HYDRODYNAMIC VARIABILITY AND BEDFORM DYNAMICS
AT AN INNER SHELF ARTIFICIAL REEF

by

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ABSTRACT

The hydrodynamics and seabed morphodynamics on the inner continental shelf are having increasing relevance with continued development of near shore structures, offshore energy technologies and artificial reef construction. Characterizing the stresses on and response of the seabed near and around objects will inform best practices for structural design, seabed mine and unexploded ordnance detection, and archaeological and benthic habitat studies. Previous studies have focused on near bed currents and bed stressors (e.g. Trembanis et al., 2004), sorted bedforms (e.g. Green et al., 2004) and object scour (e.g. Quinn, 2006), but our understanding of bedform morphodynamics is still incomplete. Consequently, this study examines the specific hydrodynamic and bedform morphodynamics occurring over an annual cycle at an inner continental shelf artificial reef site. Using the Redbird artificial reef off Delaware, this project instituted a combination of synoptic mapping techniques, through the use of an autonomous underwater vehicle and surface survey vessel, and time-series hydrodynamic data collection from acoustic Doppler current profiling and local NOAA buoy 44009. Site-wide sorted bedform evolution and sediment transport volumes were investigated through a combination of backscatter imagery segmentation and bathymetric analysis. Focusing within sorted bedforms, ripple bedform geometry was characterized using the Fingerprint Algorithm imagery.
analysis technique (Skarke and Trembanis, 2011). Using the Fingerprint Algorithm as a baseline, predictive ripple geometric models were compared, tested and applied to best characterize intra-annual ripple evolution. Further, this study considered the impacts of seabed objects on ripple geometry and ripple defects (e.g. bifurcations and terminations). Lastly, it tested automated imagery segmentation methods and bathymetric comparisons to quantify sorted bedform evolution at the site. Bedform morphodynamics were found to both dynamic, often in response to storm events, and persistent, regarding storm signatures preserved in relict seabed ripples and sorted bedform evolution in the periods following large storm events.
Chapter 1

INTRODUCTION

1.1 Scope of Research

The inner continental shelf is a region of increasing interest as a location for wind turbines, artificial reefs, archaeological investigations, and benthic habitat studies. The need to characterize the hydrodynamic conditions of this region and the subsequent seabed response is therefore becoming ever more significant. Seafloor morphology is closely tied to the feedback between hydrodynamic forcing and seabed roughness; these processes are referred to as morphodynamics (Wright, 1995). The inner shelf environment is generally considered to be energetic, with morphodynamics largely driven by large-wave events, and to a lesser degree, tidal currents (Wright, 1995). With the presence of man-made objects, alterations to near-bed hydrodynamic flow result in changes to the seabed such as scouring and modifications to morphological features.

Several studies have focused on the hydrodynamic and morphologic variability of the inner continental shelf environment (e.g. Wright, 1993; Traykovski, et al., 1999; Green et al., 2004; Murray and Thieler, 2004; Trembanis et al., 2007). Of particular interest lately has been sorted bedforms and object scour. The evolution of sorted bedforms, previously referred to as ripple scour depressions (Cocchione et al., 1984), has been linked to a combination of hydrodynamic variability between low to moderate and strong hydrodynamic forcing, which leads to the self-organization of differing sediments (Green et al., 2004). Similar studies of object scour have found
that, again, a combination of underlying sediment and hydrodynamic variability are the forces responsible for the depth and lateral extent of object scour pits and potential burial (McNinch et al., 2006; Quinn, 2006). However, our understanding of the spatio-temporal evolution of sorted bedforms and scour is incomplete. Likewise, the geometry, evolution, spatial variability and hydrodynamic effects of ripple bedforms, a typical morphological expression of sorted bedforms, have been, and continue, to be the focus of numerous studies and mathematical models (e.g. Nielson 1981, Grant and Madsen 1986; Wiberg and Harris 1994; Traykovski 2007; Soulsby et al., 2012, Nelson et al., 2013).

The goals of this study are to advance our understanding of intra-annual morphological variability of the inner-continental shelf, through the combination of hydrodynamic and morphodynamic field observations of sorted bedforms, scour and ripple bedform dynamics at an inner continental shelf artificial reef site. The primary research objectives of this study are:

1. To characterize annual and inter-annual hydrodynamic conditions at the Redbird artificial reef inner shelf site (Chapter 2)
2. To quantify the seabed geology and morphological evolution over an annual cycle (Chapters 2 and 3)
3. To investigate and characterize ripple bedform spatio-temporal evolution under various hydrodynamic conditions (Chapter 3)
4. To evaluate the performance of existing non-equilibrium ripple geometry models to inner shelf ripple bedform dynamics (Chapter 3)
5. To investigate new and more widely available automated methods for acoustic backscatter seabed classification (Chapter 4)
1.2 Inner Shelf Morphodynamics

Inner shelf morphodynamics are driven by a complex feedback between hydrodynamic forcing and bedform evolution (Wright, 1995). Wave and/or current flows are translated through the water column, and with enough energy, can interact with the seabed. Movement across the seafloor generated frictional forces, by which energy is exerted on seafloor sediment (Wright, 1995). If sufficient forces are exerted to overcome the gravitational and attractive forces acting on the sediment, sediment begins to move and the seabed morphology organizes to the magnitude and direction of the hydrodynamic force. These new morphological features can then exert influence on near bed hydrodynamics by creating turbulence or rough hydrodynamic flow (Grant and Madsen, 1986). This turbulence, in turn, impacts the fluid motion interaction with the seafloor to create the morphodynamic feedback loop (Figure 1.1).

The expression of seabed morphology is ultimately determined by the nature of the hydrodynamic stressor, the seabed morphology and geology, and, in the case of scour, large seabed objects.
Figure 1.1: Morphodynamic interactions diagram.
The spatial and temporal scaling of morphodynamic interactions range from the minute and transient to the regional and persistent, having wide ranging implications for oceanographic, biological and engineering applications. In the Middle Atlantic Bight, seabed morphodynamics are largely driven by waves and episodic storm events (Swift et al., 1976, Wright, 1995). Relatively weak tidal currents dominate the background with peak bed stress and sediment transport during high wind events (Munchow et al., 1992; Wright, 1995). While experiencing both tropical and extra-tropical storm events, ‘nor’easters’ are the more frequent systems, typically occurring from late October to early March. The episodic nature of these events creates periods of extended low to moderate conditions that tend to create low turbulence conditions favoring only fine grain sediment suspension and transport and coarse sediment bedform burial (Trembanis et al., 2004). Widespread morphologic changes are typical only during storm events, favoring coarse sediment bedform activation, object scour and sediment transport (Green et al., 2004; Trembanis et al., 2004). The interim period between storm events raises questions of the persistence of storm driven morphology; in particular the persistence of sorted bedforms and ripple bedforms, both of which appear to remain in a relict state after storm events, although subject to burial and, in the case of ripple bedforms, biogenic decay.

1.2.1 Sorted Bedforms

Sorted bedforms, previously described as ‘ripple scour depressions’ (Cacchione et al., 1984), are a predominant expression of morphodynamic on the inner shelf. Recent studies have focused on the generation (Murray and Thieler, 2004; Green et al., 2004; Coco et al., 2007; Trembanis and Hume, 2011), migration
(Murray and Thieler, 2004; Goff et al., 2005; Coco et al., 2007) and hydrodynamic roughness effects (Trembanis et al., 2004) of sorted bedforms. Sorted bedforms are characterized by juxtaposed sediment beds with distinctive sediment size (coarse and fine); the beds typically have different bedform scaling but with a small overall topographic relief (Cacchione et al., 1984; Murray and Thieler, 2004; Goff et al., 2005; Coco et al., 2007). While initially coined “ripple scour depressions” by Cacchione et al. (1984), current academic opinion favors movement away from this term to “sorted bedforms.” Recent studies have demonstrated that sorted bedform features are not always simple depressions; while up-current (relative to prevailing longshore current) sides of sorted bedforms may be depressed relative to the surrounding seabed, down-current sections may actually be raised (Murray and Thieler, 2004; Goff et al., 2005). Along with the asymmetrical bathymetry, sorted bedforms have also been characterized as typically having asymmetrical grain size distributions, with coarser material located on upcurrent side of the bedforms (Murray and Thieler, 2004; Coco et al., 2007). Ferrini and Flood (2005) went as far as to characterize three types of sorted bedforms based on observations: 1) shore normal, well defined bedforms located from 3 to 36 meters in depth, 2) broad, elongated bedforms with less defined down-drift edges ranging from 10 to 60 meters and deeper, and 3) irregular, near shore features in less then 16 meters of water.

Recent work (e.g. Green et al., 2004; Murray and Thieler, 2004; Trembanis and Hume, 2011) has proposed that the self-organization of coarse and fine grain sediments associated with sorted bedforms is due to feedback between hydrodynamic conditions and bed composition and roughness. Low to moderate-energy wave conditions favor the burial of coarse grain ripple bedforms by fine grains. Conditions
allow for the transport and settling of fine grain material over coarse bedforms when there is little turbulence occurring over the rough ripple bed. With the transition into high-energy wave conditions, fine grain material is suspended and coarse bedforms are activated. Increased turbulence over the coarse ripple bedforms during storms inhibits the settling of fine grained sediments, which instead settle, at some advected lateral distance, over less turbulent beds with finer grains or smaller wave-generated ripples. Subsequent return to low energy conditions, especially if there is fast wave energy decay, will result in reburial of coarse sediment bedforms (Green et al., 2004). Trembanis and Hume (2011) further defined this process, explicitly arguing that the resulting vertical sequences are not so reflective of temporal energy variations, but rather the feedback between differential roughness characterized by the sorted bed types and the hydrodynamic conditions that generate sediment motion.

1.2.2 Ripple Bedforms

Ripple bedforms generate when near-bed forcing reaches and surpasses respective critical threshold for unconsolidated sediment motion. Under different magnitudes of flow, non-cohesive sediment will form different morphological features. Once the threshold of sediment motion is achieved, the bed will begin to organize into bedforms. Grain specific threshold values can be estimated using the non-dimensionalized threshold formula from Soulsby and Whitehouse (1997):

\[
\theta = \frac{0.3}{1 + 1.2D_s} + 0.055[1 - \exp(-0.020D_s)]
\]  

(1.1)

where \(D_s\) is the dimensionless grain diameter:
\[
D_* = \left[ g \left( \frac{\rho_s - 1}{\rho \nu^2} \right)^{\frac{1}{3}} \right] d
\]  

(1.2)

defined by gravity (g), grain density (\(\rho_s\)), water density (\(\rho\)) and dynamic viscosity (\(\nu\)).

Current induced forces on the bed, in turn, can be parameterized by the mean current Shields parameter:

\[
\theta_c = \frac{\tau_c}{g D (\rho_s - \rho)}
\]  

(1.3)

where \(D\) is the median grain size (d50) and \(\tau_c\) is the bed shear stress generated by current. \(\tau_c\) can be calculated using the quadratic stress law:

\[
\tau_c = \rho C_D u^2
\]  

(1.4)

where \(u\) is the depth average current and \(C_D\) is the coefficient of drag dependent upon grain size. Drag values are widely available from field observations and studies.

Comparison between the critical threshold value and shields parameter demonstrate whether sediment motion occurs. After incipient motion of sediment, low flow regimes will generate unidirectional flow ripples, or current ripples. Current ripple bedforms are typically asymmetric in shape, with a long up-flow face (stoss), steeper down-flow face (lee), and crests oriented transverse to the main flow. Evaluation of flow regimes utilizing the Froude number allows for tentative prediction of bedform states. Subcritical and critical flows are typically supportive of ripple and dune formations, but supercritical flow can lead to the formation of antidunes, in which ripple propagation is counter to current direction (van Rijn, 1993).
The initial ripple height and wavelength is dependent mostly upon grain size rather than the intensity of the flow (Baas, 1999; Langlois and Valance, 2007). Current ripple heights and wavelengths have been estimated between $50d_{50}$ to $200d_{50}$ and $500d_{50}$ to $1000d_{50}$, respectively (Yalin, 1985; van Rijn, 1993, Baas, 1999).

Growth time of the bedforms are, however, dependent upon the flow intensity; flume tests by Baas (1999) demonstrated that the time for ripple growth was inversely related to the power of the flow velocity, and in fine sands, could range from minutes to days. However, Langlois and Valance (2007) found that altering the coarseness of the material affected the rate of ripple growth: finer grains grew logarithmically with time where as coarser grain ripples grew linearly with time. Ripples in current dominated conditions will move through different geometric states regardless of initial intensity (from straight crests to equilibrium linguoid plan form); movement through these ripple geometric states is dependent only upon time (Baas, 1999).

Ripple bedforms under oscillatory motion organize in three manners: those proportional to the wave orbital diameter, those proportional to grain size and those in the transitional stage in between (Clifton and Dingler, 1984). Once wave oscillatory bed stress exceeds a critical threshold, transport is initiated with ripples forming with crests orthogonal to the direction of wave propagation. In orbital ripples, ripple wavelength is dependent upon the size of the near bed wave orbital diameter:

$$d_0 = \frac{H_s}{\sinh(kh)}$$

(1.5)
which is related to significant wave height $H_s$ and local water depth $h$. The exertion of wave-induced stress on the bed can be parameterized by the Wave Shields parameter:

$$\theta_w = \frac{\tau_w}{gD(\rho_s - \rho)}$$  \hspace{1cm} (1.6)

where $\tau_w$ is wave generated bottom shear stress. This is calculated by:

$$\tau_w = \frac{1}{2} f_w \rho U_w^2$$  \hspace{1cm} (1.7)

and scales to the wave friction factor, $f_w$, and the square of the orbital velocity, $U_w$.

The wave friction factor is given by Swart (1974) as:

$$f_w = \exp \left[ 5.213 \left( \frac{K_s}{A} \right)^{0.194} - 5.977 \right]$$  \hspace{1cm} (1.8)

where $K_s$ is the Nikuradse grain roughness ($K_s = 2.5 \times d_{50}$), and $A$ is the near bottom wave orbital amplitude (half of the orbital diameter). Multiple iterations of the wave friction factor have been generated by studies over the last few decades (e.g. Soulsby et al., 1993; Madsen, 1994; Smyth and Hay, 2002). For purposes of this paper, the wave friction factor is calculated from the empirically derived formula in Soulsby et al., (1993):

$$f_w = 1.39 \times \left( \frac{A}{z_0} \right)^{-0.52}$$  \hspace{1cm} (1.9)

with $z_0$, roughness height, defined by the relationship:

$$z_0 = \frac{d_{50}}{12}$$  \hspace{1cm} (1.10)

as described in Soulsby (1997).
Under initial sediment motion, orbital ripple bedforms will begin to scale to orbital diameter (Nielson, 1981; Clifton and Dingler, 1984; Wiberg and Harris, 1994). With continued increase in forcing, ripple wavelength and height will scale to wave orbital diameter until reaching equilibrium (Doucette and O’Donoghue, 2006; Soulsby and Whitehouse, 2005). Increasing flow magnitude can result in reorganization of ripples and departure from scaling to wave orbital diameter. These ripples, termed anorbital ripples, instead scale to representative grain sizes (Wiberg and Harris, 1994; Maier and Hay, 2009). Between the two, suborbital ripples, which have intermediate wavelengths, exist under intermediate wave conditions (Wiberg and Harris, 1984).

