Image processing approach to classification of hydroacoustic products for habitat mapping

Karen Holmes[1], Ben Radford
Coastal CRC, Benthic Habitat Mapping Subproject
School of Earth and Geographical Sciences and
[1]School of Plant Biology
University of Western Australia

We explored the application of standard remote sensing imagery classification techniques to bathymetry, datasets derived from bathymetry, and hydroacoustic imagery as a potential avenue for large-area benthic habitat mapping. These types of seafloor data provide information on morphology and texture, which we hypothesize are related to the substrate composition, local current or wave energy, and hence the distribution of benthic flora and fauna. To test these methods, we used datasets collected in the Marmion Marine National Park by UWA (underwater video, sidescan) and Fugro (Multibeam bathymetry and snippets).

The most common treatment of hydroacoustic imagery has been manual classification. Maps produced in this way have been shown to do an adequate job of delineating bottom types such as high relief reef, or the contrast between flat sediments and seagrass canopy. However, manual classification is extremely time consuming, scale dependent, qualitative, and operator specific. Standard quantitative remote sensing techniques for image classification have been proven to be more effective than manual classification for terrestrial applications, but have not been rigorously tested or further developed for deep-water benthic habitats. In the case of bottom roughness, terrain analysis methods from terrestrial applications are ideally suited for differentiating features. Snippet data and sidescan imagery appear to distinguish more subtle features, such as differences among vegetation types or different sediment grain sizes. However, the datasets available typically contain a large number of artifacts that prevent the use of standard remote sensing image classification techniques. Artifacts include artificial patterns due to boat pitch and roll, missing segments between tracks, and crudely interpolated data along the nadir of each track.

We tested multiple methods for enhancing the imagery (production of secondary datasets) and classification. Techniques developed for radar remote sensing include applying filters to the imagery to enhance textural features. These are called grey-level co-occurrence matrices (GLCMs), and are considered derivative or secondary datasets. GLCMs address average spatial relationships within a moving analysis window, and help to intensify contrast between different bottom types. They include measures of entropy, homogeneity, contrast, energy, inertia, maximum probability, uniformity, and others (Shokr, 1991, Stewart *et al.*, 1994). Once the secondary datasets have been produced, they can be used in the classification along with or in place of the original imagery. This approach has been applied to hydroacoustic data in the past (Blondel, 1996, Cochrane and Lafferty, 2002, Stewart *et al.*, 1994) with varying levels of success. Standard terrain analysis techniques developed for terrestrial applications also supply a variety of secondary datasets suitable for classification. These range from simple calculations of the standard deviation in elevation values in a moving analysis window, to taking the second derivative of elevation as a measure of curvature both parallel and perpendicular to the steepest slope in an analysis window (Moore *et al.*, 1990, Moore *et al.*, 1993). A wide variety of both types of secondary datasets were calculated, and tested as input for classification.

The classification techniques applied included unsupervised methods (ISOCLASS), maximum likelihood supervised classification, and density slicing (Jensen, 1986). In unsupervised classification, the number of classes is set, then the full image or dataset is divided up statistically to minimize within class variability and maximize between class variability. Every pixel is assigned to a class, and it is left to the operator to identify the meaning of the classes. Supervised classification requires user-determined classes, and training samples of each class. The rest of the image is then classified based on strongest similarity to these training samples. Density slicing is the least adaptive technique, and consists of simply choosing a grey-level threshold in a single band image, and classifying the data above or below that threshold as different classes. This can be effective in areas with distinctive color differences, for instance using aerial photography in an area with mainly white sand and some dark patches of seagrass (Kendrick *et al.*, 2000), but it is largely operator controlled, and ineffective in areas of highly complex bottom types. Unsupervised classification was determined to be the best fit for classifying bottom types, largely because it involves fewer preconceived notions about the types and number of classes, is more statistically rigorous than simple image segmentation, and produced high quality results for the test site. Only the results from unsupervised classification will be discussed.

