

Article

Using Tourist Diver Images to Estimate Coral Cover and Bleaching Prevalence in a Remote Indian Ocean Coral Reef System

Anderson B. Mayfield ^{1,*}  and Alexandra C. Dempsey ²¹ Coral Reef Diagnostics, 150 SE 25th Rd., Miami, FL 33129, USA² Khaled bin Sultan Living Oceans Foundation, Tire Hill, PA 15959, USA; dempsey@livingoceansfoundation.org* Correspondence: anderson@coralreefdiagnostics.com; Tel.: +1-786-898-4447

Abstract

Citizen science approaches for monitoring, and even restoring, coral reefs have grown in popularity though tend to be restricted to those who have taken courses that expose them to the relevant methodologies. Now that cheap (~10 USD), waterproof pouches for smart phones are widely available, there is the potential for mass acquisition of coral reef images by non-scientists. Furthermore, with the emergence of better machine-learning-based image classification approaches, high-quality data can be extracted from low-resolution images (provided that key benthic organisms, namely corals, other invertebrates, & algae, can be distinguished). To determine whether informally captured images could yield comparable ecological data to point-intercept + photo-quadrat surveys conducted by highly proficient research divers, we trained an artificial intelligence (AI), CoralNet, with images taken before and during a bleaching event in 2015 in Chagos (Indian Ocean). The overall percent coral covers of the formal, “gold standard” method and the informal, “tourist diver” approach of 38.7 and 35.1%, respectively, were within ~10% of one another; coral bleaching percentages of 30.5 and 31.8%, respectively, were statistically comparable. Although the AI was prone to classifying bleached corals as healthy in ~one-third of cases, the fact that these data could be collected by someone with no knowledge of coral reef ecology might justify this approach in areas where divers or snorkelers have access to waterproof cameras and are keen to document coral reef condition.

Keywords: AI; Chagos; citizen science; coral reefs; image classification; marine ecology



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1. Introduction

The acquisition of coral reef benthic data for assessment of community structure, coral abundance, and other common indices of ecological condition is normally the purview of marine biologists [1] with expertise in taxonomy, survey methodology, and ecology. However, initiatives such as Reef Check and even SCUBA diving agencies (e.g., PADI) have attempted to leverage the power of the diving industry to aid in coral reef monitoring; Reef Check has trained over 8500 “EcoDivers” as of late-2025 and have even made a portion of the data acquired available via AquaLink (<https://aqualink.org/>). A plethora of other citizen science approaches for coral reef monitoring, including some with a focus on bleached corals [2], have been launched (see <https://coral.org/en/coral-bleaching/on-site-monitoring-tools/>; accessed on 18 November 2025), but most do not last longer than a year [3], nor are many submissions ever ultimately received [4]. This could be because

even divers interested in coral reefs have little motivation to bring survey equipment (e.g., transect tape, slates, or photo-quadrats) on a dive.

In contrast, it is more likely that divers bring cameras on their coral reef dives, and many are keen to not only share their photos with friends and family but also post them on websites such as iNaturalist that use a combination of machine-learning and crowd-sourcing to verify the identities of imaged organisms. Could the myriad photos from these tourist divers, which PADI estimates to be upwards of 5–10 million (at least half of whom are likely to own an underwater camera), be tapped into to extract valuable coral reef ecological data [5,6]? Many of their images will be poorly white-balanced (if at all), nor will it be possible to calibrate the spatial scale, which is important for measuring, for instance, coral size. While this may be the case, a well-trained artificial intelligence (AI) can nevertheless identify important features in these untargeted, informally acquired images [7]. For instance, if only 20% of an image encompasses the benthos, with the remainder being water, a percent coral cover could still be calculated, and the resulting value may not even vary appreciably from measurements made by divers conducting formal surveys (be they belt, point-intercept, photo-quadrat, or other). Excluding the relatively rare blue-water dives, divers typically choose to stay near the reef (be it natural or artificial), and so at least a fraction of their photos should encompass corals and other reef organisms.

To determine whether informally acquired diver images, which were taken by the lead author amidst sampling corals, could be used to accurately calculate coral cover and the percent of all coral tissue area bleached (hereafter “% bleaching”), we took advantage of a large dataset acquired during the Khaled bin Sultan Living Ocean Foundation’s (LOF) 2015 expedition to Chagos (Indian Ocean) as part of their *Global Reef Expedition* (the largest coral reef survey to date). The bleaching event we documented in Chagos in April–May 2015 (Figure 1) has been described in a prior work [8], and, despite being amongst the most remote locations on the planet, Chagos’ coral reefs are relatively well studied (see [9–12] for follow-up surveys to ours.) thanks to the multi-decadal efforts of the late Dr. Charles Sheppard (to whom we dedicate this manuscript). We hypothesized that an AI trained to identify corals from informal, tourist diver photos would yield similar coral cover and % bleaching values as those obtained by highly trained scientific divers.



