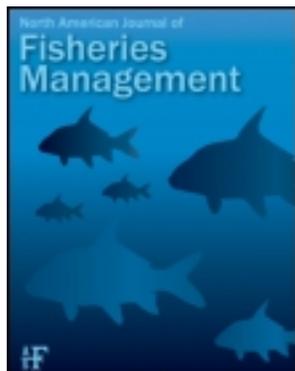


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## North American Journal of Fisheries Management

Publication details, including instructions for authors and subscription information:  
<http://www.tandfonline.com/loi/ujfm20>

### Spatiotemporal Predictive Models for Juvenile Southern Flounder in Texas Estuaries

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Published online: 06 Aug 2013.

To cite this article: Bridgette F. Froeschke, Philippe Tissot, Gregory W. Stunz & John T. Froeschke (2013) Spatiotemporal Predictive Models for Juvenile Southern Flounder in Texas Estuaries, North American Journal of Fisheries Management, 33:4, 817-828, DOI: [10.1080/02755947.2013.811129](https://doi.org/10.1080/02755947.2013.811129)

To link to this article: <http://dx.doi.org/10.1080/02755947.2013.811129>

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ARTICLE

## Spatiotemporal Predictive Models for Juvenile Southern Flounder in Texas Estuaries

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### Abstract

Southern Flounder *Paralichthys lethostigma* supports a multimillion dollar commercial and recreational fishery in the Gulf of Mexico. Despite its economic importance, the Southern Flounder population has been declining for decades. To improve the management of this fishery, both population trends and changes in environmental conditions need to be considered. Using two different statistical modeling techniques, boosted regression tree (BRT) and artificial neural network (ANN), a 29-year fisheries-independent record of juvenile Southern Flounder abundance in Texas was examined to illustrate how environmental factors influence the temporal and spatial distribution of juvenile Southern Flounder. Boosted regression trees show the presence of juvenile Southern Flounder is closely associated with relatively low temperatures, low salinity levels, and high dissolved oxygen concentrations. Both ANN and BRT models resulted in high predictive performance with slight spatial differences in predicted distribution. Both models suggested high probability of occurrence in Galveston Bay and East Matagorda Bay. The ANN accurately predicted higher probability of occurrence in Sabine Lake compared with the BRT model. Our results will provide tools for fisheries managers to enhance management and sustainability of the Southern Flounder population. Moreover, these results also identify a predictive framework for proactive approaches to ecosystem management by providing more data to identify essential habitat features and understanding relationships between abiotic and biotic factors within those habitats.

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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; Halpern et al. 2008). Human impacts have altered the distribution, quantity, and quality of marine habitats

(Pyke 2004; Lotze et al. 2006). They have contributed to the depletion of more than 90% of estuarine species, degraded water quality, and accelerated species invasions, and have reduced seagrass and wetland habitat among estuaries and coastal seas by 65% (Lotze et al. 2006). Seventy-five percent of fisheries

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Received October 16, 2012; accepted May 22, 2013

Published online August 6, 2013

worldwide are over exploited or fully exploited (NMFS 2002). Within the USA, 17% of fisheries are subject to overfishing and 24% are overfished (NMFS 2008). Impacts from recreational (Coleman et al. 2004) and commercial fishing and bycatch can be significant contributors to the decline of fisheries (Jackson et al. 2001; Pauly et al. 2002; Hilborn et al. 2003).

In the Gulf of Mexico, the Southern Flounder *Paralichthys lethostigma* supports a multimillion dollar commercial and recreational fishery, but declines in this stock (Froeschke et al. 2011) have led to reduced recreational and commercial catches. Southern Flounder populations have been on the decline for decades and are currently at all-time lows in Texas (Froeschke et al. 2011). Management efforts for Southern Flounder in Texas have focused on implementing regulations for recreational and commercial fisheries, yet the population remains in decline, suggesting that factors other than fishing may be negatively influencing the Southern Flounder population. Time-series analysis indicated that both juvenile and adult Southern Flounder are declining in Texas estuaries (Froeschke et al. 2011). Juvenile recruitment is decreasing 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 postjuvenile flounder that occurred during the 29-year study period (Froeschke et al. 2011). Stunz et al. (2000) demonstrated that a reduced proportion of Southern Flounder is reaching the age of maturity. To address these concerns, the Southern Flounder population may benefit from a shift towards an ecosystem-based approach incorporating interactions among physical and biological components of the system management (Pikitch et al. 2004; Marasco et al. 2007; Crowder et al. 2008). Within this perspective, fisheries management includes ecological factors that identify essential fish habitat (EFH) including both abiotic and biotic components of the environment.

