IDENTIFICATION AND MAPPING OF HAWAIIAN CORAL REEFS USING HYPERSPECTRAL REMOTE SENSING

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ABSTRACT

Coral reefs are an important resource to earth's ecosystem, which is why they need to be protected. A global monitoring system would be an important component in protecting the reefs by locating them and tracking their health. Hyperspectral remote sensing has been used to distinguish the spectrum of different coastal ocean bottom types. This project uses two digital processing techniques and the unique spectrums of coral, algae, sand, water at 1m – 2m depth, and water at 3m depth or greater to identify and map these bottom types. The project's methodology utilizes a supervised classification approach and a linear spectral unmixing approach. In the supervised classification approach, I made field observations of selected training sites and identified the bottom types within those sites. I then ran the 1m HICO data image through the classification program and generated a classified map of the five bottom types. I resize the HICO 1m image to 25m and ran it through the classification program. The 25m map's results indicted that there was a pronounced mixed pixel effect. The linear spectral unmixing technique was used as a way to minimize the mixed pixel problem. The approach for this technique involved collecting bottom type spectra with an ocean spectrometer then applying those spectra to a spectral library. Another spectral library was generated from selected training sites from the image. I applied both spectral libraries to the program and generated abundance maps for each of my bottom types. The results of the supervised technique indicated that there was too much of a mixed pixel problem for the technique to be used to monitor coral reefs. The linear spectral unmixing technique was effective for solving the mixed pixel problem but issues with the required spectral library for the technique need to be addressed.

INTRODUCTION

Coral reefs play an important role in the earth's ecosystem in several ways. Their symbiotic relationship with algae is important in producing energy for many marine organisms. Corals also provide shelter for other marine organisms such as fish, worms, eels, and crabs. They also act as natural buffers against hurricanes and tsunamis because they absorb some of the storms energy. Coral reefs provide a steady fishery because they are the residence to many fishes. They are also used by divers and snorkelers for recreation.

There are two major factors that limit the occurrence of coral reefs globally, light and temperature. Corals need sunlight to photosynthesize which is why they are located near the surface in shallow and clear waters instead of the sea floor. Coral reefs are found in tropical and warm areas such as the Indo-Pacific, the Western Atlantic, and the Red Sea because they cannot survive in cold water. Coral reefs are delicate systems that are subject to negative effects of human impact such as pollution, increase in global warming, and the input of land sediment into the ocean. These effects could cause massive coral bleaching which would eventually cause death (International Year of the Reef, 2007).

Since coral reefs are an important and sensitive resource, a system to identify and assess the health of the reef globally is needed. My project involves using satellite imaging to map and identify coral reefs, which could eventually be used globally. Using satellites to monitor coral reefs will allow for regular monitoring without the significant cost of field work, especially considering the widespread global distribution of coral reefs.

The purpose of my project was to map and identify coral reefs using hyperspectral remote sensing and digital image processing techniques. The digital image processing techniques I used in order to discriminate coral from other ocean bottom types (Hochberg and Atkinson, 2003). I used two hyperspectral remote sensing datasetss from an aircraft at two different spatial resolutions: 1 meter and 25 meters. I examined hyperspectral data of five bottom types: coral, algae, sand, and two water classes. After reading Goodman and Ustin (2002), I found that each of the bottom types in my project has a characteristic spectrum. Figure 1 shows an example of three bottom types and their respective characteristic spectra. Figure 2 shows a plot of two water spectrums, one at 1m – 2m depth and the other at 3m depth or greater.

