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# A Seascape Approach to Predicting Reef Fish Distribution

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NOVA SOUTHEASTERN UNIVERSITY OCEANOGRAPHIC CENTER

## A Seascape Approach to Predicting Reef Fish Distribution

By

Brian K. Walker

Submitted to the Faculty of  
Nova Southeastern University Oceanographic Center  
in partial fulfillment of the requirements for  
the degree of Doctor of Philosophy with a specialty in

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## Abstract

Linking small-scale measurements of species distributions to broad-scale seascapes is necessary to understanding and predicting organismal distributions and their dynamics. This applies to reef fish populations as well. Reef fish studies are often limited to small spatial scales because of logistical and economic constraints; however, viewing the data at larger spatial scales might elucidate unforeseen relationships and patterns and facilitate regional management and conservation efforts. To address this growing need, an empirical model was created to predict reef fish abundance and species richness for the entire seascape using the relationship between the fish, benthic habitats, and GIS-derived topographic complexity metrics from a subset of *in situ* survey data.

The essential inputs for this model included a large-scale, high-resolution bathymetric survey of the seascape; accurate, spatially defined and characterized benthic habitats of the seascape; and a spatially defined, *in situ* survey of the reef fish population with a statistically powerful number of samples within many of the defined habitats. Two studies were performed to obtain the model inputs.

The first study (Part II) integrated laser bathymetry, acoustic ground discrimination, subbottom profiling, and aerial photography to create a habitat map for the nearshore benthic habitats of Broward County, Florida, USA from 0 to 35m depth. A mosaic of interpolated, sun-shaded, high-resolution laser bathymetry data served as the foundation upon which acoustic ground discrimination, subbottom profiling, aerial photography, and groundtruthing data aided in resolving habitats. Mapping protocols similar to NOAA's Biogeography Branch Caribbean coral reef ecosystem maps were used to allow for a comparable output. Expert-driven visual interpretation outlined geomorphological features at a scale of 1:6000 with a minimum mapping unit of 1 acre, pre-defined by the NOAA protocol. Acoustic data were then used to differentiate areas of similar morphology by their acoustic diversity and look at within feature variation. Of the approximately 112 km<sup>2</sup> mapped, 56.62 km<sup>2</sup> were coral reef and colonized hardbottom (50.42%), 54.78 km<sup>2</sup> were unconsolidated sediments (46.80%), and 0.43km<sup>2</sup> were other categories (2.78%). Three linear reef complexes were depicted. The outermost linear reef has a mature windward reef morphology including a spur and groove system, which was absent on the other two reef lines. Different benthic habitats were found on the outer

versus middle and inner reefs. A considerable amount of colonized pavement was found inshore. The Broward map yielded a high overall accuracy of 89.6%, only slightly less than the photo interpreted NOAA Caribbean maps (overall accuracy of 91.1%). User and producer accuracies within each category were also comparable. Similar methodology can be used in other areas where photo interpretation is not feasible.

The second study (Part III) analyzed reef fish assemblage relationships to *in situ* and GIS topographic measurements across the seascape to evaluate the possibilities of using GIS metrics as a proxy for prediction models. *In situ* topographic complexity was measured for 370 point count fish surveys spanning the reef seascape. GIS topographic measurements were taken from a high-resolution bathymetric dataset of each survey's footprint. The sites were characterized for seascape analysis by the independent benthic habitat map from Part II. Reef fish abundance and species richness increased with increasing topographic complexity, but the data were weakly correlated due to high variability suggesting that it is not the only controlling factor on the assemblage. Seascape characterization elucidated two distinct assemblages; one shallow and one deep. Topographic complexity better correlated to species richness in the shallow habitats than in deeper ones, whereas, it correlated to abundance the strongest in the deeper habitats. *In situ* measurement yielded the highest correlations, but the GIS metrics followed the same trends therefore they can be used as proxies for reef fish distribution models.

The results from the previous two studies were assembled into a model framework to project the relationship of reef fish abundance and richness to topographic metrics in the different habitats across the entire seascape. A squared polygonal grid of the entire seascape was created at the same resolution as the fish surveys and topographic statistics were calculated for every square in the grid. Grid polygons which fell outside modeled habitats (e.g. sand) were filtered and discarded. The linear regression equations of the reef fish/GIS topography relationship (Part III) were used to predict the abundance and richness of fish for the prediction grid in each modeled habitat. The topographic statistic from each grid polygon was entered as the x value (GIS metric) in the regression equation which was then solved for y (abundance or richness). The output was rounded to the nearest whole number and populated in the GIS for the appropriate grid polygon. A similarity percentage analysis (SIMPER) between habitats calculated the dominant

percentage (top 70%) of each species in each habitat (Part IV). These percentages were used to estimate the abundance of the dominant species in each grid cell from the predicted total abundance. This resulted in a seascape of polygons (15.24m by 15.24m grid cells) with predicted abundance and richness values for three GIS topographic metrics, elevation, volume, and surface rugosity. These were then displayed as maps for viewing, querying, and statistical analyses.

Prediction model output analysis evinced similar relationships as the input data for both abundance and species richness, thus this model enabled viewing of the relationship between reef fishes and their habitats over the entire seascape. Comparison between predicted and empirical data showed significant, but low agreement for all of the topographic metrics. The elevation model performed best in this comparison with both abundance ( $r^2=0.27$ ) and richness ( $r^2=0.39$ ). The fact that the prediction data was not strongly correlated to the input data, but the statistical relationships were evident between datasets, means that the model is best used for comparative analyses instead of gross estimates.

This model has many scientific and management applications like the estimation of fish stocks, the designation of marine protected areas, and baseline comparisons to future surveys. It also gives statistical support to management and conservation decisions, giving resource managers a powerful tool to support their actions. This framework design is a simple approach that lends itself to adaptation and could easily be modified to look at different ecological processes (other than fish) and their relationships to many types of seascape variables. To increase model accuracy, better understandings of the appropriate measurement scale and fish operational scales are needed as well as more research on the dynamics of how reef fish relate to topographic complexity and the other ecological factors influencing their distributions across the seascape.



## **Preface**

This dissertation is organized as follows. Part I introduces the study and presents its scope. Included are a brief synopsis of the studies goals, a brief history of seascape ecology, and the criteria needed to accomplish the work. Part II presents the benthic habitat mapping portion of the study. It focuses on bathymetric data preparation, surface creation, and habitat delineation. Part III presents the fish data analyses. It discusses the methods to acquire the spatial measurements in GIS and the results of how the natural reef fish assemblage relates to topographic complexity. Part IV utilizes multivariate statistics to find how the variables cluster in multidimensional scaling, and to determine which species are most responsible for the clustering. Part V combines the knowledge gained from the results of Parts II, III, and Part IV into a predictive model. The model framework is presented and discussed as well as its uses and limitations.

I assimilated and analyzed the input data and developed the prediction model individually, yet this work utilized data collections involving significant work from many others. In Part II, the acoustic and groundtruthing data were collected by Ryan Moyer, Raquel Luz-Hernandez, and Greg Foster. Ryan Moyer and Raquel Luz-Hernandez processed the QTC acoustic data and Dr. Riegl processed the Echoplus data. I created the benthic habitat layers, analyzed the acoustic results and the compared the outcome to other mapping data. In Part III, the fish surveys were conducted by Dr. Spieler's lab for Fleur Ferro's master's thesis. Many people were involved in the 400+ surveys including myself. I crossed checked all electronic survey data with the original data during the quality control analysis. I filtered the data for GPS accuracy and conducted all GIS and statistical analyses. I solely designed, created, and analyzed the prediction model with some helpful advice of Dr. Riegl.

# Part I

## **Introduction**

# 1 Introduction

Advances in scientific methods over the past few decades have allowed investigators to accurately assess fish populations on a small scale, however, due to the economic constraints in acquiring marine ecological data, there is a growing need to apply these small-scale data to large-scale spatial distributions (Kendall et al. 2003, Grober-Dunsmore 2005). Studies linking small-scale measurements of abundances and species distributions to broad-scale seascapes are the key to understanding and predicting organismal distributions and their dynamics (Wiens 1989, Sale 1998, Heglund 2002, Grober-Dunsmore 2005, Iampietro et al. 2005). In view of rampant over-exploitation of marine resources, a quantitative understanding of the interactions between fish and the seascape are needed for conservation efforts and marine protection area placement (Grober-Dunsmore 2005).

Investigating these relationships requires an appropriate scale of study (Dahl 1973, Wiens 1989, Sale 1998, Pittman and McAlpine 2001, Bissonette 2003). Examining small reef organisms may require a level of study less than a few square meters yet, the study of larger, mobile reef organisms such as fish requires the synthesis of small-scale transect-level measurements like fish abundance or richness and large-scale landscape-level measurements such as topographic relief and habitat associations (Kendall et al. 2003, Grober-Dunsmore 2005). The small-scale measures of reef fish assemblages via visual censuses are the most common means of studying fish communities (i.e. transects, point-counts, etc.). Each data collection in itself does not target large-scale ecological processes; however, many data collections taken over a broad spatial area can capture these phenomena (Sale 1998). The problem with this approach is that it requires the collection of expansive physical and biological environmental parameters to relate to the fish data. *In situ* measurements of these data are often cost-prohibitive, but the emergence of remote sensing technologies, which has made large-scale comparison data more attainable, offers new perspectives. Combining these data enables study of coral reef fish and their relationships with benthic habitats and topographic complexity of a broad area (i.e. seascape) (Grober-Dunsmore 2005, Iampietro et al. 2005, Kuffner et al. 2007).

This study utilizes several remote sensing technologies and landscape ecological theory and tools to detect the interactions between reef fishes and coral reef structure and benthic habitats; a “Seascape Ecology” approach. This approach incorporates small-scale measurements ( $\sim 200 \text{ m}^2$ ) of the reef fish assemblage (i.e. point count assessment) and of reef topographic complexity (i.e. laser bathymetry) and large-scale ( $>1000 \text{ m}^2$ ) benthic habitat mapping to relate reef fish abundance and distribution to large-scale topographic complexity. Static predictive models are derived based on the relationships between the distributions of the local reef fish assemblage, the reef habitat and topography. These analyses provide unique views to our understanding of the role that reef structure plays in reef fish assemblage distributions and predictive models that resource managers can use to estimate and compare fish distributions.

### **1.1 Landscape & Seascape Ecology**

Seascape ecology is a recent offspring from the relatively new field of landscape ecology, which itself is a relatively recent branch of ecology incorporating many disciplines like ecology, geography, botany, zoology, animal behavior, and landscape architecture (Bartlett and Carter 1991). Landscape ecology originated in Eastern Europe by scientists who branched out of their professions to more practical studies in landscape appraisal, management, planning, etc (Farina 1998). In the late seventies, a large group of North American ecologists and geographers joined together with the eastern Europeans to form the International Association of Landscape Ecology (IALE). This was a large contribution to the field because of the Americans’ knowledge in technical methods such as remote sensing, GIS, and simulation models. This led recently to the development of powerful quantitative methods to examine the interactions of patterns and processes (Mladenoff 2003). Due to its recent conception, landscape ecology lacks many of its own unique definitions and concepts (Farina 1998); therefore, there are many definitions for the terms that define this discipline. One widely accepted ecological definition of the term landscape is “a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout” (Foreman and Godron 1986). The goal of landscape ecology is to focus on the patterns and processes of spatial and

temporal heterogeneity (Turner 1989) emphasizing the interaction between spatial patterns and ecological processes (Turner et al. 2001).

Seascape ecology, an even younger branch of landscape ecology, applies the landscape ecological approach to the marine environment (Bartlett and Carter 1991, Fairweather and Quinn 1993). Many of the tools and definitions are interchangeable between landscape and seascape ecology; however, the constraints of investigating the seascape are seemingly much greater due to the logistics involved in studying marine abiotic and biotic parameters. Recent advances in technology have aided acquiring marine data and allow for increased accuracy in mapping and quantifying the seascape via Geographic Information Systems (GIS). Georectified aerial photography allow for the visualization of the seafloor reflectance and either multibeam and/or laser bathymetry enable the creation of digital elevation models (DEMs) of the seafloor. Accurate benthic habitats are derived from these data to characterize the seascape (Kendall et al. 2001) which allows for many quantitative analyses to be performed in GIS including the area of different habitats, their proximity to each other, and their relationship with other data (Grober-Dunsmore 2005). Furthermore, the quantification of the DEM can measure the physical structure of the seafloor including slope, elevation, 3-dimensional surface area, and volume at multiple spatial scales (Iampietro et al. 2005, Kuffner et al. 2007). These variables can be correlated to large-scale animal distributions which may allow for the prediction of species occurrence in a given area (Grober-Dunsmore 2005, Iampietro et al. 2005).

## **1.2 Scope of study**

The purpose of this study was to create a predictive model of a reef fish assemblage based on its association with the reef seascape. The seascape in this study is defined as the shallow water (<30m) coral reef and colonized pavement habitats along a 30 Km stretch of coastline of Southeast Florida, encompassing an area of approximately 60 Km<sup>2</sup>. The criteria considered necessary for this study were: 1) Community parameters surveyed from a reef fish assemblage on a natural reef; 2) The surveys must be taken over a large area including a variety of habitats and topographic features; 3) The surveys must be accurately spatially identifiable; 4) A large-scale, high density bathymetric survey of the

study area must be available; and 5) Benthic habitat maps must be created which includes the visual interpretation of the seafloor in GIS, an *in situ* biological cover data collection, derivation of a classification scheme, ground truthing, and an independent accuracy assessment (NOAA-MIP 1999). This study assimilates several datasets to satisfy these criteria for the nearshore reef system in northern Broward County, FL.

Although modeling was the end goal, there are three main themes to this dissertation. Each section stands alone in its own right as an individual study and they also build upon one another in a progression toward the prediction model development. The first theme is benthic habitat mapping (Part II). This section uses a novel approach to benthic habitat mapping and compares it to similar studies using more traditional methods (Kendall et al. 2001). Accurate benthic habitat maps were delineated in GIS via visual interpretation and acoustic ground discrimination. A high resolution laser bathymetric survey obtained from Florida DEP and Broward County was used to create a 3-dimensional surface layer of the seafloor for visual interpretation of unseen features in aerial photography. Acoustic ground discrimination was used to enhance the visual interpretation layer by showing areas of within feature surface variability.

The second theme of this dissertation is to elucidate the relationship between reef fish and topographic complexity and how this relationship changes over the different reef habitats (Part III & IV). This section investigates the relationship between *in situ* and GIS topographic measurements and fish assemblage data to evaluate the feasibility of using them to capture this relationship on a larger scale. The habitat mapping results were used to analyze how this relationship changes between reef habitats.

The final theme is the development of a reef fish prediction model (Part V). This combined the habitat mapping data and the reef fish-topographic relationship to project the relationship over the reef seascape in GIS. This study presents a framework for analyzing the criteria data in such a way to create a predictive model. This model will predict reef fish abundance, species richness and the dominant assemblage species constituents in non-surveyed areas via GIS analysis of the seafloor topography and habitat type. The results allow for quantification and statistical comparison of reef fish abundance and richness between large, unsampled areas.

# Part II

## **Benthic Habitat Mapping**

## **2 Benthic Habitat Mapping**

### **2.1 Introduction**

Remote sensing and mapping of coral reefs and essential fish habitat has been a primary objective of resource managers since the Sustainable Fisheries Act outlined its importance in 1996 (SFA 1996). Consequently, NOAA Coastal Services Center developed its Benthic Habitat Mapping project, which focuses on mapping living resources in near-shore estuarine and marine environments such as sea grass meadows, coral reefs, hard bottoms, shellfish beds, and algal communities (NOAA-CSC-BHM 2002) including essential fish habitat. Mapping the extent and content of these and other coastal resources is now essential to all coastal marine management plans in the United States (NOAA 1996) therefore NOAA's Biogeography Branch is extensively mapping all coral reef ecosystems in the continental US and its territories for the waters found from 0 to approximately 30m depth (NOAA-MIP 1999).

Mapping areas on this large scale requires the utilization of remote sensing such as satellite and aerial photography, hyperspectral imagery, acoustic analyses, and bathymetric surveys (NOAA-MIP 1999). The output of combining several of these remote-sensing techniques yields detailed, large-scale habitat maps (Dodge et al. 2002, Andréfouët 2003, Messing et al. 2003a, Messing et al. 2003b, Moyer et al. 2003). These maps can be used as a proxy for the spatial distribution of organisms in each habitat (Pittman and McAlpine 2001, Kendall et al. 2003, Grober-Dunsmore 2005). Furthermore, the bathymetry data enable the analysis of topographic complexity (Blaszczynski 1997, Riley et al. 1999) using techniques adapted from landscape ecology that allow the comparison of species distributions to areas of increased or decreased complexity.

Passive optical sensors, like aerial photography or satellites, yield detailed, moderate- to high-resolution digital images of large areas and have been widely used to map coral reef habitat (Sheppard 1995, Chauvaud 1999, Kendall 2001, Holden and Ledrew 2002, Andréfouët et al. 2003). For visualization of coral reefs, however, useful images are limited to those environments in shallow, clear water less than approximately 20m depth (Hopley 1996, Finkbeiner 2001). Other remote sensing tools must be implemented to map turbid and/or deep reefs. Among these devices are high-resolution



bathymetry and acoustic ground discrimination (Hamilton 1999, Moyer et al. 2003, Riegl and Purkis 2005). A number of survey methods have been designed to acquire high-resolution bathymetric information, including multibeam sonar, sidescan sonar, and laser bathymetry (LIDAR, LADS) (Wells 1996, Twichell 1996, Lillicrop 1996, Galloway 2001, Anderson 2002, Brock et al. 2001 & 2004). These sensors provide detailed seafloor topography that facilitates mapping geomorphology (Storlazzi et al. 2003). However it is yet unclear how much information they can provide about the benthic community occurring on the surface of the visualized geomorphological structures.

Acoustic ground discrimination devices such as QTC View, Roxanne, and Echoplus have been extensively used to remotely map benthic habitats over the past several years (Hamilton et al. 1999). Many of these surveys were conducted in deep cold North Atlantic waters to detect areas of potential essential fish habitat, but they are equally valid in detecting changes in benthic cover on coral reefs (Moyer et al 2003, Riegl and Purkis 2005). Mapping with these devices involves categorizing sonar return wave forms into classified points and plotting and interpolating those data into a continuous surface to be used in GIS. Accuracies of such techniques are dependant on the distance between survey lines and can be lower than photogrammetric techniques (Riegl and Purkis 2005); therefore to obtain greater accuracies other, or at least additional, approaches must be explored (Hewitt et al. 2004).

In this study, the nearshore benthic habitats were mapped along the southeastern Florida Coast of Broward County from 0 to 35m depth. Much of this habitat was not clearly visible in aerial photographs and satellite images due to water clarity. Several data types were integrated. These included laser bathymetry, acoustic ground discrimination, aerial photography, and groundtruthing via video camera and SCUBA diving. These data were assembled in a GIS. Mapping followed the same constraints as the NOAA biogeographic mapping efforts in Puerto Rico and the US Virgin Islands (Kendall et al. 2001) to allow for a comparable output. A mosaic of the high-resolution bathymetry served as the foundation upon which acoustic ground discrimination and other data provided additional point information to aid in resolving the habitats on the mapped features. Mapping accuracies were then calculated by confusion matrix approach (Congalton 1991, Ma and Redmond 1995).

The resultant GIS habitat polygons are used in Part III for statistical comparison to the fish census data.

## **2.2 Methods**

### **2.2.1 Acoustic Ground Discrimination**

Acoustic ground discrimination principles based on single-beam echosounders are well-reviewed elsewhere (Chivers et al. 1990, Hamilton et al. 1999, Preston et al. 2000, Lawrence and Bates 2001, Bates and Whitehead 2001, Freitas et al. 2003a & b, Riegl and Purkis 2005). The QTC system has also been reviewed and critiqued for many uses including mapping coral reefs (Hamilton et al. 1999, Legendre et al. 2002, Preston and Kirilin 2002, Legendre 2002, von Szalay and McConnaughey 2002, Ellingsen et al. 2002, Freitas et al. 2003a & b, Moyer et al. 2003, Riegl and Purkis 2005). It is not the author's intention to fully describe the acoustic theory and evaluation of each system herein; however certain considerations and limitations were evinced in the data processing which merits their report.

Two acoustic ground discrimination systems were employed as part of the habitat mapping which utilize the shape of a return sonar wave to characterize the sea floor: the QTCView Series 5 and *Echoplus* (Hamilton 1999, Quester Tangent Corporation (QTC) 2002). Each system treats the return waveform analysis differently yet they are founded upon one assumption of acoustic properties: the complexity and hardness of the seafloor will reflect statistically detectable changes in the echoing sonar waves (Chivers et al. 1990, Preston et al. 1999, Hamilton et al. 1999) (Figure 2.2.1).

Regardless of the system being used, one of the most important decisions in acoustic ground discrimination surveying is the choice of sensor, or transducer. Several factors are involved in this decision including the transducer opening angle, the footprint size, and the amount of substratum penetration. Statistically rough surfaces scatter waveforms inversely dependent on transducer opening angle (Clay and Sandness 1971, Medwin and Clay 1998), hence a higher frequency transducer (200kHz), which has a smaller opening angle (12°), produces higher backscatter than a lower frequency transducer (42° opening angle for a 50kHz). A high-frequency transducer also has a

smaller footprint suggesting it has more precision. A low-frequency transducer, however, penetrates deeper into the substratum (Medwin and Clay 1998) than a higher-frequency equivalent, which could have implications if substratum hardness was a desired measure. This study focused on mapping the benthic habitats on the surface of the sea floor therefore the 200 kHz transducer (Suzuki TWW50-200-10L) was optimal because its small opening angle ( $12^\circ$ ) allowed for higher backscatter, its small footprint increased its measuring precision, and its high frequency minimized penetration into the substratum.

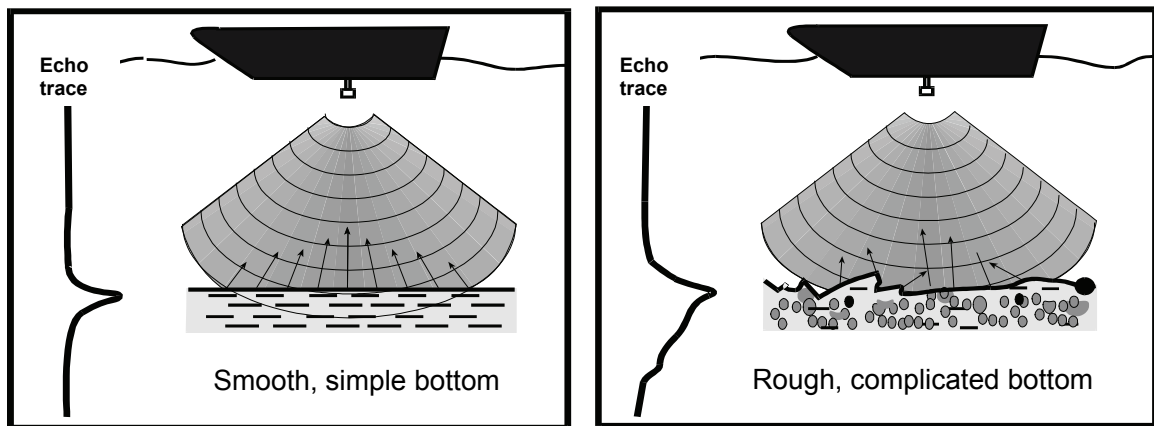


Figure 2.2.1. An illustration of how different seafloor types affect an acoustic wave form. From Questar Tangent Corp.

The acoustic ground discrimination survey area was the entire nearshore sea floor from the 6m to the 35m depth contour in Broward County, FL. Due to the size of the area of interest ( $\sim 110 \text{ km}^2$ ), it was impractical to accomplish the acoustic ground discrimination as one survey, and therefore the county was divided into 50 separate survey areas (Figure 2.2.2). Four previously surveyed areas (Corridor1, Cor2split7, Corridor3new, and Cor4seven in Fig. 2.2.2) as part of a pilot survey described in Moyer et al 2003 were surveyed in a shore-perpendicular using a 50 kHz transducer. These areas were considered completed and were not included in the new surveys. The remaining areas were surveyed using a shore-parallel survey design with a 200 kHz transducer at a 50m line spacing. Most surveys also included a “stitch line”, a survey line running across the typical orientation of the survey used for quality assessment and control in post-processing. This line helps to validate the survey by crossing many other survey lines, which should presumably have similar outputs at the intersections. During each survey, both systems (QTCview5 and EchoPlus) were running simultaneously, processing the

same sonar return signal from the same transducer. Both systems also utilized the same differential GPS data from a Trimble AgGPS 132 that auto-corrected against nearby U.S. Coast Guard differential beacons yielding positioning accuracies between 0.9 and 1.5 m (recorded on the GGA NMEA data string). The typical post processing analysis of these waveforms in each system is discussed below.

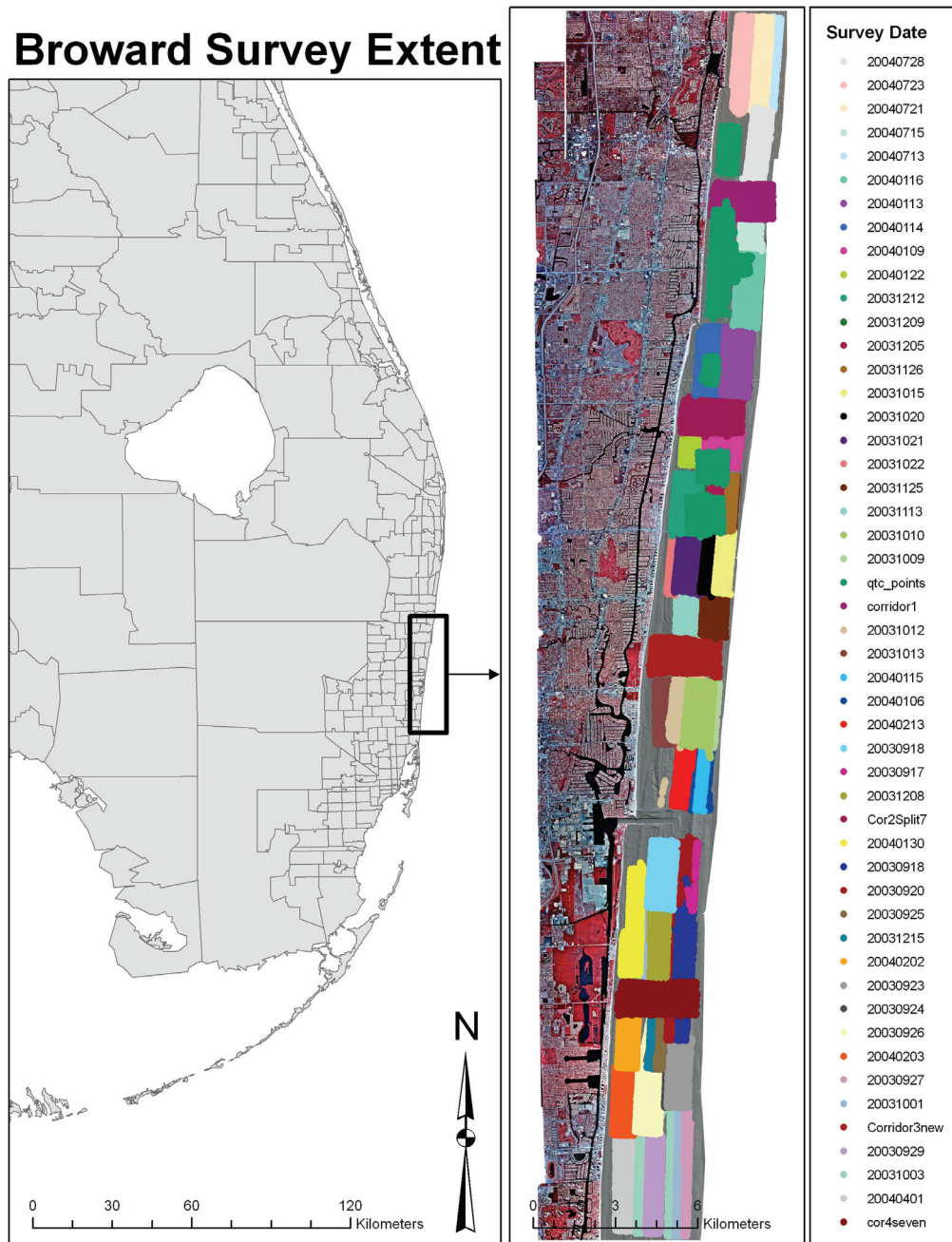


Figure 2.2.2. The study areas Broward County. The extent of this area stretches from Golden Beach in northern Dade County to southern Palm Beach County. The survey lines completed are superimposed in color.

### 2.2.1.1 QTC

Due to the high number of surveys it is impractical to explain the exact method for post processing each survey; therefore a generalized procedure is described herein.

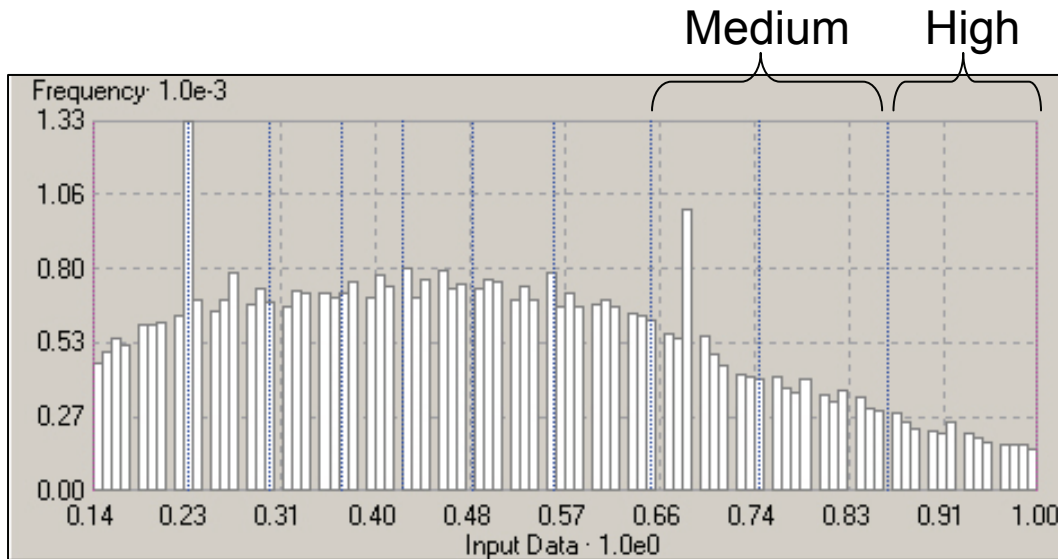
Once the waveforms were acquired in the hydrographic survey, they were digitized, subjected to Fourier and Wavelet analyses, analyzed for area under the curve and other variables in QTC Impact software (Legendre et al. 2002). The data were then normalized between 0 and unity and input into a Principal Components Analysis (PCA) for reduction. The first three major axes of each echo, which are assumed to explain the majority of variability in the data (QTC 2002), were renamed Q values. A pseudo three-dimensional space was created using the Q values as axes in which the wave-return data were plotted and subjected to cluster analysis by Bayesian approach (QTC 2002). This entire process to this point happened internally in the system. Next, expert-driven decisions were made to determine the ideal number of clusters within the three-dimensional data cloud. These decisions were aided by three statistics provided within the software: the Cluster Performance Index (CPI),  $\text{Chi}^2$ , and total score. These statistics were treated in the following manner. As the CPI increased with increasing cluster split (Freitas et al. 2003b),  $\text{Chi}^2$  decreased, reaching maximum/minimum values at optimal split level (QTC 2002). Meanwhile, the total score decreased to an inflection point indicating ‘a strong ... best split level’ (QTC 2002).

The output of the QTC acoustic dataset for each survey yielded a three-column file consisting of an  $x$  and  $y$  column for location (Easting/Northing) and a  $z$  column that contained the classification value from the cluster analysis. These outputs were imported into ArcGIS as  $x/y$  data and displayed as categorized discrete points to aid in the habitat mapping process.

### 2.2.1.2 Echoplus

Unlike the QTC, which only analyzes the tail of the first sonar return, *Echoplus* includes the entire second sonar return in its analysis as well. This makes it very similar to the RoxAnn acoustic ground discrimination system, which has been well-tested elsewhere (Hamilton et al. 1999). The *Echoplus* system is entirely self-contained meaning there is no expert-driven post-processing of the data like the QTC. According to the manufacturers, *Echoplus* internally compensates for frequency, depth, power level, and pulse length. *Echoplus* measures sonar pulse length and amplitude for every pulse, scales the output accordingly, and factors in absorption corrections. This system digitized the tail of the first sonar return and the entire second sonar return and output their measurement analyses into two variables: E1 (first echo) and E2 (second echo) respectively. The data were exported as a string of georeferenced variables (latitude, longitude, E1, E2) in a text file. It was then normalized to the 95<sup>th</sup> percentile after rejecting all values above the 95<sup>th</sup> and below the 5<sup>th</sup> percentiles. This resulted in a four column data file with x and y as the location data (Easting/Northing) and E1 and E2 as continuous data variables ranging between 0 and unity.

Each *Echoplus* survey was imported into ArcGIS as x/y data and interpolated into a prediction surface using the Inverse Distance Weighted algorithm in ArcGIS 9.0 Geostatistical Analyst. The thresholds for contours in the prediction surface were the result of expert-driven decisions based on smart quantile splitting of the E1 data into 10 classes and taking eighth and tenth quantile (Figure 2.2.3). The eighth quantile (Class 1) represents the area within the individual *Echoplus* survey with a medium level of benthic complexity and the tenth quantile (Class 2) represents a high level. These levels were exported from each survey as GIS polygons. The polygons were then clipped to their respective survey areas to minimize data artifacts created in the interpolation method on the edges.



Num	Breaks	Descriptive Statistics	
Min	0.141304	Count	43567
1	0.227885	Minimum	0.141304
2	0.302513	Maximum	1
3	0.36684	Mean	0.494289
4	0.422286	Variance	0.045642
5	0.486612	Std.Dev.	0.213639
6	0.561241	Skewness	0.308181
7	0.647821	Kurtosis	2.213874
8	0.748268	Quantile 25%	0.315217
9	0.864802	Median	0.478261
Max	1	Quantile 75%	0.652174

Figure 2.2.3. Histogram illustrating the quantiles for a single Echoplus survey. Smart quantile grouping of the data determined the thresholds chosen for the benthic complexity rating. The 8<sup>th</sup> and 9<sup>th</sup> quantile were rated medium and the 10<sup>th</sup> high.

## 2.2.2 Bathymetry Acquisition

A high-resolution laser bathymetry survey was conducted in April 2001 of the entire nearshore Broward reefs by Tenix LADS Corporation, using the Laser Airborne Depth Sounder (LADS) system. This bathymetric survey had a sounding rate of 900 Hz (3.24 million soundings per hour), a position accuracy of 95% at 5 m CEP, a horizontal sounding density of 4m x 4m, and a depth range of 70 m, depending on water clarity (Tenix LADS Corp.). Tenix was hired by Broward County Department of Planning and Environmental Protection to provide detailed bathymetric maps of the reefs and offshore areas of Broward County, FL. This survey encompassed North Dade County, the Broward County coastline, and south Palm Beach County, approximately 43 km, and

from the shore eastward to depths of 40 m, approximately 2.5-3.5 km offshore (Fig. 2.2.2). The entire survey area covered approximately 130 square kilometers of nearshore marine seafloor. The bathymetry data set was provided as a set of ascii text files (x, y, & z as eastings, northings, and depth) with almost 12 million records georeferenced to Transverse Mercator, NAD83 FL East, eastings/northings. The bathymetric data were gridded by triangulation with linear interpolation, sun-shaded at a 45° angle and azimuth, and mosaicked with aerial photography of the land. This final image was used as the foundation for habitat mapping. The x,y,z's were used to derive the 3-Dimensional data.

### **2.2.3 Habitat map creation**

The entire sub-tidal seafloor from 0 to 35m depth was mapped and classified for Broward County in southeastern Florida. For the production of benthic habitat maps, several data products were integrated including laser bathymetry (Laser Airborne Depth Sounder-LADS), acoustic ground discrimination (QTC, Echoplus), visual groundtruthing, and existing ecological data (i.e. photo quadrat data). The high resolution LADS bathymetry was used to map reef geomorphology. Acoustic data (QTC and Echoplus) were used to aid in definition of habitat types. A video camera dropped from a boat was used as groundtruthing to confirm substrate type. All data were assembled in ArcGIS9. Polygons were drawn at a scale of 1:6000 with a minimum mapping unit of 1 acre. The final map polygons conform to the NOAA hierarchical classification scheme used in Puerto Rico and the U.S. Virgin Islands NOAA Technical Memorandum NOS NCCOS CCMA 152 (Kendall et al. 2001 & 2004) with some modification.

### **2.2.4 Groundtruthing**

Groundtruthing was performed via a total of 383 video-camera drops to independently characterize the bottom type to aid in habitat determination. This is a critical step in the mapping process. Once the different features in a landscape have been classified, the classifications must be validated by *in situ* assessment. The validation process in this study involved a tethered waterproof video camera with LCD lights dropped from a stationary boat. The camera was attached to a video monitor and 8mm video recorder. The camera was dropped until the bottom type was identified, then a GPS



coordinate was taken and the boat moved to a new area. Each point was imported into ArcGIS to aid in habitat identification. Six cross-reef transects were performed throughout the survey area (Figure 2.2.4).

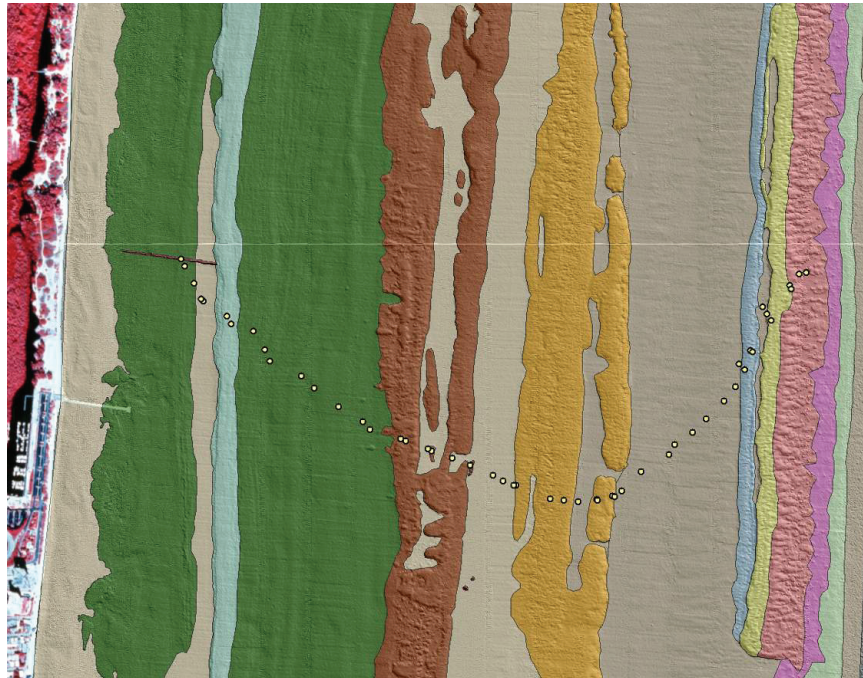


Figure 2.2.4. Example of a groundtruthing transect offshore John U. Lloyd State Park in south-central Broward County. The colored polygons represent the different classified habitats. See legend in Figure 2.3.2.

### **2.2.5 Accuracy assessment**

Accuracy assessment is another integral step in habitat mapping and must be incorporated into all mapping efforts (Congalton 1991, Kendall 2002). The accuracy assessment employed for this effort followed the “standard reporting convention” of the error matrix approach (Congalton 1991). This approach involved an independent field assessment of the habitats (reference data) to compare with the habitats on the map. The field data analysis was placed into a matrix of rows and columns from which several error statistics were calculated. These statistics included user’s accuracy derived from errors of inclusion (or commission errors), producer’s accuracy derived from errors of exclusion (or omission errors), the percentage agreement (Po), or total map accuracy, and a Tau coefficient. The first statistic, user’s accuracy, was calculated by dividing the total number of correctly mapped locations in a given habitat by the total number of samples mapped as that habitat. For example if 100 points were mapped as sand and 95 of those

points were confirmed by the reference data as sand, then the map would have a user's accuracy of 95% for sand. The second statistic, producer's accuracy, was calculated by dividing the total number of reference data for a given habitat by the number of samples actually mapped as that habitat. For example, if the reference data detected 100 locations as sand and 90 of those locations were actually mapped as sand, the map would have a producer's accuracy of 90%. The third statistic, percentage agreement or total map accuracy, was determined by adding the samples of correct point for each habitat together and dividing that number by the total number of samples. For example, if the total number of correctly mapped points between all habitats was 200 and the total number of reference data points was 250 then the map would have an overall accuracy of 80%. The final statistic calculated was the Tau coefficient. This statistic incorporates all the variables in the matrix *a priori* into one error statistic and is a better measure of mapping accuracy than percentage agreement or the Kappa statistic and eliminates the overestimation of classification associated with the percentage agreement (Ma and Redmond 1995). It also reduces the under estimation of the total map accuracy of the Kappa statistic.

For this effort, a total of 300 target points, arranged on a grid over much of Broward County were chosen for accuracy assessment (Figure 2.2.5). Target locations were arranged over an independent, regular grid that ignored the underlying substratum to minimize sampling bias. Accuracy assessment data were collected in a similar manner as the groundtruthing points with an underwater video drop camera to identify the habitat at the target locations. The benthic cover was described at each location by rating substrate and biological cover. The substrate categories (Pavement, Sand, Rubble, and Coral) and biological categories (Algae, Gorgonians, Sponge, and Coral) were estimated on a rating scale from 0 to 5, with each rating corresponding to a percent cover of the seafloor. After the map polygons were drawn and classified using the acoustic discrimination systems, groundtruth points, and LADS bathymetry, the reference data were plotted on the map and evaluated for the accuracy assessment statistics: user's accuracy, producer's accuracy, and total map accuracy.



Figure 2.2.5. Example of the accuracy assessment point grid off Hugh-Taylor-Birch State Park in central Broward County. The colored polygons represent the different classified habitats. See legend in Figure 2.3.2.

## **2.2.6 Classification Scheme**

The classification scheme used for this mapping effort was adapted from NOAA (Kendall et al 2004 & 2001). The following is a list of all the habitats identified during this study. All definitions are NOAA definitions as described in Technical Memorandum NOS NCCOS CCMA 152 (Kendall et al. 2001) and on their web site (<http://ccma.nos.noaa.gov/products/biogeography/benthic/welcome.html>) unless otherwise noted by an asterisk (\*). A full description of the mapped reef habitats is discussed in the results.

### **Coral Reef and Hardbottom**

#### **Coral Reef and Colonized Hardbottom**

##### **Linear Reef**

**Linear Reef-Outer\***

**Linear Reef-Middle\***

**Linear Reef-Inner\***

##### **Spur and Groove (drowned)**

##### **Patch Reef**

**Individual Patch Reef**

**Aggregated Patch Reef**

##### **Scattered Coral/Rock in Unconsolidated Sediment**

##### **Colonized Pavement**

**Colonized Pavement-Deep\***

**Colonized Pavement-Shallow\***

##### **Ridge\***

**Ridge-Deep\***

**Ridge-Shallow\***

### **Unconsolidated Sediments**

#### **Unconsolidated Sediments**

##### **Sand**

**Sand-Shallow\***

**Sand-Deep\***

### **Other Delineations:**

#### **Artificial**

**Wormrock\***

**Inlet Channel\***

**Sand Borrow Areas\***

## **2.3 Results**

### **2.3.1 Acoustic Ground Discrimination**

The acoustic ground discrimination survey yielded 50 total survey areas. The linear distance of all the surveys combined was about 2,319 km, covering approximately 110 km<sup>2</sup>. The data collected from these surveys was analyzed using two different systems and methods. Their results are presented below.

#### **2.3.1.1 QTC**

The QTC analysis of the acoustic ground discrimination surveys proved complicated due to high data variability. Several unsuccessful approaches were implemented in an attempt to better understand the data.

The first approach was to combine the surveys into three different regions. All of the surveys in each third of the county were combined and then categorized using the QTC PCA cluster analysis (Figure 2.3.1). The results of the combined-survey clustering statistics suggested that four clusters were the optimal number of splits (Figure 2.3.2). All classes occurred over all depths indicating that depth-contamination did not affect the clustering process, yet different classes did showed clear depth preferences (Figure 2.3.3). Four classes showed clear distributional preferences and a fifth ubiquitous class was distributed evenly over the entire depth. Each of the four preferentially-distributed classes was concentrated in the deeper areas on the outer reef (white) and beyond (brown), on the middle reef (tan), and on the nearshore ridges and hardgrounds (green) (Figure 2.3.4). The four classes encoded the same substrata in each of the three regions of Broward County and showed a split between reefs (inner, middle, outer). In the north, the difference between reefs was not as clear, however, each region followed the same general trend.

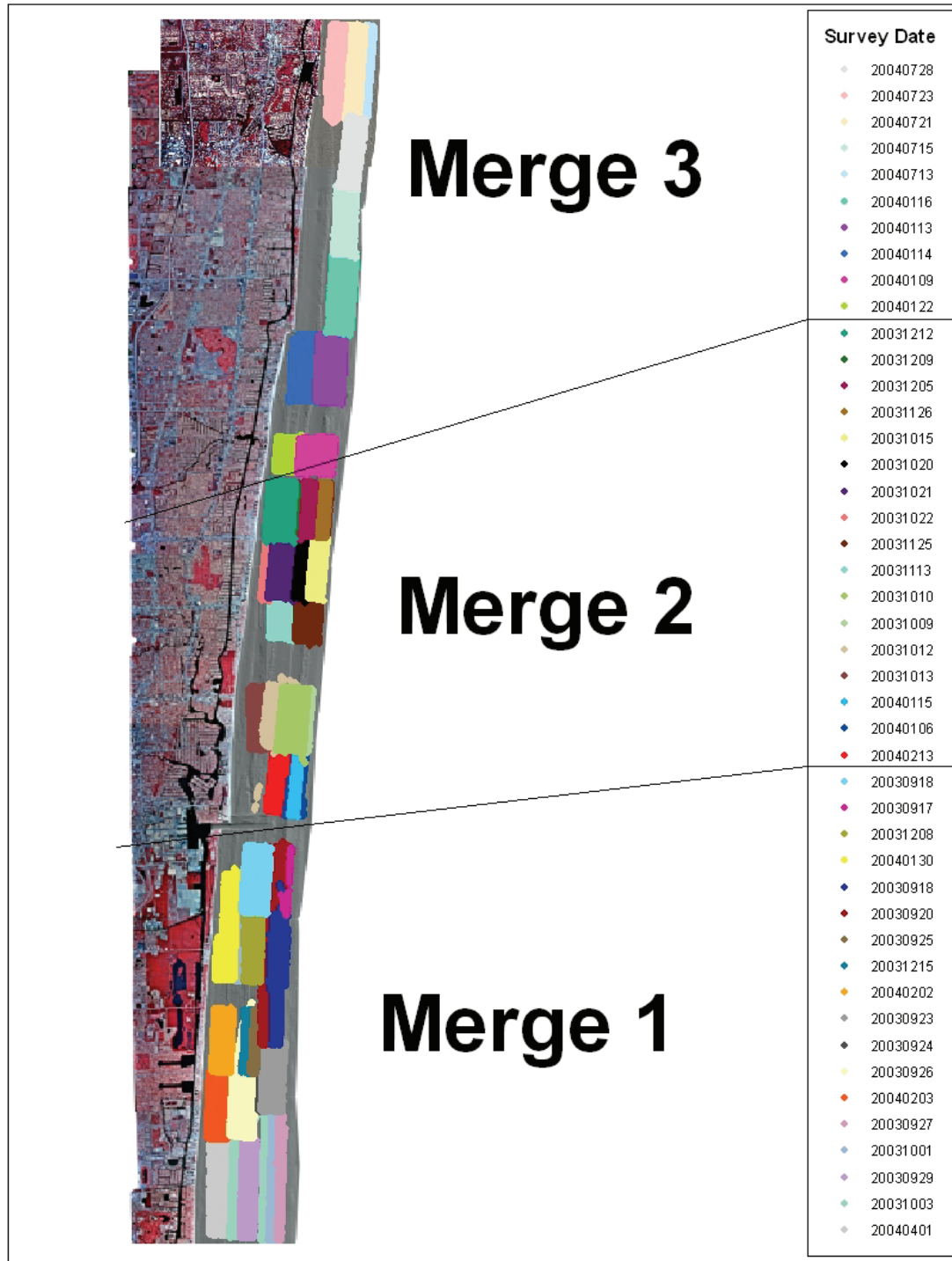


Figure 2.3.1. Illustration of the merged surveys in the combined-survey approach. The data from each survey in a given area were merged with data from all other surveys in that area and analyzed by PCA analysis in QTC view. Merge 1 was South Broward, Merge 2 was Central Broward, and Merge 3 was Northern Broward.



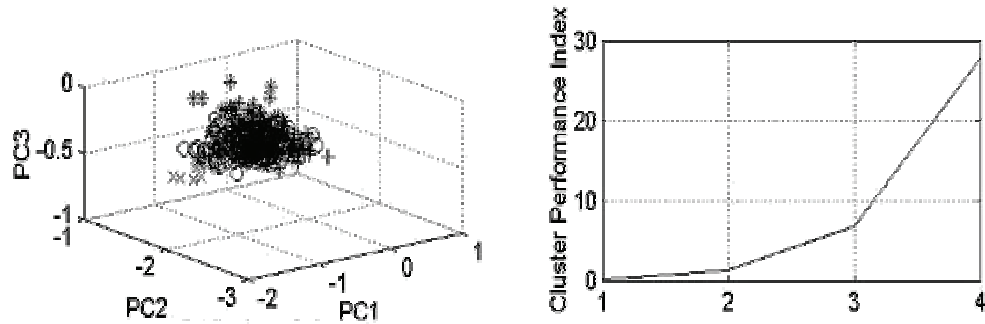


Figure 2.3.2. Ordination of all datapoints along the first three principal components (left). Data within the point cloud are coded according to class. The cluster performance index (CPI) is a measure indicating whether a splitting decision was correct, which is indicated by an increase in value (right). The CPI graph indicates that the splitting decisions to four clusters were correct.

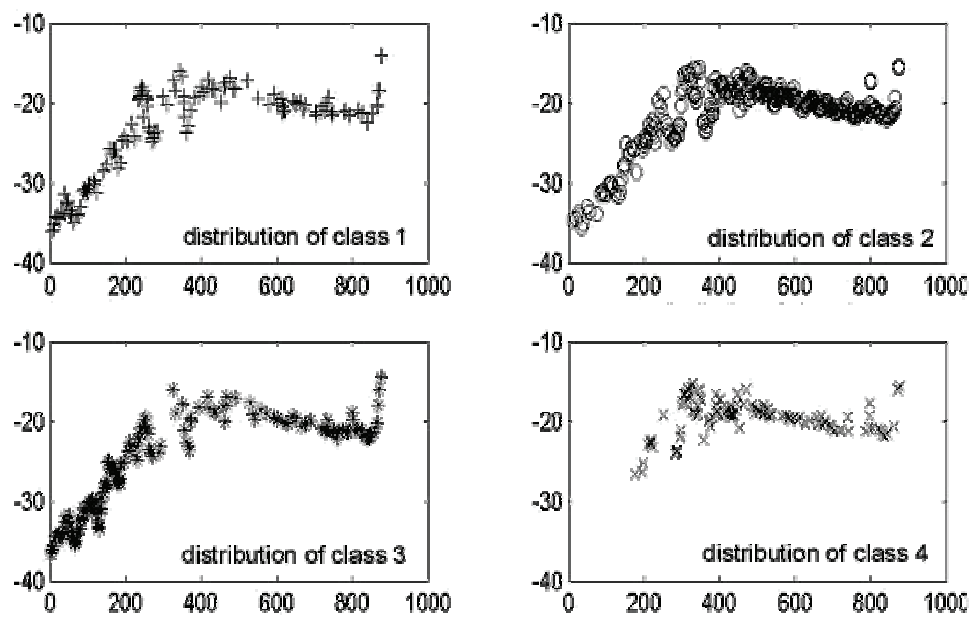


Figure 2.3.3. Depth distribution of the four classes in central Broward County. The class coded with crosses shows the most uniform distribution, and thus has the least diagnostic value. All other classes show preferential distribution in a more or less well-defined depth zone.

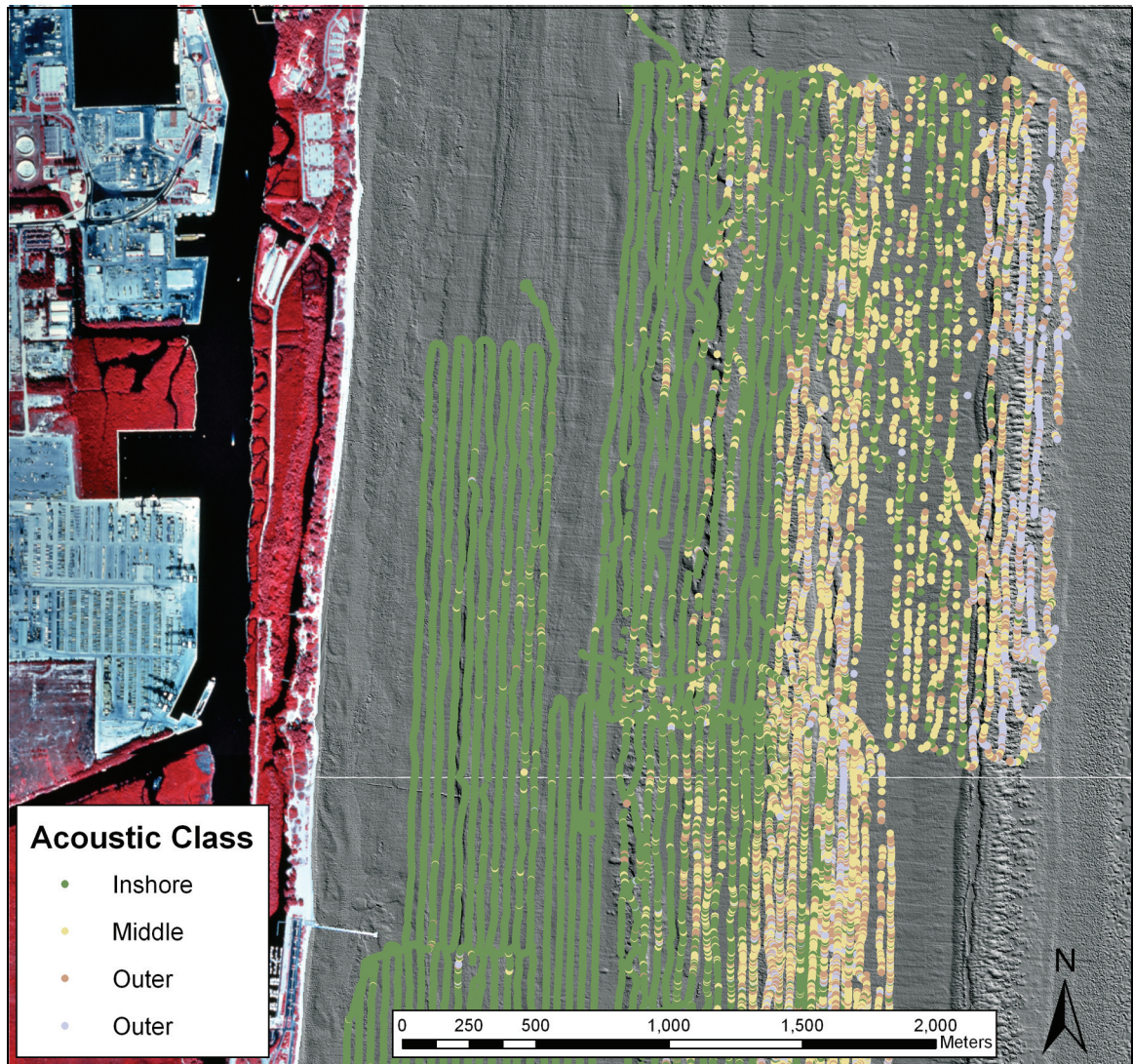


Figure 2.3.4. Merged QTC surveys for South Broward (merge 1 in Figure 2.5). The merged surveys were classified by PCA analysis in QTC view for optimal splits and imported into GIS for analysis. The merged data show clear trends evident when displayed on the hillshaded LADS bathymetric surface as reference. Four of the five classes were associated with specific areas. The green class was found most frequently inshore while the tan concentrated on the Middle Reef and the light blue and brown on the Outer.

The results of the combined-survey analysis indicated that the acoustic survey data did discriminate different seafloor types at the simplest level, however, the main purpose of employing the acoustic ground discrimination was to analyze the seafloor surface within the individual features to capture the variability of organismal cover along/within the reef. This was attempted by the cluster analysis of individual surveys. The same cluster analysis applied in the regional analyses was implemented to the individual surveys. The results of these analyses did not show any clear differentiation of



acoustic classes within the reef (Figure 2.3.5). For example, a survey from Northern Broward County was analyzed in QTC view and yielded an optimal split of three classes (Figure 2.3.5). When plotted in the GIS with the hillshaded LADS bathymetric surface underneath for reference, the points indicate some general trends. Class 1 appeared to be mostly associated with the 20m sand flat west of the reef, Class 2 was most frequent on the outer reef, and Class 3 was found mostly in the deeper sand to the east of the reef. This analysis exhibits a similar trend as the merged data analysis suggesting that QTC can discern different seafloor types at a general level, however, there is no evidence to suggest that this analysis can detect within-reef variability. Splitting the data further in the PCA analysis did not help yield any interpretable information of this kind.

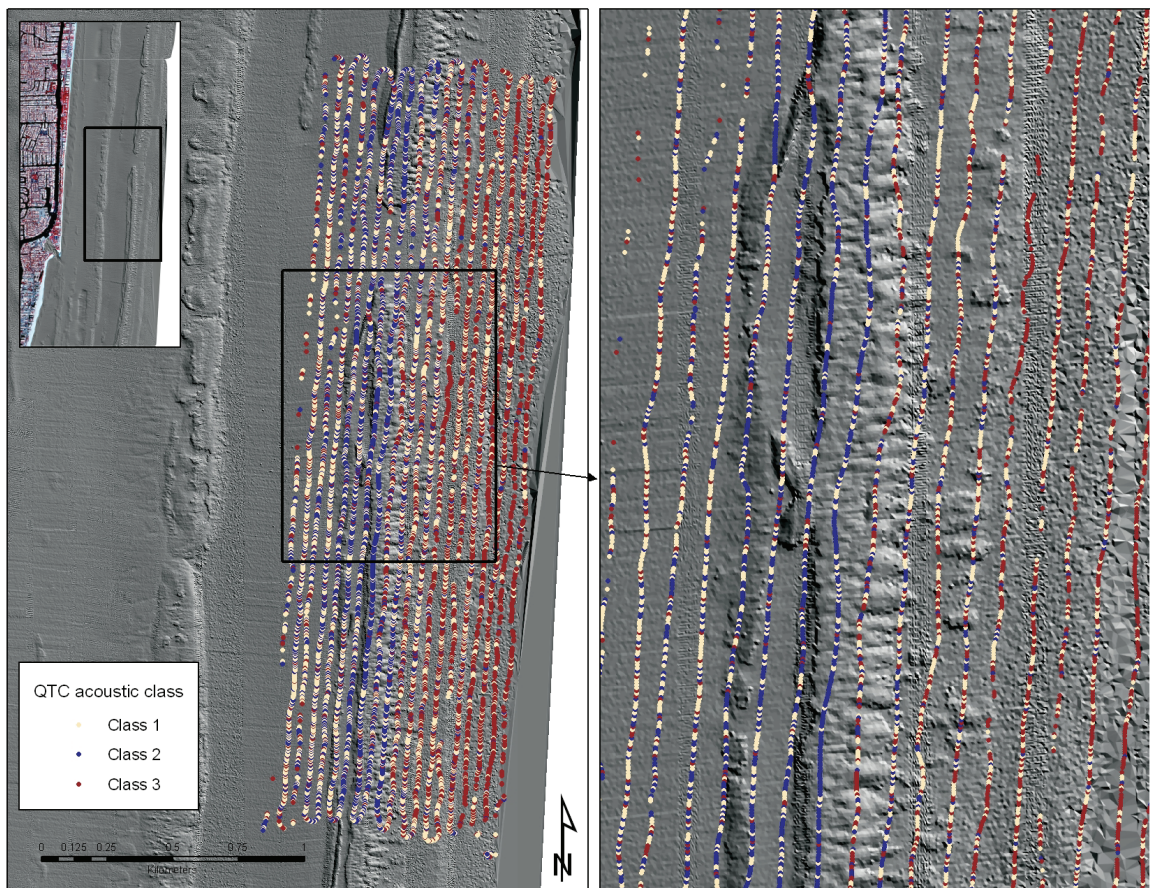


Figure 2.3.5. An example of a QTC survey from Northern Broward County in GIS showing the survey lines consisting of QTC classified points. The different color represents different acoustic class from the PCA analysis in QTC View. Class 2 appears to be mostly associated with reef features while Class 1 seems to be shallow sand and class 3 deeper sand. Variability within the reef is not evident with this method.

Many attempts were made to analyze the data in different ways to obtain interpretable within-reef variation results without success. A standardized categorization for each class was applied to the data, meaning that known acoustic classes were identified and placed in a catalogue in QTC. This catalogue file was then used to classify any waveform with similar characteristics in other surveys as the same class. For example if class 1 in survey A is known to be sand, the characteristics of the sand waveforms can be catalogued in the software and any waveform in Survey B that has the same characteristics will be classified as sand. This analysis was not successful. It appeared that data continuity between surveys was suspect and the surveys could not be standardized. This is a known problem in acoustic surveys and the causes are usually from changing weather conditions or electrical noise in the system (Foster-Smith 2001). To address the data continuity problem, the surveys were analyzed separately. Other attempts at reanalyzing the data were to split the surveys into many classes (10 or more), but the addition of classes did not yield any clearly interpretable results. It was therefore decided to split each survey according to the recommended criteria (low  $\text{Chi}^2$ , high CPI score, etc.) which yielded surveys classified between three and five classes. These interpretations are discussed in section 2.4.2.

#### **2.3.1.2 *Echoplus***

39 Echoplus surveys were acquired in total. In the Echoplus surveys, a differentiation between low-scatter and high-scatter areas was evident (Figure 2.3.6a). The Echoplus surveys allowed a delineation of the reefs and rubble areas as higher-scatter areas, however the output of the two variables was quite different. The E1 value, which measured the tail of the first wave return, correlated with reefal areas much better than the E2 value, the measure of the entire second wave echo (Figure 2.3.6b.). When the survey points were plotted in GIS and colored according to their values, the E1 measure exhibited low values (green) in areas known to be sand and high values (red) in areas known to be reef. The middle values were assumed to be areas of lower scatter associated with rubble or low relief pavements. The E2 value did not exhibit any interpretable results. It measured high scatter (red) in areas known to be reef and sand and did not appear to distinguish any features.



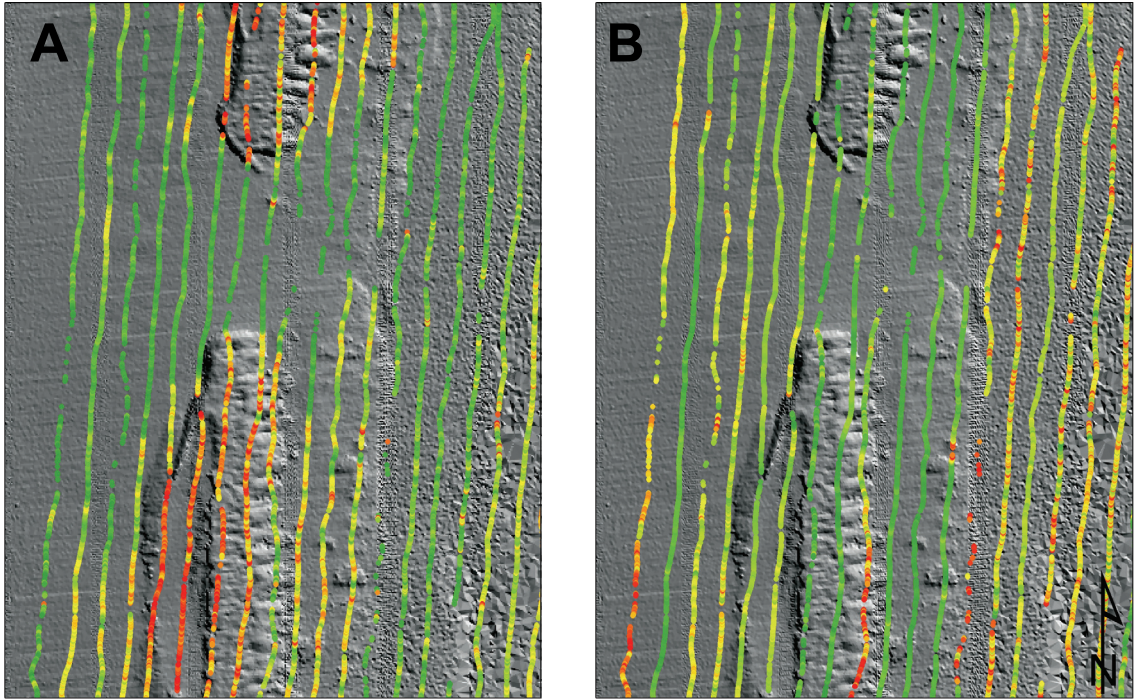


Figure 2.3.6. (A) Echoplus survey data from the tail of the first echo return (E1) and (B) from the entire second echo (E2). Colors represent a scale along the values continuum where the lowest values are green and the highest values are red. It is evident that E1 values detect the reef as a rougher surface than the surrounding sand, whereas the information E2 provides is unclear.

Further investigation into the data distribution of these parameters showed that E1 was near normally distributed, while the E2 parameter was strongly non-normal (Figure 2.3.7). It is not clear why the E2 parameter was so strongly skewed to lower values. From survey geometry and the relative distribution of hardgrounds versus sediments in Broward County, a more normal distribution was expected. Due to this result, the E1 parameter was favored in further analyses over the E2 parameter.

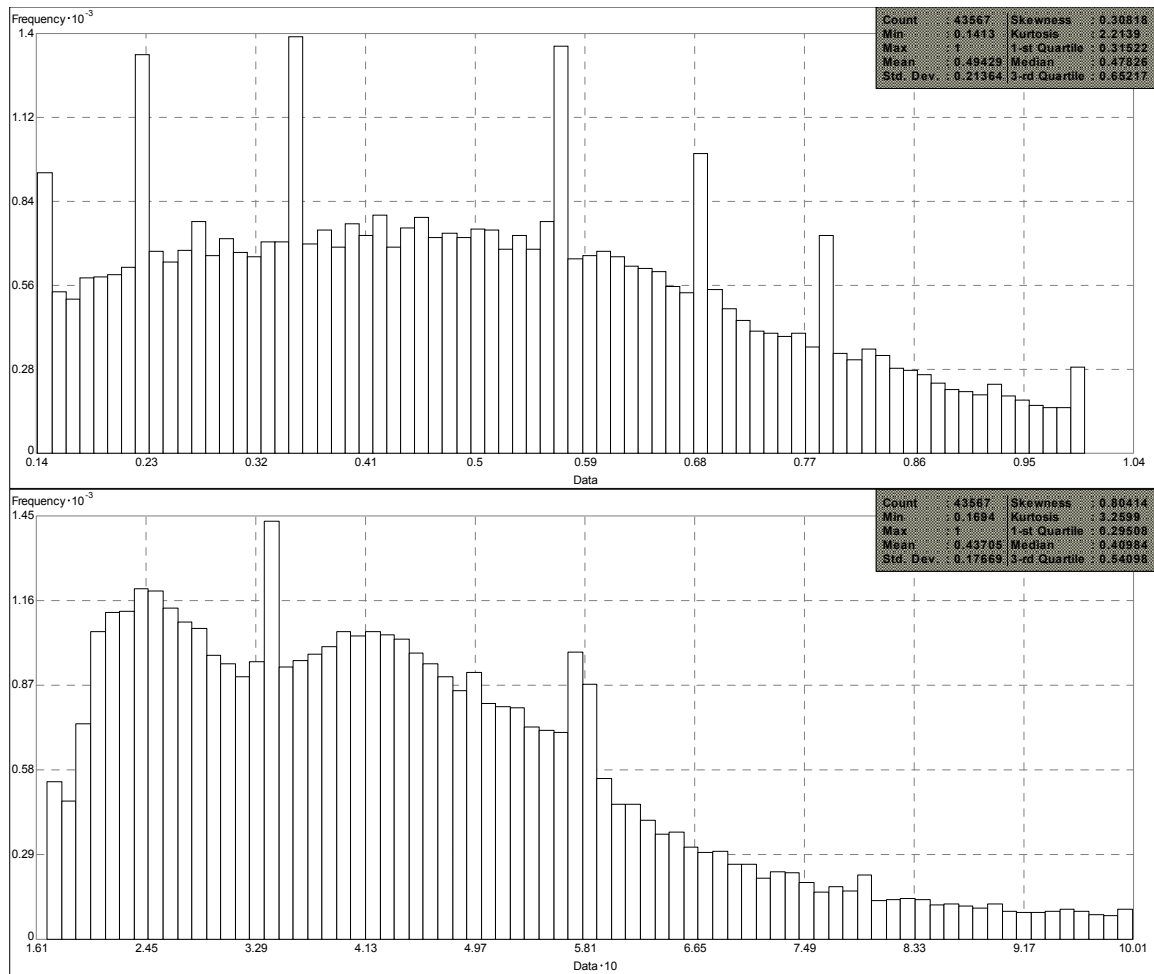


Figure 2.3.7. Histogram of E1 (top) and E2 (bottom) parameters. Data were grouped into 75 bins. Number of bins did not significantly alter the distribution pattern. E1 exhibits a more even distribution among its range of values than does E2. E2 appears to be skewed heavily towards lower values.

