (super sucker vacuum, hand removal, dental tools) were tested in Hawaii to overcome macroalgae-dominated areas, with a resulting large decrease in the abundance and biomass of macroalgae, though other ecological effects were not evaluated [32, 33]. These studies provide a solid platform for testing the macroalgae removal method on degraded reefs such as those at Magnetic Island.

Generally, it is assumed that the effectiveness of removing macroalgae may be important for gaining the desired benefit to corals. Thus long-term monitoring of the effects of removal is required. Many benthic assessment methods have been used to monitor coral reef status and trends. Most reef surveys collect information on the percent cover of benthic categories [3]. Over recent decades, benthic monitoring programs have transitioned from visual *in situ* surveys with divers recording data underwater, to the capture of digital photo and/or video images [34]. Photographic techniques can significantly reduce field survey time, and the image data can be used to compare benthic communities through time [35]. Images are analyzed through coupling with random point annotation software, such as ImageJ, Coral Point Count with the Excel extensions program (CPCe), PhotoGrid, and PhotoQuad [36, 37]. However, the major drawbacks of this approach are the time required for manual image analysis following the field surveys and potential sources of bias due to the variability of the benthic identification performance among data analysts [38].

Recent developments of automated image annotation (AIA) tools for benthic digital image data analysis represent a major advance. The automated tools estimate the percent cover of benthic categories by analyzing surveyed benthic image data and this approach significantly reduces data analysis time and increases potential spatial coverage of image-based field surveys. The Department of Computer Science and Engineering at the University of California, San Diego (UCSD), USA, developed CoralNet, an automated image annotation tool for reef benthic image data [38]. CoralNet is the most widely used automated image analysis program for coral reef surveys [34]. This program has an online repository, which allows users to manually, fully automatically, or partially automatically annotate a benthic image once the system has sufficient training data [38]. These fully automated artificial intelligence platforms can estimate benthic percent cover much faster than manual image analysis. Therefore, this approach is cost and time effective for long-term benthic monitoring surveys.

However, the accuracy of identification is critical to the AIA's efficacy, which is often dependent on the quality of the captured image. For the inshore reefs of Magnetic Island, which are subject to poor water quality and high suspended sediment loads, using captured digital images for categorizing benthic assemblages can be problematic due to poor image quality and resolution. In addition, high macroalgae abundance resulting in dense canopies can obstruct community assemblages below, which impacts the method's accuracy [39]. Moreover, image-based benthic surveys require experienced divers and/or underwater photographers and expensive photographic equipment to obtain high-quality benthic images.

This study examined the accuracy and effectiveness of CoralNet as an AIA approach and compares it directly to manual image categorization of inshore reef survey data to assess benthic community assemblages. Using this comparative approach, the study also assessed the benthic community changes in response to active interventions of macroalgal removal on reefs at Florence and Arthur Bay, Magnetic Island in the central inshore region of the GBR. Benthic digital images were obtained before and after macroalgae removal in October 2018, and then again over 4 subsequent field surveys spanning 6 months (until May 2019). This time series benthic image data collection consisted of approximately 1650 photographs, which were analyzed using manual and AIA approaches and compared to previously published *in situ* survey metrics.

2. Methods

2.1 Study sites and design

The present research was conducted on the fringing reefs located in Arthur Bay (-19º7.755, 146º52.639) and Florence Bay (-19º7.331, 146º52.834), Magnetic Island, between October 2018 and May 2019 (Figure 1). Six 5 x 5 m permanent quadrats were established in each bay, using star pickets placed at each corner, at depths between 2 m and 3 m. GPS points detailing the sites and their position relative to the orientation of the bay allowed for the relocation of all plots. Visual surveys of each site were conducted before quadrats were established to ensure general topographic consistency such that no large features (e.g. bommies) were present in any quadrat, and that chosen plot locations were characteristic of the reef community. The benthic composition of each established plot consisted of 10-20% coral cover, 60-80% algae, and 20-30% other (coral rubble, sand, rock, etc).

Three quadrats in each bay were randomly assigned for macroalgal removal and the remaining three were left untouched, representing control quadrats (Figure 2). Each quadrat was divided into 25 squares (1x1 m) using transect tapes, which form a gridline formation. These squares were photographed using a digital camera at a distance of approximately 1 m above the region of interest at each survey time point. Reef benthic monitoring photographs were obtained at all quadrats (n=12) before macroalgal removal as a baseline in October 2018 and were recorded again immediately after the manual removal of macroalgae from three of the quadrats in each bay (n=6). Four subsequent reef monitoring photograph surveys were conducted between November 2018 and May 2019 (Table 1). A total of 1650 photographs were obtained for this survey period.

