Enhanced detection of the coral *Acropora cervicornis* from satellite imagery using a textural operator

Samuel J. Purkis a,*, Soe W. Myint b, Bernhard M. Riegl a

a National Coral Reef Institute, Nova Southeastern University Oceanographic Center, 8000 N. Ocean Drive, Dania Beach, FL 33004, USA
b Department of Geography, Arizona State University, Tempe, AZ 85287-0104, USA

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Abstract

The strength of a texture-based classification lies in the fact that it detects spatial patterning as a function of spectral variation within a particular facies class, as opposed to spectral consistency which drives standard probability-driven image classifiers. Following this premise, the Moran’s *I* spatial autocorrelation metric was proven to return values which differed significantly for areas characterised by dense interlocking thickets of the coral *Acropora cervicornis* versus areas populated by a sparse mixed coral assemblage dominated by *Montastrea annularis*. The different behaviour of the metric was sufficient to facilitate spatial discrimination of the two assemblages using a supervised classifier with accuracies that surpass the level of prediction offered by standard spectral-based methods. Discrimination was optimum when autocorrelation was evaluated within a moving window with side-lengths ranging between circa. 30–70 m. The discrimination ability is postulated to be linked to intrinsic differences in the spatial-patterning of the two assemblages at scales of tens of metres. The observed patterning can be further related to the growth form and architecture of the differing coral assemblages. The study demonstrates the potential of using kernel-based autocorrelation metrics in unison with satellite data and offers a pertinent tool for monitoring ecologically important coral assemblages that are statistically indistinct using traditional spectral methods.

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1. Introduction

The traditional method for analysis of earth observation data in landscape-research is the classification of eco-types based on pixels in the same land cover class being close in spectral feature space (Burnett & Blaschke, 2003). Similarly in traditional remote sensing of reefal areas, from-image statistics are used to train a probability-driven classifier such that pixels of similar optical properties are assigned to a common class. The technique is effective in the majority of cases since different benthic types frequently display separable optical signatures (Hochberg et al., 2003a; Karpuzli et al., 2004; Purkis, 2005; Purkis & Pasterkamp, 2004). However, the probability-driven approach fails when the desired substrate classes are spectrally inseparable, as is frequently the case when observed with today’s multispectral satellite systems.

While sensors such as IKONOS offer metre-scale satellite imagery, they remain spectrally impoverished and are hence not well adapted for coastal seabed mapping. Furthermore, due to the multiple scattering of natural optical radiation an effective path of a photon in seawater is rather large, insuring high sensitivity of upwelling radiation to the content of dissolved and suspended substances in water (Haltrin et al., 2002). Consequently in optically shallow waters where the majority of corals reside, separating the spectral contribution of the seafloor from that of the water column is problematic and further compromises the accuracy of benthic classification. The contribution of the water column can be successfully modelled and removed using a radiative transfer (RT) approach (e.g. Deepak et al., 2005; Hedley & Mumby, 2003; Isoun et al., 2003; Purkis, 2005; Riegl & Purkis, 2005). When confined to multispectral satellite data, the RT strategy however is limited by the fact that water depth throughout the area of interest must be accurately constrained with a high spatial resolution, and as such, the solution is largely precluded in areas lacking ancillary...
bathymetric data. For this reason several recent studies neglect automated image classification in favour of expert visual interpretation of satellite data and/or aerial photography combined with semi-automated spectral or morphological operators (e.g., Andréfouët & Guzman, 2005; Diaz et al., 2000; Franklin et al., 2003). While it is now clear that visual interpretation can return accuracies comparable to, and in some cases exceeding, those levied by probability driven classifiers, there undoubtedly remains a niche for automated classification in areas which are too extensive and therefore prohibitively time consuming to manually digitise.

Autocorrelation denotes a method to study similarity/dissimilarity of pixel values, a property that has the potential to be substrate specific, providing that seabed patterning can be used as a proxy for benthic cover. Positive autocorrelation implies that proximate observations take on similar values, while negative values indicate high variance over small spatial scales. The use of wavelet transform algorithms in the characterization of texture features in remotely sensed images of terrestrial landscapes has been proven effective (Myint, 2003; Myint et al., 2004; Wang et al., 2004). Similarly, in the shallow marine environment the use of texture-based algorithms for facies discrimination has been deemed to be of value in coral habitats (Holden et al., 2001) and applied successfully in the context of the detection of temporal change in reef homogeneity (Dustan et al., 2001; LeDrew et al., 2004). This experiment builds on the premise that important substrate types may be spectrally similar but retain distinct autocorrelation properties by virtue of a systematic variance in albedo at a discrete spatial scale (e.g., Atkinson & Lewis, 2000; Holden et al., 2001). In this respect, spatial autocorrelation is a possible candidate for the separation of important substrate types when more traditional optical-based techniques have failed. This paper investigates whether the problem of optical inseparability can be circumnavigated using the textural component of an imaged landscape as a signal with which to discriminate between branching and massive coral assemblages. The area under investigation is of particular importance as it likely represents one of the largest remaining Caribbean populations of the coral Acropora cervicornis, a species that is presently listed as a candidate for the Endangered Species Act (Bruckner, 2002).

