IOCM Research in Support of Super Storm Sandy Disaster Relief

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1 Introduction

At 1930 EDT on October 29, 2012, Super Storm Sandy[1] made landfall on the U.S. east coast near Brigantine, NJ (Blake *et al.*, 2013). The convergence of the storm with an intense low-pressure system, its unusual approach direction (from the east rather than from the south) and its coincidence with astronomically high tides made Super Storm Sandy one of the deadliest and costliest hurricanes in U.S. history, causing 147 deaths in the U.S. and more than $50 billion in damages (costs are still being tallied) (Sullivan and Uccellini, 2013). Most of the damage caused by Super Storm Sandy was focused on the coastal zone, with flooding (the hurricane caused record high storm surges in New York, New Jersey and Connecticut), high winds and powerful waves resulting in the destruction of buildings, homes, roads, vehicles, and many other objects over hundreds of miles of coast. While the damage caused by the storm can easily be documented by airborne or satellite imagery for those areas that are above sea level, the impact of the storm on those areas at or below sea level (i.e., the presence of debris and changes in the shape of the seafloor that can create navigational hazards, or the impact on benthic habitat) is much more difficult to assess.

In the immediate aftermath of an event like Super Storm Sandy, the primary concern is for disaster relief, followed by recovery operations. In many cases delivery of relief supplies and recovery operations (even just getting first responders to the site) can rely on recovery of critical infrastructure such as ports and approaches, for example in ensuring that a channel has been cleared of any navigationally hazardous debris. After the initial relief operations, the emphasis can turn to environmental impacts and recovery of the natural resources in the affected area. In both cases, detailed and timely information on the state of the near-shore environment is essential.

The consequences of Super Storm Sandy highlighted a number of areas where the current state of the art in design of surveys, collection and processing of data, and visualization of that data in response to events of the magnitude of Super Storm Sandy were lacking. Consequently, NOAA issued a Federal Funding Opportunity (FFO) under the FY13 Disaster Relief Appropriations Act to advance understanding of these issues. This report is the eighth in a sequence of progress reports to document work conducted under this FFO at the Center for Coastal and Ocean Mapping at the University of New Hampshire.

In this eighth progress report, we report on expanded cooperation between the project and the companion contract work being conducted by the ERT team in the Integrated Ocean and Coastal Mapping Center at the Joint Hydrographic Center, extensions of the submerged aquatic vegetation habitat research, development of the components required to feed into Coastal Engineering Indices, integration and consolidation of the results of our phase-measuring bathymetric sonar research, and

[1] There is some difference of opinion on nomenclature for the event. Some sources prefer "Hurricane Sandy," others "Post Tropic Cyclone Sandy," and still others "Super Storm Sandy." For continuity with the proposal document and general usage, we have preferred "Super Storm Sandy" in this context, but use the term without intent of limitation or precise meteorological description.

the overall solution proposed for parts of the marine object detection task, including development of probability "hot spot" marine object detection maps, and communication of these results to the outside world in a common (digital) vocabulary.

Previous progress reports, and more information on the design, goals, and objectives of the project, can be found on the website, `http://sandy.ccom.unh.edu`.

2 Research Activities

2.1 Habitat Mapping

Superstorm Sandy caused substantial damage to the New Jersey and New York coast lines among other areas in the northeastern U.S. Immediate impacts of the storm included extensive coastal erosion; long-term effects of the storm on Submerged Aquatic Vegetation (SAV) such as seagrass are still being assessed, but are expected to be severe. Due to the extent of the damage in New Jersey, Barnegat Bay has become a focal point for investigating the storms impact on SAV. In the current reporting period, the emphasis of research has been on creating a time series assessment of seagrass coverage in Barnegat Bay. Manual classifications of dense and sparse seagrass, as well as mixed SAV and sand, were classified for the period between 2006 and 2013 using orthophotos collected by the state of New Jersey and the National Agricultural Imagery Program (NAIP; Figure 1). The remotely-sensed and manually classified 2006-2013 trend maps suggests a decline in seagrass cover, particularly at the southern portions of Barnegat Bay. Field campaigns in 2012 and 2013 corroborated the remotely-sensed results of the presence of seagrass along the northern portion of Barnegat Bay and Barnegat Inlet. Further, the remotely-sensed monitoring trend indicates a decline in the area of dense seagrass in 2013 vs. 2006. However, differences in image quality and the seasonal period of image acquisition may account for the differences in the mapped area and in the apparent thinning of seagrass density as imagery for the 2006, 2010, and 2013 were acquired in the growing season (July and August), while the 2007 and 2012 surveys were acquired early in the growing season in March and April.

These maps were then compared to earlier base GIS layers of SAV identified by the Center for Remote Sensing and Spatial Analysis (CRSSA) at Rutgers University. Preliminary results indicate that SAV cover is temporally variable with a noticeable decadal decline in SAV from 1968 to 2013, specifically with seagrass (Figure 2). It appears that the decline in seagrass is not confined to one particular region, but has occurred throughout the entire Bay. These results are consistent with previous studies demonstrating decadal loss of seagrass habitat (e.g., Kennish *et al*., 2008, 2010; Lathrop and Haag, 2011; Kennish *et al*., 2012; Lathrop *et al*., 2014).