Spatiotemporal models provide valuable information that may enhance management and ensure sustainability of not only the Southern Flounder fishery in particular but other fisheries as well. The use of boosted regression trees (BRT) is relatively new in ecological applications but 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; Froeschke and Froeschke 2011). Moreover, BRT can be effective in predicting the occurrence of juvenile Southern Flounder to determine EFH within the Aransas Bay, Texas, complex (Froeschke et al., in press). The artificial neural network (ANN) model is a well-established method for identifying complex hydrographical patterns associated with the abundance and dynamics of different phases in the life cycle of fish (Suryanarayana et al. 2008). Many researchers have used ANNs to predict fish recruitment (Kusakabe et al. 1997; Engelhard and Heino 2002) 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 was to provide additional information that can be used for the management of Southern Flounder by using statistical modeling techniques to explain how environmental factors influence the temporal and spatial patterns of juvenile fish. Additionally, this study compared a relatively new modeling technique (BRT) with a well-accepted technique (ANN). Specifically, this study (1) determined the 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; (2) used BRT and ANN models to make spatial predictions of the probability of presence in Texas bays; and (3) compared the predictive power and predicted spatial distribution of the trained and tested BRT and ANN.

## METHODS

**Study area.**—The study was conducted in nine major bays along the Texas coast, located along the northwestern Gulf of Mexico (Figure 1). The Texas coast is 563 km in length and contains five barrier islands that stretch approximately 161 km. There are six consistently open pathways for water exchange and animal transport between adult and nursery habitat in the nearshore bays and the Gulf of Mexico (<http://goliath.cbi.tamucc.edu/TexasInletsOnline/TIO%20Main/index.htm>).

**Data collection.**—Data were provided courtesy of the Texas Parks and Wildlife Department (TPWD) and were collected as part of their Resource and Sport Harvest Monitoring Program targeting juvenile finfish and shellfish. Sampling has occurred since 1977 for juveniles in nine bays along the Texas coast (1977–2007,  $n = 18,078$ ; Figure 1). All sampling followed protocols detailed in the Marine Resource Monitoring Operations Manual (Martinez-Andrade et al. 2009). Juvenile Southern Flounder (age < 2 years, 11–290 mm TL; 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  $18.3 \times 1.8$ -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; Froeschke et al., in press). 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 with high abundance of juvenile recruitment (January–May) were used in the models (Nañez-James et al. 2009; Froeschke et al. 2011).

Patterns of eight environmental variables relevant to fish were examined coast-wide to investigate relationships between environmental conditions and juvenile Southern Flounder