Data between surveys were considered equivalent because the data from each survey was a measurement of the wave echo and did not relate to other sonic data in the survey; most likely due to a combination of changing weather conditions and electronic noise issues. When the data were combined they did not show consistency between surveys (Figure 2.3.8), therefore each survey was treated separately in all analyses.



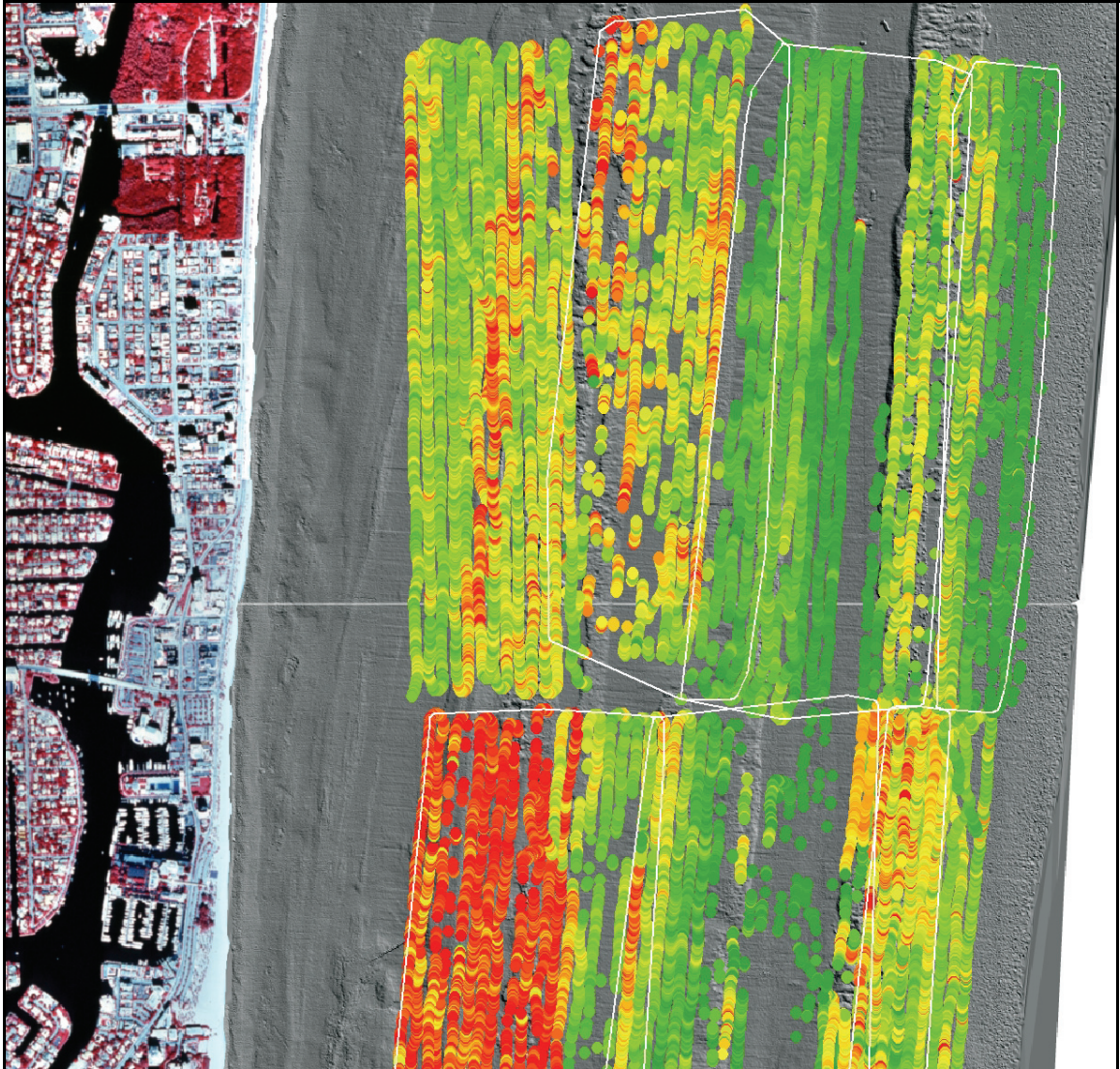


Figure 2.3.8. Merged Echoplus E1 data. After merging, the colored points according to their E1 values revealed that data were not consistent between surveys and must not be combined. Green points are the lowest E1 scatter values and red are the highest. The white lines indicate the individual survey extents.

Inverse distance weighted interpolation of the Echoplus E1 data yielded 29 usable surveys which gave a measure of seafloor complexity (Figure 2.3.9). Because the measurements were not comparable between surveys, the thresholds for the complexity rating were statistically determined by categorizing the 10<sup>th</sup> quantile of the data in the predicted surface as high complexity and the 8<sup>th</sup> and 9<sup>th</sup> quantiles as medium complexity of each survey independently. These values were chosen because they were the top 30% of the E1 values and thus should contain the highest complexity. The high category (10<sup>th</sup> quantile) is the most complex because it includes the top 10% of the E1 data and the medium category (8<sup>th</sup> & 9<sup>th</sup> quantile) contains the next 20%. The resultant polygons are



therefore a complexity rating of the area within each survey, meaning of the high complexity area of one survey equates to the highest detected seafloor surface complexity in that given area and does not necessarily equate to the high complexity rating of another survey.

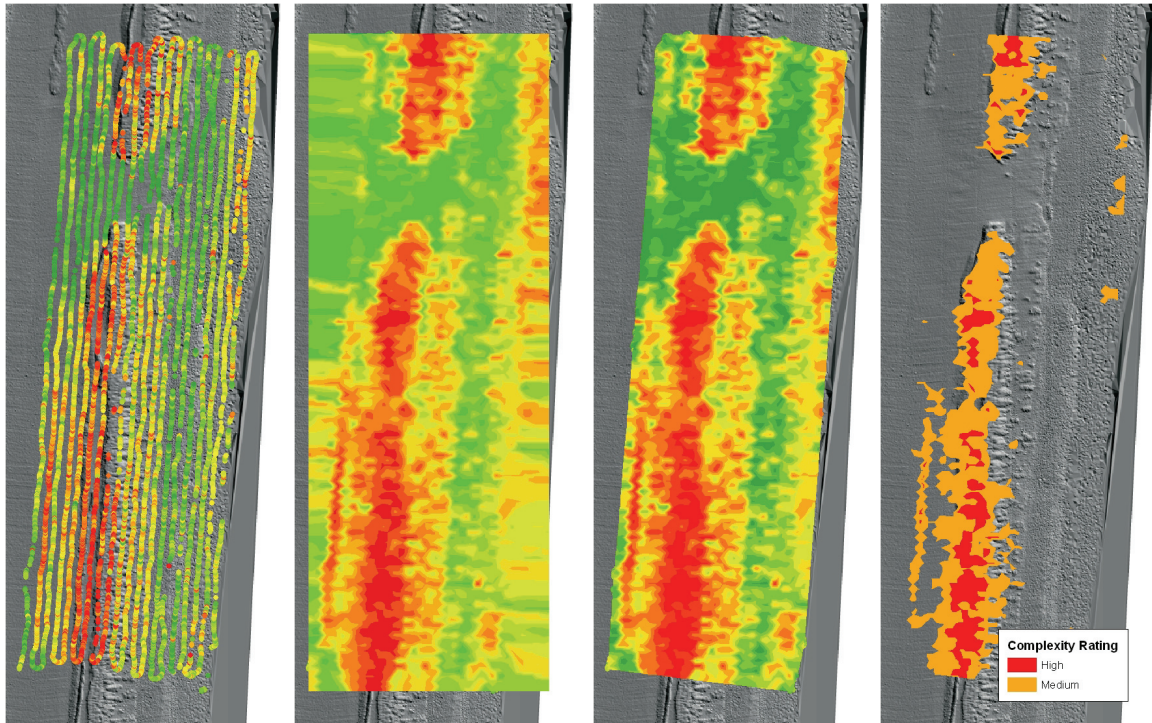


Figure 2.3.9. Results from processing one Echoplus survey with the E1 value. The process starts with the E1 point values (left) that are interpolated by IDW into a prediction surface (left center). The prediction surface is clipped to the outside survey lines to minimize artifacts (right center). Then the polygons are exported according to the smart quantile values within each survey (right).

## 2.3.2 LADS Expert-driven Habitat Classification

### 2.3.2.1 Final Classification Scheme

The NOAA hierarchical classification scheme described in Puerto Rico and the U.S. Virgin Islands NOAA Technical Memorandum NOS NCCOS CCMA 152 (Kendall et al. 2001) served as a basis upon which modifications were made to characterize the specific benthic habitats mapped in this study's region. The most notable modification was in the mapping of different zones. The Puerto Rico mapping effort classified the polygons into nine reef zones according to the feature's relationship along the shore (i.e. lagoon, back reef, fore reef, bank/shelf, etc.). These categories were useful because the NOAA effort mapped everything from land and intertidal out to the bank/shelf

escarpment. However, many of these mapped zones do not apply in South Florida. The absence of an emergent reef in South Florida precludes mapping zones such as lagoon, back reef, and reef crest. Also our effort was confined to depths between 0m and 35m, which excluded the land. The intertidal zone was not distinguished in this project. Thus, all features mapped in this project reside within the Bank/Shelf, Fore Reef, or Bank/Shelf Escarpment zones.

Changes to this scheme included the omission of submerged vegetation habitat due to the lack of detectable seagrass and macroalgae and the addition of ridge, sand borrow area, and wormrock categories (Figure 2.3.10). Acoustic ground discrimination results provided additional information that required other modifications to the classification scheme including a depth component to the colonized pavement and sand classes to indicate that habitat on these features varied with water depth. Furthermore, the acoustic distinction of the linear reefs into different acoustic classes enabled us to split the NOAA class “linear reef” into the following three subclasses- Inner linear reef, Middle linear reef, and Outer linear reef.

The following section outlines and defines the three tiers of habitat classification used in this study. All definitions are NOAA definitions as described in Technical Memorandum NOS NCCOS CCMA 152 (Kendall et al. 2001) and on their web site (<http://ccma.nos.noaa.gov/products/biogeography/benthic/welcome.html>) unless otherwise noted by an asterisk (\*).

**Coral Reef and Hardbottom:** Hardened substrate of unspecified relief formed by the deposition of calcium carbonate by reef building corals and other organisms (relict or ongoing) or existing as exposed bedrock.

**Coral Reef and Colonized Hardbottom:** Substrates formed by the deposition of calcium carbonate by reef building corals and other organisms. Habitats within this category have some colonization by live coral.

**Linear Reef:** Linear coral formations that are oriented parallel to shore or the shelf edge. These features follow the contours of the shore/shelf edge. This category is used for such commonly used terms as fore reef, fringing reef, and shelf edge reef.

**Linear Reef-Outer\*:** This category included essentially only the reef crest of the outer reef.

**Linear Reef-Middle\*:** Since the middle reef exhibited much less clear morphological differentiation than the outer reef, it was not practical to subdivide it into several units. It is therefore encompassed in one single category, “linear reef”. This category is given a unique color identifier since the acoustic roughness measures suggest a largely distinct community structure from hardgrounds, shallow reef and outer reef.

**Linear Reef-Inner\*:** Similar to the middle reef, also the inner reef is best described as linear reef since it also lacks a clearly defined zonation with a backreef and groove-and-spur system. It has a unique color identifier since acoustic and biological data indicate that it harbors a distinct benthic community from the middle and outer reefs.

**Spur and Groove:** Habitat having alternating sand and coral formations that are oriented perpendicular to the shore or bank/shelf escarpment. The coral formations (spurs) of this feature typically have a high vertical relief compared to pavement with sand channels and are separated from each other by 1-5meters of sand or bare hardbottom (grooves), although the height and width of these elements may vary considerably. This habitat type typically occurs in the fore reef or bank/shelf escarpment zone.

**Patch Reef:** Coral formations that are isolated from other coral reef formations by sand, seagrass, or other habitats and that have no organized structural axis relative to the contours of the shore or shelf edge. A surrounding halo of sand is often a distinguishing feature of this habitat type when it occurs adjacent to submerged vegetation.

**Individual Patch Reef:** Distinctive single patch reefs that are equal to or larger than the minimum mapping unit (MMU). When patch reefs



occur in submerged vegetation and a halo is present, the halo is included with the patch reef polygon.

**Aggregated Patch Reef:** Clustered patch reefs that individually are too small (smaller than the MMU) or are too close together to map separately.

**Scattered Coral/Rock in Unconsolidated Sediment:** Primarily sand bottom with scattered rocks or small, isolated coral heads that are too small to be delineated individually (i.e., smaller than individual patch reef).

**Colonized Pavement:** Flat, low-relief, solid carbonate rock with coverage of macroalgae, hard coral, gorgonians, and other sessile invertebrates that are dense enough to partially obscure the underlying carbonate rock.

**Colonized Pavement-Deep\*:** This category includes a transition zone from colonized pavement to colonized rubble. Since much of the rubble in the lee of the outer reef is at least partly consolidated, the differentiation between colonized pavement and rubble would be somewhat artificial.

**Colonized Pavement-Shallow\*:** This category includes rubble in many areas, however, consolidated rubble fields are a less frequent feature in shallow water. Especially inshore of the ridge complexes, limited rubble is found and a wide, contiguous area of pavement is encountered. This area can have variable sand cover, which shifts according to wave-energy in response to weather. Thus, some of the colonized pavement will always be covered by shifting sand and the density of colonization will be highly variable.

**Ridge\*:** Linear, shore-parallel, low-relief features that appear to be submerged cemented beach dunes. Presumably, they are the foundation upon which the Linear Reefs grew and consist of early Holocene beachrock ridges, however, verification is needed. The biological cover is similar to that of colonized pavement—a coverage of macroalgae, hard coral, gorgonians, and other sessile invertebrates that are dense enough to partially obscure the underlying carbonate rock.

**Ridge-Deep\*:** While the geological provenance of the structure is not clear, its morphology suggests it to be a ridge of older age than the outer reef, possibly the structure on which the outer reef initiated. It consists of hardground with variable and shifting sand cover and benthic communities.

**Ridge-Shallow\*:** Ridges found in shallow water near shore which are geomorphologically distinct, yet their benthic cover remains similar to the shallow colonized pavement communities on the surrounding hard-

grounds. They presumably consist of early Holocene beachrock ridges with possibly some *Acropora* framestones however verification is needed.

**Unconsolidated Sediments:** Unconsolidated sediment with less than 10 percent cover of submerged vegetation. Examples include sand and mud.

**Sand:** Coarse sediment typically found in areas exposed to currents or wave energy.

**Sand–Deep\*:** This category is primarily encountered between the inner and middle reefs and the middle and outer reefs.

**Sand–Shallow\*:** Shallow sand, besides the relatively stable sand wedge constituting the beach, is generally highly mobile. Large, mobile sand pockets are found on the areas of consolidated hardgrounds. It is believed that the sand movement is a deciding factor in the generation of benthic patterns.

#### **Other Delineations:**

**Artificial:** Man-made habitats such as submerged wrecks, large piers, submerged portions of rip-rap jetties, and the shoreline of islands created from dredge spoil. The example below illustrates several submerged ships and piles of concrete placed there as part of Broward County’s artificial reef program.

**Wormrock\*:** This category is only encountered in the immediate nearshore areas, where the polychaete worms *Phragmatopoma caudata* (Sabeleriidae) build small bioherms consisting of their collated tubes. Wormrock is generally more ephemeral than the surrounding limestones. They also persist on jetties and piers throughout the county.

**Inlet Channel\*:** All inlet channels in the survey area are maintained artificially and characterized by dredged bottom and spoil ridges at the flanks.

**Sand Borrow Areas\*:** Several borrow pits from previous dredging projects are found throughout the survey area. While they are all found in sandy areas, at the bottom many of them expose limestone and thus small ridges or patch reefs are formed that can harbor a strongly localized and patchy, but sometimes dense, benthic fauna.

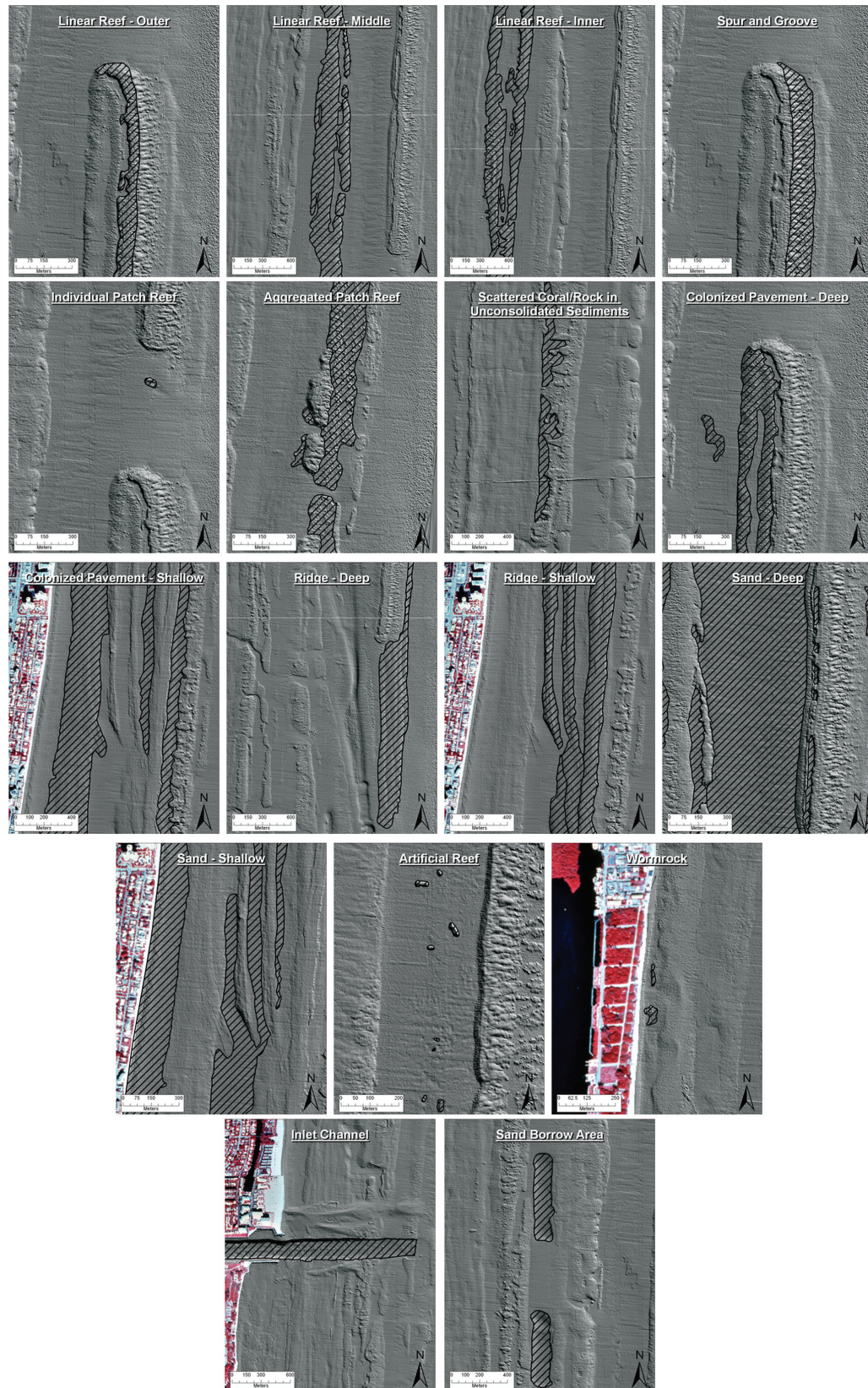
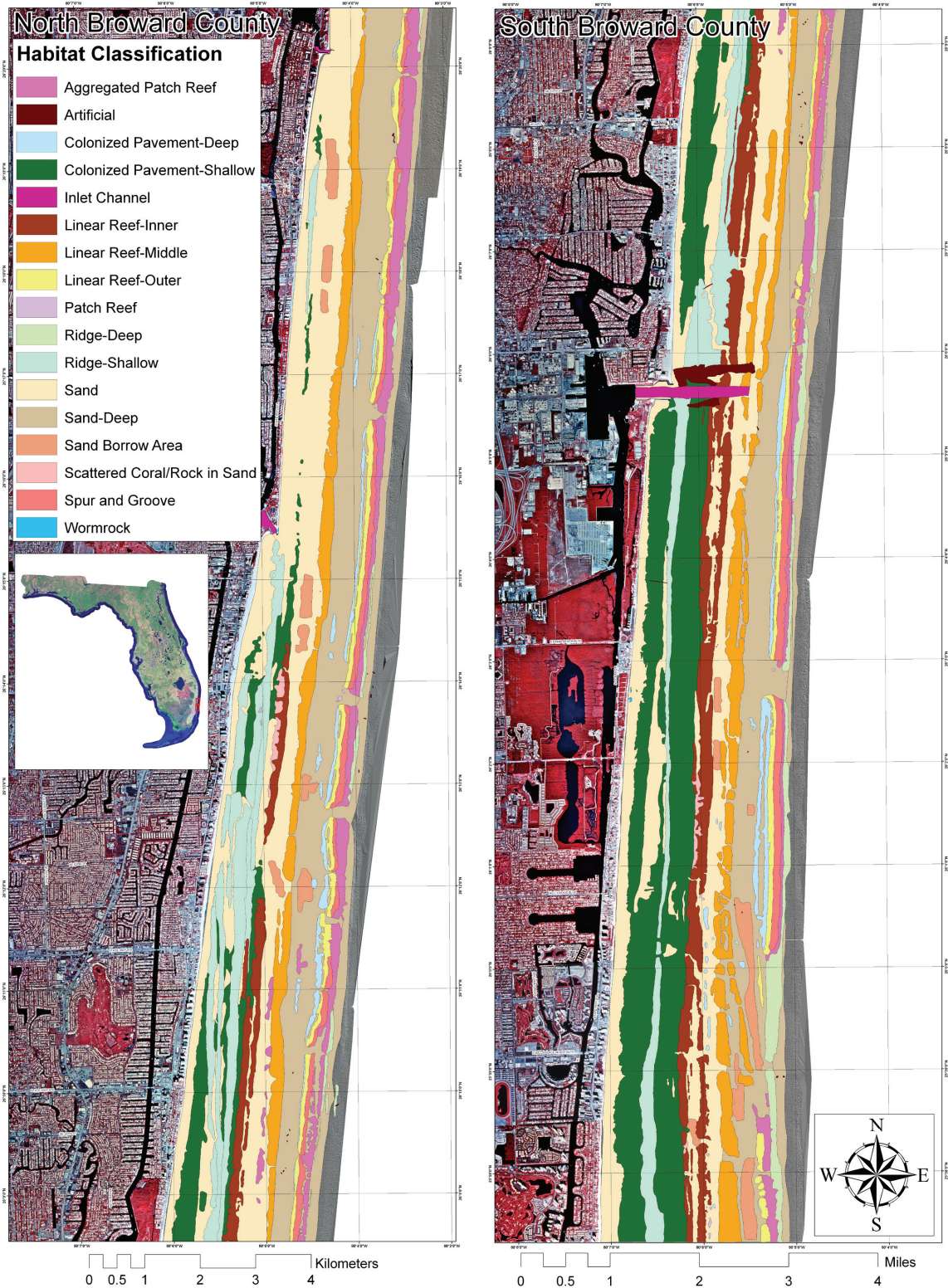


Figure 2.3.10. Examples of the different habitats delineated in GIS. The grey area is the hillshaded bathymetric surface and the black hashed areas are the specified habitat.

### **2.3.3 Area of Mapped Habitat**

Areas of the mapped classes were tabulated in ArcGIS9. In total, approximately 112 km<sup>2</sup> were mapped (Figure 2.3.11). The top level of the hierarchical classification yielded 56.62 km<sup>2</sup> of Coral Reef and Colonized Hardbottom (50.42%), 54.78 km<sup>2</sup> of Unconsolidated Sediments (46.80%), and 0.43 Other (2.78%). The second tier, habitat type, further resolved the top tier into 12 groups giving the following areas: 52.56 Km<sup>2</sup> of Sand (46.80%), 19.42 Km<sup>2</sup> of Colonized Pavement (17.29%), 18.38 Km<sup>2</sup> of Linear Reef (16.37%), 10.76 Km<sup>2</sup> of Ridge (9.58%), 4.82 Km<sup>2</sup> of Aggregated Patch Reef (4.29%), 2.90 Km<sup>2</sup> of Spur and Groove (2.58%), 2.22 Km<sup>2</sup> of Sand Borrow Area (1.98%), 0.48 Km<sup>2</sup> of Inlet Channel (0.42%), 0.42 Km<sup>2</sup> of Artificial (0.38%), 0.31 Km<sup>2</sup> of Scattered Coral/Rock in Sand (0.27%), 0.03 Km<sup>2</sup> of Patch Reef (0.03%), and 0.004 Km<sup>2</sup> of Wormrock (0.004%). The third classification tier, habitat modifier, subdivided certain classes by a depth component. This division is illustrated in Figure 2.3.12 and Table 2.3.1. See Appendix II for detailed benthic habitat maps.





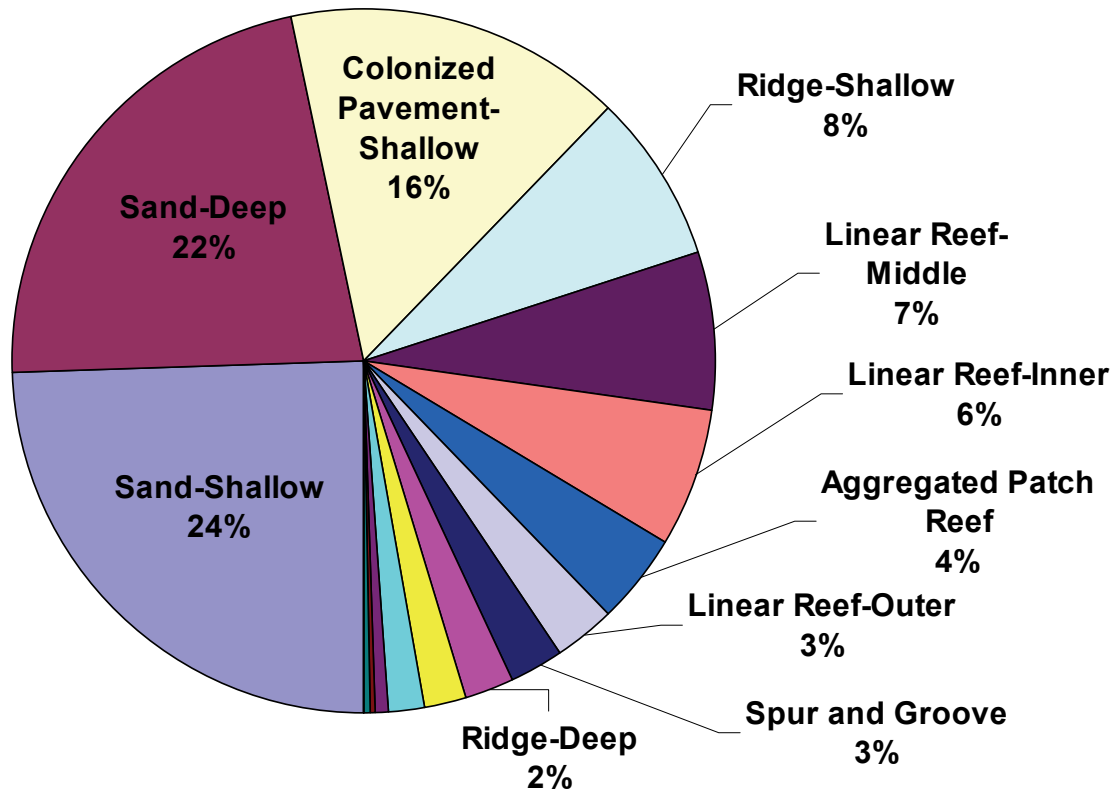


Figure 2.3.12. Relative percentages of the third tier of mapped habitats-Habitat Modifier.

Habitat	Type	Modifier	Area (km <sup>2</sup> )	% of Total Area
Coral Reef and Colonized Hardbottom	Colonized Pavement	Shallow	17.46	15.55%
		Deep	1.96	1.74%
	Patch Reef		0.03	0.03%
	Scattered Coral/Rock in Sand		0.31	0.27%
	Linear Reef	Inner	6.95	6.18%
		Middle	8.37	7.45%
		Outer	3.07	2.73%
	Spur & Groove		2.90	2.58%
	Aggregated Patch Reef		4.82	4.29%
	Ridge	Shallow	8.45	7.52%
		Deep	2.31	2.06%
Unconsolidated Sediments	Sand	Shallow	27.46	24.45%
		Deep	25.10	22.35%
Other Delineations	Sand Borrow Area		2.22	1.98%
	Artificial		0.42	0.38%
	Wormrock		0.004	0.004%
	Inlet Channel		0.48	0.42%

Table 2.3.1. Areas (km<sup>2</sup>) of all mapped polygons delineated by three classification scheme tiers; Habitat, Habitat Type, and Habitat Modifier. Note for Habitat, any polygon classified to contain coral/rock (e.g. Aggregated patch reef) was included in the Coral Reef and Colonized Hardbottom class.

### **2.3.4 Accuracy Assessment**

Accuracy assessment was performed by confusion error matrix approach in two separate analyses using the same reference data. One error matrix analyzed the map accuracy by a two-category approach: Unconsolidated Sediments and Coral Reef/Hardbottom. The second analysis was a three-category approach to look at the effectiveness of mapping Unconsolidated Sediments, Linear Coral Reef, and Colonized Pavement.

Of the 300 target reference data locations, 278 actual points were used to compare actual versus mapped habitats in the GIS. The results of the accuracy assessment yielded a high level of accuracy with a total percentage agreement (Po) of 89.6% for the two category analysis (Figure 2.3.13) and 88.1% for the three category analysis (Figure 2.3.14). Combining the linear reef and colonized pavement classes together into one class as coral reef/hardbottom yielded the highest user, producer, and total map accuracies (Figure 2.3.13). The two-category approach gave a user's accuracy of 85.3% and a producer's accuracy of 97.3% for coral reef/hardbottom and 96.3% and 80.6% for user's and producer's accuracies for unconsolidated sediments respectively. The Tau coefficient for the two-category analysis was 78.8%.

The three-category analysis (using the same reference data) split the coral reef and colonized hardbottom into two classes (colonized pavement and linear reef) based upon the location of the assessment point. This yielded a slightly lower total map accuracy of 88.1%. The user's and producer's accuracies for unconsolidated sediments were the same. The producer's accuracy for colonized pavement and linear reef were 94.7% and 94.6% respectively. User's accuracies for colonized pavement and linear reef were 82.6% and 83.3% respectively. The Tau coefficient for the three-category analyses was 81.9%.



		Reference Data		Row Totals	User's Accuracy
		Unconsolidated Sediments	Coral Reef/Hardbottom		
Mapped Classes	Unconsolidated Sediments	104	4	108	96.3%
	Coral Reef/Hardbottom	25	145	170	85.3%
Column Total		129	149	278	
Producer's Accuracy		80.6%	97.3%		89.6%
				Total Map Accuracy	

**Po = 89.6%**

**T = 78.8% (95CI's for T are 71.5% and 86.1%)**

Figure 2.3.13. Confusion matrix for two generalized mapped classes: unconsolidated sediment and coral reef/hardbottom.

		Reference Data			Row Totals	User's Accuracy
		Unconsolidated Sediments	Colonized Pavement	Linear Reef		
Mapped Classes	Unconsolidated Sediments	104	2	2	108	96.3%
	Colonized Pavement	13	71	2	86	82.6%
	Linear Reef	12	2	70	84	83.3%
Column Total		129	75	74	278	
Producer's Accuracy		80.6%	94.7%	94.6%		88.1%
					Total Map Accuracy	

**Po = 88.1%**

**$\pi$  = 81.9% (95CI's for  $\pi$  are 76.1% and 87.7%)**

Figure 2.3.14. Confusion matrix for three generalized mapped classes: unconsolidated sediments, colonized pavement, and linear reef.

## **2.4 Discussion**

### **2.4.1 Mapping Approach**

Several approaches can be taken for the evaluation of acoustic ground discrimination data. The usual method is a top-down approach (Hewitt et al. 2004) which investigates the relationship between acoustic groups and geomorphological data or findings. This approach generally takes the acoustic discrimination data, analyses it, and then tries to make sense of it in the environment. However, due to the inaccuracies of spatial interpolation between wide survey lines and multiple surveys, this may not be the best approach. Alternatively, a bottom-up approach can be utilized, which combines acoustic data with environmental data to find meaningful correlations that can then be quantitatively applied. This was the approach used in the current investigation (Figure 2.4.1). The process originated by acquiring a high resolution bathymetric data set of the study area. These data were interpolated, hillshaded, and mosaicked with a series of aerial photographs for visual reference of the coastline. The resulting product was the map upon which the benthic habitat maps were based. The benthic mapping was divided into two phases of work, Phase I- visual interpretation of the bathymetric and photograph data and Phase II-Acoustic ground discrimination hydrographic surveys and analysis. Phase I was the primary means of mapping due to the increased precision of seafloor features evident in the high resolution bathymetric data which were not present in the acoustic mapping. The acoustic ground discrimination data from Phase II supplemented the other more spatially resolved data and were added as a layer to aid in further discrimination of habitat classes. Video groundtruthing aided in the classification of the habitats outlined in the visual in Phases I and II.

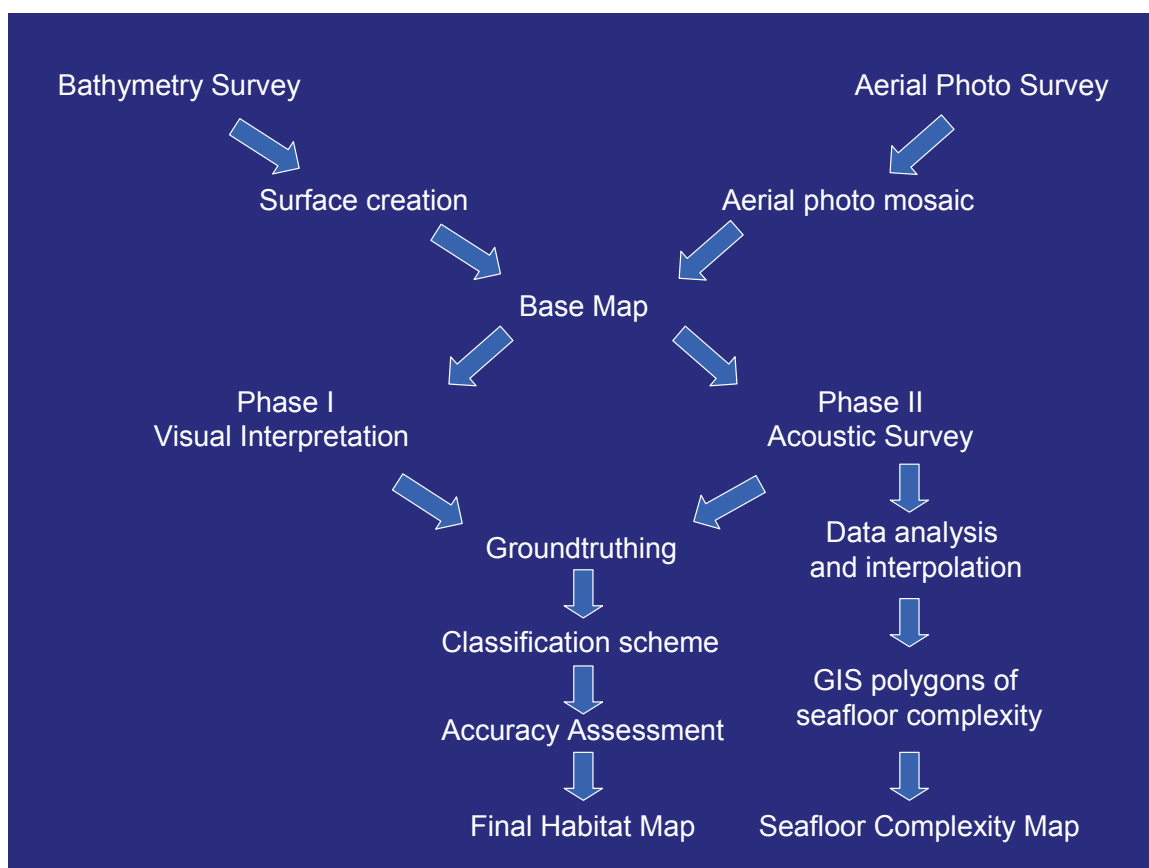


Figure 2.4.1. Workflow for the Broward County benthic habitat mapping project. Once the base map is created from the bathymetric data interpolation and the aerial photographic survey, it is visually interpreted in phase I for between-reef habitat mapping. Concurrently Phase II, the acoustic hydrographic survey takes place and is plotted on the base map for reference and interpretation for the within-reef analysis.

Phase II added further value to the benthic habitat mapping effort by detecting differences in seafloor complexity. The QTC system showed distinctions between the unconsolidated sediments, different reefs and shallow hardgrounds on a large scale (Figure 2.3.2) and the Echoplus system detected variations in seafloor complexity within the individual reefs (Figure 2.3.7). The Echoplus data were interpolated in GIS and yielded polygons of varying degrees of habitat complexity. The results of Phase II suggest that acoustic seafloor discrimination is not only able to differentiate sediment types (Hamilton et al. 1999, Morrison et al. 2001) but that it is also capable of detecting different benthic community types, such as those outlined by Moyer et al. (2002).

I believe this approach yielded a much more accurate map than assessing the acoustic data separately. The use of several data types aided greatly in the interpretation of bottom types. In particular the LADS high-resolution bathymetric survey was

extremely useful to obtain a geomorphology-driven classification of reef habitats that was compatible with vetted NOAA mapping categories. The acoustic discrimination data were essential to justify the within-reef differences of scatter types that could be related to different faunal heights or sea floor complexity that may correlate to different community types. QTC data aided in the between-reef categorizations (Figure 2.3.4) while the Echoplus data provided useful additional information in the within-reef analysis (Figure 2.3.9), since it showed well-defined roughness classes that aided in the identification of areas of increased roughness/complexity caused by benthic fauna or flora in areas of uniform bathymetry.

The acoustic systems employed herein were designed as “turn-key” systems allowing the end-user a means of classifying benthic habitats without having to be an expert in acoustic, statistical or spatial autocorrelation theory. The proprietors of these systems claim easy use and simple “out of the box” operation when in-fact their outputs can be complex and difficult to analyze. The next two sections attempt to expose some of the complexity involved in their analyses.

### **2.4.2 QTC**

Although the QTC data were useful in distinguishing broad categories like sand from reef and even between the three main reef tracts, its ability to distinguish the density of organisms within each reef remains suspect. Interpreting the within reef differences of the QTC results was problematic and complex. Each survey was classified individually according to the optimal PCA splits and then imported into GIS as point data. One of the biggest issues was determining the meaning of each class. Classes were not standardized between surveys, therefore, Class 1 in one survey might be Class 2 in another. For example, Survey A classified an area as Class 1 while due to differing weather conditions or electrical interference, an adjacent survey, Survey B, classified the same area as Class 3. Trying to manually interpret 3 to 5 classes per survey for 50 surveys was impractical and scientifically inaccurate. Another problem in interpreting the QTC data was that along any given survey line, the classification of acoustic signal could vary significantly, meaning that classes were interspersed throughout the survey. For this reason areas could not be easily outlined and categorized as a certain distinct habitat. For example, a given

stretch of survey line might have 5 Class 2 points, 4 Class 3 points, and 10 Class 1 points, all interspersed. The ratio of differently classified points might indicate some sense of the habitat but in the absence of extensive ground verification with identical system settings, there is no way of knowing. It is likely that each broad habitat category contains relative proportions of many different waveforms.

A big problem with the entire QTC output is its nature as discrete data, which negates many conventional statistically valid methods of surface prediction such as Nearest Neighbor, Kriging, Splining, etc. These methods have all been developed based on the principles of spatial autocorrelation with the underlying assumption that objects closer together are more similar to each other than objects further apart. All of these methods are good at taking spatial data and predicting a surface based on how those data and their associated values are arranged in space. QTC outputs numbers as its final classification, yet the numbers are categorical and should not be misconstrued as values. For example, if Class 1 in a given survey indicates sand or mud, the number “1” is not associated with a measurement or value along a continuum, thus there is no ordinal basis for one class to be a lower or higher value than another. If one were to plot the QTC classification outputs and run a spatial autocorrelation surface prediction model on the data, the result may look good, but may be entirely meaningless.

To illustrate this point, I ran a QTC survey in ArcGIS geostatistical analyst using the inverse distance weighted (IDW) method, which weighted the value of surround points on their distance from the point, i.e. a closer value will have more influence on the predicted value than one further away. When performing this operation an error validation screen precedes the surface creation to illustrate the validity of the data. This procedure plots the measured values versus the predicted values to indicate the accuracy of the predicated surface (Figure 2.4.2). In contrast, an analysis with the continuous Echoplus data is also shown. The prediction plot centers on the veil line in the middle of the plot from the lowest values to the highest where a slope of one is ideal. The error plot centers along the horizontal axis where a slope of 0 is ideal. An analysis of the QTC data from the same survey illustrates the plot when discrete data are used (Figure 2.4.3). The prediction plot shows the y-axis, the predicted values, on a continuum and the x-axis, the measured values, as three discrete categories. This illustrates that the predicted surface

will not follow the veil line and shows that the procedure is invalid. The error regression plot also exhibits a significant deviation from the ideal slope of zero.

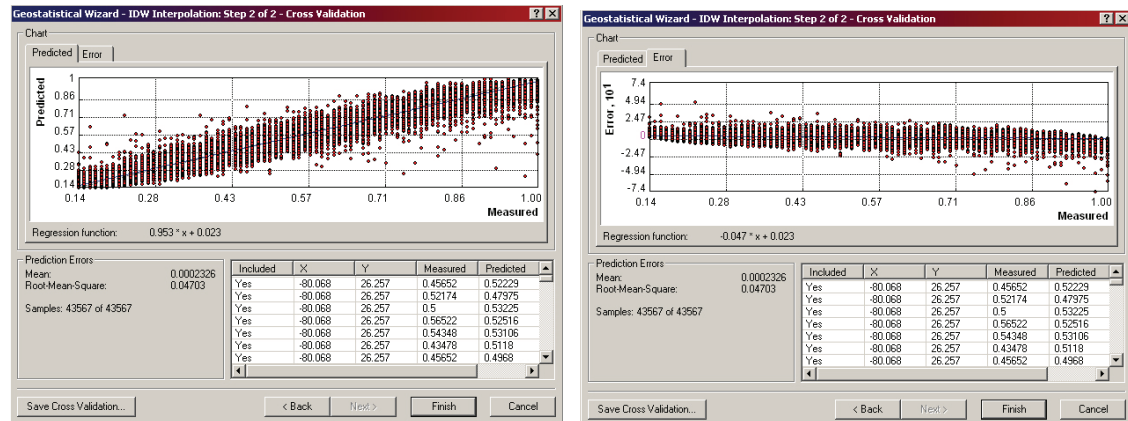


Figure 2.4.2. IDW prediction cross validation and error regression using continuous Echoplus data to create a surface in ArcGIS 9 Geostatistical Analyst.

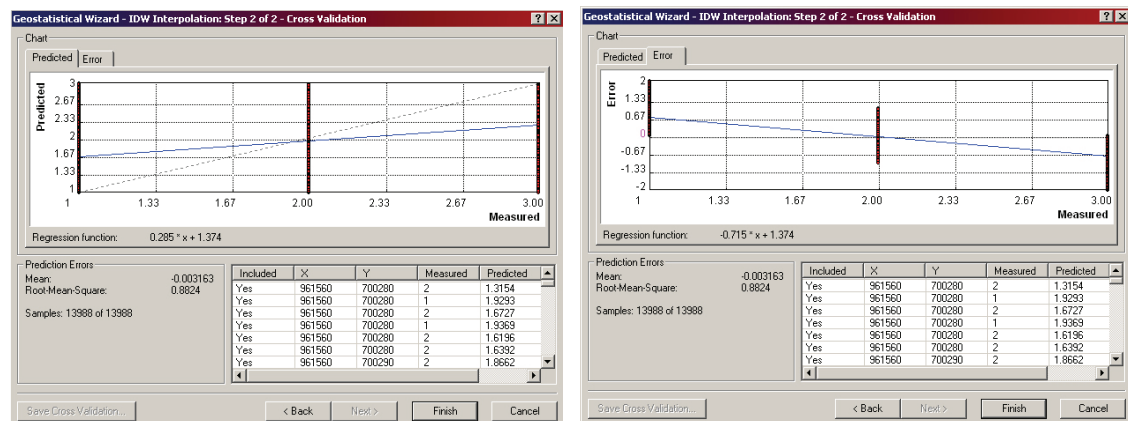


Figure 2.4.3. IDW prediction cross validation and error regression using discrete QTC data as ordinal data to create a surface in ArcGIS 9 Geostatistical Analyst.

Regardless of the outcome of the cross validation, a surface can still be created (Figure 2.4.4), however, the predicted surface is flawed. One reason this surface is flawed is that the method has created a continuum where one did not previously exist. In the categorical data set values between class, i.e. 1.3, did not exist and have no real meaning. If one is sea grass and two is reef, what is 1.3?

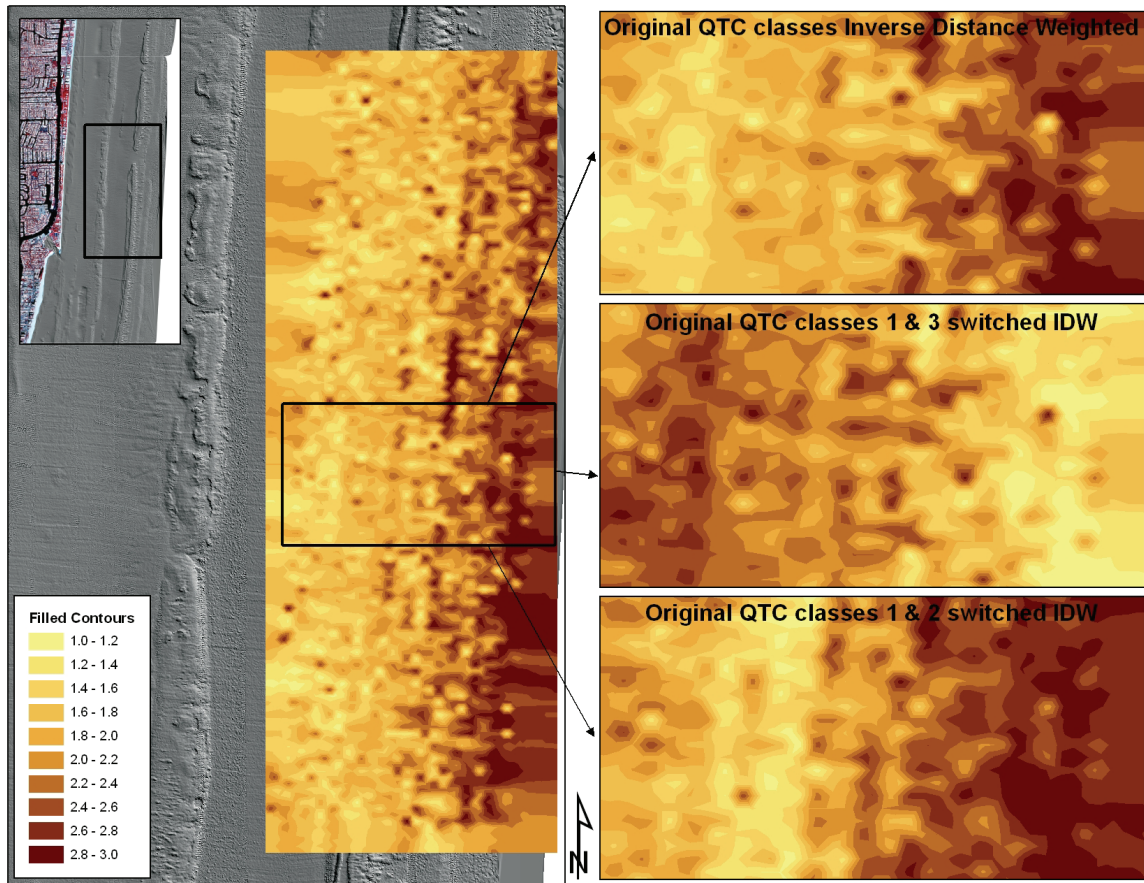


Figure 2.4.4. An example of an Inverse Distance Weighted (IDW) QTC prediction surface. The QTC data is categorical as Class 1, 2, & 3, yet when plotted the data is extrapolated along a continuum. The examples on the left show the same area (outlined by the black box) identically analyzed with the classes switched. The top shows the original QTC class IDW output, the middle is the results after class 1 and class 3 were interchanged preprocessing, and the bottom is the resulting surface after class 1 and 2 were switched preprocessing.

A bigger issue is the original ordination of the categories. QTC arbitrarily assigns each class in the PCA cluster analysis and our results have shown that class 1 in one survey might match class 2 in an adjacent survey, therefore the number assignment has no real value. For example, in figure 2.4.4, I have identically interpolated the data from a QTC survey, switching one class to another for different runs. The top left box shows the IDW data as QTC originally assigned, the middle box illustrates the IDW when classes 3 and 1 are reversed, and the lower left box shows the same IDW when classes 1 and 2 are switched. Each box is of the exact same area in the GIS, so the differences between them are strictly due to the changing of the order of the QTC classes. The top and middle boxes are inversions of one another because the highest and lowest values were switched, but the lower box is considerably different from either because the middle class was switched



to the lowest class. It is clear from this example that the ordination of the data is crucial to the prediction surface and discrete, non-ordinal data cannot be interpolated this way.

The aforementioned problems obfuscated within reef analyses of the QTC data, however, this does not mean the data are useless. New techniques should be evaluated as to their meaning and proper post processing treatment. This may require new ways of post processing not yet thought out. Other researchers at Nova Southeastern University are investigating new ways of analyzing and interpolating such data.

### **2.4.3 Echoplus**

The Echoplus results suggest that the system is capable of measuring seafloor complexity. It appears that within-reef patterns of different faunal density are encoded in the acoustic classes. For the evaluation of these smaller-scale patterns that do not necessarily follow geomorphological contours, it is difficult to evaluate the validity and meaning of either the QTC or the Echoplus acoustic ground discrimination by solely looking at the survey lines (Figure 2.4.5b). Resampled and interpolated data from individual surveys allowed a coherent mapping of within-reef patterns of sea floor complexity. In particular, the interpolated Echoplus acoustic ground discrimination information appeared useful in detecting within-reef variability of the seafloor (Figure 2.4.5c). An interpolated surface from the E1 values created using the Inverse Distance Weighted algorithm in ArcGIS 9.0 Geostatistical Analyst yielded areas within the same habitat of higher and lower surface complexity (Figure 2.4.5d). The lower E1 values (near 0) equate to lesser complex first sound wave tail returns within the survey and the higher values (near 1) equate to more complex wave returns. The more complex the wave return, the more complex the bottom. Among the benthos, it was mainly the gorgonacean soft corals and large sponges that were implicated as the reason for different scatter classes, however this is has not been confirmed. This analysis was not groundtruthed or assessed for accuracy therefore it was not included in the final benthic habitat map, but left as a stand alone product. These results merit further investigation via *in situ* quantifiable confirmation of higher complexity areas.

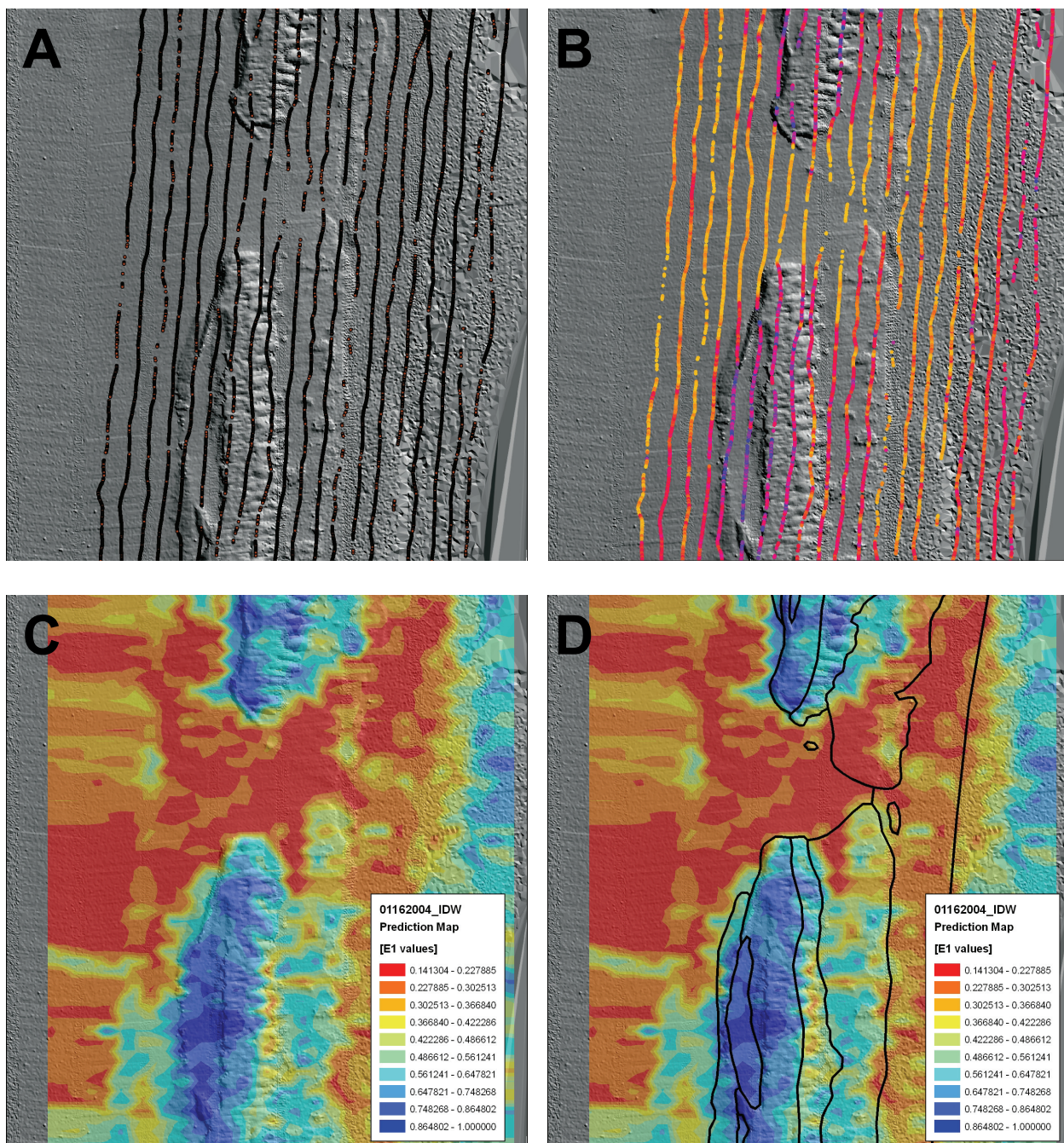


Figure 2.4.5. Echoplus data showing promising within-reef variability of seafloor acoustic return waveforms. A) The data is imported into the GIS as point data. B) The point data have an associated Echoplus waveform return value calibrated between 0 and 1. C) The point data are interpolated by Inverse Distance Weighted technique in GIS. D) The habitat polygons are overlaid for visual reference. Red values are low reef complexity areas and blue values are high reef complexity.

#### **2.4.4 Benthic Habitat Maps**

Benthic habitats were made compatible with the NOAA U.S. Caribbean mapping effort (Kendall et al. 2001) with slight modification. The most notable modification was in the mapping of different zones. The NOAA mapping effort classified the polygons into nine reef zones according to the feature's relationship along the shore (i.e. lagoon, back reef, fore reef, bank/shelf, etc.). These categories were useful in the Caribbean because everything from land and intertidal out to the bank/shelf escarpment was mapped. Many of these mapped zones did not apply in South Florida. The absence of an emergent reef in South Florida precludes mapping zones such as lagoon, back reef, and reef crest. Since our effort was confined to depths from shore to 35m, the land and shoreline intertidal zones were excluded. Therefore every mapped feature in South Florida resided in the bank/shelf zone.

The final map showed three well-developed linear reef complexes (Outer, Middle, and Inner), a series of deep and shallow ridges believed to be old shorelines, a large sand area between the middle and outer reefs, and a considerable amount of colonized pavement (Figure 2.3.2). The outer linear reef was divided into four habitats: aggregated patch reef, spur and groove, linear reef and deep colonized pavement. The aggregated patch reefs on the eastern edge of the outer linear reef consisted of an irregular environment with various sized hard bottom patches of reef interspersed amongst the deep sand. These were more prevalent close to the reef and tapered off eastward, becoming sandier. The drowned spur and groove was evident by the density of mostly continuous reef spurs and sand grooves along the eastern edge of the outer reef. The crest of the Outer Reef was mapped as the linear reef proper and the western edge was mapped as colonized pavement. The Outer Reef was separated from the Middle Reef by a wide sandy plane (deep sand), which was characterized overall by a different scattering class in QTC View than the shallow sand found inshore. The eastern boundary of the middle reef was distinct and easily mapped whereas acoustic discrimination aided in determining the western boundary. The inner reef was the least distinct reef as it does not have the appearance of a mature reef. Much of this reef is patchy growth atop an inshore ridge and reef zonation is not evident unlike a mature reef which would have a more coalesced appearance similar to the outer reef with distinct zonation like a clear reef crest, spur and

groove, etc. Shoreward of the inner reef, another sand area or a mixture of sand and colonized pavements were found. Several nearshore ridges were mapped that could be classified as linear reef habitat, but were thought to be of non-reefal origin. These ridges have been characterized by other authors as ancient cemented beach dunes (Lidz and Shinn 1991, Lidz 1997, Finkl 2005). Therefore even though similar habitat comprises the inshore ridges and the shallow colonized pavements, these structures were mapped separately due to their origins. Excluded habitats such as submerged vegetation and large rubble zones were not detected and could not be mapped during this effort.

#### **2.4.5 Accuracy Assessment**

The Broward County benthic habitat maps were accurate to a high degree. At the most basic hierarchical level as in the two-category assessment between Unconsolidated sediments and Coral Reef/Hardbottom the map accuracy was 89.6% and all producer's and user's accuracy statistics were above 80% (Figure 2.3.4). The T coefficient, perhaps the most accurate measure (Ma and Redmond 1995), yielded an accuracy of 78.8%. This suggests that the habitats were mapped at a high level of accuracy at the two-category level. An attempt to better-refine the mapping accuracy utilized a three-category approach where the Coral Reef/Hardbottom was separated into Colonized Pavement and Linear Reef. Interestingly, although the user and producer accuracies of the Colonized Pavement and Linear Reef were slightly less than when they were combined, the three-category analysis yielded a higher Tau coefficient of 81.9% (Figure 2.3.5). The slight decrease in user and producer accuracies was because 4 of the accuracy assessment points that were correctly classified as coral reef habitat in the two-category analysis were actually incorrectly identified as either linear reef or colonized pavement in the three-category analysis. Although splitting the data into three categories lowered these accuracies, it increased the Tau coefficient because the Tau coefficient weights three highly accurate categories higher than two even if the accuracy percentages of the two are slightly higher.

The accuracy assessment results reported herein are directly comparable to the NOAA Puerto Rico and Virgin Island mapping effort using photo interpretation and on-screen digitizing in GIS. Both efforts were undertaken using a similar classification

scheme for Western Caribbean habitats. The Broward map yielded a high overall accuracy (Po) of 89.6%. This was only 4 % lower than the Puerto Rico and Virgin Island maps, which had an overall map accuracy of 93.6% (Figure 2.4.6 from Kendall et al. 2004). The Tau statistic in the NOAA effort was 90.3 %; 8.4% better than the Broward effort. These accuracy statistics were heavily influenced by the ability to map certain habitats very successfully, submerged vegetation in particular. The aerial photography interpretation gave 100% accuracy for this category in the NOAA effort. This brought the overall mapping accuracy statistics up considerably. When the matrix was recalculated without this category, the accuracy statistics were very close to the Broward map accuracies (Figure 2.4.7). The NOAA map without submerged vegetation yielded a total map accuracy of 91.1%, only 1.5% better than the Broward maps, and a Tau statistic of 82.3%, only 3.5% better. These results suggest that the accuracy of visually interpreting high-resolution bathymetry supplemented by other data types is similar to that of aerial photography for mapping coral reef/hardbottom and unconsolidated sediments. Aerial photography visual interpretation is extremely good at detecting submerged vegetation in clear water. Bathymetric visual interpretation alone is likely not as good because sea grass in bathymetry usually produces a surface very similar to that of sediments and therefore is difficult to interpret. Mapping sea grasses is one important reason why a combination of data should be used for visual interpretation. Due to the absence of significant mappable submerged vegetation in Broward County, a comparison between the two methods was unattainable for this study.



		Reference Data			Row Totals	User's Accuracy
		Coral Reef/ Hardbottom	Submerged Vegetation	Unconsolidated Sediments		
Mapped Classes	Coral Reef/ Hardbottom	35	0	1	36	97.2%
	Submerged Vegetation	0	30	0	30	100%
	Unconsolidated Sediments	6	0	37	43	86.0%
Column Total		41	30	38	109	
Producer's Accuracy		85.4%	100%	97.4%		93.6%
					Total Map Accuracy	

**Po = 93.6%**

**$\pi$  = 90.3% (95CI's for  $\pi$  are 83.4% and 97.3%)**

Figure 2.4.6. Confusion matrix from photo interpretation of Buck Island St.Croix USVI using on-screen digitizing (from Kendall et al 2004).

		Reference Data		Row Totals	User's Accuracy
		Coral Reef/ Hardbottom	Unconsolidated Sediments		
Mapped Classes	Coral Reef/ Hardbottom	35	1	36	97.2%
	Unconsolidated Sediments	6	37	43	86.0%
Column Total		41	38	79	
Producer's Accuracy		85.4%	97.4%		91.1%
				Total Map Accuracy	

**Po = 91.1%**

**τ = 82.3% (95CI's for τ are 69.8% and 94.8%)**

Figure 2.4.7. Confusion matrix from photo interpretation of Buck Island St.Croix USVI using on-screen digitizing excluding the submerged vegetation class (from Kendall et al 2004).

The largest inaccuracy noted in the accuracy assessment of the Broward mapping was areas mapped as coral reef/hardground but were groundtruthed as unconsolidated sediment. This was expected because the Broward reefs contain many small-scale sand patches. These patches are below the minimum mapping unit of 1 acre and therefore were excluded. Due to scaling issues, it is unlikely that decreasing the minimum mapping unit in the visual interpretation of high-resolution bathymetry would yield higher accuracies. This can be explained in analogy to the pixel resolution limitations of photographic or satellite imagery. The bathymetric surface was interpolated from points measured at approximately every four meters. This gives a good perspective of most seafloor features at a larger scale (greater than 1:1000). At a scale smaller than 1:1000, features become much harder to delineate (Figure 2.4.7). At the 1:500 level, the data depicts features, however due to the 4m x 4m data resolution, the seafloor is not accurately modeled and it is uncertain whether the seen features are real or artifacts.

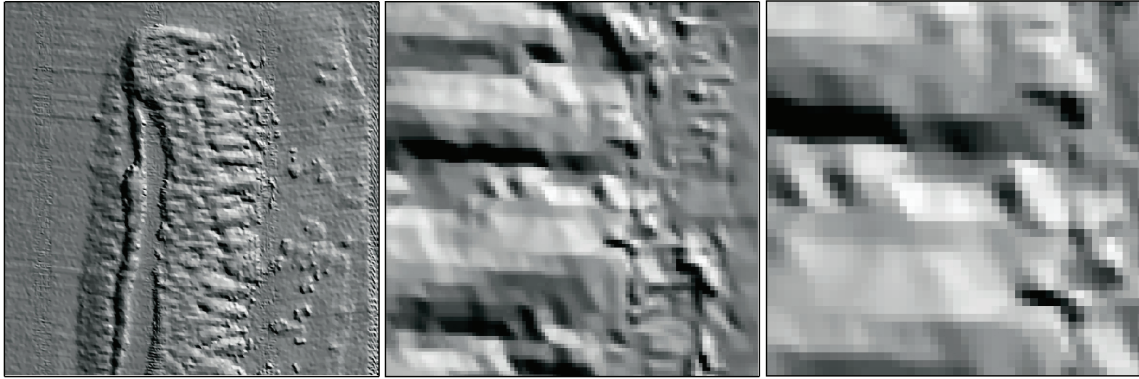


Figure 2.4.8. High-resolution bathymetry at different scales. The left image is the data at 1:6,000, the center is the same data zoomed to 1:1,000, and the right image is zoomed to 1:500. Scale becomes an issue when increases in mapping resolution are desired.

Another limitation to the visual interpretation of bathymetric data is that different habitats of low relief cannot be easily distinguished. Areas of low-relief hardbottom, sand, and submerged vegetation are difficult to delineate. Furthermore, sand veneers atop reef structure are nearly impossible to detect solely from bathymetry. This is where aerial photography interpretation is particularly useful. Pixel variation of aerial photography of shallow-water reefs in clear water allows the delineation of these types of features unattainable solely from the bathymetric surface.

## 2.5 Conclusions

Accurate maps outlining the entire Broward County sub-tidal seafloor from 0 to 35m depth classified into NOAA equivalent habitat classes were created. Production of the maps was based on a variety of data types, such as LADS bathymetry, QTC View and Echoplus acoustic seafloor discrimination, and groundtruthing. The accuracy of the Broward maps is comparable to that achieved by photo interpretation and is a good example of how similar mapping products can be attained through different means. The two phased approach ensured the highest accuracy possible by utilizing the highest resolved data (the bathymetry) as the base and then adding information from the lower resolution data (acoustic ground discrimination). This methodology depicted benthic features as accurately as traditional methods like photo interpretation and similar methodology should be used in other areas where photo interpretation is not feasible.

The visual interpretation of the high-resolution bathymetry was aided by acoustic surveys. It is possible to get similar results without the acoustic surveys; however these



surveys enhanced the interpretation with acoustic backscatter information about seafloor complexity. Although not confirmed by this study, acoustic ground discrimination appeared to detect differences in the seafloor surface within habitats. In particular, the Echoplus measurements seem to correlate to areas of increased and decreased complexity. Whether this complexity is due to the reef itself or the community on top is unknown. This type of data may be useful for the next level of mapping to further increase map resolution. This method theoretically can map the variation in faunal density within a reef system, which would yield not only Coral Reef polygons (as they do now) but also a density of biological coverage within that structure.

Economically, photo interpretation will always “win” over other remote sensing methods like high-resolution bathymetry visual interpretation and acoustic ground discrimination surveys. However sea floor mapping should always incorporate all available quality data to provide the most information to the map. In areas such as the southeast coast of Florida where full photo interpretation is precluded by turbidity, the techniques employed in this survey can be used to yield similar results.

The maps from the current effort will be useful to South Florida marine resource management. They are to be included in the South Florida Electronic Area Contingency Plan that the Florida Fish and Wildlife Research Institute (FWRI) is developing jointly with the US Coast Guard to help support oil spill response and planning. The maps will support state and county permitting activities related to sand mining and the minimization of impacts by submarine construction and excavation, such as pipeline routings etc., and they will be included in large-format maps to be shown on a future Broward County Boating and Angling Guide, which are to include extensive information about marine resources and their protection and conservation. Benthic data will be added to the SEAMAP Bottom Mapping Project, which consists of various GIS produced by the Atlantic States Marine Fisheries Commission and the States of North Carolina, South Carolina, Georgia, and Florida aiming to identify essential fish habitat. They will also be used for local and State-sponsored monitoring programs to assist in optimal site-selection.

The benthic habitat polygons developed herein are used in the proceeding sections to classify the survey area of the visual fish census.

# Part III

## **Reef fish and Topographic Complexity**

### **3 Reef Fish and Topographic Complexity**

#### **3.1 Introduction**

##### **3.1.1 Reef fish and reef structure**

A fundamental principle in ecology assumes that abiotic and biotic variables influence the distribution of all organisms, including marine fishes (Putman & Wratten 1984, Recksiek et al. 2001). Abiotic variables such as temperature, salinity, depth, current, and topographic complexity and biotic variables like recruitment, competition, food availability, and predation all play roles in determining fish species distribution and abundance (Sale 1991). Where abiotic variables such as temperature and salinity are relatively consistent, other variables structure the fish assemblage including the physical arrangement of the seafloor known as topographic complexity or rugosity (Luckhurst & Luckhurst 1978, Hixon & Beets 1989, Bell et al. 1991, McCoy & Bell 1991, McClanahan 1994, Appeldoorn et al. 1997, Chabanet et al. 1997, Friedlander & Parrish 1998, Garcia Charton and Perez Ruzafa 1998, Friedlander et al. 2003, Gratwicke & Speight 2005a & b, Iampietro et al. 2005, Kuffner et al. 2007).

Historically, reviews of ecological literature have not emphasized research pertaining to the physical structure of the environment (McCoy and Bell 1991). The few reviews that do look at this aspect categorize them into two lines of study; 1) the niche and how it limits organismal distributions and 2) how the physical structure modifies biotic interactions, in particular predator/prey interactions (McCoy and Bell 1991). In their literature review of this subject, McCoy and Bell (1991) found these lines of thought ubiquitous in textbooks, yet their relative coverage was low compared to other ecological subjects like natural selection or competition. They found similar under-representation of this subject in many peer reviewed journals until the early 1990's. It was not until very recently, however, that this subject has gained more attention (Grober-Dunsmore 2005, Iampietro et al. 2005, Kuffner et al. 2007).

Seafloor topographic complexity ranges from high rugosity with many interstitial spaces such as the case of actively accreting coral reefs to very low rugosity as in a high energy, highly-eroded, flat hardbottom. Topographic complexity has been linked to

increased species diversity in many ecological communities (MacArthur & MacArthur 1961; Petren & Case 1998; Johnson et al. 2003; Pittman et al. 2007) including reef fish on coral reefs (McCormick 1994). Many studies have also found positive correlations between topographic complexity and reef fish abundance, biomass, and/or richness (Talbot 1965, Risk 1972, Talbot & Goldman 1972, Luckhurst & Luckhurst 1978, McClanahan 1994, McCormick 1994, Green 1996, Appeldoorn et al. 1997, Friedlander & Parrish 1998, Friedlander et al. 2003, Gratwicke & Speight 2005a & b).