Numerous ripple geometry models have resulted from laboratory and field observations of oscillatory ripples. Models focus on ripple wavelength, height, ripple steepness (ripple height/wavelength ($\eta/\lambda$)) and, for influence on near bed turbulence, ripple roughness (Nielson, 1981; Grant and Madsen, 1982; Wiberg and Harris, 1994; Mogridge et al., 1994; Li and Amos, 1998; Khelifa and Ouellet, 2000; Soulsby and Whitehouse, 2005). Wiberg and Harris (1994) generated ripple wavelength estimates from laboratory flume tests for each respective oscillatory ripple expression. For orbital ripples, wavelengths are estimated at 0.62 times the wave orbital diameter. Inversely, anorbital ripple wavelengths scale to 535 times the median grain diameter. Others have since modified these equations based on respective field or laboratory data sets (e.g. Li et al. 1996; Traykovski et al., 1999).
Nielson (1981) and Grant and Madsen (1982), both using laboratory data, developed expressions for ripple height and steepness. Orbital ripple steepness is estimated by the ratio of ripple height to wavelength, and has been estimated to be 0.17 by Wiberg and Harris (1994). Using this relationship, ripple height can be derived from a known ripple wavelength. An orbital ripple steepness can instead be represented by the ratio of orbital diameter to ripple height (Wiberg and Harris, 1994). Others have included the ratio of wave Shields parameter to critical Shields parameters \( \left( \frac{\theta_w}{\theta_{cr}} \right) \) with these terms to predict orbital ripple height and wavelength, using various data-derived coefficients in addition (Grant and Madsen, 1982; Li et al. 1996). Ripple roughness \( (Kb) \), the effect of ripple geometry on near bed flow, was proposed by Grant and Madsen (1982) to be \( Kb = 27.7 \frac{n^2}{\lambda} \) based off of experimental data from Carsten et al. (1969).

Subsequent field and laboratory studies have shown, however, that the most semi-empirical ripple models do not accurately predict actual field measurements (Li and Amos, 1998; Camenen, 2009; Pedocchi and Garcia, 2009). Instead of relating equilibrium ripple height and wavelength to surface wave parameters, more recent studies have noted that established ripple bedforms can take significant amounts of time to react to changes in flow conditions (Traykovski, 2007; Voulgaris and Morin, 2008). Further, period of subcritical flow immediately following significant ripple formation conditions (i.e. storms) can result in relict ripple bedforms not scaled to present conditions (Traykovski, 2007; Austin et al., 2007; Voulgaris and Morin,
Voulgaris and Morin (2008) found that the relict ripple wavelengths after storm events were near the maximum wavelengths generated by the event. As a result, recent investigations (Traykovski 2007; Soulsby et al., 2012) have adapted a time-variable component to allow for ripple reaction to lag behind hydrodynamic conditions, based on sediment threshold and transport principles. Soulsby et al. (2012) incorporated both wave and current transport in their model. Effectively, the model does not treat wave and current forces as combined stressors, rather, alternating between conditions of wave and current dominance depending upon near bed stress values. Several studies (Amos and Collins, 1978; Li and Amos, 1998; Andersen and Faraci, 2003; Smyth and Li, 2005; Lacy et al., 2007) suggest, however, that combined flow may impact ripple geometry, either with co-linear flow accentuating ripple growth or orthogonal flow accentuating ripple sinuosity.

Non co-linear combined flow may also affect ripple defect density (Faraci and Andersen, 2002). Ripple defects are characterized as ripple crest terminations and bifurcations (Figure 1.2) (Huntley et al., 2008). While the exact cause for the formation of ripple defects is still unknown, the formation mechanisms and subsequent effect of defects on ripple evolution have been investigated both theoretically (Werner and Kocurek, 1997, 1999; Coco et al., 2007; Huntley et al., 2008; Kocurek et al., 2010), in the laboratory (Faraci and Andersen, 2002), and in the field (Maier and Hay, 2009). Werner and Kocurek (1999) relate defect density in seafloor ripple fields to bedform migration rates, while Huntley et al (2008) tie defects to the evolution of ripple height and wavelength. For anorbital ripples, rapid changes
in wave direction have been attributed to ripple defect creation (Maier and Hay, 2009). Faraci and Andersen (2002) have noted that in flume studies there is an increase in the ratio of current forcing to wave orbital forcing that will increase the density of ripple defects; vortices shed from ripple crests can be carried along-crest by non co-linear currents and interact with and accentuate irregularities in the ripple crests downstream. Field observations of combined forcing effects on ripple defects are, however, limited.

![Figure 1.2: Ripple bedforms with defects: A) bifurcation and B) termination](image)

Despite disagreement in formation mechanisms, there is consensus that ripple fields with lower defect densities are more resistant to changes in orientation (Werner and Kocurek, 1997; Huntley et al., 2008; Kocurek et al., 2010). Kocurek et al., (2010) suggest that defect creation and migration may potentially regulate the rate and direction of bedform evolution between initial and more developed states. Additionally, Huntley et al. (2008) suggest ripple defects alter the response of the seabed to changes in hydrodynamic forcing, and can act as “nucleation points” for the
creation of new bedforms. Werner and Kocurek (1997) actually modeled defect migration rates, including parameters for both bifurcation and termination defects. However, this model was derived from aeolian ripple data. Thus, future investigations are needed fully determine the cause of ripple defect creation and the spatio-temporal affects of defects on seabed ripple evolution, especially in larger scale ripple fields.

1.3 Study Site

![Figure 1.3: Location of the Redbird Artificial Reef with bathymetric relief of Delaware Bay.](image-url)
The Redbird Reef (Figures 1.3 and 1.4) encompasses a 3.4 square kilometer area located approximately 30.5 kilometers east of Indian River Inlet, Delaware (DNREC, 2009-2010). The reef, created by the Delaware Department of Natural Resources and Environmental Control (DNREC), is composed of former New York City subway cars, various military vehicles, tugboats, barges and ballasted tires placed in 28 meters water depth. The reef objects were placed starting in 1996 and continuing through 2009, resulting in 997 subway cars and 11 large vessels (DNREC, 2009a; 2009b). The site was created to serve as a benthic habitat, to nurture and increase local biodiversity, but to also attract fish for recreational fisherman and recreational SCUBA (DNREC, 2010-2011). The Redbird Reef site is located in an area also currently being studied for the potential use of offshore wind-driven turbine towers (Madsen, 2012). The underlying geological structure (the ancestral Delaware River bed) and the local hydrodynamics are a concern for foundation support and for determining the potential for undermining the footings.

The study area is a subset of the larger reef site, located near the center of the reef (Figure 1.4). It encompasses around one half square kilometer and contains significant sorted bedforms, scour pits, 6 wrecks and over 50 subway cars. The center of study area has the lowest bathymetric relief at the site at around 29 meters, which is likely the center of the ancestral channel that flowed through the area in the late Pleistocene (Fletcher et al., 1992). The local hydrodynamics and morphology make it an ideal site for this study.
1.4 Geologic Framework

1.4.1 Mid Atlantic Bight

The Redbird Reef sits in the inner shelf of the Mid-Atlantic Bight, a region of continental shelf that extends from Southern Virginia to Long Island, New York. The shelf varies in width, extending from approximately 60 km in the south to over 150 km south of Long Island. The shelf is relatively shallow, with much of the shelf lying at less than 100 meters depth, although depths can reach to over 200 meters before the shelf break. Flooded Pleistocene river valleys are incised in the shelf seafloor (Schlee, 1973), most prominent among them being the Hudson, Delaware and Chesapeake Valleys. These are offset by near shore ridge and swale topography resulting from sediment deposits from shoreline transgression (Swift, 1973). The
ridges are typically parallel to the shore face, with bathymetric relief on the order of meters.

Surficial shelf sediments are typically characterized as fine to medium quartz sands (Schlee, 1973). This sediment is subject to mobilization and transport during storm events, which can interact with the shelf floor to depths of up to 100 meters. On the shelf, sorted bedforms are a common morphological expressions, largely driven by large-wave and storm events (Swift et al., 1976; Wright, 1995; Goff et al., 2005). Sorted bedforms are characterized by the morphodynamic interaction and hydrodynamic feedback between beds with distinctive sediment sizes (Green et al, 2004; Murray and Thieler, 2004; Trembanis et al., 2004). The beds typically have different bedform scaling but with a small overall topographic relief (Cacchione et al., 1984; Goff et al., 2005; Coco et al., 2007). The Redbird Reef is characterized by these morphological expressions, and is situated within a near shore swale typical to the inner shelf.

1.4.2 Inner Mud Hole

The reef is located within the Cape May shoal-retreat massif, resulting from the recent Holocene shoreline transgression of the Delaware River estuary system (Swift et al., 1980). The shoal and swale system trends to the NE-SW around the reef, with a prominent ridge to northwest of the site. The site is situated in swale referred to as the Inner Mud Hole, over which the ancestral Delaware River and tributaries flowed. The site has relatively little bathymetric change, with a mean depth of 28 meters. The northwest of the site sits just below the ‘Pimple’ shoal, and is covered with a fine sandy sediment (Raineault et al., 2013). The central and southern areas of the site are a mixture of fine, sometimes silty, clayey sand, and coarse gravelly sand
likely deposited by the ancestral Delaware River or tributaries during the late Wisconsinian (Fletcher et al., 1992; Raineault et al., 2013). Scour moats around the objects often expose pre-Holocene coarse material, found buried as shallow as 0.25 meters from the surface (Raineault et al., 2013). In this current study, stiff, silty muds were also observed after large storm events, but are only exposed for short periods of time.

In a study of the Redbird reef, Raineault et al., (2013) noted that the boundaries between the fine, silty sand and coarse gravelly sands were persistent, although migrated southwards over the course of 2008-2011. Also noted at the site were persistent sorted bedforms. The coarse, gravelly sediment of these bedforms often formed large wave orbital ripple bedforms. Large scour pits were also observed around the reef objects. These were often comet-shaped, extending to the west-southwest, which is the typical direction of large-wave events at the site (Raineault et al., 2013). The boundaries of the comet-shaped scour pits around the reef objects were noted to change annually.

1.5 Paper Organization

The thesis is organized in a manner to illustrate the morphodynamic processes of the inner shelf, from focus on the hydrodynamic forcing events and larger morphologic expression, to the smaller spatial morphologic features and methods thereby used to quantify these changes. As such, chapter 2 describes the annual and inter-annual hydrodynamic forcing at the Redbird artificial reef site. Specifically, it looks at storm-driven morphodynamics, focusing on large-scale changes to sorted bedform features and object scour fields within an annual cycle. This is compared to findings from a previous study (Raineault et al., 2013) at the Redbird Reef to
extrapolate inter-annual morphologic changes at the site. Chapter 3 narrows the focus from sorted bedform persistence to ripple bedform geometry. It uses the Fingerprint Algorithm (Skarke and Trembanis, 2011) to quantify ripple bedform characteristics and spatial distribution, while comparing results to non-equilibrium ripple geometry models informed by in situ and local buoy hydrodynamic measurements. Chapter 4 describes a comparison to different acoustic backscatter segmentation methodologies. Particularly, it examines three widely available software suites abilities to classify seabed textural and sediment with a priori knowledge of sediment distribution at the site. The results of this chapter were used to inform the previous two chapters. Chapter 5 concludes the thesis, examining the results in a wider academic context as well as making recommendations for future studies.
Chapter 2

INTRA-ANNUAL MORPHODYNAMIC VARIABILITY AT AN ARTIFICIAL REEF

2.1 Introduction

Seafloor morphology of the inner continental shelf is closely tied to the hydrodynamic regime of the region and the feedback between hydrodynamic forcing and bedform evolution (Wright, 1995). Due the interdependent nature of the two, both hydrodynamics and seabed morphology must be considered together, in what has been described as ‘morphodynamics’ (Wright, 1995). While waves and currents interact with the bed generating seafloor ripple and bedform features, the resulting alterations to the seafloor impact benthic boundary layer flow and sediment transport. The spatial and temporal scaling of these interactions range in the fractions of seconds and centimeters to the decadal and kilometer scale, if not beyond, and have wide ranging implications for oceanographic, biological and engineering applications.

As a common morphological expression to the inner-continental shelf, questions have arisen over the spatio-temporal evolution and persistence of sorted bedforms. Studies have found spatial migration rates of sorted bedforms to range from little net migration aside from complementary incursions between coarse and fine domains (Hume et al., 2003), to large scale translations of up to 50 meters over two years (Goff et al., 2005). Further, spatial migration patterns can appear irregular, with no net migration over certain sections of sorted bedforms while other sections experience growth, reduction and translation (Hunter et al., 1988; Thieler et al., 1999).
Depth appears to be a main controlling factor in sorted bedform persistence (Coco et al., 2007). Bedforms in water depths less than 15 meters are found to be transitory in nature, appearing and disappearing on the order of a few months (Hume et al., 2003; Ferrini and Flood, 2005; Hume and Trembanis, 2011), while deeper sorted bedforms are found to remain mostly unchanged over years (Hume et al., 2003; Goff et al., 2005).

This study examines the changes in seabed morphology at a 28-meter deep artificial reef site located on the inner shelf of the Mid-Atlantic bight. Conducted over an annual cycle, this study examines the effects of major storms on sediment redistribution at the site, focusing on local hydrodynamics and seabed morphological changes. We give particular attention to the changes in area and volume of large scour pits and sorted bedform fields at the site within this study, and comparatively to the results of a previous study of scour and sediment distribution conducted at the site (Raineault et al., 2013), using backscatter and bathymetric data from repetitive autonomous underwater vehicle and ship-borne multibeam surveys. While the persistence of sorted bedform fields at the site are evident, results suggest that seabed morphology at a relatively deep sorted bedform site can largely change within the matter of weeks to months.
2.2 Methods

2.2.1 Field Location

In the Middle Atlantic Bight, seabed morphodynamics are largely driven by waves and episodic storm events (Swift et al., 1976, Wright, 1995). Relatively weak tidal currents dominate the background with peak bed stress and sediment transport during high wind events (Munchow et al., 1992; Wright, 1995). While experiencing both tropical and extra-tropical storm events, ‘nor’easters’ are the more frequent systems, typically occurring from late October to early March. The highest winds and waves from these events come out of the northeast and east-northeast, with waves often exceeding 4 meter significant wave height and mean currents over 50 cm/s offshore (Wright, 1995). Events similar to the 1991 ‘Halloween Storm’ have generated waves over 6 meters in height, mean currents near 50 cm/s and near-bed orbital velocities over 140 cm/s (Madsen et al., 1993; Wright et al., 1994).

