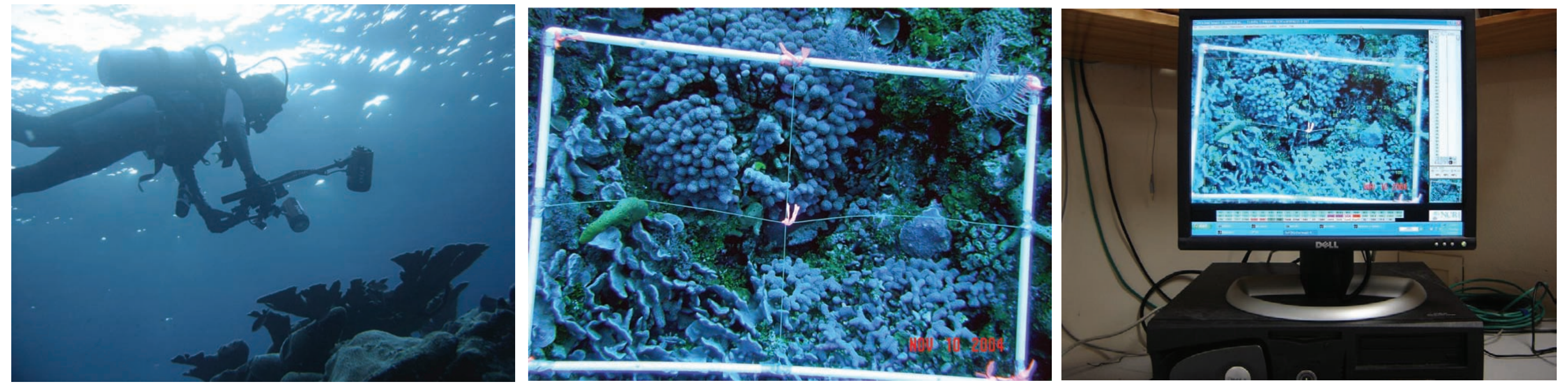
Automated classification of underwater multispectral imagery for coral reef monitoring

Art Gleason[1], Pamela Reid[1], Ken Voss[2] (contact: art.gleason@miami.edu)
University of Miami: (1) Division of Marine Geology and Geophysics; (2) Department of Physics

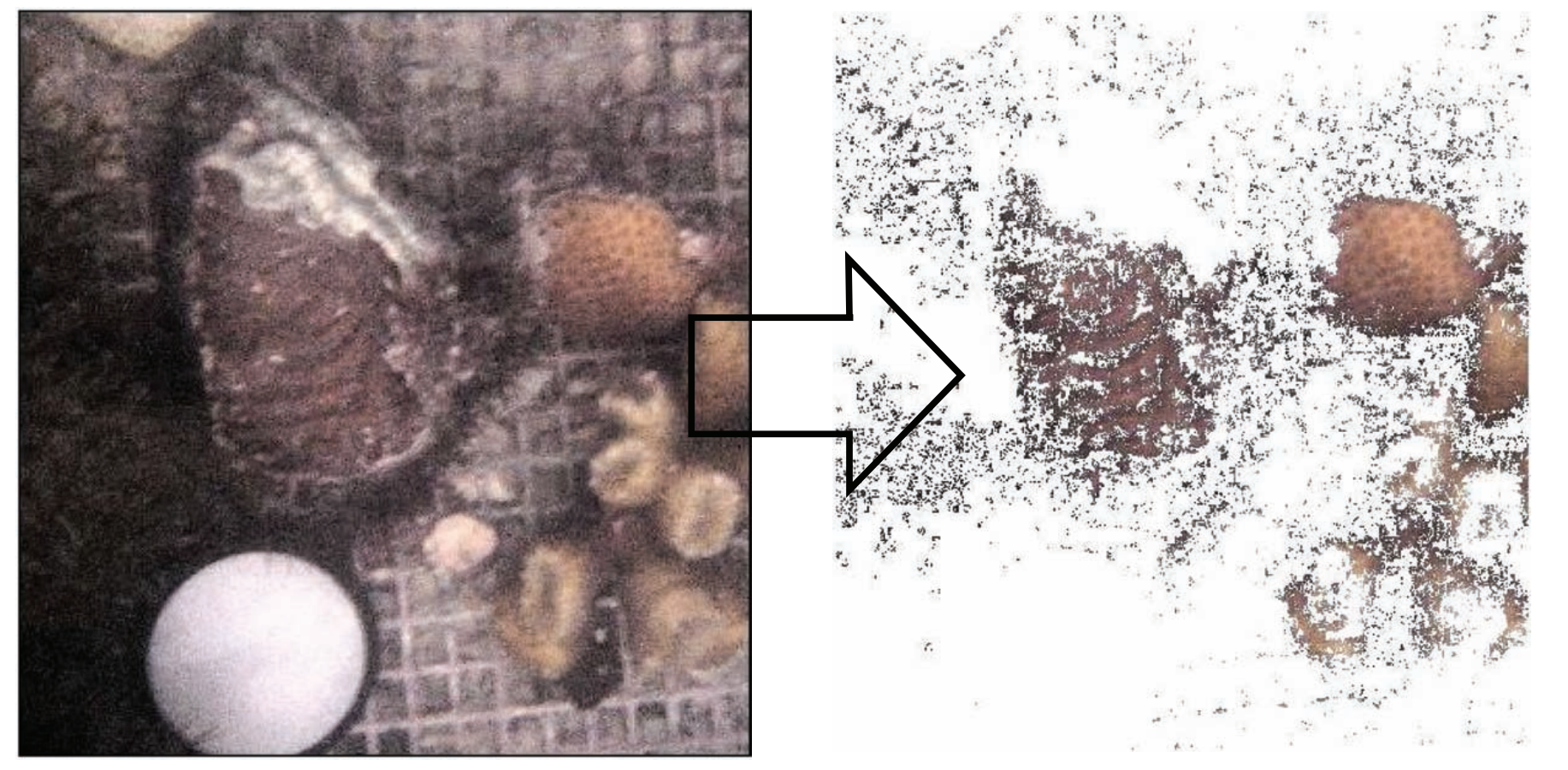
Sponsored by the Strategic Environmental Research and Development Program (CS-1333)

The Problem: Many images to classify by hand



Many coral reef monitoring programs use underwater video or still imagery to speed up data acquisition. Processing such imagery to extract useful ecological information, however, is very labor intensive because it requires manual analysis via point counting or tracing individual objects.