Secondary data development and classification were completed for a small area in Marmion Marine National Park, located just off the WA coast near Perth (**Figure 1**). This has become an equipment testing site used by Fugro for comparison of hydroacoustic equipment performance, hence multiple hydroacoustic datasets are available. The data used for habitat mapping included recent aerial photography, underwater tow video, bathymetry, sidescan imagery, and snippets (**Figure 2**). Typically, if benthic features are visible in aerial photographs, then classification of the photos (unsupervised or supervised methods) are the most economical and straight forward approach. In this case, the aerial photographs were extremely helpful as a visual check of the other classification techniques which are being developed for applications in deep water, and as a check on the georeferencing of the hydroacoustic data. The site was manually classified from the sidescan imagery using the tow video as reference information (**Figure 3**). This is the most commonly produced type of habitat map, and given the small study area extent, large amount of video footage, and complete coverage of the imagery, should closely represent reality. Again, it is impossible to eliminate some bias introduced by the operator in terms of exact determination of boundaries and the minimum mapped unit, both of which are quite difficult to control or standardize when mapping by hand.

All combinations of secondary datasets were tested for unsupervised classification, with the ultimate aim of defining the smallest number of readily calculated datasets for achieving a high quality classified map. The final set of images used were the bathymetry, standard deviation of the bathymetry calculated in a 3 x 3-m window, slope calculated in a 3 x 3-m window, and a smoothed version of the standard deviation of the sidescan grey-scale imagery (**Figure 4**). The snippet data available at the time had too many inconsistencies to work well for automated classification, although recent algorithm developments by Fugro and Curtin University may provide fixes for these problems for future datasets. The final classified map matched the manually classified map extremely closely, but supplies more detail, and was done on a cell by cell basis, removing operator bias in determining smallest mappable unit, and visual determination of image texture (**Figures 5 and 6**).

Unsupervised classification was found to be highly effective over this small field site where the seafloor habitats are closely tied to the bathymetry. It has potential for use with snippet data once clean mosaics of snippets can be produced, as snippets carry much more information than just the bathymetry. At sites where Multibeam is being used to gather bathymetry and snippets, sidescan imagery is unnecessary. The main issue to resolve before this remote sensing approach gains full functionality for benthic habitat mapping is removing the artifacts from the hydroacoustic imagery through preprocessing. As a note of caution, the ecology of the field sites must be well enough understood to choose appropriate datasets for inclusion in classification. In some areas, bathymetry is not as important as perhaps a salinity gradient, or sediment chemistry, in which case including bathymetry may only confuse the final mapped outcome. Correlations among the datasets utilized and bottom types are only correlative, and should not be interpreted as causative.

Figure 1: Location of the Marmion test site (2 x 0.5 km), west of Trigg Point, north of Perth.

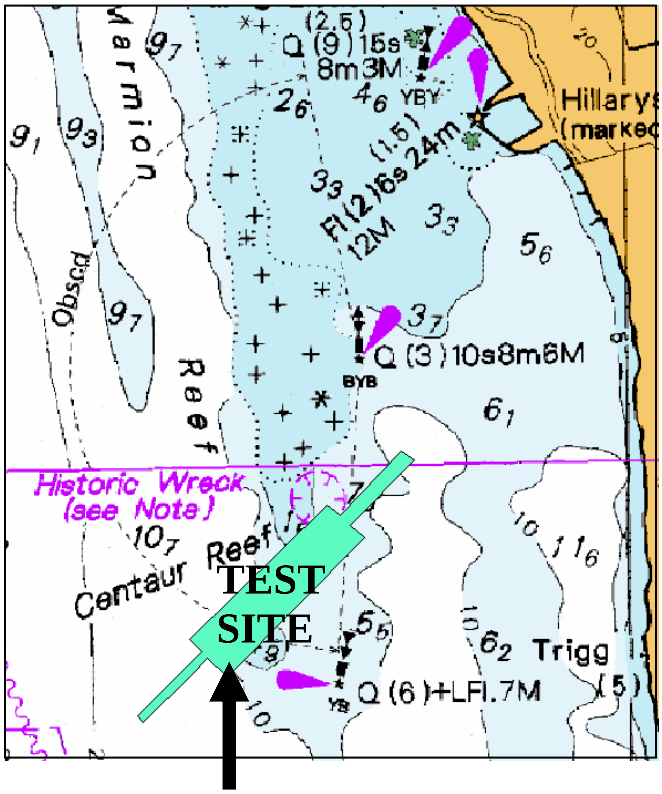


Figure 2: Aerial photograph of the Marmion test site, overlain with the test site boundaries and black dots showing georeferenced locations of video frames.

