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Seafloor characterization using multibeam and optical data at French Frigate Shoals, Northwestern Hawaiian Islands

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Abstract. Multibeam bathymetry, backscatter, and optical data collected by the NOAA Coral Reef Ecosystem Division (CRED) were used to create maps of seafloor habitats on the bank top at French Frigate Shoals (FFS) in water depths ranging from <10-100 m. Supervised classification of backscatter and optical data with user-defined classes results in seafloor maps such as hard (rock, rubble, etc.) and soft (sandy) bottom. However, they suffer from a dependence on the generally limited optical data. Uncertainties in camera sled positioning, limited availability of optical data, and user bias in the supervised class definitions suggest an alternate approach may be necessary. Unsupervised classification of different combinations of bathymetry and backscatter derivatives uses the statistical separability of the data to define unique seafloor types. The optical data are then used to define and evaluate the accuracy of the classes. A variety of methods are being evaluated to characterize benthic habitats and the resulting maps are being used to improve sampling techniques for long-term ecosystem monitoring and to guide groundtruthing operations. Future plans include using these methods to identify coral-rich and species specific environments in the Northwestern Hawaiian Islands (NWHI).

Key words: seafloor characterization, multibeam bathymetry, backscatter, Northwestern Hawaiian Islands

Introduction

Since 2002 the NOAA Coral Reef Ecosystem Division (CRED) has collected multibeam bathymetry, backscatter, and optical data as part of an effort to delineate benthic habitats of coral reef ecosystems throughout the U.S. Pacific Islands. The data provide resource managers with high-resolution maps of the seafloor and ground-truth information in water depths greater than 20 m.

Much of the mapping has focused on the islands, banks, and atolls that form the Northwestern Hawaiian Islands (NWHI) (Fig. 1), a long chain of inactive volcanoes produced by a deep seated mantle hotspot currently located beneath Kilauea Volcano (Rooney et al. 2008). Pacific tectonic plate motion slowly carries the volcanoes to the northwest away from the hotspot and they subside and become low-lying islands, atolls, flat-topped banks, and eventually guyots (Grigg 1982). Due to their remote nature, the NWHI are home to some of the healthiest coral reefs in the world and are often referred to as near-pristine coral-reef ecosystems (Page-Albins et al. 2009). It is critical that they are studied to provide baseline information for comparative analyses with degraded reef ecosystems.

Here we present results from recent efforts to create maps of seafloor substrates by applying basic image processing techniques to a combination of multibeam bathymetry, backscatter, bathymetric derivatives, and optical data collected at French Frigate Shoals (FFS) in the NWHI. These efforts have resulted in hard and soft seafloor substrate maps covering the surveyed portion of the FFS bank top. The maps are being used to determine long-term monitoring sites in the framework of a habitat-based, stratified random sampling design (Ault et al. 1999) and for continued coral reef ecosystem research in the NWHI.

Data

Figure 1 shows the bank top bathymetry data collected at FFS in 2005 using hull-mounted multibeam sonars: a 240-kHz Reson 8101 on the 8-m-long survey launch R/V *AHI* (Acoustic Habitat Investigator) and a 300-kHz Kongsberg EM3002d on the NOAA Ship *Hi'ialakai*. Both sonars provide bathymetry and backscatter data logged in the Generic Sensor Format (GSF). Vessel position, velocity, attitude, heading, predicted tides, and sound-velocity corrections are applied to the data in real-time.

The bathymetric data were edited on a swath-by-swath basis and in an area-based editor using SAIC's SABER software. Generic Mapping Tools software (Wessel and Smith 1998) was used to create ASCII grids for import and analysis in ArcGIS. The backscatter data were processed using Hawaii Mapping Research Group (HMRG) software.

