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REPORT

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Digital analysis of multispectral airborne imagery of coral reefs

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Abstract The digital airborne sensor, CASI (Compact Airborne Spectrographic Imager) has considerable potential for mapping marine habitats. Here we present an account of one of the first coral reef applications. The CASI was flown over reefs of the Turks and Caicos Islands (British West Indies) and set to view 1 m pixels in 8 spectral bands. In addition, reef habitats were sampled *in situ* by visual assessment of percent cover in 1 m quadrats. Seagrass standing crop was assessed using a calibrated visual scale. Benthic habitats were classified using hierarchical cluster and similarity percentage analyses of the field survey data. Two levels of habitat discrimination were assessed: a coarse level (corals, algae, sand, seagrass) and a fine level which included nine reef habitats. Overall accuracies of CASI-derived habitat maps were 89% and 81% for coarse and fine levels of habitat discrimination, respectively. Accuracies were greatest once CASI data had been processed to compensate for variations in depth and edited to take account of generic patterns of reef distribution. These overall accuracies were significantly ($P < 0.001$) better than those obtained from satellite imagery of the same site (Landsat MSS, Landsat TM, SPOT XS, SPOT Pan, merged Landsat TM/SPOT Pan). Results from CASI were also significantly better than those from interpretation of 1:10 000 colour aerial photographs of reefs in Anguilla (Sheppard et al. 1995). However, the studies may not have been entirely comparable due to a disparity in the areas mapped.

Key words Casi · Remote sensing · Coral Satellite Airborne

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Introduction

The capability of remote sensing technology has, on occasion, been oversold to the user community (Currey et al. 1987; Meaden and Kapetsky 1991). As a result, some reef ecologists may have experienced a degree of disillusionment when attempting to apply the technology to ecological problems. It seems that the resolution of currently available satellite imagery is too coarse to map reefs beyond their overall geomorphology (Bainbridge and Reichelt 1988) and mapping whole reef systems using aerial photography can be time consuming and technically difficult (Mumby et al. 1995). However, the emergence of digital airborne instruments offers a potential solution to many of the weaknesses which hinder existing satellite and photographic methods (Kenchington and Claasen 1988). This work focuses on this newer technology and compares it to other remote sensing methods. A plethora of techniques exist for analysing remotely sensed data and we describe and test several of those most relevant to the reef ecologist. In short, we aim to evaluate the current capability of CASI for mapping the habitats of reef ecosystems. We begin by reviewing the questions reef ecologists have asked of remote sensing and by examining the current limitations of this approach.

Use and limitations of existing optical remote sensing methods

We recently reviewed the use of remote sensing methods for assessing tropical coastal resources (Green et al. 1996) and found that most reef studies using satellites addressed reef geomorphology (e.g. Biña 1988; Bour 1988; Kuchler et al. 1988; Ahmad and Neil 1994). Some authors have made semi-quantitative or qualitative estimates of coral density from satellite images (Zainal et al. 1993; Bour et al. 1996), and coral cover has been measured using low-altitude aerial photography. While coral cover is undoubtedly a useful parameter to measure, these assessments were confined to shallow reef flats (~ 1 m depth) and small areas (Catt and Hopley 1988; Hopley and Catt 1988; Thamrongnawasawat and Catt 1994; Thamrongnawasawat and Hopley 1995).

Where the objective has been benthic habitat mapping, one of the more successful studies utilised colour aerial photography (Sheppard et al. 1995). Aerial photographs provide good spatial resolution (to tens of centimetres) but the small size of individual prints and the featureless nature of most marine areas hinders the acquisition of adequate reference coordinates. It then becomes difficult to mosaic the photographs and assign map coordinates. Further, the conventional method of interpreting polygons and digitising photographic prints into maps is subjective and time consuming. Use of digital scanners can alleviate this problem and delineation of habitats may use conventional image processing methods (Hopley and Catt 1988).

Satellites seem to be more limited for marine habitat mapping than aerial photographs and several authors have experienced difficulties using satellite data to distinguish coral reefs from seagrass beds (e.g. Luczkovich et al. 1993; Zainal et al. 1993). The specifications of most satellite sensors (Table 1) are inadequate for distinguishing marine habitats below hectare scales. The sensors with the greatest number of spectral bands (Landsats MSS and TM) have 80 m and 30 m spatial resolutions and are incapable of distinguishing reef features at sub-pixel scales. Those sensors with 20 m and 10 m spatial resolution (SPOT XS and SPOT Panchromatic) have the fewest spectral bands which inhibits their ability to separate reef spectra (spectral signatures). The problem is exacerbated by light attenuation through water which reduces the dynamic range and modifies the shapes of available spectra.

Digital airborne remote sensing – a technological advance

The emergence of digital airborne sensors has stimulated widespread interest because they offer the following advantages:

1. Greater number of spectral bands than present on satellite-borne sensors,
2. Great spectral versatility (the location and width of spectral bands can often be chosen by the operator),
3. Ability to characterise complete spectra of cover types using numerous closely spaced (hyperspectral) bands.
4. High spatial resolution (broadly comparable to aerial photography, but the data are digital and therefore more easily manipulated).