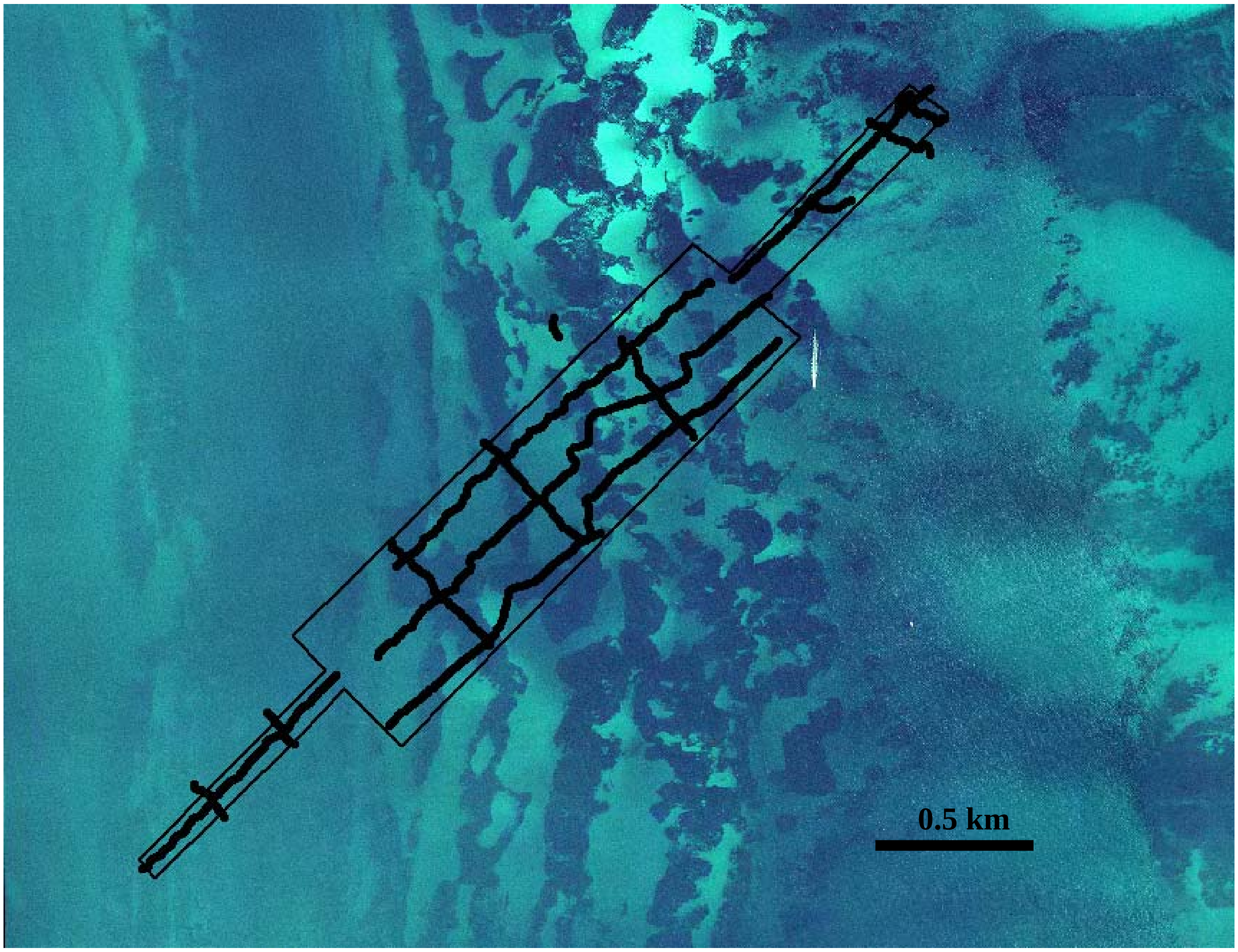


Figure 3: Manual interpretation of habitat classes from Sidescan imagery. Sidescan mosaic (left), classified map (right). Maps rotated from actual orientation for ease of presentation.

