REPORT

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The cover of living and dead corals from airborne remote sensing

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Abstract Trends in coral cover are widely used to indicate the health of coral reefs but are costly to obtain from field survey over large areas. In situ studies of reflected spectra at the coral surface show that living and recently dead colonies can be distinguished. Here, we investigate whether such spectral differences can be detected using an airborne remote sensing instrument. The Compact Airborne Spectrographic Imager (Itres Research Ltd, Canada) was flown in two configurations: 10 spectral bands with 1-m² pixels and 6 spectral bands with 0.25-m² pixels. First, we show that an instrument with 10 spectral bands possesses adequate spectral resolution to distinguish living Porites, living Pocillopora spp., partially dead Porites, recently dead Porites (total colony mortality within 6 months), old dead (>6 months) Porites, Halimeda spp., and coralline red algae when there is no water column to confuse spectra. All substrata were distinguished using fourth-order spectral derivatives around 538 nm and 562 nm. Then, at a shallow site (Tivaru) at Rangiroa Atoll, Tuamotu Archipelago (French Polynesia), we show that live and

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dead coral can be distinguished from the air to a depth of at least 4 m using first- and fourth-order spectral derivatives between 562-580 nm. However, partially dead and recently dead Poritescolonies could not be distinguished from an airborne platform. Spectral differences among substrata are then exploited to predict the cover of reef substrata in ten 25-m^2 plots at nearby Motu Nuhi (max depth 8 m). The actual cover in these plots was determined in situ using quadrats with a 0.01m² grid. Considerable disparity occurred between field and image-based measures of substrate cover within individual 25-m² quadrats. At this small scale, disparity, measured as the absolute difference in cover between field and remote-sensing methods, reached 25% in some substrata but was always less than 10% for living coral (99% of which consisted of *Porites* spp.). At the scale of the reef (all ten 25-m² quadrats), however, disparities in percent cover between imagery and field data were less than 10% for all substrata and extremely low for some classes (e.g. <3% for living Porites, recently dead Porites and Halimeda). The least accurately estimated substrata were sand and coralline red algae, which were overestimated by absolute values 7.9% and 6.6%, respectively. The precision of sampling was similar for field and remote-sensing methods: field methods required 19 plots to detect a 10% difference in coral cover among three reefs with a statistical power of 95%. Remote-sensing methods required 21 plots. However, it took 1 h to acquire imagery over 92,500 m² of reef, which represents 3,700 plots of 25 m² each, compared with 3 days to survey 10 such plots underwater. There were no significant differences in accuracy between 1-m² and 0.25-m² image resolutions, suggesting that the advantage of using smaller pixels is offset by reduced spectral information and an increase in noise (noise was observed to be 1.6-1.8 times greater in $0.25-m^2$ pixels). We show that airborne remote sensing can be used to monitor coral and algal cover over large areas, providing that water is shallow and clear, and that brown fleshy macroalgae are scarce, that depth is known independently (e.g. from sonar survey).

Keywords French Polynesia · Monitoring · Live and dead coral cover · Statistical power · Remote sensing

Introduction

Coral reefs are forecast to experience increasing levels of stress from global rises in temperature and sea level (Pittock 1999), increased frequency of ENSO events (Timmermann et al. 1999) and tropical cyclones (Knutson et al. 1998), and reductions in calcification rate resulting from high concentrations of atmospheric carbon dioxide (Kleypas et al. 1999). These global phenomena may also exacerbate local disturbances such as disease (Harvell et al. 1999), overfishing (Hughes 1994), poor fishing practices (McManus 1997), and poor watershed management (Tomascik and Sander 1987). The net effect of most disturbances is a reduction in the percent bottom cover of living coral. Temporal changes in coral cover are therefore widely used to evaluate the "health" of coral reefs (English et al. 1997).

The measurement of living coral cover is usually accomplished by field survey (English et al. 1997). Since field survey is expensive, cost-effective alternatives are required to assess coral cover over spatial scales that span hundreds or thousands of kilometers. In principle, optical remote sensing offers a solution to this problem but to date, few studies have been successful and these have been confined to very shallow water (usually < 1m), over fairly homogeneous reefs. Thamrongnawasawat (1996) predicted coral cover in very shallow and sheltered reefs using low-altitude infrared aerial photography. Hochberg and Atkinson (2000) analyzed a multispectral airborne image of a shallow patch reef and correctly predicted that the reef was dominated by living corals. The detection of live versus dead coral cover was identified as a top priority during a recent international workshop on coral reef remote sensing (ICLARM/ NOAA 1999). Most high resolution (1 m - 30 m pixels)remote sensing of coral reefs has focused on mapping reef geomorphology or major biotopes (see reviews by Green et al. 1996, Holden and LeDrew 1998a).

