Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra

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Abstract

We investigate the abilities of seven remote sensors to classify coral, algae, and carbonate sand based on 10,632 reflectance spectra measured in situ on reefs around the world. Discriminant and classification analyses demonstrate that full-resolution (1 nm) spectra provide very good spectral separation of the bottom-types. We assess the spectral capabilities of the sensors by applying to the in situ spectra the spectral responses of two airborne hyperspectral sensors (AAHIS and AVIRIS), three satellite broadband multispectral sensors (Ikonos, Landsat-ETM+ and SPOT-HRV), and two hypothetical satellite narrowband multispectral sensors (Proto and CRESPO). Classification analyses of the simulated sensor-specific spectra produce overall classification accuracy rates of 98%, 98%, 93%, 91%, 64%, 58%, and 50% for AAHIS, AVIRIS, Proto, CRESPO, Ikonos, Landsat-ETM+, and SPOT-HRV, respectively. Analyses of linearly mixed sensor-specific spectra reveal that the hyperspectral and narrowband multispectral sensors have the ability to discriminate between coral and algae across many levels of mixing, while the broadband multispectral sensors do not. Applying the results of the general mixing analyses to a specific spatial organization of coral, algae, and sand indicates that the hyperspectral sensors accurately estimate areal cover of the bottom-types regardless of pixel resolution. The narrowband multispectral sensors overestimate algae cover by 7–29% and overestimate coral cover by 24–103%. We conclude that currently available satellite sensors are inadequate for assessment of global coral reef status, but that it is both necessary and possible to design a sensor system suited to the task.

Keywords: Coral; Algae; Sand; Reflectance; Remote sensing; Classification

1. Introduction

Coral reefs are complex marine ecosystems that are constructed and maintained by biological communities that thrive in the warm, sunlit tropical ocean. For millions of people living in their vicinities, reefs serve as a larder and as a base for economic livelihood (Johns, Leeworthy, Bell, & Bonn, 2001; White, Vogt, & Arin, 2000). For the rest of the world, reefs are important as a storehouse of biodiversity rivaling that of tropical rainforests (Bellwood & Hughes, 2001). Although reef communities have evolved and persisted in the face of natural destructive processes, modern anthropogenic forces threaten to devastate reefs throughout the world, both directly and indirectly (Kleypas et al., 1999; Smith & Buddemeier, 1992). Worst-case estimates of reef degradation predict that in the next 30 years, nearly half of the world’s reefs may be irrevocably lost (Wilkinson, 2000).

A universal symptom of reef degradation is mass coral mortality followed by algal colonization of the coral skeletons (Done, 1992). Such phase shifts (change from one community structure to another) may occur slowly or precipitously. Following coral mortality, algae become the dominant form of benthic cover. Under proper conditions, coral may promptly recolonize a disturbed area (Connell, 1997). However, if conditions continue to favor algal over coral growth, disturbed areas may enter a macroalgal phase, where they remain indefinitely. Thus, phase shifts are apparent as altered relative distributions of reef bottom-types, including coral, various algae, and sand. Quantifying the areal coverage of bottom-types at a point in time, given the proper historical and geomorphological context, allows a researcher to identify the current phase of the reef, and thus assess reef status. Quantifying bottom-type cover over time enables identification of phase shifts, and thus changing reef
status. Knowledge of reef bottom-type distributions further allows straightforward estimates of rates for reef productivity, community metabolism and biogeochemical cycles (Andréfouët & Payri, 2001; Atkinson & Grigg, 1984), and identification of habitats and resources for monitoring and management (Bour, Loubersac, & Rual, 1986; Price, Kim, & Tsai, 1987). Thus, aspects of reef system function and, more importantly reef status, are reducible to the quantitative measure of areal coverage of basic reef bottom-types. There are three common methods for determining benthic cover on coral reefs: (1) 1–10-m-scale quadrats, (2) 10–100-m-scale line transects, and (3) 100–m-scale manta-tows, which entail towing a diver on a sled behind a boat, with the diver pausing periodically to record estimates of reef cover. Quadrats and transects resolve reef elements at the scale of 1s to 10s of centimeters, providing detailed and statistically rigorous estimates of reef community structure (Bouchon, 1981). Manta-tows are less rigorous because they are conducted at a much larger spatial scale without spatial reference cues, which has two main drawbacks: a decrease in resolving power and a lack of repeatability (Bainbridge & Reichelt, 1988; Miller & Müller, 1999). Nevertheless, the manta-tow is the accepted standard for the Global Coral Reef Monitoring Network (UNESCO, 1991).

Regardless of the methodology, in situ surveys have provided direct observations of only 10s to 100s km2 of reef area worldwide (Wilkinson, 2000), or 0.01–0.5% of the total reef area of 250,000 to 600,000 km2 (Kleypas, 1997; Smith, 1978; Spalding & Grenfell, 1997). Thus, syntheses such as Wilkinson’s report are best estimates of global reef status, and their accuracies are questionable. Because vast reef expanses—especially in remote areas—remain unsurveyed, and because existing data are not uniform, accurate global evaluation of reef bottom-type coverage, and thus reef status, is currently not possible (Ginsburg, 1994). One tool that has potential for providing the necessary data for assessment of global reef status is digital remote sensing (Mumby, Chisolm, Clark, Hedley, & Jaubert, 2001). This technology is the most cost-effective approach for acquiring synoptic data on reef community structure (Mumby, Green, Edwards, & Clark, 1999), and it is the only available tool that can reasonably acquire such data uniformly across the globe.