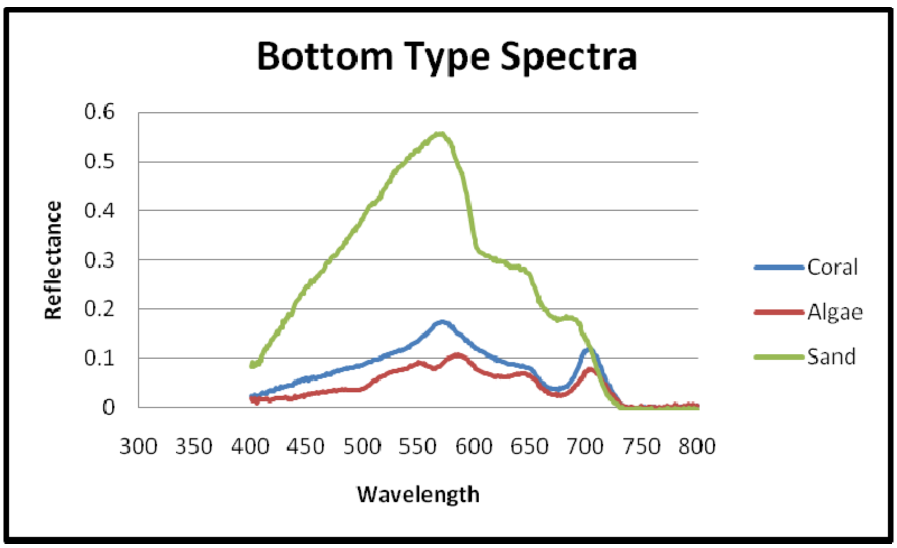

Figure 1: This figure shows a comparison of the spectra of three bottom types: coral, algae and sand. Sand can be easily distinguished from coral or algae by its much higher reflectance. Also, unlike the coral and algae spectra, the sand spectrum does not show a drop in reflectance at 675nm due to chlorophyll absorption. Coral and algae have similar reflectance values so distinguishing the two requires a closer comparison of their spectra. In this plot, coral has a slightly higher reflectance than algae and the peak between 550nm and 600nm are slightly different. Coral's peak goes straight up and then down, while algae's peak goes up then down twice.

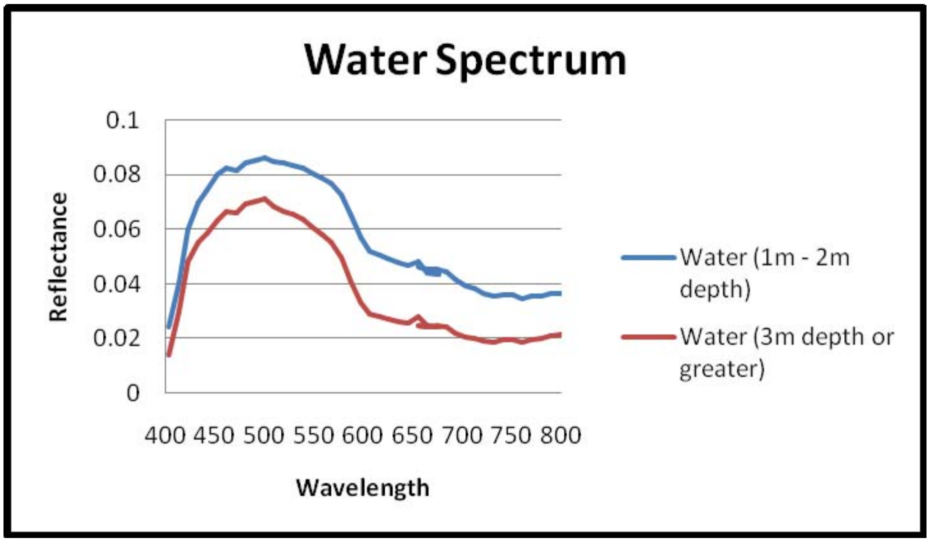

Figure 2: This water spectrum shows that water at different depths have different spectral characteristics. The top curve represents water at 1m – 2m depth which has a higher reflectance then the bottom curve which is 3m depth. Water at different depths has different characteristics because deeper water absorbs more light than reflects light.