Spectral measurements of reef biota and substrata generally suggest that major functional forms of corals and algae can be distinguished when measured using the narrow spectral bands (1–2 nm) of a hand-held spectroradiometer (Maritorena 1996, Holden and LeDrew 1998b, Holden and LeDrew 1999, Myers et al. 1999, Clark et al. 2000, Hochberg and Atkinson 2000, Lubin et al. 2001, Hedley and Mumby 2002, Minghelli-Roman et al. 2002). However, there are several steps between measuring pure spectra and making a remote sensing technique operational. First, remotely sensed data are acquired using a restricted number of relatively broad spectral bands and therefore the shape of a substrate's spectrum is defined with fewer points than can be obtained using a field spectroradiometer. Remotely sensed

spectra are therefore unable to detect more subtle shapes in spectra and this may reduce their separability. Secondly, a remote-sensing instrument is usually located on either an airborne or space-borne platform and light must pass through the water column and atmosphere before being detected by a sensor. Even if coral substrata can be distinguished spectrally, there is no guarantee that a sensor will record a strong enough signal to permit such discrimination. Thirdly, and perhaps most importantly, variations in depth severely confound recorded spectra. Observed reflectance spectra depend on the bottom type, optical water properties, and depth of each pixel. Although optical water properties can be estimated from the imagery (Maritorena 1996), depth is rarely known for each pixel and therefore bottom type cannot be identified correctly unless depth can either be factored out of the analysis or added explicitly.

This study addresses the first and second steps listed above and examines whether state-of-the-art remote sensing methods are able to distinguish reef spectra and ultimately monitor changes in the cover of reef substrata including live corals. The specific objectives were:

- 1. Demonstrate, from first principles, that the spectra of major reef substrata are distinguishable using the broad spectral bands offered by remote-sensing instruments.
- 2. Examine whether the spectra of living, partially dead, recently dead, and old-dead *Porites*can be distinguished by a state-of-the-art airborne sensor once the reflected light has passed through the water column and the atmosphere.
- 3. Exploit spectral differences among reef components to evaluate the accuracy and precision with which coral cover can be predicted from remotely sensed data at two spatial resolutions.
- 4. Assess the pros and cons of field versus remotesensing methods of monitoring coral cover.

Two resolutions of image acquisition were investigated that may affect the efficacy of remote sensing and its cost-effectiveness. Smaller pixels have the advantage of being more appropriately scaled to sample reef substrata, on which patch sizes are often measured in squared centimeters rather than squared meters. There are, however, several important disadvantages to using small pixels. First, the signal-to-noise ratio of measured reflectance is usually low because less light is collected and the high ratio of pixel perimeter to area allows "nuisance" light, originating from outside the pixel, to exert a relatively large influence on the signal. Secondly, smaller pixels necessitate high data acquisition rates that often reduce the number of spectral bands in which data are recorded. A reduction in the number of bands may reduce the degree to which reef substrata can be spectrally distinguished. Third, more flight lines are required to survey an area using small pixels and this may drive up the cost of image acquisition and time for subsequent image analysis.

Although part of the results of the study were published recently (Mumby et al. 2001a), the present paper expands the analysis to include separability of spectra both with and without a water column, compares two levels of spatial and spectral resolution, and provides a detailed description of methods, results, and discussion. The problem of variable depth on recorded spectra are not dealt with here, and we point out upfront that remote sensing of reef health will not become operational unless depth can be extracted directly from the imagery or unless reef bathymetry is surveyed independently (e.g. using sonar). New theoretical methods are emerging to resolve depth from imagery (e.g. Hedley and Mumby 2003, Stumpf et al. 2003) and will be assessed in later publications.

Methods

Study site

Studies were carried out at two sites in the lagoon of Rangiroa Atoll (15° 0' 4.3" S, 147° 52' 51.8" W) in the Tuamotu Archipelago, French Polynesia. An initial field survey was conducted in April of 1998 during the mass bleaching event. All of the data presented here were gathered 6 months later (November 1998) as part of an assessment of the effects of coral bleaching. The first site, Tivaru, was chosen because it was dominated by large colonies of Porites (mean two-dimensional surface area $= 7.3 \text{ m}^2$) in various states of health. Large colonies were sought to obtain unambiguous whole-pixel spectra of each mortality state as required for objective 2. The average depth at this site was 3.8 m. A second site, Motu Nuhi, was selected to predict coral cover (objective 3). Motu Nuhi had greater habitat heterogeneity, including beds of dead Pocillopora evdouxi, Porites spp., rubble (covered with coralline red algae, mainly Hydrolithon onkodes), and patches of the green calcareous alga, Halimeda. The site measured approx 1 km in length and depth ranged from 0.8 to 8 m. For further descriptions of reef habitats and sites see Mumby et al. (2001b).

Field methods

To relate field sites to imagery, six to ten square plastic markers with an area of 4 m² were tied to the seabed at each site. At Tivaru, five 20–30 m long transects were laid out using tape between markers and the positions of *Porites* colonies were mapped within a 16-m swathe of each tape (e.g. coral X positioned 15.6 m along tape and 4.5 m perpendicularly to left). The position, mortality state, length, width, and depth were recorded for 90 colonies. Mortality states were categorized as living coral (\geq 80% live tissue), partially dead (20–79% living tissue), recently dead (< 19% living tissue and corallite structure visible where dead), and old dead (100% dead,