Color matching on RGB images is not a solution

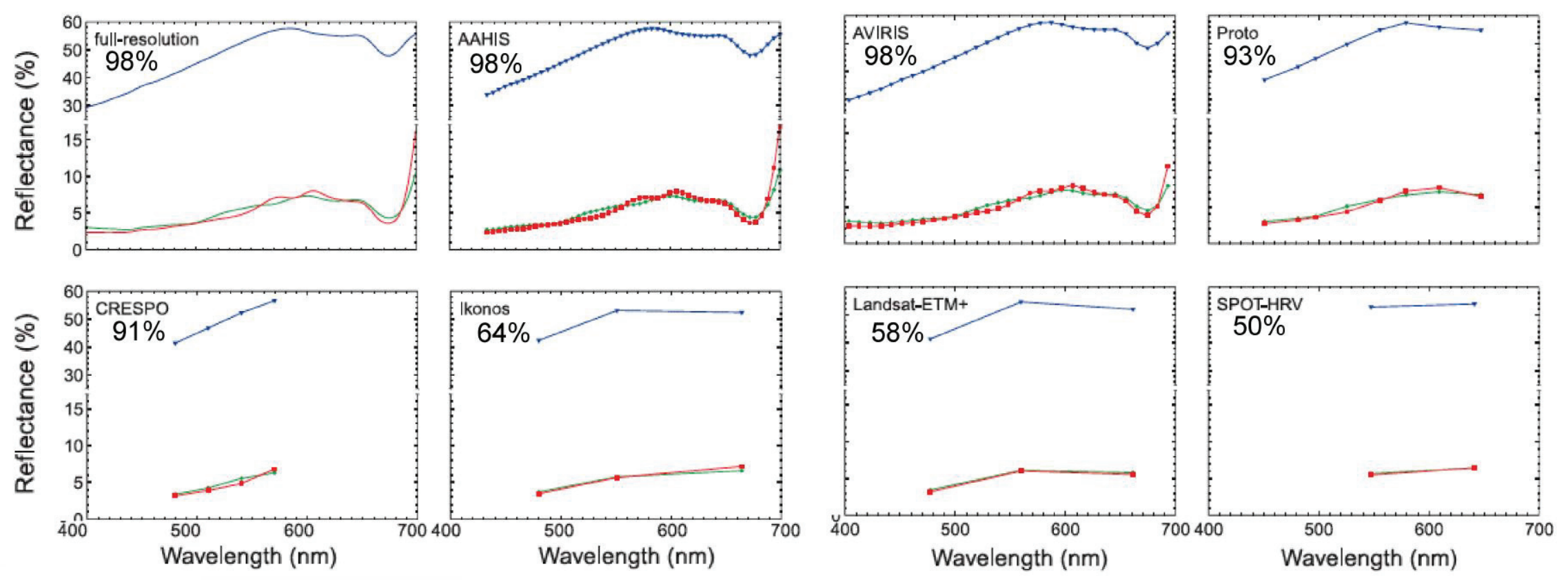


Bernhardt and Griffing (2001) showed that automated classification using color segmentation of standard underwater imagery was not successful and that interactive classification, while more successful, was very time consuming.

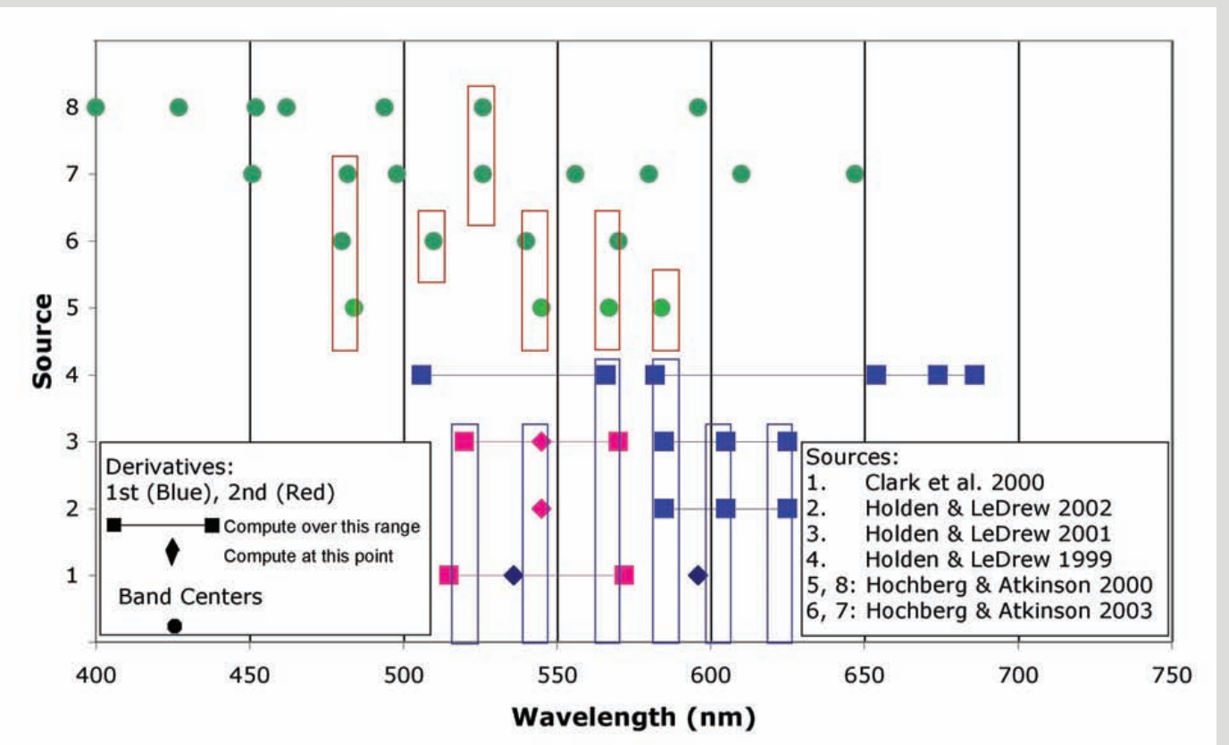
Far left: RGB image from a Sony P-93 RGB underwater camera. Left: Segmented image created with the Photoshop color matching tool by interactively picking pixels on the *Siderastrea siderea* coral colony in the upper right of the image. Note the high confusion between live corals and the image background.