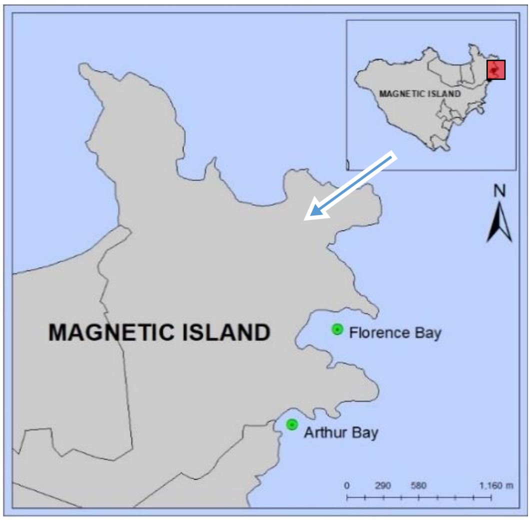

Figure 1. Map of research sites (Florence and Arthur Bay) in Magnetic Island

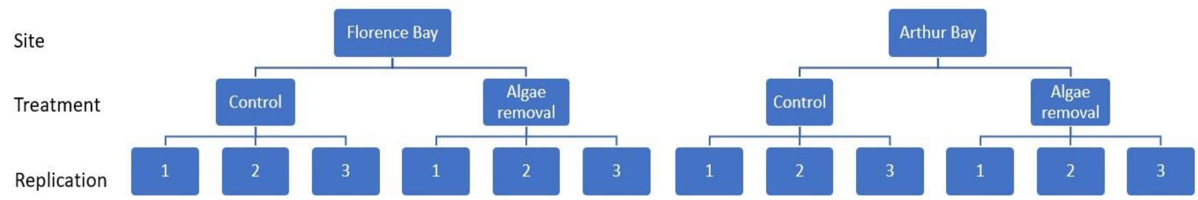

Figure 2. Research project design: 2 research sites (Florence and Arthur Bay), with 3 control and 3 macroalgae removal plots per site.

Table 1. Data monitoring timeframe of the research project

Reef Benthic Monitoring	Control	Treatment
Pre-removal	October 2018	October 2018
Post-removal	N/A	October 2018
Data monitoring 1	November-December 2018	November-December 2018
Data monitoring 2	February 2019	February 2019
Data monitoring 3	March 2019	March 2019
Data monitoring 4	May 2019	May 2019

2.2 Digital image pre-processing

Before analyzing captured photographs, the quality of all the benthic images was enhanced (Figure 3) using Adobe Lightroom classic version 9.0 (Dolby Laboratory Inc). To improve the image quality and obtain greater accuracy in category assignments, the images' contrast, clarity, texture, dehaze, and saturation were optimized. Image enhancement was essential as CoralNet classifies the data based on the extracted texture and color of the image and also relies on Deep Learning (the machine algorithms to detect patterns in data automatically) in the newest version of the program [38, 40].

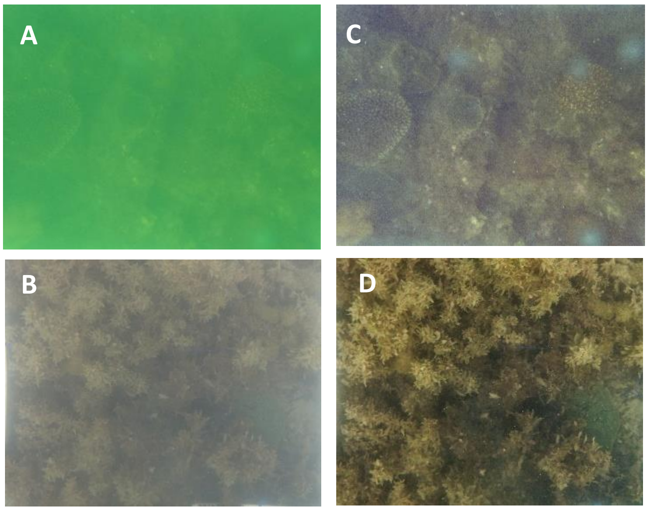

Figure 3. Visual comparison of sample original images (A, B) and enhanced versions of the same images (C, D).

2.3 Manual and automated data analysis

Photograph images (covering 1x1 m of the quadrat; 25 per quadrat) were analyzed manually using Coral Point Count with the Excel extensions program (CPCe). In the manual analysis mode of the CPCe program, which Nova Southeastern University, Florida developed, a labeled set of different benthic categories was created, including coral genera, macroalgae genera, turf algae, crustose coralline algae (CCA), sand, rubble, sponge, and dead coral. Square lines and 50 random points were placed on the image and each point was manually identified and categorized as one of the set benthic categories, with identification to genus taxonomic level where possible. The percent cover of the categorized benthic groups was automatically calculated by CPCe software.

In parallel, all the photographic images used for manual analysis were also passed through the AIA pipeline using the web-based CoralNet program (Figure 4). The same benthic categories used in the manual analysis were used in the AIA pipeline. 75 random images from the benthic photograph dataset were uploaded to CoralNet and classified manually to train the program. Subsequently, all benthic images were then uploaded to the CoralNet program to categorize benthic community assemblages automatically.

2.4 Data analysis
All data were compiled and graphed using Microsoft Excel software. Benthic image data from the October field surveys, including pre-removal, post-removal, and control quadrats from both Florence and Arthur Bay, were used as a pilot study to compare the manual and AIA methods. The percent cover of benthic categories was compared between manual and automated image analysis data sets, and statistically significant differences were analyzed with two-sided comparisons, and Benjamini-Hochberg false discovery rate correction using STAMP software [41]. To test for statistical support of patterns in the percent cover of benthic categories over the survey period (October post removal – May), a one-way ANOVA at a significance level of 5% was conducted using SPSS software. Moreover, the statistical differences of benthic cover categories between the control and removal sites at the end of the period were analyzed with one-way ANOVA at a significance level of 5%. Prior to data analysis, homogeneity and normality tests were conducted to meet the assumptions of ANOVA.

