On the Benefits of Using Both Dual Frequency Side Scan Sonar and Optical Signatures for the Discrimination of Coral Reef Benthic Communities

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1. Introduction

The importance of coral reef ecosystems is well established (McManus and Noordeloos, 1998). The threats to these highly diverse and endangered communities are well known and a large number of reports document the dramatic effects of climate change and particularly global seawater warming, coastal development, pollution, and impacts from tourism, overfishing, and coral mining on them (Grigg & Dollar, 1990; Holden & LeDrew, 1998; Lough, 2000; Buddemeier, 2002; Knowlton, 2001; Sheppard, 2003). To protect these ecosystems the extent of their degradation must be documented through large scale mapping programmes, and inventories of existing coral reef areas are particularly important (Riegl & Purkis, 2005; Mora et al., 2006). Such programmes are essential so that the health of these ecosystems can be assessed and local and global changes over time can be detected (Holden & LeDrew, 1998).

Seagrass beds are also recognized as playing a pivotal role in coastal ecosystems. They are crucial to the maintenance of estuarine biodiversity, the sustainability of many commercial fisheries, for stabilizing and enriching sediments and providing an important food resource and spawning areas for many marine organisms (Powis & Robinson, 1980; Bell & Pollard, 1989, Dekker et al., 2006). Unprecedented declines in seagrass beds have occurred in temperate and tropical meadows throughout the world; their global decline highlights the need for monitoring programmes to manage their conservation and sustainable use (Short & Wyllie-Echeverria, 1996; Ward et al., 1997).

Coral reefs, seagrass, and macroalgal habitats are commonly found in association with, and in close proximity to each other, and are linked by many pathways such as sediment deposition mechanisms, the primary productivity cycle, and the migration of many fish species (Mumby, 1997). Due to their nutritional biology and photosynthetic requirements, coral reefs generally exist in clear tropical waters and this makes them highly suited for optical remote sensing (Mumby, 1997; Green et al., 2000). Although less confined to them, macroalgal and seagrass habitats are also found in such environments. Under stress, both coral and seagrass ecosystems may retreat and become replaced by macroalgal or less productive and biologically diverse sedimentary or bare rocky habitats. Such

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impoverishment adversely affects biodiversity and productivity and ultimately local, tourist-based, economies.

The potential of marine remote sensing as an alternative mapping tool to conventional methods like *in situ* diving surveys is now well understood and recognized. Tropical coastal environments are well suited to optical remote sensing because sunlight is minimally attenuated compared to other marine regions penetrating up to depths of 25 m or greater (Mumby, 1997; Green et al., 2000; Isoun et al., 2003). The technique is recognised as being the most cost-effective and feasible means of mapping and monitoring of tropical coastal ecosystems over large areas (Bouvet et al., 2003; Maeder et al., 2002; Green et al., 2000; Luczkovich et al., 1993).

The sensors used to monitor reef ecosystems generally can be divided into either passive or active systems. Passive remote sensors measure reflected sunlight in a given bandwidth of the electromagnetic spectrum and constitute traditional optical systems, while active remote sensing systems generate their own source of energy, and measure the reflected energy. Examples of active remote sensing systems include imaging sonars (e.g. side scan sonar) and Synthetic Aperture Radar (SAR).

The mapping of both temperate and tropical marine benthic habitats using medium and high spatial resolution optical satellite systems shows that generally only a few classes can be discriminated on the basis of spectral signatures alone (Holden & Ledrew, 1999; 2001; Hochberg & Atkinson, 2000), owing to the limited spectral information available in conventional optical instruments and the similarities in reflectance of many species and habitats (Hochberg & Atkinson, 2000; 2003; Holden, 2001; Hochberg et al., 2003; Karpouzli et al., 2004). Whilst higher spectral resolution data may increase the power of habitat discrimination, limited availability of such data in future spaceborne systems restricts its application to coarse coverage only. In the last few years, high spatial resolution data from commercial satellites such as IKONOS and QuickBird has shown to be well suited for mapping coral reef systems (Maeder et al., 2002; Andrefouet 2003; Capolsini et al., 2003). In particular, the incorporation of additional information on small scale variability in higher spatial resolution remotely sensed data has been shown to improve on the accuracies of spectral centred classifications (Dustan et al., 2001; Jakomulska & Stawiecka, 2002; Palandro, 2003).

A major challenge to optical remote sensing in both temperate and tropics regions is cloud cover which reduces the number of images available over a period of time over an area of interest (Jupp et al., 1981). The attenuation of light by water also significantly limits the technique in deeper and more turbid waters (Holden, 2001; 2002). These limitations have been drivers to develop and use active remote sensing systems for imaging the seabed such as acoustic systems. However, in comparison to satellite or airborne optical sensors, acoustic systems have rarely been used to map and monitor tropical marine habitats (Prada, 2002, White et al., 2003; Riegl & Purkis, 2005) and their potential is still in need of evaluation (Bouvet, 2003). Acoustic systems such as imaging sonars may offer further advantages over optical systems such as the provision of structural information of different habitat types, and geomorphological zonation. This additional information may improve the discrimination of spectrally similar but structurally different bottom types.

Despite the increasing evidence of the benefits to be gained there is presently a lack of studies on the synergistic use of alternative remote sensing approaches for mapping shallow water marine near shore habitats (Malthus & Mumby, 2003). The most obvious advantage of using acoustic and optical methods in combination is the different depth ranges that each of the systems operate; optical systems perform best in shallow waters (generally up to a maximum of 25 m in the clearest waters), while the deployment of sonar systems (single and multibeam) can be used to depths of hundreds of metres, but it is very much limited in shallow waters.

Few studies have attempted to integrate side scan sonar data with optical data to exploit the complementarity of the two systems and which have been in temperate waters (Pasqualini et al., 1998; Piazzi et al., 2000). These studies used visual photo-interpretation methods and occasional automated methods to classify the optical imagery, and to establish the upper boundary limits, whilst the sonograms were used for detecting lower depth limits. To date, no studies have tested the potentially improved accuracy of habitat classification when the optical and acoustic signatures are used in combination.

Although the potential of incorporating additional information on small scale variability in higher spatial resolution data to improve spectrally centered classifications has been recognized by a limited number of researchers (Jakomulska & Stawiecka, 2002), few studies have incorporated textural and spectral parameters for classifying benthic habitats simultaneously where these parameters have originated from high spatial resolution multiband acoustic and optical datasets. This study represents a first attempt to test the discrimination of coral reef habitats based on textural and spectral parameters derived from side scan sonar and IKONOS datasets. The overall aim is to statistically evaluate optical and acoustic remote sensing in discriminating reef benthic communities and their associated habitats, both in isolation and in combination.

2. Methods

2.1 Study area

The study site, selected for its conservation importance and for the availability of ancillary data, was focused on the littoral habitats of San Andres island (12° 34′ N; 81° 43′ W, land area 24 km^2), Colombia, situated within the San Andres, Old Providence and Santa Catalina Archipelago in the western Caribbean Sea. Approximately 180 km east of the Nicaraguan coast and 800 km northeast of the Colombian coast, the Archipelago comprises a series of oceanic islands, atolls and coral shoals (Figure 1). The submerged habitats of the Archipelago were designated a UNESCO Biosphere Reserve in 2000. The main extent of the sublittoral platform of San Andres is to the east and northeast and is bordered by a barrier reef, where depths range between 1 and 15 m before dropping rapidly to >1000 m (Geister & Diaz, 1997). The typical submerged habitats found around San Andres are seagrass (mainly Thalassia and Syringodium genera) and algal beds in different proportions, soft and hard coral habitats, as well as sandy and rocky substrates. These communities have seen high levels of mortality during the last two decades, with studies reporting overall reductions in live coral by more than 50% and corresponding increases in algal cover and biomass of such species as Dictyotaceae and *Halimeda* (Diaz et al., 1995; Zea et al., 1998). These changes coincide with significant increases in the human population of San Andres which has risen from 5,675 inhabitants in 1952 to around 80,000 by 1992 making it the most densely populated island in the whole of the Caribbean (Vollmer, 1997).