Efforts have also centered on collaboration with Dr. Juliet Kinney (ERT-NOAA Sandy Supplemental IOCM contract leader at the Joint Hydrographic Center) to grid peak amplitude, rugosity, slope, and bottom return derived from the USGS EAARL-B topobathymetric lidar system flown post-storm (Nov. 1-5; Figure 3).

2.2 Coastal Engineering Indices

The goal of the Army Corps of Engineers Coastal Engineering Indices (CEI) is to provide comparable combined indices for engineering, environmental, and human use, that provide a snap shot of coastal conditions. CEI is intended to synthesize data needed to assess coastal conditions, compare regions, and monitor change using parameters extracted from spatial data, and examine how it can be integrated and/or transformed into a regional index. Products derived from topo-bathymetric lidar and high resolution imagery for the Super Storm Sandy habitat mapping effort in-

clude bathymetry, slope, rugosity, bottom return, and peak amplitude. There products were used to create habitat maps (Figure 3; see Progress Report Q2FY15 for further details), and can generate features for environmental applications, to be used for CEI and other indices focused on habitat analysis. The methods used to create these products are described in the procedural document "Submerged Aquatic Vegetation Mapping using Object-Based Image Analysis with Lidar and RGB Imagery", located on the project website (`http://sandy.ccom.unh.edu`). Having the products generated as standard raster imagery makes them more generally useful to the scientific and management communities. These data can also be easily crosswalked to other standard classification systems such as NOAA's Coastal Marine Ecological Classification Standard (CMECS).

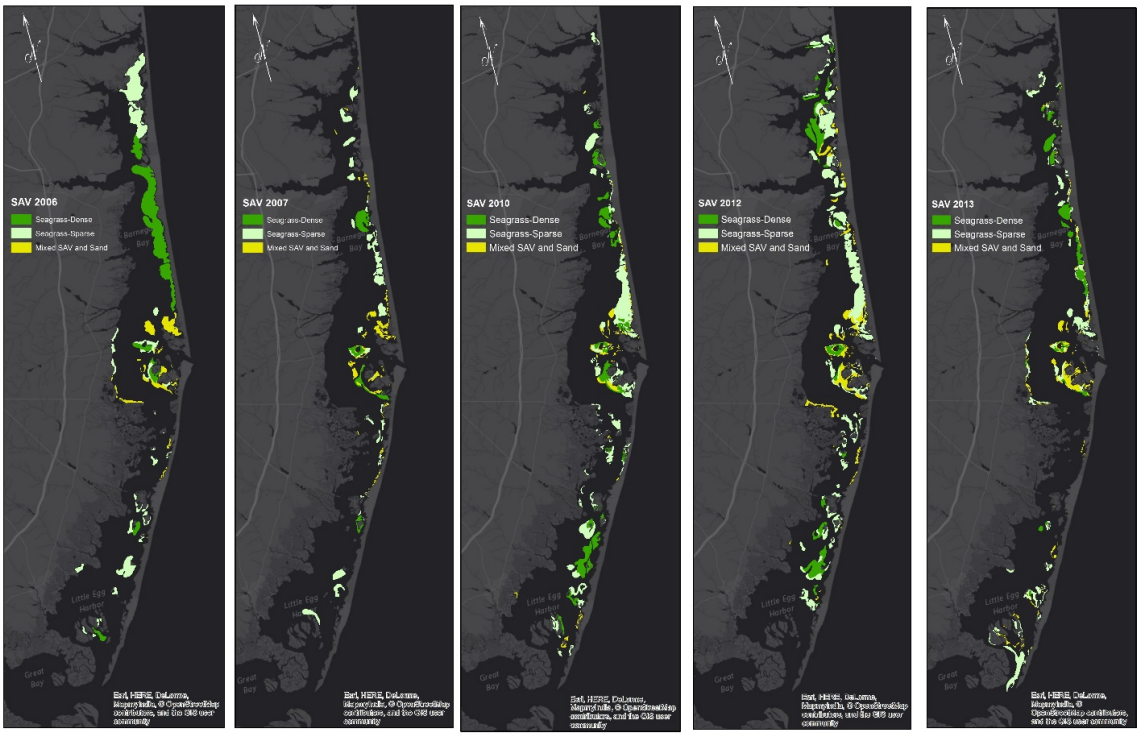

Figure 1: Time-series of seagrass, and mixed SAV/sand cover between 2006 and 2013 (manual classification).