3. Results and discussion

3.1 Manual versus automated image analysis of benthic categories
Overall, the assessment of benthic categories between manual and automated approaches was consistent. In Florence Bay, there was no statistically significant difference between manual and automated approaches in assessing macroalgae cover ($p > 0.05$), with the degree of variability ± 1.6%, 4%, and 6% for pre-removal, post-removal, and control quadrats, respectively (Figure 4A-C). In control and pre-removed plots, macroalgae cover was between 87-89%, while macroalgae cover fell to 8.8% post-removal. Similarly, coral cover was also statistically indistinguishable between manual and automated approaches, with only ± 3.3% and ± 4% for pre- and post-removal quadrats respectively (Figure 4A and 4B; $p > 0.05$). Overall, coral cover in the control and pre-removed quadrats was between 1-3%, while following algal removal, coral represented 11% of the benthic cover. In addition, SRR (sand, rock, rubble) and turf cover in Florence Bay were similar between manual and automated approaches in the pre-removal and control quadrat ($p > 0.05$), while in the post-removal quadrat, SRR and turf cover were significantly different between manual and automated approaches with the degree of variability ±12% and ±13.5%, respectively ($p < 0.05$).

In Arthur Bay quadrats, the estimated macroalgae and coral cover were similar, though did differ significantly between manual and automated categorization approaches. The differences in percent cover between manual and automated assessments were ±13%, ±15%, and ±12% (macroalgae) and ±5%, ±12%, and ±4% (corals) for pre-removal, post-removal and control quadrats respectively ($p < 0.05$; Figure 4D-F). In control and pre-removed plots, macroalgae cover in Arthur Bay was between 77 - 85 %, while macroalgae represented 8.7% cover post-removal. Coral cover in the control and pre-removed quadrats was between 4-6%, whereas following algal canopy removal coral represented 16% of the benthic cover. Turf algae categorization was also significantly different between manual and automated approaches with the degree of variability ranging from ± 2-21% across pre-removal, post-removal, and control quadrats ($p < 0.05$). However, the estimates of SRR cover were statistically similar between manual and automated approaches with the degree of variability ±4%, ±6%, and ±4% for pre-removal, post-removal, and control quadrats respectively ($p > 0.05$).