One Potential Solution:
Use high spectral resolution imagery, not broad-band RGB

Hochberg and Atkinson (2003) demonstrated that spectra of basic reef components, coral, algae, and sand, were easily distinguished with hyperspectral reflectance, but not well discriminated with few broad bands. The figure at right is adapted from their paper and shows the decrease in classification accuracy as spectral resolution decreases.



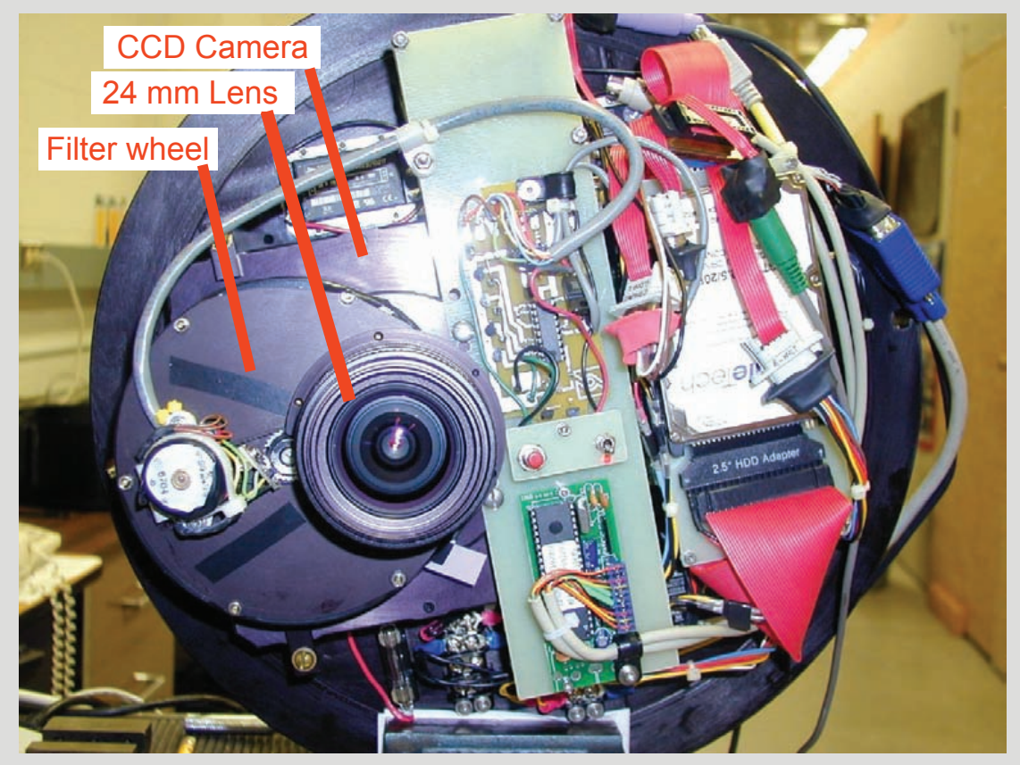
In all panels Blue = Sand; Red = Coral; Green = Algae



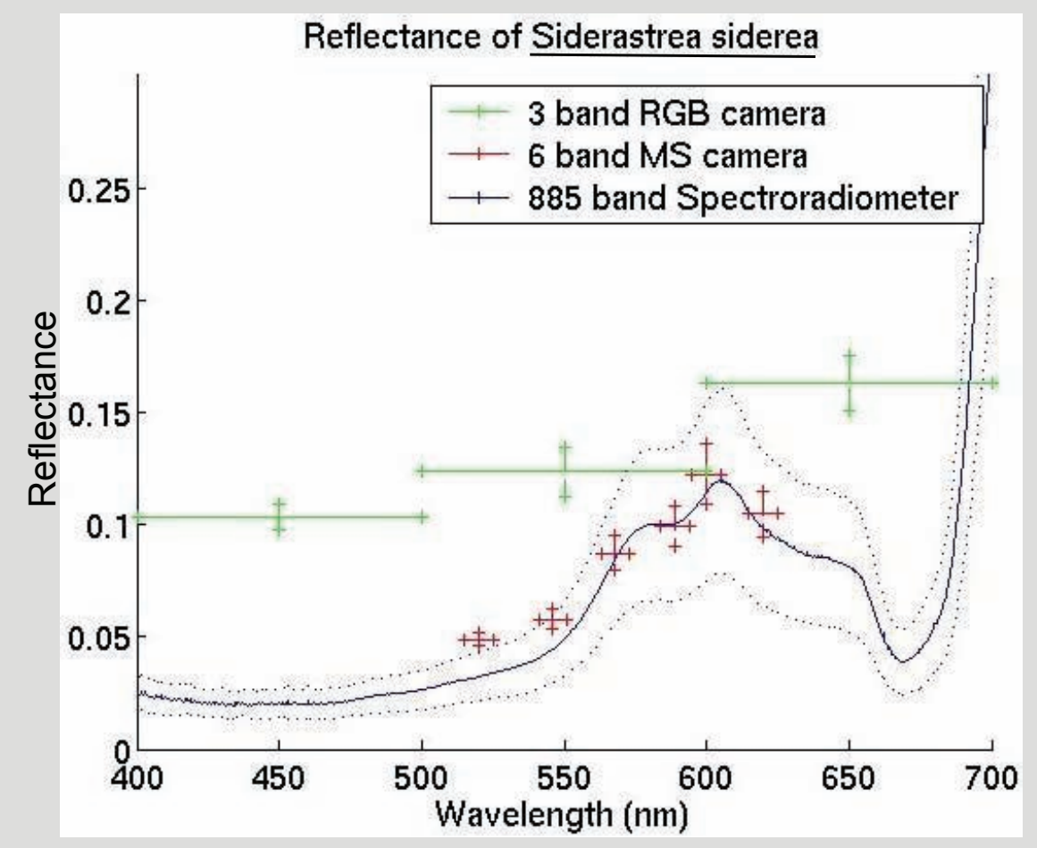
Above: Proposed bands for coral reef mapping: Each row of points corresponds to the bands proposed by a particular study. Solid points mark band centers, while squares and diamonds mark the locations of derivatives.

Several studies have suggested spectral bands that might be optimum for mapping and monitoring coral reefs from satellite or airborne imagery. The goal of the present work was to test whether the proposed spectral bands could be used to automate the classification of underwater imagery. The figure at left summarizes the recommendations from the literature.