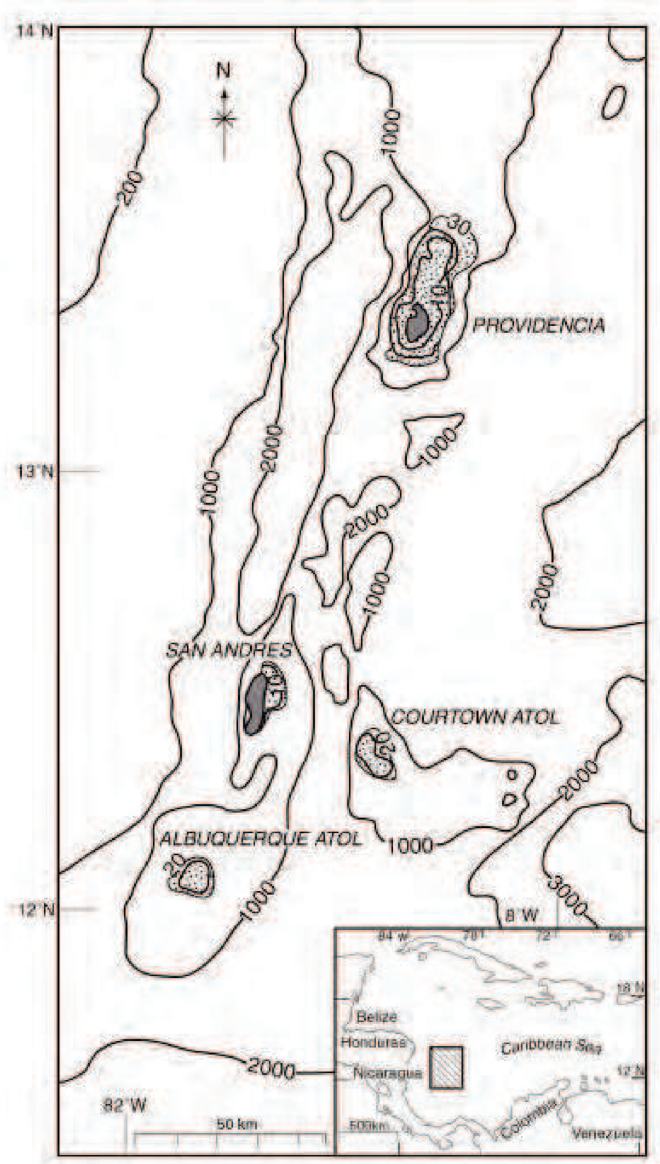

Fig. 1. Map of the western Caribbean Sea showing the location of the Archipelago of San Andres and Providencia.

2.2 Optical imagery

An IKONOS multispectral satellite image (11-bit radiometric resolution, 4-m spatial resolution) was acquired on the 9th September 2000 to coincide with a side scan sonar survey, and ground-truthing biological surveys. The weather conditions at the time of acquisition were fair, with limited patchy cloud overlying the terrestrial part of the image. An independent geometric correction (linear quadratic transformation, nearest neighbour resampling) was performed to improve on the geometric correction, based on 21 DGPS-determined ground control points, and which yielded an RMS error of 0.87 m. To atmospherically correct the image, the empirical line method was employed, based on a number of pseudo-invariant land targets of varying brightness from which *in situ* reflectances were determined at the time of image acquisition, as outlined in detail in Karpouzli and Malthus (2003).

Following land masking a water column correction was applied based on the semi-analytical approach of Maritorena et al., (1994) and Maritorena (1996) using independently obtained *in situ* water column spectral attenuation (k) and depth (z) estimates. An earlier study on the spatial variation of the attenuation of downwelling Photosynthetically Active Radiation, k_d(PAR), in the littoral zone of San Andres showed that attenuation is highly variable (Karpouzli et al., 2003). For this reason, pixel specific values of k for each of the visible IKONOS bands were estimated on the basis of field measurements and simple models (Karpouzli, 2003; Karpouzli et al., 2003). The application of Maritorena's model resulted in an image with enhanced bottom reflectance where the influence of varying bathymetry was greatly reduced, particularly where accurate estimates of depth and attenuation existed (Karpouzli, 2003).

2.3 The acoustic dataset

Dual frequency (100 and 500 kHz) Side Scan Sonar (SSS) backscatter and bathymetric data were acquired in the coastal waters of San Andres using a towed GeoAcoustics, fully digital, side scan sonar system (model: 159D, SS941, linked to an EOSCAN real time acquisition and image processing system) with the survey designed to overlap with parts of the IKONOS image and to encompass the full range of the marine habitats found in the area (coral, seagrass, algal and sediment habitats). The acoustic data were collected using a 7 m survey vessel equipped with a Trimble Global Positioning System. Differential correction of the navigation signal was conducted in real-time using the Omnisar satellite network resulting in a horizontal accuracy of about 0.5 m. Anamorphic and slant-range corrections were applied to the raw data in real time, thus eliminating lateral and longitudinal distortions in the sonograms, as were geometric corrections to reference the towed fish in respect to the position of an onboard dGPS system. Survey lines were spaced 10-30 m apart (depending on depth) to achieve a 100% backscatter cover of the selected survey areas.

Depth was determined concurrently using a FURUNO haul-mounted echo-sounder at intervals of one second, equating to a data point approximately every metre. After tidal corrections, these data were merged with soundings obtained from digitised hydrographic charts of the area and interpolated using a radial basis function in Surfer (version 7.02). The resulting DEM matched the spatial resolution of the IKONOS image and was used to undertake the water column correction of the satellite image.

A further geometric correction using an affine model was applied and the paired 100 kHz and 500 kHz subsets were corrected using image to image registration with the optical IKONOS dataset.

Texture layers - The sonograms acquired were used for extracting a number of acoustic parameters on the basis of which the discrimination of a number of habitat classes was tested. These included the mean signal intensity of the 2 original sonar bands (at 100 and 500 kHz frequencies: I_{100} and I_{500}) and two statistical models of texture which created four extra data layers for the sonograms, two for each frequency available. Firstly, a circular variance filter was passed over each frequency backscatter layer where the value of the central effective unit in the data (the 'texel, after Linnett et al., 1993) was the variance of the moving window over the original backscatter data. The result represents a measure of texture with a localised area (Var_{100} and Var_{500}). The size and the shape of the moving window was optimized for the coral dominated classes; the high spatial resolution of the sonograms enabled the visual discrimination of individual coral mounds and the size of the kernel was designed to coincide with the 3 m mean radius of coral mound aggregations found in the study site. In this context, variance is a 2nd-order algorithm, and the two textural layers produced were effectively measuring the coarseness or roughness of the original data bands in the two frequencies of operation. Homogeneous areas (e.g. sand beds) had a low variance while heterogeneous areas (e.g. rubble, coral patches) were characterised by high variance values.

The second textural parameter was represented by the standard deviation of the texels within signature areas (SD_{100} and SD_{500}). This parameter describes effectively the variation in texture coarseness and represents a measure of global nature as opposed with the previous parameter which has a local nature. The size of the signature areas varied between 60 m^2 and 400 m^2 (20 x 20 m) depending on the habitat type, and was adjusted to ensure that it was not straddling class boundaries and encompassing adjacent classes.

