ASSESSMENT OF PAST, PRESENT, AND FUTURE STATUS OF SOUTHERN FLOUNDER (*PARALICHTHYS LETHOSTIGMA*) IN TEXAS USING A TIME SERIES AND QUANTITATIVE MODELING APPROACH

A Dissertation

by

BRIDGETTE F FROESCHKE

Submitted In Partial Fulfillment Of The Requirements For The Degree of

DOCTOR OF PHILOSOPHY

Texas A&M University – Corpus Christi
Corpus Christi, Texas

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This dissertation meets the standards for scope and quality of
Texas A&M University--Corpus Christi and is hereby approved.

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May, 2011

ABSTRACT

Assessment of past, present, and future status of southern flounder (*Paralichthys lethostigma*) using a time series and quantitative modeling approach

(May, 2011)

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Declines of important fish species such as southern flounder, *Paralichthys lethostigma*, in the Gulf of Mexico underscore the importance of defining critical habitats as well as the processes contributing to habitat value. Southern flounder is a valuable commercial and recreational fishery, distributed from North Carolina to Florida on the Atlantic Coast and from Florida to Northern Mexico on the Gulf Coast. Despite the economic and ecological importance of southern flounder, current management efforts failed to recover a sharp population decline and restore back to a historical level. Therefore, it is important for resource managers to understand and predict the future status of juvenile southern flounder. The overall purpose of this study was to provide research data and decision tools needed for development of a fishery management plan for flounders by using statistical modeling techniques. Specifically, this research: 1) uses a long-term fisheries independent data set to assess abundance trends of both juvenile (1979-2007) and adult (1975-2008) life-stages of southern flounder throughout the major bay systems off the

Texas coast; 2) constructs a species habitat model for juvenile southern flounder that predicts Essential Fish Habitat (EFH) by incorporating the relationship between abiotic (temperature, salinity, turbidity, dissolved oxygen, and pH), and biotic factors (habitat, depth, and organic content) temporally and spatially within the Mission-Aransas National Estuarine Research Reserve (MANERR), Aransas Bay Complex, TX, USA; 3) compares and contrasts species-habitat models of southern flounder with a highly abundant flatfish, bay whiff (*Citharichthys spilopterus*); 4) determines a relationship between temporal (month, year), spatial (distance to the inlet), and physical (temperature, turbidity, dissolved oxygen, salinity, and depth) variables with the occurrence of juvenile southern flounder along the Texas coast; 5) uses Boosted Regression Trees (BRT) and Artificial Neural Networks (ANN) to predict the presence of juvenile southern flounder spatially among Texas Bays; and 6) compares the predictive power and spatial distribution of trained and tested BRT and ANN modeling approaches for population parameters and dynamics for juvenile southern flounder.

A long-term fisheries independent data set (1975-2008) from Texas Parks and Wildlife Department fisheries monitoring program was used to assess population trends of juvenile and adult southern flounder along the Texas coast in the northern Gulf of Mexico, USA. These data were examined for age-specific population trends using generalized least squares and extended with non-parametric bootstrapping to obtain interval estimates of regression parameters (juveniles) and linear regression (adults) and showed long-term declines in juvenile southern flounder abundance. For adult southern flounder, rate of decline was much more rapid. Results suggest that survival of post-juvenile flounder have decreased during the time series. This precipitous decline has prompted increasingly stricter harvest restrictions along the Texas coast.

However, past management measures have been insufficient to curb declines, and it is too early to assess the recent regulations.

To develop a predictive species habitat model delineating critical areas for nursery habitat field collections of juvenile bay whiff and southern flounder were collected from February to May 2010 within the Aransas Bay Complex. To determine the mechanism of habitat selection the “best” species habitat model for both species was identified using BRT. Ten predictors were included in the model: habitat type, dry weight, depth (m), dissolved oxygen (mg O_2/L), temperature (°C), turbidity (cm), salinity, pH, distance to the inlet, and month. Species habitat model for juvenile bay whiff indicated that bay whiff were not associated with any particular habitat type, but were associated with low temperatures (< 15°C), moderate percent dry weight of sediments (25-60%), salinity >10 psu, and moderate to high dissolved oxygen (6-9 mg/L, 10-14 mg/L). Species habitat model for juvenile southern flounder indicated that southern flounder were associated with low temperatures (<15°C), low percent dry weight of sediment (<30 mg/L), seagrass habitats, shallow depths (<1.2 m), and high dissolved oxygen (>8 mg/L). Results suggest EFH within the Aransas Bay Complex needs to occur among all habitat types along the eastern side of Aransas Bay, and the north corner of Copano Bay. The findings will provide a valuable new tool for fisheries managers to aid sustainable management of bay whiff and southern flounder and the Mission-Aransas Reserve ecosystem and provides crucial information needed to prioritize areas for habitat conservation and management in the Gulf of Mexico.

Modeling approaches using BRT and ANN were constructed to understand how environmental factors influence the temporal and spatial patterns of juvenile southern flounder throughout all of the major Texas bays. Data were acquired from the Resource and Sport

Harvest Monitoring Program conducted by Texas Parks and Wildlife Department. The BRT model indicated juvenile southern flounder were associated with low temperatures, low salinity levels, and high dissolved oxygen. Both spatio-temporal models (BRT and ANN) consisted of high predictive performance with slight spatial differences. Both models suggest high probability of occurrence in Galveston Bay and East Matagorda Bay whereas the Artificial Neural Network also indicated high probability of occurrence in Sabine Lake.

Overall, this study suggest that EFH within the Aransas Bay Complex for juvenile southern flounder occurs in seagrass habitats along the western edge of Aransas. On a larger spatial scale this study showed that EFH for juvenile southern flounder along the Texas Coast needs to occur in areas consisting of low salinities, cooler temperatures and areas closest to tidal inlets (e.g., Sabine Lake and Galveston Bay). The findings will provide a valuable new tool for fisheries managers to aid sustainable management of bay whiff and southern flounder and the Mission-Aransas Reserve ecosystem and provides crucial information needed to prioritize areas for habitat conservation and management in the Gulf of Mexico. The results also identified a predictive framework for proactive approaches to ecosystem management. These models will allow managers to more accurately conserve nursery habitats for the southern flounder fishery, make predictions about future distribution due to environmental changes, and gives support for conserving appropriate habitat and understanding relationships between abiotic and biotic factors within those habitats

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DEDICATION

In dedication to the strongest, bravest woman I have ever known, my beautiful granny, Faye Brackett.

CHAPTER 1

INTRODUCTION TO THE SOUTHERN FLOUNDER FISHERY ALONG THE NORTHERN GULF OF MEXICO

Declines in abundance and extensive exploitation of the world's fisheries and marine habitats have caused much concern among scientists (Jackson et al. 2001; Pauly et al. 2002; Hilborn et al. 2003; Pyke 2004; Hughes et al. 2005; Lotze et al. 2006; Halpern et al. 2008 and NMFS 2008; Worm et al. 2009). Overfishing, ocean disposal and spills, destruction of coastal ecosystems, land-based contamination, and climate change are all major issues that adversely affect fishery sustainability in the world's oceans (Costanza et al. 1998). Human impacts have altered the distribution, quantity, and quality of marine habitats (Pyke 2004; and Lotze et al. 2006). These impacts have contributed to the depletion of more than 90% of estuarine species, degraded water quality, accelerated species invasions, and destroyed greater than 65% of seagrass and wetland habitat among estuaries and coastal seas (Lotze et al. 2006). Along with habitat decline, fisheries worldwide are declining and have led to large-scale loss of biodiversity (Worm et al. 2006). Declining fisheries and loss of habitat are major threats to marine ecosystems (Crowder et al 2008).

Seventy-five percent of fisheries worldwide are over exploited or fully exploited (NMFS 2002). Within the U.S., 17% of fisheries are subject to overfishing and 24% are overfished (NMFS 2008). It is well accepted that overfishing from recreational and commercial fishing as well as commercial by-catch from shrimp trawlers are significant contributors to the decline of fisheries (Jackson et al. 2001; Pauly et al. 2002; and Hilborn et al. 2003). Long-term natural environmental fluctuations and climate change could also be contributory (Jackson et al. 2001; Pauly et al. 2002; Hilborn et al. 2003; Pyke 2004 and Crowder et al. 2008; Worm and Lotze 2010). Moreover, it has been hypothesized that fisheries that are being overfished are more susceptible to habitat decline and climate change (Jackson et al. 2001).

The Magnuson-Stevens Act (MSA) defined "overfishing" as “a rate or level of fishing mortality that jeopardizes the capacity of a fishery to produce the maximum sustainable yield in such fishery.” The MSA requires the U.S. Secretary of Commerce and regional councils (eight regional fishery management councils composed of fisheries interests and state fishery officials) to: 1) identify those fish stocks under their jurisdiction that are either approaching or are actually “overfished”; and 2) develop a plan to assist in preventing further depletion (Kalo et al. 2007). One of the difficulties in complying with this mandate is that fisheries are not always located in a single regional jurisdiction. Consequently, U.S. Congress passed the Interjurisdictional Fisheries Act of 1986 (Title III, Public Law 99-659). This act was to provide states with grant money from the U.S. Secretary of Commerce for management of interjurisdictional commercial fishery resources. The main purposes of this act were 1) to promote and encourage state activities in support of the management of interjurisdictional fishery resources; and 2) to promote and encourage management of interjurisdictional fishery resources throughout their range. Moreover, the act provides monies for regional-based management of fisheries. While this legislation governs federal fisheries, most state regulatory authorities such as, natural resource departments and Marine Fisheries commissions recognize the value of such scientific and legislative consensus and the need to use this type of management for things such as Essential Fish Habitat (EFH). Essential Fish Habitat is defined by the Magnuson-Fishery Conservation Act of 1996 as “those waters and substrate necessary to fish for spawning, breeding, feeding, or growth to maturity.” It is assumed that there is a positive relationship between the quantity of EFH and fish abundance or productivity (Hayes et al. 1996). Identification of EFH is critical for predicting the future status of a fishery, and for providing critical information needed for habitat conservation.

The flounder fishery is primarily composed of southern (*Paralichthys lethostigma*) and gulf flounder (*Paralichthys albigutta*; majority of species), but includes Mexican (*Cyclopsetta chittendenni*), spotfin (*Cyclopsetta fimbriata*), shoal (*Syacium gunteri*) and broad (*Paralichthys squamilentus*) flounder. A flounder Fisheries Management Plan (FMP) for the Gulf of Mexico was evaluated by the Gulf States Marine Fisheries Commission in 2000. Due to a lack of data on species and inshore life-history, a complete Gulf-wide stock assessment for flounder has not been possible (VanderKooy 2000). Areas that require more information include: 1) effect of change in habitat quality; 2) requirements for an optimal environment; and, 3) evaluation of existing management programs to determine their efficacy (VanderKooy 2000). The FMP also indicates that determining critical habitat (EFH) for the flounder fishery is key for the effective management of the fishery (VanderKooy 2000). In contrast, there is a lack of information on habitat requirements for flounder and extent of habitat reduction and/or degradation throughout their range. More specifically, there are no data relating abiotic and biotic factors to habitat preference for flounder in the Gulf of Mexico. Additionally, determining EFH is managed on a state-by-state and inshore basis.

Southern flounder, *Paralichthys lethostigma*, is an important multi-million dollar commercial and recreational fishery (Matlock 1991; and VanderKooy 2000) combined throughout their distribution from Albermarle Sound, North Carolina, to Florida on the Atlantic Coast, and from Florida to Laguna de Tamiahua, Mexico on the Gulf Coast (Hoese and Moore 1998). Harvest data from Texas Parks and Wildlife Department (TPWD) indicates that the southern flounder population has substantially declined in Texas waters in recent years (TPWD unpublished data). For example, inshore commercial harvest (primarily 'gigging' or spearing) there has declined from 500,000 fish per year between 1985 and 1987 to less than 100,000 fish in 2007, and recreational fish catch rates have also declined from 200,000 fish in 1987 to less than 50,000 fish in 2007. Offshore commercial catch rates have declined from 325,000 fish in 1927 to less than 50,000 in 2007 (TPWD unpublished data). In addition, the number of mature females has decreased from 2.5 million in 1985 to less than 1.5 million in 2007 (TPWD unpublished data).

In an effort to prevent overfishing, regulations for recreational fishing of southern flounder have been implemented. There currently exists a 10-fish possession law in Louisiana and Florida, and 8-fish in North Carolina. March 2009 Texas adjusted their regulations from a 10-fish possession law to a 5-fish possession for every month but November. In November, a time of year when adults migrate off shore to spawn and are particularly susceptible to fishing pressure, anglers are limited to a 2 fish possession law and commercial and recreation gigging is not allowed. Estimates of by-catch rates in Texas are highly variable, from 925,000 to 9.7 million individual southern flounder per year (TPWD unpublished data; VanderKooy 2000). To reduce by-catch mortality, a buy-back program was established in 2002 resulting in the retirement of 57% of bay/bait licenses, subsequently reducing by-catch rates by at least 40%. Despite substantial shrimping efforts, there is evidence that the fishery continues to decline.

To address the continued decline of the southern flounder fishery and avoid long term closures, management of the fishery should look to an ecosystem-based approach where interactions among physical, biological, and human components of the system are addressed (Pikitch et al. 2004; Marasco et al. 2007; Crowder et al. 2008). Within this perspective, fisheries management will likely include: 1) ecologic factors that identify prime quality habitat (EFH) by determining important interactions between both abiotic and biotic components of flounder habitat; and, 2) the value of economic factors (e.g. importance of ecological services from the habitat and/or species) (Marasco et al. 2007). These two factors are often in competition with each other (Marasco et al. 2007). To be successful, ecosystem-based management will depend on efficiently and effectively assessing relationships between organisms and their habitat, and thus identifying EFH.

It is assumed that there is a positive relationship between the quantity of EFH and fish abundance or productivity (Hayes et al. 1996). However, this assumption is not often tested because habitat requirements for fishes are rarely known. Research on EFH has focused on density patterns within habitat types (Gallaway and Cole 1999). This information is important, but EFH extends well beyond simple habitat-density relationships and includes interactions among biotic and abiotic components of the habitat (Hayes et al. 1996). For example, within the Mission-Aransas National Estuarine Research Reserve, Nañez-James et al. (2009) determined that in Aransas and Copano Bays southern flounder occurred in higher abundances in areas containing vegetated bottom located relatively close to a tidal inlet. However, the relationship between the abundance and distribution of southern flounder with abiotic factors was not evaluated. Specific relationships between abiotic and biotic factors and habitat requirements for size classes need to be determined before establishing EFH for this species. A southern flounder species-habitat model will allow natural resource managers to more accurately conserve habitats crucial for various developmental stages of the fishery.

Linking trends in fish population abundances to environmental characteristics is often difficult because fish use a variety of habitats throughout their ontogeny and often exhibit large inter-annual fluctuations in their abundance within a particular habitat type, i.e., the organism’s niche changes over time (Shutter 1990; Hayes et al. 1996; and Guisan and Thuiller 2005). For example, within the Navesink River/Sandy Hook Bay estuary, age-0 winter flounder are spatially distributed differentially according to size class and abiotic and biotic requirements (Stoner et al. 2001). Newly settled winter flounder (<25 mm total length (TL)) were associated with low temperatures, high sediment and deeper water; fish 25–55 mm TL were associated with high sediment organics and salinity around 20 ppt. The largest winter flounder were associated with temperature near 22°C, shallow depths and presence of macroalgae (Stoner et al. 2001). Thus, the complex nature of many marine life history strategies coupled with the lack of research on ecosystem-level interactions has made progress toward determining EFH problematic (Shutter 1990; and Guisan and Thuiller 2005). However, declining populations of important fish stocks such as southern flounder in the Gulf of Mexico accentuate the importance of defining critical habitats as well as the processes that contribute to habitat quality. Thus, we must understand the relationship of a fishery to the abiotic and biotic factors within particular habitats throughout their life span.

Southern flounder populations are declining (Robinson et al. 1994; VanderKooy 2000; and TPWD unpublished data) and habitat loss and climate change is occurring (Caldeira and Wickett 2003; Harley et al. 2006; and IPCC Synthesis Report 2007). Successful fisheries management must include an understanding of the relationship between these factors, and life history to southern flounder habitat requirements (Helmuth et al. 2005). An ecosystem-based approach will allow fisheries managers to identify and protect essential habitat needed for future recruits and will provide valuable tools to ensure sustainability of the southern flounder fishery in particular, and other fisheries in general.

The overall purpose of this study is to provide information/data needed for development of a fishery management plan for flounders by using statistical modeling techniques to: 1) use a long-term fisheries independent data set to assess abundance trends of both juvenile (1979-2007) and adult (1975-2008) life-stages of southern flounder throughout the major bay systems off the Texas coast, 2) construct a species habitat model for young-of-the-year southern flounder that predicts EFH by incorporating the relationship between abiotic (temperature, salinity, turbidity, dissolved oxygen, and pH), and biotic factors (habitat, depth, and organic content) temporally and spatially within the Mission-Aransas National Estuarine Research Reserve (MANERR), 3) compare and contrast species-habitat models of southern flounder with a highly abundant flatfish, bay whiff (*Citharichthys spiloterus*), 4) determine the relationship between temporal (month, year), spatial (distance to the inlet), and physical (temperature, turbidity, dissolved oxygen, salinity, and depth) with the occurrence of juvenile southern flounder along the Texas coast, 5) use trained Boosted Regression Trees (BRT) and Artificial Neural Networks (ANN) to predict the presence of juvenile southern flounder spatially among Texas Bays, and 6) compare the predictive power and predicted spatial distribution of the trained and tested BRT and ANN.

CHAPTER 2

ASSESSING SOUTHERN FLOUNDER (*PARALICHTHYS LETHOSTIGMA*) LONG-TERM POPULATION TRENDS IN THE NORTHERN GULF OF MEXICO USING TIME SERIES ANALYSIS

ABSTRACT

A long-term fisheries independent data set (1975-2008) was used to assess population trends of juvenile and adult southern flounder (*Paralichthys lethostigma*) along the Texas coast in the northern Gulf of Mexico, USA. The dataset contained a total of 46,784 sites that were sampled with bag seines to monitor small nekton abundance and 22,870 sites that were sampled with gill nets to assess adult fisheries trends. These data were examined for age-specific population trends using generalized least squares and extended with non-parametric bootstrapping to obtain interval estimates of regression parameters (juveniles) and linear regression (adults) and. showed long-term declines in juvenile southern flounder abundance (1.3% per year). For adult southern flounder, rate of decline was much more rapid (2.5% per year). Results suggest that survival of post-juvenile flounder have decreased during the time series. This precipitous decline has prompted increasingly stricter harvest restrictions along the Texas coast. However, these management measures have been insufficient to curb declines.

INTRODUCTION

Flounder have historically supported an important multi-million dollar commercial and recreational fishery along the Texas coast (Matlock 1991; VanderKooy 2000), but declines in this stock have concerned resource managers and led to substantially reduced recreational and commercial catches. While a Fisheries Management Plan (FMP) for the Gulf of Mexico flounder fishery was developed by the Gulf States Marine Fisheries Commission in 2000, a paucity of data prevented a complete Gulf-wide stock assessment for the flounder fishery (VanderKooy 2000). This fishery is primarily represented by southern flounder (*Paralichthys lethostigma*) and gulf flounder (*Paralichthys albigutta*). In Texas, southern flounder represent over ninety-five percent of harvested flounder and is one of the top three fish species targeted by anglers (Riechers 2008). Decreases in harvest (recreational and commercial fishing) suggest that southern flounder may be declining in Texas waters. For example, inshore commercial harvest has declined from 500,000 fish per year between 1985 and 1987 to less than 100,000 fish in 2007 (Riechers 2008). Recreational catches have also declined from 200,000 fish in 1987 to less than 50,000 fish in 2007 (Riechers 2008). Offshore commercial catch rates have declined from 325,000 fish in 1987 to less than 50,000 in 2007 (Riechers 2008). Although harvest catches have declined, long-term population trends for the southern flounder fishery have not been quantitatively examined in Texas.

Due to concern about regional declines, a series of increasing stricter regulations for recreational fishing of southern flounder have been implemented in both directed and shrimp trawl fisheries. Most recently in March 2009, Texas adjusted the bag-limit from a 10-fish to a 5-fish possession law for every month but November (Riechers 2008). In

November (the period when adults migrate offshore to spawn) anglers are limited to a 2 fish possession law. Estimates of by-catch rates in Texas are highly variable, from 925,000 to 9.7 million individual southern flounder per year (VanderKooy 2000). To reduce by-catch mortality from shrimp trawl by-catch, a limited entry coupled with buy-back program of shrimp vessels was established in 2002 resulting in retirement of 57% of estuary/bait licenses, subsequently reducing flounder catches by at least 40% (Riechers 2008).

Despite concern about the status of this important fishery, there is little empirical evidence documenting long-term abundance indices in the Gulf of Mexico, preventing effective evaluation of stock status or effectiveness of management actions. Thus, the objective of this study was to use a long-term fisheries independent data set to assess abundance trends of both juvenile (1979-2007) and adult (1975-2008) life-stages of southern flounder throughout the major bay systems off the Texas coast. Specifically, we examined age-specific population trends using generalized least squares with non-parametric bootstrapping to obtain interval estimates of regression parameters (juveniles) and linear regression (adults).

MATERIALS AND METHODS

Study Area

The study was conducted in nine major bays along the Texas coast, within the northwestern Gulf of Mexico (Figure 2.1). The Texas coast is 563 km in length and contains five barrier islands that stretch approximately 161 km. There are eight consistently open, federally maintained ship channels that provide pathways for water exchange and animal transport between nearshore bays and the Gulf of Mexico (http://goliath.cbi.tamucc.edu/TexasInletsOnline/TIO%20Main/index.htm). Sample sites were chosen randomly from 1-minute latitude and longitude grid cells consisting of a minimum of 15.2 m of shoreline.

Field Collection

Data were collected as part of the Texas Park and Wildlife Department Resource and Sport Harvest Monitoring Program of finfish and shellfish that has occurred since 1977 for juveniles and 1975 for adults in nine bays along the Texas coast (Figure 2.1). All sampling followed protocols detailed in the "Marine Resource Monitoring Operations Manual" (Martinez-Andrade et al. 2009). Juvenile southern flounder (< 2 years, 11-290 mmTL; Stokes 1977; Etzold and Christmas 1979; Stunz et al. 2000) were sampled monthly using a randomized, stratified sampling design along the shoreline of each bay with 18.3 x 1.8-m bag seines. The bag seines used in this study were designed to sample juvenile estuarine fish populations (Martinez-Andrade 2009). While formal gear selection studies were not performed, previous studies on this species have shown this to be an effective gear for sampling juvenile southern flounder (Nañez-James et al. 2008). Bag seines were deployed perpendicular to the shoreline and were carried parallel to the shoreline for 15.2 m. Twenty bag seines were deployed each month in Sabine Lake, Galveston Bay, West Matagorda Bay, San Antonio Bay, Aransas Bay, Corpus Christi Bay, Upper Laguna Madre, and Lower Laguna Madre, and 10 bag seines were deployed each month in East Matagorda Bay. Moreover, for each sample (bag seine) longitude and latitude coordinates were recorded, and total length (TL) of each fish was measured.

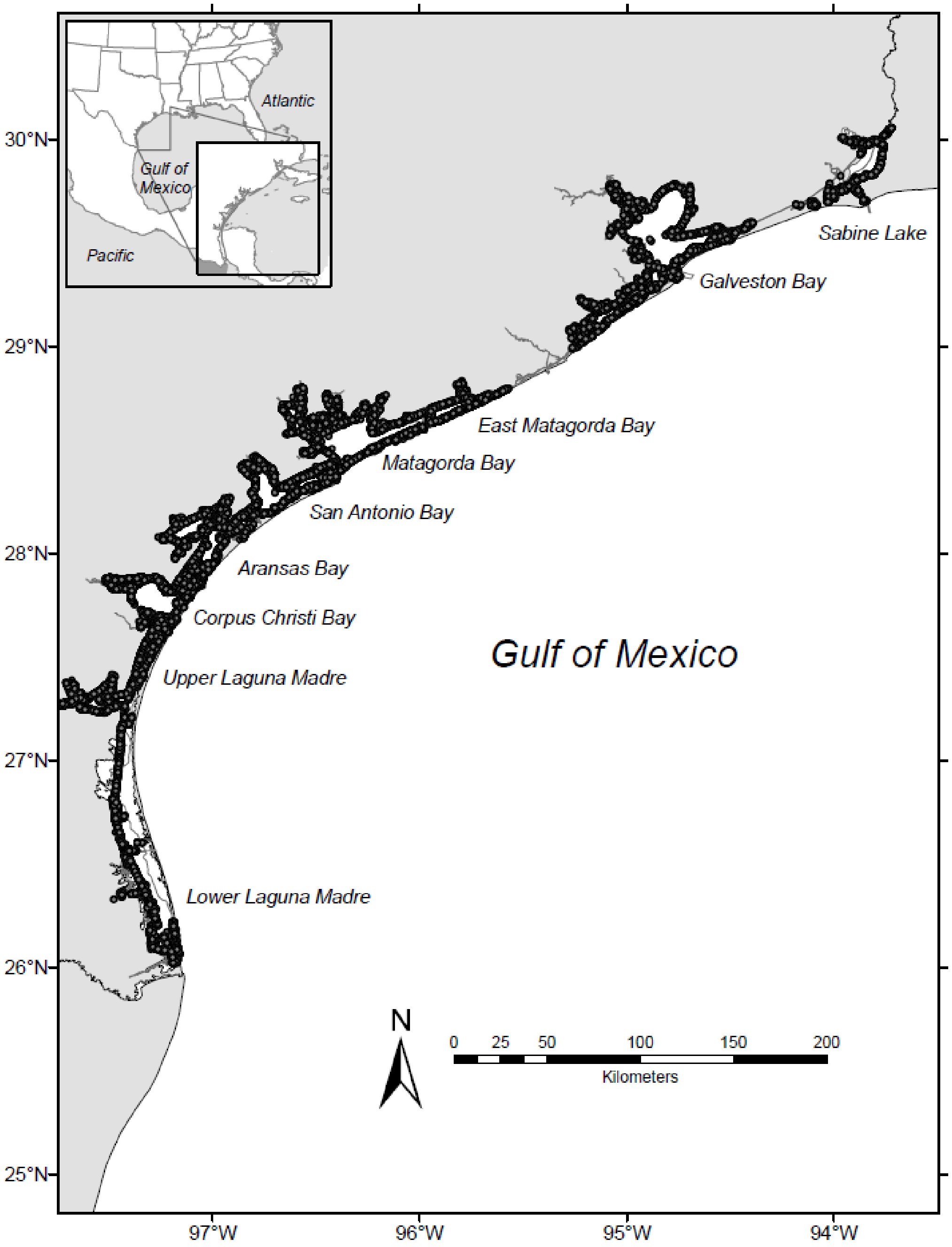


Figure 2.1: Total bag seine sampling locations (black circles, n = 46,784) for the TPWD Resource and Sport Harvest Monitoring Program from 1979 – 2007 (each site was sampled once over the course of the study).

Adult southern flounder (mature at age 1-2) were monitored twice per year (fall and spring) by deploying 183-m gill nets (Martinez-Andrade et al. 2009). Sampling locations (Figure 2.2) were selected by dividing each estuary into 5-second gridlets that were chosen randomly without replacement during each sampling period. Each year spring sampling started the second full week of April and fall sampling started the second full week of September. Both sampling periods continued for 10 consecutive weeks. Gill nets were set perpendicular to shore at or near sunset and were retrieved the following day within a few hours of sunrise. At each site, adult southern flounder (≥ 290 mmTL; Stokes 1977; Etzold and Christmas 1979; Stunz et al. 2000) were counted and total length was taken. Ninety nets were deployed yearly (45 seasonally) at Sabine Lake, Galveston Bay, West Matagorda Bay, San Antonio Bay, Aransas Bay, Corpus Christi Bay, Upper Laguna Madre, and Lower Laguna Madre (n=720 nets a year), and 40 gill nets were deployed yearly (20 seasonally) in East Matagorda Bay (Figure 2.2; Martinez-Andrade et al. 2009).

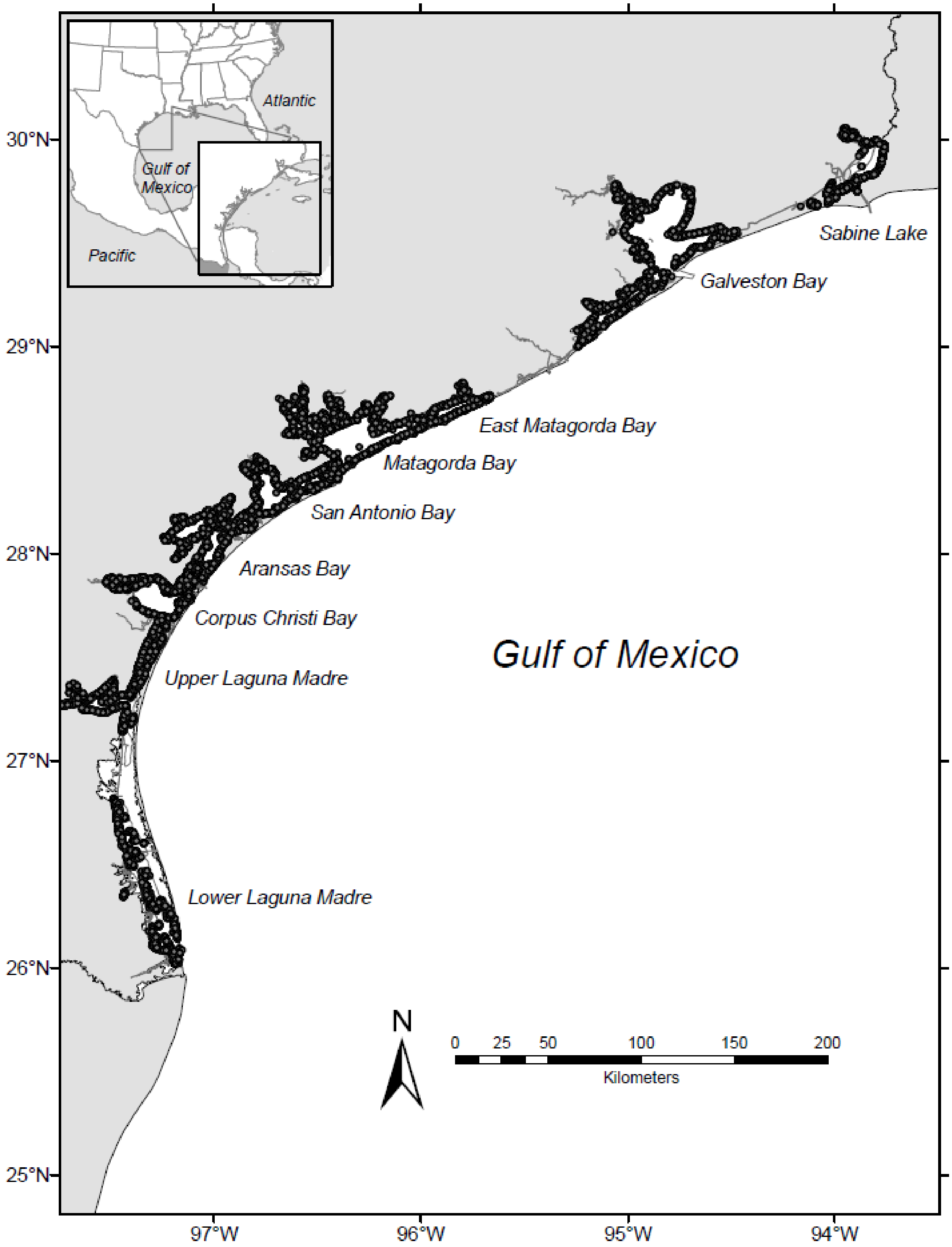


Figure 2.2: Total gill net sampling locations (black circles, n = 22,870) for the TPWD Resource and Sport Harvest Monitoring Program from 1975 – 2008 (each site was sampled once over the course of the study).