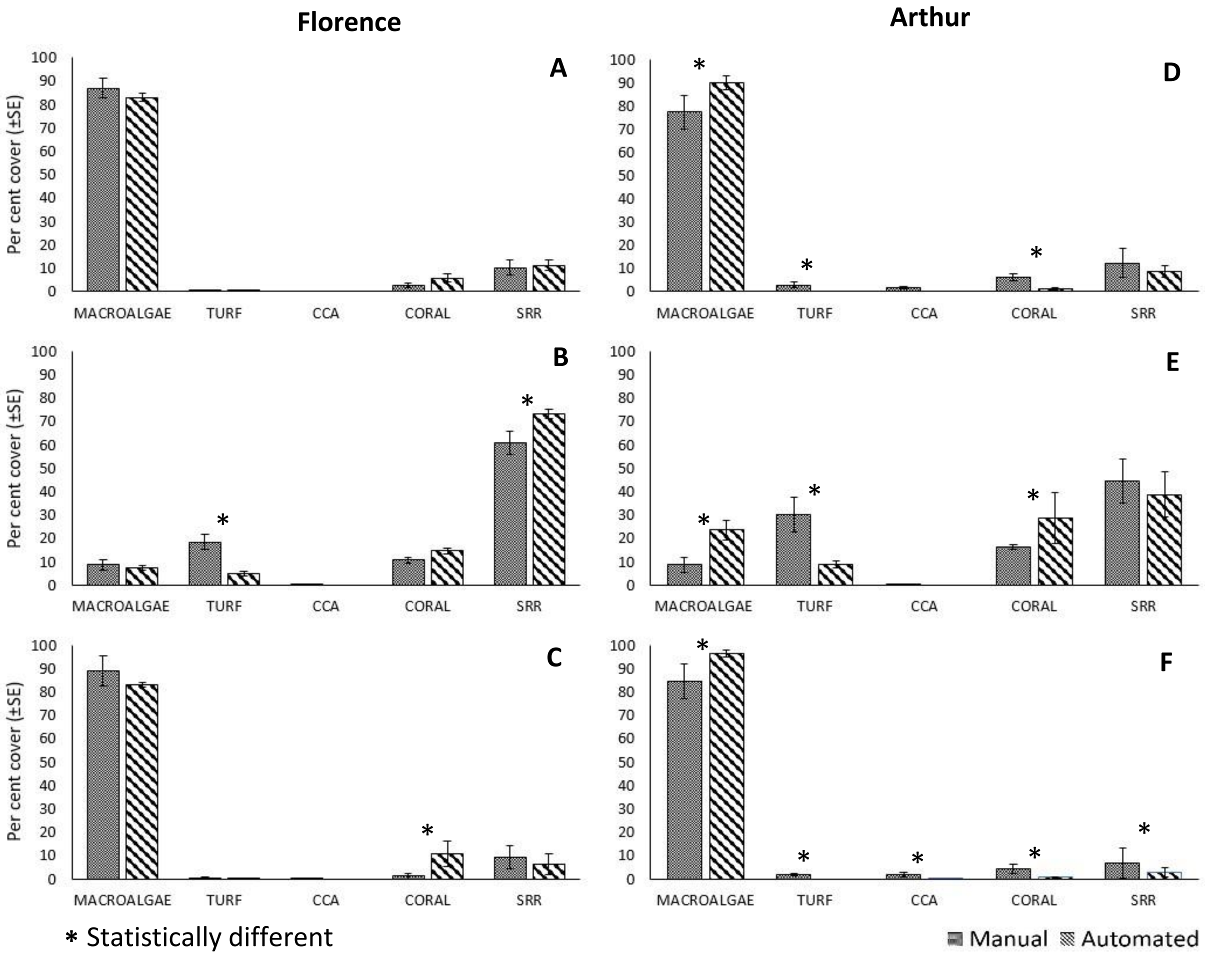

Figure 4. Comparison of benthic category coverage between manual and automated image analysis in Florence Bay (A. pre-removal, B. post-removal, C. control quadrats) and Arthur Bay (D. pre-removal, E. post-removal, F. control quadrats) in October. Note: SRR represents sand, rock, and rubble.

3.2 Performance of manual and automated image analysis at lower taxonomic levels and substrate groupings

Manual assessment of benthic categories at lower taxonomic levels identified 7 genera of macroalgae and 6 genera of corals in photographs derived from Florence and Arthur Bay experimental plots (Table 2). Manual and automated image analysis approaches were consistent for *Sargassum* and *Acropora* categories (Florence Bay: *Sargassum* percent cover variability ± 0.7%-2%; Florence and Arthur Bay: *Acropora* percent cover variability ± 0.04- 1.3%; *p*-value > 0.05; Figure 5). In contrast, rubble and *Montipora* percent cover were not similar between the manual and automated image analysis approaches for both bays ($p < 0.05$; Figure 5). As observed at the higher classification level, the *Sargassum* and *Montipora* cover was higher in the AIA approach compared to manual image analyses. Therefore, further analysis of these lower genus and substrate grouping classifications used only manual assessment.