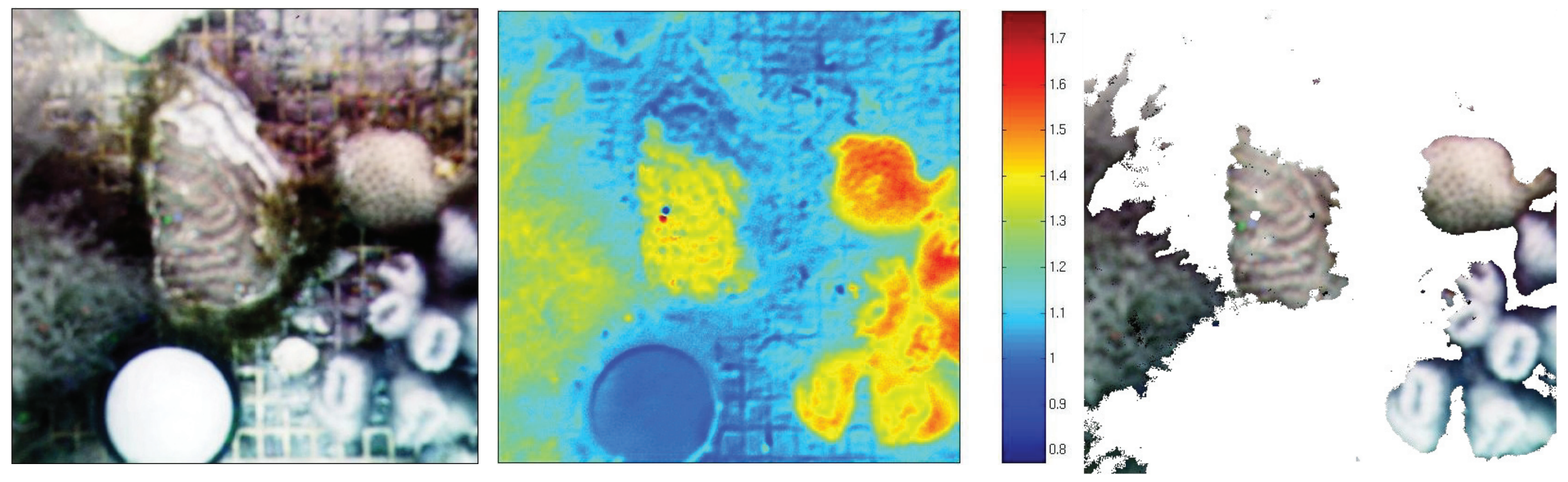
A computer controlled underwater camera (MSCAM) with a filter wheel that holds six narrow-band (10 nm) interference filters was used to acquire multispectral images both in salt water tanks at the University of Miami and on coral reefs in the Bahamas and Florida Keys. Only six filters fit in the MSCAM at once, so two sets of six filters were used; these are marked by the vertical blue and red rectangles in the figure to the left. Bands centered at 546, 568, and 589 nm were used in both filter sets.



Above: Inside of MSCAM. The lens, filter changer and CCD camera are labeled. Unlabeled components include the single board PC, disk drive, DC-DC converters and cables to interface the components.
Right: Picture of the MSCAM being deployed.



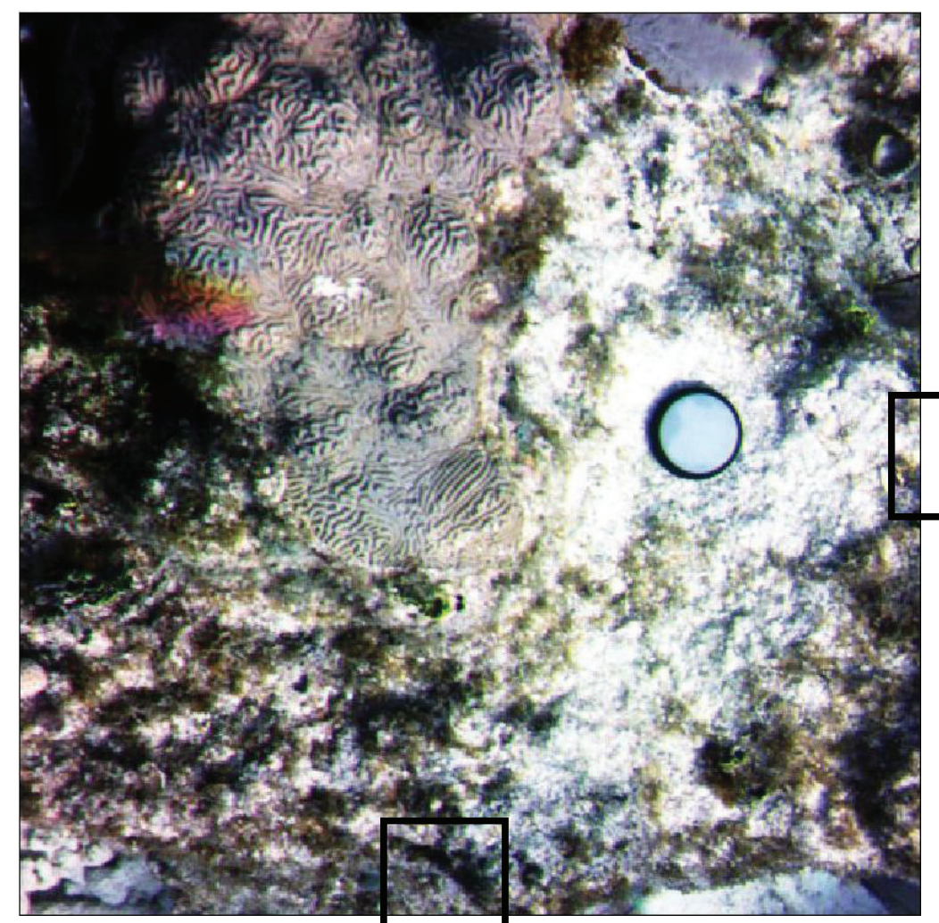
Above: Reflectance of the coral *Siderastrea siderea* at different spectral resolutions: blue = hyperspectral, red = MSCAM, green = standard RGB camera. Note how the MSCAM captures details of the hyperspectral reflectance that are averaged over by the RGB imagery.