Kuchler, Biña, and Claassen (1988) and Green, Mumby, Edwards, and Clark (1996) provide good reviews of the history and current status of coral reef remote sensing. These reviews note that most research has been conducted with data provided by satellite multispectral scanners on board the Landsat or SPOT (Satellite Pour l’Observation de la Terre) satellites. This is also the case as of early 2002, although peer-reviewed studies utilizing airborne multi- and hyperspectral imaging systems (Hochberg & Atkinson, 2000; Mumby et al., 2001; Mumby, Green, Clark, & Edwards, 1998; Mumby, Green, Edwards, & Clark, 1997) have appeared since Green et al. Satellite remote sensing has primarily enabled mapping of reef geomorphological zonation (Green et al., 1996), and given knowledge of specific morphological features and corresponding benthic habitats, maps of reef benthic habitat or community classes (Bour et al., 1986). Airborne sensors usually have higher spatial and spectral resolution than satellite sensors, providing more spectral information on more pure targets, and thus greater accuracy in detailed coral reef habitat mapping (Mumby et al., 1997).

Generally, the case studies applying remote sensing to coral reef habitat mapping have been constrained by sensor capabilities, largely because available sensor systems have not been specifically tailored to coral reefs. Sensor limitations in spectral and spatial resolution lead to ambiguous benthic classes, the resolution of which requires significant interpretation by the researcher based on prior knowledge of the scene, or extensive ground-truthing. By employing site-specific knowledge in the analysis, the accuracy of this sensor-down product is a combination of site-specific information and sensor capabilities. In contrast, the objective of assessing global reef status a priori provides unambiguous benthic classes (coral, algae, sand) that are not site-specific, which removes the burden of interpretation from the researcher and places it on the remote sensing system. From this deterministic, reef-up point of view, there are two main requirements: (1) coral, algae and sand must each have characteristic features that enable their identification/discrimination, and (2) a given remote sensor must have the ability to detect those characteristic features.

The types of features that a remote sensor can detect in reef bottom-types are spatial and/or spectral in nature. It is both possible and useful to incorporate knowledge of reef spatial organization into the classification process (e.g., Andréfouët, Roux, Chancerelle, & Bonneville, 2000), but actual spatial statistics (e.g., texture) that are characteristic of reef bottom-types have yet to be defined, at least for remote sensing purposes. The basic link between coral reef bottom-types and remote sensing imagery then lies in the spectral nature of the image data. Thus, the fundamental requirements for remote sensing of reef status become (1) that the bottom-types each have characteristic spectral features and (2) that those spectral features are detectable by the remote sensor. From the spectral classification point of view, spatial resolution is an issue only in that, for a given spatial arrangement of reef bottom-types, different pixel sizes incur different amounts of spectral mixing. Under the assumption of linear spectral mixing, a given set of proportions for coral, algae, and sand results in the same overall mixed spectrum at any pixel size. That is, as long as the proportion coral/algae/sand is constant, and as long as the coral, algae, and sand component spectra are constant, a pixel at 4 × 4 m resolution has the same mixed spectrum as a pixel at 40 × 40 m resolution (discounting differences between sensor point spread functions). Thus, spectral mixing is theoretically independent of spatial scale. Of course, it is virtually impossible for these mixing conditions to be met because reefs are heterogeneous with respect to
the spatial arrangements of bottom-types (proportions not constant), and there is spectral variability among the bottom types (spectra not constant). Therefore, if a general mixing model includes all possible proportions coral:algae:sand as well as the spectral make-ups of the bottom-types, then each pixel in a remote sensing image represents a special quantized case of the general model, with the quantization dependent on pixel size.

Previous research into spectral reflectance properties suggests that differences do exist between various reef organisms and substrates (Andréfouët, Muller-Karger, Hochberg, Hu, & Carder, 2001; Clark, Mumby, Chisholm, Jaubert, & Andréfouët, 2000; Hochberg & Atkinson, 2000; Holden & LeDrew, 1998, 1999; Lubin, Li, Dustan, Mazel, & Stamnes, 2001; Maritorena, Morel, & Gentili, 1994; Miyazaki & Harashima, 1993; Myers, Hardy, Mazel, & Dustan, 1999). However, with the exception of Holden and LeDrew (1999) who considered corals in Fiji and Indonesia, these studies have been local in nature. Without exception, the total number of reflectance spectra in each study has been few, numbering in the 10s to 100s, and the methods employed by each have been dissimilar, producing results of varying quality. Three of these studies have extended their analyses from in situ spectral reflectance measurements to discrimination of reef objects by remote sensing systems. Through radiative transfer modeling, Lubin et al. (2001) claimed that Landsat-TM should have the ability to distinguish between carbonate sand, coralline algae, green macroalgae, algal turf, and various coral species. Conversely, Andréfouët et al. (2001), in an analysis of its change detection abilities, suggested that Landsat-ETM+ is only capable of distinguishing between three broad classes including carbonate sand, “background” (rubble, pavement, heavily grazed dead coral structure), and “foreground” (living coral, macroalgae). Hochberg and Atkinson (2000), using in situ and remote sensing data, showed that simple discrimination between coral, algae, and sand can be achieved with as few as four narrow, noncontiguous wavebands. Finally, to the best of our knowledge, there has been no peer-reviewed investigation into the effects of spectral mixing on the detection of the reef bottom-types.