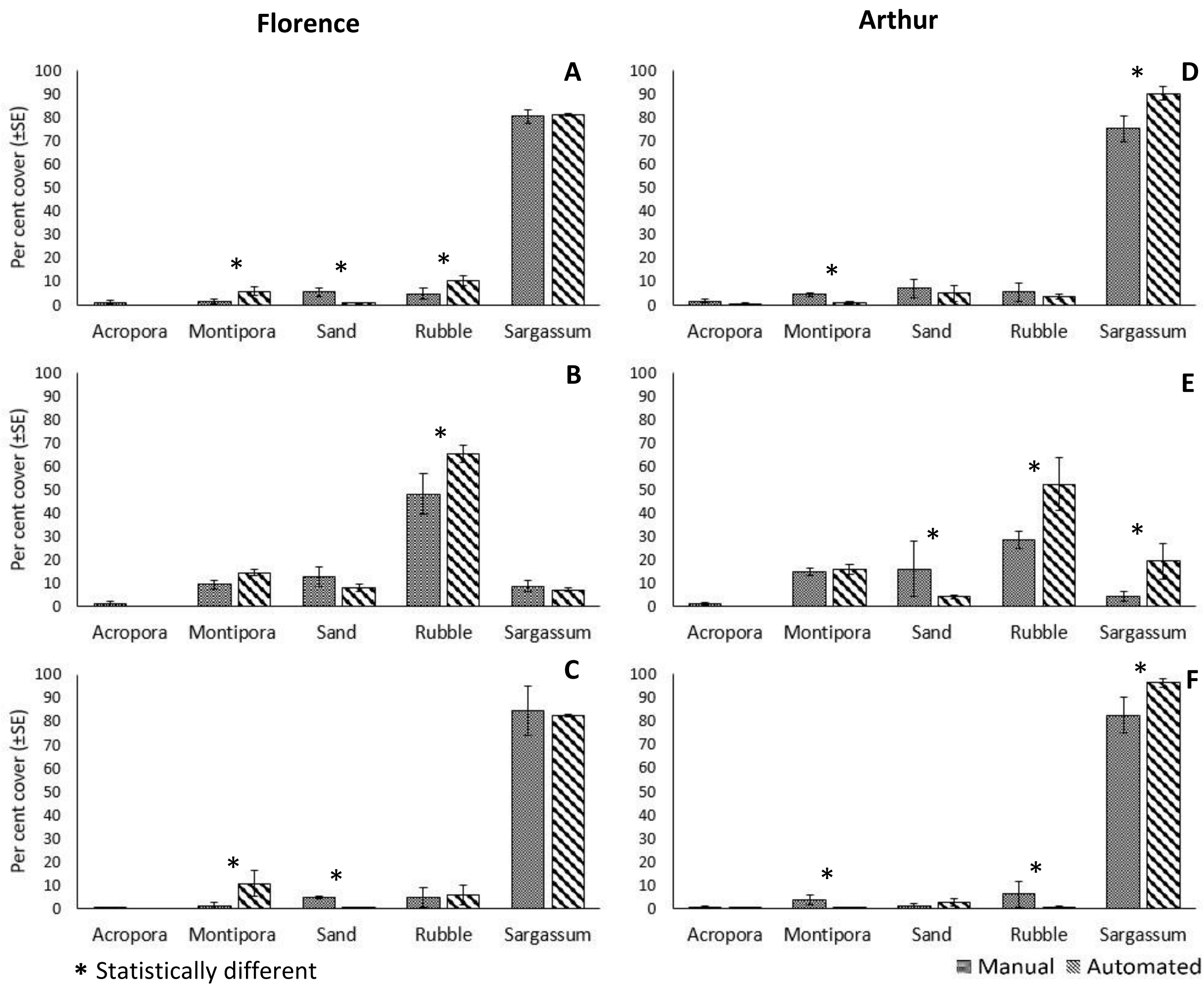

Figure 5. Comparison of dominant benthic group coverage (to genus level for coral and macroalgae) between manual and automated image analysis in Florence Bay (A. pre-removal, B. post-removal, C. control quadrats) and Arthur Bay (D. pre-removal, E. post-removal, F. control quadrats) from October field survey photographs.

Sargassum sp. was the dominant benthic category in all quadrats, representing 75-85% of the coverage across control and pre-removal quadrats. After removal, *Sargassum* sp. represented only 4-9% of the benthic cover, a greater than 70% reduction for both bays. *Montipora sp*. was the dominant coral genus in both Florence and Arthur Bay with the percent cover prior to macroalgal removal being 1.5% and 4.4%, respectively. Following algae removal, the *Montipora sp*. coverage was significantly higher at 9.5% and 14.8% in Florence and Arthur Bay quadrats respectively. Interestingly the *Acropora sp.* coverage did not change significantly in quadrats in both bays when comparing pre-and post-removal of macroalgae. However, turf algae, sand and rubble significantly increased after the algae removal compared to values pre-removal (Table 2).

Table 2. Using manual assessment, the diversity and proportion of benthic organisms in control and treatment quadrats (pre- and post- removal) in both Florence and Arthur Bay in October.

	Florence			Arthur		
Cover Categories	Control	Pre-Removal	Post-Removal	Control	Pre-Removal	Post-Removal
Macroalgae						
Sargassum	84.6 ± 10.5	80.5 ± 2.8	8.7 ± 2.2	82.6 ± 7.4	75.3 ± 5.5	4.4 ± 2.2
Dictyotales	-	0.4 ± 0.3	-	1.1 ± 1.0	1.6 ± 1.6	0.03 ± 0.03
Padina	0.2 ± 0.2	0.1 ± 0.1	-	0.3 ± 0.3	-	0.3 ± 0.1
Amphiroa	-	-	-	-	0.03 ± 0.03	-
Eucheuma sp.	1.7 ± 1.3	4.4 ± 2.7	-	-	-	0.2 ± 0.1
Colpomenia sp.	-	-	-	-	-	3.6 ± 1.8
Other Macroalgae	2.6 ± 2.6	1.3 ± 1.0	0.03 ± 0.03	0.5 ± 0.2	0.5 ± 0.2	0.2 ± 0.1
Coral						
Montipora sp.	1.2 ± 1.2	1.5 ± 1.0	9.5 ± 1.9	3.6 ± 2.1	4.4 ± 0.9	14.8 ± 1.5
Acropora sp.	0.04 ± 0.04	1.0 ± 0.8	1.1 ± 1.0	0.7 ± 0.1	1.5 ± 0.7	1.3 ± 0.7
Pocillopora sp.	-	-	-	-	0.1 ± 0.03	-
Favites sp.	-	-	-	-	0.03 ± 0.03	-
Porites sp.	-	-	-	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2
Platygyra sp.	-	-	-	-	-	0.1 ± 0.1
Turfing Algae	0.3 ± 0.3	0.4 ± 0.2	18.4 ± 3.2	1.9 ± 0.6	2.7 ± 1.3	30.0 ± 7.5
CCA	0.1 ± 0.1	-	0.1 ± 0.1	2.0 ± 1.0	1.4 ± 0.5	0.5 ± 0.2
Sponge	-	-	-	0.2 ± 0.2	0.1 ± 0.03	-
Sand	4.5 ± 0.6	5.5 ± 1.9	12.9 ± 4.1	1.0 ± 1.0	6.9 ± 3.9	16.0 ± 11.8
Rubble	4.7 ± 4.3	4.7 ± 2.5	48.1 ± 8.5	6.0 ± 5.5	5.4 ± 4.0	28.6 ± 3.6
Dead Coral	-	-	1.0 ± 0.8	-	-	-

3.3 Temporal changes in benthic assemblages following macroalgal removal assessed through manual digital image analyses

Macroalgal abundance in control quadrats of Florence Bay significantly decreased by 47% over the entire survey period (Oct-May; ANOVA $F_{4,9} = 46.419$, $p = 0.000$), with a concurrent significant increase of SRR (~35%; ANOVA $F_{4,9} = 19.889$, $p = 0.000$) and turf algae (~3%; ANOVA $F_{4,9} = 8.088$, $p = 0.005$). Between November and February surveys, macroalgae initially decreased in cover by approximately 63%, followed by a subsequent increase in coverage in March and May surveys. Similarly, in Arthur Bay, macroalgae cover in the control plots decreased from approximately 85% in October to 57% in May, a reduction of 28% over the period (ANOVA $F_{4,10} = 0.866$, $p = 0.517$). In control quadrats of both bays, the proportion of coral cover followed an increasing trend during the study period, increasing by 7.4% in Florence Bay (ANOVA $F_{4,9} = 9.207$, $p = 0.003$) and 3.8% in Arthur Bay (ANOVA $F_{4,10} = 0.496$, $p = 0.739$; Figure 6A and 6C).

