A “Reef-Up” Approach to Classifying Coral Habitats From IKONOS Imagery

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Abstract—Monitoring coral reef benthos with satellites has typically followed a “sensor-down” approach, with the classification algorithm driven by statistics derived from the imagery. I adopt a “reef-up” method, drawing on statistics derived from hyperspectral optical field measurements of substrate reflectance to train image classification. In order to calibrate the satellite data with direct physical measurements of reflectivity, it is necessary to process both the imagery and in situ data to common units of albedo. Building upon a proof-of-concept study conducted by the author in the Red Sea, the link is made by correcting the remote sensing data for the effect of varying bathymetry using in situ measurement of water column optical properties and a digital elevation model constructed from a vessel-based acoustic survey, thereby yielding units of substrate reflectance. Extensive ground verification of the predictive benthic habitat map resulting from image classification showed that eight substrate classes were resolved with an overall accuracy of 69% down to a depth of 6 m, including live and dead coral framework. As compared to conventional from-image classification techniques, the reef-up method offers the potential for higher thematic accuracy while maintaining a greater degree of flexibility for repeat survey using platforms of higher spectral and spatial resolution, expected to come online in the near future. The fact that image acquisition and optical ground-truthing did not occur concurrently, is of particular relevance in confirming that in situ measurements can be made independent of image acquisition and retrospectively linked to appropriate substrate classes. Considering the wealth of hyperspectral data already acquired for shallow reef facies, the work highlights the potential of the reef-up approach for quantifying substrate distribution in coral environments using both air- and spaceborne platforms.

Index Terms—Coral reef, hyperspectral field observations, IKONOS, reef-up.

I. INTRODUCTION

The efficiency of spaceborne remote sensing to quantify the areal extent of coral reef habitats is unsurpassed with respect to lateral coverage and cost. Satellite imagery can provide data at spatial scales unobtainable using ground-based techniques [1]–[3]. Since its inception in the early 1970’s, digital remote sensing of coral reefs has generally followed a sensor-down approach, in which scene-specific image statistics drive image classification and interpretation [4] a technique frequently employed (e.g., [2], [5]–[8]). Conversely, Hochberg and Atkinson [9] analyzed reflectance spectra of coral reef benthic communities evaluated using a field spectrometer to identify the wavelengths of characteristic features that facilitate spectral separation. The spectral features were subsequently targeted through airborne remote sensing and since the classifier statistics are defined independently from the imagery, the approach was termed “reef-up.” Similarly and with favorable results, Roelfsema et al. [10] and Purkis and Pasterkamp [11], explored a reef-up approach to classifying benthic microalgae and substrate distribution, respectively, on coral reefs using Landsat imagery. This essay builds upon the study of Purkis and Pasterkamp [11] in the Red Sea, which was performed under comparatively favorable conditions, atypical to the majority of reef settings, with submergence depth limited to less than 1 m and constant across the study area. Although not trivial, the influence of the water column is moderate for the Red Sea case, and more importantly, the near-flat topography of the reef-top meant that the submergence effect was both predictable and spatially homogeneous. The aim of this essay is to employ the techniques developed in the Red Sea in a more typical reef setting, with greater water depth and less predictable seafloor topography. Jebel Ali Marine Protected Area (U.A.E.) was identified for these characteristics and in addition, offers a spatially complex habitat distribution of spectrally similar substrates.

Although remote mapping of reef areas has been conducted both with [5], [12], [13], and without [9], [14] correction for submergence effects, it is widely recognized that the spectral influence of the intervening water column hampers benthic habitat classification [11], [15], [16] and correction for the effects of submergence have been rigorously studied [17]–[23]. Providing that the apparent optical properties and thickness of the water column were known, it is possible to retrieve values of substrate reflectance ($R_b$) from a reflectance measurement evaluated above the water surface ($R_{sw}(\zeta_{iw}))$ using radiative-transfer equations (e.g., [24]–[26]). Purkis and Pasterkamp [11] used an equation modified from Bierwirth et al. [12] to this effect, to satisfactorily retrieve $R_b$ for both hyperspectral in situ measurements and multispectral Landsat imagery. In a remote sensing case, it was recognized that the technique would be limited by the difficulty in obtaining a spatially detailed bathymetric map of sufficient accuracy at the scale required for use in combination with satellite imagery. However, in addition to passive optical instruments, vessel-based active acoustic techniques can also be used for ground discrimination purposes [27]–[29] and recently evaluated in reefal areas [30], [31] including Jebel Ali [32]. As important coral resources may be situated in areas that cannot be resolved using passive optical remote sensing, due to excessive turbidity and/or depth, acoustic techniques can be used in combination with optical sensors for mapping [30], [33]. Following the optical campaign, an acoustic survey was conducted over the study area to collect data for substrate discrim-
Fig. 1. Study area near Jebel Ali in the southern Arabian Gulf.

In the Red Sea Purkis and Pasterkamp [11] employed Landsat data, a moderate-resolution sensor with a 30 m² pixel size, commonly used for reef monitoring [34]–[37]. For Jebel Ali, I utilize Space Imaging’s recent “hyperspatial” IKONOS sensor, the worth of which has already been adequately proven in comparable studies [5], [26], [38]. The spectral bands of IKONOS closely match those of Landsat Thematic Mapper (TM), but the superior spatial resolution (4 versus 30 m) and higher digitization rate (11 versus 8 bit) enables the sensor to outperform the Landsat satellites in terms of the number of benthic classes that can be resolved [13], [14]. The measurement strategy employed in Jebel Ali builds upon the lessons learnt in the Red Sea, utilizing a wider range of optical instruments in order to more fully parameterize the light field, as required for a more rigorous approach to radiative-transfer modeling. The IKONOS image used in the study was acquired May 2, 2001 under favorable conditions. To maximize the dynamic range of the data, the product was purchased with full 11-bit radiometric resolution and no preprocessed dynamic range adjustment.

II. MATERIALS AND METHODS

A. Study Area

The Jebel Ali marine protected area is situated between Abu Dhabi and Dubai in the United Arab Emirates (U.A.E) in the south-eastern Arabian Gulf (Fig. 1). The area has been the focus of numerous ancillary studies [39]–[41] and the spatial and temporal dynamics of the site are well constrained [42]. The study area differs from that in the Red Sea (Marsa Shagra/Egypt, [11]), as water depth is greater (ranging from 2–8 m) and variable, with the seabed profile approximating to a shore perpendicular ramp with a slope angle of 0.5° (homoclinal). The substrate types of both the Red Sea and Jebel Ali are comparable, with clear shore-parallel zonation of patches of sand, algae and seagrass beds, but unlike the Red Sea study, Jebel Ali offers extensive areas inhabited by coral communities, particularly on the lower portion of the ramp, in water depths >5 m (Fig. 2). Retesting the reef-up algorithm under more demanding conditions in a coral area will serve to increase the global validity of the technique, since it is the estimation of coral cover that is the aim of many reef monitoring programs (e.g., [2], [17], [43], and [44]). From a remote sensing point of view, both the Red Sea and the Arabian Gulf sites make excellent remote sensing targets, rarely compromised by cloud cover, with clear water conditions unaffected by fluvial or anthropogenic inputs and the extreme aridity resulting in stable and predictable atmospheric aerosol assemblages.