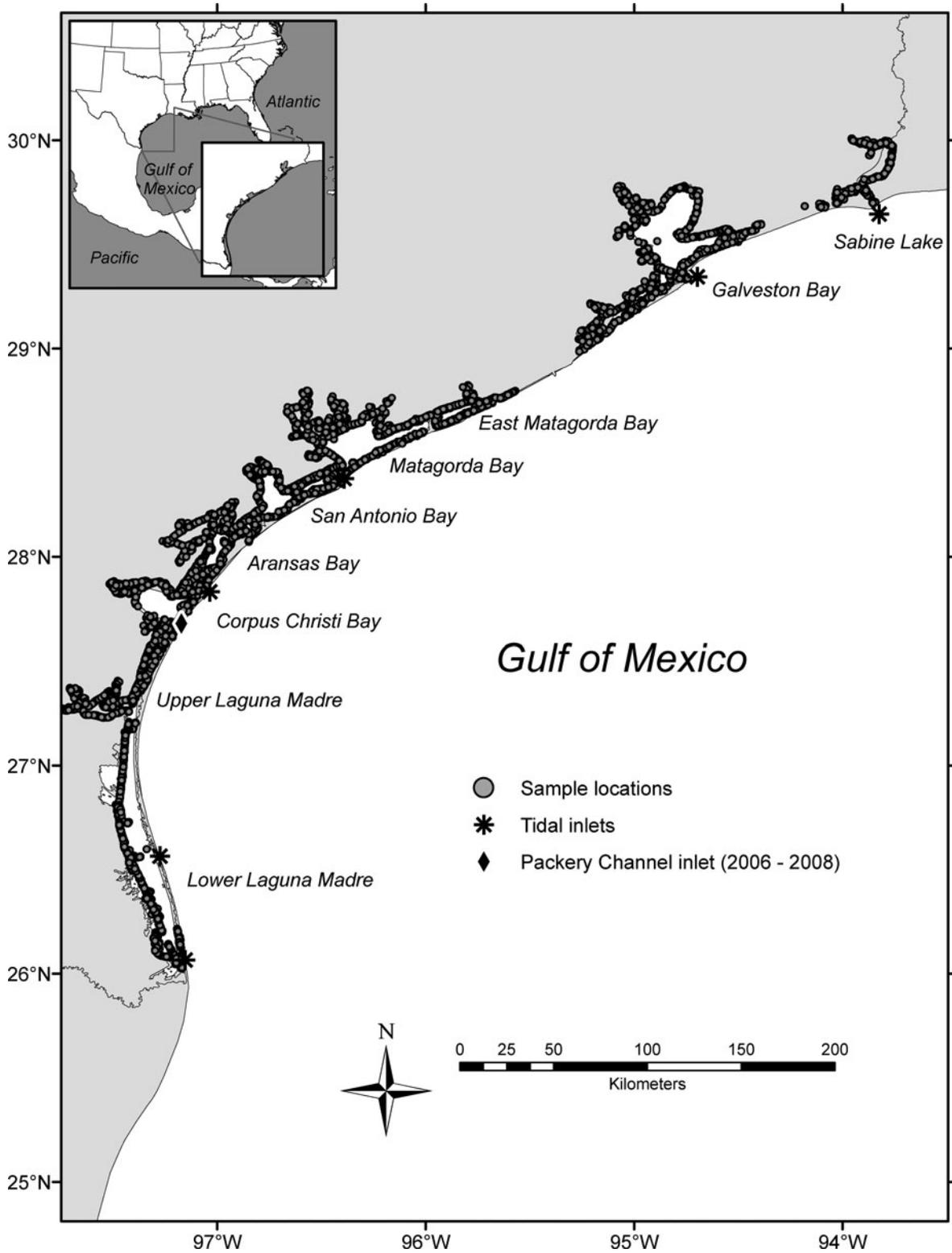


FIGURE 1. Bag seine sampling locations (circles,  $n = 18,078$ ) for the TPWD Resource and Sport Harvest Monitoring Program from January through May 1979–2007 (each site was sampled once over the course of the study).

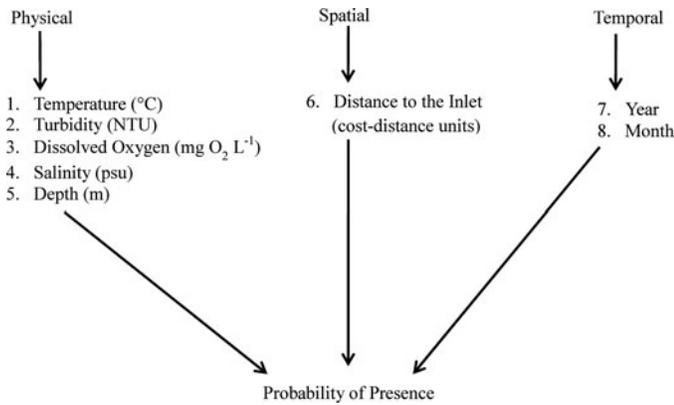


FIGURE 2. Input factors for boosted regression trees and artificial neural networks to identify probability of presence for juvenile Southern Flounder along the Texas coast.

distributions (Figure 2). Salinity (psu), temperature (°C), turbidity (NTU), and dissolved oxygen (mg O<sub>2</sub>/L) 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 depth, sampling time, and location were also recorded for each sample. All variables were measured during each sampling (i.e., all years and bays). The increase of variance estimates of the estimated regression coefficient for each variable from collinearity was tested using the variance inflation factor (VIF; Table 1).

To examine potential relationships between the distribution of juvenile Southern Flounder and connection to the Gulf of Mexico, distance from each sampling location to the nearest tidal connection to the Gulf of Mexico (Figure 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; Froeschke and Froeschke 2011). The cost–distance function calculates the shortest distance between two points while accounting for geographic boundaries (i.e., land) to provide more accurate relative distance estimates than Euclidian (straight-line) techniques (Froeschke et al. 2010; Froeschke and Froeschke 2011). For Corpus Christi Bay, two distance matrices were calculated. One

TABLE 1. Variance inflation factors (VIF) of the variables included in the boosted regression trees and artificial neural network models indicated no collinearity of the variables.

Variables	VIF
Year	1.0515092
Month	2.8223845
Salinity (psu)	1.2764295
Temperature (°C)	2.8601381
Dissolved oxygen (mg O <sub>2</sub> /L)	1.2642134
Turbidity (NTU)	1.0531671
Depth (m)	1.1686556
Distance to the inlet (cost-distance units)	1.0250715

distance matrix was developed without the Packery Channel inlet and applied to all samples collected before 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.

**Boosted regression trees.**—Relationships of juvenile Southern Flounder with physical, spatial, and temporal variables were determined using a forward fit, stage-wise, binomial BRT model (De'ath 2007). Analyses were conducted in R (version 2.9; R Development Core Team 2009) using the 'gbm' library supplemented with functions from Elith et al. (2008). The adjustable model parameters for BRT are tree complexity (*tc*), learning rate (*lr*), and bag fraction (*bf*), where *tc* controls whether interactions are fitted, *lr* weights the contribution of each tree to the growing model, and *bf* specifies the proportion of data selected at each step (Elith et al. 2008). The model was fit to allow interactions using a tree complexity that had a value of 5 and a learning rate of 0.01 to minimize predictive deviance and maximize predictive performance. Tenfold cross validation of training data ( $n = 12,651$ ) was used to determine the optimal number of trees.

The BRT technique 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) resist effects of outliers, and (4) fit interactions between predictors (Elith et al. 2006, 2008; Leathwick et al. 2006, 2008). This is a relatively new method to address ecological questions but can be effective to identify relationships between fish distribution patterns and environmental predictors (Leathwick et al. 2006, 2008; Froeschke et al. 2010; Froeschke and Froeschke 2011).

Unlike traditional regression techniques, BRT combines 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, 2008; Leathwick et al. 2006, 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, 2008; Leathwick et al. 2006, 2008).