In macroalgae removal quadrats, the cover of macroalgae in Florence Bay significantly decreased by 52% (Oct-pre - May; ANOVA $F_{4,10} = 8.753$, $p = 0.003$), while macroalgae cover in Arthur Bay decreased by 45% (Oct-pre - May; ANOVA $F_{4,10} = 2.643$, $p = 0.097$). Between November and February surveys, a slight decrease in macroalgal cover (6% and 10% respectively) was observed with a subsequent increase in coverage in the March and May surveys (Figure 6B and 6D). A gradual decrease of SRR cover was observed in both Florence and Arthur Bay, by 11.8% and 9.7% respectively (Oct–post–May). In addition, a slight increase of coral cover was observed in the macroalgae removal quadrats of both Florence and Arthur Bay, by 1.8% and 0.1% respectively following macroalgal removal (Oct-post – May; Florence: ANOVA $F_{4,10}$ = 0.080, p = 0.987; Arthur: ANOVA $F_{4,10}$ = 0.262, p = 0.895; Figure 6B and 6D).

Overall, there was no statistically significant difference in coral cover between control and macroalgae removal quadrats for both Florence and Arthur Bay over the survey period (Florence: ANOVA $F_{1,4}$ = 4.010, p = 0.116; Arthur: ANOVA $F_{1,4}$ = 2.471, p = 0.191). However, macroalgae cover was significantly different between control and macroalgae removal quadrats (Florence: ANOVA $F_{1,4}$ = 188.711, p = 0.000; Arthur: ANOVA $F_{1,4}$ = 90.483, p = 0.001). The patterns in benthic cover over the entire period (October-May) were similar between the manual and AIA approaches.

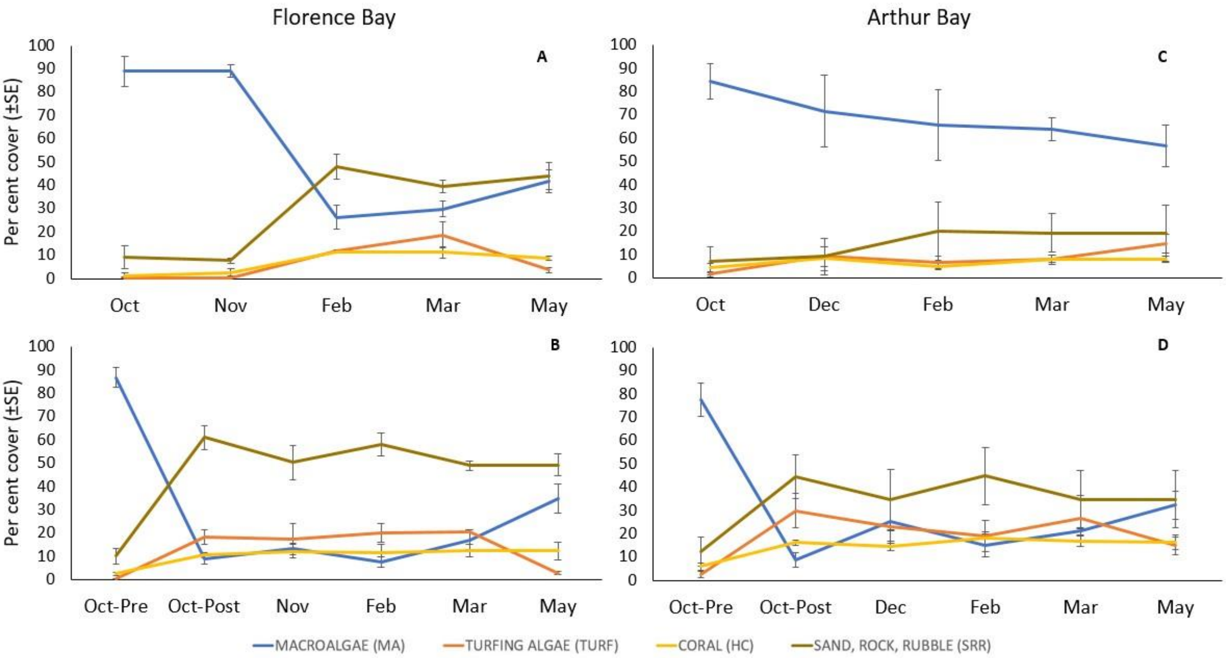

Figure 6. The proportion of dominant benthic category cover in Florence Bay (A. control quadrats, B. treatment quadrats) and Arthur Bay (C. control quadrats, D. treatment quadrats) following the macroalgae removal (October-May), using manual image analysis.