Figure 1. A bleaching reef within the lagoon at Peros Banhos, Chagos (Indian Ocean). Photo by ABM.

2. Materials and Methods

2.1. Coral Reef Surveys: Formal Method

A standardized survey methodology [13] was used to assess the benthos of 109 primarily coral-based sites across the Chagos Archipelago. Details can be found in the field report ([14]; <https://www.livingoceansfoundation.org/publication/global-reef-expedition-chagos-archipelago-final-report>; accessed on 18 November 2025). Briefly, 66 benthic categories were assessed by 5–10 surveyors at each site: barren substrate (inc. sand, rocks, or other abiotic material), non-scleractinian invertebrates, six morphotypes of algae (macroalgae, crustose coralline algae [CCA], erect algae, turf algae, turf algae with sediment, & cyanobacteria), and 58 genera of scleractinian coral. Both point-intercept surveys (ranging from 10 to 50 m, with observations made at 10-cm intervals) and photo-quadrat surveys ($1 \times 1 \text{ m} \times$ several dozen/depth at each site) were undertaken at depths of <8 m (D1), 8–12 m (D2), 12–18 m (D3), 18–25 m (D4), and 25–30 m (D5). We refer to this approach as the “formal method” and assume that it yields the more “correct” representation of the coral reef benthos (i.e., the “gold standard”). The “informal,” tourist diver approach is described in the following section. With the formal method, benthic classifications along the point-intercept transects were made *in situ*, while manual classifications (30 random points on each of ~15,000 photo-quadrat images) were conducted with CoralNet [15], which was relatively new and unproven at the time (mid-2015), several weeks after the completion of the field trip.

To assess bleaching at Peros Banhos, a different method was used; the LOF photo-quadrat images were assessed as described above, with the results combined with those of Sheppard et al. [8]. Briefly, the latter team used a drop-cam approach to record bleaching from 5 to 25 m (in 5-m intervals), and 50 random screenshots from each depth ($n = 250$ images) were analyzed with CPCe [16] using 16 randomly placed points. Although we do not have access to the raw data due to the unfortunate passing of Dr. Sheppard, we were able to determine the % bleaching values calculated from Figure 7 of Sheppard et al. [8] and so refer to the data from this figure as the formally acquired coral bleaching data against which we compare the results of our informal method discussed below.

2.2. Coral Reef Surveys: Informal, “Tourist Diver” Method

At the same time as the formal surveys, images of the coral reef habitat (from 0.5 to 35 m) were taken by the first author with an Olympus TG-2 underwater camera within Olympus underwater housing (Tokyo, Japan) amidst sampling pocilloporid corals (see <https://coralreefdiagnostics.com/biot-overview> for details & images, accessed on 18 November 2025); although these pictures were not associated with any transect, they were taken in their vicinity (<200 m), and all were white-balanced *in situ*. Details of the technique itself can be found in prior works [5,6] but, briefly, involved a random swimming method in which the diver hovered 1–2 m above the benthos and took images of the reef either directly below (~1–10 m² reef area/photo) or at a 45-degree angle such that the majority of the area of the photo was benthos (avg. benthos & water column percentages were 76 & 24%, respectively). White-balancing frequently was critical while moving up and down the water column and was oftentimes conducted over 50 times on a 60-min dive. Poorly or non-white-balanced photos were discarded from analysis.

While the method is simple and lends itself to anyone with (1) a valid SCUBA certification and (2) a means of capturing underwater images, the lead author possessed extensive experience in underwater photography, and only several dozen photos out of the 2619 total (which ranged from ~1 m² to upwards of 100 m²) were discarded due to low resolution or quality. Novice citizen scientists may need to practice both buoyancy and underwater white-balancing for several dives in order to capture images that will be useful for benthic

characterizations. All images can be downloaded alongside both human and AI annotations from the CoralNet website under accession 6447 (<https://coralnet.ucsd.edu/source/6447/>, accessed on 18 November 2025). Images lacking any benthic features (e.g., fish swimming in the water column) were removed, resulting in a final total of usable image of 2500.