2.3 Biological surveys

Biological surveys were carried out for the purpose of groundtruthing the satellite and side scan sonar images. The survey methodology was optimized for the 0.35 m side scan sonar as opposed to the 4 m resolution IKONOS data, employing a combination of transects and 1 x 1 m and 0.25 x 0.25 m quadrats. The principal attribute recorded was percentage cover of the top layer of the dominant vegetation/lifeforms since this is the attribute recorded by optical remote sensors. In the case of seagrass and calcareous green algae, density was also recorded. Due to the penetrative nature of certain sonar frequencies (100 kHz or less, Blondel and Murton, 1997) which may penetrate the top few centimeters of sediments, detailed *in situ* notes of overlapping lifeforms and substrate to a depth of 5 cm below were also made, even when they were not exposed. Substrate types were recorded in the categories: bedrock, rubble, sand (coralline, terrigenous), mud, dead coral, boulders, and thin layer of sand on bedrock. Lifeforms were recorded most often to species level for hard corals, macroalgae and seagrass species and to a higher level taxon for soft corals, sponges, sea anemones, sea urchins and sea cucumbers.

The biological surveys were conducted in two phases. The first phase (April-July 1999) collected rapid spot-check data to identify the broadscale habitats found around San Andres. Three replicate 1 x 1 m quadrats were employed at each site. General notes were also made of the type of habitats in the area within approximately a 5 m radius. Depth and position (DGPS) of each site were also recorded. A total of 57 spot-check sites were surveyed. During the second phase (September-October 2000) more detailed targeted surveys were conducted at 17 sites around the island, covering all available habitats, and guided by the results of the rapid spot check surveys. Each site measured 500 square metres (50 x 10 m), to match the average range of the sonar tracks (50 m). A 50 m transect, laid within a homogeneous patch of each habitat type at each site, was sampled at 10 m intervals, totalling 10 quadrats per site. These quadrats were not considered replicates since the distance of 10 m between them was enough in a number of cases to cause a change in the composition of the observed communities, and totalled to 170 samples. The depth at the individual sites, as with the spot-check surveys, ranged between 1 and 16 m. The start and the end of the central transect lines were positioned using DGPS, and the position of each quadrat was also determined. Video footage and still images of the whole transect and each quadrat were produced using a Hi-8 Sony Video recorder. Although the footage was not used to directly estimate benthic cover, it was used as a permanent record of the site and to support the surveyor's results.

Classification scheme – With minor modifications, the hierarchical habitat classification system of Mumby and Harborne (1999) was used for this study (Table 1). This system was found suitable because it is based on field data from Caribbean habitats, and due to its hierarchical structure it could accommodate both the variable availability of data from the two phases of the groundtruthing surveys, as well as the different spatial scales of the satellite and sonar images. Some amendments were made in thresholds of different classes to account for regional differences. Only the first and second tiers (coarse and medium descriptive resolution) of the ecological component of the classification system were used to assign each spot-check or survey quadrat to a benthic class. The third tier (detailed descriptive resolution) of the scheme was considered too detailed for using with the remotely sensed data. In total, 4 coarse habitats were identified (coral, algal dominated, bare substratum, and seagrass dominated classes), and 20 bottom types in the medium descriptive resolution.

2.4 Discriminant function analysis for habitat classification

Discriminant function analysis (DFA) was used to test the discrimination of the sub-littoral habitat types found around San Andres, based on the IKONOS optical data and acoustic data in isolation and in combination. Water column corrected spectral and SSS acoustic backscatter and textural signatures for 125 of the detailed, ground-truthing sites were extracted. Only the areas for which acoustic data were also available were selected, so that the synergy of the two datasets could be tested. The DFA analysis was performed at both the coarse and medium descriptive habitat classification levels. To build a model of discrimination, individual bands or sonogram layers were chosen as independent variables within the DFA by a forward stepwise selection process. Confusion matrices were produced to assess the accuracy of the classifications at each level and to identify misclassifications, and overall accuracy rates and user's accuracy for the individual classes were calculated. This was done by comparing the *a posteriori* classification of the habitat members with their *a priori* membership. Although this is a biased measure of discrimination, since the same datasets were used to derive the functions and evaluate the accuracy of the predictions (as opposed to using an independent dataset), this was necessary given the restricted number of data points available. These values were, however, useful for comparing accuracies between the results of the DFA based on the acoustic, optical, and combined datasets, as well as between the classifications at different descriptive resolutions. The study is also primarily concerned with estimating relative rather than absolute separability so this approach is a justifiable one.

3. Results and discussion

3.1 Optical results

At both classification levels the stepwise DFA selected only the Blue IKONOS band, as best discriminating the habitat types and discarded the green and red bands as statistically redundant for separating the classes. Whilst this is expected for the red band as red light is attenuated within the top 1-3 m of the water column due to absorption by water itself, it was more surprising for the green band. The classification results are discussed bearing in mind that they were achieved on the basis of the blue band brightness alone.

Coarse level Label and characteristics	Medium descriptive level Label and characteristics
1. Coral classes	1.1 Branching corals - Majority of corals are branching (eg Acropora spp.)
> 1% hard coral cover	1.2 Sheet corals - Majority of corals are branching (eg Agaricia spp.)
	1.3 Blade fire corals with green calcified algae - Majority of corals are blade fire corals
	1.4 Massive and encrusting corals - Majority of corals are massive and encrusting
	1.5 Dead coral - Dead coral ≥ live coral
	1.6 Gorgonians - Gorgonians ≥ hard coral
2. Algal dominated	2.1 Green algae - Majority of algae are green
≥ 50% algal cover &	2.2 Fleshy brown and sparse gorgonians - Majority of algae are fleshy brown
< 1% hard coral cover	2.3 Lobophora - Monospecific Lobophora beds
	2.4 Red fleshy and cructose algae - Majority of algae are red. Encrusting sponges present
3. Bare substatum	3.1 Bedrock and rubble with dense gorgonians - ≥ 30% gorgonians and ca 30% algal cover
> 50% bare substratum	3.2 Bedrock and rubble with sparse gorgonians - < 30% gorgonians and little algal cover
< 1% hard coral	3.3 Sand and rubble with sparse algae - Both sand and rubble present and occasionally boulders; No gorgonians
	3.4 Sand with sparse algae - No rubble present
	3.5 Mud - Mud is the predominant substrate
	3.6 Bedrock - Bedrock is the predominant substrate; Sand and algae met be present but sparse
4. Seagrass dominated	4.1 Sparse seagrass - 10-30 % seagrass
> 10% seagrass cover &	4.2 Medium density seagrass - 31-69 % seagrass
< 50% algae	4.3 Dense seagrass - > 70 % seagrass
	4.4 Seagrass with distinct coral patches

Table 1. The hierarchy of classes contained within the ecological component of the modified classification scheme by Mumby and Harborne (1999) with quantitative diagnostic descriptors.

The Discriminant function analysis (DFA) results from the extracted IKONOS signature data yielded an overall accuracy of 29% at the medium resolution level (10 classes) and 40% for the coarse level of descriptive resolution (4 classes). The greater accuracy at the coarser level is in agreement with findings of classification accuracies of similar habitats from optical imagery (Mumby and Edwards, 2002). Individual class (user's) accuracies ranged from 12-100% at the medium level, and 0-58% at the coarse level (Tables 2 and 3). At the medium descriptive level, the highest user's accuracy was achieved for dense seagrass (100%) followed by sand and algae (50%), massive corals (45%) and sparse seagrass (43%). Least discrimination was achieved for the dead coral class (12%), sheet corals (16%) green algae

(17%), and medium density seagrass (18%). Most confusion at this descriptive level occurred between the different coral classes, the algal, coral and seagrass classes, the medium and dense seagrass classes, and the sand and sheet coral classes.