B. Acoustic Ground Truth

The bathymetry survey was conducted from a 15-m survey vessel equipped with a differentially corrected Fugro SeaSTAR 3200LR12 global positioning system (dGPS), facilitating a real-time over-view of the vessels position on the IKONOS satellite image, loaded onto a laptop computer within the moving-map software Fugawi. Differential correction of the GPS data was conducted against the network of omniSTAR satellites which was confirmed to yield data of submeter accuracy when tested against a known geodetic point. The antennae of the GPS unit was mounted directly above the acoustic transducer, enabling the position of the acoustic lines to be recorded with minimal error. To ensure an adequate degree of accuracy, three independent acoustic surveys were used to build the bathymetric DEM. Bathymetry lines were obtained over the entire study area using both a 50- and 200-kHz signal on a 10-Hz sampling frequency. A beam width of 24° was provided by a Suzuki 5200 depth
sounder using a postprocessed QTCView5 bottom picking algorithm. A line spacing of 100 m was used to cover the entire study area (7 × 1.5 km).

An additional near-shore commercial bathymetry survey with a 15-m line spacing provided high-resolution bathymetry in the first 500 m from shore (the most problematic area due to the limited water depth and difficulty manoeuvring the vessel close to the shoreline). Throughout the survey period, tidal data were collected in situ at 5-min intervals, using a submerged Van Essen DI-240 pressure logger. A duplicate logger was used to record atmospheric pressure above the water surface and therefore remove any effect from atmospheric variation. Tidal influence was removed from the bathymetry data by correcting the acoustic lines against the coincident in situ tidal record, with the result that each bathymetry point was normalized to a common lowest astronomical tide (LAT) datum. The bathymetric DEM was built by combining the tidally corrected 50 kHz and near-shore high-resolution commercial survey.

The merged bathymetry data were interpolated to a regular grid of equal size to the pixel elements of the IKONOS image (4 × 4 m) using triangle-based linear interpolation implemented using code written in Matlab 6.1, yielding a single depth value per satellite pixel. The accuracy of the resulting DEM was assessed against the 200-kHz survey lines and independent soundings made with a weighted line. Throughout the study area, the along-track average deviation in depth prediction was 0.05 m. The between-track depth prediction in the first 500 m from shore (surveyed with a maximum line spacing of 15 m) had an average deviation in depth of 0.10 m and for the remainder of the study area (surveyed with a line spacing of 100 m), the average deviation was 0.35 m.

C. Optical Ground Truth and Spectral Processing

Optical ground-truthing was conducted in situ from the survey vessel during the period October 5–November 10, 2002. The measurement strategy employed a suite of four intercalibrated field spectroradiometers to coincidently parameterize the optical properties of the atmosphere, water column and benthic substrates in rapid succession. For each measurement, the geographic position, time, wind speed and sea surface conditions were recorded. All optical measurements were conducted over suitably large and spatially homogeneous patches of substrate, between 10:00 and 17:45 hrs local time, therefore ensuring that the sun was a minimum of 30° above the horizon, to preclude the effects of directional illumination. The notation called upon in the text is established in Table I, the equipment setup is shown in Fig. 3 and the specifications of the optical instruments and procedures adopted are as follows. For brevity, from here onwards the symbol Λ has been suppressed for wavelength specific terms.

1) SD2000: The OceanOptics SD2000 fiber-optic spectrometer was the principal optical instrument used by Purkis and Pasterkamp [11] to evaluate \( H_{\text{ref}(z=\infty)} \) spectra of substrate groups in the Red Sea. Conversely, for this study I used the instrument exclusively for measurements beneath the water surface and in the vicinity of the bottom, at a depth to be close enough to estimate the substrate reflectance and, yet, not so close as to be compromised by instrument self-shading. The methodology employed is comparable to that of Hochberg et al. [4] and Hochberg and Atkinson [9]. The SD2000 has two input channels, each consisting of a 2048-pixel CCD array. Best efficiency is between 400 and 900 nm, with an optical dispersion of 0.32 nm/pixel and an optical resolution of 1.3 nm (full-width half maximum). To each of the two input channels of the SD2000, a 10-m fiber optic cable was added, in order to transmit light from the underwater sensor heads to the spectrometer aboard the boat. The sensor heads were handled by two SCUBA divers. One diver positioned the down-looking senor head (FOV 20°) 10 cm from the target (e.g., [1] and [45]).
to measure signals proportional to the radiance emanating from the substrate \( (L_{\text{w}}) \). The remaining diver positioned the second up-looking fiber optic at the same elevation and in close proximity to the down-looking sensor head. The up-looking sensor was fitted with an OceanOptics CC-3 cosine corrector to measure signals proportional with the irradiance downwelling from the sea surface \( (E_d) \) (Fig. 3). Once the divers were in position and the spectral signal had stabilized, an electronic signalling device was used to instruct the computer operator aboard the boat to record the spectral measurement. Each reflectance measurement is an average of five readings, collected at a frequency of 5 Hz and internally averaged by the SpectraWin software. For each substrate, a minimum of 15 measurements were made over a period of approximately 10 min. Cross-calibration between the radiance and irradiance channels of the instrument was conducted according to Fargion and Mueller [46] with the same near-Lambertian reflectance panel as used with the PR650. Substrate reflectance \( (R_b) \) was calculated for each measured substrate using standard procedure [11]. The SD2000 was cross-calibrated with the PR650, against radiometrically stable terrestrial reflectance targets [Fig. 4(a)].

