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CORAL REEF ECOSYSTEM EVALUATION BASED ON SPATIAL AUTOCORRELATION OF MULTISPECTRAL SATELLITE DATA

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ABSTRACT

Rather than attempt to remotely identify specific benthic habitats with similar optical properties, a more appropriate use of available satellite technology may be to examine benthic homogeneity of a coral reef ecosystem with the hypothesis that a healthy reef will display great heterogeneity, but a dead algae-covered reef will be relatively homogeneous. Such an approach to ecosystem analysis could prove to be efficient with respect to time, human resources, and data storage, and would produce results that could be directly applied to a realistic management scheme with "minimal regrets". A measure of spatial autocorrelation, the Getis Statistic, used in a case study of SPOT imagery shows potential in evaluating the well-being of a coral reef ecosystem.

INTRODUCTION

Over the past decade, there have been increased efforts to establish better management and conservation measures to protect the diversity of the biologically rich areas of coral reefs and related benthic habitats. Remote sensing can be used as a management tool to map and monitor the geographic extent of coral reefs to a limited degree with available satellite imagery, given the spatial, spectral, radiometric and temporal resolution limitations. While currently available satellite sensors have global mapping and monitoring capabilities, the accuracy and precision attainable when applied to reef ecosystems is relatively low due mainly to the large pixel size and broad spectral bandwidths. Because of the deteriorating global state of coral reef and related benthic ecosystems, however, waiting for the ideal technology for accurate and precise imaging of submerged benthic habitats is not realistic.

Instead, there is a need to utilize the available imaging technology, assess the accuracy and acknowledge the limitations. SPOT HRV, Landsat TM and possibly

SeaWiFS data are viable options since they provide moderate spatial and spectral resolution in the visible wavelengths while covering large geographic areas at regular time intervals. The spectral resolution of these sensors is limiting if optically similar substrates, such as healthy coral and algae-covered surfaces, need to be discriminated due to the small number of broad wavebands, however little conclusive research has been conducted to examine the optimal spectral resolution requirements for bottom type detection (See Hardy et al., 1992; Myers et al., 1999; Holden and LeDrew, 1998 and 1999; Clark et al., 2000; Holden and LeDrew, 2000). Additionally, the spatial characteristics are limiting if small features, such as discrete coral heads, need to be definitively located since the pixel sizes are relatively large compared to the size of common coral reef features (techniques such as sub pixel feature identification could minimize this limitation). Similarly, satellite technology may not be appropriate if a high temporal resolution data set is required to examine rapid changes because of infrequent revisit times and cloud-cover issues. The alternative is to conduct (often prohibitively) expensive and logistically complex hyperspectral airborne surveys at a higher spatial, spectral and temporal resolution, which may not be operationally feasible in the developing regions in which coral reefs are found.

Analysis of *in situ* hyperspectral data has produced encouraging results in the discrimination of common and optically similar coral reef features such as healthy corals, bleached corals, sea grass, and algae-covered surfaces (Holden and LeDrew, 1998, 1999, 2000; Hardy et al., 1992; Myers et al., 1999; Clark et al., 2000), but at the present time, such high spectral resolution data is unavailable from a satellite platform. Furthermore, analysis of simulated coarse spectral resolution data reveals that the discrimination possible with hyperspectral reflectance is not possible with multispectral data (Holden and LeDrew, 2000).

An appropriate approach to using available satellite imagery to monitor coral reef ecosystems is the use of benthic homogeneity as indicated by spatial autocorrelation to evaluate the ecosystem (LeDrew et al, 2000). Spatial autocorrelation is defined as the situation where one variable (reflectance value of a pixel in this case) is related to another variable located nearby (surrounding pixels). Spatial autocorrelation is useful since it not only considers the value of the pixel (magnitude of reflectance), but also the relationship between that pixel and its surrounding pixels. Our hypothesis is that a healthy coral reef ecosystem will be heterogeneous, but a dead, algae-dominated coral reef will be relatively spatially homogeneous. This approach does not necessarily facilitate direct identification of substrate type, but it does allow for fast assessment of changes in ecosystem composition over a large geographic area if a time series of imagery is available. The results of such an approach utilizing currently available satellite technology may contribute to more effective management of coral reef resources.

The specific objective of this paper is to perform a case study using a local indicator of spatial autocorrelation (the Getis Statistic) based on SPOT imagery of Bunaken National Marine Park, North Sulawesi, Indonesia. This case study is performed to examine the feasibility of using measures of spatial homogeneity to evaluate benthic habitat. The accuracy of the Getis Statistic approach is estimated based on familiarity with the study site and field data collection during time of satellite image acquisition (1997 and 2000).