no corallite structure visible). Many of the recently dead colonies had died 6 months previously during the mass bleaching event (Mumby et al. 2001b). Ten 5 m \times 5 m quadrats were located haphazardly at Motu Nuhi and referenced to plastic markers. The percent cover of all living and dead substrata exceeding 0.001 m²were recorded throughout the entire 25 m² using video. Large quadrats were used to minimize the effect of misregistration between the quadrat and the grid of pixels present in the imagery. Such errors should not exceed one pixel and would only constitute a problem if the percent cover of substrata differed significantly between two overlapping 25-m^2 quadrats, offset by 0.5 - 1 m. The effects of such misregistration were estimated conservatively by calculating percent cover of substrata from a 4×4 m subset located at a randomly selected corner of the 5×5 m quadrat. The effect of a 1-m misregistration at the side and bottom of the quadrat was then simulated by recomputing the percent covers from another 4×4 m subset placed at the opposite side of the 25-m² quadrat. Since this study focused on reefscale estimates of coral cover, the effects of misregistration were then expressed as the mean difference in percent cover between the two 16-m² subsets of each quadrat. The difference in estimates of cover was < 0.4% for living and dead coral. Sand created a much larger disparity of 1.7%.

Quadrat depth varied from 1.5 to 7.5 m. Airborne imagery was acquired during the field survey, and output images were laminated in plastic and extensively ground-truthed in situ.

Imagery and analysis

Multispectral imagery was acquired using the Compact Airborne Spectrographic Imager (CASI, manufactured by Itres Research Ltd, Canada) in two configurations (see Fig. 1 for examples).

- a. Ten spectral bands with 1-m² pixels. Band centers (nm) and widths (parentheses) were: 413.3 (9.7), 449.6 (10.7), 506.1 (6.2), 550.0 (5.3), 565.0 (5.3), 575.4 (4.3), 599.9 (6.2), 625.5 (5.3), 650.2 (5.3), and 674.9 (5.3).
- b. Six spectral bands with 0.25-m² pixels. The first band center was 469.9 nm (20 nm width) and the remaining five bands corresponded exactly to the fourth, fifth, seventh, ninth, and tenth bands of the 1-m²set-up.

Bands were selected based on a review of published coral and algal spectra (see Hedley and Mumby 2002). A wider blue band was used in the 0.25-m² set-up to compensate for smaller pixel sizes and reduced signal.

Each row of pixels was radiometrically corrected to reflectance using an incident light sensor. Correction for light attenuation in water was undertaken at Motu Nuhi because depth was highly variable. The natural logarithm of reflectance was obtained for a uniform substratum (sand) and regressed against depth from the



Fig. 1a–d CASI imagery of Motu Nuhi showing hard substratum, sand patches, and white targets used to register the imagery to field sites. Plates **a** and **c** reveal the difference in feature definition between 0.25-m^2 and 1-m^2 pixels, respectively. Spectral bands were subjected to principal components analysis and the first 3 eigenvectors plotted in false color. The distribution and detail of spectral information differ between 6-band (**b**) and 10-band (**d**) imagery. Scale represents approximately 600 x 400 m

ground-truth maps. The gradient of each linear regression yielded an in-band diffuse attenuation coefficient (k, Jupp 1988) with a coefficient of determination of 0.66 to 0.85. The reflectance (R_z) of each ground-truthing site and quadrat was then standardized to a depth (z) of zero meters (R_o) using equation 1. Depth variations did not exceed 2 m at Tivaru, so diffuse attenuation coefficients could not be calculated from the imagery. Instead, analyses were stratified into two depth zones (2–3 m, 3–4 m).

$$\boldsymbol{R}_z = \boldsymbol{R}_o e^{-kz} \tag{1}$$

All spectra were converted to first, second, third, and fourth derivatives (Tsai and Philpot 1998) to emphasize differences between substrata. First derivatives were calculated as the rate of change of reflectance against wavelength between the mid-point of adjacent spectral bands. This process was repeated for higher order derivatives but wavelengths related to the midpoint of lower derivatives rather than spectral bands. Submerged habitats at Motu Nuhi were mapped using unsupervised classification of depth-compensated spectral derivatives. Unsupervised methods allowed many (25) habitat classes to be identified without imposing statistical constraints on the spectra (as in supervised methods). Independent ground-truth data were used to assign each spectral category to a habitat class or mortality state.

Direct measurement of reef spectra and scaling to remotely sensed data (objective 1)

To demonstrate that the spectra of major reef substrata can be distinguished from first principles, small samples were collected, kept moist, and placed over a black background. The spectra of algae, living coral, and dead coral were then measured using a pair of GER 1500 spectroradiometers. One instrument measured downwelling irradiance reflected from a white lambertian surface (Spectralon panel), while a second sensor simultaneously recorded reflected radiance from a circular part of the specimen measuring 4 cm in diameter. Radiance was measured at 2-nm intervals and ratioed to provide a measurement of spectral remote sensing reflectance (Mobley 1994). At least 20 spectra were taken per specimen and a minimum of three specimens was used per coral or algal category. Spectral variation within categories was much less than variation between categories so spectra were pooled.

A number of studies have investigated reef spectra measured at a high spectral resolution (see above). However, remotely sensed data are acquired using a restricted number of relatively broad spectral bands and therefore the shape of a substrate's spectrum is defined with fewer points. Original reflectance spectra were therefore adjusted to simulate the CASI band settings described above. Each spectral band of the CASI comprises the sum of the signal from several adjacent sensor bands spaced at 1.9 nm, each with a full width at half maximum (FWHM) of 2.2 nm. Since the resolution of GER spectroradiometers and CASI elements are similar (2.0 and 2.2 nm, respectively), CASI spectra were simulated as the mean of adjacent spectroradiometer bands over the width of the respective CASI band.