Actual class	Predicted class										Row Total
	1.2	1.4	1.5	2.1	3.1	3.3	3.4	4.1	4.2	4.3	
1.2 Sheet corals (mainly *Agaricia*) > 1%	4										4
1.4 Massive and encrusting corals		13	4		1	3					21
1.5 Dead coral (Dead > live coral cover)	3	4	2			1	1	1			12
2.1 Green algae (≥ 50% algal cover, majority green algae)		2		1	1	1			1		6
3.1 Bedrock and rubble with dense gorgonians (> 50% bare)			1		3	1					5
3.3 Sand & rubble with some algae (> 50% bare)	2		3		3	2	1	1			12
3.4 Sand with some algae (> 50% bare)	15		1	2	4		2	2	1		27
4.1 Sparse seagrass and algae (<50%)		3	6		1			3			13
4.2 Medium density seagrass and algae (<50%)		3		3					2		8
4.3 Dense seagrass and algae (<50%)		4							7	3	14
Column Total	24	29	17	6	13	8	4	7	11	3	122
User classification accuracy (%)	**16**	**45**	**12**	**17**	**23**	**25**	**50**	**43**	**18**	**100**	

Table 2. Classification error matrix for spectral signatures extracted from IKONOS imagery at the medium descriptive resolution (10 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy: 29%.

Although the coarser descriptive resolution achieved a greater overall accuracy of 40%, this is still poor for scientific or management applications. The best discrimination was achieved for the bare substratum class (58%, Table 3) which is in agreement with other IKONOS case studies that report sand to be always well classified (Andrefouet et al., 2003). Two-way misclassification existed between the bare substratum and algal dominated classes. The next best discriminated class was seagrass (53%) with the main confusion of this class being with algae. This is not surprising considering that the algal class here was dominated by green algae and which was spectrally similar to the seagrass class. These similarities contributed to the entire misclassification of the algal class. Similarly, the coral class was wholly misclassified as seagrass or bare substratum.

There are difficulties in comparing classification accuracies between different reef studies. Green et al., (1996) pointed out this difficulty due to inconsistencies in the classification schemes used, the different number and type of classes, differences in *in situ* data collection, image processing methods, and the means by which accuracy is assessed. Furthermore, the particulars of the different sites, e.g. in depth and differences in the dominant species, will greatly influence the accuracy rates. However, our results are in general agreement with those obtained elsewhere using real or simulated IKONOS data where sand-dominated habitats are the best discriminated, while coral classes are generally poorly classified, especially when algal-dominated areas or dense seagrass beds that are spectrally similar to deep corals are included in the analysis (Hochberg and Atkinson, 2003; Andrefouet et al., 2003).

Actual class	Predicted class				
	1. Coral classes	2. Algal dominated	3. Bare substratum	4. Seagrass dominated	Row total
1. Coral classes	0	7	15	17	39
2. Algal dominated		0	3	4	7
3. Bare substratum	3	15	25	1	44
4. Seagrass dominated	1	9	0	25	35
Column Total	4	31	43	47	125
User classification accuracy (%)	**0**	**0**	**58**	**53**	

Table 3. Classification error matrix for spectral signatures extracted from IKONOS imagery at the coarse descriptive resolution (4 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy: 40%.

The key factors which contribute to poor classification are the similarity in spectral signatures between many habitat classes and the limited umber of IKONOS wavebands. Seagrasses, algae and reef habitats are dominated by photosynthetic organisms resulting in similar spectral signatures. Differences between classes are often subtle and require high spectral resolution and often spectral derivative analysis for segregation (Clark et al., 2000; Hochberg and Atkinson, 2000; Hochberg et al., 2003; Karpouzli et al., 2004). IKONOS spectral bands are too broad and poorly placed to detect subtle differences needed to discriminate between such classes.

Mumby and Edwards (2002) and many of the case studies in Andrefouet et al., (2003) reported higher overall classification accuracies, and higher coral class accuracies using IKONOS imagery. However, our results are not directly comparable with these studies which employed supervised image classifications rather than classifications from extracted spectral signatures using DFA. After supervised classification has been applied to an image it is possible to improve the map accuracy for the classified image by contextual editing where contextual rules can be used to reclassify misclassified classes to the correct categories to optimise results (Andrefouet et al., 2003). However, another study that did not use contextual editing to improve the accuracy of the classification of IKONOS data reported similarly disappointing user's accuracies for coral classes of 9.7% and 9.5% for a nine-class medium resolution scheme and a four-class coarse resolution scheme, respectively (Capolsini et al., 2003).

3.2 Acoustic results

Example sonograms of the two backscatter intensity bands (100 kHz and 500 kHz) from some of the habitat classes surveyed are shown in Figure 2. Areas of high backscatter appear bright, while low backscatter appears dark. Rocks and coral mounds can be seen as distinct features yielding a strong and highly textured return (Figure 2a, d). Due to their complex morphology and bathymetric relief, areas of acoustic shadows (appearing black in the SSS data) can be observed adjacent to them. The result is that for coral targets both 100 and 500 kHz images appear highly textured with rough and irregular surfaces; signatures from these areas would be expected to be characterized by high variance. Sand is less reflective and more homogeneous in character compared to the highly textured coral patch (Figure 2a). The 500 kHz sonogram shows a better definition of the coral mounds and higher reflectivity over sand. This is due to the fact that higher frequency sound experiences less attenuation in penetrating sediment than lower frequency sound, resulting in overall less penetration and a higher backscatter (Mitchell, 1993).

Syringodium generates bright but fuzzy backscatter indicative of a strong echo return while the fuzziness indicates that the return is not from a distinct hard object (Figure 2b). Seagrass typically returns a strong echo in comparison to the sediment surrounding the beds, especially in the 100 kHz sonogram attributed to the existence of lacunae in the seagrass leaves (Sabol et al., 2002; Siljestrom et al., 2002). Mixed algal cover exhibits highly textured and strong backscatter of an intermediate coarseness (Figure 2c). *Halimeda* has also been reported to have a strong backscatter in other studies (Blondel and Murton, 1997), possibly due to its highly calcified leaves and stems.

Medium-fine sand produces a much weaker acoustic return than either coral or rubble showing a fine texture especially in the 100 kHz band (Figure 2d). In this example, the gorgonian reef patch shows higher reflectivity in the direction of sonification and the long shadows of sparse massive coral mounds suggest a change in the angle of the seabed, and therefore the higher relief of the reef patch. This was confirmed by dive survey. Similar findings for rocky, gravel and sand substrates are reported from Barnhardt et al., (1998).

The Discriminant function analysis (DFA) results for the acoustic data yielded higher accuracies compared with the optical data. At the medium level of resolution (10 classes) an overall accuracy of 34% was achieved, which was 5% higher than achieved for the optical data at the same level (Table 4). Similar to the DFA results of the optical data, classification accuracy increased at the coarse level of descriptive resolution reaching 50%, 10% more than achieved with the optical data at that level (Table 5). This finding is in agreement with findings of classification accuracies of similar habitats from acoustical single beam data (White et al., 2003).

Individual class user's accuracies ranged from 22-50% at the medium descriptive level, and 5-78% at the coarse level of descriptive resolution (Tables 4 and 5). However, the results of the DFA at the medium level suggest that it is not possible to discriminate all classes on the basis of their acoustic properties alone. Among them the hard coral classes were best discriminated with user accuracies ranging from 40 – 50%, followed by dense gorgonian habitats (40%), the sand and rubble classes (40%), and the sand classes (40%). The seagrass classes had the lowest accuracies (22 – 29%) with misclassifications occurring between them, as well as between them and sand or rubble habitats with some algal cover. Most confusion occurred between the sparse seagrass classes and the sand and rubble with sparse algae classes, and the medium dense, and sparse seagrass classes (Table 4). The green algae class (2.1) was also poorly discriminated with a classification rate of only 25%. Confusion existed between that class and sand and algae (3.4), the sand with rubble class (3.3), the two seagrass classes, and the massive coral class (1.4). With the exception of the latter, the rest of the classes showed a similar coarseness in texture in the sonograms, especially the seagrass and algal habitats which may partly explain their poor discrimination. The typical green algal habitats found around San Andres were on sandy substrate and most often mixed with seagrass species which may explain their apparently similar acoustic responses. Coarse sand

and seagrass also had similar textures with the main difference being in the intensity of the backscatter and their different response in the two frequencies.