METHODS

Measures of spatial autocorrelation indicate the strength of the relationship between values of the same variables, and may be either global or local in nature

(Goodchild, 1986). Global measures provide a single value that indicates the level of spatial autocorrelation within the variable distribution, while local measures provide a value for each location within the variable distribution. Local indicators of spatial autocorrelation, such as the Getis statistic used here, are therefore able to identify discrete spatial patterns that may not otherwise be apparent by quantifying the spatial dependence between each pixel and a surrounding kernel of defined pixel dimensions (Wulder and Boots, 1998).

The Getis Statistic was first developed for application to point data, and has proven appropriate for identifying spatial "hotspots" (Getis and Ord, 1992). One form of the Getis statistic, G_i^*, has been modified and successfully applied to analysis of remotely sensed data at a range of spatial scales (Wulder and Boots, 1998; Derksen et al., 1998). The calculation of G_i^* using predefined window sizes surrounding a central pixel make it suitable for investigating the distance at which maximum spatial autocorrelation occurs. For its first application to remotely sensed imagery, Wulder and Boots (1998) provide a thorough description of G_i^*, and conclude that its ability to assess the strength of inter-pixel relationships, as well as the magnitude of spatial autocorrelation is valuable for digital image analysis. The equation for G_i^* is:

$$\frac{\sum_j w_{ij}(d)x_j - W_i * x}{s[W_i * (n - W_i *)/(n-1)]^{1/2}}$$

where $\sum_j w_{ij}(d)x_j$ is the sum of the variates within distance d of observation i (including i), W_i* is the count of the pixels within distance d of pixel i, x is the mean of the entire scene, s is the global standard deviation (entire scene), and n is the total number of pixels in the image.

The output values from the above equation can be interpreted similar to standardized Z scores. The largest G_i^* value for all distances (d) considered represents the maximum spatial autocorrelation. If the maximum G_i^* occurs when the window size is small (i.e. 3x3 pixels), then maximum autocorrelation covers a small area, but if maximum G_i^* corresponds to a large window size (i.e. 9x9 pixels), then maximum autocorrelation extends to a larger area. A cluster of high pixel values is represented by a large positive G_i^* value, while a cluster of low pixel values is indicated by a negative G_i^* value.

SPOT HRV imagery (August 1997 and July 2000) of Bunaken National Marine Park, North Sulawesi, Indonesia is used for the case study based on spatial autocorrelation. A common subset of a coral reef within the park was selected from the atmospherically corrected (ACORN Atmospheric Correction extension to ENVI) and georeferenced image for the case study corresponding to a region in which extensive fieldwork was performed. For each SPOT band, four distances were considered in the calculation of G_i*: d=1, d=2, d=3, and d=4, representing increasingly larger kernels or windows. These distances refer to window sizes of 3x3, 5x5, 7x7, and 9x9 respectively. The resultant G_i* values for each pixel are compared and the largest value retained to compile a Max G_i* image: the larges Gi* value for all distances represents the maximum spatial autocorrelation. A general overview of the spatial dependence characteristics of the data is provided by this Max G_i* image, which illustrates clusters of high and low digital numbers. Next, for each pixel, the distance at which the Max G_i* occurs is identified; for pixels where Max G_i* occurs at d=1, spatial dependence is local and the region can be considered heterogeneous, and for pixels where Max G_i* occurs at d>1, spatial dependence is not local therefore the region can be considered homogeneous.

RESULTS

Because identification of specific substrate type may not be the most appropriate and reliable use of available coarse spatial and spectral resolution satellite images, an alternative approach is needed to address the immediate problem of rapidly changing coral reef ecosystems worldwide to aid management of resources. The approach that is tested here is one based on spatial autocorrelation. The hypothesis is that a healthy reef will display relatively great spatial heterogeneity due to the diverse bottom types and benthic habitats, but an unhealthy coral reef will display spatial homogeneity if it is bleached or colonized by macroalgae. This indirect approach to evaluating the overall well being of coral reef ecosystems has the strength of allowing quick and straight forward change detection based on increasing or decreasing diversity/heterogeneity of bottom cover and is not reliant upon substrate identification.