Situated in the inner shelf of the Middle Atlantic Bight, the Redbird Artificial Reef is subject to the episodic storm events typical to the region. Located approximately 30.5 km east of Indian River Inlet, Delaware, the site is nestled in a swale of the Cape May retreat massif averaging 28 meters depth, on what was most likely an ancestral tributary of the Delaware River (Fletcher et al., 1992; Raineault et al., 2013). Previously studied by Raineault et al. (2013), the site is characterized by sorted bedforms and large ripple bedform fields and scour pits. During their study, sediment distribution, bathymetric and scour changes were noted over a three-year period (Raineault et al., 2013). Backscatter and bathymetry data from the site is available from that study, as is the hydrodynamic data, which was collected from NOAA buoy 44009. Regional background significant wave height and peak period
during the study averaged around 1.3 meters and 7.6 seconds respectively with near bed orbital velocities calculated to average 12-14 cm/s, while peak events reached over 5 meters wave height multiple times (Raineault et al., 2013).

2.2.2 Data Collection and Instrumentation

Field observations for this study consisted of six geoacoustic surveys of a 1.0 by 0.5 km subsection of the reef in combination with four time-series acoustic and backscatter instrument deployments taking place between August 2012 and November 2013. The primary geoacoustic surveys were conducted using a Reson 7125 SV2 200/400 kHz multibeam sonar mounted on University of Delaware’s R/V Hugh R. Sharp. Surveys were conducted in both 400 and 200 kHz, the former being ideal for higher resolution (~0.25m near-nadir horizontal resolution at depths of 27m) bathymetric products, and the latter better for Angular Response Analysis (ARA) seabed classification products. Global Positioning System (GPS) and vessel motion data were collected using an Applanix POSMV 330 (V5) to correct for motion in the data. Four secondary surveys, concurrent to four of the multibeam surveys, were conducted using a Teledyne Gavia Autonomous Underwater Vehicle (AUV). The vehicle collected data with a Marine Sonics dual-frequency side-scan sonar (900 kHz and 1800 kHz), a GeoAcoustics GeoSwath phase measuring bathymetric sonar (500 kHz), and a Point Grey Scorpion 20SO color camera. Repetitive 900 kHz surveys were conducted over a 0.25 km² subsection of the primary survey area, as well as multiple additional side-scan and camera surveys throughout the entire reef site.
Time series hydrodynamic and sonar data were recorded using an instrumented frame equipped with a 600 kHz upward facing Teledyne RDI Sentinel Workhorse Acoustic Doppler Current Profiler (ADCP) collecting wave and current data, a 2 MHz Nortek Aquadopp high-resolution Pulse-Coherent ADCP (PC-ADCP) to analyze near bed turbulence and a 2.25 MHz Imagenex 881 tilt-head rotary fan-beam sonar for bedform geometry backscatter (Figure 2.1). The ADCP was configured to collect current data twice an hour at 10-minute sampling bursts, and waves data every hour at 5-minute bursts. Vertical current data was binned at 1-meter with vertical blanking distance of 2.1 meters, yielding water column current data from the surface down to 2.6 meters above the bed. The Aquadopp sampled near-bed currents at 4 Hz with 2400 total samples per burst, recording over a 10-minute interval. The system was configured to sample 3 cm vertical bins with a 10cm blanking distance, yielding current data from 0.3 m to the seabed. The rotary sonar conducted two imaging sweeps once an hour, the first at a range of 9 meters and the
second at 6 m, both with 120 degree sector stepped at a 0.3-degree interval. Full
survey and instrument deployment details are outlined in table (Table 2.1).

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| **Gavia AUV**    |           |           |           |          |           |           |           |
| 900 kHz SS       | X         | X         | X         | X        | X         |           |           |
| 1800 kHz SS      |           |           |           | X        | X         |           |           |
| 500 kHz BS       | X         | X         |           | X        |           |           |           |
| Camera           |           |           |           |          | X         | X         |           |

|                  |           |           |           |          |           |           |           |
| **Instrument Frame** |       |           |           |          |           |           |           |
| Aquadopp         | 10/26-11/10 |           | 3/29 - 6/6 |           |           |           |           |
| Rotary Sonar     | (Flooded) |           |           |           |           |           |           |
|                  |           |           |           |          |           |           |           |

Table 2.1: ONR Redbird Reef deployment summary.

### 2.2.3 Hydrodynamic Data Processing

The RDI ADCP data was processed using RDI’s WavesMon and WinADCP and brought into MathWorks Matrix Laboratory (Matlab) for analysis. The Aquadopp data were converted to .txt files and brought into Matlab for cleaning and analysis. Rotary sonar data was not collected during the Oct. 26, 2012 deployment due to the instrument flooding, and data from the July 30, 2013 deployment were deemed unusable due to improper gain settings for the newly replaced sonar unit. The ADCP recorded conditions over a total of 158 days, while the Aquadopp captured bottom conditions for 84 of those days. Combined current vectors from the total
ADCP record were processed for tidal harmonics and currents using the Matlab toolbox ‘t_tide’ (Pawlowicz et al., 2002). Residual current data were extracted from the ADCP current record based on t_tide tidal current model. Near bed current predictions were extrapolated from t_tide tidal current predictions based on ADCP current measurement at approximately 2.6 meters above the bed.

Since onsite hydrodynamic data could not be recorded for a complete annual cycle with the instrument frame, observations were augmented by wave data from NOAA buoy 44009, as with the study conducted by Raineault et al., (2013). The buoy is situated 23 kilometers south of Redbird Reef, and is moored at a similar distance from the coast (30.5 km) and in similar water depth (30.5m). The buoy has been operational since 1984, and offers a nearly complete historical record of wave height and period since that time. Comparisons between buoy 44009 and Redbird ADCP significant wave height show an $r^2 = 0.958$ correlation, with the buoy recording slightly higher wave heights on average (Figure 2.2). During the research collection period, the buoy was down between Dec. 2012 and March 2013. NOAA WaveWatch3 (WW3) hind casting was used to fill in this gap. The Wave Watch 3 data under represents wave heights for the Redbird Reef area, so a linear transform was preformed to correct the difference. Comparison between the corrected WW3 and Redbird ADCP Hs show an $r^2 = 0.95$ correlation, with the WW3 corrected data being sufficient to complete the wave record. Bottom orbital velocities were estimated using linear wave theory, specifically:

$$ Ub = \frac{\pi H_s}{T \sinh(kh)} $$

(2.1)
where $H_s$ is significant wave height, $T_p$ is peak period, $h$ is depth and wave number $(k)$ is defined by:

$$k = \frac{2\pi}{L} \quad (2.2)$$

and $L$ is surface wavelength.

Bottom orbital velocity estimations derived from buoy 44009 wave conditions showed a $r^2 = 0.86$ correlation with those calculated from ADCP wave measurements.

![Figure 2.2: Redbird ADCP correlation to a) Buoy 44009 and b) Wave Watch 3 hindcasts significant wave height.](image)

**2.2.4 Morphodynamic Data Processing**

Multibeam bathymetry was proceed with GPS and motion data from the R/V Sharp using Applanix POSpac MMS to reduce horizontal and vertical uncertainties, yielding a vertical repeatability of 10-15 cm between surveys (Trembanis et al., 2013). Issues occurred in the recording of POS motion data during the Nov. 2013 survey, and as such, the data from that survey is not included in this analysis. The vertical offsets
of 10-15 cm between multibeam datasets pose no issues for textural analysis, but for purposes of calculating volumetric changes in at the site, these offsets, site-wide, result in large deviations from actual values. To correct for these offsets, all five datasets were altered vertically to an averaged site-specific value. The most immobile object on the site is a 50 m long Navy barge in the middle of the dataset. Specific values derived from the barge in all five bathymetric maps were averaged to generate a vertical datum. All values for each site are corrected to this specific vertical datum. Figure 2.3 shows the effect that this vertical datum offset method has on volumetric calculation.

Figure 2.3: Original volumetric change between October 2012 and November 2012 data before (a) and after (b) vertical datum correction. Note the difference in net sediment loss (positive values) between the two. Image (b) is more representative of expected and observational changes (qualitative) to the site.
Bathymetric textural and sediment volume changes were calculated in ESRI ArcGIS. To calculate volume changes, the ArcGIS Cut and Fill tool compares two datasets and generates a volumetric change based on vertical offsets over given areas. The output file batches volume changes in areas of similar vertical change, generating values with little comparable reference. To correct for this issue, the data were normalized over the area of each calculated unit (i.e. pixel value) to present the data in a more useable format and additionally remove outlier values. For textural changes, rugosity, the ratio of the actual surface area to the geometric surface area, values were calculated for the five usable datasets. These calculations were performed using the NOAA developed Benthic Terrain Modeler suite for ArcGIS with a built in rugosity function (for more on Benthic Terrain Modeler see Wright et al. 2012).

Additional textural analysis was preformed on backscatter from the AUV’s phase measuring bathymetric sonar. The backscatter was brought into Chesapeake Technologies, Inc., sonar-processing suite SonarWiz for bottom detection and gain correction. Finalized backscatter images were processed for sediment and textural changes using various classification methods (see Chapter 4) for best results. Forty-three surface grab samples and ROV video cataloguing sediment distribution at the site were used to constrain sediment class types.
2.3 Results

Figure 2.4: Hydrodynamic conditions from January 2012-2014. A) Significant wave height. B) Peak wave period. C) Near-bed significant orbital velocity. D) Near-bed tidal current predictions.

2.3.1 Hydrodynamic Conditions

Hydrodynamic conditions were compiled and calculated from the combined buoy 44009 and Wave Watch 3 data from January 2012 through December 2013. Figure 2.4 shows the significant wave height (Hs), peak period (Tp), estimated bottom orbital velocity (Uw), and estimated tidal near bed current (Uc). Wave height averaged between 1.14 and 1.15 meters between with 2012 and 2013, while wave period averaged around 7.3 second for both years. Annual mean orbital velocity averaged around 0.1 m/s for both years. These statistics are comparable to annual wave height, period and near-bed orbital velocity statistics calculated by Raineault et
al. (2013) for the Redbird reef site from 2008 through 2011. Predicted tidal near bed currents ranged from 0.1 to 20 cm/s over both years, averaging around 7.7 cm/s. This compares to measured ADCP near bed currents from the four deployments, which averaged 9.6 cm/s but ranged from less than 0.1 cm/s to over 50 cm/s due to storm event influence. Tidal harmonic analysis derived from the longest ADCP dataset (March deployment – see table 2.1), indicates the semi-diurnal M2 as the major tidal force, corresponding with Muscarella et al. (2011), with several additional constituents (see table 2.2).

<table>
<thead>
<tr>
<th>Constituent</th>
<th>O1</th>
<th>K1</th>
<th>N2</th>
<th>M2</th>
<th>S2</th>
<th>MO3</th>
<th>2MK5</th>
<th>M6</th>
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</thead>
<tbody>
<tr>
<td>Major Axis (cm/s)</td>
<td>3.254</td>
<td>4.153</td>
<td>3.94</td>
<td>23.14</td>
<td>2.911</td>
<td>0.947</td>
<td>0.745</td>
<td>0.95</td>
</tr>
<tr>
<td>Minor Axis (cm/s)</td>
<td>-0.055</td>
<td>-2.848</td>
<td>-1.759</td>
<td>-5.056</td>
<td>-0.062</td>
<td>0.153</td>
<td>-0.011</td>
<td>0.471</td>
</tr>
<tr>
<td>Orientation (°) (Major Axis)</td>
<td>56</td>
<td>358</td>
<td>300</td>
<td>296</td>
<td>289</td>
<td>295</td>
<td>343</td>
<td>289</td>
</tr>
<tr>
<td>Signal to Noise Ratio</td>
<td>2.3</td>
<td>6.2</td>
<td>5.7</td>
<td>210</td>
<td>3.3</td>
<td>2.7</td>
<td>2.1</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Table 2.2: Major tidal constituents at Redbird Reef and corresponding velocities.

During the course of the study, three large storm events took place. Hurricane Sandy passed north of the reef on Oct. 28-29, 2012, generating wave heights measured over 7.1 meters with up to 14-second periods at the site. This was followed by a nor’easter 7 days later, which generated waves over 4.8 meters with periods up to 14 seconds. The instrument mooring at the site, as well as buoy 44009, captured both events. The third storm event took place March 6-8, 2013, which generated waves up to 7.8 meters, again with periods up to 14 seconds, as captured by buoy 44009 alone. A fourth, smaller event took place Oct 10-11, 2013 with waves up to 4.1 meters, but
with only 9-second periods. Residual surface currents during Hurricane Sandy and the trailing nor’eastern indicate wind generated surface velocities with magnitudes up to 78 cm/s. From buoy 44009, sustained wind speeds averaged up to 23 knots (11.8 m/s) during Sandy, with gusts up to 30 knots (15.4 m/s). During the nor’eastern, sustained winds averaged up to 16 knots (8.2 m/s) with gusts up to 19 knots (9.8 m/s).

Estimated bottom orbital velocities peaked at over 1.5 m/s during hurricane Sandy, and nearly 1.2 m/s in the following nor’eastern. Corresponding orbital velocity measurements derived from the bottom facing PC-ADCP showed orbital velocities 20 cm above the bed to be up to nearly 1.6 m/s for both Sandy and the following nor’eastern. Measured mean bottom currents during the storms peaked at 73 cm/s and 63 cm/s respectively. Estimated orbital velocities for the March 2013 nor’eastern reach over 1.5 m/s, with sustained orbital velocities between 0.5 and 1 m/s lasting for 72 hours after the storm. Shields sediment threshold and shear stress values calculated from grab samples indicate high levels of fine grain sediment suspension and transport (Figure 2.5). This is corroborated by the amplitude backscatter from the PC-ADCP. While it was not calibrated to yield particle suspension concentrations, high backscatter values throughout the storm events suggest high particle suspension concentrations (Figure 2.6).
Figure 2.5: Wave Shields critical threshold and observed Wave Shields values for three representative samples from Redbird Reef during Hurricane Sandy.

Figure 2.6: Backscatter amplitude counts from a bottom facing PC-ADCP during Hurricane Sandy and following nor’easter.
2.3.2 Morphologic Changes

The first and second geoacoustic surveys took place immediately prior to Hurricane Sandy and following the coupled nor’easter event. Prior to the Sandy, the seabed was nearly uniform in texture with small hummocky bedforms and small scour pits near the objects. Sediment classification (see Chapter 4) shows areas of coarse sand and gravels and fine sands with poorly sorted fines and gravels in between (Figure 2.7). A sediment distribution plot generated from the samples shows the sediment to be predominantly sandy, with the fine sands incorporating silts and clays and the coarse sands with gravels, confirming the findings of Raineault et al. (2013). Following the two storms, large scour pits appeared to the west - southwest of the reef artificial objects, exposing coarse sediments. The large sorted bedform field in the center of the study area was exposed with large wave-orbital ripple bedforms. The overall size of the sorted bedform features captured within the survey grew with respect to pre-storm conditions from an initial estimate of 59,163 m$^2$ to approximately 68,529 m$^2$, as calculated from the classification maps. The boundaries between the coarse and fine domains were also well defined. Additionally, the storms exposed two large areas of cohesive muds (Figure 2.7) that were not previously noted by Raineault et al. (2013) and seen only following the Oct/Nov 2012 and March 2013 storm events. Since grab samples were not taken of the mud until the Dec. 04 cruise, fine sand from the surrounding region had already mixed with the mud, skewing samples taken in the muddy areas to the fine sand domain (Figure 2.8 and 2.9).
Figure 2.7: ENVI classification results of the October 2012, November 2012, and July 2013 GeoSwath backscatter. Note the poorly sorted sediment rimming the coarse sands in both the October 2012 and July 2013 data.
Figure 2.8: Mean grain size for three main sediment classes at Redbird Reef. Note, mud samples taken 1 month after storm, so fine grain sand sediment burial is likely to have skewed samples coarser.