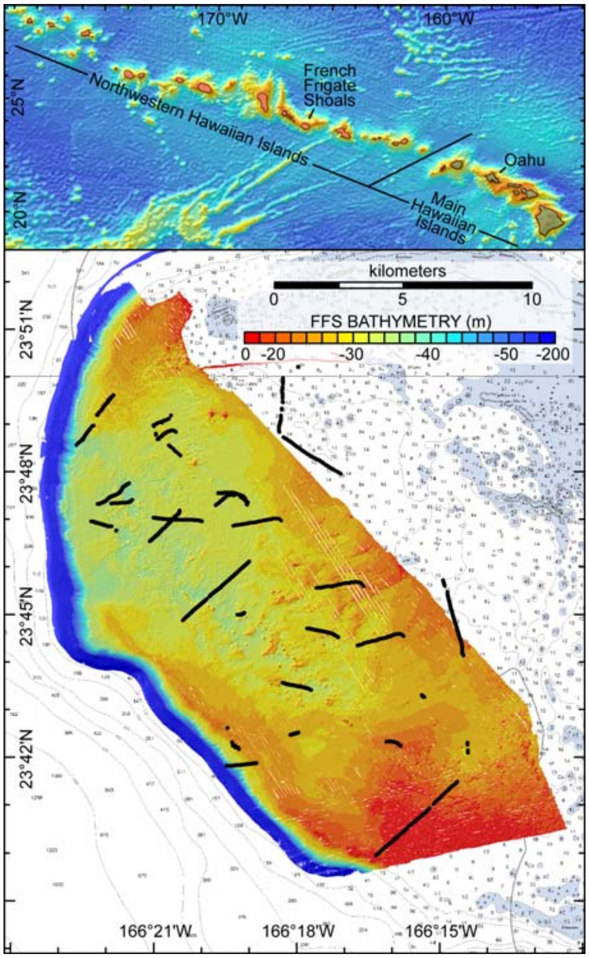

Figure 1: (Top) Seafloor topography of the Hawaiian archipelago derived from satellite altimetry and ship soundings (Smith and Sandwell 1997). The subaerial extents of the MHI and the prominent islands, atolls, banks in the NWHI and the shelves around them are outlined. (Bottom) Multibeam bathymetric data collected by NOAA over of a portion of the bank top at FFS. TOAD tracks are shown in black. The data are overlain on a NOAA NOS nautical chart where shoal depths are colored.

Optical data were collected at FFS from 2001-2005 using the Towed Optical Assessment Device (TOAD) and were analyzed according to the CRED classification scheme (www.soest.hawaii.edu/pibhmc) that includes factors such as substrate type, living growth on the seafloor, geomorphic zone, and the size and abundance of holes in the substrate.

Methods

Initially we took a qualitative approach to seafloor characterization by visually comparing the data. For example, we related backscatter intensity and seafloor slope to the substrate type, as determined by the optical data, by observing that hard (rock, rubble) and coral-rich substrate correspond to high backscatter intensity and slope, while soft (sandy) substrate correspond to lower backscatter intensity and slope.

However, coral-reef and fisheries managers generally have little experience in interpreting optical and acoustic datasets to form management and monitoring plans. They stated the need for integrated map products and in particular the NWHI Papaha‘naumokua‘kea Marine National Monument (NWHIMNM) managers requested maps showing areas of hard and soft seafloor substrate that could be used in the framework of a habitat-based, stratified random sampling design (Ault et al. 1999). To accomplish this goal we took an image processing approach using the ENVI software package commonly used to analyze satellite imagery by the remote sensing and planetary science communities.

Acoustic backscatter data are the most useful dataset available for FFS for identifying hard and soft seafloor. Initially a supervised classification technique, which clusters pixels into pre-defined classes, was applied to the data. Region of interest (ROI) classes were chosen by querying TOAD data based on photos that were classified as either ≥80% hard bottom or ≥80% soft bottom (Fig. 2).

