Detection of shallow subtidal corals from IKONOS satellite and QTC View (50, 200 kHz) single-beam sonar data (Arabian Gulf; Dubai, UAE)

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Abstract

We compared the results of seafloor classifications with special emphasis on detecting coral versus non-coral areas that were obtained from a 4×4-m pixel-resolution multispectral IKONOS satellite image and two acoustic surveys using a QTC View Series 5 system on 50 and 200 kHz signal frequency. A detailed radiative transfer model was obtained by in situ measurement of optical parameters that then allowed calibration of the IKONOS image against in situ optical measurements and a series of ground-truthing points. Eight benthic classes were distinguished optically with an overall accuracy of 69% and a Tau index T of 65. The classification of the IKONOS image allowed discrimination of three different coral assemblages (dense live, dense dead, sparse), which were confirmed by ground-truthing. Data evaluation of the acoustic surveys involved culling of datapoints with <90% confidence and <30% probability, two QTC-provided statistics, and the deletion of data classes without clear spatial patterns (visualized by single-class trackplots). The deletion of these ubiquitous classes was necessary in order to obtain any clearly interpretable spatial pattern of echo classes after the surveys were resampled to a regular grid and areas between the lines interpolated using a nearest neighbor algorithm. The 50 kHz acoustic seafloor classification was able to determine two classes (unconsolidated sand versus hardground) but was not able to determine corals. The 200 kHz survey determined high rugosity (=corals and sand ripples) versus low rugosity (=flat areas) but was not able to determine consolidated and unconsolidated sediments. Classes were extrapolated to the entire grid and polygons obtained from the two surveys were combined to provide maps containing four classes (rugose hardground=coral, flat hardground=rock, rugose softground=ripples and algae, flat softground=bare sand). Compared with the classification map derived from the IKONOS image, they were 66% accurate (T=59) when the most highly processed data (only selected classes, >90% accuracy and >30% probability) were used, and 60% accurate (T=53) when less processed data (selected classes only, all data) were used. Accuracy against ground-truthing points of the most highly processed dataset was 56% (T=46). These results indicate that results from optical and acoustic surveys have some degree of commonality. Therefore, there is a potential to produce maps outlining coral areas from optical remote-sensing in shallow areas and acoustic methods in adjacent deeper areas beyond optical resolution with the limitation that acoustic maps will resolve fewer habitat classes and have lower accuracy.

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1. Introduction

Against a background of global climate change severely impacting coral reefs and associated carbonate systems world wide (Houghton et al., 2001; Lough, 2000) and claims that their long-term persistence may be in doubt (Buddemeier, 2001; Buddemeier & Fautin, 2002; Knowlton, 2001; Sheppard, 2003), inventories of existing coral areas are of increasing importance. Since coral reefs can be structures of significant lateral dimensions, remote-sensing assisted mapping is the tool of choice (see papers in Andréfoué & Riegl, 2004).
Coral reefs in their strictest definition (strongly three-dimensional carbonate structures built by organisms reaching near the surface) are only one of the sedimentary systems dominated by corals. Alternative systems, usually found in deeper water, are coral biostromes also called coral carpets, defined as coral frameworks draping seafloor morphology without reaching the surface (found in depths of 60 m to the surface), and non-framebuilding coral communities consisting of individual, usually well spaced corals on hardgrounds. These systems have been identified as covering larger areas than true coral reefs in some oceans and are being considered potential refuges during the emerging biotic crisis caused by global climate change (Riegl & Piller, 2003).

Coral reefs in shallow water can be mapped and characterized by using active or passive optical sensors (Brock et al., 2001, 2002, 2004; Hochberg & Atkinson, 2003; Holden & LeDrew, 2002; Purkis et al., 2002). In particular the sensor on the IKONOS satellite with a multispectral resolution in the blue (445–516 nm), green (506–595 nm) and red (632–698 nm) bands of 4 m (Dial et al., 2003) has been demonstrated to provide enhanced thematic accuracy (Andre`fou¨et et al., 2003; Maeder et al., 2002; Mumby & Edwards, 2002). It appears therefore an ideal tool for mapping the lateral extent of reefs and/or any framework type while possibly allowing discrimination of important coral community characteristics due to the image’s fine-scale resolution (Palandro et al., 2003).

However, important coral resources are situated outside the shallow areas of passive optical resolution and it is equally important to accurately map their distribution. One way of doing this is by employing acoustic systems (Foster-Smith et al., 2004; White et al., 2003). Acoustic ground discrimination can be based exclusively on backscatter working from swath, multibeam or side-scanning sonars (Hamilton, 2001; Lyons & Anderson, 1994; Preston et al., 2001, 2003), or it can be based on near-nadir reflected signals that can not only take backscatter, but also surface reflection and subsurface reverberation into account (Anderson et al., 2002; Chivers et al., 1990; Hamilton, 2001; Hamilton et al., 1999; Preston et al., 1999).

We endeavored to evaluate how comparable the performance of ground discrimination from passive optical and single-beam active acoustic methods was with particular reference to detecting corals. To learn more about this, we utilized both methods in an area that was easily accessible for ground-truthing and control. For this exercise, we chose to investigate a shallow carbonate ramp with dense biostromal coral growth in the Arabian Gulf (Dubai, United Arab Emirates). The area evaluated was entirely within the shallow photic zone and could therefore be classified using an IKONOS satellite image. Acoustic ground discrimination was performed using a QTC View Series 5 unit operating on both 50 and 200 kHz signal frequency. The classifications and maps derived from all three surveys (optical, 50 kHz and 200 kHz acoustic) were compared.