Figure 2.9: Schlee sediment distribution diagram.
A month following the storms, the rugosity of the seabed decreased significantly. Figure 2.10 shows shaded bathymetric images exemplifying transition from pre-Sandy (a) to 10 days (b) and 1 month (c) after the storms. The storm systems energized the bed, exposing coarse sediments and forming large wave-orbital ripples. Fine sands with silts and clays formed highly irregular bedforms. After 1 month, the rough bedforms transitioned, appearing similar to the hummock bedforms apparent before the storms (Figure 2.10c). The large wave orbital ripples underwent burial or erosion, though relict ripples remained evident.

The fourth geoacoustic survey took place three weeks after the March 2013 nor’easter. As found with the December 2012 survey, the seabed had already begun to recover from the effects of the storm. Ripple bedforms in side-scan sonar data from the AUV had smaller average wavelengths (chapter 3). Further, many ripples bedforms exhibited flattened profiles, possibly indicating decay or plaining by strong, post-storm currents. Despite suggested recovery by the bed, the scour marks, especially in the lee of the larger reef objects, exhibited growth to the west-southwest.
direction (see Figure 2.7). Additionally, the prominent sorted bedform field appeared more extensive in both the multibeam backscatter and side-scan data, though GeoSwath backscatter was not available for classification from this survey. This growth largely remained evident in the July 2013 GeoSwath backscatter, although the rugosity, or the measure of three-dimensional surface roughness (Figure 2.11), of the seabed dropped to values similar to those calculated before Hurricane Sandy. Typically low to moderate wave and current conditions recorded or estimated between the March 2013 and July 2013 surveys, and classification also shows conditions similar to the pre-Sandy survey; poorly sorted fines with gravels rim the sorted bedform feature. Despite partial obscuring from the fine grain intrusion, the total area of the sorted bedforms was calculated to have grown an additional 4000 m$^2$ since November 2012, totaling approximately 72,588 m$^2$ by July 2013.

The volumetric change calculations were unable to further inform sorted bedform evolution between the GeoSwath classification surveys. Despite the vertical offset correction, issues arose when comparing all five datasets, in particular when comparing the December 2012 dataset to the earlier two sets (see Figure 2.12). Here it was apparent that there were tidal correction issues that could only be corrected by reprocessing the raw bathymetry data and attempting to find the offset, which would not be easily accomplished. As well, the November 2012-March 2013 and March 2013- July 2013 comparisons displayed the same offset issues, though the latter only in the northwest corner of the image. However, the pre and post Sandy comparison (Oct and Nov. 2012) was successful, yielding useful information of sediment transport and scour.
Figure 2.11: Rugosity for the Redbird Reef from Oct. 2012 to July 2013. Note the cycle from smooth bed to rough from October to November, then the eventual return to smooth bed by July 2013.
Figure 2.12: The comparison between the November 2012 and December 2012 datasets shows the issues of tidal correction offsets.

The volumetric change calculated in ArcGIS demonstrates the amount of sediment transport that occurred at the site after Hurricane Sandy (Figure 2.13a) and from Oct. 2012 to July 2013 (Figure 2.13b). In Figure 2.13a, the areas of volume loss are associated with the coarse sediment ripple fields and scour pits, while the areas of volume gain are associated with fine sands and muds. After Sandy, ArcGIS calculations estimated a total volume loss of 4085 m$^3$ of sediment over a half square kilometer. By July 2013, the total volume loss had increased to 5903 m$^3$ of sediment, suggesting that a net transport of sediment away from the site had occurred in the interim period.
2.4 Discussion

Sediment threshold values and near bed shear stress estimates from the hydrodynamic data reaffirm the wave-dominated morphodynamics typical of the Mid Atlantic Bight inner shelf (Swift et al., 1976; Wright, 1995). Similarly, sediment distribution, scour and sorted bedform patterns captured in the geoacoustic surveys reflect this morphodynamic paradigm. The evident alterations to scour and sorted bedform size are largely associated with the three main storm events captured within this study. Scour fields extend to the west-southwest, corresponding to the direction that the storm waves propagated towards in the Nov. 2012 and March 2013.
nor’easterns (and too a lesser degree the latter half of Hurricane Sandy). Surveys following these events, after short and long periods of time, show almost immediate reburial or reorganization of coarse domain bedforms. Poorly-sorted fines and gravels rimming the sorted bedform features suggest partial intrusion and burial or mixing of the coarse grain domain prior to and after the storm events, which is also reflected in the low rugosity values. Buoy data shows no wave event reaching above 3 meters in the 6 months prior to the storm events, and calculated near-bed orbital velocities never topped 40 cm/s, although wave periods grew in the month or two leading up to the storms. With the storms, the sorted bedform features grew substantially in area with well-defined boundaries between the fine and coarse domains. This reflects the expected post storm sorted bedform stage, where fines settled out over the less turbulent fine sand beds (Trembanis et al., 2004; Green et al., 2004). Following the return to extended periods of low wave conditions, coarse grain bedforms underwent decay or partial burial by fine grain sediments, as evidenced in the December 2012 bathymetry. Essentially, the site exhibited the cyclical evolution of sorted bedforms as noted by numerous previous papers (e.g. Green et al., 2004; Murray and Thieler, 2004; Trembanis et al., 2004; Coco et al., 2007).

Results from the bathymetric analysis indicate an overall net loss of sediment at the site, with little evidence of recovery. However, there is no way to compare to this final volume loss to the volume loss up to the March 2013 nor’easter to know whether or not the volume loss had decreased from March 2013 to July 2013, since this data comparison was affected by tidal offsets. These issues highlight the effects small vertical offsets have on volume calculation, and thus the overall reliability of these volume totals, without any form of validation, may be in question. Regardless, partial
burial was expected when conditions were low in many of the areas that scoured out during the stormy season. Sediment classification from the July 2013 backscatter shows fine grain intrusion into the large scour pits and sorted bedform fields, but we see, despite this, that the net loss of sediment largely increased from Nov. 2012 to July 2013 (Figure 2.13b). This is partially supported by the growth in area of the scour pits and sorted bedform features at the site, as calculated from the sediment classification results, which are inherently lower in bathymetry than the surrounding seabed suggesting at the very least net sediment transport occurred away from the sorted bedform and scour pits.

Raineault et al. (2013) also noted an overall growth in the sorted bedform features and scour pits at the site over a three-year period. While they did not calculate area measurements for the sorted bedform fields and scour pits, linear measurements showed, for instance, the scour field behind the barge extending from 29 meters southwest of the barge in 2008 to 53 meters in 2010 and 62 meters in 2011 (Raineault et al., 2013). The reliability of the side-scan survey data used by Raineault et al. (2013) is at question, in regards to a classification comparison, with the results of the paper here. However, their 2010 field data also included a GeoSwath survey covering the area of this study, which was classified and compared to datasets from this study. Interestingly, the 2010 bedform measurements and the initial measurements from the 2012 survey do not indicate continual growth (see Figure 2.14). The 2012 scour and sorted bedform fields were much smaller in area than the 2010 measurements (59,163 sq. meters verses 65,102 sq. meters). During the period between this survey conducted by Raineault et al. (2013) in August 2010 and the first survey of this study in October 2012, the buoy record indicates only one event,
Hurricane Irene on Aug. 28, 2011, where waves topped five meters and bottom orbital velocity topped 1 m/s (this storm occurred after the final 2011 Raineault et al. (2013) survey). This suggests that in the period between the Aug. 2011 and Oct. 2012 storm events, low to moderate energy conditions dominated. Consequently, scour pits were almost completely filled in by fine sediments and the sorted bedform fields underwent partial burial, which is what is found in the October 2012 data. This supports the hypotheses that scour-hole filling (McNinch et al., 2006) and sorted bedform burial (Green et al. 2004; Murray and Thieler, 2004; Trembanis et al., 2007; Trembanis and Hume, 2011) occur with fine grain sediment transport between storm events.

Figure 2.14: Sorted bedform evolution from Aug 2010 to July 2013. Note the decrease in coarse sand exposure between Aug 2010 and October 2012.
The exposure of the cohesive mud fields was unexpected in this study. Since these muds had not been uncovered in the surveys conducted by Raineault et al. (2013), there was no prior evidence of the mud fields. While the sorted bedform sediments are ubiquitous to the inner continental shelf, the mud is a curiosity. Likely, these are overbank deposits from the ancestral tributary that ran down the center of the Redbird Reef. However, their transitory exposure at the site and proximity to the initial seabed reflector in subbottom profile data has made any further characterization of the mud deposits difficult.

2.5 Conclusions

Previous studies (Hume et al., 2003; Goff et al., 2005; Coco et al. 2007) have suggested that deeper sorted bedforms typically do not undergo much change in the span of a few years. While the relative persistence of the sorted bedforms at the Redbird Reef remains unquestioned, the results of this study suggest that large-scale changes can occur within the matter of weeks to months. These changes are largely dependent upon episodic storm events, but evidence collected in this study shows that sorted bedform decay and burial can occur within weeks after a large storm event. Despite this intra-annual morphologic variability, long-term analyses support the observations that overall change in site-wide sediment distribution is negligible over a several year span (e.g. Raineault et al., 2013). While net sediment loss and sorted bedform growth occurred within a season, results indicate that the continual cycle of burial and exposure of sorted bedforms and scour pits transpires over a longer period of time in deeper sites such as the Redbird Reef.

Ideally, a future study on deep-water bedforms would span over a several year period, and fully capture the long-term time-series evolution of sorted bedforms. As
well, the loss of the rotary sonar in this study removed another helpful data source. Short-term bed evolution and ripple bedform migration rates, which can be derived from rotary sonar data, would benefit such as study. While direct hydrodynamic measurements would be ideal as well, the incorporation of Buoy 44009 data added strongly to this study, and such a model lends itself well to similar studies going forward.
3.1 Introduction

Bedform morphology directly influences the wave boundary layer conditions (Ardhuin et al., 2003; Traykovski, 2007) and mean flow (Grant and Madsen, 1986), which, in turn, affects sediment transport processes. One such bedform type, seabed ripples, are abundant in the inner continental shelf, where current and wave forces exert sufficient stress on the bed to suspend and transport unconsolidated sediments. Here, the relationship between near bed hydrodynamic forcing and bed morphological roughness is bi-directional; the bed responds to hydrodynamic forcing and in turn, influences turbulence of near bed flow (Nielsen, 1981; Wright, 1995; Coco and Murray, 2007). Parameterizing this relationship has not proven simple, and modeling formation processes and evolution of ripple bedforms remains at a focus of near-shore morphodynamics (e.g. Traykovski, 2007; Soulsby et al., 2012; Nelson et al., 2013).

The combination of different hydrodynamic stressors (e.g. wave, current or combined forcing), bidirectional influence, and ripple defects (e.g. bifurcation and terminations) complicates attempts to model ripple morphodynamics. Ripple geometric response to unidirectional, oscillatory and combined flow has characteristics respective to each, but fluid in nature. Organization of ripples can be dependent upon dominant hydrodynamic conditions, sediment composition, or some combination of the two (see Wiberg and Harris, 1994). This variance results in different configurations of ripple bedforms spacing (wavelength), orientation and
defect density, characteristics that are important to ripple evolution (Werner and Kocurek, 1999) and not fully understood.

In past studies, ripple geometry was quantified using various methodologies. Manual qualitative interpretation is perhaps the most rudimentary means of deriving ripple data from backscatter images (e.g. Traykovski et al., 1999). The subjectivity of individual interpretations lends to issues of repeatability and variability between observers, aside from the impracticality of characterizing large fields of ripple bedforms (Skarke and Trembanis, 2011). Studies have thus turned to more automated methods, such as frequency-transform analysis (e.g. Voulgaris and Morin, 2008; Maier and Hay, 2009). This method converts acoustic imagery into the frequency domain through Fourier or other transforms, resulting in two-dimensional power spectrum in frequency space (Skarke and Trembanis, 2011). Despite the improvement over manual analysis, Skarke and Trembanis (2011) note significant limitations to this method, including but not limited to the inability to quantify ripple orientation and wavelength variability.

Instead, Skarke and Trembanis (2011) adapted a methodology for extracting ripple statistics, built around algorithms designed to extract bio-fingerprint statistics (see Hong et al., 1998; Felzenberg, 2009). This method, the fingerprint algorithm, analyzes images and assigns statistical values to each individual pixel, allowing the user to quantify ripple variability and distribution across a wide area. Orientation values are estimated using Gaussian filtered backscatter gradients to locate ripple crests, from which localized ripple wavelength values are derived (for further information on methods see Skarke and Trembanis 2011). Additionally, the algorithm contains a method for isolating ripple defects by filtering and thinning backscatter
images to isolate ripple crest lines. In all, Skarke and Trembanis (2011) found the fingerprint algorithm to be a robust improvement over previous ripple analysis methods. For this study, the overall combination of spatial and statistical methods for orientation, wavelength and defect characterization and representation makes the fingerprint algorithm an ideal candidate for large-scale ripple bedform analyses.

As such, this paper examines ripple bedform intra-annual variability at an inner shelf artificial reef utilizing the Fingerprint Algorithm technique to derive ripple geometric statistics from acoustic backscatter imagery. Further, it examines the performance of non-equilibrium ripple bedform predictions in light of the Fingerprint Algorithm findings, and considers factors complicating ripple geometric predictions. Lastly, it investigates the impact of objects on ripple geometries, specifically focusing on ripple defect distribution at an artificial reef.

3.2 Methods

3.2.1 Data Collection and Instrumentation

Ripple bedform imagery used in this study was collected on four surveys conducted with a Teledyne Gavia Autonomous Underwater Vehicle (AUV). The vehicle gathered data with a Marine Sonics dual-frequency side-scan sonar (900 kHz and 1800 kHz), and a GeoAcoustics GeoSwath phase measuring bathymetric sonar (500 kHz). Repetitive 900 kHz surveys were conducted over a 0.25 km² subsection of the primary survey area, as well as multiple additional side-scan and camera surveys throughout the entire reef site. While a total of six additional surveys were conducted using a shipborne Reson 7125 200/400 kHz dual frequency multi-beam, the backscatter from the Reson, despite nearly 0.25-meter resolution horizontally, did not
holly resolve ripple bedforms in the backscatter. Thus the primary method data for ripple bedform analysis from this study comes from the four AUV surveys.