Time Series Analyses

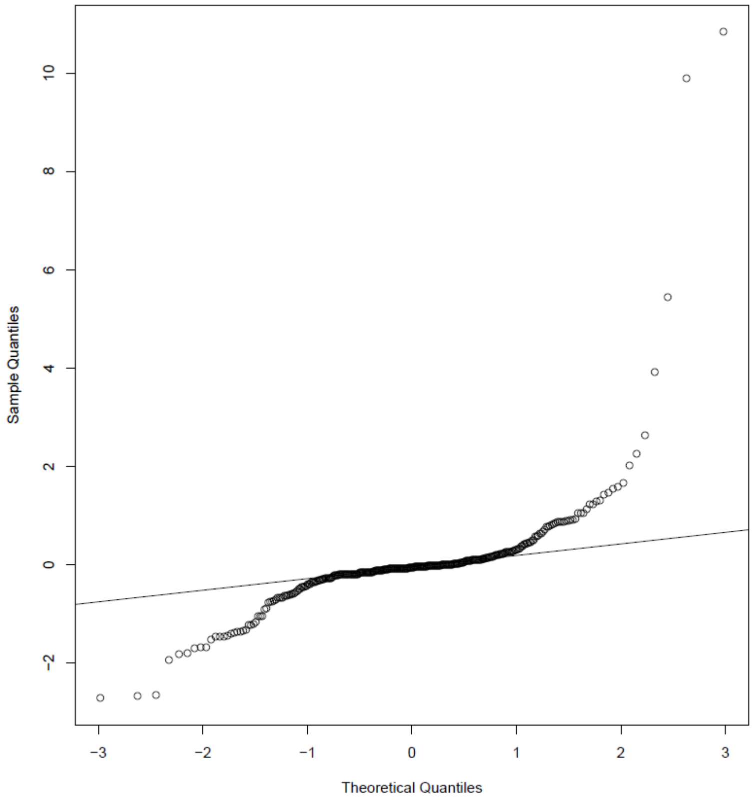
All analyses were conducted in R 2.9 (R Development Core Team 2009) using the following libraries: "TSA" (Chan 2008), "nlme" (Pinheiro et al. 2009), and “lmtest" (Zeileis and Hothorn 2002). Prior to analyses, counts of juveniles were standardized to catch per unit effort (CPUE) as the number of fish per hectare (ha) and adult counts were standardized to CPUE as the number of fish per net per hour ($CPUE_{juv}$= juvenile; $CPUE_{a = }$ adult). Principal components analysis indicated that there was not a spatial difference among the bays for juveniles and adults. Therefore, all bays were pooled together for both juvenile and adult southern flounder. Mean $CPUE_{juv}$ was calculated on a monthly basis per year and $CPUE_a$ mean was calculated on a yearly basis. Both data sets were tested for assumptions of linear regression using models:

1a: Juveniles: $CPUE_{ij} = \text{Intercept} + Y_i + M_j + \text{Residuals}_{ij}$

2b: Adults: $CPUE_i = \text{Intercept} + Y_i + \text{Residuals}_i$

where $CPUE_{ij}$ equals $CPUE_{juv}$ for year i and month j, $CPUE_i$ equals $CPUE_a$ for year i, Y_i equals the year of collection (i = 1975, 1976, . . ., 2008), and M_j is a factor corresponding to month of collection (j = 1, 2, . . ., 12). Assumptions tested included normality and homogeneity of variance in residuals, independence between variables and linearity between dependent and independent variables (Zuur et al. 2007). The presence of outliers was evaluated graphically with density plots and box plots of the dependent variables, $CPUE_{juv}$ and $CPUE_a$. Normality of residuals was examined using a Quantile-Quantile plot (Figure 2.3A), while homogeneity of variance in residuals was examined using a plot of standardized residuals versus fitted CPUE's. Autocorrelation of $CPUE_{juv}$ and $CPUE_a$ was tested by computing sample autocorrelation function of the residuals (Figure 2.3B).

A


Sample Quantiles
Theoretical Quantiles
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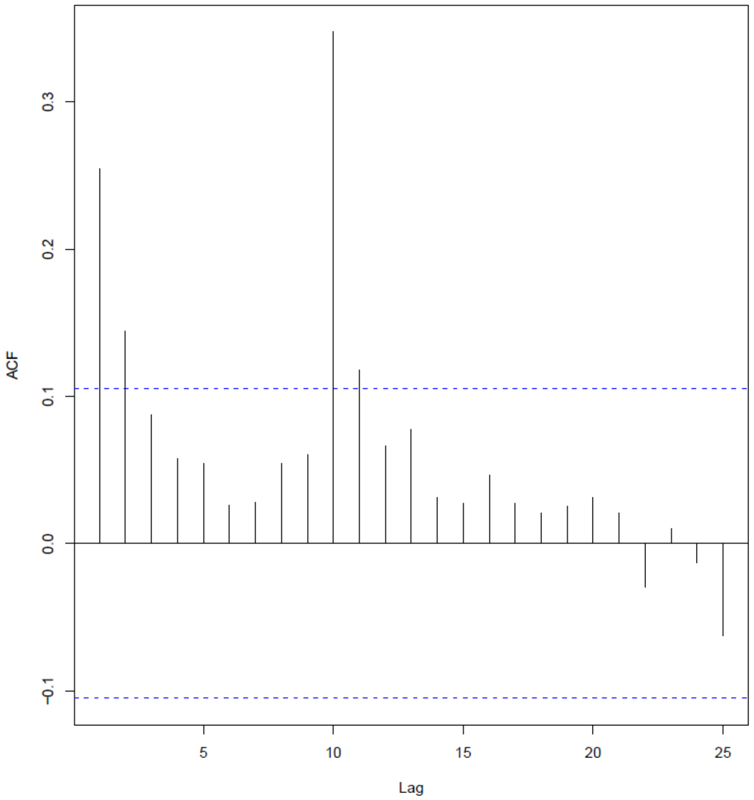
B


ACF
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25

Figure 2.3: A) Quantile plot of the standardized residuals obtained from the juvenile southern flounder regression model (Monthly mean CPUE_{juv} ~ Intercept +Year + Month + $\text{Residuals}_{)}$ indicating residuals are not normally distributed. B) Autocorrelation of standardized residuals on a monthly basis. Vertical bars beyond the dashed horizontal lines at approximately 0.1 and -0.1 indicate significant autocorrelation of the residuals at time 1 and 10 months ($p < 0.05$). Lag time of months is on the X-axis and the estimated autocorrelation function composes the Y-axis.

Exploratory analysis of juvenile catch data indicated both a large proportion of zeros and outliers. Regression residuals were not normally distributed and contained heterogeneity (Figure 2.3A). There was a significant 10-month autocorrelation lag within the juvenile time series (Figure 2.3B). To correct for a large proportion of zeros (zeros were included in the model) and heterogeneity of variance, the data were analyzed using generalized least squares (gls) to test the null hypothesis of no difference in mean CPUE_{juv} among months or years:

3c: $\text{CPUE}_{ij} \sim \text{Intercept} + Y_i + M_j + \text{CPUE}_{i(j-1)} + \text{Residuals}_{ij}$

where CPUEij, Y_i, and M_j have the same meaning as model 1a, and $\text{CPUE}_{i(j-1)}$ equals CPUE_{juv} for the previous month. $\text{CPUE}_{i(j-1)}$ was added as a covariate to model 3c to account for autocorrelation within the data set. The residuals were fitted using a varIdent variance structure from the “nlme” library in R, where each month was allowed to have a different variance (Zuur et al. 2007). All months were tested for significance against January, due to January being shown as the first month of recruitment in Texas (King 1971; Stokes 1977; Nañez-James et al. 2009). Nonparametric bootstrapping with replacement (n = 1000) of the resulting coefficients were used to estimate confidence intervals of the gls model parameters without making assumptions about the population distribution. Confidence intervals at 2.5% and 97.5% were calculated using the bias-corrected accelerated method (Bca). The Bca was chosen to reduce the influence of the outliers on the confidence intervals for Y_i and M_j.

Exploratory analysis conducted on southern flounder $CPUE_a$ indicated that residuals were normally distributed and homogenous, and there was no autocorrelation detected, indicating independence of residuals through time. To test the null hypothesis that the slope of the trend line for adult CPUE over time was not significantly different from zero, a least-squares linear regression was used where:

4d: $CPUE_i \sim Intercept + Y_i + Residuals_i$

where $CPUE_i$ and Y_i have the same meaning as model 2b.

Comparison of Time Series

To evaluate the relationship between juvenile and adult time series a lagged regression was conducted using the yearly mean CPUE of adults from 1982-2008 and juvenile yearly CPUE from 1979-2007. Yearly mean juvenile CPUE was shifted to date back from one year to three years for each yearly mean adult CPUE. Dating back three years was used due to southern flounder reaching adult sizes and maturity around 2 years of age. Akaike's information criterion (AIC) was used to determine the “best” model and an ANOVA was used to determine if there was a significant difference between model 4d and 5e.

5e: $CPUE_i \sim Intercept + Y_i + FY_j + SY_k + TY_l + Residuals_{ijkl}$

where $CPUE_i$ and Y_i have the same meaning as model 2b and FY_j is the yearly mean CPUE for juveniles from the previous year, SY_k is the yearly mean CPUE for juveniles two years back, and TY_l is the yearly mean CPUE for juveniles three years back.

Percent of decline was calculated for both $CPUE_{juv}$ and $CPUE_a$ using the following formula:

6f: Pct decline = $1 - (CPUE_{imax}/CPUE_{imin})^{(1/\Delta i)}$

where *imax* equals the final year in the time series (2007 for the juvenile population and 2008 for the adult population), *imin* equals the first year in the time series (1979 for the juvenile population and 1975 for the adult population), and Δi equals number of years in the time series (juvenile time series = 29 years and adult time series = 33 years). Also, $CPUE_{imax}$ and $CPUE_{imin}$ are the predicted mean annual values from the 3c gls model for juvenile population and the 4d linear model (lm) model for the adult population.

RESULTS

Juvenile Time Series

Over 29 years of monitoring juvenile populations with bag seine sampling (1979 through 2007), 46,784 sites were sampled covering a total of 1,460 ha. Juvenile southern flounder were present at 2.33% of the sites (n=1,088) with a total of 5,712 juvenile southern flounder collected (Figure 2.1). The overall arithmetic mean of all of the sampling locations was 0.12 fish/haul. The maximum count of juvenile southern flounder was 85 fish/haul and occurred in Aransas Bay in April 1989.

The total length of southern flounder collected ranged from 11 - 203 mm TL and were considered to be juveniles based on published length at age studies (Stokes 1977; Etzold and Christmas 1979; Stunz et al. 2000). Mean length of captured individuals was 66.99 mm TL (Figure 2.4).

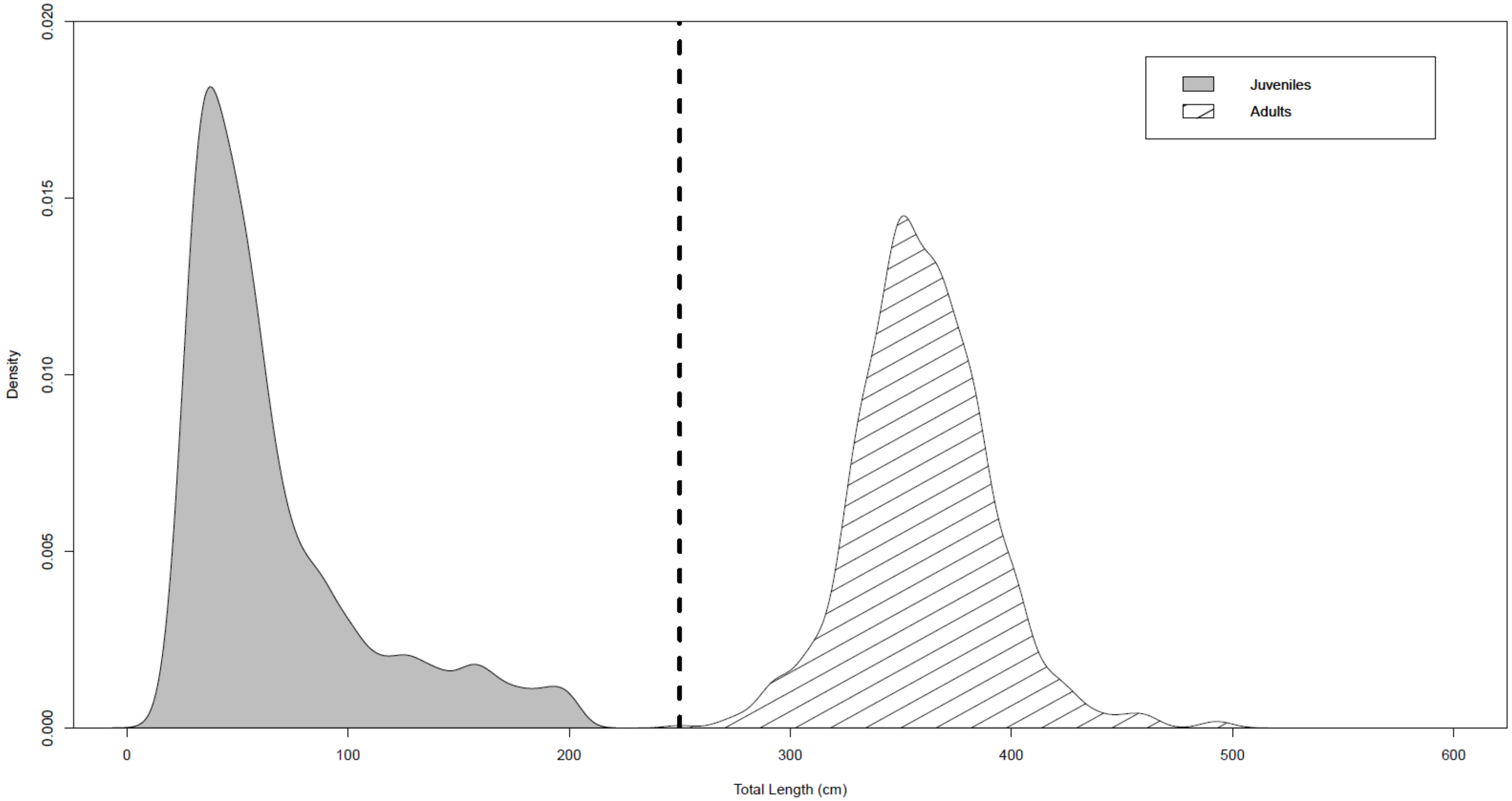

Figure 2.4: Density Graph of TL of juvenile southern flounder and TL of adult southern flounder. All lengths to the left of the vertical dotted line indicate lengths of juveniles (shaded grey). Mean length = 66.99 mmTL. All lengths to the right of the vertical dotted line indicate lengths of adults (horizontal lines). Mean length = 360.02 mmTL.

The juvenile patterns over time (1979-2007) showed yearly and monthly variation in recruitment of southern flounder (Figure 2.5). December had lowest mean $CPUE_{juv}$ and March had highest (Figure 2.5). January, and August through December, had lowest minimum $CPUE_{juv}$ and were consistent over time (Figure 2.5). April had highest maximum $CPUE_{juv}$ and November had lowest maximum $CPUE_{juv}$. Moreover, February, March, and April had the three highest mean $CPUE_{juv}$, but those months also had the largest ranges, with April having the largest range. Catch-per-unit-effort ($CPUE_{juv}$) was typically highest in March (21 out of 29 years sampled) (Figure 2.5). There were three years, 1982 (March), 1989 (April), and 1990 (February) where $CPUE_{juv}$ was substantially higher than all other years (Figure 2.5). Over all years, the minimum monthly mean ranged from 0.0 to 54.6 $CPUE_{juv}$. Maximum monthly mean was 54.63 $CPUE_{juv}$ (occurred April 1989), the overall mean of the monthly means was 4.007 $CPUE_{juv}$, and median was 1.176 $CPUE_{juv}$ (Figure 2.5).

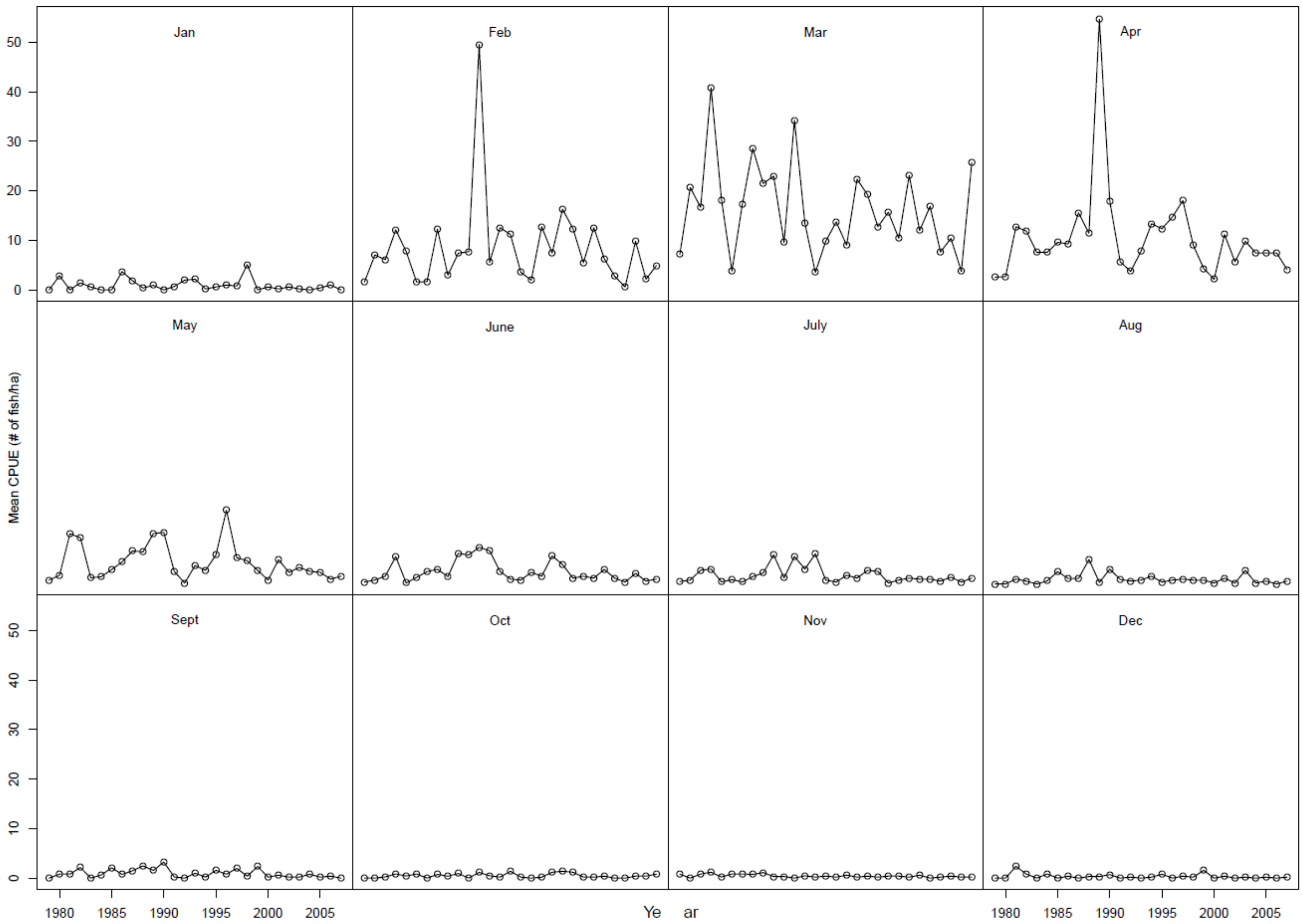

Figure 2.5: Mean $\mathrm{CPUE}_{\mathrm{juv}}$ of juvenile southern flounder by month from 1979 to 2007. In most years, the highest monthly mean $\mathrm{CPUE}_{\mathrm{juv}}$ occurred in March (72%); for the remaining years, the monthly high occurred in February or April.

A Generalized least squares model (gls) indicated that there was a slight but significant decline in yearly CPUE_{juv} from 1979 to 2007 (slope = -0.0117, 95% confidence interval of (-0.022, -0.0007)), which corresponds to a decline of 1.3% per year since 1979 using formula 6f (Table 2.1).

Table 2.1: Summary of results obtained from the generalized least squares model for juvenile southern flounder time series, including confidence intervals obtained from bootstrapping.

	Value	**Standard Error**	**t-value**	**2.50%**	**97.50%**
Intercept	24.25	9.15	2.65	3.58	42.28
Year	-0.01	0.004	-2.56	-0.022	-0.0007
February	7.34	1.68	4.37	4.705	11.081
March	13.09	1.53	8.56	10.032	16.084
April	5.41	1.88	2.88	1.771	9.715
May	0.69	0.68	1.01	-0.674	1.883
June	0.47	0.44	1.05	-0.527	1.359
July	0.22	0.34	0.64	-0.475	0.929
August	-0.37	0.29	-1.25	-0.967	0.158
September	-0.21	0.27	-0.78	-0.781	0.313
October	-0.64	0.25	-2.6	-1.157	-0.192
November	-0.58	0.24	-2.45	-1.072	-0.146
December	-0.65	0.25	-2.58	-1.163	-0.178
Previous Month (PM)	0.27	0.03	7.77		

In comparison with the base CPUE_{juv} in January, the CPUE_{juv} was significantly higher in February, March, and April, and significantly lower in October, November, and

December. Additionally, standardized residuals from model 3c for each month were evenly distributed (Figure 2.6), normally distributed, and the previously significant autocorrelation at 10 months was much reduced.

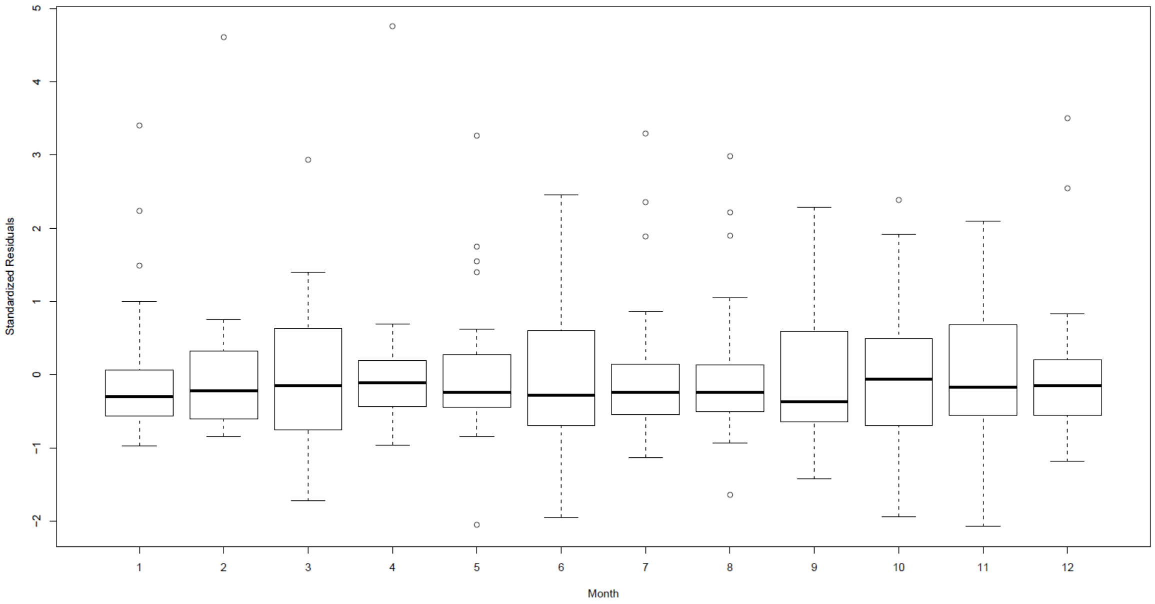

Figure 2.6: Boxplots of the residuals per month from the juvenile southern flounder fitted generalized least squares model (3c). Along the x-axis, 1=January, 2=February, 3=March, 4=April, 5=May, 6=June, 7=July, 8=August, 9=September, 10=October, 11=November, and 12=December.

Adult Time Series

A total of 22,870 sites were sampled over the 33-year period (1975-2008). Out of the 22,870 sites adult southern flounder were collected in 40% of the samples (n = 9,188) with a total of 18,542 adult southern flounder collected. The count of adult southern flounder collected at a sampling location ranged from 0 to 31 (mean = 0.81). The maximum count of adult southern flounder occurred in Upper Laguna Madre in April

1991. For each sampling location a mean length was calculated for all southern flounder collected. Overall, mean length was 360 mmTL and ranged from 250 - 497 mmTL (Figure 2.4). The minimum $CPUE_a$ was 0.02 (occurred in 2007) and maximum $CPUE_a$ was 0.103 (occurred in 1980; Figure 2.7) with all bays pooled together. There was a highly significant decrease of mean yearly $CPUE_a$ of adult southern flounder ($R^2 = 0.5441$, $F_{1,32} = 38.19$, Slope = -0.00148). Overall adult southern flounder have decreased on average by 2.5% per year since 1975 (Figure 2.7).

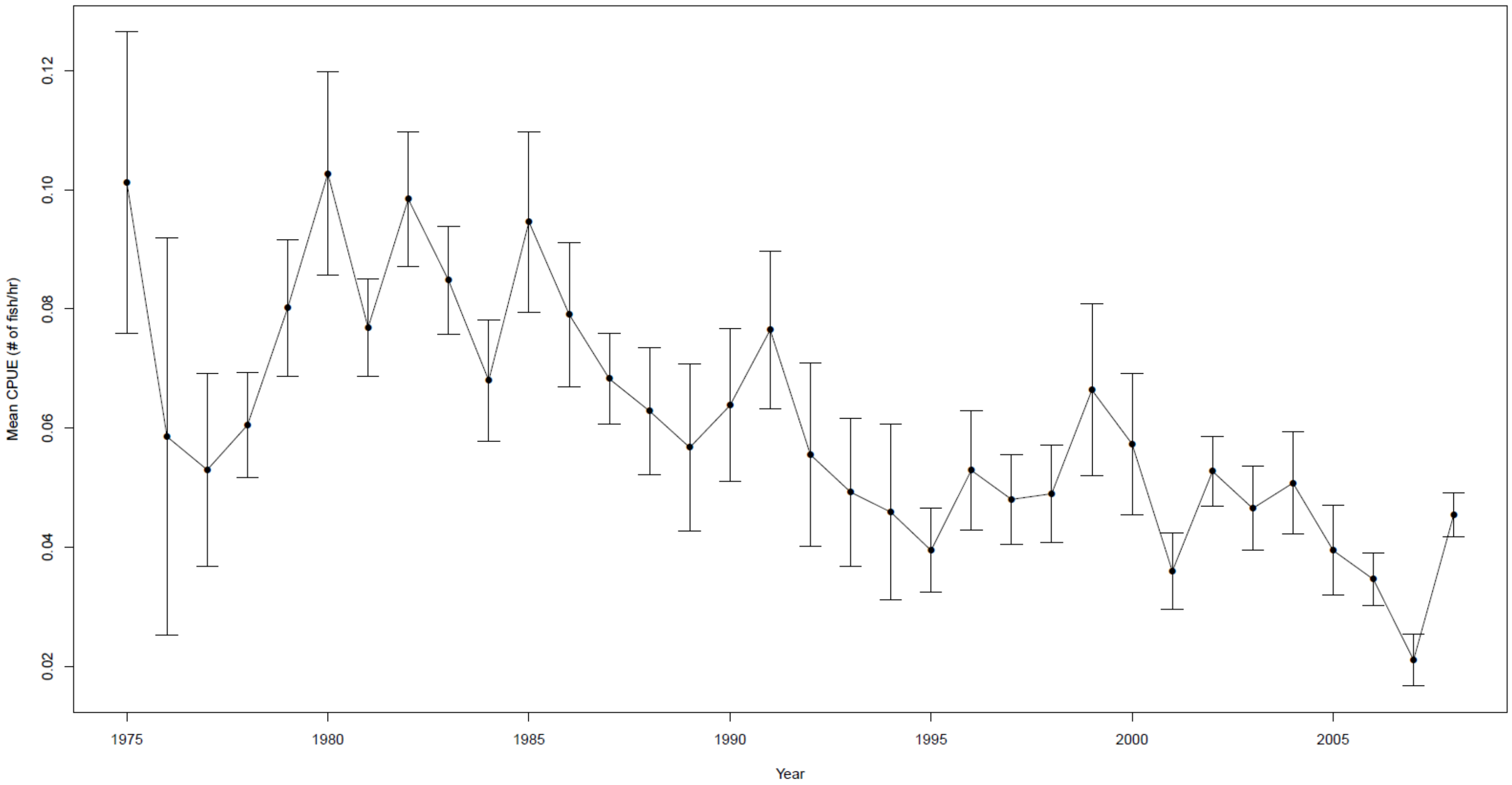

Figure 2.7: Adult mean (± SE) $CPUE_a$ from 1975 to 2008. Linear regression model (R^2 = 0.5441, $F_{1,32}$ = 38.19, Slope = -0.0015) indicated a significant decline in the adult southern flounder population.