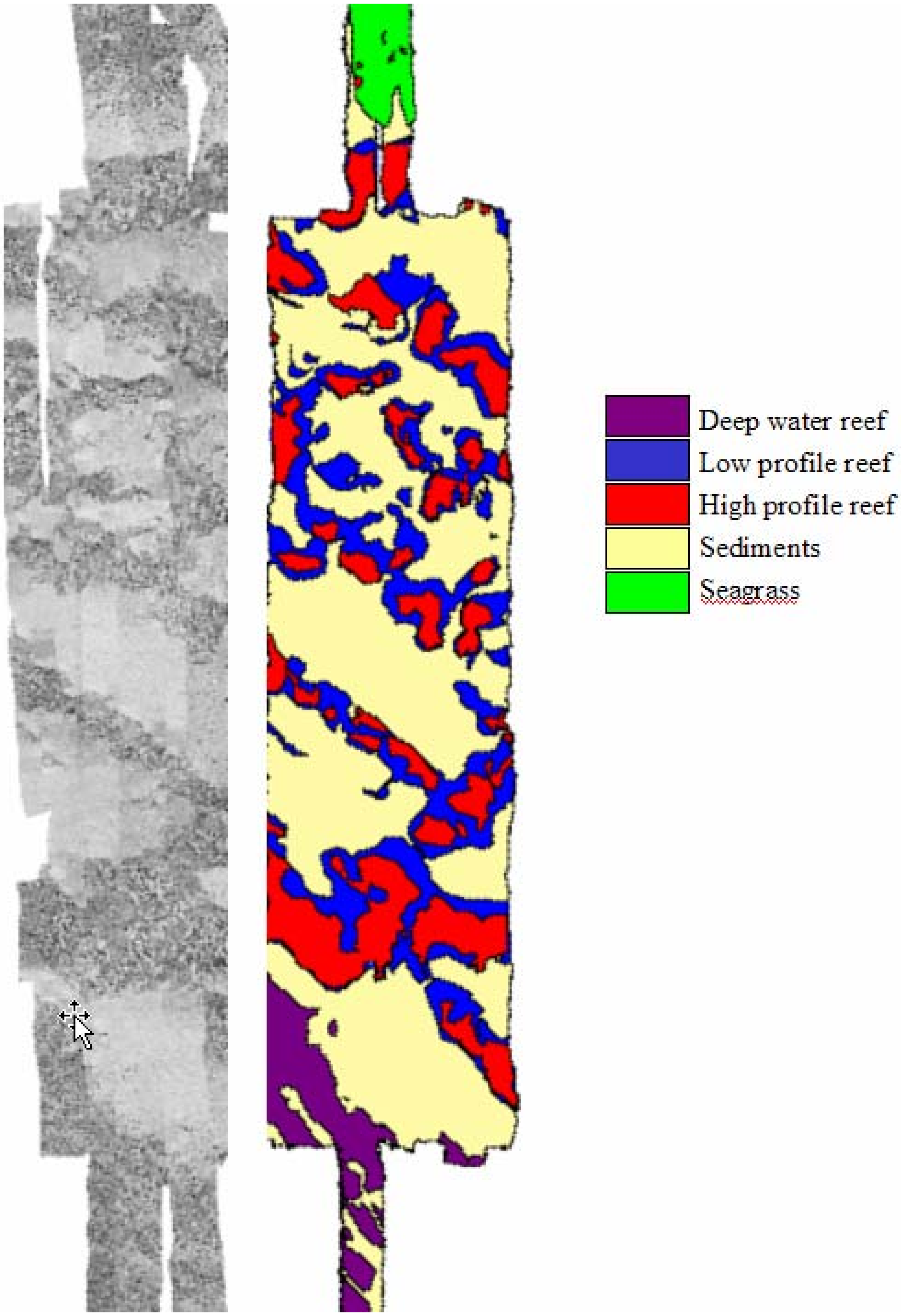


Figure 4: Datasets used for final unsupervised classification: (1) raw bathymetry, (2) standard deviation of bathymetry, calculated in a 3 x 3-m moving window, (3) slope calculated in a 3 x 3-m moving window, and (4) standard deviation of sidescan in a 3 x 3-m moving window, then smoothed with a majority filter.