Time series hydrodynamic and rotary sonar data were recorded using an instrumented frame equipped with a 600 kHz upward facing Teledyne RDI Sentinel Workhorse Acoustic Doppler Current Profiler (ADCP) collecting wave and current data, a 2 MHz Nortek Aquadopp high-resolution Pulse-Coherent ADCP (PC-ADCP) to analyze near bed turbulence and a 2.25 MHz Imagenex 881b rotary fan-beam sonar for bedform geometry backscatter. The ADCP was configured to collect current data twice an hour at 10-minute sampling bursts, and wave data every hour at 5-minute bursts. Vertical current data was binned at 1-meter with vertical blanking distance of 2.1 meters, yielding water column current data from the surface down to 2.6 meters above the bed. The Aquadopp sampled near-bed currents at 4 Hz with 2400 total samples per burst, recording over a 10-minute interval. The system was configured to sample 3 cm vertical bins with a 10 cm blanking distance, yielding current data from 0.3 m to the seabed. The rotary sonar conducted two imaging sweeps once an hour, the first at a range of 9 meters and the second at 6 m, both with 120 degree sector stepped at a 0.3-degree interval.

3.2.2 Time-Dependent Ripple Bedform Calculation

Studies of late (Soulsby and Whitehouse, 2005; Doucette and O’Donoghue, 2006; Traykovski, 2007; Voulgaris and Morin, 2008, Soulsby et al., 2012) have noted that established ripple bedforms can take significant amounts of time to react to changes in flow conditions. Until recently, ripple geometry models have not incorporated a time dependency for ripple equilibration. Traykovski (2007) adapted a
non-equilibrium ripple model to allow for ripple reaction to lag behind hydrodynamic conditions. The lag is quantified using a variable timescale defined by the ripple cross-sectional area divided by the sediment transport rate (Traykovski, 2007). The resulting parameters from the Traykovski (2007) investigation are still limited, however, by focus upon wave oscillatory dominance.

Soulsby et al., (2012) instituted both wave and current-dominated conditions for ripple reorganization in their non-equilibrium model. In additional to the dual forcing conditions, the Soulsby et al. (2012) includes changes in ripple orientation. The Soulsby et al. (2012) time-dependent ripple calculations are based around the general derivative:

\[
\frac{dx}{dt} = a(t) - b(t)x(t)
\]  

(3.1)

where x may represent ripple wavelength (\(\lambda\)), height (\(\eta\)), or orientation (\(\phi\)). The equation coefficients a(t) and b(t) are time varying values calculated by the expressions:

\[
a(t) = \frac{\beta}{T_e} x_{eq}
\]  

(3.2)

\[
b(t) = \frac{\beta}{T_e} + \frac{1}{T_b} bio
\]  

(3.3)

where the ‘bio’ variable is a switch for biodegradation to ripple height. The coefficient \(T_e\) is defined as the time scale for ripple evolution (such as wave period for wave dominant conditions), and \(\beta\) describes the rate change in ripple characteristics.
based on hydrodynamic conditions, derived from the wave mobility parameter ($\psi$) and critical threshold values.

The model incorporates wave or current dominated conditional statements, based on near bed shear stress values, to determine which ripple geometry prediction will be fed into the calculation at time (t). Current and wave ripple geometries in Soulsby et al. (2012) are initially modeled off of equilibrium ripple predictors. For their study, Soulsby et al. (2012) used equilibrium ripple predictors from Soulsby and Whitehouse (2005). However, Skarke (2013) found that the time-varying model can be modified to take any equilibrium ripple predictor, comparing, in his study, the wave-induced ripple prediction from Wiberg and Harris (1994), Soulsby and Whitehouse (2005) and Traykovski (2007). Similarly, this study investigated the wave-induced equilibrium ripple wavelength predictions from Soulsby and Whitehouse (2005), Traykovski (2007) and Nelson et al. (2013).

Current ripple wavelength and height predictions are calculated using Soulsby et al., 2012 equations:

$$\eta_{max} = d_{50}202D_*^{-0.554}$$

$$\lambda_{max} = d_{50}(500 + 1881D_*^{-1.5})$$

where $D_*$ is the non-dimensionalized grain parameter outlined in equation 3.2. The Soulsby et al. (2012) model includes conditions for current sheet-flow and washout also based on $D_*$ values, which are integrated here. Likewise, we have incorporated conditional statements for anorbital ripple formation during strong orbital currents based on Wiberg and Harris (1994). As stated, anorbital ripple formation occurs
when the ratio of orbital diameter to anorbital ripple height exceeds 100, as calculated by the non-iterative expression (Malarkey and Davies, 2003) from Wiberg and Harris (1994):

\[
\frac{d_o}{\eta} = \exp \left[ C_1 - \sqrt{C_2 - C_3 \ln \left( \frac{d_o}{\lambda} \right)} \right]
\]  

(3.6)

where \(C_1 = 7.59\), \(C_2 = 33.60\), \(C_3 = 10.53\) and \(\lambda\) is anorbital wavelength or 535d.

Ripple height values were calculated in our models using Nelson et al. (2013) empirically derived expression for ripples under irregular waves:

\[
\eta = 0.126\lambda^{1.05}
\]  

(3.7)

excluding the calculations driven by Soulsby and Whitehouse (2005) equations, which use their inherent ripple height calculations.
3.3 Results

3.3.1 Fingerprint Algorithm

Each of the four surveys was processed through the fingerprint algorithm for ripple wavelength and orientation data. The initial survey took place on Oct. 26, 2012, only two days prior to Hurricane Sandy’s approach to the reef site. Acoustic backscatter mosaics showed very little morphological variability and no detectable ripple bedforms (Figure 3.1a), which was confirmed by the Fingerprint Algorithm.

The second survey followed shortly after, on Nov. 10, 2012, trailing a nor’easter storm that hit the site a week after Hurricane Sandy. Both multibeam and side-scan sonar data revealed a completely altered seabed: coarse sediment ripple bedforms,
fine sediment hummocky bedforms and even large, previously unmapped cohesive mud fields were exposed by the storms (Figure 3.1b). Near bottom wave-orbital velocities during the storms exceeded 1.5 m/s (see chapter 2). Sediment threshold estimates were calculated from Smith-Mac sediment grab samples taken across the site, with estimates indicating widespread sediment entrainment (Figure 3.2).

![Redbird Shields Entrainment Plot](image)

Figure 3.2: Wave Shields critical threshold and observed Wave Shields values for three representative samples from Redbird Reef during Hurricane Sandy

The Fingerprint Algorithm results from the Nov. 10, 2012 survey showed extensive mega-ripple bedform fields, with orbital ripple bedforms also found within the scour fields behind large reef objects. Spatial distribution maps (Figure 3.3) from the Fingerprint Algorithm show ripple orientation (normal to the ripple crest) varied as much as 40 degrees (standard deviation 6.4 degrees). Despite apparently widespread orientation ranges, an orientation distribution plot (Figure 3.4) shows a nearly normal distribution of ripple orientation, centered over a median orientation of 83.2 degrees. Observationally, ripple wavelength values vary spatially to a lesser
degree (standard deviation 0.36 meters), with large, ‘mega-ripples’ found throughout the large sorted bedform field. Ripple wavelength values (Figure 3.5) range from around 0.25 to 2.4 meters, with a median wavelength value of 0.975 meters. The wavelength distribution is skewed towards smaller wavelength values (skewness 0.6).
Figure 3.3: Fingerprint algorithm orientation (b) and wavelength (c) calculations from Nov. 2012 imagery (a).
Figure 3.4: Ripple orientation distributions at Redbird calculated from the GeoSwath backscatter mosaics taken Nov. 10, 2012 (blue), March 29, 2013 (red), and July 29, 2013 (green). Note the shift in median orientation.

Figure 3.5: Ripple wavelength distributions at Redbird calculated from the GeoSwath backscatter mosaics taken Nov. 10, 2012 (blue), March 29, 2013 (red), and July 29, 2013 (green).
The dataset from March 29, 2013 revealed further sorted bedform and scour field growth (see Chapter 2). The AUV survey occurred approximately 21 days following a strong Spring nor’easter that generated waves higher than Hurricane Sandy, though with near bed orbital velocities of slightly less magnitude. Within the three weeks following the storm, the ripple bedforms had already undergone decay and burial. Figure 3.6 shows flattened or planed orbital ripples exemplifying those found throughout the site. Ripple orientation distribution (Figure 3.4) shows greater standard deviation (9.6 degrees) than November, but a more peaked distribution (kurtosis 56.3) centered on an 87.5 degrees median orientation. Ripple wavelength values (Figure 3.5) still range from around 0.25 to 2.5 meters, but with a much lower median (0.63 m) and larger trend (skewness 2.95) to lesser wavelength values.

Figure 3.6: Ripple bedforms surveyed March 29, 2013. Note the flattened ripple crests.
By the July 29, 2013 dataset, very few ripple bedforms were detected by the fingerprint algorithm. The majority of the orbital ripples in the sorted bedform and scour fields had undergone decay or burial (see Chapter 2) in the extended period of low to moderate wave conditions following the March 2013 nor’easter (see Figure 3.15). Ripple orientation (Figure 3.4) distribution centered around 91.6 degrees, but with high site-wide standard deviation (18.4 degrees). Likewise, wavelength values (Figure 3.5) varied more (0.52 standard deviation), despite a similar range (0.25-2.5 meters). The median wavelength value was much higher than the previous datasets, at 1.15 meters.

### 3.3.2 Ripple Geometry Model Comparison

An initial comparison test of the various equilibrium ripple predictors was conducted using the Nov. 10, 2012 ADCP data. The models used grain size estimates generated from sediment samples collected at the sorted bedform field within the backscatter data analyzed with the Fingerprint Algorithm. Nine samples were chosen to help demonstrate predicted ripple geometric distributions from models versus calculated geometric distributions from the Fingerprint Algorithm. While it is typical to use d50 (median) grain sizes for ripple model predictions, we utilized available sediment grain size distribution data to generate a weighted mean grain size for each sample (Table 3.1). Model calculations using Traykovski (2007) equilibrium ripple wavelength predictions showed that d50 values (Figure 3.7a) tended to under predict the majority of the wavelength distribution versus the weighed mean values and the d84 values tended to over predict the majority destruction (Figure 3.7b). Each model result of the ripple wavelength values taken from the nor’easter was compared to the fingerprint algorithm ripple wavelength distribution plot.
### Table 3.1: Redbird grab sample weighted mean sediment sizes.

<table>
<thead>
<tr>
<th>Sample Number</th>
<th>1</th>
<th>5</th>
<th>6</th>
<th>8</th>
<th>9</th>
<th>11</th>
<th>18</th>
<th>21</th>
<th>22</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grain Size (mm)</td>
<td>0.445</td>
<td>0.452</td>
<td>0.483</td>
<td>0.472</td>
<td>0.33</td>
<td>0.425</td>
<td>0.952</td>
<td>0.679</td>
<td>0.927</td>
</tr>
</tbody>
</table>

Figure 3.7: Ripple wavelength predictions using a) d50 and b) d84 sediment sizes. Vertical dashed lines represent wavelength predictions after Hurricane Sandy versus Fingerprint Algorithm wavelength distributions.
The Soulsby et al. (2012) model (based on SW05 ripple equations) largely underpredicted the ripple wavelength values (Figure 3.9). No ripple wavelengths were predicted greater than 1 meter, while 46.9 percent of the total ripple wavelength distribution from the fingerprint algorithm results was greater than 1 meter. Likewise, the Nelson et al. (2013) wavelength predictors underpredicted, predicting no ripple wavelengths greater than 1.17 meters; thirty-three percent of the ripple distribution was greater than 1.17 meters (Figure 3.10). The Traykovski (2007) wavelength predictions were considerably higher than the other two models. The model predicted the largest ripple wavelength at 1.55 meters, with only 12 percent of the wavelength distribution falling above that prediction (Figure 3.11). Likewise, the minimum wavelength prediction (0.6 meters) excluded only 8 percent of the wavelength distribution. Since the Traykovski (2007) equilibrium model encapsulated 80% of the
wavelength distribution measured by the fingerprint algorithm, the remaining non-equilibrium wavelength predictions in the study utilized the Traykovski (2007) model.

Figure 3.9: Soulsby et al. (2012) wavelength predictions compared to Nov. 10, 2012 Fingerprint Algorithm ripple wavelength distribution.
Figure 3.10: Nelson et al. (2013) wavelength predictions compared to Nov. 10, 2012 Fingerprint Algorithm ripple wavelength distribution.

Figure 3.11: Traykovski (2007) wavelength predictions compared to Nov. 10, 2012 Fingerprint Algorithm ripple wavelength distribution.
3.3.3 Ripple Geometry Predictions

Non-equilibrium ripple predictions based on the ADCP data during Hurricane Sandy and nor’easter events indicated a high level of bedform activation and reorganization. During the highest intensity of both storms, the ripple orientation predictions focus to nearly identical values, ranging around 100 degrees during Sandy and 80 degrees during the nor’easter (Figure 3.12), reflecting the dominant historical storm wave approach. As the storm conditions slackened, the orientation values deviated. The highest wavelength values were predicted during the peaks of the storms for the coarser samples. Samples with a weighted mean below 0.6 mm during Sandy and 0.47 mm during the nor’easter slipped into an orbital ripple conditions (Figure 3.13). Ripple height never topped 20 cm for the coarsest samples, but averaged around 10 cm (Figure 3.14). Despite largely different significant wave heights between storms, the model predicted nearly identical ripple wavelength maximum values for both Sandy and the nor’easter. Ub calculations from the in situ Aquadopp showed nearly as high near orbital velocities during the nor’easter (>1.4 m/s) as with Sandy (>1.5 m/s), although not as sustained. The ripple wavelength predictions do not decay much at the end of the ADCP record, but rather maintain values near the peak wavelength estimates during the nor’easter. While, this matches well what we see in the fingerprint algorithm, this is likely an artifact by the model due to an incomplete future record.
Figure 3.12: Non-equilibrium orientation predictions from Oct. 26 to Nov. 10, 2012 showing the impacts of Hurricane Sandy and the nor’easter on ripple orientation distribution. Subplot is Hs (blue) and Dp (green).

Figure 3.13: Non-equilibrium wavelength predictions from Oct. 26 to Nov. 10, 2012 showing the impacts of Hurricane Sandy and the nor’easter on ripple wavelength distribution. Subplot is Hs (blue) and Tp (green).
Figure 3.14: Non-equilibrium ripple height predictions from Oct. 26 to Nov. 10, 2012 showing the impacts of Hurricane Sandy and the nor’easter on ripple height distribution. Subplot is Hs (blue) and Tp (green).

While direct hydrodynamic observations were unavailable prior to the March 29 and July 29, 2013 surveys, we were able to estimate ripple wavelength and height values using wave data from NOAA Buoy 44009 and near-bed tidal current estimates. NOAA buoy and Redbird Reef Hs show an $r^2 = 0.956$ correlation (see Chapter 2), and buoy Ub estimates data have a strong correlation ($r^2 = 0.865$) with Redbird Reef ADCP Ub estimates. Using the buoy estimates, non-equilibrium ripple predictions can be modeled at the Redbird Reef over much larger time-spans. Likewise, this allows us to estimate the ripple geometric conditions prior to the March and July 2013 surveys.
Figure 3.15 shows the coarsest sample (d50 ~ 1 mm) wavelength prediction over a 2012-2014 timespan. The model estimates a ripple reactivation between the March nor’eastern and the March 29 survey, with peak ripple values topping out around 1 meter. Fingerprint algorithm statistics shows that only 8 percent of ripple wavelengths fell above 1 meter. However, the model indicates bedform wavelength decay for the coarsest sample at the time of the geoacoustic survey to only 0.62 meters, for which over 52 percent of the wavelength distribution was greater (Figure 3.16). Likewise, the largest predicted wavelength value at the time of the July survey was only 0.42 meters, having dropped off from over 0.5 meters only days before due to conditions just above critical threshold (Figure 3.17). This estimate is lower than 99 percent of the ripple wavelength distribution.
Figure 3.16: Non-equilibrium wavelength predictions compared to Mar. 29, 2013 Fingerprint Algorithm ripple wavelength distribution.

