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Coral reef habitat mapping: how much detail can remote sensing provide?

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Abstract The capability of satellite and airborne remote-sensing methods for mapping Caribbean coral reefs is evaluated. Reef habitats were categorised into coarse, intermediate and fine detail, using hierarchical classification of field data (percent cover in 1 m quadrats and seagrass standing-crop). Habitats were defined as assemblages of benthic macro-organisms and substrata and were mapped using the satellite sensors Landsat MSS, Landsat TM, SPOT XS, SPOT Pan and merged Landsat TM/SPOT Pan. Habitats were also mapped using the high-resolution digital airborne sensor, CASI (compact airborne spectrographic imager). To map areas >60 km in any direction with coarse detail, Landsat TM was the most accurate and cost-effective satellite sensor (SPOT XS when <60 km). For maps with intermediate habitat detail, aerial photography (from a comparable study in Anguilla) exhibited similar accuracy to Landsat TM, SPOT XS, SPOT Pan and merged Landsat TM/SPOT Pan. Landsat MSS was consistently the least accurate sensor. Maps from CASI were significantly ($p < 0.001$) more accurate than satellite sensors and aerial photographs. Maps with detailed habitat information (i.e. >9 reef classes) had a maximum accuracy of 37% when based on satellite imagery, but aerial photography and CASI achieved accuracies of 67 and 81%, respectively. Commissioning of new aerial photography does not appear to be a cost-effective option; satellites are cheaper for coarse habitat-mapping, and detailed habitat-mapping can be conducted more accurately and cheaply with CASI. The results will guide practitioners in matching survey objectives to appropriate remote-sensing methods.

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Introduction

Ever since Smith first examined Landsat data of the Great Barrier Reef (Smith et al. 1975), the search for applications of satellite imagery to coral reef science and management has been almost exhaustive (see reviews by Jupp 1986; McCracken and Kingwell 1988; Green et al. 1996). Satellite imagery has been used for cartographic-base mapping (Jupp et al. 1985), detecting change in coastal areas (Loubersac et al. 1989; Zainal et al. 1993), environmental-sensitivity mapping (Biña 1982), charting bathymetry (Benny and Dawson 1983), fisheries management (Populus and Lantieri 1990) and even stock assessment of commercial gastropods (Bour 1989). The most widespread use of satellite imagery has been the mapping and inventory of coastal resources (e.g. Kuchler et al. 1986; Bastin 1988; Luczkovich et al. 1993). Maps of reef habitat are a useful planning tool which, among other uses, allows management boundaries to be located (Kenchington and Claasen 1988) and the identification of representative reef systems (McNeill 1994). This paper is specifically concerned with the use of remote sensing for mapping coral-reef systems.

The past three decades have witnessed development of a multitude of sensors and a plethora of analytical (processing) methodologies. The main sensors pertinent to reef assessment are listed in Table 1. This list is not exhaustive, since it ignores recent instruments which have not been widely reported in the literature [e.g. LISS (linear imaging self-scanning) sensors on the Indian Remote Sensing satellite). The most widely used satellites are Landsat MSS, Landsat TM, SPOT XS and SPOT Pan (see Table 1 for explanation of abbreviations). The literature concerning their relative capabilities for habitat mapping is disparate, and very few comparative assessments have been undertaken. Ahmad and Neil (1994) found that Landsat TM gave greater

Table 1 Principal specifications of relevant remotely-sensed data sources. Satellite costs based on 1996 prices. Costs for airborne-imagery are based on commercial quotes for surveying an area of $\simeq$ 1 500 km^2 at a photographic scale of 1:10,000 and a CASI pixel size of 3 m (*MSS* multispectral scanner; *TM* thematic mapper; *SPOT* système probatoire de l'observation de la terre; *XS* multispectral scanner; *Pan* panchromatic; *CASI* compact airborne spectrographic imager)

Specification	Landsat MSS	Landsat TM	SPOT XS	SPOT Pan	CASI (airborne)	Aerial photography
Spatial resolution (m)	80	30	20	10	10–0.5	variable → 0.2
No. spectral bands available for reef mapping	2	3	2	1	8–21 user defined	1 analogue
Area covered (km)	185 × 172	185 × 185	60 × 60	60 × 60	variable	variable
Cost/image (£)	160	2838	1700	2205	81,000	160,000
Cost (£ km^{-2} $image^{-1}$)	0.005	0.08	0.47	0.61	540	1070

geomorphological detail on reef structure than Landsat MSS. When correlating reef-survey data to satellite imagery, Bainbridge and Reichelt (1989) found SPOT XS to be better correlated than Landsat MSS, which has poorer spatial resolution. Studies of reef flats in Thailand (Thamrongnawasawat and Sudara 1992) suggested that whilst Landsat TM was more useful than SPOT Pan, a merged data source might prove superior to either. However, this hypothesis was not tested.

Until the relative capabilities of these sensors have been rigorously assessed, practitioners will continue to be faced with the difficult problem of matching survey objectives to the most appropriate sensor. This problem is exacerbated by a general overselling of remote-sensing capabilities to the user community (Currey et al. 1987; Meaden and Kapetsky 1991). Whilst intuition and some published literature indicate that sensors with the greatest spatial and spectral resolution should provide the most detailed (and possibly accurate) information on reef systems, we need to quantify such relationships. In addition, the adequacy of satellite remote sensing of coral reefs must be considered in relation to other methods. There are two principal alternatives: (i) conventional mapping using aerial photography and (ii) more recently developed digital airborne remote-sensing. The latter instruments have good spatial and spectral resolutions (Table 1) and therefore possess great potential for habitat mapping (Kenchington and Claasen 1988; Clark et al. 1997; Mumby et al. 1997b).

Given the need to compare various remote-sensing methods, this paper embraces the following questions with respect to coral reef habitat-mapping, where habitats are defined as assemblages of benthic macro-organisms and substrata: (1) What are the relative capabilities of satellite sensors? (2) How does satellite imagery compare to aerial photography? (3) How does satellite imagery compare to digital airborne multispectral imagery (CASI)?