The main objective of this study is to evaluate the capabilities of different remote sensors to provide data that is useful for assessing global coral reef status. First, we define the bottom-types that are important for determining reef status: coral, algae, and carbonate sand. We explore the fundamental spectral separability of these bottom types by performing discriminant and classification analyses on 10,632 1-nm-resolution reflectance spectra measured in situ on reefs in the Atlantic, Indian, and Pacific Oceans. To investigate the spectral limitations of different remote sensors, we repeat the discriminant and classification analyses on spectra treated with spectral response functions for each of seven sensors: three satellite sensors, two airborne sensors, and two hypothetical sensors optimized for coral reefs. The satellite sensors are SPOT-HRV (High-Resolution Visible), Ikonos, and Landsat-ETM+ (Enhanced Thematic Mapper Plus), and the airborne sensors are AAHIS (Advanced Airborne Hyperspectral Imaging System) and AVIRIS (Airborne Visible/Infrared Imaging Spectrometer). The hypothetical sensors are Proto (for prototype), with wavebands entirely determined through statistical analysis of the spectral data, and CRESPO (Coral Reef Ecosystem Spectro-Photometric Observatory), which has been presented to NASA as a fully developed concept study (Atkinson et al., 2001). For each sensor, we numerically describe the general mixing model, independent of spatial scale, for 5050 possible proportions of coral/algae/sand and for 10,000 possible component spectral compositions. Finally, we create special mixing cases by simulating remote sensing imagery for each sensor. Analysis of the pure spectra and the general and special mixing models provides insight into the relative capabilities of the different sensors to provide data that is useful for assessment of coral reef status.

2. Methods

2.1. Measurement of in situ reflectance spectra

The spectral reflectance \( R \) (implicitly a function of wavelength) of a material is defined as the ratio of the reflected radiant flux to the incident radiant flux (Morel & Smith, 1993). In our case, \( R \) is the fraction of incident light flux that is reflected by the different bottom-types. We measured and processed in situ \( R \) for visible wavelengths (400–700 nm) following methods described in Hochberg and Atkinson (2000). Our sampling unit consisted of a 30-m-long fiber optic cable (400 \( \mu \)m diameter) attached to an Ocean Optics S2000 portable spectrometer (wavelength range 330–850 nm, with ~0.3 nm sample interval and ~1.3 nm optical resolution), which was in turn operated by a laptop computer. The fiber optic cable tip collected light over a solid angle of ~0.1 sr, which at a distance of 10 cm projected to a circular area of 10 cm². For each single measurement of \( R \), a diver pointed the collecting tip of the fiber optic cable at the desired bottom-type and depressed a button at the end of a 30-m-long trigger cable, prompting the computer to store the spectrum (in units of digital counts). Immediately thereafter, the diver pointed the collecting tip at a Spectronal diffuse reflectance target (same depth as the target bottom-type) and triggered the storage of its spectrum. In this manner, both spectra could be acquired within 1–2 s. To maximize the signal-to-noise ratio, a 10% Spectronal was used for dark substrates (e.g., corals, algae), and a 99% Spectronal was used for bright substrates (i.e., carbonate sand). To ensure a constant ambient light field between the two measurements, the Spectronal was immediately placed adjacent to the target bottom-type, and the diver’s position was held constant for the 1–2 s required for the measurements. Measurement depths ranged between 0 and 15 m. For shallow (<5 m) samples, we shaded both target bottom-
type and Spectralon to minimize the influence of wave focusing (light "flashes"). We employed a submersible flashlight (Underwater Kinetics Sunlight C8) to supplement flux at red wavelengths for deeper (>5 m) samples.

We corrected all spectra for baseline electrical signal, then calculated $R$ as the ratio of the bottom-type to Spectralon for each pair of measurements. We interpolated $R$ to 1-nm intervals over the wavelength range 400–700 nm and filtered the result using the Savitsky–Golay method (Savitsky & Golay, 1964; Steiner, Termonia, & Deltour, 1972). In all, we measured 10,632 $R$’s at the following sites in the Atlantic, Indian, and Pacific Oceans (Fig. 1): (1) St. Croix, USVI; (2) Puerto Rico; (3) Florida Keys; (4) Oahu, HI; (5) Maui, HI; (6) Rangiroa, French Polynesia; (7) Moorea, French Polynesia; (8) Palau; (9) Bali, Indonesia; and (10) the Waikiki Aquarium (Indo-Pacific corals grown in aquaria). The algae class included 5500 spectra from the Cyanophyceae, Phaeophyceae, Chlorophyceae, and Rhodophyceae, and the coral class consisted of 4490 spectra from the Acroporidae, Poritidae, Siderastreidae, Agariciidae, Merulinidae, Faviidae, and Caryophylliidae. The sand class consisted of 642 spectra.

### 2.2. Determination of Proto and CRESPO wavebands

Determination of the spectral response curve for Proto was an entirely statistical process. We first used the multivariate technique of stepwise selection (Rencher, 1995) to determine the individual 1-nm wavelengths that best separate the bottom-types. In stepwise selection, wavelengths were added one at a time based on their scores in a partial $F$ test, which assessed the contribution of the newly added wavelength to the class separation provided by wavelengths already included in the selected list. As each new wavelength was added to the list, all previously selected wavelengths were checked for statistical redundancy. The stepwise selection process ended when no new wavelength could contribute to class separation above a preselected threshold value (partial $p = 0.05$). The final stepwise selected list contained 24 wavelengths that together, and without redundancy, best separated the bottom-types. For each of the 24 wavelengths, we created an arbitrary relative Gaussian spectral response, centered at the selected wavelength and with a band width (FWHM) of 10 nm. We summed the resulting 24 spectral responses to produce an overall spectral response for Proto.

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**Fig. 1.** Relative spectral responses of airborne hyperspectral and satellite multispectral sensors often used in coral reef remote sensing. Also included are the hypothetical Proto and CRESPO sensors, with wavebands specifically designed for discrimination of coral, algae, and carbonate sand.
response. The final spectral response curves for the Proto wavebands were determined by identifying bandcenters and band widths of nodes in the overall spectral response. The final Proto spectral response had eight wavebands centered at 451, 482, 498, 526, 556, 580, 610, and 647 nm with band widths (FWHM) of 10, 10, 18, 10, 14, 25, and 14 nm, respectively.

Selection of CRESPO wavebands was partly based on a statistical analysis similar to that for Proto, but as it was the result of a fully developed concept study to NASA, the CRESPO development also considered engineering constraints that were not considered for Proto. To achieve a low-cost, low-energy, compact system, it was ultimately determined that CRESPO would have four wavebands dedicated to reef mapping, centered at 480, 510, 540, and 570 nm, each with a band width of 20 nm (FWHM). The final wavebands for CRESPO and Proto, as well as for the other sensors utilized in this study, are shown in Fig. 1.