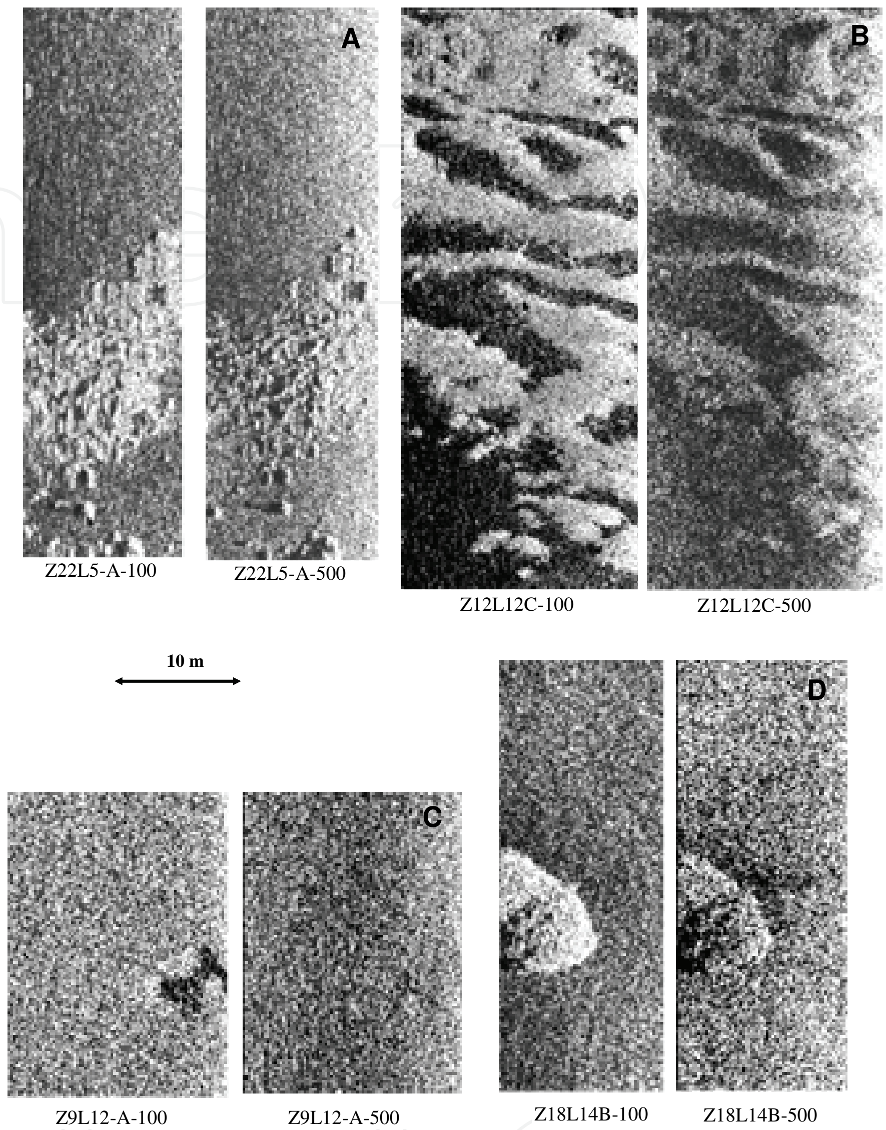

Fig. 2. 100 kHz and 500 kHz side scan sonar images from a number of habitat classes surveyed. Frequency is indicated by "100" or "500" at the end of the area ID. Areas of high backscatter are bright, low backscatter is dark. A) Medium density massive and encrusting coral amongst sand, B) *Syringodium* seagrass among fine sand, C) Medium algal density (principally *Dictyota* and *Halimeda*) mixed with *Syringodium*, D) Medium fine sand with oval patch of dense gorgonian coral on bed rock.

Reducing the descriptive resolution of the DFA increased the accuracies of all classes except for the algal class which was reduced to 5% from 25% (Table 5). This class was largely misclassified as seagrass although many seagrass cases were misclassified as algal classes. However, seagrass classification was improved over the medium level, demonstrating the potential for seagrass discrimination using acoustic data at a coarser level where subclasses of different densities are not considered. The bare substratum class also showed an increase of accuracy at the coarser level of resolution, to 52%.

Actual class	**Predicted class**										Row Total
	1.2	1.4	1.5	2.1	3.1	3.3	3.4	4.1	4.2	4.3	
1.2 Sheet corals (mainly Agaricia) > 1%	3	1									4
1.4 Massive and encrusting corals	2	6	2	3	2	2			4		21
1.5 Dead coral (Dead > live coral cover)	1	2	6	1				1	1		12
2.1 Green algae (≥ 50% algal cover, majority green algae)				4		2					6
3.1 Bedrock & rubble with dense gorgonians (>50% bare)	1	1			2				1		5
3.3 Sand & rubble with some algae (>50% bare)						8		3	1		12
3.4 Sand with some algae (>50% bare)		2	4	4	1	4	2	2	5	3	27
4.1 Sparse seagrass and algae (<50%)		2		2		4		4		1	13
4.2 Medium density seagrass and algae (<50%)									5	3	8
4.3 Dense seagrass and algae (<50%)		1		2			3	4	2	2	14
Column Total	7	15	12	16	5	20	5	14	19	9	122
User classification accuracy (%)	**43**	**40**	**50**	**25**	**40**	**40**	**40**	**29**	**26**	**22**	

Table 4. Classification error matrix for acoustic signatures extracted from the acoustic data at the medium descriptive resolution (10 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy: 34%.

The class best discriminated on the basis of its textural parameters was coral with a user's accuracy of 78% at the coarse descriptive resolution (Table 5). Many of the processes that drive coral reef dynamics such as recruitment processes or hurricane damage result in patchy distributions which, together with variable three dimensional structures, contribute to this class showing the greatest variance measures (Mumby & Edwards 2002).

Few other studies have reported accuracy rates for mapping coral reef habitats using acoustic remote sensing methods (White et al., 2003; Riegl & Purkis, 2005, Lucieer, 2007). Whilst the results this study are not strictly comparable with those obtained using AGDS by White et al., (2003) and Riegl and Purkis (2005) their single beam acoustic signatures measured parameters of "roughness" and "hardness" of the habitats under investigation. White et al., (2003) reported similarly poor (28%) overall accuracies for a 10 class level of resolution and a higher overall accuracy (60%) at a coarser level of four classes. At the coarse level coral was the best discriminated class with a user's accuracy of 68%, comparable to the results of this study. Riegl and Purkis (2005) presented similar classification accuracies of 56% when attempting to classify 4 classes (coral, rock, algae and sand) on the basis of two signal frequencies, 50 and 200 kHz.

Actual class	Predicted class				
	1. Coral classes	2. Algal dominated	3. Bare substratum	4. Seagrass dominated	Row total
1. Coral classes	25	1	9	3	39
2. Algal dominated		1	2	4	7
3. Bare substratum	7	5	18	14	44
4. Seagrass dominated		12	5	18	35
Column Total	32	19	35	39	125
User classification accuracy (%)	**78**	**5**	**52**	**46**	

Table 5. Classification error matrix for acoustic signatures extracted from the acoustic data at the coarse descriptive resolution (4 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy: 50%.

