INT. J. REMOTE SENSING, 1998, VOL. 19, NO. 1, 203–210

Benefits of water column correction and contextual editing for mapping coral reefs

P. J. MUMBY†, C. D. CLARK†, E. P. GREEN‡
and A. J. EDWARDS‡

†Sheffield Centre for Earth Observation Science and Department of Geography, University of Sheffield, Sheffield S10 2TN, England, U.K.

‡Centre for Tropical Coastal Management Studies, Department of Marine Sciences and Coastal Management, University of Newcastle, Newcastle upon Tyne NE1 7RU, England, U.K.

(*Received 19 March 1997; in final form 17 June 1997*)

Abstract. Classification accuracy of coral reefs can be increased significantly by compensation for light attenuation in the water column and contextual editing to account for generic patterns of reef distribution. Both processes are easily implemented and collectively constitute an accruement in accuracy of 22 per cent for airborne multispectral imagery (CASI) and up to 17 per cent for satellite sensor imagery, for each extra days effort using the technique (up to maximum accuracies of 89 and 73 per cent respectively).

1. Introduction

One of the most commonly cited difficulties with remote sensing of underwater environments is the confounding influence of variable depth on bottom reflectance (Cracknell *et al.* 1987, Green *et al.* 1996). Removal of the influence of depth on bottom reflectance would require (*i*) a measurement of depth for every pixel on the image, and (*ii*) a knowledge of the attenuation characteristics of the water column (e.g., concentrations of dissolved organic matter). Good digital elevation models of depth are rare, particularly for coral reef systems where charts are often inaccurate (but see Zainal 1994). As a compromise, Lyzenga (1978, 1981) put forward a simple image-based approach to compensate for the effect of variable depth when mapping bottom features (hereafter referred to as water column correction). Rather than predicting the reflectance of the seabed, the method produces a depth invariant bottom index from each pair of spectral bands. The attractive aspect of this approach is that *in situ* or ancilliary data are not required. Spitzer and Dirks (1987) used a two-flow radiative transfer model to predict the sensitivity of the model to bottom depth and water quality and concluded that increased turbidity was a major limiting factor. More recently, Tassan (1996) modified the model to extend its validity to waters of greater turbidity.

Surprisingly, Lyzenga's model (1981) has not been widely adopted as a pre-processing step for the remote sensing of tropical coastal waters which often satisfy the exponential attenuation requirements of the model (Mumby *et al.* in press). Reviewing relevant papers, we found that only four studies out of forty five (9 per cent) had attempted water column correction which may reflect a general unawareness of these methods on the part of reef scientists. From a practical perspect-

0143–1161/98 $12.00

ive, this prompted us to ask what benefits, in terms of thematic map accuracy, should accrue from water column correction and whether the extra processing time is cost-effective?

Similarly, contextual editing has not been widely adopted for digital remote sensing of coral reefs despite terrestrial studies such as Groom *et al*. (1996) which have demonstrated that contextual editing can improve map accuracies where the landscape can be segmented according to predictable decision rules (e.g., area A favours cover type 1 but not cover type 2). Since coral reefs often exhibit predictable geomorphological and ecological zonation with gradients of depth and wave exposure (Huston 1994), contextual editing should substantially improve the accuracy of coral reef habitat maps.

This letter evaluates the practical effects of water column correction and contextual editing for mapping Caribbean coral reefs with satellite and airborne multispectral data.