**Artificial neural network.**—A sigmoidal–sigmoidal, multilayer feed-forward ANN model with back-propagation Levenberg–Marquardt learning algorithm was used to predict the presence and absence of juvenile Southern Flounder along the Texas coast. The model used the same eight predictor variables as the BRT model (Figure 3), one hidden layer with four hidden neurons, and the output layer with the presence and absence of Southern Flounder as the target ( $n = 12,651$ ; Figure 3).

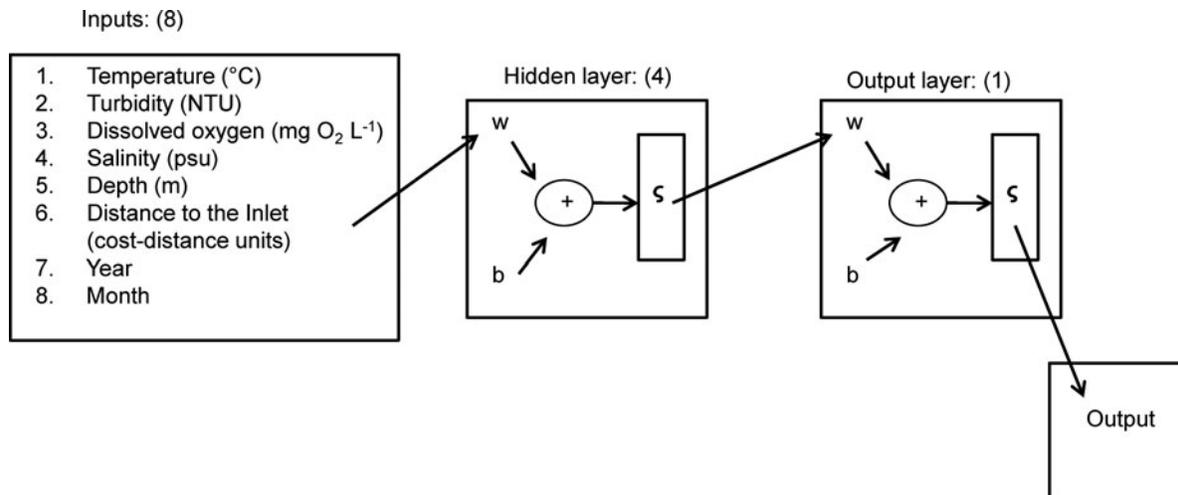


FIGURE 3. Input factors for the sigmoidal-sigmoidal, multilayer, feed-forward artificial neural network model with back-propagation learning algorithm, consisting of eight inputs, one hidden layer, four hidden neurons, and one output layer.

The number of hidden neurons was determined by comparing areas under the curve (AUCs) for each receiver operating characteristic (ROC) curve while varying the number of hidden neurons, and a validation, training, and testing set was used to avoid overfitting. Analyses were conducted using the *nprtool* package in MATLAB (2010b, The MathWorks, Natick, Massachusetts).

Artificial intelligence neural network models do not have assumptions of linearity, normality, or homogeneity (Campbell et al. 2007), can model multivariate and nonlinear data with discontinuous regions, and do not require transformation of data (Suryanarayana et al. 2008). Therefore, an ANN model provides an appropriate technique to approximate nonlinear relationships and has been suggested as one of the best choices for modeling spatiotemporal patterns of fish (Suryanarayana et al. 2008). Artificial neural networks consist of neurons (processing units) with weights and biases (parameters) fitted by training a model over a portion of the data set. The result is a model that maps a set of given values (inputs) to an associated set of targets (output; Salia 2005; Zuur et al. 2007). Model weights are trained by passing through a pair set of inputs and outputs and adjusting progressively to the weights to minimize the error between the answer predicted by the ANN and the true answer provided in the training set (Zuur et al. 2007). All inputs are individually weighted and combined prior to being transformed in a hidden layer (consisting of a variable number of neurons) that performs a nonlinear transformation of the derived linear value (Zuur et al. 2007). Values of predictor variables varied widely and the sigmoid function of the neural network was used as it is more resistant to the effects of extreme values than regression-based models (Campbell et al. 2007).

*Model selection.*—Prior to model fitting, data ( $n = 18,078$ ) were randomly split into training (70%,  $n = 12,651$ ) and independent testing sets (30%,  $n = 5,427$ ). Model performance and comparison of BRT and ANN models was assessed for predic-

tions computed for the independent testing set. For each model, AUC calculated from the ROC performance metric was determined (Wilks 2006). To identify spatial patterns of recruitment the probability of capture was predicted for the study area using a form of logistic regression based on the fitted BRT and ANN models (Elith et al. 2008). Predictions were computed based on the probability that a species occurs ( $y = 1$ ) at a location with covariates  $X$  and  $P(y = 1|X)$  using the logit:  $\text{logit}[P(y = 1|X)] = f(X)$  scale. Suites of environmental conditions were developed for each month (January–May) based on environmental variables measured during each month included in the analysis using ordinary kriging (Saveliev et al. 2007). The BRT and ANN model outputs were then used to predict probability of capture coastwide 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 with the independent testing data set (i.e., not used in model building).