For each band of the SPOT imagery, a series of calculations must be performed to use the Getis statistic to investigate the spatial autocorrelation within the region of interest. The first examination will be of the derived Max G_i* value, which is determined by finding the largest G_i* value among those calculated for the four distances (d=1, d=2, d=3, and d=4) for each pixel. This derived image is found by comparing G_i* for all kernels and assigning the largest value of G_i* to the central pixel of the kernel. A high Max Gi* magnitude indicates a cluster of high digital number values, while a low Max Gi* magnitude indicates a cluster of low digital number values. Max Gi* results for SPOT bands 1 and 2 of the 1997 and 2000 imagery of Bunaken Marine Park are shown in Figure 1 (SPOT band 3 is excluded due to its comparative inability to penetrate the water). The land is masked out of the subscene (shown in black in Figure 1) and not included in the calculations.

The largest G_i* value (i.e. Max G_i*) for all distances represents the maximum spatial autocorrelation such that a cluster of large positive Gi* values reveals high pixel values while a cluster of lower G_i* values reveals low pixel values. For both years, there is great homogeneity observed over the deep-water areas indicated by the extensive G_i* values of zero. There are observable clusters of relatively high G_i* values (G_i* > 37) indicating a conglomeration of high digital number pixel values; this area corresponds to a shallow water zone, which is often exposed at low tide and consists of highly reflective sand and dead coral debris. Surrounding the land mass is a zone of moderate G_i* values (20 < G_i* < 37) revealing areas of maximum spatial autocorrelation between midrange digital numbers; this zone contains healthy coral and a great diversity of benthic habitats.

The next step is to identify exactly which distance (*d*) produces the Maximum Gi*. If the Max Gi* is found at a small distance (d=1 kernel), then spatial dependence is local and similar values are found within close proximity. If Max Gi* occurs at a greater distance (d>1 kernel), then similar pixel values can still be found when larger distances are considered: the spatial dependence is not local. A single binary image for each SPOT band can be used to visualize the spatial autocorrelation (Figure 2). Interpretation of the images in Figure 2 reveals areas that have shifted from a relatively heterogeneous to a homogeneous surface as well as areas that have shifted from a relatively homogeneous to a heterogeneous surface. Examination of the "distance" images for SPOT band 1 reveals that the shallow coral reef area in the south west quadrant has experienced only a very slight shift from a relatively heterogeneous healthy reef to a more homogeneous algae-dominated reef, which is confirmed by our observations during field data collection in 1997 and 2000.

CONCLUSIONS

There are several limitations to the use of satellite imagery in monitoring submerged coral reef ecosystems, but given the rapid rate at which coral reefs are reportedly degrading, it is necessary to accept the errors and acknowledge the restrictions. Significant mixing of several different substrate types within the relatively large pixels of SPOT HRV images (20x20m) compounds the issue of classification inaccuracy. Other complicating factors include the effects of attenuation and multiple scattering from the overlying water column (Holden and LeDrew, In Press), refraction of light at the air-water interface, scattering and absorption in the atmosphere, and effects of the variable morphology of the substrate with respect to slopes and self-shading.

The interpretation of a derived spatial autocorrelation image based on the Getis Statistic is a simple matter of understanding the series of basic calculations. A measure of spatial autocorrelation, Gi*, is calculated for the central pixel of kernels of increasingly larger size; following this, a single image is compiled whereby for each pixel, for each band, the largest value of Gi* is assigned (Max Gi*). This image reveals the actual value of the Max Gi* for each pixel whereby the magnitude of Gi* provides the interpreter with information regarding the magnitude of reflectance of the particular cluster.

The final step in the process is to answer the question: at which distance, or kernel size, is the Max Gi* found? This information allows the interpreter to take the analysis one step further and determine if the spatial dependence is local or spatially extensive. The interpreter can determine the degree of spatial dependence based on the distance at which the Max Gi* is found such that if it is found when the kernel size is small (d=1) then dependence is local in nature, but if it is found with the kernel is large (d>1), then dependence is not as local and can be considered spatially extensive. This provides the information for the interpreter to infer if the degree of homogeneity or heterogeneity extends over a large or a small area. The main benefits of this approach are that it results in an increased dynamic range of pixel values; it creates an image in which the values are normally statistically distributed; and produces an easily interpretable image to be used as an effective visualization tool.