2) PR650: The PhotoResearch PR650 is a robust hand-held spectroradiometer which was used to quantify the remote sensing reflectance just above the water/air boundary \( (R_{\text{w}(z=a)}) \) of benthic substrates at 8-nm increments between 380 and 780 nm. As with a conventional camera, the operator can aim the instrument using a view-finder, through the water surface and onto the submerged substrate target. The measurement protocols of Pasterkamp et al. [47] were adhered to, namely each reflectance measurement consists of a cycle of three radiance measurements (Fig. 3). The measurements can be completed in less than one minute and in order of collection are: 1) radiance emanating from the water surface \( (L_d) \); 2) radiance from the sky \( (L_{\text{sky}}) \); 3) radiance from the near-Lambertian reflectance panel \( (L_p) \). Each radiance measurement is an average of five readings, internally averaged by the radiometer, which also automatically selects the optimum integration time, depending on the brightness of the target. As conducted by Pasterkamp et al. [47], the measurement geometry was in accordance with the findings of Fougnie et al. [48] and Mobley [49] with a view zenith and view azimuth (with respect to the sun) of 40° and 135°, respectively. The sky-radiance measurement (acquired with the same geometry, but skyward, as the proceeding water measurement) was used to correct the total surface radiance for the effect of sky-radiance reflected at the water surface to yield water-leaving radiance

\[
L_{\text{w}} = L_d - \rho_{\text{sky}} L_{\text{sky}}
\]

where \( \rho_{\text{sky}} \) is the effective Fresnel reflection coefficient for the wind-roughened sea surface, calculated according to Hecht [50].

The radiance measurement of the Lambertian reflectance panel is used to calculate downwelling irradiance in air

\[
E_{\text{ad}} = \pi \frac{L_p}{\rho_{\text{panel}}}
\]

where \( \rho_{\text{panel}} \) is the known reflectance of the Lambertian reflectance panel.

In the majority of cases, values for \( L_{\text{sky}} \) were of a magnitude where the use of a standard 98% reflectance panel resulted in
saturation of the instruments CCD array, even with a minimal integration time. For this reason, $L_p$ was estimated using a gray panel of 10% reflectance.

$$R_{rs(z=a)} \text{ can then be calculated using the ratio of (1) and (2)}$$

$$R_{rs(z=a)} = \frac{\pi L_{wp}}{E_{wp}},$$

(3)

Sufficient spectra were collected using the PR650 over all the dominant substrate types encountered during ground-truthing and reported in ancillary studies of the region [5], [39]–[41].

3) PRR-600/610: PRR-600 Profiling Reflectance Radiometer system (Biospherical Instruments, Inc.) is a hand-deployed instantaneous profiler of downwelling irradiance ($E_d$), upwelling irradiance ($L_{wp}$), in the SeaWiFS wavelength bands and depth ($z$). The data from this can be used to calculate the attenuation of the water body ($k$). The PRR-600 was operated in unison with a PRR-610 Reference Radiometer, equipped with a cosine-corrector to simultaneously measure downwelling irradiance in air ($E_d$) in the same wavelength bands. The data from this reference instrument was used according to the protocols of Mueller [51] to normalize the profile measurements to $E_{wp}$ yielding normalized downwelling irradiance ($E_d'$). The normalization step is of particular importance if changes in cloud cover occur during a cast, a problem not encountered in this case as the optical campaign was conducted under clear skies. Immediately prior to and following each set of three profiles, a measurement of instrument dark current was made on the deck of the boat, by covering each sensor ($L_{wd}, E_d$, and $E_{wd}$) with a neoprene cap, the values from which, were subtracted from the respective raw datasets prior to further processing. At each station, a set of three profiles, with each profile consisting of an up- and down-cast, were made from the stern in a position to avoid shadow from the boat. $k$ was calculated for each of the up- and down-casts, yielding a replicate of six measurements

$$k(z) = \frac{\ln(E_d'(z))}{dz},$$

(4)

$k$ profiles were only conducted in areas where water depth was sufficient to profile a over a minimum $\Delta z$ of 4 m (e.g., [52] and [53]). Since the PRR-600/610 instrument can only be used to evaluate $k$ as far as 550 nm, the spectra are not of sufficient length for use with the third (red) spectral band of IKONOS, which would require data up until 700 nm. Since at wavelengths >600 nm, $k$ is progressively more dominated by the absorption characteristics of pure water and therefore less influenced by water quality [11], I extrapolated the spectra up until 700 nm using values for $k$ from Jerlov water type 1, as determined by Austin and Petzold [54]. The selection of Jerlov’s water type 1 was deemed to be optimal since, without exception, the in situ derived $k$ spectra closely approximate the data of Austin and Petzold [Fig. 4(b)].

D. Optical Model

Purkis and Pasterkamp [11] used a modified optical equation of Bierwirth et al. [12] to retrieve values of substrate reflectance ($R_b$) from a reflectance measurement made above the water ($R_{rs(z=a)}$), given the water depth ($z$), the attenuation coefficient ($k$) and the reflectance of optically deep water ($R_w$)

$$R_b = \frac{1}{1 + k} R_{rs(z=a)} - \frac{(1 - e^{-2kz}) R_w}{e^{-2kz}}.$$  

(5)

As for the Red Sea case, all parameters were evaluated in situ, coincident to the predicted overpass of the IKONOS satellite. Unfortunately, the satellite did not acquire data during the overpass and I therefore used an archive image of the same area, acquired under ideal conditions. The fact the optical field campaign and imagery were not acquired simultaneously has implications for the values of $k$ and $R_w$, which, being apparent optical properties, vary with space and time and therefore precludes the direct implementation of the optical equation, as in the Red Sea case. For this study I adapted the methodology and aimed to relate the imagery and in situ optics over an invariant reflectance target, common to both datasets. The invariant target used was an area of optically deep water, the location of which, constrained by dGPS, was visited daily throughout the optics campaign at local times appropriate to ensure comparable solar geometry to that of sensor overpass. In rapid succession, $k$ and $R_{rs(z=a)}$ were evaluated using the PRR-600 profiler and PR650, respectively. The data were used to construct a lookup-table of $R_{rs(z=a)}$ versus $b$ for a number of sea conditions. The target area was subsequently identified on the atmospherically corrected satellite image and the pixel values compared to the $R_{rs(z=a)}$ spectra, resampled to the bandwidths and sensitivity of the IKONOS sensor, acquired using the PR650. A match was sought between the satellite and PR650 values of $R_{rs(z=a)}$ and the date of the best approximation was identified [Fig. 4(c)]. PR650 data from October 29, 2002 provided the optimum match (absolute error for bands 1, 2, and 3 was 0.10%, 0.16%, and 0.13%, respectively) and the associated $k$ spectrum was resampled to the bandwidths and sensitivity of the IKONOS sensor and used as input to the optical equation. Similarly, an in situ spectrum of the reflectance of optically deep water acquired following the selected profiler measurement was also resampled and used as input.