2. Methods

Satellite images were acquired for the Turks and Caicos Islands, British West Indies (figure 1). Image acquisition dates were June 1992 for Landsat MSS, November 1990 for Landsat TM and March 1995 for SPOT-XS and SPOT Pan. All data were subjected to basic image processing which involved full radiometric and atmospheric correction (Tanré *et al*. 1990) and geo-coding. Images were geo-coded to Ordnance Survey maps (series E8112 DOS 309P) using a first order transformation and nearest neighbour resampling (to avoid changing pixel data). Geo-coding was conducted prior to supervised image classification so that field data could be located on imagery and used to develop spectra. Data from the Compact Airborne Spectrographic Imager (CASI) were obtained in July 1995 around the island of South Caicos (see Clark *et al*. 1997, Mumby *et al*., in press). To examine the sensors' ability to discriminate different levels of habitat detail (i.e. their descriptive resolution), field data were arranged into a hierarchical categorisation. For satellite imagery, coarse, intermediate and fine habitat discrimination corresponded to 4, 8 and 13 reef habitats respectively. CASI imagery was confined to a smaller area and only coarse and fine levels of descriptive resolution were used (4 and 9 reef habitats respectively; for details see table 1 and Mumby *et al*. in press). Up to 180 visited field sites were used to direct supervised classification of imagery using the maximum likelihood decision rule. The depth of field sites varied from 0·5 m to 18 m.

2.1. *Water column correction*

Compensation for variable depth was accomplished using the model derived by Lyzenga (1978, 1981) for clear water. The model 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 (X_i and X_j). First, the relationship between radiance and exponential attenuation with depth was linearised (equation (1)). Second, the ratio of attenuation of coefficients (K_i/K_j) was determined from a bi-plot of transformed radiance in the two bands (L_i and L_j). The bi-plot comprised data from a bottom of uniform substratum (sand) but variable depth (equation (2)). A depth invariant band was created using equation (3). For a fuller explanation, readers are directed to Lyzenga's papers.