## RESULTS

### Physicochemical Conditions

Southern Flounder were captured in 1,255 of 12,651 samples (frequency of occurrence = 10%) from January to May in the training data set and in 550 of 5,427 samples in the independent (testing) data set. On the Texas coast, physical conditions varied widely among bay systems. Salinity increased 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 to 64 psu (mean = 21 psu). Mean sea surface temperature also increased slightly from north to south along the coast, and water temperatures ranged

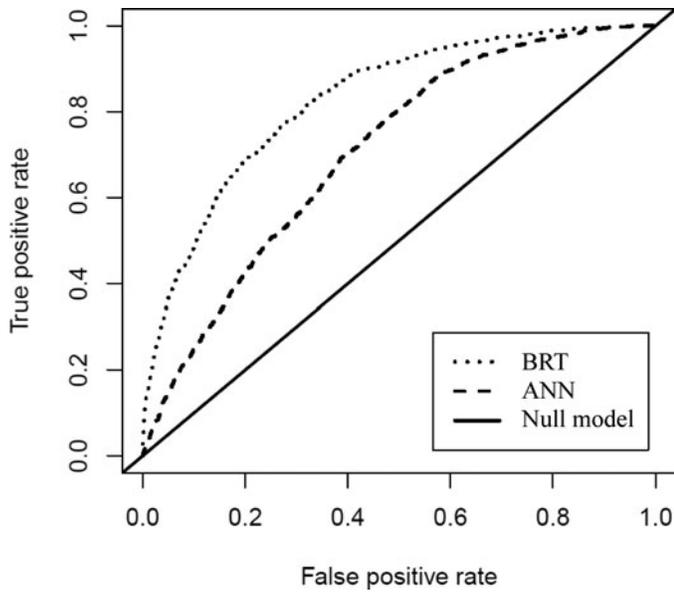


FIGURE 4. Receiver operating characteristic curve obtained from the trained boosted regression tree (BRT) model (AUC = 0.828) and trained artificial neural network (ANN) model (AUC = 0.707) indicating strong predictive power.

from 1.4°C to 36.5°C with a mean of 20.9°C during sampling events. Dissolved oxygen concentrations (range, 0–28.00 mg O<sub>2</sub>/L; mean = 8.21 mg O<sub>2</sub>/L; Figure 4C), turbidities (range, 0–999 NTU; mean = 33.16 NTU), and sampling depths (range, 0–6.6 m; mean = 0.44 m) were similar among bay systems.

### Boosted Regression Trees

The BRT model evaluation suggested good predictive performance based on the result predictions to independent data ( $n = 5,427$ , AUC = 0.76; Table 2). Evaluation of the training model also indicated good predictive performance (AUC = 0.83; Figure 4). The BRT model calibrated over the training set and all variables provided insight into the relationship between the spatial, physical, and temporal input variables and the distribution of juvenile Southern Flounder. The variable months (17.5%) and distance to inlet (16.7%) explained the greatest proportion of deviance. Probability of occurrence increased from January to March and declined after March to May. Year of capture (15.2%) predicted the highest probability of occurrence in the late 1980s and mid-1990s. Overall, the probability of occurrence

of juvenile Southern Flounder has been decreasing since 1997 (Figure 5). Temperature (14.8%) explained the most deviance of the physical variables considered, followed by salinity (11.5%), turbidity (11.5%), dissolved oxygen (7.6%), and depth (5.1%) (Figure 5). The fitted functions from the BRT model indicated that the highest occurrence rates of juvenile Southern Flounder were in March, were closest to the inlet, and had water temperature greater than 10°C but lower than 20°C, salinity less than 40 psu, turbidity of around 200 NTU and greater than 300 NTU, and depth greater than 1 m (Figure 5).

The independent testing set ( $n = 5,427$ ) was used to examine spatial predictions for the presence of Southern Flounder along the coast. For locations that were sampled multiple times through the course of the study the mean probability of occurrence for these sampling events was determined by averaging all data points for the site. The resulting data set used for the calibration of the spatial prediction model consisted of  $n = 3,375$  predictions. Spatially explicit models predicted the probability of capture based on the BRT model output for each month (January–May) by making predictions of the fitted BRT model to an interpolated surface of environmental variables. The spatial model exhibited good predictive performance based on independent data (AUC = 0.719; Figure 6). Capture probability increased each month from January to March, declined slightly in April, and was low during May (Figure 7). Probability of capture began increasing first in Galveston Bay and East Matagorda Bay in February (Figure 7B). 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 7C). In April, probability of occurrence started to slightly decrease between East Matagorda Bay and Corpus Christi Bay (Figure 7D). Overall, probability of capture increased within areas with low salinities, cooler temperatures, and closest to tidal inlets.

### Artificial Neural Network

The “best” neural network model based on AUC for predicting the presence and absence of Southern Flounder consisted of eight inputs and four hidden neurons (Figure 3). Model evaluation demonstrated good predictive performance to independent data ( $n = 5,427$ ). Furthermore, evaluation of the training model also exhibited good predictive performance (mean square error = 0.08, AUC = 0.707; Figure 4).