Implicit to this approach is the assumption that: 1) the interplay between absorption and scattering governing the observed reflectance of the water column, is relatively consistent; 2) the optical properties of the water column are homogeneous over the study area. The lack of fluvial input into the area and personal experience leads us to believe that the initial assumption is reasonable. Observations made during this and previous campaigns in the area reveal that the dominant cause of water turbidity is high sediment loading, caused by the suspension of unconsolidated sand during storm events. This being the case, suspended particulates are the dominant parameter influencing both $R_{rs(z=a)}$ and $k$. Both the in situ optical measurements and image acquisition occurred during extensive calm periods with a high degree of water clarity. Additionally, the sun elevation for both in situ and satellite acquisition was constant (±65°), as was the observation angle of the IKONOS and PR650 (±25° off nadir). It is reasonable to assume that the excellent match between PR650 and satellite evaluated reflectance [average deviation for bands 1–3 is <0.15% Fig. 4(c)], will be accompanied by a robust match in $k$. Last, considering the limited size of the study area and the fact that sediment plumes are clearly absent in the imagery [Fig. 8(a)], it is not unreasonable to assume that
the optical properties of the water body were likely to be relatively homogeneous at the time of image acquisition. An analogous use of the model of Bierwirth et al. [12] was employed by Malthus and Karpouzli [26] on IKONOS data in waters with $k$ values double that measured in the study area, who report that the model performed adequately down to depths of 8.5–9.0 m, confirming the viability of the approach.

E. Image Processing

Once it had become apparent that the overpass had not resulted in an image, I selected an alternate image, acquired on the most favorable conditions possible. The optimum image fulfilling the required criteria was acquired May 2, 2001 (scene 75 209) at 06:49 UTC. Sun elevation and nominal collection azimuth at the time of acquisition were 67° and 65°, respectively, the tidal stage was 3 h after high-water (0.9 m above LAT), water clarity was high, and the surface was calm. The image was unaffected by atmospheric dust and there was no cloud cover. Although the level of geographic accuracy of the raw image was reasonable, further geocorrection was conducted against 40 ground control points acquired using a portable Leica 500 dGPS system with a horizontal accuracy of ±30 cm, yielding an average root mean square (RMS) error of 0.66 pixels or 2.65 m. Prior to quantitative analysis, the radiometric calibration coefficients of Peterson [56] were applied to the IKONOS imagery to convert from pixel values of digital-numbers (DN) to at-sensor radiance ($L$).

Since image acquisition was not coincident with the in situ optical measurement of atmospheric conditions ($AOT_{550}$ and $E_{al}$), correction for atmospheric path radiance via standard radiative transfer approaches (e.g., Modtran4; see [11]) was not attempted. Instead, the empirical line method [57]–[59] was followed. In situ measurements of surface reflectance were made over suitably large and spatially uniform, light and dark pseudoinvariant features (PIFs) (i.e., spectrally and radiometrically stable) using the PR650. For PIFs, I selected a large homogeneous area of desert sand and a large asphalt car park, the positions of which were constrained using dGPS measurements, which were subsequently located on the imagery. Both areas of desert [60]–[62] and asphalt [58], [63], [64] are known to be spectrally stable over extensive time periods and are used as vicarious (inflight) calibration targets for spaceborne sensors. A systematic assessment of uniformity was made throughout the PIFs through comparison of numerous PR650 measurements. As expected, the spectral quality of each site was proven to be spatially constant. The literature suggests (e.g., [60]) that directional effects are a dominant factor determining the spectral stability of desert reflectance targets with time. Therefore, in situ measurements were made under comparable solar geometry to that at the time of image acquisition. A calibration curve was generated to relate satellite-recorded radiance to field-recorded reflectance over the PIFs. The rest of the imagery was then converted to apparent surface reflectance using linear interpolation. Implicit in this method is the assumption that the condition of the terrestrial atmosphere can be extrapolated to represent conditions over the near-shore marine. The assumption is not unreasonable, as the study area is in close proximity to the terrestrial PIFs (circa 0.5 km) and multiple near-coincident measurement of $AOT_{550}$ using a Microtops II Sunphotometer, from both the marine study area and adjacent terrestrial PIFs, did not differ significantly. Since the prevailing wind direction is onshore [65], the area is not prone to offshore transport of atmospheric dust from the adjacent desert, which will adversely affect image quality.

Following the protocols of Purkis and Pasterkamp [11] the imagery was further corrected for the influence of the water column using the optical model (5), where $R_{atm}(z=a)$ are the atmospherically corrected pixel values. $R_{al}$ and $k$ were evaluated in situ and retrospectively matched over optically deep water, and $z$ was taken on a pixel-by-pixel basis from the interpolated acoustic bathymetric data. The unit of albedo for the processed image was therefore $R_b$.

F. Classification

Prior to implementing the classifier, the depth-of-penetration (DOP) for each of the three visible bands of the imagery was determined against a region of optically deep water [18]. The DOP quantifies the depth beyond which the seafloor does not affect the remote sensing signal and was 22.5, 13.5, and 3.8 m for the blue, green, and red bands, respectively. Clearly, in water depths exceeding 3.8 m, the spectral quality of the red band contains no information pertaining to the seabed and therefore is redundant to the classification algorithm. The 3.5-m isobath was used to presegment the imagery into two zones (e.g., [5]). The “shallow” (<3.5 m) segment was subsequently classified with a three-band classifier, thereby retaining maximum spectral information to discriminate between seagrass and algae, two spectrally similar substrates commonly encountered in this depth range. This segment lay within the first 500 m from shore and therefore within the area covered by the high-resolution acoustic survey (15 m line spacing), and so maximum constraint on bathymetry was retained. This is of particular importance, since errors in depth prediction introduce most noise in the derivation of $R_b$ into band 3. At a depth of 2 m, the average deviation in depth prediction of 0.10 m between acoustic lines, translates to noise in band 3 of 8% of $R_b$, but <2% in bands 1 and 2.

The imagery beyond the 3.5-m isobath was classified using only the first two visible bands, under the assumption that sufficient spectral information remains to render the deeper substrates separable (e.g., [66]). In this segment, the spacing between acoustic lines was 100 m, which was accompanied by an average error in depth prediction of 0.35 m. This error translates to noise in $R_b$ derivation of only 2% and 5% in bands 1 and 2, respectively, and therefore mitigates the influence of greater line spacing in the deeper area. Classification was implemented using a multivariate-normal probability density function implemented using code written in Matlab v6 [11]. In line with ancillary ground-based ecological studies of the area [39]–[41] and the natural grouping of the spectral data following hierarchical cluster analysis, eight spectral classes were defined. For classifier training, the $R_b$ spectra evaluated close to the submerged target using the SD2000 were used. Since the 3.5-m isobath did not represent a natural break between shallow and deep water assemblages (isolated coral patches were found in shallow water and seagrass beds extended to depths greater than 3.5 m), both image segments were classified using the full suite of eight substrate classes. The spectra assigned to each of the eight spectral classes were transformed to simulate values for the three visible spectral bands of the IKONOS sensor by integrating the data.
were 3 pixel neighborhood. The within-class mean, in each band. Axes are substrate reflectance ($R_h$).