2.3. CoralNet AI Training

A custom lablesset featuring 34 labels was used (Supplemental File S1). Briefly, we considered water, sand, several types of algae, the three most dominant coral genera, namely, *Acropora*, *Pocillopora*, and *Porites*, as well as these same genera as fluorescing or bleached (with the remaining genera grouped under “other hard coral” [OTH-HC]). We also considered soft corals as either normally pigmented or bleached, sponges, other invertebrates (“Other Inv;” those not mentioned above), fish, and divers (Figure 2). Of the original 34 labels, 10 were either unused (seagrass, bleached CCA, & “other”) or later combined with other labels: the fluorescing poritids, pocilloporids, acroporids, and OTH-HC were combined with their respective bleached groups (since fluorescing corals nearly always proceed to bleach), and crown of thorns seastars were added to the “Other Inv” group; the lone point classified as “Rock” was later found to be a dead coral (“D_coral”). Bleached soft corals were seen, but they were later combined with normally pigmented corals because soft coral bleaching was not a focus of this work. The level of resolution was higher for the formal method: 66 benthic categories vs. 24 benthic + open-water features in the informal approach. In the latter, three non-benthic features—water, fish, and divers—were removed from calculations of coral cover and bleaching. The % bleaching is not the same as the percentage of colonies exhibiting signs of bleaching; instead, it reflects the portion of total live coral surface area bleached to a color score of ~1 [17] (B1, C1, D1, or E1, depending on the genus). This scoring, while subjective and not based on an exact brightness level (e.g., [18]), was effectively calibrated by visualizing unbleached corals and stark-white objects (e.g., sand) in the same frame of reference.

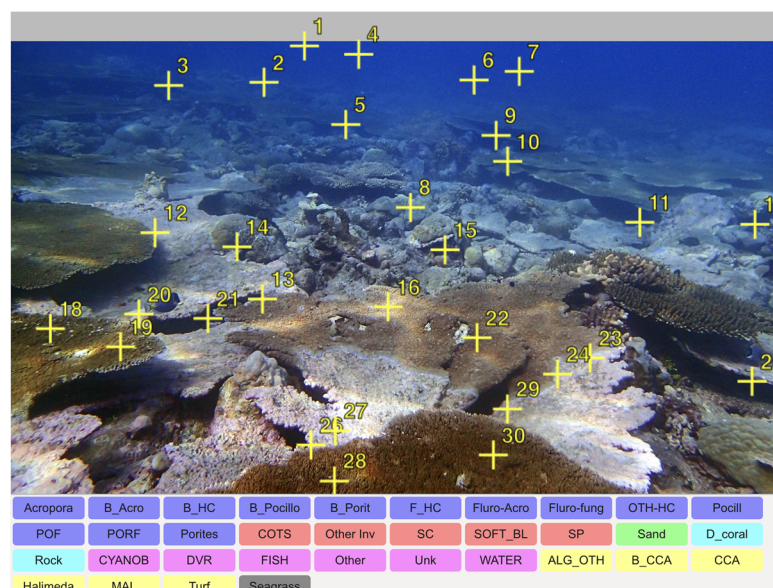


Figure 2. A representative “tourist diver” image undergoing annotation in CoralNet, with the original full lablesset shown below. In this example from Egmont (site BiEg05), CoralNet’s accuracy was 83.3%. Several misclassifications are worth noting. Point 9 was determined to be water when it was actually an *Acropora* colony; to the naked eye, without the use of zoom, this is indeed difficult to discern. A more concerning error is the classification of Point 29 as a poritid coral, when it in fact appears to be dead coral substrate covered in turf algae.

Each of the 2500 images was randomly overlaid with 30 points via CoralNet (Figure 2), and 270 ($n = 8100$ classifications) were manually scored to train the AI, whose accuracy gradually increased from <70% after the first 20 images to 84% by the 270th (Figure S3). Further training did not result in an increase in accuracy, and a *post-hoc* manual accuracy verification was performed on 100 additional images. Since few corals were bleaching in the training set, 230 images from primarily Peros Banhos (Figure 3), whose reefs were in the midst of bleaching during the second series of surveys in late April–early May 2015 (Figure 1), were manually scored to calculate both false-positive (FP) and false-negative (FN) bleaching classification rates. A FP was defined as when the AI determined a coral to be bleached when it was normally pigmented. A FN was defined as when the AI determined a coral to be normally pigmented when it was actually bleached:

$$\text{FP rate} = \# \text{ of FP} / (\# \text{ of FP} + \# \text{ of true negatives [TN]}) \times 100 \quad (1)$$

$$\text{FN rate} = \# \text{ of FN} / (\# \text{ of FN} + \# \text{ of true positives [TP]}) \times 100 \quad (2)$$

In total, 18,000 image features were manually scored/classified across 600 images, with CoralNet annotating the remaining 1900 images automatically ($n = 57,000$ benthic features scored by CoralNet & 75,000 features scored in total across both human & AI).