Materials and methods

Imagery-acquisition details

All field studies were carried out near the island of South Caicos, Turks and Caicos Islands, British West Indies (Fig. 1). To enable

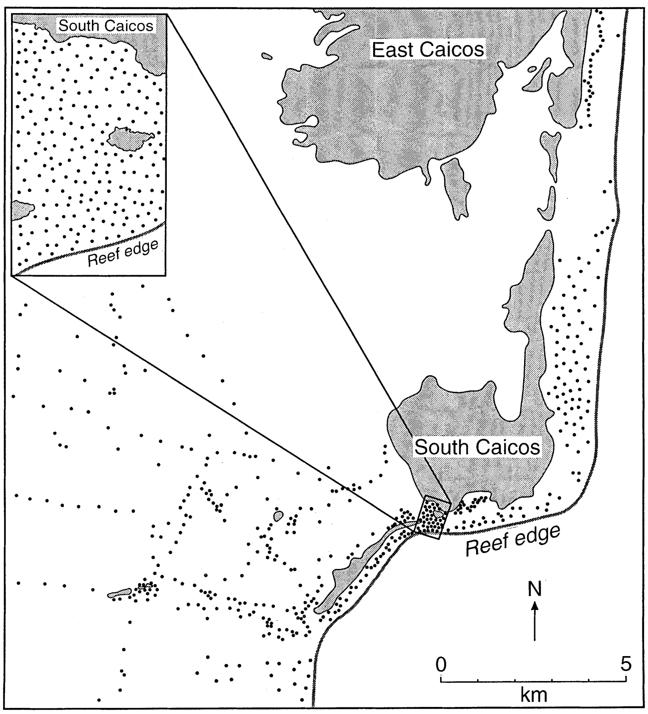

Fig. 1 Study area in Turks and Caicos Islands, showing locations of all field sites. The compact airborne spectrographic imager (CASI) was flown across Cockburn Harbour (*inset*)

comparisons to be made between satellite imagery and CASI, three considerations were made: (1) Data for use in habitat categorisation were drawn from a wide area to represent the range of habitats present in all image types (2) To obtain replicate pixels of each habitat type and mitigate spatial autocorrelation (Cliff and Ord 1973), a larger area was visited for satellite sensors than for CASI (i.e. a single seagrass bed may represent hundreds of CASI pixels but only a few, relatively autocorrelated pixels in a satellite image) (3) The high costs associated with flying and processing CASI dictated that only a relatively small area of Caicos Bank could be surveyed. Cockburn harbour was chosen because most habitats were represented in a microcosm of the bank (Fig. 1: inset).

Imagery-acquisition dates were June 1992 for Landsat MSS, November 1990 for Landsat TM and March 1995 for SPOT XS and SPOT Pan. CASI data were obtained in July 1995 (see Clark et al. 1997; Mumby et al. 1997c). The CASI data presented here are for comparison purposes: a full analysis is presented elsewhere (Mumby et al. 1997b). Aerial photographs were not available for the Caicos Bank, but the results of Sheppard et al. (1995) from Anguilla are comparable to the habitats examined in the present study. These authors used colour aerial photography at a scale of 1:10 000.

Field survey

A wide variety of sampling techniques exist for coral reefs (for reviews see Stoddart and Johannes 1978; English et al. 1994; Rogers et al. 1994). Semi-quantitative methods such as manta tow (Kenchington 1978) and plotless belt-transects (Mumby et al. 1995) are fast and well-suited to mapping reef geomorphology and broad ecological zonation (Bainbridge and Reichelt 1989; Mumby et al. 1996). However, these methods are unlikely to provide accurate estimates of benthic cover at small scales (e.g. < 10 m). Given the disparity in spatial resolution between sensors (i.e. from 1 m in CASI to 80 m in Landsat MSS), sampling was optimised for the most detailed imagery (CASI) and the overall extent of habitat at each site was estimated to allow scaling-up to larger pixel sizes.

Compared to most other quantitative sampling techniques, quadrats have the advantage that data are acquired rapidly in the field and are moderately accurate (Rogers et al. 1994). The main disadvantages of quadrat sampling are (i) quadrats cannot be used to measure spatial relief (rugosity), (ii) large branching corals such as elkhorn coral (*Acropora palmata*) are difficult to sample, and (iii) quadrats only provide data on a two-dimensional surface area, thus underestimating coverage of features which have a predominant orientation in the vertical plane. However, although the latter limitation is pertinent to ecological assessment, it may in fact be advantageous in the context of remote sensing where the sensor also samples a two-dimensional (flat) surface area.

In July and August 1995, 180 sites were sampled using a minimum of six replicate 1 m quadrats per site (up to 18 samples were used for more heterogeneous habitats on the fringing reef). Percent cover was visually estimated using a 1% grid. Data were recorded to species level for hard corals and macroalgae but to higher level taxon for sponges. The density of soft corals was also recorded. Seagrass composition and standing crop were measured using a calibrated, rapid visual-assessment method (Mumby et al. 1997a). The diameter of each site was visually estimated and usually exceeded 80 m. The location of field sites was determined using a differential global positioning system with a "circle error probable" of 2 to 5 m (Trimble Navigation Ltd. 1993).

Categorisation of field data into habitat classes

Our use of the term "habitat" is fairly open and embodies species assemblages and associated substrata. The term "descriptive resolution" is used to describe the biological detail to which a sensor will map a given area and is used inter-changeably with "habitat discrimination". A coarse descriptive resolution would be simply coral, algae, sand and seagrass. A finer descriptive resolution would include species/substrata assemblages, variations in seagrass standing crop and so on.

Many methods exist for classifying multivariate data sets (reviewed by Greig-Smith 1983). Agglomerative hierarchical classification with group-average sorting was used here because it is one of the most popular and widely available algorithms (Clarke and Warwick 1994). The ecological similarity between sites was measured using the Bray–Curtis similarity coefficient (Bray and Curtis 1957), because this has a number of biologically desirable properties such as ignoring joint absences of species, taking a value of 0 when two sites have no species in common, and taking a value of 1 when the abundances for all species are identical. Further, simulation experiments with various similarity measures have found the Bray–Curtis similarity coefficient to be a particularly robust measure of ecological distance (Faith et al. 1987). Percent cover data were not transformed, so that dominant cover features were allowed to exert an appropriately large influence on the classification. This was because it was deemed more likely that satellite imagery would discriminate habitats on the basis of dominant benthic features rather than more cryptic species/substrata. The species composition of seagrass samples was square-root transformed to place values in the same range as standing-crop estimates.