2. Methods

2.1. Study area

The island of Roatán (Fig. 1) is situated ~55 km off the south coast of mainland Honduras and has been the focus of numerous studies of coral status (Deepak et al., 2005; Fonseca, 1997; Keck, 2000, 2004; Keck et al., 2005; Maeder et al., 2002). Roatán is the largest of the Bay Islands with an area of 12,740 ha, and is surrounded by an extensive fringing reef system. Like many of the Caribbean islands, Roatán is undergoing rapid development to accommodate a surge in tourism, with reef-based nature-tourism comprising the dominant market-share (e.g., Luttinger, 1997). In concert with the rise in visitor numbers has been an increased exploitation of the reef systems, combined with concurrent degradation of the resource. Development has been particularly rapid on the north coast of the island where the relative proximity of the shore to deep water is attractive for recreational dive operators. The Smith and Cordelia banks are part of a single bank-reef system that rises out of deep water (>150 m) ~2 km off the end of the airport’s landing strip, situated on the south-western tip of Roatán. Lying on the windward side of the island, high winds, rough seas, and strong currents render the reef-system inaccessible for much of the year and therefore anthropogenic impact is limited to a few local fishermen and dive operators. Initially described by Keck et al. (2005) it is clear that both Smith and Cordelia banks are unique in the fact that they are characterised by dense and well developed thickets of the branching coral A. cervicornis, unrivalled in size as compared to that presently observed in the wider Caribbean region. Prior
to the mid 1970s, the branching corals *Acropora palmata* and *A. cervicornis* accounted for more than 30–50% of the total coral cover to a depth of 20 m in the Caribbean (Aronson et al., 2002; Gardner et al., 2003; Goreau, 1959). By the early 1980s the coral zonation pattern dominated by these coral species had essentially disappeared on many, if not most, of the Caribbean's reefs (Aronson & Precht, 2001; Bythell & Sheppard, 1993; Bruckner, 2002; Jackson, 1992), with the decline attributed to a combination of white-band disease, temperature stress, predation and hurricanes. Given the catastrophic Caribbean-wide decline of *A. cervicornis*, the occurrence of large and dense, mono-specific thickets of the species on the Smith and Cordelia banks is relevant to the coral’s continued persistence. It is plausible that this area represents one of the largest remaining populations of *A. cervicornis* in the Caribbean and thus maybe a critical spawning source of propagules which could allow this species to repopulate reef communities in the region.

Fieldwork was conducted over Smith and Cordelia banks 15–25th October 2004 for the purpose of ground verification. A total of 200 spot-checks were dived from a boat at semi-regular intervals across the study area, without a priori knowledge of substrate distribution. The position of each check was constrained using a differentially corrected global positioning system (dGPS) and substrate coverage was recorded to the lowest possible taxonomic level at each site. Substrate character of the seabed was estimated for each point using a digital photograph of a 1 x 1 m quadrat, which was later analysed using standard image processing routines to retrieve a percentage estimate of benthic cover. The corals in the area could be partitioned into two distinct assemblages (Fig. 2). Hereafter termed the “dense acroporid assemblage”, this consisted of extensive dense interlocking thickets of live *A. cervicornis* with occasional colonies of *A. palmata* and *Agaricia tenuifolia*. Average coverage of *A. cervicornis* exceeded 80% of the available substrate. A second grouping was characterised by patchy cover dominated by *M. annularis*, *A. tenuifolia* and occasional *Porites porites*, interleaved with sandy hardgrounds and hereafter is referred to as the “sparse mixed assemblage”. Average coverage of live corals in this assemblage was less than 50%. In addition to the two coral dominated assemblages, three broad non-coral classes were defined to encompass the remaining benthic diversity:

i) A rubble assemblage consisting of a rampart of semi-consolidated to consolidated coral rubble bound by calcifying algae and perceived to be a storm deposit.

ii) A groove assemblage corresponding to grooves of several metres in relief characterised by extensive deposits of carbonate sand and semi-consolidated coral rubble. Isolated and occasional sparse *M. annularis* and *Siderastrea siderea* colonies. Live coral cover <1%.

iii) A hardground assemblage representing a class of very sparse coral cover particularly dominant in deeper areas and frequently associated with sloping sandy hardgrounds. Cover dominated by *M. annularis* carpets with live coral cover <5%.