Juvenile Time Series vs. Adult Time Series

There was no relationship between the juvenile and adult southern flounder time series. Including up to three years of previous yearly mean CPUE of juveniles did not contribute any significance to the adult time series model. The AIC for model 4d was -242.93 and -239.35 for model 5e. Moreover, the comparison ANOVA between the two models indicated no significant difference between model 4d and model 5e ($F_{25,22}$ = 0.6897, p = 0.568).

To compare relative rates of change in juvenile and adult populations, percentage decline was calculated for $CPUE_{juv}$ from 1979 to 2007 and $CPUE_a$ from 1975 to 2008. Juvenile population indicated an annualized decline of 1.3% (1-(3.22/4.73)^(1/29)) and the adult population indicated an annualized decline of 2.5% (1-(0.037/0.085)^(1/33)). Thus, the adult population is declining twice as fast as the juvenile population.

DISCUSSION

Our results show high monthly recruitment variability of juvenile southern flounder with significant increases in abundance from February to May with a peak in March. Low juvenile abundances in June and subsequent months indicate that the recruitment period ends by May each year. Juveniles present have either moved to different habitats or have grown large enough to avoid the sampling gear. Recruitment of southern flounder has been reported in December (Günter 1945; King 1971) although in this study, the abundance of juveniles was significantly lower in both December and January. These results suggest that substantial recruitment begins in February each year. Others have reported high recruitment variability in flatfish populations (Van deer Veer et al. 2000). Günter (1945) reported southern flounder recruitment in December and from February to April, whereas Stokes (1977) reported the presence of juveniles starting in January with a peak in February. Simmons and Hoese (1959) stated that recruitment occurred from March to May with a peak in April. Rogers and Herke (1985) and Nañez-James et al. (2009) reported a January to March recruitment period with peaks occurring from February to March. Overall, observed recruitment patterns were consistent with seasonal patterns described previously.

The southern flounder population in Texas is declining and adults are declining two times faster than the juveniles. Catch-per-unit-effort of juveniles decreased only slightly during the 29-y study period (decreasing by 1.3% per year), indicating that the larger decline seen in the adult population may not be due to recruitment limitation and could be the result of over harvesting. A recruitment limited population has been defined as, " a population that is undersaturated as a result of a finite larval supply and could support greater abundance given enhanced recruitment" (Doherty 1998). Results of the present study indicate that recruitment of southern flounder may not be the primary cause of the adult population decline given that catch rates of juveniles are nearly stable and the rate of decline in adults exceeds what can be explained by the decline in juveniles. The decline in adult southern flounder abundance may be attributed to lower survivorship of adults and late juveniles nearing maturity (sub-adult stage) due to increased fishing and/or natural mortality. Other researchers have shown that survival of juvenile fishes just prior to maturity may be more important for population stability/recovery than young-of-year fish (Gaullucci et al. 2006; Kinney and Simpfendorfer 2009). Thus, we suggest that management of southern flounder focus on increasing survivorship of one and two year old fish.

The recruitment limitation literature shows that for many marine species recruitment levels can be good predictors of subsequent population size (Hixon 1998; Armsworth 2002). However, this was not observed for southern flounder population in Texas as high recruitment levels were observed despite adult declines. For example, this time series encompassed three years with unusually high abundances of juveniles (1982, 1989, and 1990), yet these large abundance peaks were not detected in the adult time series in subsequent years, suggesting density dependent survivorship of juveniles, during periods of peak recruitment. Moreover, there were small peaks in the abundance of adult southern flounder in 1980, 1982, 1985, and 1991 but these peaks were not detected in juvenile population surveys in prior years. Including previous year CPUE of juveniles to the overall adult model was not significantly different than without. These results suggest that abundance trends of juvenile and adult southern flounder were independent, particularly with high mortality rates of post-juvenile flounder that occurred during the time series.

Stunz et al. (2000) demonstrated that a reduced proportion of southern flounder are reaching age of maturity. Both recreational and commercial fishing rates have ranged from 50,000 fish/year to 500,000 fish/year and by-catch rates have been estimated by TPWD at 925,000 fish/year to 9.7 million fish/year, demonstrating that commercial by-catch contributes most to the fishing mortality rate of southern flounder occur as. Clearly, by-catch rates are well established as major contributors to the decline in fisheries (Jackson et al. 2001; Pauly et al. 2002; Hilborn et al. 2003), and might be a driving force in the decline of adult southern flounder. Regulation and management efforts for southern flounder in Texas have focused on implementing guidelines for recreational and commercial fisheries, yet the population remains in decline. These continued declines were of major concern for the managing agency prompting increasing regulation of size, bag limits, and seasonal closures beginning in 2009 (Riechers 2008). Currently, it is too early to assess the population response to these new regulations.

Despite harvest limits on both recreational and commercial fishing, these data show that the southern flounder fishery remains in decline, and indicate that the southern flounder management program in Texas up to 2008 was not sufficient to maintain southern flounder populations along the Texas coast. We suggest that with continued improvements on recreational and commercial fishing regulations and increased knowledge and management of essential fish habitat for all life-stages of southern flounder may contribute to increased abundances of both juvenile and adult southern flounder.

ACKNOWLEDGEMENTS

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CHAPTER 3

A MODELING AND FIELD APPROACH TO IDENTIFY SOUTHERN FLOUNDER AND BAY WHIFF ESSENTIAL FISH HABITAT WITHIN THE ARANSAS BAY COMPLEX, TX

ABSTRACT

Declines of important fish species such as flatfish in the Gulf of Mexico underscore the importance of defining critical habitats as well as the processes that contribute to habitat value. The goal of this study was to use an ecosystem-based approach to incorporate environmental changes into fisheries management plan for two flatfish species. Specifically, this study developed predictive species habitat model that delineated critical nursery habitat for juvenile bay whiff (*Citharichthys spilopterus*) and southern flounder (*Paralichthys lethostigma*) that can be used to determine mechanisms habitat selection within the Aransas Bay Complex. Species habitat models that predicted the occurrence for both species were identified using Boosted Regression Trees (BRT). Ten predictors were included in the model: habitat type, dry weight of sediments, depth (m), dissolved oxygen (mg O_2/L), temperature (°C), turbidity (cm), salinity, pH, distance to inlet, and month. Species habitat model for juvenile bay whiff indicated that bay whiff were not associated with any particular habitat type, but were associated with low temperatures (< 15°C, 20-23°C), moderate percent dry weight of sediments (25-60%), salinity >10, and moderate to high dissolved oxygen (6-9 mg/L, 10-14 mg/L). Species habitat model for juvenile southern flounder indicated that southern flounder were associated with low temperatures (<15°C), low percent dry weight of sediment (<25

mg/L), seagrass habitats, shallow depths (<1.2 m), and high dissolved oxygen (>8 mg/L). Due to many differences between the environmental variables, we suggest that management of EFH for flatfishes within the Aransas Bay Complex needs to include areas consisting of both high probabilities of occurrence for juvenile bay whiff and juvenile southern flounder in the same locations. Therefore, we suggest that EFH within the Aransas Bay Complex needs to occur among all habitat types along the eastern side of Aransas Bay, and the north corner of Copano Bay. These findings will provide a valuable new tool for fisheries managers to aid sustainable management of bay whiff and southern flounder and the Mission-Aransas Reserve ecosystem and provides crucial information needed to prioritize areas for habitat conservation and management in the Gulf of Mexico.

INTRODUCTION

Anthropogenic impacts such as overfishing, ocean disposal and spills, degradation of coastal ecosystems, land-based contamination, and climate change are all major issues that are adversely affecting fishery sustainability in the world's oceans (Costanza et al. 1998). Habitat loss due to human impacts is one of the main causes of population depletion in fishes (Ruckelshaus et al. 2002; Hughes et al. 2002; Dulvy et al. 2003; Pyke 2004; Levin and Stunz 2005; Lotze et al. 2006), and have contributed to depletion of more than 90% of estuarine species, degraded water quality, accelerated species invasions, and destroyed greater than 65% of seagrass and wetland habitats in estuaries and coastal seas (Lotze et al. 2006). Declining fisheries and loss of habitat are major threats to marine ecosystems (Crowder et al 2008). It has been hypothesized that fisheries that are being overfished are more susceptible to anthropogenic impacts (Jackson et al. 2001; Halpern et al. 2008). Thus, it is important to recognize the importance of certain habitat type and areas to fishery species in order to prioritize areas and affected species for conservation and management measures (Levin and Stunz 2005).

Linking trends in fish population abundance to environmental characteristics is difficult because fish often use a variety of habitats throughout their ontogeny and exhibit large inter-annual fluctuations in their abundance (Shutter 1990; Hayes et al. 1996; Pittman and McAlpine 2003; Guisan and Thuiller 2005). For example, southern flounder along the Texas coast are estuarine dependent, only leaving the estuaries to spawn in the Gulf of Mexico. Furthermore, within estuaries young-of-year southern flounder are typically associated with seagrass and marsh edge habitats near tidal inlets (Nañez-James et al. 2009). The complex nature of many marine life history strategies such as southern flounder coupled with a paucity of ecosystem-level research on interactions has made progress toward identifying Essential Fish Habitat (EFH) problematic (Shutter 1990; Guisan and Thuiller 2005; Levin and Stunz 2005).

Essential Fish Habitat is defined by the Magnuson-Fishery Conservation Act of 1996 as “those waters and substrate necessary to fish for spawning, breeding, feeding, or growth to maturity.” It is assumed that there is a positive relationship between the quantity of EFH and fish abundance or productivity (Hayes et al. 1996), making identification of EFH an important step toward sustainable population. Moreover, declining populations of important fish stocks such as southern flounder (*Paralichthys lethostigma*; Froeschke et al. 2011) in the Gulf of Mexico accentuate the importance of defining critical habitats as well as the processes that contribute to habitat quality (Houde and Rutherford 1993; Allen and Baltz 1997). While flatfish support an important fishery in the Gulf of Mexico, essential fish habitat has not been described distribution-wide for this species (Vanderkooy et al. 2000). An improved understanding of the relationship between abiotic (e.g. temperature, hydrodynamics, oxygen, salinity) and biotic factors (e.g. organic content, habitat), with respect to life history habitat requirements as well as regulating harvest and by-catch rates is essential for robust management of these fisheries. Such ecosystem-based approaches to fisheries management have been endorsed (Pikitch et al.2004), and the benefits of these types of data allow fisheries managers to identify and protect essential habitat needed at all life history stages for multiple species and will provide valuable tools to ensure sustainability of fisheries.

Along the Texas coast flounder have historically supported a multi-million dollar commercial and recreational fishery (Matlock 1991; VanderKooy 2000). Southern flounder represent over ninety-five percent of harvested flounder and is one of the top three fish species targeted by recreational anglers (Riechers 2008). Despite increased regulation in Texas, the southern flounder population decline is alarming. Juveniles are declining by 1.3% per year and adults declining by 2.6% per year (Froeschke et al. 2011). Moreover, these data suggested that with continued improvements on recreational and commercial fishing regulations and increased knowledge and management of EFH for all life-stages of southern flounder may contribute to increased abundances of both juvenile and adult southern flounder (Froeschke et al. 2011). A Fisheries Management Plan (FMP) for the Gulf of Mexico flounder fishery was developed by the Gulf States Marine Fisheries Commission in 2000 (VanderKooy 2000). The FMP indicated that determining critical habitat (EFH) for the flounder fishery is crucial for the effective management of the fishery (VanderKooy 2000). Due to the lack of information on habitat requirements for flounder and extent of habitat reduction and/or degradation throughout their range management has been hindered. Initial studies on essential fish habitat for young-of-the-year southern flounder in Aransas Bay and Copano Bay, TX showed they occurred in vegetated habitats (seagrasses and marsh edge) that occur near tidal inlets in Aransas Bay (Nañez-James et al. 2009). However, interactions between the abundance and distribution of southern flounder with abiotic factors were not evaluated.

Juvenile southern flounder (< 2 years, 11-290 mmTL; Stokes 1977; Etzold and Christmas 1979; Stunz et al. 2000) are historically found along the Texas coast, but in low numbers. For example, juvenile southern flounder collected as part of the Texas Park and Wildlife Department Resource and Sport Harvest Monitoring Program of finfish and shellfish since 1977 were only present in 1,255 of 12,651 samples during recruitment months (January to May; Chapter 4). Although southern flounder are found in low numbers, flatfish as a group are important components of the Texas coastal ecosystem. For example bay whiff (*Citharichthys spilopterus*) are one of the most common flatfishes among estuaries in the Gulf of Mexico (Castillo-Rivera et al. 2000), comprising one of the top two abundant flatfishes in Barataria Bay, Louisiana (Allen and Baltz 1977) and in Newport River and Back Sound estuaries in North Carolina (Walsh and Cyrus 1999). While bay whiff are not a recreational or commercially targeted species they exhibit similar temporal recruitment patterns as southern flounder, although little is known about their habitat usage along the Texas coast. Moreover, it has been hypothesized that bay whiff are habitat generalists (Allen and Baltz 1997; Walsh and Cyrus 1999). For example, in North Carolina, the abundance of bay whiff were not significantly different among the 21 stations sampled, which included variation in marsh, seagrass, and non-vegetated habitats, implying that bay whiff are associated with all habitats within estuaries (Walsh and Cyrus 1999).

While our knowledge concerning flatfish populations increases, clearly more data is needed for improved management strategies including status and trends of populations as well as habitat requirements. Thus, the objectives of this study were; 1) compare mean abundances of juvenile bay whiff and southern flounder by habitat type; and 2) to construct a species habitat models for two important flatfish species; 1) southern flounder which support a large recreational fishery, and 2) bay whiff which is an abundant and ecologically important ecosystem species in Texas' coastal estuaries. Specifically, the relationship between abiotic (temperature, salinity, turbidity, dissolved oxygen, and pH), and biotic factors (habitat, depth, and organic content) on the frequency of occurrence of bay whiff and southern flounder were investigated within the Aransas Bay Complex (Mission-Aransas National Estuarine Research Reserve; MANERR). The species-habitat models of southern flounder and bay whiff will allow natural resource managers crucial information needed to conserve habitats selected for various developmental stages of flatfish within the Aransas Bay Complex, TX.

MATERIAL AND METHODS

Study Site

Field collections were conducted in the estuarine waters in the northern Gulf of Mexico in Aransas and Copano Bays (Figure 3.1). The focus areas were in the Mission and Aransas National Estuarine Research Reserve (MANERR). The reserve covers

751.53 km^2 of seagrass beds (primarily *Halodule wrightii*), oyster reefs (*Crassostrea virginica*), salt marsh (*Spartina alterniflora*), and unvegetated bottom (sediment consisting of sand with small amounts of clay and silt). Aransas Bay contains extensive coastal wetlands and submerged aquatic vegetation, while Copano Bay is the largest secondary bay connected to Aransas Bay, and freshwater inflow (mean daily inflow of $28m^3/s$) occurs primarily via the Aransas and Mission Rivers and virtually all of the saltwater exchange occurs via the Aransas Pass tidal inlet (Figure 3.1). Cedar Bayou is a small natural and ephemeral tidal inlet that currently provides little to no saltwater exchange except during tropical events or unusually high tidal events.

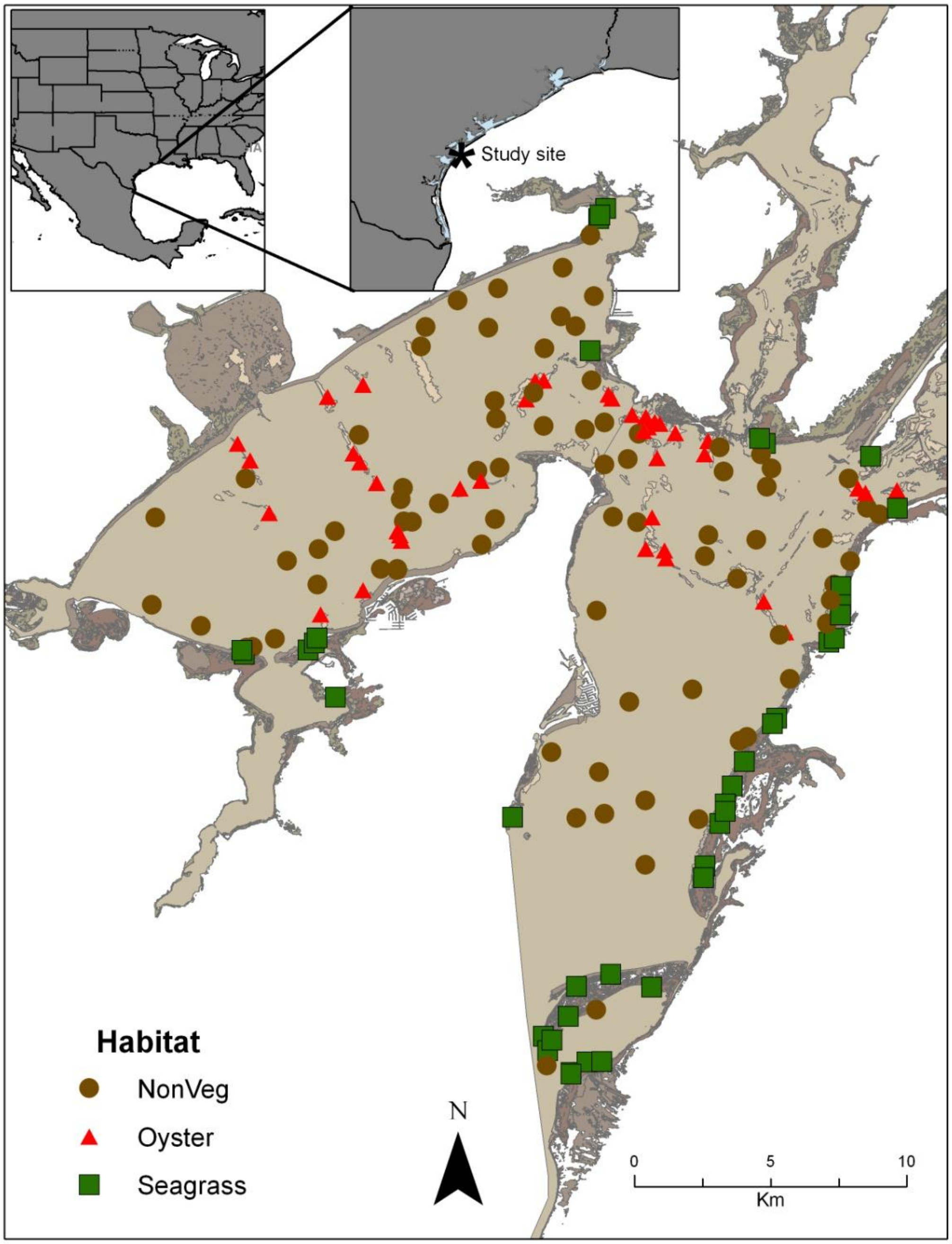

Figure 3.1: Map of Aransas Bay Complex located along the Northwestern Gulf of Mexico. Sampling locations (n=160 sites) within the Aransas Bay Complex from February – May 2010, 80 non-veg (brown circles), 40 seagrass sites (green squares), and 40 oyster sites (red triangles).

Field Collection

A stratified, randomized experimental design was used to identify EFH for juvenile bay whiff and southern flounder within the Aransas Bay Complex from February – May 2010. Sites were selected by converting the study area into 100m^2 grid cells and each cell habitat type for each cell was determined using the data source and description of habitat layer. Using this grid, forty 100- m^2 sampling sites per month (n = 160 total sites sampled) encompassing three habitat types, seagrass (n=10), oyster (n=10), and non-vegetated (non-veg) habitats (n=20), were sampled during peak flatfish recruitment season (Nañez-James et al. 2009; Froeschke et al. 2011; Figure 3.1). Sample sites were selected without replacement using a randomized selection of sites from the sampling grid (n = 40 per month). Habitat shape- files (non-vegetated, seagrass, and oyster reefs) obtained from National Oceanic Atmospheric Administration (NOAA), were broken up into 100 m cells. Each cell was assigned a number using a random number generator and then organized from the smallest to the largest random number. The top 20 non-veg, 10 seagrass, and 10 oyster reef sites were chosen per month. Sites were discarded and replaced by the next possible choice if the original chosen site was not feasible to get to by boat. Additionally, sites were only moved in the field if the location was not safe to sample.

Physical variable sampling protocol

Prior to sampling at each site, physical parameters were measured just above the bay bottom using a Hydrolab 5S Sonde. Physical parameters measured were temperature

(°C), dissolved oxygen (DO) in mg O_2/l, pH, salinity (psu), and depth (m). Turbidity was measured using a Secchi disk (cm). Sediment samples were taken at non-vegetated and seagrass sites using a modified Van-Veen grab. Sediment samples were not collected at oyster sites as shells prevented sediment collection. Sediment samples were placed on ice and transported back to laboratory for dry weight analysis. Analyses were conducted by placing 25 (g) of sediment from each sample for each site into an oven at 104°C for 24 hours. After drying, samples were reweighed and the new weights (dry weights) were subtracted from the original wet weight of 25 g, using the following formula:

$$Dry\ weight = (Sediment\ after\ drying\ (g)\ )/(wet\ weight\ (g))$$

Fish sampling

Juvenile bay whiff and southern flounder were collected using a 2 m wide beam trawl with 6 mm stretch mesh liner towed for 50 m (total area 100 m^2) towed at constant speed (5 knots). Trawl samples were rough-sorted in the field to remove excessive algae, seagrass, and debris, then preserved in 10% formalin and returned to the laboratory for further processing. All flatfishes were identified, enumerated, and measured to the nearest mm standard length (SL).

Spatial Analyses

Saltwater and larval exchange occurs via the Aransas tidal inlet, and flatfish use the tidal inlet to migrate offshore for spawning as adults and as a ingress pathway during the larval stage. Therefore, to examine a potential relationship between juvenile bay whiff and southern flounder with the connection to the Gulf of Mexico, the distance from the Aransas tidal inlet to each sampling location was calculated using the cost distance function in the spatial analyst extension in the ArcGIS (ESRI, Redlands CA, USA) software package, using the shoreline as a buffer (Whaley et al. 2007). The cost-distance function is a spatial statistical method that can be used to calculate the shortest distance between two points that are constrained with in geographic boundaries to provide more accurate relative distance estimates than Euclidian methods (Froeschke et al. 2010).

Abundance

Mean abundance (fish/100m^2) of bay whiff and southern flounder was calculated by habitat type. To test the null hypothesis that is no difference in mean abundance by habitat type an one-way ANOVA with a tukey post hoc test was conducted for each species.

Boosted Regression Trees

Relationships for both juvenile bay whiff and southern flounder with biological, physical, spatial and temporal variables were determined using a forward fit, stage-wise, binomial boosted regression tree model (De'ath 2007). Boosted regression trees (BRT) is an ensemble method and is a combination of techniques between statistical and machine learning traditions that has the power to: 1) accept different types of predictor variables; 2) accommodate missing values through the use of surrogates; 3) resistant to effects of outliers; and 4) capable of fitting interactions between predictors (Elith et al. 2006; Leathwick et al. 2006; Elith et al. 2008; Leathwick et al. 2008). This method is a relatively new method to ecological questions but has shown to be an effective method to identify relationships between fish distribution patterns and environmental predictors (Leathwick et al. 2006, 2008; Froeschke et al. 2010).

Unlike traditional regression techniques, BRT combine the strength of two algorithms, regression trees and boosting, to combine large numbers of relatively simple tree models instead of a single “best” model (Elith et al. 2006; Leathwick et al. 2006; Elith et al. 2008; Leathwick et al. 2008). Each individual model consists of a simple regression tree assembled by a rule-based classifier that partitions observations into groups having similar values for the response variable based on a series of binary splits constructed from predictor variables (Friedman 2001, Leathwick et al. 2006, Elith et al. 2008). The BRTs often have a higher predictive performance than single tree methods due to the inherent strengths of regression trees and the robustness of model averaging that improves predictive performance. Overfitting is minimized by incorporating 10-fold cross validation into the model fitting process (Elith et al. 2006; Leathwick et al. 2006; Elith et al. 2008; Leathwick et al. 2008).

Analyses were conducted in R (version 2.9, R Development Core Team) using the ‘gbm’ library supplemented with functions from Elith et al. (2008). Initially, ten predictors were included in the model: habitat type, dry weight, depth (m), dissolved oxygen (mg O_2/L), temperature (°C), turbidity (cm), salinity, pH, distance to the inlet, and month (treated as a categorical variable; Figure 3.2).

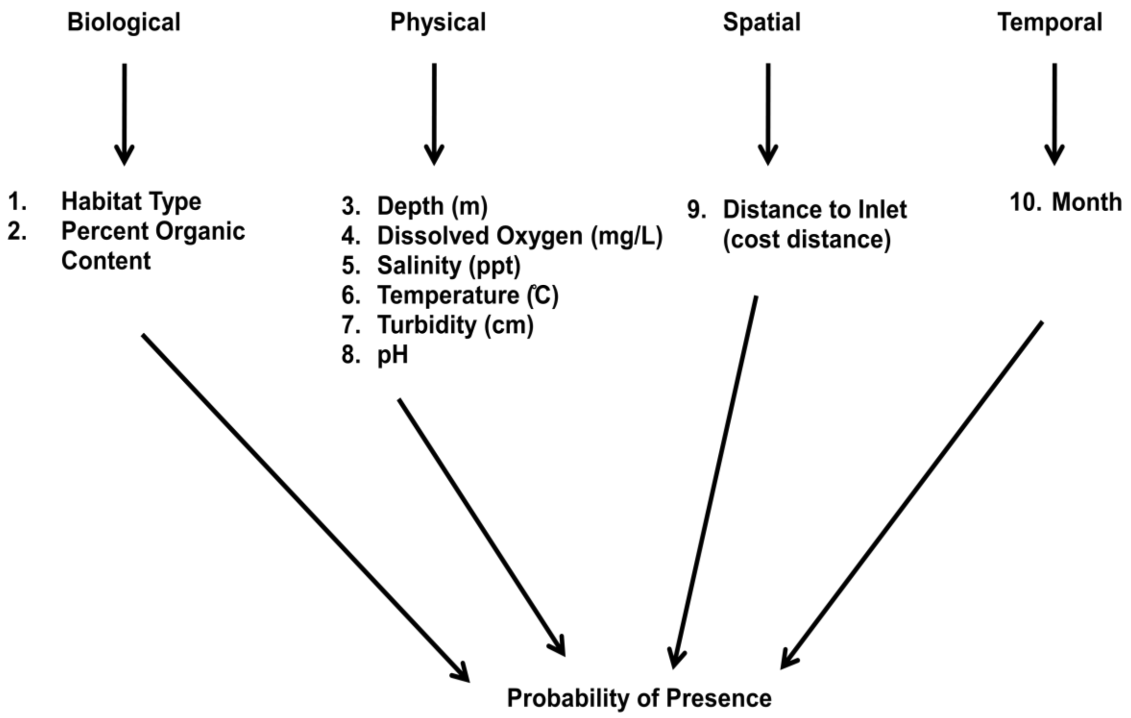

Figure 3.2: Flowchart for Boosted Regression Trees to identify essential fish habitat for juvenile bay whiff and juvenile southern flounder within the Aransas Bay Complex.

The adjustable model parameters for BRT are tree complexity (*tc*), learning rate (*lr*), and bag fraction, where *tc* controls whether interactions are fitted, *lr* determines the contribution of each tree to the growing model, and *bf* specifies the proportion of data to be selected at each step (Elith et al. 2008). Model selection was based on two performance metrics: 1) area under the receiver operating characteristic curve (ROC) and 2) explained deviance on cross-validated data. Selection of predictor variables was done using the gbm.simplify routine from Elith et al. (2008), while the tuning parameters were optimized by cross-validation selecting a final model larger than 1000 trees with maximum explained deviance on cross-validated data.

RESULTS

Model Parameters

During this study temperature ranged from 12.88°C (February) to 30.48°C (May) and the depth among the sites ranged from 0.08 m (seagrass) to 3.54 m (non-vegetated; Table 1). The lowest salinity (6.22) occurred in an oyster reef in Copano Bay sampled in February and the highest salinity (33.50) occurred in seagrass in Aransas Bay sampled in March (Table 1). The lowest dissolved oxygen (2.72 mg/L) occurred in April in seagrass in Copano Bay and the highest dissolved oxygen (14.49 mg/L) also occurred in April but in non-vegetation in Aransas Bay (Table 3.1). Percent dry weight was the lowest (10.09%) in March in Copano Bay at a non-vegetated site and was the highest (75.58%) in May in Aransas Bay at a non-vegetation site (Table 3.1). Turbidity ranged from 20 cm to 200 cm with the lowest turbidity occurring in seagrass in February in Copano Bay and the highest turbidity occurring in non-vegetation in May in Aransas Bay (Table 3.1).

Table 3.1: Mean (± standard error) parameter ranges by habitat from 160 sites (seagrass n=40, oyster reef n=40, and non-vegetated n=80) sampled from February to May 2010 within the Aransas Bay Complex

	Non-vegetation	**Oyster**	**Seagrass**
Temperature (°C)	21.55 ± 2.41	21.97 ± 3.47	22.99 ± 3.64
Salinity (psu)	14.74 ± 1.65	13.13 ± 2.08	18.93 ± 2.99
Turbidity (cm)	81.12 ± 9.07	73.10 ± 11.56	56 ± 8.85
Depth (m)	3.59 ± 0.40	2.78 ± 0.44	2.15 ± 0.34
Dissolved Oxygen (mg O2/l)	7.26 ± 0.81	7.89 ± 1.25	9.03 ± 1.43
pH	8.14 ± 0.91	8.22 ± 1.30	8.44 ± 1.33
Dry Weight (%)	47.83 ± 5.49	N/A	29.06 ± 4.59

Abundance and Length Frequency

In 160 samples bay whiff comprised 95.7% (n = 715) of flatfishes collected (Figure 3.3) and ranged in size from 8.1 -56.7 mm SL (mean 19.68 ± 0.35 mm SL; Figure 3.4). Mean abundance was significantly higher in seagrass (mean = 10.32 ± 2.58, $F_{2,157}$ =11.139, $p < 0.001$) compared to non-vegetation habitat (mean=3.3 ± 0.74) and oyster reefs (mean = 0.95 ± 0.26; Figure 3.5).