METHODS

The goal of this project was to identify and map coral reefs using hyperspectral remote sensing data. I worked both with high-resolution (1m/ pixel) data as well as coarser resolution (25m/ pixel) data, both having been obtained from an aircraft. I used two techniques to identify coral reefs for this project: supervised classification and linear spectral unmixing. The supervised classification technique involved first selecting training sites that defined "end-member" bottom types. This semi-automated technique then compared pixels of unknown bottom types ("unknown pixels") in the image with the selected bottom type classes and decided which class the unknown pixel most closely resembled. The linear spectral unmixing technique required spectra from a spectral library to derive the abundances for each bottom type that comprised a pixel. Unlike the supervised classification technique which assigns the most spectrally similar class to each pixel, the spectral unmixing program determines the fraction of each bottom type to best fit the spectrum for each pixel. This results in an abundance map for each bottom type. I chose Kāne‘ohe Bay (Figure 3) for the study area because it was easily accessible and it contained all of the bottom types that I wanted to map. The methods I used to conduct these techniques were divided into three sections which are described below.

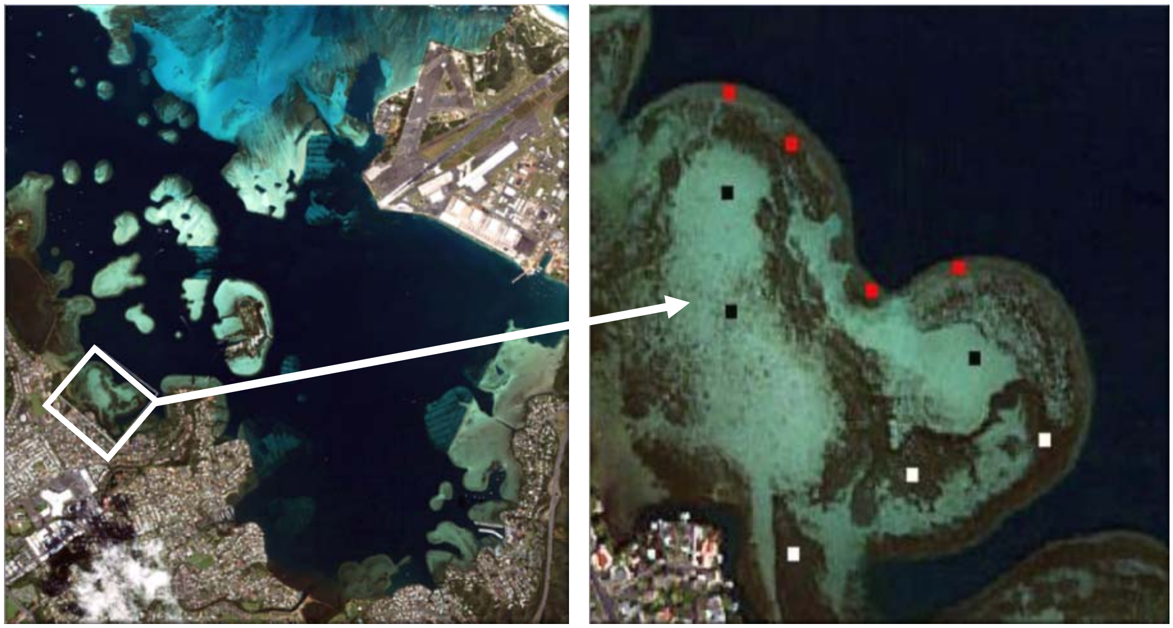

Figure 3: Kāne‘ohe Bay was selected as the study area because it contained the desired bottom types and there was easy access to the bay. The white square outlines the area containing the training sites. The arrow points to an enlarged view of the training sites. The red points represent coral, the white represent algae, and the black represent sand.