### 2.2. Image processing

The IKONOS image used in the study was acquired 29th December 2003 under favourable conditions with low water turbidity and cloud cover. The data were purchased with full 11-bit radiometric resolution and were acquired with solar azimuth and elevation angles of 153° and 45°, respectively. The image was radiometrically calibrated using the coefficients of Peterson (2001) to retrieve at-sensor radiance. The imagery was further corrected for atmospheric effects using the Fast Line-of-Site Atmospheric Analysis of Spectral Hypercubes (FLAASH) software package in ENVI (by Research Systems Inc.). FLAASH incorporates MODTRAN4 radiative transfer code and in addition to atmospheric absorption and scattering, models and corrects for adjacency effects. FLASH output is scaled irradiance reflectance that scales to irradiance reflectance in the case of Lambertian surfaces. The image was moderately compromised by surface effects in shallow areas where wave action accentuated sunglitz to a degree where the seabed was partially obscured. Prior to further processing, the glint-removal algorithm of Hochberg et al. (2003b) was employed to correct for the wave-induced specular reflection, which successfully delivered a largely glint-free image (cf. inset Fig. 2). Areas of deep water (circa. >15 m) were masked using a spectral threshold and were not processed further. Prior to textural analysis, the pixels identified during ground-truthing to belong to each of the five defined community-types were extracted and analysed for spectral separability in the first three bands of the IKONOS data (Fig. 3). The ground-truth data were subsequently partitioned into two groups, the first was used for the purpose of classifier training and the second, for accuracy assessment of classification products.

### 2.3. Detection of spatial autocorrelation

A conventional univariate measure of spatial autocorrelation is Moran’s (1950) *I* statistic which ranges between −1.0 and +1.0 depending on the degree and direction of correlation within the sample. Band 1 of the IKONOS data, centred at 480 nm is optimised for retrieval of benthic character because its short wavelength affords a high degree of water column penetration. For this reason, band 1 was targeted for textural analysis using Moran’s *I* spatial autocorrelation index. Moran’s *I* was calculated according to Myint et al. (2004) using the formula:

\[
I(d) = \frac{\sum \sum W_{ij} C_{ij}}{S^2 \sum \sum W_{ij}}
\]

where \( W_{ij} \) is the weight at distance \( d \) so that \( W_{ij} = 1 \) if point \( j \) is within distance \( d \) from point \( i \); otherwise, \( W_{ij} = 0 \); \( C_{ij} \) are deviations from the mean (i.e., \( C_{ij} = (Z_i - \bar{Z}) (Z_j - \bar{Z}) \)), where \( \bar{Z} \) is the mean brightness value in the local window. \( S^2 \) is the mean of the major diagonal of \( C_{ij} \). Moran’s *I* varies from +1.0...
for perfect positive correlation (a clumped pattern) to $-1.0$ for perfect negative correlation such as would be returned for a checkerboard pattern, while values close to zero indicate no autocorrelation (as would be returned by a random pattern of pixel brightness) (Legendre & Legendre, 1998). A worked example showing the step by step calculation of $I$ for a $2 \times 2$ pixel kernel is given in Fig. 4.

A local window of variable size was moved throughout the whole image and used to calculate Moran’s $I$ index according to Myint et al. (2004). By iteratively increasing the dimension of the window, autocorrelation was assessed over a range of spatial scales. The index was calculated for window sizes of $5 \times 5$ through $25 \times 25$ pixels, which equates to windows of length 20 m through 100 m, with an increment of 8 m (i.e. 11 iterations in total). It should be noted that the window edge-length was always an odd number of pixels since the computed autocorrelation value is assigned to the centre pixel of the local moving window (e.g. Fig. 5). However, if the local window size is $w \times w$ and the autocorrelation value is assigned to the centre of the local window (i.e. at $(w+1)/2$th pixel position) and the window is moved throughout the image, we will lose $(w-1)/2$ pixels on the top, bottom, left, and right side of the image. To combat this artefact we used mirror extension of $(w-1)/2$ pixels around the image prior to initiating the

Fig. 2. True-colour IKONOS image of the Smith and Cordelia bank-reef system corrected for radiometric and atmospheric effects. Inset shows the image prior to correction for surface effects (Hochberg et al., 2003b). Red dots indicate the position of ground-verification points and an overview of the spatial distribution of the ecologically important (though optically inseparable) “dense acroporid” and “sparse mixed” coral assemblages is provided. For clarity not all observations are graphed. The relative size of the 11 moving-window sizes with edge lengths spanning from 20 to 100 m within which the Moran’s $I$ spatial autocorrelation index was calculated is shown for comparison.
computation. The algorithm was designed to automatically extend the boundary of the image with \((w - 1)/2\) pixels if the selected window size is \(w\). Hence, the size of the extended image was \((\text{original image size} + (\text{window size} - 1))\). Mirror extension is to copy the second-last row or column and add next-to-last row and column, respectively. Then, copy the third-last row and column and add the next to the second-last row and column, respectively, and so on depending on the number of rows and columns required for extension (Myint, in press). It should be noted that this extension is executed only during the computation process and the output image has the same number of rows and columns as the original image. An example illustrating the original image, extended image, local moving window, and assignment of Moran’s \(I\) value in the local window is presented in Fig. 5.