The relationship between fish assemblage variables and topographic complexity is especially evident in artificial reef studies (Bohnsack 1991, Walker et al. 2002, Gratwicke & Speight 2005a, Arena et al. 2007). Many artificial reef studies show that increasing habitat complexity increases local fish abundance (Bohnsack 1991). Walker et al. (2002) showed “extensive faunal enhancement” with the addition of 12 artificial reefs on a nearshore, shallow-water sand habitat in Miami, FL. Fish abundance increased from  $5 \pm 1.4$  individuals pre-artificial-reef-deployment to  $40.6 \pm 10.1$  individuals two years post-deployment, an 800% increase. Species richness also increased from  $1.8 \pm 0.3$  pre-deployment to  $6.6 \pm 1.3$  post, a 500% increase. This was determined not to be immigration of fish from the nearby reef because surveys of the surrounding areas showed increases in abundance, species richness, and biomass as well.

The addition of artificial reefs to an area indeed increases the topographic complexity and almost instantaneously attracts fish, but their placement, configuration, and form is also influenced by many factors that are reflected in the accompanying fish assemblage such as the depth of water (Chang 1985), the proximity to each other (Jordan et al 2005), the proximity to natural reefs (Shulman 1985, Gratwicke & Speight 2005b), the proximity to recruitment pulses (Doherty and Williams 1988), and the number and size of holes (Hixon and Beets 1989). Although useful as experimental tools, artificial reef experiments can not detect the natural assemblage’s relationship to topographic complexity. This can only be accomplished by obtaining topographic metrics and assemblage data of the natural system.

In order to develop a predictive model of the natural reef fish assemblage, it must be studied in the natural environment. On a local/regional scale, (several  $\text{Km}^2$ ) the abundance and richness of the fish assemblage should be equally affected by temperature,

salinity, and other water chemistry components. Therefore, other components of the natural system may be used as indicators to predict fish abundance and richness. Since topographic complexity has been linked to fish abundance and richness in many small-scale studies, comparing these variables on a larger scale may yield statistical trends which can be used to predict the occurrence of fish in their natural environment.

### **3.1.2 Topography**

Topography is comprised of two components: 1) frequency and amplitude of corrugation (complexity), and 2) the degree of angulation (slope) (Hobson 1972, McCormick 1994). For this measurement to be useful it must be conceptually descriptive, easily measured, and useful on several scales (Hobson 1972). Several methods have been developed to fit these criteria of measuring reef surface topography *in situ* over the past thirty years (Brock et al. 2004, McCormick 1994, Underwood and Chapman 1989).

#### **3.1.2.1 Linear Rugosity**

Over the past thirty years, several methods have been developed to measure reef surface topography (Underwood & Chapman 1989, McCormick 1994, Brock et al. 2004). The most frequently used method for measuring rugosity has been the chain and tape method (McCormick 1994), whereby a ratio of the length of a chain draped across the surface of the reef to the horizontal stretched length is calculated (Hobson 1972, Risk 1972, Talbot & Goldman 1972). This ratio provides a rugosity index by which linear regressions of fish abundance, biomass, species richness, and/or species diversity can be used to determine correlations to this variable. This measurement is referred to herein as linear-rugosity. McCormick (1994) reviewed 6 measures of substratum topography and found that rugosity indices which measure vertical relief in some form gave more accurate results. The linear-rugosity method performed well in his field trials exhibiting positive correlations to total abundance and species richness for 100 3x3 m quadrats. Many other studies have used this method to find positive correlations between fish assemblage parameters and rugosity as well (Friedlander and Parrish 1998, Friedlander et al. 2003, Luckhurst and Luckhurst 1978, McCormick 1994, Risk 1972, Talbot 1965, Talbot and Goldman 1972).

### 3.1.2.2 Surface Rugosity

The limitation of linear-rugosity is that it measures rugosity only along a single line. This may provide effective topographic measurements for linear surveys (e.g. transects), but it may not be the best measurement for other survey types (e.g. point-counts) (Figure 3.1.1). Due to the time constraints in acquiring rugosity data (McCormick 1994), measuring the rugosity of a complete area underwater usually isn't feasible; Therefore, a transect must be chosen by the researcher to represent the rugosity for the study area. The placement of this line is critical in determining the rugosity index for that site. A more accurate representation of rugosity for a large survey area is to obtain an average of several rugosity transects in the area (McCormick 1994), however, these *in situ* measurements are cumbersome, time consuming, and costly (Gratwicke and Speight 2005b, Kuffner et al. 2007). Techniques have been developed to avoid these constraints by using remote sensing data in Geographic Information Systems (GIS) to analyze topography. The analysis of high resolution bathymetric data facilitates the measurement of several topographic metrics on a larger scale (Kuffner et al. 2007). One of these metrics is an index (termed herein as surface-rugosity) that resolves the linear bias of linear-rugosity by dividing the surface area by its planar area in a given region (Dahl 1973, Blaszczyński 1997, Riley 1999, Brock et al. 2004, Jenness 2004). Several other relevant topographic measurements can be taken from high resolution bathymetry within a survey area, including a minimum and maximum depth, elevation, and volume (Figure 3.1.2). If relationships between biotic assemblages and topography evident in the *in situ* data are also present using GIS metrics, then surface rugosity can be effectively measured on a large scale by analyzing remote sensing data in GIS. This outcome would allow a seascape-level analysis of reef fish populations and facilitate the development of predictive models based on seafloor topography.

This study investigated the relationship between reef fish (abundance and richness) and several topographic complexity metrics (elevation, surface-rugosity, and volume) throughout the natural reef habitats in southeast Florida. Statistical analyses of the reef fish assemblage were conducted to elucidate their relationship to *in situ* and GIS topographic measurements across the seascape and evaluate the possibilities of using these large-scale metrics as a proxy for prediction models.

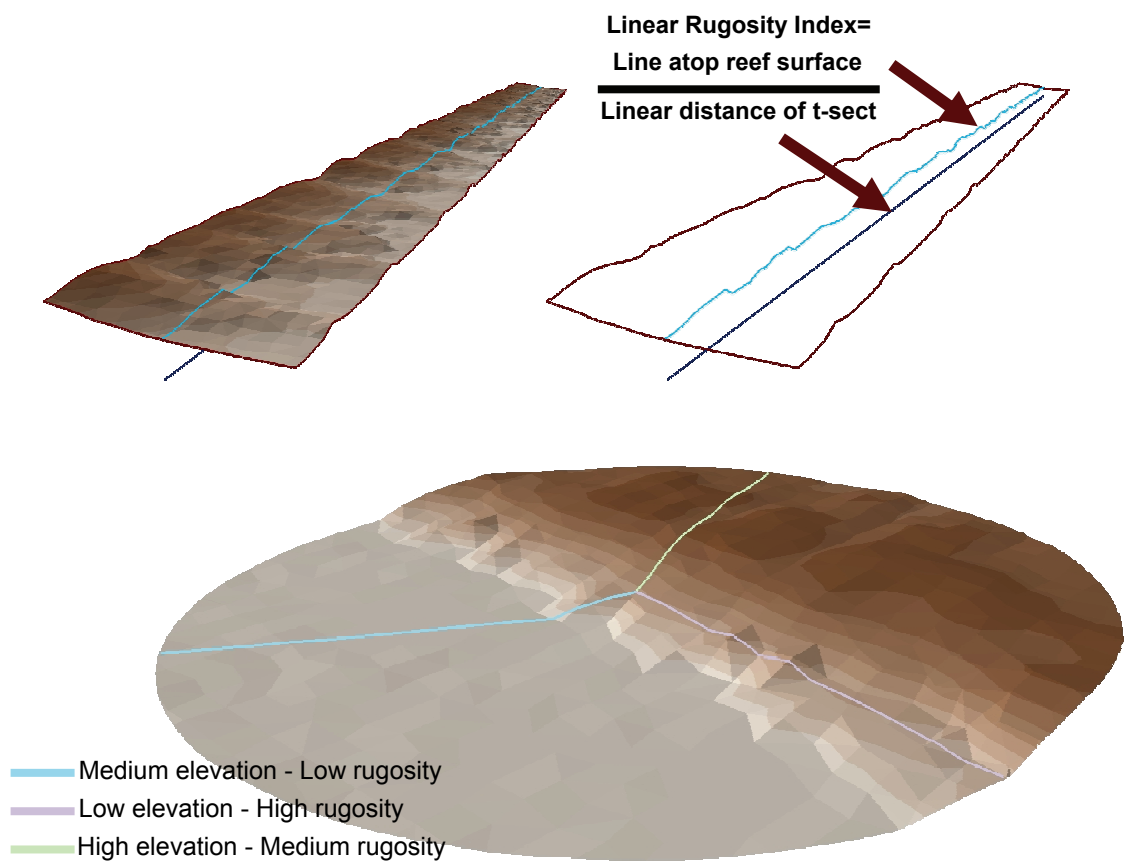


Figure 3.1.1. The linear rugosity method entails taking the length of a measuring device draped along the surface of the substrate for a specified straight-lined distance (light blue) and dividing it by the length of the straight-line distance to obtain the index value. The surface rugosity method analyzes the surface area of the entire survey area in which a fish count was performed by dividing the 3D surface area by the planar surface area of the same space. This method takes the entire survey's rugosity into account and is not bias towards any survey type. The lines show possible bias of the linear survey method conducted within wide survey areas.



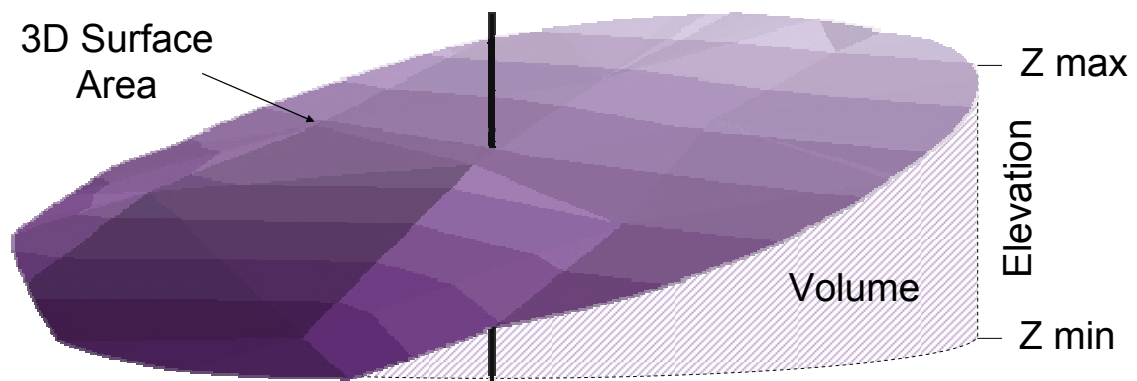


Figure 3.1.2. Calculating the volume from the bathymetric data in GIS gives a combined metric of elevation and surface area. The volume metric is the entire space under the surface to the minimum Z of that surface. Elevation is the difference in minimum and maximum Z values.

## 3.2 Methods

### 3.2.1 Visual Fish Assessments

Fish data were collected as part of a quantitative effort to acquire a baseline census of the coral-reef-associated fishes in Broward County, Florida (Ferro et al. 2005). Ferro et al. (2005) conducted over 400 GPS-located point count fish surveys using the Bohnsack and Bannerot (1986) method between 2000 and 2002 in central and northern Broward County, FL, USA. These surveys were conducted along 54 cross-shelf transects spanning 24.5 kilometers along Broward County's reef tract from Port Everglades (26° 06.000' N) North to the county line (26° 19.250' N), each separated by approximately 0.5 km (Fig. 3.2.1). Most transects consisted of nine point-count site locations on the eastern edge, crest, and western edge of each of the three main reef tracts (Fig. 3.2.2). These locations were categorized as Reef Sites. Their descriptions were as follows: IW, IC, IE, MW, MC, ME, OW, OC, OE, where I = inshore reef, M = middle reef, O = outer reef, W = western edge, C = center or crest, and E = eastern edge (i.e. ME is the eastern edge of the middle reef).

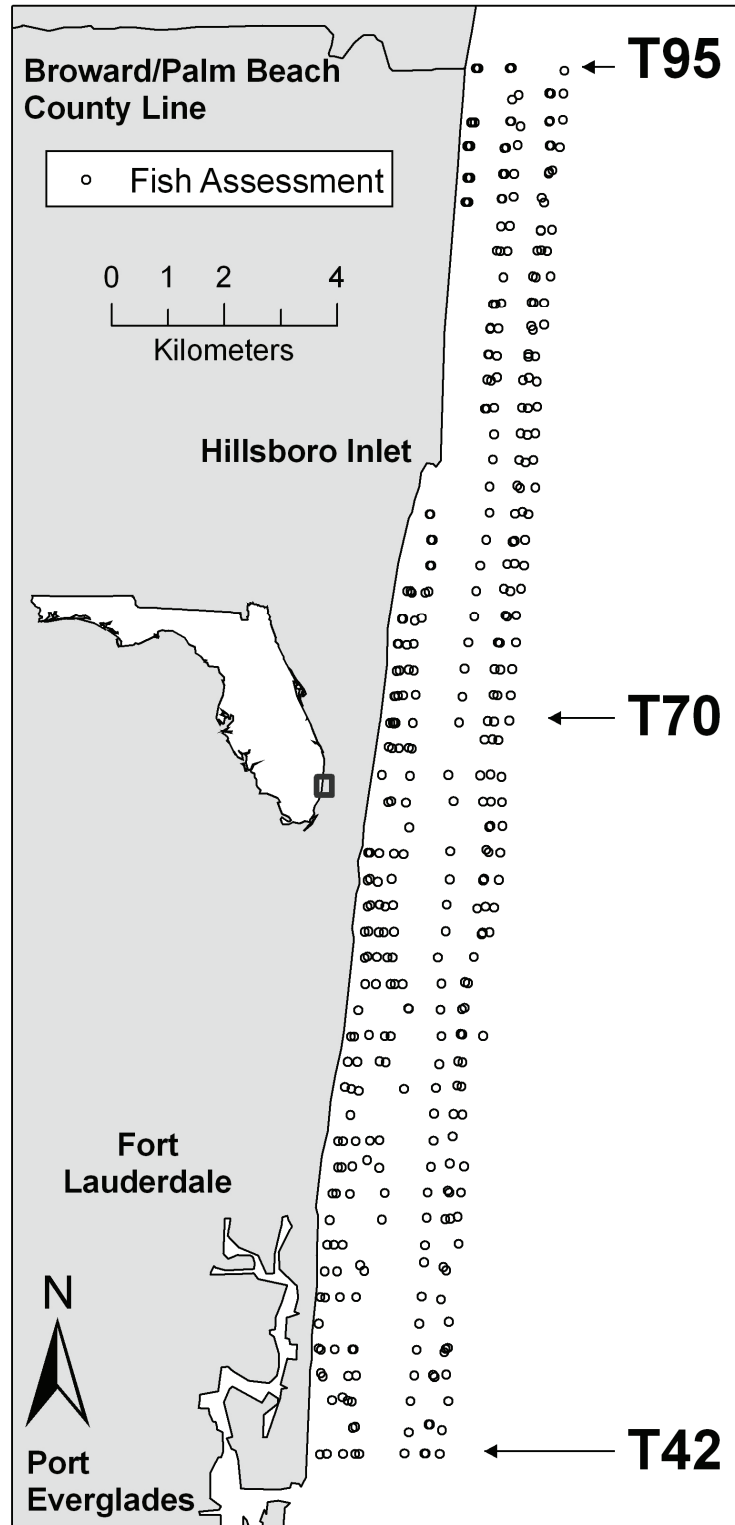


Figure 3.2.1. Map illustrates point-count fish assessment sites along the 54 east-west transects, which span from Port Everglades North to the Broward/Palm Beach County line. Transects were placed on east-west parallels every 0.250 minutes (approximately every 0.45 km) and are numbered sequentially from South to North. T42 = transect 42; T70 = transect 70; T95 = transect 95.

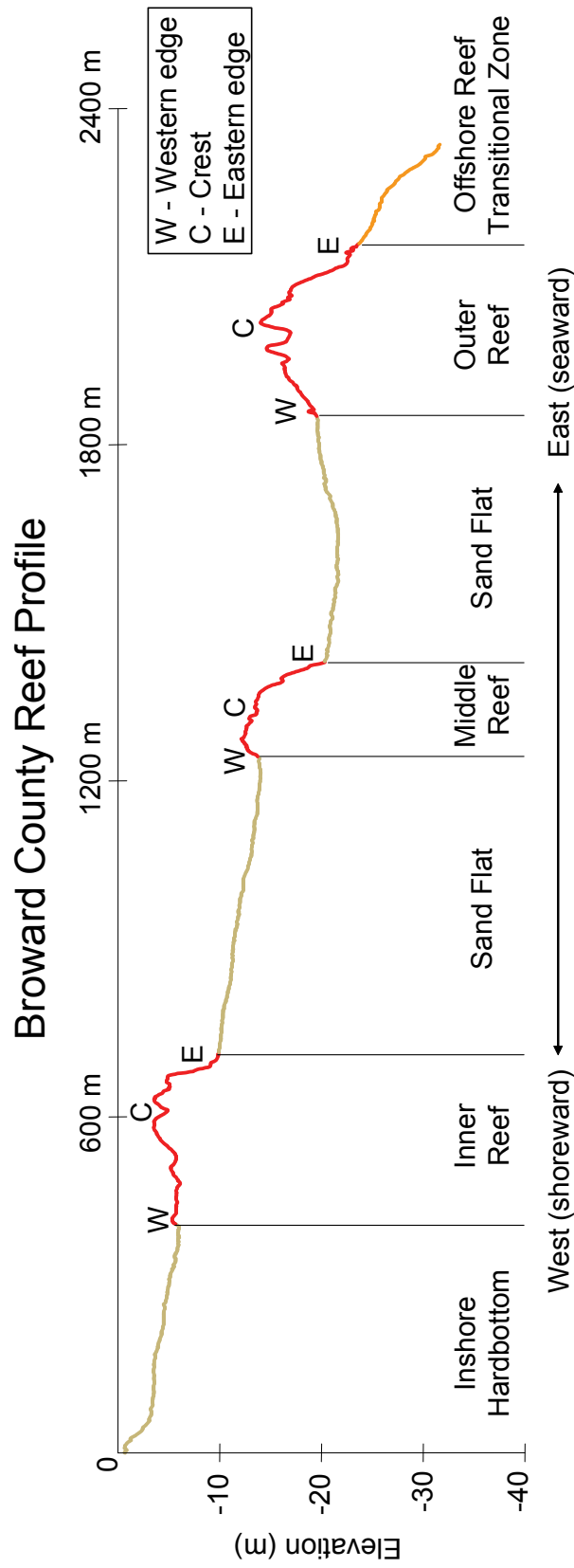


Figure 3.2.2. Broward County reef profile taken from an east-west transect of the LADS bathymetry data from 0 to ~30m off central Broward County, FL. X-axis represents distance from shore and y-axis represents elevation. The seafloor of the profile is categorized in the sections below the profile line. The dark line along the profile represents the three main shore-parallel reef tracts. The letters above the profile indicate the nine areas targeted along each transect for the point-count fish assessments.

Each transect was predetermined along equally spaced lines of latitude and GPS located in the field. Each point-count census site (eastern edge, crest, and western edge of each reef) was determined in two ways: 1) driving the boat along the transect latitude using an echo sounder to generate a depth profile of the transect by which the survey sites were chosen, or 2) choosing the points from a GIS based bathymetric map in the lab and confirming their locations in the field with the depth sounder. The latter method was preferred; however, the bathymetric map was not available at the onset of the fish assessment data collection, thus the sites were chosen by a mixture of the above methods.

For each point-count survey, a buoy was deployed upon which a diver(s) descended. The diver(s) tightened the buoy line, swam it to the reef edge if necessary, and extended a 7.5 meter (m) weighted line outward from the buoy. This line was used as a reference to aid the diver in judging a 15 m diameter imaginary cylinder within which to survey the fish. The diver, located in the center of the cylinder, noted only species presence within the cylinder for an initial five minute period. Then the diver noted abundance and estimated minimum, maximum, and average lengths of the fish observed in the cylinder during the initial period. If a new species entered the cylinder after the initial period, only its presence was recorded.

Following the fish survey, the 7.5 m line was extended from the cylinder center, across the area of highest rugosity within the cylinder. A fiberglass measuring tape was used to measure the distance of the reef surface along the 7.5 m linear distance, following all the contours of the reef. This measure was later used to create the linear rugosity index by dividing the contour distance by the linear distance (7.5m).

### **3.2.2 Quality Control of Survey Locations**

A GPS coordinate of each site was taken from the boat prior to removal of the buoy. The coordinates were imported into ArcGIS and overlaid onto the LADS bathymetry layer. Their locations were compared to GIS data to assure each survey location was correct. *In situ* diver estimates of depth, elevation, and proximity to the reef edge were compared to the areas surrounding the survey point in the GIS. If the data did not agree, that specific fish count was discarded. Of the 427 surveys conducted north of

Port Everglades, 57 were discarded during the quality control analysis leaving a total of 370 surveys for these analyses.

Upon importing the fish survey locations into GIS, it was noted that the original site description was an inaccurate characterization of the survey area. For Example, many of the “Middle” and “Inner” reef sites were actually conducted inshore of the Inner Reef proper (Figure 3.2.3) due to the lack of spatial data available at the time of the surveys. Consequently, the site nomenclature was reclassified to reflect a more accurate depiction of the surveyed area including the addition of a new category, the inshore ridges. The sites were named Inshore Ridge and maintained their W, C, and E classification according to their orientation on the feature.

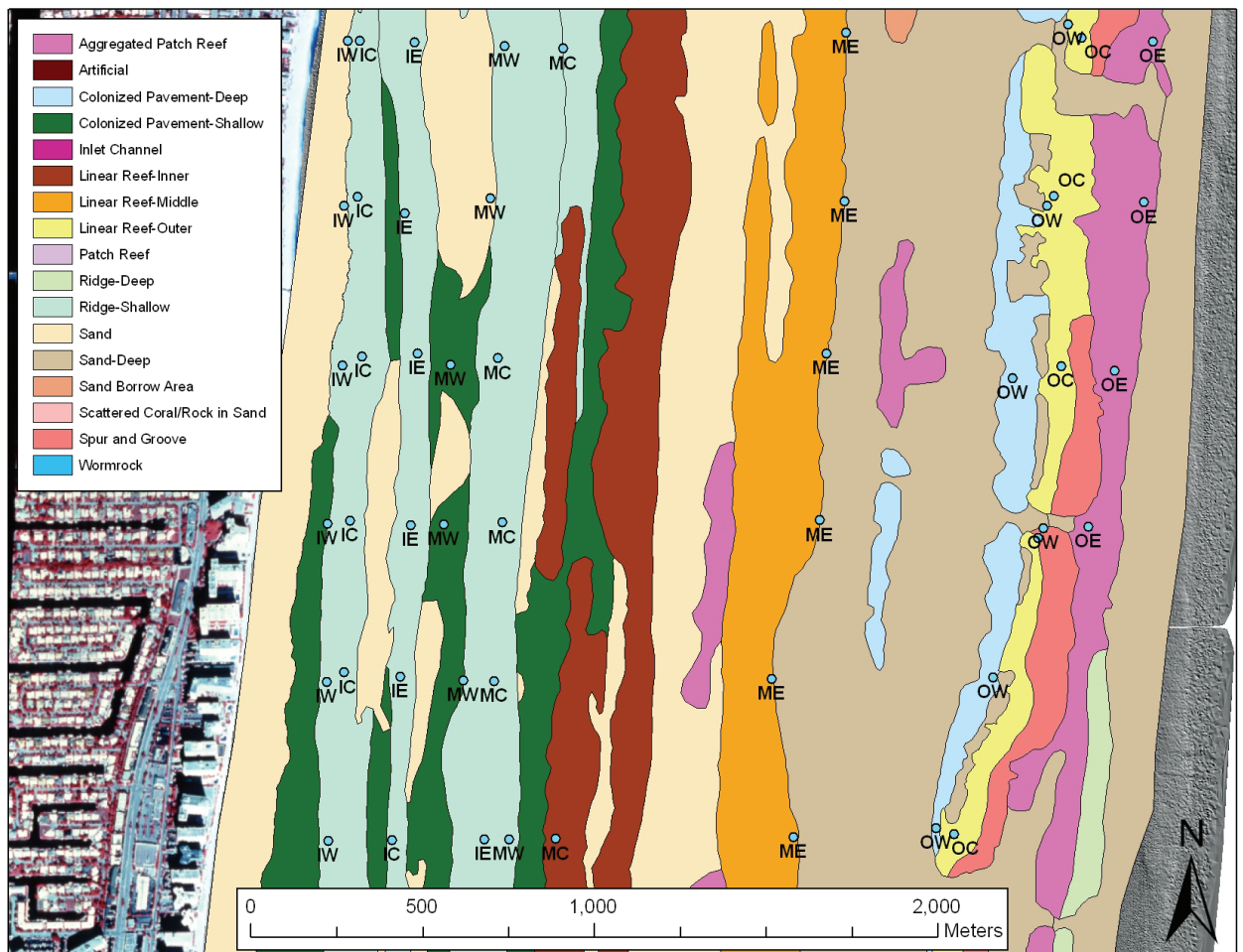


Figure 3.2.3. GIS image of the fish survey locations labeled by their original nomenclature (IW, IC, IE etc.) The Outer Reef sites were well placed, however the Middle Reef Crest and West sites were taken inshore of the Inner Reef proper (dark red) and the Inner Reef Sites were performed on the Shallow Ridges (Light green). This is a clear example of why GIS mapping is essential for accurate site characterization.

### **3.2.3 3-Dimensional Analyses in GIS**

The 3-Dimensional analyses were performed using ArcGIS 9.0 with the 3-D Analyst, Spatial Analyst, and Geostatistical Analyst extensions. This section discusses the methods for measuring the topographic variables in ArcGIS in detail. I have also included a protocol for extracting minimum (min) and maximum (max) elevation, surface area, and volume in ArcGIS in Section 3.2.3.1 giving step-by-step instructions on how to repeat the analysis.

The laser bathymetry points from the LADS survey described in section 2.2.2 of Part II were imported into ArcGIS as X/Y data (Fig 3.2.4). A triangulated irregular network (TIN) was created from the points to generate a three dimensional surface (Fig 3.2.5). The TIN is a surface interpolation model that represents a surface as a set of irregularly located points linked to form a network of triangles with z-values stored at the nodes. TINs allow calculations of measurements such as planimetric area, surface area, and volume; therefore they are commonly used for high-precision modeling of smaller areas (Booth 2000, Jenness 2004).



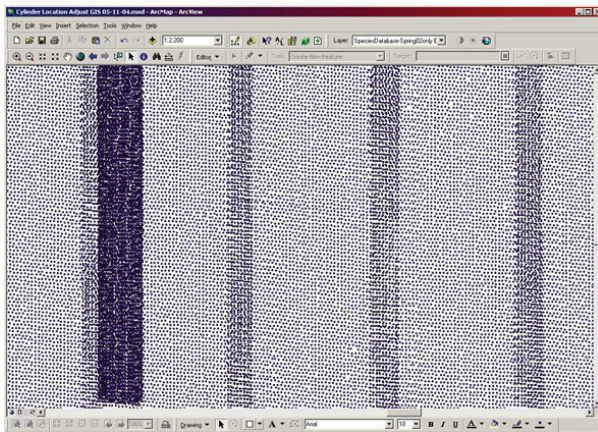


Figure 3.2.4. A screen shot of the imported bathymetric data in ArcGIS.

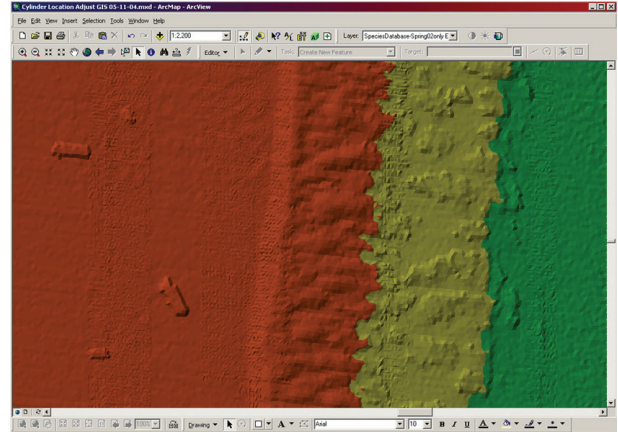


Figure 3.2.5. A screen shot of the TIN created by the imported bathymetric data in ArcGIS. Colors represent the depth of the TIN surface between gradients; Orange is the surface from 0 to 21 meters depth, Yellow is from 21 to 27 meters depth, and Green is 27+ meters depth.

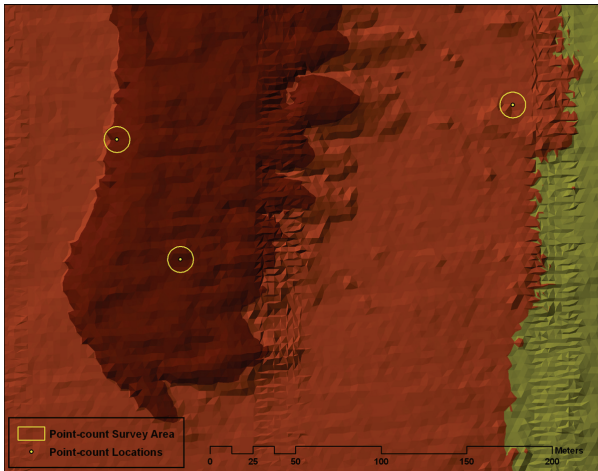


Figure 3.2.6. 7.5 meter buffers (yellow circles) were created around each fish survey to represent the survey area. Colors represent the depth of the TIN surface between gradients; Red is the surface from 0 to 19 meters depth, Orange is from 19 to 34 meters depth, and Green is 34+ meters depth.

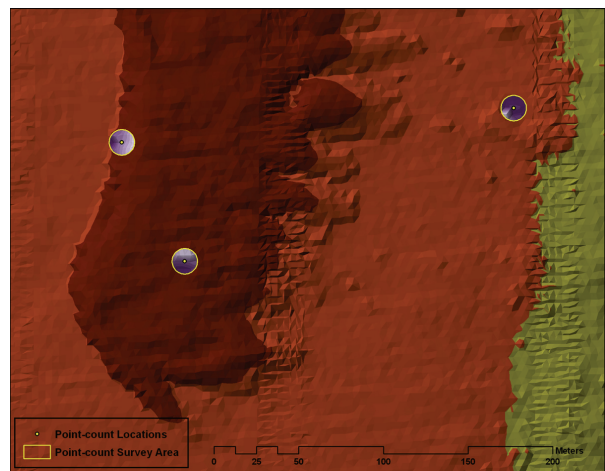


Figure 3.2.7. The buffers (yellow circles) were used to clip the data from the large TIN to create individual TINs for each survey (purple areas within circles). Colors represent the depth of the TIN surface between gradients; Red is the surface from 0 to 19 meters depth, Orange is from 19 to 34 meters depth, and Green is 34+ meters depth.



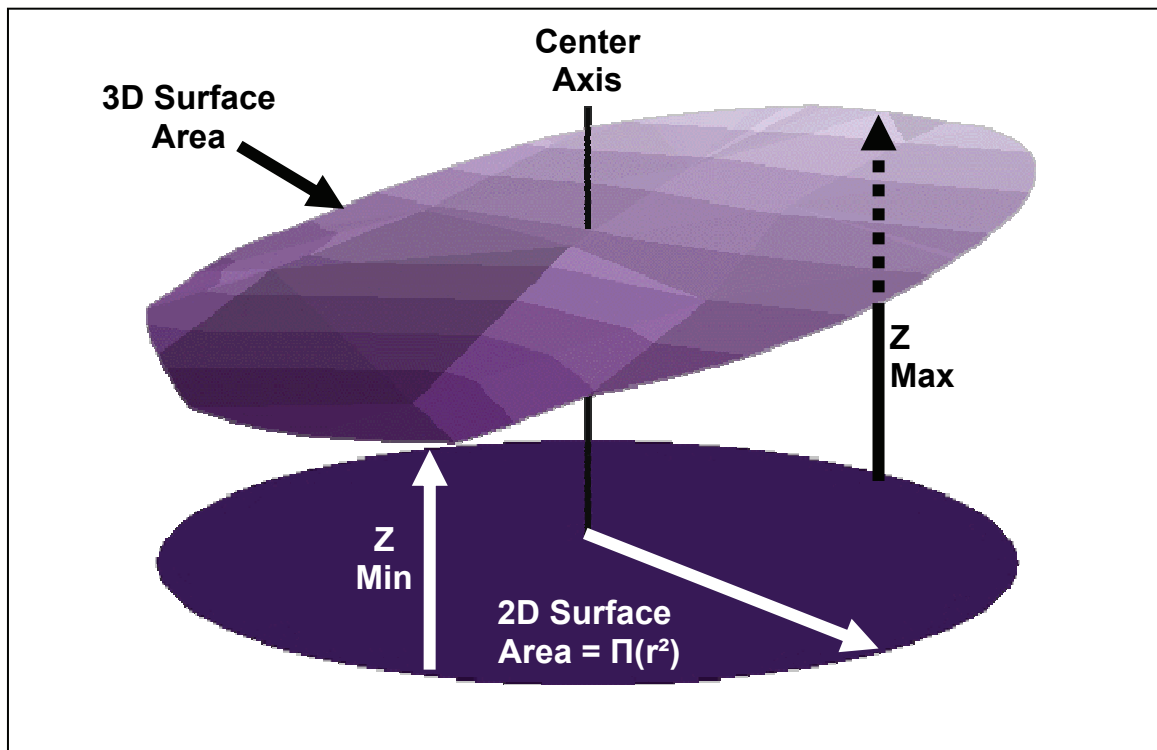


Figure 3.2.8. An example of the different measurements taken in 3D Analyst. The 3D area is an actual survey TIN and is spatially represented as the left-most survey in Fig.3.2.7.

The TIN of the LADS bathymetric survey area was clipped to a 7.5 m radius buffer around each of the DGPS located visual fish survey sites (Fig 3.2.6), converted to feature data, and converted back to individual TINs for each survey site (Fig 3.2.7).

The individual TINs were then analyzed in ArcGIS 3D Analyst for Z min, Z max, 2D area, 3D surface area, and volume (Fig 3.2.8). The depth of each survey was the minimum Z value (Z min) within the individual TIN. Z max, the maximum elevation within an individual survey, was used to calculate the maximum elevation for each survey area as the positive difference between Z min and Z max. The volume was measured by calculating the space between the 3D surface and a horizontal reference plane, which was always the Z min value. The 2D area was calculated as the area within the 7.5 m buffer. The 3D surface area was calculated by measuring the area of each triangle in the TIN along the slope of each triangle to account for the variations in height of the 3D surface. The surface rugosity index was calculated by dividing the surface area of the TIN by the planar area of the buffer.

Please note the linear rugosity measurement was an in situ measurement taken by the diver during the fish survey. This measurement was not acquired in the GIS analysis of the seafloor.

### **3.2.3.1 Protocol for Calculating Rugosity Index in GIS**

#### **Using TINs (with edge effects)**

1. Set map coordinate system to correspond with point count data.
2. Bring in Fish data as east/north with associated data in a dbf table as an event theme.
3. Look for erroneous GPS points and clean data accordingly.
4. Import cleaned point count data as a shapefile.
5. Use buffer tool to create 7.5m buffer shapefile around each point count.
6. Add X/Y bathy data (bathymetry dbf from Access DBF Export)
7. Export bathy data as shapefile and accept to add it to the map.
8. Create TIN of bathy data shapefile in 3D analyst.
9. In 3D analyst, Convert Features to 3D: Input Feature should be the buffer feature and source of heights should be the bathy data tin. Rename the Output your new buffer file with heights. (The output file only creates shapes of which both areas (TIN & Buffer) overlap)
10. In 3D Analyst, Create/Modify TIN/Add features to TIN. Select the new buffer file with heights, choose hard clip, Feature Z values as height source, and rename output file. This clips the TIN to every buffer feature.
11. Next is to create features from the clipped TINs: choose convert, TIN to Features. The input TIN is your newly created TIN of all clipped buffer features; Conversion is nodes to points (data nodes only). Rename output file the same as input but with “features” added on.
12. Select all data node features for a single point count.
13. Create TIN from Features of this subset, name the file the Point Count location. The new TIN should only contain depths within the range of the bathy data and should be a discrete TIN of a single survey.
14. Choose Area/Vol in Surface analysis.
15. Select the TIN, hit calculate stats, save stats file.
16. Add 2D and 3D stats from clipped TIN to Xcel and calculate index.

**Using ESRI grid (reduced edge effects)** - This method was discarded for the present study due to its inefficiency with regard to creation time and large computer storage space.

1. Follow steps 1-7 above.
2. Zoom to an individual survey buffer area.
3. Select a sufficient number of bathy points from around the AOI. Be sure that points have been selected outside of the buffer in every direction.

4. Create a TIN of the selected points: Create/Modify TIN-create TIN from features. Select the bathy data in the Layers window, Height source: Depth, Tag field value: Depth. And browse to name output file.
5. Now convert the small TIN to Raster: Convert-TIN to Raster. Input TIN should be the small one just created. Attribute: elevation. Z factor: 1. Cell size should be as low as possible. Too low will crash the program. Usually a cell size that yields over 4000 rows and columns is sufficient. Browse to name output grid file.
6. In Arc toolbox go to Spatial Analyst Tools-Extraction-Extract by circle.
7. Select the New ESRI grid as the raster image to be clipped.
8. Enter the Easting and Northing of the survey location in the X/Y and the radius of the extraction area in map units (24.60622 ft for the 7.5m point count radius). Browse to name the output file and select inside for extraction area.
9. Calculate surface area measurements: Surface Analysis- Area and Volume-calculate stats. Select save file to text and browse to rename file. Then select the calculate stats button to save the text file.
10. Use this raster to calculate slope in 3D analyst.

The latter method will take much longer and use up much more memory due to the size of the raster images created. Care must be taken to calculate the stats, back up and remove the rasters for storage.

### **3.2.4 Benthic Habitats**

Benthic habitats are described in Part II, Benthic Habitat Mapping. The habitats for each survey were defined by the GPS location of the survey in relation to the benthic habitat map in GIS. Upon initial review of the data it was apparent that the Middle Reef was comprised of two separate habitats (Figure 3.2.9). The data, illustrated in a categorized scatterplot below, showed a clear separation in the Middle Reef with regards to depth. This trend was evident for all topographic data plotted against depth for the Middle Reef. In GIS these sites were all associated with a shallow ridge on top of the Middle Reef in the extreme Northern extent of the county (Figure 3.2.10). The hillshaded LADS surface revealed the presence of a North-South shore-parallel ridge running approximately 6 Km along the Middle Reef north of Hillsboro Inlet. A depth profile of this feature further illustrated its distinction as a shallower feature. Because depth is one of the metrics in this analysis and two distinct areas appeared within one habitat, it was decided to separate the data accordingly. Therefore the Middle Reef habitat data were split into the Linear Reef-Middle and Linear Reef-Middle Shallow.

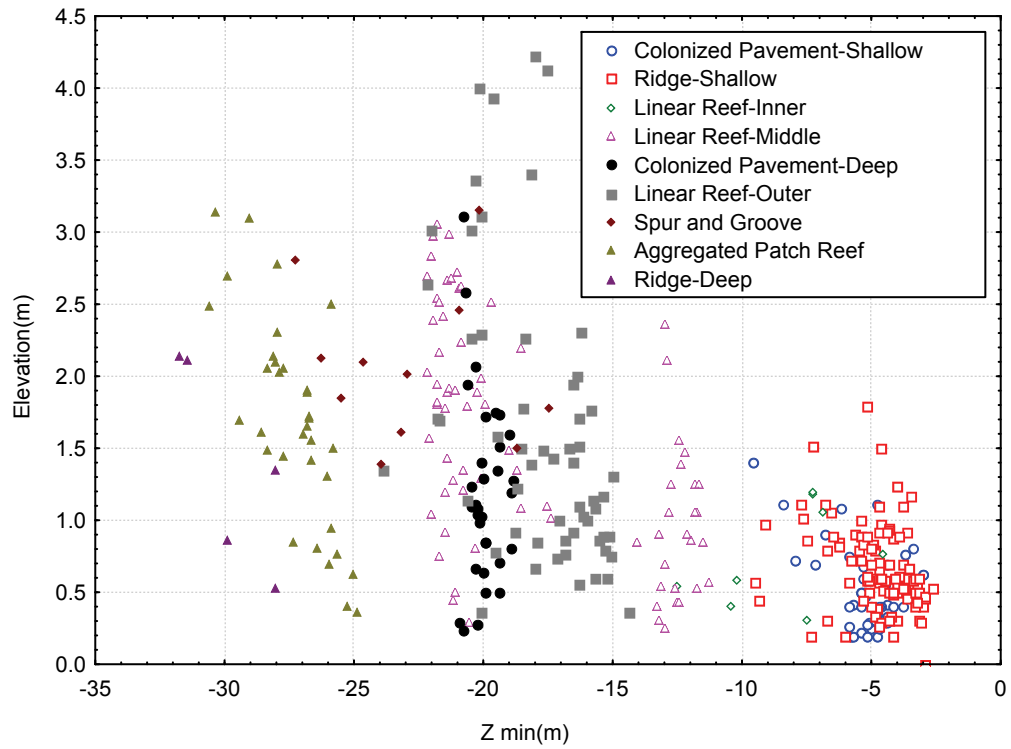


Figure 3.2.9. Scatterplot of LADS-derived elevation vs. depth (Z min) in meters within each fish survey. Data is categorized by their benthic habitat association. The Middle Reef data was concentrated in two depth regimes; 10-15m and 15-25m.

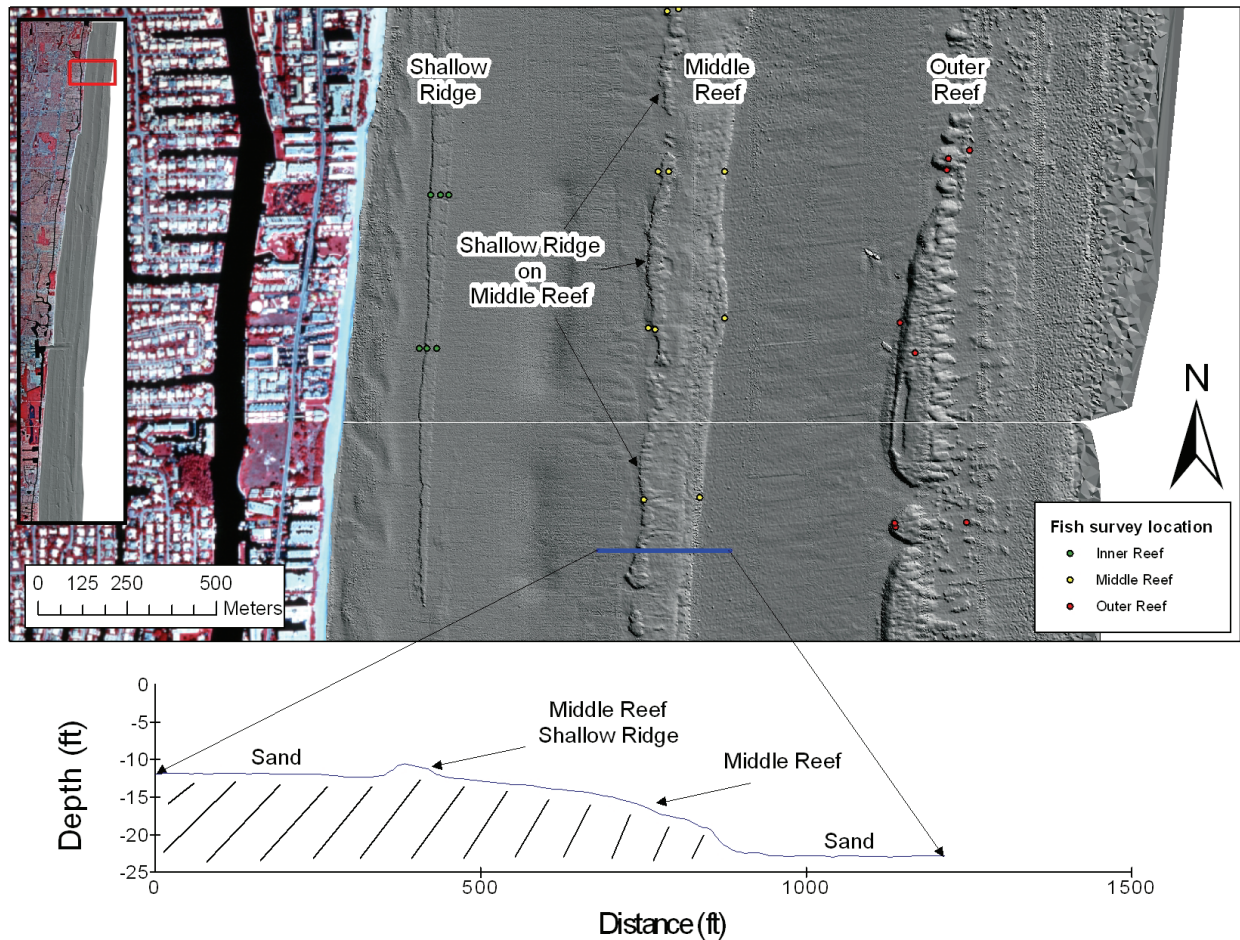


Figure 3.2.10. Illustration of the shallow ridge in GIS evinced by the depth scatterplot. The blue line in the graph represents the depth data under the blue line in the map. This profile illustrates a clear shallow hump along this transect where the ridge is present.

### 3.2.5 Data Analysis

The point-count visual fish survey data were entered into the Reef Visual Census (RVC) (Weinbuerger 1998) computer data entry system. This system was developed by the National Marine Fisheries Service in 1998 as a data entry system point-count visual reef fish survey data. The data were then exported as a spreadsheet and analyzed in Statistica 6.0 (Stat Soft Inc, Tulsa, OK). General one-way Analyses of Variance (ANOVAs) were performed and significance was delimited at the 0.05 alpha level (i.e.  $p < 0.05$ ). Student Newman-Keuls post-hoc tests were used to indicate significance. Letters were placed above each bar in the ANOVA graphs. Bars that were not significantly different below the 0.05 level had the same letter designation. Bars with different letters were significant at the 0.05 level.

Scatterplots were used to understand the relationship between variables. Scatterplots were calculated in Statistica 6.0 and an  $r^2$  value for each was given for a best-fit linear regression line. The scatterplot data were categorized according to the benthic habitat in which the survey was conducted. The fish data versus GIS data analyses included additional separate categorized scatterplots which broke out each benthic habitat category into its own graph. This was used to illustrate the difference in slope of the linear regression line between habitats.

### **3.3 Results**

#### **3.3.1 Topographic metric between reefs and reef sites**

The following are graphs of the results of the Analysis of Variance (ANOVA) between the different GIS measured variables (Depth, Elevation, Volume, and Surface Rugosity), in situ measurements (Linear Rugosity) and the Reefs and Reef Sites (see section 3.2.1). Student Newman-Keuls post-hoc test results are noted as letters above the bars. Different letters above the bars indicate significance ( $p < 0.05$ ). Scatterplots categorized by benthic habitat are also included to show the distribution of the data.

##### **3.3.1.1 Depth per Reef and Reef Site**

The reefs off Broward County, FL are sequentially deeper with the exception of the Inshore Ridges (IR) and the Inner Reef (I). The mean maximum depth (Z min) of the combined survey sites along each reef tract (Inner, Middle and Outer) varied significantly from each other ( $p < 0.05$ ) (Fig. 3.3.1a). The mean depth of all the inshore reef surveys was -5.35m, the mean middle reef survey depth was -18.0m, and the mean offshore reef survey depth was -21.42m.

There were also depth differences between reef sites, the survey orientations within each reef tract (Eastern edge, Crest, and Western edge) (Fig. 3.3.1b). The Inshore Ridge (IR) and Inner Reef sites were mostly similar with the exception of the Inshore Ridge Eastern edge ( $p < 0.05$ ). The Middle West (MW) and Middle Crest (MC) sites were not significantly different from each other ( $p > 0.05$ ) but were significant ( $p < 0.05$ ) from all others as were the Middle East (ME) and Outer West sites. The Outer Crest (OC) and Outer East (OE) sites were significant from all others.

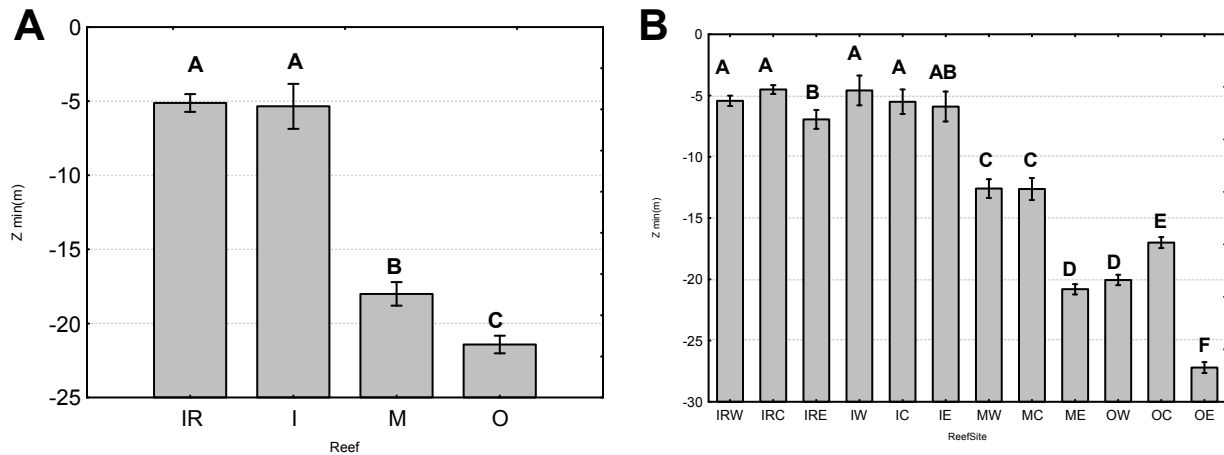


Figure 3.3.1. A) Mean max depth (m) of all fish survey areas by reef tracts: Inshore Ridges (IR), Inner Reef (I), Middle Reef (M), and Outer Reef (O). B) Mean max depth (m) of all fish survey areas by reef sites: W, C, and E in x axis labels refers to site orientation on the reef. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

### 3.3.1.2 Elevation per Reef and Reef Site

Mean elevation (the positive difference between the minimum and maximum depths within a 7.5 radius area of each fish survey location) significantly differed between the shallow reefs and the deep reefs (Fig. 3.3.2a). Significantly higher mean elevations ( $p < 0.05$ ) were noted on the outer and middle reef sites, 1.57m and 1.53m respectively, than the inner reef (0.75m) and inshore ridges (0.62m). Mean elevation among reef sites exhibited significant differences between the shallower and deeper sites (Fig. 3.3.2b). The main difference was between the three deepest reef sites, Middle East (ME), Outer West (OW), and Outer East (OE), and all other reef sites ( $p < 0.05$ ). Reef elevation increased with increasing depth (Fig. 3.3.2c). Z min is a negative elevation value which equates to depth (a decreasing Z min value is an increasing depth value). Most of the low elevation values were concentrated in the shallower depths, however a wide range of elevation values were observed between 17 and 23 m depth. This wide range probably accounts for the low  $r^2$  (.38). The categorized scatter plot identifies the benthic habitat of each data point from the GIS. The elevation in the shallower habitats like the shallow ridge (red squares) and colonized pavement (blue circles) were lower than the elevations in deep habitats like the outer reef (grey squares).



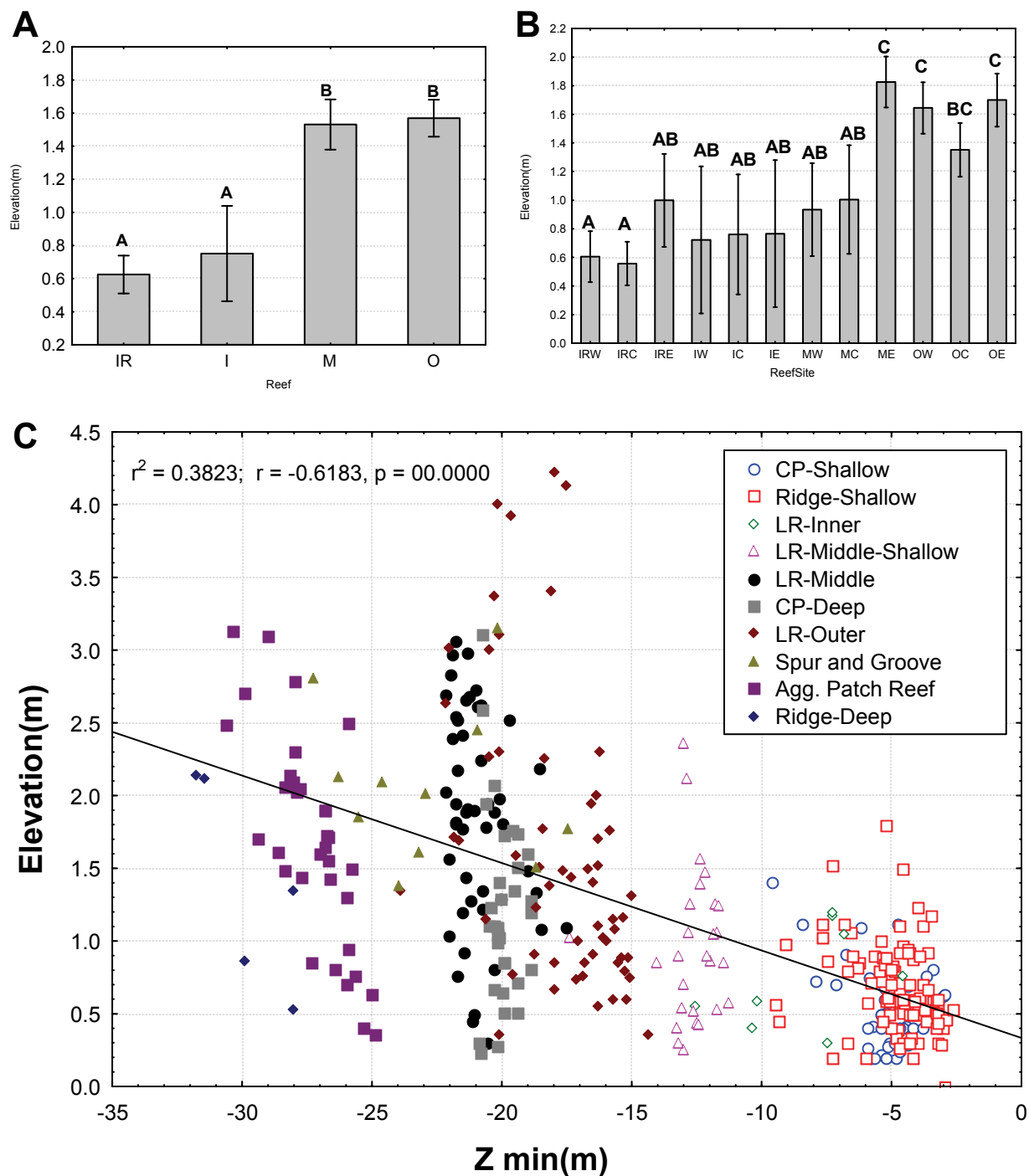


Figure 3.3.2. A) Mean elevation (m) of all fish survey areas by reef tracts: Inshore Ridges (IR), Inner Reef (I), Middle Reef (M), and Outer Reef (O). B) Mean elevation (m) of all fish survey areas by reef sites: W, C, and E in x axis labels refer to site orientation on the reef. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. C) Categorized scatterplot of elevation vs. depth (Z min) in meters by benthic habitats. Black line represents the best fit linear regression.

### **3.3.1.3 Volume per Reef and Reef Site**

Similar to elevation, mean reef volume of the fish survey sites on the Inshore Ridge and Inner Reef were significantly lower than the Middle Reef and Outer Reef ( $p < 0.05$ ) (Fig. 3.3.3a). Differences in mean reef volume among reef sites were less notable, however, volumes of the Middle East and Offshore Crest were significantly greater than those of the Inshore Ridge West and Crest and Inner Reef East ( $p < 0.05$ ) (Fig. 3.3.3b). Although not significant due to high heteroscedasticity, a general trend of increasing reef volume from the Inshore Ridges to the Outer Reef was evident. Reef volume also increased with increasing depth ( $r^2 = .24$ ) (Fig. 3.3.3c). A large concentration of low volume data points can be seen in the fish surveys conducted in the shallowest depths around -4m. The habitats most associated with these points are the shallow ridge and shallow colonized pavements. The low volume survey sites are less frequent in the deeper water. Reef volume was highly variable in the outer reef sites (17 to 23m depth range from), similar to elevation. The counts in shallow habitats had much less reef volume than deeper habitats.

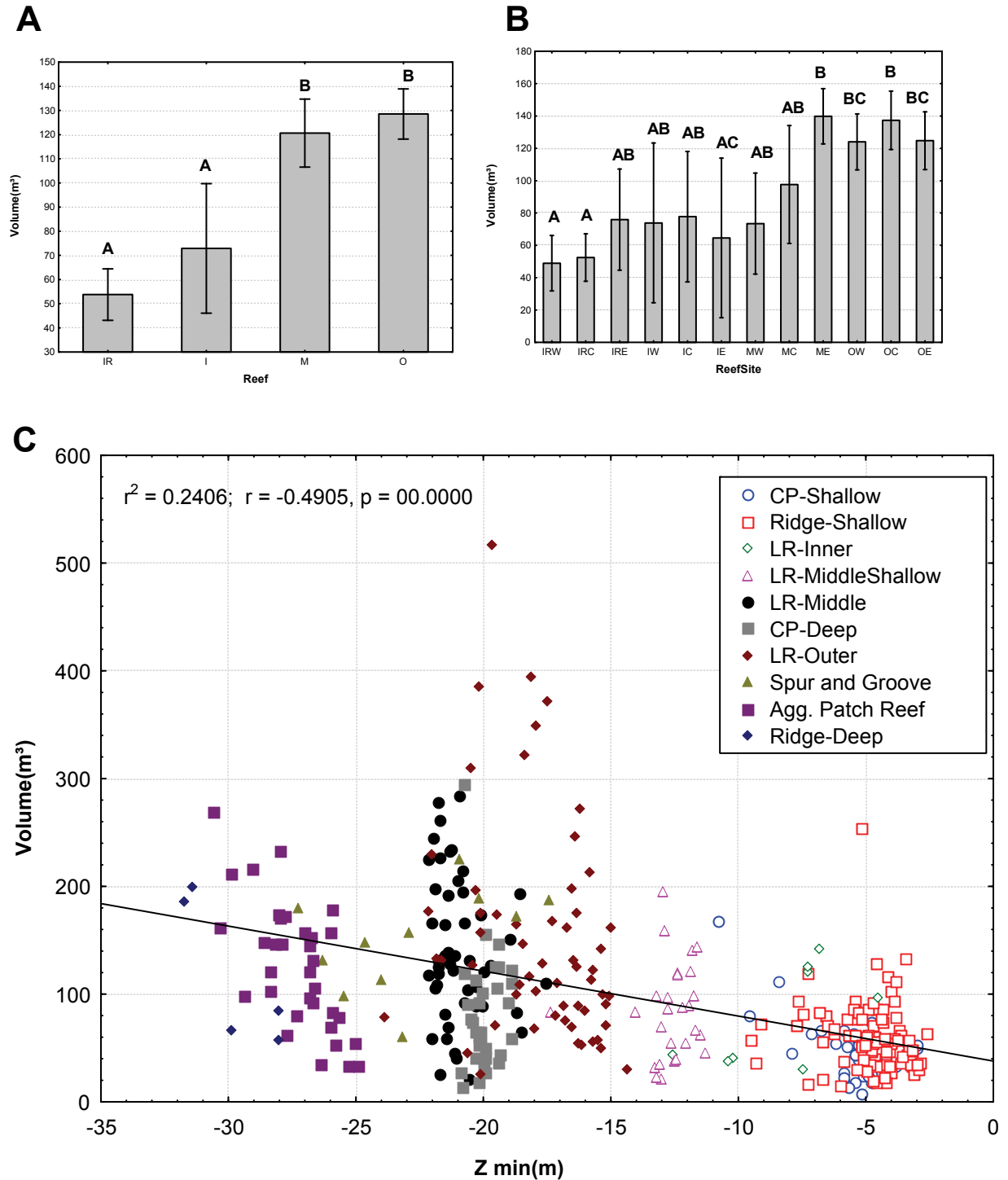


Figure 3.3.3. A) Mean reef volume (m³) of all fish survey areas by reef tracts: Inshore Ridges (IR), Inner Reef (I), Middle Reef (M), and Outer Reef (O). B) Mean reef volume (m³) of all fish survey areas by reef sites: W, C, and E in x axis labels refer to site orientation on the reef. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. C) Categorized scatterplot of reef volume vs. depth (Z min) in meters by benthic habitats. Black line represents the best fit linear regression.

#### **3.3.1.4 Linear Rugosity per Reef and Reef Site**

Mean Inner Reef *in situ* linear rugosity indices exhibited significantly lower values ( $p < 0.05$ ) than the Inshore Ridge, the Middle Reef and the Outer Reef, yet these three did not significantly differ from each other ( $p > 0.05$ ) (Fig. 3.3.4a). The mean linear rugosity among the Outer Reef East sites was significantly higher than all of the Inner Reef sites ( $p < 0.05$ ), but none other (Fig. 3.3.4b). The Middle West mean linear rugosity was significantly greater than the Inner Reef East sites ( $p < 0.05$ ). No clear trends were evident from these data. The linear rugosity index doesn't exhibit much of a relationship with depth (Fig. 3.3.4c). The low  $r^2$  value (0.04) indicates that there is no relationship. The variability in the shallow habitats is nearly as high as the deeper ones.

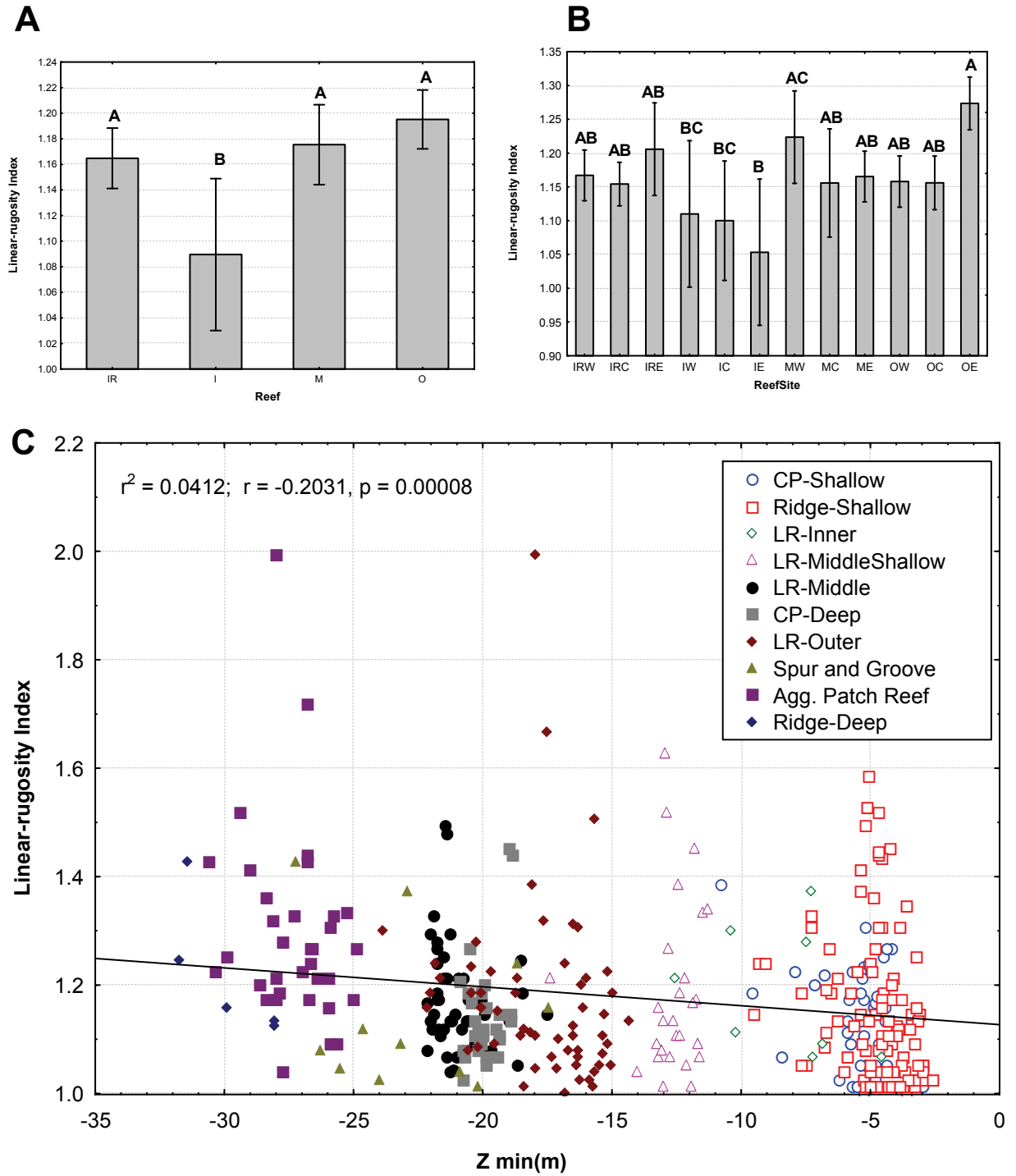


Figure 3.3.4. A) Mean *in situ* linear-roughness indices of all fish survey areas by reef tracts. B) Mean linear-roughness indices of all fish survey areas by reef sites. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. C) Categorized scatterplot of linear roughness indices vs. depth (Z min) in meters by benthic habitats. Black line represents the best fit linear regression.

### **3.3.1.5 Surface Rugosity per Reef and Reef Site**

Surface rugosity indices significantly differed between Reefs. Indices at the Inshore Ridge and Inner Reef sites were significantly smaller than those of the Middle and Outer Reefs ( $p < 0.05$ ) (Fig. 3.3.5a). Neither the Inshore Ridge and Inner Reef nor the Middle and Outer Reefs statistically differed from each other. A trend similar to reef volume was evident with increasing surface rugosity from the Inshore Ridges to the Outer Reef, however variability about the mean was very high (Fig. 3.3.5b). The Outer Reef East Reef Site was significantly greater than the Inshore Ridge Sites, the Inner Reef Sites, and the Middle West and Crest Sites ( $p < 0.05$ ). The surface rugosity index shows a slight positive increase in rugosity with increasing depth (Fig. 3.3.5c). All of the shallow habitat sites contained much lower rugosity than deeper sites. The outer reef and aggregated patch reef habitats had the most extreme surface rugosity values.

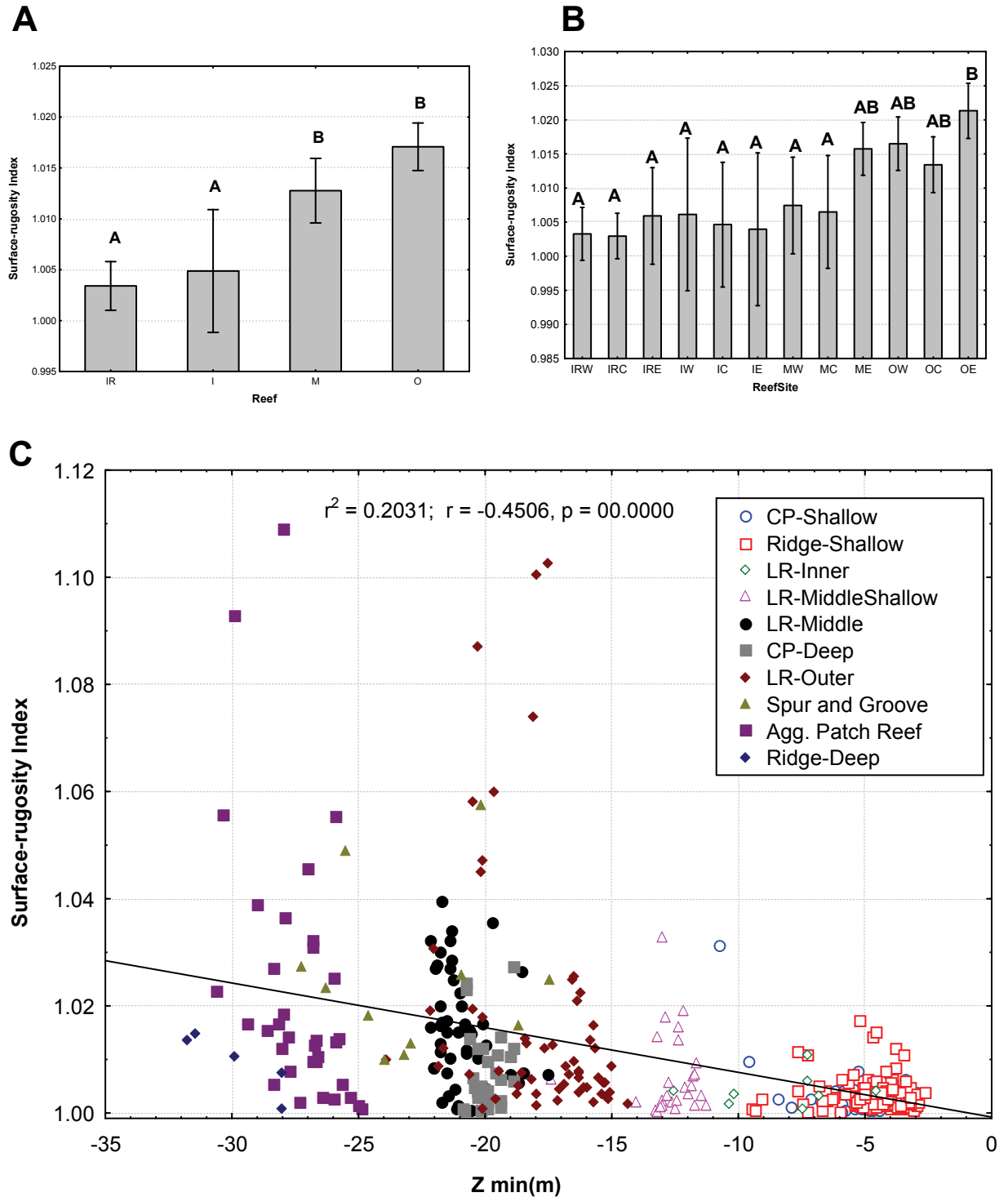


Figure 3.3.5. A) Mean surface-roughness indices of all fish survey areas by reef tracts. B) Mean surface-roughness indices of all fish survey areas by reef sites. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. C) Categorized scatterplot of Surface-roughness vs. depth (Z min) in meters by benthic habitats. Black line represents the best fit linear regression.