Fig. 5. Eight spectral classes derived from beneath water hyperspectral measurements resampled to the bandwidths and sensitivity of IKONOS spectral bands 1, 2, and 3. The error bars represent 1 standard deviation around the mean, in each band.

The output from the analysis was an eight-band “probability image” which was reduced to a single band thematic map by extracting the band number accounting for the highest $\Phi$ value, on a pixel-by-pixel basis. The eight-class thematic map was smoothed with a median filter to reduce noise [13], [25] constructed using a 3 x 3 pixel neighborhood.

G. Ground Verification and Accuracy Assessment

As in the Red Sea a rigorous approach to ground-truth data was taken, with mapping carried out at a resolution higher than the spatial resolution of the imagery, using a hierarchical key to substrate type. Twenty-two substrate classes were sufficient to encompass the sedimentary and biotic diversity of the area, which could be collapsed into eight broad groups (Fig. 6). A combination of point and continuous data were collected to maximize the statistical validity of the assessment. First, and without any a priori knowledge of substrate distribution, 52 spot-checks were dived from the boat at semiregular intervals across the study area. The position of each check was constrained by dGPS and substrate coverage was recorded to the lowest possible taxonomic level. Second, the location of 15 transects were predetermined on the imagery and as for Bouvet et al. [2], positioned to bisect areas deemed to represent patch boundaries and therefore areas likely to be misclassified. The transects were distributed at various locations from the shore, in differing water depths and orientated differently with respect to north. The end coordinates of the transects were extracted from the imagery and used to locate the positions in the field. The end points were marked with buoys and the positions redetermined using the dGPS unit. The mapping technique of Purkis et al. [37] was adapted for SCUBA divers. Mapping was conducted with use of multiple PVC 4 x 4 m quadrants (i.e., 1 IKONOS pixel), subdivided into 1 x 1 m squares, lain either side of a weighted rope. With a team of four SCUBA divers working in unison, one transect of typical dimensions 160 x 8 m (equivalent to 80 IKONOS pixels) could be mapped per day. Following the field campaign, the mapped sheets were scanned and digitized (Fig. 6). Seven ground-verification transects were completed, covering an area equivalent to 472 IKONOS pixels. Unlike the use of point data, the transects assess substrate coverage within an area of equivalent size to an IKONOS pixel (4 x 4 m), in its entirety. Since the data are not spatially explicit, it is not predisposed to being influenced by small-scale inhomogeneity around the point of observation and therefore offers a more viable dataset for comparison with an image pixel. A principal advantage of the transect technique is that the decision on the dominant substrate coverage, when the area is viewed at a 4 x 4 m resolution, is not made on the seafloor by a SCUBA diver. Instead, the mapped data are postprocessed using digital image analysis routines written in Matlab 6.1 to obtain a quantitative estimate of benthic coverage. Maximum flexibility is retained, as the ground-verification data can be resampled to be coincident with the spatial resolution of an alternate sensor, by grouping pixels (up until 8 x 8 m) or resampling at a higher interval, down until the resolution of observation (0.1 x 0.1 m). Retention of the ability to redefine the grouping of ground-validation data is paramount, if the area is likely to be resurveyed with imagery from a sensor of differing spatial resolution. This arises from the fact that due to varying levels of intrapixel variability, the substrate-cover thresholds

\[
\Phi = \frac{\exp \left( -\frac{1}{2}(X - \mu)^T \Sigma^{-1}(X - \mu) \right)}{\sqrt{(2\pi)^n |\Sigma|}},
\]

(6)
for one sensor will not necessarily be relevant to another (e.g., [14]). The collection of the transect data was logistically more intensive than the point data, but with a combination of the two techniques, 524 validation points were available for accuracy assessment.

III. RESULTS

Spectra acquired above and beneath the water using the PR650 and SD2000, respectively, were deemed to be directly comparable following an intercalibration test between the two instruments over light and dark terrestrial targets [Fig. 4(a)]. Comparing reflectance spectra collected concurrently beneath and above the water surface (Fig. 7), a clear disparity in the reflectance values is observed. Most pronounced is the rapid decline in reflectance for the spectra evaluated above the water column, at wavelengths longer than 575 nm, attributed to the rapid attenuation of light by water, in this spectral region. For the shorter wavelengths, less influenced by attenuation, both the spectral shape and magnitude of the two datasets are comparable, although the relationship weakens as depth increases. As reported by Holden and LeDrew [45] for spectral measurements of comparable benthos evaluated at the top of the water column but beneath the surface, the above water spectra also
Fig. 7. Concurrently measured reflectance spectra of four homogeneous substrate types, evaluated beneath the water surface and 0.1 m above the target with the SD2000 fiber optic spectrometer (solid lines) and just above the water surface with the PR650 spectroradiometer (broken lines).

display a slight drop in reflectance at approximately 515 nm, absent in the spectra acquired at the base of the water column. The feature is therefore attributed to arise wholly from the reflectance of the water column and corresponds to the position of an absorption peak of pure water [67], an assumption confirmed by its prevalence in the spectrum acquired over optically deep water ($R_w$) [Fig. 4(b)—second ordinate]. Although the above water spectra exhibit similarities to optically deep water, there are marked differences in both magnitude and shape. This confirms that substrate albedo contributes markedly to the water-leaving signal, as would be expected since seafloor is clearly resolved in the IKONOS imagery, at comparable depths [Fig. 8(a)]. The spectra measured at the base of the water column for seagrass and live coral display generic chlorophyll features, namely low values in blue and green spectral region (<500 nm) due to the strong absorption of photosynthetic pigments. Higher values are observed at longer wavelengths and correspond to a lack of absorbance, culminating in the “red-edge” signature with a pronounced reflectance minima in the region of 675 nm, rising rapidly beyond 680 nm to values as high as 50% by 750 nm. The red-edge signature, although related to both canopy density and plant cellular structure, is of little use in spectra acquired over targets submerged greater than 4–5 m, as it becomes dominated by noise arising from the very low signal in this spectral region resulting from rapid water column attenuation. Retrieval of data beyond 700 nm can be facilitated with the addition of an artificial light source (e.g., [4]), but was not employed in this case. The spectral signature of unconsolidated carbonate sand increases with increasing wavelength and is generally devoid of the generic chlorophyll features, but does contain a slight reflectance minimum at 675 nm, likely to be related to micro-phytobenthos within interstitial pore spaces (e.g., [10] and [68]). As for unconsolidated sand, spectra acquired for algal-mats, do not exhibit a reflectance minimum below 500 nm, but do display a strong chlorophyll reflectance minimum at 675 nm as well as being of lower overall spectral magnitude for all wavelengths. Live coral spectra, with a more exotic pigment composition than the algal mats or seagrass, display a prominent triple-peaked reflectance pattern at 570–600–650 nm [9], [69], possibly related to pocilloporin fluorescence (e.g., [70]). The red-edge for coral trends toward infinity and is likely to be related to a combination of the high signal-to-noise ratio expected at this water depth (5.4 m) and a dominance of upwelling red light resulting from chlorophyll fluorescence, as observed for corals at comparable depths by [44].