If significant positive autocorrelation exists, pixels with similar optical characteristics can be inferred to be present within the window. Conversely, if spatial autocorrelation is weak or non-existent, adjacent pixels within the window have dissimilar spectral values. Multiple window sizes were tested in order to ascertain the optimum distance over which \(I\) should be calculated in order to best capture the textural component of the target benthic classes.

The spatial patterning within the image could be investigated to determine whether texture is indeed substrate specific.

The discriminate ability of the raw textural transform imagery was tested through classification using a supervised Mahalanobis classifier trained using regions of interest of known benthic cover extracted from the ground-truth data.

Classification was completed for each window size over Cordelia and Smith banks and accuracy statistics were generated against one hundred ground-verification points that had not been used for classifier training. We subsequently used a combination of two spectral and a single textural transform bands to generate optical–textural layer composites (e.g. Wang et al., 2004). The blue and green spectral bands were retained in all cases because they offer the highest degree of penetration into the water column. For all window sizes the textural bands were layered with the blue and green bands and classified into 5 classes using the Mahalanobis algorithm. Both the atmospherically corrected visible bands and the textural data were normalised to values spanning zero and one, so as to ensure that both data types were assigned equal weighting in the classification.

For comparison between classifications we used the producer’s accuracy which as a measure of omission error, indicates how well training set pixels of a cover type are classified. Next, considering that the
raw image was compromised by surface effects (wave induced glint) the degree to which Moran’s $I$ was sensitive to these artefacts was assessed. The comparison is important because imagery of remote reef areas is often scarce and therefore sub-optimal data is more commonly utilised as compared to terrestrial studies. Lastly, a test was implemented to ascertain whether the textural data showed evidence of stability in areas of variable depth. If this was the case, textural analysis would hold a distinct advantage over traditional optical classifiers which are impeded when depth effects are not corrected for (e.g. Purkis & Pasterkamp, 2004).

3. Results

Through analysis of the spectral signature of the ground-truthed pixels, the dense acroporid and sparse mixed assemblages were shown to overlap significantly (Fig. 3) resulting in a consistently low-level of classification accuracy (Fig. 8c) — producer’s accuracy <60% in both cases). The objective of autocorrelation characterisation is to identify spatial structure that is unique to a particular facies type. Ideally differences in spatial structure would allow separation of patches that are indistinguishable in conventional spectral space. In this case, the ecologically important dense acroporid and $M. \text{ annularis}$ dominated sparse classes are spectrally inseparable and proof that they could be identified texturally would be relevant to future detection of $A. \text{ cervicornis}$ using IKONOS. The separability of the two target substrate assemblages on the basis of the Moran’s $I$ autocorrelation index (Fig. 6) varies with window size. At a window size of 20 m, both the dense acroporid and mixed corals assemblages return strong negative values of $I$ and are inseparable at the 95% confidence interval. With a window size of 36 m, the acroporid assemblage is characterised by negative values but the sparse mixed coral assemblage displays a pronounced departure to positive autocorrelation with the result that the two classes are distinct and statistically separable. The assemblages remain distinct until a window size of 68 m, beyond which both the acroporid and mixed sparse coral classes return values of $I$ close to zero (broken vertical line Fig. 6), indicating spatial randomness in the patterning of pixel values. As the values of autocorrelation converge towards zero for the larger window sizes, the assemblages become inseparable at the 95% confidence interval. contour plots of the spatial distribution of Moran’s $I$ (Fig. 7) further reveal differences in the performance of the index with varying window size. As identified in Fig. 6, increasing window size returns a shift from negative to positive values of Moran’s $I$. At 20 m extent, the majority of the bank is characterised by values of negative autocorrelation interspersed with discrete zones of local-strong positive autocorrelation. A predominance of negative values persists for window sizes up to 52 m at which point the index is ubiquitously positive and still punctuated with limited areas of high correlation (Moran’s $I \approx 1$). At the smaller window sizes, the negative departure of the index is to be expected as pixel heterogeneity at scales of 3 to 5 pixels (12–20 m) is clearly evident in the true-colour image of the area (Fig. 2). At larger spatial scales, pixel variation is clearly more homogeneous and correspondingly values of positive autocorrelation are returned for larger window sizes. Regardless of window size the zones characterised by high autocorrelation values are located in areas occupied by sand fields infilling the larger groove systems on the deeper portion of the bank (cf. Fig. 2). Conversely, negative values are preferentially situated in areas of high rugosity which during ground-truth were shown to be characterised by live coral cover. The findings show that irrespective of window size, sand-filled groove structures are distinct from optically more complex areas in terms of their textural component, but this is also the case for a standard classification of a true-colour image (Fig. 3).