2. Materials and methods

2.1. Study area

The study site was selected for the availability of ancillary data and is part of an ongoing study. It is situated in the south-eastern Arabian Gulf, about halfway between Abu Dhabi and Dubai, near Jebel Ali, in the United Arab Emirates (U.A.E., Fig. 1). Corals grow on a flat subtidal ramp with variable density, diversity and surface cover of living coral (Riegl, 2002). The different assemblages can be classified as non-framebuilding coral communities sensu Geister (1983) and framebuilding coral carpets. Corals experienced mass mortality during 1996 and 1998 due to positive temperature anomalies (George & John, 1999, 2000; Riegl, 2002). The study area extends shore-parallel for ~7 km and extends ~1.5 km offshore, where a typical depth of 8 m beneath lowest astronomical tide (LAT) is attained (mean slope angle is 0.5°, Fig. 1). Previous studies (Riegl, 2002; Riegl et al., 2001) identified five typical coral assemblages of variable live cover of which three could be used for the present study since two assemblages consisted of small, <10 cm, widely spaced colonies that did not allow remote detection. Also areas covered by unconsolidated carbonate sand, macro-algae and seagrass, underlain in wide

Fig. 1. Study area in the Arabian Gulf between Jebel Ali and Ras Hasyan in Dubai Emirate, UAE.
areas by early diagenetically cemented calcarenites (Evans et al., 1973; Shinn, 1969), in this paper referred to as hardground, were identified. Thus, for the sake of this study, we could test whether the optical sensor would allow us to spectrally discriminate corals from other, potentially spectrally similar benthos like algae. And we could test whether the acoustic sensor was capable of detecting corals, which we could define in this study area as areas of rugose hardground as opposed to areas of flat hardground, not settled by corals. Rubble areas, as alternative rugose hardground areas, coincided with, and were derived from, coral growth and therefore needed not to be separated.

2.2. The optical dataset

The image-base underlying our research consisted of an IKONOS-2 11-bit multispectral satellite image of 4-m pixel resolution in the red, green and blue bands and 1-m resolution in the panchromatic band. For the present work, only the red, green and blue bands were used due to the low level returns from subsurface features with the panchromatic band, which was deemed not useful for work underneath the ocean surface. The image was acquired on 02 May 2001 (scene 75209) 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.

2.3. Optical ground-truthing

The optical techniques employed in this paper are adapted and improved from previous work in the Red Sea by Purkis and Pasterkamp (2004) and described in detail by Purkis (2004, in press) and therefore only briefly revisited here. Optical measurements were collected between 5th October and 10th November 2002 using a suite of optical tools, used concurrently to parameterize the reflectance of the dominant reef substrata, both above and beneath the water surface and the apparent optical properties of the water column. All optical measurements were conducted over suitably large and spatially homogeneous patches of substrate, between 10:00 and 17:45 h local time, therefore ensuring that the sun was a minimum of 30° above the horizon, to preclude the effects of directional illumination. Measurements were conducted from the survey vessel and the location constrained with dGPS. To obtain a measurement approximating to substrate reflectance \( R_b \), an OceanOptics SD2000 fibre-optic spectrometer was used beneath the water surface, at an elevation of 10 cm from the target substrate (e.g. Hochberg & Atkinson, 2003; Holden & LeDrew, 2002). The spectrometer was operated from the vessel and twin 10-m fibre-optic cables were used to transmit simultaneously acquired measurements of substrate radiance and downwelling irradiance from the two submerged sensor heads. Cross-calibration between the radiance and irradiance channels of the instrument was conducted according to Fargion and Mueller (2000) with use of a standard near-lambertian reflectance panel and reflectance was calculated according to Purkis and Pasterkamp (2004). Nearly coincident to the beneath water measurement, a PhotoResearch PR650 spectroradiometer was used to evaluate remote-sensing reflectance just above the water/air boundary \( R_m \) \((z=a)\) where \( z \) is depth, and \( a \) is air; standard notion for measurements made above the water surface) of the submerged substrate, sighted through the ‘camera-style’ lens of the instrument. The measurement protocols of Pasterkamp et al. (2003) were adhered to, and a near-concurrent sky radiance measurement was used to correct for the effect of sky radiance reflected at the water surface. Immediately prior to, and following the substrate measurements, atmospheric aerosol optical thickness at 550 nm (\( AOT_{550} \)), was measured using a hand-held Microtops II Sunphotometer and the attenuation of the water body \( (k) \), was evaluated using a hand-deployed PRR-610 Profiling Reflectance Radiometer system (Biospherical Instruments) between 400 and 700 nm. In accordance with the protocols of Mueller (2003), a PRR-610 Reference Radiometer, equipped with a cosine-corrector to simultaneously measure downwelling irradiance in air, was used to normalize the downwelling irradiance data acquired beneath the surface.

2.4. Image acquisition and processing

To improve upon the already reasonable level of geographic accuracy for the IKONOS data, further geocorrection was conducted against 40 ground control points acquired using a portable Leica 500 real time kinematically (rtk) corrected dGPS system with a horizontal accuracy of ±30 cm, yielding an average root mean square (RMS) error of 0.66 pixel or 2.65 m. Prior to quantitative analysis, the radiometric calibration coefficients of Peterson (2001) were applied to convert pixel values from digital number to at-sensor radiance units. Lacking in situ estimates of atmospheric status at the time of image acquisition, we adopted the empirical line method (Karpouzli & Malthus, 2003; Schott, Salvagio, & Volchok, 1988; Smith & Milton, 1999) for the removal of atmospheric path radiance. In situ measurements of surface reflectance were made over suitably large and spatially uniform light and dark terrestrial pseudo-invariant features (PIFs) (i.e. spectrally and radiometrically stable), using the PR650. We 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. The literature shows that both asphalt (Emery, Milton, & Felstead, 1998; Lawless, Milton, & Anger, 1998; Schott et al., 1988) and desert sand (Cosnefroy, Leroy, & Briottet, 1996; Lenny, Woodcock, Collins, & Hamdi, 1996; Miesch, Cabot, Briottet, & Henry, 2003) are spectrally stable over long time periods and in addition, are commonly used as vicarious (inflight) calibration targets for satellites. Against the PIFs, the imagery was...
subsequently converted to apparent surface reflectance using linear interpolation. The first 3 bands (blue (445–516 nm), green (506–595 nm) and red (632–698 nm)) of the imagery were further corrected for the influence of the water column, to retrieve values equivalent to substrate reflectance ($R_s$). The correction was implemented using the optical equation described by Purkis and Pasterkamp (2004) (Eq. (6)), where the bathymetric DEM (produced by acoustic survey, see later sections) was used to provide a depth ($z$) value on a pixel by pixel basis and the apparent optical properties of the water column ($R_w$ and $k$) were derived from in situ measurements. The fact that 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 for Purkis and Pasterkamp (2004). For this study the imagery and in situ optics were related over a deep water reflectance target, the position of which was constrained with DGPS. The target 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 $R_w$ ($z=a$) were evaluated using the PRR-600 profiler and PR650, respectively. The data was used to construct a look-up table of $R_w$ ($z=a$) versus $k$ for a number of sea conditions. A match was subsequently sought between satellite and PR650 values of $R_w$ ($z=a$), with the result that in situ data acquired 29/10/02 provided a match with an absolute error in reflectance of 0.10%, 0.16% and 0.13% for bands 1, 2 and 3, respectively. The associated $k$ and $R_w$ spectra, evaluated directly following the PR650 measurement were resampled to the bandwidths and sensitivity of the IKONOS sensor and used as input to the optical equation. 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 $R_w$ ($z=a$) 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 ($\pm 65^\circ$), as was the observation angle of the IKONOS and PR650 ($\pm 25^\circ$ 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%), will be accompanied by a robust match in $k$. Lastly, considering the limited size of the study area and the fact that sediment plumes are clearly absent in the imagery, 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.