Resampling the spectra within the eight classes to the bandwidths and sensitivity of IKONOS spectral bands (Fig. 5) shows an increase in class variance with increasing magnitude of substrate reflectance. Two distinct clusters are formed within the plots, with the three brighter substrates (sand, algal-mats, and seagrass) grouping separately from the remaining darker sub-
The predictive habitat map resulting from image classification adequately resolves the eight substrate assemblages [Fig. 8(b)]. It is encouraging that the segmentation of the image into two zones, the shallower of which was processed with a three-band and the deeper with a two-band classifier, yielded a result without apparent edge effects [Fig. 8(b)], but a smooth transition of predicted substrate distribution between the zones. Accuracy assessment of the predictive map yielded an overall accuracy (\(P_o\)) of 69% and a Tau coefficient (T) [71] of 65% [Table II(a)]. It should be noted that the accuracy assessment is likely to be pessimistically biased since the transect positions were selected to span heterogeneous areas of seafloor in an effort to capture and quantify classification errors at patch boundaries. Therefore, the accuracy of 69% can be considered...
a true worst case 69%. If accuracy is assessed against only the spot check points, which were collected without any a priori knowledge of substrate distribution and therefore more likely to fall within homogeneous patches, an accuracy of 81% is achieved ($\tau_{\text{all}} = 77\%$).

To facilitate a comparison between the classification results of the Red Sea [11] reef-top and the deeper bathymetric setting of the Arabian Gulf site, the eight classes of the Gulf classification were reduced to seven, so as to equal the number of classes resolved in the Red Sea. The reduction was made by merging sparse coral and hardground into a single class [Table II(b)]. It was deemed logical to merge the two classes, as they were both spectrally very similar (Fig. 5) and coded similar substrate assemblages (coverage in both cases is dominated by hardground). The comparison between the two sites is indirect as the substrate assemblages of the two sites are not identical. The deeper Arabian Gulf site is characterized by a greater diversity of carbonate assemblages (coverage in both cases is dominated by hardground). In comparison, the shallow Red Sea site is dominated by algae and seagrass with minimal areas of unconsolidated carbonate sand, but does contain a zone of aggregated coral rubble on the reef edge, postulated to be a storm deposit. Comparing the seven class classification in the deeper bathymetric setting of the Arabian Gulf [Table II(b)] with the classification results of the Red Sea reef-top [Table II(c)] reveals that classification accuracy of the Arabian Gulf map are lower than that of the Red Sea ($P_0 = 70\%$ versus 76% and $T = 61\%$ versus 71%, respectively). However, the more rigorous approach to accuracy assessment (524 versus 89 validation points) yields tighter confidence intervals (Fig. 9) and the difference is not significant ($P = 0.06\%$). Assessing the accuracy of the Gulf map using only the validation data collected without a priori knowledge of substrate distribution and therefore deemed to be without pessimistic bias, accuracy increases markedly, but still does not differ significantly from the Red Sea (Fig. 9).

**IV. Discussion**

Although yielding stable, reproducible results over terrestrial targets [Fig. 4(a)], the PR650 measurements conducted from the boat, through the water surface and onto the submerged substrate did not display the pronounced spectral features contained within the spectra evaluated in close proximity to the seabed. The result is to be expected, considering the attenuative influence of the water column. In addition, the PR650 data were observed to be of lower quality than the beneath water measurements, with a high occurrence of noisy spectra attributed to a combination of surface effects and the difficulty for the operator to consistently sight the submerged target through the instruments view-finder. The combination of these factors was sufficient to deem the PR650 spectra unsuitable for classifier training. The results are in opposition to the experience of the Red Sea, where the beneath water spectra were found to be unreliable, subsequently attributed to a rapidly fluctuating downwelling irradiance field arising from the lens effect (focusing) of surface waves in the limited water depth. Following the field campaign, it is recommended that above water measurements are better suited to situations of limited water depth, such as with the Red Sea study. In such cases, the optical instrument can be mounted on a stable platform, in such a way that the measurement geometry can be optimized and correction for submergence effects can be postprocessed using a standard radiative transfer approach (e.g., [11]).

In comparison, where depth is greater, spectra evaluated beneath the surface and in close proximity to the substrate, are optimal. From a logistical stand point, beneath water measurements are more complex, requiring more advanced instrumentation operated by a SCUBA diver. However, for obtaining a signal that approximates to substrate reflectance, the beneath water strategy is commonly preferred since the spectra are evaluated in close proximity to the target (0.1 m), correction for the intervening water column is not required, as its effect is typically less that the precision of the instrument (e.g., [44]) and generally considered negligible (e.g., [72]). By virtue of the fact that the aperture of the majority of field spectrometers is fixed, measurements made at different height increments above a target will integrate over a variable IFOV (e.g., [11], [15], [45], [72], and [73]). This scaling effect is both complex and nonlinear in cases where the target substrate is inhomogeneous at scales less than the measured IFOV.

In the Red Sea, the image classifier was trained using spectra evaluated over an IFOV of approximately 0.33 m² (equivalent to a spot diameter of 0.65 m), as compared to an IFOV diameter of 0.035 m diameter for the Arabian Gulf spectra. Obtaining an optical measurement with a larger IFOV is advantageous for classifier training [11] and mitigates the spatial disparity between the resolution of the in situ and satellite data. In the comparatively deep water of the Arabian Gulf, increasing the IFOV would have required moving the sensor head further from the target substrate, but in doing so, the influence of the intervening water column would have become more pronounced. Balancing the effect of scaling against signal attenuation, it was deemed most efficient to follow the measurement protocols previously established in the literature and collect end-member type spectra, in close proximity to the target.
A. Accuracy of the Predictive Habitat Map

Sufficient ground-validation points were collected to facilitate an unbiased calculation of errors arising from both omission and commission via the user’s and producer’s accuracy, according to the guidelines of Congalton [74]. Firstly, there does not seem to be a correlation between how reliably a class is predicted and depth, indicating that the optical equation is effectively correcting for the influence of the water column across the bathymetric range of the study area.