The results from the supervised classification of single band Moran’s $I$ data (Fig. 8a) reveal that window sizes spanning 28 – 60 m return highest accuracy in the discrimination of the acroporid and mixed coral classes. The outcome therefore supports the statistical analysis (Fig. 6) which correspondingly showed that at the 95% confidence interval these two classes were only separable between the same window sizes. Highest accuracy is attained using a window size of 36 m, where coral dominated areas visited during ground-verification were correctly identified with accuracies of 90% and 72% for $A. \text{ cervicornis}$ and $M. \text{ annularis}$, respectively. For window sizes exceeding 60 m, the producer’s accuracy falls to levels of approximately 60% for the two classes.

The three non-coral classes (Fig. 8b) similarly show a varying level of prediction accuracy with increasing window size. Reacting in a similar manner, the groove and rubble assemblages show maximum accuracy (>70%) for window
sizes of 20–60 m, followed by an incremental decrease in accuracy for window sizes up to 100 m. The pattern is similar to that of the two coral assemblages and is to be expected considering that the groove systems are associated with coral dominated spurs and therefore react on a comparable spatial scale. In contrast, the hardground assemblage is predicted poorly (accuracy <55%) using a window of size 20–44 m, yet accuracy increases rapidly for window sizes >44 m, attaining accuracies >70% for all window sizes up until 100 m. The finding is consistent with the assumption that the hardground assemblage is consistently found in deeper waters than the spatially limited spur and groove system and is typically expansive, operating over scales of hundreds as opposed to tens of metres.

A hybrid classification was tested by combining the Moran’s I textural image with the blue and green spectral bands to form a layered texture–optical composite (Fig. 8c) for the detection of the two target coral classes. The composite imagery was normalised between zero and unity and again classified using the Mahalanobis algorithm. The accuracy returned from the composite data was less variable than when only Moran’s I was considered, such that the producer’s accuracy exceeded 50% in all cases apart from the very largest window sizes. As with the single-band classifications the highest accuracy was found for window sizes 28–60 m but the prediction of *M. annularis* dominated areas was marginally higher when the spectral data were included in the composite. For the majority of window sizes the composite classifications perform better than when only three spectral bands are considered (horizontal grey lines, Fig. 8c), indicating that the textural data is a positive addition to the classification process. For all window sizes exceeding 84 m, this is not the case for the mixed *M. annularis* class where the composites return lower producer’s accuracies than the spectral classification. For identification of *A. cervicornis* thickets, prediction remains slightly higher than that offered spectrally, but becomes sub-optimal when the window size reaches 100 m. The results suggest that the larger window sizes introduce noise that is detrimental to the identification of the target coral classes.

For classifications conducted using 3 spectral bands and 3 band spectral-textural composites, derived from imagery that had not been corrected for surface-effects (Fig. 2, inset), accuracy was sub-optimal for all window sizes and therefore is not presented. For aquatic remote sensing, examples of scene specific noise characteristics include atmospheric variability,
effects from the air–water interface such as swell, wave and wavelet-induced reflections, and refractions of diffuse and direct sunlight (Brando & Dekker, 2003; Wettle et al., 2004). In this study, sun-glint arising from specular reflection off faceted wave fields strongly skewed the Moran’s $I$ index, masking substrate-specific patterns and forcing a global-shift to negative autocorrelation values (by virtue of increased heterogeneity of pixel values). For this reason, robust correction of surface effects would seem a critical precursor to textural analysis. As confirmed by this study and that of LeDrew et al. (2004), this is unlikely to limit the usefulness of the technique because the algorithm offered by Hochberg et al. (2003b) was shown in both cases to be capable of retrieving an image that in its raw state seemed largely compromised by surface effects.

4. Discussion

Investigation into separability (Fig. 6) and classification accuracy (Fig. 8) clarifies that window size influences the degree to which the textural operator can be used to discriminate between areas occupied by dense acroporid coral forms and the more sparse mixed assemblage. The result is logical under the assumption that autocorrelation should remain constant once sufficient pixels are included within the window to summarise the textural component of the facies in question. When the window size reaches a point where it is large enough to straddle a class boundary, a mixed signal will be returned and discrimination ability will rapidly decrease. For this reason and as indicated by the prediction accuracy of the non-reefal classes (Fig. 8b), the optimum window size for separation is likely to be substrate specific because different benthic classes are typically characterised by unique patch-sizes and geometry. This was clearly demonstrated to be the case in the Arabian Gulf (Purkis et al., 2005), where different benthic cover types were shown to display different patch-size distributions as well as unique patch-boundary patterning. It is also clear that since window size is critical to class separation, then the appropriate size for the target substrate must be known.
a priori if textural analysis is to be of value. This is a conceivable limitation to the technique and requires further investigation into whether spatial patterning is site-specific by class, else if global rules can be derived (i.e. valid for several reef or facies types). The step is beyond the scope of this paper but should be addressed in the future.