Supervised Classification of the 1m Dataset

The first part of this project involved using the supervised classification technique on 1m spatial resolution data. These data were obtained from the Hyperspectral Imager for Coastal Ocean (HICO) sensor and were provided by Jeffrey Gillis-Davis, a faculty member of the Hawai‘i Institute of Geophysics and Planetology (HIGP). These data consisted of three flight lines which covered most of the southern portion of Kāne‘ohe Bay. This imagery consists of 60 narrow spectral bands ranging from 380 to 980nm. I also acquired maps and digital aerial photographs of the bay from the Hawai‘i Coastal Geology Group website (Coastal Geology Group, 2008), which I used to navigate to the training sites. After selecting a study area and training sites, I conducted a kayak-based field reconnaissance to inspect the study area for safety and make observations. In the field, I made visual observations of the bottom types represented in my training sites. Back in the computer lab, I used my training sites to represent my bottom type classes and ran the flight lines through the supervised classification program to generate a set of preliminary maps. A second field visit was conducted to refine my training sites and to check the classification results to see if they were accurate. I did this by selecting certain areas within my training area in which I logged down information about the bottom type present in that area. When I returned to the computer lab I compared what I saw in the field with the preliminary classified map. Based on my observations and understanding the spectra of the five bottom types, I chose refined training sites from the image. I then applied these training sites to the images and reran the supervised classification technique.

Supervised Classification of the Simulated 25m Dataset

The first part of this project involved testing out the technique to see if it would produce accurate results, so for the next part I needed to test the technique to see if it could be used on data collected from satellites. Since some global monitoring satellites will be collecting data at coarser resolutions such as 25m, I decided to resize the HICO 1m dataset to 25m. I mosaicked the 1m and 25m image together and selected training sites from the 1m image because the 25m image was extremely small and blurry which made identifying and selecting training sites difficult. After I selected the training sites, I ran the mosaic image through the supervised classification program. I then compared the results of the 1m spatial resolution dataset to the 25m spatial resolution data in order to evaluate the effectiveness of the technique.

Linear Spectral Unmixing of the AVIRIS Dataset

The third step in this project involved using the linear spectral unmixing technique on a 25m spatial resolution dataset. The 25m spatial resolution was acquired from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and covered the Kāne‘ohe Bay area. This data was made available to my mentor after a previous graduate student wrote a proposal requesting the data from NASA’s Jet Propulsion Laboratory. I ran a remote sensing atmospheric correction program called FLAASH on these datasets. I then conducted a field reconnaissance of Kāne‘ohe Bay in order to collect bottom type spectra with a towed ocean spectrometer system (Provided by the Center for Microbial Oceanography: Research and Education, C-MORE). The ocean spectrometer recorded bottom type spectra, GPS location, temperature, ocean depth, and captured photos. Kahoali‘i Keahi, a C-MORE Scholar working on developing the spectrometer system, my mentors, and I towed the ocean spectrometer with a kayak over areas that were rich in coral, algae, and sand in order to make sure I collected the desired bottom type spectra. The spectra collected from the ocean spectrometer were used to build my spectral library which then was used for the linear spectral unmixing technique. I also generated a spectral library from training sites on my AVIRIS 25m image to compare the effectiveness of the two spectral libraries. The training sites represented each of my five bottom type classes. The last step involved applying both spectral libraries to the image and running the linear spectral unmixing program.

RESULTS

I ran the 1m HICO dataset through the supervised classification technique after the second field visit and generated a final map (Figure 4). The final map shows a distribution of my five bottom types, coral, algae, sand, water at 1m – 2m depth, and water at 3m depth or greater. Coral is located along the fringe of the coast line in the bay, while algae and sand are both located within the fringe. The water bottom types are specifically located where they are supposed to be. The only down side I found was that there were some misclassifications and overestimating of bottom types. There were areas in the field that were algae but in the classified map were coral and there were areas in the field that were both coral and algae but in the map were coral. I feel that the misclassifications were caused by not selecting training sites that were representative of these spectra. In the case of a mixed pixel, the program will overestimate or underestimate a bottom type because the program will assign a single bottom type class to an area made up of a fraction of that class along with one or more other components. I created a validation chart which consisted of twenty validation pixels, located within all three flight lines, which are presented in Table 1. Thirteen out of the twenty validation pixels were classified accurately, three were overestimated, and four were misclassified. These results indicate that the methods for generating the training sites need to be close to perfect when using this technique.