A 2-class maximum likelihood supervised classification algorithm was run on ENVI software using the 2 ROI classes and a 3-band image containing backscatter and small- and large-scale bathymetric variance. Variance, derived from the bathymetric data, is the square of the standard deviation of a pre-defined number of neighboring pixel cells. Variance calculations were performed using ArcGIS Spatial Analyst tools. Small-scale variance, calculated for a 3x3 pixel cell neighborhood, is useful for defining topographic features such as sediment ripples or possible coral-rich regions, whereas the large-scale variance, calculated for a 5x5 neighborhood, is useful for defining seafloor ridges, pinnacles, and significant changes in slope. Variance proved to be a useful bathymetric derivative in previous efforts to map seafloor habitats by Dartnell and Gardner (2004) and including both the small- and large-scale variance in our analyses generally gave better results despite their visual similarity (Fig. 3). The acoustic data were resampled to a 5 m grid cell size prior to running the ENVI analyses. Additionally, the Reson 8101 and Kongsberg EM3002D datasets were processed separately due to their different frequency contents and the resulting classified images were combined during post-processing.

Initial results from the supervised classification were unsatisfactory because obvious artifacts around data gaps were apparent. There was also concern that the technique relied too heavily on the optical data. Uncertainties in camera sled positioning, absence or limited availability of optical data for many areas, and bias in the supervised class definitions made it necessary to investigate an alternative approach.

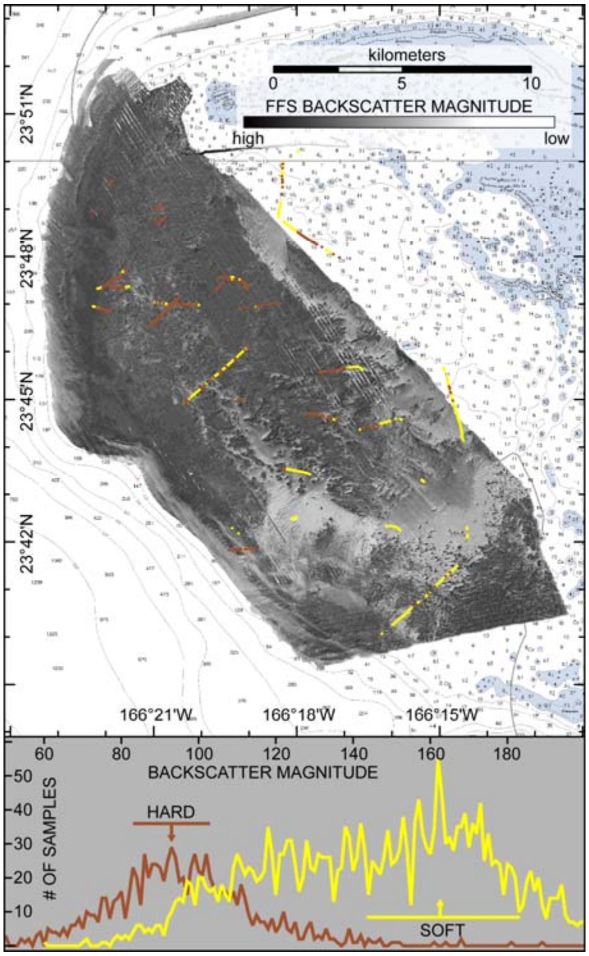

Figure 2: (Top) Backscatter imagery and TOAD tracks colored yellow for ≥80% sand/soft bottom and brown for ≥80% hard/rock bottom. (Bottom) Backscatter magnitude vs. number of samples for hard (brown) and soft (yellow) seafloor ROI's. Lower backscatter values are harder bottom due to the reversed polarity dataset used to extract the backscatter magnitude values for the plot. Vertical arrows and horizontal bars indicate the mean and standard deviation for each ROI respectively.