Comparison of field and remotely sensed data

Conventionally, the accuracy of a thematic map is assessed using pixel-specific comparisons between predicted and field-verified classes (Congalton 1991). While this approach is appropriate for large pixels and general habitat classes (e.g. 30 m pixels denoted 'reef'), it would be virtually impossible to compare individual $1-m^2$ or $0.25-m^2$ quadrats and pixels without any misregistration.

A new method was established to measure the accuracy of coral cover from remote sensing which is meaningful for reef monitoring. The survey quadrats at Motu Nuhi were used to estimate the mean cover of various substrata at a reef scale (from all ten 25-m² quadrats), based on detailed field survey. Since the composition of each 25-m² quadrat had also been mapped using remote sensing, equivalent image-based estimates of mean substratum cover were generated

Fig. 2 Reflectance spectra of emergent reef substrata measured in situ using a spectroradiometer and resampled to 10 CASI spectral bands. Error bars denote 95% confidence interval about the mean reflectance per spectral band from the 10 quadrats. Thus, the analysis addressed the question 'Does a field-based estimate of coral cover, usually estimated at whole reef scales, match that derived from remote sensing?'. Accuracy was calculated as the difference between field and image-based estimates of mean percent cover at a reef scale. Precision was compared by calculating the number of quadrats needed to have a 95% power of detecting a 10% change in coral cover based on an ANOVA design (sensu Carleton and Done 1995).

Results

1. Distinguishing the spectra of major reef substrata using the broad spectral bands offered by remote-sensing instruments

The spectra of reef substrata, measured without an overlying water column and using the same spectral bands as those used with the CASI, are shown in Fig. 2. Although the shapes of some spectra appeared to be visually similar (e.g. old-dead and partially dead Por*ites*), no two substrata overlapped spectrally across the full visible spectrum (Fig. 2). The spectrum of recently dead Porites was particularly smooth and lacking in obvious features. Fourth-derivative spectra (Fig. 3) amplified the spectral differences between substrata, and inspection of the 95% confidence intervals revealed that approximately half of the substrata were distinguishable using a single derivative. All substrata could be distinguished using two or more derivatives. Coral genera (Porites and Pocillopora) and mortality states were distinguished using the fourth derivatives around 538 nm and 562 nm (Fig. 3). Halimeda was effectively distin-



Fig. 3 Histograms of fourthderivative spectra from the re-sampled emergent spectra shown in Fig. 2. Error bars denote 95% confidence interval about each fourth derivative. X-axis is not continuous, and derivatives are ordered in ascending wavelength. Wavelengths refer to the midpoint between upper and lower wavelengths from which each derivative was calculated



guished from corals and red algae at 601 nm and 625 nm. Coralline red algae were most effectively distinguished using the fourth derivative centered on 625 nm (Fig. 3).

2. Distinguishing among Porites colonies using an airborne sensor

Fig. 4a, b Mean reflectance

in four states of health at a

depth of 2-3 m. Spectra from 10-band data are shown in (a)

and from 6-band data in (b)

spectra acquired by the CASI

at Tivaru from Porites colonies

Spectra extracted from CASI imagery of Tivaru suggested subtle differences between *Porites* states. These were more obvious in the 10-band imagery than in the 6band data with 0.25-m² pixels (Fig. 4). The majority of spectral differences occurred between 500 nm and 600 nm and reflectance dropped rapidly at wavelengths exceeding 600 nm. Again, differences in raw spectra were amplified by calculating derivatives. For 1-m (10-band) imagery in shallow water (2–3 m), first derivatives revealed a downward progression at 528 nm from live to partially dead to recently dead *Porites* (Fig. 5a). A corresponding progression was absent from corals in slightly deeper water of 3–4 m (Fig. 5b). Fourth derivatives were similar at depths of 2–3 m and 3–4 m (Fig. 6). Visual inspection of these derivatives suggested:



Fig. 5a, b First derivatives of reflectance spectra acquired by the CASI at Tivaru from *Porites* colonies in four states of health. Pixel size is 1 m^2 . Corals at a depth of 2–3 m are shown in (a) and at 3–4 m in (b). Error bars denote 95% confidence interval about the mean first derivative



(i) that 538 nm offered less discriminatory power than in the in situ spectra (Fig. 3); (ii) that maximum discrimination between states occurred at 562 - 580 nm (Fig. 6); (iii) that partially dead and recently dead colonies were difficult to distinguish; and (iv) that live and old-dead colonies differed markedly in their spectra. The latter observations were confirmed using non-parametric Kruskal-Wallis tests of multiple comparisons (Zar 1996) among the medians of fourth-derivative spectra at 3–4 m centered on a wavelength of 580 nm. Overall, fourthderivative spectra were significantly different between coral states (H = 37.64, p < 0.001), but partially dead colonies could not be distinguished from recently dead colonies (see Table 1). Similar results were obtained using spectra from shallower corals (2–3 m) and derivatives from 562 nm (not shown).