Assessment of the shallow and deep algal assemblages and seagrass return high user’s accuracies (i.e., there is a high probability that an area predicted to be dominated by these classes in the imagery would also be so within the reference data) but only the shallow algal assemblage offers an equally high producer’s accuracy, indicating that pixels of this class are equally well identified in the imagery. For the carbonate benthos, hardground and sparse coral are both consistently predicted from a user’s and producer’s perspective. In saying this, in the error matrix, the highest off-diagonal element arises through confusion between hardground and sand, which during ground validation, was determined to arise from the prevalence of thin (centimeters) sand sheets that cover the periphery of the hardground plates [42].

Surprisingly, despite the spectral similarity between the dense live and dense dead assemblages (Fig. 5), the two classes are rarely confused by the classifier. Instead, dense live was frequently assigned to the sparse coral class, which is not considered an alarming result as the absolute percentage cover threshold that divides the two is arbitrary and does not represent a natural break in reality. Such confusions reflect in part, the weakness of the accuracy assessment rather than the potential of the classification algorithm [75]. Areas of dense dead coral are frequently wrongly assigned to the deep algae and sand classes. The dead areas consist of dense and interlocking growths of Acropora, mostly killed during the 1996 temperature induced mass mortality event [42]. Since 1996, the Acropora tables have been heavily encrusted by coralline algae which render the spectral signature similar to that of the deep algal class and accounts for the frequent misclassification. In some areas, the integrity of the Acropora framework has been completely lost as the corals already weakened by the high rates of bioerosion mainly due to boring by clionid sponges [40], collapse under the weight of the encrusting coralline algae. In such cases, the collapsed Acropora tables leave depressions in the remaining framework, which, being sheltered from the prevailing currents, rapidly fill with unconsolidated sand and branch fragments. The process leads to a high occurrence of mixed pixels containing the optical signature of both dense dead and sand classes, resulting in misclassification.

In Turks and Caicos, Mumby and Edwards [13] showed that the overall accuracy of coarse-level habitat maps did not differ significantly between IKONOS and Landsat TM over a common area. The comparison between the accuracies realized in the Red Sea using Landsat TM [11] and in the Arabian Gulf using IKONOS, appear to support their prediction, with no significant difference observed despite the use of two different accuracy assessment protocols and different substrate classes (Fig. 9). The result is surprising considering the different bathymetric settings of the two sites (Fig. 2). I can conclude that either: 1) the IKONOS imagery outperforms the capability of Landsat, but the advantage is balanced by errors arising from the greater variability in depth encountered in the Gulf or 2) that the sensors indeed have a similar capacity to resolve benthic habitats and the optical model used to correct for submergence effects, performs equally well in deep and shallow environments. To test which scenario is true, it would be necessary to evaluate the Red Sea study site with IKONOS or the Gulf using a Landsat image. The appraisal is beyond the scope of this essay and it is important to bear in mind that a direct comparison between the results from the Red Sea and Arabian Gulf is not possible, since the spatial resolution between IKONOS and Landsat differ by nearly an order of magnitude and the protocols for accuracy assessment are not identical.

Despite these differences, it is interesting that the Red Sea and Gulf sites yield map accuracies which are not significantly different. By omitting ground-validation data collected with a priori knowledge of substrate distribution (transects), the accuracy of the Gulf map increases markedly (Po = 69% versus 81%), highlighting the degree to which the accuracy statistic is dependent on the strategy of assessment (Fig. 9). However, by virtue of the increase in statistical uncertainty accompanied by the decrease in number of available validation points, the increase in accuracy is rendered insignificant (P = 0.05). Approximating to the spectral capability of Landsat, the position of the bands of the IKONOS sensor are reasonably well optimized for coral reef identification (e.g., [76]). Hochberg and Atkinson [9] showed through the use of stepwise wavelength selection and linear discrimination function, that spectral separation of coral communities is possible with as few as four non-contiguous wavebands. However, IKONOS can only offer three noncontiguous bands over shallow areas, further reduced to two, in areas greater than approximately 5 m.

Using a coupled atmospheric-ocean discrete ordinates radiative-transfer model, Lubin et al. [76] predicted that atmospheric Rayleigh scattering would reduce radiance contrast to an extent where detailed coral reef mapping would not be possible, a theory supported by Mumby and Edwards [13]. The results from this study corroborate these findings. Atmospheric path radiance inferred from the PIFs was 0.05, 0.03, and 0.02 W · m⁻² · sr⁻¹ · nm⁻¹ for IKONOS bands 1, 2, and 3. Under typical irradiance conditions this translates to 11%, 8%, and 6% of Rrg(z=α) in the same bands. In both, for bands 1, 2, and 3, Rths(z=α) evaluated in situ just above the water surface for sand submerged under 2 m of water, was 10%, 12%, and 5%. In this case, the reflectance contribution from atmospheric path radiance is therefore of the same order as the reflectance arising from the seafloor. As water depth increases, the Rths(z=α) will decrease in all bands, but particularly rapidly in band 3, so that a point is reached whereby the contribution of the atmosphere will greatly exceed the reflectance arising from the seafloor (e.g., Rths(z=α) for sand submerged under 4 m of water is <1% in band 3). The calculation highlights the importance of precise atmospheric correction and emphasises that in terms of noise in the retrieval of Rth, the contribution of the atmosphere rivals that of the water column.
In study areas that lack suitable adjacent PIFs, correction for atmospheric effects will have to be implemented using radiative transfer code (e.g., Modtran4). Presently, the majority of radiative transfer code is optimized for terrestrial targets and does not adequately handle water covered areas, unless an independent measure of atmospheric loading is available for calibration (e.g., [11]). Considering that atmospheric effects can be as disruptive as water column attenuation, it is clear that the development of radiative transfer code capable of correction over tropical coastal targets may yield a tangible improvement in the reef mapping capability of IKONOS. Furthermore, the eight benthic classes considered in this study do not constitute a level of reef discrimination that can be described as “detailed” and indeed the overall accuracy of 69% is in concert with the findings of Andréouet et al. [5] who report a 71% accuracy for a comparable seven to eight substrate classes, during multisite validation.