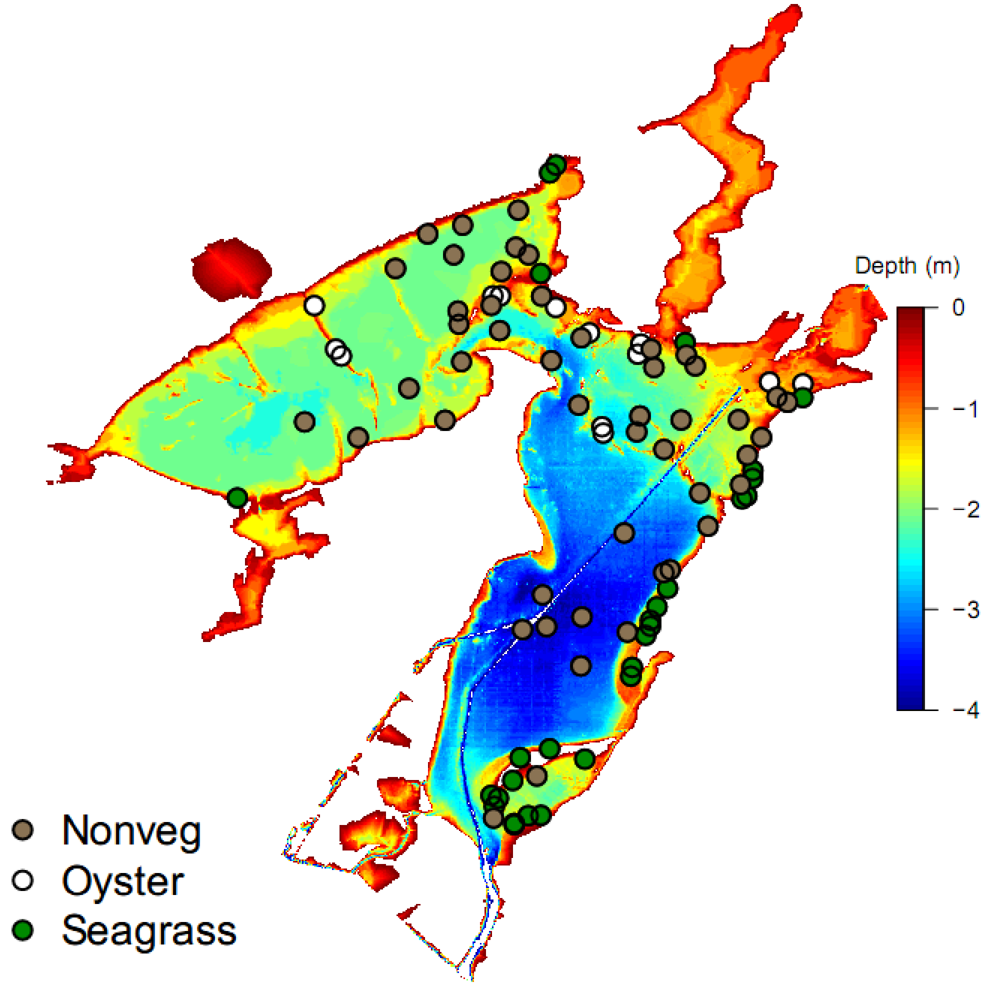

Figure 3.3: Sampling sites by habitat and depth within the Aransas Bay Complex where juvenile bay whiff were captured from February to May 2010. Non-vegetated sites are indicated with brown circles, oyster sites are indicated with white circles, and seagrass sites are indicated with green circles.

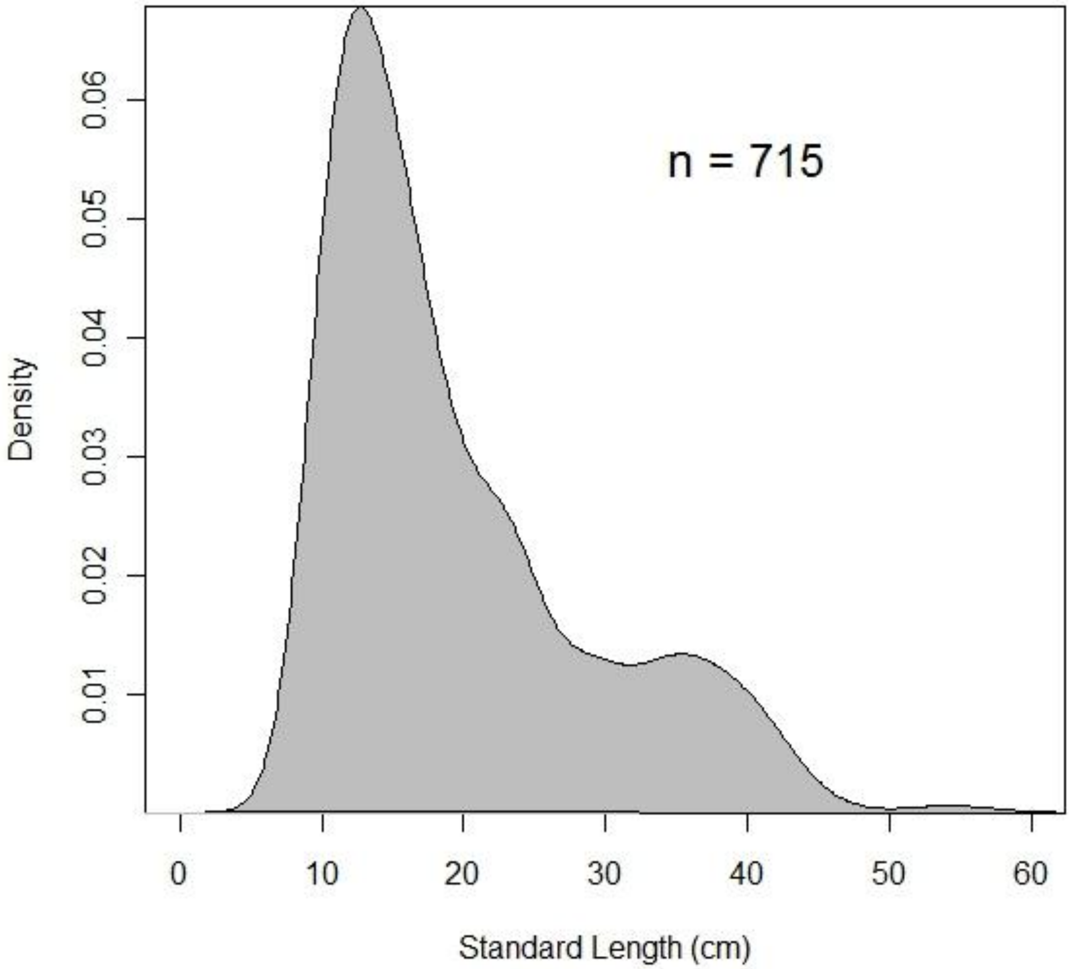

Figure 3.4: Density Graph of standard length (SL) for juvenile bay whiff captured in the MANERR from February to May 2010. Mean length = 19.68 ± 0.35 mm SL.

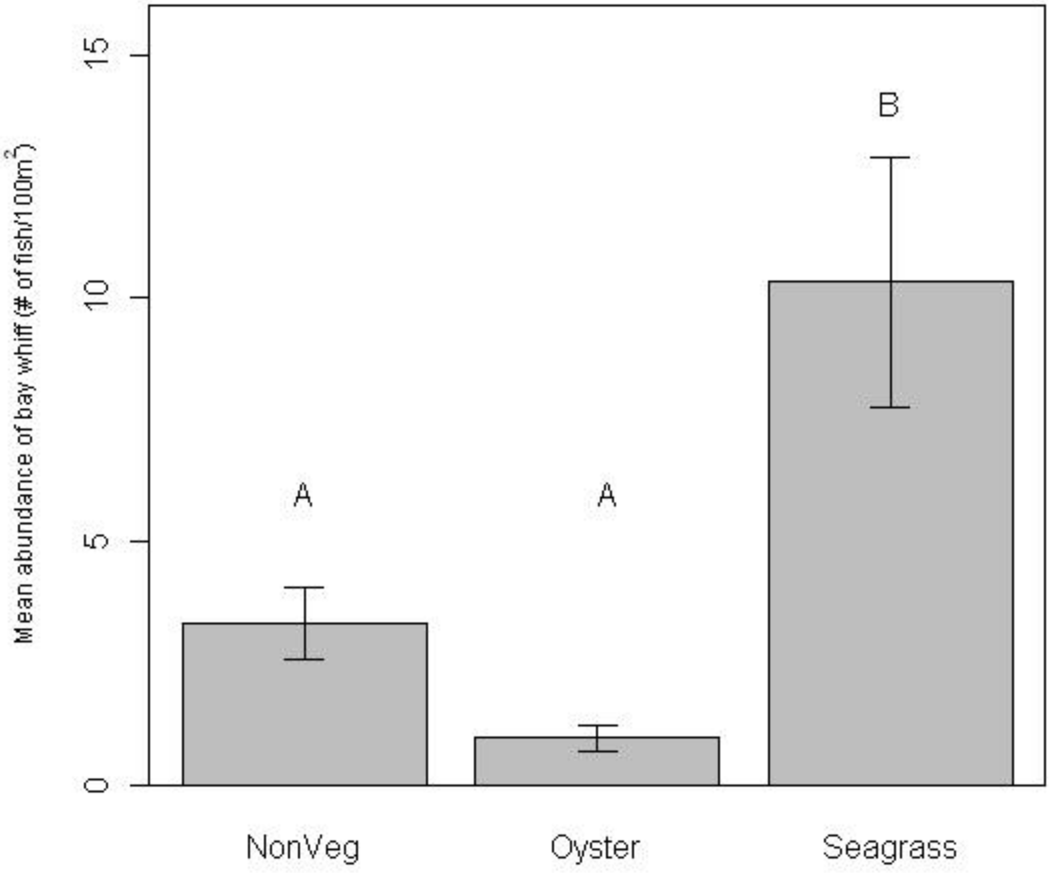

Figure 3.5: Mean abundance of juvenile bay whiff. Mean abundance was significantly higher in seagrass (mean = 10.32 ± 2.58, $F_{2,157}$ =11.139, $p < 0.001$) compared to non-vegetation habitat (mean=3.3 ± 0.74) and oyster reefs (mean = 0.95 ± 0.26)

In 160 samples southern flounder comprised 4.3% (n = 33) of flatfishes collected (Figure 3.6) and ranged in size from 10.4 mm SL to 75.8 mm SL (mean = 30.9 ± 2.98; Figure 3.7). Overall there was a significant difference in the mean abundance of juvenile southern flounder among habitats ($F_{2,157}$ =6.25, p = 0.002). The mean abundance of southern flounder was significantly higher in seagrasses (mean = 0.5 ± 0.14) compared to non-vegetation habitats (mean=0.11 ± 0.06) and oyster reefs (mean = 0.08 ± 0.0.06; Figure 3.8).

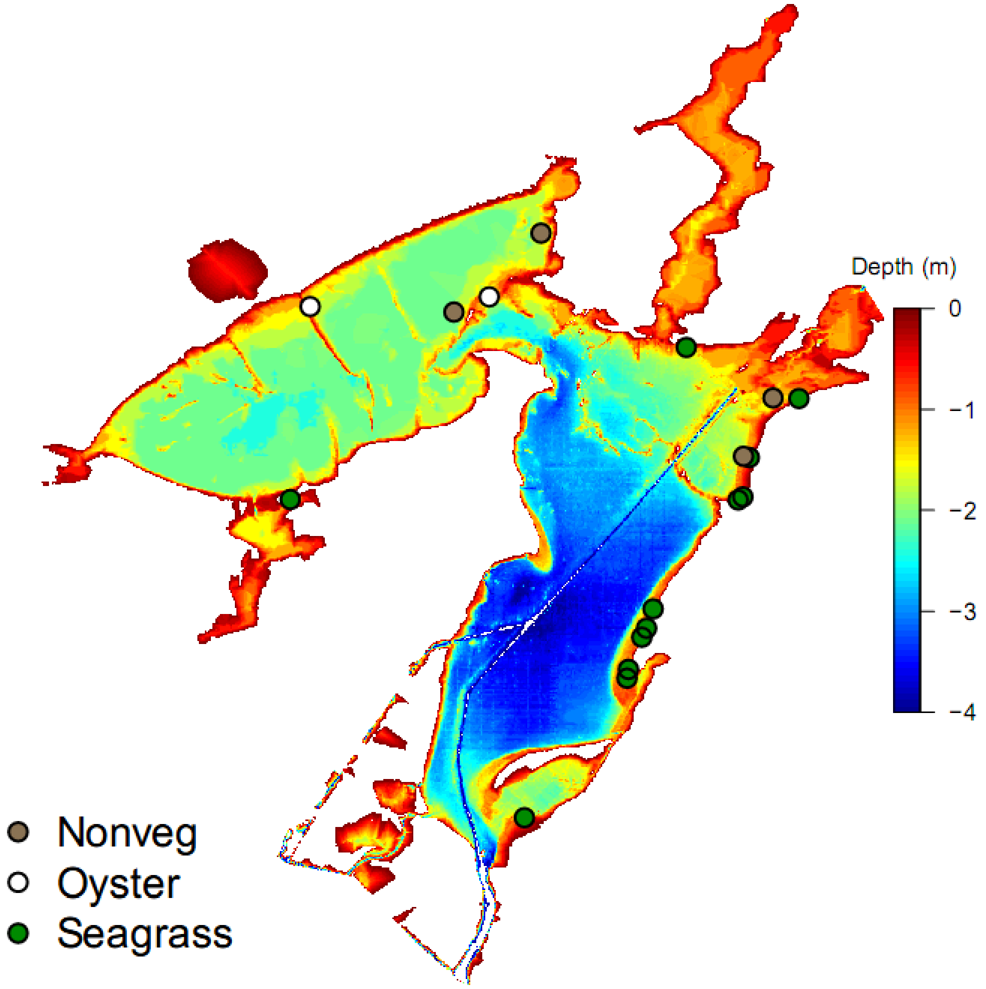

Figure 3.6 Sampling sites by habitat and depth within the MANERR where juvenile southern flounder were captured from February to May 2010. Non-vegetated sites were indicated with brown circles, oyster sites were indicated with white circles, and seagrass sites were indicated with green circles.

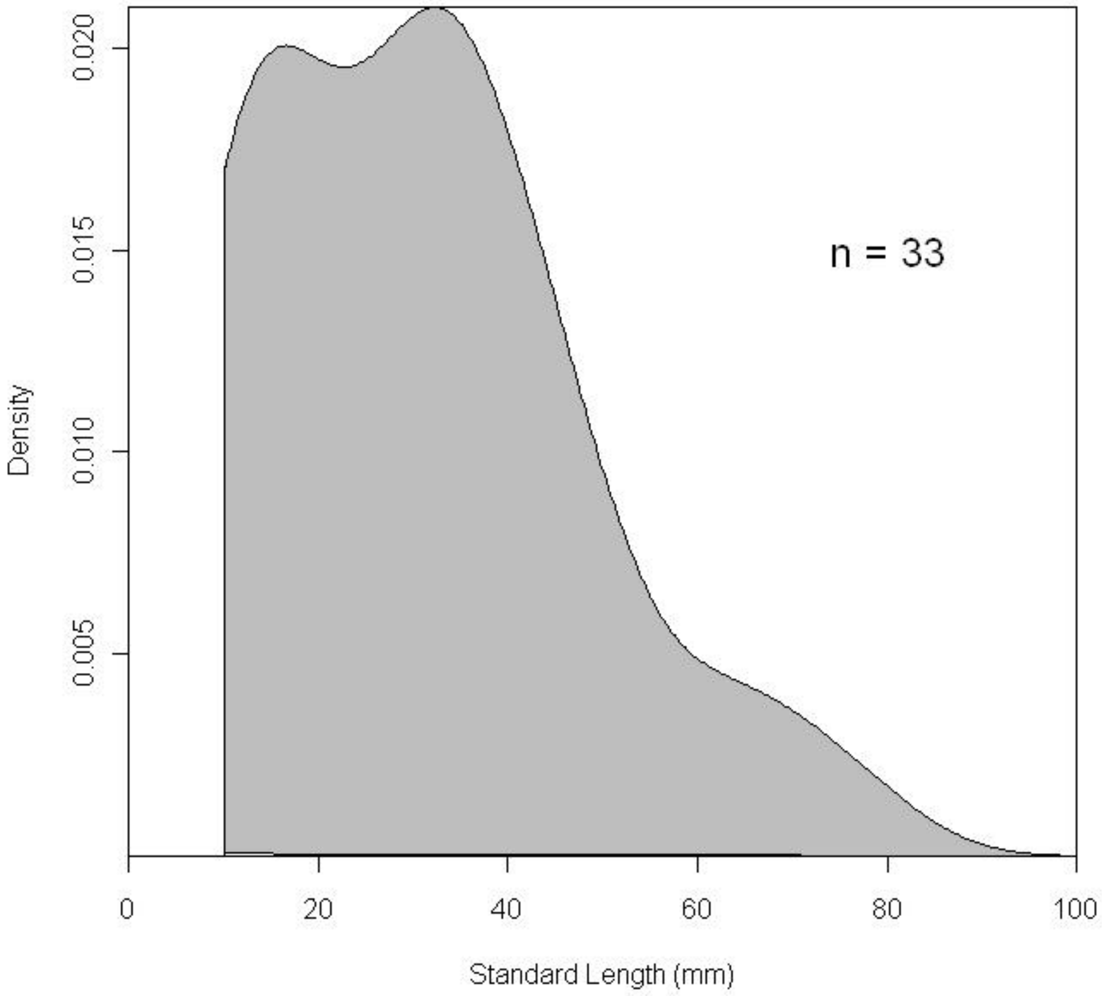

Figure 3.7: Density Graph of standard length (SL) for juvenile southern flounder captured in the MANERR from February to May 2011. Mean length = 30.90 ± 2.98 mm SL.

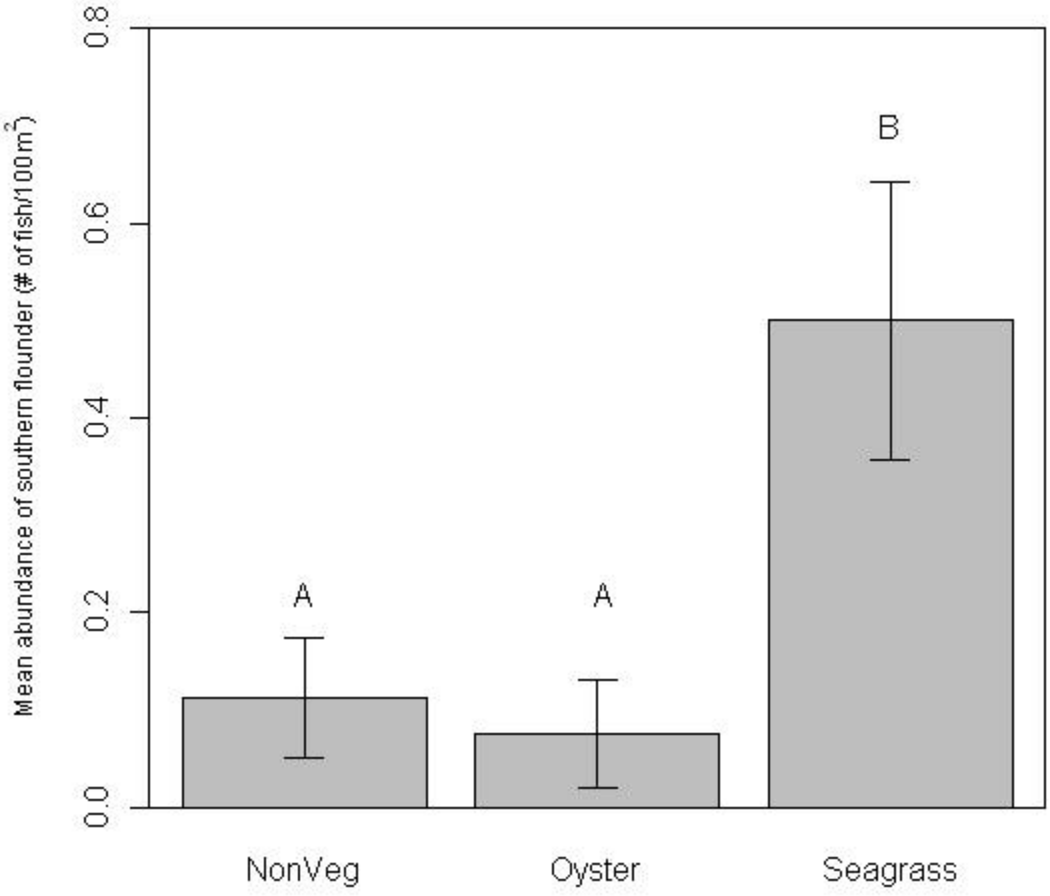

Figure 3.8: Mean abundance of juvenile southern founder. Overall there was a significant difference in the mean abundance of juvenile southern flounder among habitats ($F_{2,157}$ =6.25, p = 0.002), significantly higher mean in seagrasses (mean = 0.5 ± 0.14) compared to non-vegetation habitats (mean=0.11 ± 0.06) and oyster reefs (mean = 0.08 ± 0.0.06).

Table 3.2: Predictive performance of boosted regression trees (BRT) models for juvenile bay whiff and southern flounder. *tc* = tree complexity, *lr* = learning rate, and *bf* = bag fraction.

				Percentage Deviance Explained				
Species	*tc*	*lr*	*bf*	Cross-Validation	Training	Total Deviance	ROC Cross-Validation	ROC Cross-Validation SE
Bay whiff	2	0.001	0.65	21.70%	46.80%	1.374	0.817	0.022
Southern flounder	5	0.001	0.6	15.07%	45.50%	0.703	0.841	0.059

Habitat model for Bay whiff and southern flounder

The models were chosen to maximize explained deviance and on cross-validated data and the “best” models were different between the species. The simplified habitat BRT model for bay whiff incorporating five out of the ten variables was selected as the “best” fit model (ROC = 0.817; Table 3.2) over the full model including all of the variables(ROC = 0.804) to predict the relationship of biological, spatial, physical and temporal variables with the distribution of juvenile bay whiff. The five variables included were dry weight of sediments, distance to inlet, temperature, salinity, and dissolved oxygen. Dry weight of the sediment explained the most explained deviance in the model (29.5%) followed by distance to inlet (21.3%), temperature (20%), salinity (15.3%), and dissolved oxygen (14%; Figure 3.9). The fitted functions from the “best” fit BRT habitat model indicated that juvenile bay whiff occurs in areas with sediment containing 25% - 45% dry weight, with the highest distribution occurring between 30% - 45% and a rapid decline at 45% (Figure 3.9). Moreover, probability of occurrence of bay whiff were most common in areas ≤ 120 units from the Aransas tidal inlet, temperatures less than 15°C, salinities greater than 10 psu (with the highest peak occurring at 20 psu), and dissolved oxygen levels greater than 6 mg O_2/L (Figure 3.9).

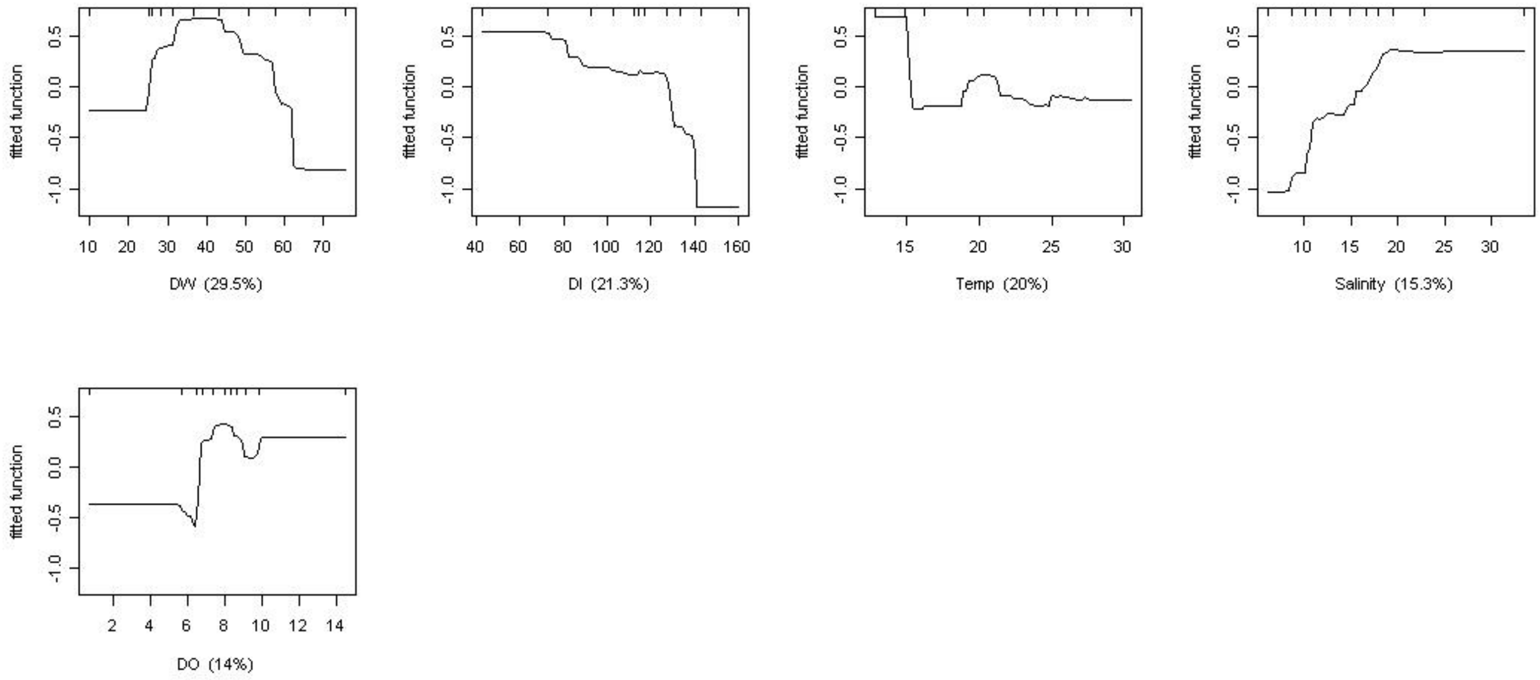

Figure 3.9: Functions fitted for the five important predictor variables by a boosted regression trees (BRT) model relating the probability of capture of juvenile bay whiff to the environment in order to identifying Essential Fish Habitat (EFH) within the MANERR. Y-axes are on the logit scale with mean zero. X-axes parameters: percent dry weight (DW), distance to the nearest inlet (DI), temperature (Temp; ˚C), salinity (psu), and dissolved oxygen (DO; mg O_2/l).

Spatial prediction (kriging) of juvenile bay whiff from the “best” boosted regression trees (BRT) model indicating the highest probability (> 0.8) of collection would occur among habitats (seagrass and non-vegetation) located along the east and north areas of Aransas Bay and the north-west corner of Copano Bay (seagrass and non-vegetation; Figure 3.10). Moderate probability (0.5-0.8) of occurrence for bay whiff occurred along the very west side along Aransas Bay and the north-east corner of Copano Bay (oyster reefs). The lowest probability (< 0.05) of occurrence for bay whiff occurred along the middle and south areas of Copano Bay (Figure 3.10).

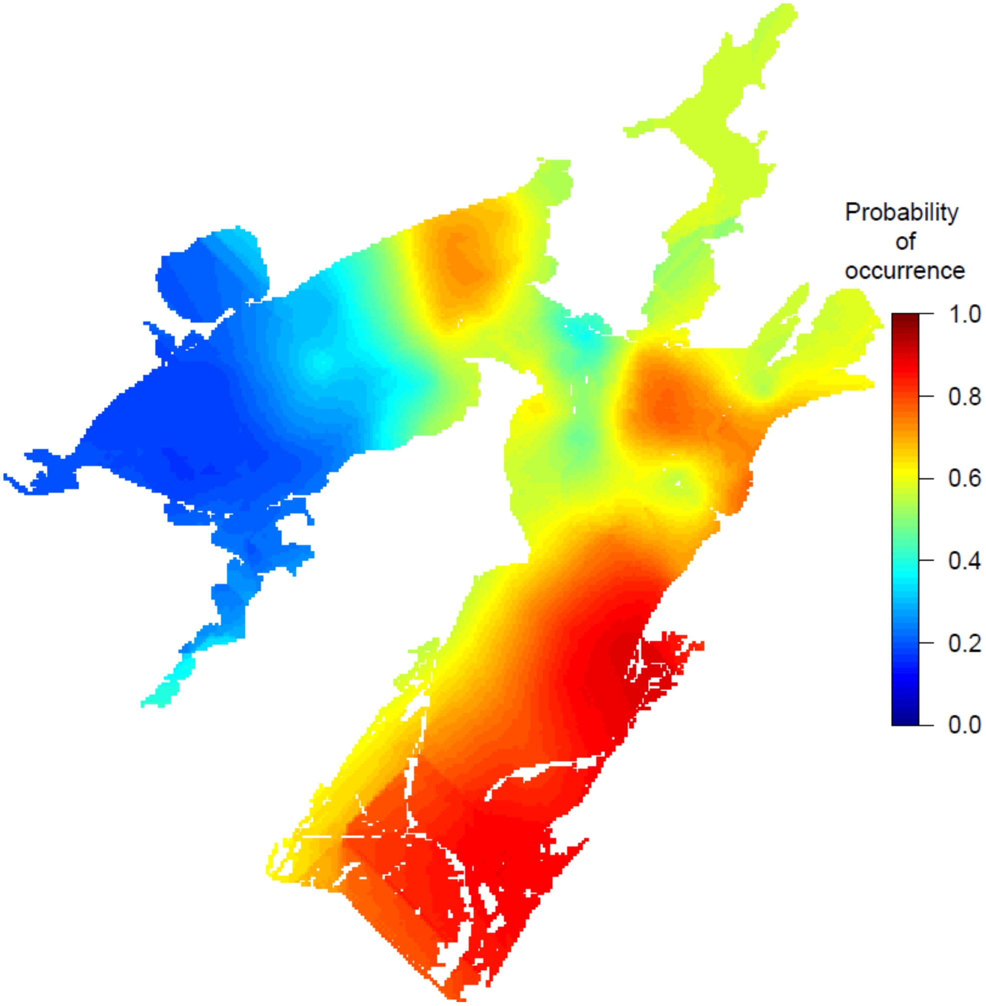

Figure 3.10: Spatial prediction of juvenile bay whiff from the boosted regression trees (BRT) model indicating the highest probability of collection would occur among habitats located along the east and north areas of Aransas Bay and the north-west corner of Copano Bay. Moderate probability of occurrence for bay whiff occurred along the very west side along Aransas Bay and the north-east corner of Copano Bay. The lowest probability of occurrence for bay whiff occurred along the middle and south areas of Copano Bay.