Characteristic and discriminating species/substrata of each class were determined using similarity percentage (SIMPER) analysis (Clarke 1993). A summary of the classification scheme (with quantitative descriptors) was used to direct a second survey period in March 1996. Since habitats had been defined earlier, all non-seagrass sites were assigned to their appropriate habitat class by visual inspection of the benthos, using a glass-bottomed bucket. This method was approximately four times faster than quadrat sampling. The standing crop of seagrass sites was estimated using the visual-assessment technique. More than six hundred sites were surveyed during this second phase, and these data were set aside for assessing the accuracy of imagery classifications.

Imagery analysis

Image data were geo-coded using Ordnance Survey maps (root mean square error < width of a single image pixel) and radiometrically corrected to account for sensor calibration, time of year and atmospheric conditions (see Price 1987; Tanre et al. 1990).

One of the most commonly cited difficulties with remote sensing of underwater environments is the confounding influence of variable depth on bottom reflectance (e.g. Cracknell et al. 1987). For example, the spectra (spectral signature) of sand at 20 m may be similar to that of seagrass at (say) 3 m. The effects of variable depth were compensated using the model derived by Lyzenga (1978, 1981).

For the first field survey, 180 field sites were located on the imagery. At each site (pixel), field data identified the habitat type and the overall extent of the habitat. A spectral signature was created from the image data at each site using the software Erdas Imagine 8.2. Signatures were developed using the region-growing tool, which allows neighbouring pixels to be incorporated into the signature. A geographic constraint was set on this process so that only those pixels found within the overall extent of each habitat were selected. For example, if the habitat at a site was considered to have a diameter of at least 100 m (7860 m^2) and a signature was created for SPOT XS imagery whose pixels cover 400 m^2 each, up to 20 ($\sim$7860 $\div$ 400) pixels were allowed to contribute to the signature for that site. Pixels further from the field site could not be expected to represent the same habitat type reliably.

The habitat type at each site was defined to its finest descriptive resolution. Individual signatures for each habitat type were then progressively merged to provide characteristic habitat spectra. Spectra were then used to train a supervised image classification which is a multivariate discriminant function (Mather 1987). Pixels were assigned to habitat classes using the maximum-likelihood decision rule (Mather 1987). The resulting thematic map of habitats was evaluated visually and obvious areas of pixel mis-assignment were identified (e.g. pixels classified as *Montastrea* spp. reef which were situated in known seagrass beds). The spectra of habitats which had over-classified (in this example, *Montastrea* spp. reef) were then down-weighted and the supervised image classification was repeated. All habitat spectra had equal weighting in the first classification ($P = 1$). Down-weighting was achieved by reducing the probability that pixels would be assigned to specific habitat classes (in this example, the new probability, P, for *Montastrea* spp. was 0.7). This heuristic procedure was repeated and refined up to six times, beyond which no further improvements were noticed by visual inspection.

The success of a supervised image classification is dependent on the separability of spectra for different habitats in the imagery. Similar spectra may lead to confusion in the supervised classification and misclassifications in the output-image map. If the sources of misclassification are known, it is possible to improve map accuracy by contextual editing (Groom et al. 1996). This process is perhaps best thought of as "the application of common sense to habitat mapping". Contextual rules may be applied to pairs of habitats which have similar spectra but exist in different, yet predictable, physical environments, such as seagrass beds and forereef escarpments. Pixels which classified as seaward patches of seagrass were reclassified to the appropriate reef categories. Similar reclassification was carried out for fringing reef pixels which had been incorrectly classified as sheltered communities of calcified rhodophytes with sponge (Class F7, Table 2).

Table 2 Description and characteristics of benthic habitats determined from hierarchical classification of field data (except for *A. palmata* which was added later), showing mean percent cover, densities and standing crop where appropriate. Class assignment is described for three levels of habitat discrimination: coarse (C), intermediate (I) and fine (F). Fine-level habitat categories present in aerial imagery (AI) are also listed

Description and characteristic features	Class Assignment No.			
	C	I	F	AI
Living and dead stands of *Acropora palmata*				1
Microdictyon marinum (77%), *Sargassum* spp. (4%), medium soft-coral density (5 m^{-2}) and rubble (10%)	1	1	1	
Bare substratum (40%), low soft-coral density (3 m^{-2}), *Microdictyon marinum* (30%), *Lobophora variegata* (12%)	1	2	2	2
Bare substratum (80%), medium soft-coral density (5 m^{-2})	1	2	3	3
Bare substratum (60%), high soft-coral density (8 m^{-2}), *Lobophora variegata* (14%), high live coral cover (18%) of which ~9% is *Montastrea* spp.	1	2	4	4
Lobophora variegata (76%) and branching red/brown algae (9%)	2	3	5	5
Sand and occasional branching red algae (< 6%)	3	4	6	6
Amphiroa spp. (40%), sand (30%), encrusting sponge (17%), sparse *Thalassia testudinum* and calcareous green algae	2	5	7	
Thalassia testudinum of low standing crop (5 g m^{-2}) and *Batophora* spp. (33%)	3	6	8	
Thalassia testudinum of low standing crop (5 g m^{-2}) and sand	3	6	9	
Medium-dense colonies of calcareous algae – principally *Halimeda* spp. (25 m^{-2}) *Thalassia testudinum* of medium standing crop (~80 g m^{-2})	3	7	10	
Dense colonies of calcareous algae – principally *Penicillus* spp. (55 m^{-2}) and *Halimeda* spp. (100 m^{-2}) *Thalassia testudinum* of medium standing crop (~80 g m^{-2})	2	7	11	7
Thalassia testudinum and *Syringodium filiforme* of 5–80 g m^{-2} standing crop	4	8	12	8
Thalassia testudinum and *Syringodium filiforme* of 80–280 g m^{-2} standing crop	4	8	13	9

Accuracy assessment

The accuracies of habitat maps were determined using three complementary measures which are based on error matrices derived from independent field data. An error matrix compares true reference data (from habitats visited in the field) to the habitat types predicted from image classification (see Congalton 1991):

Overall accuracy. This is the overall degree of agreement in the matrix (i.e. the sum of correctly labelled test sites divided by the total number of test sites). It is a reasonable way to describe the overall accuracy of a map, but does not account for the component of accuracy resulting from chance alone. A chance component of accuracy exists because even a random assignment of pixels to habitat classes would include some correct assignments.

User accuracy. This is the probability that a classified pixel actually represents that category on the ground (Congalton 1991). It is particularly useful for assessing the accuracy of individual habitat classes.