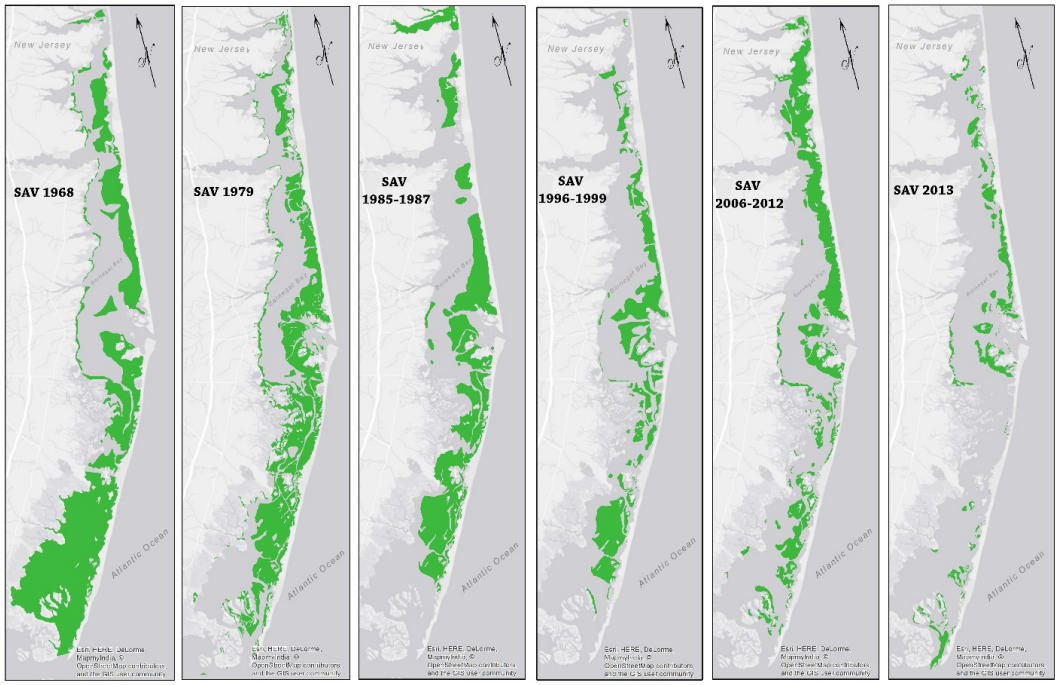

Figure 2: Remotely-sensed maps showing SAV coverage from 1968 to 2013. Orthophotos were collected by the State of New Jersey, and SAV from 1968 to 1999 were identified and analyzed by the Center for Remote Sensing and Spatial Analysis (CRSSA, Rutgers University).

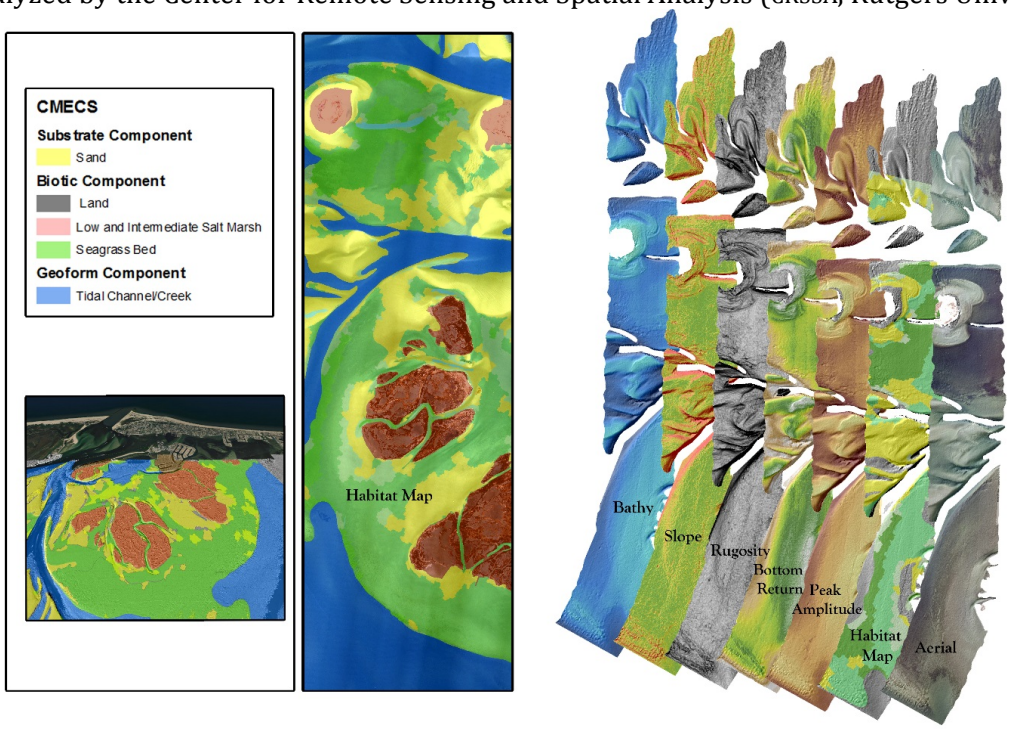

Figure 3: Products derived from the USGS EAARL-B topobathymetric lidar system that can be incorporated into a Coastal Engineering Index.