For distribution patterns of juvenile southern flounder the full model including all variables (ROC = 0.841; Table 3.2) was selected over the simplified model (ROC = 0.787) to predict the relationship of biological, spatial, physical and temporal variables. Temperature explained the most deviance in the model (27.2%) followed by percent dry weight of sediment (15.3%), habitat (13.3%), month (11.8%), depth (11.7%), dissolved oxygen (7.3%), pH (5.7%), distance to inlet (3.6%), salinity (2.9%), and turbidity (1.2%; Figure 3.11). The fitted functions from the BRT model indicated that the highest occurrence rates of juvenile southern flounder were in water temperatures less than 15°C, dry weight of the sediment less than 30%, water depth less than 1.2 m, and dissolved oxygen greater than 8 mg/L (Figure 3.11). Moreover, the fitted functions indicated that there is a higher probability of occurrence of juvenile southern flounder in seagrass as compared to non-vegetated or oyster reefs. With respect to pH, distance to inlet, salinity, and turbidity the fitted functions from the BRT indicated that there is not an increase or decrease with the occurrence of juvenile southern flounder (Figure 3.11).

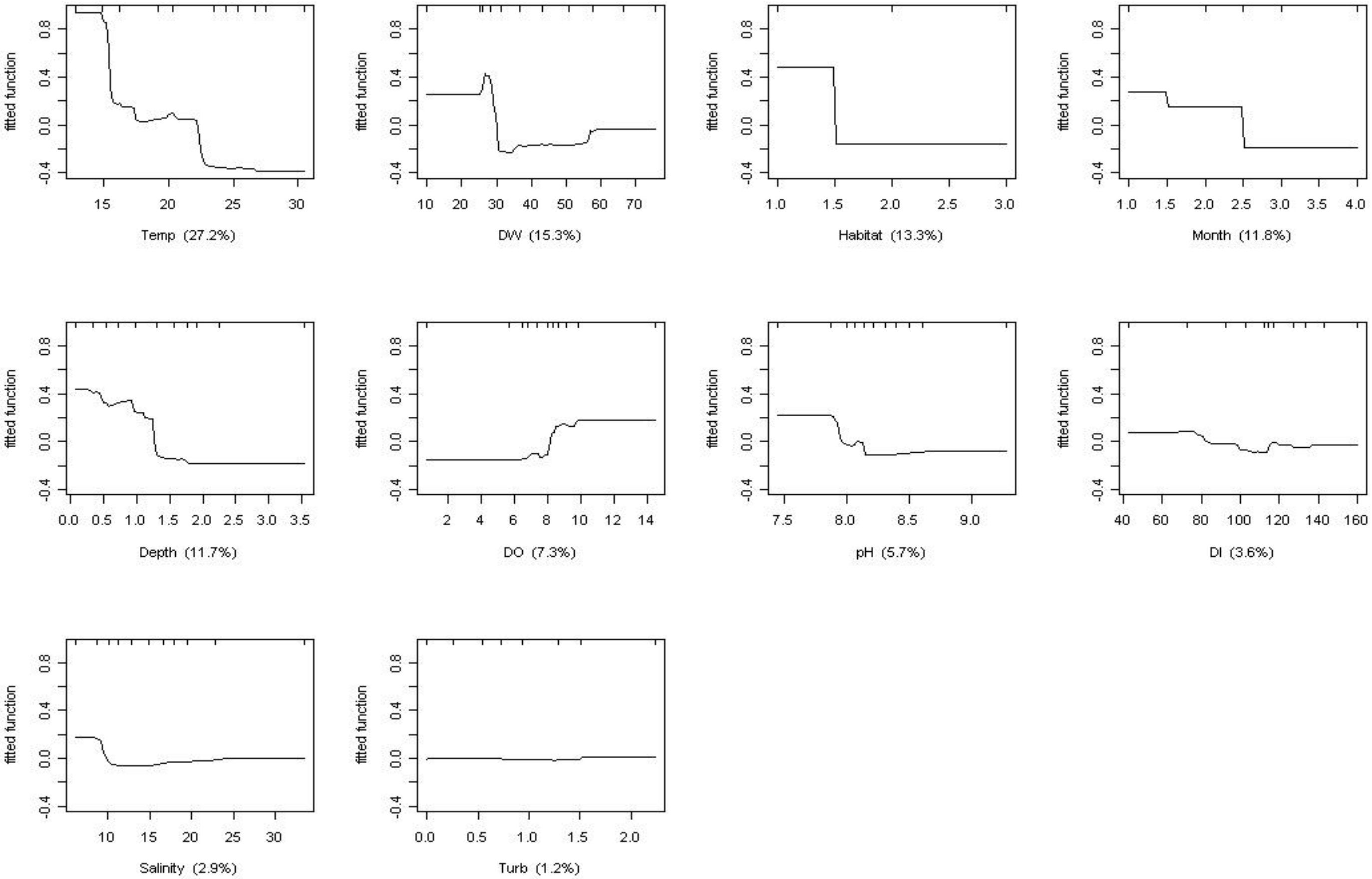
fitted function
-0.4
0.0
0.4
0.8
15 20 25 30
Temp (27.2%)
10 20 30 40 50 60 70
DW (15.3%)
1.0 1.5 2.0 2.5 3.0
Habitat (13.3%)
1.0 1.5 2.0 2.5 3.0 3.5 4.0
Month (11.8%)
0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
Depth (11.7%)
2 4 6 8 10 12 14
DO (7.3%)
7.5 8.0 8.5 9.0
pH (5.7%)
40 60 80 100 120 140 160
DI (3.6%)
10 15 20 25 30
Salinity (2.9%)
0.0 0.5 1.0 1.5 2.0
Turb (1.2%)

Figure 3.11: Functions fitted for the ten predictor variables by a boosted regression trees (BRT) model relating the probability of capture of juvenile southern flounder to the environment in order to identifying Essential Fish Habitat (EFH) within the Aransas Bay Complex. Y-axes are on the logit scale with mean zero. X-axes parameters: temperature (Temp; ˚C), percent dry weight (DW), habitat (1 = seagrass, 2 = non-vegetated, and 3 = oyster reef), month (1= February, 2=March, 3=April, 4=May), depth (m), dissolved oxygen (DO; mg O_2/l), pH, distance to the nearest inlet, salinity (psu), and turbidity (cm).

Spatial prediction of juvenile southern flounder from the BRT model indicated the highest probability (> 0.25) of collection was in seagrass beds along the eastern edge of Aransas Bay (Figure 3.12). Moderate probability of collection (0.25 – 0.15) was in seagrass located in the southern region, and northern regions of Aransas Bay and Copano Bay (Figure 3.12). The lowest prediction for probability of occurrence (< 0.15) was in non-vegetated and oyster locations throughout Copano Bay, and in the middle non-vegetated sites in Aransas Bay (Figure 3.12).

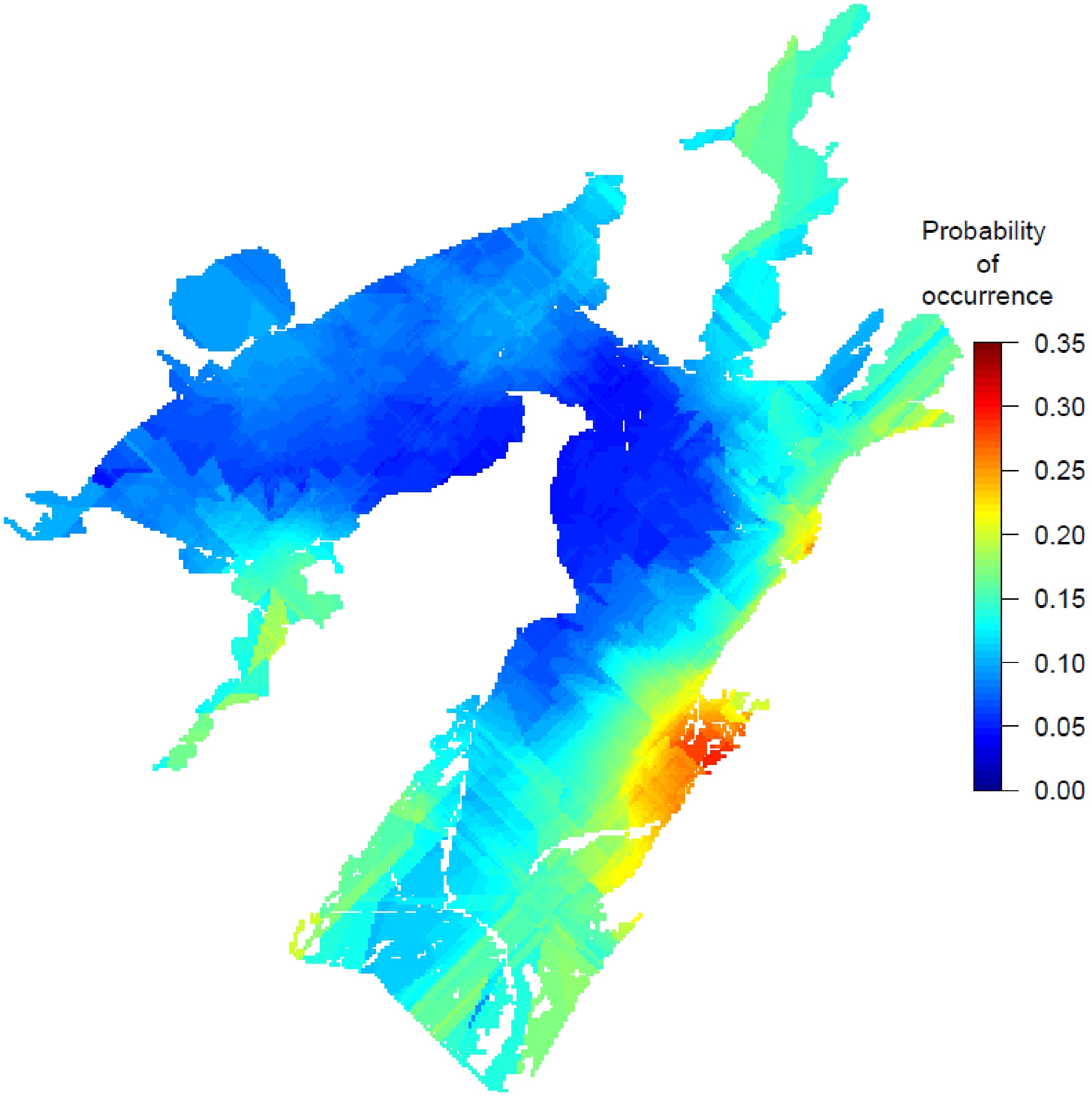

Figure 3.12: Spatial prediction of juvenile southern flounder from the BRT model indicated the highest probability of collection was in seagrass beds along the eastern edge of Aransas Bay. Moderate probability of collection was in seagrass located in the southern region, and northern regions of Aransas Bay and Copano Bay. The lowest prediction for probability of occurrence was in non-vegetated and oyster locations throughout Copano Bay, and in the middle non-vegetated sites in Aransas Bay.

DISCUSSION

The occurrence of juvenile bay whiff and southern flounder demonstrated strong relationship with biological (habitat type, dry weight of sediments), physical (depth, dissolved oxygen, temperature, turbidity, and pH), and spatial (distance to the inlet) variables. Based on the abundance pattern shown here, these data demonstrated that the occurrence of bay whiff was mostly influenced by percent dry weight of sediments, distance to inlet, water temperature, salinity, and dissolved oxygen. Occurrence of southern flounder was mostly influenced by water temperature, percent dry weight of sediments, habitat type, month of collection, depth, and dissolved oxygen. Thus, further supporting the hypothesis that the interaction between habitat quantity and habitat quality effects survivorship of flatfish, with the largest recruitment potential to occur in areas with both high habitat quantity and quality, and the smallest recruitment potential to occur in areas where they are low (Gibson 1994). Others have shown biological variables such as prey abundance, predators, habitat structure, water depth, and physical factors such as, temperature, salinity, oxygen, and hydrodynamics are all major factors exhibited to effect growth and survival of flatfish recruitment (Gibson 1994; Allen and Baltz 1997; Stoner et al. 2001; Glass et al. 2008).

Bay whiff were very common in my study at all locations, and much higher than southern flounder, with the mean abundance of bay whiff significantly higher in seagrass than non-vegetation habitats and oyster reefs. However, the simplified BRT model did not incorporate habitat has an important variable in predicting the occurrence of bay whiff. Instead the probability of occurrence for juvenile bay whiff was associated with low temperatures, moderate percent dry weight of sediments, low salinities, and dissolved oxygen levels greater than 6. Thus, the results of the BRT model indicated that habitat quality was more influential than particular structured habitat type (e.g., seagrass etc.) and an interaction between seagrass and habitat quality. These results suggest bay whiff are habitat generalists, and supportive of what others have hypothesized about this species being capable of using a variety of habitat types (Allen and Baltz; Walsh and Cyrus 1999). In North Carolina, the abundance of bay whiff was not significantly different among the 21 stations sampled, which included variation in marsh, seagrass, and non-vegetated habitats (Walsh and Cyrus 1999). I found bay whiff most associated with seagrasses in the Aransas Bay complex; nonetheless, they were still very common and abundant among all areas. Similar relationships to physical variables have been observed for another abundant flatfish, winter flounder. Stoner et al. (2001) demonstrated that newly settled winter flounder (<25 mm total length (TL)) were associated with low temperatures, high sediment and deeper water; fish 25–55 mm TL were associated with high sediment organics and salinity around 20, and the largest winter flounder were associated with temperature near 22°C, shallow depths and presence of macroalgae within the Navesink River/Sandy Hook Bay estuary (Stoner et al. 2001). These results suggest that management of bay whiff should focus more on habitat quality rather than structured habitat type. More specifically, these results suggest that management of this highly abundant generalist flatfish needs to incorporate water quality aspects in addition to management of habitat type.

Juvenile southern flounder were relatively rare in our collected samples, particularly compared to bay whiff, which is a common occurrence in other studies (Hoese and Moore 1998; Walsh and Cyrus 1999; McEachran and Fechhelm 2006;

Nañez-James et al. 2009). The low densities will most likely have important implication to managing their recovery. Similar to bay whiff the abundance of juvenile southern flounder was significantly higher in seagrass habitats than non-vegetation and oyster reefs. Furthermore, prediction results indicated that when incorporating physical variables with biological variables in a species habitat model, juvenile southern flounder are more likely to occur in areas with low temperatures, low percent dry weight of sediment, seagrass habitats, shallow depths, and high dissolved oxygen. Essential fish habitat for young-of-the-year southern flounder in Aransas Bay and Copano Bay, TX was demonstrated to occur in vegetated habitats (seagrass and marsh edge) that occur closest to the tidal inlet between Aransas Bay and the Gulf of Mexico and in high salinity (Nañez-James et al. 2009), and my results support those results However, based on results of this study, I suggest that when incorporating both habitat type and distance to inlet, habitat selection contributes more to EFH selection of juvenile southern flounder then distance to the inlet. This relationship implies that there is a correlation with habitat type and the distance to the inlet which is likely caused by habitat quality near the inlets (increase water exchange with the Gulf of Mexico). Clearly, identifying these particular areas will be essential in protecting these areas for southern flounder nurseries. Moreover, in Newport River and Back Sound estuaries in North Carolina no size-specific patterns in habitat utilization was found but abundance of southern flounder were significantly higher in the spring in the middle and upper estuary on mud substrates with detritus and in the fall in areas near marsh edges with mud substrates and detritus (Walsh and Cyrus 1999). Glass et al. (2008) concluded that variation seen in density of southern flounder is more influenced at the bay scale than at the habitat scale. These results underscore the value of considering biotic factors (e.g. seagrass) as well as the suite of environmental characteristics and how these factors interact to ultimately determine habitat quality.

Percent dry weight of sediments and dissolved oxygen were both important physical variables aiding in the prediction of bay whiff and southern flounder. However, the ranges of both variables were different for each species. Percent dry weight and dissolved oxygen are habitat descriptors that give an indication of things such as detritus and submerged aquatic vegetation (SAV). Due to many differences between the environmental variables, I suggest that management of EFH for flatfishes within the Aransas Bay Complex needs to include areas consisting of both high probabilities of occurrence for juvenile bay whiff and juvenile southern flounder in the same locations. For example, percent dry weight of sediments occurrence of bay whiff was associated with values greater than 25%, whereas occurrence of southern flounder was associated with values less than 25%. Additionally, higher probability of capture for southern flounder was at dissolved oxygen levels greater than 8 mg/L, whereas bay whiff are able to tolerate dissolved oxygen levels less than 8mg/L. These results suggest that juvenile bay whiff and southern flounder have different habitat quality preferences from one another. Similar results have also been demonstrated for seawater temperature. Gibson (1994) showed cooler temperatures predicted high abundance of both species but bay whiff were also associated with warmer temperatures (between 20-23°C) than southern flounder. Other differences in this study occurred among variables salinity and distance to the nearest inlet. Probability of bay whiff was highly explained by salinity and distance to the nearest inlet whereas the probability of southern flounder was not highly explained by these variables. These results suggest that EFH within the Aransas Bay Complex needs to occur among all habitat types along the eastern side of Aransas Bay, and the north corner of Copano Bay.

This study demonstrated the importance of incorporating environmental and biological variables in species habitat models to identify areas suitable EFH designation. Habitat is a driving factor for most estuarine dependent species. However, establishing EFH should also extend beyond the first steps of delineating habitat-density relationships by including interactions among suitable biotic and abiotic constraints within particular areas (Hayes et al. 1996). The complex nature of many marine life history strategies coupled with the lack of research on other ecosystem-level interactions has made progress toward determining EFH problematic (Shutter 1990; and Guisan and Thuiller 2005), and these types of relationships had not been established for flatfish in this area. Clearly, evidence from this study will lead to increased knowledge and management of EFH for all life-stages of southern flounder needs to be completed in order to increase the abundances of both juvenile and adult southern flounder. Moreover, this study provides a frame work to assess coastal areas for EFH fisheries.

The results of the study contribute information towards acquiring knowledge on EFH of flatfish in subtropical estuaries. These results are particularly timely in that the southern flounder population in Texas is declining with adults (decreasing by 2.5%) two times faster than the juveniles (decreasing by 1.3% per year; Froeschke et al. 2011). The southern flounder and bay whiff species habitat models constructed provides much needed information to identify areas critical for habitat conservation of nursery grounds of juvenile flatfishes within the Aransas Bay Complex. The models provide tools for natural research managers to conserve nursery habitats crucial for the various developmental stages of fisheries. Conserving appropriate habitat and understanding relationships between abiotic and biotic factors within those habitats will lead to the knowledge needed to improve the abundance of these species, specifically southern flounder. In addition, anthropogenic climate changes will certainly alter abiotic factors within all marine environments; therefore, we must understand the importance of these changes to develop a more effective ecosystem-based management system (Chittaro et al. 2009).

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CHAPTER 4

COMPARISON OF SPATIO-TEMPORAL PREDICTIVE MODELS FOR JUVENILE SOUTHERN FLOUNDER (*PARALICHTHYS LETHOSTIGMA*) HABITAT USE ALONG THE NORTHERN GULF OF MEXICO USING BOOSTED REGRESSION TREES AND ARTIFICIAL NEURAL NETWORKS

ABSTRACT

Southern flounder, *Paralichthys lethostigma*, is an important multi-million dollar commercial and recreational fishery along the Gulf of Mexico. Despite the economic importance of southern flounder, the population has been declining for decades and currently at all-time low. Moreover, population trends show a negative response to climate change. Future management will need to consider both population trends and responses to temperature fluctuation to improve management of this fishery. The main objectives of this study were to provide statistical modeling techniques that predict how environmental factors alone can influence the temporal and spatial patterns of juvenile southern flounder using two different approaches. I compare a relatively new modeling technique Boosted Regression Trees with the well accepted technique of Artificial Neural Network using a 29-year long-term data set. Data were acquired from the Resource and Sport Harvest Monitoring Program conducted by Texas Parks and Wildlife Department. Boosted Regression Trees showed juvenile southern flounder were associated with relatively low temperatures, low salinity levels, and high dissolved oxygen. Both spatio-temporal models consisted of high predictive performance with slight spatial differences. Both models suggest high probability of occurrence in Galveston Bay and East Matagorda Bay. Artificial Neural Network analyses indicated higher probability of occurrence in Sabine Lake. Our results provide valuable tools for fisheries managers to enhance management and ensure sustainability southern flounder fisheries. The results also identified a predictive framework for proactive approaches to ecosystem management. These models will more accurately determine and conserve nursery habitats for the southern flounder fishery, by protecting essential habitat features and understanding relationships between abiotic and biotic factors within those habitats

Keywords: Essential Fish Habitat; Boosted Regression Trees; Artificial Neural Networks; Southern flounder; Gulf of Mexico

INTRODUCTION

Declines in abundance and extensive exploitation of the world's fisheries and marine habitats have caused concern among many researchers (Jackson et al. 2001; Pauly et al. 2002; Hilborn et al. 2003; Pyke 2004; Hughes et al. 2005; Lotze et al. 2006; Halpern et al. 2008; NMFS 2008). Human impacts have altered the distribution, quantity and quality of marine habitats (Pyke 2004; Lotze et al. 2006) and have contributed to depletion of more than 90% of estuarine species, degraded water quality, accelerated species invasions, and reduced seagrass and wetland habitat among estuaries and coastal seas by sixty five percent (Lotze et al. 2006). Seventy-five percent of fisheries worldwide are over exploited or fully exploited (NMFS 2002). Within the U.S., 17% of fisheries are subject to overfishing and 24% are overfished (NMFS 2008). It is well accepted that impacts from recreational (Coleman et al. 2004) and commercial fishing as well as commercial by-catch from shrimp trawlers can be significant contributors to the decline of fisheries (Jackson et al. 2001; Pauly et al. 2002; and Hilborn et al. 2003). In the Gulf of Mexico, important fishery species are not exempt from this pattern. Southern flounder, a common flat fish have been on the decline decades and are currently at all-time lows in Texas.

Flounder have historically supported an important multi-milliondollar commercial and recreational fishery along the Texas coast (Matlock 1991; VanderKooy 2000), but declines in this stock (Froeschke et al. 2011) have concerned resource managers and led to substantially reduced recreational and commercial catches. While a Fisheries Management Plan (FMP) for the Gulf of Mexico flounder fishery was developed in 2000, a paucity of data prevented a complete Gulf-wide stock assessment for the flounder fishery (VanderKooy 2000). This fishery is primarily composed of southern flounder (*Paralichthys lethostigma*) and gulf flounder (*Paralichthys albigutta*). In Texas, southern flounder represents over ninety-five percent of harvested flounder and is one of the top three fish species targeted by anglers (Riechers 2008).

Time series analysis indicated that both juvenile and adult southern flounder are declining (Froeschke et al. 2011). Juveniles are decreasing by a rate of 1.3% per year (1977-2007), whereas the adult population is decreasing at a rate of 2.5% per year (1975-2008; Froeschke et al. 2011). Moreover, abundance trends of juvenile and adult southern flounder are independent, particularly with high mortality rates of post-juvenile flounder that occurred during the 30 y study period (Froeschke et al. 2011). Stunz et al. (2000) demonstrated that a reduced proportion of southern flounder are reaching age of maturity.

Regulation and management efforts for southern flounder in Texas have focused on implementing guidelines for recreational and commercial fisheries, yet the population remains in decline suggesting that other factors may be negatively influencing the southern flounder population. Froeschke et al. (2011) showed that recruitment of southern flounder may not be the primary cause of the adult population decline given that catch rates of adults are declining at a quicker rate than can be explained by juveniles. In addition, Froeschke et al. (2011) suggested that continued improvements on recreational and commercial fishing regulations and increased knowledge and management of Essential Fish Habitat (EFH) for all life-stages of southern flounder needs to be completed in order to increase the abundance of southern flounder. Coupled with population decline are habitat loss and climate change. Evidence has shown that southern flounder may be responding to climate change, and it will become increasingly important to use data available to understand and predict the occurrence of juvenile southern flounder with respect to physical, spatial and temporal variables. To address these concerns, it is imperative that management of the flounder fishery shifts towards an ecosystem-based approach where the importance of interactions among physical, biological, and human components of the system is considered (Pikitch et al. 2004; Marasco et al. 2007; Crowder et al. 2008).

Forecasting models will provide valuable information for fisheries managers to enhance management and ensure sustainability of the southern flounder fishery in particular but other fisheries as well. Boosted Regression Trees (BRT) is a relatively new method to ecological applications, and has proven to be an effective method to identify relationships between fish distribution patterns and environmental predictors (Leathwick et al. 2006, 2008, Froeschke et al. 2010). Moreover, BRT has shown to be effective in predicting the occurrence of juvenile southern flounder for determining EFH within the Aransas Bay complex (Chapter 3). Artificial Neural Networks (ANN) are a well-established method for identifying complex hydrographical patterns with abundance and dynamics of different phases in the life cycle of fish (Suryanarayana et al. 2008), and many researchers have used ANN's to predict fish recruitment (Kusakabe et al. 1997; Engelhard and Heino 2002; Megrey et al. 2005) and age of fish (Potter et al. 1993; Robertson and Morison 1999; Engelhard et al. 2003) from explanatory variables (Suryanarayana et al. 2008).

The goal of this study is to provide information for the fishery management plan of southern flounder by using statistical modeling techniques to understand how environmental factors influence the temporal and spatial patterns of juvenile southern flounder and to compare a relatively new modeling technique (BRT) with a well accepted technique (ANN). More specifically, the purposes of this research are to: 1) determine the relationship between temporal (month, year), spatial (distance to the inlet), and physical (temperature, turbidity, dissolved oxygen, salinity, and depth) variable with the occurrence of juvenile southern flounder; 2) used trained BRT and ANN to predict the presence of juvenile southern flounder spatially among Texas Bays; and 3) compare the predictive power and predicted spatial distribution of the trained and tested BRT and ANN.

MATERIALS AND METHODS

Study Area

The study consisted of the nine major bays along the Texas coast, located along northwestern Gulf of Mexico (Figure 4.1). The Texas coast is 563 km in length and contains five Barrier Islands that stretch approximately 161 km. There are six consistently open, federally maintained ship channels that provide pathways for water exchange and animal transport between the nearshore bays adult/nursery habitat and the Gulf of Mexico (http://goliath.cbi.tamucc.edu/TexasInletsOnline/TIO%20Main/index.htm) spawning location.

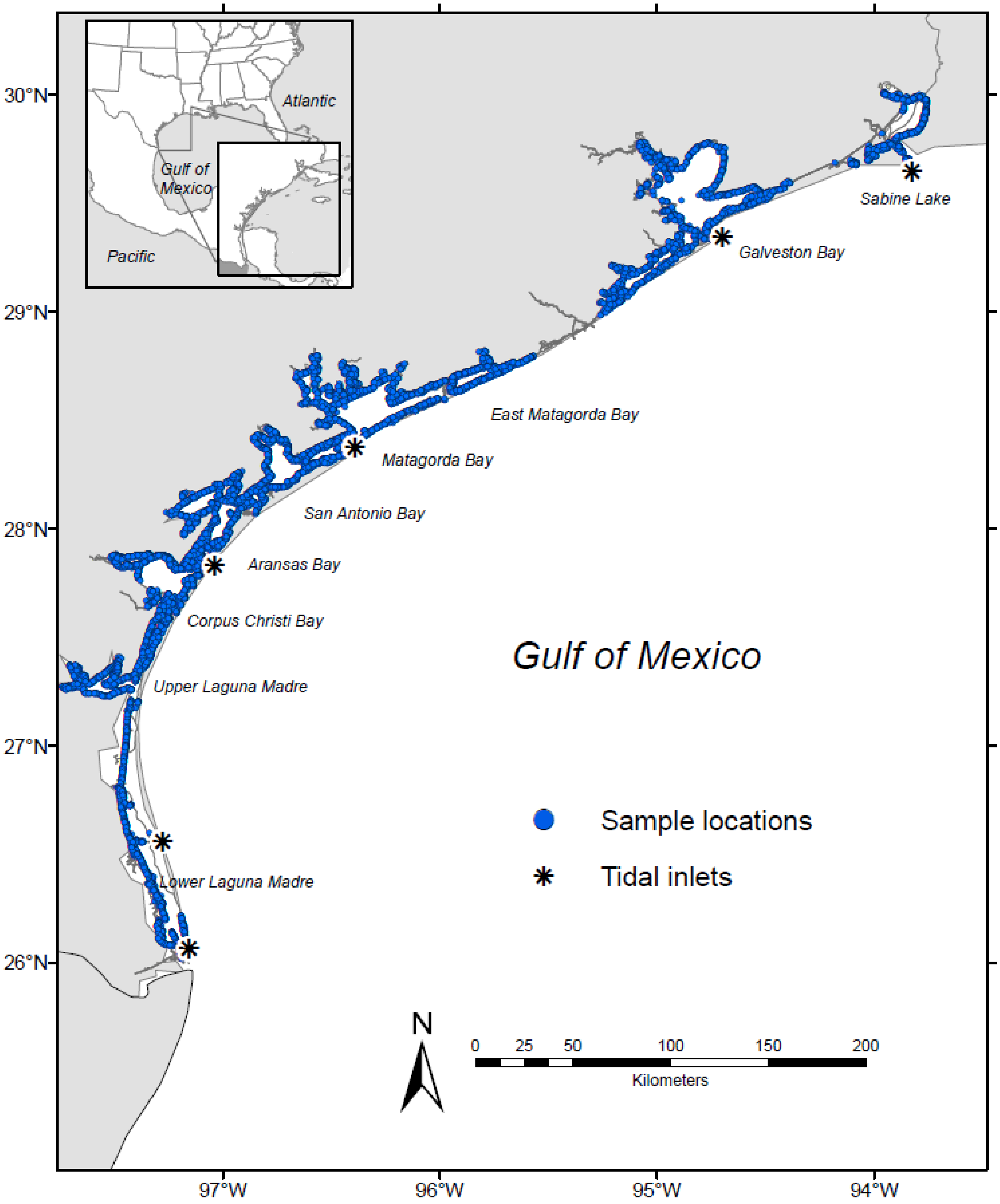

Figure 4.1: Bag seine sampling locations (blue circles, n = 18,078) for the TPWD Resource and Sport Harvest Monitoring Program from January through May, 1979 – 2007 (each site was sampled once over the course of the study).