The case study utilizing readily available satellite imagery based on spatial autocorrelation has produced encouraging results. The next stage will be to operationally use change in spatial autocorrelation to evaluate management decisions within Bunaken National Marine Park, North Sulawesi, Indonesia. For example, zones of limited use have been defined for the park such as “No Take” and “Recreational Use” and it would be useful to know the extent to which these zones are aiding reef recovery or resulting in reef degradation. Significant logistical improvements will be made to the methodology once the approach is operational: (1) more thorough atmospheric correction using ENVI ACORN software; (2) water column correction using radiative transfer model Hydrolight 4.1 combined with rasterized bathymetric data and vertical optical water column measurements.

This approach to image analysis is appropriate for change detection such that the interpreter can determine (1) the degree of spatial autocorrelation (whether homogeneous or heterogeneous), and (2) the area affected (whether spatially extensive, or local in nature). Furthermore, the approach is superior to change detection based on magnitude of reflectance alone because of the value added information of spatial autocorrelation. A simpler approach to examining detection of heterogeneity versus homogeneity, such as variance based on a moving window, would be more useful to resources managers as it would be less time consuming and require less significant training. Our results using simple image variance are inferior to those using Getis because with Gi* we have the ability to examine both autocorrelation as well as magnitude of reflectance. This is an important additional source of information since a spatially cohesive patch of bright white sand could be discriminated from a spatially cohesive patch of dark algae-covered dead coral using magnitude of reflectance even if the degree of spatial autocorrelation is similar.

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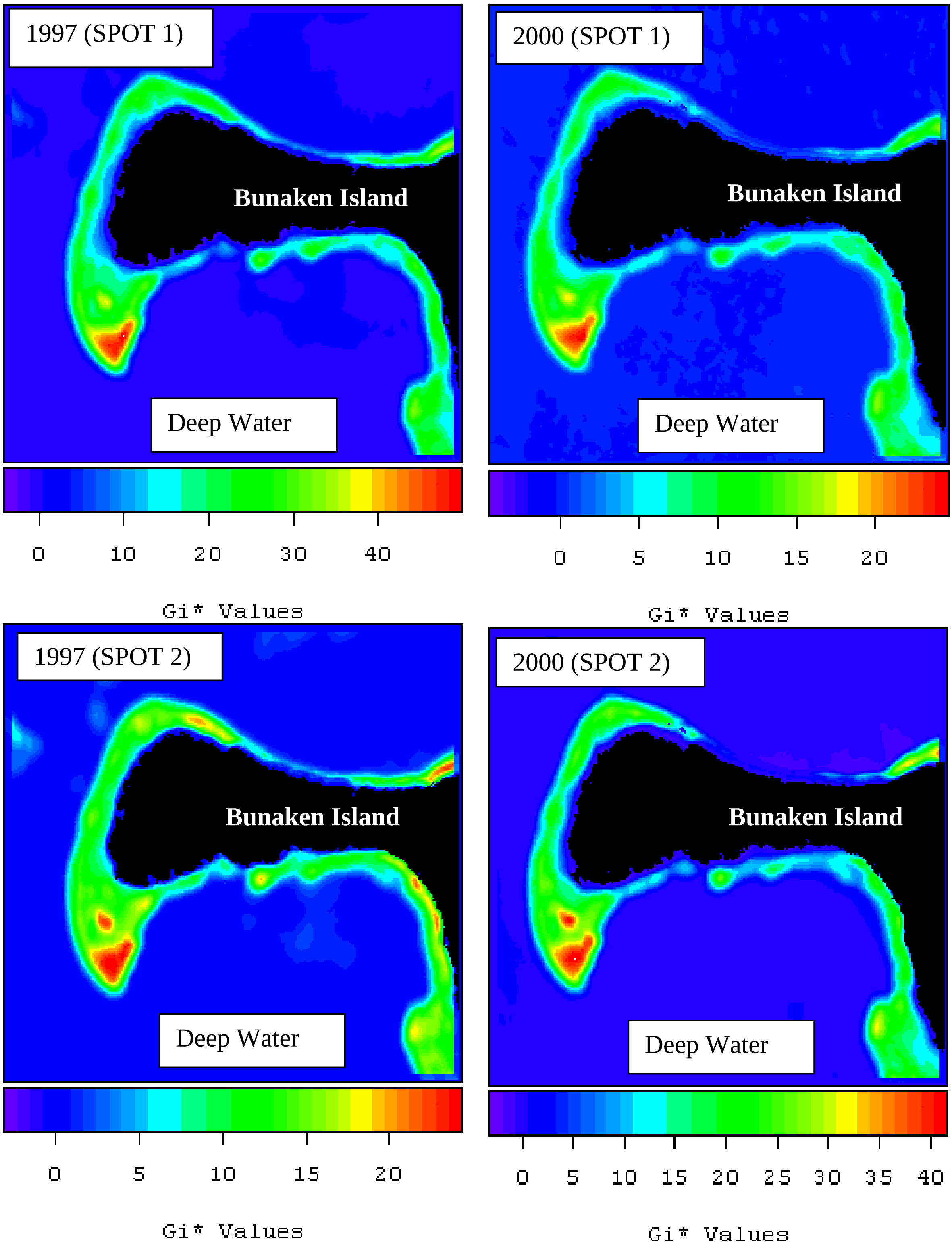