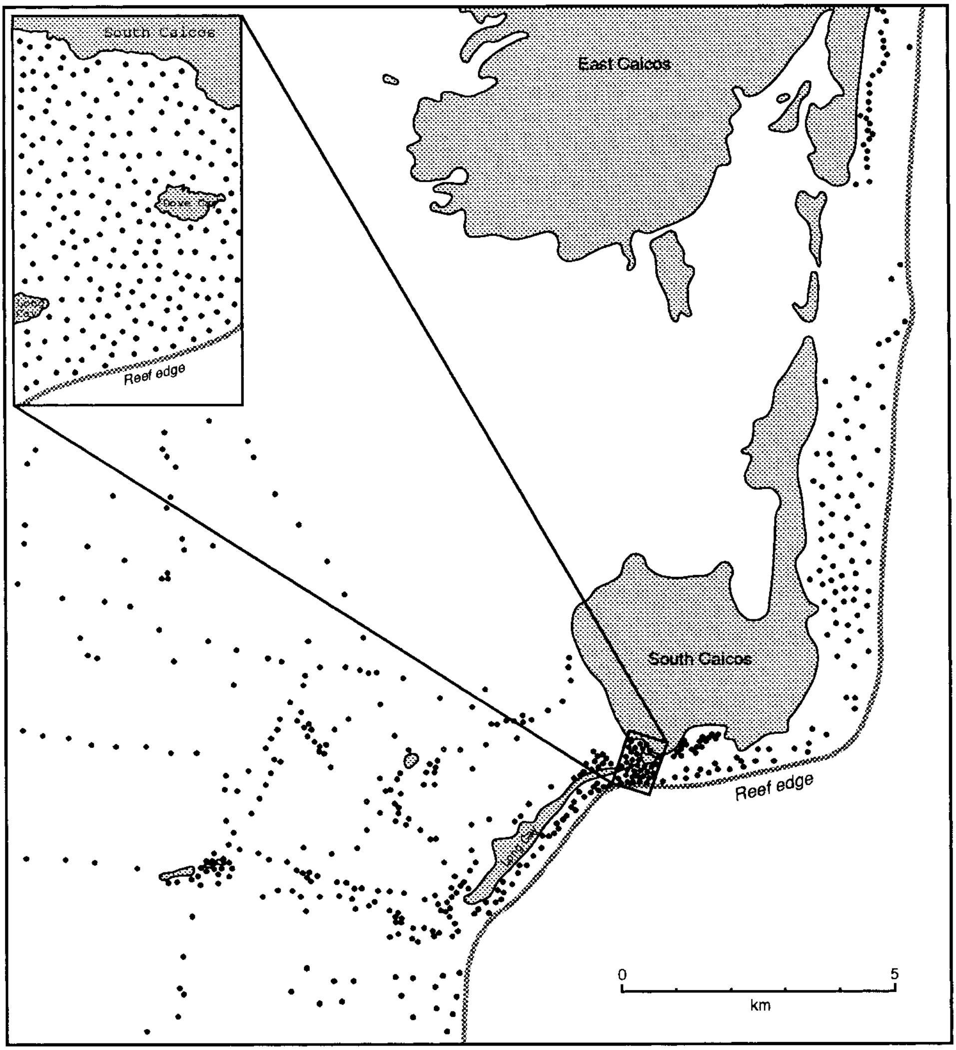

Figure 1. Study area in the Turks and Caicos Islands (British West Indies) showing the locations of all field sites. CASI was flown across Cockburn Harbour (inset).

$$X_i = \ln(L_i) \tag{1}$$

$$K_i/K_j = a + \sqrt{(a^2+1)} \text{ where } a = \frac{\sigma_{jj} - \sigma_{ii}}{2\sigma_{ij}} \text{ and } \sigma_{ij} = \overline{X_i X_j} - \bar{X}_i \bar{X}_j \tag{2}$$

$$\text{depth invariant band}_{ij} = \ln(L_i) - \left[\left(\frac{k_i}{k_j} \right) \ln(L_j) \right] \tag{3}$$

Six depth invariant bands were created for CASI and three for Landsat TM. SPOT XS and Landsat MSS only allowed production of single depth invariant bands because only two of their spectral bands penetrate water adequately. Water column correction could not be carried out for SPOT Pan since it only has a single monochrome band. Given the turbidity of water at the study site (horizontal Secchi

Table 1. Habitat types of the Caicos Bank showing three levels of descriptive resolution, fine (F), intermediate (L) and coarse (C) for satellite and airborne. The habitats present in the CASI imagery are identified separately.

	Class assignment no.			
Description and characteristic features	F	L	C	casi
Living and dead stands of *Acropora palmata*				1
Microdicyton 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%)	2	2	1	2
Bare substratum (80%), medium soft coral density (5 m^{-2})	3	2	1	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.	4	2	1	4
Lobophora variegata (76%) and branching red/brown algae (9%)	5	3	2	5
Sand and occasional branching red algae (<6%)	6	4	3	6
Amphiroa spp. (40%), sand (30%), encrusting sponge (17%), sparse *Thalassia testudinum* and calcareous green algae	7	5	2	
Thalassia testudinum of low standing crop (5 g m^{-2}) and *Batophora* spp. (33%)	8	6	3	
Thalassia testudinum of low standing crop (5 g m^{-2}) and sand	9	6	3	
Medium dense colonies of calcareous algae—principally *Halimeda* spp. (25 m^{-2}). *Thalassia testudinum* of medium standing crop (∼80 g m^{-2})	10	7	3	
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})	11	7	2	7
Thalassia testudinum and *Syringodium filiforme* of standing crop 5–80 g m^{-2}	12	8	4	8
Thalassia testudinum and *Syringodium filiforme* of standing crop 80–280 g m^{-2}	13	8	4	9

distance at a depth of 0·5 m ranged from 20 m–50 m), correction was possible where the depth of the water column was between 1 m and 16 m.

2.2. *Contextual editing*

Classification results were edited to take account of generic patterns of habitat distribution (i.e., although some misclassification of habitat categories is inevitable on the classified image, it was possible to recode some misclassified areas to the correct habitat category based on their context in the reef system). For example, pixels which classified as seagrass but were clearly present on the forereef slope, were reclassified to the appropriate reef categories. Similar recoding was carried out for fringing reef pixels which had been incorrectly classified as calcified rhodophytes with sponge (the latter habitat was confined to more sheltered lagoon environments).