2.3. Simulation of sensor-specific spectral reflectance

We used the in situ spectral reflectance data to model the bottom-types as the different sensors would “see” them. This model simulated the sensors’ spectral views of the bottom-types as pure pixels and without atmosphere or water column radiative transfer effects, thus defining a theoretical upper limit to the discriminative abilities of the sensors. To create these sensor-specific reflectance spectra, we simply applied each sensor’s relative spectral response (Fig. 1) to the full-resolution spectra.

2.4. Discriminant analysis

Discriminant analysis is a procedure that describes the separation of two or more predefined classes based on linear functions of multiple variables (Rencher, 1995). As they are the linear combinations of the variables that best separate the classes, the discriminant functions describe the plane or planes on which the original multivariate data can be projected to optimally represent class configuration. The discriminant function coefficient vectors \( a_1, a_2, \ldots, a_s \) are the \( s \) eigenvectors of \( E^{-1}H \), where \( E \) is the within-sample sum of products and cross-products matrix, and \( H \) is the between-sample sum of products and cross-products matrix. These \( s \) coefficient vectors are transformed into \( s \) discriminant functions \( z_1 = a_1'Y, z_2 = a_2'Y, \ldots, z_s = a_s'Y \), where \( Y \) is an observation vector (i.e., a spectrum = a single \( R \)), and both \( a \) and \( Y \) are column vectors. For more details of discriminant analysis as described here, see Rencher (1995).

We used discriminant analysis to develop simple graphic representations of coral, algae, and sand for each spectral resolution considered. Because we only considered three classes, optimal group separation could be achieved with the first two discriminant functions \( z_1 \) and \( z_2 \). Thus, for a given sensor, a scatter plot of \( z_1 \) versus \( z_2 \) illustrated the class separation provided by that sensor. That is, if a particular waveband set provided good spectral separation of the classes, then a plot of the discriminant functions should show the classes as three well-defined clusters of points.

2.5. Classification analysis

Classification analysis is a procedure in which a sampling unit of unknown identity is assigned to one of a set of predefined classes based on functions of several variables (Rencher, 1995). The classification functions may or may not be linear combinations of the variables, but they are generally based on some measure of multivariate distance, and the unknown sampling unit is allocated to the class to which the distance is minimized. The coefficients \( C \) for linear classification functions (LCFs) based on the Mahalanobis distance are \( c_i' = \bar{y}_i S_{pi}^{-1} \), where \( \bar{y}_i \) is the mean vector for predefined class \( i \) (i.e., the mean of all \( R \)'s for a class), and \( S_{pi}^{-1} \) is the inverse of the pooled sample covariance matrix for all the predefined classes. A coefficient constant is also added: \( c_0 = -1/2S_{pi}^{-1} \bar{y}_i \). The classification functions \( L \) are evaluated as \( L_i(y) = c_i'y + c_0 \), and the unknown sampling unit is assigned to the class \( i \) for which \( L_i(y) \) is a maximum (rather than a minimum: in the calculation of \( c \), the sign of the distance measure was reversed). For more details of classification analysis as described here, see Rencher (1995).

To determine the overall spectral separability of the three bottom-types, we performed a classification analysis following the partition method (Rencher, 1995): we used half of the \( R \)'s in each class to train LCFs, and the other half to test classification accuracy. We calculated classification rates as the number of individual \( R \)'s in the predicted class divided by the total number of \( R \)'s in the actual class, multiplied by 100. In an error matrix calculated in this manner, the diagonal elements were the rates of correct classifications for each class (equivalent to so-called producer’s accuracies, Congalton, 1991), and the off-diagonal elements were the rates of misclassification. We followed the same procedures for each of the sensor-specific spectral reflectance data sets.

We also used LCFs to evaluate the effects of spectral mixing on the spectral separation of the classes. For the full-resolution data and for each sensor, we used all of the \( R \)'s to train LCFs, which were tested with mixed spectra of varying composition. Then, for each of coral, algae, and sand, we computed the classification frequency as the number of mixed spectra assigned to the given class divided by the total number of mixed spectra. For example, for a particular mixed spectrum composition (e.g., 80% coral, 15% algae, 5% sand, total = 100%), the classification frequency for coral was the number of spectra classified as coral divided by the total number of spectra. Thus, in the spectral mixing analysis, there were no “misclassifications,” only classification frequencies.
2.6. Spectral mixing analysis

For the spectral mixing analysis, we assumed linear mixing: each component $R$ of a mixed spectrum was weighted by its proportional contribution to the overall mixed $R$, which was calculated through simple summation of the weighted component $R$’s. That is, each mixed spectrum was the sum of varying proportions of coral, algae, and sand, and the sum of their proportions always equaled 1. The equilateral triangle in Fig. 2 illustrates this proportional mixing model. The corners of the triangle represent spectral purity, where a mixed spectrum is composed entirely of a single component (proportion = 1). The edge opposite a given corner is where the contribution of that component is zero, and there is linear mixing between the other two components. At any point inside the triangle, there is linear mixing between all three components. It can be seen that analysis of pure spectra is simply a special case of the mixing triangle, in which all spectra arise from one of the corners.

We analyzed mixing in the form of a sensitivity analysis. First, we randomly selected 10,000 each of coral, algae, and sand $R$’s and fixed them in the order selected. Then, at a given set of proportions, we multiplied each $R$ by the appropriate coral, algae, or sand proportion, and summed the results, thus computing 10,000 mixed spectra with the components appropriately weighted. We used the same ordering of pure coral, algae, and sand $R$’s at each of the 5050 points shown in Fig. 2, but the weightings were different at each point. In total, the analysis considered 50,500,000 spectra. At each point, we performed a classification analysis as described above using the LCFs trained with pure spectra. The entire mixing analysis was conducted with full-resolution spectral data, as well as with all sensor-specific spectral data.