The Compact Airborne Spectrographic Imager (CASI), manufactured by ITRES instruments (Canada), offers up to 16 user-specified spectral bands depending on the spatial resolution required. The user may specify bands anywhere within the blue to near infrared portion (400–1000 nm) of the electromagnetic spectrum. Each band must have a minimum width of 2 nm and the instrument set-up can be modified during flight. Pixel size may be set between 10 m and 0.5 m according to altitude and allowable data volume (there is a trade-off between the number of bands used and spatial resolution). The instrument can also be deployed in "spectral mode" whereby up to 288 bands are used to determine the spectra (signatures) of surface features. In short, airborne digital remote sensing combines the desirable properties of both satellite imagery and aerial photography; namely, digital data in discrete spectral bands and high spatial resolution.

Our approach is field-orientated and begins with an ecological determination of benthic habitats before attempting to map their boundaries using remote sensing. The study aims to evaluate whether CASI can map reef habitats of the Eastern Caribbean and embraces four questions:

1. What is the optimum method of data processing for benthic habitat mapping?
2. Given the optimum analytical approach, how accurately can habitats be mapped?
3. To what degree is CASI superior to satellite imagery?
4. To what degree is CASI superior to aerial photography?

Methods

Imagery acquisition details

The CASI data presented here were obtained in July 1995 for an area exceeding 100 ha near the island of South Caicos, Turks and Caicos Islands, British West Indies (Fig. 1). Logistical details have been presented elsewhere (Clark et al. 1997; Mumby et al. 1997a). Satellite

Table 1 Principal specifications of satellite, airborne and photographic media. AVIRIS, Airborne Visible InfraRed Imaging Spectrometer

Specification	Landsat MSS	Landsat TM	SPOT XS	SPOT Pan	CASI (airborne)	Aerial photography	AVIRIS (airborne)
Spatial resolution (m)	80	30	20	10	10–0.5	Variable – >0.2	20
Number of spectral bands available for reef mapping	2	3	2	1	8–16 *User defined*	1 *Analogue*	32
Area covered (km)	185 × 172	185 × 185	60 × 60	60 × 60	Variable	Variable	Variable

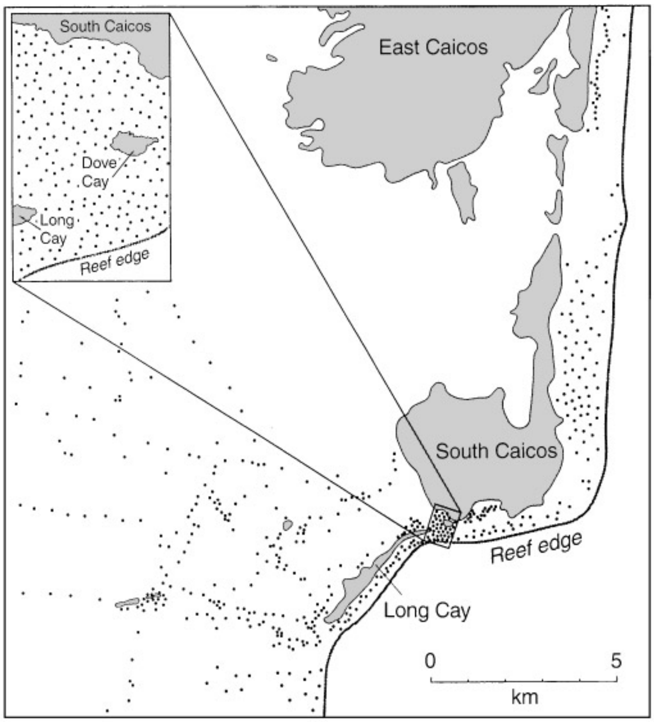

Fig. 1 Study area in the Turks and Caicos Islands (British West Indies) showing the locations of all field sites. CASI was flown across Cockburn Harbour (inset)

images were obtained for the entire Caicos Bank between 1990 and 1995 and subjected to geometric and radiometric correction (Price 1987; Tanre et al. 1990). Aerial photographs were not available for the Caicos Bank so the data of Sheppard et al. (1995) from comparable habitats in Anguilla were examined for comparison. These authors used colour aerial photographs at a scale of 1:10 000.

CASI should, ideally, have been configured to measure the characteristic reflectance spectra of coral reefs. However, since airborne multispectral studies of reefs is an emerging field, suitable reference data were not available. Reflectance spectra could have been obtained by initially deploying CASI in spectral mode but the cost of having the instrument on standby whilst spectra was identified were prohibitive (derivation of characteristic spectra from hyperspectral imagery is not a trivial task). Consequently, five spectral bands were assigned to the region of the electromagnetic spectrum which best penetrates water (approx. 400–650 nm). Three bands with red and near infrared wavelengths were added to assess nearshore mangrove (Green et al. in press), but are not discussed further here.