Data Collection

Data were provided courtesy of the Texas Parks and Wildlife Department (TPWD) collected as part of their Resource and Sport Harvest Monitoring Program of finfish and shellfish that has occurred since 1977 for juveniles in nine bays along the Texas coast (Figure 4.1; 1977-2007, n = 18,078). All sampling followed protocols detailed in the "Marine Resource Monitoring Operations Manual" (Martinez-Andrade et al. 2009). Juvenile southern flounder (< 2 years, 11-290 mmTL; Stokes 1977; Etzold and Christmas 1979; Stunz et al. 2000) were sampled monthly using a randomized, stratified sampling design along the shoreline of each bay with 18.3 x 1.8-m bag seines. The bag seines used in this study were designed to sample juvenile estuarine fish populations (Martinez-Andrade 2009). While formal gear selection studies were not performed, previous studies on this species have shown this to be an effective gear for sampling juvenile southern flounder (Nañez-James et al. 2009). Bag seines were deployed perpendicular to the shoreline and were carried parallel to shore for 15.2 m. Twenty bag seines were deployed each month in Sabine Lake, Galveston Bay, West Matagorda Bay, San Antonio Bay, Aransas Bay, Corpus Christi Bay, Upper Laguna Madre, and Lower Laguna Madre, and 10 bag seines were deployed each month in East Matagorda Bay. Months January through May were used in the analysis due to these months showing high juvenile recruitment among Texas bays (Nañez-James et al. 2009; Froeschke et al. 2011).

Patterns of eight variables relevant to fish were examined coast-wide to investigate relationships between environmental conditions and juvenile southern flounder distributions (Figure 2). Data including salinity (psu), temperature (°C), turbidity, and dissolved oxygen (mg O_2 l^{-1}) were collected in the surface waters (0-15 cm) for each sampling event. Turbidity readings were processed in the laboratory within 24 h using a calibrated turbidimeter. Water elevations at the sampling time and location were also recorded for each sample. All variables were measured during each sampling (i.e., all years and bays).

To examine potential relationships between juvenile southern flounder distribution and the connection to the Gulf of Mexico, distance from each sampling location to the nearest tidal connection to the Gulf of Mexico (Figure 4.1) was calculated using the cost-distance function in the ArcGIS software package with the spatial analyst extension (ESRI), using the shoreline as a barrier (Whaley et al. 2007; Froeschke et al. 2010, Chapter 3). For this purpose, two distances matrices were calculated. One distance matrix was developed without Packery Channel inlet and applied to all samples that occurred prior to the opening of this channel. A second matrix was calculated including Packery Channel and the distance estimates were applied to all sampling events after June 2005. Cost-distance functions calculate the shortest distance between two points but were constrained within geographic boundaries (i.e., water) to provide more accurate relative distance estimates than Euclidian (straight-line) techniques (Froeschke et al. 2010, Chapter 3).

Spatio-Temporal Models

Relationships of juvenile southern flounder with physical, spatial and temporal variables were determined using a forward fit, stage-wise, binomial boosted regression tree model (De'ath 2007). Boosted regression trees (BRT) is an ensemble method and is a combination of techniques between statistical and machine learning traditions that has the power to: 1) accept different types of predictor variables; 2) accommodate missing values through the use of surrogates; 3) resistant to effects of outliers; and 4) capable of fitting interactions between predictors (Elith et al. 2006; Leathwick et al. 2006; Elith et al. 2008; Leathwick et al. 2008). This method is a relatively new method to ecological questions but has shown to be an effective method to identify relationships between fish distribution patterns and environmental predictors (Leathwick et al. 2006, 2008, Froeschke et al. 2010, Chapter 3).

Unlike traditional regression techniques, BRT combine the strength of two algorithms, regression trees and boosting, to combine large numbers of relatively simple tree models instead of a single “best” model (Elith et al. 2006, Leathwick et al. 2006, Elith et al. 2008, Leathwick et al. 2008). Each individual model consists of a simple regression tree assembled by a rule-based classifier that partitions observations into groups having similar values for the response variable based on a series of binary splits constructed from predictor variables (Friedman 2001, Leathwick et al. 2006, Elith et al. 2008). The BRTs often have a higher predictive performance than single tree methods due to the inherent strengths of regression trees and the robustness of model averaging that improves predictive performance. While overfitting can occur, this is minimized by incorporating 10-fold cross validation into the model fitting process (Elith et al. 2006; Leathwick et al. 2006; Elith et al. 2008; Leathwick et al. 2008).

Analyses were conducted in R (version 2.9, R Development Core Team) using the ‘gbm’ library supplemented with functions from Elith et al. (2008). Eight predictors were included in the model: year, month, depth (m), dissolved oxygen (mg O_2 l^{-1}), temperature (°C), turbidity, salinity (psu), and distance to the inlet, (Figure 4.2). The adjustable model parameters for BRT are tree complexity (*tc*), learning rate (*lr*), and bag fraction, where *tc* controls whether interactions are fitted, *lr* determines the contribution of each tree to the growing model, and bf specifies the proportion of data to be selected at each step (Elith et al. 2008). The model was fit to allow interactions using a tree complexity of 5 with a learning rate of 0.01 to minimize predictive deviance and maximize predictive performance. Ten-fold cross validation of training data (n = 12,651) was used to determine the optimal number of trees.

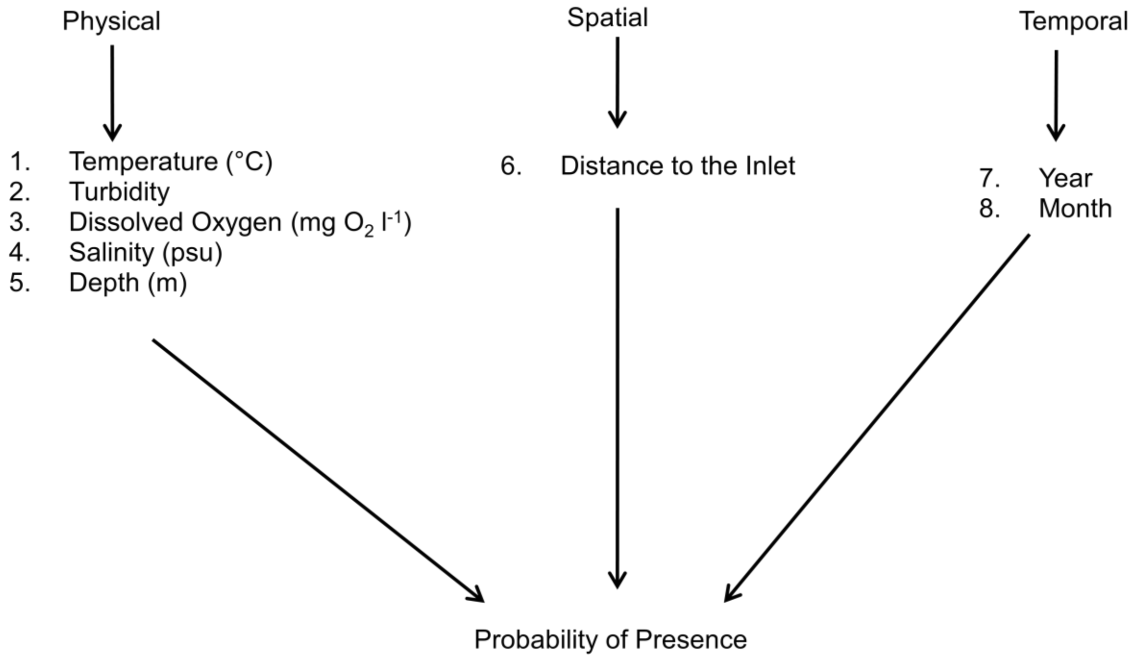

Figure 4.2: Road map for Boosted Regression Trees and Artificial Neural Networks to identify probability of presence for juvenile southern flounder along the Texas coast.

Artificial Neural Networks

Artificial Intelligence Neural Network models (ANN) do not have assumptions of linearity, normality or homogeneity (Campbell et al. 2007), model multivariate and non-linear data with discontinuous regions, and do not require transformation of data (Suryanarayana et al. 2008) . Therefore, ANN provides an appropriate technique to approximate nonlinear relationships and have been suggested as one of the best choices for modeling spatio-temporal patterns of fish (Suryanarayana et al. 2008). Fishery data sets consist of complex hydrographical patterns with abundance and dynamics of different phases with the life cycle of fishes (Suryanarayana et al. 2008). The data set used in the project consisted of a wide range of variables and the sigmoid function of the neural network is more resistant to the effects of extreme values than regression based models (Campbell et al. 2007). Moreover, Chen and Ware (1999) showed that a multilayer feed-forward neural network with back-propagation learning algorithm was a sufficient model to predict the recruit biomass of Pacific herring.

ANN are well-accepted classification tools that consist of neurons (processing units) with weights and biases (parameters) are fitted by training over a portion of the data set. The result is a model mapping a set of given values (inputs) to an associated set of values (output; Saila 2005; Zuur et al. 2007). Model weights are trained by passing through a pair set of inputs and outputs and adjusting progressively the weights to minimize the error between the answer predicted by the ANN and the true answer that was provided (Zuur et al. 2007). All the inputs are individually weighted and combined prior to being transformed in a hidden layer (consisting of a variable number of neurons) that performs a non-linear transformation of the derived linear value (Zuur et al. 2007). A sigmoidal-sigmoidal, multilayer feed-forward ANN model with back propagation learning algorithm was used to predict the presence and absence of juvenile southern flounder along the Texas Coast. The model consisted of 8 inputs (year, month, depth (m), dissolved oxygen (mg O_2 l^{-1}), temperature (°C), turbidity, salinity (psu), and distance to the inlet, (Figure 4.3), one hidden layer consisting of 4 hidden neurons, and the output layer with the presence and absence of southern flounder as the target (n= 12,651; Figure 4.3). The number of hidden neurons was determined by comparing area under the curve for each Receiver Operating Characteristic (ROC) graph and a validation set was used to avoid overfitting. Analyses were conducted using the nprtool package in MATLAB^R (2010b, The MathWorks, Natick, MA).

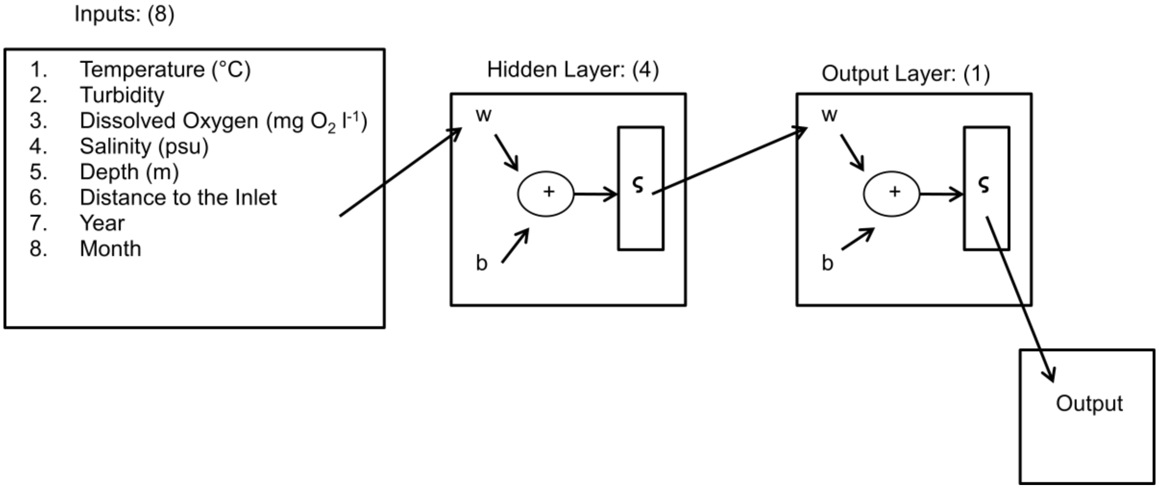

Figure 4.3: Road map for the sigmoidal-sigmoidal, multilayer feed-forward ANN model with back propagation learning algorithm, consisting of eight inputs, one hidden layer, four hidden neurons, and one output layer.

Model Selection

The data set (n = 18,078) was randomly split into a training (70%, n = 12,651) and independent testing set (30%, n = 5,427). Model performance and comparison for BRT and ANN was assessed on predictions to the independent testing set. For each model, six performance metrics were determined 1) the area under the ROC curve (ROC), 2) percent correct, 3) critical success index (CSI), 4) false alarm rate (FAR), 5) hit rate, and 6) odds ratio (Wilks). To identify spatial patterns of recruitment the probability of capture was predicted to the study area using a form of logistic regression based on the fitted BRT and ANN models (Elith et al. 2008). Predictions were conducted based off the probability that a species occurs (y =1), at a location with covariates X, $P(y = 1|X)$ using the logit: logit($P(y = 1 \mid X) = f(X)$ scale. Suites of environmental conditions were developed for each month (January - May) based on environmental parameters measured during each month included in the analysis using ordinary kriging (Saveliev et al. 2007). The BRT and ANN model output was then used to predict probability of capture coast wide during these specific seasonal conditions. To evaluate the performance of the mapped probability of occurrence for each model (ANN and BRT), probability of occurrence at each sampling location was compared to the independent testing dataset (not used in model building). Using this approach, predicted probability of occurrence model was evaluated using the area under the receiver operator characteristic curve (ROC).

RESULTS

Model Parameters

On the Texas coast, physical conditions vary widely among bay systems creating an ideal study region. Salinity increases with decreasing latitude from hyposaline positive (Sabine Lake and Galveston Bay) to moderate (15-35 psu) along the central coast, and hypersaline negative estuaries (> 35 psu) in the southernmost Upper and Lower Laguna Madre. Over the course of the study salinity ranged from 0 psu to 64.30 psu and consisted of a mean of 20.95 psu (Figure 4.4A). Mean sea surface temperature also increases slightly from north to south along the coast, ranging from 1.4°C to 36.50°C with a mean of 20.95°C (Figure 4.4B). Dissolved oxygen concentration (range = 0 – 28.00 mg O_2 l^{-1}, mean = 8.21 mg O_2 l^{-1}, Figure 4.4C), turbidity (range = 0 – 999, mean = 33.16; Figure 4.4D), and sampling depths (range = 0-6.6 m, mean = 0.44 m; Figure 4.4E) are similar among bay systems.

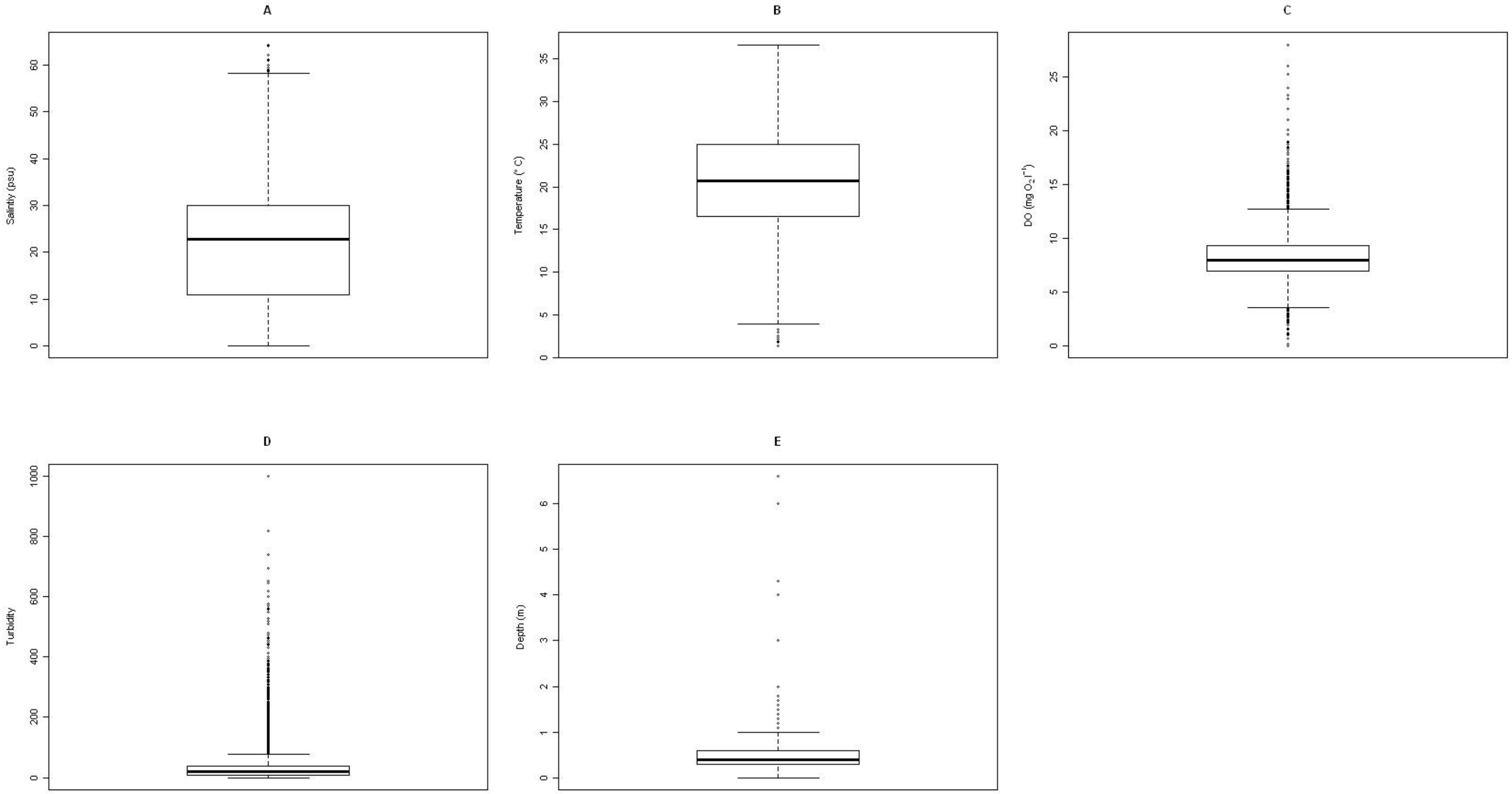

Figure 4.4: Box plots of the physical variables included in both the Boosted Regression Trees and Artificial Neural Networks.

A) Salinity (psu); B) Temperature (°C); C) Dissolved oxygen (mg O_2 l^{-1}); D) Turbidity; E) Depth (m)

Table 4.1: Predictive performance of boosted regression trees (BRT) models for juvenile southern flounder. *tc* = tree complexity, *lr* = learning rate, *bf* = bag fraction, and *nt* = number of trees.

					Percentage Deviance Explained				**Area under the receiver operating characteristic curve (ROC)**		
	tc	*lr*	*bf*	*nt*	Cross-Validation	Training	Total Deviance	Independent	ROC Cross-Validation	ROC Cross-Validation SE	Train
southern flounder	5	0.01	0.6	1550	9.70%	19.30%	0.647	0.757	0.735	0.004	0.828

Boosted Regression Trees

Southern flounder were captured in 1,255 of 12,651 (frequency of occurrence = 10%) samples from January to May in the training data set and in 550 of 5,427 samples in the independent (testing) data set. Model evaluation suggests good predictive performance to independent data (n = 5,427; ROC = 0.757; Table 4.1). Furthermore, evaluation of the training model also suggests good predictive performance (ROC = 0.828; Figure 4.5) and with a threshold value of 0.15, 775 southern flounder were observed and predicted, 1,754 were not observed but were predicted, 480 were observed but not predicted and 11,396 were not observed and were not predicted (Table 4.2). Overall, a threshold of 0.15 consisted of 82% correct, a CSI ratio of 0.26, FAR = 0.69, and odds ratio was 3.12 (Table 4.2).

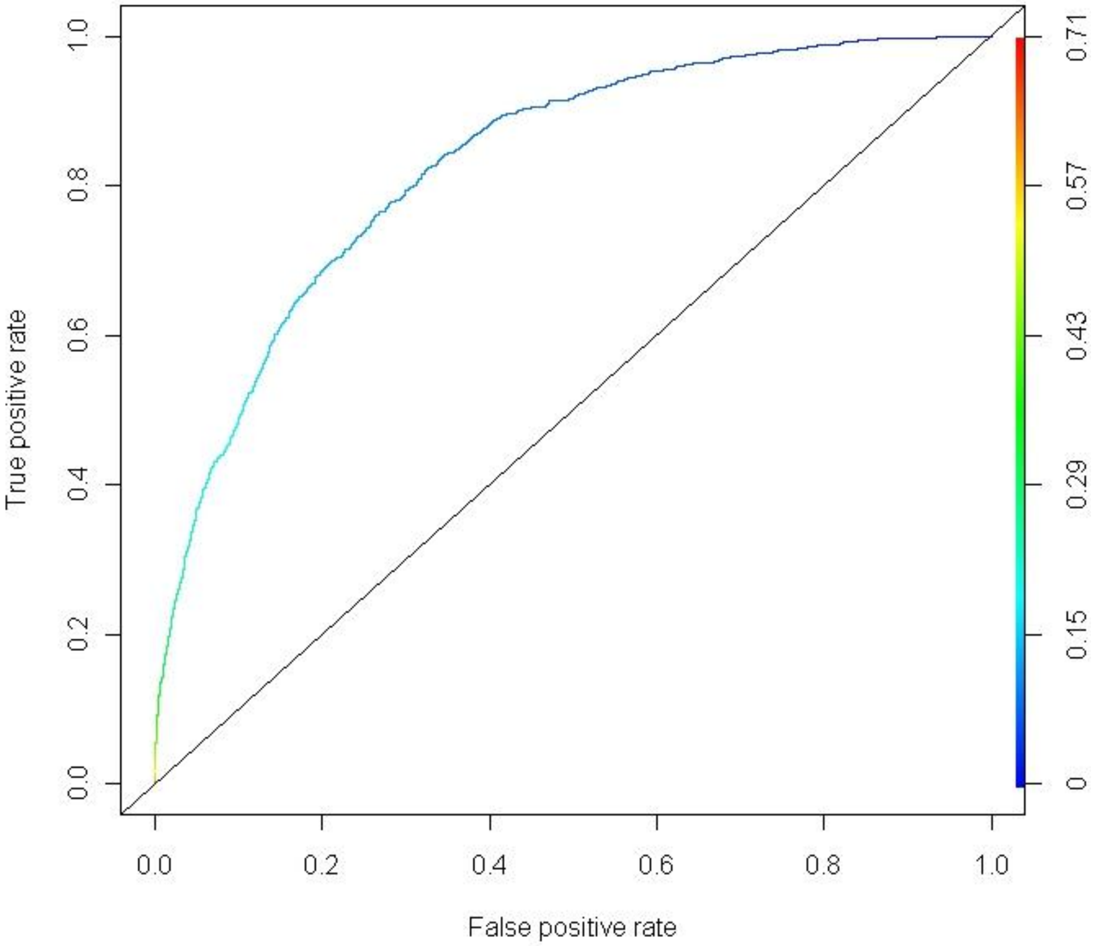

Figure 4.5: Receiver operating characteristic curve obtained from the trained Boosted Regression Tree model indicating strong predictive power (ROC=0.828).

Table 4.2: Contingency table obtained from receiver operating characteristic curve (threshold = 0.15) constructed from the trained Boosted Regression Tree spatio-temporal model for juvenile southern flounder along the Texas coast.

Threshold = 0.15				
		Observed		
		Yes	**No**	
Forecast	**Yes**	775	1,754	
	No	480	9,642	
	Total	1,255	11,396	12,651

The training model including all variables to predict the relationship of spatial, physical and temporal variables with the distribution of juvenile southern flounder was used to evaluate the relationship of model parameters with the occurrence of juvenile southern flounder. Temporal variable month (17.5%) and spatial variable DI (16.7%) explained the highest deviance with probability of occurrence substantially increasing from January to March and decreasing after March to May and there was a bimodal distribution with respect to the distance from the nearest inlet (Figure 4.6). Year of capture (15.2%) indicated the highest occurrence of capture occurred in the late 1980s and mid 1990s and that the probability of occurrence of juvenile southern flounder decreases since 1997 (Figure 4.6). Temperature explained the most deviance out of the physical variables (14.8%) followed by salinity (11.5%), turbidity (11.5%), DO (7.6%), and depth (5.1%; Figure 4.6). The fitted functions from the BRT model indicated that highest occurrence rates of juvenile southern flounder were in march, closest to the inlet, water temperature greater than 10°C, salinity less than 40 psu, turbidity of 200 and greater than 300, and depth greater than 1m (Figure 4.6).

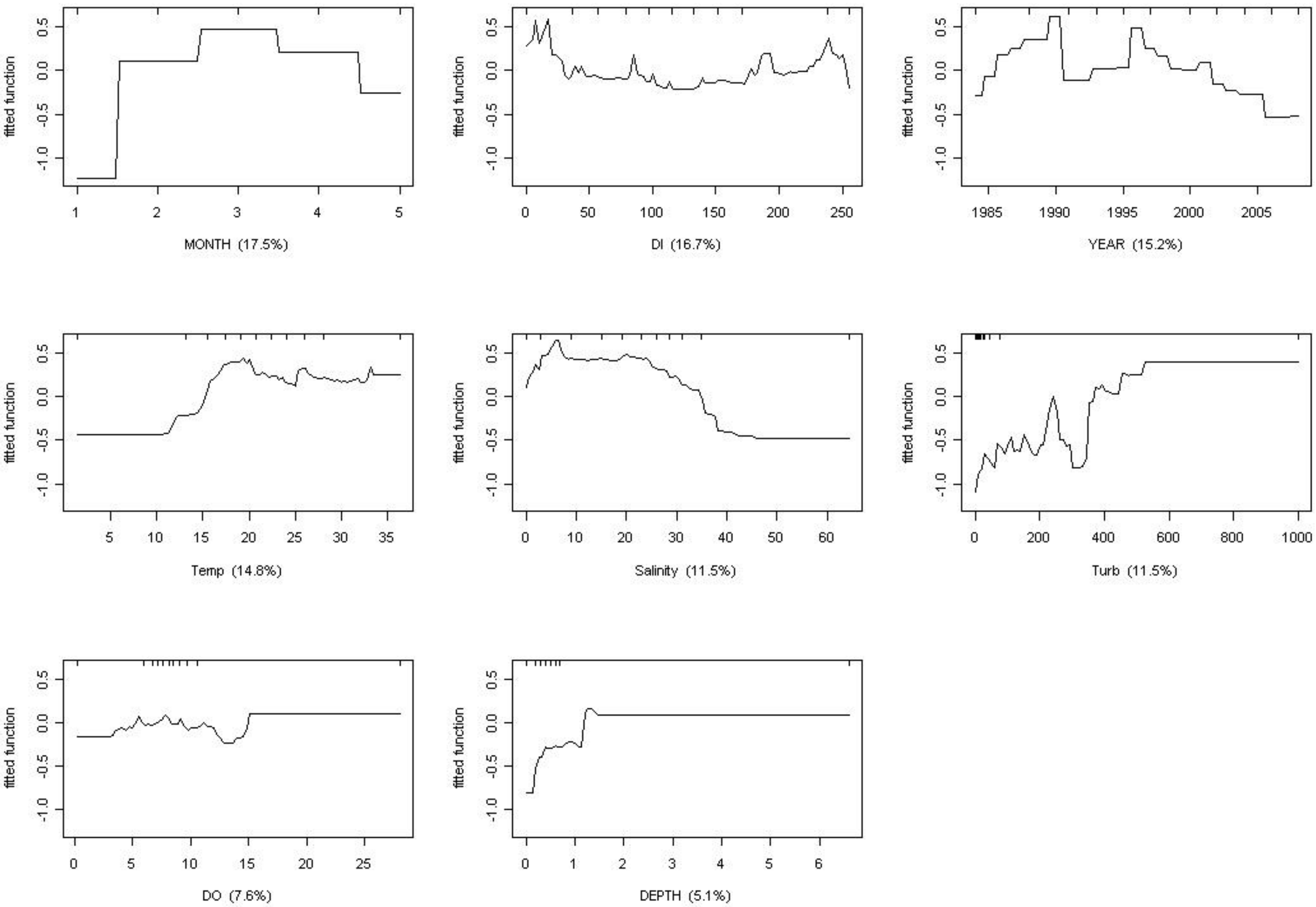
fitted function
0.5
0.0
-0.5
-1.0
1
2
3
4
5
MONTH (17.5%)
0
50
100
150
200
250
DI (16.7%)
1985
1990
1995
2000
2005
YEAR (15.2%)
5
10
15
20
25
30
35
Temp (14.8%)
0
10
20
30
40
50
60
Salinity (11.5%)
0
200
400
600
800
1000
Turb (11.5%)
0
5
10
15
20
25
DO (7.6%)
0
1
2
3
4
5
6
DEPTH (5.1%)

Figure 4.6: Functions fitted for the eight predictor variables by a boosted regression trees (BRT) model relating the probability of capture of juvenile southern flounder to the environment in order to identifying probability of capture along the Texas coast. Y-axes are on the logit scale with mean zero. X-axes parameters: month (1= January, 2 = February, 3= March, 4=April, 5=May), distance to the nearest inlet, year, temperature (Temp; ˚C), salinity (psu), turbidity, dissolved oxygen (DO; mg O_2/l), and depth (m).