Transforming the six-band CASI data (for 0.25-m^2 pixels) to fourth derivatives was limited because six spectral bands only yielded derivatives at two regions of the spectrum. Therefore, analysis focused on first derivatives that would, in practice, offer a greater number of axes (five) with which to distinguish substrata. Visual inspection of first-derivative spectra (Fig. 7) revealed that coral states were poorly distinguished in most derivatives and that 558 nm offered the greatest potential for separation. In shallower water (2–3 m), derivatives from the 558 nm region appeared to divide into two groups: live and partially dead *Porites*

Fig. 6a, b Histograms of fourth-derivative spectra measured at Tivaru in 10-band (1-m²) imagery. Error bars denote 95% confidence interval about each fourth derivative. Xaxis is not continuous, and derivatives are ordered in ascending wavelength. Wavelengths refer to the midpoint between upper and lower wavelengths from which each derivative was calculated. Corals at a depth of 2–3 m are shown in (a) and 3–4 m in (b)



Wallis (K-S) test significance of *** represents p < 0.001). Ticks indicate significant multiple comparisons among medians (p <0.05). Crosses indicate non-significant differences (p > 0.05). 50 colonies were located at 2–3 m and 40 at 3–4 m

Coral States (Porites sp.)		Live			Partially dead			Recently dead		
Partially dead	Depth (m) Wavelength (nm) Pixel size (m ²) Derivative K-S significance	2-3 558 0.25 1 st ***	2-3 558 0.25 1 st ***	3-4 580 1 4 th ***	2–3 558 0.25 1 st ***	2-3 558 0.25 1 st ***	3-4 580 1 4 th ***	2–3 558 0.25 1 st ***	2–3 558 0.25 1 st ***	3–4 580 1 4 th ***
Old dead		~	×	~	V	~	~	~	×	~

Fig. 7a, b First derivatives of reflectance spectra acquired by the CASI at Tivaru from *Porites* colonies in four states of health. Pixel size is 0.25 m². Corals at a depth of 2–3 m are shown in (a) and at 3–4 m in (b). Error bars denote 95% confidence interval about the mean first derivative



versus recently dead and old-dead *Porites* (Fig. 7a). Such contrast was absent or much reduced at 3–4 m depth (Fig. 7b). Kruskal-Wallis multiple comparison tests (Zar 1996) revealed that first derivatives at 558 nm offered fair discriminatory power between colony states (Table 1). Spectral confusion occurred between live and partially dead *Porites*, and between recently dead and old dead *Porites* at 2–3 m depth (Table 2). In deeper water, spectral confusion occurred between live *Porites* and both recently dead and old dead colonies (Table 1).

3. Accuracy and precision with which coral cover can be predicted from remotely sensed data at two spatial scales

3a. Accuracy

1-m² pixels and 10 spectral bands:

Considerable disparity occurred between field and image-based estimates of substratum cover at Motu Nuhi within individual 25-m² quadrats (Table 2). At this

small scale, disparity, measured as the absolute difference in cover between field and remote-sensing methods, reached 25% in some substrata but was always less than 10% for living coral (99% of which consisted of *Porites* spp.). At the scale of the reef (among all 10 quadrats), however, disparities in percent cover between imagery and field data were less than 10% for all substrata (Table 2, Fig. 8) and extremely low for some classes (e.g. < 3% for living *Porites*, recently dead *Porites*, and *Halimeda*). The least accurately estimated substrata were sand and coralline red algae, which were overestimated by absolute values 7.9% and 6.6%, respectively.

Pairwise *t*-tests of mean substrate cover between field and image data were all non-significant (p > 0.05), but power analysis (Zar 1996) was carried out to determine the sensitivity of these tests (Table 2). For example, at a power of 95%, a *t*-test would have concluded that fieldand image-based estimates were significantly different had the disparity in mean coral cover exceeded 7.1%. Alternatively, estimates of the mean cover of coralline red algae could differ by 18.2% before a significant re**Table 2** Comparison of field- and image-determined estimates of substrate cover in ten 25-m^2 quadrats at Motu Nuhi using CASI imagery at two spatial resolutions. Pairwise comparisons for each substratum using *t*-tests were all non-significant (p > 0.05). Minimal detectable difference represents the minimal disparity in mean cover between field and image estimates that would result in a

significant *t*-test with 95% power. Note that old-dead *Porites* were encrusted with coralline red algae and are therefore treated as a single class. There were insufficient *Porites* colonies in a state of partial mortality to identify this as a separate class in the imagery. Standard errors shown in parentheses

Substratum	Mean percent cover (%)			Disparity (%)		Maximum disparity (%)		Minimal disparity	Minimal detectable disparity of	
	Field	Imagery						means (76)		
Pixel size (m ²)		1	0.25	1	0.25	1	0.25	1	0.25	
Live Porites	11.5 (2.7)	8.8 (2.9)	10.1 (3.1)	-2.7	-1.4	-9	10.1	7.1	7.0	
Recently dead Porites	7.8 (1.6)	6.8 (3.1)	11.5 (3.6)	-1.0	3.7	18.9	34.2	13.5	16.2	
Dead Pocillopora	32.5 (8.3)	37.2 (12.6)	34.9 (11.0)	4.7	2.4	28.9	39.4	21.9	22.1	
Coralline red algae	21.8 (2.4)	15.2 (4.8)	23.8 (7.5)	6.6	2.0	-25.7	30.6	18.2	18.7	
Sand	18.9 (6.0)	26.8 (9.1)	12.1 (3.8)	7.9	-6.8	27.2	34.3	15.4	14.8	
Halimeda	3.9 (1.6)	5.1 (2.1)	7.3 (2.3)	1.2	3.4	-9.7	29.8	10.5	14.4	