Tau coefficient (T). This statistic is readily interpretable, permits hypothesis testing, and accounts for chance agreement within the matrix (Ma and Redmond 1995). A T of 0.80 indicates that 80% more pixels were classified correctly than would be expected by chance alone. The coefficient's distribution approximates to normality, and Z-tests (Mar and Redmond 1995) can be performed to examine differences between matrices. Tau is calculated from:

$$T = \frac{P_0 - P_r}{1 - P_r} \quad , \quad \text{where } P_r = \frac{1}{N^2}\sum_{i=1}^{M} n_i \cdot x_i \quad ,$$

P_0 = overall accuracy; M = number of habitats, i = ith habitat, N = total number of sites, n_i = row total for habitat i, and x_i = diagonal value for habitat i (i.e. number of correct assignments for habitat i).

Results

The hierarchical cluster analyses described (at least) three levels of inter-habitat similarity. These were treated as three levels of descriptive resolution, the simplest level being habitats dominated by either corals, algae, sand or seagrass. The intermediate and fine levels consisted of 8 and 13 habitats, respectively, and their principal attributes are described in Table 2.

What are relative capabilities of satellite sensors?

A pronounced and usually significant drop in accuracy of image-derived maps was consistently found between coarse, intermediate and fine habitat-discrimination (Fig. 2). For mapping at coarse descriptive resolution (i.e. four habitat classes; sand, coral, algae, seagrass), Landsat TM was significantly more accurate than other satellite sensors (overall accuracy 73%). SPOT XS also achieved a relatively high overall accuracy (67%). The accuracy of merged Landsat TM/SPOT Pan was lower than that of SPOT XS, but not significantly so ($\alpha = 0.05$). The maps derived from Landsat MSS and SPOT Pan had an accuracy of < 60% (Fig. 2).

Overall, the difference in accuracy between intermediate and fine descriptive resolution was considerably larger than the variation between sensors for a given level of descriptive resolution. In practical terms, if the objective is to map more detail than coral reef, algae, sand and seagrass, then the accuracy of a habitat map is more sensitive to the choice of descriptive resolution

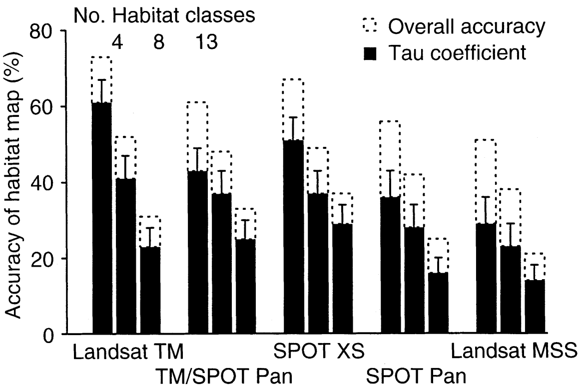

Fig. 2 Comparison of satellite sensors for mapping coral-reef habitats of Caicos Bank, showing overall accuracies and tau coefficients (*error bars* upper 95% confidence intervals of tau coefficient). Three levels of descriptive resolution are described for each sensor: coarse (4 habitat classes), intermediate (8 habitat classes) and fine (13 habitat classes). (See Tables 1 and 2 for explanation of sensor abbreviations and definition of habitat classes, respectively)

than the choice of sensor. Overall accuracies for both of the higher descriptive resolutions were low; intermediate (8 habitats) 38 to 52%, fine (13 habitats) 21 to 37%.

Coral and sand habitats were generally more accurately distinguished than algal and seagrass habitats (Table 3). At detailed scales of reef habitats, there was considerable variability in accuracy among sensors (Table 3).

How does satellite imagery compare to aerial photography?

Satellite-based map accuracies were re-calculated for the habitat classes mapped from 1:10,000 aerial photography (Sheppard et al. 1995). The accuracies for satellite sensors in Fig. 3 were higher than those in Fig. 2 because the re-calculation necessitated exclusion of several rarer habitat categories (see Table 2) which, when mapped, reduced overall accuracy. Inclusion of these categories in Fig. 2 would have reduced accuracy for two reasons. First, being fairly rare, the accuracy associated with mapping these classes was disproportionately low. Second, inclusion of these categories increased the total number of habitat classes for intermediate and fine descriptive resolution and, in probabilistic terms, reduced the chances of obtaining such high accuracies.

Table 3 User accuracies of habitat classes for all sensors and at two levels of descriptive resolution (coarse and fine). Note: details of habitat types do not apply directly to API categories which were described by Sheppard et al. (1995); however, categories of Sheppard et al. are broadly analogous to those described in table (*MSS* Landsat MSS; *TM* Landsat TM; *TM/P* merged Landsat TM/SPOT Pan; *XS* SPOT XS; *Pan* SPOT Pan; *API* aerial photo interpretation; *CASI* compact airborne spectrographic imager). The most accurate satellite sensors for each habitat are underlined to facilitate comparison with airborne remote sensing

Habitat type	Accuracy/sensor (%)						
	MSS	TM	TM/P	XS	Pan	API	CASI
Living and dead stands of *Acropora palmata*						52	90
Microdictyon marinum (77%), *Sargassum* spp. (4%), medium soft-coral density (5 m^{-2}) and rubble (10%)	0	0	69	19	13		
Bare substratum (40%), low soft-coral density (3 m^{-2}), *Microdictyon marinum* (30%), *Lobophora variegata* (12%)	32	44	57	54	32		81
Bare substratum (80%), medium soft-coral density (5 m^{-2})	4	34	44	39	10	48	80
Bare substratum (60%), high soft-coral density (8 m^{-2}), *Lobophora variegata* (14%), high live coral cover (18%), of which ~9% is *Montastrea* spp.	33	18	36	51	47	66	83
Lobophora variegata (76%) and branching red/brown algae (9%)	13	41	31	41	0	38	82
Amphiroa spp. (40%), sand (30%), encrusting sponge (17%), sparse *Thalassia testudinum* and calcareous green algae	11	25	24	75	7		
Sand and occasional branching red algae (<6%)	11	45	64	46	50	73	75
Thalassia testudinum of low standing crop (5 g m^{-2}) and *Batophora* spp. (33%)	100	8	14	22	14		
Thalassia testudinum of low standing crop (5 g m^{-2}) and sand	49	50	35	73	36		
Medium-dense colonies of calcareous algae - principally *Halimeda* spp. (25 m^{-2}) *Thalassia testudinum* of medium standing crop (~80 gm^{-2})	6	3	5	8	0		
Dense colonies of calcareous algae – principally *Penicillus* spp. (55 m^{-2}) and *Halimeda* spp. (100 m^{-2}) *Thalassia testudinum* of medium standing crop (~80 g m^{-2})	0	12	8	0	0	68	77
Thalassia testudinum and *Syringodium filiforme* of 5–80 g m^{-2} standing crop	6	15	37	2	15	40	72
Thalassia testudinum and *Syringodium filiforme* of 80–280 g m^{-2} standing crop	48	40	34	56	46	100	93
Coral	67	86	80	81	53	76	93
Algae	14	47	28	41	21	58	92
Sand	46	83	74	78	80	73	75
Seagrass	32	59	44	45	65	63	87