2.7. Image simulation

Image simulation was based on an existing thematic map of a portion of Kaneohe Bay, Oahu, HI, produced through supervised classification of $2 \times 2$ m airborne hyperspectral imagery acquired by AAHIS. Every pixel in the map was identified as either coral, algae, or sand (i.e., a “hard” classification). Ground-truth data indicated that the map had a high accuracy (>90%). More importantly, as reef scientists, we believed the map to be representative of the general...

Fig. 2. General linear mixing model for coral, algae, and sand. The corners of the triangle represent the points where a spectrum is entirely composed of a single component. The edges of the triangle are the lines of two-component mixing, and the area within the triangle represents all possible combinations of three-component mixing. The axis (edge) labels show the component proportions for any given point in the triangle. The black dots indicate each of the 5050 different proportion combinations used in the general mixing analyses.
spatial organizational scales of coral, algae, and sand on many reefs worldwide. This classified image was taken to be the “truth” from which we derived the sensor simulations. To simulate image classifications for each sensor, we computed the proportions of the three bottom-types that contributed to the spatially upscaled pixels (e.g., the number of $2 \times 2$ m coral pixels in a $4 \times 4$ m Ikonos pixel or in a $20 \times 20$ m AVIRIS pixel). The spatial resolutions of the sensors were taken to be $2 \times 2$, $2 \times 2$, $20 \times 20$, $10 \times 10$, $10 \times 10$, $4 \times 4$, $30 \times 30$, and $20 \times 20$ m for full-resolution spectra, AAHIS, AVIRIS, Proto, CRESPO, Ikonos, Landsat-ETM+, and SPOT-HRV, respectively. Then, we determined classification probabilities based on the given sensor’s general spectral mixing model, using the mixing triangles as lookup tables. We used a pseudo-random number generator to choose among these probabilities and thereby assign pixel class membership as one of coral, algae, or sand. Thus, we did not directly model the spectral/spatial characteristics of, and classify imagery for, each sensor; instead, the result for each sensor was a convolution of the sensor’s general mixing model, its spatial resolution, and the spatial arrangement of bottom-types on the reef. For each “classified” image, absolute areal cover was calculated for each bottom-type simply by multiplying the number of pixels classified as that bottom-type by the area (in m²) of a pixel in the given image. Finally, we compared the different sensors’ areal cover estimates to those of the “truth” image.

Fig. 3. Spectral signatures of coral (red), algae (green), and sand (blue), as full-resolution (1 nm) spectra and as sensor-specific spectra.
3. Results

3.1. Spectral reflectance of coral, algae, and sand

Fig. 3 shows the mean spectral reflectance for each bottom-type as full-resolution and sensor-specific spectra. All three bottom-types increase in reflectance from 400 to 700 nm, and all three exhibit some degree of chlorophyll absorption, evidenced by a local minimum near 675 nm. Clearly, sand is much brighter than coral and algae, which have mean full-resolution spectra that are nearly equivalent except for slight differences in curvature in the range 500–625 nm. These differences are also apparent in the AAHIS, AVIRIS, and Proto sensor-specific spectra, and to a lesser extent in CRESPO. However, in the Ikonos, Landsat-ETM+, and SPOT-HRV spectra, coral and algae appear virtually identical.

3.2. Discriminant analysis

These spectral separations become more apparent through examination of the linear discriminant function (LDF) results in Fig. 4. In all sensors, sand is clearly separated from the other two classes, indicating its spectral distinctiveness. In the full-resolution data, coral and algae are unmistakably visible as two very distinct clusters of

Fig. 4. Linear discriminant function (LDF) scores for full-resolution and sensor-specific spectra. Discriminant functions project the multivariate spectra onto the plane that best describes the separation between coral (red), algae (green), and sand (blue). See text for details.
A relatively few coral points fall in the algae cluster, and, similarly, there are few algae points in the coral cluster. By projecting the multivariate data onto the plane that best separates the classes, the LDFs effectively reduce the dimensionality of the spectra. Thus, the LDF scatterplot is a concise representation of the full data set, and it becomes clear that spectral variability within the classes is lower than spectral variability between the classes.

AAHIS and AVIRIS show the same LDF distributions as the full-resolution spectra, indicating that hyperspectral data at resolutions of 5.5 and 10 nm, respectively, provide spectral separation nearly equivalent to that of 1 nm data. With Proto, the distributions are rearranged, but despite slightly more overlap between coral and algae, there still appears to be strong separation between the three classes. CRESPO LDFs are also rearranged with respect to the full-resolution results. In this case, however, there is greater overlap between coral and algae. Ikonos and Landsat-ETM+ exhibit virtually the same LDF distributions due to their very similar spectral responses. In both cases, as well as in SPOT-HRV, the coral cluster almost completely overlies that of algae. The LDF results for CRESPO, Ikonos, Landsat-ETM+, and SPOT-HRV suggest that these sensors may not provide adequate spectral separation of coral and algae.