Fig. 8 Benthic community structure of coral reefs at Motu Nuhi derived from field survey and 10-band (1-m²) CASI imagery. Mean percent covers from field survey are shown in black, and image-based estimates are given in grey. Error bars denote 95% standard error about mean



sult was concluded correctly. These estimates of minimal detectable difference provide a statistical caveat to the study, which is necessary when dealing with nonsignificant results. Failure to reject the null hypothesis of "no significant difference between field and remote-sensing-based estimates of cover" may be because the methods really are similar or because the data were so variable that the *t*-test had barely any power to detect differences.

0.25-m² pixels and 6 spectral bands:

Increasing the spatial resolution of the sensor fourfold had little overall effect on the accuracy with which mean substrate cover was estimated (Table 2). Mean live coral cover was estimated to within a few percent, and sand was again estimated with relatively low accuracy. Differences in the accuracy of coral cover estimates between the 1-m² and 0.25-m² imagery were investigated for each substratum using matched-pair *t*-tests. All results were non-significant (p > 0.05) with or without Dunn-Šidák adjustments to alpha to correct for multiple testing (see Sokal and Rohlf 1995).

3b. Precision

A hypothetical sampling program was designed to use 25-m^2 quadrats at each of three reefs with a view to detecting a 10% difference in coral cover at one reef with 95% power. With effect size (10%), alpha (5%), and beta (5%) held constant, the sample size required for each sampling methodology depended purely on the

180 standard devia

standard deviation among samples obtained using that method (standard errors given in Table 2). It is evident from Table 3 that sample size was similar for both field and remote-sensing methods. A slightly larger sample size was needed to detect a 10% difference in coral cover using the higher spatial resolution imagery because the standard deviation of percent coral cover estimates was slightly larger than that for 1-m²pixels. Sampling precision was greatest for the field survey, and of the two remote sensing methods, precision was marginally greater in the higher resolution imagery.

Discussion

Although Caribbean reef habitats have been mapped to a depth of ca 18 m using CASI (Mumby et al. 1998), the present study differs to this earlier work because it moved beyond the scale of habitats. In the earlier study, reef habitats were defined at a spatial scale of 20 x 20 m where each habitat represented an assemblage of living and dead components of the reef. In the present study, we attempted to estimate the cover of individual components directly. This difference in objective constitutes a major departure from conventional habitat mapping and explains some of the differences in accuracy between this study and others. For example, the habitat category 'sand' is assigned where sand is the predominant cover type within a pixel, and is usually mapped very accurately because it has a high albedo. However, sand occurs in many other habitat types even though it does not predominate. The presence of sand in these other habitats is not reflected in a standard assessment of accuracy for the habitat 'sand'. Therefore, estimating the cover of sand is a fundamentally different objective from accurately mapping the habitat 'sand'. It does not follow that the cover of sand will be estimated accurately even if large patches of sand are easy to identify (as they are in Fig. 1). In the present study, the presence of sand was measured in situ at a scale of 0.01 m², much of which cannot be seen directly in the imagery unless it dominates an entire pixel or group of pixels.

Re-sampling emergent reef spectra to CASI bands revealed that multispectral airborne instruments have the spectral capability to distinguish among the major

Table 3 Comparison of required sampling precision between fieldsurvey and remote-sensing methods for estimating percent living coral cover. Each sample is a 5×5 m quadrat. Sample size required to detect a 10% difference in coral cover among three reefs (coral cover 10%, 10%, 20%) with a statistical power of 95% and Type I error of 5% (Zar 1996) is estimated. Precision is also given as the ratio of standard error to the mean. Standard deviations were generated from a sample of 10 quadrats at Motu Nuhi

Sampling method	Sample size for 90% power	Precision
Field survey (quadrat inspection)	19	0.24
CASI 1 m ² , 10 bands	21	0.33
CASI 0.25 m^2 , 6 bands	23	0.29

types of reef substrata. Whereas red wavelengths (exceeding 600 nm) were found to offer good discriminating power in emergent spectra, high attenuation of light in these wavelengths greatly restricted their use for separating spectra once light had passed through the water column twice and been recorded by the CASI. The remotely sensed data were consistent with in situ studies (Clark et al. 2000) in suggesting that discrimination of live and dead coral is most likely between wavelengths of 515 nm and 596 nm (bands 3-7 of the 10-m CASI imagery). Gil-Turnes and Corredor (1981) found that peridinin comprises ca. 39% of zooxanthellar pigments. The absorption of this pigment peaks at 475 nm, and declines to around 550 nm (Jeffery et al. 1997). Since the zooxanthellate densities of live, partially dead, and dead corals differ markedly, it was expected that their spectra would reflect a gradient of peridinin concentration. This would manifest itself in the spectra as either an increase in absolute reflectance at around 475 nm from live to partially dead to dead coral, or as a decrease in the first derivative above 475 nm. Such spectral patterns were seen in the first derivatives of both CASI data sets in shallow waters, but not in the 3-4 m depth zone or resampled emergent spectra. The absence of a peridininbased gradient in spectra from some data remain enigmatic, although in situ studies by Holden and LeDrew (1998b) found a peridinin-like feature in coral spectra that was absent from bleached corals, a finding consistent with our expectation.