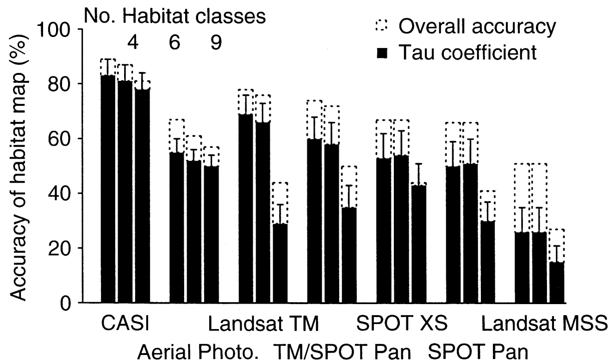

Fig. 3 Comparison of satellite sensors, aerial photography and airborne multispectral (CASI) data for mapping coral-reef habitats, showing overall accuracies and tau coefficients (*error bars* upper 95% confidence intervals of tau coefficient). Three levels of descriptive resolution are described for each sensor; coarse (4 habitat classes), intermediate (6 habitat classes) and fine (9 habitat classes). (See Tables 1 and 2 for explanation of sensor abbreviations and definition of habitat classes, respectively.) Data for aerial photography were recalculated from Sheppard et al. (1995)

The results can be segregated according to descriptive resolution. First, for coarse and intermediate habitat types, results from Landsat TM were found to be significantly ($p < 0.01$) more accurate than those from aerial photography. The accuracy of aerial photography did not differ significantly from that of merged Landsat TM/SPOT Pan, SPOT XS or SPOT Pan. In general, coral reef and sand habitats were more accurately mapped than algal and seagrass habitats (Table 3). Second, for fine descriptive resolution, aerial photography was more accurate than all satellite sensors (Fig. 3, Table 3).

Maps from Landsat MSS were significantly less accurate than those from aerial photography regardless of the descriptive resolution employed.

How does satellite imagery compare to digital airborne multispectral imagery (CASI)?

For all three levels of descriptive resolution, CASI imagery gave significantly more accurate results than satellite sensors and aerial photography (Fig. 3, $p < 0.001$). The accuracy with which individual habitats were mapped was more consistent than that of satellite sensors or aerial photography (Table 3).

Discussion

Most remote-sensing studies of coral reefs have focused on mapping geomorphological classes (Green et al. 1996). Labelling such classes is relatively straightforward because several geomorphological classification schemes exist (Hopley 1982; Kuchler 1986; Holthus and Maragos 1995) and geomorphology may be interpreted directly from remotely-sensed imagery. Ecological assemblages do not lend themselves to standard classifications so easily. Species/substrata assemblages can be highly variable, and several distinct assemblages may be present in each geomorphological zone (see Fagerstrom 1987). Further, some field survey is required to identify ecological assemblages. Even if an image-interpreter has some field knowledge of an area, assigning classes based on a "best guess" principle is likely to result in either vague habitat labels or, at worst, labels which are incorrect or meaningless to potential users of the map.

An important aspect of this study is the ecological approach to defining habitats. We described habitats using standard reef-sampling techniques and then attempted to map the boundaries of these habitats by remote sensing. This approach differed to the frequent remote sensing strategy of deriving mapped classes from spectral data followed by a posteriori assignment of habitat labels according to perceived differences between spectral classes. While this has often been done with some field data, the resulting maps have been difficult to interpret on either a biological or geomorphological basis.

Accuracy requirements

Before specific accuracies and the suitability of various satellite sensors for habitat mapping are discussed, it is necessary to comment on the importance of accuracy. It is extremely difficult to suggest a threshold accuracy which may be considered adequate or acceptable – even for the purposes of general guidance. As scientists or decision-makers, our first instinct might be to think in terms of statistical error margins where a permissible Type I error may be $< 5\%$. In most situations, however, it would be unrealistic to expect map accuracies to exceed 95%. This is because habitat maps impose an ordered classification on a benthos which actually exhibits semi-continuous gradients of structure and composition (usually with depth or wave exposure). There is, therefore, a degree of natural uncertainty in the placement of most habitat boundaries and this incurs error.

An alternative viewpoint might be to ask whether an accuracy of (say) 40% is worthwhile when the alternative is no mapped information at all? This is a difficult question to answer at present. The solution may become clearer once research addresses the economic importance of habitat data in various coastal management contexts. Similarly, insight might be drawn from the consequences of taking inappropriate management action on the basis of inaccurate information. However, to the best of our knowledge, such data are not available.

Given the arguments above, we have elected to use a different type of accuracy benchmark; that achieved with aerial photography. This is because aerial photography has been the conventional mapping medium for many decades and is widely available.

Coarse and intermediate habitat-discrimination

On the basis of the results from Sheppard et al. (1995), satellite sensors compared favourably to aerial photog-

Table 4 Relative cost-effectiveness of satellite sensors, CASI and 1:10 000 colour aerial photography for mapping marine habitats with coarse, intermediate and fine detail. Note: satellite sensors cannot be used for mapping reefs with fine habitat discrimination (where accuracy is < 37%) (*Abbreviations* as in legend to Table 1)

Method	Cost-effectiveness
Landsat TM	For areas >60 km in any direction (size of single SPOT image), Landsat TM is likely to be most cost-effective option. While being approximately £1140 more expensive than SPOT XS, it covers nine times the area and may offer greater habitat-mapping accuracy. If two SPOT scenes are required, SPOT would be more expensive than Landsat TM
SPOT XS	This is cheaper than SPOT Pan and offers greater habitat-map accuracy
Merged Landsat TM/SPOT Pan	This is not a cost-effective option. It is particularly expensive and does not provide a corresponding improvement in accuracy
CASI	CASI is significantly more accurate than satellite imagery for all levels of reef-habitat mapping It is at least as accurate, if not more so, than aerial photography for the same purpose It is less expensive to acquire than aerial photography and is, therefore, more cost-effective

raphy for coarse and intermediate levels of habitat discrimination. Aerial photography was found to be inferior to Landsat TM and similar to merged Landsat TM/SPOT Pan, SPOT XS and SPOT Pan. This may appear surprising given the superior spatial resolution of aerial photography. However, digital satellite sensors have better spectral resolution and at coarse/intermediate descriptive resolutions, the habitats were sufficiently dissimilar from one another (Bray–Curtis similarity, 10 to 15% and 30 to 50%, respectively) to enable a crude discrimination of their spectra.