2.5. Classification and accuracy assessment

Image classification was conducted using the multivariate normal probability driven classifier described by Purkis and Pasterkamp (2004). The classifier was trained solely using the sub-surface in situ spectral measurements of substrate reflectance, resampled to the bandwidths and sensitivity of the IKONOS sensor. To remain comparable to the previous work in the region, both on the ground (Riegl, 2002) and satellite (Andréfouët et al., 2003), the in situ spectra were assembled into 8 broad facies classes (Table 1).

As with the previous studies, 8 classes were found to adequately represent the substrate diversity of the area. In addition, other studies using IKONOS in comparable environments (Andréfouët et al., 2003; Capolino et al., 2003; Maeder et al., 2002; Mumby & Edwards, 2002), indicate that 8 classes is a realistic level of discrimination to be expected from the capability of the sensor. The classification was implemented on the IKONOS imagery after it had been corrected for the radiative transfer effects of both the atmosphere and water column. In this way, the link between the in situ optical measurements and IKONOS data was made at the level of substrate reflectance ($R_s$). A discussion concerning the advantages and rationale behind this approach, as opposed to the more traditional use of ‘from-image’ trained classifiers, is given by Purkis and Pasterkamp (2004).

During the field campaign, extensive ground-truthing was conducted using SCUBA for the purpose of providing validation data against which classification accuracy could be assessed. A transect technique similar to that used by Purkis et al. (2002) was employed, but adapted for use in deeper water. The transects were typically 160×8 m (equivalent to 80 IKONOS pixels) and substrate was mapped to metre-resolution. The transect data was supplemented by a large quantity of spot checks throughout the study area. Details concerning the collection and processing of the ground-truth data are given in Purkis (2004). The accuracy of the classified image was assessed against 15 transects and 52 spot checks, which totalled 524 validation points. Since the classifier was trained exclusively using in situ optics, all of the ground truth data remained independent and therefore available for accuracy assessment, with the result that sufficient validation points were available to support a statistical analysis of classification error without bias (e.g. Congalton, 1991). Post-classification smoothing is a commonly employed technique to improve accuracy by reducing noise in the classified imagery (Mumby & Edwards, 2002). A median filter was selected to smooth the classification result, since it simultaneously reduces
Table 1
Summary of the typical substrate assemblages encompassed within each of the eight facies classes

<table>
<thead>
<tr>
<th>Bottom class</th>
<th>Typical assemblage composition</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense live coral</td>
<td><em>Porites lutea</em> and <em>Porites harrissoni</em> intermingled with <em>Favia</em> spp. and <em>Platygrya</em> spp.</td>
<td>Dense colonies over hardground, commonly maintaining a low-relief but in places forming non-framebuilding coral carpets. Coverage 50–100%.</td>
</tr>
<tr>
<td>Dense dead coral</td>
<td><em>Acropora clathrata</em> and <em>A. downingi</em></td>
<td>Dense dead tabular colonies, frequently overtopping and heavily overgrown with algal turf and coralline algae. In places the tabular framework has disintegrated into piles of branch rubble. Average size of intact colonies is 1 to 1.5 m and coverage is 80–100%.</td>
</tr>
<tr>
<td>Sparse coral</td>
<td><em>Porites</em>, <em>Favia</em> spp. and <em>Siderastrea savignyana</em> with occasional small colonies of <em>Acropora clathrata</em></td>
<td>Widely spaced patches of Faviid and Siderastrea colonies on hardground with occasional large <em>Porites</em> boulder corals. The <em>Acropora</em> were mostly dead at the time of image acquisition. Coverage is generally 10–40%.</td>
</tr>
<tr>
<td>Seagrass</td>
<td>Mainly <em>Halodule uninervis</em> with occasional <em>H. ovalis</em></td>
<td>Dense seagrass stands had generally found over sandy-silty substrate and had a coverage of 60–80%.</td>
</tr>
<tr>
<td>Shallow algae</td>
<td><em>Rhizoclonium tortuosum</em>, <em>Chaetomorpha gracilis</em> and <em>Cladophora coelothrix</em></td>
<td>Extensive mats over sandy-silty substrates, often associated with seagrasses. Coverage 80–100%.</td>
</tr>
<tr>
<td>Deep algae</td>
<td><em>Sargassum binderi</em>, <em>S. decurrens</em>, <em>Avrainvillea amedeaphila</em> and <em>Padina</em></td>
<td>Moderately dense stands of macro-algae on patches of unconsolidated sediment. Coverage 30–60%.</td>
</tr>
<tr>
<td>Hardground</td>
<td>–</td>
<td>Large slabs of lithified carbonate sediment, fringed by ‘tepee’ structures. Coverage 100%.</td>
</tr>
<tr>
<td>Sand</td>
<td>–</td>
<td>Unconsolidated carbonate sand. Coverage 100%.</td>
</tr>
</tbody>
</table>

Coverage refers to the percentage of the seabed occupied when a 1×1 m area of substrate is viewed from nadir at an altitude of 1 m. Assemblage description is based on Riegl (2002).