A small (1 m) pixel size was specified and, therefore, the signal to noise ratio of the sensor required consideration. To ensure that the CASI sensor measured adequate signal (radiance), a relatively broad spectrum was selected for each band (mean width 13.1 nm). Band settings (nanometres) were: 402.5–421.8; 453.4–469.2; 531.1–543.5; 571.9–584.3; 630.7–643.2; 666.5–673.7; 736.6–752.8; 776.3–785.4. The CASI was mounted on a Cessna 172 aircraft. An upward-facing incident light sensor (ILS) was fixed to the fuselage so that simultaneous measurements of irradiance could be made. A differential global positioning system (DGPS) was mounted to provide a record of the aircraft's flight-path.

Field survey

To compare CASI and satellite imagery, three considerations were made (see Fig. 1): (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 against spatial autocorrelation (Cliff and Ord 1973), a greater area was visited for satellite sensors (e.g. a single seagrass bed may represent hundreds of CASI pixels but only a few, autocorrelated satellite pixels), (3) the high costs associated with flying and processing CASI, dictated that only a relatively small area of the Bank could be surveyed. Cockburn Harbour (Fig. 2) was chosen because all habitats were represented.

Field survey was conducted in two phases. In the first phase (July and August 1995), 180 sites were sampled using a minimum of six replicate 1 m^2 quadrats per site. Sites measured approximately 100 m^2 and were distributed throughout the range of physical environments of the Caicos Bank (Fig. 1). Percent cover was recorded to species level for hard corals and macroalgae but to higher level taxon for sponges. The density of soft corals (number per m^2) was also recorded. Seagrass composition and standing crop were measured using a calibrated rapid visual assessment method (Mumby et al. 1997b). These data were used to develop a categorisation scheme of benthic habitats and to create spectra (spectral signatures) of each habitat in the imagery. CASI data covered a smaller area than satellite imagery (Fig. 1) and therefore only 14 (of a total of 180) sites were used to develop spectra for habitats in the CASI region. The second phase of field work (March 1996) gathered 600 independent data for testing the accuracy of image-derived habitat maps. The habitat type at each site was identified quickly using a glass-bottomed bucket. 450 of these sites were used to test maps from satellite imagery and 200 were used to assess the accuracy of CASI-derived maps.

The location of all field sites was determined using DGPS with a "circle error probable" of 2–5 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. A coarse descriptive resolution would simply be coral, algae, sand, seagrass. A finer descriptive resolution would include reef zones, variations in seagrass standing crop and so on.

A habitat classification was developed objectively using hierarchical agglomerative clustering of field data with group-average sorting (Clarke 1993). 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 CASI imagery would discriminate habitats on the basis of dominant benthic features rather than more cryptic species or 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 or substrata of each class were determined using similarity percentage (SIMPER) analysis of Bray-Curtis similarities (Clarke 1993).

Standard image processing

The CASI operator performed two pre-processing steps on the imagery: compensation for aircraft roll during flight and radiometric correction of data to reflectance values at the aircraft (i.e. the ratio of upwelling radiance recorded by the sensor to downwelling irradiance incident upon the aircraft). This process aimed to compensate for variations in light intensity during imagery acquisition. Imagery was geo-coded using the DGPS mounted in the aircraft plus ground control points. By locating field sites on the imagery, characteristic spectra were obtained for each habitat. These spectra were used to create a multivariate discriminant function which was used to assign each pixel in the image to an appropriate habitat class (Mather

1987). This process is known as supervised imagery classification and used the maximum likelihood decision rule (Mather 1987). All image processing used the commercial software Erdas Imagine running on a UNIX workstation. Two additional processing steps were carried out to determine their effect on the accuracy of habitat maps. These steps offer great potential for coral reef remote sensing yet they have not been widely adopted.

Additional image processing step I: compensation for light attenuation through water

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 of sand at 20 m may be similar to that of seagrass at (say) 3 m. Lyzenga (1978, 1981) developed a model-based approach to compensate for variation in depth. The method was derived for clear water and assumes that light attenuation follows an exponential decay curve with increasing depth. Processing creates a single depth invariant band from each pair of spectral bands (for further details, readers are directed to Lyzenga's papers).

The effectiveness of the depth invariant processing was illustrated by calculating the average coefficient of variation (COV) for reflectance data over sand at different depths. In raw imagery, the variation in reflectance is partly attributable to actual variation in sand reflectance (e.g. with different coverage of epipelic algae) but more importantly, it is attributable to variations in depth. The COV for the same pixels in depth invariant data will reflect the same differences in bottom type, but the variation due to depth should be greatly reduced.

The blue and green CASI channels yielded six depth invariant bands for subsequent classification. With the exception of SPOT Pan, which only has a single band, all satellite data also underwent depth invariant processing. Implementation of this processing step took 6 days; 4 days to check the theory and a further 2 days to develop and implement the model.

Additional image processing step II: addition of contextual information after supervised classification

The success of supervised image classification is highly 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 the misclassification are known, it is possible to improve map accuracy by contextual editing (Groom et al. 1996). Contextual editing 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 versus forereef escarpments" or "sheltered communities of branching red algae versus more exposed coral reef areas". In this study, pixels classified as seaward patches of seagrass were reclassified to the appropriate reef categories, changing approximately 8% of the imagery.

Accuracy assessment

The accuracies of habitat maps were determined using three complementary measures. All three 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 supervised image classification (Tables 2 and 3).