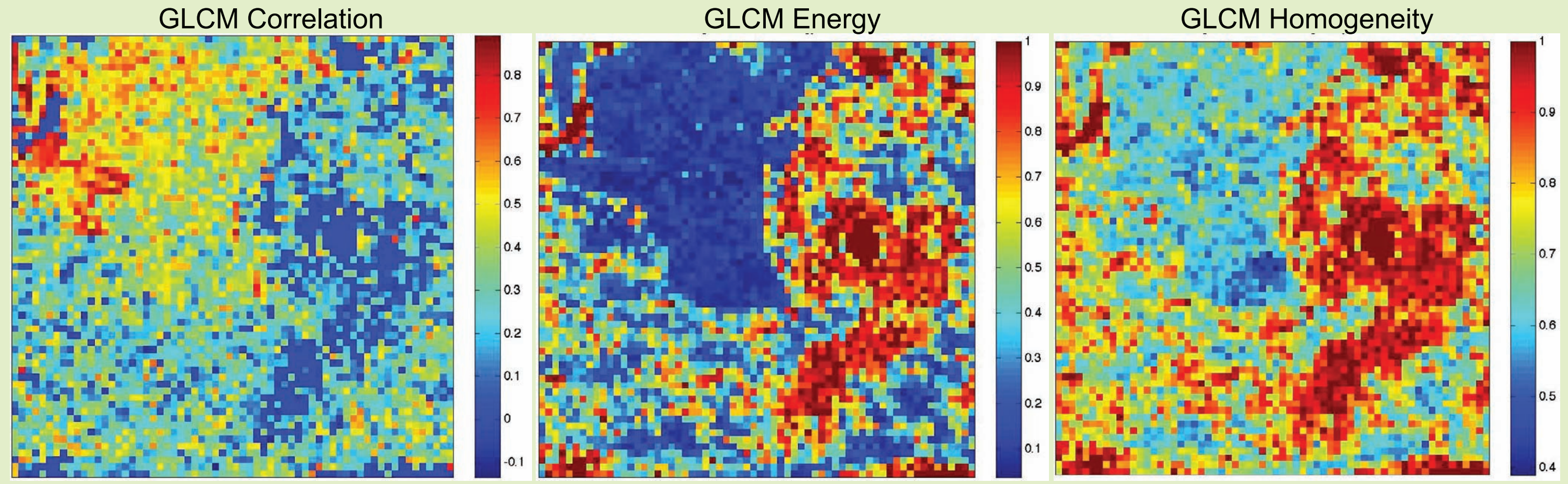
Classification using the algorithms suggested by the literature were not successful. It was noted, however, that a ratio of 546 to 568 nm was able to segment coral and algae, together, from other objects but was not able to separate coral from algae. Left: False color composite of MSCAM bands at 600, 589, 568 nm. Center: Normalized Difference Ratio = (568 nm - 546 nm) / (568 nm + 546 nm). Right: Segmented version of the left image created from a threshold of the $ND_{568-546}$ image.

An Improved Solution: Combine high spectral resolution imagery with image texture metrics

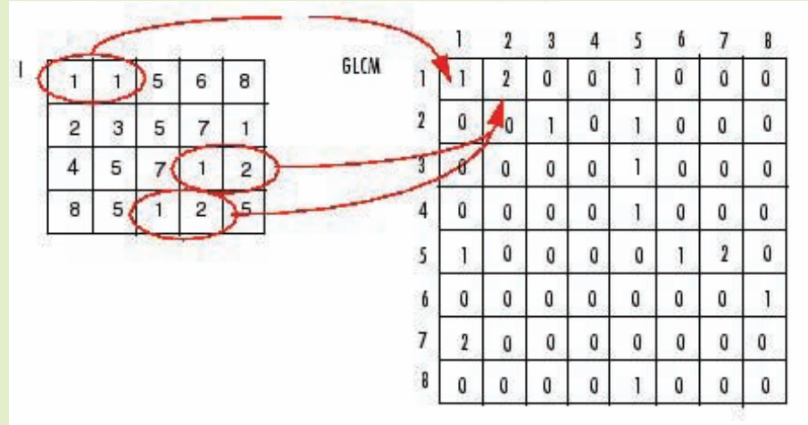
1) Reflectance image



2b) Gray Level Co-occurrence Matrix Texture Metrics



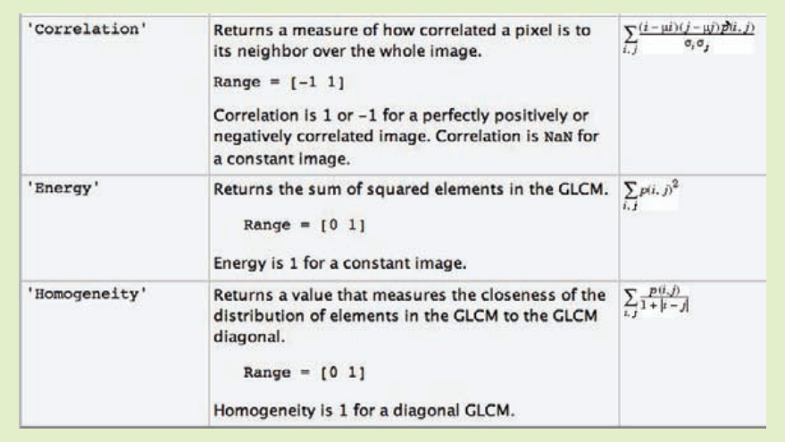
Process used to create the GLCM



A gray-level co-occurrence matrix (GLCM) is computed by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. The figure above illustrates the process using a spatial relationship defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent). Each element (i,j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image.

In this paper, four GLCMs were computed with spatial offsets one pixel to the right, left, top and bottom. The four results for each offset were averaged to produce a single image for each metric (2B, to the left).