The acoustic dataset

The acoustic survey was conducted from a 15-m survey vessel equipped with a real-time kinematic (rtk) differentially corrected Fugro SeaSTAR 3200LR12 global positioning system (dGPS). The differential correction of the positioning data was conducted in real-time against the OmniStar network of satellites with a horizontal accuracy of ±50 cm. The geo-rectified satellite image was loaded into the softwares Fugawi and Hypack, which were interfaced with the dGPS unit and allowed the operator monitoring vessel position with respect to the imagery in real-time. To ensure an adequate degree of accuracy, three independent acoustic surveys were used to build the bathymetric DEM for interface with optical remote-sensing. Bathymetry lines were obtained over the entire study area using both a 50 and 200 kHz signal with 0.4-ms pulse width and a 5-Hz sampling frequency with a beam angle of 42° and 12°, respectively, for the two sampling frequencies provided by a Suzuki 5200 depth sounder with a minimum depth of operation of 1 m. Surveys were executed in sequence (first 50, then 200 kHz) over a period of 5 days. The same planned line files were used for navigation in order to ensure closest possible spatial coincidence of data in the two surveys. The 50 kHz survey covered a wider overall area than the 200 kHz survey, but for this study only lines coincident in both surveys were used. Depth was determined by using the QTC View 5 bottom picking algorithm, which was accurate to 10 cm. Accuracy of the algorithm was tested with bar checks (Brinker & Minnick, 1994) and by direct cross-checks of displayed bathymetry and measured depth with a weighted line at several sites. Survey lines were spaced by 100 m to cover the entire study area (7×1.5 km). An additional 50 kHz acoustic near-shore bathymetry survey with a 15-m line spacing provided high-resolution bathymetry in the first 500 m from shore, these data were only used in optical algorithms but not for acoustic ground discrimination. Throughout the survey period, tidal data was collected at five-minute intervals in situ, 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 influence from atmospheric variation. Tidally corrected 50 kHz data were used to construct a DEM referenced to lowest astronomical tide (LAT). The merged bathymetry data was 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 error was found to be less than 0.05 m.

Acoustic habitat classification was performed using the QTC View Series 5 system which consists of hydrographic survey hard- and software geared towards acoustic ground discrimination based on the shape of sonar returns (Quester Tangent, 2002). It records the characteristics of reflected waveforms to generate habitat classifications based on the diversity of scattering and penetration properties of different
types of seafloor (Preston et al., 1999). The typical process involves a hydrographic survey where raw acoustic data are collected as time-stamped, dGPS-geolocated, digitized envelopes of the first echo. Data were processed in the software QTC Impact and were checked by the operator for correct time-stamps, correct depths and correct signal strengths. All signals that did not pass an appropriate level of quality control were discarded. Data were displayed on a bathymetry plot, where recorded depths were checked against the blanking (minimum recordable) and maximum depths set for the survey and any faulty depth picks were removed manually before further processing.

In QTC Impact software, the echoes were digitized, subjected to Fourier Analysis, Wavelet analysis and were analysed for kurtosis, area under the curve, spectral moments and other variables by the acquisition software (Legendre et al., 2002). After being normalized to a range between 0 and unity, they were subjected to Principal Components Analysis (PCA) in order to eliminate redundancies and noise. The first three principal components of each echo were retained (called Q values), according to the logic that these typically contain 95% of the information (Quester Tangent, 2002). Datapoints were then projected into pseudo-three-dimensional space along these three components, where they were then subjected to cluster analysis (Quester Tangent, 2002).

2.7. Acoustic classification and accuracy assessment

Cluster analysis using a Bayesian approach was performed within the software package QTC Impact, which is companion software to the QTC View survey package. In clustering, the user decides on the number of desirable clusters and also chooses which cluster to split and how often. Clustering decisions are guided by three statistics that are offered by the program called “CPI” (Cluster Performance Index), “Chi^2” and “Total Score”. Total score decreases to an inflection point which is ‘a strong indication of best split level’ (Quester Tangent, 2002). CPI increases with increased cluster split, while Chi^2 decreases, reaching maximum/minimum values at optimal split level (Quester Tangent, 2002). We plotted Total Score against the number of clusters to investigate ideal cluster split. However, we always split acoustic data until as many acoustic classes were found as optical classes could be distinguished on the IKONOS image. This was done because we wanted to evaluate whether both methods allowed comparable discrimination accuracy.

Reviews of the functioning of the QTC system and critiques can be found in Hamilton et al. (1999), Hamilton (2001), Legendre et al. (2002), Preston and Kirlin (2002) and Legendre (2002).

For each individual signal, the following data were exported from QTC Impact for further processing: latitude, longitude, depth (uncorrected for tidal state, correction was performed during data re-processing), the first three PCA axes (called Q-axes), a class category, a class assignment confidence value and a class probability value both ranging from 0 to 100%. Class confidence is ‘a measure of the covariance-weighted distances between the position of the record and the positions of all cluster centers’ while class probability is ‘a measure of closeness to the cluster center, weighted by the covariance of the cluster in the direction of the record’ (Quester Tangent, 2002). These indices are useful for the detection of class boundaries (Morrison et al., 2001) and we used them to evaluate the overall “quality” of individual data-points and classes following the rationale that anything with predominantly low confidence and/or probability could be good candidates for deletion from the dataset. We used these statistics to create several levels of datasets that were tested against each other: one level with all data and all classes included, and several levels in which all data that did not fulfill specified quality control criteria (i.e. <90%, 60% confidence, <90%, 60% probability) and all classes that did not show clear spatial patterns, were culled. The discrimination accuracies of the datasets were then compared against each other. Datasets were reduced to three-column matrices consisting of a single x,y geo-referenced class category z. The trackplots for each data class were individually plotted to allow assessment of their spatial distribution. Classes that showed a preferential distribution in well-defined parts of the survey area were considered to show promise for distinguishing different seafloor types. Classes that were found in comparable density across the entire survey area were considered to carry signals with no discrimination ability. Classes that were found to be redundant were iteratively removed from the dataset.

Finally, we resampled the irregular grid of categorical data consisting of the georeferenced class categories obtained from the cluster analysis to a regular grid and used a nearest neighbour interpolation to fill the grid and then to obtain a filled contourplot of class distribution (Middleton, 2000). The nearest neighbor algorithm was used to not produce fractions of classes such as would be produced by, for example, kriging, which, in the present case of categorical variables on a nominal scale, would have been non-sensical.

Groundtruthing used a total of 75 points to determine accuracy of the maps derived from 50 and 200 kHz surveys (Fig. 8). The correspondence of the acoustic and the optic dataset was estimated by using 97 gridded points that were projected onto the overlaid maps (Fig. 8).