### 3.3.2 Fish Assemblage Analyses

The 370 point-count visual reef fish assessments used from Ferro et al. (2005) in this study yielded 52,680 total fish of 194 different species from 51 families. The following are the statistical results between total reef fish abundance and the different GIS measured variables (Depth, Elevation, Volume, and Surface Rugosity), *in situ* measurements (Linear Rugosity), and the Reefs and Reef Sites. The continuous variables were binned into groups in order to be analyzed categorically. Decisions on bin size depended on the histogram distribution of each variable. Student Newman-Keuls post-hoc test results are noted as letters above the bars. Different letters above the bars indicates significance ( $p < 0.05$ ).

#### 3.3.2.1 Abundance

Mean reef fish abundance between reefs showed a stepwise increasing trend from lowest on the Inshore Ridge to highest on the Outer Reef (Fig. 3.3.6). The Inshore Ridge ( $\bar{x}=72.6$ ) was significantly lower in abundance than the Middle ( $\bar{x}=144.7$ ) and Outer Reefs ( $\bar{x}=162.3$ ) ( $p > 0.05$ ) and the Inner Reef ( $\bar{x}=110.8$ ), not significantly different from the Inshore ridges and Middle Reef due to high heteroscedasticity, was significantly lower than the Outer Reef ( $p > 0.05$ ). No clear trends were evident for the mean fish abundance between Reef Site ANOVA (Fig. 3.3.6). High variability among Reefs Sites limited most differences between them, however the Outer Reef Crest and Middle Reef West reef fish abundance were significantly greater than all of the Inshore Ridges and the Inner Reef East ( $p < 0.05$ ).

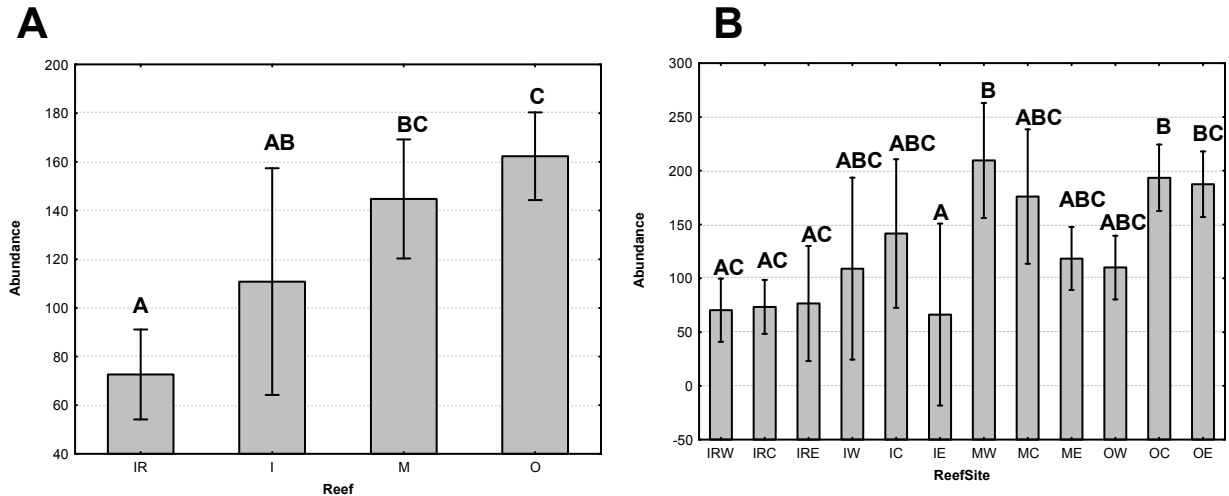


Figure 3.3.6. A) Mean reef fish abundance of all visual surveys by Reef. B) Mean reef fish abundance of all visual surveys by Reef Sites. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

### 3.3.2.1.1 Depth

Significant differences of mean reef fish abundance were noted between different depth ranges (Fig. 3.3.7a). The 0-5m and 5-10m ranges contained significantly less fish than the 10-15m, the 15-20m, and the 25-30m surveys. Abundance in the 20-25m depth range was significantly greater than the 0-5m range and significantly less than the 10-15m, the 15-20m, and the 25-32m ranges ( $p < 0.05$ ). The scatterplot did not show a clear relationship with depth (Fig. 3.3.7b). Although the regression line was slightly positive, the low  $r^2$  (0.08) indicated that there was no clear trend. High and low abundances of reef fish were found in surveys spanning many depths from around -2m to -33m. Many of the benthic habitats had highly variable reef fish abundances, ranging from near 0 to >700.

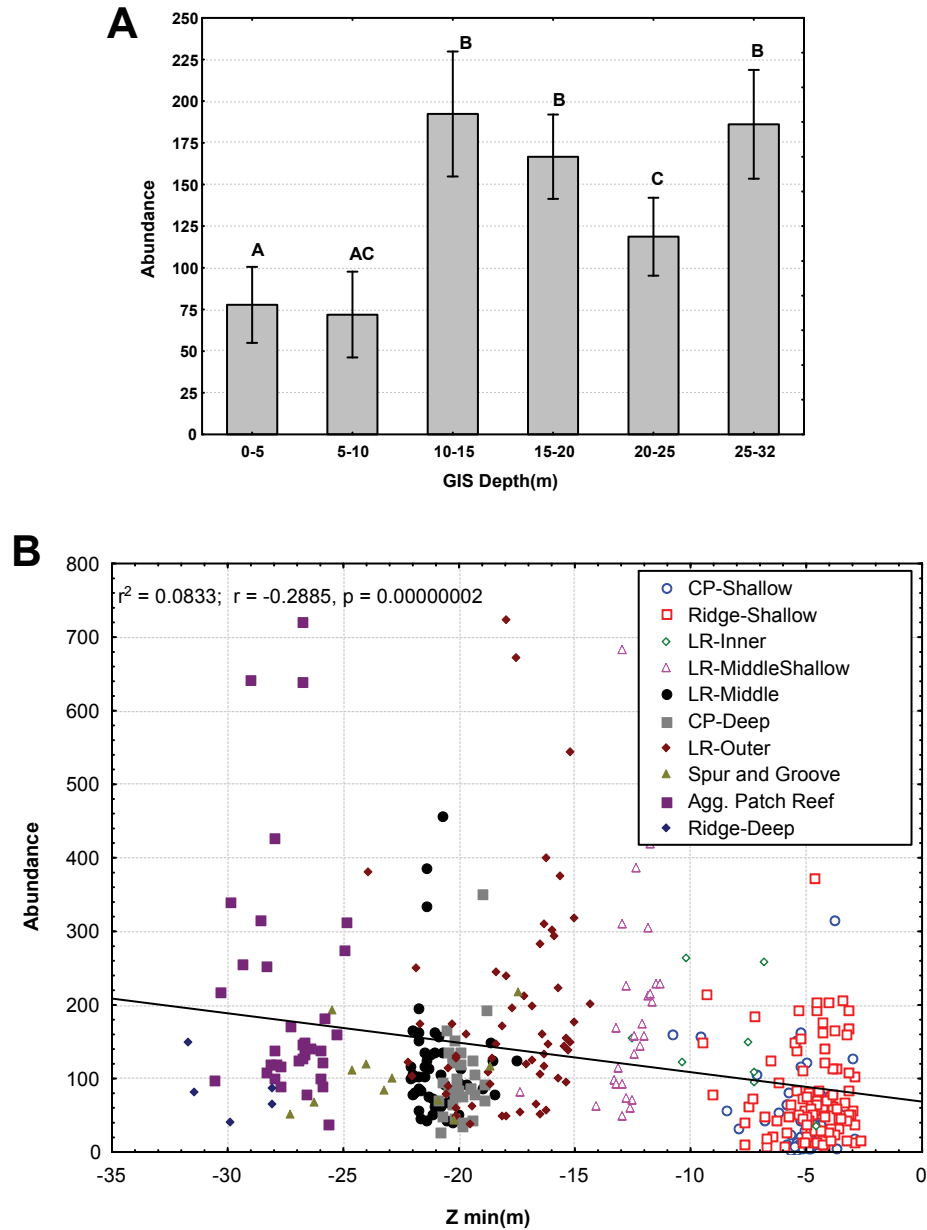


Figure 3.3.7. A) Mean reef fish abundance of all visual surveys by maximum Depth within the survey area. ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of reef fish abundance vs. depth (Z min) in meters by benthic habitat. Black line represents the best fit linear regression.

### 3.3.2.1.2 Elevation

Reef fish abundance exhibited a stepwise increasing trend from low to high reef elevation, however, only the highest elevation class was significantly higher than any other class ( $p < 0.05$ ) (Fig. 3.3.8a). The upward trend in mean abundance per elevation class, although not significant, was especially evident from the 0-0.5m class to the 1.5-

2.0m class. The 2.0-2.5m class to the 3.5-4.0m class mean abundance was very similar. The scatterplot showed slight correlation with the maximum elevation within the survey sites (Fig 3.3.8b). There was a positive relationship between the two variables ( $r^2=0.14$ ), however high and low abundances were evident throughout the entire range of elevations. The shallow benthic habitats, ridge and colonized pavement, were almost exclusively lower abundance and lower elevation with few exceptions whereas the deeper habitats were highly variable. The relationship between abundance and elevation changes between benthic habitats (Fig 3.3.9). The slope of the regression line changes from a positive relationship on the shallow habitats (Shallow CP, Shallow Ridge, and Shallow MR) to no relationship in the deeper ones (Middle Reef through Deep Ridge). The inner reef, spur and groove, and deep ridge habitats did not have enough samples to justify the relationship between variables and will not be discussed in this analysis.

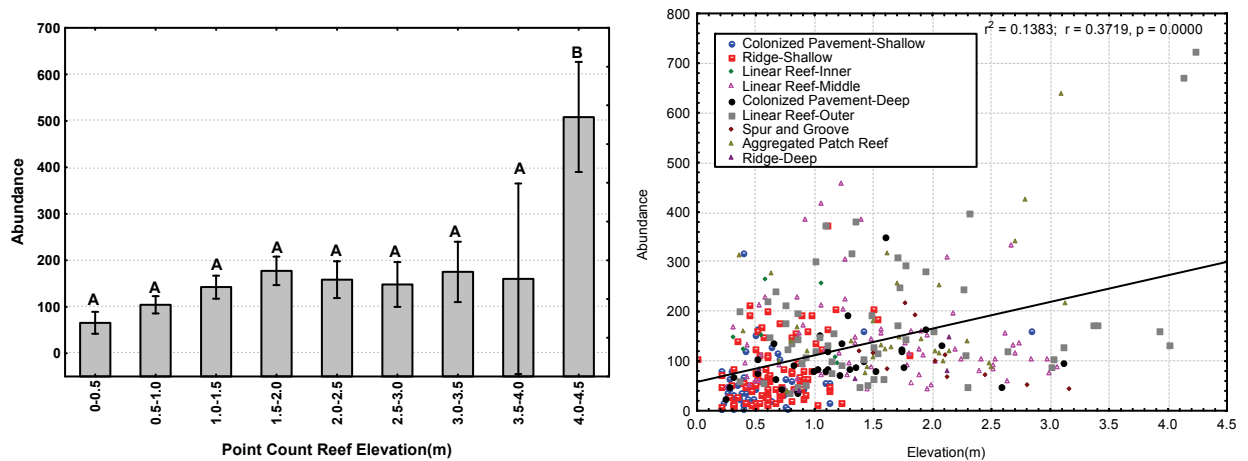


Figure 3.3.8. A) Mean reef fish abundance of all visual surveys by Elevation. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of abundance vs. elevation in meters by benthic habitat. Black line represents the best fit linear regression.

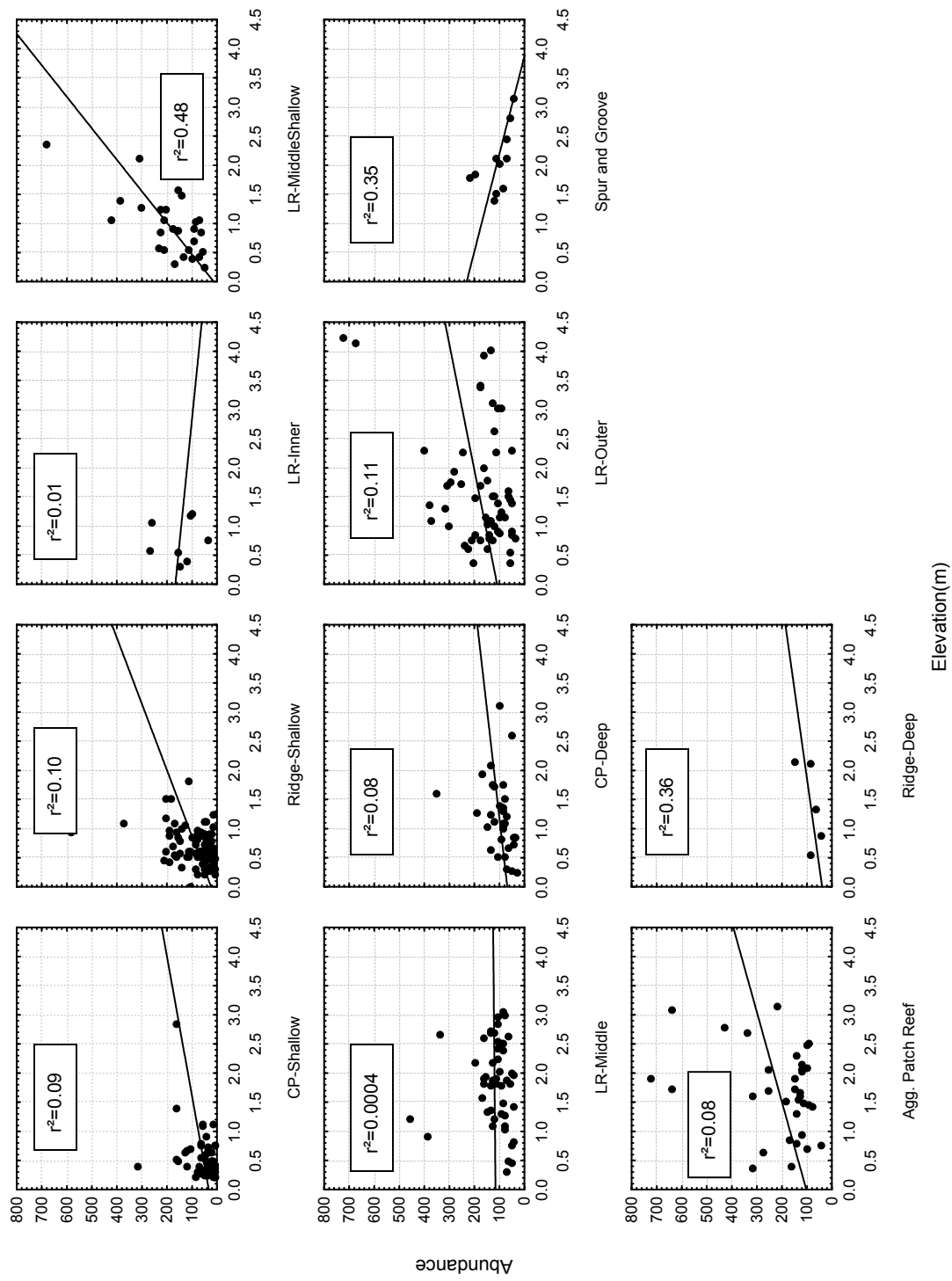


Figure 3.3.9. Categorized scatterplot of elevation (x-axis) and abundance (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect elevation has on abundance within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.2.1.3 Volume

Similar to Elevation, an increasing stepwise trend was evident in reef fish abundance by volume classes (Fig. 3.3.10a). Though not significant, an increasing trend from the lowest volume class (0-35m<sup>3</sup>) to a moderately high class (142-168m<sup>3</sup>) in abundance was clear. After the 142-168m<sup>3</sup> class, mean fish abundance grossly fluctuated. Only fish abundance of the 300-400m<sup>3</sup> volume class was significantly higher than any other class ( $p < 0.05$ ). The scatterplot shows this weak relationship as well ( $r^2 = 0.14$ ) (Fig. 3.3.10b). High and low abundances were evident throughout the range of reef volume measurements. High variation in abundance and volume were also noted throughout the different habitat types, although the shallow habitat sites consisted of lower volume and lower abundances than the other habitats. The shallow habitats showed a stronger positive relationship with abundance and volume than the deeper habitats (Fig. 3.3.11). The shallow middle reef had the strongest positive relationship ( $r^2 = 0.47$ ). The slope of the regression line flattens in the deeper habitats.

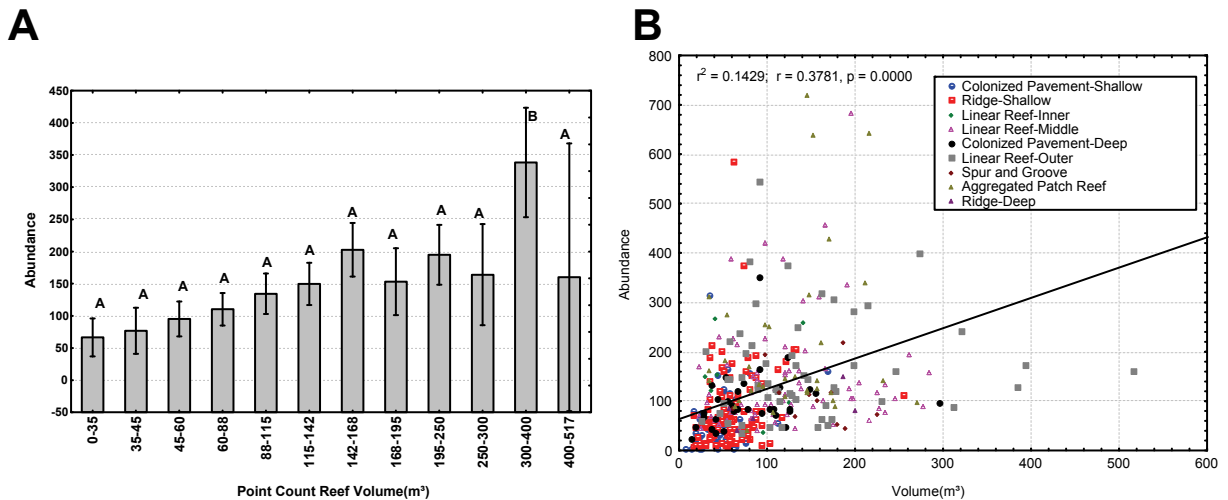


Figure 3.3.10. A) Mean reef fish abundance of all visual surveys by Volume. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of abundance vs. reef volume (m<sup>3</sup>) by benthic habitats. Black line represents the best fit linear regression.

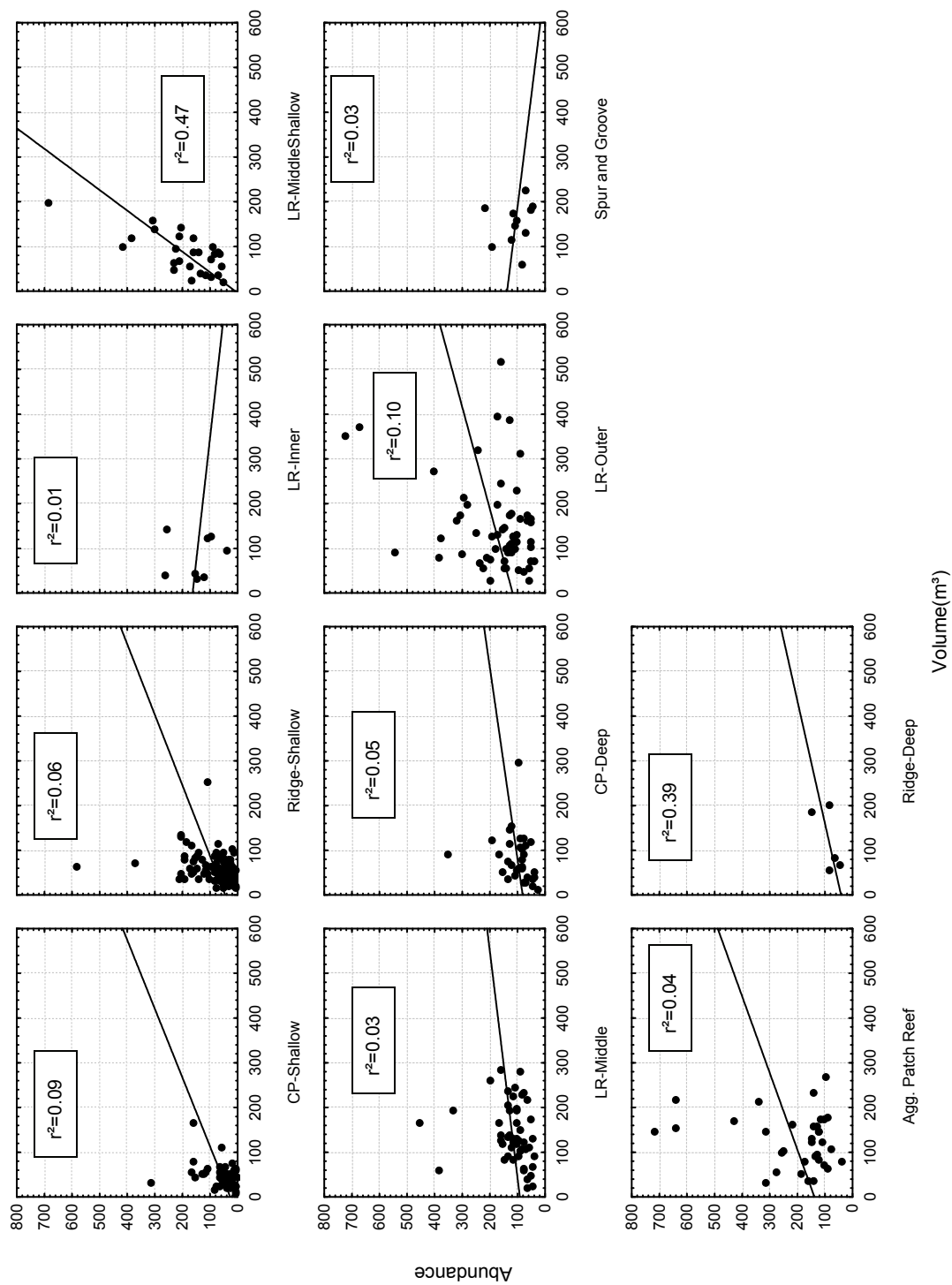


Figure 3.3.11. Categorized scatterplot of reef volume (x-axis) and abundance (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect volume has on abundance within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.



### 3.3.2.1.4 Surface Rugosity

The ANOVA of reef fish abundance with binned surface rugosity index values showed again an increasing stepwise trend without significance for the four lowest classes (Fig. 3.3.12a). The two highest surface rugosity index bins contained significantly more reef fish than any other class except with each other ( $p < 0.05$ ). The scatterplot showed that abundance increased with increasing surface-rugosity ( $r^2 = 0.17$ ) (Fig. 3.3.12b). High and low abundances were found throughout the range of surface-rugosity measurements. Although a wide range of abundances were found in the shallow habitats, most of the data were constrained by abundances  $< 200$  and surface-rugosity  $< 1.01$ . The strongest correlation between abundance and surface-rugosity was in the shallow middle reef habitat ( $r^2 = 0.48$ ) (Fig. 3.3.13). The slope of the regression line from the shallow habitats to the deep ones flattened although many of these were statistically weak ( $r^2 = 0.10$ ). The outer reef had a positive increase in abundance with increasing surface-rugosity ( $r^2 = 0.20$ ), but the variation was high.

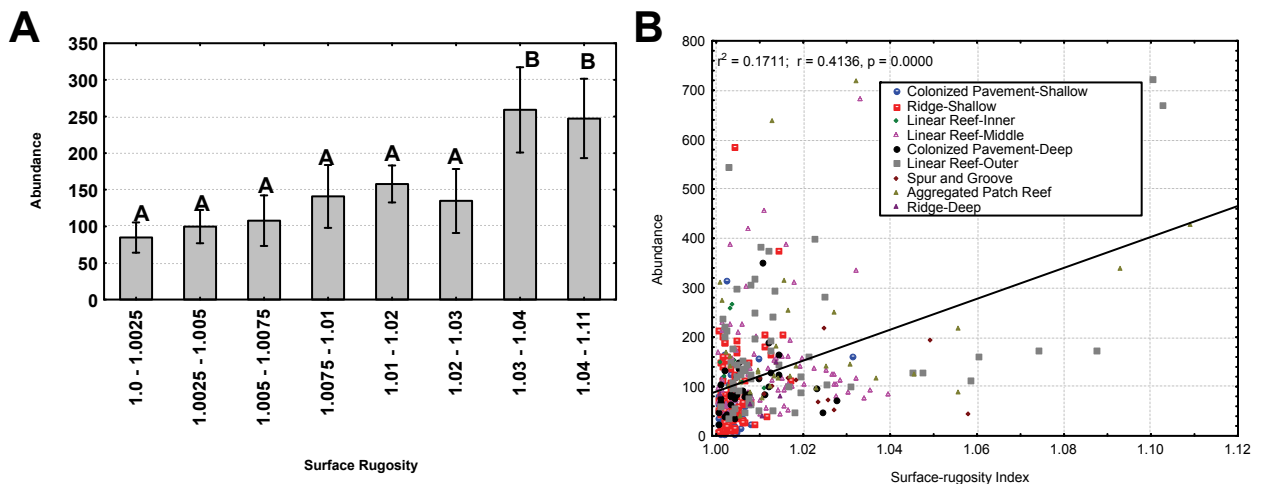


Figure 3.3.12. A) Mean reef fish abundance of all visual surveys by Surface Rugosity. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of surface-rugosity vs. abundance by benthic habitat. Black line represents the best fit linear regression.

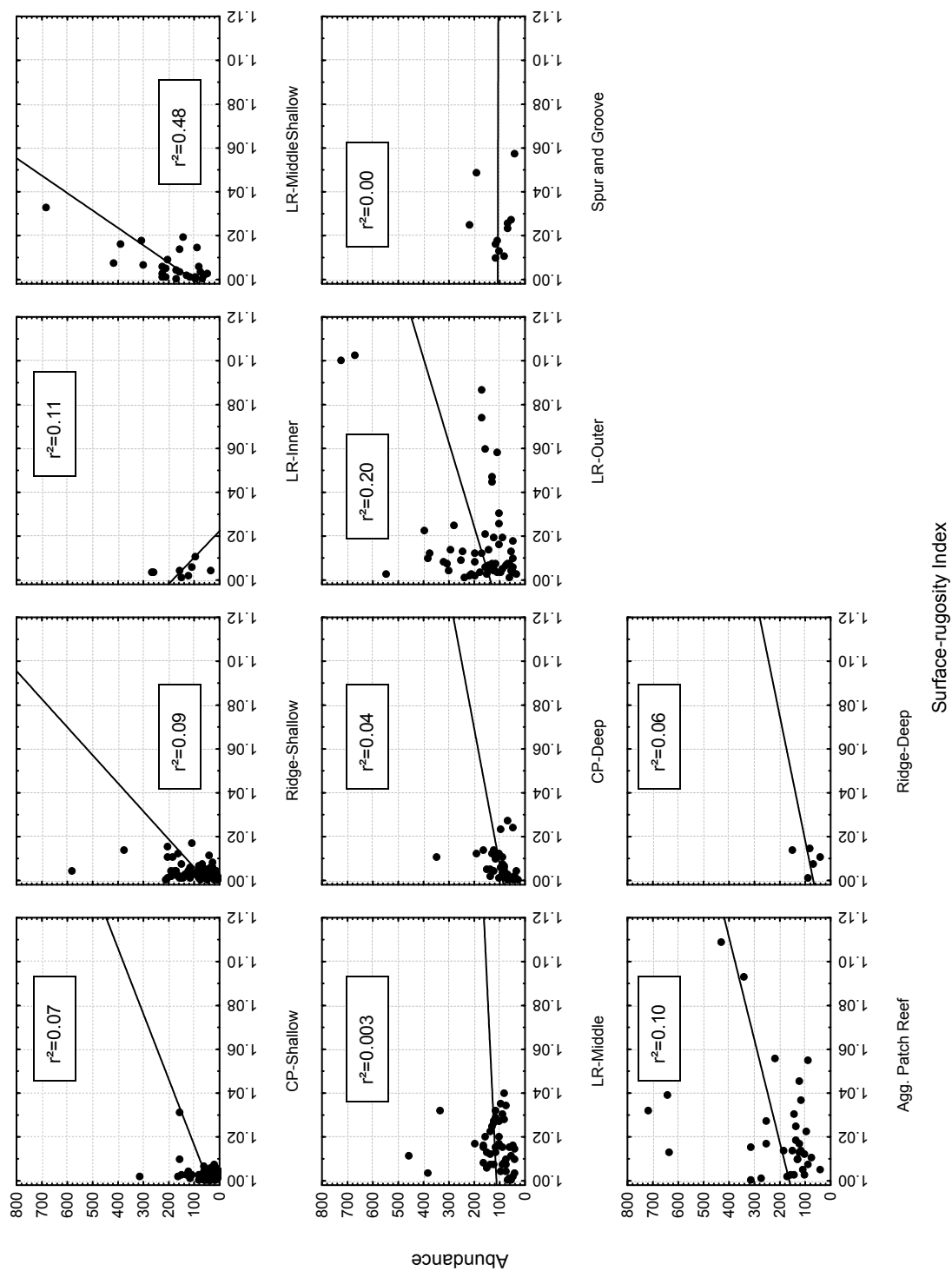


Figure 3.3.1.3. Categorized scatterplot of surface-roughness (x-axis) and abundance (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect surface-roughness has on abundance within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.2.1.5 Linear Rugosity

The ANOVA of reef fish abundance with the *in situ* linear rugosity index bins exhibited more significance between classes (Fig. 3.3.14a). The increasing stepwise trend of abundance from low values (1.0) to high values (2.0) was evident, with significance between several increasingly higher groups. The 1.3-1.4 class was significantly higher in abundance than the three lowest classes and 1.4-2.0 class was significantly greater than all other classes ( $p < 0.05$ ). This was also evident in the scatterplot ( $r^2 = 0.28$ ) (Fig. 3.3.14b). Abundance in the lower linear-rugosity range ( $< 1.1$ ) was highly variable, but did not exceed 300 whereas the abundance in the upper range ( $> 1.6$ ) was very high ( $> 400$ ). This positive relationship was noted throughout most of the habitats (Fig. 3.3.15) and was strongest in the outer reef ( $r^2 = 0.53$ ) and colonized pavement ( $r^2 = 0.52$ ) habitats. The shallow middle reef ( $r^2 = 0.41$ ), middle reef ( $r^2 = 0.29$ ), and aggregated patch reefs ( $r^2 = 0.23$ ) showed strong positive relationships between abundance and linear-rugosity as well. The shallow habitats, shallow colonized pavement ( $r^2 = 0.08$ ) and shallow ridges ( $r^2 = 0.11$ ), exhibited a weaker relationship as evidenced by the less steeply sloped regression line.

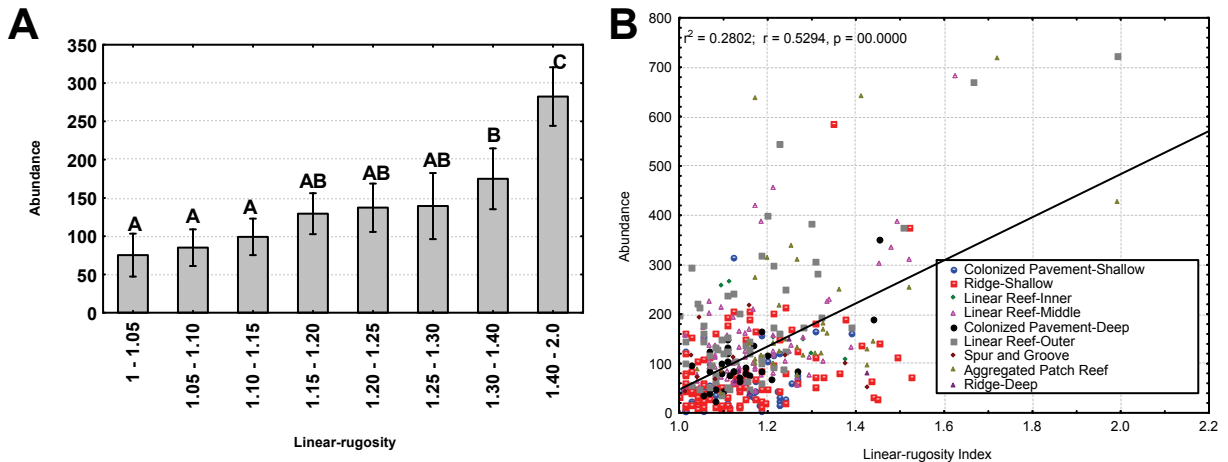


Figure 3.3.14. A) Mean reef fish abundance of all visual surveys by Linear Rugosity. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of linear-rugosity vs. abundance by benthic habitats. Black line represents the best fit linear regression.

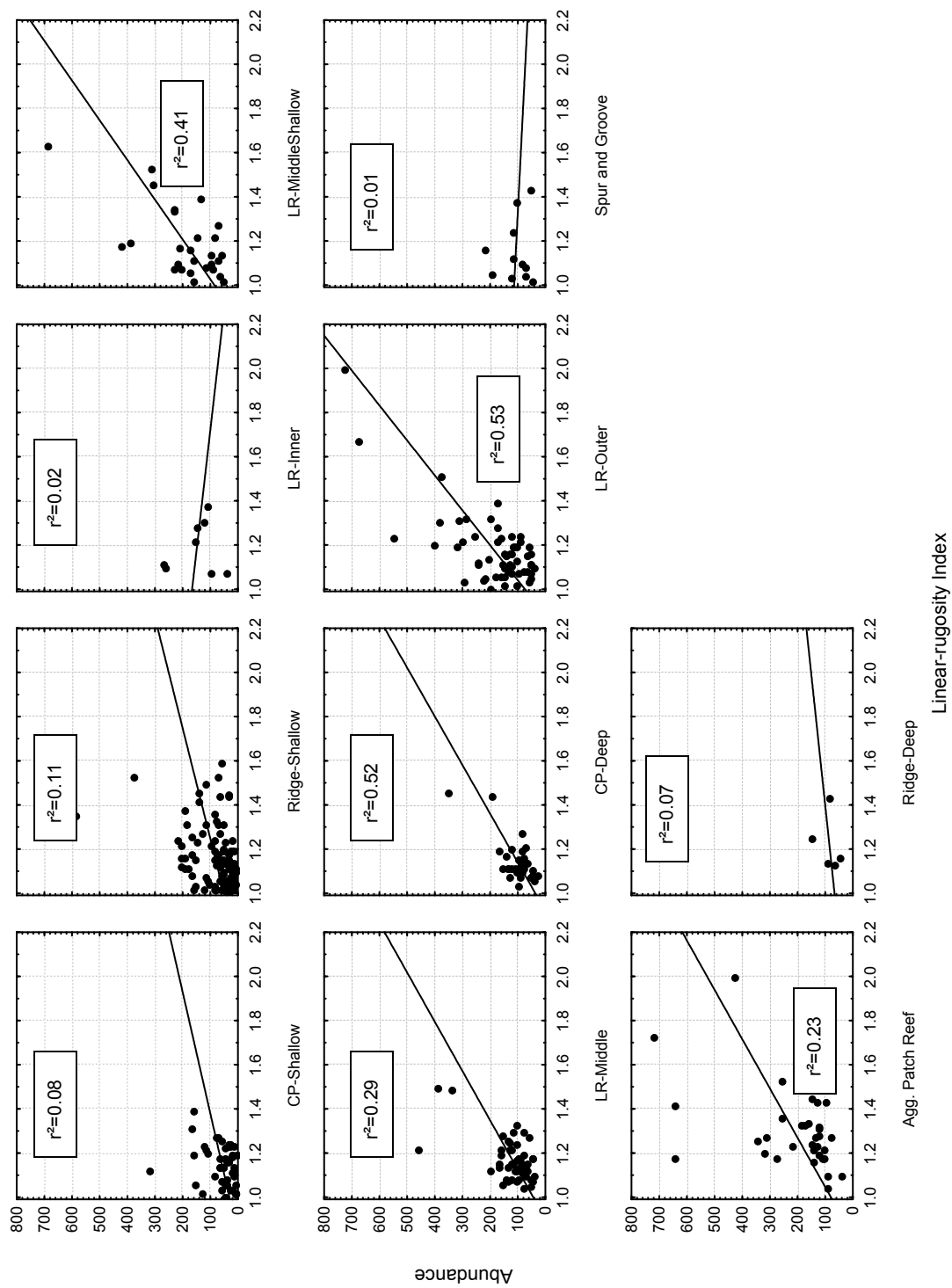


Figure 3.3.15. Categorized scatterplot of linear-rugosity (x-axis) and abundance (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect linear-rugosity has on abundance within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.2.2 Species richness

Reef fish species richness was significantly lower on the Inshore Ridge and Inner Reef sites ( $p < 0.05$ ) (Fig. 3.3.16a). Low values of mean species richness were noted on the Inshore Ridge sites ( $\bar{x}=13.4$ ) and the Inner Reef sites ( $\bar{x}=14.5$ ) while much higher means were recorded for the Middle Reef ( $\bar{x}=20.7$ ) and Outer Reef sites ( $\bar{x}=19.8$ ). The ANOVA of species richness by Reef Sites showed the distinction between the Inshore Rides and Inner Reef sites to the Middle and Outer Reef sites (Fig. 3.3.16b). All of the Middle and Outer Reefs sites were statistically similar, yet they had significantly greater species richness than all of the Inshore Ridge sites and Inner Reef sites save the Inshore Ridge East and the Inner Reef Crest ( $p < 0.05$ ).

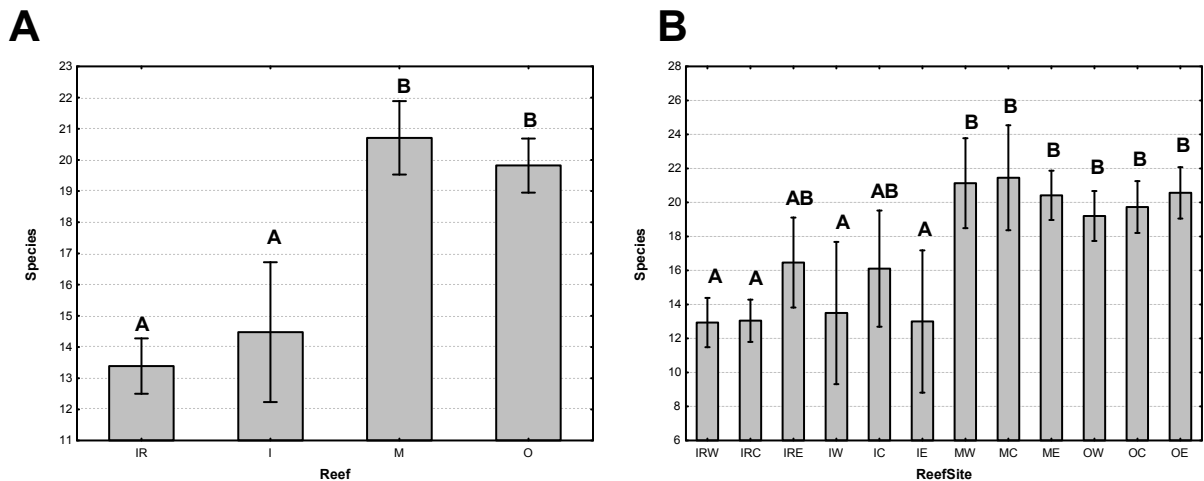


Figure 3.3.16. A) Mean species richness of all fish survey sites by reefs. B) Mean species richness of all fish survey sites by reef tracts. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

#### 3.3.2.2.1 Depth

Species richness varied significantly with respect to depth (Fig 3.3.17a). The ANOVA of species richness by depth class exhibited a significantly lower number of species in the 0-5m and 5-10m depth classes than all other classes ( $p < 0.05$ ). These classes were not significant from each other, nor were the 10-15m through 25-32m classes ( $p > 0.05$ ). Species richness of reef fish exhibited a stronger relationship to depth (Fig. 3.3.17b). As depth increased, species richness increased ( $r^2=0.24$ ), however the range of

species richness around the regression line was quite large. For example near the -5m depth species richness ranged from 1 to 31. The categorized scatterplots showed species richness to be highly variable within the different benthic habitats but there were many more shallow habitats with low richness values (<10).

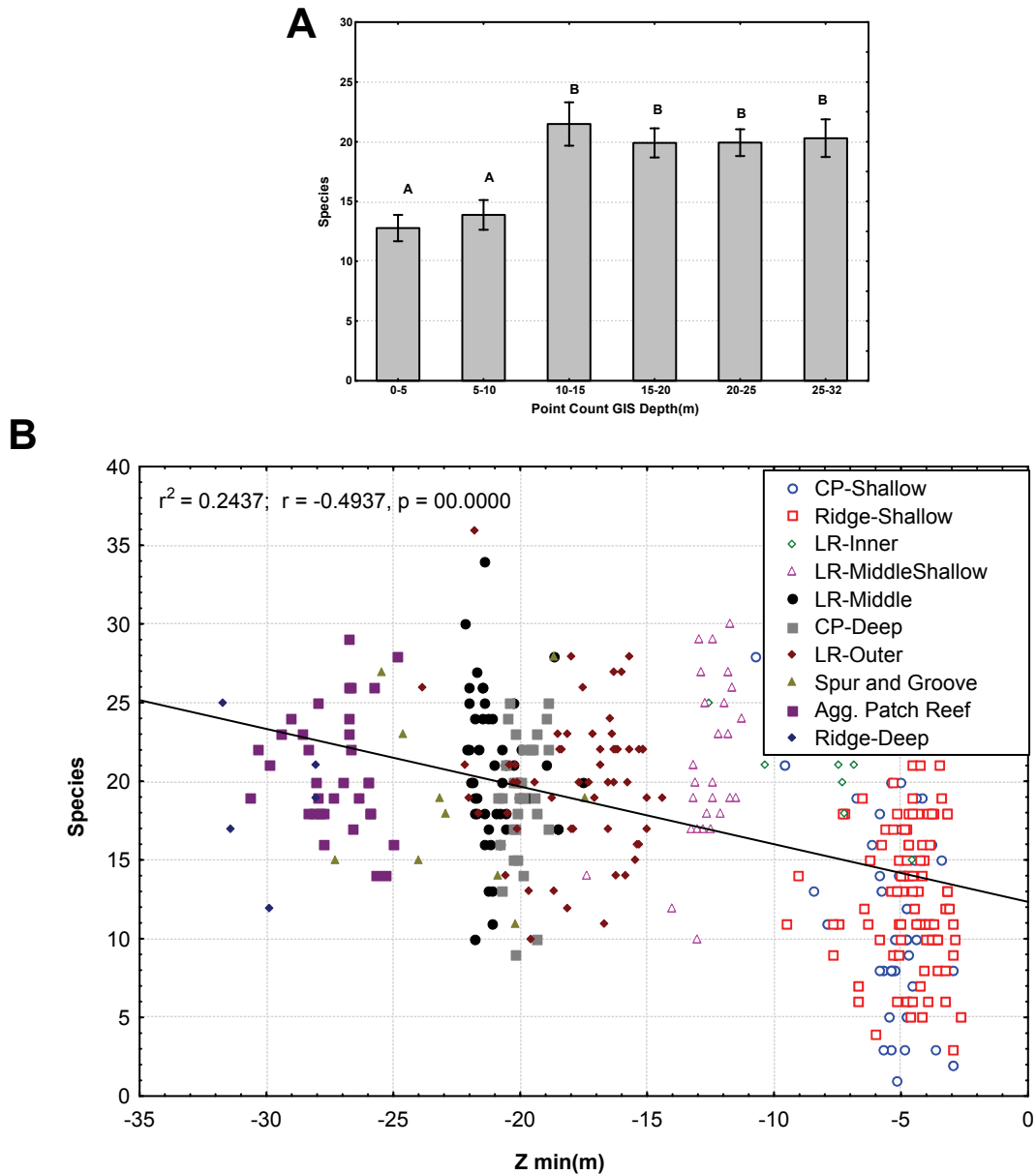


Figure 3.3.17. A) Species richness of all fish survey sites by Depth. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of species richness vs. depth (Z min) in meters by benthic habitat. Black line represents the best fit linear regression.

### 3.3.2.2.2 Elevation

Species richness exhibited an increasing stepwise trend similar to abundance (Fig. 3.3.18a) for elevation and abundance. Richness values were lowest in the lowest elevations and increased, though not significantly, upward for the first four elevation classes (0-5m to 1.5-2.0m). The only significant difference was that the 4.0-4.5m elevation class had a greater number of species than the 0-0.5m and the 3.5-4.0m classes ( $p < 0.05$ ). Species richness exhibited a slight positive increase with increasing elevation (Fig. 3.3.18b), however there was extreme variability throughout the range of elevation values. The shallow habitats dominated the samples with very low richness values ( $< 10$ ) and the deep habitats dominated the elevations above 1.5m. The relationship of species richness and elevation changed between habitats (Fig. 3.3.19). The shallow ridge, shallow colonized pavement, and shallow middle reef exhibited increased slope in the regression line. The slope of this line decreased to nearly flat in the deeper habitats.

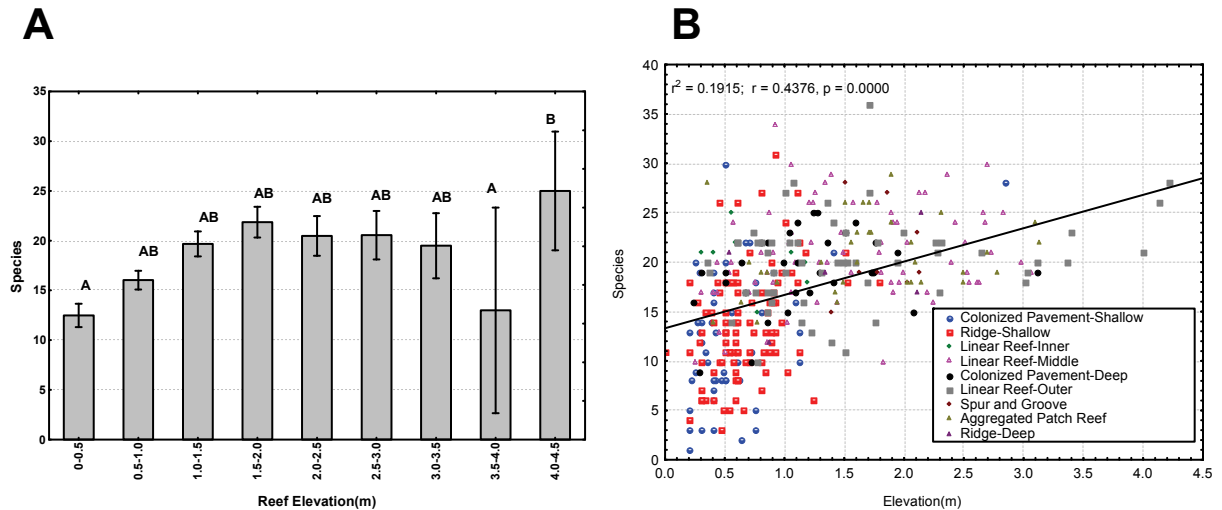


Figure 3.3.18. A) Species richness of all fish survey sites by Elevation. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of species richness vs. elevation in meters by benthic habitat. Black line represents the best fit linear regression.

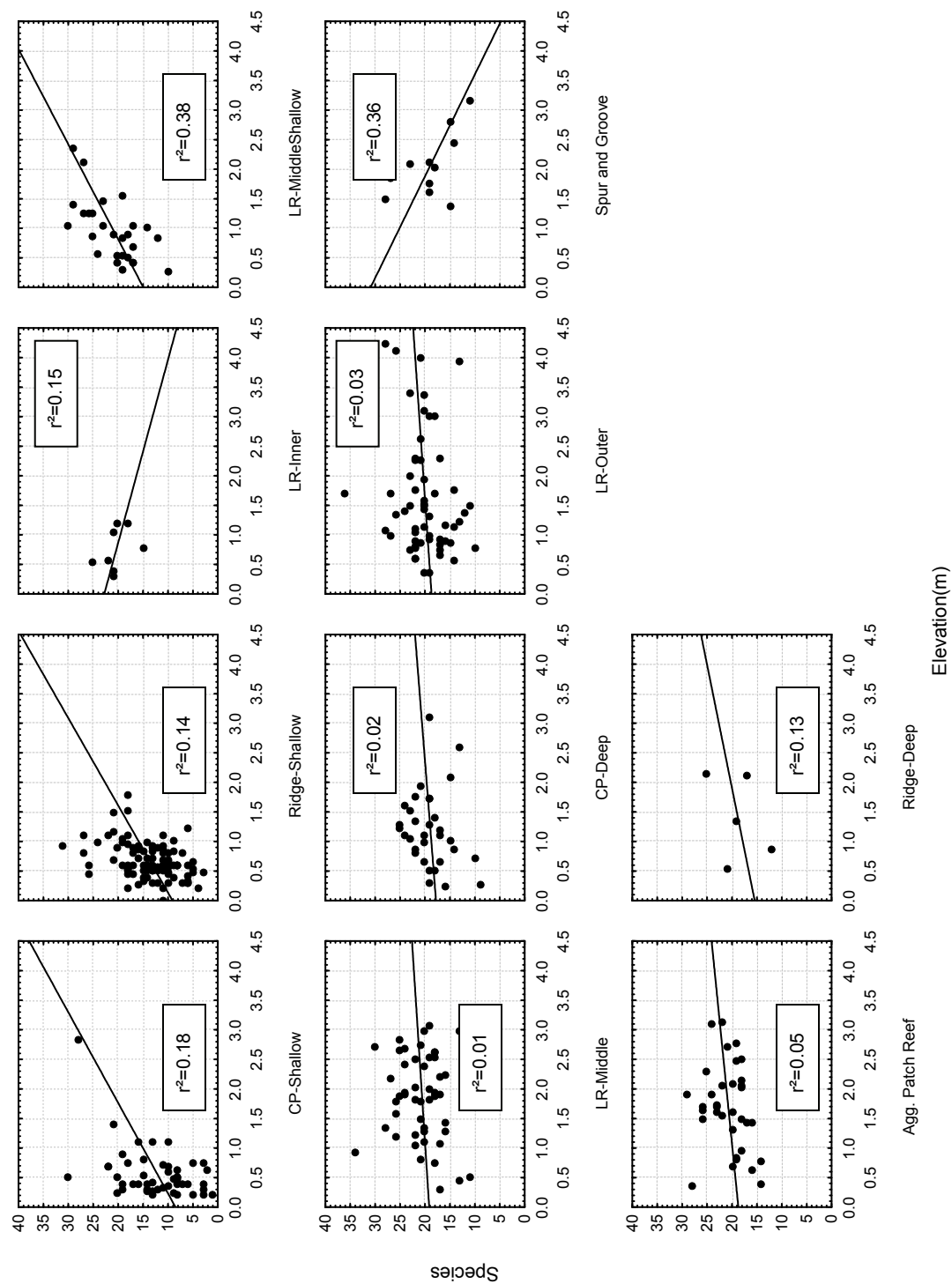


Figure 3.3.19. Categorized scatterplot of elevation (x-axis) and species richness (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect elevation has on species richness within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.



### 3.3.2.2.3 Volume

Species richness values also increased in a similar manner with increasing volume demonstrating a non-significant linear upward trend from the lowest volume value bin class, 0-35m<sup>3</sup>, to a middle value bin class, 115-142m<sup>3</sup> (Fig. 3.3.20a). Mean values of volume classes higher than these became erratic with higher heteroscedasticity. The only significance noted was the 300-400m<sup>3</sup> volume class was higher than the 0-35m<sup>3</sup> and the 440-517m<sup>3</sup> classes. The scatterplot showed an overall positive relationship with reef volume as well ( $r^2=0.15$ ) (Fig. 3.3.20b), but this relationship was questionable as an extreme variability was found in the low volume sites (<100m<sup>3</sup>). In these site species richness ranged from 1 to 34. All sites with 10 or less species present were low volume sites. The positive relationship between richness and volume was stronger in the shallow habitats (Fig. 3.3.21). The shallow colonized pavement ( $r^2=0.18$ ), shallow ridge ( $r^2=0.10$ ), and shallow middle reef ( $r^2=0.44$ ) showed the strongest correlations and steepest slopes. None of the other habitats exhibited a relationship between these variables.

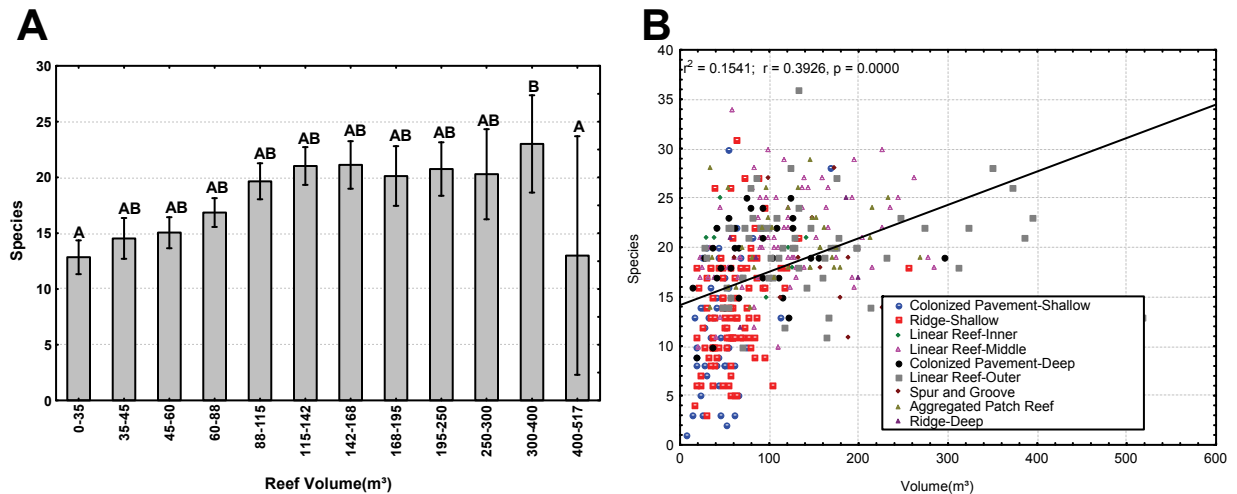


Figure 3.3.20. A) Species richness of all fish survey sites by Volume. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of species richness vs. reef volume (m<sup>3</sup>) by benthic habitats. Black line represents the best fit linear regression.

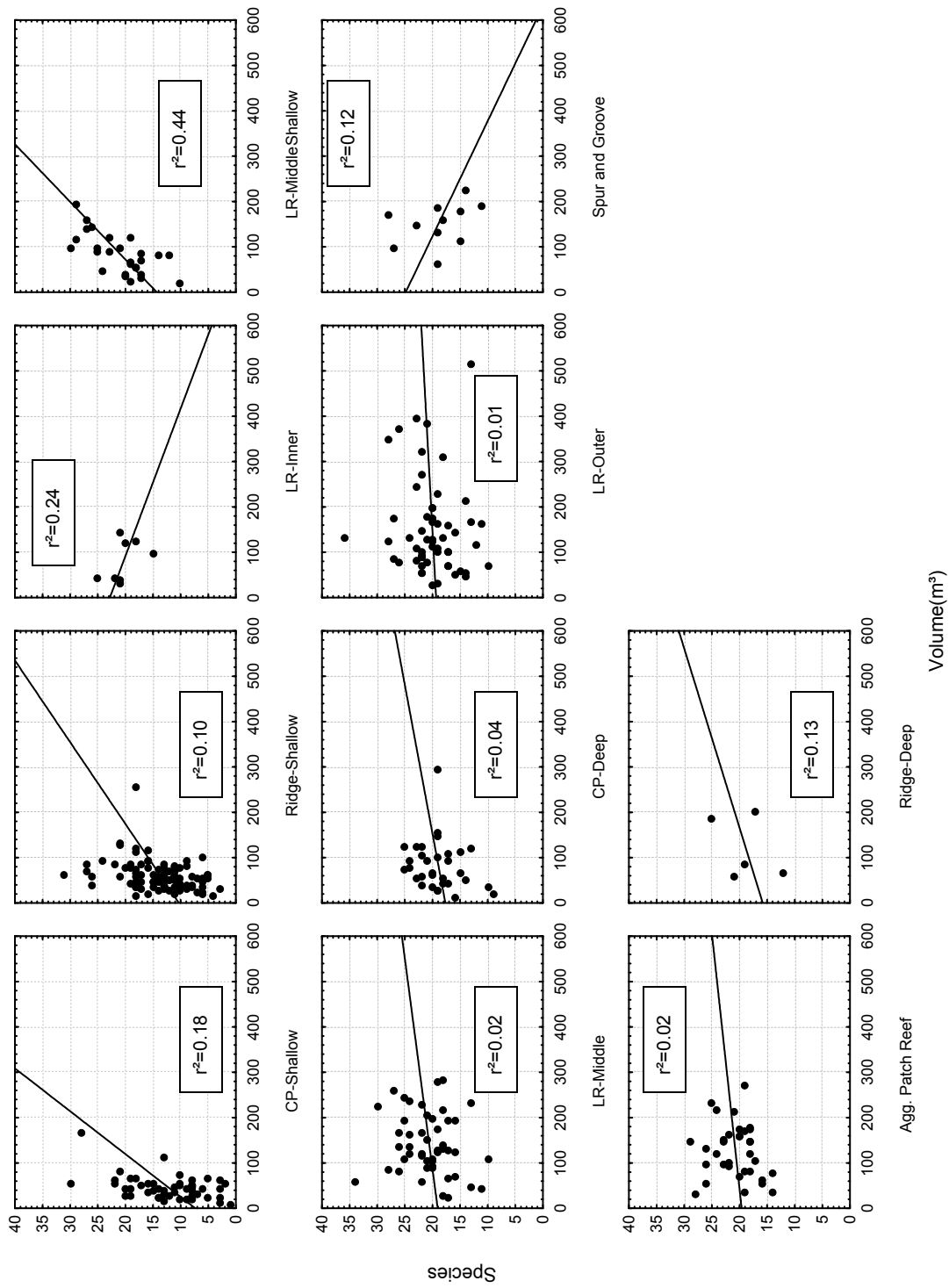


Figure 3.3.21. Categorized scatterplot of reef volume (x-axis) and species richness (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect volume has on richness within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.2.2.4 Surface Rugosity

Species richness showed an increasing trend with respect to surface rugosity and linear rugosity (Fig. 3.3.22a). The mean number of species per survey increased significantly ( $p < 0.05$ ) as surface rugosity classes increased. The richness in the two lowest classes was significantly lower than the third class (1.005-1.0075) and the seventh class (1.03-1.04). The seventh class was significantly greater than the third class. The scatterplot showed richness increased with increasing surface-rugosity although there was high variation ( $r^2 = 0.09$ ) (Fig. 3.3.22b). The most variable habitat were the shallow ridge and shallow colonized pavement were richness values ranged from 0 to 30 but surface-rugosity was low ( $< 1.01$ ). The strongest positive correlations were evident in the shallow habitats with the shallow middle reef being the strongest ( $r^2 = 0.31$ ) (Fig. 3.3.23). The deep habitats did not show any significant relationship between these variables.

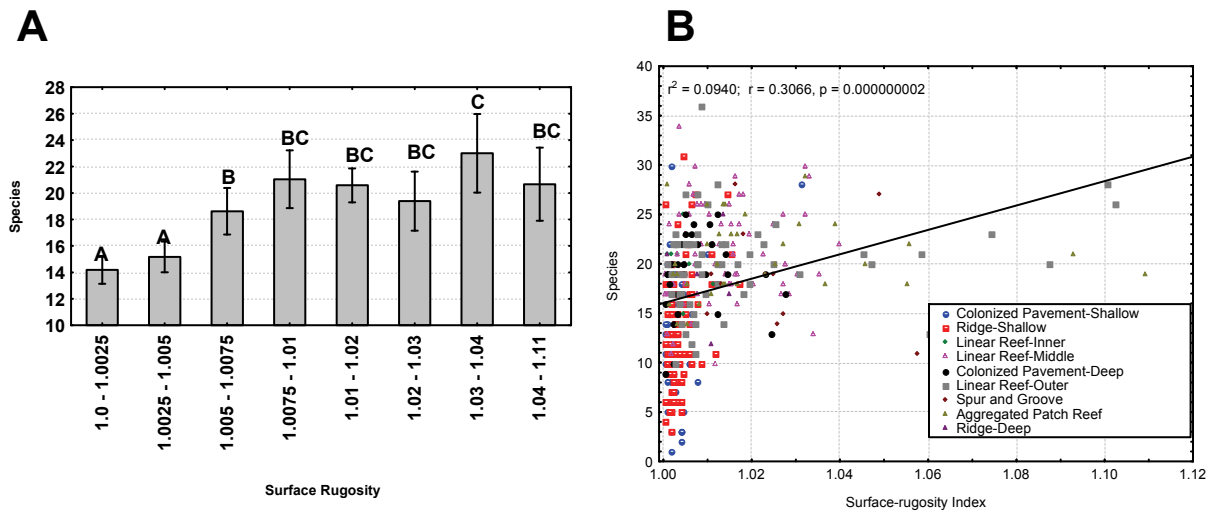


Figure 3.3.22. A) Species richness of all fish survey sites by Surface rugosity. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of surface-rugosity vs. species richness by benthic habitat. Black line represents the best fit linear regression.

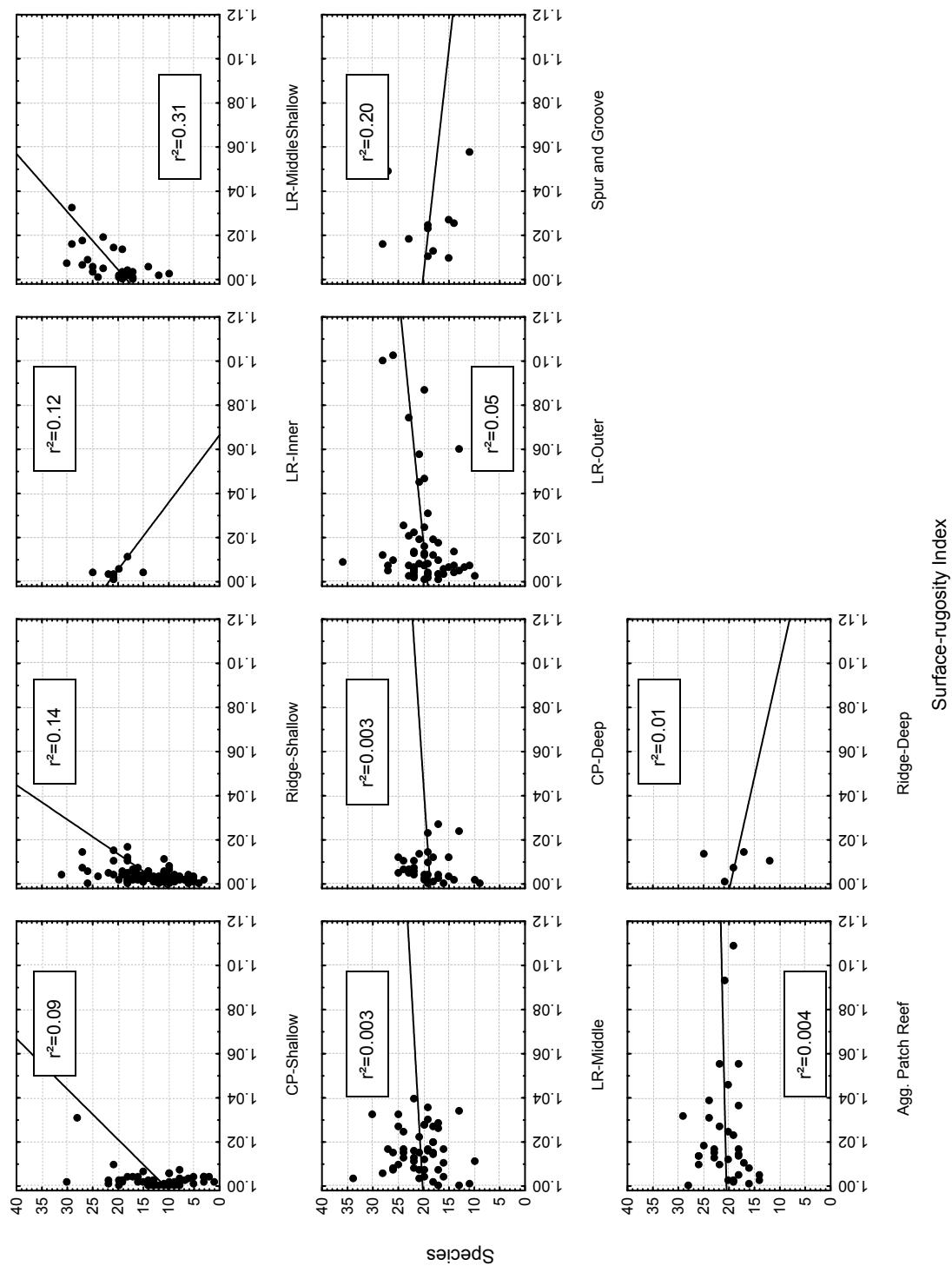


Figure 3.3.23. Categorized scatterplot of surface-roughness (x-axis) and richness (y-axis) by benthic habitat type. The changes of slope in regression lines between graphs indicates the effect surface-roughness has on richness within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.2.2.5 Linear Rugosity

Species richness exhibited a positive relationship with linear-rugosity (Fig. 3.3.24). The ANOVA showed the lowest class was significantly lower than any other class and the highest class was significantly greater than the five lowest classes ( $p < 0.05$ ). The scatterplot showed this positive relationship ( $r^2 = 0.17$ ) was highly variable in the lower linear-rugosity range ( $< 1.2$ ) with richness values ranging from 1 to 30. Richness values were higher in the upper linear-rugosity range ( $> 1.3$ ), and no surveys with high linear-rugosity measurements had a richness of less than 11. The strongest relationship was noted in the shallow colonized pavement ( $r^2 = 0.38$ ) (Fig. 3.3.25), yet the shallow ridge ( $r^2 = 0.25$ ), shallow middle reef ( $r^2 = 0.21$ ), deep colonized pavement ( $r^2 = 0.22$ ), and outer reef ( $r^2 = 0.21$ ) all showed positive increases.

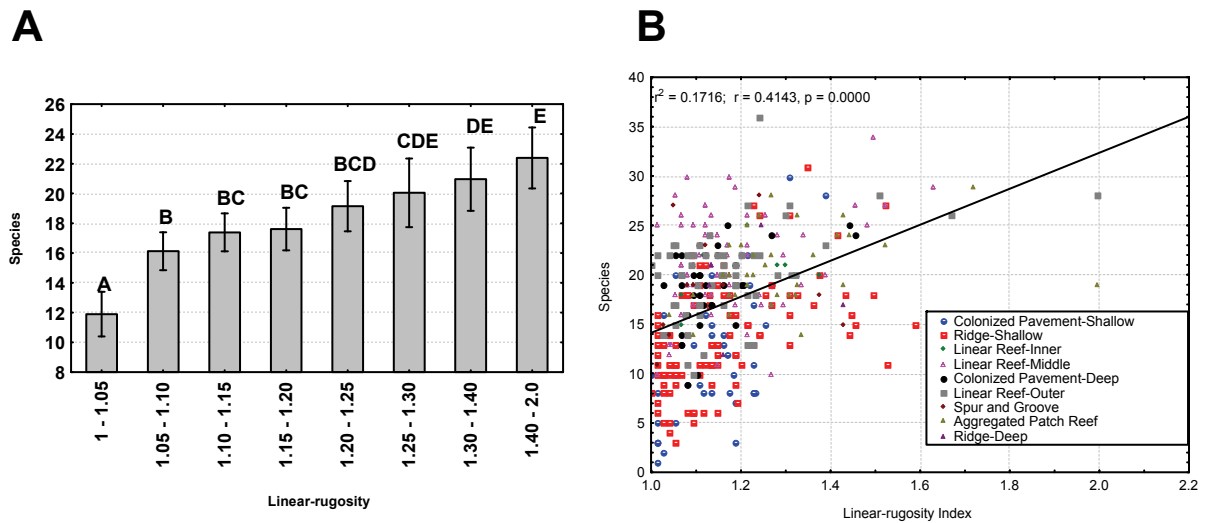


Figure 3.3.24. A) Species richness of all fish survey sites by Linear rugosity. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals. B) Categorized scatterplot of linear-rugosity vs. species richness by benthic habitat. Black line represents the best fit linear regression.