Validation Pixel	Supervised Classification	Field Work Observations	Validation
1	Coral	Algae	Misclassification
2	Coral	Algae	Misclassification
3	Algae	Algae	Accurate
4	Sand	Sand	Accurate
5	Coral	Coral	Accurate
6	Sand	Sand and Algae	Overestimating Sand
7	Coral	Coral	Accurate
8	Coral	Coral	Accurate
9	Algae	Algae	Accurate
10	Algae	Algae	Accurate
11	Sand	Sand and Algae	Overestimating Sand
12	Coral	Algae	Misclassification
13	Sand	Sand and Algae	Overestimating Sand
14	Coral	Coral	Accurate
15	Coral	Coral	Accurate
16	Algae	Algae	Accurate
17	Coral	Algae	Misclassification
18	Sand	Sand	Accurate
19	Sand	Sand	Accurate
20	Algae	Algae	Accurate

Table 1: Validation chart for the 1m supervised classification map.

The results from the 25m dataset contained more misclassifications then the 1m dataset. The final map shows my five bottom types classified (Figure 4), but because of the coarser resolution the percentage of coral in the image dropped compared to the 1m image. I expected these results because the coral in my study area were no more than 3m in width and the image covered 25m of ground area, so the coral may have gotten mixed in with other larger bottom types such as the algae, sand, or water at 1m – 2m depth. These results further proved that the supervised classification technique would not accurately classify the coral reefs.