### 3.3. Classification analysis

Classification analysis using full-resolution spectra further indicates that coral, algae, and sand have very high spectral separability, with an overall classification accuracy of 98% (Table 1A). Overall classification accuracies were 98%, 98%, 93%, 91%, 64%, 58%, and 50% for the AAHIS, AVIRIS, Proto, CRESPO, Ikonos, Landsat-ETM+, and SPOT-HRV sensors, respectively (Table 1B–H). For all sensors, including the full-resolution spectra, sand has very high spectral separability, and its lowest accuracy rate among all sensors is 98.8%. In agreement with the LDF results, coral and algae are well separated by AAHIS, AVIRIS, and Proto. LCFs with CRESPO wavebands appear to perform better at separating algae from coral than is suggested by the LDF graphical representation. Ikonos, Landsat-ETM+, and SPOT-HRV, however, still exhibit considerable confusion between these bottom-types. Interestingly, Ikonos is significantly more accurate at identifying algae (76%) than coral (44%). Landsat-ETM+ shows a similar but weaker trend, with coral and algae accuracies of 49% and 60%, respectively. Given that SPOT-HRV has

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**Note to Table 1:** Subtable A shows results for full-resolution (in the range 400–700 nm at 1-nm resolution) in situ spectral reflectances. Subtables B through H show results for in situ spectral reflectances binned to match the spectral response each sensor, representing hyperspectral (AAHIS, AVIRIS) and multispectral (Proto, CRESPO, Ikonos, Landsat-ETM+, SPOT-HRV) sensors. Values represent numbers of individual spectra. Values in parentheses are classification rates (matrix elements divided by column totals and multiplied by 100).

Coral classification frequency
Algae classification frequency
Sand classification frequency
Combined classification frequencies

full-resolution

AAHIS

AVIRIS

Proto

CRESPO

Ikonos

Landsat-ETM+

SPOT-HRV

Classification frequency

0 0.2 0.4 0.6 0.8 1
100% accuracy for sand, its accuracies for coral and algae near (but less than!) 50% are not much different than would be achieved by pure chance.

3.4. Spectral mixing analysis

Fig. 5 shows the results of the general mixing analysis. For each sensor, the first triangle represents the coral classification frequency as a function of the proportion coral/algae/sand. The coral classification frequency is the number of spectra designated as coral, divided by the total number of spectra (always 10,000). Color indicates frequency, with blue and red representing low and high frequencies, respectively. The black contour lines indicate the 0.1 to 0.9 frequency levels, at intervals of 0.1, and the axis tick marks indicate the proportion or “purity” of coral, algae, and sand.
algae, and sand contributions over the range 0 to 1, also at intervals of 0.1. The second and third triangles are the algae and sand classification frequencies, respectively. The fourth triangle is a combination (RGB composite) of the three individual classification frequencies, with coral represented by red intensity, algae by green intensity, and sand by blue intensity. Yellow is the mixing boundary between coral and algae, magenta is the boundary for coral and sand, cyan for algae and sand, and white for mixing of all three bottom-types.

For all sensors, the classification frequency for sand (third triangle in each sensor) decreases from >0.9 to <0.1 at sand purities of 0.65 and 0.4, respectively. The decrease is constant across all algae and coral purities, suggesting a classification boundary near a sand purity of 0.5, where on one side sand spectral characteristics dominate, while on the other side sand spectral characteristics are dominated by either or both of the other two bottom-types. This result is consistent with linear classification of linearly mixed bright (sand) and dark (not sand) spectra: because these are “hard” classifications (class membership is assigned completely), a spectrum that is more than 50% bright is most likely to be classified as bright.

Coral and algae, however, share a much less clear boundary that is influenced by the presence of sand. For the full-resolution, AAHIS and AVIRIS cases, coral classification is slightly skewed toward higher frequencies—at the expense of algae—when sand purity is between 0.5 and 0.2. When sand purity is less than 0.2, the classification frequencies are skewed in favor of algae, with the 0.1 algae classification frequency occurring at algae purity 0.2 (coral purity 0.8) and the 0.1 coral classification frequency occurring at coral purity 0.3 (algae purity 0.7). The relative broadness of the coral—algae boundary can be seen in the composite frequency triangle, where the width of the yellow region is greater than that of either the magenta (coral-sand) or cyan (algae-sand) regions. Overall, for the full-resolution and hyperspectral data, the three bottom-types are well separated by spectral purity, with a mixed spectrum most often being classified as the proportionally dominant constituent.

The pattern for Proto is similar to those of the full-resolution and hyperspectral sensors, but the boundary between coral and algae is even less well defined. In fact, the coral classification frequency is never greater than 0.9, even at very high coral spectral purities. With CRESPO, the classification pattern changes significantly: algae dominate much of the area not already dominated by sand, and its classification frequency appears enhanced by the presence of sand. When sand is not present, coral classification frequency is roughly similar to that of Proto, once again never reaching 0.9. Ikonos, Landsat-ETM+, and SPOT-HRV each assign nearly all mixed spectra to either algae or sand. For these sensors, the highest coral classification frequencies occur only along the algae–coral mixing edge and never exceed 0.5, even at the pure coral endpoint (Table 1). The ramification is that, for the broadband multispectral sensors, all non-sand pixels have a higher likelihood of being classified as algae than as coral. In contrast, the narrowband multispectral sensors Proto and CRESPO do, to greater or lesser extent, classify mixed pixels according to the degree of spectral dominance.

### 3.5. Image simulation

The thematic maps from the image simulation are shown in Fig. 6, along with an RGB composite of the original AAHIS imagery and the “truth” image. It is immediately apparent that the full-resolution, hyperspectral, and narrowband multispectral data fairly accurately reproduce the actual scene, although Proto and CRESPO exhibit many noticeable coral-algae “misclassifications.” Conversely, the results of the broadband sensors less faithfully reproduce the truth image. In terms of areal cover statistics, as expected, all sensors very accurately estimate sand cover (Table 2). The hyperspectral sensors also provide very accurate algae and coral estimates. Proto and CRESPO slightly underestimate algae cover but more significantly overestimate coral cover. Ikonos, Landsat-ETM+, and SPOT-HRV increasingly underestimate algae cover and overestimate coral cover, in the case of SPOT-HRV predicting twice the actual coral area. As will be discussed, the patterns of these errors in estimated cover are the product of the actual bottom-type areas and the sensors’ classification frequencies for each bottom-type.