3. Results

3.1. Optical results

The results of the optical classification allowed the mapping of the previously assigned eight classes (Fig. 2). Classes were split into unconsolidated sediments (shallow
sand) and the associated bottom-types (seagrass, shallow algae) in nearshore areas, and hardgrounds, sparse coral, dense coral and some sand in the deeper areas.

Accuracy assessment of the predictive map yielded an overall accuracy of 69% and a Tau coefficient (Ma & Redmond, 1995) of 65% (Table 2). 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=77%).

3.2. Acoustic results

The 50 kHz data, when plotted along the first three principal components after signal processing, formed a relatively homogeneous cluster, indicating that overlap between data classes could be expected (Fig. 3). Since the number of splits performed in the employed version of QTC Impact software is user-defined, we iteratively increased the number of splits from two clusters to eight clusters, the highest number of bottom classes derived from the optical image classification. Since the data cloud was more or less spherical, clusters were split first along the PC1 (Q1) axis and then along the PC2 (Q2) axis. Splitting along the PC2 axis resulted in a pattern of parallel, relatively discrete, clusters and was preferred over the clusters obtained by splitting along the PC1 axis, which showed more overlap and less clear separation. The Total Score statistic showed the strongest drop after the first split both for PC1 and PC2 splits. The splits along the PC1 axis showed an inflexion point after five splits, along the PC2 axis after 6 splits (Fig. 3), which indicated that this would be the optimal number of classes. We nevertheless proceeded to obtain 8 clusters, for comparability reasons with the optical dataset. Of these, classes 6 and 8 had the highest probability scores. However, class 6 had low confidence scores, while those of class 8 were high (Fig. 3C and D). Probability scores were more uniformly distributed among classes than confidence scores. In general, the distribution of the probability statistic was

<table>
<thead>
<tr>
<th>Ground-truth data</th>
<th>Classified data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>0 10 0 0 0 3 12</td>
</tr>
<tr>
<td>Hardground</td>
<td>0 1 1 3 3 10 73</td>
</tr>
<tr>
<td>Deep algae</td>
<td>0 1 4 0 0 26 2 0</td>
</tr>
<tr>
<td>Seagrass</td>
<td>0 0 0 0 17 2 0 2</td>
</tr>
<tr>
<td>Swallow algae</td>
<td>0 0 0 11 91 0 0</td>
</tr>
<tr>
<td>Sparse coral</td>
<td>0 5 71 6 1 4 7</td>
</tr>
<tr>
<td>Dense dead coral</td>
<td>0 0 0 11 91 0 0</td>
</tr>
<tr>
<td>Dense live coral</td>
<td>0 12 0 5 1 6 1</td>
</tr>
<tr>
<td>Column totals</td>
<td>18 47 91 32 101 56 86 93</td>
</tr>
</tbody>
</table>

P_{\text{O}}=69\% (95\% confidence intervals of P_{\text{O}} are 73\% to 65\%)
T=65\% (95\% confidence intervals of T are 69\% to 61\%)

The ground-truth pixels that are classified as the correct substrate classes are located along the major diagonal of the matrix, while all non-diagonal elements represent errors of omission or commission. T=Tau index.
clearly skewed towards lower values in all classes, while confidence was markedly skewed towards high values.

Fig. 4A shows the first three principal components of the processed 200 kHz data. The data cloud was less compact than that of the 50 kHz signals and shows better separation, although also in this case no distinct clusters are visible. All clusters were consecutively split along their PC1 axis, which resulted in parallel groups. In this case, a split along the PC2
axis was not performed, since the datacloud was markedly oblong along the PC1 axis and therefore suggested one natural direction of cluster separation. Total score, as a measure of ideal clustering level, showed three inflexion points, one each after three, five and seven splits (Fig. 4B). The strongest inflexion occurred after three clusters, suggesting that this might be the ideal number of clusters.

This assumption was later confirmed, three classes (2, 3 and 7) had a well-defined spatial pattern (Fig. 6). However, data were also in this case split to an eight-cluster level to check for comparability with the optical dataset. Class 1 had the highest observed confidence values (Fig. 4C). Probability values were similar between the classes and no clear trend was evident (Fig. 4). Also in the 200 kHz dataset,
probability scores were more uniform than confidence scores among classes. In general, the distribution of probabilities was clearly skewed towards lower values in all classes, while confidence classes were markedly skewed towards high values.

Since the PC2 axis splits produced the better cluster separation in the 50 kHz survey, we used these data to plot the trackplots of each class in order to understand their spatial pattern. In the 200 kHz survey, we used the splits obtained along the PC1 axis. Two sets of trackplots were made for each survey; one with all data, and one with data only exceeding certain confidence and probability values that were then superimposed over the classified IKONOS image. Three levels of confidence (>80%, 90%, 95%) and probability (30%, 50%, 60%) were tested and data were repeatedly plotted. Useful levels were 90% confidence and 30% probability for both frequencies. These manipulations eliminated 26.2% of 50 kHz data and 37.8% of 200 kHz data when the confidence criterium was applied, but 55.4% of 50 kHz data and 52.8% of 200 kHz data when the probability criterium was applied. When probabilities >50% were required, entire classes could no longer be evaluated for any coherent spatial patterns in both frequencies. Also, when accuracies >95% were demanded, overall less than half of the datapoints remained. This, besides the tight packing of clusters in Figs. 3 and 4, we considered another indication for the relatively homogeneous nature of the dataset with poor definition of individual clusters.

Fig. 5 shows the distribution of eight 50 kHz acoustic classes along the survey lines. The lines obtained with >90% confidence data were similar to those of the full dataset since about two thirds of data was retained. Spatial
patterns were comparable between points with high confidence and points with high probability. The 8-cluster dataset produced several groups of data with similar spatial distribution (Fig. 5), which suggested significant redundancy between the classes and the possibility to remove some classes from the dataset to evaluate whether this would increase accuracy of discrimination. Although the total score values indicated six clusters to be probably the best number of splits, also the spatial distribution of six clusters showed significant overlap (not illustrated) and the situation was not very different from the eight-cluster split illustrated in Fig. 5. Class 8 was distributed evenly over the entire study area and was thus considered to consist of signals carrying no substratum specific information, suggesting that it could essentially be considered background noise. Groups of signal classes showed favored distribution either in the offshore hardground area–classes 1, 2, 3 and 5–or nearshore and offshore areas of unconsolidated sediments—classes 4, 6 and 7. Further splits of each of these classes did not change the spatial distribution of new classes, but only resulted in new classes with a similar spatial distribution to that of the parent, however, with fewer, more widely spaced datapoints along the tracks (not illustrated). Results obtained with the complete datasets (no deletions following confidence and probability criteria) were similar (not illustrated).