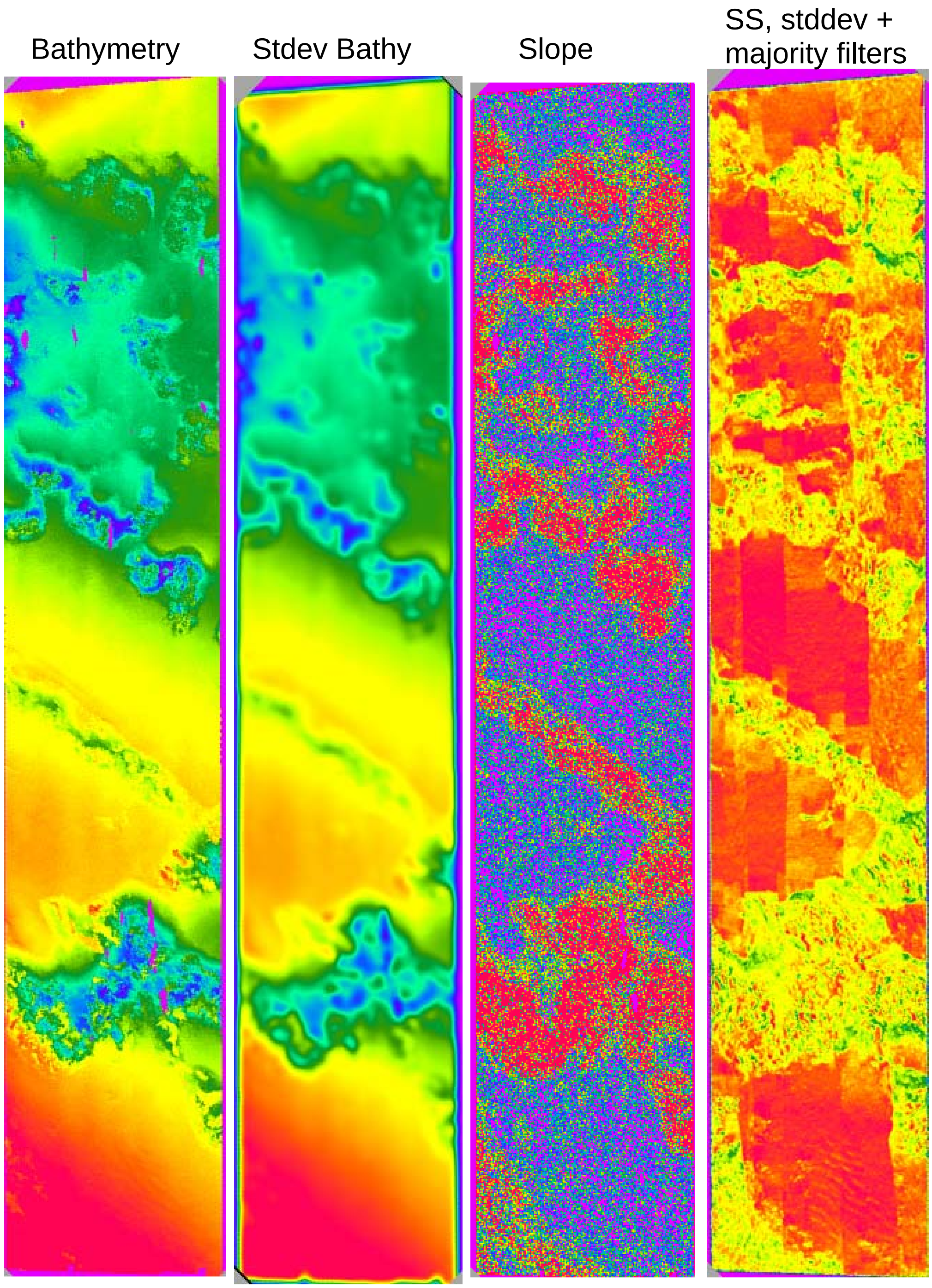


Figure 5: Final map produced using unsupervised classification.