3.4. Manual and AIA detect similar benthic community patterns

Reef monitoring projects have implemented various approaches to capture accurate patterns in community assemblages and their changes over time. The recent adoption of automated approaches that use machine learning to categorize communities offers many advantages, including improved accuracy, removal of human biases, and most importantly, reduction in analysis time. The application of AIA approaches to inshore reefs of the GBR, which are characterized by poor water quality and high macroalgal abundance offers additional challenges for such approaches. In this study, it was demonstrated that CoralNet is a robust AIA program for assessing inshore reef benthic cover, and can generate a cover estimation of broad benthic categories that were highly comparable to those obtained by manual analysis. Importantly, there were no significant differences in the percent cover of benthic groups of macroalgae, corals, CCA, and SRR between the manual and automated approaches in Florence Bay. Previous studies in the fore reef and hard-bottom habitats in Hawaii and American Samoa have similarly highlighted close correlations for coral cover (0.6-1% variability) and turf cover (6.2-10.9% variability), between manual and CoralNet analysis [34]. Therefore, AIA is likely to be widely applicable to various habitats, including the inshore reefs of Magnetic Island.

The accuracy of AIA approaches often depends on the captured images' quality [38]. In contrast to the Florence Bay site, CoralNet demonstrated a higher degree of variability in identifying coral, turf, and macroalgae cover compared to manual analysis for the post-removal quadrats in Arthur Bay. In addition to the importance of image quality, previous studies have highlighted that algal functional groups, particularly turf algae, are challenging categories for AIA approaches, due to substantial differences in color, texture, and shape (nearly bare substrate or relatively thick turf mats), which are difficult to capture accurately in photographs [34, 38]. CoralNet learns from a huge amount of image benthic data and automatically detects the patterns in data (color, shape, texture of the images). Hence, if the quality of the images is poor, or have similarities in terms of color, shape, and pattern between different species or categories, the program struggles to make an accurate identification. When analyzing the captured images, it was apparent that the digital images obtained from Florence Bay were of higher quality than those obtained from Arthur Bay and this difference is likely to have contributed to the higher variance observed between the AIA and manual approaches for Arthur Bay. The images were obtained for both bays on different days which experienced different conditions of wind and localized sediment resuspension, which may have contributed to image quality. Turbidity and low light conditions reduce color and image clarity, creating challenges for manual and automated benthic classification [38]. This result alone highlights the importance of obtaining the best quality digital images possible to aid analysis, though in the current study the adoption of photo pre-processing greatly improved the image resolution and benthic identification, and thus should form a key part of any photo analysis pipeline.

At lower taxonomic classifications (i.e., genus), benthic category identification was more variable between manual and AIA than with broad benthic categories. In particular, the identification of rubble and *Montipora* corals demonstrated high variability between the manual and automated approaches in Florence and Arthur Bay. CoralNet functions based on "deep learning" computer vision capabilities, where the algorithm is initially trained by the user (human) on a subset of data and subsequently utilizes color and texture patterns to identify benthic categories. It is possible, therefore, that increasing the amount of source data (i.e. training dataset) may increase the accuracy of the AIA program in detecting these lower taxonomic levels.

Overall CoralNet was an effective AIA program to estimate the cover of broad functional group benthic categories at inshore sites of Magnetic Island characterized by poor water quality. The AIA approach's main advantage is the greatly reduced data analysis time. For example, the time required to analyze the 1650 photos in this study manually was approximately 2 months. The AIA approach undertook the equivalent analysis in only 2 days, which included training the machine learning algorithms. While small differences were observed at Arthur Bay between the manual and AIA approaches, similar variance has been reported when comparing two different human analysts. For example, Beijbom, Edmunds, Roelfsema, Smith, Kline, Neal, Dunlap, Moriarty, Fan, Tan, Chan, Treibitz, Gamst, Mitchell, and Kriegman [38] suggested that the accuracy of experts varies for assessment of benthic substrate types, and thus manual identification does not perfectly describe reef benthic cover [34]. Therefore, at the broad categorization level employed in this study, AIA using CoralNet offers advantages by reducing image data analysis time and the financial expense of manual image-based benthic analysis [38].

3.5. High macroalgal abundance influences benthic assemblage patterns measured in digital images

Both manual and AIA approaches identified macroalgae as the dominant benthic category in all quadrats, with *Sargassum* species representing 75-85% cover on average. Earlier studies similarly identified *Sargassum* as the dominant species in the inshore reefs of Magnetic Island, contributing 50% and 45% cover specifically in Florence and Arthur Bay, respectively [18]. Ceccarelli, Evans, Logan, Mantel, Puotinen, Petus, Russ, and Williamson [11] proposed that a phase shift from coral to macroalgae dominance has occurred on the inshore reefs of Magnetic Island. Coral cover declined from 40% to 20% between 2004 and 2012, while macroalgae cover increased significantly, followed by a stable state period of macroalgae dominance between 2012 and 2016 [11]. These earlier studies assessed the macroalgal cover through *in situ* monitoring surveys (e.g. line intercept transect, LIT), with an average reported cover of approximately 40%, in contrast to the greater than 75% coverage obtained in the current study using image-based analysis. Canopy effects likely cause this discrepancy as a result of high macroalgae abundance. Despite the canopy occupying large amounts of space, *in situ* benthic surveys such as LITs must intersect the holdfast to record this cover. The unique morphological shape of macroalgae, particularly *Sargassum* species, can cause a canopy effect, whereby tall-growing thalli obstruct the benthic organisms beneath [39]. Photo quadrat approaches, such as the one used in the present study, may not be effective in assessing the true reef benthic composition for macroalgae-dominant habitats since the planar view of photography overwhelms the benthic organisms beneath the macroalgal canopies [39], however, there is a trade-off between different monitoring techniques. The three-dimensional complexity of the habitat is near impossible to record in linear-view monitoring techniques, and alternative approaches, such as stereoscopic imaging technologies, may potentially represent a better way to assess these structurally complex habitats [16]. However, this technology is currently impractical and challenging for large-scale research due to the data analysis and collection complexity. Digital image-based surveys are therefore effective for low-abundance macroalgae habitats. However, the threshold of macroalgae cover at which digital image-based assessments are effective is currently not defined, though a priority for future research.