In general terms, algal and seagrass habitats were spectrally and spatially confused with one another, resulting in lower overall accuracies than coral and sand habitats. This result is not unusual (e.g. Kirkman et al. 1988), and has several causes. Whilst the photosynthetic pigments in algae and seagrass (e.g. chlorophyll, phycoerythrin and fucoxanthin) have different reflectance characteristics, satellite spectral bands are generally unsuitable for distinguishing them (see Maritorena et al. 1994), because at wavelengths of > 580 nm penetration of water is poor, preventing the characteristic reflectance minima and maxima of photosynthetic pigments being detected. For example, whilst most photosynthetic pigments show reflectance minima below 450 nm, the maxima lie between 670 and 700 nm and, therefore, the "red edge" lies beyond the range of penetrating irradiance. Where distinguishing minima and maxima exist within the water-penetrating spectrum, satellite bands may be too broad to distinguish them. For example, the reflectance minima for both green and brown algae are below 500 nm and their maxima are 550 and 575 nm, respectively (Maritorena et al. 1994). SPOT XS band 1 cannot differentiate these maxima because it detects radiance within the range 500 to 590 nm. Landsat TM can, in principle, distinguish these maxima because Band 1 is sensitive to 450 to 520 nm and Band 2 detects within the range 520 to 600 nm. However, given sensor noise and light-attenuation problems, precise discrimination is unlikely.

Coral habitats also possess a high cover of macroalgae, and the corals themselves contain photosynthetic pigment-bearing algae (zooxanthellae). Whilst they may be spectrally confused with seagrass and some algal habitats, coral reefs may be spatially distinguished. This is because their location (context) within the reef landscape is usually confined to the seaward margin of the coastal zone (i.e. fringing reef), where wave exposure is moderate to high. In this study, contextual discrimination of algal and seagrass habitats was difficult because gradients of exposure were generally less obvious and it was not easy to predict the location of habitats.

Although Landsat TM and SPOT sensors provided similar accuracies to aerial photography for reef habitat-mapping with moderate detail, there are other reasons for choosing satellite imagery in preference to photography. First, the generation of a geo-coded map is simpler when based on a single satellite image than when faced with mosaicing and geo-coding, for example, fifty aerial photographs. Second, the time required to visually interpret and digitise aerial photography is likely to be 1 to 2 orders of magnitude greater than that required for processing digital satellite imagery. Third, existing aerial photographs for a particular study site may be quite old (especially if they were collected for the purposes of cartographic mapping), and satellite imagery will generally provide a more recent data source. This does, however, open up the wider issue of cost-effectiveness.

If new imagery is required for a site, the most cost-effective solution depends on the mapping objectives, required accuracy, the size of the area, climate of the area (e.g. persistence of cloud cover), the volume of data required, and the availability of technical expertise and equipment. An analysis of these issues is beyond the scope of this paper and will be reported at a later date. However, a few simple rules emerge (Table 4).

Fine habitat-discrimination

The results presented in this study suggest that satellite imagery is not well suited to detailed mapping of benthic habitats; aerial photography provided consistently greater accuracies. This conclusion is in agreement with Bainbridge and Reichelt (1989), who concluded that satellite imagery is more appropriate for studying reef geomorphology than reef biology. The combined spatial and spectral resolutions of satellite sensors were not capable of reliably distinguishing habitats with relatively high inter-habitat similarity (Bray–Curtis similarity, 60 to 80%). This was borne out by the high variability in accuracy associated with individual habitat classes. The poor separability of spectra rendered the underlying discriminant function (supervised classification) unable to assign pixels to appropriate habitat classes, and resulted in large and variable allocation errors.

CASI consistently provided the most accurate results. Even fine habitat-discrimination was possible with an accuracy of 81% (almost double that achieved with any satellite). CASI has the advantage of offering tremendous flexibility to the user. In this case, four narrow spectral bands were set to penetrate water which increased the likelihood of distinguishing habitat spectra (band settings 402.5 to 421.8 nm, 453.4 to 469.2 nm, 531.1 to 543.5 nm, 571.9 to 584.3 nm). (Note: if we had not also been interested in mangrove habitats, up to eight spectral bands could have been selected for this purpose.)

Whilst CASI was found to provide significantly greater accuracies than aerial photography, the comparison was not entirely balanced. Although the habitat categories were comparable, Sheppard et al. (1995) mapped a much larger area than that tested for CASI (14 600 ha vs 100 ha). It is perhaps safest to conclude that for comparable areas, CASI would be at least as good as aerial photography (for further discussion see Mumby et al. 1997b).

The cost-effectiveness of remote-sensing methods for detailed habitat-mapping is detailed in Table 4.

Potential limitations of this study

Satellite imagery is usually acquired from an image archive and it is common to find considerable disparity between the date of imagery acquisition and the date of field work (Luckzovich et al. 1993). If the landscape (or seascape) has undergone change in the intervening period, field data may be inappropriate and may result in lower map accuracies than would have been expected if sampling dates were similar. It is difficult to predict what effect such temporal disparity might have had on the present study. However, since Landsat TM was the oldest data source and was still found to be the most accurate, it seems unlikely to have affected our conclusions markedly. It is possible that greater accuracies may have been obtained for Landsat TM if more recent satellite data had been available. We attempted to ameliorate such effects wherever possible by avoiding habitat boundaries when sampling.

Representativeness of results

The results presented here should be representative of most Caribbean reef systems with banks and fringing reefs (e.g. the Bahamas, Belize, Lesser Antilles, etc.). In more general terms, the Caribbean has a higher proportion of deep reef to reef flat than the Indo-Pacific (Done 1983), and the transferability of results to such areas is unclear. However, because there is less light attenuation at shallower depths, all forms of optical remote sensing would logically be favoured in the Indo-Pacific.