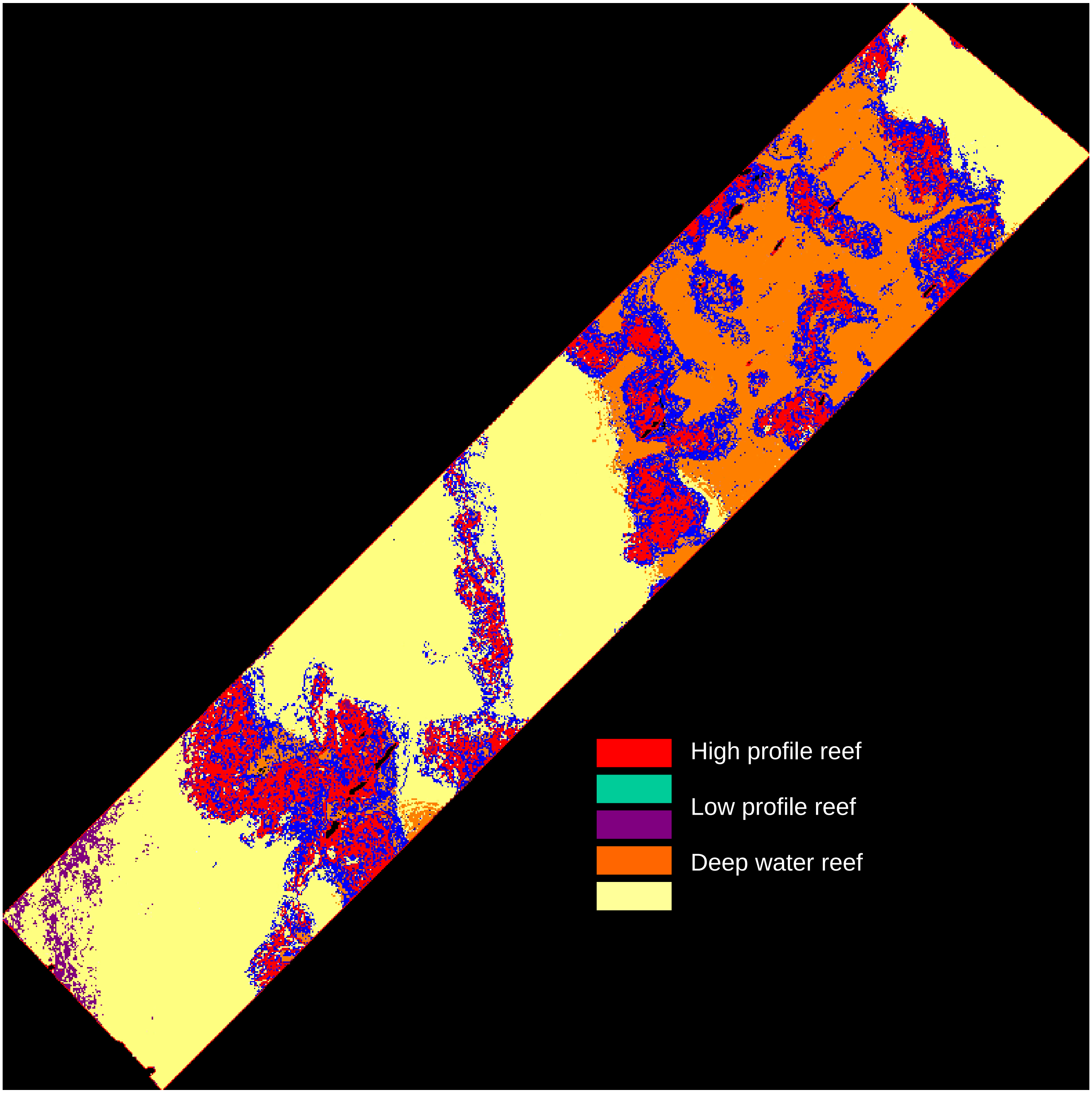
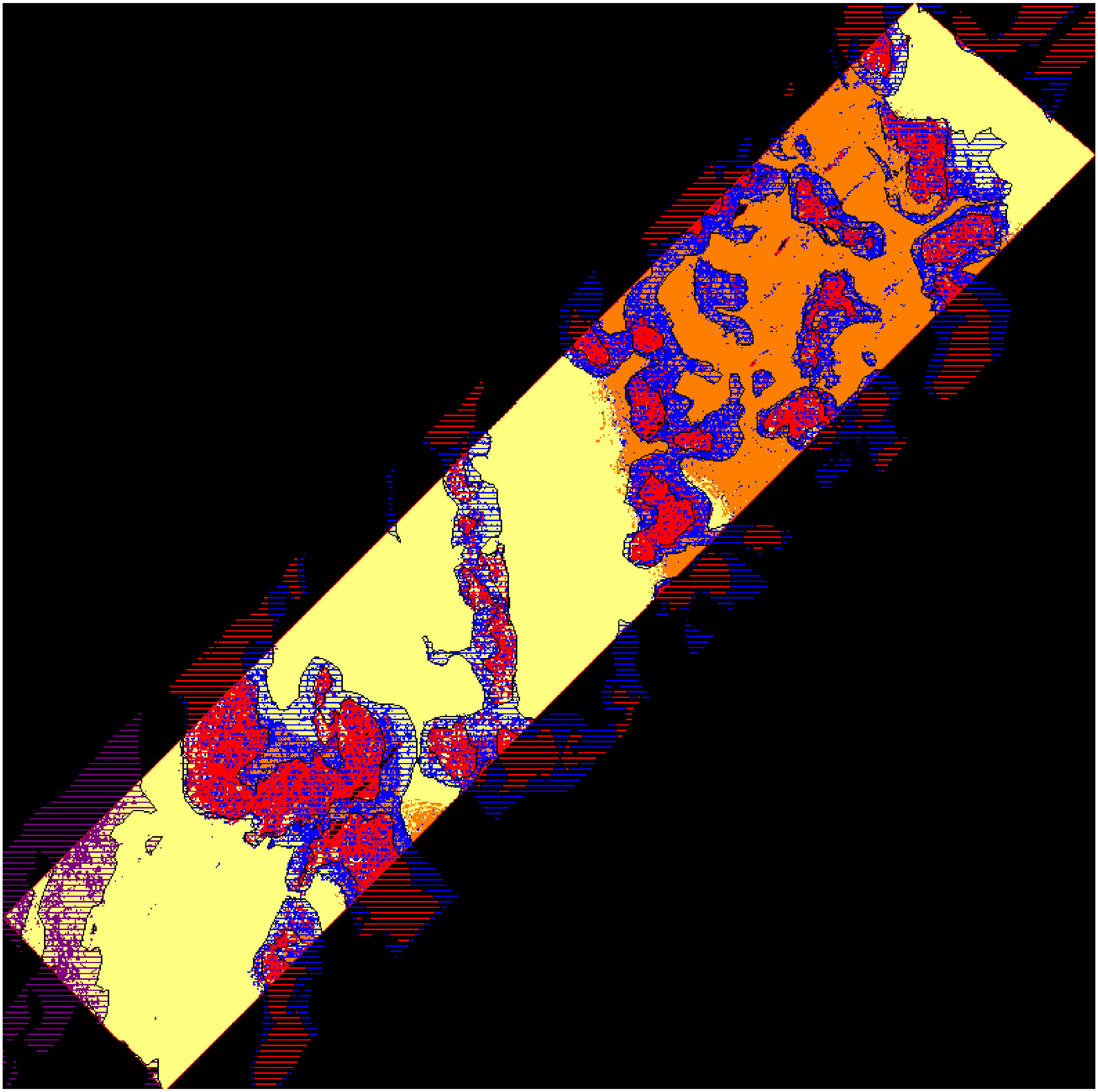


Figure 6: Overlay of final map produced with unsupervised classification of hydroacoustic datasets and polygons that were manually drawn on the sidescan imagery (see Figure 3).



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