Figure 3.17: Non-equilibrium wavelength predictions compared to July 29, 2013 Fingerprint Algorithm ripple wavelength distribution.
3.3.4 Ripple Defect Density

Without rotary sonar data available, it was impossible to view spatio-temporal ripple defect creation. However, Fingerprint Algorithm analysis was conducted for ripple defect densities spatially from the three backscatter mosaics above. Spatial defect density distributions from the Nov. 10, 2012 dataset show increased defect densities especially around the southern terminus of the ripple bedform field (Figure 3.18). The lowest density values occur throughout the largest ripple bedform field, while the highest values occur in the sporadic pockets of ripple bedforms around the reef objects in particular. Comparisons to ripple wavelength distributions show the highest densities to be in areas of smaller ripple wavelengths: the areas of the highest 10 percent defect densities are situated in areas with the mean wavelengths of 0.6 meters (versus mean values of 1.1 meters throughout the site).

These patterns are reflected in the March 29, 2013 backscatter as well (Figure 3.19). Again, density analysis of March backscatter shows the highest defect densities around the southern terminus of ripple bedform fields, with high defect densities in the vicinity of objects. Overall, defect densities increased across the entire site. It is notable that the March 2013 wavelength distributions also tended to shorter wavelength values, which, as seen in the Nov. 2012 data, were associated with the areas of highest total defects occurred (mean ripple wavelength of 0.39 versus 0.7 site wide). There was also a significant increase in defect densities in the scour pits of the larger reef objects (e.g. naval barge, and tug), which had grown after the March 2013 nor’easter.

The July 2013 dataset tended to lower defect density values (Figure 3.20). It should be reiterated that few ripple bedforms were detected in the backscatter. The pattern of low ripple wavelength and high defect density continues, albeit inversely
here (large ripple wavelengths to low defect densities). The July 2013 backscatter had the highest median ripple wavelength and highest overall percentage above 1-meter wavelength. In light of the patterns suggested by the previous two datasets, it is likely that areas of higher defect density were areas obscured or buried by July 2013.

Figure 3.18: November 10, 2012 defect density map overlaying sonar backscatter.
Figure 3.19: March 29, 2013 defect density map overlaying sonar backscatter.

Figure 3.20: July 29, 2013 defect density map overlaying sonar backscatter.
Qualitative observations of defect density shows distinguishable increases in defect density ripple bedforms near the southern extent of the sorted bedform field and reef objects. To determine whether there is a quantitative pattern concerning defect density relative to proximity and orientation to reef objects, three subway car test subjects were analyzed for proximal defect densities. Defect densities were averaged from 25 square meter boxes in ranges from 0-5, 5-10 and 10-15 meter in the four cardinal directions from the respective directional extents of the cars. For control, a test point was selected in the middle of the ripple bedform in areas with no objects within at least 50m. All test points were processed for both the Nov. 10, 2012 and March 28, 2013 datasets. The control point and one representative subway car from both surveys are shown in Figure (3.21).
Figure 3.21: Defect density observations within a ripple bedform field (left) and around a subway car (right) for both the Nov. 2012 and March 2013 data sets. Note the higher densities around the reef object.
It is immediately apparent that the defect densities in the proximity of the subway cars are not only greater than those than around the control point, but are also more variable. Defect densities in both the control point never topped 0.36 and 0.42 defects/m² during the Nov and March surveys respectively. Comparatively, densities around the cars topped 0.68 and 0.93 defects/m² during the two surveys. With respect to the affects of proximity, we see little variation between the ranges on the control points (standard deviation of 0.092 and 0.087 defects/m² for November 2012 and March 2013). With the subway cars, highest defect densities are found anywhere between 5 - 15 meters away, with much wider distributions: standard deviations for Nov. 2012 and March 2013 were 0.14 and 0.2 defects/m² for the subway car in Figure 3.21. There is a tendency for lower values immediately next to the subway cars, where scour pits and acoustic shadows disrupt ripple measurements. Orientation with respect to the object appears to have little influence on variations in defect density: higher defect densities occur on every side of the objects (see Figure 3.21). Regardless, the pattern of increased defect densities around the reef objects warrants future considerations.

3.4 Discussion

There is a clear discrepancy between the fingerprint algorithm and non-equilibrium model wavelength predictions for the March and July 2013 surveys. Looking at the buoy 44009 prediction, this would likely be the case for the Nov. 2012 survey as well; while the ADCP driven model shows sustained peak wavelengths, the buoy driven model shows immediate ripple wavelength drop off following the Nov., 2012 nor’easter. As discussed above, the hanging values at the end of the model based on the ADCP data are likely artifacts. Consequently, this indicates that it is the
peak storm predictions that match well with the fingerprint algorithm distribution from the Nov. 10, 2012 survey, not predictions concurrent to the geoacoustic survey. Further, the wavelength predictions from the small event that took place just prior to the March 29, 2013 survey and after the March 5 nor’easter are also a strong match to the Fingerprint Algorithm distribution: only 8 percent of the recorded wavelengths were greater than the 1 meter prediction, and 11.2 percent were less than the smallest prediction (figure 3.22).

Figure 3.22: Non-equilibrium wavelength predictions from mid-March 2013 event compared to Mar. 29, 2013 Fingerprint Algorithm ripple wavelength distribution. Note much greater agreement than to Mar. 29 predictions.
Only the July 29, 2013 survey does not reflect wavelength values estimated from the last ripple-generating event prior to the survey. The last ripple growth event prior to the survey took place in early June, with peak values barely exceeding 0.8 meters wavelength. However, the 76.2 percent of the survey wavelength distribution falls above this mark. Two factors likely account for this: one, the detectable ripple sample size for the July 29, 2013 data is only 15 percent of the size of the March 29, 2013 survey data, and two, there was an extended period of low to moderate conditions preceding the July survey, during which many of the smaller ripple bedforms were likely buried by fine sediments or decayed. Ripple burial is commonly noted with sorted bedforms over periods of low-energy hydrodynamic conditions (see Chapter 2; Murray and Thieler, 2004; Green et al., 2004; Coco et al., 2007; Trembanis et al., 2007). The combination of the two factors likely skewed the remaining data to a larger wavelength distribution.
These results suggest that many of the ripple bedforms surveyed were likely relict ripples, with wavelengths near the maximum wavelengths generated by the storm events. Several studies (Traykovski, 2007; Austin et al., 2007; Voulgaris and Morin, 2008) have come to similar conclusions. In fact, many of the ripple wavelengths from the July 2013 (Figure 3.23b) Fingerprint Algorithm results appear nearly identical to the wavelengths generated from the March 2013 (Figure 3.23a) storm, sharing $r^2=0.81$ correlation. None of the ripple reorganization events were strong enough to generate ripple wavelengths above 1.1 meter after the March
nor’easter, yet 54 percent of the ripple wavelengths recorded in July were above 1.1 meters wavelength – much larger than the 8 – 12 percent distribution values found higher than the storm wavelength predictions in the previous two surveys. As mentioned before, Voulgaris and Morin (2008) found that the relict ripple wavelengths after storm events were near the maximum wavelengths generated by the storms. It is possible, then, that the relict ripples recorded in July remained from the March 2013 nor’easter, which occurred nearly five months before.

While no anorbital ripples were observed in the sonar to validate the model’s anorbital condition, the Aquadopp may shed light on the subject. The downward facing sensors backscatter amplitude was analyzed for seabed height, assuming the highest backscatter values in a sample reflected the detectable seabed. Using this method, peak bed height values are detected all the way up to the sensors third bin (while sensor says up to 30 cm above bed during the storm, values are likely less due to scour of the frame). These values are likely ripple bedforms migrating through the sensors observation field. According to the model, during the peak of Hurricane Sandy, several test sediment samples switched into anorbital conditions. The sample nearest to the frame (RBR6) was a sample that switched to anorbital conditions. Intriguingly, large, orbital ripples cease to appear in the Aquadopp backscatter during peak observed shear stress values, or when anorbital conditions were predicted (Figure 3.24). This may support the model’s anorbital predictions.
Figure 3.24: Shields (blue) for local sediment sample (RBR6) versus bedform height (orange). Note the lack of bedform height peaks during and after the highest Shields values during Hurricane Sandy.

With ripple defects, there appears to be an inverse relationship between ripple wavelengths and ripple defect densities. The highest density values occurred in regions of the smallest ripple wavelengths. As well, these tended to be in ripple fields adjacent to reef objects. Skarke and Trembanis (2011) noted that effect of object scour could result in numerous small bedforms with shorter wavelengths, which, as they note, would appear as higher density regions of ripple defects. The data here supports this hypothesis, although in their study, Skarke and Trembanis (2011) found no distinct relationship between ripple wavelength and defect density. As well, they found higher defect densities associated with periods of poor bed definition, which is supported by the high defect densities in March 2013 backscatter where the ripples had undergone erosion, but not by the low-density values in the less defined ripples of the July 2013 backscatter.
The question remains as to what affect true combined flow has on ripple geometry and defect density. Shear stress estimates using Trowbridge (1998) eddy correlation, derived from the Aquadopp velocity vectors, shows much higher shear stress than estimated wave oscillatory stress during peak storm conditions (Figure 3.25), which could have affected overall magnitude of sediment transport and bedform geometry. Further, there was variation between the combined flow direction during both storm events, with wave-to-bottom current directions varying as much as 40 to 70 degrees. While lower overall defect density values were found in Nov. 2012 backscatter, the fingerprint algorithm orientation mosaics in this study indicated strong variations in ripple crest orientations over relatively small areas in all datasets. It is conceivable, as several studies have suggested (e.g. Amos and Collins, 1978; Li and Amos, 1998; Andersen and Faraci, 2003; Smyth and Li, 2005; Lacy et al., 2007) that storm surge and tidal driven currents orthogonal to wave orbital current vectors, as exemplified by the October 2012, might account for these variations.
3.5 Conclusions

It is apparent from this study that ripple bedform morphology is paradoxically both dynamic and persistent. Within the matter of a few hours, storm events can generate wide areas of large ripple bedforms from a texturally homogenous seabed. Yet, the signature of these storms can be detected for several months after the event in relict ripple bedforms, which, despite erosion and burial, appear to maintain, in part, peak storm wavelengths. The Fingerprint Algorithm allows us to quantify large spatial ripple variability with a degree of precision and repeatability that was not available before. While it gave only snapshots of bedform conditions in this study, Skarke and Trembanis (2011) demonstrated the Fingerprint Algorithms ability to quantify ripple geometry temporally. Further, it allowed for comparison between ripple geometry and rippled defect distributions. Without time-series imagery available for direct ripple measurements, this study used non-equilibrium ripple models to illustrate likely ripple bedform states over the course of year. While the model preformed well predicting peak-storm ripple geometries, there was a tendency for the model to indicate ripple reorganization when likely relict ripple states were observed. As well, this model did not incorporate combined stressors, but instead alternated between wave and current dominated conditions. Shear stress observations demonstrated here, for instance, that oscillatory bed stress estimates did not fully account for the total observed shear stress.

Few investigations have considered the relationship between interacting waves and currents and ripple morphology. Difficulties in replicating combined flow conditions in the lab (Lacy et al., 2007) and non-linear hydrodynamics may account for this. While some lab studies have considered ripple bedforms generated by co-linear wave and current interactions (Tanaka and Shuto, 1984; Van Rijn and Havinga,
1995; Tanaka and Dang, 1996; Dumas et al., 2005; Cataño-Lopera and Garcia, 2006a, 2006b), and others orthogonal or oblique angle interactions (Khelifa and Oullet, 2000; Andersen and Faraci, 2003), the forcing magnitudes considered have been far lower that actual field conditions (Lacy et al., 2007). Field studies have, however, noted that rising orthogonal or oblique angle current forcing compared to wave orbital forcing does accentuate ripple crest eccentricity (Amos and Collins, 1978; Li and Amos, 1998; Andersen and Faraci, 2003; Smyth and Li, 2005; Lacy et al., 2007), which may be supported by spatial deviations in ripple orientation found after the non-colinear flow from Hurricane Sandy and trailing nor’easter. Consensus over the effect of combined flow on ripple height and wavelength, however, is still lacking and many questions regarding the effects of combined flow on bedform morphology, particularly the effects on sinuosity and ripple defects, should be the focus of further studies.
Chapter 4

AN EVALUATION OF SEGMENTATION CLASSIFICATION METHODS USING ACOUSTIC BACKSCATTER IMAGERY

4.1 Introduction

With increasing use of the inner continental shelf, the need to map and classify seafloor texture and habitats is becoming ever more apparent (Hasan et al., 2012). Using sonar backscatter, bottom textural data can be analyzed through acoustic seabed segmentation to define differences in seabed morphology, benthic habitats, and surficial sediment characteristics (Anderson et al., 2008; Brown and Collier, 2008; Brown and Blondel, 2009). Investigators have developed various approaches to seabed segmentation, from manual interpretation of backscatter (e.g. Hughes Clark et al., 1997; Todd et al., 1999) to imagery segmentation (Preston 2009; Brown et al., 2011). There are obvious issues to manual interpretation, included but not limited to determining the boundaries in highly heterogeneous seabeds (Brown and Collier, 2008), and Hamilton and Parnum (2011) argue that imagery segmentation removes important angular backscatter data. It is this particular angular data from which studies using Angular Response Analysis (ARA) derive quantitative seafloor data (Hughes Clark, 1994; Fonseca et al., 2009; Rzhanov et al., 2012). There are limitations to ARA, though, as spatial resolution is limited to half of the multibeam swath width (Hughes Clark, 1994; Hughes Clark et al., 1997; Hasan et al., 2012). Recent studies (Fonseca et al., 2009; Hasan et al., 2012; Rzhanov et al., 2012) have dealt with this issue by combining ARA with high-resolution backscatter imagery into
thematic regions of interest within the overall mosaic. Regardless, ARA remains an involved and often in house process (McGonigle et al., 2009) not easily accessible to the wider scientific community.

Despite the issues listed by Hamilton and Parnum (2011), imagery segmentation remains a commonly used seabed classification technique. Commercialized software has been developed for imagery classification for many applications. Specific to seabed image segmentation, Quester Tangent Corp. MULTIVIEW and SWATHVIEW has been utilized in a number of studies (see Preston 2009; McGonigle et al., 2009; Brown et al., 2011; Raineault et al., 2013). In-depth descriptions of the MULTIVIEW segmentation is described in Preston (2009), and it is necessary here only to describe the process as one of unsupervised classification, i.e., no known or user-defined sediment classes are created to aid the segmentation process. Both McGonigle et al. (2009) and Brown et al. (2011) found QTC MULTIVIEW performed well when classifying multibeam backscatter over large and texturally complex areas. Raineault et al. (2013) applied QTC SWATHVIEW to backscatter from a GeoAcoustics GeoSwath 500 kHz phase-measuring bathymetric side-scan sonar mounted on an autonomous underwater vehicle. In their study, Raineault et al. (2013) segmented sonar imagery from an artificial reef site, and found QTC capable of disseminating both sedimentary boundaries and artificial reef objects.