2.3 Chart Adequacy

Over the past three months, effort has been focused on supporting the NOAA Sandy Supplemental IOCM contract group at the Joint Hydrographic Center ("IOCM group") in chart preparation from NOAA Remote Sensing Division's Airborne Lidar Bathymetry (ALB) data sets (which should be delivered to IOCM in November 2015). The IOCM group, with the guidance of Marine Chart Division (MCD), have been working on collection of publically-available survey data for chart preparation. MCD and IOCM are planning to use the chart adequacy procedure cook book written by Shachak Pe'eri and Anthony Klemm in order to find any discrepancies between the charted bathymetry and the current reconnaissance data set. This project provided assistance with satellite-derived bathymetry (SDB) to the IOCM efforts. SDB from Landsat 8 imagery of the Barnegat Bay region of New Jersey was provided to IOCM for the time period between 2013-06-01 and 2014-09-17. Details on the creation of SDB have also been provided to the IOCM group via previous reports documented on the project website (`http://sandy.ccom.unh.edu`). SDB imagery along all of the New Jersey coastal region (NOAA Charts 12324 and 12316) has also been collaboratively processed with IOCM.

Landsat 8 satellite imagery was downloaded from EarthExplorer covering the chart areas. Imagery with minimum cloud cover and sediment turbulence in the water were prioritized. Several images were tested and only images acquired on 2014-04-10 and 2015-08-26 were selected as suitable for satellite derived bathymetry. An EAARL-B lidar survey, post Super Storm Sandy, from Little Egg Harbor (Figure 4) was used for vertically referencing the algorithm results of the satellite derived bathymetry to chart datum.

The extinction depth was calculated for remaining areas in the south, and was found to be 1.85 m. Areas with depths past the extinction were removed as well as other areas that were considered poor quality for chart adequacy applications. The final satellite derived bathymetry rasters (with pre-calibrated rasters and Excel spreadsheets used for calibration) were provided to IOCM (Figure 5). The IOCM group will continue to derive bathymetry for the New York coastal areas based on the techniques developed for this project.

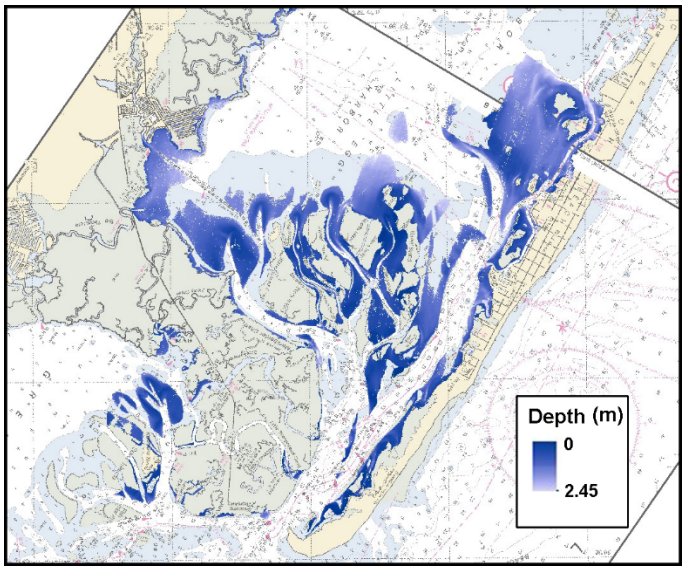

Figure 4: EAARL-B lidar survey coverage within Little Egg Harbor, New Jersey.

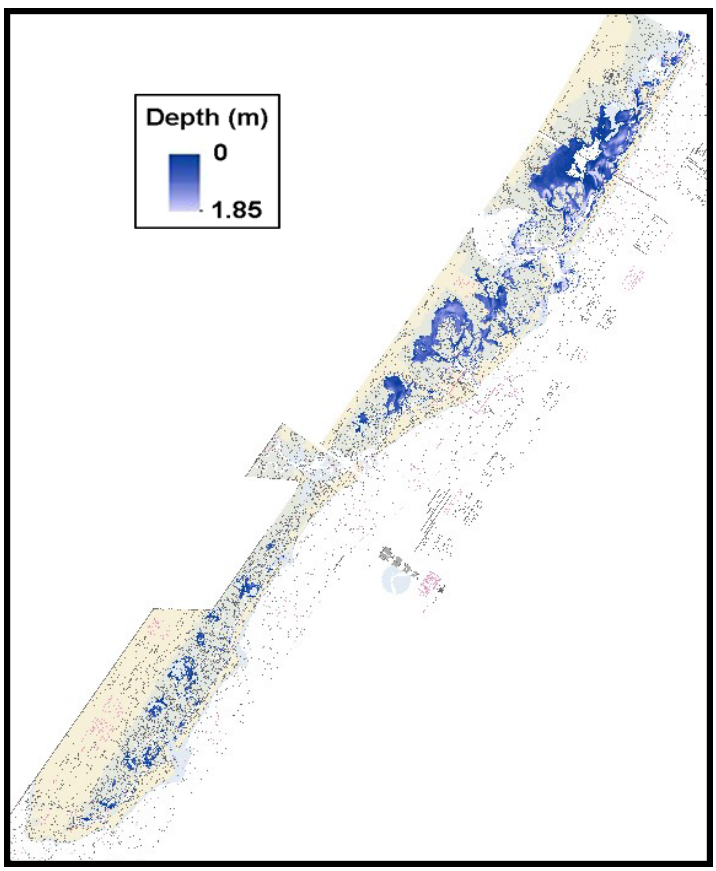

Figure 5: Coverage of satellite-derived bathymetry provided to the IOCM group. The bathymetry is based on Landsat 8 imagery collected on 2014-04-10.