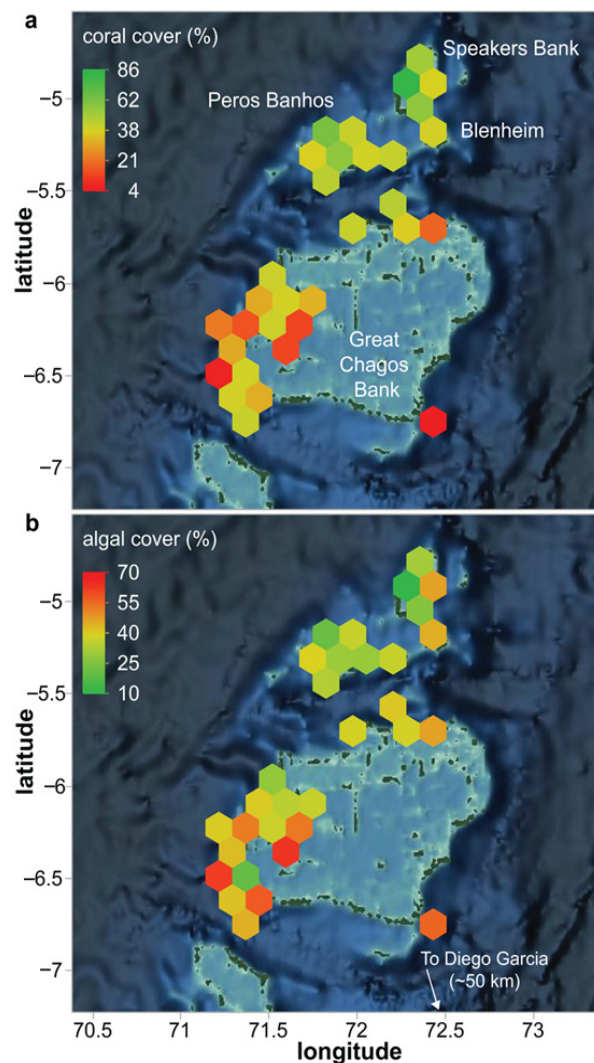


Figure 3. Map showing spatial extent of surveys alongside both coral (a) and algal (b) cover (%). Hexagonal colors represent the means of all sites within the respective hexagon (rather than each hexagon representing a unique site). The algal cover scale is inverted relative to that of coral cover.

2.4. Drivers of Variation in the Benthos of Chagos' Coral Reefs

Although the primary objective of this work was to compare coral cover and bleaching data acquired formally via diver transects vs. random habitat images, we were also interested in describing more general coral reef features from our formal survey (*sensu* [19]) since it was the last one before these remote reefs underwent a series of catastrophic bleaching events (discussed in more detail below). This analysis is discussed in the online supplement (Supplemental File S2).

3. Results

3.1. Coral & Algal Cover from the Formal Surveys

Coral cover across the 109 sites was $38 \pm 16\%$ (std. dev. for this & all other error terms), ranging from <5% at Cauvin Bank to 86% at one site at Speakers Bank (BiSp96; see Supplemental File S1 for site means.), and there was marked spatial variation (Figure 3a). Of note, coral cover was generally higher in the north, particularly around Speakers Bank, Salomon, Blenheim, and Peros Banhos (of which the latter three are obscured by data in the map; see Figure 1 of Sheppard et al. [8] for a data-free map.). However, it should be mentioned that these coral cover values include bleaching corals that had not yet died. This is one reason for our integrating data from Sheppard et al. [8] with our own to better characterize the Peros Banhos bleaching event. Algal cover (Figure 3b) showed the inverse trend: higher in the south, albeit with a wide range: from 10% at Speakers Bank site BiSp96 (which resulted in the highest coral/algal ratio of 8.3) to >70% at BiCc51 (Central Chagos). The bleaching event was catastrophic, with 2017 surveys documenting coral cover of only 10% [8], and oftentimes far worse in the shallows (<15 m). It is unclear whether coral abundances over 35–40% will ever again be witnessed at this remote Indian Ocean archipelago.

3.2. Drivers of Variation in the Benthic Assemblage

Although the primary goal of this work was to attempt to validate a citizen scientist-like approach for collecting valuable coral reef benthic data, we were also interested in looking at Chagos-wide patterns in benthic community structure and ecology. A detailed treatise on this topic can be found in Supplemental File S2, which includes Figures S1 and S2 and Table S1.