The effectiveness of water column correction and contextual editing was evaluated by measuring the improvements to habitat map accuracy. The accuracies of habitat maps were determined rigorously using up to 600 independent survey points and described using two complementary measures: (*i*) the overall agreement in the error matrix (i.e., percentage of correctly labelled reference sites), and (*ii*) the Tau coefficient,

T, which permits hypothesis testing and accounts for chance agreement within an error matrix (Ma and Redmond 1995).

3. Results and discussion

3.1. *Classification on original bands with no contextual editing*

Habitat map accuracies were lowest for this level of image processing (figure 2 (*a*)) irrespective of the descriptive resolution.

3.2. *Water column correction*

Water column correction of CASI imagery made a significant ($p<0{\cdot}01$) improvement to maps with fine habitat discrimination (figure 2 (*b*)). At this descriptive resolution, inter-habitat similarity was high (Bray-Curtis Similarity, 60–80 per cent) and variable depth exerted a strong effect on accuracy such that water column correction improved accuracy by 13 per cent. At coarse descriptive resolutions (coral, algae, sand, seagrass), the habitats were sufficiently dissimilar to one another (Bray-Curtis Similarity, 10–15 per cent) that depth invariant processing was not essential for habitat mapping (although it did make a minor (6 per cent) improvement).

Map accuracy was significantly ($p<0{\cdot}01$) improved for Landsat TM at coarse and intermediate descriptive resolutions. Water column correction was not significantly beneficial for sensors which produced a single depth invariant band (SPOT-XS and Landsat MSS). Supervised classification of a single band is limited because the statistical separation of habitat spectra is confined to one dimension. Therefore, whilst depth invariant processing of SPOT-XS and Landsat MSS data may have reduced the effects of variable depth, it did so at the expense of the number of spectral bands available to the classifier (i.e., dimensions of the discriminant function). Landsat TM and CASI were amenable to depth invariant processing because three and six depth invariant bands were available for supervised classification. It seems that when only two spectral bands are available from which to derive a single depth invariant band, the loss of a dimension to the classifier more than outweighs the benefit of correcting for variable depth. This conclusion is undoubtedly site specific and may not hold in areas where variation in bathymetry is much greater. However, the study site is considered to be fairly representative of Caribbean fringing reef and bank systems.

3.3. *Contextual editing*

To ensure that contextual editing does not create bias or misleading improvements to map accuracy, the decision rules must be applicable throughout an image and not confined to the regions most familiar to the interpreter. The simplest of these for coral reefs is the presence/absence of coral/seagrass habitats on the fringing reef. Spectral confusion between these habitats was greatest in Landsat MSS and SPOT Pan which had the poorest spatial and spectral resolutions respectively. Consequently, thematic maps from these sensors showed the greatest improvements in accuracy (figure 2 (*c*)). The capability of Landsat TM was improved for coarse-level habitat mapping but more detailed maps were unaffected. Accuracies derived from SPOT-XS and CASI were not significantly affected by contextual editing in the absence of water column correction.

3.4. *Water column correction and contextual editing*

When combined, depth compensation and contextual editing made a significant ($p<0{\cdot}01$) improvement upon simple classification of original bands (6–23 per cent; figure 2 (*d*) and (*a*). The combined approach was collectively more accurate than the implementation of water column correction or contextual editing alone (although the improvement was not always significant). The relative importance of depth compensation and contextual editing varied between sensors. Habitat maps from Landsat-TM and CASI benefited from depth invariant processing whereas Landsat-MSS was more amenable to contextual editing. Accuracies from SPOT-XS showed the greatest improvement when depth compensation *and* contextual editing were used together. This resulted from a change in inter-habitat misclassification which was brought about by water column correction. Prior to water column correction,