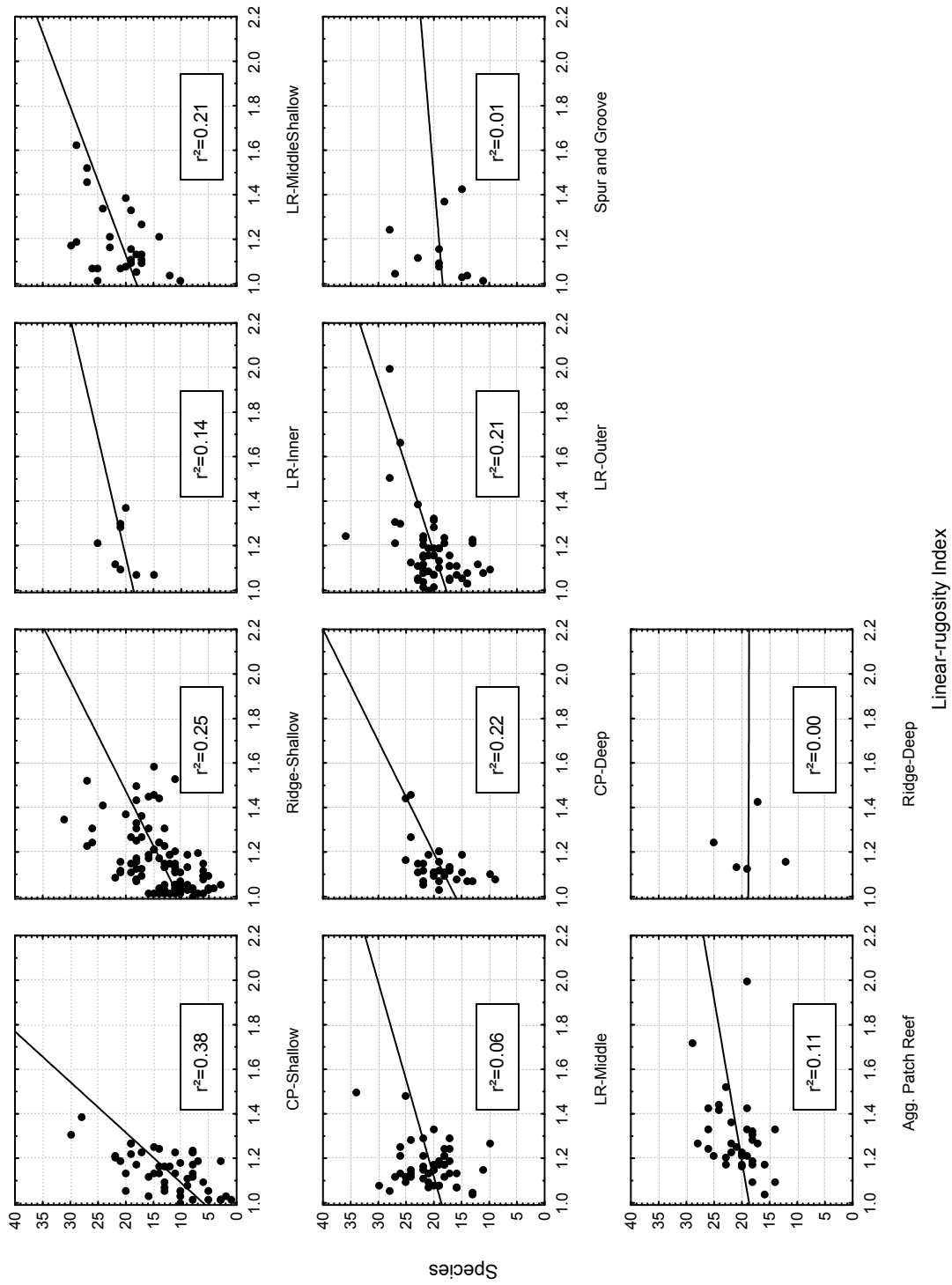


Figure 3.3.25. Categorized scatterplot of linear-rugosity (x-axis) and species richness (y-axis) by benthic habitat type. Changes of slope in regression lines between graphs indicates the effect linear-rugosity has on richness within each habitat. Habitats are arranged from shallowest, nearest shore in the upper right to deepest, furthest from shore in lower left. Black line represents the best fit linear regression.

### 3.3.3 Habitat Analysis of Variance between all variables

The ANOVA of fish abundance between benthic habitats showed high variability between and within habitats (Fig. 3.3.26a). There were significantly more fish in the Linear Reef-Middle Shallow, Linear Reef-Outer and Aggregated Patch Reef habitats than the Shallow Colonized Pavement ( $p<0.05$ ). The Aggregated Patch Reef also contained significantly more fish than the Shallow Ridge, the Deep Colonized Pavement, the Spur and Groove, and the Deep Ridge habitats ( $p<0.05$ ). The Middle Reef-Shallow contained significantly more fish than Shallow and Deep Ridge habitats.

The ANOVA showed less variability between habitats for species richness (Fig. 3.3.26b). The Shallow Colonized Pavement and Shallow Ridge habitats, which did not significantly differ, both contained significantly fewer species than any of the other habitats ( $p<0.05$ ), which also did not significantly differ from one another.

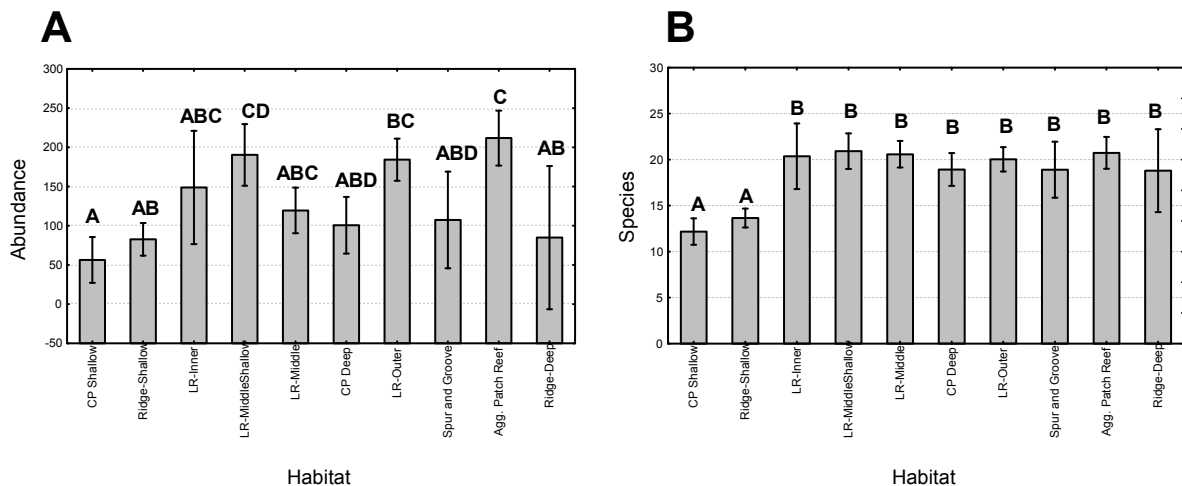


Figure 3.3.26. A) Mean reef fish abundance of all fish survey areas by benthic habitats. B) Mean species richness of all fish survey areas by benthic habitats. Letters indicate significance ( $p<0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

Many of the benthic habitats are separated by depth, getting deeper as they appear further away from shore (Fig. 3.3.27a). All but two pairs of habitats significantly differed from every other habitat ( $p<0.05$ ). The Shallow Colonized Pavement and Shallow Ridge were statistically similar as were Middle Reef and Deep Colonized Pavement, but these two pairs significantly differed from each other and all other habitats.

The significance of elevation between the different habitats was more complicated (Fig. 3.3.27b). The surveys within the shallower habitats, Shallow Colonized Pavement, Shallow Ridge, and Inner Reef, had significantly lower elevations than almost all other habitats ( $p < 0.05$ ). The Spur and Groove had the greatest mean elevation and significantly differed from all but three other sites, the Aggregated Patch Reef, the Middle Reef and the Outer Reef ( $p < 0.05$ ).

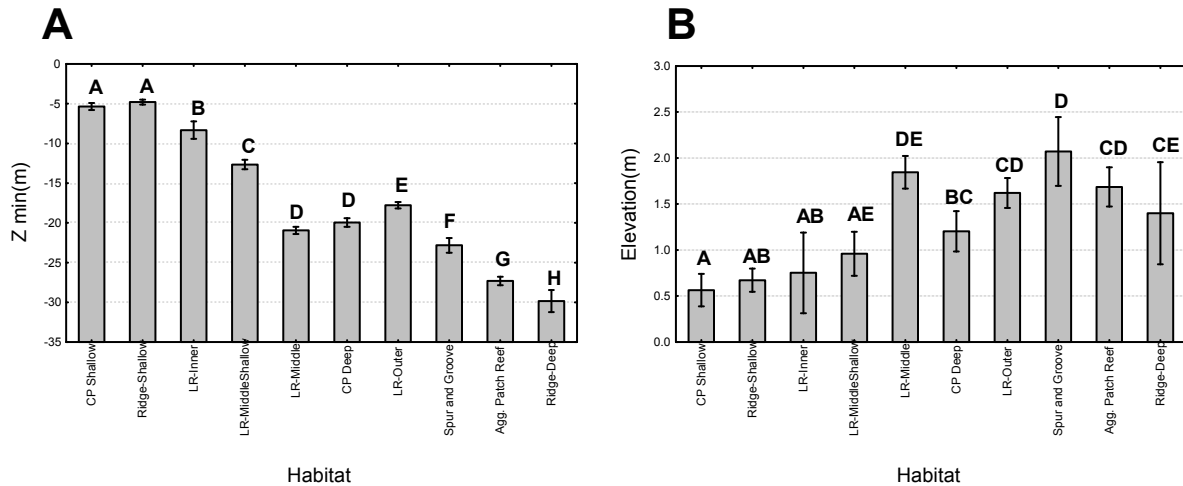


Figure 3.3.27. A) Mean minimum depth of all fish survey sites by benthic habitats. B) Mean reef elevation within all fish survey sites by benthic habitats. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

Significant differences in reef volume were evident between habitats (Fig. 3.3.28a). The Middle Reef, Outer Reef, and Spur and Groove had significantly more reef volume than the Deep and Shallow Colonized Pavement, the Shallow Middle Reef, the Shallow Ridge, and the Inner Reef ( $p < 0.05$ ). The Shallow Colonized Pavement and Shallow Ridges had significantly less reef volume than all other sites except for the Inner Reef, Shallow Middle Reef, and the Deep Colonized Pavement ( $p < 0.05$ ).

Surface Rugosity also significantly differed between several habitats (Fig. 3.3.28b). The Spur and Groove, Aggregated Patch Reef, and Outer Reef had significantly higher surface rugosity values than the Shallow Colonized Pavement, the Shallow Ridge, and the Inner Reef ( $p < 0.05$ ).



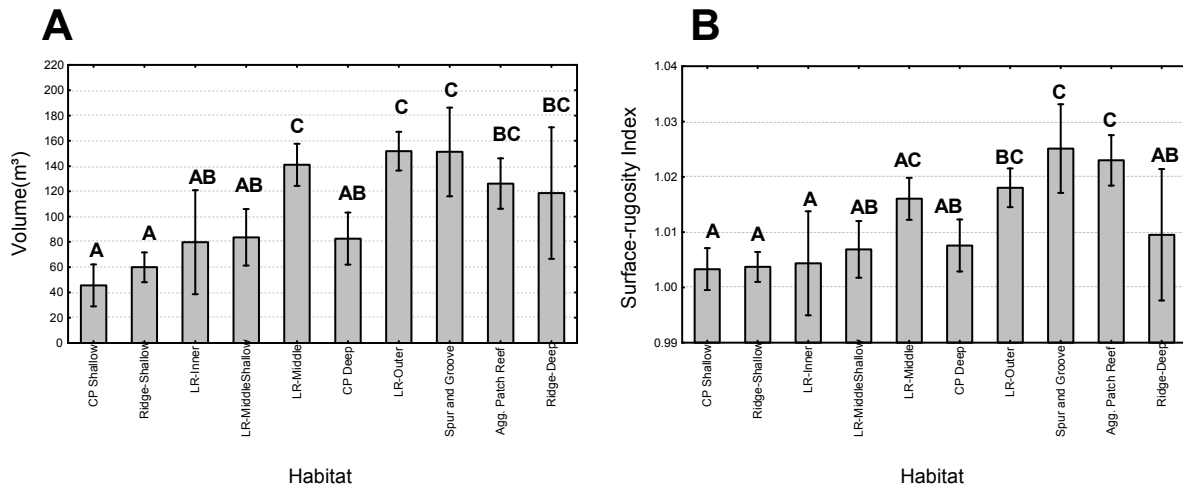


Figure 3.3.28. A) Mean reef volume (m³) of all fish survey areas by benthic habitats. B) Mean surface rugosity of all fish survey areas by benthic habitats. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

Linear rugosity showed high heteroscedasticity between habitats and little significance was evident (Fig. 3.3.29). The Aggregated Patch Reef contained a significantly higher mean linear rugosity value than the Shallow Colonized Pavement, the Shallow Ridge, the Deep Colonized Pavement, and the Spur and Groove ( $p < 0.05$ ).

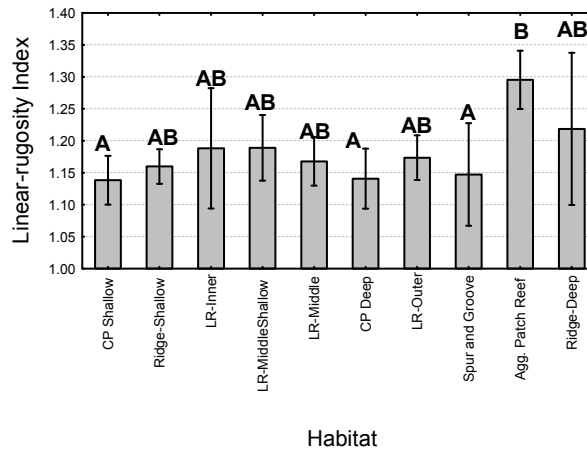


Figure 3.3.29. A) Mean linear rugosity indices of all fish survey areas by benthic habitats. Letters indicate significance ( $p < 0.005$ , ANOVA, SNK). Vertical lines represent 0.95 confidence intervals.

### 3.3.4 Relationships of Topographic Metrics to Each Other

Reef elevation showed a strong relationship with reef volume (Fig. 3.3.30). The high  $r^2$  value of 0.81 indicates that as reef elevation increases, reef volume increases. This is expected because the elevation within the survey TIN is used to calculate reef volume. The categorized scatter plot indicates that the pattern of this relationship is consistent between habitats. There are low elevation/low volume locations and high elevation/high volume locations amongst the surveys in many of the benthic habitats.

Reef elevation exhibited a similar trend with regards to surface rugosity (Fig. 3.3.31). The high  $r^2$  value (0.65) shows a strong relationship between these two variables. As elevation increases, surface rugosity index increases. Again, the categorized scatterplot showed this trend holds true amongst the different habitats.

Reef elevation did not show a substantial trend with linear rugosity (Fig. 3.3.32). High and low linear rugosity index measurements were found throughout the range of elevation values. The low  $r^2$  value (0.09) indicates there is no clear relationship between these variables.

Reef volume showed a positive relationship with increased surface rugosity (Fig. 3.3.33). The  $r^2$  value of 0.50 indicated a fairly strong relationship between these two variables, which was expected since both of these measurements incorporate elevation of the TIN. The categorized scatterplot indicated this trend to be consistent between habitats.

Reef volume did not exhibit a relationship with the linear rugosity index (Fig. 3.3.34). High and low reef volume measurements were evident throughout the range of linear rugosity index values and the  $r^2$  of 0.07 indicated there was no relationship between these variables.

The surface rugosity index showed a slightly positive relationship to the linear rugosity index (Fig 3.3.35). Although the  $r^2$  value was low (0.16) a positive trend was noted, an increase in surface rugosity was likely to also have an increase in linear rugosity.

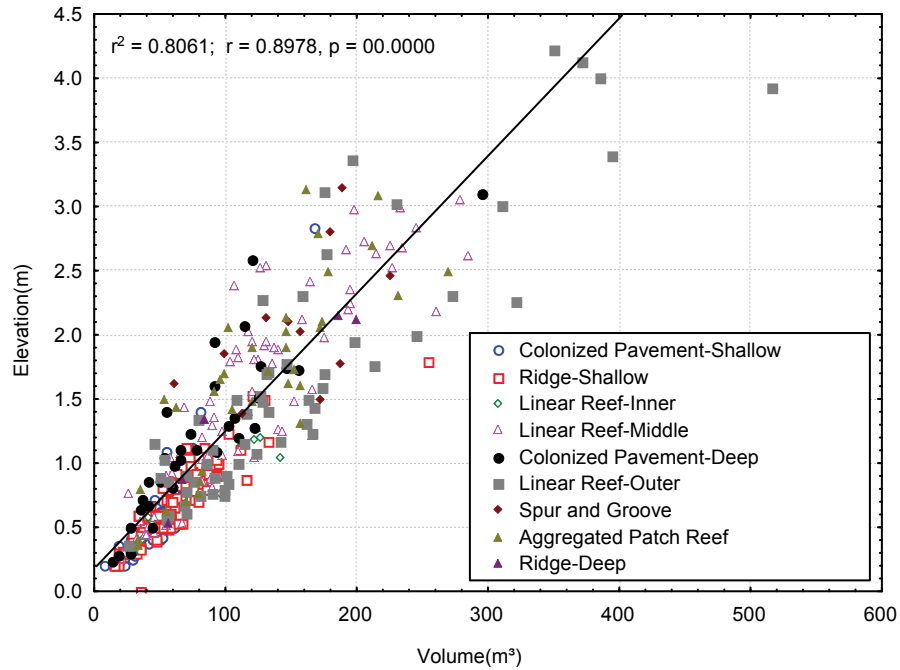


Figure 3.3.30. Categorized scatterplot of elevation (m) vs. volume (m³) by benthic habitats. Black line represents the best fit linear regression.

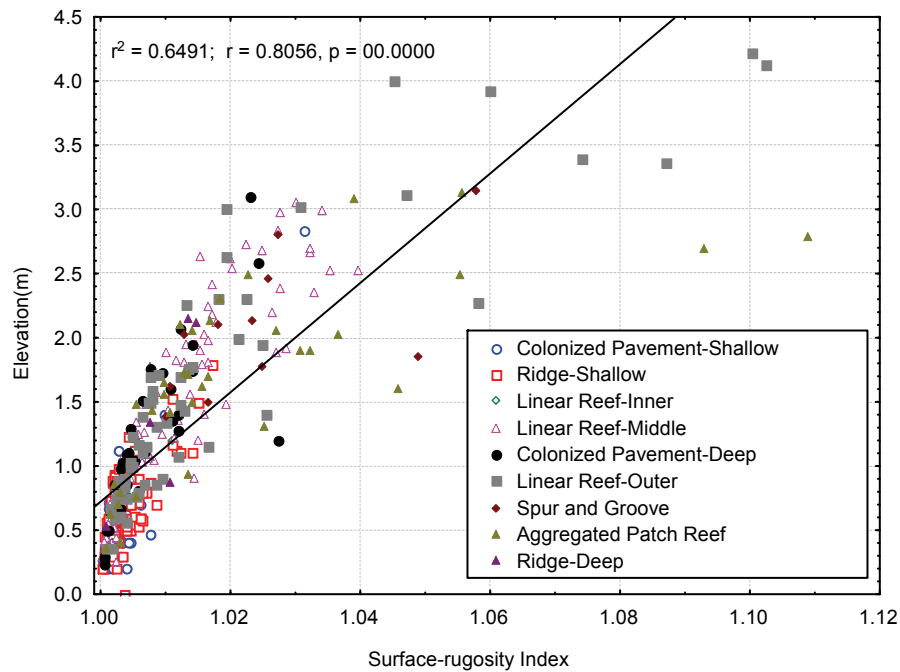


Figure 3.3.31. Categorized scatterplot of elevation (m) vs. surface-roughness index by benthic habitat. Black line represents the best fit linear regression.

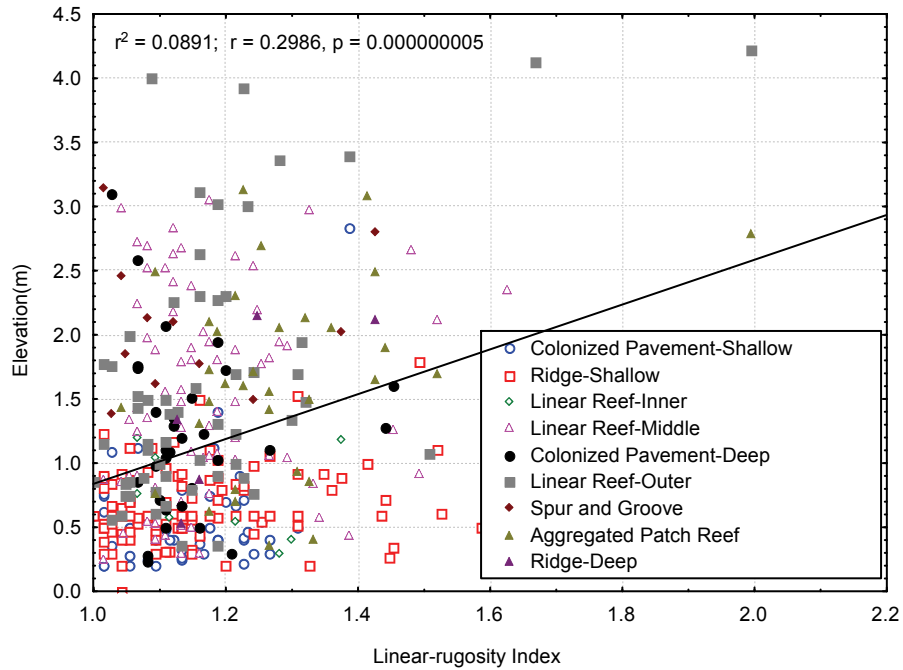


Figure 3.3.32. Categorized scatterplot of elevation (m) vs. linear-rugosity index by benthic habitat. Black line represents the best fit linear regression.

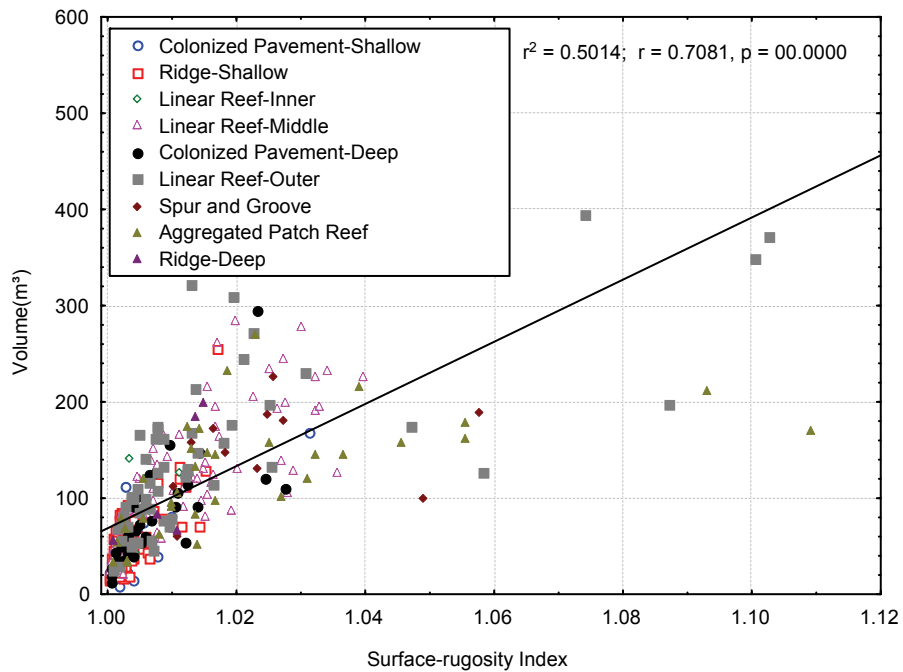


Figure 3.3.33. Categorized scatterplot of volume (m³) vs. surface-rugosity index by benthic habitat. Black line represents the best fit linear regression.

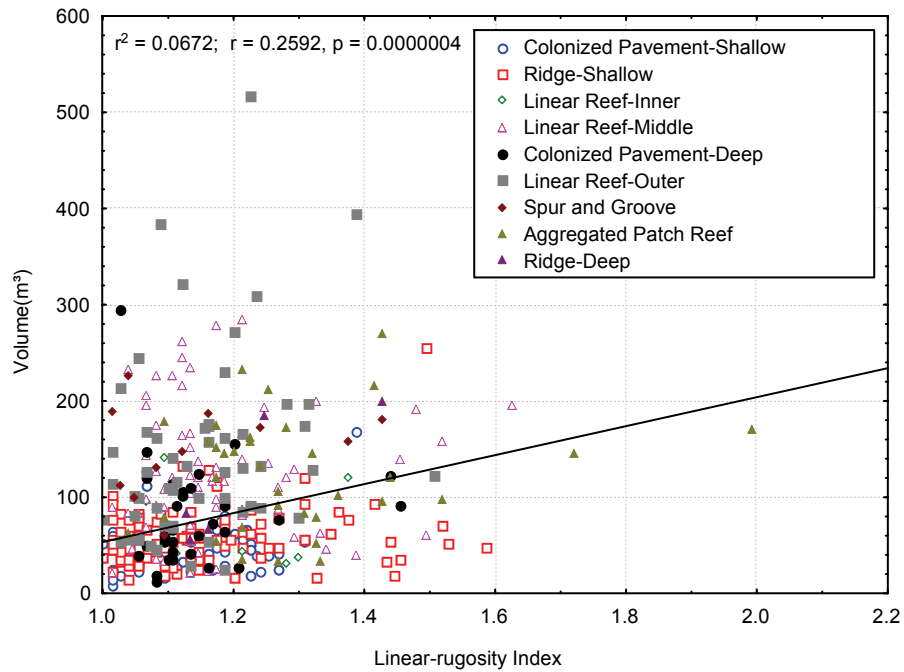


Figure 3.3.34. Categorized scatterplot of volume (m³) vs. linear-rugosity index by benthic habitat. Black line represents the best fit linear regression.

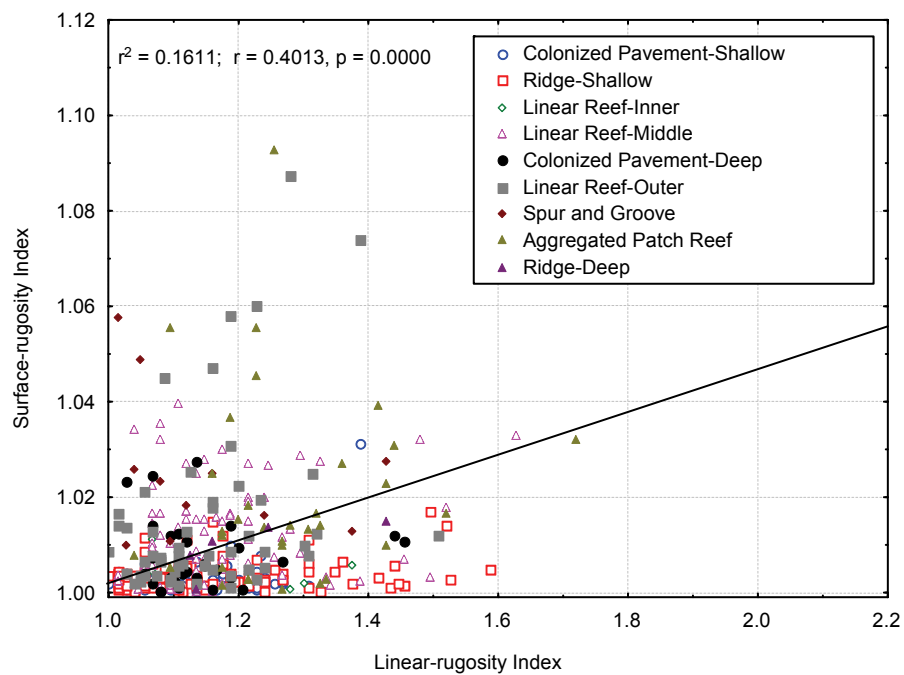


Figure 3.3.35. Categorized scatterplot of surface-rugosity index vs. linear-rugosity index by benthic habitat. Black line represents the best fit linear regression.

### 3.4 Discussion

Broward County reefs deepen with increasing distance from shore (Figure 3.3.1). Elevation, volume, and surface rugosity follow a similar trend and are greatest in deeper water (Figs 3.3.2, 3.3.3, & 3.3.5). If reef fish abundance and/or species richness were directly linked to these variables, it would follow that they would increase with distance from shore. In general this is true (Figs. 3.3.6a, 3.3.7a, 3.3.16a, & 3.3.17a); however, the relationship is complex. The following discussion explores this relationship in greater detail.

#### 3.4.1 Abundance

Fish abundance showed an increasing trend with increasing elevation (Fig 3.3.8a), volume (Fig 3.3.10a), surface rugosity (Fig 3.3.12a), and linear rugosity (Fig 3.3.14a) however little significance was detected by ANOVA between most of these relationships. For example, the mean value for each of the four lowest bins in the elevation ANOVA progressively increased from 65 mean fish in surveys with 0-0.5m elevation to 177 mean fish in surveys containing 1.5-2.0m elevation. Although not significant, this trend was also noted in the volume ANOVA from 0 to 168 m<sup>3</sup>, in the surface rugosity ANOVA from 1 to 1.02, and throughout every bin in the linear rugosity ANOVA. These results suggest that total abundance increases with increasing topographic complexity to a certain level and then flatten out. One could conclude from this analysis that abundance is only affected by topographic complexity to a certain level after which increased topographic complexity does not increase fish abundance. This result supports Patton et al. (1985) who found that changes in fish densities of natural reefs in California with regard to habitat complexity were saturation functions (Bohnsack 1991). Abundance increased with increasing resources to a point, beyond which there was no effect. This makes sense on an intuitive level because once complexity has reached a threshold, the assemblage might become density dependant due to other factors such as inter or intraspecific competition. In the current study however, this trend may be an artifact of topographic measuring techniques. The remotely-sensed topographic variables all show this leveling trend while linear rugosity, the only *in situ* measurement, shows a positively increasing trend of abundance throughout the entire range. This suggests that the leveling

in abundance with the GIS variables may be due to a limited ability to detect rugosity at the proper scale. These implications are further discussed in section 3.4.4.

The scatterplots of reef fish abundance also showed slightly positive relationships with depth (Fig 3.3.7b), elevation (Fig 3.3.8b), volume (Fig 3.3.10b), surface rugosity (Fig 3.3.12b), and linear rugosity (Fig 3.3.14b). These relationships were significant but not highly correlated suggesting that the correlates (topographic complexity metrics) were not the only limiting factor for reef fish abundance and richness. According to Liebig's Law of the Minimum, the limiting factors in a correlation will have the strongest relationship (Liebig 1840). This law originates from a study published by J. Liebig in 1840 on the necessity of certain chemicals required for plant growth. Many chemicals/elements are needed for plant growth and the limitation of one single element is critical. Liebig found this critical element will be highly correlated with plant growth at the time of its limitation however, once the element is no longer limited, the next limiting factor becomes highly correlated. Meanwhile the other essential elements to plant growth will be less correlated. For example, when nitrogen is limited in soils it correlates strongly to plant growth, but when another factor is limiting growth, nitrogen does not correlate as strongly (Huston 2002). Ecological processes are influenced by many factors. Of these influential factors, the critical limiting ones may shift due to temporal and spatial variation (Huston 2002). When the factor being measured is limiting, a high correlation between that factor and the process is expected, yet this factor may only be limiting at certain times or in certain areas (Huston 2002). Additional limiting factors will weaken the relationship between the process and the variable being studied. "Although Liebig's Law of the Minimum was originally proposed in relation to plant growth, the same phenomenon can occur with any process that is regulated by more than one factor, which includes virtually all ecological processes" (Huston 2002). Because the fish abundance-topographic complexity relationship is not strong, Liebig's Law of the Minimum suggests that other factors play an important role along with topographic complexity in determining the distribution of reef fish in South Florida. For example, fish abundance in an area may be habitat limited for a time until a disturbance in recruitment patterns limits the number of juveniles supplied to that area. This diminished population

may then become recruitment limited which may not show a relationship to topographic complexity because there would be more areas of reef without fish.

Evidence explaining the determining factors in reef fish assemblages was found in an experiment conducted in the same region (Gilliam 1999). Gilliam used artificial reefs to test the ecological processes forcing reef fish distributions in Broward County. Forty 1m<sup>3</sup> identical artificial reefs were deployed in a grid in a nearshore sand habitat 30m away from each other and any natural reef. The experiment used caging material for predator exclusion and rotenone for “cleaning” existing fish off of the reefs to monitor new fish recruitment and post recruitment processes in an effort to determine which ecological process was most responsible for the distribution of reef fishes in South Florida. The tests conducted found that recruitment variability coupled with predation and refuge limitation were the most influential process in affecting reef fish distributions. When recruitment into the system was high, prey refuge became the limiting factor, but when recruitment was low, refuge availability did not matter. Hence, the association between the reef fish assemblage and topographic complexity is likely driven by temporal recruitment events and that space resources are not limited during a large part of the year. This supports the result of a weaker fish-topographic relationship according to Liebig’s Law of the Minimum, because if space resources are not limited a strong reef fish/topographic complexity relationship would not be expected.

In this study, the strongest relationship was between abundance and linear rugosity ( $r^2=0.28$ ). Given Liebig’s Law of the Minimum, these results suggest that either topographic complexity was not the limiting factor at the time of many of the surveys or this relationship varies spatially and assemblages in different habitats may relate differently to topographic complexity.



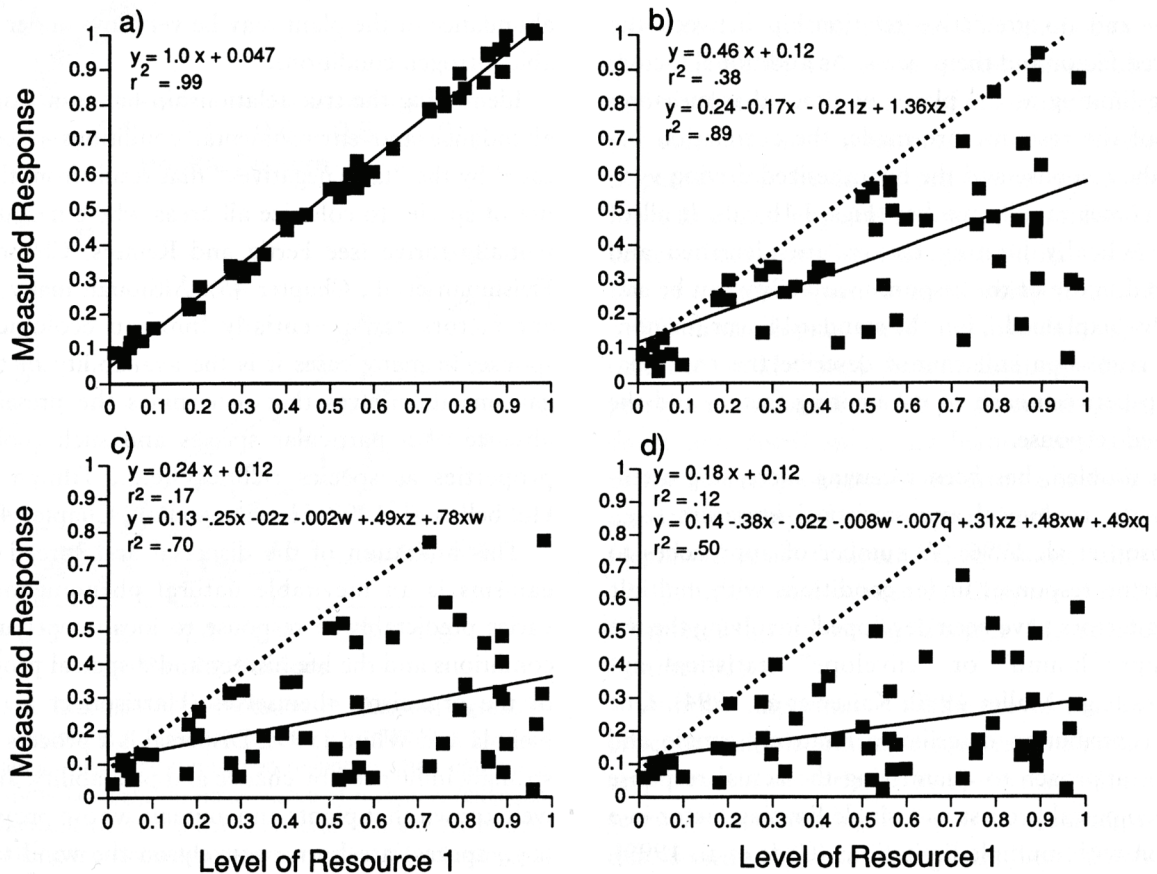


Figure 3.4.1. “Interactive effect of one through four limiting resources on an ecological response regulated according to Liebig’s Law of the Minimum. (a) Response of a hypothetical measured response to random variation in Resource 1, when Resource 1 is the only limiting factor. The only variance is added random error. (b) Observed response to Resource 1, with random variation in one additional limiting resource. The solid regression line is the predicted response using only Resource 1. The dotted lines in b, c, and d indicate the upper bound of data, which is a close approximation of the ‘true’ response of (a). The lower regression equation is based on precise measurement of both resources (x and z), with multiplicative interaction term. (c) Observed response to Resource 1, with random variation in two additional limiting resources. The solid regression line is the predicted response using only Resource 1. The lower regression equation is based on precise measurement of all three resources (x, z, and w), with multiplicative interaction terms. (d) Observed response to Resource 1, with random variation in three additional limiting resources. The solid regression line is the predicted response using only Resource 1. The lower regression equation is based on precise measurement of all four resources (x, z, w, and q), with multiplicative two-way interaction terms. Note that (1) the departure of the statistical relationship of the response to Resource 1 from the actual response (a) increases with additional limiting factors (b, c, d); (2) the increasing variance of the measured response at increasing levels of Resource 1 with one or more additional limiting factors (i.e., variance amplification); and (3) that the same phenomenon occurs with complex nonlinear relationships as with the linear relationship illustrated here.” (Huston 2002, Figure I.1; figure text is verbatim)

The relationship between abundance and topographic complexity became more evident when the data were categorized by benthic habitat. The categorized scatterplots illustrate these relationships. The GIS measured topographic variables (elevation, volume, and surface rugosity) all showed similar relationships to fish abundance. The shallow colonized pavement, shallow ridge, shallow middle reef, and outer linear reef exhibited a positive relationship indicating that as the topographic variables increase, fish abundance also increases (Figs 3.3.9, 3.3.11, and 3.3.13). Interestingly, the middle reef, the deep colonized pavement, and aggregated patch reef habitats show little relationship between topographic complexity variables and abundance. This could lead to the conclusion that only certain habitat assemblages are affected by topographic complexity, but this may not be the case. Linear rugosity, the only *in situ* measurement, yielded the best results for illustrating a positive relationship between abundance and topographic complexity (Fig 3.3.15). Abundance increased with increasing linear rugosity in almost every habitat with relatively high  $r^2$  values for the outer reef (0.53), the deep colonized pavement (0.52), the shallow middle reef (0.41), the middle reef (0.29), and the aggregated patch reef (0.23) (Inner reef, spur and groove, and deep ridge were not statistically valid due to the lack of power/low sample size). This result coupled with the abundance/linear rugosity ANOVA suggests that the reef fish abundance in Broward County is affected by topographic complexity and following Liebig's Law of the Minimum, this relationship was not the sole limiting factor determining reef fish abundance.

### 3.4.2 Species Richness

Species richness ANOVAs indicated that richness increased with increasing distance from shore, but the increase appeared as more of a step than a gradual upward trend (Fig 3.3.16a & b). Richness values on the inshore ridge and inner reef sites were significantly lower than the middle reef and outer reef sites, but it appears as if there were two distinct assemblages, one with a significantly low number of species (~14) and one with a higher value (~20) (Fig 3.3.16a). This change in the assemblage was evident at the threshold of 10m depth, meaning all sites less than 10m had a significantly lower number of species. Species richness exhibited an increasing trend with the increase of all

topographic variables in the ANOVAs and the scatterplots (Figs 3.3.18, 3.3.20, 3.3.22, & 3.3.24). Similar to the abundance ANOVAs, species richness exhibited an increasing trend with increasing GIS-measured topographic complexity to a point before leveling off. However, species richness exhibited a statistically significant increase with increasing linear rugosity without leveling off, indicating, like abundance, that the leveling may not be due to a saturation affect but rather measurement scale.

The data distribution in the scatterplots of species richness versus the topographic variables suggested a possible nonlinear distribution. For example the data in the scatterplot of species richness versus elevation suggests the best-fit line would be a curve with a decreasing slope with increasing linear rugosity (Figure 3.4.2). This upward trend appeared to level out near 24 where the topographic variable no longer affected the species richness. One might conclude from this that species richness is influenced by topographic complexity logarithmically, similar to Patton et al (1985). Further scrutiny of the data revealed that the logarithmic relationship is not nonlinear when categorized by habitats (Fig 3.3.19). All three GIS-measured, topographic complexity variables (elevation, volume, and surface rugosity) exhibit a positive correlation with species richness for the shallow colonized pavement, the shallow ridge, and the shallow middle reef habitats (Figs 3.3.19, 3.3.21, & 3.3.23). This relationship is not evident in the deeper habitats suggesting that topographic complexity affects the number of species in the fish assemblage in the shallow (<10m) habitats. The topographic metric yielding the strongest statistical correlation (highest  $r^2$  values) to species richness was the linear rugosity index (Fig 3.3.25). Species richness was positively correlated with linear rugosity in every habitat with a substantial number of samples except for the middle reef. The shallow colonized pavement had the highest  $r^2$  (0.38) and the steepest linear regression slope indicating that rugosity had a greater affect on species richness in the shallow habitats. This result was not evident when looking at the uncategorized scatterplot of the entire data. Further support for two distinct fish assemblages comes from the multivariate analyses in Part IV.

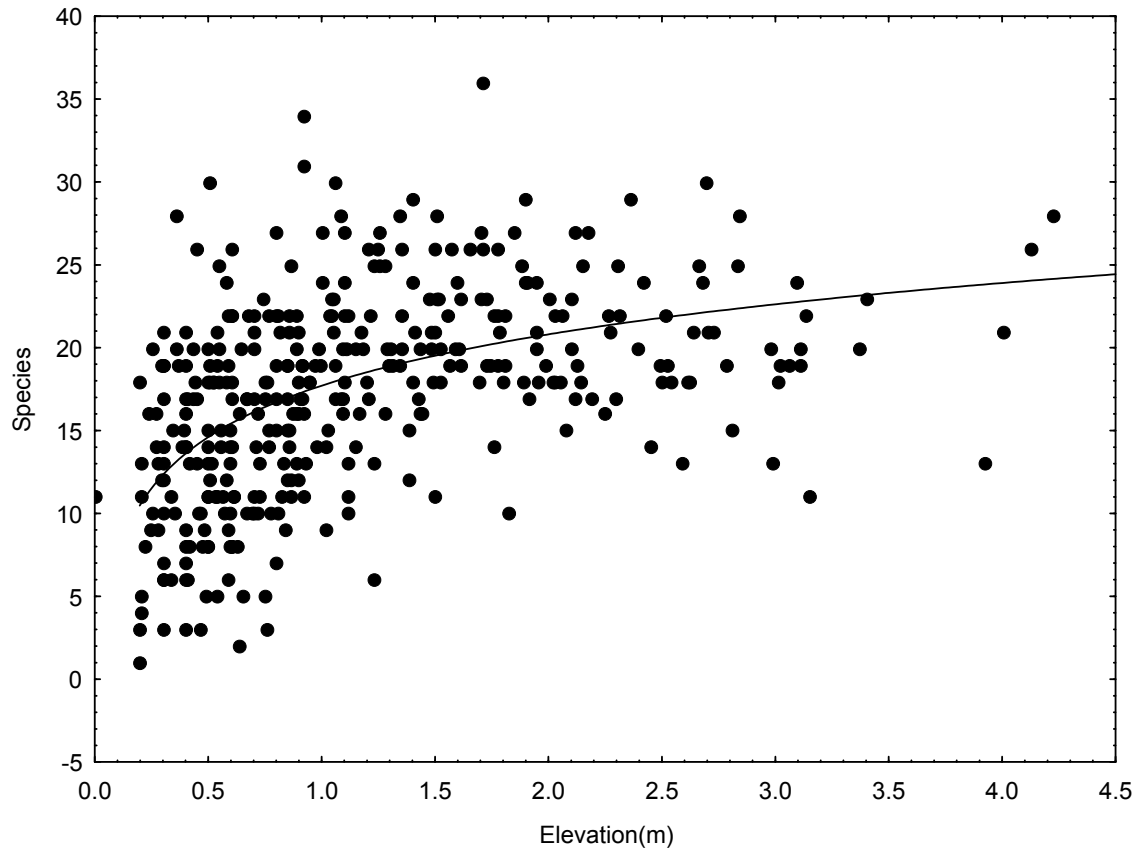


Figure 3.4.2. Scatterplot of species richness versus elevation (m). The black line shows the best fit logarithmic curve in the data.

Every GIS-measured topographic complexity variable exhibited a similar trend with the steepest linear regression slopes in the shallow ridges, shallow colonized pavements, and shallow middle reef. These results suggest that topographic complexity has a greater affect on species richness in the shallowest environments however this trend was not as evident with linear rugosity. Only the shallow colonized pavement showed a steeper linear regression slope than the other habitats. According to Liebig's Law of the Minimum, the relationship between factor and process strengthens as the factor becomes more limiting (Fig 3.4.1). Since the relationship between species richness and topographic complexity is strongest in the shallow environments, this may be a more limiting factor of the number of fish species in the shallow-water habitats than in the deep-water habitats.

The seascape analysis evinced stronger correlations and revealed that the relationship between reef fish and topographic complexity varied between habitats.

Linear regressions by habitat showed that topographic complexity strongly related to species richness in the shallow habitats (<10 m) but not as strong in deeper ones. Conversely, it related to abundance the strongest in the deeper habitats (>10 m) and was unrelated in the shallow ones. These findings are supported by Gratwicke & Speight (2005a & b) who recently found that rugosity affected species richness but not abundance on a shallow water Caribbean reef fish assemblage. They did not, however, investigate this relationship in deep habitats (>10m).

These results differed from previously published analyses of the same data (Ferro et al. 2005). Ferro et al. (2005) found that abundance and richness significantly differed between all three reefs. This discrepancy was likely due to a misclassification of the survey sites. GIS spatial analysis indicated that Ferro et al. (2005) classified many of the sites as Middle Reef when they actually plotted shoreward of the Inner reef on the Inshore Ridges. This mistaken inclusion of nearshore sites pulled down their middle reef mean richness and abundance values resulting in significant differences between all three reefs. These errors were evident in their MDS plot as well (Figure 22, Ferro et al. 2005), showing a high dispersal of Middle Reef sites among the Inner reef sites. This illustrates the value of seascape analyses to obtain proper site characterization.

### **3.4.3 GIS topographic complexity variables**

The results of the fish assemblage analyses showed that all of the topographic metrics detected relationships between topographic complexity and fish abundance and species richness. These results support other recent findings that large-scale rugosity measurements correlate to reef fish abundance and richness (Kuffner et al. 2007).

Of the GIS metrics, it was difficult to determine which topographic variable best captured this relationship because they all showed similar trends in the data analysis with each other and the *in situ* metric. Depth is a useful variable when looking at the entire dataset because it shows general trends in the data (Figs 3.3.7 & 3.3.17), yet depth alone cannot be used to predict species occurrence; other categorical predictors are needed to distinguish different areas in similar depths (Pittman et al. 2007). Elevation is a good metric because it is intuitive and areas with high reef elevations are known to have higher abundance (Kellison and Sedberry 1998, Rilov and Benayahu 2002), but it is a limited

metric because it does not account for surface variations within the survey area. Surface-rugosity is a useful metric because it applies the linear-rugosity measurement to the entire survey surface. This accounts for variations in the surveys that elevation does not, however surface rugosity is biased by extreme elevations. When elevation is low (<1 m), surface-rugosity must be low. When elevation is higher (1-4 m), it allows for much more variation to be introduced into the surface-rugosity calculation. When elevation is extremely high (>4 m), surface-rugosity will actually decrease because the extreme difference in elevation creates a flatter surface thus the values of the 3D surface area and the 2D surface area are not much different, yielding a low surface-rugosity value in a complex area. This affect is evident in Figure 3.3.31. Reef volume is perhaps the best GIS metric. Although, it is not a true volume measurement because it does not detect overhangs or reef porosity, it is a combination of the surface area and elevation metrics. It accounts for the surface variations and differences in elevation, thus eliminating the limitations of the other metrics. All of these metrics, however, are easy enough to calculate, and should all be considered in future studies. In this study, none of them appeared to relate better to the fish assemblage than the other.

#### **3.4.4 GIS metric limitations**

The use of GIS metrics to calculate topographic complexity must meet two criteria: (1) the survey data must be spatially accurate and (2) the bathymetric data must be of sufficient resolution to measure the parameter at an operational scale. Correlations between Linear-rugosity and elevation ( $r^2=0.09$ ), volume ( $r^2=0.07$ ), and surface-rugosity ( $r^2=0.16$ ) were low. This result suggests that either spatial location errors critical to the determination of the topographic parameters obfuscated the data or the resolution of the bathymetric data limited the ability to detect topographic complexity at the operational scale of the fish.

Spatial accuracy is critically important in this process because all of the GIS measurements rely on location. For this study, precautions were taken to minimize and avoid location errors by the quality control process described in section 3.2.2. The quality control process eliminated 57 fish surveys from the analysis due to conflicts between field data notes and the GIS data (depth, reef features etc.), however, it is still possible

that spatial errors were introduced into the GPS points taken at the survey sites. Spatial errors of at least 25-30 ft are inherent in the GPS. This error was possibly compounded on deeper sites by strong current carrying the buoy away from the survey center. Deeper sites would exacerbate this error due to increased scope of the buoy line. Although relatively small, these minute errors could have implications when trying to calculate accurate GIS topographic statistics. An artifact of the spatial errors in the data may be evident in the ANOVAs. Reef fish abundance and species richness showed a statistically significant increasing trend against linear-rugosity throughout the range of the data but the GIS topographic measurements leveled off. This asymptote occurred in the higher GIS topographic variable range corresponding to the deeper sites. Since the deeper areas have increased topographic complexity, it is possible that spatial errors from the deeper sites caused miscalculations in the GIS metrics.

An artifact of the spatial errors in the data may be evident in the ANOVAs. Reef fish abundance and species richness showed a statistically significant increasing trend against linear rugosity throughout the range of the data but the GIS topographic measurements leveled off. (Figs 3.3.12, 3.3.14, 3.3.22, & 3.3.24). This occurred in the higher GIS topographic variable range, corresponding to the deeper sites (Figs 3.3.2, 3.3.3, & 3.3.5). Since the deeper areas have increased topographic complexity, it is possible that spatial errors from the deeper sites caused miscalculations in the GIS metrics. This is logical to assume because the deeper sites have more scope in the buoy line and usually more current. Both of these factors could exaggerate spatial errors on the deep sites.

Spatial errors may have created noise in the correlations with the GIS metrics, but were likely not the sole cause. Two types of scale, measurement and operational, were important possible contributors to these weak relationships. The topic of scale can be confusing because there are many facets to the word. The four main definitions of scale are cartographic, geographic, operational, and measurement (Lam and Quattrochi 1992). Cartographic scale refers to the proportion of a map distance to that on the ground, the geographic scale is the spatial extent of a study, the operational scale is the scale at which a process operates, and the measurement scale is the resolution of data (Cao and Lam

1997). The measurement and operational scales are most pertinent to the results of this study.

The measurement scale for the GIS metrics was dependant upon bathymetric resolution, the density of depth samples per area. Bathymetric resolution was a critical component to the GIS topographic complexity analysis and the difference in calculations of topographic variables can be pronounced between surveys of different densities (Walker 2007). The bathymetric resolution in this study was 4 meters. This gave about twelve depth sample points within each survey to model the seafloor topographic features. Calculations from these data may have been too crude to depict the seafloor complexity within the surveys at the precision of the *in situ* measurement. This difference in scale would likely show a weaker GIS metric relationship to abundance and richness than the *in situ* measurements.

To illustrate this point, an extremely high resolution multibeam dataset was compared to the LADS data. This multibeam dataset was a survey acquired aboard NOAA ship “Whiting” in 2000. This survey spanned about 3km along the Middle and Outer reefs off the coast of Fort Lauderdale and acquired bathymetry at a 0.5 m density. Ten usable fish surveys were taken coincidentally within the confines of the Whiting survey. In a comparison between the two datasets, topographic complexity measurements were calculated in an identical way at the ten sites using each bathymetric data set. At a large scale, 1:10,000 for example, the difference between the two surveys was not evident (Figure 3.4.3 a&b). Both surveys showed the reef and many of the smaller features visible at this scale. The differences became more evident at the 1:2,000 scale (Figure 3.4.4 c&d). At this scale the 4m data (C) depicted the general features of the reef but there was little detail within the feature, whereas the 0.5m survey (D) depicted many details of the feature beyond the other survey. The surface was much more resolved at this scale.

The differences in measurement scale have implications on the topographic measurements calculated in the GIS. This is best illustrated in Figure 3.4.5 where two surveys are visible at a 1:650 scale. The underlying feature of the 0.5m survey are clearly better defined and this difference in data resolution is evident in the TINs of the fish surveys in a and b. The upper left circle in Figure 3.4.5 a&b are the individual TINs



created from the bathymetry of the same area. The striping pattern is a depth gradient within the TIN to aid in the illustration. This pattern is very linear and uniform in the TIN created using the LADS (4m) data (Figure 3.4.5a) whereas the pattern in the TIN created with the multibeam (0.5m) data is highly irregular (Figure 3.4.5b). This is due to the amount of depth sample points taken within a given area. The LADS data yielded 12 points in the fish survey area (blue dots in lower right circle of Fig 3.4.5a) and the Whiting survey yielded about 692 in the same area (blue dots in lower right circle of Fig 3.4.5b). The resolution of the 0.5m survey allowed for a much better characterization of the seafloor at this scale. A 3-dimensional comparison of the two upper right circles in Fig 3.4.5 illustrates this further (Figure 3.4.6). The topographic statistics were affected by the increasing resolution as well (Figure 3.4.6). A comparison of the mean percentage difference of every topographic variable between the two data sets showed that the volume calculation is 90.7% greater when using the 0.5m data (Table 3.4.1). The other statistics were not nearly affected by the increased resolution. There was a 13% difference in elevation, a 1.97% difference in Surface Rugosity, and a 0.5% difference in Z min (depth).

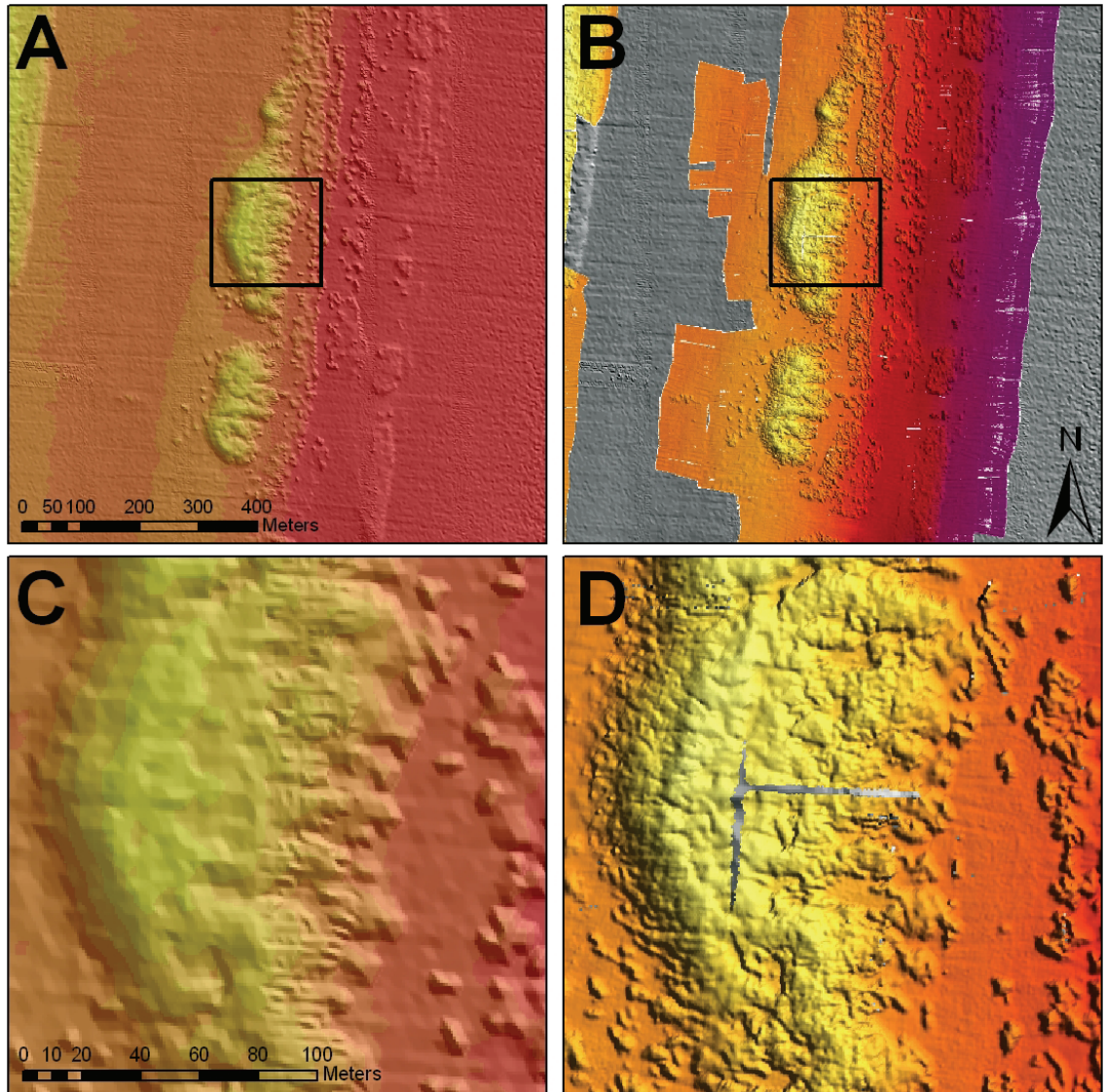


Figure 3.4.3. Comparison of two bathymetric surveys of different resolutions of the same area. (A) The LADS survey acquired bathymetry at 4m resolution which gave a nice depiction of the seafloor at larger scales (1:10000). (B) A multibeam survey of a limited area was taken using 0.5m resolution. These surveys do not show many differences at the large scale. The difference becomes more evident between the 4m and the 0.5m survey at smaller scales (1:2000) as evident in (C) and (D) respectively. The 4m survey picks up some of the features (C) but the 0.5m survey models the seafloor much more accurately (D).

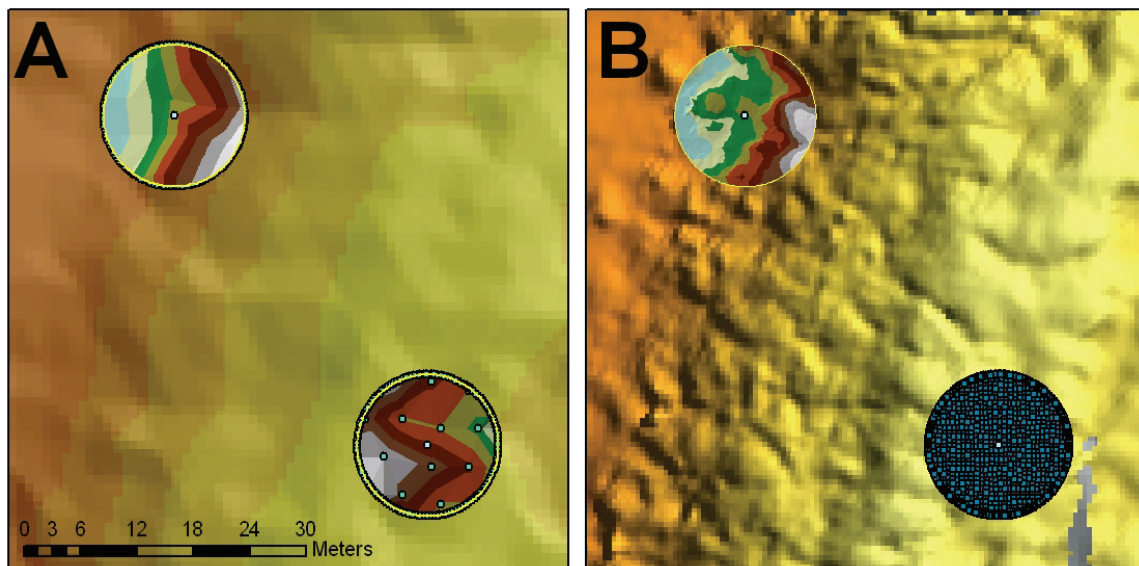


Figure 3.4.4. The implications of the data resolution are more evident at the scale of the fish survey (image at 1:650 scale). The lower right circle illustrates the data points associated with the TIN. (A) shows the twelve points captured during the LADS survey and (B) shows the 692 points captured during the multibeam survey. This enables a much better depiction of the seafloor and most likely allows for more accurate topographic statistics. The upper left colored circle is a TIN of the data within the fish survey 45OW. (A) shows the TIN created by the LADS data and (B) shows a TIN of the same area created by a higher resolution dataset.

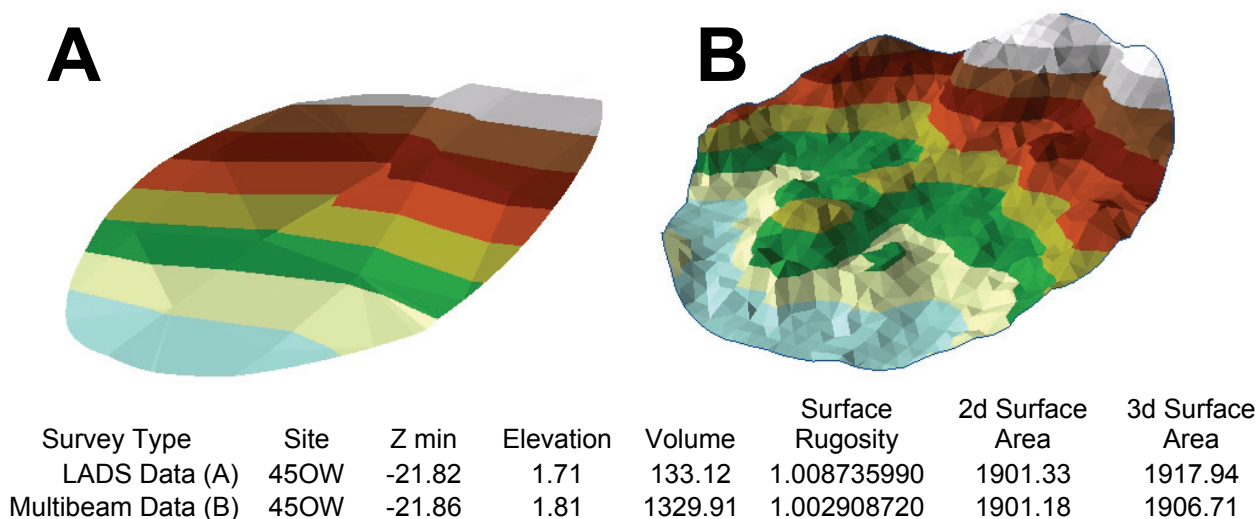


Figure 3.4.5. 3-dimensional comparison of the TIN seafloor model of the 0.5m multibeam survey (B) and the 4m LADS survey (A). The different colors are depth gradients. The 0.5m survey (B) gives much more detail of the seafloor than the 4m survey (A). This result affects the topographic statistics. Volume is ten times greater in the higher resolution survey and the 3d surface area and surface rugosity are also affected.

Site	Elevation	Volume	Zmin	Surface Rugosity
45OC	21.83%	91.62%	0.56%	0.08%
45OW	5.53%	89.99%	0.18%	0.58%
44ME	1.98%	90.61%	0.64%	2.54%
44OE	21.36%	92.71%	0.60%	0.85%
45OE	5.02%	91.15%	0.30%	9.18%
46ME	16.80%	89.58%	1.14%	0.24%
46OC	38.33%	86.64%	0.62%	0.07%
46OE	6.68%	91.78%	0.34%	2.69%
47OC	3.04%	90.48%	0.33%	2.19%
47ME	9.47%	92.09%	0.06%	1.26%
Mean %	<b>13.00%</b>	<b>90.67%</b>	<b>0.48%</b>	<b>1.97%</b>

Table 3.4.1. Percentage difference of the topographic variable for each site between the 0.5m Whiting survey and the 4m LADS.

The outcome of this comparison illustrates that differences in measurement scale can affect the GIS calculations of topographic metrics. These differences can be pronounced between bathymetric surveys of higher and lower densities due to changes in the resolution (measurement scale) between the two data sets; the 0.5m density data modeling the topography at a finer scale. The remotely-sensed topographic variables measured in this study were based on a bathymetric dataset with 4m centers (LADS). Calculations from these data may have been too crude to depict the seafloor complexity within the surveys at the same precision of the *in situ* measurement. No current bathymetric survey can model the seafloor with precision and accuracy enough to capture the minute variations in topography that an *in situ* measurement can, mainly because bathymetry cannot model overhangs or reef porosity. Therefore no matter how dense the data, the modeled seafloor surface using present techniques will always be a plane. *In situ* measurements of the seafloor follow the contours of the surface on a much finer measurement scale and account for overhangs and small reef crevices. This does not mean that GIS metrics cannot be used, only that the relationships may not be as strong.

Operational scale, the scale at which a process operates, is also important because a process operating at one scale may not be evident at a different scale (Wiens 1989, Bian 1997, Cao & Lam 1997, Sale 1998, Shriner 2004). For example, it is conceivable that different sized fish respond to topographic complexity at varying operational scales (Sale 1998, Grober-Dunsmore 2005, Kuffner et al. 2007). Large fish may relate to topographically complexity on a meter scale while small fish may respond to it on a

centimeter scale (Sale 1998). In other words, a 30cm grunt may be associated with a 2m elevation reef ledge while a 2cm goby may be associated with a 5cm elevation area. Using larger measurement scale variables like the GIS metrics may not capture the relationship between fish and topography at finer operational scales (e.g. the goby level) (Kuffner et al. 2007). Therefore, a coarse bathymetric survey may correlate well to topographic measurements in an assemblage dominated by large fishes whereas a higher density survey may be needed to detect a similar relationship in a small-fish-dominated assemblage.

The affect of scaling issues on the collection and analyses of reef fish data are diverse and need to be better understood (Sale 1998). The seascape analysis elucidated previously unobserved changes in the assemblage-topography relationship simply by better characterizing the survey sites. Similar results may be evinced in studies designed to test this relationship at different scales. The scale used in the current study ( $\sim 176 \text{ m}^2$ ) was within the recommended range of scales from other studies (Grober-Dunsmore 2005, Kuffner et al. 2007); however, these recommendations arose from studies assessing the relationship of fish to reef parameters using similar point count methodology. Because the recommended scales were those closest to that of the survey data, it may be an artifact of the analysis (Sale 1998). Clearly this is an area in need of more investigation.

### **3.4.5 Topographic complexity limitations as a predictor**

Many studies have shown reef fish have an affinity towards increased topographic complexity, making it a logical environmental variable to use to predict their occurrence. Using this variable as a predictor requires some major assumptions. The foremost assumption is that the fish assemblage is habitat limited (i.e. wherever there is habitat, there is fish). Numerous factors restrict a species' ability to occupy a given location including its physiology, ecology, morphology and behavior (Wiens 1989). This relates to the niche concept of which there are many definitions (Heglund 2002, Morrison and Hall 2002). For simplicity, let us view the niche as the distribution of resource use along one or more resource axes for a species (Cao 1995). All of these combined factors define a species' fundamental niche; the space that contains all the proper conditions for a species to successfully occupy (Putman and Wratten 1984). "In reality, the fundamental

niche is unlikely to be seen in the world because the presence of competing individuals necessarily restricts a given species to a narrower range of conditions—its ‘realized’ niche” (Heglund 2002). The realized niche is a smaller portion of the fundamental niche where the species optimally thrives due to biological interactions such as competition/predation (Putman and Wratten 1984). Depending on the interactions and their intensity, the realized niche may be much smaller than the fundamental niche. This would skew prediction studies based on criteria that do not account for such population dynamics (Heglund 2002). If the realized niche for reef fish in South Florida is severely limited by a factor other than topographic complexity, then areas predicted to have high abundance and/or species richness due to high topographic complexity may have very little.

Several ecological models have been developed based on ecological processes that could limit a reef fish species’ realized niche and affect its distribution within its fundamental niche: (1) the competition model, (2) the lottery model, (3) the predation disturbance model, and (4) the recruitment limitation model (Sale 1991). Classically, the competition model, developed by Smith and Tyler, was thought to be ideal. This claims that competition during the post recruitment phase structures the diverse reef communities. It assumes that living space on the reef is in short supply and there is always too many recruits trying to colonize. Recruitment is therefore determined by competition for space. The second model, the lottery hypothesis model, suggests patterns in the community structure are driven by random events and whichever species gets there first occupies the vacancy (Sale 1976 & 1991). This model maintains fish still compete for space but also adds that competition only influences the overall numbers not the relative abundance of fish. The predation disturbance model (Talbot et al. 1978, Hixon 1991 & 2002) hypothesizes that fish distribution is driven by predation and the mortality of adults during post recruitment keeps populations below the carrying capacity, reducing competition for space. This is similar to the competition model in that it states recruitment is modified by post recruitment processes but it differs in that post recruitment competition is weak (Sale 1991). The most recent of the models is the recruitment limitation model which states that low larval supply levels will not allow a reef fish population to reach carrying capacity. There has been much debate about the

four models for many years. According to G.P. Jones (Jones 1991) “The fact that recruitment is variable in space and time is arguably the only undisputed fact to come out of 20 years of research on the numerical structure of coral reef assemblages.” Although no model characterizes the distribution for all reef fishes, experiments have shown that each one is valid in certain reef systems (Doherty 2002).