3.6. Response of benthic communities to macroalgae removal

Macroalgal removal is one active management option for degraded reefs that have been proposed to enhance reef resilience by reducing the competition between macroalgae and corals and providing space for the recruitment of corals [5]. For treatment plots in both Arthur and Florence Bays, the manual removal of macroalgae in October 2018 significantly reduced the algal cover as expected. Following removal, an increase in coral cover and other broad categories was observed. However, this increase was not a true increase in benthic cover, but rather due to the removal of *Sargassum* canopy effects. In the middle of the study (February 2019), the cover of macroalgae in both treatment and control plots declined significantly, which was correlated with an extreme flood event that decreased the salinity level and increased the turbidity of the surface waters around Magnetic Island [42]. Based on visual data from eReefs Hydrodynamic modeling [42], the salinity level during the flood event was below 32 PSU, which, in conjunction with limited light availability due to high turbidity, potentially directly impacted macroalgae cover. Steen [43], and Marker and Sand-Jensen [44], previously reported that low salinity and reduced light availability affect the growth and reproduction of the brown macroalgae, *Sargassum*. However, macroalgae also go through natural senescence cycles on Magnetic Island reefs [5, 45]. Reproduction of macroalgae, particularly *Sargassum*, occurs in December (warmer months) followed by the senescence of the *Sargassum* [45]. The decrease of *Sargassum* biomass after the summer period observed in the control quadrats of Florence and Arthur Bay is therefore likely due to the combined effects of the flood event and natural degeneration of the primary thallus of *Sargassum* after the reproductive period [45].

As the macroalgae cover declined, the coral cover in the treatment removal site tends to increase during the period. There was no significant difference between the control and treatment sites as a small increase in coral cover was also observed in the control quadrats. We did not expect a significant increase in coral cover across the treatment sites, as this research project was only conducted over a short-term period of around 7 months (October 2018 – May 2019). However, this research project will be ongoing for 3 years, to determine the longer-term effects of macroalgae removal on reef benthic community assemblages. The small increase of coral cover in the treatment quadrats likely reflects the removal of canopy effects, revealing the other benthic categories beneath the *Sargassum* canopies and reflecting chance variation in random point placement on the photographs. However, Ceccarelli, Loffler, Bourne, Al Moajil-Cole, Boström Einarsson, Evans-Illidge, Fabricius, Glasl, Marshall, McLeod, Read, Schaffelke, Smith, Jorda, Williamson, and Bay [5] suggested that macroalgae removal may be a potential tool to diminish the competition for space, resources, and light between macroalgae and corals. This could enhance the output of coral reproduction and recruitment, leading to the re-establishing coral dominance in the ecosystem [27]. The results of the present study showed a significant difference in macroalgae cover between control and treatment quadrats with macroalgae significantly lower in removal quadrats at the end of the study period. This may positively influence coral demographics over long periods if macroalgal removal is conducted regularly. For example, previous studies have shown the positive effects of macroalgae removal on coral cover, growth rate, and coral recruitment in pilot studies at Heron Island, Fiji, and French Polynesia [29-31]. However, a long-term collection of community dynamics is required for the current research sites at Magnetic Island.

4. Conclusion

In conclusion, automated image analysis by CoralNet is robust and comparable with manual approaches for assessing inshore reef benthic cover. The main benefit of this AIA program is a substantial decrease in the time required to process benthic images after field surveys (2 months manual versus 2 days AIA). However, the precision of AIA depends on the image quality with pre-processing critical for identification accuracy. On degraded inshore reefs with high macroalgal abundance, digital image analysis may not be appropriate, as this method overestimates the abundance of macroalgae and underrepresents coral cover due to canopy effects, irrespective of the use of AIA or manual approaches. However, in the present study, macroalgae removal showed that once macroalgal abundance is low and canopy effects minimized, AIA is highly effective for analyzing broad-scale benthic community assemblages. However, the threshold of the abundance of canopy-forming organisms at which photographic methods may be effective is yet to be determined. Moreover, CoralNet is effective at identifying broad taxonomic levels but less effective in more complex classification schemes. The manual approach would be preferred if the identification of lower taxonomic levels is key to future study outcomes. Future research would be valuable to compare CoralNet with other AIA programs (such as BenthoBox, AIMS) and *in situ* surveys to determine the best method for accuracy and efficiency (time and financial expense) for classifying inshore reef benthic communities.

Overall, macroalgae removal programs are an effective approach to reducing macroalgae cover. However, there was no significant difference in coral cover between control and treatment quadrats over the short period of this study. Increases in coral cover observed in the treatment quadrats were likely due to the effect of macroalgal canopy removal (canopy effects). Longer-term monitoring is required to assess the effects of macroalgae removal on coral cover and coral recruitment at the Florence and Arthur Bay study sites.

5. References

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