Metrics used to analyze the GLCM

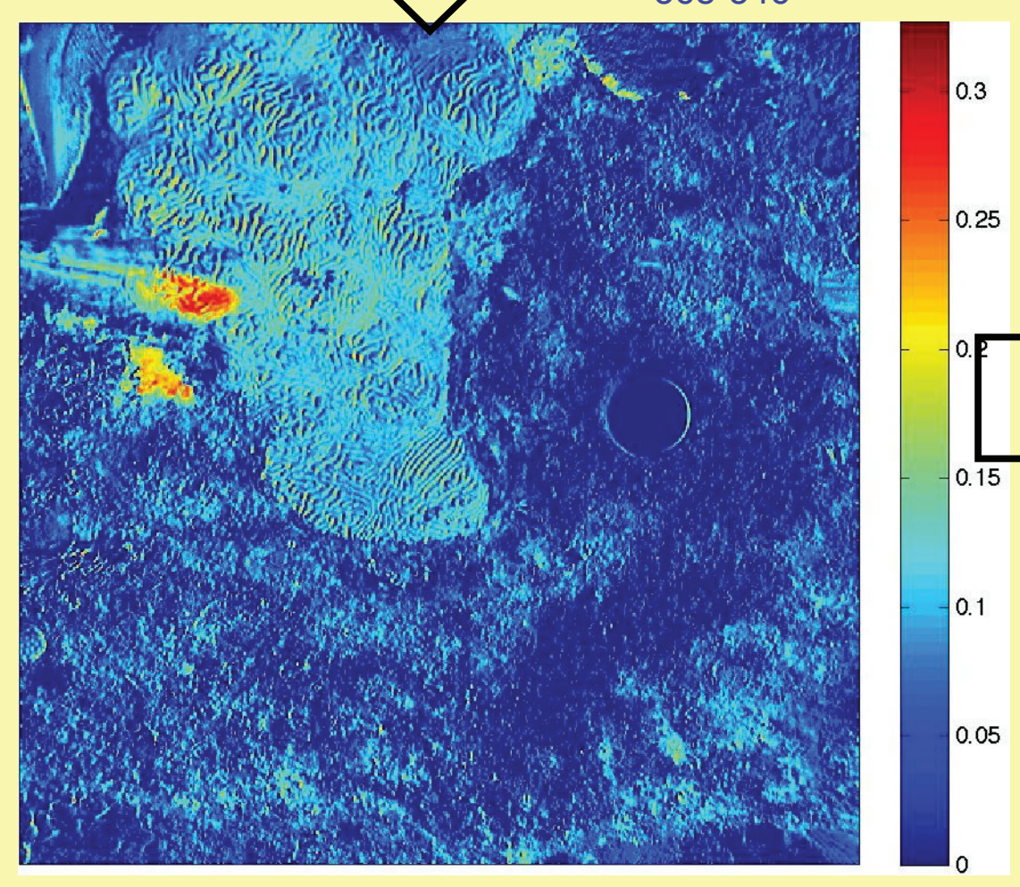


'Correlation'	Returns a measure of how correlated a pixel is to its neighbor over the whole image. Range = [-1 1] Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.	$\sum_{i,j}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i\sigma_j}$
'Energy'	Returns the sum of squared elements in the GLCM. Range = [0 1] Energy is 1 for a constant image.	$\sum_{i,j}p(i,j)^2$
'Homogeneity'	Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Range = [0 1] Homogeneity is 1 for a diagonal GLCM.	$\sum_{i,j}\frac{p(i,j)}{1+\lvert i-j\rvert}$

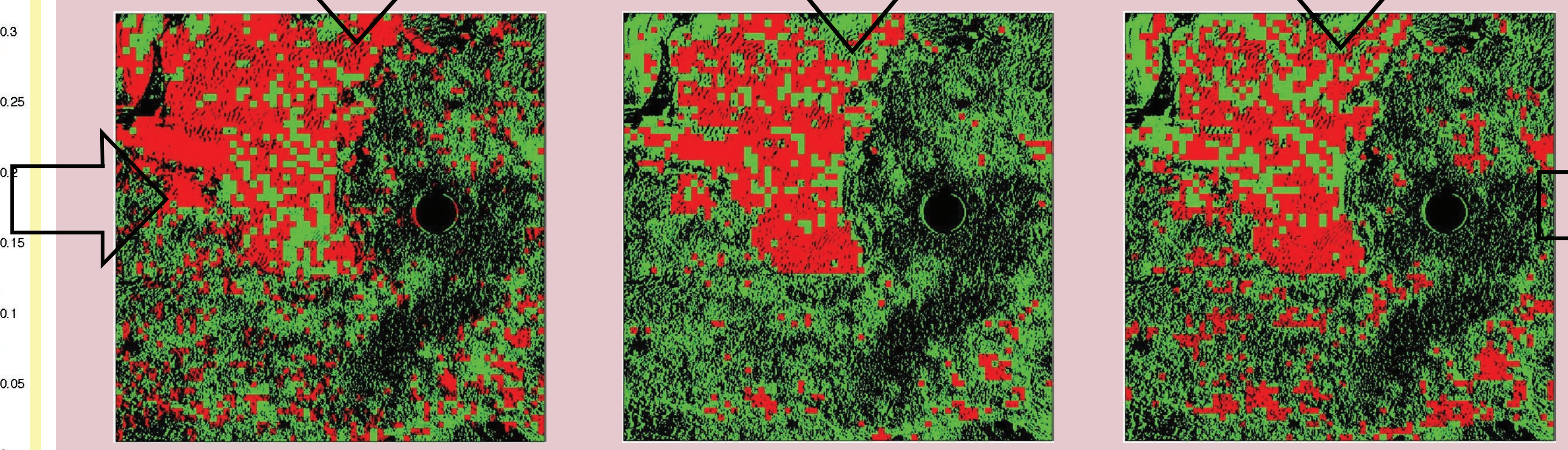
Analysis of the GLCM is performed by computing several metrics (table above). First, the GLCM in units of counts is normalized to form a probability matrix (p) such that the sum of the elements in (p) equals one. Then the elements of the matrix (p) are summed in various ways to emphasize different aspects of texture.