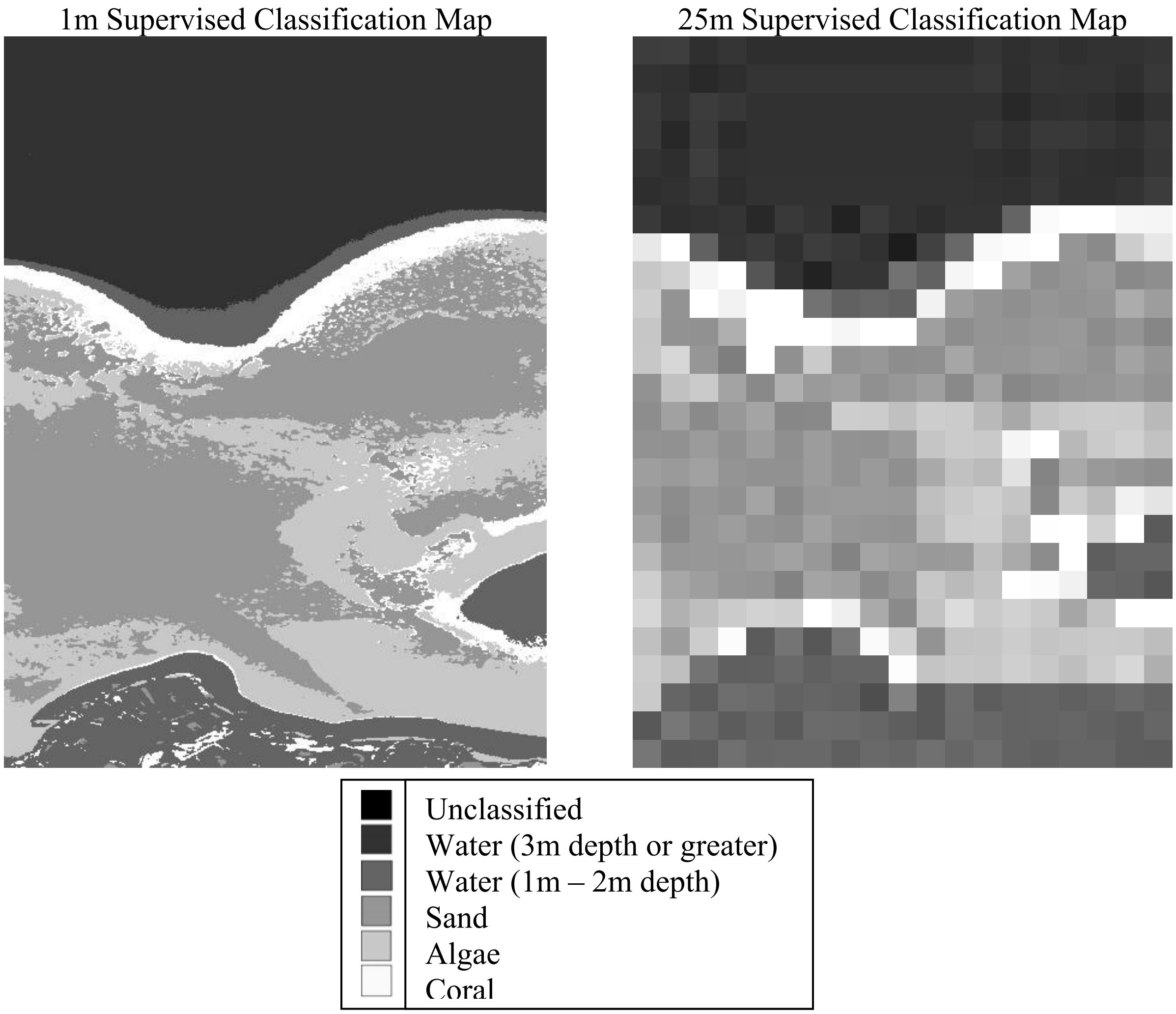

Figure 4: These two maps are the final supervised classification maps from the 1m and 25m HICO dataset. The 1m map shows the bottom types clearly. The 25m was resized because it was extremely small and hard to recognize any of the bottom types. The color key on the bottom shows the different classes I used.

I used the linear spectral unmixing technique to produce an abundance map for each bottom type class present in my spectral library. I had two sets of results by running the unmixing using two separate spectral libraries, one came from the ocean spectrometer and the other came from training sites I selected from the image. The results from the unmixing using the ocean spectrometer spectral library's results were not reasonable. The ocean spectrometer is still being experimented with and needs further testing to establish the correct calibration method. There are also problems regarding the lighting conditions while collecting spectra within the spectrometer which need to be addressed before these data can be used for building a useful spectral library. So I decided to select pixels from the AVIRIS image which I felt were representative of pure bottom types, which are pixels fully made up of a single bottom type. I used the spectra from these pixels to build the image based spectral library.

The abundance maps that I generated from the training sites on the 25m AVIRIS spectral library showed more promising results (Figure 5). The coral abundance map shows that there are low values, 0 to 20 percent, of coral along the fringe reef near the coast. There were also some small areas that showed a large percent of coral but those areas are most likely inaccurate because the fringe reef only covers a small percentage of the pixel. This problem could be the result of not selecting a pure coral pixel, but one which possibly contained a significant portion of algae, when I selected my training sites.