Useful acoustic variables - At the coarse classification level, the stepwise procedure selected three acoustic variables as best discriminating the four habitat types and discarded the rest as redundant for separating these classes (Table 6). The variables selected were the mean values of the class signatures of the 2 texture bands (Var_{100} and Var_{500}) and the class standard deviation of the 100 kHz frequency texture bands (SD_{100}). At the medium classification level, the stepwise procedure selected slightly different acoustic variables to best discriminate the 10 habitat classes (Table 6). The variables selected were the class mean values of the 500 kHz texture band (Var_{500}) and the class standard deviations of the 100 kHz and 500 kHz frequencies texture bands (SD_{100} and SD_{500}). At both classification levels, the mean signal intensity data bands (I_{100} and I_{500}) were discarded. Similarly, among the variables selected SD_{100} had the largest discriminant coefficients for both the first and second discriminant functions indicating that it was the most significant variable at both classification levels.

Coarse level	Medium level
Var_{100}	Var_{500}
Var_{500}	SD_{100}
SD_{100}	SD_{500}

Table 6. The acoustic parameters identified by the stepwise discriminant analysis to provide the best discrimination between habitat classes at the coarse and medium descriptive levels.

The standard deviation of the signature areas represents large-scale spatial variability in the images while the two texture (variance) layers indicate small-scale spatial variability in the backscatter signal. The kernel size of the moving window that produced the texture layers is significant in determining their texel values. These values would be directly related to the window homogeneity and the size of the objects in the original image would influence the choice of kernel size, e.g. in this case the size of coral mounds. Hence, it is perhaps inappropriate to measure all classes and objects with the same measure, and each data set and application should have different kernel sizes that maximize their discrimination. In the case of this study, the size of the moving window was optimized for the coral classes and this must have contributed to the improved classification accuracy, when compared to the other classes. Further research could investigate using more texture layers created by changing kernel sizes to optimize them for different habitat types. The applicability of variogram-derived texture measures using a moving window, the size of which is determined by the range of the variogram could also be investigated. Such variogram-derived texture measures have been extracted from microwave images of agricultural landscapes with partial success and warrants further investigation (Jakomulska & Stawiecka 2002)

The use of dual frequency sonograms improved texture and pattern recognition since products from both bands were selected by the DFA, even though the 500 kHz band seemed visually more noisy. The lower frequency (100 kHz) seemed more useful at the coarse classification level, while the higher frequency (500 kHz) was more useful for the discrimination of the detailed scale habitats. This may be partly due to the higher resolution provided by the 500 kHz band, resulting in more detailed sonograms, even after the re-sampling process. This would be translated in the textural bands of the higher frequency. Additional frequency bands could potentially further improve the discrimination between the classes and increase the classification rates.

The side scan sonar survey had a number of limitations which may have contributed to the misclassifications of some of the classes. Positional and locational errors are in general greater for acoustic data compared with satellite data (Malthus & Mumby, 2003). Positional errors may have been introduced from a variety of sources including inadequate positioning of the towfish in relation to the survey boat, and the approximate nature of the manual georectification of the sonograms. Similarly, system resolution, which dictates the minimum size of the feature identifiable at a particular distance from the survey instrument, is a function of both instrumental limitations (sonar instrument specifications) and practical/operational considerations which will be affected by navigational errors, location errors of the instrument and acoustic noise (Bates et al., 2002).

3.2 Optical and acoustic synergy results

With the inclusion of both optical and acoustic signatures in the DFA classification accuracy improved significantly compared to either method used in isolation, at both the coarse and medium level of descriptive resolution (Tables 7 and 8). The overall accuracy of the classifications improved to 52% at the medium level (10 classes) and to 61% at the coarse level (4 classes).

The textural information derived from the high resolution side scan sonar data made a significant improvement to the user's accuracies of each class at both discrimination levels compared to the original spectral discrimination performed used the IKONOS data alone (Table 10). All except one habitat class, showed an increase of at least 10% from their optical classification accuracy when the acoustic data were included in the DFA. The classes that benefited most from the inclusion of the textural acoustic data at the detailed level of resolution were the three coral classes (classes 1.2, 1.4 and 1.5), the green algae class and the sand class (3.4), where % increases were 27%, 19%, 38%, 23% and 28%, respectively. Even though the overall accuracy at this level is still low (52%) and probably inadequate for management purposes (Mumby and Edwards, 2002), at the individual class level, classes 1.4 and 3.4 were well discriminated. This separation is further illustrated in scatterplots of the first three discriminant functions in Figure 3.

Actual class	Predicted class										Row Total
	1.2	1.4	1.5	2.1	3.1	3.3	3.4	4.1	4.2	4.3	
1.2 Sheet corals (mainly *Agaricia*) > 1%	3						1				4
1.4 Massive and encrusting corals		9		2	3	3			3	1	21
1.5 Dead coral (Dead > live coral cover)	3	5	2					1		1	12
2.1 Green algae (≥ 50% algal cover, majority green algae)				2		2				2	6
3.1 Bedrock and rubble with dense gorgonians (> 50% bare)	1		1		2				1		5
3.3 Sand & rubble with some algae (> 50% bare)						6	3	3			12
3.4 Sand with some algae (> 50% bare)			1		1	4	21				27
4.1 Sparse seagrass and algae (<50%)							2	8		3	13
4.2 Medium density seagrass and algae (<50%)									5	3	8
4.3 Dense seagrass and algae (<50%)				1				3	4	6	14
Column Total	7	14	4	5	6	15	27	15	13	16	122
User classification accuracy (%)	**43**	**64**	**50**	**40**	**33**	**40**	**78**	**53**	**38**	**40**	

Table 7. Classification error matrix for combined acoustic and optical signatures extracted from the sonar and IKONOS imagery at the medium descriptive resolution (10 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy 52%.

Actual class	Predicted class				
	1. Coral classes	2. Algal dominated	3. Bare substratum	4. Seagrass dominated	Row total
1. Coral classes	25	3	5	6	39
2. Algal dominated		1	2	4	7
3. Bare substratum	7	7	28	2	44
4. Seagrass dominated		11	2	22	35
Column Total	32	22	37	34	125
User classification accuracy (%)	**78**	**5**	**76**	**65**	

Table 8. Classification error matrix for combined acoustic and optical signatures extracted from the sonar and IKONOS imagery at the coarse descriptive resolution (4 classes). Cases in row categories are classified into column predicted classes. Overall classification accuracy: 61%.

Coarse level	Medium level
Blue Ikonos	Blue Ikonos
Var_{100}	Var_{100}
Var_{500}	Var_{500}
SD_{100}	SD_{100}
	SD_{500}

Table 9. The acoustic and optical parameters identified by the stepwise discriminant analysis to provide the best discrimination between habitat classes at the coarse and medium descriptive levels.

The better discrimination achieved at the coarse level of descriptive resolution was demonstrated, with the exception of the algal class, by high class user's accuracy values close to or over 70% (Table 10, Figure 4). Similar to the medium level classification, the class that showed the greatest improvement when the textural parameters were added to the DFA was the coral class exhibiting an improvement in its accuracy from 0% to 78%. This was followed by the bare substratum class with an increase from 58% to 76%, and by the seagrass class where accuracy increased from 53% to 65%.

The only classes which did not benefit from the inclusion of the textural acoustic information in the DFA were dense seagrass class (medium classification level) and the algal class (coarse level). Dense seagrasses, along with the other seagrass classes, showed relatively poor discrimination based on their acoustic properties alone. At the coarse level, when all seagrass subclasses were amalgamated into one class, the sonar classification accuracy was higher (46%) which had the overall effect of improving the classification accuracy to 65% for the combined dataset. These results may indicate the inability of sonar data to differentiate between different seagrass densities, and demonstrates that if a class has very good discrimination on the basis of one dataset as in this case (100%) but low discrimination on the basis of the other, then it is best classified only on the basis of the single dataset that gives the best results.