1. *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. User accuracy is calculated by dividing the number of correctly labelled pixels by the row total in the error matrix.

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.

Tau coefficient (T): this statistic compares matrices and 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 can be performed to examine differences between matrices.

Tau is calculated from;

$$T = \frac{P_o - P_r}{1 - P_r}$$

where

$$P_r = \frac{1}{N^2} \sum_{l=1}^{M} n_i . x_i$$

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

Results

The hierarchical cluster analysis described (at least) two levels of inter-habitat similarity. These were treated as two levels of descriptive resolution, the simplest being habitats dominated by either corals, algae, sand or seagrass (Bray-Curtis similarity, 10–15%). The finer level (Bray-Curtis similarity, 60–80%) consisted of nine habitats whose principal attributes are described in Table 4.

Lyzenga's model of depth compensation (Lyzenga 1981) was found to be appropriate. The mean coefficient of variation (COV) for raw CASI bands over sand was 0.54 ($n = 340$) whereas the COV of depth invariant bands was reduced to a mean of 0.14. Visual comparison of raw data and depth invariant data (Fig. 2) clearly reveals greater detail in deeper areas once depth has been accounted for.

What is the optimum method of data processing for benthic habitat mapping?

Of the three approaches to analysing CASI imagery, standard image processing (i.e. geo-coding and supervised classification) took approximately two days and returned the poorest accuracy (Fig. 3a, b). Adding contextual information did not significantly improve accuracy.

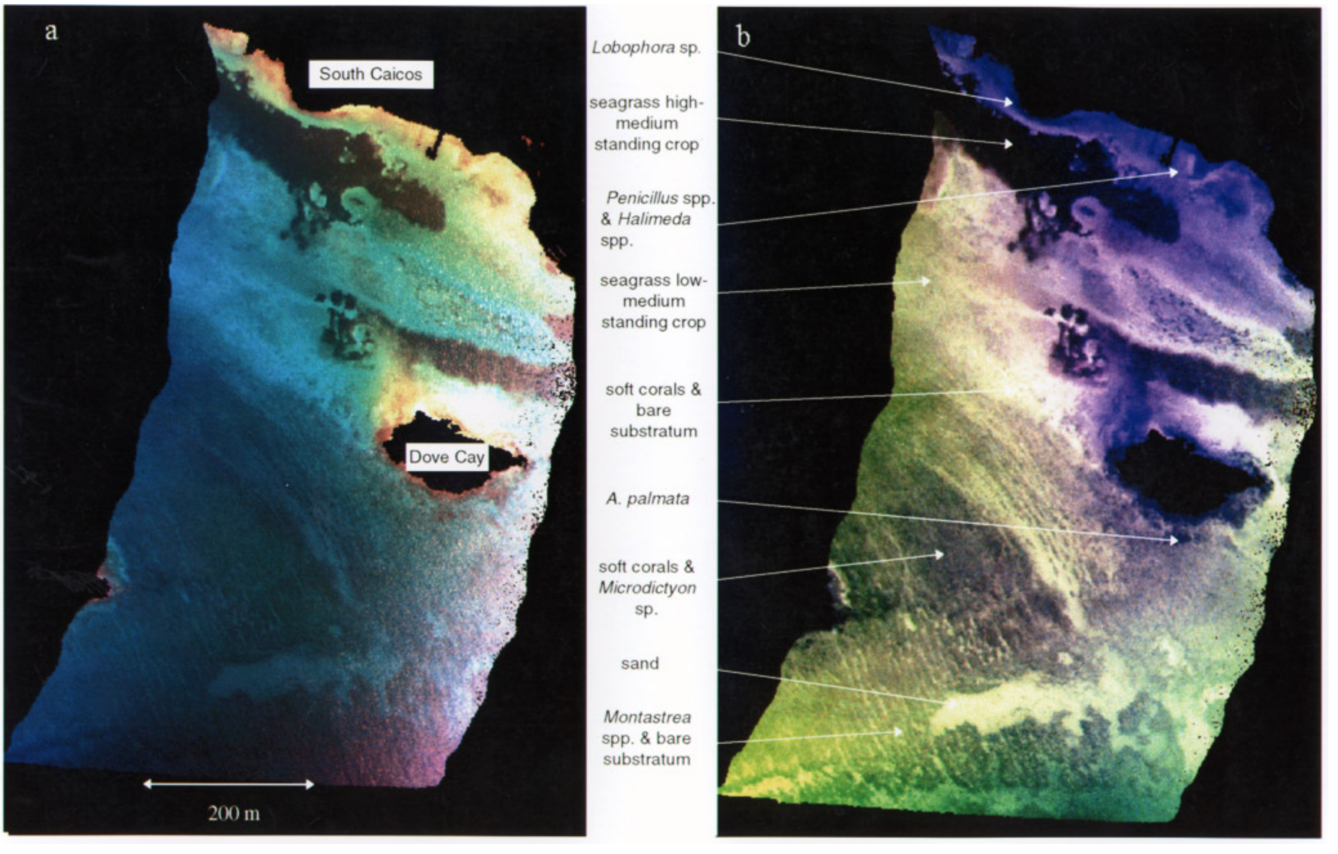

Fig. 2a, b CASI imagery of Cockburn Harbour (South Caicos) showing the visual improvement of depth invariant processing. Land has been masked out and the principal benthic habitats have been labelled. Depth increases towards the bottom of the image. Raw data are presented **a** but details of the benthos are much clearer in the depth invariant data **b**. *NB*. These are not aerial photographs, they comprise false colour composites of just three spectral **a** or depth invariant **b** bands