3.3. CoralNet Accuracy

Upon training the CoralNet AI with the 24-feature lablesset, classification accuracy approached 85% (Figure S3). One hundred images from Egmont, Blenheim, and Peros Banhos were randomly chosen for secondary manual verification, and a similar accuracy of 84.4% was achieved (Table 1). These accuracies are similar to the 83.1% value reported in the original CoralNet publication [15] and higher than that reported in a more recent analysis (80% in [20]). However, the authors of the latter reference sought species-level resolution, unlike herein, where only the most common coral genera were included as distinct categories; as such, a lower accuracy would be expected in their work. In a meta-analysis, Williams et al. [21] found that the typical CoralNet user only used the AI-generated predictions when the accuracy exceeded 90%. For our purposes, we considered an accuracy of 85% to be sufficient, especially given the large time savings compared to manually classifying upwards of 30 benthic features in the remaining 1900 images, which would take several weeks (vs. several minutes by CoralNet).

Table 1. Summary of findings of formal (transect + photo-quadrat-based) vs. informal (random “tourist diver” images) coral reef survey comparison. CoralNet was used to predict both coral cover and percent (%) bleaching from 1900 images taken by a non-survey diver (CoralNet accession #6447) after manually training at various stages. Error terms represent standard deviation. The mean % bleaching values represent those from surveys at Peros Banhos conducted in late April through early May 2015; the overall % bleaching across all survey sites and dates was $9.8 \pm 8.6\%$ (informal method only). FNR = false-negative rate; FPR = false-positive rate.

Metric	Value	Notes/Details
# Images taken for informal analysis	2619	
# Images used in informal CoralNet analysis	2500	
# Images used for initial CoralNet AI training	270	Scored 8100 features manually
# Features scored by CoralNet AI	60,000	
CoralNet-calculated classification accuracy	84%	
# Images for <i>post-hoc</i> accuracy verification	100	Scored 3000 features manually
Manually calculated classification accuracy (%)	$84.4 \pm 12\%$	
# Images for assessment of FPR and FNR	230	Scored 6900 features manually
# Coral colonies scored for assessment of FPR and FNR	1748	
Overall accuracy of coral bleaching analysis	89.2%	
Bleaching classification FPR (%)	0.4%	
Bleaching classification FNR (%)	34.3%	
Mean coral cover—formal analysis (%)	$38.7 \pm 16.8\%$	
Mean coral cover—informal analysis (%)	$35.1 \pm 21\%$	Formal > informal (Figure 4)
Mean % bleaching—formal analysis	$30.5 \pm 2.9\%$	
Mean % bleaching—informal analysis	$31.8 \pm 7.3\%$	Formal = informal

With our simple, 24-label labelsset, it is likely that a well-trained technician could indeed achieve significantly higher accuracy than the 85% from CoralNet, and so the degree to which a practitioner relies on CoralNet to automate image annotations might ultimately depend on both the taxonomic resolution and the total number of images to be analyzed. CoralNet relies on a deep convolutional neural network architecture known as VGG-16, with the 16 referring to the number of layers. It is now common to use 19 layers (VGG-19), which offers a modest increase in accuracy in theory, albeit at an increased computational demand. It stands, then, that AI-driven image classification will only improve with time, with newer approaches like ReefCloud and ReefLearning [22] already showing promise (both were inactive as of 25 December 2025).

3.4. Coral Cover Comparison: Informal vs. Formal Survey Approaches

The formal, LOF point-intercept + photo-quadrat data yielded a mean coral cover across the 109 sites of $38.7 \pm 17\%$ vs. $35.1 \pm 21\%$ from the tourist diver analysis; despite the relatively modest difference, these values differ significantly (student’s *t*-test, $p < 0.0001$) due to the large number of data points. This is equivalent to a mean percent difference across methods of $\sim 10\%$ ($[38.7 - 35.1] / \text{mean } [38.7, 35.1] \times 100$), and the correlation across approaches of 0.42 was statistically significant (Figure 4a). In a second analysis, a matched-pairs test was run whereby the mean absolute % coral cover differences were assessed across methods at each of the sites for which there were data from both methods, and the mean difference in coral cover was $\sim 5\%$. This value differs slightly from the 3.6% difference presented above (i.e., 38.7 vs. 35.1%) because the mean % difference is not necessarily

equal to the mean difference in percentages since the degree of correlation across methods differed over the coral cover spectrum (Figure 4b); the informal and formal methods were more likely to agree at percentages near the global Chagos mean of 35–40%. At far lower and far higher coral cover levels, the accuracy of the informal method decreased. For instance, at a real coral cover of ~4% (the lower left-most point in Figure 4b), the two methods diverged by 100%. This signifies that the informal approach performs better on reefs with more typical coral cover values, becoming less accurate at both the lower and upper ends of the spectrum.