B. Implications of Nonconcurrent Image Acquisition

The Arabian Gulf case study differed significantly from that of the Red Sea in that the acquisition of field optics and imagery could not be conducted coincidentally. This does not seem to have adversely affected classification accuracy, with comparable estimates returned through statistical analysis. The fact that it has been proven that optical field measurements can be used to retrospectively train the classification of satellite imagery, is particularly relevant considering the wealth of hyperspectral in situ data already collected in reef environments [1], [9], [11], [15], [21], [24], [43], [45], [69], [72], [76]–[78]. If concurrent acquisition is to be guaranteed, fieldwork has to be timed to coincide with the satellite overpass (which was done) and the IKONOS has to be specifically “tasked” to acquire the scene, which adds approximately US $3000 plus 20% of the order value to the image price [13]. Furthermore, providing that the tasked acquisition fulfills the minimum cloud cover threshold, the user is obliged to purchase the image, regardless of whether minimum acceptable water column conditions are met. If the acquisition corresponded to a time of high turbidity, a large portion of the project budget would be expended on imagery of no practical use for benthic mapping, therefore making sensor tasking a risky business. However, proving that good quality archive imagery collected independently to the field optics can provide acceptable results, the risk is mitigated and the use of IKONOS is greatly enhanced.

\[ R_b \] is deemed to be the optimum unit of albedo with which to compare satellite imagery and spectral measurements made in the field [11]. Being an intrinsic property of the substrate and virtually independent of illumination, atmospheric and water column conditions at the time of measurement (i.e., an apparent optical property), \( R_b \) does not have to be measured simultaneously to image acquisition. However, if measurements of \( R_b \) are to be used in tandem with an image acquired nonconcurrently, attention must be paid to ensure that the water column parameters input into the optical model, are representative of the conditions at the time of sensor overpass. In this case, the predictability of the apparent optical properties of the water column in the study area combined with an adequate lookup-table of \( R_{T_b}(z=0) \) versus \( k \), allowed values for \( k \) to be retrospectively estimated. However, in areas susceptible to turbidity through terrigenous input or seasonal algal blooms, the matching technique would not be valid and the lack of information pertaining to the water column may compromise the reef-up approach. In such cases, external parameters required as input to the optical model for each subsequent image can be derived remotely. The in-band attenuation coefficient \( k \) of the water body can be obtained over uniform substratum with knowledge of depth [12], [18]. However, the estimate may be susceptible to error in optically shallow water where, through seafloor reflection, the propagation of diffuse incoming radiation may not follow a negative exponential with respect to depth (e.g., [79]).

To ensure depth assumptions are valid, tidal status, which can affect the spectral characteristics of a submerged reef (e.g., [6]), can be modeled, else retrieved from port-authority monitoring stations. Last, data pertaining to the atmospheric status at the time of image acquisition, can be estimated over the deep ocean [23], [80], from a concurrent SeaWiFS image [81], else against invariant terrestrial features [57]–[59].

C. Practicality of Reef-Up

The principal requisite for the reef-up strategy is a spatially detailed bathymetric DEM, required as input for correction for the water column on the radiation field. However, accurate bathymetric DEMs are rare for coastal areas, particularly for coral reef systems where hydrographic charts are often inaccurate. Derivation of depth from multispectral satellite imagery is possible [18], [22], [82], but to use this estimate to correct for submergence and subsequently derive substrate type from the spectral quality of the data is likely to produce biased results, as two inherently linked parameters are being extracted from the same pixel values.

To test the degree to which both depth and substrate type can be extracted from IKONOS data without the acoustically derived DEM, bathymetry over the study area was calculated directly from the spectral content of the image. The empirical solution of Stumpf et al. [22] was used, with the coefficients for the ratio algorithm being tuned manually against 40 independently collected depth points. The spectrally and acoustically derived bathymetry varied with a RMS error of 1.4 m, which for a sandy seabed submerged under 2 m of water, translates to an absolute error in retrieved \( R_b \) of 10% and 26% in bands 1 and 2, respectively. Such an error does not preclude the derivation of both depth and substrate type, but would drastically reduce the separability of the eight classes (Fig. 5) and therefore map accuracy, unless the number of substrate classes was correspondingly reduced.

The problem of data dependency is solved with airborne hyperspectral imagery, since there are sufficient bands available to model both depth and bottom albedo using optimization techniques [83], spectral unmixing [77] and site-specific band ratios [24]. From-image statistics do not require absolute accuracy, since only relative interband variations are used to identify different substrate types. The reef-up approach is mathematically more demanding since a comparison is made between reflectance values acquired from the satellite and values evaluated in the field, between which, a reasonable degree of optical-closure must be achieved. Radiative-transfer modeling can only deliver pseudo-optical closure since absolute closure is unattain-
able in shallow water as adjacency and surface effects (e.g., white caps) are not accounted for in the model. However, the reef-up strategy operates under the assumption that errors in the model are balanced by the flexibility of the probability driven classifier, so that a close match between the two datasets is sufficient to allow the correct assignment of pixels to classes. Indeed, this seems to be the case as the classification result is satisfactory and optically similar substrates such as algae and seagrass are successfully separated. The inclusion of covariance in the classifier is likely to aid this process by providing an additional data characteristic with which to discriminate between spectral classes.

D. Significance of Reef-Up

The advantages of training the classifier independently to the image data are multifold. Once an area has been surveyed for depth and providing seafloor topography does not change significantly through short-term sediment flux, repeat monitoring can be conducted with a time-series of imagery without further intensive field study. Training the classifier solely using hyperspectral in situ optics retains maximum flexibility as the spectral library can be resampled to the bandwidths and sensitivity of any future passive-optical instrument, including airborne or hyperspectral spaceborne sensors (e.g., Hyperion, [84]), as they become available. Field study is subsequently only required to provide quality control through continued ground verification. The reef-up strategy presented in this paper offers a physical pathway between substrate spectra and spaceborne imagery and has the potential to be used with alternative sources of hyperspectral data. It is reasonable to assume that hyperspectral data acquired remotely (space- or airborne), could be combined with IKONOS imagery to considerably improve both map accuracy and mapping scale.

Requiring an accurate depth value for each pixel of the remotely sensed imagery has the disadvantage of limiting the area which can be processed using the reef-up strategy. Although a suitable DEM can be built from either passive airborne hyperspectral imagery [24], [77], [83], airborne Lidar [85], or vessel-based acoustic survey (this study), the cost of the technology becomes prohibitive over areas much exceeding 50 km². The approach is therefore limited to reef-scale studies and should be used in unison with more typical sensor-down techniques, if landscape-scale coverage is required.

V. CONCLUSION

1) As postulated by Purkis and Pasterkamp [11], the study confirms that in situ measurements can be made independent of image acquisition and linked to appropriate substrate classes. Substrate reflectance is deemed to be the optimum unit of albedo with which to compare spectral measurements acquired retrospective to sensor overpass.

2) The work has proven the reef-up strategy to have significance in the field of coral reef research. In water depths up to 6 m, both common reef biota (seagrass, algal-mats, and macro-algae) and more importantly, carbonate ben-thos (live corals and dead coral framework) can be resolved with comparable accuracies to studies employing a more standard, sensor-down approach.

3) The modular arrangement of the reef-up strategy retains maximum flexibility for repeat survey with sensors of high-spectral resolution without the need for additional fieldwork, since the classifier is trained with statistics down-sampled from hyperspectral data. Flexibility is pertinent considering the evolutionary trend toward hyperspectral spaceborne sensors.

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REFERENCES

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