25m Linear Spectral Unmixing Coral Map

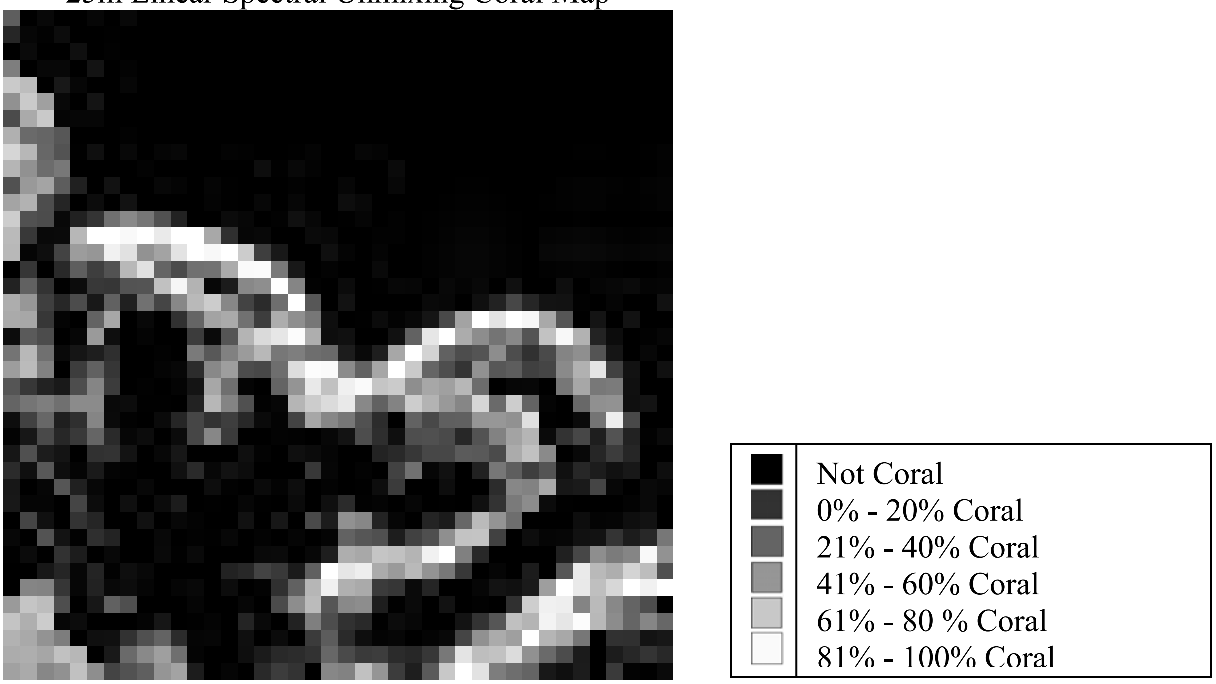

Figure 5: The linear spectral unmixing coral abundance map (resized to show percentage abundances) and a percentage key.

Table 2 shows the percentage of each bottom-type in a selected area. The selected area is the same for all three images so that I could compare the percentage of coral for each map. The coral in the 1m HICO supervised classification map was around 6.4% while the classification map from the resized 25m HICO data showed a decrease to 4.3%. This was caused by the averaging in the resizing process which resulted in more mixed pixels and a lower percentage of coral in the image. It should also be recognized that the classification even at the 1m scale can over or underestimate the area of a single class because it will assign a mixed pixel a single bottom type.

The AVIRIS 25m map was processed through the linear spectral unmixing program. The map has 12.5% of coral in the image almost twice as much as the HICO 1m map. This is possibly due to the coral pixel chosen for the spectral library not being a pure pixel but instead a mixed pixel. This is highly likely considering the distribution of the coral within the reef. It is interesting to note that the coral and algae for all three methods sum to about the same percentage, about 26.5 percent.

	HICO 1m (%)	HICO 25m (%)	AVIRIS 25m (%) Training Sites Spectral Library
Coral	6.4	4.3	12.5
Algae	20.9	22.0	16.2
Sand	31.8	32.6	24.5
Water (1m – 2m depth)	9.7	6.5	33.2
Water (3m depth or greater)	31.2	34.5	13. 7

Table 2: Table of bottom type percentage. The AVIRIS 25m map which was processed through the linear spectral unmixing program showed a high value of coral compared to the HICO 1m and 25m supervised classification maps.

CONCLUSION

The supervised classification technique was an effective tool at classifying pixels that were pure bottom types. However, mixed pixels which contained more than one bottom type proved to be problematic. In these cases, the program tended to overestimate, underestimate or misclassify the mixed pixel. This was a problem in both the 1m and 25m HICO datasets, but particularly in the latter, coarser resolution dataset. Since global monitoring satellites generally acquire data at best 25m spatial resolution, the supervised classification technique as implemented here would not be a wise program to use. Further study could address the use of mixed pixel classes to minimize this effect.

The linear spectral unmixing program appears better suited to mixed pixels because it gives percentage abundances of each bottom type in a pixel, rather than simply classifying the entire pixel as one bottom type. The process is highly sensitive to the quality of the spectral library used as input to the unmixing process. This was highlighted by our difficulty using the ocean spectrometer system to generate a spectral library and using a possibly mixed pixel for our coral end-member in the image based spectral library. Before the linear unmixing technique could be used in a monitoring system, a suitable library needs to be built and validated. The ocean spectrometer is possibly an effective tool for collecting bottom type spectra although questions about calibration and lighting effects remain to be solved.

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