When supervised classification of all nine benthic habitats was conducted using depth invariant bands, there was a highly significant improvement in accuracy ($P < 0.001$, Fig. 3b). However, when habitats were mapped to a coarse descriptive resolution, depth invariant processing did not convey a significant advantage (Fig. 3a). The combination of contextual editing and depth invariant processing led to a significant improvement in accuracy regardless of the descriptive resolution. In summary, depth invariant processing was necessary when attempting to resolve many benthic habitats. Contextual editing was particularly advantageous when implemented in conjunction with depth invariant processing.

Given the optimum analytical approach, how accurately can habitats be mapped?

Map accuracies were highest when depth invariant processing and contextual editing were employed (Tables 2 and 3). For a fine descriptive resolution of nine reef habitats, the overall accuracy was 81%. Individual classes had user accuracies of 72 to 93%. The class with lowest overall accuracy was seagrass of low-medium standing crop. This was partially confused with higher biomass seagrass, calcareous green algae (*Penicillus* spp. and *Halimeda* spp.) and sparse soft corals. The confusion was not unexpected. Cuq (1993) experienced similar problems with satellite data. Perhaps most notably, CASI achieved overall map accuracies exceeding 80% for three reef assemblages which had a high Bray-Curtis similarity (88%): soft corals and *Microdictyon* sp.; soft corals and bare substratum; *Montastrea* spp. and bare substratum. The *Acropora palmata* zone was also mapped well but given the relatively small area of living coral, it is doubtful whether living and dead stands would be distinguishable.

While there was a drop in accuracy from general to fine descriptive resolution (Tables 2 and 3), the decline was not significant once depth invariant processing had been carried out ($Z = 0.38$, $P > 0.70$).

To what degree is CASI superior to satellite imagery?

Using Z-tests (Ma and Redmond 1995), CASI data were found to be significantly ($P < 0.01$) more accurate

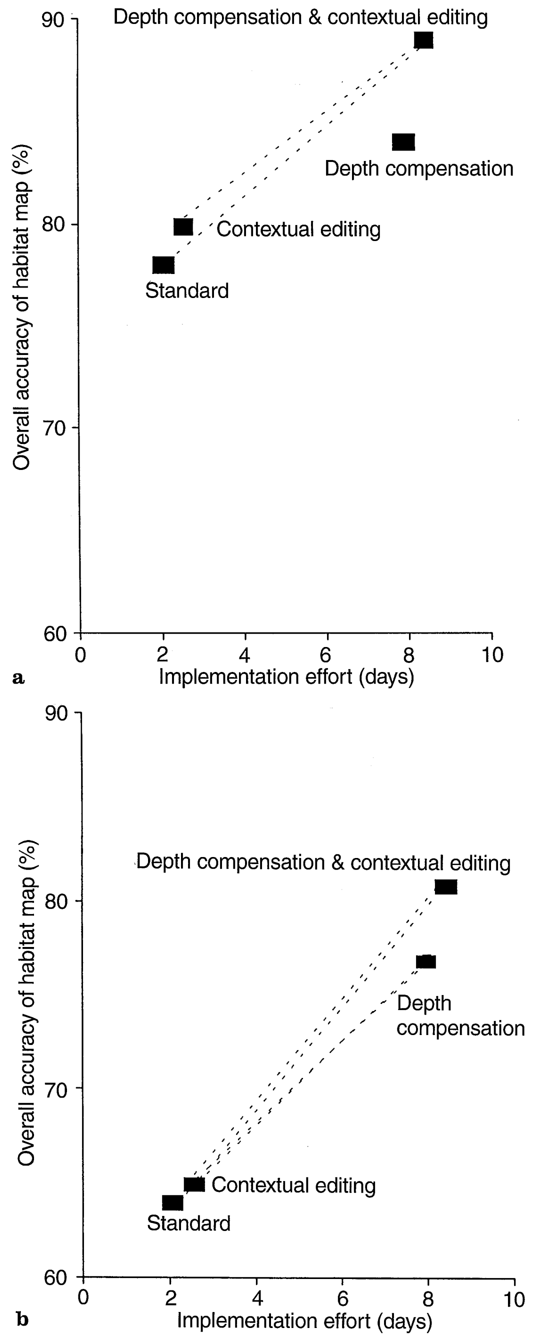

Fig. 3a, b Overall map accuracies from CASI showing different methods of image processing and the time required to implement them for the first time. Results are presented for **a** habitat maps with coarse descriptive resolution and **b** fine descriptive resolution. Dotted lines mark significant differences in accuracy (Z-tests, $P < 0.001$)

than satellite imagery of comparable habitats (Fig. 4a, b). The difference was more pronounced ($P < 0.001$) for finer descriptive resolutions (Fig. 4b) than for simply "corals, algae, sand, seagrass" (Fig. 4a). Figure 4 presents results of supervised classification without contextual editing because such editing may have disguised some of the limitations present in each sensor. The *Acropora palmata* class was too narrow (20 m) to resolve in satellite imagery and was excluded from the comparison with CASI imagery.