TABLE 2. Predictive performance of boosted regression tree models for juvenile Southern Flounder; *tc* = tree complexity, *lr* = learning rate, *bf* = bag fraction, *nt* = number of trees, ROC = receiver operating characteristic curve.

<i>tc</i>	<i>lr</i>	<i>bf</i>	<i>nt</i>	Percentage deviance explained			Area under the receiver operating characteristic curve (AUC)			
				Cross validation	Training	Total deviance	Independent	ROC cross validation	ROC cross-validation SE	Train
5	0.01	0.6	1,550	9.70%	19.30%	0.647	0.757	0.735	0.004	0.828

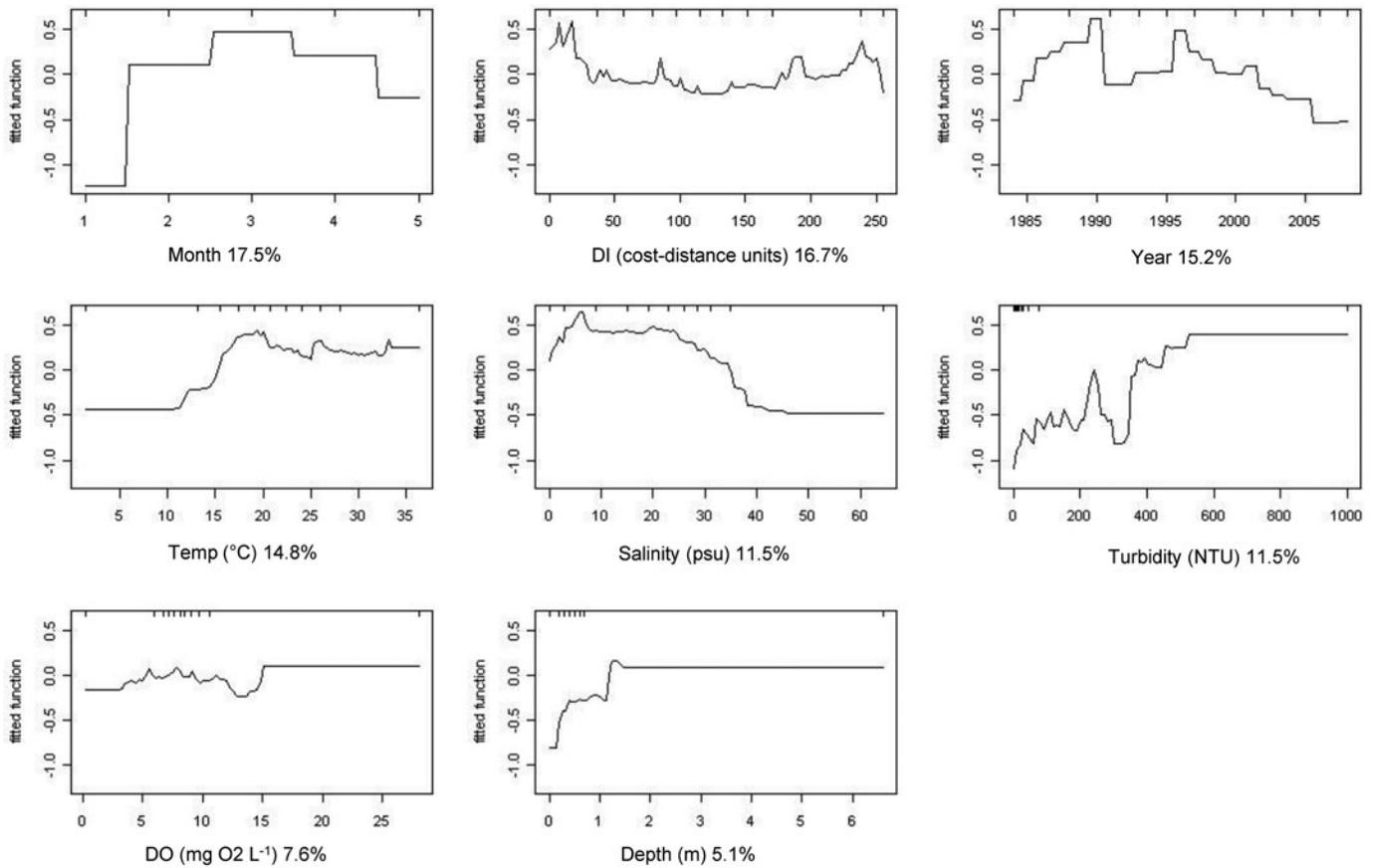


FIGURE 5. Functions fitted for the eight predictor variables by a boosted regression tree (BRT) model relating the probability of capture of juvenile Southern Flounder to the environment in order to identify the probability of capture along the Texas coast. *Y*-axes are on the logit scale with mean of zero. Tic marks at inside top of plots show distribution of data across that variable, in deciles. *X*-axes parameters: month (1 = January, 2 = February, 3 = March, 4 = April, 5 = May), distance to the nearest inlet (DI; cost-distance units), year, temperature (temp; °C), salinity (psu), turbidity (NTU), dissolved oxygen (DO; mg O<sub>2</sub>/L), and depth (m).