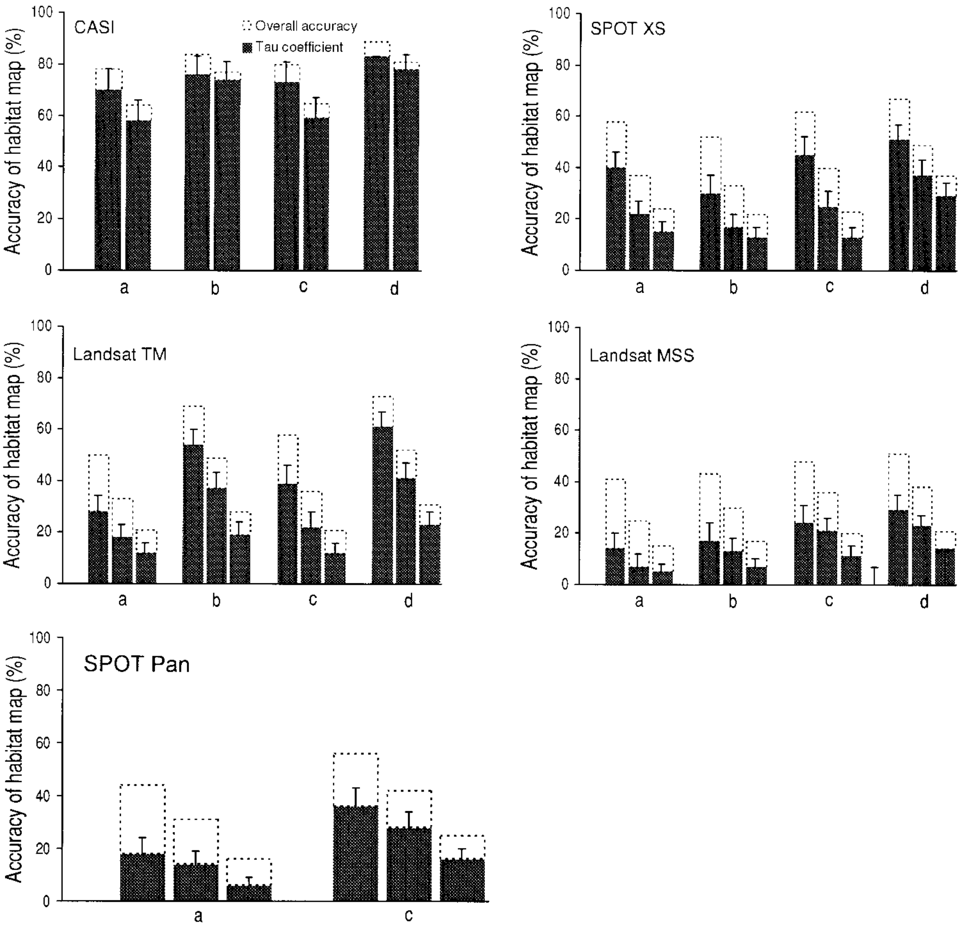

Figure 2. Effect of image processing methods on the accuracy of coral reef habitat maps. Results shown for various satellite sensors and the Compact Airborne Spectrographic Imager, CASI. Overall accuracies and the Tau coefficient (with upper 95 per cent confidence interval) are displayed for appropriate levels of descriptive resolution (see text). (*a*) Data are presented for basic image processing, (*b*) the addition of water column correction, (*c*) the addition of contextual editing and (*d*) the addition of both water column correction and contextual editing.

Table 2. Summary of processing steps for habitat mapping showing the total implementation time (days) and the % gain in overall accuracy per days processing effort. % accuracy gains for satellites are averaged across relevant sensor types. Rates are expressed for coarse (C), intermediate (L) and fine (F) descriptive resolution.