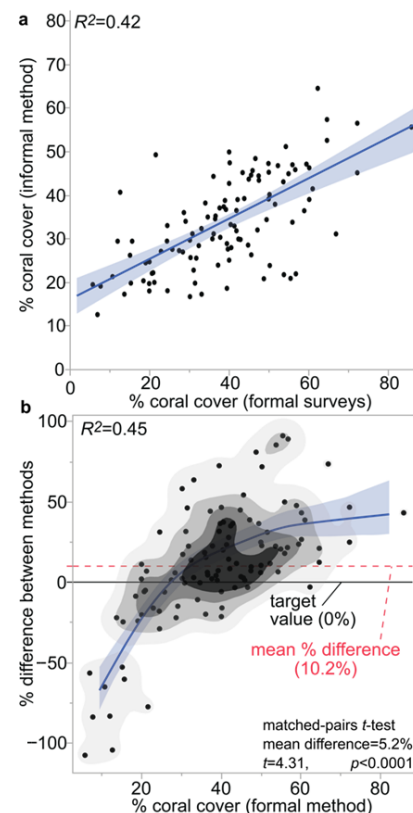


Figure 4. Comparison of coral cover percentages obtained from two methods. Results from a formal, “gold standard” method that incorporated data from both point-intercept and photo-quadrat surveys were compared to those from an informal one based on the AI analysis of images taken by a diver in the vicinity of the formal surveyors. The correlation across methods is shown (a), with the shading around the best-fit line representing 95% confidence. Panel (b) shows the relationship between the mean coral cover of the formal method (x-axis) and the percent difference across methods, as well as reference lines for the optimal value of no difference (black line), and the mean percent difference across methods for all survey sites (red, hatched line). A spline has been plotted to show the relationship, and the shading around it represents 95% confidence. A contour plot has been used to show data point density, highlighting that accuracy of the informal method was maximized when the actual coral cover was in the 30–35% range (darkest coloration). Note that the matched pairs difference (5.2%) is lower and represents the mean difference by site (vs. the overall mean difference across methods of 10.2%).

When taking formally acquired benthic imagery and comparing the data from a trained scientist using an approach like CPCE vs. CoralNet, Williams et al. [21] documented Pearson’s R values between 0.92 and 0.97, far higher than those obtained herein. This is to be expected because in their work, the exact same images were analyzed by both a human and an AI. Herein this comparison could not be made because a large portion of the benthic data produced by LOF scientists were from point-intercept surveys, in which images were not taken (divers instead noted the organisms along the transect whilst

underwater.). Instead, the same general reefs areas were encompassed. This likely explains why, although the overall coral cover means were similar, there was high variability amongst sites. Interestingly, there was no correlation between the number of images taken at a site and the percent difference in coral cover estimates across methods ($R^2 = 0.00$); it could be envisioned that better-imaged sites would, all else being equal, be associated with more accurate coral cover estimates. Instead, a predictor screen identified that reef region was the largest contributing factor to inter-method discrepancies (Figure 5a); this likely stems from AI training bias. Additional images from primarily Egmont were analyzed as a secondary accuracy estimation check. Hence, better and more accurate training data were included for this region; consequently, the lowest mean percent difference in coral cover between the formal and informal methods (8%) was documented at Egmont.

Although not quantified, another factor that would likely drive differences between the formal and informal methods is water clarity. At clearer sites, image quality should be better, making it easier for the AI to correctly classify benthic organisms in the informal approach. As forereef sites were generally clearer than lagoonal ones (as tends to be the case elsewhere; [23]), we compared the mean percent coral cover difference across these reef locations, and there was indeed a statistically significant difference ($p < 0.01$); only 1.8% difference between survey methods in the forereef sites vs. 22.3% in the lagoons (Figure 5b). This difference, while likely linked to visibility and image quality in part, could also be explained by the fact that the first author was more dedicated to sampling corals (*Pocillopora acuta* & various *Seriatopora* spp.) that were found in lagoonal habitats. Therefore, less of the reef area may have been encompassed by photos in these habitats (as he would not have had to have swum long distances to find corals to samples), despite the overall number of images taken per site not differing significantly between forereef and lagoonal sites (student's t -test, $p = 0.03$).

As mentioned above, there is surely a positive relationship between image quality and accuracy. This would extend not only across sites of differing visibility, but within a site; given the attenuation of light through the water column, images taken in shallow water will, all else being equal, be of higher resolution, with a better representation of the organisms' colors. All analyzed images were white-balanced, but no strobes were used at depth, nor was flash photography used; images taken at greater depths were therefore darker. Unfortunately, we could not assess accuracy over depth because the depths at which images were taken were not noted in the informal surveys (unless the surface could be seen in the image). Regardless, it is almost certain that there was a depth effect; the informal analysis would likely be more accurate (closer to the formal, gold standard data) at shallower depths. The difficulty in accurately identifying corals in deeper, darker images could, in fact, explain why the formal method, overall, yielded higher coral cover estimates. In future informal surveys using Olympus TG cameras without the housing (as of TG7), a depth stamp can now be added to the image provided that the diver stays within the recommended depth range of the camera (<15 m). For future shallow surveys, then, it will be possible to better assess the potential drop in accuracy of the informal photography method with depth using this newer line of Olympus underwater cameras.