Figure 1. Maximum G_i* images for SPOT bands 1 and 2 in 1997 and 2000. The size of this SPOT image subset is 256x256 pixels.

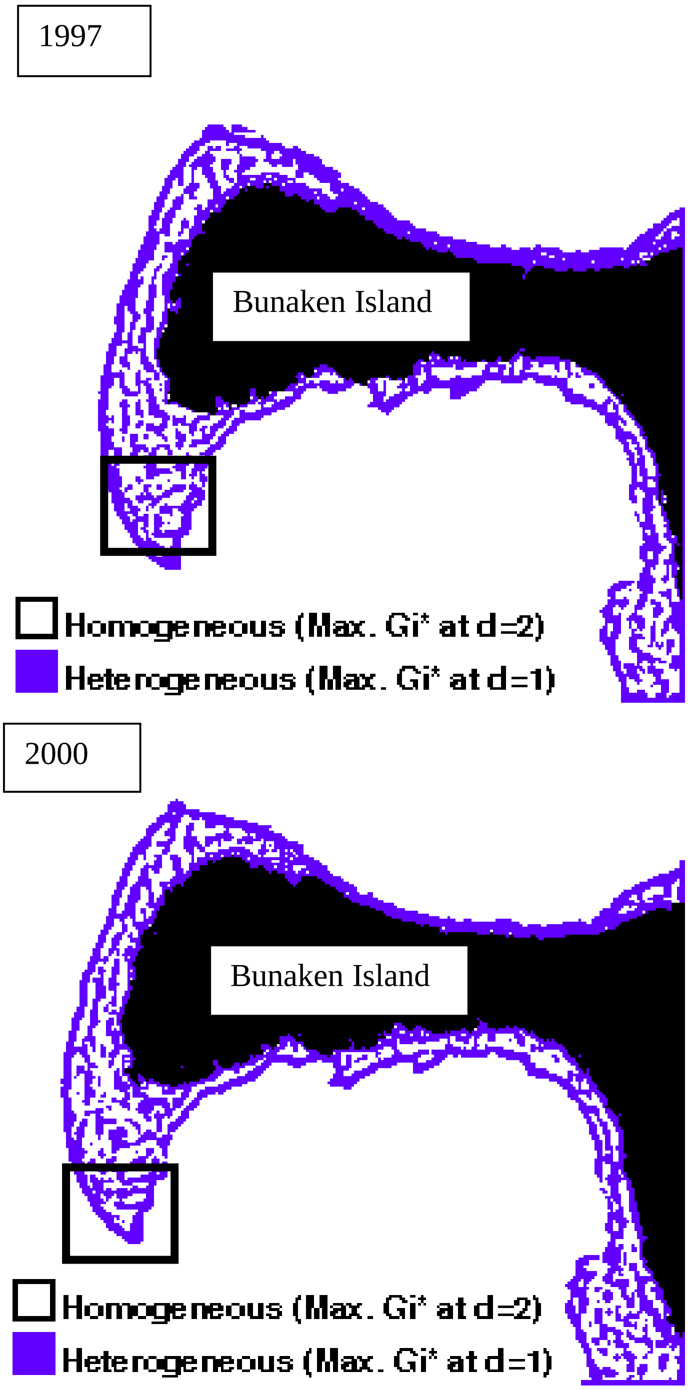

Figure 2. Binary images indicating the distance at which Max G_i* was found for SPOT 1997 (top) and 2000 (bottom). The size of this SPOT image subset is 256x256 pixels.

Figure 1. Maximum G_i* images for SPOT bands 1 and 2 in 1997 and 2000. The size of this SPOT image subset is 256x256 pixels.

Figure 2. Binary images indicating the distance at which Max G_i* was found for SPOT 1997 (top) and 2000 (bottom). The size of this SPOT image subset is 256x256 pixels.