Peridinin concentrations are only one of several spectral factors that will change as coral progresses through mortality states. Increased exposure of the calcium carbonate skeleton will tend to raise overall reflectance, masking specific changes in absolute reflectance. The effects of changing absolute reflectance reinforce the need to use derivative spectra, which are independent of absolute reflectance. Another potentially important aspect of coral reflectance is fluorescence (Mazel 1995, Hedley and Mumby 2002). Corals often fluoresce at a peak of 575 nm (Mazel 1995), which may explain the high degree of separation of living coral in derivatives around 562 nm and 580 nm. Once dead, most coral colonies were colonized by filamentous and short turf algae whose taxonomic composition can be diverse (Adey and Goertemiller 1987). It seems likely that the diversity of possible algal taxa potentially comprising such turfs may explain the lack of a pigmentspecific spectrum, associated with recently dead *Porites*. Other functional categories of algae were more easily identified. Coralline red algae contain phycoerythrin which has an absorption peak at 570 nm, coinciding with a reflectance peak in many corals (Hedley and Mumby 2002). These features were consistent with the spectra presented here (Fig. 2) and probably underpinned the difference in fourth derivatives between live corals and coralline red algae. Of the targets considered in this study, only *Halimeda* contains chlorophyll-b, which has an absorption peak at around 650 nm. It was evident as a small dip in reflectance in the re-sampled in situ spectra, and was detectable using remote sensing because a CASI band was placed at 650 nm.

Differences in the spectra of *Porites*states were detectable using remote sensing to a depth of 4 m (the maximum depth of colony surfaces at Tivaru). Living *Porites* could be distinguished from all other states using a single fourth derivative from the 10-band imagery. Partially dead and recently dead colonies were difficult to distinguish and spectral confusion was greater in the sixband data. However, despite the observed difficulty in separating some substrata using a single derivative, the results are encouraging because they provide direct evidence that living and dead corals can be distinguished under field conditions using remote sensing. The degree of spectral confusion implied by these analyses is conservative and needs to be carefully considered. Spectral derivatives are not statistically independent because the shape of a curve at one point will partly depend on its shape in adjacent regions. Many multivariate testing procedures cannot be applied legitimately to these data, and therefore the analyses were confined to univariate analyses at a single derivative. A single derivative can, however, only represent a limited amount of spectral information, and this is why most remote sensing studies use multivariate discriminant functions, applied to multiple derivatives, in order to classify pixels (Green et al. 2000). Although the latter procedure may involve nonindependent variables, it is tolerated because the discriminant functions are used to force spectral data into substratum categories rather than to test hypotheses. Indeed, the science of extracting information from spectra is in its infancy. Our results concur with others in that derivatives help discriminate reef substrata (Hochberg and Atkinson 2000, Lubin et al. 2001), but the use of derivatives here is by no means exhaustive. The range of possible derivatives from a 10-band data set is bewildering: not only are there several orders of derivatives from which to choose, but a derivative can be calculated between any pair of start and end points along the spectrum. In short, the univariate analyses presented here are inadequate, and reef spectra may be better distinguished in the future after further developments are made in extracting spectral information and in conducting multivariate hypothesis testing with autocorrelated data.

Mapping errors arise from three key sources, and it is instructive to discuss these in terms of sand, which consistently had the greatest error. First, misregistration errors between imagery and field quadrats were found to be most acute for sand, presumably because the distribution of sand patches at scales of meters is more aggregated than in other substrata surveyed. Second, sand has the highest albedo (brightness) of all substrata and will tend to overwhelm the signal of other substrata from a pixel. For example, a pixel containing 70% sand and 30% *Halimeda* will probably be classified as sand, contributing a 30% overestimation of sand from that pixel. Such overestimation events are less likely to occur in smaller pixels because the ratio of pixels to mixels will increase with decreasing pixel size. This phenomenon may account for the overestimation of sand in 1-m^2 imagery and underestimation in 0.25-m^2 imagery. Third, because sand presents a highly reflective surface, a degree of 'color casting' may occur in which light reflected from adjacent substrata hits the sand and is reflected towards the sensor. The reflected light will resemble the neighboring substrate and could lead to spectral confusion and an underestimation of sand cover. It is not possible to speculate on the importance of color casting in the present study, but work is in progress to model these non-linear radiative transfer processes.