2.4 Marine Debris Detection

The main aim of this research theme is to facilitate the identification of marine debris by developing an approach (and the required implementation tools) that can be

used to assess the presence of debris in the event of a storm. This goal is made more difficult by the extreme variability of marine debris. There has been a lot of work done on object detection, mostly from the mine counter measures and pipeline inspection fields, and several of these of techniques have been modified for adoption in this research theme, although this is made more complex by the variability inherent in marine debris. That is, in mine-like objects, the shape of the object is often (approximately) known; with marine debris, this is typically not the case. NOAA's Marine Debris program definition for marine debris is, paraphrasing, essentially anything that should not be there. This vagueness in the definition makes it difficult to design a single algorithm that is able to detect it.

This consideration has dictated the solution developed: robust methods for reliable detections, which are then combined. The algorithm starts with multiple layers of information, which can be collected through depth measurements or backscatter, or some kind of *a priori* information (such as the outcomes of a predictive model, or something as simple as a binary land/sea mask derived from the current ENC) able to meaningfully constrain the problem. The approach is to combine the information content of these layers into a map that defines the probability of there being objects in a particular area. It is then possible to further customize the map to filter specified areas, for example to focus on the marine debris present only in depths shallower that a defined threshold. It is then straightforward to reduce this probability map to a list of point objects for inclusion in a database to be communicated to the outside world.

The workflow can be divided in three stages:

- a predictive model, used as a means to structure the problem, to control some of the complexity, and to obtain a general idea on where debris are liked to be;
- the detection model which implements robust detection; and
- data exchange, which is required to make the results useful.

Although problems of this type notoriously have multiple possible solutions, the goal of the prediction model is to emphasize a likely solution. The approach adopted is to study the correlation between several available explanatory layers collected in the wake of recent Gulf of Mexico and East Coast storms (such as Katrina and Sandy) and the likelihood of generation and deposition of marine debris. Data related to the track and the intensity of the storm, to the human environment in the area (as sources of many marine debris), and to the size of the effects (significant wave, storm surge, and so on) were selected as potentially informative layers. The combination of these layers provides a means to generate a rough prediction, for any given storm, on where there is a larger likelihood of their being significant marine debris creation. This information is then used to balance out the predictions of the detection algorithms, for example by allowing the overall estimator to discount (false positive) detections where debris is considered unlikely.

A simple detection model is generally precluded by the complexity of the marine debris detection problem. The core model is to use a selection of detection al-

gorithms, each one not necessarily individually reliable, but that together provide a more reliable output.

During the development of the model the three main questions to answer were:

- What products to use as data input;
- The selection of detection algorithms; and
- How to fuse the outcomes of the different detection algorithms.

For inputs, the algorithm uses only standard hydrographic data products, so that the approach will not require the acquisition of particularly 'exotic' data. This is mainly so that the algorithm can be implemented in the event of a storm-like scenario, when a disaster response is in progress and there is unlikely to be time and resources to do anything more. For backscatter, detection algorithms were developed from the results of long-term research at CCOM (i.e., Geocoder) combined with well-known image processing techniques. For the bathymetric component, the statistical layers that are created by bathymetric processing algorithms such as CUBE were of particular interest. In addition to the DTM, the uncertainty associated with each node as well as the hypothesis count and the hypothesis strength were used. From these two layers extra area information on how likely it is that there is a problem/object in the area can be obtained.

In marine object detection, large areas with no debris can cause problems due to the generation of many false positive detections. To avoid, or at least contain, this problem, the algorithm developed segments the area under analysis into smaller (but significantly related) seafloor patches, and then calculates for each of these small areas a vector of metrics that captures various aspects of the backscatter. This provides a mechanism to adapt the context (the local conditions of the data) to each particular seafloor patch, making the problem a lot simpler because each problem to be solved is local rather than global.

The predictive model developed highlights areas of higher likelihood of there being an object. The output provides an estimate of the likelihood of a detection given that there is an object present, but what is required is the probability of an object given all of the detection algorithms. A Bayesian hierarchical model was selected resolve this by providing a probabilistic structure that can be used to combine together the information gathered from the detectors and the extra prior information obtained from the predictive model. The Bayesian model implements the fusion portion of the problem, and is solved numerically, resulting in a probability map (Figure 6) which shows areas of high debris probability.