Gilliam (1999) tested which ecological processes best explained reef fish distributions in Broward County and found that recruitment variability coupled with predation and refuge limitation was the most influential process in affecting reef fish distributions. When recruitment into the system was high, prey refuge became the limiting factor, but when recruitment was low refuge availability did not matter. This means the association between the reef fish assemblage and topographic complexity is likely driven by temporal recruitment events.

Gilliam’s (1999) study also supported the lottery hypothesis, finding that species composition was randomly influenced by a “temporally and spatially changing recruitment pool”. This means that when a fish is removed from the system, the supplanting fish recruit species is random. This has implications for any prediction model because recruitment is a stochastic process of which there is currently no way to predict density or species composition, therefore a system driven by recruitment may be very hard to predict.

Gilliam’s (1999) study suggested that space resources are not limited during a large part of the year. This may explain the high variability in the assemblage data relationship to topographic complexity and could confound any predictions made by overestimating abundance. Prediction models based on topography must assume that where there is increased topographic complexity there will be more fish, however, this may not necessarily be true as there may be unfilled niches due to increased fishing pressure (predation) and/or variable recruitment.

### **3.5 Conclusions**

Topographic complexity affects reef fish distributions in Southeast Florida. Reef fish abundance and species richness both positively correlated with *in situ* and GIS topographic metrics. Linear-rugosity yielded the highest correlations between reef fish



abundance and species richness, but the correlations were relatively weak suggesting that topographic complexity is not the only controlling factor on the reef fish assemblage and this relationship is not static. Other important ecological factors such as variable recruitment have been implicated in shaping the assemblage (Gilliam 1999).

Seascape analysis revealed two distinct reef fish assemblages; one associated with the shallow water habitats and one with the deeper habitats. Furthermore, species richness related to topographic complexity stronger in the shallow habitats than deeper ones, whereas, the abundance relationship was stronger in the deeper habitats. These results were substantially different from previously published analyses of the same data and illustrate the necessity for detailed benthic habitat mapping and GIS analyses in future studies.

It is difficult to determine which GIS factor best-captured the assemblage relationship to topographic complexity because they all showed similar trends with the assemblage data. Elevation is useful because it accounts for differences in surface height, but does not account for surface variation. Surface-rugosity is useful because it accounts for surface variation but has some biases in extreme cases. Volume may give the best result because it incorporates both surface-rugosity and elevation into its calculation. All of these metrics are easy enough to calculate in GIS, and thus all should be considered in future studies.

Accurate spatial data is essential for the GIS metric calculation and spatial errors need to be reduced as much as possible. Scale is also important as bathymetric resolution can affect the calculations, especially with regard to volume. Taking bathymetric data at the highest possible density will lessen this confounding problem by modeling the seafloor topography more precisely.

GIS measured topographic complexity can be used as a proxy for reef fish distribution models. Since the relationship changes across the seascape, modeling the relationship for each separate reef habitat would likely produce more accurate results. Such predictive models would have many scientific and management applications like the estimation of fish stocks, the designation of marine protected areas, and the estimation of impacts on essential fish habitats. They could also be used as a baseline for



comparison to future subsequent surveys to help understand temporal changes in the fish assemblages.

Topographically-based prediction models will likely be confounded by factors such as spatial accuracy and measurement and operational scales. Better understandings of the appropriate measurement scale and the scales at which different reef fish operate are needed to more accurately model their distributions. More research is also needed to better understand the dynamics how reef fish relate to topographic complexity and to the other ecological factors influencing their distributions.

This chapter shows that a relationship between GIS topographic metrics and fish assemblage structure exists. This is the first step in being able to use these data in the development of seascape reef fish prediction models. The relationship between reef fish and the GIS topography in each survey between each habitat can be extrapolated to the entire 3 dimensional bathymetric surface, yielding a seascape level view of the relationships detected in the survey data. The next chapter further explores the relationship between the fish assemblage and benthic habitat via multivariate analyses. These analyses will provide the final piece of input data for the predictive model to show how the fish surveys relate to one another categorized by different factors and determining the relative contribution of the constituents of the assemblage in each habitat that formed this relationship.

# Part IV

## **Multidimensional Scaling Analysis**

## **4 Multidimensional Scaling Analyses**

### **4.1 Introduction**

The previous section showed that total reef fish abundance and richness both statistically significantly increased with greater topographic complexity. This information is useful; however, it may be oversimplifying a more complex relationship. Total abundance and species richness are single indices and do not account for the percentages of individual species in the data. For example a fish count may have the same richness value but the species that compose each survey could be markedly different. Furthermore, two surveys may have the same total abundance, but the ratio of species may not be the same (i.e. two surveys may have 100 total fish but one may be dominated by Haemulids while another Labrids). These single index data are known as univariate data. Univariate data analyses are very useful in looking at single-factor relationships; however, techniques are available that look at the complete sample data set. These are known as multivariate techniques. These methods “base their comparisons of two (or more) samples on the extent to which these samples share particular species, at comparable levels of abundance” (Clarke and Warwick 2001). They are based on similarity indices which facilitate clustering of the data into similar groups and mapping the data in ordination plots which illustrates the samples’ relationship to one another (Clarke and Warwick 2001). Several multivariate techniques have been developed including Principle Components Analysis (PCA) and Multidimensional Scaling (MDS). MDS is one of the best multivariate analyses available (Everitt 1978, Clarke and Warwick 2001). It is conceptually simple, is based on relevant sample information, is generally applicable, avoids species deletions, and can appropriately weight similarities (Clarke and Warwick 2001). Therefore MDS is the preferred multivariate method in this study.

Another useful analysis derived from the multivariate analysis is the analysis of similarity percentages between species within certain groups. This procedure, outlined in Clarke and Warwick (2001), calculates the percentage contribution of each species to sample similarity. It ranks the species in a specified category, such as habitat. If, for example, habitats are determined to be a good categorical predictor by their distribution

in the MDS plot, this analysis will help determine the dominant species within those habitats.

In this chapter, multivariate statistics are employed to look at the relationship between the surveys without condensing the data into single factors. MDS plots are created from Bray-Curtis dissimilarity matrices to illustrate, or map, this relationship. *A priori* categorization of the survey points in the MDS plot by different factors will help determine which factors show the best clustering in the data. These factors are the same categories used and defined in Part III: depth, elevation, volume, surface rugosity, linear rugosity, reef sites, and benthic habitats. A similarity percentage analysis is then performed on the factor with the best clustering to show the differences in the assemblages between those clusters.

## 4.2 Methods

Multivariate statistics were performed using PRIMER 5 (PRIMER-E, Ltd., Plymouth, UK) to look for assemblage similarities between sites. The data were imported into the program from an Excel spreadsheet where the abundance of every species in every survey was tabulated. The samples were in rows, the species were in columns, and the abundance was entered for each cell. If a species did not occur in a particular count a zero was entered for that species. A Bray-Curtis dissimilarity matrix between samples was created from this spreadsheet within the program. A draftsman plot of the data indicated non-normality, thus the data were normalized by a 4<sup>th</sup> root transformation during this process. The resultant matrix ranked each sample according to its dissimilarity amongst the group of samples. Multidimensional Scaling (MDS) graphs were plotted using these data to illustrate the results. The data were displayed in the MDS graphs according to different factors. These factors were categorical data derived from the GIS analyses and *in situ* data. Topographic complexity data from the GIS analyses were continuous. These data were categorized into discrete classes by smart quantile analysis of their histogram distributions or by expert-driven decisions. For example, depth was categorized by expert-driven classes of 5 meter intervals instead of its smart quantile data frequency distribution because this intuitively made sense. Viewing the depth categories in familiar ranges is much easier than the ones chosen by the smart quantile method.

Similarly, elevation was categorized in 0.5 m classes. Categorizing the other variables was not intuitive, thus smart quantiles, which evenly determined the categorization of the data throughout the dataset according to their frequency distribution of values, were used to categorize surface rugosity, linear rugosity, and reef volume. Other factor categories such as reef sites and benthic habitats were categorical in nature and were directly compatible as factor classes.

All of the following graphs are of the same data in the same orientation classified differently according to the different variable, and therefore one can follow one point from graph to graph to see how it changed between different factors.

## **4.3 Results**

### **4.3.1 Total Assemblage MDS**

The total assemblage MDS plot showed a wide scatter of points in the center and a more concentrated group to the lower right. When the original reef site categories (pre-GIS analysis) were applied to the data, the sites classified as middle west (MW) and middle crest (MC) were spread throughout the center of the plot mixed with the inshore surveys and the middle east and offshore surveys clustered together scattered amongst each other in the lower right (Fig. 4.3.1).

The MDS of the survey data classified by elevation showed that there were low elevation sites throughout the data (Fig. 4.3.2). The 0-0.5, 0.5-1.0, and 1.0-1.5 classes were scattered throughout the plot, whereas all of the higher elevation sites clustered in the lower right. Categorizing the data by depth showed that the widely spread sites in the center of the graph were almost exclusively from surveys performed in the 0-5 and 5-10 meter depths (Fig. 4.3.3). All of the deeper surveys clustered more tightly together in the lower right. Classifying the data points by surface-rugosity and reef volume showed similar trends as reef elevation (Figs. 4.3.4 and 4.3.5). Both showed a scattering of lower values throughout the entire plot but surveys with higher values of surface-rugosity and volume clustered together in the lower right. Linear-rugosity categorization did not show any apparent clustering in the MDS plot (Fig. 4.3.6). High and low valued linear-rugosity surveys were evident throughout the range of the plot.

The categorization which showed the best groupings of reef fish surveys in the MDS plot was the benthic habitats (Fig. 4.3.7). The colonized pavement and shallow ridge habitats clustered separately from almost all other habitats. The wide scattering within this grouping indicated a highly variable assemblage. The almost exclusive second grouping was more tightly packed and consisted of the deeper habitats. The tighter clustering of this group indicated a less variable assemblage. There was weak evidence of clustering within this group as well.

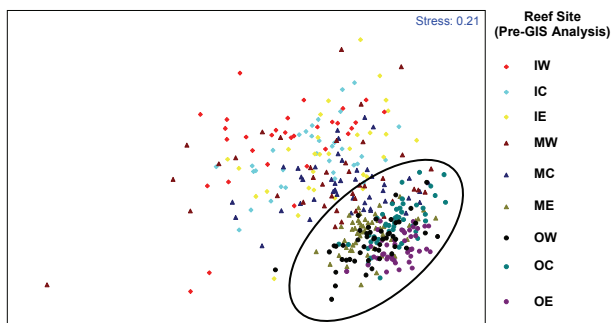


Figure 4.3.1. MDS plot of reef fish survey data classified as the original reef site nomenclature before GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

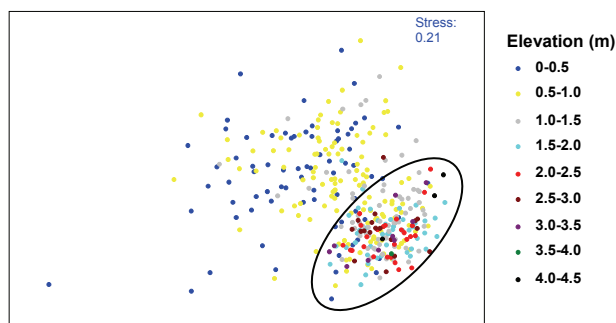


Figure 4.3.2. MDS plot of reef fish survey data classified as the maximum elevation (m) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

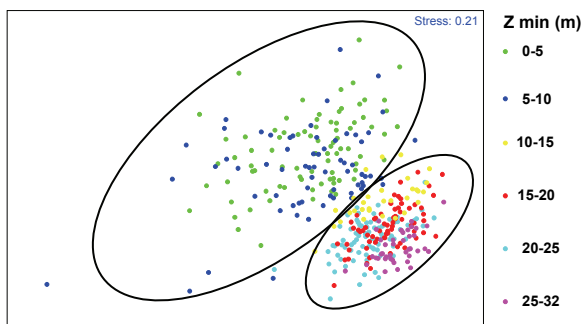


Figure 4.3.3. MDS plot of reef fish survey data classified as the minimum Z (m) (maximum depth) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

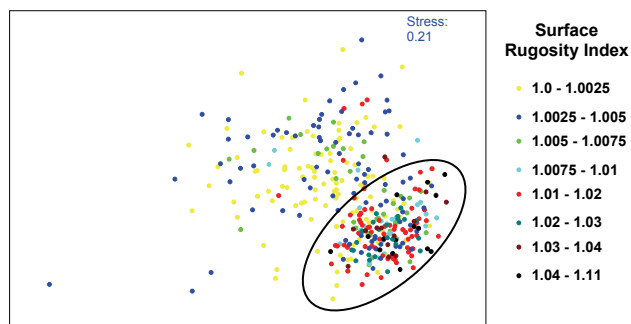


Figure 4.3.4. MDS plot of reef fish survey data classified as the surface-rugosity index calculated within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

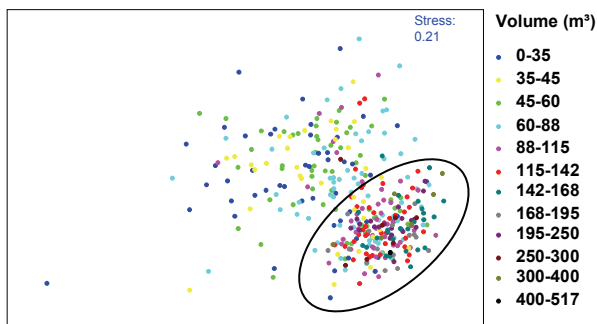


Figure 4.3.5. MDS plot of reef fish survey data classified as the reef volume (m³) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

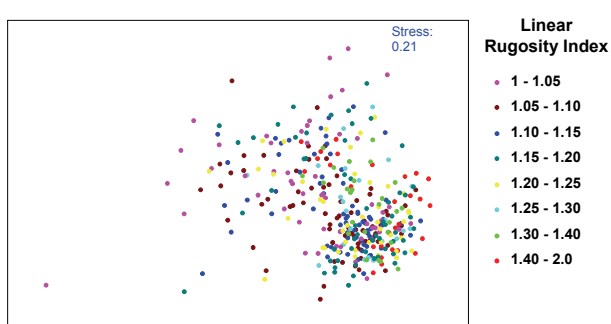


Figure 4.3.6. MDS plot of reef fish survey data classified as the linear-rugosity index calculated *in situ* by divers during the survey. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

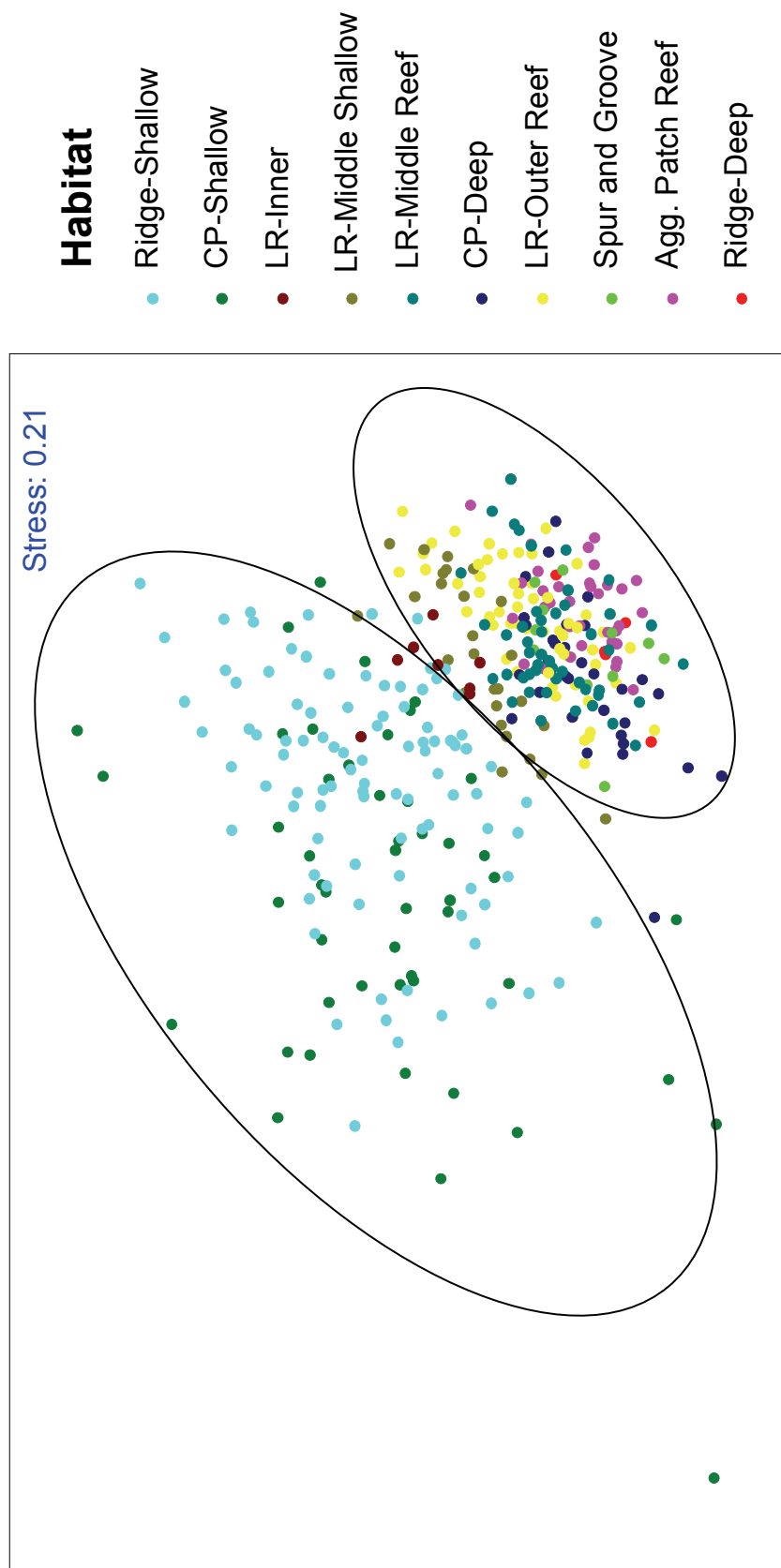


Figure 4.3.7. MDS plot of reef fish survey data classified as the benthic habitat defined by the survey location from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.



### 4.3.2 Seasonal Assemblage MDS

The reef fish surveys were taken over a two year period introducing temporal variation as another variable in the data. In order to ensure the trends in the data were not temporally influenced, the data were separated into three month seasons (e.g. March, April, May of 2002 were grouped as Spring02). The seasons with the strongest statistical power (i.e. the most samples in the given period containing the most reef sites) were analyzed separately to determine if the trends were temporally consistent. For brevity only one of the seasonal analyses is presented herein, yet they showed similar trends.

The Spring02 MDS plot was performed under the same manner as the total assemblage plot. When categorizing the data with the original reef site nomenclature, the deep sites (ME, OW, OC, & OE) formed a tight cluster to the lower right however the other data points were a scattered mix of inner and middle reef sites (Fig. 4.3.8). When the renamed reef site categories were applied to the same plot, a clear separation between groups was evident (Fig. 4.3.9). As with the total assemblage, the inner ridge sites were grouped in a widely scattered area indicating high variability within, but were separate from the deep sites. The deep sites also showed evidence of grouping within the larger group however too few data points were present to allow such an analysis.

The categorization of the MDS data into physical environmental parameters measured in the GIS for the Spring02 data also showed patterns similar to those of the total assemblage. The data were clearly separated by depth (Fig 4.3.10). The scattered points left of center which classified as the inshore ridges were in the 0-5 or 5-10 meter classes whereas the tight cluster to the lower right was all deep sites. Reef elevation (Fig. 4.3.11), volume (Fig. 4.3.12), and surface-rugosity (Fig. 4.3.13) all plotted lower values throughout the range of the data but the higher values were constrained within the lower right grouping. The linear-rugosity categorization did not show any evidence of clustering (Fig. 4.3.14). The benthic habitat categorization showed groupings similar to the renamed reef sites (Fig. 4.3.9) with the colonized pavement and shallow ridge comprising the widely scattered data group left of center and the deep habitats in the lower right group (Fig. 4.3.15). The lower right group also showed signs of clustering within but there were not enough data points to justify these groupings.

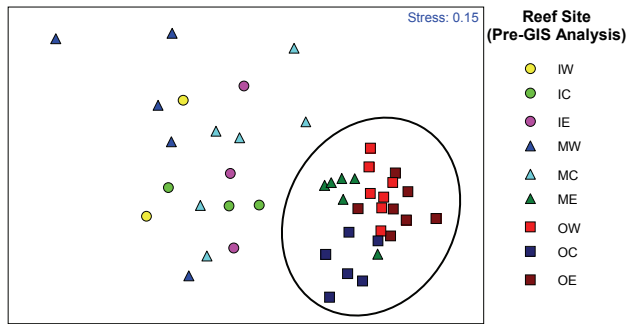


Figure 4.3.8. MDS plot of reef fish survey data for Spring 2002 classified as the original reef site nomenclature before GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

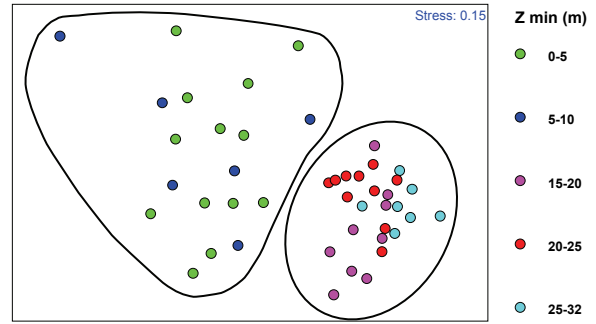


Figure 4.3.9. MDS plot of reef fish survey data for Spring 2002 classified as the minimum Z (m) (maximum depth) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

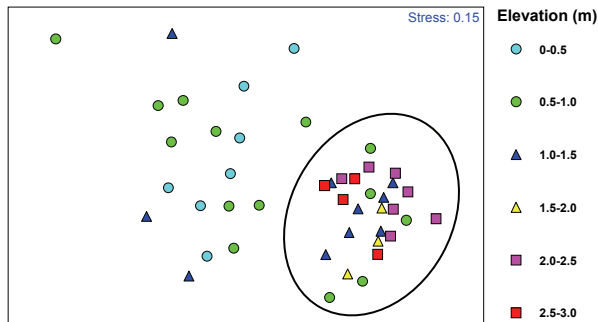


Figure 4.3.10. MDS plot of reef fish survey data for Spring 2002 classified as the maximum elevation (m) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

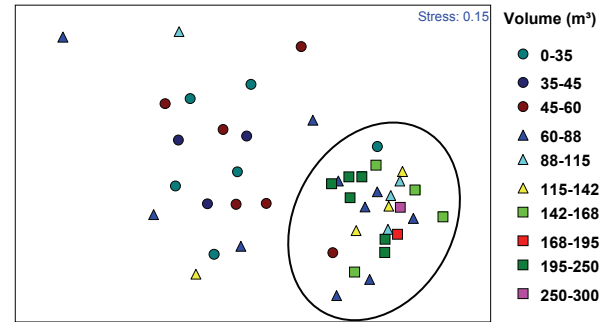


Figure 4.3.11. MDS plot of reef fish survey data for Spring 2002 classified as the reef volume (m³) within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

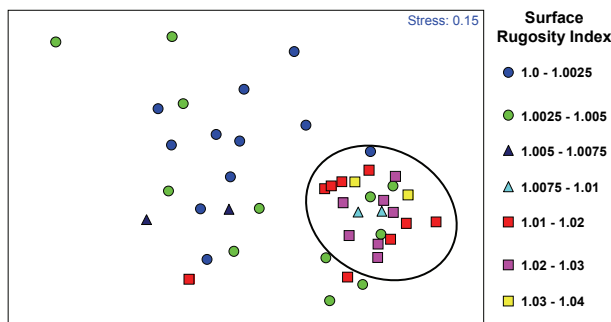


Figure 4.3.12. MDS plot of reef fish survey data for Spring 2002 classified as the surface-rugosity index calculated within the survey area from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

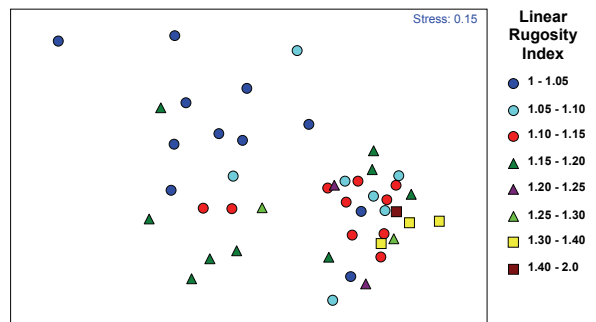


Figure 4.3.13. MDS plot of reef fish survey data for Spring 2002 classified as the linear-rugosity index calculated *in situ* by divers during the survey. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

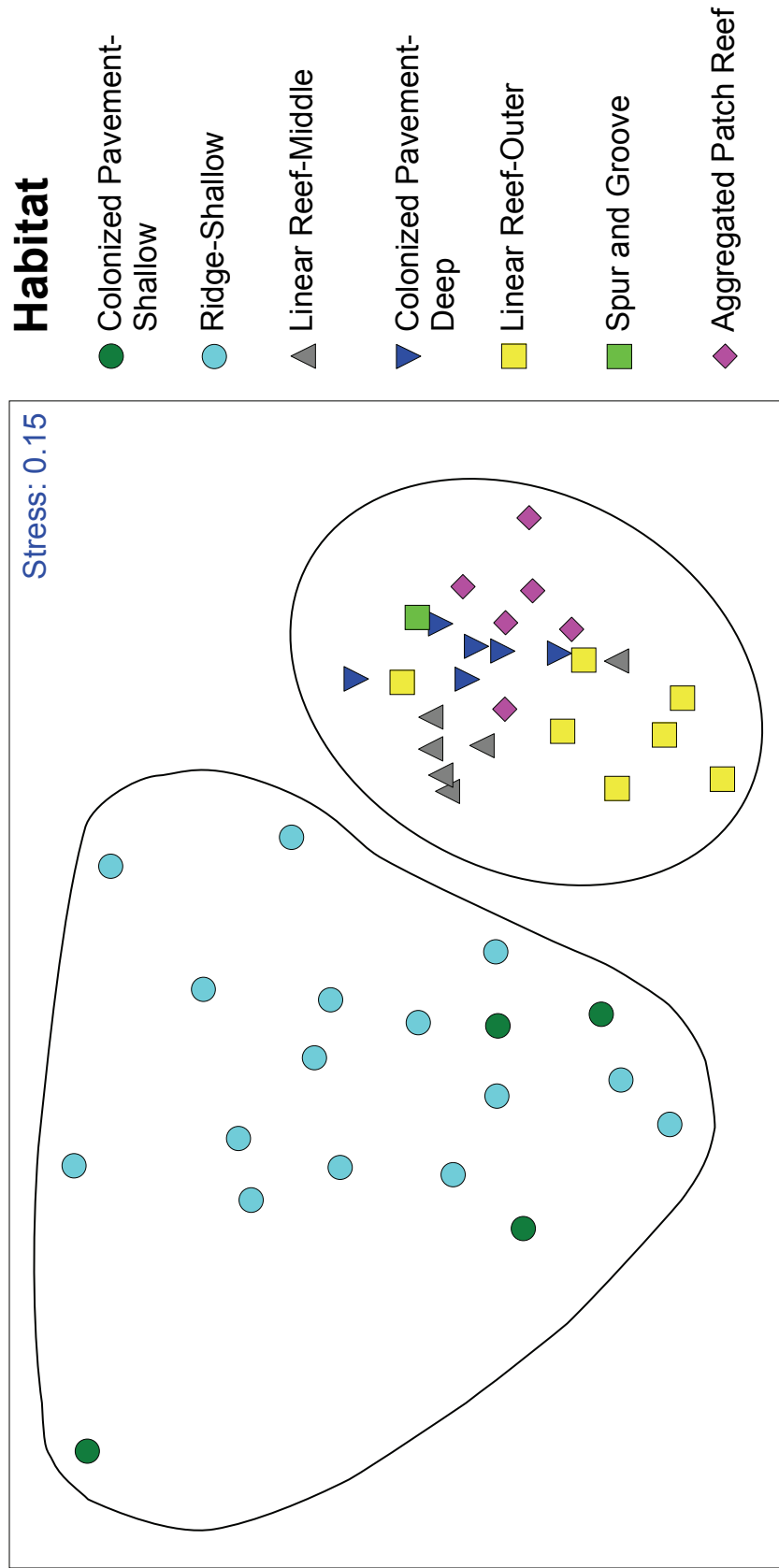


Figure 4.3.14. MDS plot of reef fish survey data for Spring 2002 classified as the benthic habitat defined by the survey location from GIS analysis. Data were transformed to the fourth root and plotted by means of a Bray-Curtis dissimilarity matrix.

### 4.3.3 Similarity Percentages between Habitats

Examination of the multivariate data in Primer by similarity percentage (SIMPER) analysis identified the species responsible for the clustering patterns in the benthic habitat MDS plot (Fig. 4.3.7). The contribution percentage of each species in the similarity matrix was determined for each habitat and plotted in Excel as a pie chart. See Appendix II for the key to species name abbreviations in the following charts.

Species contributions were different between benthic habitats. The reef fish species which contributed most to the Shallow Colonized Pavement MDS plot were *Halichoeres bivittatus* (23%), juvenile *Haemulon*s (13%), *Acanthurus bahianus* (12%), *Stegastes variabilis* (6%), and *Thalassoma bifasciatum* (Fig. 4.3.15). The Shallow Ridge habitat assemblage was primarily comprised of *Halichoeres bivittatus* (21%), *Acanthurus bahianus* (18%), *Thalassoma bifasciatum* (12%), and *Ancanthurus chirurgus* (7%) (Fig. 4.3.16). The Inner Reef survey dominant fishes were *Stegastes partitus* (14%), *Thalassoma bifasciatum* (12%), *Sparisoma aurofrenatum* (11%), *Halichoeres bivittatus* (10%), *Acanthurus bahianus* (18%), and *Stegastes variabilis* (8%) (Fig. 4.3.17). The Shallow Middle Reef assemblage was dominated by *Stegastes partitus* (16%), *Thalassoma bifasciatum* (15%), *Halichoeres garnoti* (10%), *Acanthurus bahianus* (10%), and *Sparisoma aurofrenatum* (8%) (Fig. 4.3.18). The Middle Reef was dominated by *Stegastes partitus* (14%), *Thalassoma bifasciatum* (11%), *Halichoeres garnoti* (10%), *Serranus tigrinus* (7%), *Acanthurus bahianus* (6%), and *Sparisoma aurofrenatum* (6%) (Fig. 4.3.19). The Deep Colonized Pavement dominant fishes were *Halichoeres garnoti* (14%), *Stegastes partitus* (13%), *Thalassoma bifasciatum* (10%), *Serranus tabacarius* (8%), and *Sparisoma aurofrenatum* (8%) (Fig. 4.3.20). The Outer Reef was mostly

comprised of *Thalassoma bifasciatum* (14%), *Stegastes partitus* (14%), *Halichoeres garnoti* (12%), *Acanthurus bahianus* (9%), and *Sparisoma aurofrenatum* (9%) (Fig. 4.3.21). The species that contributed most to the MDS plot of the Spur & Groove habitat were *Stegastes partitus* (16%), *Halichoeres garnoti* (13%), *Thalassoma bifasciatum* (11%), *Sparisoma aurofrenatum* (9%), and *Canthigaster rostrata* (6%) (Fig. 4.3.22). The Aggregated Patch Reef habitat was mainly composed of *Stegastes partitus* (16%), *Thalassoma bifasciatum* (12%), *Halichoeres garnoti* (11%), *Sparisoma aurofrenatum* (6%), and *Scarus taeniopterus* (5%) (Fig. 4.3.23). The Deep Ridge sites were most affected by *Stegastes partitus* (22%), *Halichoeres garnoti* (15%), *Thalassoma bifasciatum* (15%), *Sparisoma aurofrenatum* (7%), and *Acanthurus bahianus* (9%) (Fig. 4.3.24).

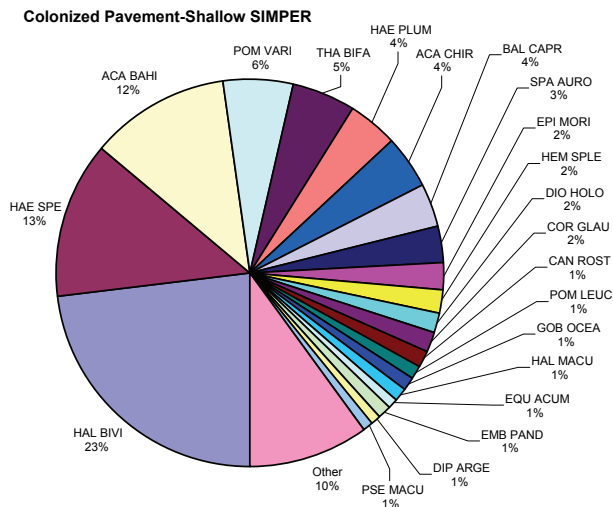


Figure 4.3.15. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Shallow Colonized Pavement. Other is a combination many species of less than 1% contribution each.

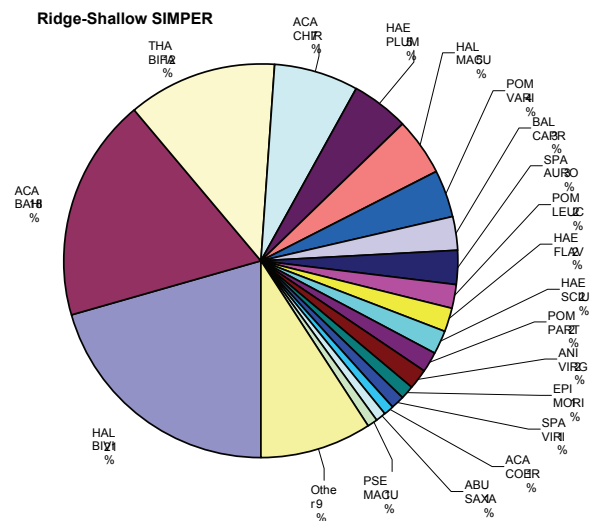


Figure 4.3.16. The species contribution percentage to MDS of the visual fish surveys by SIMPER analysis in Primer of the Shallow Ridge. Other is a combination many species of less than 1% contribution each.

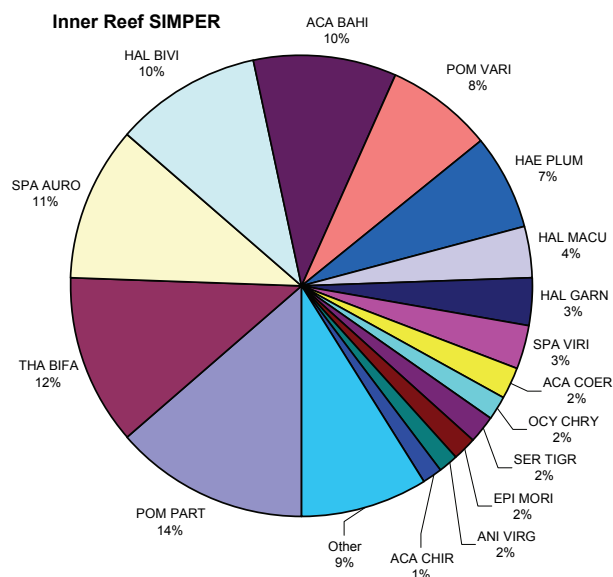


Figure 4.3.17. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Inner Reef. Other is a combination many species of less than 1% contribution each.

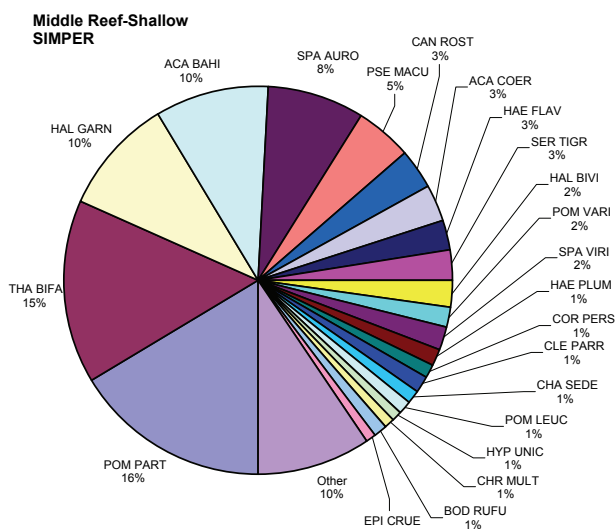


Figure 4.3.18. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Shallow Middle Reef. Other is a combination many species of less than 1% contribution each.

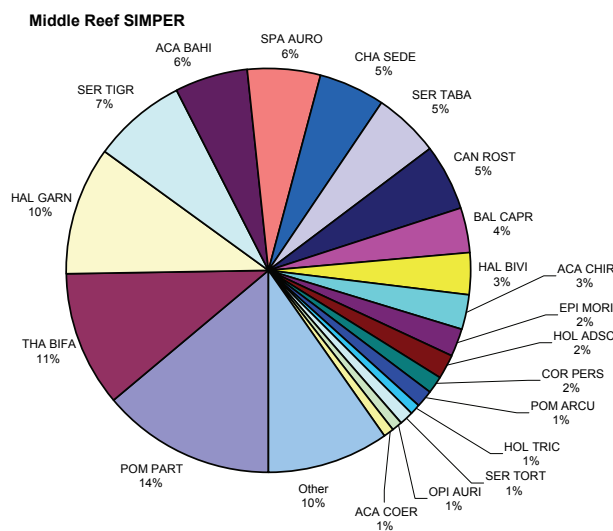


Figure 4.3.19. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Middle Reef. Other is a combination many species of less than 1% contribution each.

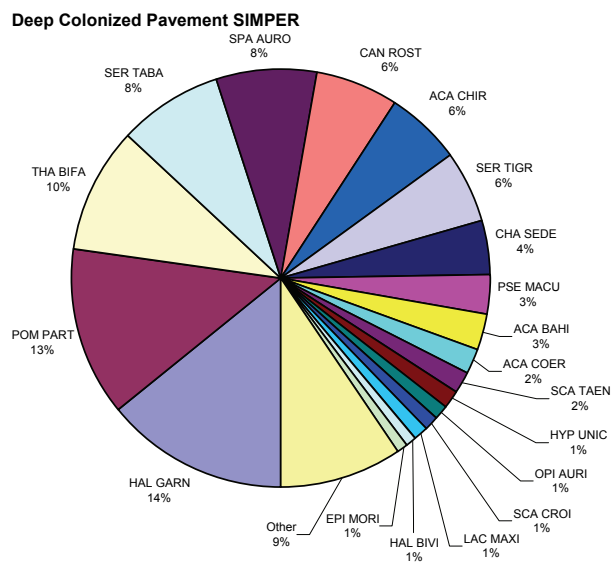


Figure 4.3.20. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Deep Colonized Pavement. Other is a combination many species of less than 1% contribution each.

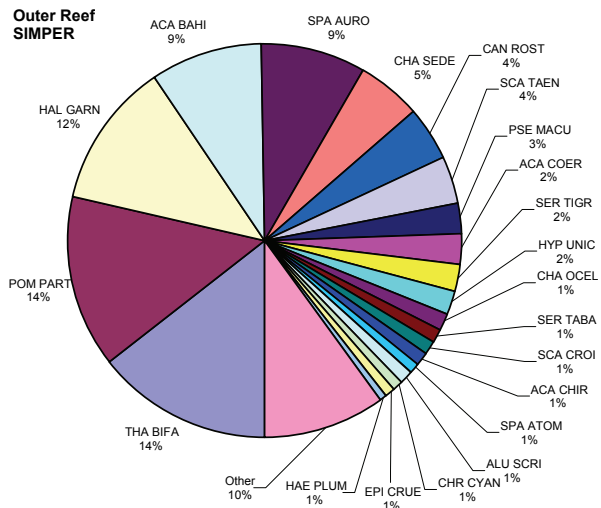


Figure 4.3.21. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Outer Reef. Other is a combination many species of less than 1% contribution each.

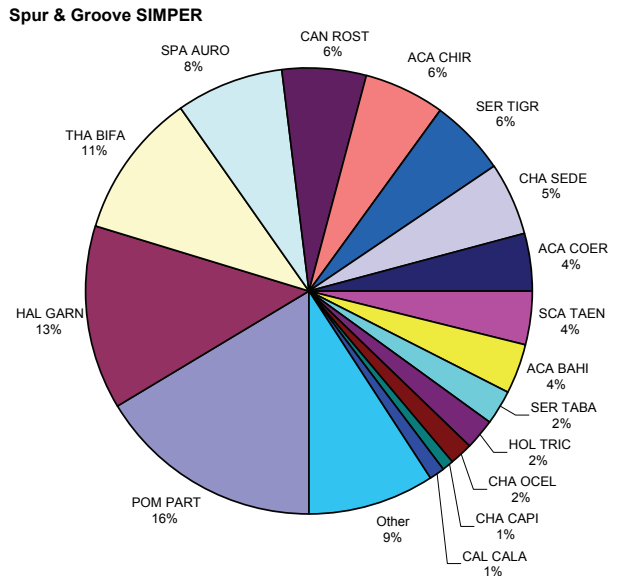


Figure 4.3.22. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Spur & Groove. Other is a combination many species of less than 1% contribution each.

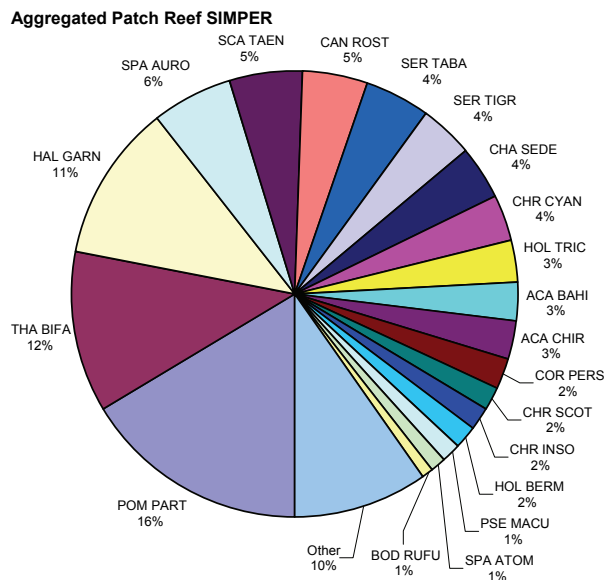


Figure 4.3.23. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Aggregated Patch Reef habitat. Other is a combination many species of less than 1% contribution each.

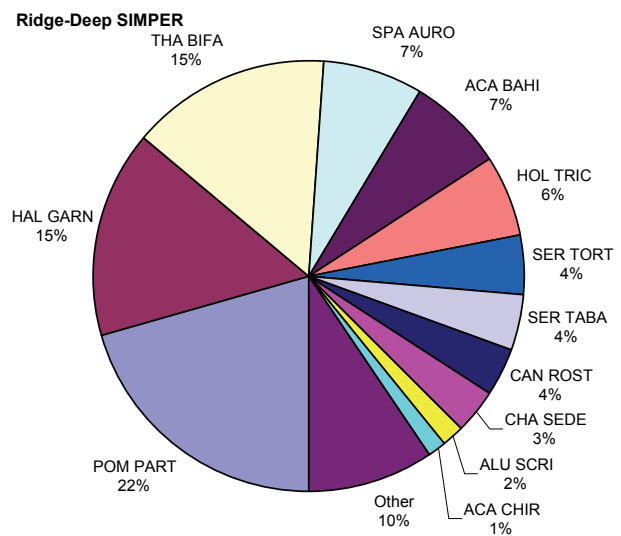


Figure 4.3.24. The species contribution percentage to multidimensional scaling of the visual fish surveys by SIMPER analysis in Primer of the Deep Ridge. Other is a combination many species of less than 1% contribution each.

## 4.4 Discussion

### 4.4.1 MDS Categorical groupings

The points in the MDS are placed relative to their dissimilarity of the relative contribution of species within each fish survey calculated in the Bray-Curtis dissimilarity matrix. In other words, fish surveys that are very similar will plot close together while ones that are quite different will be further away. The variability of the data is evident by the size of the data cluster. In this study the data were highly variable as evinced by the wide spread of the data throughout the plot and the high stress level (0.21). Despite the high variability, clustering was still evident within the MDS plot. The performance of the clustering in the MDS depended on which factor was used to categorize the data. The classification of those points was based on *a priori* measurements made independently from the MDS results, therefore the classifications that exhibited the best clustering were assumed to be the best indicator of what is shaping the assemblage.

In general the MDS showed the shallow, inshore reefs had the highest variability and were the least similar and the deep, offshore reefs were less variable and most similar (Fig 4.3.3). The assemblage in the 0-5 and 5-10 meter depths formed a highly variable and highly interspersed cluster (Fig 4.3.3 green and blue dots). These data were distinguished from the deeper data almost exclusively. There was a small overlap of 10-15m depth samples between the two groups, but it seems that 10m was a definite break in the data. The deeper surveys were also interspersed but were more tightly clustered. There may be clustering within this deep cluster as well. The 10-15m surveys (Yellow) were separate from the 25-32m surveys (Pink) although both classes overlapped with the 15-20m and 20-25m surveys.

The result that the Broward County fish assemblage is driven by depth supports Ferro et al. (2005) who concluded the same. Depth categorizes the data well because the factors driving the fish assemblage also change with depth. For example, Part III showed that topographic complexity affects the fish assemblage and every topographic variable measured in this study increased with increasing depth (Part III Figs. 3.3.18-3.3.21). This was evident in the MDS plots as well. The highest values of elevation (Fig. 4.3.2), surface rugosity (Fig. 4.3.4), and volume (Fig. 4.3.5) all appeared in the cluster



corresponding with the deep sites. Furthermore, Moyer et al. (2003) showed that different habitats were detectable in Broward County through acoustic diversity. The results of the habitat mapping in Part II support these findings; the different reefs in Broward County varied according to changes in acoustic diversity, which was interpreted into different habitats. These habitats were found to be highly constrained with depth at a statistically significant level (Part III Fig. 3.3.15a). This suggests that the factors controlling the fish assemblages might best be illustrated by a habitat categorization.

Ferro et al. (2005) used the reef site categorization as their habitat classifiers. Their plot with their original reef site categorization did not illustrate good cluster results (Fig 4.3.1). This pre-GIS reef site classification showed a high dispersal of Middle reef sites (triangles) in and among the Inner reef sites (diamonds). This was due to the misclassification of the fish surveys (see Part II, Section 3.2.2). When the fish surveys were plotted on the LADS data in the GIS, it was evident a new classification was necessary. Many of the sites originally labeled as Middle Reef actually plotted on the Inshore Ridges, shoreward of the Inner reef. Also clustering between reef edge and crest sites was not evident in the MDS. In other words, the eastern edge, western edge, and crest sites of a given reef type were interspersed and did not form separate clusters. This suggests that the old site classifications did not adequately characterize the sites.

Classifying the data according to the benthic habitats developed in Part II yielded much better results in the MDS (Fig. 4.3.7). Comparing the pre-GIS analysis reef sites MDS plot with the benthic habitat plot exhibited distinct differences. The benthic habitat categorization showed a second cluster in the data similar to the depth categorization. The dispersal of the pre-GIS analysis Middle reef sites prohibited a second cluster from being inferred. The benthic habitat categorization identified a second highly variable, widely spread cluster as one of two habitats; shallow colonized pavement or shallow ridge. The surveys taken in these two habitats were clearly different from the other surveys and the extreme dissimilarity between shallow habitat survey sites evident by the spread of the cluster may suggest that the inshore reef fish assemblages are less predictable than the other habitat assemblages.

Apart from the interspersed shallow colonized pavement and ridge cluster, a second, tighter cluster was evident in the MDS. This was a much more compact cluster,

indicating the data within were less variable. This cluster, composed of all the other habitats, exhibited subtle trends within the cluster as well. There appears to be a gradient from the top left side of the cluster to the lower right. Although distinct clusters were not evident, the Middle Reef-Shallow sites all plotted in the upper left of the cluster; separate from the Spur and Groove, the Aggregated Patch Reef, and the Deep Ridge habitats. The overlapping between the Outer Reef, the Middle Reef-Deep, the Colonized Pavement-Deep, the Spur and Groove, the Aggregated Patch Reef, and the Ridge-Deep habitats in the MDS suggests that the fish assemblages in these habitats are more similar. This could be because the variability within these habitats was too great to elucidate a difference between them.

#### **4.4.2 Seasonal evaluation**

The seasonal MDS plots showed similar trends with less stress (0.15). Two clusters were evident; a shallow and a deep (Fig. 4.3.9); the topographic variables were highest in the second, tighter cluster corresponding to the deep sites (Figs. 4.3.10-4.3.13); and the benthic habitats characterized the data well (Fig. 4.3.14). The absence of temporal variability yielded similar but less variable results than the entire dataset. The Spring 2002 MDS showed better clustering within the deep habitats. Little overlap was evident between the habitats within the lower right cluster. This could be the result of reducing temporal variation in the data however the sample size was low. The low number of samples per habitat may not have been enough to exhibit the variation shown in the complete data set. Since some overlap between habitats was evident, the pattern of the whole dataset must be assumed.

#### **4.4.3 Benthic Habitat Species Composition**

The benthic habitat classification categorized the fish survey data in the MDS plots well, thus the similarity percentage (SIMPER) analysis was applied to the benthic habitat categories to show which species most contributed to the dissimilarity of surveys between each category. The main contributors to the assemblage varied between habitats and the largest difference was between the groups of habitats in the two clusters of the MDS. The differences between the two clusters in the MDS plots was most evident in the

abundance of *Halichoeres bivittatus* (Hal bivi), juvenile Haemulids (Hae spe), and *Acanthurus bahianus* (Aca bahi). *Halichoeres bivittatus* was the dominant species in the two shallow habitats comprising 23% of the colonized pavement and 21% of the shallow ridge (Fig. 4.3.15 & 4.3.16). This species' contribution to the assemblage lessened as the habitats deepened from 10% in the Inner Reef to 2% in the shallow Middle Reef, 3% in the deep Middle Reef, and less than 1% further offshore. The juvenile Haemulids dominated the shallow Colonized Pavement, being the second most prominent species in that habitat at 13% (Fig. 4.3.15). Unlike the *H. bivittatus*, juvenile Haemulids did not significantly contribute to the assemblages in any of the other habitats (<1%). *A. bahianus* was another dominant species in the shallow habitats. Similar to *H. bivittatus*, *A. bahianus* was more dominant in the shallow habitats and became less of a contributor to the assemblage in the deeper ones. Unlike *H. bivittatus*, *A. bahianus* remained a significant contributor to the assemblage in many of the habitats. Due to the survey methodology, accurate size class information was not available; however, it is likely that the increased contribution of *A. bahianus* in the shallow habitat assemblages was due to increased number of juveniles. The nearshore habitats are typically dominated by juvenile fishes and Haemulids and Acanthurids are a large part of that assemblage (Lindeman 1986, Baron et al. 2004). These results are consistent with other reef fish assemblages on gorgonian dominated pavements in the U.S. Virgin Islands (Monaco et al., 2007).

The main contributors to the habitats in the second tighter cluster in the MDS were *Stegastes partitus* (Pom part), *Thalassoma bifasciatum* (Tha bifa), *Halichoeres garnoti* (Hal garn), and *Sparisoma aurofrenatum* (Spa auro). These four fish dominated the habitats in the second cluster and, aside from *T. bifasciatum*, were an almost negligible contributor of the nearshore assemblage in the other MDS cluster. Another interesting result evident in the SIMPER analysis was that there were fewer dominant contributing species nearshore habitats. For example, the Shallow Ridge habitat had seven main contributing species (>3%) while the Middle Reef had ten. The dominant constituents in the nearshore sites were also more dominant than those offshore. For example *H. bivittatus*, the most dominant fish in the nearshore habitats, contributed to over 20% of the assemblage whereas the most dominant fish in the offshore habitats contributed 16% (*S. partitus*, Patch Reef). These differences in major species'

contributions to the assemblage help explain why the data clustered into two main groups and demonstrate that the assemblage changes between habitats.

## 4.5 Conclusions

The multivariate analysis was crucial in the examination of the fish assemblage data. Mapping the data in MDS plots according to their Bray-Curtis dissimilarity matrix values elucidated valuable information about how the data relate without having to lose information via a univariate statistical approach. The multivariate approach showed that the fish assemblage in Broward County's hardbottom/reef system form two separate groups; a nearshore assemblage and an offshore assemblage. The MDS showed that the fish data were highly variable in the nearshore habitats and became more similar offshore. Categorization of the data in the MDS showed that the fish assemblage is heavily influenced by depth. Since the benthic habitats are highly correlated with depth, they were ideal for categorizing the data. The benthic habitat categorization of the data yielded better results than the original site nomenclature due to the misclassification of the original sites; especially the Middle Reef sites. The GIS topographic metrics showed highest values in the offshore (deep) cluster yet they did not show any meaningful clustering in the data. Temporal variation was evident by the lessening of the MDS stress value but the results were similar to the total assemblage MDS analyses. The similarity percentage analysis gave insights as to what species were driving the differences between the clusters in the MDS. The nearshore assemblage was dominated by different species than the offshore assemblage. *H. bivittatus*, juvenile haemulids, and acanthurids were the main constituents of the inshore assemblage while *S. partitus*, *T. bifasciatum*, *H. garnoti*, and *S. aurofrenatum* dominated the offshore assemblage. Furthermore, there were fewer dominant species in the nearshore assemblage and more dominant species in the offshore habitats.

The analyses in this chapter yielded the information necessary to predict the fish assemblage. The MDS showed that the benthic habitat mapping categorized the assemblage well and the SIMPER analysis yielded the major species contributors for each of those habitats. This information can now be used in conjunction with the topographic analysis to develop a prediction model. This is the focus of the next chapter.

# Part V

## **Fish Assemblage Prediction Model**

## 5 Fish Assemblage Prediction Model

### 5.1 Introduction

Studies linking small-scale measurements of abundances and species distributions to broad-scale seascapes are the key to understanding and predicting organismal distributions and their dynamics (Wiens 1989, Heglund 2002). This applies to reef fish populations as well (Sale 1998). Reef fish studies are often limited to small spatial scales because of logistical and economic constraints; however, viewing the data at larger spatial scales might elucidate unforeseen relationships and patterns (Sale 1998, Pittman and McAlpine 2001) and facilitate regional management and conservation efforts.

Remote sensing allows the acquisition of large amounts of data quickly and economically and provides the foundation for large-scale resource mapping and modeling. Mapping the resource on large scales allows an understanding of how the seascape (or landscape) is arranged. These maps are then the basis upon which seascape analyses and modeling efforts are constructed (Grober-Dunsmore 2005). For fishes, the appropriate characterization of the seascape must include essential fish habitats (Rubec et al. 1998a & b). For this reason, mapping of coral reefs and essential fish habitat has been a primary objective of resource managers since the Sustainable Fisheries Act outlined its importance in 1996 (NOAA 1996). The Sustainable Fisheries Act defines essential fish habitat as “those waters and substrate necessary for spawning, breeding, feeding, or growing to maturity”. Research has shown that essential fish habitat should consist of highly rugose areas (Grigg 1994, Friedlander et al. 2003) because many studies (including this one) have shown that increased habitat complexity/rugosity positively influence reef fish abundance and/or species richness (Luckhurst and Luckhurst 1978, Hixon and Beets 1989, Bell et al. 1991, McCoy and Bell 1991, McClanahan 1994, Appeldoorn et al. 1997, Chabanet et al. 1997, Garcia Charton and Perez Ruzafa 1998, Friedlander and Parrish 1998, Friedlander et al. 2003, Gratwicke & Speight 2005a & b). All of these previous studies used an *in situ* measure of topographic complexity, which is not practical on a large spatial scale (McCormick 1994). Measuring topographic complexity on larger scales (>Km<sup>2</sup>) requires different techniques (Iampietro et al. 2005,

Kuffner et al. 2007). One large-scale technique is to analyze 3-dimensional topographic surfaces in GIS (see Part III).

The need for these types of large-scale spatial analyses of reef fish is growing due to the over-exploitation of marine resources and the need for management and conservation of large areas (Kendall et al. 2003, Gorber-Dunsmore 2005). To address this growing need, I have created an empirical model to predict reef fish abundance and species richness for the nearshore seascape (<30m contour) using the relationship between the fish, benthic habitats, and GIS-derived topographic complexity metrics from *in situ* survey data. The essential components for this model (discussed in Part I Section 1.2) have been met: 1) a large scale high resolution bathymetric survey of the seascape (Part III), 2) spatially defined and characterized accurate benthic habitats (Part II), and 3) spatially defined, *in situ* survey of the reef fish population spanning the entire seascape and many of the defined habitats (Part III). Using the data from these essential components, I developed a reef fish assemblage prediction model to project the relationship of fish to habitat and topographic complexity from the small-scale fish survey data (i.e. *in situ* surveys) over a broad area of unsampled locations.

This chapter outlines the methodology and presents the predictive data derived from the regression equations in a GIS to view and analyze the small-scale *in situ* data on a seascape-level scale. The model framework design, accuracy, strengths, weaknesses, applications and recommended uses are discussed.

## **5.2 Methodology**

This model was developed by combining all the analyses from the three previous chapters and projecting the results across the seascape. The model work flow for the entire process is shown in Figure 5.2.1. This figure shows the processes involved and the sections they correspond to in order to create the prediction model. Part III of this study (dark blue) described the relationship between reef fish assemblage abundance and species richness in Broward County with topographic complexity and its effect between different habitats. Part IV of this study (green) illustrated the relationship of the reef fish surveys in multivariate analyses, which showed that the benthic habitats from Part II (light blue) adequately categorized the assemblage data thus validating a similarity

percentage analysis to identify the major constituent species responsible for the dissimilarities evident in the MDS between habitats. Predictions of reef fish abundance and species richness were made based on the regression line equation of the topographic measurements and the major species constituents of the assemblage were predicted from the SIMPER analysis based on the benthic habitat from the GIS benthic habitat map (red).

### **5.2.1 Abundance and Species Richness Predictions**

The main requirement for developing this model was to define areas from which to derive the topographic statistics. Since the observed fish data were collected at the scale of 15m diameter surveys, it was critical that the topographic statistics be created at a similar scale (Sale 1998). This was accomplished by projecting a rectilinear vector grid of square polygons over the entire survey area with 50ft (15.24m) length and width spacing. A grid of squares was preferred over the circular visual census design because it was ideal for presenting the spatial data. The grid acted as a pixel-based approach allowing for complete coverage of the survey area (~55Km<sup>2</sup>). The 50ft (15.24m) grid spacing was used because the base map data were projected in State Plane NAD83 FL East feet so the 15m diameter survey area was converted to feet (49.21ft) and rounded up. Since this produced a grid with over 11 million polygons, to make this amount of data manageable, the area was split up into 15 smaller sub regions within which each step was performed.

Some of the mapped areas did not have enough fish surveys to warrant modeling, therefore, grid polygons that fell within those habitats were filtered. All grid polygons that fell outside of the usable mapped habitats (e.g. sand, spur & groove, Deep Ridge, etc.) were discarded. This limited the topographic calculations to only those polygons that were to be included in the prediction model. The habitats used were Ridge-Shallow, Colonized Pavement-Shallow & Deep, Linear Reef Middle Shallow & Deep, Linear Reef Outer, and Aggregated Patch Reefs. All of these habitats were modeled from Port Everglades to Boca Inlet except for Linear Reef Middle Shallow, which was modeled from Hillsboro inlet to Boca inlet due to fish survey data coverage.

Topographic statistics for the polygon grids were calculated in ArcView3.3 by using “Surface Tools for Points, Lines and Polygons” (v. 1.6) (Jenness 2005). This is an



arcsript created by Jeff Jenness of the USDA Forestry Service in Flagstaff AZ, available for download on his website <[http://www.jennessent.com/arcview/surface\\_tools.htm](http://www.jennessent.com/arcview/surface_tools.htm)> or at ESRI's arcsript website <<http://arcsripts.esri.com/>>. It allows the user to calculate specific topographic statistics of a shape file from a Triangulated Irregular Network (TIN). In this case it was particularly useful due to the volume of statistics that needed to be calculated. Even though the arcsript was used, the methodology is conceptually the same as described in Part III section 3.2.3. The arcsript allows for a faster, automated process. For each individual 50ft by 50ft (15.24m x 15.24m) square grid polygon, the script clipped the TIN to that area, calculated the specified topographic statistics (elevation range, volume, and surface area), then wrote the results to a table which was joined to the shapefile's database. This process took about 18 seconds per polygon and needed to be repeated for each of the 134,704 polygons resulting in 28 continuous days of processing time if run sequentially on a single computer. By splitting the files into 15 separate areas, the statistics were calculated concurrently on several machines, reducing the single machine time required to obtain the results.

Once the topographic statistics were calculated, the polygon-habitat association was associated with the correct habitat in order to allow application of the proper regression equation. This was accomplished in ArcGIS 9.1 using the query function to select all grid polygons that had their centers in a particular habitat (e.g. outer reef) and exporting the data as a separate shapefile. The exported topographic data values were then input into the appropriate regression equation based on the metric predictor and its habitat derived in Part III. For example, the Outer Reef elevation range calculated from the process above was inserted as the x value into the equation  $109.2243610 + 46.30834270 * x$  (see Appendix III Table 1 for regression equations) to obtain the fish abundance value for that grid polygon. Therefore, if the GIS measured maximum elevation in a given square on the outer reef was 2.0 meters, then predicted abundance from the regression equation is 202 (rounded to the nearest whole number). This was repeated for all values in the table using the different regression equations for the different habitats and for each GIS metric to generate six columns of predicted data, a predicted abundance and richness for each GIS metric- Elevation Abundance, Elevation Richness, Volume Abundance, Volume Richness, Surface Rugosity Abundance, and

Surface Rugosity Richness. These data were then saved as a shapefile database file and retained their associations with the polygons in the GIS. Once all the predictors were calculated for each habitat, the data were combined in the GIS into one shapefile, containing six columns of predicted values. These values were then displayed in the GIS as a chloropleth map using a ramped color scheme to denote a range of values.

### **5.2.2 Reef fish assemblage constituents predictions**

The dominant assemblage species constituents were taken from the SIMPER analyses in the previous section (Part IV). For each habitat, the top 70% of contributors to the assemblage were used to calculate a predicted abundance of each of the dominant species (Appendix IV). This was accomplished by taking the SIMPER percentage for each dominant species, dividing it by 100, and multiplying it by the predicted total abundance from reef volume. These abundance values were added to the GIS.

### **5.2.3 Prediction Model ANOVA**

Statistical analyses of the model predicted abundance and richness were performed via ANOVA using Statistica 6.0. The predicted abundance and richness were compared to the empirical data to confirm the model showed similar trends in the predicted data as in the original data. These analyses compared the predicted abundance and species richness values for each of the GIS metrics (elevation, volume, and surface rugosity) between the three reef lines: inner ridge, middle, and outer.

### **5.2.4 Prediction Model Validation**

Validation of the prediction model was completed by comparing the fish survey data (measured data) with the nearest prediction model polygon. This was accomplished by querying the prediction model in GIS for all polygons that contained the center points of the fish surveys. The predicted abundances and richness for all predictive metrics were statistically compared to the measured values by ANOVA. Correlations of the data between the predicted and measured values were performed for all GIS metrics in Statistica. The correlation values were compared to infer each model's performance.

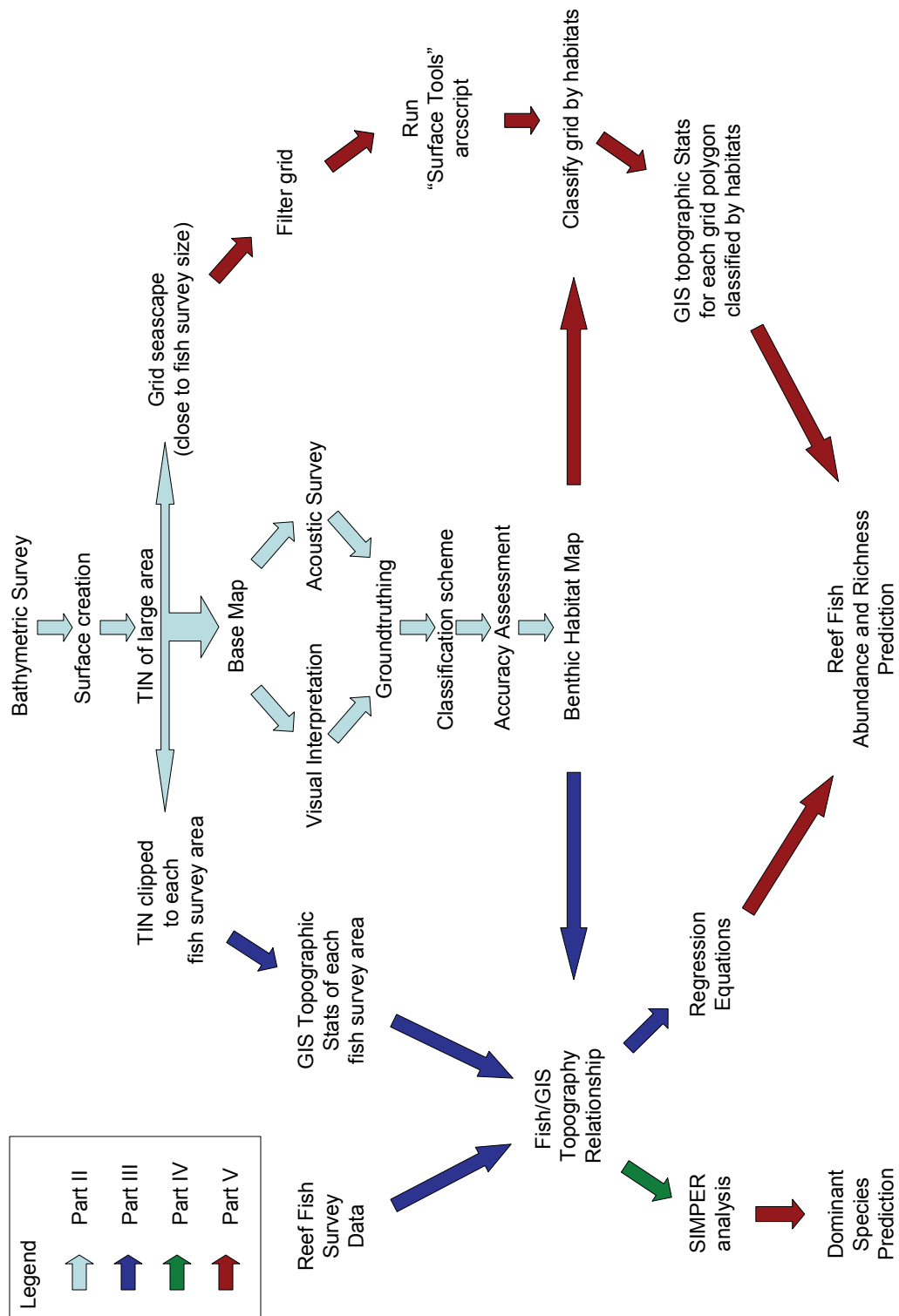


Figure 5.2.1. Work flow of the reef fish prediction model. Arrows indicate direction to the necessary steps for creating the reef fish prediction model. Arrow color corresponds to the different dissertation sections in which this work was presented and discussed; Light Blue = Part II, Dark Blue = Part III, Green = Part IV, and Red = Part V.

## **5.3 Results**

### **5.3.1 Prediction Model Results**

The results of the seascape prediction model yielded 6 separate prediction maps, one for abundance and one for species richness for each of the three metrics-Elevation, Volume, and Surface Rugosity. The full maps are illustrated in Appendix V. To facilitate the results presentation, an identical section from each map has been assembled in Figure 5.4.1. The maps are composed of 134,704 square polygons, each with a value for predicted fish abundance and richness using the elevation, volume, and surface rugosity values generated from the regression equations in their respective habitats. The data illustrated in each of the six maps are display changes in the GIS to illustrate one attribute of the polygon. In other words, the polygons are colorized to the metric of choice. Each map utilizes a similar color ramp however the values for each color do not equate between maps. In all the maps, yellow is the lowest value and blue/purple is the highest. The values of the colors are labeled in each map legend. Some features are displayed as almost a single color.