In light of the fact that the optimum size of the moving window was derived to lie between 28 and 60 m for the identification of *A. cervicornis* and *M. annularis*, subsequent classification could be tuned to operate on data created using these window sizes. The synergy of spectral and textural bands into a composite dataset did not serve to elevate the accuracy with which the facies could be identified. The addition of spectral data is therefore superfluous, especially if the optimum kernel size for the target benthos has already been determined analytically else through field measurement of substrate patterning. Indeed, prediction of *A. cervicornis* with accuracies greater than 80% (as returned from single-band textural data) is sufficient for ecological analysis (e.g. Purkis & Riegl, 2005) and surpasses the capability reported for spectral-based classifiers used on IKONOS in comparable reef settings (Andréfouët et al., 2003; Maeder et al., 2002; Purkis, 2005).

With knowledge that Moran’s *I* is a useful statistic with which to identify branching versus massive coral assemblages, it is worthwhile postulating which mechanisms facilitate the separation. To detect the different spatial expression of the two coral assemblages at colony level would require a pixel of finer resolution that the 4 metres offered by IKONOS, let alone the smallest textural window employed in this analysis (20 m). Indeed, it is clear from the literature that coral growth forms are only separable at pixel sizes of centimetre to metre scale (i.e. at a spatial scale commensurate with the size of individual coral colonies) as offered by modern airborne platforms (e.g. Mumby et al., 2004). Clearly it is the textural expression of multiple colonies (i.e. the assemblage) that the Moran’s *I* index encodes and is significantly different (p = 0.05) between the areas dominated by branching (dense acroporid assemblage) and massive (sparse mixed) corals.

At assemblage-scale (i.e. tens of metres), spatial patterning is dependent on the growth form of the target coral since different structures order and space themselves with respect to their life cycle. *A. cervicornis* is possibly the fastest growing of all corals (linear growth rates can exceed 100 mm/year, Lewis et al., 1968; Shinn, 1976) and the species is able to rapidly monopolise available substrate to form a climax-community consisting of a dense inter-locking branching framework (e.g. Purkis & Riegl, 2005). Conversely, massive coral species such as *M. annularis* exhibit linear growth rates of only ~6–10 mm/year (e.g. Dodge et al., 1974). By virtue of its slow growth, *M. annularis* corals tend to form more isolated colonies interspersed with areas of bare substrate. This facilitates the settlement and growth of slower growing species, such as *P. porites* in the case of the sparse mixed coral assemblage. At scales of metres to hundreds of metres, the intrinsic spatial patterning of the assemblage dominated by *A. cervicornis* and that dominated by *M. annularis* is likely to be different.

In the case of the Smith and Cordelia bank system, the sparse mixed assemblage contains coral colonies (mostly *M. annularis*) interspersed with sandy low-relief hardgrounds. Being heterogeneous, this assemblage should return lower autocorrelation values than the dense interlocking growth form of the acroporid assemblage. However, this is clearly not the case (Fig. 6) as the acroporid assemblage is distinct in returning negative values of Moran’s *I*, indicating a departure from spatial randomness towards organised heterogeneity. Although this result may be counterintuitive, the patterning of the dense acroporid assemblage at scales of tens of metres is punctuated by discrete areas of collapsed *A. cervicornis* framework, likely caused by storm events. Such breaks in the otherwise homogeneous live interlocking framework is a plausible mechanism for the departure to negative autocorrelation and may explain why the assemblage differs texturally from the sparse mixed coral assemblage. In the latter case, heterogeneity arises by virtue of sand sheets interleaving between individual coral colonies which promotes ordered heterogeneity at metaseale, as opposed to tens of metres in the case of the acroporid framework. It should be noted that dense-interlocking acroporid frameworks can persist for many years after the corals have died because the structure is sufficiently robust to retain the carbonate skeleton in life-position (e.g. Purkis & Riegl, 2005). Moran’s *I* is likely to also be able to detect the spatial patterning associated with dead skeletons, but unlikely to be capable of separating live from dead without additional spectral information.