The relative accuracies of satellite sensors will be discussed in detail elsewhere. However, it is worth noting that the images with the greatest number of spectral bands fared better (i.e. Landsat TM and merged TM/SPOT Pan).

To what degree is CASI superior to aerial photography?

Sheppard et al. (1995) presented an error matrix for nine benthic habitats mapped using colour aerial photography from Anguilla. Eight of these habitats are virtually identical to those described in this study (at a fine level of descriptive resolution). The main differences are presence of a "bare sublittoral rock" category in Sheppard et al. (1995) and an additional soft coral class in the present study.

Taking the eight comparable habitats, the overall accuracy from aerial photography was 57% and that from CASI was higher at 81%. Using the Tau coefficient, the difference was found to be highly significant ($Z = 5.4$, $P < 0.001$).

Discussion

Maps of benthic habitats are useful for several reasons. In a planning context, a geographic coverage of habitats may be used to identify representative areas of the coastal zone (McNeill 1994) or for assessing patterns and hotspots of habitat diversity (Loehle and Wein 1994). This is becoming increasingly important since research is focusing on multiple scales including those of habitats and ecosystems (Levin 1992). Another important issue is measurement of habitat dynamics and disturbance effects on habitat coverage. Until benthic habitats can be mapped repeatedly and accurately, the detection of change will be confined to large scale phenomena such as seagrass die-off (e.g. Robblee et al. 1991) or mangrove deforestation (e.g. Chaudhury 1990).

The results presented here suggest that CASI is capable of mapping benthic habitat classes with a high level of accuracy (70–90%). While it is difficult to pin down a threshold accuracy requirement for successful habitat mapping, a general rule of thumb for remote sensing is approximately 65–70% (Clark *personal observation*). At coarse descriptive resolutions (coral, algae, sand, seagrass), the habitats were sufficiently dissimilar to one another (Bray-Curtis similarity, 10–15%) that depth invariant processing was not essential for habitat mapping (although it did make a minor improvement). However, at finer descriptive resolutions where inter-habitat similarity was high (Bray-Curtis

Table 2 Error matrix for benthic habitats showing user and overall map accuracies. Habitats represent the coarsest descriptive resolution of habitats which were chiefly determined from hierarchical classification of field data. CASI data were subjected to depth invariant processing, supervised image classification and post-classification contextual rules. Numbers represent 1 m pixels in the imagery

Habitat type	Reference data				
	Coral dominated	Algal dominated	Sand dominated	Seagrass dominated	Row total
Coral dominated	93		4	3	100
Algal dominated		22		2	24
Sand dominated	6		18		24
Seagrass dominated	1	4	2	45	52
Column total	100	26	24	50	200
User (%)	93	92	75	87	
Overall (%)	89				

Table 3 Error matrix for benthic habitats showing user and overall map accuracies. Habitats represent the finest descriptive resolution determined from hierarchical classification of field data. CASI data were subjected to depth invariant processing, supervised image classification and post-classification contextual rules. A full description of habitats is given in Table 4. Numbers represent 1 m pixels

Habitat type	Reference data									
	A. palmata	Soft corals and *Micro-dictyon* sp.	Soft corals and bare substratum	*Montastrea* spp. and bare substratum	*Lobophora* sp.	Sand	*Penicillus* spp. and *Halimeda* spp.	Seagrass low-medium standing crop	Seagrass high-medium standing crop	Row total
A. palmata	9	1								10
Soft corals and *Microdictyon* sp.	1	33	5	1					1	41
Soft corals and bare substratum		1	16			1		2		20
Montastrea spp. and bare substratum		2		24		3				29
Lobophora sp.					9		2			11
Sand		3	2	1		18				24
Penicillus spp. and Halimeda spp.					1		10	2		13
Seagrass low-medium standing crop			1		2	2	2	18		25
Seagrass high-medium standing crop								2	25	27
Column total	10	40	24	26	12	24	14	24	26	200
User (%)	90	81	80	83	82	75	77	72	93	
Overall (%)	81									

similarity, 60–80%), variable depth exerted a strong effect on accuracy and required compensatory processing. Whether the extra implementation time warrants a 12% rise in accuracy remains the practitioner's decision. It should be pointed out, however, that the implementation time specified here included understanding the theory and constructing the algorithms and that successive executions were much faster (i.e. half a day each).