It was evident that the 50 kHz acoustic survey could not resolve the eight optical classes, but rather that the signal primarily differentiated between essentially only two seafloor classes. The most useful classes allowing comparison to the optical image classification were classes 2 and 6 (Fig. 5). This also corresponded to high probability values in

![Fig. 6. Distribution of eight 200 kHz acoustic classes over the survey area. The classes with the clearest spatial distribution are classes 2, 3, and 6, expressing areas with corals. Coordinates are shown in Fig. 8.](image-url)
these two classes (Fig. 3C and D). However, class 6 had low confidence values. The uniformity of probability values across all eight classes would not have made this choice obvious from the beginning (Fig. 3). Also confidence values would not have allowed us to predict immediately after the cluster analysis and before the visualization of the trackplots which classes were likely to have the clearest and easiest-to-interpret spatial distribution. While other data classes also had a distinct spatial distribution, such as classes 3 and 7 (offshore), the data in these classes were too sparse to be useful.

In order to be able to better interpret the spatial patterns of the classes, we resampled the data to a regular grid and used a nearest neighbor interpolation to obtain filled contourplots of the distribution of the class variables. We attempted to produce four different maps—firstly with all data in classes 2 and 6, secondly with only those data with >90% confidence and >30% probability in classes 2 and 6, thirdly with all data in all classes and finally with all classes but only those data with >90% confidence and >30% probability. Of these four surfaces, only those produced uniquely with data in classes 2 and 6 were successful (Fig. 7). The high density of the classes with no spatial preference (in particular class 8) led to no useable gridding and interpolation results when all classes were plotted (not illustrated). Accuracy was poor overall. In particular in the offshore area, significant confusion between visually identified sand and optically identified hardgrounds existed. However, much of the offshore sand is only a few centimeter-thick sheet overlying hardgrounds, resulting in a visual (optical) sand signature but an acoustic hardground signature.

Also the distribution of the >90% confidence and >30% probability 200 kHz data in each of the eight classes was plotted along the survey lines (Fig. 6). Classes 1, 2, 3, 5 and 7 showed clear spatial patterns, but classes 1 and 5 contained few data and coincided in distribution with the other classes, therefore, they were not considered useful. When all data (no deletion of points <90% confidence and/or 30% probability) were used, the spatial patterns were less apparent. Class 8 was almost ubiquitous and was therefore considered to carry little information.

In both evaluations (full dataset and >90% confidence, >30% probability only), classes 1, 2, and 3 showed a clearly preferential distribution in the offshore area where most coral growth was found, while classes 4 and 7 were preferentially distributed in non-coral areas (Fig. 6). Four different spatial prediction maps were produced by nearest neighbor interpolation—firstly with all data in classes 2, 3 (both coded as class 1) versus 4 and 7 (both coded as class 2), secondly with only those data with >90% confidence and >30% probability in classes 2, 3 versus 4 and 7, thirdly with all data in all classes and finally with all classes but only those data with >90% confidence and >30% probability. The maps produced with all classes did not provide any useful results, which is not surprising in view of the ubiquitous class 8 (not illustrated).

The resampled and extrapolated map of classes 2, 3 versus 4 and 7 corresponded largely to areas covered by corals and/or macro-algae in the offshore area (Fig. 7). Also some parts of the nearshore area fell into this group (only class 7 had a marked inshore component, classes 1 and 2 occurred almost exclusively in the offshore area). These were areas near permanent wavebase, characterized by ripple fields in mobile sediment. We therefore believe that the differentiation picked up by the 200 kHz survey was largely along lines of surface rugosity-caused by corals (and possibly also macro-algae) in the offshore area, by ripples in the nearshore. The nearshore area encoded by class 7 consisted largely of bare sand, sparse Halodule seagrass meadows and some green algae.

From the evaluation of the trackplots and the apparent information content of the individual classes in both surveys, we concluded that no matter how many splits were forced onto the data of any individual survey, only a limited set of classes actually appeared to be carrying information that allowed the determination of different seafloor types. In the case of both the 50 and 200 kHz surveys, we only obtained two meaningful classes each out of 8 clusters. It was found more useful to first split the dataset to a higher number of classes and then remove classes with no clear spatial pattern than to only perform a single two-class split. The interpolated surfaces produced from the reduced datasets were preferable to those produced by a simple two-class split when compared to ground-truth and optical data (not illustrated).

The surveys showed a distinction into areas of high rugosity and areas of low rugosity and areas of soft and hard substrates and the polygons obtained from the two surveys could be combined without excessive overlap. This provided a four class differentiation consisting of the 50 kHz classes hardground/softground and the 200 kHz classes rugose/flat. The 50 kHz survey appeared to carry more information regarding the hardness or the substratum, while the 200 kHz survey appeared to carry primarily rugosity information. The 50 kHz survey essentially showed only one class each in the nearshore and the offshore—it did not pick up the nearshore rugosity caused by ripples as well as the 200 kHz survey. Surface complexity was known from previous field surveys and the classes obtained from the IKONOS image, which confirmed that high surface rugosity on hardgrounds was caused mainly by corals, on softgrounds mainly by sand ripples.

Thus, the two surveys distinguished a total of four classes that were interpreted as:

- flat hardground (mainly offshore),
- flat, unconsolidated softground (mainly nearshore sand),
- rugose hardground (=coral areas, mainly offshore),
- rugose unconsolidated softground (=algae or sand ripples, mainly inshore).
Each survey distinguished two classes: the 200 kHz survey distinguished between rugose and flat areas of seafloor and was thus found more useful for detecting corals. The 50 kHz survey distinguished primarily between hard and soft substrates and was found to be sensitive to subsurface texture (i.e. hardgrounds underlying unconsolidated sand sheets) and was in the present case not useful for the detection of corals.