The strategy of classification adopted in this study is a ‘sensor-down’ approach, whereby autocorrelation and classification statistics are derived entirely from the image. Consequently, the results are inherently tied to the scene analysed and not relevant to imagery acquired at a later date and/or with a different sensor, even if environmental conditions are comparable. As with spectral data, *I* values could be incorporated into a ‘reef-up’ strategy (e.g. Purkis, 2005) and a spatial library tied to community types (i.e. analogous to a spectral library) could be populated. Using this library a classifier could be driven by the generic spatial properties of the benthos as opposed to the scene-specific variables used in this study. Such an approach is beyond the scope of this paper, but worthy of consideration for future work.

As outlined at the beginning of this essay, depth related filtering of electromagnetic energy serves to decrease the intensity of water leaving radiation to a level that can preclude the discrimination of optically similar substrates from orbit (e.g. Lubin et al., 2001). Attenuation also reduces the dynamic range of pixel values at depth as compared to shallow water areas, precluding the comparison of absolute autocorrelation values between depth zones. Correction for depth effects is best achieved with knowledge of bathymetry over the entire area of study (e.g. Deepak et al., 2005; Purkis, 2005), else using hyperspectral data sets (e.g. Mumby et al., 2004). The strength of a texture-based classification lies in the fact that it detects spatial patterning as a function of spectral variation within a particular facies class, as opposed to spectral consistency which drives standard probability-driven classifiers. It is a lack of
spectral consistency that inhibits accurate identification of constant substrate type over depth gradients. Without correction for depth effects, a substrate patch colonising sloping or complex topography is therefore split into multiple, spectrally different classes, which do not mirror the actual distribution of the ecotype.

For this study we lacked an independent constraint on bathymetry. The analysis showed that the ability of the Moran’s I index to discriminate between the target assemblages was not compromised by a lack of depth correction (there was no correlation evident between the depth of the ground-verification sites and their accuracy of prediction). Moran’s I therefore appears to hold promise as a largely depth-invariant index of spatial coverage. The study therefore supports LeDrew et al. (2004) who correspondingly report that textural algorithms are relatively uncoupled from depth changes. The mechanism with which this is achieved is likely to be related to the fact that while submergence serves to inflict a relative reduction of seabed albedo, the absolute pattern of inter-pixel variation particular to a given class is preserved. However, with seafloor depth and water column optical properties relatively consistent across the scene presented in this study, it is not possible to be definitive as to the depth dependence of the index.

To ascertain the true depth dependence of I to depth variation, a test was carried out on a 500 × 500 m section of imagery which contained significant variation in water depth associated with spurs and grooves, had extensive areal coverage of the five defined benthic cover types and contained a high concentration of both ground-verification data and depth soundings (Fig. 2 subset). Without an independent constraint on bathymetry, analysis of the imagery had to this point been conducted without correction for radiative transfer effects. However, this is obviously not the case for all potential studies and thus it is implicit to examine the sensitivity of the index to radiative transfer effects if the results are to hold meaning in a more global context.

As an initial test, the overall accuracy of a standard optical classification was compared to that returned by a Moran’s I textural transform using a window size of 36 m (deemed most appropriate for detection of the majority of classes). The imagery had been corrected for glint and atmospheric influence, but radiative transfer effects were not tackled, therefore pixel values were at the level of remote sensing reflectance just above the water/air boundary (\( R_{rs(z=0)} \)). Secondly, and following the empirical procedure of Stumpf et al. (2003), a bathymetric digital elevation model (DEM) was derived for the 500 m² test area. The coefficients of the derivation were tuned manually against 17 in situ soundings and the output predication varied with an RMS error of 0.4 m to known water depths. Using the empirically derived DEM as input, a radiative transfer solution (Purkis 2005; Purkis & Pasterkamp, 2004) was used to retrieve substrate reflectance (\( R_s \)) which is the reflectance of the seabed without the influence of the water column. The resulting image (perceived to be largely free of water column effects) was analysed using both the optically and texturally driven classifier. Lastly, in order to quantify the influence of variable bathymetry, water column effects were implicitly ‘forward’ modelled back into the imagery by inverting the model of Purkis & Pasterkamp (2004) (Fig. 9), but using a synthetic DEM constructed by adding the water depth model derived following Stumpf et al. to a synthetic depth ramp varying from 0 to 6 m across the diameter of the test image (Fig. 9). The result of this exercise was the addition of the optical effect of an artificial depth gradient across the study site, rendering pixel values in units of modelled remote sensing reflectance just above the water/air boundary (\( R_{rs(modelled)} \)).

\[
R_{rs(modelled)} = 0.54(R_0e^{-2kz} + (1 - e^{-2kz})R_w). \tag{1}
\]

As for the inverse model, the attenuation coefficient (k) of the water body was set to that of Jerlov water type I and the reflectance of optically deep water (\( R_w \)) was set to values experimentally determined in a comparable setting (Purkis, 2005). Water depth is denoted by z and a factor of 0.54 (Morel & Prieur, 1977) was applied to compensate for refraction at the water/air boundary. As before, the resulting image was analysed using both the optically and texturally driven classifier.