Apart from the strong mathematical framework, this model admits the specification of spatial correlations, which allows it to adapt to the local behaviors of the detectors in the presence (or, equivalently, absence) of objects. An auto-logistic model is used to fuse the binary outputs from the various detection algorithms in this case.

A partially open question is whether having more detection algorithms actually improves the detection. Empirically, this appears not to be consistently the case. Experimental results appear to support the idea that having more metrics in the detection algorithms can cause more confusion in the detection than is gained from

having the extra algorithms involved. A limited number of independent algorithms that give independent views of the data are likely to be more effective.

Although the algorithm developed has a number of robust features, no algorithm is perfect. Consequently, a suite of operator interaction tools have been developed in conjunction with the automated scheme in order to support human intervention. By way of example, tools are available to extract shapes of objects by hand, or in a semi-automated manner, and the visualization of objects can be driven by the probability of detection (i.e., so objects that are very likely are either treated first, or are accepted as true objects directly, rather than being sent to a human operator for inspection).

To be useful it is not sufficient just to generate detections: these detections must also be usable elsewhere. The method developed here derives from the GML object model to obtain a Marine Debris Markup Language, which can be used as a common vocabulary for describing debris objects between data collection and analysis tasks. By building on a standard feature profile, the result is easy to reconstruct in standard Open Geospatial Consortium (OGC) tools, such as the Geospatial Data Abstraction Library (GDAL). This provides a mechanism to import the results into many common GIS-style tools without any extra effort.

More details about the approach developed are provided as a report on the project's website. The approach has also been the subject of a presentation at the Shallow Survey conference (Plymouth, UK, 14-18 September, 2015) and of an invited talk at the Wrecks of the World III conference (Gothenburg, Sweden, 12-13 October, 2015).

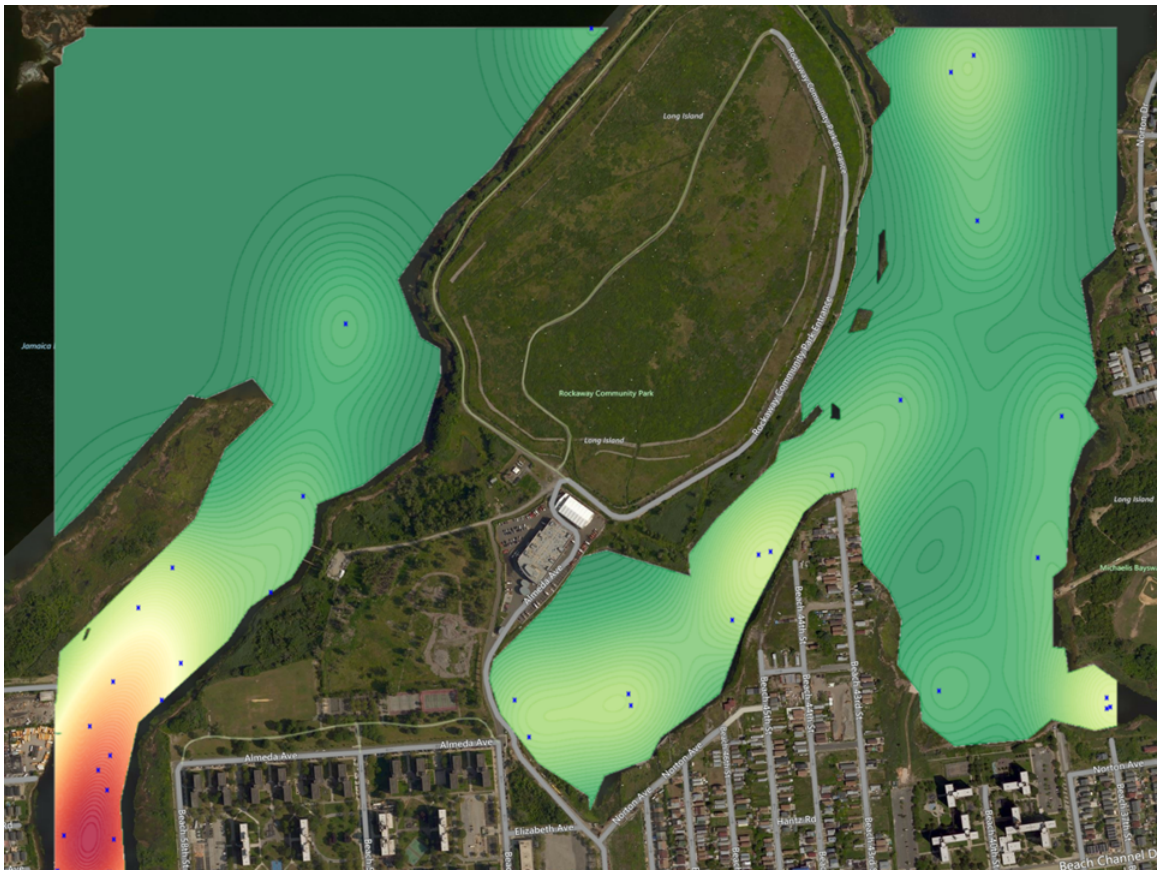

Figure 6: Probability map of Jamaica Bay, NY, with the ground-truth positions of marine debris designated by human analysts shown as blue dots.