### 4. Discussion

All of the analyses in this study are entirely based on reflectance spectra measured in situ. Consequently, the results are globally meaningful only to the extent that the data represent the actual spectral distributions of coral, algae, and sand worldwide. By compiling such a large spectral database from the major reef biogeographic regions (Veron, 1995) under a range of ecological conditions, we have attempted to encompass as much spectral variation as possible and so obtain an unbiased estimate of the spectral

### Table 2

<table>
<thead>
<tr>
<th>Image</th>
<th>Algae</th>
<th>Coral</th>
<th>Sand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>1,667,508</td>
<td>477,492</td>
<td>735,000</td>
</tr>
<tr>
<td>Full-resolution</td>
<td>1,673,296 (0.3)</td>
<td>471,420 (–1.3)</td>
<td>735,284 (0.0)</td>
</tr>
<tr>
<td>AAHIS</td>
<td>1,668,412 (0.1)</td>
<td>475,512 (–0.4)</td>
<td>736,076 (0.1)</td>
</tr>
<tr>
<td>AVIRIS</td>
<td>1,678,800 (0.7)</td>
<td>478,000 (0.1)</td>
<td>723,200 (–1.6)</td>
</tr>
<tr>
<td>Proto</td>
<td>1,618,200 (–3.0)</td>
<td>531,800 (11.4)</td>
<td>730,000 (–0.7)</td>
</tr>
<tr>
<td>CRESPO</td>
<td>1,602,300 (–3.9)</td>
<td>548,100 (14.8)</td>
<td>729,600 (–0.7)</td>
</tr>
<tr>
<td>Ikonos</td>
<td>1,554,976 (–6.7)</td>
<td>592,672 (24.1)</td>
<td>732,352 (–0.4)</td>
</tr>
<tr>
<td>Landsat-ETM+</td>
<td>1,456,200 (–12.7)</td>
<td>705,600 (47.8)</td>
<td>718,200 (–2.3)</td>
</tr>
<tr>
<td>SPOT-HRV</td>
<td>1,182,800 (–29.1)</td>
<td>968,400 (102.8)</td>
<td>728,800 (–0.8)</td>
</tr>
</tbody>
</table>

Integer values are area in m² of each bottom-type. Values in parentheses are percent difference from truth image.
characteristics of the three bottom-types. Though greatly abbreviated here, our data compare favorably with spectra published elsewhere (Andréfouët et al., 2001; Clark et al., 2000; Hochberg & Atkinson, 2000; Holden & LeDrew, 1998, 1999; Lubin et al., 2001; Maritorena et al., 1994; Miyazaki & Harashima, 1993; Myers et al., 1999).

The mean coral spectrum (Fig. 3) reasonably represents the 4490 spectra in our database, although there are many variations which are attributable to a variety of factors, including fluorescence (Salih, Larkum, Cox, Kühl, & Hoegh-Guldborg, 2000) and absorption by pigments in the coral tissue (Dove, Takabayashi, & Hoegh-Guldborg, 1995). To first order, however, our data indicate that coral color results from spectral absorption by zooxanthellae, which are autotrophic dinoflagellates that live endosymbiotically within the tissue of all reef-building corals (Hochberg, Atkinson, & Andréfouët, 2003, this issue). It is not coincident that our mean coral spectrum is essentially the inverse of the absorption spectrum of free-living peridinin-containing dinoflagellates (Johnsen, Samset, Granskog, & Sakshaug, 1994).

With regard to algae, the spectrum in Fig. 3 is truly a geometric mean that represents our amalgamation of 5500 spectra from physiologically and taxonomically diverse algae that have different and distinctive suites of pigments. Because of this natural variability, one might assert that there is no reason to a priori expect that all algae should be spectrally separable from all coral. Yet there is also no reason that the spectral differences between different algae should necessarily cause there to be a less spectral difference between coral and algae. In fact, this is what LDFs and LCFs (or other multivariate classifiers) accomplish: within-class spectral differences are minimized while between-class differences are maximized. Thus, the fact that we find spectral differences between all algae and all coral does not imply that all algae are spectrally the same.

There are certainly many scientific reasons why it might be desirable to separate algae into various subclasses, perhaps to address specific ecological or management questions (Hochberg et al., 2003, this issue). However, our stated objective of using remote sensing to assess reef status simply requires quantification of coral, algae, and sand cover. Unfortunately, as spectral resolution decreases among the various sensors, so does the spectral separation between coral and algae. It is possible that division of the various algae and/or corals into their own subclasses at the outset may produce a different spectral separation that is useful for the broadband sensors. However, based on the analyses of pure spectra as well as of the general mixing models for the full-resolution, AAHIS, AVIRIS, Proto, and CRESPO wavebands, there appears to be no reason to break up our algal agglomeration.

The discriminant and classification analyses of full-resolution in situ spectra demonstrate that there is clear spectral separation between coral, algae, and sand. Class discrimination ultimately relies on spectral contrasts between the classes (Okin, Roberts, Murray, & Okin, 2001). It is therefore not surprising that sand is so easily distinguished, as its spectral reflectance is essentially an aragonite mineral curve modified by slight chlorophyll absorption features. The characteristic spectral reflectance feature of sand is its brightness, and the brightness is so characteristic that even SPOT-HRV with its limited spectral response has no trouble discriminating sand from the other classes.

Coral and algae have very nearly the same magnitude of reflectance. Their distinctive spectral characteristics must therefore be a function of their spectral shapes, which are shown to differ in the region 500–625 nm (Fig. 3). Spectral differences in this region have also been pointed out in previous studies (Hochberg & Atkinson, 2000; Holden & LeDrew, 1998, 1999; Myers et al., 1999). This wavelength range then provides the greatest spectral contrast between coral and algae, and is therefore the most useful region for class discrimination. Thus, to accurately distinguish between coral and algae, a remote sensor must have adequate resolution and sensitivity across these wavelengths. Our analyses suggest that a four-channel, narrow-band sensor (CRESPO) provides the requisite spectral contrast.