Correlation measures the joint probability occurrence of the specified pixel pairs. Energy, also known as uniformity or the angular second moment, provides the sum of squared elements in the GLCM. Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

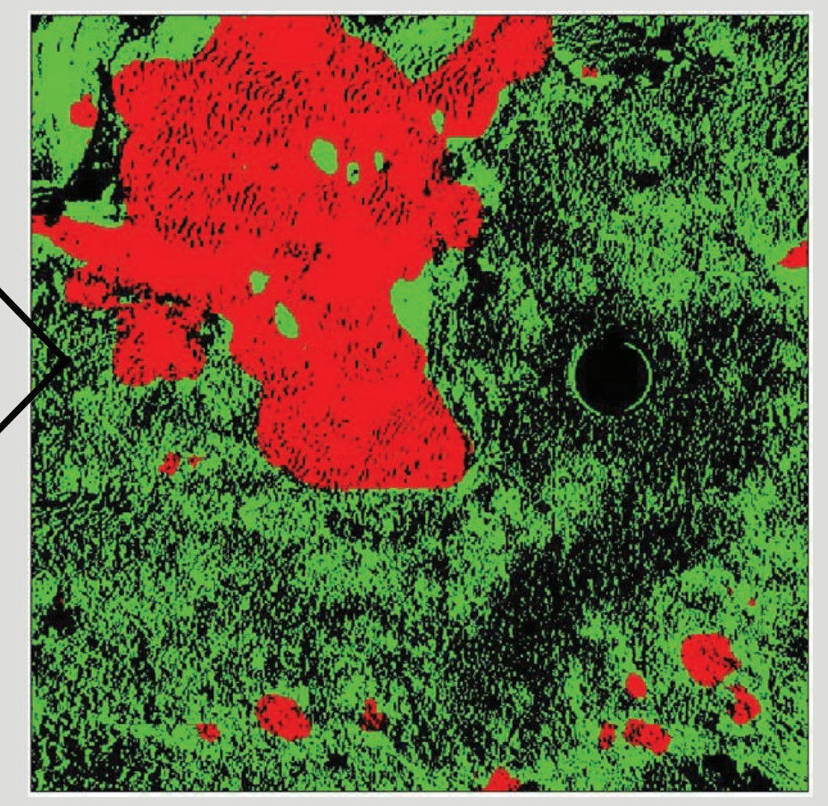
2a) Spectral Ratio: $ND_{568-546}$



3) Threshold texture images and mask background with thresholded spectral ratio image



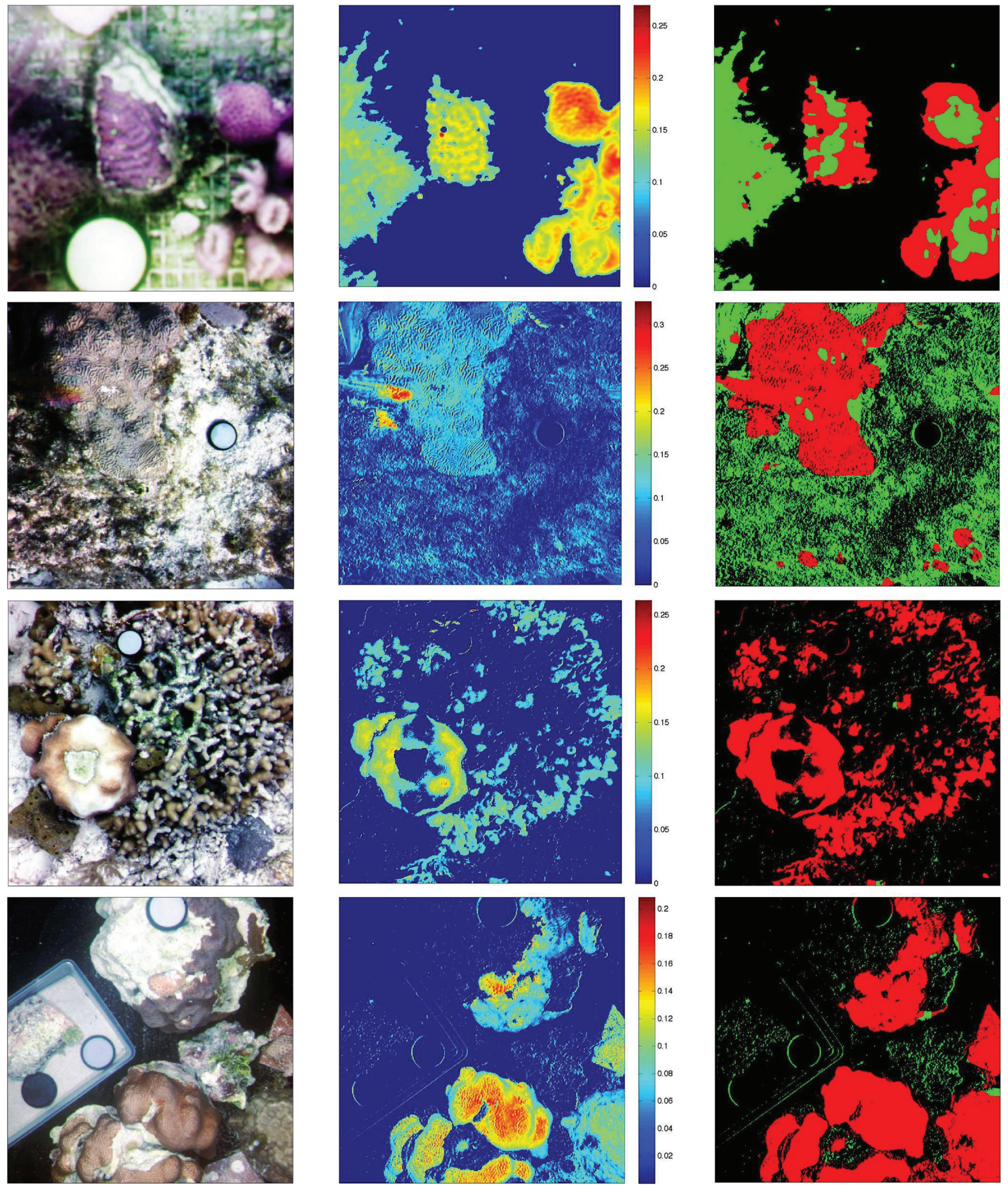
4) Smooth to create final result



Example of processing for one dataset. Step 1: False color image composed of three multispectral camera bands (589, 548, 487 nm) displayed in RGB. Step 2A: Normalized difference ratio of bands at 568 and 546 nm. Step 2B: GLCM texture images for correlation, energy, and homogeneity. Step 3: Classified images computed from thresholds on GLCM images (2B) and masking with spectral ratio (2A). Step 4: The final classified image created by smoothing the three images in step 3 with a majority filter.

Colors in steps 3 and 4 are: coral (red), algae (green), background (black).

Results with field and test tank data sets



Accuracy

86%

67%

84%

87%

Left column: False color images composed of three multispectral camera bands (589, 548, 487 nm) displayed in RGB. Center column: Normalized difference ratio of bands at 568 and 546 nm with low values set to zero. Right Column: Final smoothed classified images with three classes: coral (red), algae (green), background (black).

Accuracy was assessed by point-counting the false color RGB images with 400 points.