The cover of living and dead corals was predicted accurately from multispectral remote sensing, even though inaccuracies occurred at the scale of individual 25-m^2 quadrats. Inaccuracies in the prediction of live coral cover never exceeded an absolute value of 10%, and were on average only 3% different from the field estimate. For general management of reefs with moderate coral cover (i.e. not <10%), a reef-scale estimate of coral cover within 10% of the actual value may be adequate (it will clearly depend on the purpose of the survey). Video-based coral monitoring methods used by the Australian Institute of Marine Science are able to detect an inter-annual change of 10% with a power of 95% (Carleton and Done 1995). Using this as a benchmark for the present study, 19 field quadrats or 21 "remote-sensing quadrats" would be required to detect an equivalent change in coral cover at Motu Nuhi. However, this comparison is of limited practical value beyond showing the similarity in precision of remote sensing and field methods. Field methods estimate a population mean for live coral cover from the variance among samples. In contrast, remote sensing samples much larger areas (up to the entire whole reef population) and therefore a sample size of 21 quadrats is not relevant to the methodology. It took 1 h to acquire imagery over 92,500 m² of reef, which represents 3,700 plots of 25 m² each, compared with 3 days to survey 10 such plots underwater.

Both resolutions of imagery provided similar overall accuracy and precision, suggesting that the pros and cons of moving to higher spatial resolution probably balance at the scales used in this study. Visual inspection of imagery from Motu Nuhi revealed that coral reef features could be defined more clearly in the higher (spatial) resolution imagery (Fig. 1A vs. C). However, the spectral information associated with each image type followed an opposite trend in that first eigenvalues easily accounted for the information content of 6-band data (84%) but not so in 10-band data (59%, see Figs. 1B,D). To provide further insight, a measure of signal to noise was calculated for each image resolution using an emergent sand bank near Tivaru. To remove variance owing to real submeter patchiness in the reflectance of sand, high-resolution imagery at 0.25 m² was re-sampled to 1 m²by taking the mean reflectance of four adjacent pixels. The coefficient of variation (proportion of standard deviation to mean) was then calculated for original and re-sampled 1-m² pixels in five identical CASI bands. Larger coefficients of variation indicate a larger amount of noise in the signal and were found to be 1.6 to 1.8 times greater in the re-sampled high resolution imagery. Therefore, any gains accrued from using a smaller pixel, which is putatively closer in scale to the size of substrate patches, were offset against the reduction in meaningful signal in the data. In this case, $1-m^2$ imagery would be the more cost-effective proposition for mapping reefs (image costs ca. US\$26 k for 500 km²).

Airborne remote sensing of coral cover should probably be deployed within a nested design that uses satellite imagery to stratify reefs according to the expected threat from a particular disturbance (e.g. proximity to hurricane tracks, accumulated thermal stress, etc.). Reefs within each stratum would then be selected randomly and included in an airborne flight plan. Field survey would then be carried out in a random subset of the reefs subjected to remote sensing. Surveys would provide ground-truthing information to classify imagery and independent data to assess the accuracy of coral cover estimates. Finally, predicted levels of coral cover would be adjusted according to the accuracy assessment (e.g. actual coral cover is 2.7% less than that predicted in imagery). Although the need for some field survey is inescapable, remote sensing would allow reef health to be monitored over vast areas. Not only are such assessments more representative of the reef as a whole but, if repeated through time, they provide fresh insight into the scales of reef dynamics. Remotely sensed data would, for example, reveal the spatial patchiness of bleaching-induced coral mortality and improve the matching of pattern with process (e.g. do the scales of mortality coincide with those of particular reef features or hydrological phenomena?). It should also be borne in mind that detailed maps of reef community structure have applications beyond monitoring reef health. For example, habitat maps are used in the design of marine protected areas (Stevens 2002) and assessment of coastal beta diversity (Mumby 2001).

A recent study showed that the (full) spectra of reef taxa could be distinguished in many coral reef regions (Hochberg et al. 2003). Our study reveals that spectral separation of taxa is still possible using a subset of 10 spectral bands placed within the visible spectrum. On the basis of these results, multispectral discrimination of reef taxa should be possible in many reef environments. Other aspects of the results are more heavily site-specific. First, airborne sensors were shown to be able to detect spectral differences between coral colony states, suggesting that remote sensing of coral cover should, in principle, be possible. This was then confirmed at a second reef. However, the conclusions require several caveats before being extrapolated to other reef systems. First, successful application of remote sensing will depend on selecting the most appropriate spectral bands, pixel sizes, and analyses. Second, water clarity must be reasonably high (k = 0.05 below 540 nm) because increasing depth will significantly reduce the differentiation of spectra (Clark et al. 2000). Depth did not exceed 8 m in this study. Third, while the plots incorporated considerable benthic heterogeneity, phaeophytes were virtually absent on the reefs surveyed. Spectral confusion between macroalgae and corals might occur on reefs with an abundance of phaeophytes (but see Myers et al. 1999). Fourth, depth was measured throughout the study site and this may not be feasible for large areas of reef. Radiative transfer models are currently being developed to provide a more generic understanding of the physical and biological limitations of remote sensing for coral reef monitoring.

To conclude, airborne remote sensing has the spectral capability to distinguish living and dead colonies of *Porites* through a shallow and clear water column. Practical application of these methods should favor larger pixels (1 m² rather than 0.25 m^2) with greater spectral information. At this stage, independent data are required on reef bathymetry (e.g. using sonar), but new methods are being tested to avoid additional survey requirements (e.g. Hedley and Mumby 2003).

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