It is also worth reiterating a caveat raised in the Materials and Methods. All photos analyzed herein were taken by the first author, a coral reef scientist with extensive experience in underwater surveys and photography. Although the method advocated is simple and requires only the ability to SCUBA dive and capture photos, smart phone and GoPro white-balancing algorithms are, as of late-2025, still unsatisfactory for taking pictures with accurate colors. As color can be a key feature that both humans and AIs use to differentiate corals from each other, as well as other benthic features like rocks, this means that manual underwater white-balancing, regardless of the phone/camera used, is still critical for the

success of the approach. In other words, the degree of congruency/correlation between the formal and informal approaches described above likely represent a “best-case scenario,” though as underwater photography becomes cheaper, more common, and better at capturing underwater colors without expensive strobes, we are optimistic that actual citizen scientists (vs. a scientist “pretending” to be a citizen, as was the case herein) will gradually take photos that are comparable to, if not better than, those of scientists and underwater photographers whose images are, at present, still those that normally feature in datasets and publications.

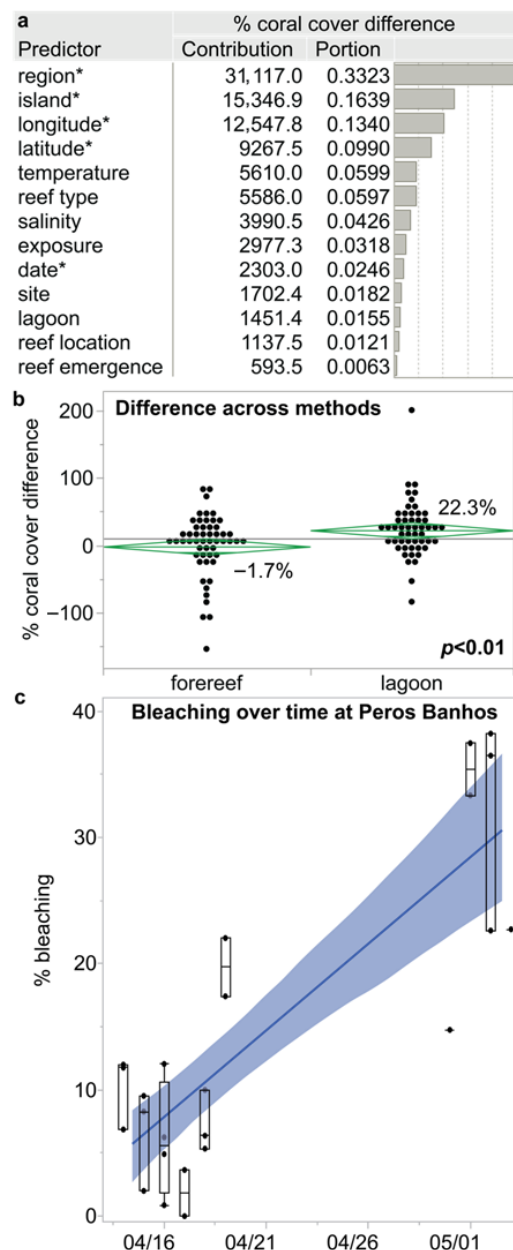


Figure 5. Drivers of variation in percent difference in coral cover values across the formal, gold standard point-intercept + photo-quadrat survey method and the informal tourist diver approach. A predictor screen showing a summary of 100 random bootstrap forest models of the environmental parameters’ effects on inter-method variation (a). Those for which a response screen documented a statistically significant impact (false discovery rate-adjusted $p < 0.05$) are denoted by asterisks (*). Given its link with visibility (foreereef > lagoon), the effect of reef location (foreereef vs. lagoon) on the percent difference across methods has been plotted (b). Coral bleaching data at Peros Banhos have been plotted over time (c), and the mean percent bleached coral surface area rose from ~5–10% in mid-April to over 30% by early May. Shading around the best-fit line represents 95% confidence.