Consequently an unsupervised classification technique was chosen, which relies only on the data statistics. Using this technique, no user defined training classes or inputs other than the acoustic data are required for creating the classified image. After testing different combinations of input data and various classification algorithms a 2-class K-Means unsupervised classification algorithm was run on ENVI software using a 4-band image containing backscatter, bathymetric rugosity, and small- and large-scale bathymetric variance (Fig. 3) to derive regions of hard and soft substrate for the mapped portion of the bank top. Rugosity is calculated using the Benthic Terrain Modeler in ArcGIS (Jenness 2003). The unsupervised classification algorithm calculates class means evenly distributed in the data space and then iteratively clusters the pixels into the nearest class using a minimum distance technique. In general, the unsupervised classification dealt better with data gaps and delineation of isolated hard bottom areas surrounded by sand, such as pinnacles, than did the supervised technique. The hard and soft classes were assigned to the resulting unsupervised image by visually comparing the optical data with the classified image.

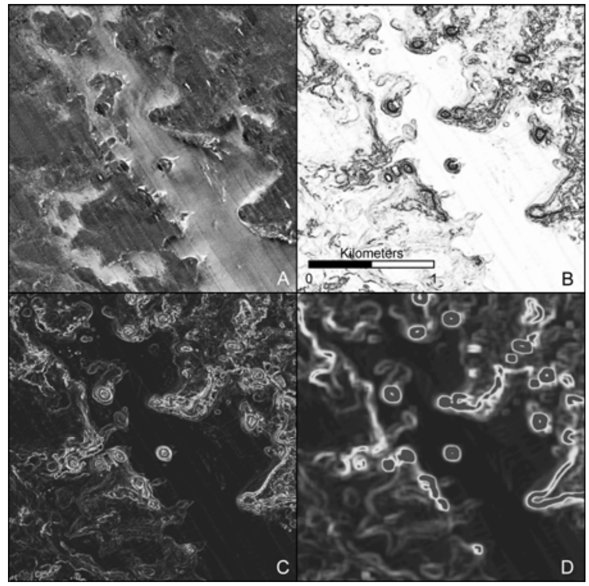

Figure 3: (A) Backscatter, (B) bathymetric rugosity, (C) small-scale bathymetric variance, and (D) large-scale bathymetric variance for a small subset of the FFS bank top. Note the 1-km-long scale bar in (B). Higher backscatter is indicated by darker colors in (A), higher rugosity is indicated by darker colors in (B), and higher variance is indicated by lighter colors in (C, D).

Results and Conclusions

Figure 4 shows the hard and soft seafloor substrate map created using the unsupervised classification technique for a portion of the bank top at FFS. A confusion matrix was calculated to compare the classification results with the ground truth (TOAD) data. The overall accuracy of the classification results when compared to the user-defined ROI classes is ~80% but the accuracy is much less (~30%) when the results are compared with the entire TOAD dataset. This difference is most likely associated with the positional uncertainties of the TOAD data and errors in the unsupervised classification and suggests that visual comparison of the classification results with the optical data is imperative for assigning substrate types to classes. Subsequent optical and SCUBA-based ground truth operations at FFS suggest the ~80% accuracy is a realistic overall assessment of the unsupervised classification results.

Substrate maps, produced as describe above, are currently being used by NWHIMNM scientists and managers to determine long term monitoring sites. It appears that this is an appropriate approach for integrating high-resolution multibeam survey datasets covering large areas with limited coverage optical datasets. This method can easily be expanded if high quality acoustic and optical data are available, it has been applied to a number of other areas, and the resulting maps and data are available for download at www.soest.hawaii.edu/pibhmc. The processing approach described above and error assessment techniques continue to be refined to create accurate seafloor substrate maps.

CRED study sites span the tropical Pacific Ocean basin and data acquisition is often limited by the amount of time available to survey in remote locations. This can result in maps covering a wide area with sparse coverage and some data gaps. The NOAA Biogeography Branch is applying similar image processing techniques to create spatially limited seafloor substrate maps with dense coverage and few data gaps around islands in the Caribbean, such as Puerto Rico (Costa et al. 2008). However, the specific method described here has been developed to meet needs of resource managers in coral reef ecosystems with somewhat sparse multibeam and minimal optical data.