Turbid waters are possibly the greatest constraint to any coastal habitat-mapping programme utilising optical remote-sensing methods. Where coral reefs occur in waters of high suspended sediment concentration (e.g. Hong Kong), light transmittance through water is inadequate for describing the coverage of reef habitats. Even where sufficient light penetration exists, compensation for the effects of variable depth becomes more complex as turbidity increases. Lyzenga's depth-invariant model requires clear water, and high water-turbidity exerts a major (though currently not quantified) effect on the applicability of the model (but see Spitzer and Dirks 1987). Horizontal Secchi distance at a depth of 0.5 m in the Turks and Caicos Islands was of the order of 30 to 50 m and PAR (photosynthetically active radiation) attenuation coefficients were 0.108 and 0.065 for the upper 5.5 m and lower 4.5 m of the top 10 m of the water column, respectively (AJE and CDC unpublished results). At present it is not possible to give a threshold turbidity at which satellite imagery will be ineffective. In the absence of such information, we point out that Tassan (1996) has described a depth-invariant model for water of greater turbidity than that required by Lyzenga (1981).

Conclusions

Whilst some of the results presented here were expected (e.g. the superiority of CASI over satellite imagery), at least three of the conclusions were surprising. First, given the disparity in spatial resolution, we did not expect satellite imagery to compare so favourably against aerial photography. Second, although CASI imagery was expected to map benthic habitats with greater accuracy than satellites (and to some extent, aerial photography), it was surprising that CASI was capable of mapping a comprehensive range of benthic habitats with such high accuracy (72 to 93%). Third, merging the spectral qualities of Landsat TM with the spatial resolution of SPOT Pan was expected to provide an optimum satellite-based approach to habitat mapping. This was not the case, and may reflect the difficulty of merging satellite data sources and the overall limitation of satellite imagery for benthic habitat-mapping. It is hoped that the conclusions presented above will help practitioners match their coastal habitat-mapping objectives to the most appropriate sensor(s).

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References

Ahmad W, Neil DT (1994) An evaluation of Landsat thematic mapper (TM) digital data for discriminating coral reef zonation: Heron Reef (GBR). Int J remote Sensing 15: 2583–2597

Bainbridge SJ, Reichelt RE (1989) An assessment of ground truthing methods for coral reef remote sensing data. Proc 6th int coral Reef Symp 2: 439–444 [Choat JH et al. (eds) Sixth International Coral Reef Symposium Committee, Townsville]

Bastin J (1988) Measuring reef areas using satellite images. In: Proceedings of Symposium on Remote Sensing of the Coastal Zone, Gold Coast, Queensland. Department of Geographic Information, Brisbane, pp VII1.1–VII1.9

Benny A, Dawson GJ (1983) Satellite imagery as an aid to bathymetric charting in the Red Sea. Cartogr J 20: 5–16

Biña RT (1982) Application of Landsat data to coral reef management in the Philippines. In: Proceedings of Great Barrier Reef Remote Sensing Workshop. James Cook University, Townsville, pp 1–39

Bour W (1989) SPOT images for coral reef mapping in New Caledonia. A fruitful approach for classic and new topics. Proc 6th int coral Reef Symp 2: 445–448 [Choat JH et al. (eds) Sixth International Coral Reef Symposium Committee, Townsville]

Bray JR, Curtis JT (1957) An ordination of the upland forest communities of Southern Wisconsin. Ecol Monogr 27: 325–349

Clark CD, Ripley HT, Green EP, Edwards AJ, Mumby PJ (1997) Mapping and measurement of tropical coastal environments with hyperspectral and high spatial resolution data. Int J remote Sensing 18: 237–242

Clarke KR (1993) Non-parametric multivariate analyses of changes in community structure. Aust J Ecol 18: 117–143

Clarke KR, Warwick RM (1994) Change in marine communities: an approach to statistical analysis and interpretation. Natural Environment Research Council, Plymouth

Cliff AD, Ord JK (1973) Spatial autocorrelation. Pion Press, London

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing Envir 37: 35–46

Cracknell AP, Ibrahim M, McManus J (1987) Use of satellite and aircraft data for bathymetry studies. In: Mather PM (ed) Advances in digital image processing. Remote Sensing Society, Nottingham, pp 391–402 (Proc 13th A Conf Remote Sensing Society, University of Nottingham)

Currey B, Fraser AS, Bardsley KL (1987) How useful is Landsat monitoring? Nature, Lond 328: 587–589

Done TJ (1983) Coral zonation: its nature and significance. In: Barnes DJ (ed) Perspectives on coral reefs. Brian Clouston Publishing, Canberra Australia, pp 107–147

English S, Wilkinson C, Baker V (1994) Survey manual for tropical marine resources. ASEAN–Australia marine science project: living coastal resources. Australian Institute of Marine Science, Townsville

Fagerstrom JA (1987) The evolution of reef communities. John Wiley & Sons, New York

Faith DP, Minchin PR, Belbin L (1987) Compositional dissimilarity as a robust measure of ecological distance. Vegetatio 69: 57–68

Green EP, Mumby PJ, Edwards AJ, Clark CD (1996) A review of remote sensing for the assessment and management of tropical coastal resources. Coastal Man 24: 1–40

Greig-Smith P (1983) Quantitative plant ecology. Blackwell Scientific Publications, Oxford

Groom GB, Fuller RM, Jones AR (1996) Contextual correction: techniques for improving land cover mapping from remotely sensed data. Int J remote Sensing 17: 69–89

Holthus PF, Maragos JE (1995) Marine ecosystem classification for the tropical island Pacific. In: Maragos JE, Peterson MNA, Eldredge LG, Bardach JE, Takeuchi HF (eds) Marine and coastal biodiversity in the tropical island Pacific region. East-West Center, Honolulu, pp 239–278

Hopley D (1982) Geomorphology of the Great Barrier Reef: quaternary development of coral reefs. Wiley-Interscience, New York

Jupp DLB (1986) The application and potential of remote sensing in the Great Barrier Reef region. Great Barrier Reef Marine Park Authority, Townsville, Queensland (Res Publ)

Jupp DLB, Mayo KK, Kuchler DA, Claasen DV, Kenchington RA, Guerin PR (1985) Remote sensing for planning and managing the Great Barrier Reef, Australia. Photogrammetria 40: 21–42