The advantages to be gained from synergistic use of the two datasets is best illustrated by the fact that, for most classes, the discrimination achieved when both datasets were used in combination was equal to or greater than the best discrimination achieved on the basis of each dataset in isolation. This was the case for eight out of the total of ten classes at the medium level and for all classes at the coarse level. However, the results also indicate that some classes will not be successfully differentiated using either dataset (e.g. algal class 2 at the coarse level).

Mumby and Edwards (2002) used textural information to improve the spectral classification of IKONOS data for mapping coral reef habitats and found that their inclusion improved overall accuracy of the thematic map at the medium level by 9%, and at the coarse level by 7%. This study achieved a much greater improvement in accuracy: 23% at the medium level and 21% at the coarse level, attributable to the higher spatial resolution of the sonar data, its greater depth penetration, and the information contained in the sonograms regarding the structural organisation of the habitats. As with the present study, the high coral cover classes showed the greatest texture due to their greater structural heterogeneity, while sand had the least, but both benefited from improved classification accuracy with its inclusion.

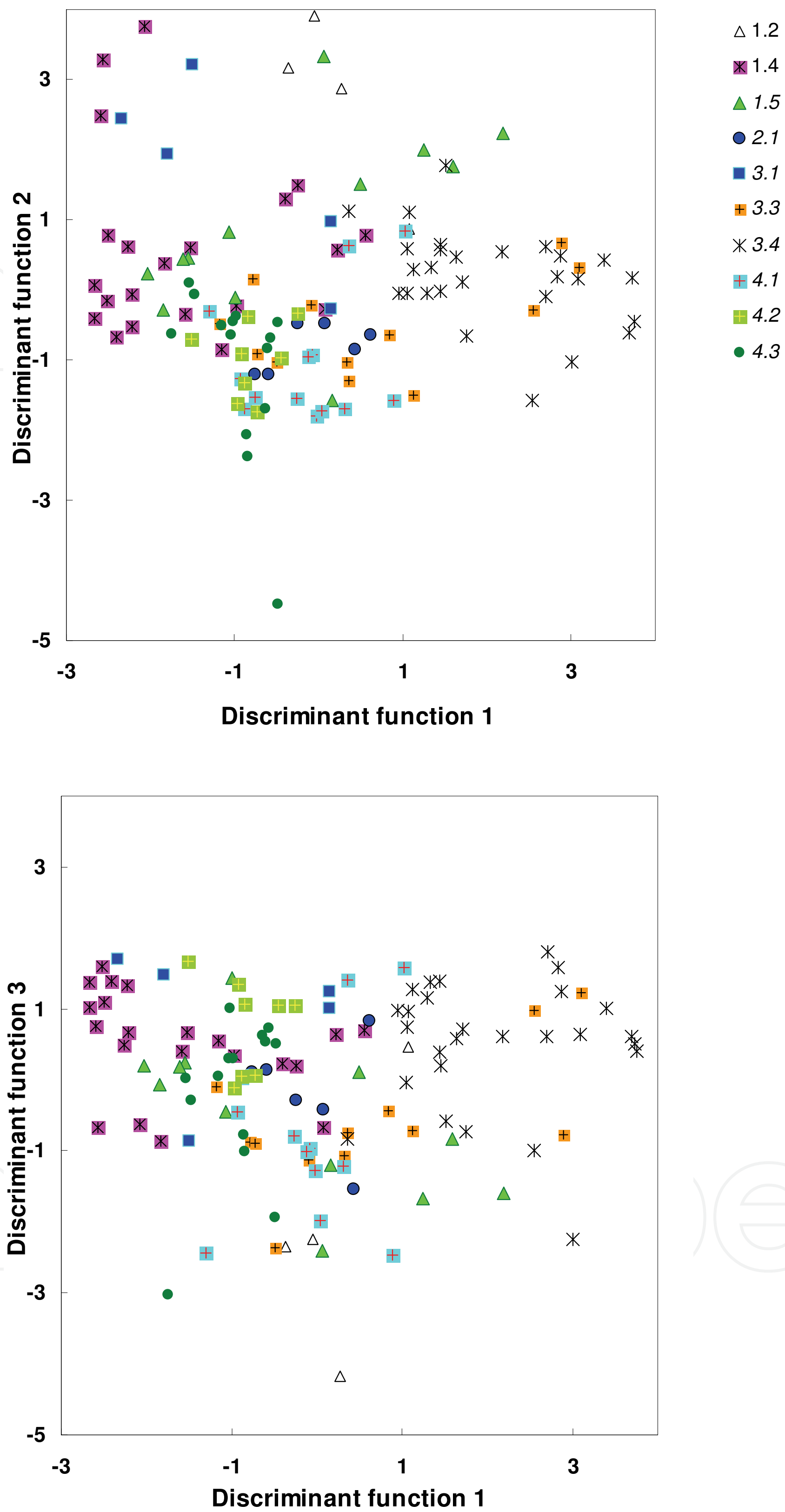

Fig. 3. DF scores from the analysis of the combined optical and acoustic signatures at the medium descriptive level projected in discriminant function space. First and second functions (top graph), first and third functions (bottom graph).

Classification	IKONOS data	Side Scan Sonar data	IKONOS & side scan sonar data
Medium resolution classification:			
1.2 Sheet corals (mainly Agaricia) > 1%	**16**	43	**43**
1.4 Massive and encrusting corals	**45**	40	**64**
1.5 Dead coral (Dead > live coral cover)	**12**	50	**50**
2.1 Green algae (≥ 50% algal cover)	**17**	25	**40**
3.1 Bedrock and rubble with dense gorgonians (> 50% bare)	**23**	40	**33**
3.3 Sand & rubble with some algae (> 50% bare)	**25**	40	**40**
3.4 Sand with some algae (> 50% bare)	**50**	40	**78**
4.1 Sparse seagrass and algae (<50%)	**43**	29	**53**
4.2 Medium density seagrass and algae (<50%)	**18**	26	**38**
4.3 Dense seagrass and algae (<50%)	**100**	22	**38**
Overall accuracy (%):	**29**	34	**52**
Coarse resolution classification:			
1. Coral classes	**0**	78	**78**
2. Algal dominated	**0**	5	**5**
3. Bare substratum	**58**	52	**76**
4. Seagrass dominated	**53**	46	**65**
Overall accuracy (%):	**40**	50	**61**

Table 10. Individual class user's accuracies and overall accuracies (%) from the discriminant function analysis of the optical, acoustic, and combined datasets at the medium and coarse descriptive levels.

The improvement in the discrimination of the dead coral class with the inclusion of the acoustic textural data is particularly significant for monitoring coral health. The results of the optical classification showed that diseased coral cannot be discriminated spectrally on the basis of IKONOS bands alone as, due to their rapid colonization by macroalgae, they are spectrally indistinguishable from macroalgal beds. This is evident in the misclassifications of the other classes (seagrass, sand with algae, and massive coral classes into this class) into the dead coral class (Table 2). Even after the inclusion of the sonar data the classification accuracy of this class is still not satisfactory (50%), but the combination of the two datasets shows potential for improving the discrimination of diseased or dead coral. This may be attributed to the acoustic signatures of algae overlying dead coral mounds; it still identifies the distinct texture of coral, even though spectrally the signature is similar to algal or seagrass classes.