In the next step, the polygons obtained from the 50 and 200 kHz surveys were combined into single, four-class maps. Two such four class maps were produced (Fig. 8): one which used all data in clusters 2 and 8 (50 kHz) and 2, 3 versus 4, 7 (200 kHz), and one which used only the data >90% confidence and >30% probability. Both were superimposed on the classified IKONOS imagery and error matrices were calculated (Tables 3 and 4). The map produced from the more intensely processed data (>90% confidence and >30% probability) was more accurate than the map incorporating all data (66%, \(T=59\) versus 60%, \(T=53\)). This supports the importance of significant data-processing. The accuracy of the more intensely processed map against ground-truthing points was 56% (\(T=46\)) (Table 5).

Seagrass, which in the study area consisted only of very sparse *Halodule uninervis* and *Halophila ovalis*, was not observed to provide any acoustic signature. This was verified by obtaining short sample datasets over seagrass and nearby bare sand. The acoustic data, when treated in the same way as described above, did not split into any interpretable clusters. The three different classes of coral communities that were discriminated by the IKONOS classification were not at all resolved by the acoustic survey, but corals were nevertheless distinguished acoustically with relatively high accuracies as rugose hardground.

Finally, to evaluate whether the clusters were caused by depth contamination of the signal, we plotted the relative frequency of each of the eight classes obtained in both surveys against depth (Fig. 9). Although some of the 50 kHz classes showed depth preference, they occurred across much of the survey area’s depth range and showed wide overlap. If depth had influenced the signal, the substantial overlap in the depth distribution of the classes should not have been observed.

Also the 200 kHz classes did not show a clear depth preference (Fig. 9). It was therefore concluded that depth...
contamination of the signal was not the cause for class differentiation in either of the two surveys.

4. Discussion

The optical technique is discussed in detail elsewhere (Purkis, 2004, in press) and we will therefore only briefly comment on its suitability for this shallow subtidal area. In agreement with Purkis and Pasterkamp (2004), the use of a large-scale independent (acoustic) measure of water depth to quantify the thickness of the intervening water column on a pixel-by-pixel basis, used in combination with an optical equation to correct the imagery for the spectral effect of submergence, yielded values of substrate reflectance highly comparable to those obtained in situ. Furthermore, the
agreement between in situ and remote measurements held, despite the fact that acquisition of IKONOS image and measurements characterizing radiative transfer did not occur concurrently. Capitalizing on the performance of the optical equation and training, the image classification solely through in situ optical measurements has the advantage of allowing the production of an accurate predictive map of substrate distribution, while retaining all of the ground-truth data as independent and therefore available for a rigorous accuracy assessment (Purkis, 2004) (Table 5).

The availability of the detailed and ground-truthed satellite-based habitat map allowed evaluation of the

<table>
<thead>
<tr>
<th>Optical classes</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Class 7</th>
<th>Class 8</th>
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<tbody>
<tr>
<td>Acoustic classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>high rugosity/hard</td>
<td>20</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>23</td>
<td>97%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>low rugosity/hard</td>
<td>16</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>27</td>
<td>19%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>high rugosity/soft</td>
<td>3</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>19</td>
<td>84%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>low rugosity/soft</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td>17</td>
<td>23</td>
<td>81%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Column totals</td>
<td>41</td>
<td>8</td>
<td>25</td>
<td>23</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Producer accuracy</td>
<td>49%</td>
<td>63%</td>
<td>64%</td>
<td>74%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

P$_O$=60% (95% confidence intervals of P$_O$ are 49% to 71%)
P$_T$ are 53% (95% confidence intervals of P$_O$ are 42% to 64%)

Table 3
Error matrix for the combined 50 kHz (class 2 versus 6), 200 kHz (classes 2, 3 versus 4, 7) four-class map in Fig. 8A using all data in the selected classes versus the IKONOS 8-class map

The high level of discrimination clearly shows that the IKONOS sensor is indeed suitable for detailed coral monitoring. Three different coral assemblages could be differentiated: the dense, during the time of survey dead Acropora thickets, the surrounding dense coral assemblage dominated by the coral genus Porites and various faviids, and an adjacent sparse coral assemblage dominated by the same genera. It is somewhat surprising how well the image classification was able to differentiate hardgrounds from unconsolidated sand. The reason for that can be sought in the overall somewhat darker color of hardgrounds which is caused by algae (endolithic as well as surface dwelling) and fauna, however sparse. A more detailed discussion of the optical image processing techniques, development of digital elevation model, and geomorphological as well as biological interpretation based on the classified image can be found in Purkis (2004, in press).

The availability of the detailed and ground-truthed satellite-based habitat map allowed evaluation of the

Table 4
Error matrix for the combined 50 kHz (class 2 versus 6), 200 kHz (classes 2, 3 versus 4, 7) four-class map in Fig. 8B using only data >90% confidence and >30% probability in the selected classes versus the IKONOS 8-class map

Fig. 9. Normalized frequency of occurrence for each of the eight QTC Impact acoustic classes with respect to depth, as obtained through (A) 50 kHz, (B) 200 kHz surveys. In both cases, the overlap of the acoustic classes provides clear evidence that class separation is not caused by depth contamination of the acoustic signal.
information content within the acoustic QTC View classes obtained during our surveys. The analysis of the present dataset showed how the statistics provided by the QTC Impact software can be used to refine results by deleting datapoints and entire classes. This procedure (deletion of datapoints with low confidence/probability, deletion of classes without clearly visible spatial patterns) increased the ease of interpretation as well as accuracy in the case of our study. The finding that increased levels of data processing also increases the accuracy of the product concurs with the report by Purkis and Pasterkamp (2004) for Landsat imagery. The result is also important when considering the validity of the QTC View as an operational tool in an area of unknown bottom-type mosaic since the evaluation of what classes and level of data processing should be the final output may be difficult. Without having a known habitat mosaic for comparison (in our case the IKONOS image), it may not be evident how to select the best classes from the provided statistics. Our presented analyses here may be helpful to guide selection of what data should be used and what should be discarded. Also Morrison et al. (2001) found the probability and confidence statistics useful in finding habitat boundaries in soft sediments.