		% Accuracy accrued per day	
		CASI	Satellite sensors
Processing method	Time taken (h)	C, F	C, L, F
Basic	3	26, 21	16, 11, 6
Water column correction	3+1/2	24, 22	16, 11, 7
Contextual editing	3+1/4	24, 20	17, 12, 7
Water c.c. & contextual e.	3+3/4	24, 22	17, 12, 8

sand habitats showed considerable confusion with other habitats. Since water column correction was optimised for sand, implementation of the correction algorithm resulted in improved mapping of sand habitats but confusion between coral and seagrass spectra increased (presumably because of the dependency on a single depth invariant band). Therefore, whilst overall accuracy was not improved by water column correction, the predominant classification error changed to coral verses seagrass which permitted subsequent contextual editing to make a significant improvement to accuracy ($p<0{\cdot}05$).

3.5. *Cost-effectiveness*

Refinements to simple classification may be considered cost-effective if the additional investments in time are justified by improved map accuracy. Since thematic map accuracy is finite, continued effort will inevitably reach a stage where the accuracy pay-off declines and extra effort provides diminishing returns. The increase in percentage accuracy accrued per effort day from water column correction and contextual editing remains high (table 2) and on the premise set out above, it seems that both processing steps are cost-effective.

Acknowledgments

This research was funded by the Environment Research Programme of the Department for International Development. We are grateful to the Turks and Caicos Islands' Ministry of Natural Resources for their logistical assistance during fieldwork. Ariel Geomatics Incorporated are thanked for their dedication to the CASI component and Angie Ellis is acknowledged for her untiring assistance in the field.

References

Clark, C. D., Ripley, H. T., Green, E. P., Edwards, A. J., and Mumby, P. J., 1997, Mapping and measurement of tropical coastal environments with hyperspectral and high spatial resolution data. *International Journal of Remote Sensing*, **18,** 237–242.

Cracknell, A. P., Ibrahim, M., and McManus, J., 1987, Use of satellite and aircraft data for bathymetry studies. *Proceedings of 13th Annual Conference of the Remote Sensing Society, University of Nottingham* (Nottingham: Remote Sensing Society), 391–402.

Green, E. P., Mumby, P. J., Edwards, A. J., and Clark, C. D., 1996, A review of remote sensing for the assessment and management of tropical coastal resources. *Coastal Management*, **24,** 1–40.

Groom, G. B., Fuller, R. M., and Jones, A. R., 1996, Contextual correction: techniques for improving land cover mapping from remotely sensed data. *International Journal of Remote Sensing*, **17,** 69–89.

Huston, M. A., 1994, *Biological diversity: the coexistence of species on changing landscapes* (Cambridge: Cambridge University Press).

Lyzenga, D. R., 1978, Passive remote sensing techniques for mapping water depth and bottom features. *Applied Optics*, **17,** 379–383.

Lyzenga, D. R., 1981, Remote sensing of bottom reflectance and water attenuation parameters in shallow water using aircraft and Landsat data. *International Journal of Remote Sensing*, **2,** 71–82.

Ma, Z., and Redmond, R. L., 1995, Tau coefficients for accuracy assessment of classification of remote sensing data. *Photogrammetric Engineering & Remote Sensing*, **61,** 435–439.

Mumby, P. J., Green, E. P., Clark, C. D., and Edwards, A. J., in press, Reefal habitat assessment using (CASI) airborne remote sensing. *Proceedings of the 8th International Coral Reef Symposium, Panama, June 1996*.

Spitzer, D., and Dirks, R. W. J., 1987, Bottom influence on the reflectance of the sea. *International Journal of Remote Sensing*, **8,** 279–290.

Tanré, D., Deroo, C., Dahaut, P., Herman, M., and Morcrette, J. J., 1990, Description of a computer code to simulate the satellite signal in the solar spectrum: the 5S code. *International Journal of Remote Sensing*, **11,** 659–668.

Tassan, S., 1996, Modified Lyzenga's method for macroalgae detection in water with non-uniform composition. *International Journal of Remote Sensing*, **17,** 1601–1607.

Zaiwal, A. J. M., 1994, WEW Technique for enhancing the detection and classification of shallow marine habitats. *Marine Technology Journal*, **28,** 68–74.