Contextual editing only mildly improved the results from standard supervised classification. This is because standard processing of depth-dependent bands led to

Table 4 Description and characteristics of benthic habitats determined from hierarchical classification of field data (except "*A. palmata*" which was added later). Mean percent cover and densities are given based on replicate 1m quadrats

Summary title	Description and characteristic features
A. palmata	Living and dead stands of *Acropora palmata*
Soft corals and *Microdictyon* sp.	Bare substratum (40%), low soft coral density (3 m^{-2}), *Microdictyon marinum* (30%), *Lobophora variegata* (12%)
Soft corals and bare substratum	Bare substratum (80%), medium soft coral density (5 m^{-2})
Montastrea spp. and bare substratum	Bare substratum (60%), high soft coral density (8 m^{-2}), *Lobophora variegata* (14%), high live coral cover (18%) of which ~9% is *Montastrea* spp.
Lobophora sp.	*Lobophora variegata* (76%) and branching red/brown algae (9%)
Sand	Sand and occasional branching red algae (< 6%)
Penicillus spp. and *Halimeda* spp.	Dense colonies of calcareous algae –principally *Penicillus* spp. (55 m^{-2}) and *Halimeda* spp. (100 m^{-2}). Some *Thalassia testudinum* of low standing crop
Seagrass low-medium standing crop	*Thalassia testudinum* and *Syringodium filiforme* of standing crop 5–80 $g.m^{-2}$
Seagrass high-medium standing crop	*Thalassia testudinum* and *Syringodium filiforme* of standing crop 80–280 $g.m^{-2}$

many inaccuracies which could not be corrected for with contextual rules (i.e. the locations of errors were not predictable). Once several of these inaccuracies were removed by depth invariant processing, contextual editing was highly beneficial. The impact of contextual editing was similar for both levels of descriptive resolution because the rules sought to correct misassignments of seagrass and reef classes. These classes were independent from one another irrespective of the descriptive resolution employed.

Seagrass of low standing crop, calcareous green algae and sand were difficult to identify using the CASI bands selected in this study. We suggest that future work examines the spectral characteristics of these habitats with a view to improving the configuration of CASI.

Given that the CASI had great spatial and spectral resolution, it was not suprising that CASI yielded significantly better results than satellite imagery; we have made similar observations for mangrove habitat mapping (Green et al. in press). Of greater interest was how the disparity between CASI and satellite accuracy varied with descriptive resolution. The greatest disparity occurred for fine descriptive resolution which indicated that satellites were particularly ineffective at that scale. The spatial resolution of CASI was identical to the sampling units used to describe marine habitats (1 m^2 quadrats) whereas the spatial resolution of satellites is considerably larger and apparently inappropriate for distinguishing reef habitats. In addition, the limited spectral resolution of satellites reduces the sensors' ability to distinguish similar-looking habitats. Unfortunately, the relative importance of these limitations is difficult to model. The spatial element requires an understanding of habitat patchiness at different spatial scales (see Wiens 1989). Changes of patchiness with scale infer fractal geometry (Sugihara and May 1990) but fractal measures of *habitat pattern* have not been calculated for coral reef environments. Fractals can be measured from habitat maps (Sugihara and May 1990) and a more detailed examination of habitat patchiness will be reported at a later date.

Progress is being made to identify the electromagnetic spectra of corals and reef habitats (Hardy et al. 1996). This is being carried out using boat-based spectro-radiometers but airborne methods such as the Airborne Visible Infrared Imaging Spectrometer (Richardson et al. 1994) and deployment of CASI in spectral mode are also required. Quantification of reef spectra offers two principal advantages. First, knowledge of the spectra of target habitats will allow users to make a more informed selection of CASI bands. CASI offers great spectral versatility but this cannot be fully utilised unless an *a priori* expectation of spectra is available. Second, spectral classification of CASI data may become better automated or guided through reference to spectral libraries, conceivably to the exclusion of a field work requirement. Another major avenue of remote sensing research for coral reef assessment is the deployment of airborne laser for measurement of fluorescence spectra in different reef communities (Hardy et al. 1992, 1996). This may prove useful for monitoring coral/algal cover and bleaching events (Hardy et al. 1992).

CASI compared favourably to the results obtained by Sheppard et al. (1995) using 1:10 000 colour aerial photography. However, the comparison was not entirely balanced. Although the habitat categories were comparable, Sheppard et al. (1995) mapped a much larger area than that tested here (14 600 ha versus 100 ha). Whilst CASI was found to be significantly better at mapping benthic habitats, it is perhaps safest to