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 the interpolated surface of environmental variables. The spatial model showed good predictive performance on the independent data (AUC = 0.69; Figure 6). Capture probability increased each month from January to March, declined slightly in April, and was low during May (Figure 8). Spatial patterns were also evident. Probability of capture began increasing first in Sabine Lake, Galveston Bay, and East Matagorda Bay in February (Figure 8B). In March, probability of capture was the highest near the tidal inlets (Figure 8C). However, there was a relatively moderate to high probability of occurrence among all of the bays (Figure 8C). In April, probability of occurrence started to slightly decrease between East Matagorda Bay and Corpus Christi Bay, but remained relatively high in Sabine Lake, Galveston Bay, and the lower edge of lower Laguna Madre (Figure 8D). In May, probability of occurrence consisted of a similar pattern as observed in January but with a moderate probability of occurrence still prevalent for Sabine Lake and

Galveston Bay (Figure 8E). Overall, probability of capture increased in areas with low salinities, cooler temperatures, and areas closest to tidal inlets.

## 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, and spatial variables and their interactions in species habitat models to identify frequency of occurrence patterns of juvenile Southern Flounder. Probability of occurrence increased in February and 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). Peak abundances of juvenile Southern Flounder have been reported from February to May with a peak in March along the Texas coast (Froeschke et al.

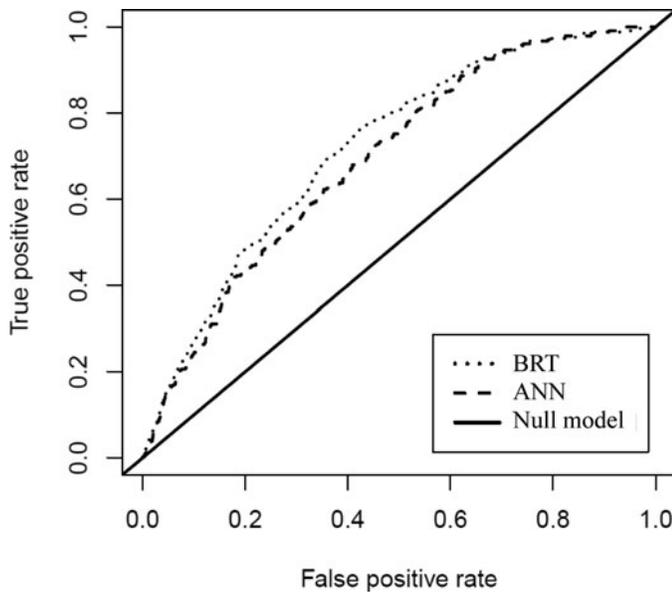


FIGURE 6. Receiver operating characteristic curve obtained from the spatial tested data set against the trained boosted regression tree (BRT) model (AUC = 0.71) and tested artificial neural network (ANN) model (AUC = 0.69) indicating good predictive power to an independent data set.

2011). 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) reported recruitment from March to May, peaking in April. Rogers and Herke (1985) reported recruitment from January to March, and peaks occurred from February to March.

Distance to the nearest inlet was the second most important predictor of occurrence with the highest probability of occurrence closest to the inlets. Many estuarine species (including Southern Flounder) spawn offshore and juveniles recruit into estuaries via tidal inlets. As a result, juvenile abundance is often greatest near inlets (Whaley et al. 2007; Froeschke et al. 2010).

Essential fish habitat for age-0 Southern Flounder in Aransas Bay and Copano Bay, Texas, was suggested to occur in high salinity, vegetated habitats (seagrass and marsh edge) that occur closest to the tidal inlet between Aransas Bay and the Gulf of Mexico (Nañez-James et al. 2009). Overall, 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.

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 bays (Froeschke et al. 2011).

With respect to environmental variables, temperature was the most important predictor of occurrence, and the highest occurrence was observed 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 recruitment temperature range of Southern Flounder is 16–16.2°C (Stokes 1977). However, juvenile Southern Flounder in Texas bays have been captured in water temperatures between 14.5°C and 21.6°C (Günter 1945). A study on juvenile Southern Flounder in the Aransas Bay complex (Mission–Aransas National Estuarine Research Reserve) indicated the highest probability of occurrence was at temperatures less than 15°C (Froeschke et al., in press). Due to a 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 et al. (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.