2.5 Phase-measuring Bathymetric Sonar Data Processing

Research in the final quarter on data processing techniques for phase-measuring bathymetric sidescan (PMBS) echosounders has focused on tying together the results of various approaches for improving detection of objects and seafloor features for post-storm surveys. As discussed in previous quarters, several examples of objects and seafloor features have been examined from a variety of datasets, including the Redbird Reef surveys collected after Super Storm Sandy and the Shallow Survey 2015 Common Dataset collected in Plymouth Harbor, England. It has become clear that the challenges of detecting manmade objects and small natural features for sea-floor change analysis by visual scrutiny of both PMBS and multibeam echosounder (MBES) data are similarly limited by several factors. Regardless of echosounder type, these factors include the target size relative to sampling and gridding dimensions, the character of the ambient seafloor, and the uncertainty or 'noisiness' of the depth data on these surfaces.

In many of the available datasets, the presence of an object or seafloor feature remains ambiguous with the available data and tools for examination. Figure 7 provides an example of object detection testing in a tank using a multibeam echosounder with water column imagery. In these tests the depth data alone do not provide clear evidence of the presence of many targets and the subsequent process of grid-

ding would often mask their presence. Although the tank tests are not directly indicative of the performance of this echosounder (or any other) for object detection in a true open water environment, they do demonstrate the types of challenges associated with object detection from acoustic measurements alone.

In order to better understand the factors affecting visual detection of objects in depth data alone, a gridded bathymetric surface with randomly placed objects has been modeled in MATLAB to include simulated uncertainties of the seafloor roughness and depth measurement for each grid cell (Figure 8). By introducing objects of different sizes at random locations and testing the ability to identify these features in the model surface, qualitative trends in the object detection confidence as a function of object size relative to seafloor roughness, measurement uncertainty, and grid cell size can be identified. These tests inform some of the recommendations included in the deliverable document for this quarter describing modified processing techniques.

As discussed frequently during this project, PMBS systems offer sidescan imagery that can be used to extend the useful swath width for detection of objects at longer ranges and lower angles of incidence on the seafloor, where depth data typically become least reliable for this purpose. A conceptual model for a near-real-time data processing interface has been developed which enables the sonar operator to examine raw soundings, full-resolution sidescan imagery, and processed depths under a variety of filtering and gridding strategies.

The conceptual model and results of the evaluations from previous quarters have now been consolidated into a single document. The guiding principle of the recommendations is simply that, for the purposes of detection of marine debris for post-storm assessment, bathymetry, whether from MBES or PMBS systems, cannot stand alone. It must be augmented with water column or sidescan imagery, ideally monitored in real-time and viewable in post processing in conjunction with the bathymetry, illustrated both as surfaces and point clouds. In short, all information must be brought to bear on the problem.