Although logistical constraints may limit the coverage of acoustic datasets (multibeam and backscatter), experience has demonstrated the importance of designing surveys to collect high quality backscatter data. Greater coverage can be attained by concentrating only on maximizing data collection. However, the slower survey speeds and other constraints that may be required to collect high quality backscatter data have been found to be justified because it is undoubtedly the best discriminator of hard and soft seafloor. Additionally, dense grids of optical ground truth data aid tremendously in class determination, derived layer validation, and error assessment.

The coral reef community has only begun to apply image processing techniques (e.g. Dartnell and Gardner 2004; Blondel and Sichi 2008; Marsh and Brown 2008) to acoustic and optical datasets for habitat classification and characterization. These methods represent emerging techniques with much broader characterization and predictive possibilities. For example, predictive habitat mapping (Pittman et al. 2007) expands the utility of acoustic and biologic datasets to predict biomass and fish species abundances based on marine organism seafloor habitat preferences.

Acknowledgement

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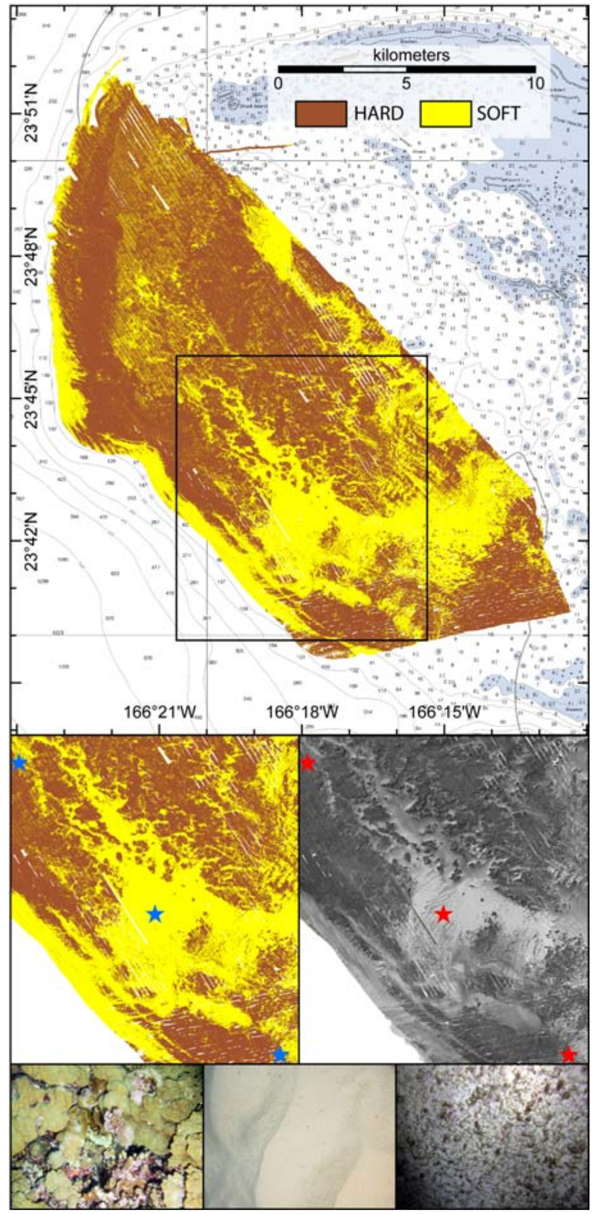

Figure 4: (Top) Hard and soft seafloor map created using the ENVI K-Means unsupervised classification algorithm on a 4-band input image. Black box corresponds to the area shown in the images beneath. (Middle) A portion of the hard and soft (left) and backscatter (right) data. Stars indicate the TOAD frame grab locations shown beneath. (Bottom) TOAD frame grabs that, from left to right, correspond to the star locations from top to bottom (northwest to southeast). Coral-rich (left), sandy (middle), and pavement (right) seafloor substrates match the hard and soft classes.

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