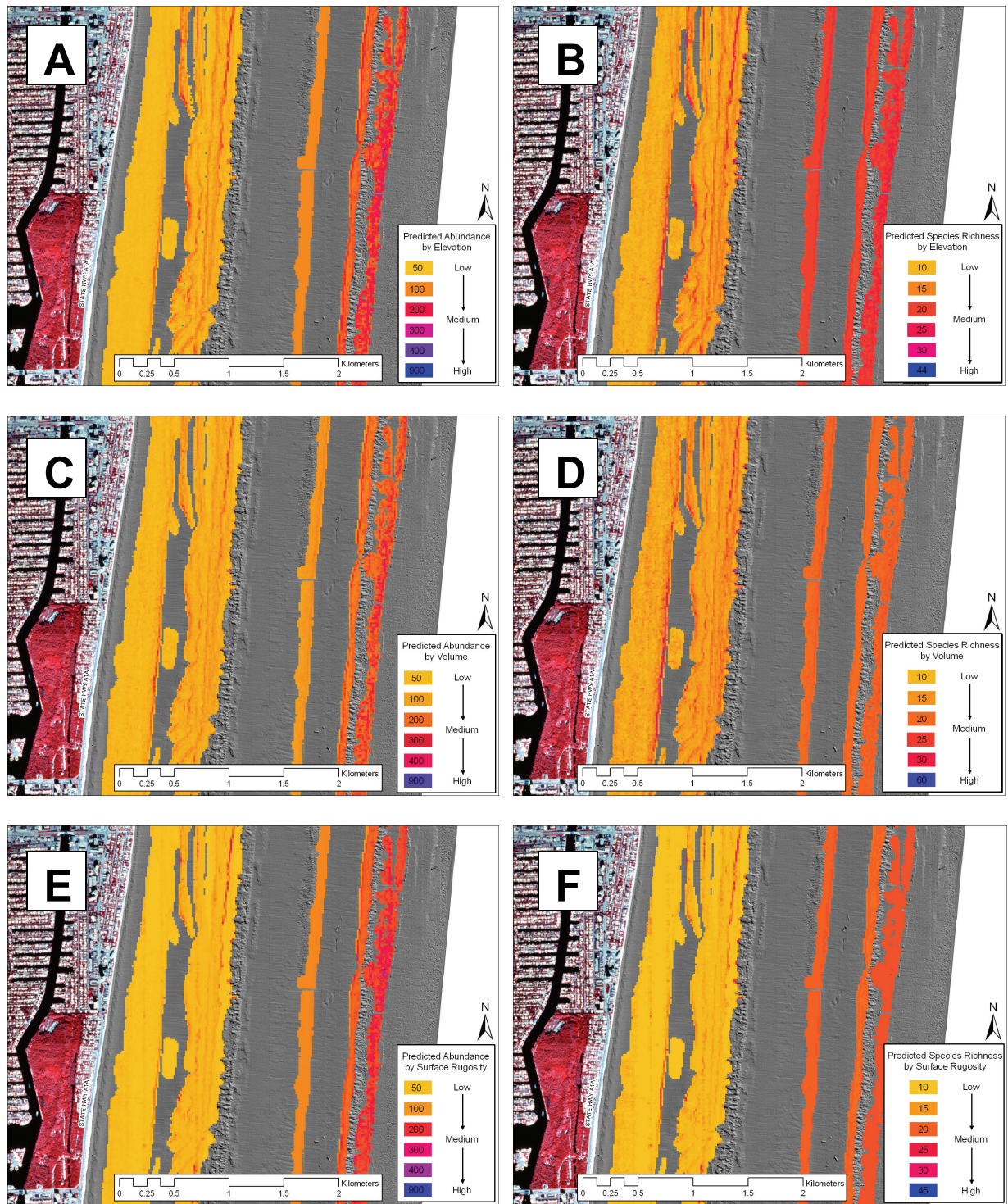


Figure 5.3.1. 1:16,000 scale maps of a portion of the prediction data off Fort Lauderdale, FL. The left column images are reef fish abundance models (A,C,&E) and the right column are species richness models (B,D,&F). The top row used elevation as the predictor, the middle row used volume, and the bottom row used surface rugosity. The images were displayed according to the full range of values in the data, thus the legend for each image is unique, albeit very similar.

### 5.3.2 Prediction Model ANOVA Results

The ANOVA of the predicted abundance data (Fig. 5.3.2) showed statistically significant differences between reefs ( $p < 0.05$ ). The Inshore Ridge predicted mean abundance for elevation ( $\bar{x} = 66.9 \pm 0.21$  standard error of the mean (SEM)), volume ( $\bar{x} = 73.1 \pm 0.65$  SEM) and surface rugosity ( $\bar{x} = 60.7 \pm 0.14$  SEM) was significantly lower than the Middle Reef abundances for elevation ( $\bar{x} = 118.3 \pm 0.03$  SEM), volume ( $\bar{x} = 120.4 \pm 0.33$  SEM) and surface rugosity ( $\bar{x} = 115.5 \pm 0.08$  SEM) which was significantly lower than the Outer Reef abundances for elevation ( $\bar{x} = 187.8 \pm 0.58$  SEM), volume ( $\bar{x} = 208.6 \pm 0.66$  SEM) and surface rugosity ( $\bar{x} = 174.0 \pm 0.49$  SEM).

The ANOVA of the predicted species richness data (Fig. 5.3.2) also showed significant differences ( $p < 0.05$ ). Predicted species richness for the Inshore Ridge habitat was significantly lower than the Middle and Outer Reefs. The Inshore Ridge mean species richness for elevation ( $\bar{x} = 12.6 \pm 0.02$  SEM), volume ( $\bar{x} = 13.5 \pm 0.07$  SEM) and surface rugosity ( $\bar{x} = 12.1 \pm 0.01$  SEM) was significantly lower ( $p < 0.05$ ) than the Middle Reef richness values for elevation ( $\bar{x} = 20.2 \pm 0.01$  SEM), volume ( $\bar{x} = 20.7 \pm 0.02$  SEM) and surface rugosity ( $\bar{x} = 20.1 \pm 0.01$  SEM) which was significantly lower than the Outer Reef abundances for elevation ( $\bar{x} = 20.2 \pm 0.01$  SEM), and surface rugosity ( $\bar{x} = 20.4 \pm 0.01$  SEM) but not volume ( $\bar{x} = 20.6 \pm 0.01$  SEM) ( $p > 0.05$ ).

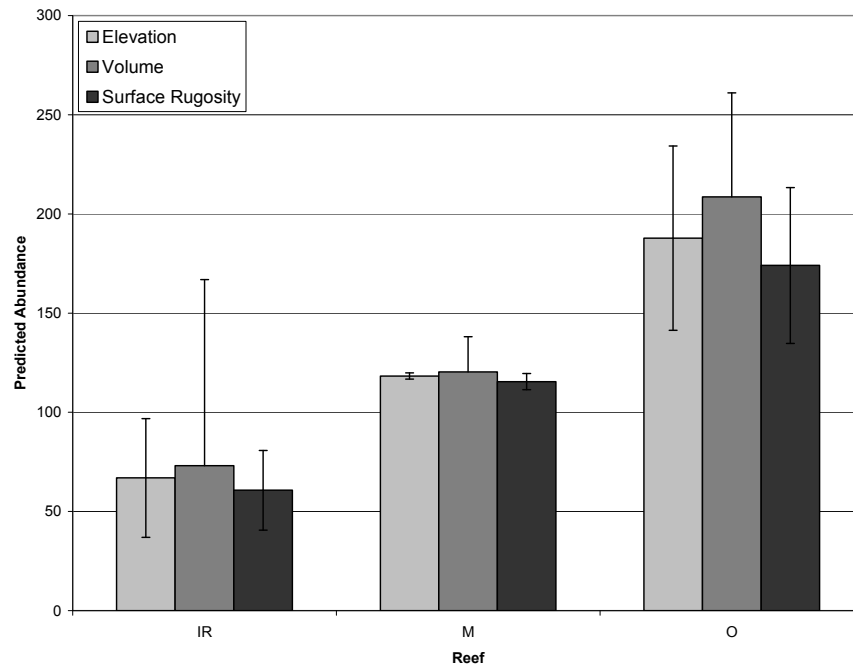


Figure 5.3.2. Predicted abundance of reef fish by GIS calculated elevation (light grey), volume (medium grey), and surface rugosity (black). Error bars show one standard deviation about the mean. Each metric was significantly different between reefs ( $p < 0.05$ ).

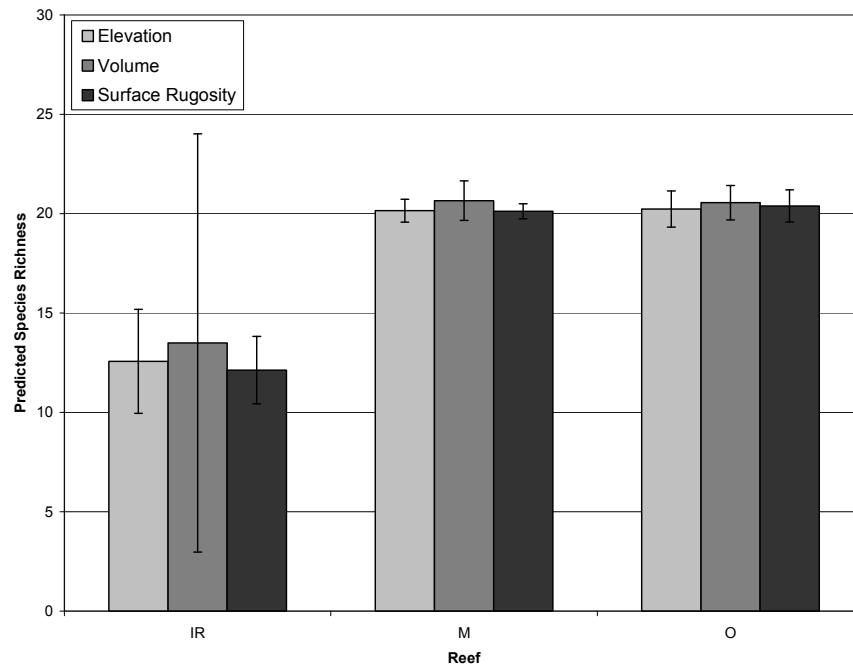


Figure 5.3.3. Predicted species richness of reef fish by GIS calculated elevation (light grey), volume (medium grey), and surface rugosity (black). Error bars show one standard deviation about the mean. Each metric was significantly different between reefs ( $p < 0.05$ ) with the exception of volume between the Middle and Outer reefs.



### 5.3.3 Prediction Model Validation Results

Comparisons of mean reef fish abundance of the fish surveys present in the prediction model with the mean abundances from the polygons containing the survey locations in the prediction model yielded statistical differences. The ANOVA of the abundance data (Fig. 5.3.4) showed a statistically significant difference ( $p < 0.05$ ) between the reef volume predicted abundance ( $\bar{x} = 152.74 \pm 5.04$  SEM) and all others. The predicted mean abundance of elevation ( $\bar{x} = 133.77 \pm 3.88$  SEM) and surface rugosity ( $\bar{x} = 121.9 \pm 3.33$  SEM) were not significantly different ( $p > 0.05$ ) from the measured mean abundance from the surveys ( $127.23 \pm 6.61$  SEM). Comparisons of mean richness values were similar to the abundance comparisons (Fig. 5.3.5). Mean species richness of the survey data ( $\bar{x} = 17.47 \pm 0.34$  SEM) did not significantly differ ( $p > 0.05$ ) from elevation ( $\bar{x} = 17.7 \pm 0.22$  SEM) or surface rugosity ( $\bar{x} = 17.18 \pm 0.21$  SEM) predicted richness, but did differ from reef volume ( $\bar{x} = 18.71 \pm 0.25$  SEM). Predicted reef volume mean richness was always significantly higher than all other mean abundances ( $p < 0.05$ ).

Linear regressions between the measured fish abundance and richness versus the predicted values for all metrics showed statistical relationships (Table 5.3.1). Every correlation was significant at the 0.05 level ( $p < 0.05$ ). Elevation showed the strongest relationship in both abundance and richness, having the highest  $r$  values of the three GIS metrics, 0.52 and 0.62 respectively. Surface rugosity had the second strongest relationship with the measured values albeit slightly lower  $r$  values than elevation for abundance (0.50) and richness (0.61). Volume exhibited the worst relationship in regards to both abundance (0.44) and richness (0.56). These relationships were evident in the scatterplots as well (Figure 5.3.6).

	Correlation r values	Predicted		
		Elevation	Volume	Surface Rugosity
Measured	Abundance	0.52	0.44	0.50
	Species	0.62	0.56	0.61

Table 5.3.1. Correlation  $r$  values for comparisons between the measured values (rows) and the predicted values for each of the three GIS metrics (columns). All were significant at  $p < 0.05$  level.



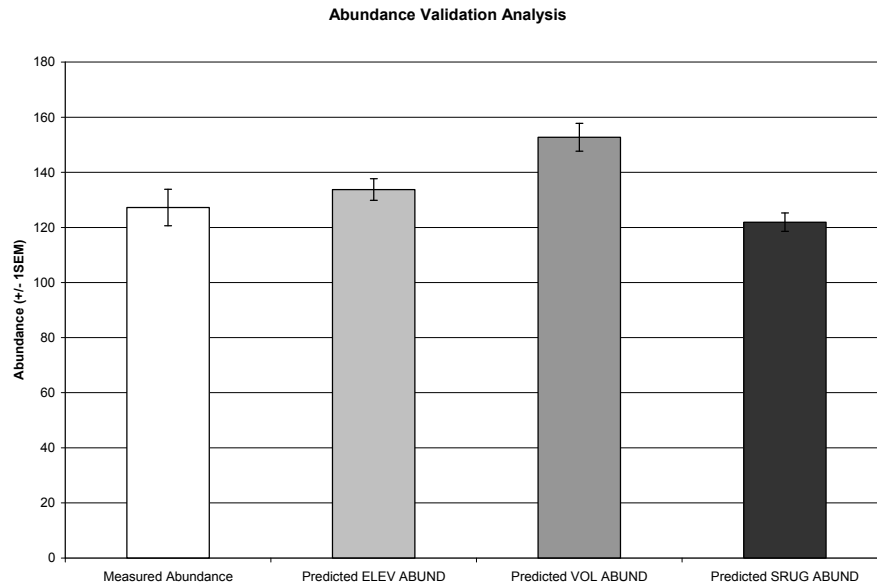


Figure 5.3.4. Mean abundance of survey data and predicted data of the same area in all habitats combined. Trends evident here were seen by individual habitat analyses as well. Of the predictive metrics, elevation (light grey) most closely matched the measured values. Volume (medium grey) consistently overestimated abundance and was significantly higher ( $p < 0.05$ ) in every test. Surface rugosity (black) was usually lower than the survey data although not always significant. Error bars show one standard deviation about the mean.

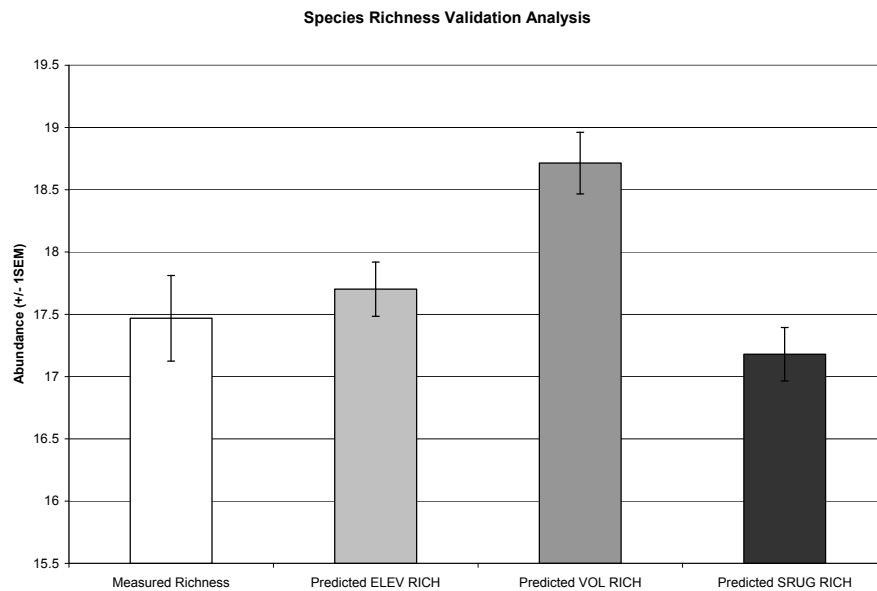


Figure 5.3.5. Mean richness of survey data and predicted data of the same area in all habitats combined. Trends evident here were seen by individual habitat analyses as well. Of the predictive metrics, elevation (light grey) most closely matched the measured values. Volume (medium grey) consistently overestimated richness and was significantly higher ( $p < 0.05$ ) in every test. Surface rugosity (black) was usually lower than the survey data although not always significant. Error bars show one standard deviation about the mean.

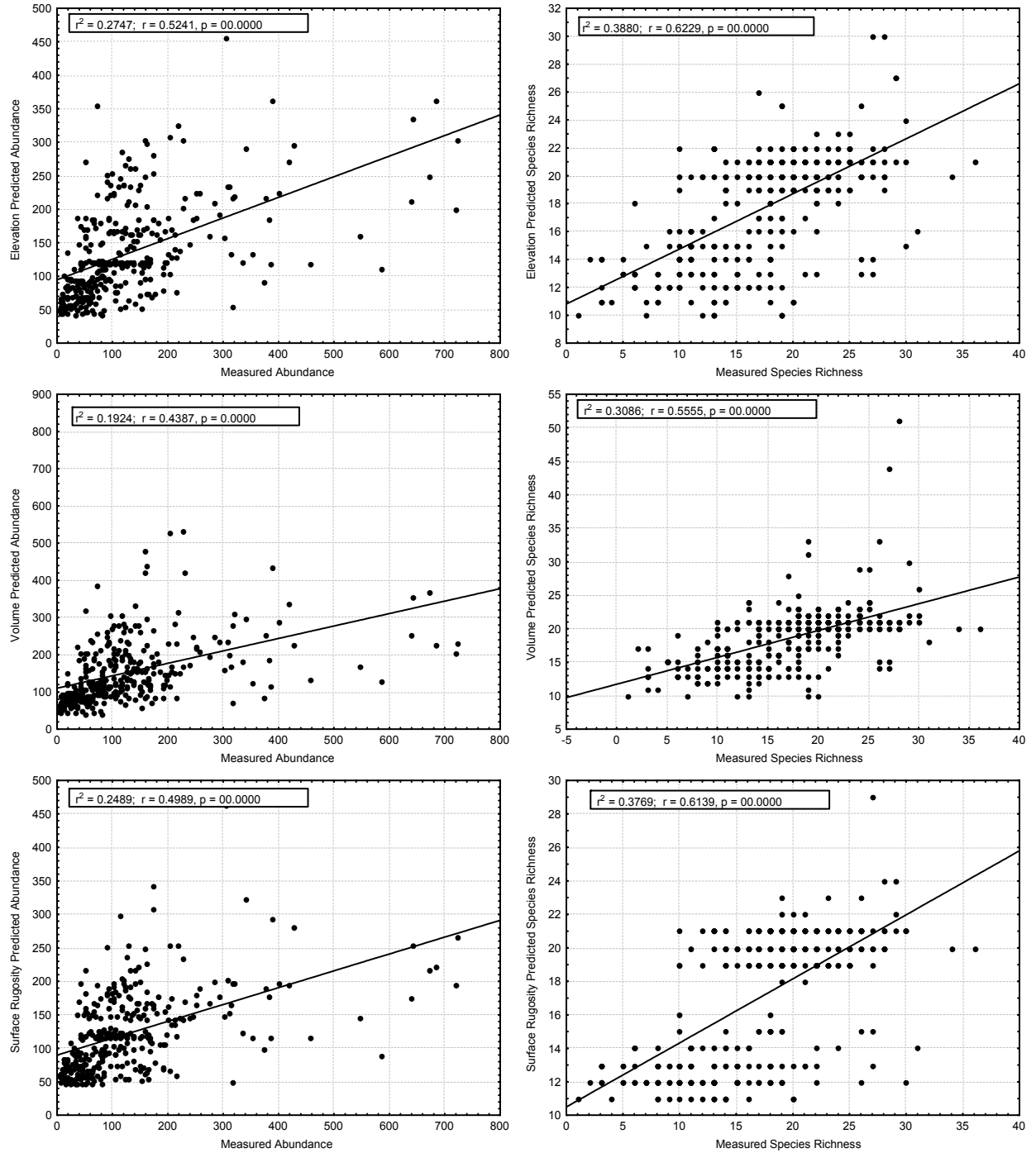


Figure 5.3.6. Scatterplots of the measured values from each fish survey (x-axis) versus the prediction model values for the three GIS metrics, elevation (top row), volume (middle row), and surface rugosity (bottom row). Elevation best correlated with the measured values for both abundance (top left) and richness (top right).

## **5.4 Discussion**

### **5.4.1 Model Framework**

Modeling is a broad term with many applications and there are many types of models (Guisan and Zimmermann 2000, Austin 2002, Goodchild 2005). This study adopts a definition of modeling in the context of GIS defined as “to emulate geographic processes in the real world at one point in time” (Goodchild 2005). More explicitly this is a static model based on empirical data; not a dynamic model trying to forecast changes over time. The model design employed herein is not new. The use of linear regression models to obtain a relationship between variables is one of the most frequently used methods in modeling species distributions (Guisan and Zimmermann 2000, Austin 2002). One difficulty in static modeling is choosing the most appropriate of the many statistical approaches available. There is currently no consensus on which statistical approach works best (Austin 2002) and it has been hypothesized that “the correct mix of ecological and statistical expertise is more important than the particular technique used” (Austin 2002); Therefore, linear regression was used herein to obtain the relationship between variables because of its widespread use and simplistic nature.

Modeling has grown in ecology in recent years with the availability of GIS and statistical software (Guisan and Zimmermann 2000, Goodchild 2005), especially the use and development of dynamic models. Not surprisingly, ecological modeling is further developed for terrestrial landscapes. Marine science has consistently lagged behind terrestrial science because input data are more expensive and harder to obtain. This study used many of the tools and techniques developed for terrestrial ecology and applied them to predicting reef fish distributions. Although developed independently, the framework is a similar design to some terrestrial studies. For example, Shriner (2004) correlated empirical point count data to topography and other GIS layers to successfully predict the occurrence of many bird species in the Appalachian Mountains. There are very few previous studies attempting this framework in the marine environment and none to this study’s capacity.

Other studies have employed different methods to estimate south Florida fisheries species with limited success. Habitat suitability index models (HSI) have been used to

map fisheries species in Florida (Rubec et al. 1998 and 1999). HSI models assimilate different datasets into a spatial database to map potential and optimal ranges of species. The HSI models inputs include GIS polygons of temperature, salinity, dissolved oxygen, substrate type, and depth. It analyzes the spatial relationship between these variables and creates a new GIS layer based on the set criteria yielding polygons of optimal habitat for species responding to those criteria. Success of the HSI model depends heavily on the knowledge of the input criteria for each species and the accuracy of the input GIS data. The HSI was useful in mapping general species distributions but not so accurate in predicting abundance (Rubec et al. 1999). Similar to the HSI models, a cross shelf habitat approach was developed to map the distribution of juvenile grunts and snappers in Biscayne Bay, FL (Lindeman et al. 1998). This effort used similar techniques as the HSI, but the input values were habitat indices, not environmental gradients, and it looked at multiple scales. This effort was also successful at mapping the potential range of different juvenile species but did not attempt to predict abundance.

More recently, Iampietro et al. (2004 & 2005) employed HSI models to map rock fish distributions using seafloor topography indicators in California. They counted rockfish abundance and species with ROV surveys and tested different HSI models to determine which one best predicted rockfish distribution. Their models were limited strictly to different topographic indicators (rugosity, depth, etc.) in an effort to evaluate using seafloor topography as a predictor. Interestingly, their most successful model was one using a single factor: distance to maximum elevation peaks. Their results support this model's design in that single factor models can be accurate.

Although these previous types of models were useful in accomplishing their specific goals, they are single species or genera models, which limits their applicability to the more recently recommended ecosystem approach to marine conservation and management (Leslie et al. 2003, Carr et al. 2003). Not until very recently has the multispecies approach been applied to predictive modeling of fish assemblages (Pittman et al. 2007). Pittman et al. (2007) applied the multispecies approach to predicting reef fish species richness across shallow-water seascapes in the Caribbean. They used 5 years of transect data throughout 3 regions in the Western Caribbean as inputs to three types of predictive models and evaluated which model best predicted species richness. This novel,

innovative approach was useful in testing the different models' performance, evaluating relationships on multiple scales, and accurately predicting general reef fish species richness across the seascape. Their results showed that regression tree modeling outperformed other models. However, they also found that linear models provided accurate results for higher species areas ( $<15$ ) and that significantly more non-linearity is added to models spanning soft and hard substrate types. This supports the current study's approach because only hard substrates were surveyed habitats thus limiting significant non-linearity and all but two habitats had mean richness values less than 15, Shallow Colonized Pavement and Shallow Ridge, and the mean richness for these was above 10. Unfortunately, Pittman et al. (2007) was limited to predicting richness and their classification of species richness into high, medium, and low categories limited their prediction capability. They did not attempt to model fish abundance.

Kuffner et al. (2007) recently reported using a methodology similar to the study herein in Biscayne National Park, FL. They evaluated reef fish assemblages on patch reefs in relation to topographic complexity at several scales and concluded that GIS-measured rugosity correlated with fish abundance and richness on individual patch reefs. Although reaching similar conclusions as reported here, they did not report attempting to relate these data to benthic habitat coverage and/or use the relationship as a proxy for reef fish distribution prediction.

Presently, I have not found any other reported model that attempts the same approach to predicting species distribution's (both richness and abundance) as the model presented herein. It takes the analysis to the next level by using the latest technologies (high resolution LIDAR and GIS) to project the relationship of both species richness and abundance to topographic complexity across the seascape, providing the ability to view and quantify these predicted data. It focuses on the entire assemblage instead of one species or genera, allowing for not only the quantification of assemblage abundance, but the prediction of the major species constituents and their relative abundances and statistical comparisons between discrete areas within the region.

The proceeding sections discuss this model's strengths, weaknesses, applications, and recommended uses.

## **5.4.2 Prediction Model Evaluation**

### **5.4.2.1 Prediction Model Similarities to Empirical Data**

Relationships described in the statistical results of the data were evident in the GIS model. The ANOVA results of reef fish abundance versus the different reef types (Fig. 3.3.6) showed a clear statistically significant trend from lower abundances inshore to higher ones offshore. All three data model maps illustrate this relationship (Fig. 5.3.1a,c,&e), with the low values (yellow) inshore, moderate values on the middle reef (orange), and the highest values offshore (red). An ANOVA of the predicted abundance data (Fig. 5.3.2) supports this illustration showing a statistically significant trend ( $p < 0.05$ ) of increasing abundance and richness between the inner, middle, and outer reefs respectively. Also evident in the maps are areas of relatively high abundance in the nearshore habitats associated with ledges and outcrops. These features indicate higher abundances in these habitats which help explain the variation in the predicted abundance and richness data among each reef.

The statistically significant relationship of species richness between the inshore habitats and the offshore habitats (Fig. 3.3.10) was also evident in the models (Fig. 5.3.3). Similar to the statistically significant trends of the empirical species richness data, the predicted species richness for the Inshore Ridge habitat was significantly lower than the Middle and Outer Reefs. The maps for all three metrics illustrate the species richness predictions for the inshore habitats as much lower (yellow) than the Middle and Outer Reef (orange/red) (Fig. 5.3.1b,d,&f). Similar to the abundance predictions, higher variation of the inshore habitats is also explained by the high values associated with ledges and outcrops.

The fact that the predicted data show similar statistical trends makes intuitive sense because the model was derived from the empirical data, yet it also validates the prediction data. If the prediction model methodology was flawed, then the output would not likely show similar statistical trends as the input data. The fact that these trends are evident in the output data supports the prediction models methodology.

### 5.4.3 Prediction Model Comparison to *in situ* Data

The comparison between abundance and richness values of the surveys (model training data) and the predicted values gives some insight into how well the models performed and which metric best modeled the assemblage. ANOVA comparisons were performed with all the data combined and split into the appropriate habitat designation. Each of the separate analyses resulted in similar trends as the whole, thus it was decided to only present the analysis of the combined data for brevity. This showed clear trends in the data. The most significant trend was that mean reef volume abundance and richness were always significantly higher than the training data and the other predictor metrics. This suggests that the reef volume maps will consistently overestimate assemblage data. This was further evident in the scatterplots (Figure 5.3.6). Reef volume abundance and richness were the lowest correlated data of the GIS metrics to the model training data. For these reasons, reef volume was the least preferred metric to use in modeling fish assemblages. Mean surface rugosity and elevation abundance and richness were not significantly different to the training data. This makes it more difficult to determine which metric performed better. Although not significant, mean elevation predictions were always higher than the mean training data and surface rugosity was always lower. This suggests that elevation slightly overestimates richness and abundance while surface rugosity slightly underestimates it. Thus surface rugosity is the more conservative predictor of the two. The scatterplots show that both elevation and surface rugosity were statistically correlated with the training data. Elevation performed slightly better than surface rugosity as evinced in the slightly higher  $r$  and  $r^2$  values (Figure 5.3.6, Table 5.3.1), therefore it is considered to be the best GIS metric to use in the model. However, this should not discourage the calculation and use of the other metrics in future endeavors. They are all easily calculated in the topographic modeling process and should be evaluated according to each training data set in a similar way as presented here.

Although statistically relevant, the correlations show a relatively low agreement with the training data. The best predictor, elevation, showed an  $r^2$  of 0.27 (Figure 5.3.6). The logic for comparing the model data to the actual data is to evaluate how closely the model data predicted the correct value. The model is considered more accurate the closer its values are to the original training data. Since the model was developed using the

training data, its relationship should be very high ( $r^2 > 0.80$ ). Because the relationship is low, its output is not expected to yield a high degree of accuracy. This means the predictive data are more powerful as a comparison tool than a tool to estimate gross abundance in an area. This is illustrated and discussed further in the context of several management applications in the next section.

There are many possible explanations for the low performance of the GIS predictors. This type of modeling involves less certainty than models based on physics or chemistry, which are derived from fundamental laws (Mitasova and Mitas 2002). The accuracy of the model presented herein relies heavily on the observed data. The accuracy of the model was not very high for several reasons. Firstly, the relationships between the variables and the metrics were very weak as evident in the low  $r^2$  values in Part III. This could be due to a multitude of reasons as have been discussed in Part III and for this model to become more accurate those issues need to be addressed. Secondly, temporal variation was incorporated into this model by design to look at the fish assemblage as a whole. Temporal variation was not significant in this study due to high variation between time periods. This temporal variation in the data may have affected the accuracy of the model. Seasonal migrations of fishes have been detected in numerous local studies and stochastic springtime recruitment events are common, especially nearshore where the highest variation was detected (Walker et al. 2003, Jordan et al. 2005). Thirdly, the habitat mapping was completed at a scale that did not take into account within-reef habitat variability. The habitats within a given polygon were assumed to be consistent, which is unlikely the case in reality. And lastly, fish behavior likely affected the accuracy of the prediction model. For example all observations were taken during daylight hours, thus many nocturnal fishes were hidden in the reef and therefore were probably underestimated. Also many fish activities were not taken into account like the daytime schooling behavior of Haemulids. Little is known about their local distributions on a daily basis. They are known to congregate on the reef during the day and leave at night to forage, but little is known as to whether they come back to the same spot daily (Kendall et al 2003). These types of behaviors could have significant affects on the accuracy of prediction models.



Another possible explanation has to do with the differing ranges of different species and the likely overestimations associated with this problem. It is common during the surveys to have fish move in and out of the survey area. The model restricts the range of predictions to the survey size not the range of each individual species; hence if a species range was 100ft<sup>2</sup> and the species entered the area during the survey, then it would be included in the survey. Predicting its abundance for 50ft<sup>2</sup> would overestimate its actual abundance.

#### **5.4.4 Management Application**

The results of the seascape-level model show the utility of this study. Predictions of reef fish abundance, species richness, and major assemblage constituents have been made from remotely sensed data in Broward County and mapped in a GIS on a seascape-level scale to view the relationships in the data. These data can satisfy several resource manager's needs in a variety of capacities, for example, the estimation of fish stocks, the designation of marine protected areas, the estimation of impacts on essential fish habitats, and future comparisons to this baseline to understand temporal changes. Several examples of the application of the model to resource management are presented below.

##### **5.4.4.1 Estimation of Fish Stocks**

Worldwide, fisheries managers are interested in mapping and quantifying their fish stocks (NRC 1998, Rubec et al. 1998). This model can aid in those endeavors. Each colored polygon has an associated abundance and richness value with it, therefore simple GIS queries of the data can quickly yield fish stock information. For example, if quantification of reef fish were needed in a desired area (figure 5.4.1, red box), then all the polygons in the selected area can be queried to yield summary information. In this example, there are 98,892 fish predicted to be in the ~64 acre red box using reef volume as the predictor. The red box also contains a mean of 15 (14.8) species. The relative abundance of species depends on the SIMPER percentages for the specific habitat. In this case the habitat is Shallow Colonized Pavement and therefore the dominant species are *Halichoeres bivittatus* (23%), juvenile *Haemulon*s (13%), *Acanthurus bahianus* (12%), *Stegastes variabilis* (6%), and *Thalassoma bifasciatum* (5%) (Fig. 4.3.15). Using these percentages, of the total population in the red box, there is an estimated 22,745

*Halichoeres bivittatus*, 12,856 juvenile *Haemulon*s, 11,867 *Acanthurus bahianus*, 5,934 *Stegastes variabilis*, and 4,945 *Thalassoma bifasciatum*.

This information is easy to obtain in GIS once the model prediction surfaces have been created. All one has to do to get estimates on the general parameters of fish stocks in the desired modeled habitat is to select a desired area and query the data.

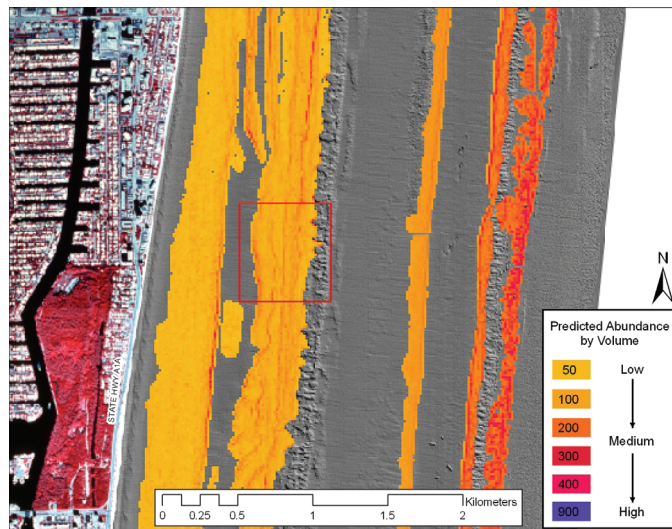


Figure 5.4.1. 1:16,000 scale map of a portion of the abundance prediction using reef volume off Fort Lauderdale, FL. The red box indicates a hypothetical area of interest from which the GIS data can be queried. In this case the red box contains an estimated 98,892 fish on the shallow colonized pavement.

#### 5.4.4.2 Aid in MPA designation

The information obtained in this modeling effort facilitates a better look at the fish assemblage data and how they relate to topographic complexity. This could have implications in aiding resource managers for designating areas of use within the system, especially marine protected areas (Pitcher 1997, Baker 2000, Wusinich-Mendez and Trappe 2007). Marine Protected Areas (MPAs) representing a full range of habitats are most effective (Leslie et al. 2003, Carr et al. 2003). They should also contain essential fish habitat (Rubec et al. 1998 and 1999, Rieser 2000, Conover et al. 2000) and highly rugose areas (Grigg 1994, Friedlander 2001, Friedlander et al. 2003, Friedlander et al. 2007a, Friedlander et al. 2007b). The bathymetric maps alone show areas of high and low topographic complexity, however there is no biological data associated with it. The strength of this model is its ability to show how topographic complexity relates to

biological data. This enables one to not only look at highly rugose areas as potential protection sites but view the biological relationships to that topography as well.

As discussed in the previous section, the prediction model data is best used to show areas of relative abundances and richness on the reef. This is very useful information for decisions on MPA placement. A MPA's location is of key importance to optimize its potential (Pitcher 1997, Baker 2000, Grober-Dunsmore 2005). The predictive fish model in this study facilitates such an analysis by allowing the calculation of assemblage statistics for selected regions which can then be statistically compared.

For example, if a small scale MPA was wanted in Broward County, one might be interested in areas of highest biological richness and abundance to optimize the park's conservation potential. Since fish assemblages are typically composed of higher trophic level organisms, their high richness and abundance might reflect a higher increase of biological productivity in an area (impacts from heavy fishing aside). Therefore, one could use the fish assemblage parameters as a proxy for general reef health. A quick look at the prediction model map shows an area of high abundance and diversity on the middle reef in northern Broward. A quick comparison of a 1Km stretch of this reef versus a 1Km stretch of the same reef further south shows clear differences. Figure 5.4.2 illustrates this point.

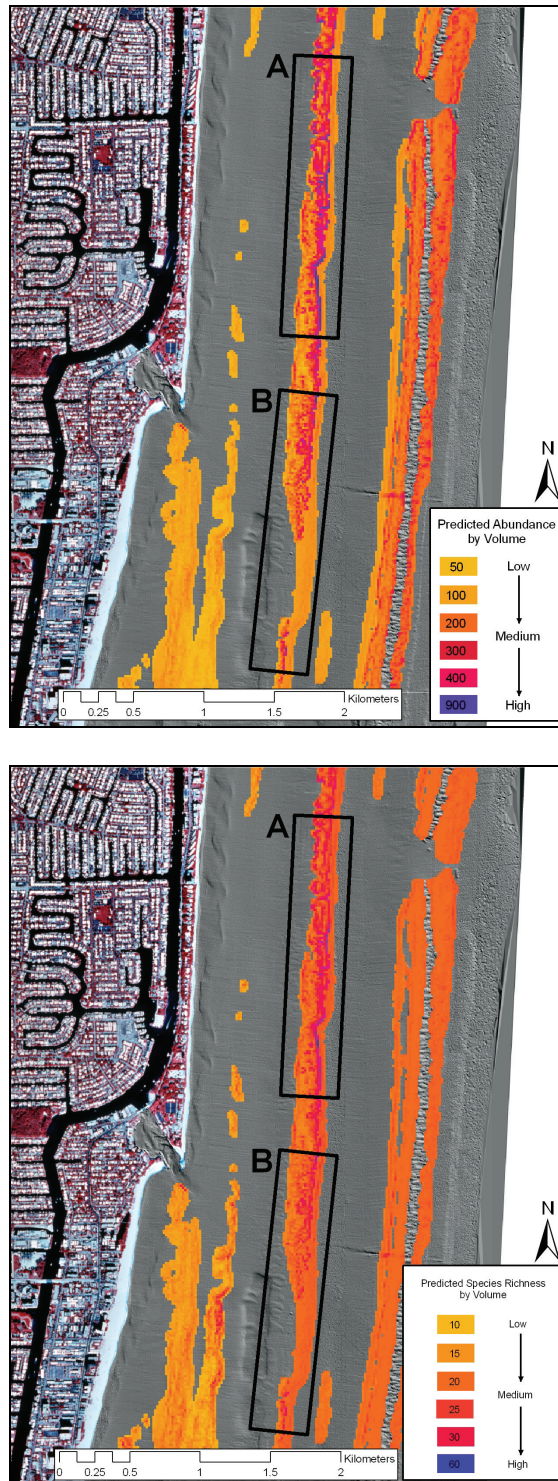


Figure 5.4.2. Maps of the predicted fish abundance (left) and richness (right) by reef volume. Box A is a 1km stretch of higher abundance and richness middle reef versus box B. The data from the polygons in each box were exported and used in a statistical comparison to support this claim.

Visualization of the GIS data suggests that the 1Km stretch of Middle Reef in area A contains more fish than the same stretch of reef further south (area B). The data from both areas were extracted and statistically compared for a more definitive answer to this observation. A T-test showed predicted abundance of all polygons in area A ( $\bar{x}=253.9\pm4.5$  SEM) to be significantly higher than area B ( $\bar{x}=178.8\pm2.7$  SEM) (Figure 5.4.3). Significant differences in richness were also noted. The prediction data in area A ( $\bar{x}=23.8\pm0.16$  SEM) contained significantly higher species richness than area B ( $\bar{x}=21.6\pm0.09$  SEM).

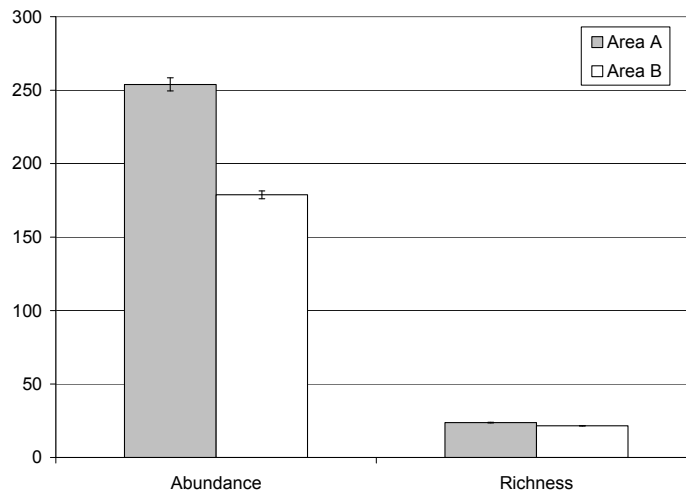


Figure 5.4.3. Statistical comparison of prediction model data between two 1 km stretches of the middle reef in northern Broward. Area A (defined in Figure 5.4.2) was significantly higher in predicted abundance and richness than Area B on the same reef to the south.

The ability to statistically analyze the data without lengthy and costly field-work illustrates the power of this model. In this example, area A would be a better conservation area than area B based on a significantly higher relative fish abundance and richness. This analysis was prepared on a small scale for illustration purposes but the same analysis could be performed on larger scales to include the entire seascape in the statistical comparisons. Because these data are in GIS, they can also be looked at in relation to other data. For example, MPA designation of an area might entail looking at current use data to see what areas of the reef are being used most frequently and how that relates to estimated assemblages. Any data pertinent to MPA design and implementation could be

included in a GIS along with the prediction model to aid in the complex decision making involved in creating an MPA.

### **5.4.5 Management Recommendations**

This model could be applied to other coastal areas in the Western Atlantic once all the model input data were collected. These input data include high resolution bathymetry, accurate benthic habitat maps drawn at the appropriate spatial scale and an appropriate number of fish surveys in each habitat incorporating a variety of topographic complexities within each habitat. Below are some recommendations for resource managers considering the use of this model in coastal management efforts.

#### **5.4.5.1 Bathymetry**

The high resolution bathymetry is one of the most valuable mapping data to acquire in mapping submerged lands. These data, which have many uses beyond the scope of this study, were essential to mapping the benthic habitats and to developing the regression lines that allowed the prediction of abundance and richness. As discussed in Part II the 4m resolution bathymetry was sufficient to map the habitats to the desired resolution for this study. It facilitated the outlining of different features detected by the acoustic surveys at a much higher resolution than the acoustic data would allow. The 4m survey was not ideal for measuring the topographic variables at a sufficient operational scale to the fish assemblage (Part III). The 4m survey showed some correlations with the assemblage data however the strongest relationships were with the *in situ* measurement. When the 4m survey (laser) was compared to a 0.5m survey (multibeam sonar), the latter measured the same area on a finer scale. These data were not sufficiently available to allow for a statistical comparison between the two, but it was concluded that the 0.5m bathymetric survey would more accurately measure the topographic parameters at an operational scale closer to that of the fish assemblage. Although the 4m survey was not ideal, it did detect positive relationships between topographic complexity variables and the fish assemblage and thus was still usable in this study to estimate abundance and richness. It is recommended that bathymetric surveys be taken at the highest density possible if accurate topographic information on a local scale is desired.

Unfortunately the cost of acquiring bathymetric data is higher than some other mapping methodologies. The Broward County LADS survey cost about \$80,000 to map nearly 112 km<sup>2</sup>; a cost of approximately \$714 per square kilometer (sq km). This cost did not include the benthic habitat mapping acoustic survey which cost another \$2000 per sq km. Compare this to the cost of NOAA's Caribbean habitat mapping effort of about \$400 per square kilometer (from image acquisition to final benthic habitat maps) and it is obvious which method is more cost effective (Mark Monaco, pers comm.). The cost however inevitably depends upon the level of mapping detail (resolution) needed and the conditions in the area of interest. The use of satellite imagery is restricted to clear, unturbid waters and has larger scale limits than other technologies. The acoustic data have the potential to add another layer of information not available by satellite imagery interpretation. Although not utilized or presented in the present study, new acoustic analyses are showing clear evidence of being able to discern differing levels of epibenthic biota within the larger-scale benthic habitats (Foster, Walker, and Riegl, 2008).

#### **5.4.5.2 Benthic Habitat Mapping**

Benthic habitat mapping was another essential tool in being able to predict reef fish assemblages on the reef. Mapping the resources not only aids resource managers in the determination mitigation for impacts, the designation for marine protected areas, and the identification of essential fish habitat (NOAA-CSC-BHM 2007), it also can elucidate previously unforeseen relationships in data brought on by the proper classification of the sample sites. As shown in Part III and Part IV, the benthic habitat classification of the survey sites gave better results than the sites' previous classifiers. This classification illustrated that changes occurred in the assemblage's topographic relationship between habitats, and that the richness relationship with topographic complexity was linear, not logarithmic, when categorized by benthic habitats. Measuring this change between habitats is essential to the accuracy of the predictions. Kuffner et al. (2007) found a similar problem on a patch reef system in Biscayne National Park, FL. They found no significant differences between abundance and richness with rugosity in pooled data, but found significance when the data were split by individual patch reef.

Although the benthic habitat map created in this study characterized the fish surveys well, a map at a finer scale might produce better results. In the current map, the

area within each polygon is homogenous as described by each classifier. The absence of within-polygon variation might significantly underestimate the total variance of the polygonal data (Myers 1997, Bian 1997). The variation of benthic cover within habitats could introduce significant variation in the data, obscuring other relationships (Battista 2003, Aaby et al. 2004). Since variations (patchiness) within habitats were acoustically detected (Part II), it is possible that this confounded the reef fish-topographic complexity relationship. For example on the Middle Reef, some areas may have denser benthic cover than others. Fish surveys taken in these denser areas may have had a considerably different fish assemblage than less dense areas, but all the surveys were lumped into one category creating variance within the category. This could explain the within habitat variation of surveys evident in the MDS plots (Part IV). Other studies that do not account for habitat variation may have similar problems (Battista 2003, Aaby et al. 2004). For example, Kuffner et al. (2007) only found significant differences between reef fish and rugosity when stratifying by each patch reef. They concluded that this was due to high variability in recruitment, but variations in benthic cover were not considered. Although not measured or reported, variations in density of benthic cover between these patch reef may have confounded their analysis.

Mapping the habitats on a finer scale might resolve this issue. High density acoustic surveys or multibeam/LIDAR backscatter habitat classification may facilitate the creation of a higher resolution habitat map adding another hierarchical level to indicate changes in density. These technologies are new and their potentials have not yet been realized, however early results like the Echoplus analysis in Part II show promise.

#### **5.4.5.3 Fish/Topography Relationship**

The final piece of information needed for the prediction model is to measure the fish assemblage topographic relationships in the area. It is unlikely that the relationships detected in Broward County would apply to another area (Grober-Dunsmore 2005). Current regimes, water temperature, turbidity, recruitment patterns are just a few factors affecting the local fish assemblage. A study in a different environment will require a study of the local assemblage relationship to topographic complexity. In this study 370 point counts were used because they were available by a previous study. Because the surveys were taken before the GIS analysis and habitat mapping, equal survey locations



were not performed in each habitat, thus some habitats did not contain a sufficient number of sample to allow for fish assemblage predictions; namely Linear Reef-Inner, Spur & Groove, and Ridge-Deep. Although this number of surveys was statistically sufficient in most habitats, fewer well-placed surveys might yield the same data. Ideally, a statistically powerful equal number of surveys should be performed in each benthic habitat. The survey locations within each habitat should incorporate an equal number of low, medium, and high topographically complex areas as well. The number of surveys needed should be determined by the number and size (area) of the mapped benthic habitats. An investigation under these parameters would measure the full range of topographic complexity variables and give us a better understanding the local fish assemblage's relationship with those variables (Heglund 2002).

## **5.5 Conclusion**

An empirical static model has been developed based on the statistical analyses of observed data. This model enables viewing of the relationship between reef fishes and their habitats on a large scale ( $>100 \text{ Km}^2$ ). It also allows for statistically comparable analyses between areas based on empirical data and thus gives statistical support to resource management decisions. This model is unlike previously reported models in that it uses high resolution bathymetry and benthic habitat types to predict abundance, species richness, and the relative species contribution to the assemblage instead of focusing on species specific approaches providing pertinent data to an ecosystem approach to conservation and management. Its simple framework design makes it highly adaptable to other uses. The framework can easily be modified to look at different ecological processes and their relationships to many types of variables. For example, one might use this methodology to predict coral reef biodiversity via topographic complexity. Sample stations could be designed to survey a variety of topographically complex reef sites for total species biodiversity which could then be correlated to develop the regression equations and project the data in GIS. The grid size could be lessened or expanded to represent a different type of data collection and the benthic habitat resolution could be tuned to a smaller scale if/when a mapping technology has been developed to refine its capabilities. This system could also be taken to the next level as a spatial decision support

system- a computer-based system designed to assist decision making (Corbett et al 2002). The framework could be assembled in a program where the process could be much more automated and the user could redefine the relationship between process and variables in a much faster, more user-friendly way and obtain instant viewable results in a GIS. Once the grid has been created and the topographic statistics calculated, fine tuning the ecological process relationship is a statistical procedure that could be self-contained in a program that would allow a user to specify the relationship (i.e. input the regression equations) and view the results rather quickly. This could be extremely useful to scientists studying different ecological processes and resource managers in making decisions on resource use and/or mitigation.

As with any model the predictions are only as good as the input data. In this case, the relationship between the fish assemblage and topographic complexity was low; therefore the model's accuracy was low. This limited the model's use in predicting accurate gross abundances in a given area, but not its comparative use. The model data showed similar differences between reefs for abundance and species richness as the *in situ* data and validation confirmed that locations on the prediction maps showing a high abundance of reef fishes are statistically likely to have higher abundances on the reef. Therefore, predicted abundance and richness values can be used in comparative analyses to visualize and statistically analyze how the data relate on a large scale as shown in section 5.4.2.2. This will allow for statistical support in management and conservation decisions, giving resource managers a powerful tool to support their actions.

Future research could greatly increase this model's accuracy. Increasing the resolution of the habitat mapping and the bathymetry data would eliminate some possible sources of confounding scale effects. Increasing these resolutions would also allow for finer scale analyses of the fish data and more precise seafloor topography measurements. Better understandings of the appropriate measurement scale and the scales at which different reef fish operate are needed to more accurately model their distributions. More research is also needed to better understand the dynamics how reef fish relate to topographic complexity and to the other ecological factors influencing their distributions. As these relationships are evinced modeling efforts will become increasingly more accurate.

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## **7 Appendices**

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Appendix I – Benthic habitat maps

Appendix II – Species List

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Appendix IV – SIMPER species percentages by Habitat

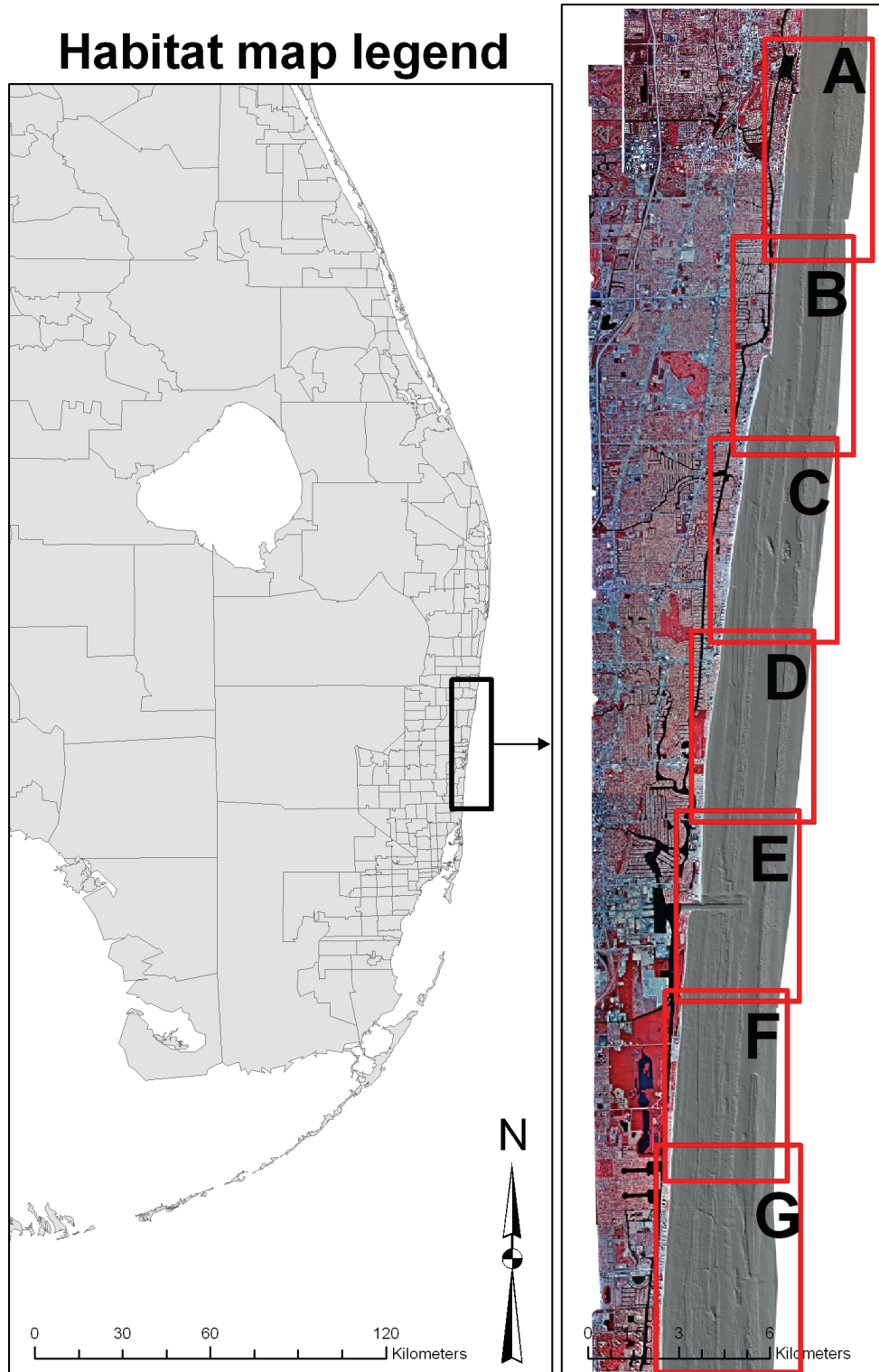
Appendix V – Prediction Model Maps

# Appendix I

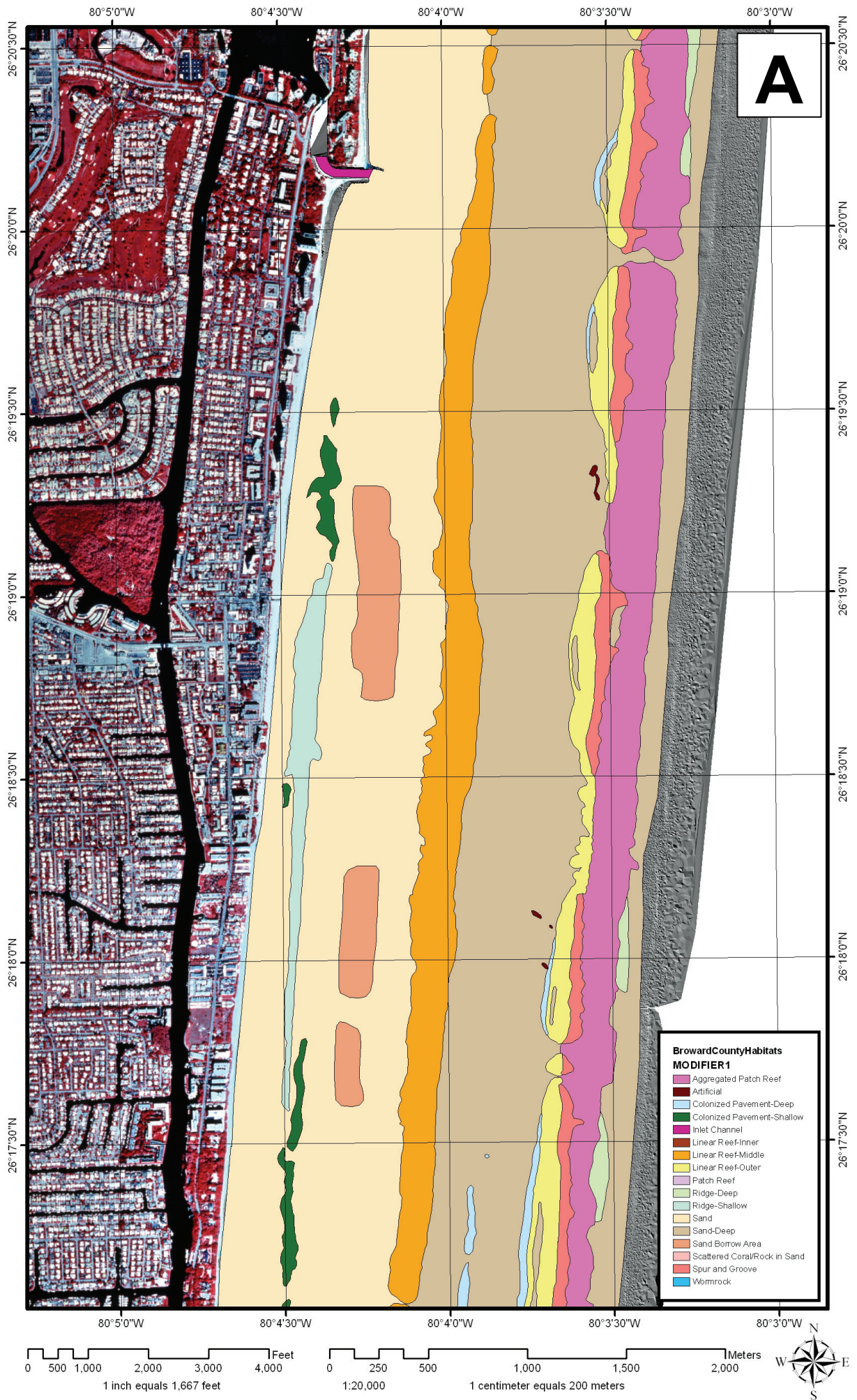
## **Benthic Habitat Maps**

## Benthic Habitat Maps of Broward County, FL.

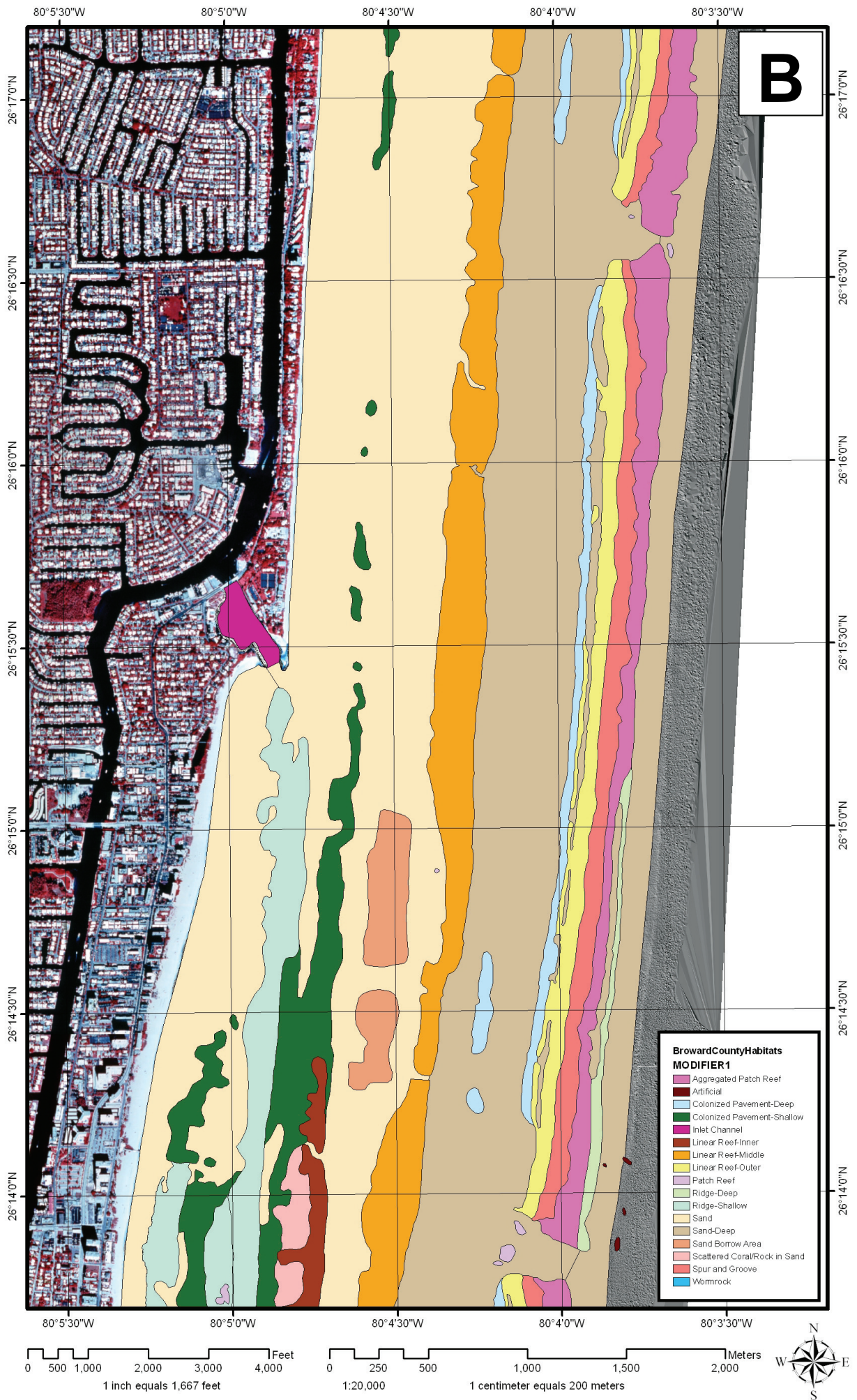
The maps are in order from North to South with some overlap. Use the reference map below as a guide to the location of each detailed habitat map in the appendix. All maps are scaled to 1:20,000 with the exception of mapG which is 1:24,000.