Kenchington RA (1978) Visual surveys of large areas of coral reefs. In: Stoddart DR, Johannes RE (eds) Coral reefs: research methods. UNESCO, Paris pp 149–161

Kenchington RA, Claasen DR (1988) Australia's Great Barrier Reef – management technology. In: Proceedings of Symposium on Remote Sensing of the Coastal Zone, Gold Coast, Queensland. Department of Geographic Information, Brisbane, pp KA2.1–KA2.12

Kirkman H, Olive L, Digby B (1988) Mapping of underwater seagrass meadows. In: Procedings of Symposium on Remote Sensing of the Coastal Zone, Gold Coast, Queensland. Department of Geographic Information, Brisbane, pp VA2.1–VA2.9

Kuchler DA (1986) Geomorphological nomenclature: reef cover and zonation on the Great Barrier Reef. Great Barrier Reef Marine Park Authority, Townsville, Australia (Tech Memo No. 8)

Kuchler DA, Jupp DLB, Claasen DR, Bour W (1986) Coral reef remote sensing applications. Geocarto int 4: 3–15

Loubersac L, Dahl AL, Collotte P, LeMaire O, D'Ozouville L, Grotte A (1989) Impact assessment of Cyclone Sally on the Almost atoll of Aitutaki (Cook Islands) by remote sensing. Proc 6th int coral Reef Symp 2: 455–462 [Choat JH et al. (eds) Sixth International Coral Reef Symposium Committee, Townsville]

Luczkovich JJ, Wagner TW, Michalek JL, Stoffle RW (1993) Discrimination of coral reefs, seagrass meadows, and sand bottom types from space: a Dominican Republic case study. Photogramm Engng remote Sensing 59: 385–389

Lyzenga DR (1978) Passive remote sensing techniques for mapping water depth and bottom features. Appl Optics 17: 379–383

Lyzenga DR (1981) Remote sensing of bottom reflectance and water attenuation parameters in shallow water using aircraft and Landsat data. Int J remote Sensing 2: 71–82

Ma Z, Redmond RL (1995) Tau coefficients for accuracy assessment of classification of remote sensing data. Photogramm Engng remote Sensing 61: 435–439

Maritorena S, Morel A, Gentili B (1994) Diffuse reflectance of oceanic shallow waters: influence of water depth and bottom albedo. Limnol Oceanogr 37: 1689–1703

Mather PM (1987) Computer processing of remotely-sensed images: an introduction. John Wiley & Sons, Chichester

McCracken KG, Kingwell J (1988) Marine and coastal remote sensing in the Australian tropics. CSIRO Office of Space Science and Applications, Canberra

McNeill SE (1994) The selection and design of marine protected areas: Australia as a case study. Biodiversity Conserv 3: 586–605

Meaden GJ, Kapetsky JM (1991) Geographical information systems and remote sensing in inland fisheries and aquaculture. FAO Fish tech pap 318: 1–22

Mumby PJ, Clarke KR, Harborne AR (1996) Weighting species abundance estimates for marine resource assessment. Aquat Conserv mar Freshwat Ecosystems 6: 115–120

Mumby PJ, Edwards AJ, Green EP, Anderson CW, Ellis AC, Clark CD (1997a) A visual assessment technique for estimating seagrass standing crop. Aquat Conserv mar Freshwat Ecosystems (in press)
Mumby PJ, Green EP, Clark CD, Edwards AJ (1997b) Digital analysis of multispectral airborne imagery of coral reefs. Coral Reefs (in press)
Mumby PJ, Green EP, Clark CD, Edwards AJ (1997c) Reefal habitat assessment using (CASI) airborne remote sensing. Proc 8th int coral Reef Symp (in press) [Lessios HA, Macintyre I (eds) Smithsonian Tropical Research Institute, Panamá]
Mumby PJ, Harborne AR, Raines PS, Ridley JM (1995) A critical assessment of data derived from Coral Cay Conservation volunteers. Bull mar Sci 56: 737–751
Populus J, Lantieri D (1990) High resolution satellite data for assessment of tropical coastal fisheries. Case study in the Philippines. In: Proceedings of International Workshop on Remote Sensing and Insular Environments in the Pacific: integrated approaches, ORSTOM/IFREMER, Noumea, New Caledonia pp 523–536
Price JC (1987) Calibration of satellite radiometers and the comparison of vegetation indices. Remote Sensing Envir 21: 15–27
Rogers C, Garrison G, Grober R, Hillis Z-M, Franke MA (1994) Coral reef monitoring manual for the Caribbean and Western Atlantic. National Park Service, Virgin Islands National Park, St. John
Sheppard CRC, Matheson K, Bythell JC, Murphy P, Blair Myers C, Blake B (1995) Habitat mapping in the Caribbean for management and conservation: use and assessment of aerial photography. Aquat Conserv marine Freshwat Ecosystems 5: 277–298
Smith VE, Rogers RH, Reed LE (1975) Automated mapping and inventory of Great Barrier Reef zonation with Landsat data. Ocean 75 conference record, Institute of Electrical and Electronics Engineers, Inc, New York
Spitzer D, Dirks RWJ (1987) Bottom influence on the reflectance of the sea. Int J remote Sensing 8: 279–290
Stoddart DR, Johannes RE (1978) Coral reefs: research methods. UNESCO, Paris
Tanre D, Deroo C, Dahaut P, Herman M, Morcrette JJ (1990) Description of a computer code to simulate the satellite signal in the solar spectrum: the 5S code. Int J remote Sensing 11: 659–668
Tassan S (1996) Modified Lyzenga's method for macroalgae detection in water with non-uniform composition. Int J remote Sensing 17: 1601–1607
Thamrongnawasawat T, Sudara S (1992) Image processing techniques for studying fringing reefs in Thailand using Landsat and SPOT data. In: Chou LM, Wilkinson CR (eds) Third ASEAN Science and Technology Week Conference Proceedings. Vol 6. Marine science: living coastal resources, University of Singapore, Singapore, pp 391–399
Trimble Navigation Ltd (1993) GPS Prolite. Survey and mapping division, 645 North Mary Avenue, Sunnyvale, California
Zainal AJM, Dalby DH, Robinson IS (1993) Monitoring marine ecological changes on the east coast of Bahrain with Landsat TM. Photogramm Engng remote Sensing 59: 415–421