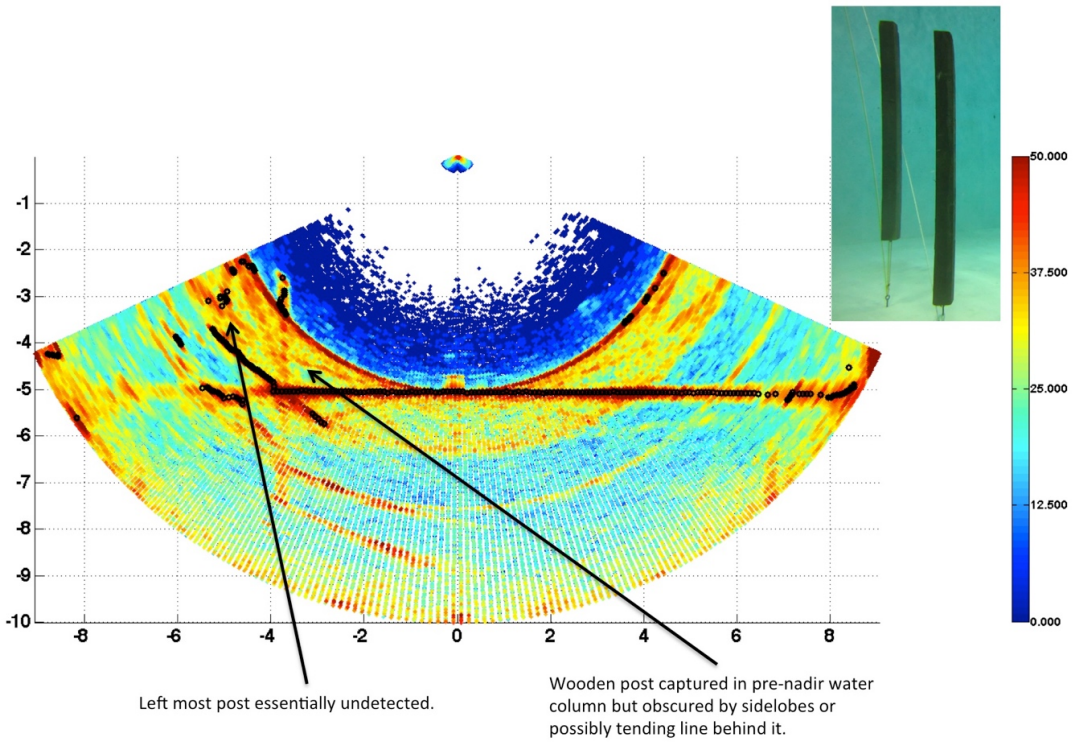

Figure 7: One swath of multibeam data collected during object detection testing in a tank demonstrate the limitations of depth data alone to indicate the presence of two posts (shown in the upper right). The color scale is uncalibrated backscatter amplitude in dB. Bottom detections are represented by black dots. The water column data show vertically oriented anomalies in the post locations, but these are obscured by sidelobe interference from the strong specular reflection at nadir (i.e., the 'nadir ring'). As with PMBS systems providing both depth data and sidescan imagery, all available MBES data products must be evaluated to improve confidence in object detections.

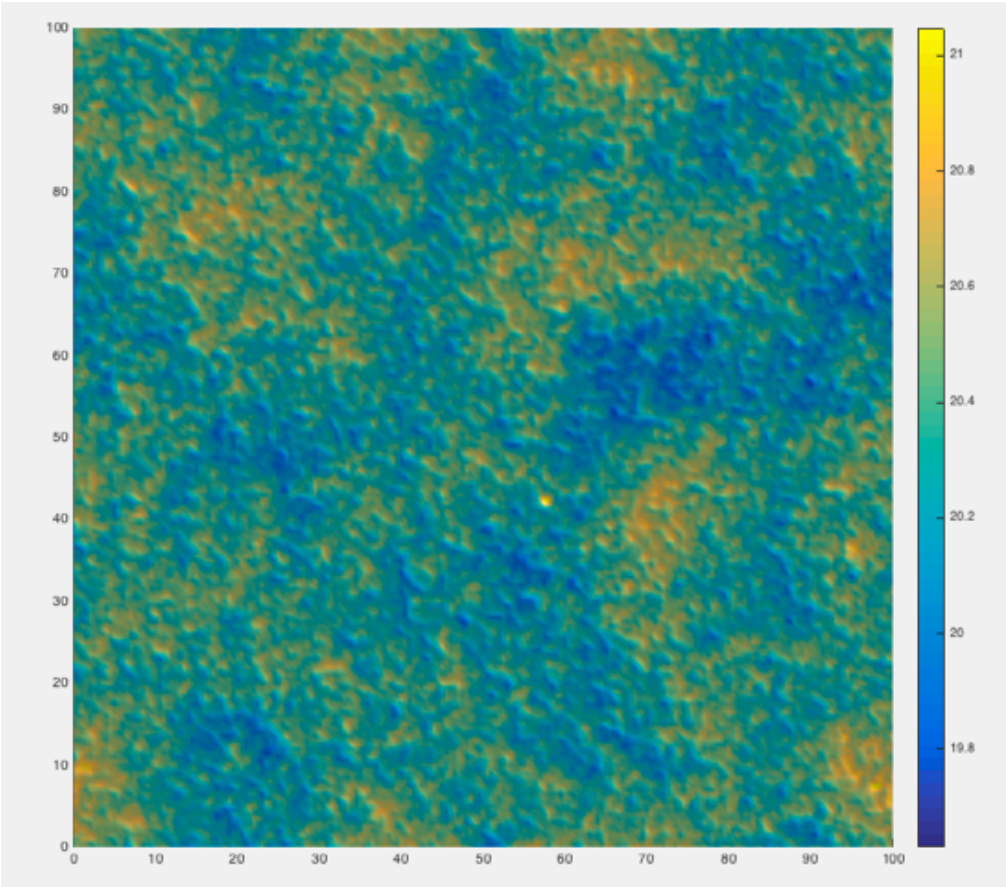

Figure 8: A MATLAB model of a 100 x 100 gridded bathymetric surface over seafloor with 1-2 m undulations and random measurement noise. The color scale is simulated depth in meters. A simulated object of 2 x 2 grid cells in horizontal extent is positioned just below and to the right of center. Varying the horizontal and vertical extents of the simulated object as a function of grid size and depth standard deviation has provided insight into the confidence associated with visual detection of objects. In a real survey, these patterns have implications for the sizes of objects that can be expected to be detected by visual analysis, given the rugosity of the ambient seafloor, data density, measurement uncertainty, and gridding parameters.

3 Milestones

The milestones for the current reporting period were a series of documents detailing the various components of the research, along with improvements in the "citizen science" tools, and a demonstration of the data visualization tools. Many of the documents required have been completed during previous reporting periods, and are available on the project's website; the final components (particularly those on CEI-facilitating metrics) have been completed, and are, at the time of writing, being added to the website. The "citizen science" effort has been expanded on the project's website, and reported on at the OCEANS 2015 meeting in Washington, D.C., including a demonstration of the visualization techniques.

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