It was easily visible that of the eight acoustic classes obtained from the supervised classification process not all did carry useable information. More classes had a more or less ubiquitous than spatially preferential distribution. Acoustic signals show a lot of random variability, which is caused by ship and sensor movement, hardware configuration, natural variability, electromagnetic interference, random signal noise, etc. (Hamilton, 2001; Hamilton et al., 1999). To obtain signal stability, a given number of pings are stacked to produce an averaged signal which helps to avoid fluctuations and the averaged signals thus make the detection of patterns easier. In QTC View, while every individual echo is collected and digitized, four consecutive echoes are then stacked for averaging. Different ways of stacking are recommended for different bottom types (Hamilton, 2001; Hamilton et al., 1999) and different systems stack different numbers of pings (Walter et al., 2002). While stacking is necessary to compensate for the semi-random nature of the returns and yet harness their usability, it also has the effect of producing averaged footprints. When the survey vessel moves, the stacked footprint can include several bottom classes and will increase in size with vessel speed. Since coral reefs are notorious for their spatial heterogeneity, it is not surprising that only relatively few pure stacked echoes of any one substratum class were obtained, while a majority of signals were in reality an average of several bottom classes. We believe that this mechanism, coupled with natural and survey-dependent (hardware, weather, etc.) signal variability, helped create the data classes that were distributed evenly over the survey areas and did not distinguish any bottom types (Figs. 5 and 6).

The footprint of the 50 kHz transducer was much bigger than that of the 200 kHz transducer. Consequently, spatial resolution was higher and ecological grain finer in the 200 kHz survey. This was important for distinguishing ecologically relevant units, such as coral versus bare hardground. Corals, the main target to be mapped, had average diameters of less than 1 m in the study area, which translates to 2 adjacent 200 kHz footprints, but only one half 50 kHz footprint at 5 m depth, where the densest coral assemblages are found (Riegl, 2002). It can be easily seen that each individual 50 kHz footprint was bigger than several fully-grown coral colonies (0.84–3.36 m² footprint size versus 0.8 m² maximum expected coral size). When adding the fact that four consecutive signals were stacked, the footprint actually increased fourfold since survey speed was such that individual footprints did not overlap. In our survey, 50 kHz footprints had areas of 3.36 (at 5 m depth)–13.44 m² (at 10 m depth) at a speed of 10 km/h and a ping rate of 5 Hz. Except in very dense coral areas, such footprints were likely to include more bare substratum than coral. The 200 kHz footprint, in contrast varied in the same depth range from 0.21 to 0.84 m² pre-stacked and 0.84 (at 5 m depth)–3.36 m² (at 10 m depth). This was sufficiently small to include enough “pure coral” footprints to obtain acoustic classes determining corals. Also, over rough terrain, such as corals, signal averaging can indeed degrade the signals and lead to misclassifications (Hamilton, 2001; Hamilton et al., 1999) and McKinney and Anderson (1964) found scattering to vary widely over corals (Hamilton et al., 1999). It is therefore not surprising that signal classes encoding corals were not very well defined (classes 2, 3, and 7 of the 200 kHz

<table>
<thead>
<tr>
<th>Grountruthed classes</th>
<th>Corals</th>
<th>Hardground</th>
<th>Algae and seagrass</th>
<th>Bare sand</th>
<th>Column totals</th>
<th>Producer accuracy</th>
<th>Row totals</th>
<th>User accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>high rugosity/hard</td>
<td>19</td>
<td>10</td>
<td>2</td>
<td>4</td>
<td>35</td>
<td>54%</td>
<td>66%</td>
<td>73%</td>
</tr>
<tr>
<td>low rugosity/hard</td>
<td>10</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>16</td>
<td>54%</td>
<td>66%</td>
<td>73%</td>
</tr>
<tr>
<td>high rugosity/soft</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>1</td>
<td>6</td>
<td>54%</td>
<td>66%</td>
<td>73%</td>
</tr>
<tr>
<td>low rugosity/soft</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>16</td>
<td>18</td>
<td>54%</td>
<td>66%</td>
<td>73%</td>
</tr>
</tbody>
</table>

| Row totals            | 29     | 12         | 12                 | 22        | 66%           | 73%               | 73%        | 73%           |

P₀=56% (95% confidence intervals of P₀ are 42% to 70%) T are 46% (95% confidence intervals of P₀ are 32% to 60%)
survey, Figs. 7 and 8). Hamilton (2001) and Hamilton et al. (1999) suggest using the variability in the pings rather than averaging in such areas.

It is also known that surface scatter from a statistically rough surface is inversely dependent on transducer opening angle (Clay & Sandness, 1971; Medwin & Clay, 1998). The smaller-opening angle 200 kHz transducer therefore not only had a smaller footprint allowing for higher “ecological” precision, but it also produced relatively higher backscatter, which would suggest that this makes it a good tool for detecting surface structures, such as the scatter caused by corals, maroalgae, or sand ripples. It is believed that the detection of the corals was mostly based on their backscatter strength, since the surface scatter and subsurface reverberation components should not have been too different from that of the substratum (the corals consist of a massive aragonite skeleton, while the substratum consists of a mixture of aragonite and calcite grains cemented by aragonitic and high-magnesium calcite cements). Therefore, the 200 kHz survey fared better with respect to finding corals. It is also known that a lower-frequency signal will enter more deeply into the substratum than a higher frequency signal (Medwin & Clay, 1998). We believe that this mechanism caused some misclassifications in the offshore areas that were visually identified as sand, but acoustically identified as hardground (Fig. 7). It is possible that the 50 kHz signal penetrated the relatively thin sand layer (only few cm to less than 1 m) to reach the underlying hardground.

5. Conclusion

The juxtaposition of optical and acoustic remote-sensing techniques has proven that both are capable of discriminating between unsettled (bare) and settled (corals, macro-algae) substrata. A key question was their capability to detect corals, and both methods succeeded. High-resolution optical images such as IKONOS, provide a very clear and highly defined picture of the spatial heterogeneity of coral communities. When outside the range of passive optical resolution, i.e. in waters of greater than 10 m depth, acoustic methods, even relatively simple ones, have the potential of providing reasonably accurate maps. While one single satellite image was enough to provide an accurate discrimination of consolidated versus unconsolidated sediments and of different density coral communities versus bare areas, only the 200 kHz acoustic survey was capable of discriminating coral from non-coral substrata and the results of the 50 and 200 kHz survey needed to be combined to provide a plausible four-class map. The discrimination accuracy of the acoustic surveys was lower than that of the satellite imagery but nevertheless has proven to be potentially useful for the detection of deep coral areas outside the optical range. Further research into the comparison of optical with acoustic results promises to yield interesting and useful results.

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