Despite successful implementation, QTC SWATHVIEW and MULTIVIEW are no longer actively supported software. With a vacancy in commercially available imagery segmentation software designed for acoustic backscatter data, this project investigates the effectiveness of multiple software packages to classify bottom texture.
and sediment distribution patterns using Delaware’s Redbird artificial reef site as a testing area. Using surficial sediment samples taken during this study, and prior classification results from Raineault et al. (2013), this study will evaluate the success of the acoustic classification processes with a prior knowledge of sediment distribution.

4.2 Methods

4.2.1 Data Sample and Software

Backscatter data was collected using a Teledyne Gavia autonomous underwater vehicle (AUV) equipped with a GeoAcoustics GeoSwath 500 kHz phase-measuring bathymetric sonar and dual frequency 900/1800 kHz Marine Sonics sidescan sonar. The AUV allows for a high degree of repeatability and surveys were run with identical settings and transects. Surveys were conducted at the Redbird Artificial Reef site, located 30 km east of Indian River Inlet, Delaware. The site is located in the Cape May retreat massif over what was an ancestral tributary to the Delaware River (Swift et al., 1980). The site is an ideal candidate for testing seabed classification methods. Aside from numerous artificial reef objects, the site contains multiple sorted bedform fields, defined by sharply divergent sediment characteristics.

Forty-three grab samples were collected at the site over five separated cruises, twenty-three of which were analyzed for grain size. These twenty-three samples were taken during field work at Redbird on October, 26, 2012, Nov. 10, 2012 and Dec. 04, 2012, the dates of which surround the passing of Hurricane Sandy and a following nor’easter near the site (Oct. 29 and Nov. 7th respectively). Figure 4.1 shows the classification results from Raineault et al. (2013). The QTC classification process
highlighted the sorted bedform and scour fields common at the reef site, and likewise
detected the artificial reef objects. Sediment samples processed by Raineault et al.
(2013) defined the specific sediment classes and distribution, characterized two
sediment types at Redbird: fine sand with silts and clays, coarse sand with gravel and
shell hash.

Figure 4.1: Sediment distribution classification plot from Raineault et al. (2013).

A sediment distribution plot generated from the samples taken in this study
(Figures 4.2 and 4.3) shows the sediment to be predominantly sandy, with the fine
sands incorporating silts and clays and the coarse sands with gravels, confirming the
Raineault et al (2013) findings. Unexpectedly, at third sediment type was uncovered
at the site immediately following the storms, mud, which became apparent in the
backscatter as dark returns. Following surveys revealed that the exposure of mud is
transient, becoming obscured in the matter of weeks to months (see chapter 2). Since
grab samples were not taken of the mud until the Dec. 04 cruise, fine sand from the
surrounding region had already began to rebury the mud, skewing samples taken in
the muddy areas to the fine sand domain (see Figure 4.3). Each sediment type can qualitatively be identified from backscatter data by their backscatter intensity, with the coarse sands returning brighter than the fine sands, and muds appearing almost black (see Figure 4.2).

Figure 4.2: Sediment sample locations (N = 23) over multibeam backscatter from the Nov. 10, 2012 survey. Note the distinct returns from the fine sands (medium-grey), coarse sands (light grey), and muds (dark grey/black)
Figure 4.3: Schlee sediment distribution diagram. Note, mud samples taken one month after storm, so fine grain sand sediment burial is likely to have skewed samples coarser.

Three separate software packages were tested for their ability to classify the seabed from acoustic data: 1) Chesapeake Technology SonarWiz, 2) ESRI ArcGIS and 3) Exelis VIS ENVI. Of the three, only the SonarWiz classification function was designed with acoustic backscatter data in mind. SonarWiz is designed for processing and mosaicking side-scan and backscatter data, and thus has the added advantage of combining a classification function with these roles within the software package. On the other hand, both ArcGIS and ENVI image classification toolboxes were designed primarily around satellite imagery analysis. All three software packages are currently supported, and in the case of ArcGIS, widely available and utilized in many sectors of academic, business and government.
4.2.2 Data Processing

As discussed by Preston (2009) and Hamilton and Parnum (2011), sonar backscatter must be gain corrected prior to imagery segmentation, to remove any influence that variations will have on the classification process. For this study, the GeoSwath backscatter was processed and gain corrected using a beam angle correction in SonarWiz to remove across track variations in backscatter intensity due to a non-linear response of sonar transducers (see Danforth, 1997). While five surveys were conducted at Redbird Reef, GeoSwath data was not available during the December 2012 and March 2013 cruises due to mechanical issues, leaving 3 available datasets for analysis (Oct. and Nov. 2012 and July 2013). Further, the side-scan data, available from all but the December 2012 cruise, does not yield optimal imagery for seabed classification compared to the GeoSwath backscatter (Figures 4.4a and 4.4b). Thus, the GeoSwath backscatter data was bottom tracked and gain adjusted to yield the most consistent imagery in terms of backscatter intensity, texture, etc. Figure 4.4b and 4.4c illustrate the difference between no gain correction and gain corrected backscatter, demonstrating the need for gain corrections for better segmentation. This was conducted for the three available datasets. The final products were exported as geotiffs for sediment classification with a resolution of 25 centimeters per pixel, though the SonarWiz classification function works off the .csf files inherent to the software.
The SonarWiz classification processing tool classifies sediment via “textural” analysis (SonarWiz, 2013). This process involves a training function, which can best be described as semi-supervised (see Figure 4.5). The initial training function runs independently, though user settings can modify the training process before and after the training function has run. The user cannot predefine a class through manual selection. However, it is possible to remove classes that are unwanted. The classification process can use two texture classification methods: simple textures and Grey Level Co-Occurrence Matrix (GLCM) textures. The former is defined by running only one statistical calculation on each image window (a predefined pixel size), while the GLCM builds a matrix based on the number of times two image brightness values are concurrent and performs statistical analyses on the matrix (SonarWiz, 2013). Both texture groups contain several different statistical functions and any combination can be used (for more on these see the SonarWiz User Guide).
For this study, three different combinations were applied to test the best resulting classification products for each of the three backscatter mosaics. The first method was a simple textures method using standard deviation and entropy statistical functions. The second method was GLCM textures method using homogeneity and entropy statistical functions. The final method was a combination of simple and GLCM textures, using standard deviation, entropy, GLCM mean horizontal, GLCM mean vertical and GLCM correlation).

While not specifically designed for acoustic data segmentation, seabed classification methods using ArcGIS is not a novel approach. Erdey-Heydorn (2008) developed a workflow for classifying not only seafloor morphology, but also benthic habitat types using backscatter and bathymetry. Likewise, the Benthic Terrain
Modeler, developed by NOAA and several partnering institutions, uses ArcGIS driven tools to classify specifically bathymetric data, utilizing a user-defined classification file outlining specific depth and slope values for classes (see Wright et al., 2012). However, both of these processes involved the creation of python scripts in ArcGIS to carry out analysis. Instead, multiple methods inherent to the software were investigated here. Using an “unsupervised” ArcGIS classification method, backscatter imagery was brought in as geotiffs from SonarWiz. The number of classes and sampling size was set using the Iso Cluster tool, which outputs a signature file (.gsg) containing these parameters and raster clustering results. The Iso Cluster algorithm separates cells into user-specified classes based on minimum Euclidean distance to arbitrary class mean pixel values set by the tool (ESRI). While the user specifies class number, the Maximum Likelihood Classification tool, which classifies the original geotiff based on the Iso Cluster signature file determines the ultimate class number. Maximum likelihood classification is based on Bayes’ theorem of decision-making, and uses both variances and co-variances of the class signatures from the signature file to generate a mean vector and covariance matrix for each class (Figure 4.6). With these values, the software computes the probability for each class to each individual cell (ESRI).
Figure 4.6: Unfiltered bottom sediment classification of the Nov. 2012 GeoSwath backscatter based on an unsupervised ArcGIS classification workflow. Note that the objects are not represented, but instead reflect sediment classifications.

ArcGIS also offers a method for supervised classification using their Interactive Supervised Classification toolbox. With this method, the user is able to train the classification process by choosing representative samples. Polygons are drawn around the specified area, and when the proper number of classes is made, a signature file is created. This is then imported into the Maximum Classification Method, as above, to output a classified image. Much like Figure 4.6, areas remain that need to be cleaned and filtered. The Spatial Analyst toolbox has tools, under the Generalization tab, that work to filter and clean the image. The process includes a Majority filter, which filters through local statistical functions, Boundary Cleaning to
smooth the edges and Null Value mask and Nibble Function to illuminate “salt and pepper” pixilation (Figure 4.7).

![Classification](image)

**Classification**
- Muds
- Fine Sands
- Coarse Sands with Gravel

Figure 4.7: ArcGIS Supervised Classification image with filtering and smoothing. Note that the reef objects are still present but not highlighted as a separate class.

Designed for satellite imagery analysis, ENVI software has a built in image classification toolbox with multiple statistical methods for classification. Not all methods are applicable or usable with typical imagery (those with only three raster bands), nor could all be used with the sonar backscatter imagery. To assist in the process, a classification workflow wizard walks the user through the necessary steps. In the wizard, either supervised or unsupervised classification methods can be selected. For this project, the supervised classification method was used, where, like ArcGIS, polygons are used to train the classification function. Unlike ArcGIS,
multiple polygons can be assigned to one class, which allows the user to capture all the variability that may lie within one class (Figure 4.8). Once the classes are defined, the statistical method is chosen (and limited by raster band numbers), which, here, was the minimum distance function. Not unlike the ArcGIS Maximum Likelihood classification, the ENVI Minimum distance function calculates mean vectors for each class and assigns cells to the nearest class by Euclidean distance (ENVI). After classification, smoothing and aggregations filters clean the image and remove noise. The smoothing window size and aggregation minimum sizes can be specified. The final results were exported and brought into ArcGIS for final map design.

Figure 4.8: The ENVI classification wizard allows the user to assign multiple samples to one class.
4.3 Results

The multiple statistical options in the SonarWiz classification function allow for method refinement. Figure 4.9 demonstrates that one combination of statistical function may have greatly different results than another, and a combination that works well on one dataset, as did the simple textures with the Oct. 2012 data, may not work well with another, as with the July 2013 backscatter. Here, only artifacts from the original track lines are present, and the in Nov. 2012 dataset, only the mud fields were classified. Despite this, the simple textures method was the only method that detected the mud field in the Nov. 2012 data. In general, the simple textures method worked well only for the Oct. 2012 backscatter. The combination of the simple and GLCM textures excelled at highlighting the coarse grain sediment and scour pits in all three backscatter images, but again, it failed to classify the muddy sediments. Alone, the GLCM textures method did not correctly identify the sediment distribution as clearly seen in the backscatter imagery, highlighting some areas that were not detected in other classification methods. Overall, no method highlighted the artificial reef objects.

Despite gain correction, each classification method highlighted differences in the backscatter image that are clearly track line related, and not picked up by the other two software packages. This result is likely due to the classification process. Instead of working across the mosaic by sample windows, the process moves along each sonar file individually, classifying along track. Thus, outer swath areas that are normally covered by subsequent track lines influence classification across the swath width. While a filtering function is built into the process to correct line-to-line class offsets, SonarWiz could not produce an image with smooth transitions between transects.
Figure 4.9: Comparison of different SonarWiz classification functions on the October 2012 (A), November 2012 (B), and July 2013 (C) GeoSwath backscatter. No one method had optimal results for all three images.
In the case of the ArcGIS unsupervised classification, the unfiltered output was unable to segment the wrecks and objects separately from the sediment, regardless of class number specified. Further analysis of this method was abandoned in favor of supervised classification method, which allowed for more user control. This method turned out more promising results, though issues still occurred surrounding the reef objects. Despite creating a class specifically for the reef objects, the classification process was unable to detect the objects themselves, rather classifying the objects’ shadows (Figure 4.10a) or the object scour pits (Figure 4.10c). With the November 2012 backscatter (Figure 4.10b), the software ignored a fourth class created for the objects and instead grouped objects’ shadows in with the muds, which appeared in the backscatter as dark returns. Regardless, the ArcGIS method did highlight the changes that occurred after Hurricane Sandy and the following months afterwards. The exposure and subsequent burial of the extensive mud field is most apparent. As well, the scour pits in the lee of the barge and the tug wrecks clearly grow over time, extending to the southwest. This reflects the dominant wave direction of the two nor’easter events that occurred in early November (after Sandy and prior to the survey) and early March.
Figure 4:10: ArcGIS classification results of the October 2012, November 2012, and July 2012 GeoSwath backscatter. Note the halo around the reef objects in the July 2013 data.
Figure 4.11: ENVI classification results of the October 2012 (A), November 2012 (B), and July 2013 (C) GeoSwath backscatter. Note the poorly sorted sediment rimming the coarse sands in both the October 2012 and July 2013 data.
The ENVI classification method showed the most intriguing results, though it was also unable to detect the reef objects. Instead, the classification process captured the third class of sediment rimming the coarse sands, similar to the results from the SonarWiz methods above. These show up in both the October 2012 (Figure 4.11) and July 2013 backscatter (Figure 4.12c), but are not apparent in the post-storm November 2012 dataset (Figure 13b). The Nov. 2012 classified image is almost identical to the ArcGIS image, down to grouping the object shadows into the mud class. In terms of sediment distribution, the ENVI process was perhaps the most successful of the three methods.

4.4 Discussion

Both the SonarWiz GLCM textures and combined textures noted a transitioning sediment class between the coarse and fine domain during the July 2013 data, although the overall extent of the class varies in each. Likewise, the simple textures indicated a transitional class with the Oct. 2012 data set. However, no one method captured this class in both the Oct. and July data set. From this experiment, it became apparent that trial and error and multiple iterations are often required to find a desired result with SonarWiz. Because of the different statistical methods required to find the optimal result for each dataset, time-series analysis of sediment distribution changes at the site is difficult with the SonarWiz classification results. On the other hand, the ENVI classification results noted this transitional class in both surveys. ROV video analysis from the July 2013 survey of the tug scour pit showed a transition zone between the coarse sands and gravels to the fine sands, consisting of poorly sorted fine sands and gravels. While the ArcGIS classification didn’t highlight this
class, it was the only method able to detect the objects and was most similar in result to the QTC classified image from Raineault et al. (2013).