The spectral mixing analyses are based on the assumption of linear mixing, where an overall spectrum is simply the weighted average of its component spectra. A natural reef environment, however, is a three-dimensional arrangement of coral, algae, and sand that is spatially heterogeneous on scales of mm to 10s of meters. Both the three-dimensional structure and the millimeter-scale arrangement virtually ensure multiple interactions of light with reef objects, a process enhanced (relative to air) by scattering of light within the water column. Such multiple interactions have the ultimate effect of nonlinear mixing (Ray & Murray, 1996), which therefore is certain to make some contribution to any remote sensing signals. However, nonlinear mixing predominates only at microscopic scales, while at the macroscopic scales of remote sensing, linear mixing models have been shown to effectively describe natural systems (Okin et al., 2001; Tompkins, Mustard, Pieters, & Forsyth, 1997). Thus, to first order, our assumption of linearity is valid, and the models accurately portray the effects of spectral mixing on classification of coral, algae, and sand. It should be noted that these linear models are easily expandable to include more than the three classes considered here. As there is currently little (or no) knowledge concerning the linear/nonlinear issue with respect to reef bottom-types, however, providing the proper constraints for a nonlinear mixing model is problematic at best.

Two important points may be learned from the mixing models. First, as might be expected, sensors with higher spectral resolution are more robust with respect to classification of mixed spectra. For the broadband sensors, confusion that exists in classification of pure spectra is maintained or enhanced in classification of mixed spectra.
Second, the behavior of the mixing models is very predictable (at least for narrowband sensors), thus affording the potential for spectral unmixing of mixed pixels (Matsakis, Andréfouët, & Capolsini, 2000; Schowengerdt, 1996).

During the course of this study, we repeatedly encountered difficulty interpreting the “true” class of a large coral reef pixel. This led directly to our “image” analysis, which is simply a theoretical exercise designed to illustrate the capabilities of the various sensors by placing the results of the spectral mixing models into a realistic reef spatial context. The images in Fig. 6 merely represent special cases of the general spectral mixing models. For larger pixel sizes, the images reasonably portray various levels of mixing, but small pixels represent far fewer mixing levels, as, by definition, 2 × 2 m pixels were taken to be the smallest spatial unit. Therefore, the full-resolution and AAHIS images are entirely comprised of pure pixels, which is the pure spectra special mixing case (i.e., the triangle corners or values in Table 1). Even at 30 × 30 m, however, most image pixels are homogeneous with respect to bottom-type, which points to the limitations of our virtual reef. We suggest that it is important to acquire better quantitative understanding of the spatial organization of reef bottom types, both to help constrain spectral mixing analyses, and for development of spatial classification rules.

The areal cover statistics suggest that the hyperspectral sensors each very accurately estimate coverage of coral, algae, and sand, regardless of the spatial/spectral mixing amount (i.e., AAHIS versus AVIRIS). This accuracy arises from the fact that the hyperspectral data provide very good spectral contrast between coral and algae. Because the scene is dominated by algae, a small algae → coral misclassification rate can result in a significant overestimate of coral area (error of commission) while providing a robust estimate of algae area. This is the case with both Proto and CRESPO, which underestimate algae area by only 3.0% and 3.9%, respectively, while overestimating coral cover by 11.4% and 14.8%, respectively. Ikonos, Landsat-ETM+, and SPOT-HRV have significant errors in their estimates of the areal cover statistics. Despite the fact that these sensors have higher probabilities of classifying any pixel—pure or mixed—as algae than as coral, their algae → coral misclassification rates are still so high that they overestimate coral cover by no less than 24%. Thus, as might be expected, the hyperspectral sensors provide the best areal cover estimates, followed by the narrowband then the broadband multispectral sensors. Because the hyperspectral and narrowband multispectral sensors have very predictable mixing behaviors, it is possible to design classification algorithms that are tuned for more accurate coral cover estimates. It is unlikely that similar tuning will be profitable for the broadband sensors, given the poor spectral separabilities that they provide.

The analyses in this study considered neither radiative transfer nor sensor effects, and all computations were made with 64-bit double-precision floating-point values. The water column and atmosphere both have wavelength-dependent light absorption and scattering properties, which may serve to confound interpretation of a remotely sensed signal (Gordon & Clark, 1980; Maritorena et al., 1994). Sensor bit-depth and signal-to-noise ratios further reduce the sensitivity of a given sensor to spectral contrasts of the bottom-types (Andréfouët et al., 2001; Lubin et al., 2001). From this perspective, the results of this study represent the best possible case for each sensor.

Our analyses confirm that narrowband hyperspectral sensors (AAHIS and AVIRIS) and multispectral sensors (Proto and CRESPO) provide better spectral separation than broadband multispectral sensors (Ikonos, Landsat-ETM+, and SPOT-HRV). Importantly, the results demonstrate the great potential for using knowledge of reef bottom-type spectral reflectances to design a narrow-band multispectral sensor with wavebands appropriate for assessing coral reef status. In fact, the same philosophy is behind the design of Ikonos, Landsat-ETM+, and SPOT-HRV, except that those sensors were designed to target land classes.

5. Conclusion

We do not mean to suggest that Ikonos, Landsat-ETM+, and SPOT-HRV are useless for coral reef study. On the contrary, we feel that the 30-year history of coral reef remote sensing demonstrates the profitability of using these types of sensors. We do conclude, however, that they are not suitable for our goal of assessing the global status of reefs. We propose (as we and others have in the past) that a sensor should be designed and flown with the specific purpose of mapping the extent of coral, algae, and sand worldwide. Given that the world’s reefs are believed to be threatened with severe degradation or extinction, it is imperative to acquire accurate data on their status.

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