For the initial test case where the imagery was processed solely for glint and atmospheric effects (\( R_{rs(z=0)} \)) (Fig. 9), the optical and textural classification both yield similar overall accuracies of 58% and 61% for optical and textural, respectively. Upon processing for depth effects and the retrieval of substrate reflectance (\( R_s \)), the accuracy of the optical classification increases markedly (79%) while the textural classifier only increases by 1% to an overall accuracy of 62% for the five benthic classes. Working on spectral consistency within the 5 classes, the optical classification benefits from the correction of depth effects and therefore returns a higher accuracy. In contrast, the textural character of the seabed is largely unaltered by the correction for radiative transfer effects since the increase in reflectance for the pixel values is relative and therefore uncoupled from the output I value. The difference in behaviour of the two approaches is most stark when the imagery processed using the modelled depth ramp is considered. Here, the optical classification becomes unreliable (overall accuracy=31%) while the texturally based classifier returns only a slightly lower accuracy (52%) than observed in the previous two scenarios. The optical classification is understandably compromised as the imposition of the depth gradient greatly affects the spectral consistency of pixels of a similar class across the image, therefore preventing reliable assignment of pixels to classes during classification. The modelled depth ramp similarly alters the textural component of the imagery, yet the output autocorrelation image still contains sufficient textural difference between the five benthic classes to facilitate an acceptable classification. Assuming a constant seabed albedo of 40% \( R_s \) across the 500 m diameter of the image and by forward modelling a 6 m depth gradient onto it (as for the third case of Fig. 9), the added water column creates a 5% absolute variance in \( R_{rs(z=0)} \) across the 36 m diameter of the Moran’s I kernel used for the test.
The 5% variance in above surface reflectance caused by the synthetic bathymetric variation is less than the within-class textural variation caused by heterogeneity of seafloor albedo and/or heterogeneous surface and water column effects. However, if the kernel size is increased to 76 m, the variance in above surface reflectance attributed to the depth gradient exceeds 20% across the kernel (by virtue of the increased disparity in water depth across the kernel) and introduces variance of a magnitude great enough to disrupt any substrate specific autocorrelation response. Therefore, providing that the assigned Moran’s I kernel is significantly smaller than the scale of bathymetric variation within the scene, the textural operator is relatively uncoupled from depth changes and not compromised to the same degree as standard optical classifiers. However, the test also highlights the fact that if the kernel size and the spatial scale of bathymetric change are of a similar magnitude, the textural approach, as for the optical, is similarly compromised by varying depth. This imposes an important limitation to the use of texture as a tool for benthic classification and user’s must be aware that although a textural approach may outperform standard optical techniques in cases where radiative transfer effects cannot be tackled, the scale of bathymetric variation within the scene must be considered. An added complication is that as proven earlier in the paper, the optimum kernel size must relate to the intrinsic scale of patterning of the target benthos, which may be incompatible with the size of kernel required to minimise depth effects. In saying this, the textural approach in certain situations would seem to be a powerful tool if used in conjunction with knowledge of the scale of variation of the components influencing seafloor albedo.

Spatial autocorrelation also has potential to classify benthic character in non-spectral raster datasets such as marine topographic LIDAR (Light Detection and Ranging), such as demonstrated by Brock et al. (2001, 2004) who used seabed rugosity as a habitat proxy. Fractal metrics have also been used as a measure of spatial dependency in satellite data and used to drive classification in terrestrial habitats (e.g., Emerson et al., 1999; Jaggi et al., 1993; Myint, 2003). Purkis et al. (2005) showed that coral facies in the Arabian Gulf displayed substrate-specific fractal properties and postulated that this could be explored for habitat differentiation. As such, this manuscript is seen as a precursor to the exploration of a fractal based classifier for coral dominated habitats. As for Moran’s I, the fractal dimension can be assessed through a moving kernel of varying size (e.g., Myint, 2003).

In summary, Moran’s I was shown to have the potential to differentiate two ecologically important coral assemblages within an IKONOS image that could not be separated using a standard spectral-based classifier. Furthermore, sensitivity analysis showed the textural algorithm to be relatively uncoupled, and therefore insensitive to bathymetry, providing that the scale of depth variation is dissimilar to that of the heterogeneity of the targeted benthic classes. The finding highlights the potential of textural operators for coral monitoring when applied at ecologically meaningful spatial scales. We
postulate that different coral growth forms at sub-metre scale promote assemblage-specific patterning properties that can be detected at the scale of metres to decametres. A priori knowledge of the intrinsic geometry of the target coral assemblage and length scale of bathymetric variation is valuable in tuning the textural algorithm with respect to the selection of the optimum local-window size employed during computation.

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