Overall, the improvement in classification accuracies brought about by the inclusion of the acoustic data in the DFA was mainly due to the improved discrimination of spectrally similar classes but which had contrasting textural characteristics, or of classes whose distribution could not be resolved by the spatial resolution of the IKONOS imagery. A limitation of the combined dataset that may have resulted in misclassifications is the imperfection in the co-registration of the optical and sonar datasets. Scale differences

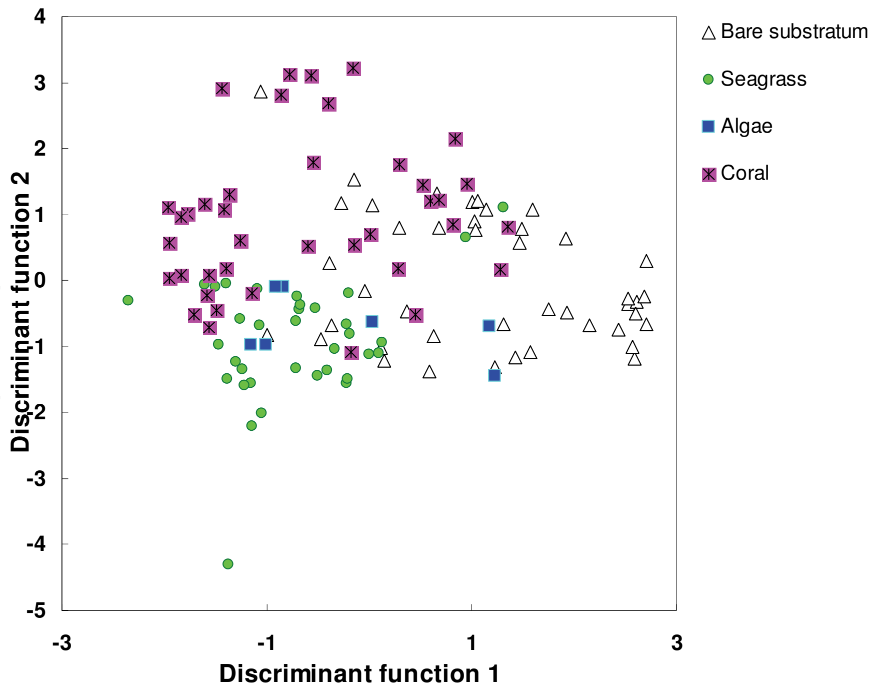

Fig. 4. DF scores from the analysis of the combined optical and acoustic signatures at the coarse resolution level projected in discriminant function space; first and second functions.

between the two datasets exacerbate the co-registration process. Further improvements in the classification accuracies reported here could be expected to be achieved by improved methods of co-registration, using a supervised classifier on the IKONOS image and sonograms themselves, which would allow contextual editing to be implemented, or by entering complementary data in the classification process, such as bathymetry.

4. Conclusion

IKONOS imagery and dual frequency side scan sonar data were acquired in the coastal waters of San Andres island encompassing diverse coral, seagrass, algal and sediment habitats. The characteristics of both data types were compared with the aim of determining if synergistic use of both methods improved the accuracy of classification of these habitats. The optical classification showed that only a few classes can be discriminated by their IKONOS spectral signatures alone, and the incorporation of spatial information, in the form of fine scale, acoustically-derived texture, greatly improved the accuracy of the classification at both the coarse (habitat) and medium (community) levels. The results indicate that the combined use of both techniques provides a means by which the rich diversity of tropical reef ecosystems can be mapped and monitored with significantly greater accuracy than with either technique alone.

In this study, greatest accuracies were achieved at both classification levels based on the Blue IKONOS water column corrected spectral band, and texture parameters derived from the dual frequency high spatial resolution sonograms, which best exploited the differences between classes, although fewer of these parameters were required at the coarse classification level of discrimination.

Overall, the improvement in classification accuracies brought about by the inclusion of the acoustic data in the DFA was due to the improvement of the individual class accuracies that were spectrally similar but had contrasting textural characteristics, or of classes whose distribution could not be resolved by the spatial resolution of the IKONOS imagery. Textural (spatial) information was of particular benefit for discriminating classes characterized by a complex spatial pattern, represented by heterogeneous acoustic response, and even though the overall classification accuracies were still not satisfactory (at 52% for the detailed level and 61% at the coarser level), the improvement from the optical classification of 23% at the fine level and 21% at the coarse level was very encouraging.

The advantages of the synergistic use of the two datasets was illustrated by the fact that, for many classes, when both datasets were used in combination, accuracies were greater than the discrimination achieved on the basis of each of the datasets in isolation. Significant increases in classification accuracies were noted with the inclusion of the acoustic textural data, for the highly textured coral classes in particular, where individual class accuracy levels at 78% (coarse level resolution) were very satisfactory. The improvement in the discrimination of the dead coral class, the differentiation of which is very problematic when based on spectral data alone, has significant implications for monitoring coral health.

The selection of a single IKONOS band for classification highlights the limited capacity of high and medium spatial resolution terrestrial satellite sensors to discriminate reef bottom types compared to higher spectral resolution systems (Maeder et al., 2002; Bouvet et al., 2003; Karpouzli, 2003). These results confirm that sensors with wavebands different to those used by conventional terrestrial satellites are required for detailed mapping of reef biotic systems. It can be expected that higher spectral resolution data would further improve the classification accuracies obtained when optical and acoustic data are combined. Thus, the need for increased spectral resolution is highlighted – a conclusion also reached by other investigators (Hochberg & Atkinson 2003).

The most obvious advantage of using acoustic and optical methods in combination is the different depth ranges to which each system operates. Knowledge of the upper and lower limits of habitats is important for management purposes (Malthus & Mumby, 2003), and the synergistic use of optical and acoustic data can be useful for such studies since optical systems perform best in shallow waters while sonar systems, are limited to depths generally over 2 m but can be used to depths of hundreds of metres, depending on the system employed. Similar conclusions were reached by Riegl and Purkis (2005) when investigating the synergy of IKONOS and single-beam sonar data.

A limitation of this analysis was that the overall and user's accuracies reported were not obtained from an independent dataset. Although these accuracies were useful for comparing relative accuracy levels between different classification levels and dataset, they do not necessarily reflect the accuracy with which another dataset would classify the same classes. This limits comparison with results from other studies where accuracies might be expected to be lower than those obtained here. However, as most studies report accuracies following supervised classification combined with contextual editing, it might be expected that the use of these techniques on combined optical and acoustic data may lead to greater accuracies than those achieved here using DFA.

Overall, the results of this study are particularly encouraging for the benefits to be gained from the synergistic use of optical and acoustic data. It is perhaps easy to understand why the combination of texture or coarseness, and morphological information (represented by acoustic data) and 'colour' characteristics would facilitate the discrimination of different habitats instead of one based on colour alone. Limitations, such as those related to the side scan sonar survey, can be reduced or removed, and hence accuracy levels of the combined dataset are likely to be higher. Discrimination of the habitats could be further improved with the use of contextual editing and the use of complementary data such as bathymetry. Few studies have used spectral and textural variables in conjunction to improve the classification of high spatial resolution images fewer still have derived textural parameters from high spatial resolution side scan sonar data. The lack of research in this area in general and the encouraging results presented here highlights the need for significant development in the synergistic use of optical remote sensing and acoustic data.

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The demand to explore the largest and also one of the richest parts of our planet, the advances in signal processing promoted by an exponential growth in computation power and a thorough study of sound propagation in the underwater realm, have lead to remarkable advances in sonar technology in the last years.The work on hand is a sum of knowledge of several authors who contributed in various aspects of sonar technology. This book intends to give a broad overview of the advances in sonar technology of the last years that resulted from the research effort of the authors in both sonar systems and their applications. It is intended for scientist and engineers from a variety of backgrounds and even those that never had contact with sonar technology before will find an easy introduction with the topics and principles exposed here.

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