Conclusions

1) High spectral resolution imagery is an improvement relative to broad band (RGB) for classifying underwater imagery of coral reefs.

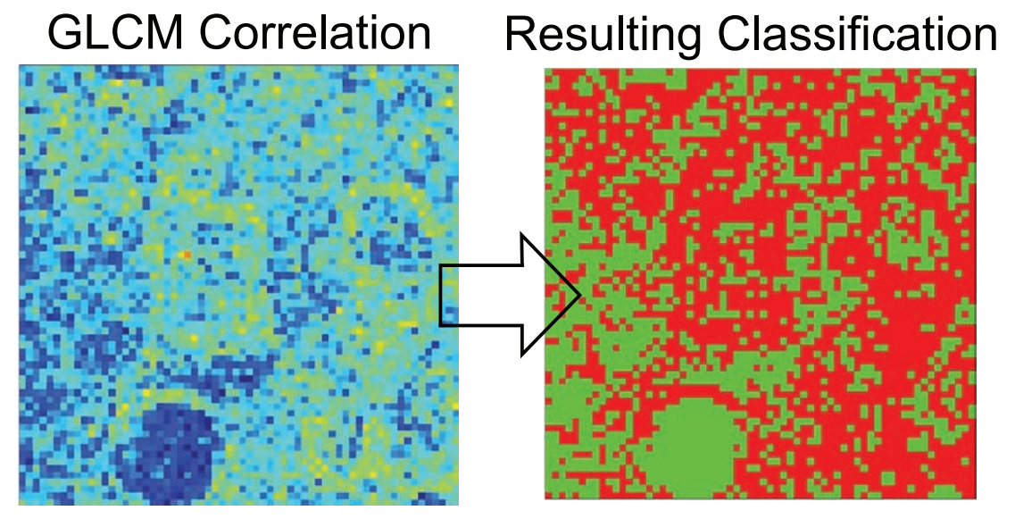
$ND_{568-546}$ accurately segments coral + algae whereas color matching cannot.

2) Narrow spectral bands alone are not a complete solution for automated classification of reef images, however.

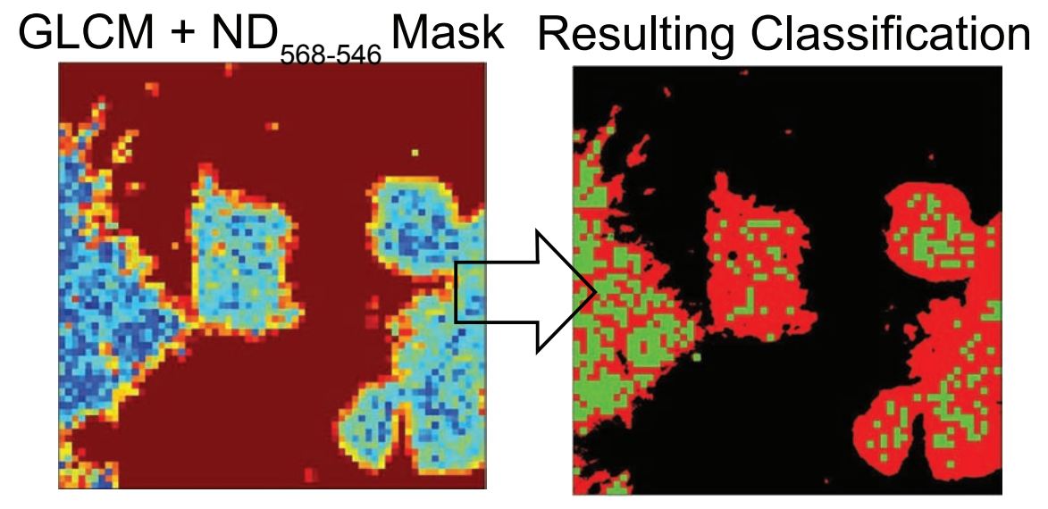
Segmenting coral and algae, together as one class, from the background is not a useful end in itself. On the other hand, segmenting coral and algae with a narrow spectral band ratio was useful in this study when combined with image texture measures. The evidence for this was that thresholds of texture images computed with the GLCM algorithm were able to separate coral and algae after the background had been identified with the narrow band ratio, but they could not do so without the prior application of the narrow band ratio.

3) Acquiring underwater imagery in narrow spectral bands and pre-processing the data with a band ratio greatly simplified texture classification.

GLCM texture metrics calculated from the ND568-546 image without spectral thresholding gave no indication that GLCM texture can be used to segment background from coral and algae. Texture values in areas of the background were very similar to those found over coral and algae (top row, right).



GLCM texture metrics work well to distinguish coral from algae, however, after removing the background with the spectral threshold (bottom row, right).



Using a narrow-band spectral ratio simplified the texture classification problem.

4) The combination of high spectral resolution and texture classification has a strong potential for further progress towards full automation.

- GLCM was used for convenience and to prove the point that high spectral resolution data can improve results with even the most simple texture metric. More advanced texture classifiers exist and may be expected to produce even better results.
- Much is known about the spectral reflectance of corals, algae etc.. but much less is known about their textural properties. Research in this area should also improve results.

References

Bernhardt, S. P. and L. R. Griffing (2001). An Evaluation of Image Analysis at Benthic Sites Based on Color Segmentation. Bulletin of Marine Science 69(2): 639-653.
Clark, C. D., P. J. Mumby, J. R. M. Chisholm, J. Jaubert and S. Andrefouet (2000). Spectral discrimination of coral mortality states following a severe bleaching event. International Journal of Remote Sensing 21(11): 2321-2327.
Hochberg, E. J. and M. J. Atkinson (2000). Spectral discrimination of coral reef benthic communities. Coral Reefs 19(2): 164-171.
Hochberg, E. J. and M. J. Atkinson (2003). Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. Remote Sensing of Environment 85: 174-189.
Hochberg, E. J., M. J. Atkinson and S. Andrefouet (2003). Spectral reflectance of coral reef bottom-types worldwide and implications for coral reef remote sensing. Remote Sensing of Environment 85(2): 159-173.
Holden, H. and E. LeDrew (1998). Spectral Discrimination of Healthy and Non-Healthy Corals Based on Cluster Analysis, Principal Components Analysis, and Derivative Spectroscopy. Remote Sensing of Environment 65: 217-224.
Holden, H. and E. LeDrew (1999). Hyperspectral identification of coral reef features. International Journal of Remote Sensing 20(13): 2545-2563.