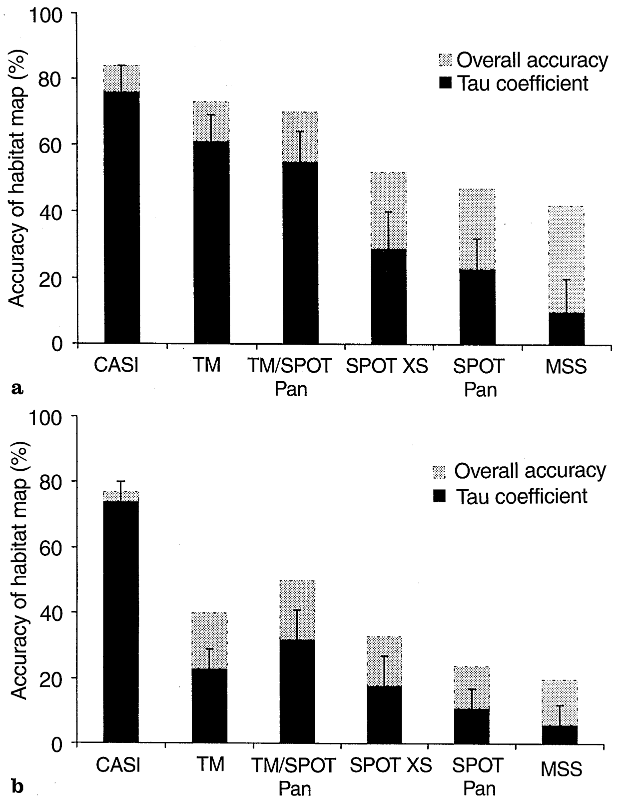

Fig. 4a, b Accuracies of habitat maps derived from CASI and satellite-borne sensors. Two levels of descriptive resolution (habitat discrimination) are presented: **a** coarse and **b** fine. The *upper part* of *each bar* represents the overall accuracy, and the *lower* (*solid*) part, the Tau coefficient and its upper 95% confidence limit. *TM*, Landsat Thematic Mapper; *SPOT XS*, Systeme Probatoire de l'Observation de la Terre, Multispectral; *TM/SPOT* Pan, merged Landsat TM and SPOT Panchromatic; *MSS*, Landsat Multispectral Scanner

conclude that for comparable areas, CASI would be at least as good as aerial photography.

As a practical tool for mapping at high resolution, the relative merits of CASI and aerial photography require closer inspection. While photographs offer greater spatial resolution than CASI, making use of this resolution is not straightforward. It is highly unlikely that a photo-interpreter would delineate features smaller than several metres because to do so would be too time consuming. This statement is borne out in the trace illustrated by Sheppard et al. (1995) in which the minimum polygon size was probably several metres or more. In contrast, polygon size does not constrain a digital classification of pixels. Thus, the spatial resolution of CASI may, in effect, be finer than the practical resolution of aerial photography. In addition, the delineation of habitats is likely to be both faster and more objective. It would be interesting to make an explicit evaluation of this issue, i.e. how does efficiency of each method vary with area covered? Further, it would be useful to compare the effectiveness of digital remote sensing (i.e. CASI) and thematic classification of photographs which have been digitised using a scanner. Scanned aerial photographs have been used successfully for mapping small areas (Thamrongnawasawat and Hopley 1995; King et al. 1996). A similar argument may be made for the new generation of digital cameras which are capable of taking images in a few broad spectral bands. Theoretically, however, CASI would be expected to fare better because of its greater spectral resolution (up to 16 spectral bands available to distinguish habitats).

The issues raised beg the wider question of cost-effectiveness. Given different user requirements, habitat types, operating expenses, technical facilities and expertise, what is the most cost-effective approach for a particular objective? In assessing the cost-effectiveness of remote sensing, it is important to compare fixed and marginal costs. For example, aerial photography of small areas may be less expensive than satellite imagery but in countries where survey aircraft are unavailable, high mobilisation costs for imported aircraft may alter cost-effectiveness dramatically (Kam et al. 1992). A detailed analysis of cost-effectiveness is in preparation but commercial quotes for making a digital map of the Caicos Bank (15 000 km^2) provide a benchmark. Map production using 1:10 000 colour aerial photography would cost £160 000 which is twice as expensive as CASI (£81 000 based on 3 m spatial resolution in 12 bands). Mapping with Landsat TM would cost approximately £5000 although high descriptive resolution would not be possible (overall accuracy $< 50\%$). CASI would be the most cost-effective solution for detailed habitat mapping and for coarse descriptive resolution, the cost-effectiveness of Landsat TM would be 16 times greater than CASI and 32 times greater than aerial photography.

The technical constraints and key considerations prior to using CASI have been discussed elsewhere (e.g. Jupp et al. 1993; Green et al. 1996; Mumby et al. 1997). In the context of the present study, it is worth emphasising that successful deployment of CASI requires careful project planning, and readers are directed to these other publications for further details.

Although habitat types vary throughout the Caribbean region, the results presented here should represent the capability of CASI for mapping Caribbean fringing reefs, seagrasses and macroalgal habitats. 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, shallower depths exhibit reduced light attenuation which would logically favour deployment of CASI. The most fundamental limitation to the use of CASI for benthic habitat mapping is high water turbidity. Horizontal Secchi distance at a depth of 0.5 m in the Turks and Caicos Islands is of the order of 30–50 m. At present, it is not possible to give a threshold turbidity with which CASI will be ineffective. Continued experimentation with CASI elsewhere and developments in radiative transfer modelling may shed light on this issue in future. In the absence of such information, we point out that Tassan (1996) has described a depth invariant model for water of greater turbidity than specified by Lyzenga (1981).

In conclusion, CASI is capable of accurately mapping benthic reef habitats providing that the water is sufficiently clear (i.e. >20 m horizontal Secchi distance). For detailed benthic mapping, CASI is the most cost-effective approach examined here, but wider uptake of the technology will depend on the cost-benefits of obtaining quantitative mapped information on reef habitats. Since the emergence of such data is relatively new, we predict that the role of CASI as a monitoring tool for coastal environments will grow considerably over the next decade.

Finally, this study requires a temporal context. The CASI sensor and associated software are continually being refined and the results presented here will undoubtedly be outdated in the near future, such is the pace of remote sensing development.

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