The independent testing set (n=5,427) was used to determine spatial predictions. However, for sites that were sampled multiple times through the course of the study the mean probability of occurrence for each sampling event determined by averaging all data points for each site, thus consisting of a spatial testing data set where n=3,375 predictions. Spatially explicit model (n=3,375) predictions of probability of capture from the BRT models were determined for each month (January - May) by making predictions of the fitted BRT model to interpolated surface of environmental variables. Spatial model suggested good predictive performance to independent data (ROC = 0.719; Figure 4.7). Southern flounder were captured in 334 of 3,375 (frequency of occurrence = 10%) samples from January to May in the spatial testing data set. Based on the spatial testing ROC, with a threshold value of 0.10, 243 southern flounder were observed and predicted, 1,199 were not observed but were predicted, 91 were observed but not predicted and 1,842 were not observed and were not predicted (Table 4.3). Overall, a threshold of 0.10 consisted of 62% correct, a CSI ratio of 0.16, FAR = 0.83, and odds ratio was 4.10 (Table 4.3).

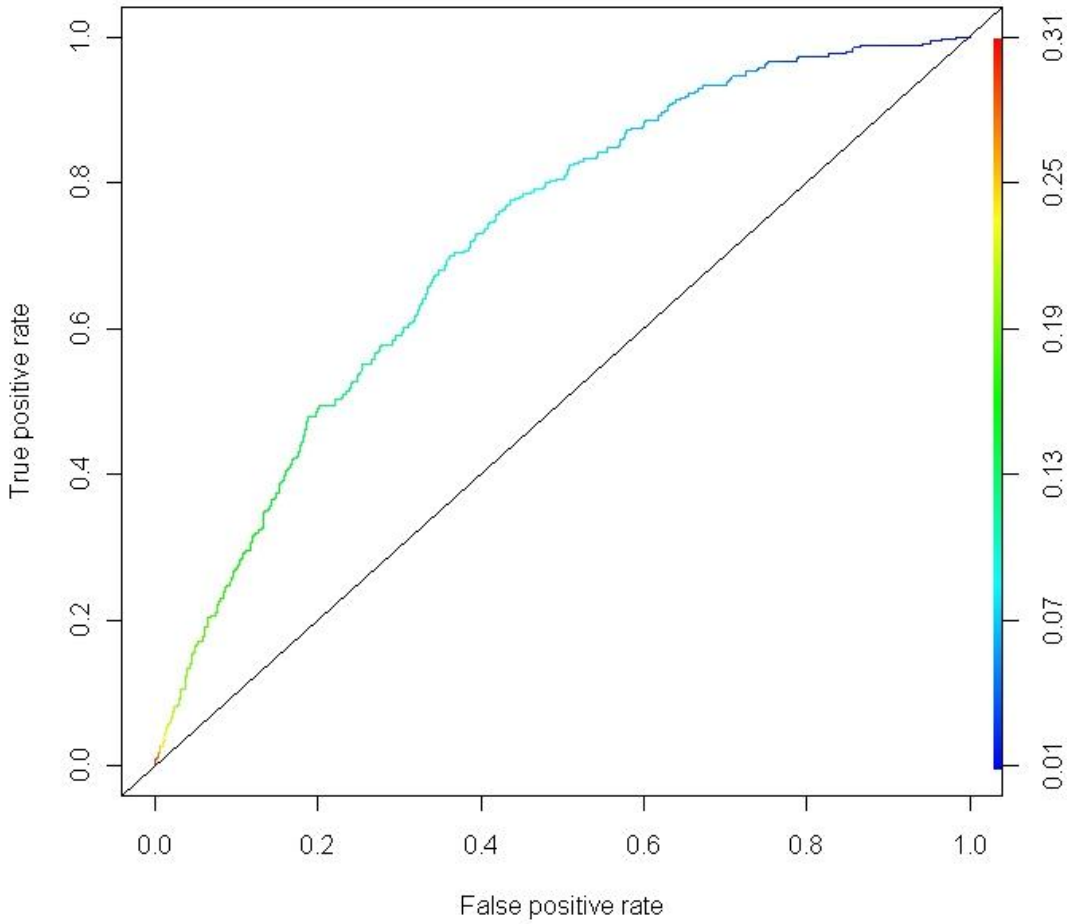

Figure 4.7: Receiver operating characteristic curve obtained from the spatial tested data set against the trained Boosted Regression Tree model indicating good predictive power to an independent data set (ROC=0.719).

Table 4.3: Contingency table obtained from receiver operating characteristic curve (threshold = 0.10) constructed from the spatial testing Boosted Regression Tree spatio-temporal model for juvenile southern flounder along the Texas coast.

Threshold = 0.10				
		Observed		
		Yes	**No**	
Forecast	**Yes**	243	1,199	
	No	91	1,842	
	Total	334	3,041	3,375

Probability of capture varied both temporally and spatially. Capture probability increased each month from January to March, declined slightly in April and was low during May (Figure 4.8). Spatial patterns were also evident. Probability of capture began increasing first in Galveston Bay and East Matagorda Bay in February (Figure 4.8B). In March probability of capture was the highest near the tidal inlets from Galveston Bay to Corpus Christi and between Galveston and East Matagorda Bay (Figure 4.8C). In April probability of occurrence started to slightly decrease between East Matagorda Bay and Corpus Christi Bay (Figure 4.8D). Overall, probability of capture increased with areas consisting of low salinities, cooler temperatures and areas closest to tidal inlets.

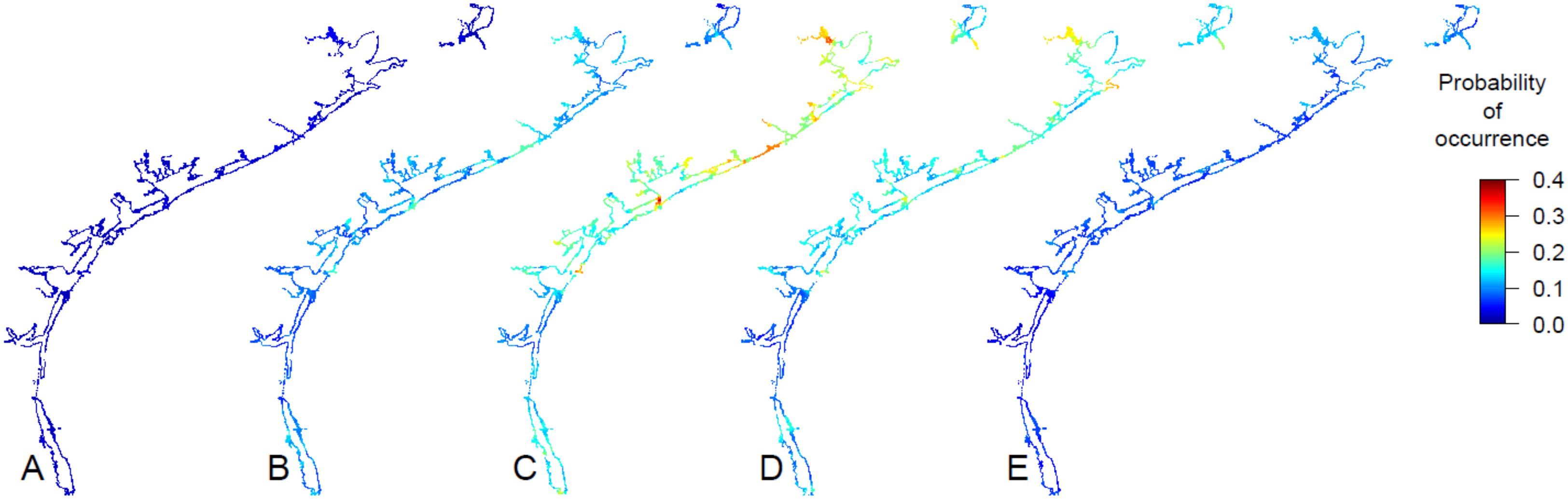

Figure 4.8: Spatial prediction of juvenile southern flounder from the “best” boosted regression trees (BRT) model indicating the highest probability of collection would occur in March in Galveston Bay, East Matagorda Bay, and areas closest to the inlets. BRT spatial predictions of juvenile southern flounder capture for the months of A) January, B) February, C) March, D) April, and E) May

Neural Network

The "best" neural network model based off of ROC for predicting the presence and absence of southern flounder consisted of eight inputs and 4 hidden neurons (Figure 4.3). Model evaluation suggested good predictive performance to independent data (n = 5,427; mean square error = 0.09). Furthermore, evaluation of the training model also suggested good predictive performance (mean square error = 0.08; ROC = 0.707; Figure 4.9) and with a threshold value of 0.08, 782 southern flounder were observed and predicted, 3,950 were not observed but were predicted, 473 were observed but not predicted and 7,446 were not observed and were not predicted (Table 4.3). Overall, a threshold of 0.12 consisted of 65% correct, a CSI ratio of 0.15, FAR = 0.83, and odds ratio was 3.12 (Table 4.3).

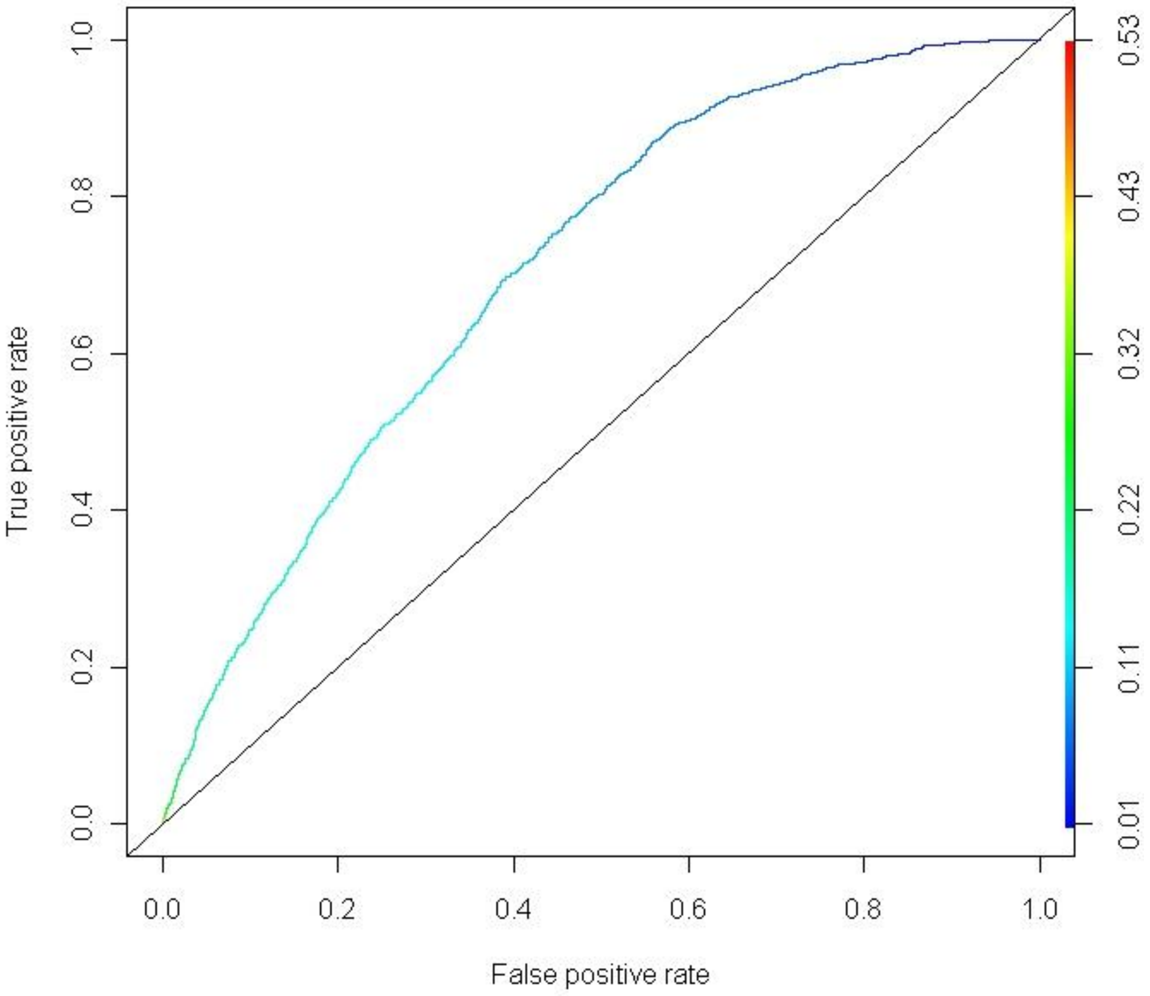

Figure 4.9: Receiver operating characteristic curve obtained from the trained Artificial Neural Network model indicating strong predictive power (ROC=0.707).

Table 4.4: Contingency table obtained from receiver operating characteristic curve (threshold =0.12) constructed from the trained Artificial Neural Network spatio-temporal model for juvenile southern flounder along the Texas coast.

Threshold = 0.12				
		Observed		
		Yes	**No**	
Forecast	**Yes**	782	3,950	
	No	473	7,446	
	Total	1,255	11,396	12,651

Spatially explicit model predictions of probability of capture from the ANN model were determined for each month (January - May) by making predictions of the fitted ANN model to interpolated surface of environmental variables. Spatial model suggested good predictive performance to independent data (ROC = 0.69; Figure 4.10). Spatial testing set, with a threshold value of 0.10, 239 southern flounder were observed and predicted, 1,352 were not observed but were predicted, 95 were observed but not predicted and 1,689 were not observed and were not predicted (Table 4.2). Overall, a threshold of 0.10 consisted of 57% correct, a CSI ratio of 0.14, FAR = 0.85, and odds ratio was 3.07 (Table 4.4). Probability of capture varied both temporally and spatially. Capture probability increased each month from January to March, declined slightly in April and was low during May (Figure 4.11). Spatial patterns were also evident. Probability of capture began increasing first in Sabine Lake, Galveston Bay, and East Matagorda Bay in February (Figure 4.11B). In March probability of capture was the highest near the tidal inlets (Figure 4.11C). However, there was a relatively moderate to high probability of occurrence among all of the bays (Figure 4.11C). In April probability of occurrence started to slightly decrease between East Matagorda Bay and Corpus Christi Bay, but remained relatively high in around Sabine Lake, Galveston Bay, and the lower edge of Lower Laguna Madre (Figure 4.11D). In May probability of occurrence consisted of a similar pattern as January but moderate probability was still prevalent in Sabine Lake and Galveston Bay (Figure 4.11E). Overall, probability of capture increased with areas consisting of low salinities, cooler temperatures and areas closest to tidal inlets.

Table 4.5: Contingency table obtained from receiver operating characteristic curve (threshold =0.10) constructed from the spatial tested Artificial Neural Network spatio-temporal model for juvenile southern flounder along the Texas coast.

Threshold = 0.10				
		Observed		
		Yes	**No**	
Forecast	**Yes**	239	1,352	
	No	95	1,689	
	Total	334	3,041	3,375

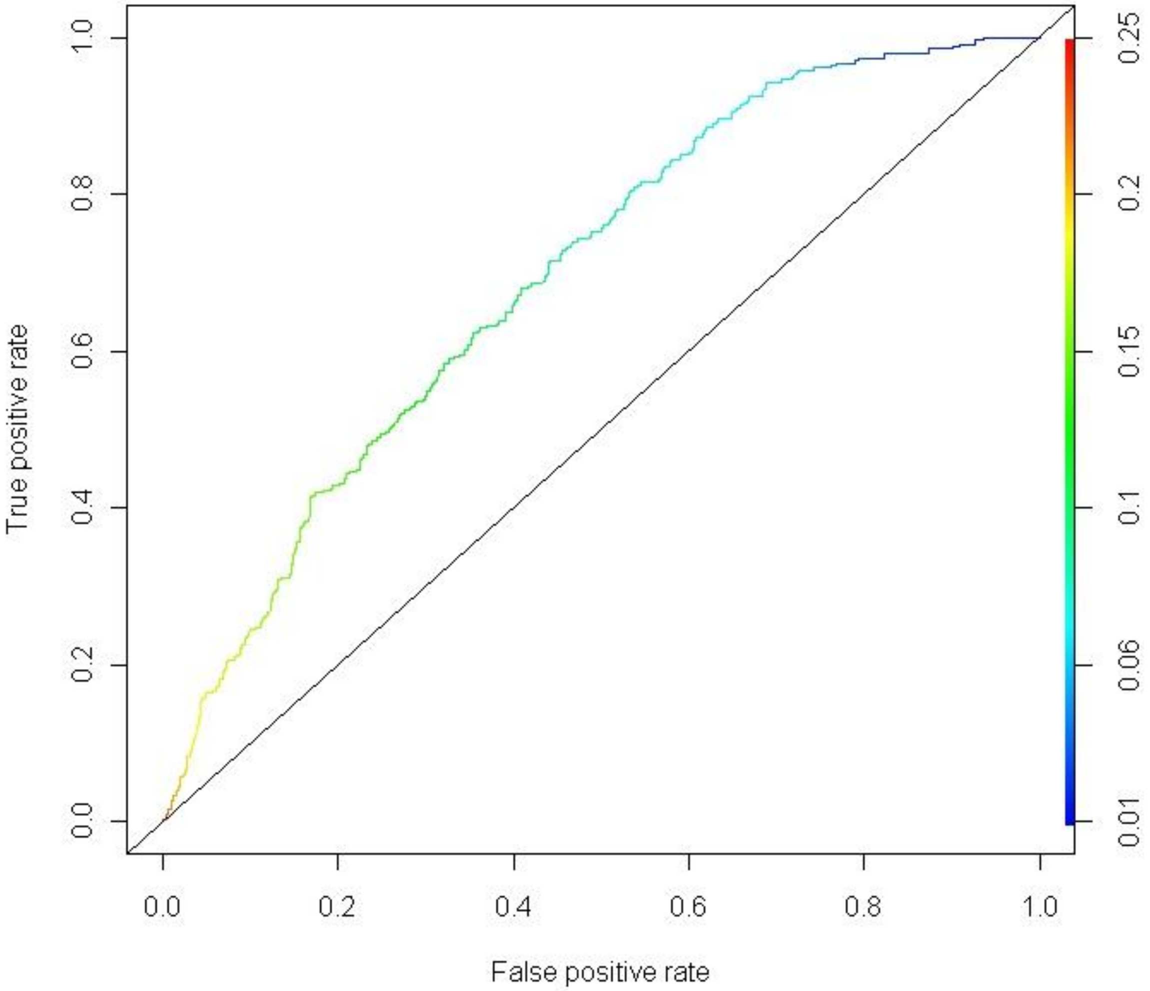

Figure 4.10: Receiver operating characteristic curve obtained from the spatial tested data set against the trained Artificial Neural Network model indicating good predictive power to an independent data set (ROC=0.69).

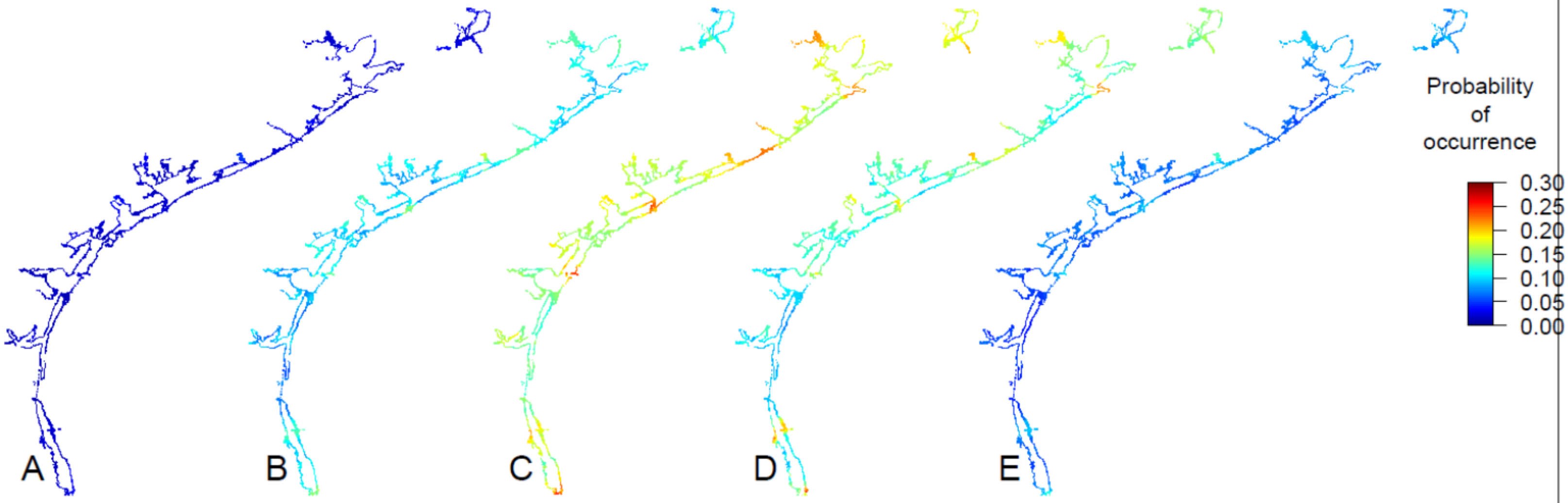

Figure 4.11: Spatial prediction of juvenile southern flounder from the “best” Artificial Neural Network (ANN) model indicating the highest probability of collection would occur in March in Sabine Lake, Galveston Bay, East Matagorda Bay, and areas closest to the inlets. ANN spatial prediction of juvenile southern flounder capture for the months of A) January, B) February, C) March, D) April, and E) March

DISCUSSION

Distribution and occurrence rates of juvenile southern flounder were influenced by temporal, physical, and spatial variables. Occurrence patterns exhibited strong seasonal variation and sampling month was the most influential variable in the BRT model. This study demonstrated the importance of incorporating temporal, physical, spatial variables, and their interactions in species habitat models to identify frequency occurrence patterns of juvenile southern flounder. Frequency of occurrence patterns exhibited strong seasonal variation and sampling month was the most influential variable in the BRT model. Probability of occurrence increased in the late winter months (February to March) before a slight decrease in April and May. Overall, juvenile recruitment patterns observed were consistent with seasonality of recruitment reported previously (Froeschke et al. 2011). Significantly higher abundances of juvenile southern flounder have been reported to occur along the Texas coast from February to May with a peak in March (Froeschke et al. 2011) while others have reported high recruitment variability in flatfish populations (Van deer Veer et al. 2000). Günter (1945) reported southern flounder recruitment in December and from February to April, whereas Stokes (1977) reported presence of juveniles starting in January with a peak in February. Simmons and Hoese (1959) stated recruitment time from March to May with highest abundance present in April, and Rogers and Herke (1985) reported January to March with peaks occurring from February to March.

Sampling year was the third most important variable demonstrating increasing probability of occurrence until 1990 and then a large decline followed by an increase in

1996 before a steady decline until the end of the study period in 2007. Results are consistent with reported time series analysis demonstrating a long-term decline in recruitment of this species in Texas (Froeschke et al. 2011).

Distance to the nearest inlet, was the second most important predictor of occurrence with the highest probability of occurrence closest to the inlet, indicating that EFH occurs among habitats closest to the inlets. Many estuarine species increase in abundance near inlets (Whaley et al. 2007, Froeschke et al. 2010). Essential fish habitat for young-of-the-year southern flounder in Aransas Bay and Copano Bay, TX was suggested to occur in vegetated habitats (seagrass and marsh edge) that occur closest to the tidal inlet between Aransas Bay and the Gulf of Mexico and in high salinity (Nañez-James et al. 2009) However, this study was limited to single inlet and the vegetated habitats are most abundant near the inlets, thus a broader investigation was necessary to identify spatial patterns of recruitment with respect to tidal inlets. The current study considered inlets with a variety of habitat types nearby and suggests that inlet proximity remains an important feature of habitat quality across biotic habitat types.

With respect to environmental variables, temperature was the most important predictor of occurrence with the highest occurrence at temperatures less than 20°C. These results indicate temperatures less than 20°C are optimal for recruitment of juvenile southern flounder. Previous work has shown that the optimum temperature recruitment of southern flounder is 16°C – 16.2°C (Stokes 1977). However, juvenile southern flounder in Texas have been captured in water temperatures between 14.5°C – 21.6°C (Gunter 1945). Moreover, a study on juvenile southern flounder in the MANERR (Aransas Bay complex Texas, USA) indicated the highest probability of occurrence at temperatures less than 15°C (Chapter 3.). Due to selected preference of cooler temperatures, projected sea temperature increases are of potential concern for this species. Seawater temperature is projected to increase by 4°C in the 21st century (Thuiller 2007). Both AppleBaum and Montagna (2005) and Fodrie et al. (2010) have previously reported rising sea temperatures within the Gulf of Mexico. Additional predicted increases in temperature could have substantial effects on the temporal and spatial recruitment patterns and ultimately, population size of southern flounder

Salinity was also an important predictor of frequency occurrence; southern flounder frequency of occurrence was highest at salinities less than 10 psu and decreased at salinities greater than 40 psu. Spatial predictions from both the BRT and ANN indicated highest probability of juvenile southern flounder occurring in Sabine Lake and Galveston Bay and lowest probability of occurrence in the Upper and Lower Laguna Madre. Along the Texas coast, salinity increases with decreasing latitude from hyposaline positive (Sabine Lake and Galveston Bay) to moderate (15-35 psu) along the central coast, and hypersaline negative estuaries (> 35 psu) in the southernmost Upper and Lower Laguna Madre. Southern flounder are considered highly euryhaline (Deubler 1960), but it has been shown that survivorship and growth rates are increased in lower salinity waters (Stickney and White 1974, Hickman 1968). Thus, these data support that characteristics of Sabine Lake and Galveston Bay are more conducive to southern flounder based on low salinity levels and cooler water temperatures. These results highlight the potential ramifications of reduced freshwater inflow into these bay systems as historic inflows are diverted for human usage.

Turbidity and dissolved oxygen were less important predictors of occurrence. This is consistent with Froeschke et al. (Chapter 3) that did not find an effect of turbidity on the probability of occurrence of juvenile southern flounder in the MANERR. While dissolved oxygen levels can influence the distribution, abundance, and diversity of organisms (Breitburg 2002, Vaquer-Sunyer 2008, Montagna and Froeschke 2009), this primarily occurs at low oxygen levels (i.e., < 2 mg O_2 l^{-1}). In this study, few samples were taken in low DO conditions. However, low dissolved oxygen events (e.g., hypoxia) are increasing in frequency and spatial extent in Texas estuaries (Applebaum et al. 2005, Montagna and Froeschke 2009), and these data suggesting oxygen level could influence the distribution and abundance of southern flounder.

Southern flounder spawning and recruitment success may be directly influenced by estuarine conditions highlighting the importance of high quality habitat necessary to support important fishery species. The interaction between habitat quantity and quality has been shown to effect survivorship of flatfish, with the largest recruitment potential occurring in areas with high habitat quantity and quality, and smallest recruitment potential in areas with low habitat quantity and quality (Gibson 1994). Biological variables such as prey abundance, predators, habitat structure, water depth, and physical factors such as, temperature, salinity, oxygen, and hydrodynamics affect growth and survival of flatfish (Gibson 1994; Allen and Baltz 1997; Stoner et al. 2001; Glass et al. 2008).

Both models indicated high probability of occurrence near the tidal inlets from Galveston Bay to Corpus Christi and between Galveston and East Matagorda Bay. Overall, probability of capture for both spatio-temporal models increased with areas consisting of low salinities, cooler temperatures and areas closest to tidal inlets. Although overall accuracy of the ANN was slightly lower than the BRT spatially tested model, the ANN correctly predicted higher probability of occurrence in Sabine Lake whereas the BRT did not. Based on the biology of the species we suggest that the high probability of occurrence in Sabine Lake is accurate. Moreover, BRT and ANN both displayed good predictive performance to the spatial prediction independent data set (BRT ROC = 0.719; ANN ROC = 0.69). The spatially tested BRT had a higher percent correct of predicting juvenile southern flounder (62%) than the ANN (57%). The ANN consisted of a similar possibly lower number of observed and predicted (n=239) than the BRT (n=243). However, the BRT (ROC = 0.828) had a higher predictive performance among the training set versus the ANN (ROC = 0.707). The BRT had a higher percent correct of predicting juvenile southern flounder (82%) than the ANN (65%). The ANN consisted of a similar possibly higher number of observed and predicted (n=782) than the BRT (n=775). The primary difference between the overall percent correct between the two models for the training and testing sets was the number of fish predicted that were not observed (ANN = 3950, BRT = 1754), suggesting, that the ANN and possibly the BRT could be overfitting these data among, a common feature of correlation based predictive models including ANN (Zuur et al. 2007). Despite this limitation, ANN remains among a powerful tools for prediction and often outperforms other methods (Suryanarayana et al. 2008). These results also suggest the need to evaluate a variety of potential methods to identify the most robust modeling approaches for a particular application which is difficult or impossible to identify apriori given the complexity of large multivariate data sets typically used to guide management of natural resources.

Mapped distribution patterns permit rapid identification and delineation of important areas in a spatio-temporal context that is essential for ecosystem based management approaches (Pikitch et al. 2004). Predicted mapped distribution patterns were very similar among the two spatio-temporal models indicating probability of capture varied both temporally and spatially, but in a predictable manner. For both models, capture probability increased each month from January to March, and declined slightly starting in April. Salinity levels in Sabine Lake are the lowest among the Texas bays, thus suggesting that the high predicted frequency of occurrence from the ANN is consistent with salinity preference seen among juvenile southern flounder (Stickney and White 1974, Hickman 1968, Chapter 3)

Despite the utility of our modeling approaches, there are some limitations to both methodologies. Model evaluation indicated good performance of the BRT and ANN at predicting independent testing data, although the inference value may be limited due to high residual deviance in the models. This suggests that some important variables in the habitat usage of these species may not have been included in the study. For example, biotic components: spawning location, prey and predator density, movement patterns of individuals were not considered in this study. However, I was able to examine several variables simultaneously that were related to habitat suitability providing timely information for conservation and management of this species. Spatially explicit models permit applications that are not feasible with other approaches (e.g., prediction of distribution patterns related to dynamic environmental patterns).