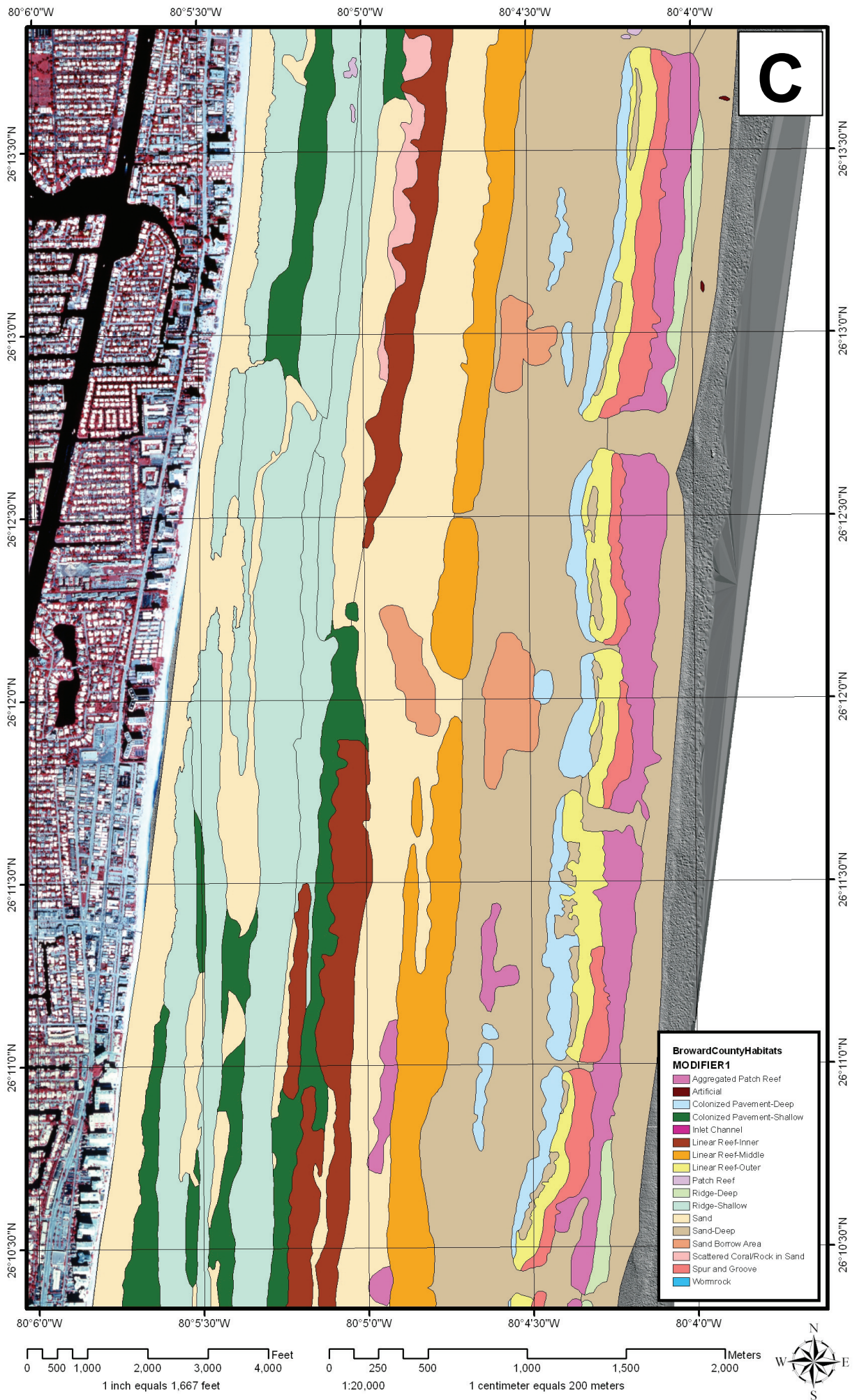


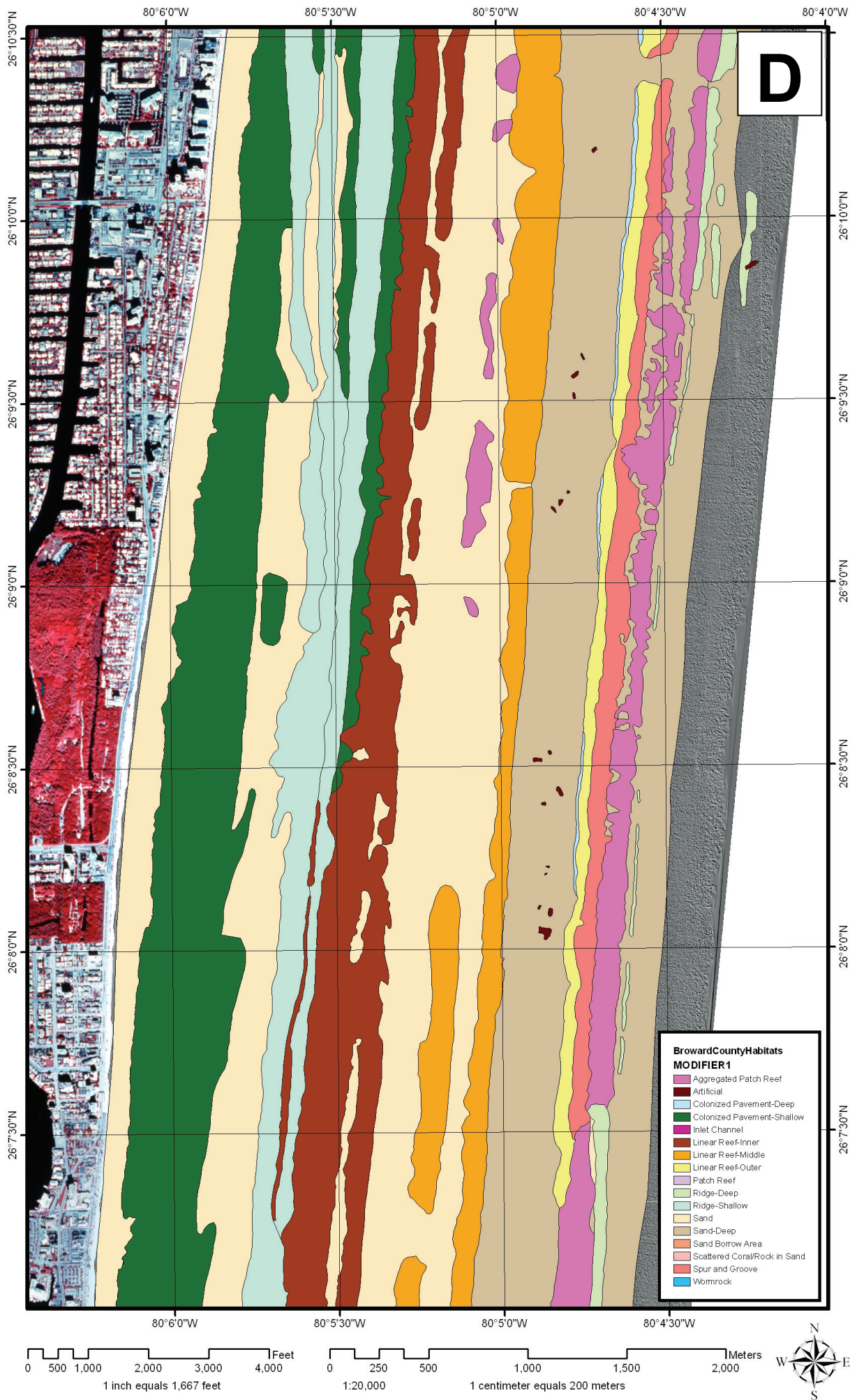




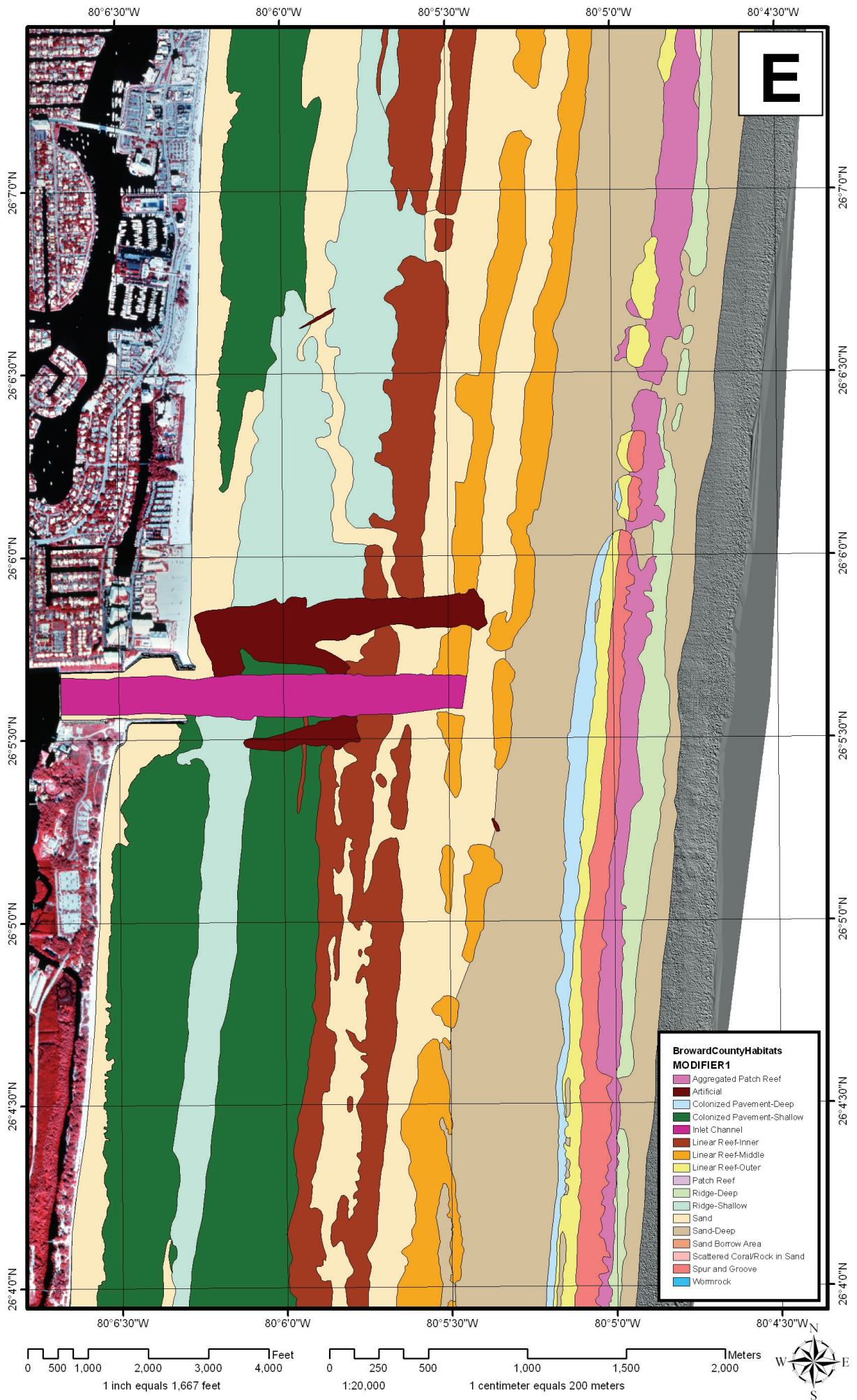


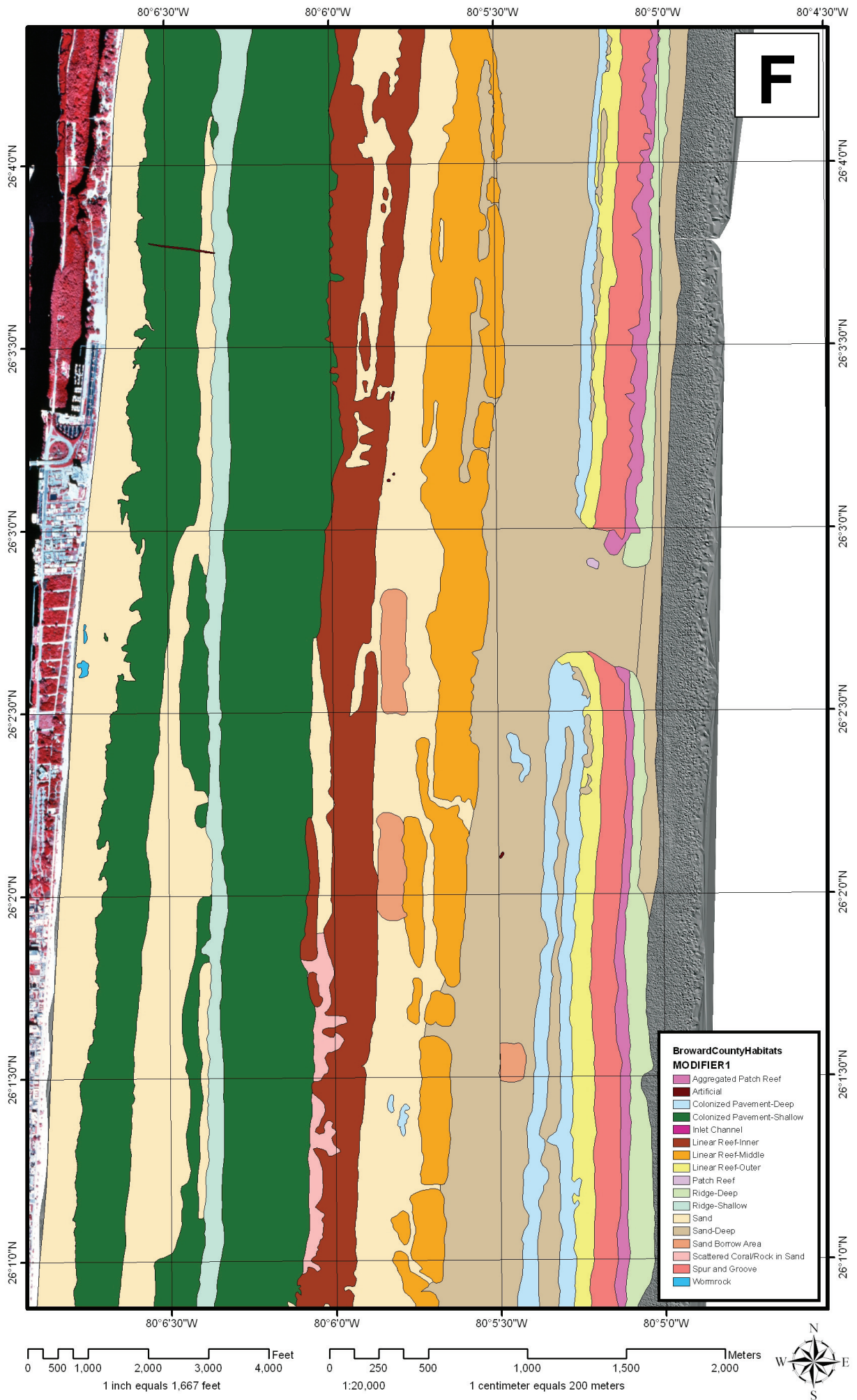




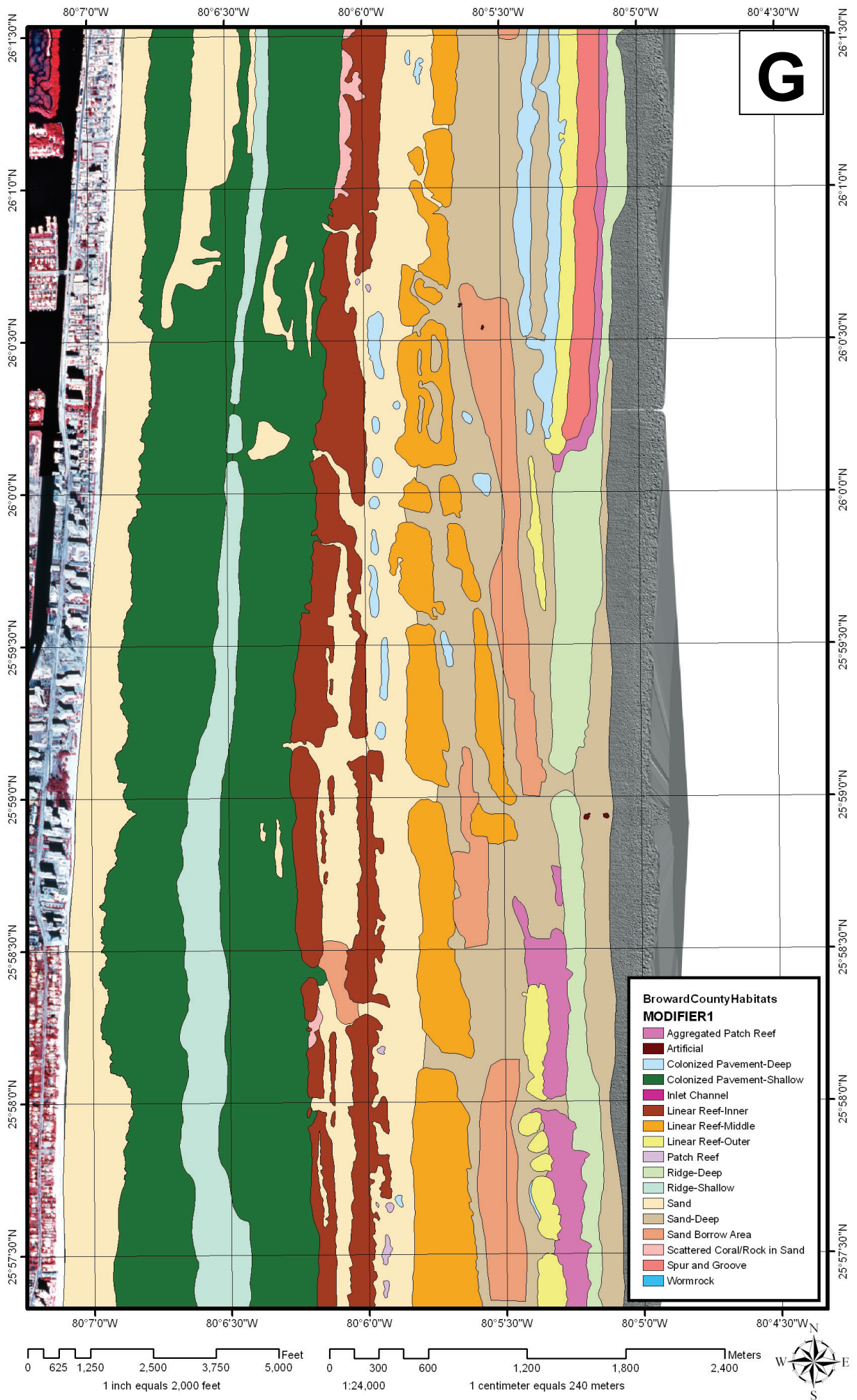












# Appendix II

## Species List

Abbreviation	Species Name	Common Name	Family
ABU SAXA	<i>Abudefduf saxatilis</i>	Sergeant major	Pomacentridae
ACA ASPE	<i>Acanthemblemaria aspera</i>	Roughhead blenny	Chaenopsidae
ACA BAH	<i>Acanthurus bahianus</i>	Ocean surgeon	Acanthuridae
ACA CHIR	<i>Acanthurus chirurgus</i>	Doctorfish	Acanthuridae
ACA COER	<i>Acanthurus coeruleus</i>	Blue tang surgeonfish	Acanthuridae
ACA SPIN	<i>Acanthemblemaria spinosa</i>	Spinyhead blenny	Chaenopsidae
ALU SCHO	<i>Aluterus schoepfii</i>	Orange filefish	Monacanthidae
ALU SCRI	<i>Aluterus scriptus</i>	Scrawled filefish	Monacanthidae
ANI SURI	<i>Anisotremus surinamensis</i>	Black margate	Haemulidae
ANI VIRG	<i>Anisotremus virginicus</i>	Porkfish	Haemulidae
APO BINO	<i>Apogon binotatus</i>	Barred cardinalfish	Apogonidae
APO MACU	<i>Apogon maculatus</i>	Flamefish	Apogonidae
AUL MACU	<i>Aulostomus maculatus</i>	Trumpetfish	Aulostomidae
BAL CAPR	<i>Balistes capriscus</i>	Grey triggerfish	Balistidae
BAL VETU	<i>Balistes vetula</i>	Queen triggerfish	Balistidae
BOD PULC	<i>Bodianus pulchellus</i>	Spotfin hogfish	Labridae
BOD RUFU	<i>Bodianus rufus</i>	Spanish hogfish	Labridae
BOT SPE.			Bothidae
CAL BAJO	<i>Calamus bajonado</i>	Jolthead porgy	Sparidae
CAL CALA	<i>Calamus calamus</i>	Saucereye porgy	Sparidae
CAL NODO	<i>Calamus nodosus</i>	Knobbed porgy	Sparidae
CAL PENN	<i>Calamus penna</i>	Sheepshead porgy	Sparidae
CAL PROR	<i>Calamus proridens</i>	Littlehead porgy	Sparidae
CAL SPE.			Sparidae
CAN MACR	<i>Cantherhines macrocerus</i>	American whitespotted filefish	Monacanthidae
CAN PULL	<i>Cantherhines pullus</i>	Orangespotted filefish	Monacanthidae
CAN ROST	<i>Canthigaster rostrata</i>	Caribbean sharpnose-puffer	Monacanthidae
CAN SUFF	<i>Canthidermis sufflamen</i>	Ocean triggerfish	Monacanthidae
CAR BART	<i>Carangoides bartholomaei</i>	Yellow jack	Carangidae
CAR CRY	<i>Caranx crysos</i>	Blue runner	Carangidae
CAR LATU	<i>Caranx latus</i>	Horse-eye jack	Carangidae
CAR RUBE	<i>Carangoides ruber</i>	Bar jack	Carangidae
CHA ACUL	<i>Prognathodes aculeatus</i>	Longsnout butterflyfish	Chaetodontidae
CHA CAPI	<i>Chaetodon capistratus</i>	Foureye butterflyfish	Chaetodontidae
CHA FABI	<i>Chaetodipterus faber</i>	Atlantic spadefish	Ephippidae
CHA OCEL	<i>Chaetodon ocellatus</i>	Spotfin butterflyfish	Chaetodontidae
CHA SEDE	<i>Chaetodon sedentarius</i>	Reef butterflyfish	Chaetodontidae
CHA STRI	<i>Chaetodon striatus</i>	Banded butterflyfish	Chaetodontidae
CHI ANTI	<i>Chilomycterus antillarum</i>	Web burrefish	Diodontidae
CHI SCHO	<i>Chilomycterus schoepfii</i>	Striped burrefish	Diodontidae
CHR CYAN	<i>Chromis cyanea</i>	Blue chromis	Pomacentridae
CHR ENCH	<i>Chromis enchrysur</i>	Yellowtail reeffish	Pomacentridae
CHR INSO	<i>Chromis insolata</i>	Sunshinefish	Pomacentridae
CHR MULT	<i>Chromis multilineata</i>	Brown chromis	Pomacentridae
CHR SCOT	<i>Chromis scotti</i>	Purple reeffish	Pomacentridae
CLE PARR	<i>Clepticus parrae</i>	Creole wrasse	Labridae

Abbreviation	Species Name	Common Name	Family
COR EIDO	<i>Coryphopterus eidolon</i>	Pallid goby	Gobiidae
COR GLAU	<i>Coryphopterus glaucofraenum</i>	Bridled goby	Gobiidae
COR PERS	<i>Coryphopterus personatus</i>	Masked goby	Gobiidae
CRY ROSE	<i>Cryptotomus roseus</i>	Bluelip parrotfish	Scaridae
DAS AMER	<i>Dasyatis americana</i>	Southern stingray	Dasyatidae
DEC MACA	<i>Decapterus macarellus</i>	Mackerel scad	Carangidae
DIO HOLO	<i>Diodon holocanthus</i>	Long-spine porcupinefish	Diodontidae
DIO HYST	<i>Diodon hystrix</i>	Spot-fin porcupinefish	Diodontidae
DIP ARGE	<i>Diplodus argenteus caudimacula</i>	Silver porgy	Sparidae
DIP FORM	<i>Diplectrum formosum</i>	Sand seabass	Serranidae
DIP HOLB	<i>Diplodus holbrooki</i>	Spottail pinfish	Sparidae
EMB PAND	<i>Emblemaria pandionis</i>	Sailfin blenny	Chaenopsidae
EPI ADSC	<i>Epinephelus adscensionis</i>	Rock hind	Serranidae
EPI CRUE	<i>Cephalopholis cruentata</i>	Graysby	Serranidae
EPI FULV	<i>Cephalopholis fulva</i>	Coney	Serranidae
EPI GUTT	<i>Epinephelus guttatus</i>	Red hind	Serranidae
EPI MORI	<i>Epinephelus morio</i>	Red grouper	Serranidae
EQU ACUM	<i>Pareques acuminatus</i>	High-hat	Sciaenidae
EQU LANC	<i>Equetus lanceolatus</i>	Jack-knifefish	Sciaenidae
EQU PUNC	<i>Equetus punctatus</i>	Spotted drum	Sciaenidae
EUC JONE	<i>Eucinostomus jonesii</i>	Slender mojarra	Gerreidae
FIS TABA	<i>Fistularia tabacaria</i>	Cornet fish	Fistulariidae
GER CINE	<i>Gerres cinereus</i>	Yellow fin mojarra	Gerreidae
GIN CIRR	<i>Ginglymostoma cirratum</i>	Nurse shark	Ginglymostomatidae
GNA THOM	<i>Gnatholepis thompsoni</i>	Goldspot goby	Gobiidae
GOB MACR	<i>Elacatinus macrodon</i>	Tiger goby	Gobiidae
GOB OCEA	<i>Elacatinus oceanops</i>	Neon goby	Gobiidae
GOB SAEP	<i>Ctenogobius saepepallens</i>	Dash goby	Gobiidae
GYM FUNE	<i>Gymnothorax funebris</i>	Green moray	Muraenidae
GYM MILI	<i>Gymnothorax miliaris</i>	Goldentail moray	Muraenidae
GYM MORI	<i>Gymnothorax moringa</i>	Spotted moray	Muraenidae
GYM VICI	<i>Gymnothorax vicinus</i>	Purplemouth moray	Muraenidae
HAE AURO	<i>Haemulon aurolineatum</i>	Tomtate grunt	Haemulidae
HAE CARB	<i>Haemulon carbonarium</i>	Caesar grunt	Haemulidae
HAE CHRY	<i>Haemulon chrysargyreum</i>	Smallmouth grunt	Haemulidae
HAE FLAV	<i>Haemulon flavolineatum</i>	French grunt	Haemulidae
HAE MACR	<i>Haemulon macrostomum</i>	Spanish grunt	Haemulidae
HAE MELA	<i>Haemulon melanurum</i>	Cottonwick grunt	Haemulidae
HAE PARR	<i>Haemulon parra</i>	Sailor's grunt	Haemulidae
HAE PLUM	<i>Haemulon plumierii</i>	White Grunt	Haemulidae
HAE SCIU	<i>Haemulon sciurus</i>	Bluestriped grunt	Haemulidae
HAE SPE		Juvenile grunt	Haemulidae
HAE STRI	<i>Haemulon striatum</i>	Striped grunt	Haemulidae
HAL BIVI	<i>Halichoeres bivittatus</i>	Slippery dick	Labridae
HAL CYAN	<i>Halichoeres cyanocephalus</i>	Yellowcheek wrasse	Labridae
HAL GARN	<i>Halichoeres garnoti</i>	Yellowhead wrasse	Labridae
HAL MACU	<i>Halichoeres maculipinna</i>	Clown wrasse	Labridae



Abbreviation	Species Name	Common Name	Family
HAL PICT	<i>Halichoeres pictus</i>	Rainbow wrasse	Labridae
HAL POEY	<i>Halichoeres poeyi</i>	Blackear wrasse	Labridae
HAL RAD	<i>Halichoeres radiatus</i>	Puddingwife wrasse	Labridae
HEM BRAS	<i>Hemiramphus brasiliensis</i>	Ballyhoo	Hemiramphidae
HEM MART	<i>Xyrichtys martinicensis</i>	Rosy razorfish	Labridae
HEM SPLE	<i>Xyrichtys splendens</i>	Green razorfish	Labridae
HET HALI	<i>Heteroconger longissimus</i>	Garden Eel	Congridae
HOL ADSC	<i>Holocentrus adscensionis</i>	Squirrelfish	Holocentridae
HOL BERM	<i>Holacanthus bermudensis</i>	Blue Angelfish	Pomacanthidae
HOL CILI	<i>Holacanthus ciliaris</i>	Queen angelfish	Pomacanthidae
HOL RUFU	<i>Holocentrus rufus</i>	Longspine squirrelfish	Holocentridae
HOL TRIC	<i>Holacanthus tricolor</i>	Rock beauty	Pomacanthidae
HOL VEXI	<i>Sargocentron vexillarium</i>	Dusky squirrelfish	Holocentridae
HYP BERM	<i>Hypleurochilus bermudensis</i>	Barred blenny	Blenniidae
HYP GEMM	<i>Hypoplectrus gemma</i>	Blue hamlet	Serranidae
HYP GUTT	<i>Hypoplectrus guttavarius</i>	Shy hamlet	Serranidae
HYP PUEL	<i>Hypoplectrus puella</i>	Barred hamlet	Serranidae
HYP SPE			Serranidae
HYP UNIC	<i>Hypoplectrus unicolor</i>	Butter hamlet	Serranidae
INE VITT	<i>Inermia vittata</i>	Boga	Inermiidae
IOG CALL	<i>Ptereleotris calliura</i>	Blue goby	Microdesmidae
IOG HELE	<i>Ptereleotris helenae</i>	Hovering goby	Microdesmidae
KYP SECT	<i>Kyphosus sectator</i>	Bermuda sea chub	Kyphosidae
LAB KALI	<i>Labrisomus kalisherae</i>	Downy blenny	Labrisomidae
LAC MAXI	<i>Lachnolaimus maximus</i>	Hogfish	Labridae
LAC POLY	<i>Acanthostracion polygonius</i>	Honeycomb cowfish	Ostraciidae
LAC QUAD	<i>Acanthostracion quadricornis</i>	Scrawled cowfish	Ostraciidae
LAC TRIG	<i>Lactophrys trigonus</i>	Buffalo trunkfish	Ostraciidae
LAC TRIQ	<i>Lactophrys triqueter</i>	Smooth trunkfish	Ostraciidae
LUT ANAL	<i>Lutjanus analis</i>	Mutton snapper	Lutjanidae
LUT APOD	<i>Lutjanus apodus</i>	Schoolmaster snapper	Lutjanidae
LUT GRIS	<i>Lutjanus griseus</i>	Grey snapper	Lutjanidae
LUT SYNA	<i>Lutjanus synagris</i>	Lane snapper	Lutjanidae
MAL MACR	<i>Malacoctenus macropus</i>	Rosy blenny	Labrisomidae
MAL PLUM	<i>Malacanthus plumieri</i>	Sand tilefish	Malacanthidae
MAL TRIA	<i>Malacoctenus triangulatus</i>	Saddled blenny	Labrisomidae
MAN BIRO	<i>Manta birostris</i>	Giant manta	Myliobatidae
MEG ATLA	<i>Megalops atlanticus</i>	Tarpon	Megalopidae
MEL NIGE	<i>Rachycentron canadum</i>	Cobia	Rachycentridae
MIC CARR	<i>Microgobius carri</i>	Seminole goby	Gobiidae
MIC CHRY	<i>Microspathodon chrysurus</i>	Yellowtail damselfish	Pomacentridae
MON CILI	<i>Monacanthus ciliatus</i>	Fringed filefish	Monacanthidae
MON HISP	<i>Stephanolepis hispidus</i>	Planehead filefish	Monacanthidae
MON TUCK	<i>Monacanthus tuckeri</i>	Slender filefish	Monacanthidae
MUL MART	<i>Mulloidichthys martinicus</i>	Yellow goatfish	Mullidae
MYC BONA	<i>Mycteroperca bonaci</i>	Black grouper	Serranidae
MYC INTE	<i>Mycteroperca interstitialis</i>	Yellowmouth grouper	Serranidae

Abbreviation	Species Name	Common Name	Family
MYC PHEN	<i>Mycteroperca phenax</i>	Scamp	Serranidae
MYR JACO	<i>Myripristis jacobus</i>	Blackbar soldierfish	Holocentridae
OCY CHRY	<i>Ocyurus chrysurus</i>	Yellowtail snapper	Lutjanidae
OLI SAUR	<i>Oligoplites saurus</i>	Leatherjack	Carangidae
OPH ATLA	<i>Ophioblennius atlanticus</i>	Redlip Blenny	Blenniidae
OPI AURI	<i>Opistognathus aurifrons</i>	Yellowhead jawfish	Opistognathidae
OPI MACR	<i>Opistognathus macrognathus</i>	Banded jawfish	Opistognathidae
OPI WHIT	<i>Opistognathus whitehursti</i>	Dusky jawfish	Opistognathidae
PAR MARM	<i>Parablennius marmoreus</i>	Seaweed blenny	Blenniidae
PEM SCHO	<i>Pempheris schomburgkii</i>	Glassy sweeper	Pempheridae
POM ARCU	<i>Pomacanthus arcuatus</i>	Gray angelfish	Pomacanthidae
POM DIEN	<i>Stegastes diencaeus</i>	Longfin damselfish	Pomacentridae
POM FUSC	<i>Stegastes fuscus</i>	Dusky damselfish	Pomacentridae
POM LEUC	<i>Stegastes leucostictus</i>	Beaugregory	Pomacentridae
POM PART	<i>Stegastes partitus</i>	Bicolor damselfish	Pomacentridae
POM PARU	<i>Pomacanthus paru</i>	French angelfish	Pomacanthidae
POM PLAN	<i>Stegastes planifrons</i>	Threespot damselfish	Pomacentridae
POM SPE.			Pomacentridae
POM VARI	<i>Stegastes variabilis</i>	Cocoa damselfish	Pomacentridae
PRI CRUE	<i>Heteropriacanthus cruentatus</i>	Glasseye	Priacanthidae
PSE MACU	<i>Pseudupeneus maculatus</i>	Spotted goatfish	Mullidae
REM REMO	<i>Remora remora</i>	Common remora	Echeneidae
RHI LENT	<i>Rhinobatos lentiginosus</i>	Atlantic guitarfish	Rhinobatidae
RYP SAPO	<i>Rypticus saponaceus</i>	Greater soapfish	Serranidae
SCA COER	<i>Scarus coeruleus</i>	Blue parrotfish	Scaridae
SCA CROI	<i>Scarus iseri</i>	Striped parrotfish	Scaridae
SCA GUAC	<i>Scarus guacamaia</i>	Rainbow parrotfish	Scaridae
SCA SPE.			Scaridae
SCA TAEN	<i>Scarus taeniopterus</i>	Princess parrotfish	Scaridae
SCA VETU	<i>Scarus vetula</i>	Queen parrotfish	Scaridae
SCO CAVA	<i>Scomberomorus cavalla</i>	King mackerel	Scombridae
SCO MACU	<i>Scomberomorus maculatus</i>	Spanish mackerel	Scombridae
SCO PLUM	<i>Scorpaena plumieri</i>	Spotted scorpionfish	Scorpaenidae
SCO REGA	<i>Scomberomorus regalis</i>	Cero	Scombridae
SEL CRUM	<i>Selar crumenophthalmus</i>	Bigeye scad	Carangidae
SER ANNU	<i>Serranus annularis</i>	Orangeback bass	Serranidae
SER BALD	<i>Serranus baldwini</i>	Lantern bass	Serranidae
SER PHOE	<i>Serranus phoebe</i>	Tattler bass	Serranidae
SER RIVO	<i>Seriola rivoliana</i>	Almaco jack	Carangidae
SER TABA	<i>Serranus tabacarius</i>	Tobaccofish	Serranidae
SER TIGR	<i>Serranus tigrinus</i>	Harlequin bass	Serranidae
SER TORT	<i>Serranus tortugarum</i>	Chalk bass	Serranidae
SPA ATOM	<i>Sparisoma atomarium</i>	Greenblotch parrotfish	Scaridae
SPA AURO	<i>Sparisoma aurofrenatum</i>	Redband parrotfish	Scaridae
SPA CHRY	<i>Sparisoma chrysopteron</i>	Redtail parrotfish	Scaridae
SPA RAD1	<i>Sparisoma radians</i>	Bucktooth parrotfish	Scaridae
SPA RUBR	<i>Sparisoma rubripinne</i>	Redfin parrotfish	Scaridae

Abbreviation	Species Name	Common Name	Family
SPA SPE.			Scaridae
SPA VIRI	<i>Sparisoma viride</i>	Stoplight parrotfish	Scaridae
SPH BARR	<i>Sphyaena barracuda</i>	Great barracuda	Sphyaenidae
SPH SPEN	<i>Sphoeroides spengleri</i>	Bandtail puffer	Tetraodontidae
SYN INTE	<i>Synodus intermedius</i>	Sand diver	Synodontidae
THA BIFA	<i>Thalassoma bifasciatum</i>	Bluehead wrasse	Labridae
URO JAMA	<i>Urobatis jamaicensis</i>	Yellow stingray	Urolophidae

# Appendix III

## **Regression Equations**

<b>Abundance</b>				
<b>Habitat</b>	<b>Elevation (m)</b>	<b>Volume (m<sup>3</sup>)</b>	<b>Surface Rugosity</b>	<b>Linear Rugosity</b>
C P Shallow	32.8260484 + 41.78428330*x	26.7944 + 0.6498*x	-3302.22 + 3347.5717*x	-150.7289 + 181.9598*x
Ridge-Shallow	23.6281355 + 88.04120000*x	44.858 + 0.6333*x	-7758.481 + 7812.3218*x	-149.0112 + 199.8615*x
L R-Middle Shallow	12.9316005 + 184.95134000*x	8.7514 + 2.1723*x	-12474.4807 + 12578.5662*x	-470.4881 + 555.8091*x
L R-Middle	115.6394810 + 2.11903496*x	91.6529 + 0.1979*x	-299.1169 + 412.0641*x	-403.6039 + 447.9692*x
C P Deep	68.6437850 + 26.62369070*x	81.3722 + 0.2338*x	-1531.7904 + 1620.1932*x	-416.9184 + 453.7086*x
LR-Outer	109.2243610 + 46.30834270*x	117.673 + 0.4389*x	-2462.7314 + 2600.1966*x	-556.9578 + 631.6242*x
Agg. Patch Reef	102.5989590 + 64.79755440*x	138.160 + 0.5841*x	-1976.8498 + 2139.5179*x	-367.9245 + 447.5351*x
<b>Species</b>				
<b>Habitat</b>	<b>Elevation (m)</b>	<b>Volume (m<sup>3</sup>)</b>	<b>Surface Rugosity</b>	<b>Linear Rugosity</b>
C P Shallow	8.4992 + 6.5283*x	7.362 + 0.1058*x	-427.4197 + 438.1562*x	-38.0255 + 44.1063*x
Ridge-Shallow	9.1041 + 6.7768*x	10.334 + 0.0555*x	-629.0668 + 640.3517*x	-9.8143 + 20.2375*x
L R-Middle Shallow	14.9599 + 6.216*x	14.3474 + 0.0787*x	-362.5589 + 380.8699*x	3.0707 + 15.0153*x
L R-Middle	19.175 + 0.7675*x	19.0705 + 0.0108*x	-4.3597 + 24.5579*x	7.1897 + 11.476*x
C P Deep	17.8122 + 0.935*x	17.6774 + 0.0153*x	-10.2117 + 28.9298*x	-3.7519 + 19.8885*x
L R-Outer	18.7079 + 0.8183*x	19.3562 + 0.0045*x	-24.2609 + 43.5117*x	4.7284 + 13.0424*x
Agg. Patch Reef	18.7238 + 1.193*x	19.6141 + 0.0089*x	11.1812 + 9.3394*x	11.8301 + 6.874*x

Table 1. The equations in this table were derived from the categorized scatterplot regression lines. The first group should be used to estimate abundance and the second group to estimate species richness. The equations for each metric have been included however linear rugosity yielded the best results in this study. Elevation was perhaps the best GIS variable to use. To use these equations the user must measure the desired parameters in accordance to the methods described herein, use that measurement as the x value, and solve the equation. The resultant number, rounded to the nearest whole number value, will be the estimate of which ever fish assemblage parameter the equation is associated with.

# Appendix IV

## **SIMPER Species Percentages by Habitat**

Ridge-Shallow

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
HAL BIVI	20.68	8.39	6.4	1.38	20.68
ACA BAH1	18.23	9.42	5.64	1.43	38.92
THA BIFA	12.21	9.93	3.78	0.87	51.12
ACA CHIR	6.92	2.75	2.14	0.66	58.05
HAE PLUM	4.86	3.7	1.5	0.57	62.91
HAL MACU	4.7	3.64	1.45	0.52	67.6
POM VARI	3.83	1.46	1.19	0.52	71.44
BAL CAPR	2.84	0.66	0.88	0.37	74.28
SPA AURO	2.63	1.77	0.81	0.41	76.91
POM LEUC	2.07	0.78	0.64	0.34	78.98
HAE FLAV	2	7.04	0.62	0.34	80.98
HAE SCIU	1.89	1.96	0.58	0.34	82.87
POM PART	1.7	1.45	0.53	0.32	84.57
ANI VIRG	1.56	0.76	0.48	0.32	86.13
EPI MORI	1.14	0.37	0.35	0.25	87.27
SPA VIRI	1.04	0.62	0.32	0.27	88.31
ACA COER	0.85	0.58	0.26	0.26	89.16
ABU SAXA	0.82	1.84	0.25	0.19	89.97
PSE MACU	0.82	0.43	0.25	0.21	90.79
Other	9.21				

Colonized Pavement-Shallow

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
HAL BIVI	22.93	6.69	5.38	1.07	22.93
HAE SPE	13.08	29.84	3.07	0.5	36
ACA BAH1	11.69	5.78	2.75	0.63	47.7
POM VARI	5.96	1.39	1.4	0.56	53.66
THA BIFA	5.11	4.63	1.2	0.44	58.77
HAE PLUM	4.37	3.84	1.03	0.45	63.14
ACA CHIR	4.23	4.8	0.99	0.38	67.37
BAL CAPR	3.74	0.98	0.88	0.41	71.11
SPA AURO	3	1.12	0.71	0.4	74.11
EPI MORI	2.38	0.51	0.56	0.31	76.49
HEM SPLE	1.93	0.63	0.45	0.24	78.42
DIO HOLO	1.61	0.37	0.38	0.21	80.03
COR GLAU	1.52	1.92	0.36	0.23	81.55
CAN ROST	1.38	0.41	0.32	0.26	82.93
POM LEUC	1.21	0.67	0.28	0.22	84.14
GOB OCEA	1.19	1.94	0.28	0.23	85.33
HAL MACU	1.01	1.67	0.24	0.22	86.34
EQU ACUM	0.99	0.49	0.23	0.19	87.33
EMB PAND	0.98	0.35	0.23	0.17	88.31
DIP ARGE	0.88	0.59	0.21	0.12	89.19
PSE MACU	0.87	0.45	0.2	0.19	90.05
Other	9.94				

Middle Reef-Shallow

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
POM PART	16.49	36.52	7.02	4.94	16.49
THA BIFA	15.19	41.22	6.47	2.87	31.67
HAL GARN	9.74	7.37	4.15	2	41.42
ACA BAH	9.55	4.48	4.07	2.7	50.97
SPA AURO	7.86	5.3	3.35	1.52	58.83
PSE MACU	4.87	3.26	2.07	0.93	63.7
CAN ROST	3.31	2.11	1.41	0.76	67.01
ACA COER	2.88	1.48	1.23	0.7	69.89
HAE FLAV	2.56	6.52	1.09	0.63	72.45
SER TIGR	2.5	0.96	1.07	0.58	74.95
HAL BIVI	2.19	3.15	0.93	0.41	77.14
POM VARI	1.85	1.7	0.79	0.52	78.99
SPA VIRI	1.8	0.96	0.77	0.58	80.79
HAE PLUM	1.44	0.81	0.61	0.48	82.23
COR PERS	1.23	12.93	0.52	0.33	83.46
CLE PARR	1.19	19.04	0.51	0.33	84.65
CHA SEDE	1.12	0.7	0.48	0.37	85.78
POM LEUC	1.09	0.93	0.46	0.42	86.87
HYP UNIC	0.96	0.44	0.41	0.37	87.83
CHR MULT	0.91	6.7	0.39	0.29	88.74
BOD RUFU	0.89	1.11	0.38	0.37	89.63
EPI CRUE	0.85	0.52	0.36	0.38	90.48
Other	9.53				

Middle Reef-Deep

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
POM PART	13.85	18.94	6.58	4.51	13.85
THA BIFA	10.96	15.16	5.2	2.32	24.81
HAL GARN	10.14	9.22	4.81	2.33	34.95
SER TIGR	7.47	2.84	3.55	1.87	42.42
ACA BAH	6.04	4.47	2.87	1.22	48.47
SPA AURO	5.61	4	2.67	1.11	54.08
CHA SEDE	5.38	2.04	2.55	1.18	59.46
SER TABA	5.36	2.78	2.55	1.07	64.82
CAN ROST	5.12	2.31	2.43	1.18	69.94
BAL CAPR	3.6	2.45	1.71	0.82	73.54
HAL BIVI	3.31	2.18	1.57	0.7	76.84
ACA CHIR	2.79	3.06	1.32	0.63	79.63
EPI MORI	2.42	0.94	1.15	0.68	82.05
HOL ADSC	1.81	0.98	0.86	0.55	83.86
COR PERS	1.51	18.2	0.72	0.36	85.37
POM ARCU	1.17	0.71	0.56	0.41	86.55
HOL TRIC	1.07	0.59	0.51	0.41	87.62
SER TORT	1.05	3.98	0.5	0.3	88.67
OPI AURI	0.84	1.14	0.4	0.33	89.5
ACA COER	0.83	1.02	0.39	0.36	90.33
Other	9.67				



## Colonized Pavement-Deep

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
HAL GARN	14.09	11.31	5.94	2.94	14.09
POM PART	13.02	15.25	5.48	2.37	27.11
THA BIFA	9.74	13.5	4.1	1.27	36.86
SER TABA	8.04	3.41	3.39	1.41	44.89
SPA AURO	8	5.53	3.37	1.3	52.9
CAN ROST	6.33	2.09	2.67	1.19	59.23
ACA CHIR	5.69	3.78	2.4	0.87	64.92
SER TIGR	5.55	1.59	2.34	1.09	70.47
CHA SEDE	4.32	1.88	1.82	0.78	74.79
PSE MACU	2.88	1.38	1.21	0.66	77.68
ACA BAHI	2.81	4.59	1.19	0.55	80.49
ACA COER	2.09	1.63	0.88	0.51	82.58
SCA TAEN	1.56	1.25	0.66	0.43	84.14
HYP UNIC	1.39	0.66	0.58	0.43	85.53
OPI AURI	1.18	1.84	0.5	0.29	86.71
SCA CROI	1.1	1.22	0.46	0.35	87.81
LAC MAXI	0.96	0.63	0.41	0.31	88.77
HAL BIVI	0.9	0.91	0.38	0.27	89.67
EPI MORI	0.88	0.38	0.37	0.31	90.55
Other	9.47				

## Outer Reef

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
THA BIFA	14.47	38.53	6.27	2.36	14.47
POM PART	14.19	34.14	6.15	2.75	28.65
HAL GARN	11.86	10.83	5.14	2.28	40.51
ACA BAHI	9.28	6.07	4.03	1.94	49.8
SPA AURO	8.65	7.07	3.75	1.52	58.45
CHA SEDE	5.21	1.91	2.26	1.01	63.66
CAN ROST	4.39	1.95	1.9	0.9	68.05
SCA TAEN	3.78	4.34	1.64	0.76	71.83
PSE MACU	2.6	1.91	1.13	0.64	74.43
ACA COER	2.49	1.22	1.08	0.61	76.92
SER TIGR	2.21	0.91	0.96	0.56	79.13
HYP UNIC	2.08	0.97	0.9	0.58	81.22
CHA OCEL	1.29	0.88	0.56	0.39	82.51
SER TABA	1.1	1.05	0.48	0.35	83.61
SCA CROI	1.09	1.81	0.47	0.35	84.7
ACA CHIR	1.05	2.1	0.46	0.33	85.75
SPA ATOM	0.98	1.66	0.42	0.31	86.73
ALU SCRI	0.93	0.48	0.4	0.36	87.66
CHR CYAN	0.87	1.6	0.38	0.33	88.53
EPI CRUE	0.81	0.43	0.35	0.33	89.34
HAE PLUM	0.77	1.6	0.33	0.31	90.1
Other	9.9				

Aggregated Patch Reef

Species	Contrib%	Av.Abund	Av.Sim	Sim/SD	Cum.%
POM PART	16.38	45.38	7.75	5.79	16.38
THA BIFA	11.74	17.41	5.55	2.97	28.12
HAL GARN	11.2	15.5	5.3	3.09	39.32
SPA AURO	6.07	4.56	2.87	1.23	45.39
SCA TAEN	5.03	2.94	2.38	1.25	50.42
CAN ROST	4.98	2.71	2.36	1.14	55.4
SER TABA	4.48	3.06	2.12	0.94	59.88
SER TIGR	3.92	1.97	1.86	0.95	63.8
CHA SEDE	3.84	2.68	1.81	0.81	67.64
CHR CYAN	3.54	7.18	1.67	0.74	71.18
HOL TRIC	3.01	1.18	1.42	0.82	74.19
ACA BAH1	2.79	2	1.32	0.7	76.98
ACA CHIR	2.77	3	1.31	0.64	79.75
COR PERS	2.15	47.06	1.02	0.4	81.9
CHR SCOT	1.77	7.15	0.84	0.47	83.67
CHR INSO	1.74	7.53	0.82	0.46	85.42
HOL BERM	1.53	0.56	0.73	0.51	86.95
PSE MACU	1.37	1.15	0.65	0.47	88.32
SPA ATOM	1.21	1.47	0.57	0.39	89.53
BOD RUFU	0.85	0.65	0.4	0.36	90.38
Other	9.63				

# Appendix V

## **Prediction Model Maps**

A – Predicted Reef Fish Abundance by Elevation

B – Predicted Reef Fish Abundance by Volume

C – Predicted Reef Fish Abundance by Surface Rugosity

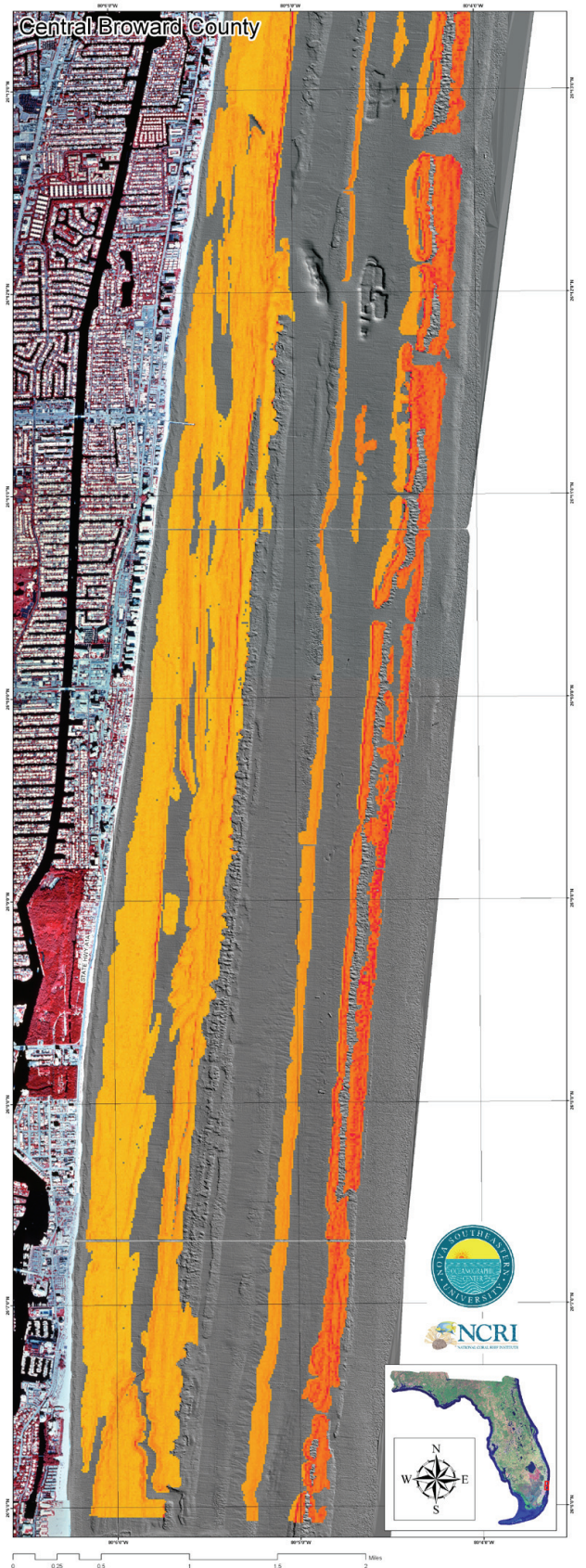
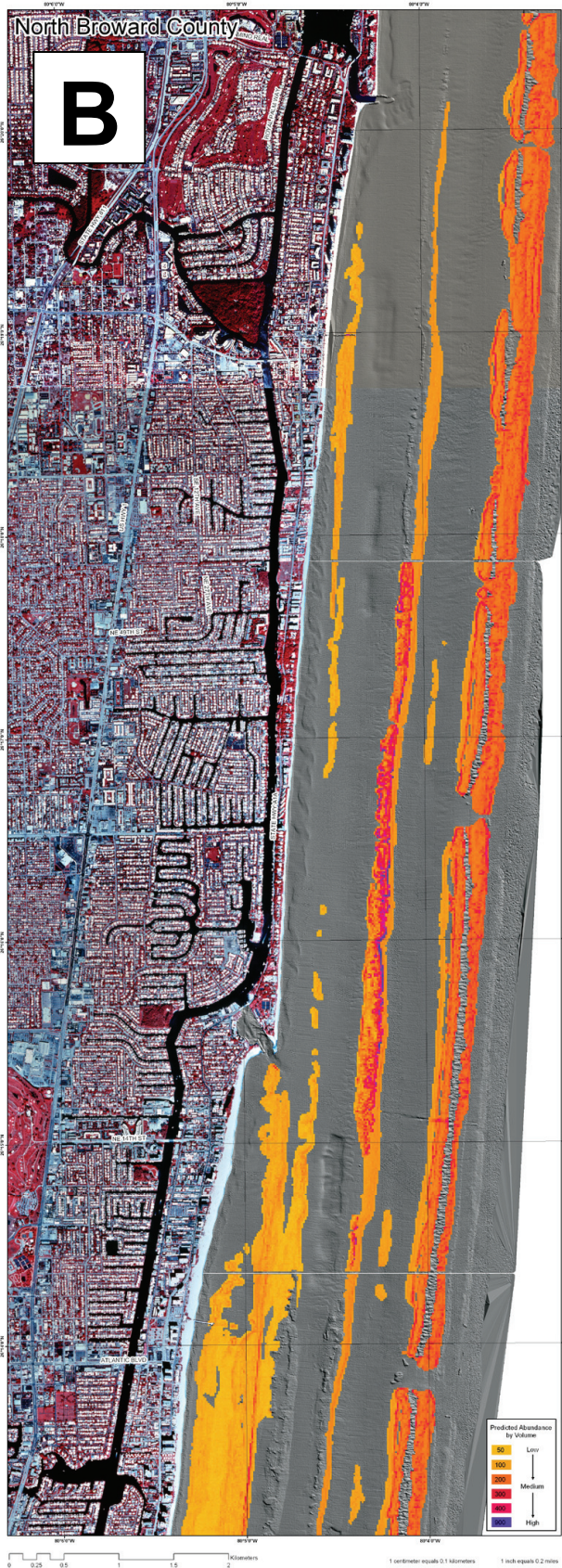
D – Predicted Reef Fish Species Richness by Elevation

E – Predicted Reef Fish Species Richness by Volume

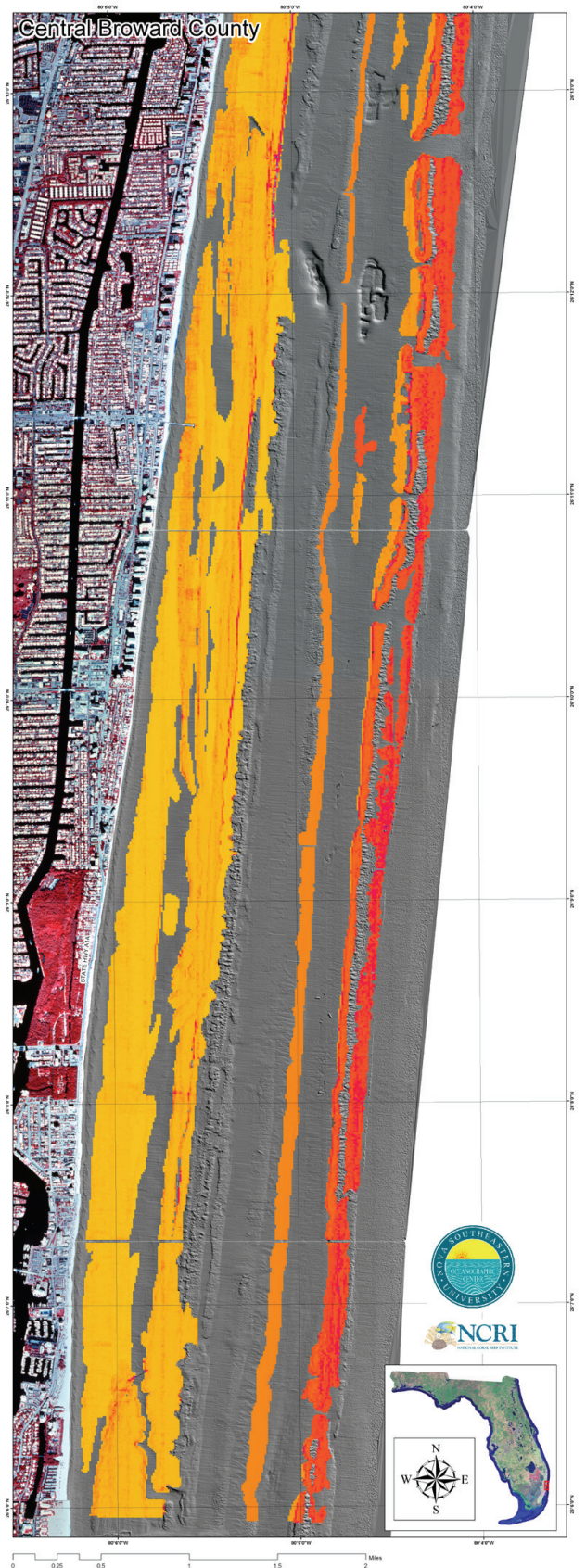
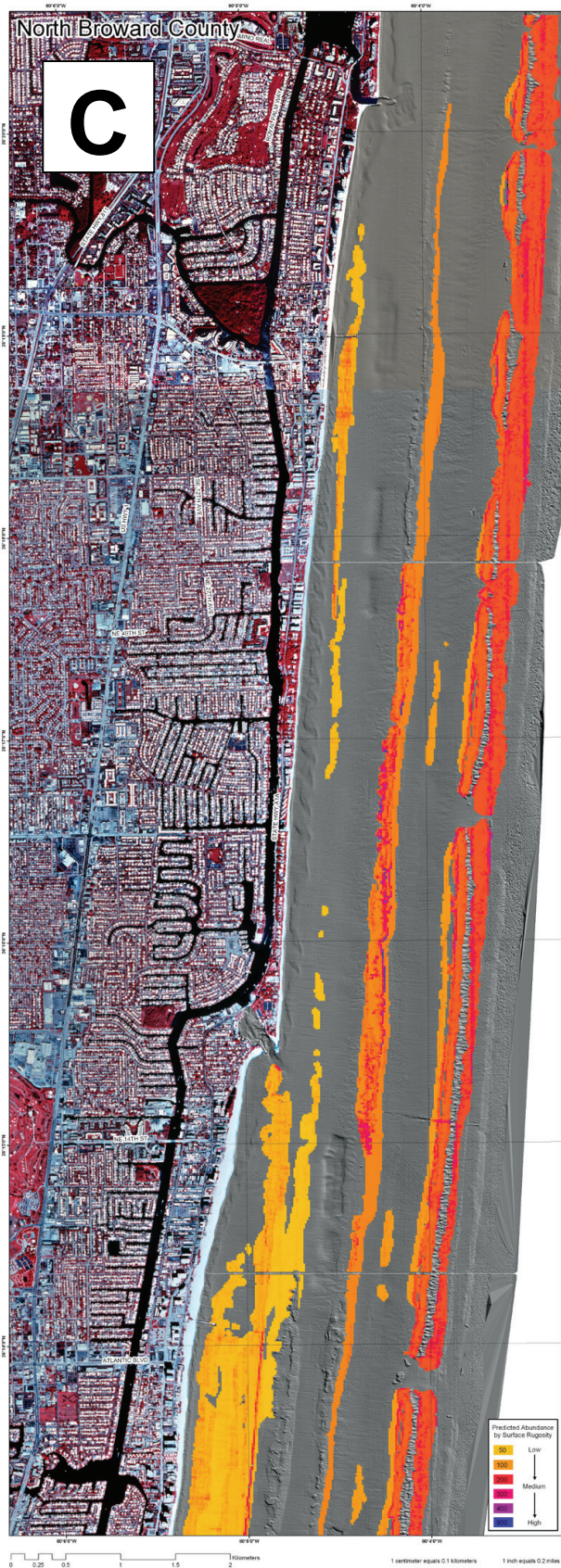
F – Predicted Reef Fish Species Richness by Surface Rugosity





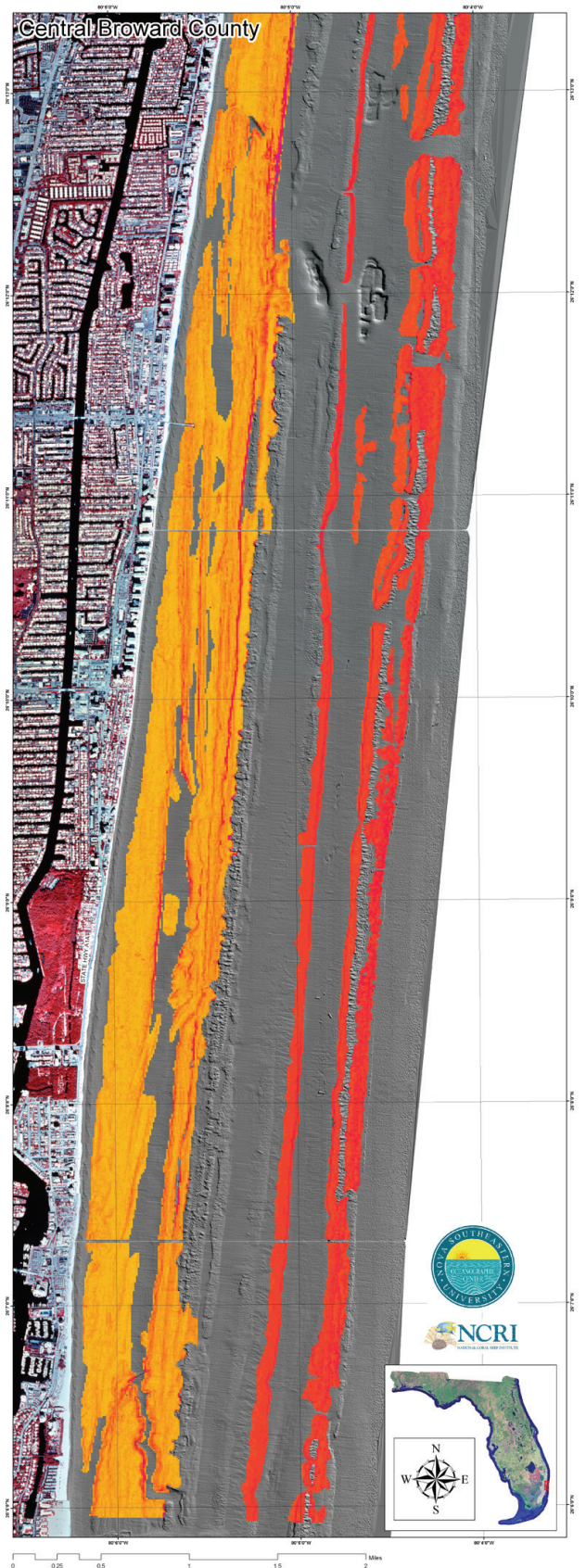
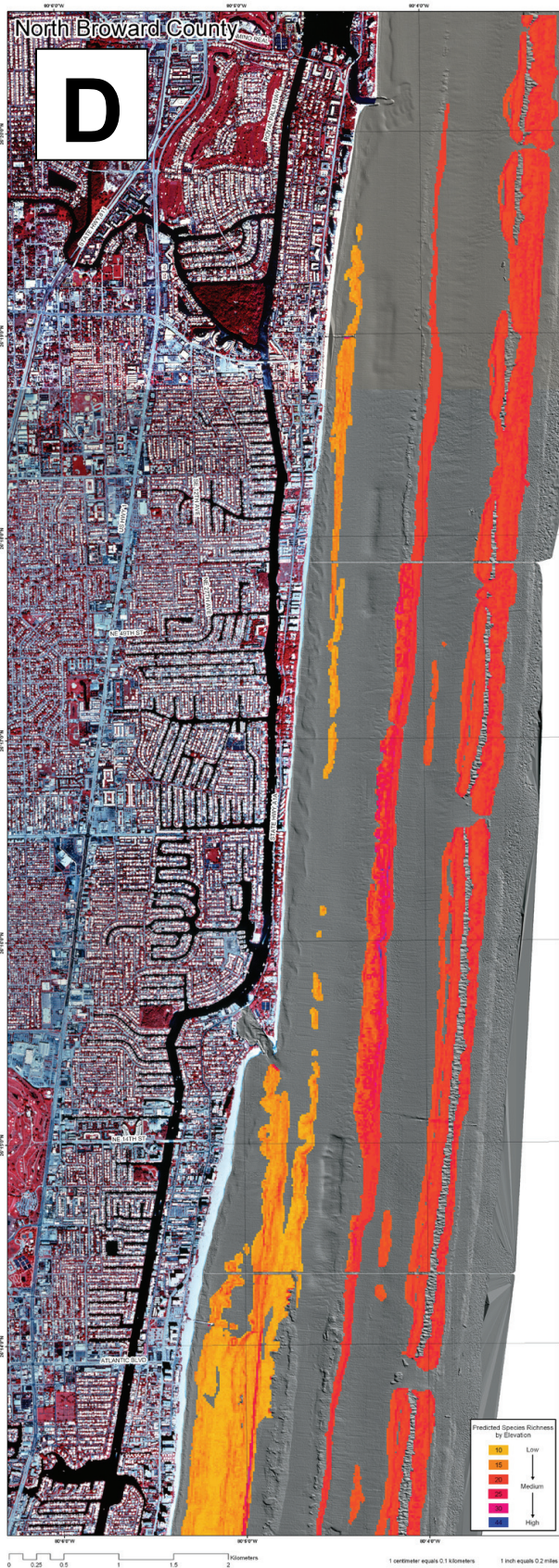






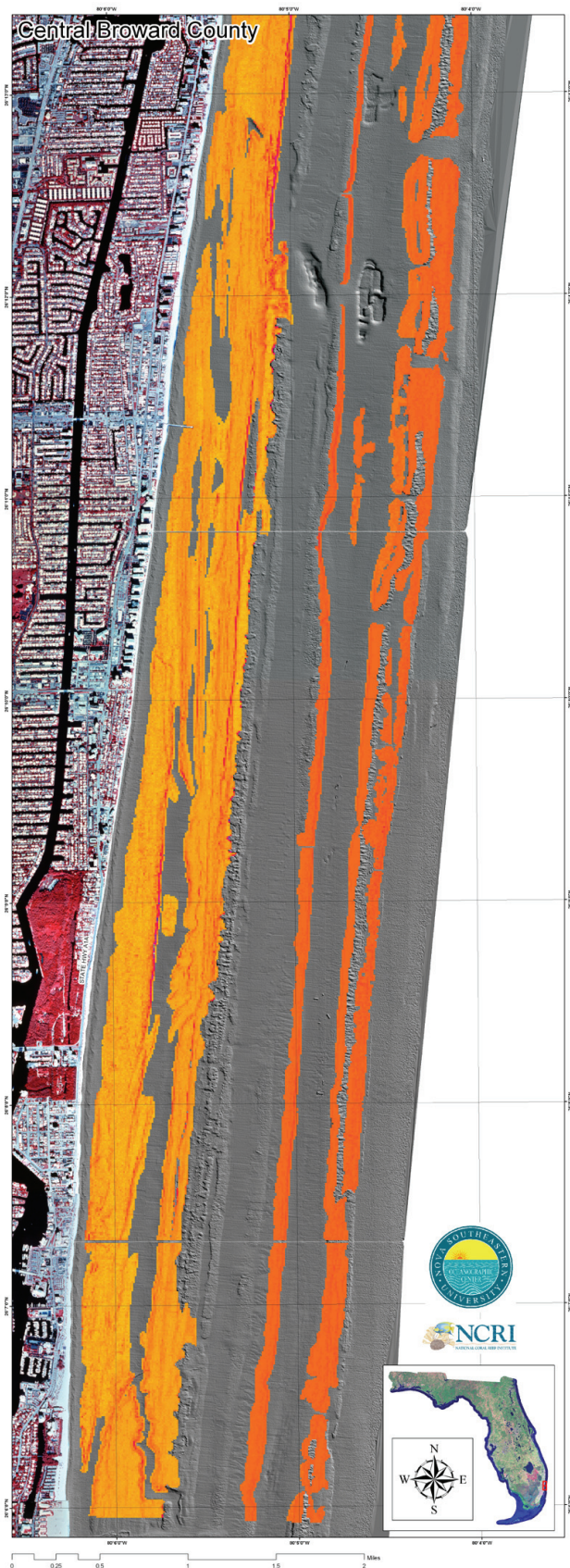
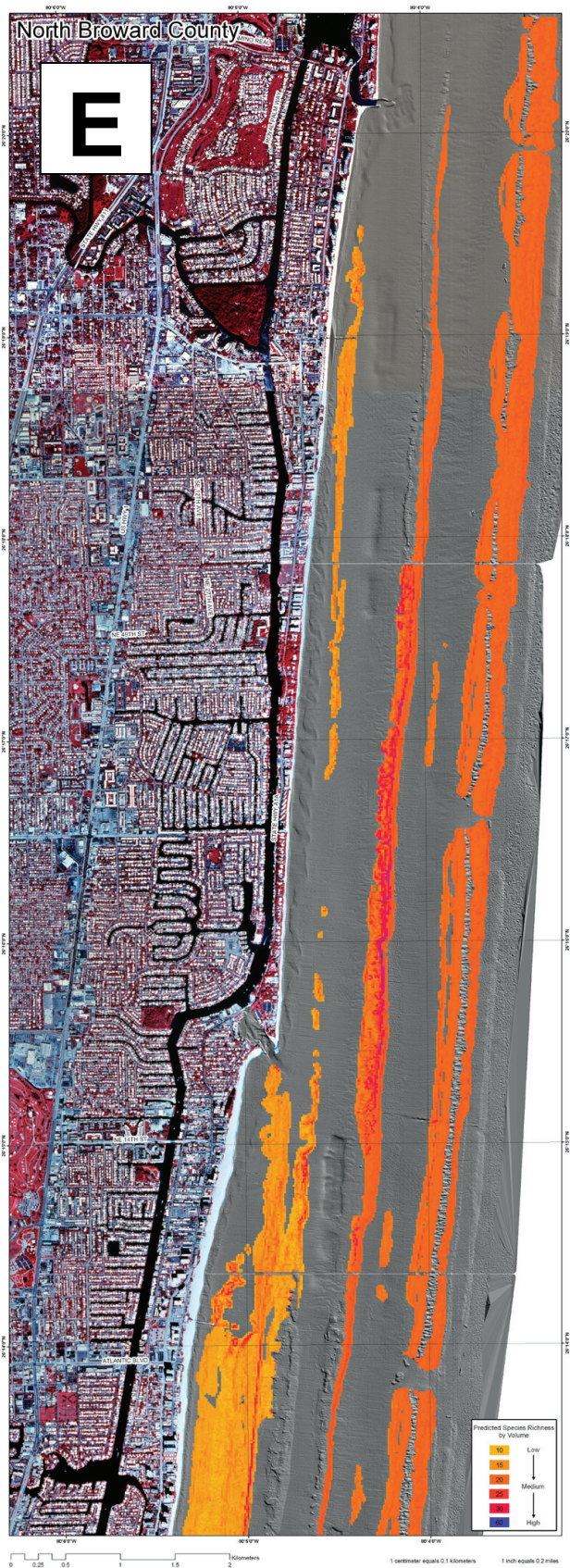
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 FL reef image supplied by Florida Marine Research Institute. Laser Altimetry Depth Sounder (LADS) bathymetry data supplied by Broward County's Department of Planning and Environmental Protection. Predicted reef habitat abundance data described in Stohler et al. 2007. From Stohler et al. 2007. Oceanographic Center.



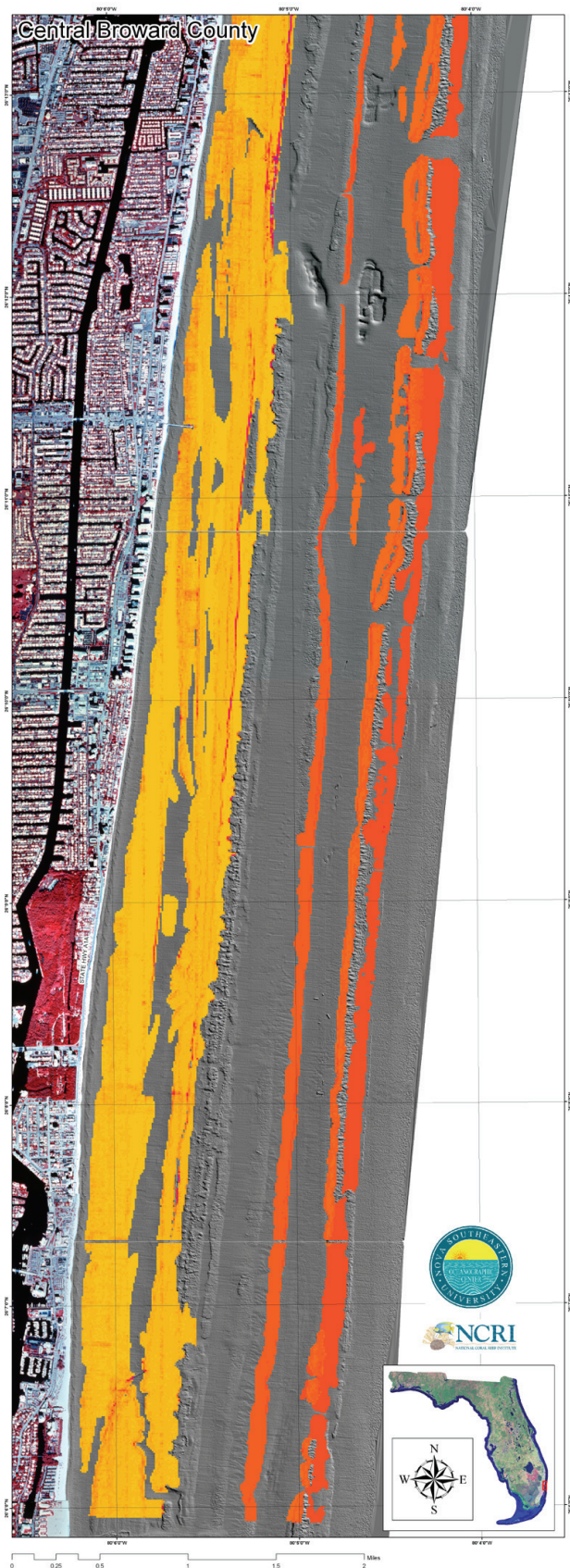
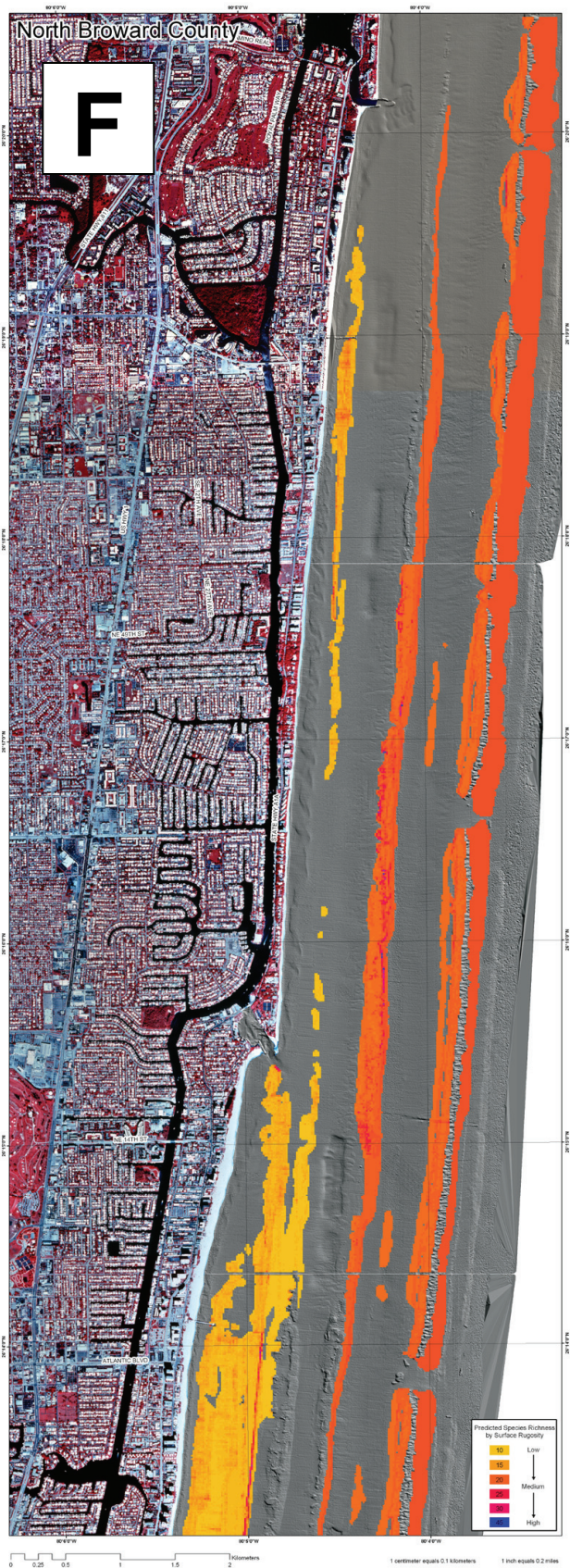


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