3.5. Coral Bleaching Comparison: Informal vs. Formal Survey Approaches

In addition to coral cover, we also sought to determine whether the informal method could be used to acquire accurate coral bleaching data. In contrast to the coral cover analysis, we did not have access to the entire dataset used to calculate the coral bleaching percentages shown in Figure 7 of Sheppard et al. [8], which involved a mix of LOF-acquired data and those from the late Dr. Sheppard. Therefore, we instead manually extracted the bleaching percentages by depth presented in Figure 7 of Sheppard et al. [8] to calculate the mean (across 0 to 30 m) from Peros Banhos of $30.5 \pm 2.9\%$ in May 2015. The mean % bleaching from our 2500-image CoralNet analysis in this same region in late-April–early-May 2015 was instead $31.8 \pm 7.3\%$; this is statistically similar to the formal, LOF + Sheppard value (Wilcoxon rank-sum test, $p > 0.05$), and the accuracy of the informal analysis was 89% (Table 1). Several of these sites had been surveyed earlier in April, at which point only 5–10% of the colonies had bleached (Figure 5c). According to a later study [9], the 7.5 degree-heating weeks documented in Chagos during our 2015 surveys resulted in a 60% decrease in coral cover over the course of 2015 through early 2016, with live coral cover at Peros Banhos at only 10% by April 2017 (down from $49 \pm 6\%$ during our 2015 surveys). A more recent report [12] documented 35% bleaching across the entire Chagos region in response to a 2024 heat wave; this resulted in a mean coral mortality 23%. These results highlight the wide reach of climate change; even reefs far from human population centers can no longer be said to be in a pristine state. Whether the reefs recover as quickly (<10 years) as they did following the 1998 bleaching event [24] remains to be determined, though it is likely that recovery will differ across reef zones given the marked differences in their benthic composition documented herein and in prior works [25].

Despite similar bleaching percentages derived from the formal and informal analyses, not to mention the high classification accuracy of CoralNet in the latter, the vast majority of the corals used in the AI training were unbleached. When manually analyzing a subset of 230 images from the worst bleaching sites at Peros Banhos, false-positive and false-negative bleaching classification rates of 0.4 and 34%, respectively, were documented; the latter result is particularly high and signifies that over one-third of bleaching corals were incorrectly classified as healthy. In contrast, only 5 out of the subset of 1742 coral colonies assessed in this analysis were determined to be bleaching when they were actually healthy. Although some of the 185 FN colonies displayed intermediate shading between healthy and bleached corals, the majority of them were stark white and obviously bleached to the untrained, naked eye. In theory, these should have been amongst the simplest images to classify. This discrepancy could be related to the dominance of acroporids at the sites, whose apical corallites lack dinoflagellate endosymbionts and so are consequently white. Therefore, the AI would have been trained with a plethora of healthy *Acropora* spp. photos that encompassed white portions at the branch tips. Why poritids, which do not possess asymbiotic regions, were also misclassified as being healthy when they were paling is perhaps instead due to their turning blue in the days leading up to bleaching; light blue colonies that were evidently in the process of bleaching to a scientist were classified as healthy by CoralNet. In future analyses, we will adopt a “blue *Porites*” category that encompasses these stressed, but oftentimes not-yet-bleaching corals; this will surely result in a dramatic reduction in the currently high false-negative AI bleaching classification rate.

4. Conclusions

Despite the fact that the tourist diver + CoralNet approach yielded an accuracy of only 84%, as well as a tendency for false-negative bleaching classifications, the overall coral cover and bleaching prevalence data agreed well with those from a rigorous, laborious survey effort using tried-and-true point-intercept and photo-quadrat approaches. In instances

where trained scientists are available to conduct formal surveys, this is clearly still the superior option. However, in areas where scientific training is minimal or lacking entirely, those equipped with underwater cameras or smart phones that can be suitably protected could conceivably capture a large number of coral reef images, as well as a modicum of meta-data (including date, GPS coordinates, &, ideally, depth). These individuals could either reach out to us, local coral scientists, or, for those more motivated and with internet access, directly create a profile on CoralNet and freely upload their photos. Although manual training must still be done by someone before the AI begins its own annotations, this labor could effectively be crowd-sourced to the coral community at large. Those desiring information from the hypothetical reef area in question could annotate the 20–30 images (at minimum) required to train the AI and trigger automated annotations. This citizen science approach could allow us to acquire data from far-flung locations and track coral reef conditions over time, a task that is becoming increasingly more important as corals the world over continue to disappear [26].

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/oceans7010001/s1>, Supplemental File S1: the online supplemental data (Excel) file. Supplemental File S2 (supplemental methods & results), which contains Supplemental Table S1 (Discriminant analyses testing for effects of key environmental parameters (EP) on the benthic assemblage) and Figures S1–S3 (Figure S1. PCA, MDS, and a predictor screen of coral cover; Figure S2. A partial least squares correlation loading plot depicting the influence of all environmental parameters (EP) on the coral reef benthic composition of the survey sites (n = 336 site x depth observations); Figure S3. CoralNet AI accuracy improvement over course of training).

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
EP	Environmental parameters
FNR	False-negative bleaching classification rate
FPR	False-positive bleaching classification rate
LOF	Living Oceans Foundation

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