Construction of spatio-temporal models for juvenile southern flounder along the Texas coast addresses state and national estuarine and coastal resource management issues because it provides information on the spatial distribution and nursery habitat requirements for this fishery species. My results provide tools for fisheries managers to promote sustainability of the southern flounder fishery. The results also provide a predictive framework for proactive approaches to ecosystem management. Moreover, the spatio-temporal southern flounder predictive models provide crucial information needed to identify areas for habitat conservation. In addition, anthropogenic climate changes will certainly alter abiotic factors within marine environments; therefore, we must understand the importance of these changes to develop a more effective ecosystem-based management system. The data suggest that even if the best biotic habitat (e.g., seagrass meadow) is available this species may not be present if the physical environment (e.g., salinity) is not within the tolerable range for that species. The modeling approaches employed in this study provide a predictive framework from which changes in environmental conditions or management measures could be evaluated to promote development of sustainable management strategies for southern flounder in Texas.

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CHAPTER 5

CONCLUSIONS: THE CURRENT STATUS AND RECOMMENDATIONS OF THE SOUTHERN FLOUNDER (*PARALICHTHYS LETHOSTIGMA*) FISHERY IN THE NORTHERN GULF OF MEXICO

Fisheries management is beginning to focus on sustaining critical habitats and maintaining trophic linkages by managing entire ecosystems instead of single species by implementing an ecosystem-based fishery management (EBFM) approach, where interactions among physical, biological, and human components of the system are addressed (Pikitch et al. 2004; Marasco et al. 2007; Crowder et al. 2008; Zhou et al. 2010). The overall goals of EBFM are to sustain healthy marine ecosystems and the fisheries they support by addressing some of the unintended consequences of fishing, such as habitat destruction, incidental mortality of non-target species, and changes in the structure of ecosystems (Pikitch et al. 2004; Zhou et al. 2010). However, this type of EBFM relies on our ability to efficiently and effectively assess critical relationships between organisms and their habitat and has been problematic because of significant knowledge gaps regarding ecosystem use, population dynamics, and habitat use by marine species. To address these concerns EBFM will depend on efficiently and effectively assessing relationships between organisms and their habitat leading to identifying Essential Fish Habitat (EFH). Identification of EFH is critical for predicting the future status of a fishery, and for providing critical information needed for habitat conservation. Additionally, for EBFM to be successful we must understand the current status of single species fisheries and their relationship with the ecosystems. Declines of important fish species such as southern flounder in the Gulf of Mexico underscore the importance of defining critical habitats as well as the processes that contribute to habitat value as well as future changes to our climate. The purpose of my dissertation was to determine the current status of the southern flounder fishery, and to evaluate the relationship between juvenile southern flounder and the environment to make prediction about EFH for the species. This included current designation of EFH but also how this may change, as environmental condition changes affect southern flounder distribution patterns.

To address my objectives, I used field sampling in conjunction with a long-term fisheries independent data set (1975-2008) to assess population trends of juvenile and adult southern flounder (*Paralichthys lethostigma*) along the Texas coast in the northern Gulf of Mexico, USA. The long-term dataset, provided by Texas Parks and Wildlife Department, contained a total of 46,784 sites that were sampled with bag seines to monitor small nekton abundance and 22,870 sites that were sampled with gill nets to assess adult fisheries trends. These data were examined for age-specific population trends using generalized least squares and extended with non-parametric bootstrapping to obtain interval estimates of regression parameters (juveniles) and linear regression (adults). These data showed long-term declines in juvenile southern flounder abundance.For adult southern flounder, rate of decline was much more rapid. Results indicate that recruitment of southern flounder may not be the primary cause of the adult population decline given that catch rates of juveniles are nearly stable and the rate of decline in adults exceeds what can be explained by the decline in juveniles. The decline in adult southern flounder abundance may be attributed to lower survivorship of adults and late juveniles nearing maturity (sub-adult stage) due to increased fishing and/or natural mortality. Thus, leading to the need of understanding the way in which southern flounder respond to environmental variability (Beddington et al. 2007).

The next step of my research was to use data obtained from field collections within the Aransas Bay Complex from February – May 2010 to construct species habitat models for juvenile southern flounder that predicted EFH by incorporating the relationship between abiotic, and biotic factors temporally and spatially within MANERR of the Aransas Bay Complex; and 2) compare and contrast species-habitat models of southern flounder with a highly abundant flatfish, bay whiff (*Citharichthys spiloterus*; Allen and Baltz 1997; Walsh and Cyrus 1999). Interaction between habitat quantity and habitat quality has been demonstrated to effect survivorship of flatfish, with the largest recruitment potential to occur in areas with high habitat quantity and high habitat quality, and the smallest recruitment potential to occur in areas with low habitat quantity and quality (Gibson 1994). More specifically, it has been suggested that biological variables such as prey abundance, predators, habitat structure, water depth, and physical factors such as, temperature, salinity, oxygen, and hydrodynamics are all major factors exhibited to effect growth and survival of flatfish recruitment (Gibson 1994; Allen and Baltz 1997; Stoner et al. 2001; Glass et al. 2008).

The most robust species habitat model for both species was identified using Boosted Regression Trees (BRT). Ten predictors were included in the model: habitat type, dry weight, depth (m), dissolved oxygen (mg O_2/L), temperature (°C), turbidity (cm), salinity, pH, distance to the inlet, and month. The results demonstrated the importance of incorporating environmental and biological variables in species habitat models to identify areas suitable EFH designation. Species habitat model for juvenile bay whiff indicated that habitat type was not an important variable in predicating the occurrence of bay whiff, but were associated with low temperatures (< 15°C, 20-23°C), moderate percent dry weight of sediments (25-60%), salinity >10, and moderate to high dissolved oxygen (6-9 mg/L, 10-14 mg/L). Species habitat model for juvenile southern flounder indicated that southern flounder were associated with low temperatures (<15°C), low percent dry weight of sediment (<30 mg/L), seagrass habitats, shallow depths (<1.2 m), and high dissolved oxygen (>8 mg/L).

I suggest that EFH within the Aransas Bay Complex for juvenile bay whiff needs to occur among habitats (seagrass and non-vegetation) located along the east and north areas of Aransas Bay and the north-west corner of Copano Bay (seagrass and non-vegetation (Figure 5.1). For juvenile southern flounder I suggest EFH needs to occur in seagrass beds along the eastern edge of Aransas Bay (Figure 5.2). The southern flounder and bay whiff species habitat models constructed provides crucial information needed to identify areas critical for habitat conservation of nursery grounds of juvenile flatfishes within the Aransas Bay Complex. The models provide crucial information for natural research managers within the Aransas Bay Complex to conserve nursery habitats crucial for the various developmental stages of fisheries. By conserving appropriate habitat and understanding relationships between abiotic and biotic factors within those habitats the status of fisheries will improve.

Next my research objectives were to provide information needed for the fishery management plan of southern flounder by using statistical modeling techniques to understand how environmental factors influence the temporal and spatial patterns of juvenile southern flounder and to compare a relatively new modeling technique (BRT) with a well accepted technique (Artificial Neural Network) using the data acquired from the Resource and Sport Harvest Monitoring Program conducted by TPWD. This work demonstrated the importance of incorporating temporal, physical, and spatial variables in species habitat models to identify occurrence of juvenile southern flounder. Flounder distribution patterns exhibited strong seasonal variation and sampling month was the most influential variable in the BRT model. Probability of occurrence increased in the late winter months (February to March) before a slight decrease in April and May. Overall, juvenile recruitment patterns observed were consistent with seasonality and variation of periods of recruitment previously stated (Froeschke et al. 2011). Year of capture was the third most important variable demonstrating increasing probability of occurrence until 1990 and then a large drop and another slight increase in 1996 before a sharp decline. The results were consistent with reported time series analysis (Froeschke et al. 2011).

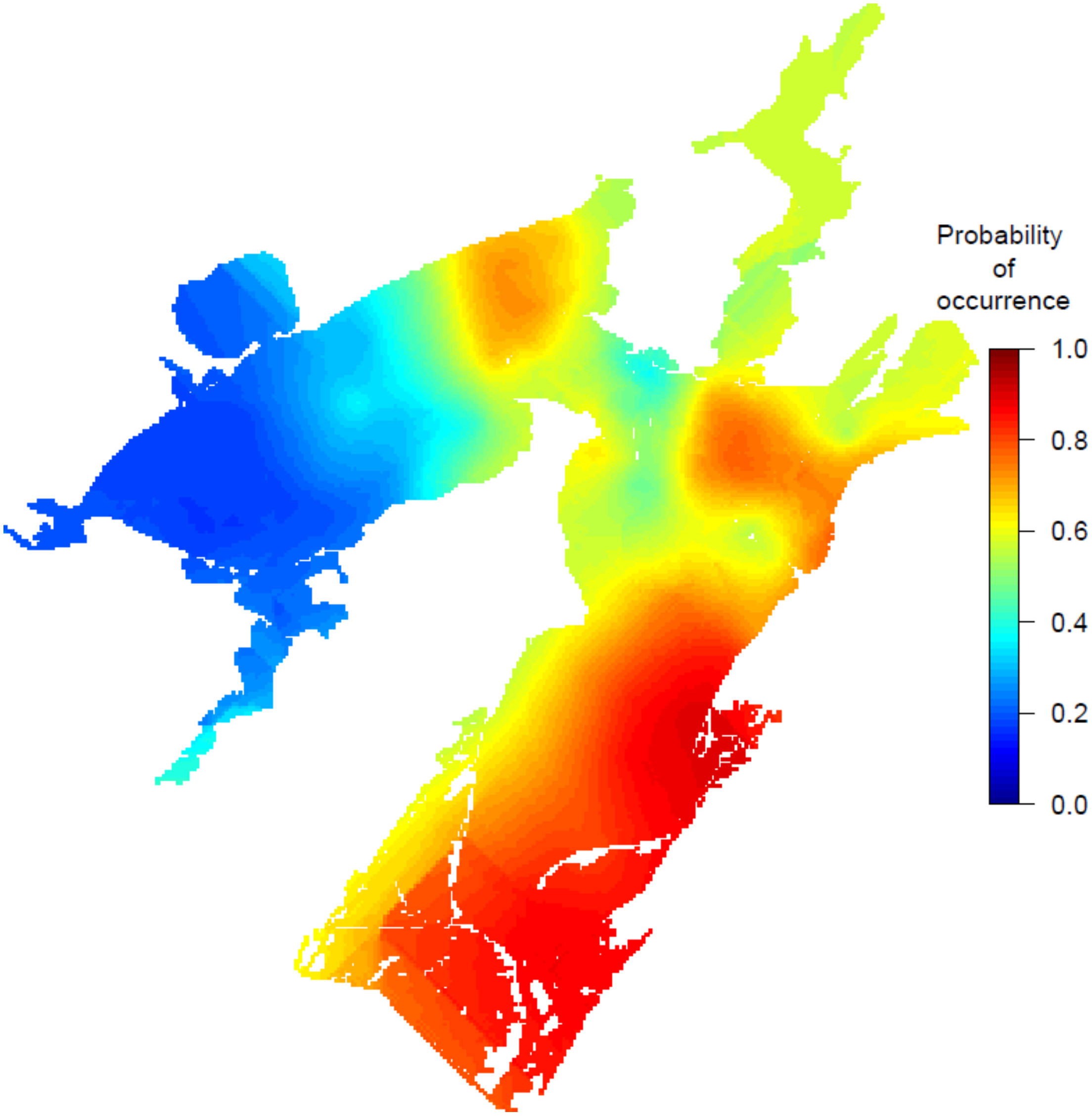

Figure 5.1: Spatial prediction of juvenile bay whiff from the “best” boosted regression trees (BRT) model indicating the highest probability of collection would occur among habitats located along the east and north areas of Aransas Bay and the north-west corner of Copano Bay. Moderate probability of occurrence for bay whiff occurred along the very west side along Aransas Bay and the north-east corner of Copano Bay. The lowest probability of occurrence for bay whiff occurred along the middle and south areas of Copano Bay.

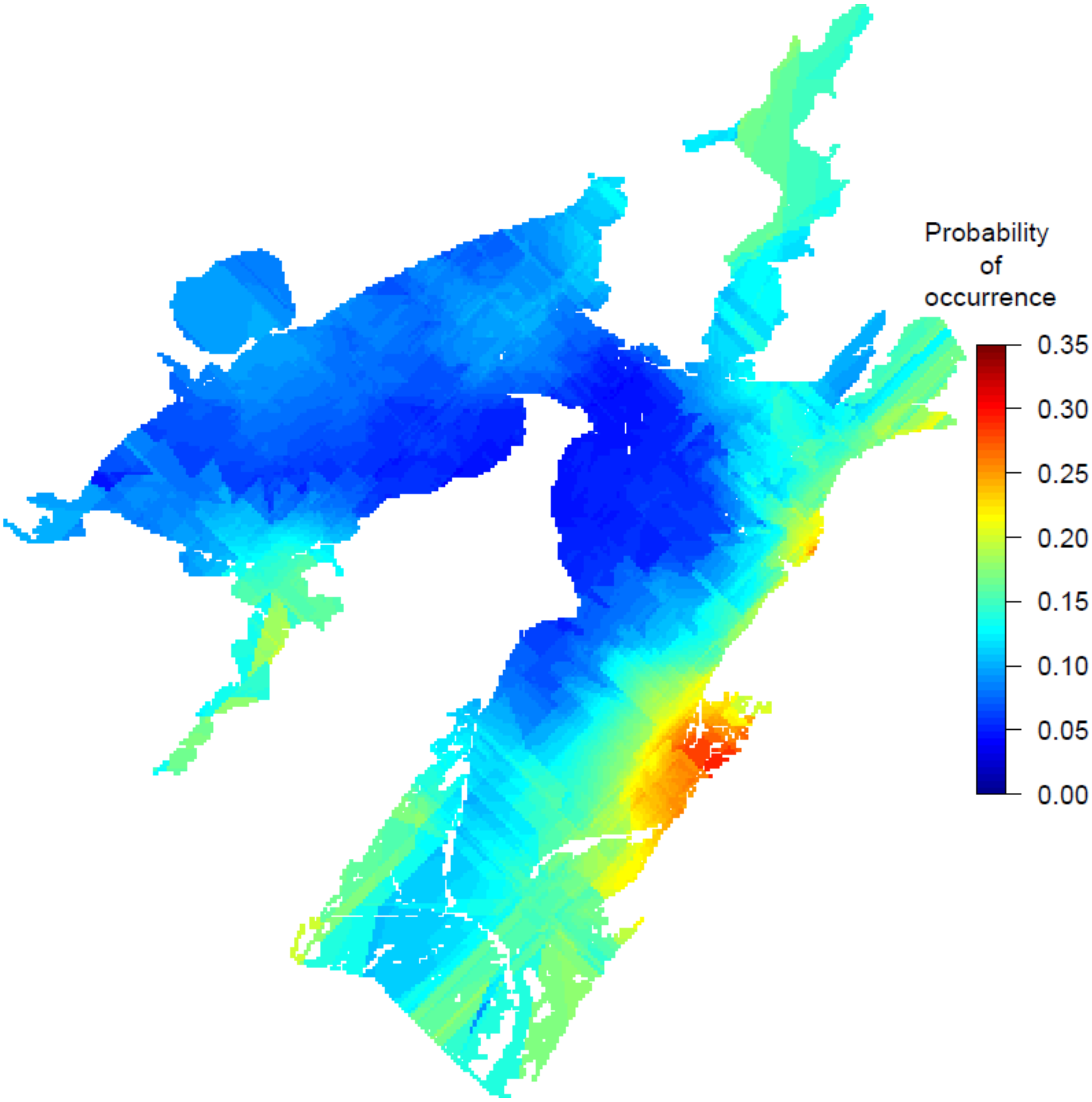

Figure 5.2: Spatial prediction of juvenile southern flounder from the BRT model indicated the highest probability of collection was in seagrass beds along the eastern edge of Aransas Bay. Moderate probability of collection was in seagrass located in the southern region, and northern regions of Aransas Bay and Copano Bay. The lowest prediction for probability of occurrence was in non-vegetated and oyster locations throughout Copano Bay, and in the middle non-vegetated sites in Aransas Bay.

Spatial variable, distance to the nearest inlet, was the second most important predictor of occurrence indicating the highest probability of occurrence closest to the inlet. Many estuarine species increase in abundance near inlets (Whaley et al. 2007, Froeschke et al. 2010). Essential fish habitat for young-of-the-year southern flounder in Aransas Bay and Copano Bay, TX was shown to occur in vegetated habitats (seagrass and marsh edge) that occur closest to the tidal inlet between Aransas Bay and the Gulf of Mexico and in high salinity (Nañez-James et al. 2009). Results have also indicated that when incorporating both habitat type and distance to the inlet, habitat selection contributes more to probability of juvenile southern flounder then distance to the inlet (Chapter 3). Thus, these data support that distance to the inlet also implies selected habitat choice.

With respect to environmental variables, temperature was the most important predictor of occurrence. Occurrence rates rapidly increased at 10°C and the highest probability of occurrence occurred between 15°C and 20°C. The optimum temperature for peak recruitment of southern flounder is 16°C – 16.2°C (Stokes 1977). However, juvenile southern flounder in Texas have been captured at water temperatures between 14.5°C – 21.6°C (Gunter 1945). Moreover, BRT model conducted on juvenile southern flounder in the MANERR indicated the highest probability of occurrence at temperatures less than 15°C and a large decline at 15°C before another small peak at 20°C (Chapter 3.). My results are supportive of temperatures less than 20°C for optimal recruitment temperature of juvenile southern. Due to selected preference of cooler temperatures temperature increases is of potential concern. Seawater temperature is project to increase by 4°C in the 21st century (Thuiller 2007). Both AppleBaum and Montagna (2005) and

Fodrie et al. (2010) have previously reported rising sea temperatures within the Gulf of Mexico. Clearly, if these trends continue then the recruitment success of southern flounder will be substantially influenced. Increase temperatures are likely to be correlated with the movement of juvenile southern flounder to cooler bays along the northern areas of the Gulf of Mexico with very little to no population among the southern areas of the Gulf of Mexico (Texas Bays).

Salinity was also an important predictor of occurrence. Occurrence rates were the highest at salinities less than 10 psu and decreased at salinities greater than 40 psu. Among the Texas Bays salinity increases with decreasing latitude from hyposaline positive (Sabine Lake and Galveston Bay) to moderate (15-35 psu) along the central coast, and hypersaline negative estuaries (> 35 psu) in the southernmost Upper and Lower Laguna Madre. Spatial prediction from both the BRT and ANN indicated highest probability of juvenile southern flounder occurring in Sabine Lake and Galveston Bay and lowest probability of occurrence in the Upper and Lower Laguna Madre. Southern flounder are considered highly euryhaline (Deubler 1960) but it has been suggested that lower salinity waters stress juvenile southern flounder less, thus resulting in lower mortality and better growth rates (Stickney and White 1974, Hickman 1968). Thus, I predict that Sabine Lake and Galveston Bay are preferred habitat locations based on low salinity levels for juvenile southern flounder. However, less fresh water is predicted to occur among Texas Bays due to population growth and climate changes which could alter the southern flounder population. This type of scenario similar to increases in temperature could also cause the southern flounder population to move to more northern regions of the Gulf of Mexico.

Turbidity and dissolved oxygen were less important predictors of occurrence. This is consistent with Froeschke et al. (Chapter 3) that did not find an effect of turbidity on the probability of occurrence of juvenile southern flounder in the MANERR. While dissolved oxygen levels can influence the distribution, abundance, and diversity of organisms (Breitburg 2002, Vaquer-Sunyer 2008, Montagna and Froeschke 2009), this primarily occurs at low oxygen levels (i.e., < 2 mg O_2 l^{-1}). In this study, few samples were taken in low DO conditions. However, dissolved oxygen levels in Texas estuaries are falling (Applebaum et al. 2005, Montagna and Froeschke 2009) suggesting potential impacts on the distribution and abundance of estuarine organisms.

Interaction between habitat quantity and habitat quality has been demonstrated to effect survivorship of flatfish, with the largest recruitment potential to occur in areas with high habitat quantity and high habitat quality, and the smallest recruitment potential to occur in areas with low habitat quantity and quality (Gibson 1994). More specifically, it has been suggested that biological variables such as prey abundance, predators, habitat structure, water depth, and physical factors such as, temperature, salinity, oxygen, and hydrodynamics are all major factors exhibited to effect growth and survival of flatfish recruitment (Gibson 1994; Allen and Baltz 1997; Stoner et al. 2001; Glass et al. 2008). Thus, southern flounder spawning and recruitment success may be directly influenced by estuarine conditions highlighting the importance of high quality habitat necessary to support important fishery species.

Both spatio-temporal models consisted of high predictive performance with slight spatial differences. For both models capture probability increased each month from January to March, and declined slightly starting in April (Figure 5.3 and Figure 5.4).

Spatially, high probability of occurrence started in Galveston Bay and East Matagorda Bay for both models but the ANN also indicated high probability of occurrence in Sabine Lake. Sabine Lake contains the lowest salinity levels among the bays in Texas, thus suggesting that the high prediction of occurrence from the ANN is consistent with salinity preference seen among juvenile southern flounder (Stickney and White 1974, Hickman 1968, Chapter 3.) Both models indicated high probability of occurrence near the tidal inlets from Galveston Bay to Corpus Christi and between Galveston and East Matagorda Bay. Overall, probability of capture for both spatio-temporal models increased with areas consisting of low salinities, cooler temperatures and areas closest to tidal inlets. Based on my results, I suggest that both modeling techniques consist of similar predictive performance. Although, the ANN consisted of lower percent correct it predicted higher probability of occurrence in Sabine Lake whereas the BRT did not. Based on the biology of the species I suggest that the high probability of occurrence in Sabine Lake is accurate.

Construction of spatio-temporal models for juvenile southern flounder along the Texas coast addresses state and national estuarine and coastal resource management issues, because it provides critical information on the spatial distribution and nursery habitat requirements for this important recreational and commercial fishery. My results provide valuable tools for fisheries managers to enhance management and ensure sustainability of the southern flounder fishery in particular and other fisheries in general. The results also identified a predictive framework for proactive approaches to ecosystem management. Moreover, the spatio-temporal southern flounder predictive models provide crucial information needed to identify areas for habitat conservation. These models allow managers to more accurately conserve nursery habitats for the southern flounder fishery. By conserving appropriate habitat and understanding relationships between abiotic and biotic factors within those habitats the status of fisheries populations should improve. Crucial habitat for juvenile southern flounder needs to include areas of overlap in order to manage preferred habitat for growth and , and habitat conservation for juvenile southern flounder among Texas Bays needs to occur in the northern bays and areas closest to the inlet (Figure 5.3 and Figure 5.4).

Southern flounder populations are declining (Robinson et al. 1994; VanderKooy 2000; Froeschke et al. 2011) and habitat loss and climate change is occurring (Caldeira and Wickett 2003; Harley et al. 2006; and IPCC Synthesis Report 2007). I have demonstrated a strong relationship with interactions among environmental factors (temperature, salinity, turbidity, dissolved oxygen, depth) and spatial factors (distance to the inlet). Therefore, I suggest that with continued improvements on recreational and commercial fishing regulations and increased knowledge and management of essential fish habitat for all life-stages of southern flounder may contribute to increased abundances of both juvenile and adult southern flounder. By conserving appropriate habitat and understanding relationships between abiotic and biotic factors within those habitats the status of fisheries will improve. In addition, anthropogenic climate changes will certainly alter abiotic factors within all marine environments; therefore, we must understand the importance of these changes to develop a more effective ecosystem-based management system. Thus, the required next step for this fishery is to evaluate the way sub-adult and adult southern flounder respond to environmental variability. This information would allow us to compare EFH among ontogenetic shifts of southern flounder and determine the environmental needs throughout their life span. By understanding these environmental needs and changes throughout ontogenetic shifts we will be able to construct adaptive management plans to address a wide variety of issues facing this important fishery.

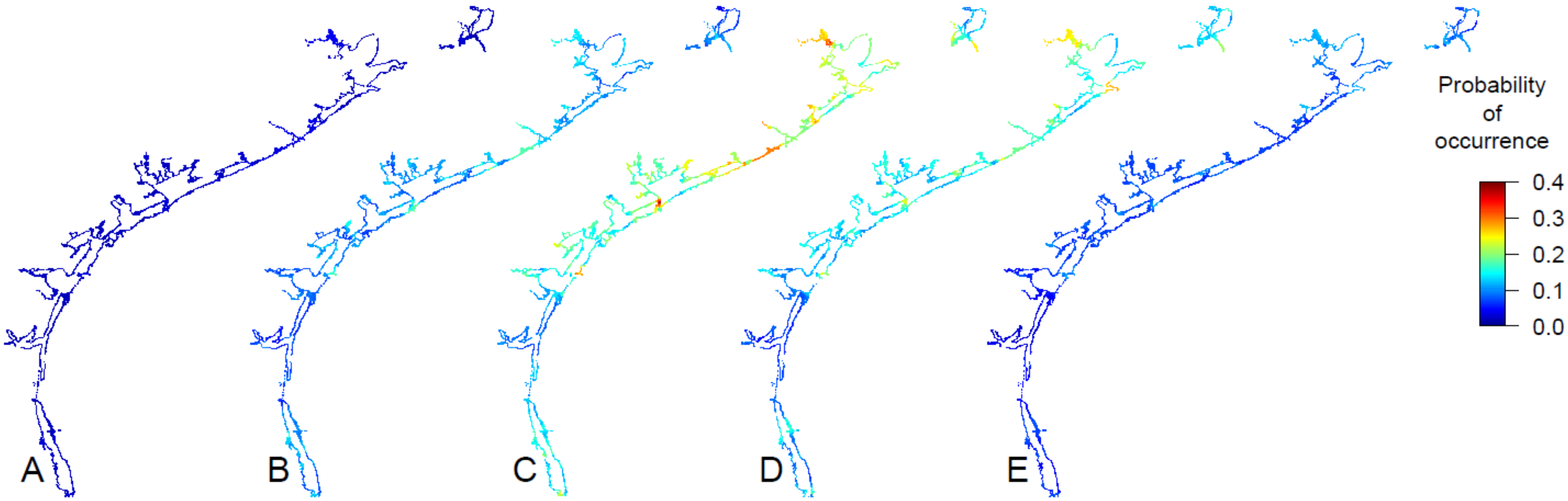

Figure 5.3: Spatial prediction of juvenile southern flounder from the "best" boosted regression trees (BRT) model indicating the highest probability of collection would occur in March in Galveston Bay, East Matagorda Bay, and areas closet to the inlet. A) January prediction of juvenile southern flounder, B) February prediction of juvenile southern flounder, C) March prediction of juvenile southern flounder, D) April prediction of juvenile southern flounder, and E) March prediction of juvenile southern flounder

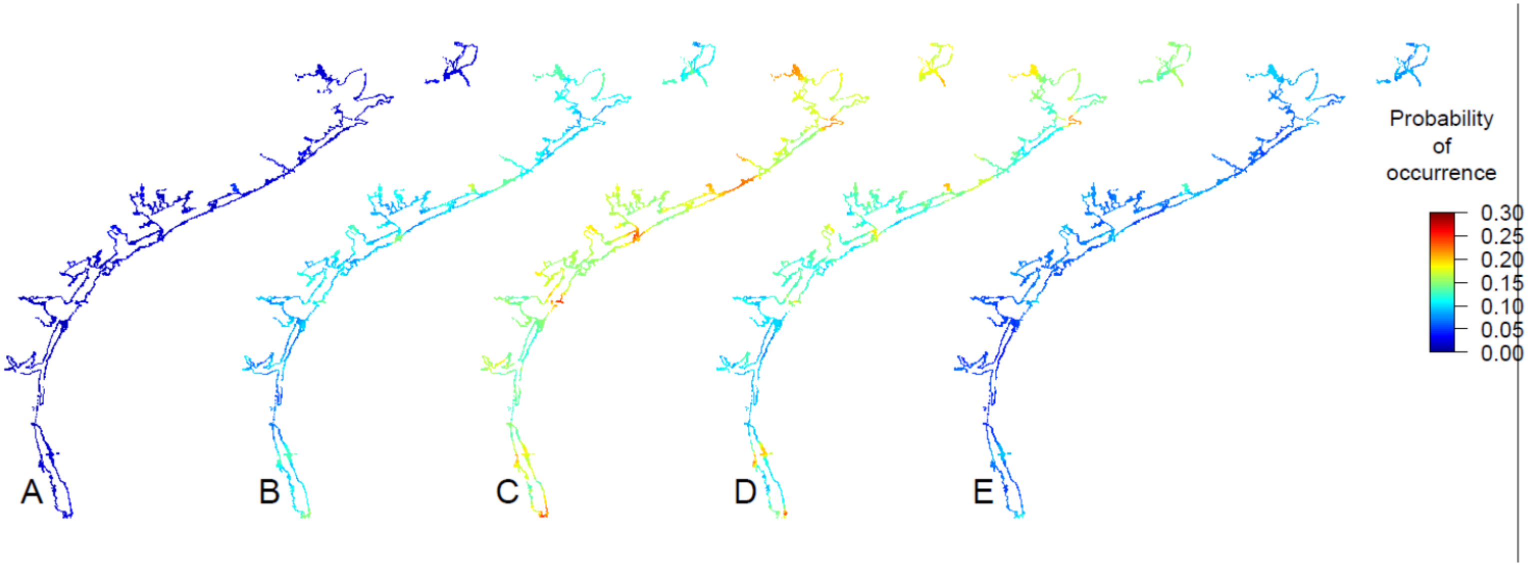

Figure 5.4: Spatial prediction of juvenile southern flounder from the “best” Artificial Neural Network (ANN) model indicating the highest probability of collection would occur in March in Sabine Lake, Galveston Bay, East Matagorda Bay, and areas closet to the inlet. A) January prediction of juvenile southern flounder, B) February prediction of juvenile southern flounder, C) March prediction of juvenile southern flounder, D) April prediction of juvenile southern flounder, and E) March prediction of juvenile southern flounder.

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