Much of what can be seen throughout these classified images, and specifically the ENVI classification sets, is representative of sorted bedform features, as sorted bedforms are theorized to be self-organizing (Green et al. 2004; Murray and Thieler, 2004). The prevailing theory postulates that self-organization of coarse and fine grain sediments is due to feedback between hydrodynamic conditions and bed composition and roughness (Green et al. 2004; Murray and Thieler, 2004). Low to moderate-energy wave conditions favor the burial of coarse grain ripple bedforms by fine grains. Conditions allow for the transport and settling of fine grain material over coarse bedforms when there is little turbulence occurring over the rough ripple bed. With the transition into high-energy wave conditions, fine grain material is suspended and coarse bedforms are activating. Turbulence over the coarse ripple bedforms inhibit the settling of fine grained sediments, which instead settle over less turbulent beds with finer grains or smaller wave-generated ripples. Subsequent return to low energy conditions, especially if there is fast wave energy decay, will result in reburial of coarse sediment bedforms (Green et al., 2004). The areas of poorly sorted sediment are evidence of this intrusion of fine sands into the coarse sand ripple beds. In essence, the ENVI classification set highlights the cycle of sorted bedforms, from burial of coarse sediment by fines, to exposure during storm events, and to eventual reburial in low energy conditions.
4.5 Conclusion

Different methods for seabed classification were tested and the strengths and weaknesses of each were highlighted. With additional ground-truthing of sediment types on the seabed, the ENVI image classification best captured the sediment distribution changes at the site and the cycle of bedform evolution, though all three methods are viable options given the right conditions and processing settings. Additionally, this study also sheds light onto the dynamics of the inner continental shelf. The results from this project begin to characterize intra-annual sediment transport at the Redbird artificial reef site, highlighting times of large, storm-driven textural changes to the seabed (see chapter 2). Sediment distribution shows smoother, more uniform beds during calm conditions and more sorted and textured beds following storm conditions. As expected, the data suggest the Redbird Reef site follows the cycle of bedform evolution, where periods of scour and sediment transport away from the site occur during storm events, while influx of sediment and burial occur during calmer conditions (Green et al., 2004; Murray and Thieler, 2004). The ability of imagery segmentation to highlight this cycle suggests that, despite previously noted shortcomings, this method is a viable, largely available, and simple method for seabed classification.
Chapter 5

CONCLUSIONS

5.1 Inner Continental Shelf Morphodynamics

The complexity of inner continental shelf morphodynamics is evident from this study. Within an annual cycle, the Redbird artificial reef went from a texturally uniform seabed, to a self-sorted, rippled and scoured seabed, and back again. Of everything discussed in this thesis, above all, this study highlights the short-term variability of morphodynamics as well as the long-term persistence of sorted bedform dynamics in a site typically deeper than most sorted bedform studies have focused on (e.g. Murray and Thieler, 2004; Goff et al., 2005; Ferrini and Flood, 2005; Coco et al., 2007). If an example of the sorted bedform cycle need be found, the Redbird Reef is a prime example. Evidence from this study and the previous work by Raineault et al. (2013) suggest that the site undergoes cyclical activation and burial within annual to inter-annual cycles. As well, the persistence of sorted bedform boundaries, while fluctuating annually, appear to remain fairly consistent over several year cycles. Further, this study suggests that ripple bedforms may be more persistent than expected; ripples may not respond to changes in hydrodynamic forcing quickly, or at all, in cases of rapid decrease in hydrodynamic forcing, with relict ripples existing on site for over five months after the conditions that formed them. Such behavior and response makes ripple geometric modeling difficult. Future efforts are needed to address both topics, since without a more comprehensive understanding of ripple
formation and migration processes, models will not be able to capture, more thoroughly, ripple geometric variations.

The effect of objects on ripple defect densities was one question of this thesis that will become a focus of work that will continue after this study. Initial results suggest that a) ripple defect densities are inversely related to ripple wavelengths and b) that ripple wavelengths are smaller around objects, leading to the conclusion that c) objects increase ripple defect creation. As noted in previous studies (Skarke and Trembanis, 2011; Mayer et al., 2007; Trembanis et al., 2007; McNinch et al., 2006), increases in bedform defects could be used to detect seafloor objects of interest, including shipwreck artifacts, debris from aviation and maritime disasters, seabed mines and unexploded ordnance. With an increasing use of the inner continental shelf, the ability to rapidly locate objects of high-interest in bedform fields that typically obscure object signals (Skarke and Trembanis, 2011) is becoming increasingly imperative. The Fingerprint Algorithm, imagery segmentation and initial findings from this study may lay an effective foundation for future studies on object – ripple defect relationships and automated object detection processes.

5.2 Future Morphodynamic Investigations

This study used a multi-platform, multi-dataset approach to studying morphodynamic variability at an inner shelf artificial reef. It is apparent from this study that such an approach is paramount, and that similar studies in the future should utilize a combination of bathymetry, backscatter, time-series acoustic imagery and time-series hydrodynamic data. The incorporation of the Fingerprint Algorithm in study opened up the prospects of truly analyzing ripple bedform geometries spatially. While the use of a rotary sonar was not an option here, the successful implementation
of the Fingerprint Algorithm on spatio-temporal evolution of ripple bedforms has been demonstrated before (Skarke and Trembanis, 2011). Any future investigation should most certainly use a combination of the two approaches, to take the small scale, temporal evolution of ripple bedforms to define and constrain our understanding of the larger spatial distributions.

The need for future studies in morphodynamics has been stated numerously in this thesis. In many ways, we are only beginning to define morphodynamic interactions on differing spatio-temporal scales and hydrodynamic regimes. It was the goal of this study to, in some manner, contribute to the ongoing research into sorted bedforms and ripple bedforms in particular. If alone, by defining a successful methodological and processing pipeline for studying ripple bedforms, future efforts will benefit from implementing those used here.
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Appendix A

RESON BATHYMETRY AND BACKSCATTER REDBIRD REEF

A.1 Introduction

This appendix includes both backscatter and bathymetric maps taken by the 400 kHz setting of the Reson 7125 of the Redbird Reef from the October, November and December 2012 surveys and the March and July 2013 surveys. The figures are shown in chronological order.
A.2 Reson Bathymetry and Backscatter Maps

20121026

Bathymetry
- High: -19.4
- Low: -29.18

Meters
0 75 150 300 450 600
Appendix B

AUV SIDE-SCAN AND GEOSWATH BACKSCATTER

B.1 Introduction

This appendix contains the main sonar products the 900 kHz Marine Sonics Technology, Ltd. side-scan sonar and 500 kHz GeoAcoustics GeoSwath phase-measuring bathymetric side-scan mounted on a Teledyne Gavia autonomous underwater vehicle (AUV). Four AUV surveys were conducted at the Redbird Reef site in October and November 2012 and March and July 2013. GeoSwath backscatter was not available during the March 2013 survey.
B.2 AUV Backscatter Maps

20121026

*Side-Scan Sonar*

*GeoSwath Backscatter*
20130328

Side-Scan Sonar
20130729

Side-Scan Sonar

GeoSwath Backscatter
Appendix C

FINGERPRINT ALGORITHM MAPS

C.1 Introduction

This appendix includes additional Fingerprint Algorithm results. Section C.2 includes the orientation and wavelength results from the March and July 2013 AUV surveys. The maps from the November 2012 survey are included in Chapter 3. Section C.3 includes the additional two subway car defect density test maps.
C.2  Fingerprint Algorithm Maps

March 29, 2013
C.3 Defect Density Subplots

November 10, 2012

March 30, 2013
Appendix D

T_TIDE PREDICTED TIDE PLOTS

D.1 Introduction

This section includes results from T-Tide tidal harmonic analysis from the combined Redbird ADCP and Buoy 44009 data. This include U and V directional tidal velocities and tidal height.
D.2 Tidal Plots
Appendix E

NON-EQUILIBRIUM RIPPLE CODE

E.1 Introduction

This appendix includes an example of the non-equilibrium ripple code adapted from Soulsby et al. (2012) with Traykovski (2007) equilibrium ripple wavelength algorithms and Nelson et al. (2013) ripple height algorithm. The code is written for use in Mathworks® MATLAB.
E.2 Non-Equilibrium Ripple Code

function [s] = noneqripple(Ub, Ucur, Tp, d, Dp, Dcur)

%INPUTS
%   Ub = Bottom significant wave orbital velocity
%   Uc = Near-bed currents
%   Tp = Peak Period
%   d  = Grain diameter (e.g. d50) in meters
%   Dp = Dominant wave direction (degrees)
%   Dcur = Current Direction
%OUTPUTS
%   s = struct containing ripple wavelength, height, orientation and
%       various threshold values (see below)

%%%% Ripple Model Calculations%%%%
%% Carter DuVal, 2014
%% University of Delaware
%% Adapted from Adam Skarke, 2013

for i=1:numel(Ub);

W = (Ub(i)^2)/(((2650/1027)-1)*9.8*d); % wave mobility number
Bw = (2.996*(W^1.07))/(21700+(W^1.07)); % eqn 16 Soulsby et al. 2012

% orbital diameter
do = (Ub(i)*Tp(i))/(pi);

% Current Shields
z0 = d/12;
Cd = (0.4/(log(28/z0)-1))^2;
Thetac = (1027*Cd*Ucur(i)^2)/(9.8*d*(2650-1027));
Thc(i) = Thetac;

% Waves Shields
A = (Ub(i)*Tp(i))/(2*pi);

% Bed roughness condition
if i == 1;
    kN= 2.5*d; % Nikuradse Roughness
else
    if eta(i) > 2.5*d;
        kN = 8*eta(i-1)^2/lam(i-1); %Nielson (1981) form roughness
    else
        kN = 2.5*d;
    end
end
end

%f(i) = exp((5.213.*(kN./A).^.194)-5.977); %Swart 1974
fw(i) = 1.39*(A/z0).^-0.52; %Soulsby 1993
Thetaw = (0.5*1027*fw(i)*Ub(i).^2)/(9.8*d*(2650-1027));
Th(i) = Thetaw;

D=((9.8*((2650/1027)-1)))/(0.00000136^2)^1/3*d; %Dimensionless
%grain size Soulsby and Whitehouse

%Grain critical shear stress
Tcr = 0.3/(1+1.2*D)+0.0550*(1-exp(-0.02*D));

Bl = real((12*((Thetac-Tcr)^1.5))/(2.5+((Thetac-Tcr)^1.5)));%use
%for wavelenaght and orientation model
Beta = (20*(Thetac-Tcr)^1.5)/(2.5+(Thetac-Tcr)^1.5);%use for ripple height model

T = Tp(i); %wave period

etamc=d*202*(D^-0.554); %equation 4 Soulsby et al. 2012
lammc=d*(500+(1881*(D^-1.5))); %equation 5 Soulsby et al. 2012

%lammc=1000*d; %Modified by Skarke - possibly from Yalin (commonly used)
%etamc=lammc*0.16;

Tc = (etamc*lammc)/(((2650/1027)-1)^4.9.81*(d^3)^.5; %equivelent period for currents
%see Soulsby et al., 2012 pg. 52 eqn. 19

SHwo=(1.66)*D^(-1.3);
SHsf=(2.26)*D^(-1.3);

ws=(0.00000136/d)*(((10.36^2+1.049*D^3)^.5)-10.36);

AH(i) = exp(7.59-sqrt(33.6-10.53*log(A/(535*d)))); %Malarkey and Davies 2003
%non-iterative solution to WH 1994 anorbital condition
if AH(i) > 100; %Wiberg Harris anorbital condition
    lammw = d*535;
    etamw = 1/(AH(i)/do);
else
    if (Ub(i)<(4.2*ws));% Traykovski prediction of equilibrium
        lammw=0.75*do;
        %lammw = 1.5*Ub(i)/(2*pi/T);
        etamw = 0.126*lammw^1.05;%Nelson et al 2013 eq. 46 irreg wave
    elseif (Ub(i)>(4.2*ws));
        lammw=1.5*(4.2*ws)/(2*pi/T);
        etamw = 0.126*lammw^1.05;
    end
end

%lammw=exp((693-
0.37.*(log(W)).^7)./(1000+0.75.*(log(W)).^8)).*(HC06Sod(i)/2);%mielsen field
%lammw=(2.2-0.34*W^0.34)*(HC06Sod(i)/2);%nielsen lab
%lammw= ko06(i);% kalifa-Oullett haris for equilibrium
%lammw= td06(i);% Tanaka Dang for equilibrium
%lammw= wh06(i);% Wiberg haris for equilibrium
%n=0.22*(HC06Sod(i)/2)*(HC06SHm(i)/0.05)^-0.16;%grant madsen
%v=(HC06Sod(i)/2)/0.00025;
%lammw=(HC06Sod(i)/2)*((1+0.00187*v*(1-exp(-(0.0002*v)^1.5)))^-1);

if i == 1;
    direqc = Dcur;
    if (Thetac >= Tcr)
        lameqc = lammc;
        etaeqc = etamc;
    else
        lameqc = 0;
        etaeqc = 0;
    end
else
    if ((Thetac >=0) && (Thetac <= Tcr));% Soulsby and Clark for equilibrium
        lameqc(i)=lameqc(i-1);
        etaeqc(i)=etaeqc(i-1);
        direqc(i)= Dcur(i-1);
    elseif ((Thetac > Tcr) && (Thetac <= SHsf))
        lameqc(i)=lammc;
        etaeqc(i)=etamc;
        direqc(i)=Dcur(i);
elseif (Thetac > SHsf)
    lameqc(i) = 0;
    etaeqc(i) = 0;
    direqc(i) = direqc(i-1);
end
end

if i == 1;
    direqw = Dp;
    if (Thetaw >= Tcr)
        lameqw = lammw;
        etaeqw = etamw;
    else
        lameqw = 0;
        etaeqw = 0;
    end
else
    if ((Thetaw >= 0) && (Thetaw <= Tcr));% Soulsby and Clark for equilibrium
        lameqw(i) = lameqw(i-1);
        etaeqw(i) = etaeqw(i-1);
        direqw(i) = Dp(i-1);
    else
        elseif ((HC06SHc(i) > 0.05) && (HC06SHc(i) <= SHsf));
            lameqw(i) = lammw;
            etaeqw(i) = etamw;
        elseif (SHsf < HC06SHc(i))
            lameq(i) = 0;
        end
end

% Equations 26 and 27 Soulsby et al., 2012
if (Thetaw >= Thetac);
    a = (Bw/T)*lameqw(i);
    a_e = (Bw/T)*etaeqw(i);
    a_d = (Bw/T)*direqw(i);
    b = (Bw/T);
    theta(i) = Thetaw;
elseif (Thetaw < Thetac);
    a = (Bl/Tc)*lameqc(i);
    a_e = (Beta/Tc)*etaeqc(i);
    a_d = (Bl/Tc)*direqc(i);
    b = (Bl/Tc);
theta(i) = Thetac;
end

if i == 1; %Initialize ripple conditions
dir(1) = Dp(1);
if Thetaw > Thetac;
lam(1) = lameqw;
eta(1) = etaeqw;
else
lam(1) = lameqc;
eta(1) = etaeqc;
end
end

% equation 28 wavelength non-equilibrium
lam(i+1) = lam(i) + ((a/b) - lam(i)) * (1 - exp((-b)*3600));
eta(i+1) = eta(i) + ((a_e/b) - eta(i)) * (1 - exp((-b)*3600));
dir(i+1) = dir(i) + ((a_d/b) - dir(i)) * (1 - exp((-b)*3600));
end

s = struct('lam', lam, 'eta', eta, 'dir', dir, 'tcr', Tcr, 'thw', Thw, 'thc', Thc,...
'theta', theta, 'fw', fw);