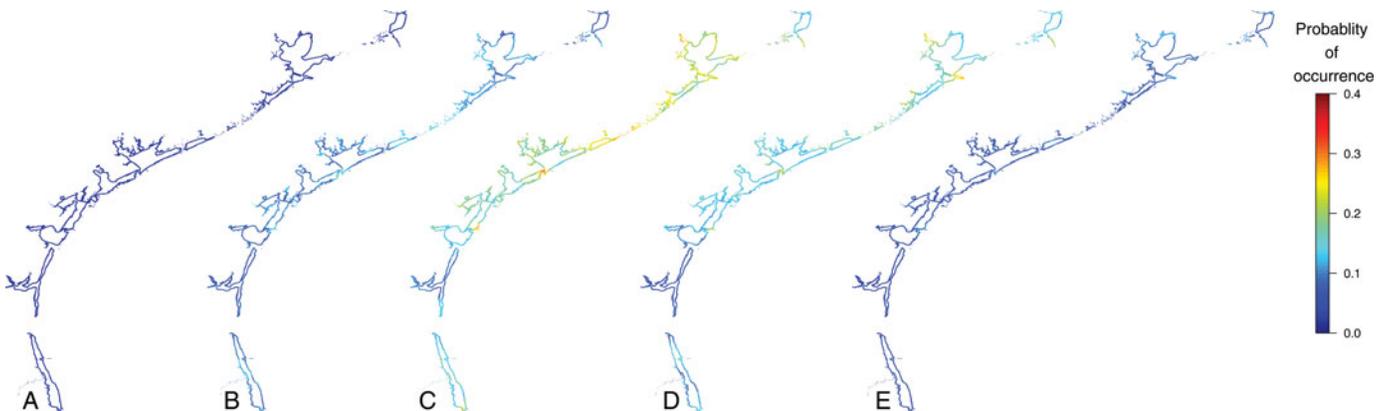


FIGURE 7. Spatial prediction of juvenile Southern Flounder from the “best” boosted regression tree (BRT) model indicating the highest probability of collection would occur in March in Galveston Bay, East Matagorda Bay, and areas closest to the inlets. Spatial predictions from BRT of juvenile Southern Flounder capture for the months of (A) January, (B) February, (C) March, (D) April, and (E) May. [Figure available in color online.]

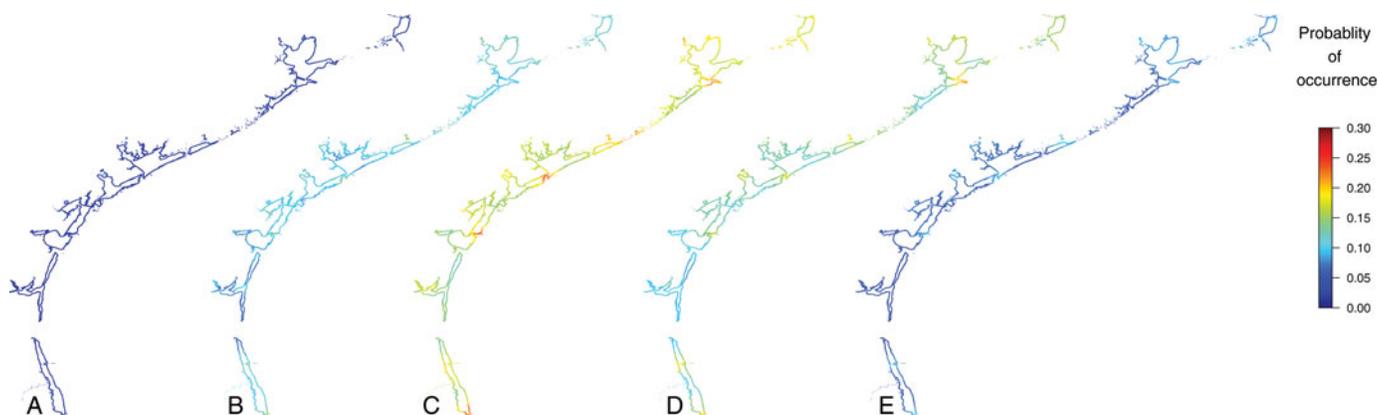


FIGURE 8. Spatial prediction of juvenile Southern Flounder from the “best” artificial neural network (ANN) model indicating the highest probability of collection would occur in March in Sabine Lake, Galveston Bay, East Matagorda Bay, and areas closest to the inlets. Spatial predictions from ANN of juvenile Southern Flounder capture for the months of (A) January, (B) February, (C) March, (D) April, and (E) May. [Figure available in color online.]

Salinity was also an important predictor of frequency of 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 models indicated the highest probability of juvenile Southern Flounder occurred in Sabine Lake and Galveston Bay and the lowest probability of occurrence was 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 euryhaline (Deubler 1960), but survivorship and growth rates increase in lower salinity waters (Hickman 1968; Stickney and White 1974). This study supports these previous findings as Southern Flounder were more prevalent in the low salinity and cooler water temperature environments of Sabine Lake and Galveston Bay. This result illuminates potential ramifications of reduced freshwater inflow into these bay systems as historic inflows are increasingly diverted for human use.

Turbidity and dissolved oxygen were less important predictors of occurrence. This is consistent with Froeschke et al. (in press) who did not find an effect of turbidity on the probability of occurrence of juvenile Southern Flounder in the Mission–Aransas National Estuarine Research Reserve. While dissolved oxygen levels can influence the distribution, abundance, and diversity of organisms (Breitburg 2002; Vaquer-Sunyer and Duarte 2008; Montagna and Froeschke 2009), this primarily occurs at low oxygen levels (i.e., <2 mg O<sub>2</sub>/L). In this study, few samples were taken in low dissolved oxygen conditions, but 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). These data suggest that oxygen levels 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 can affect the survivorship of flatfish, in which the largest recruitment potential occurs 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, dissolved 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 higher 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 models increased with decreasing salinities, cooler temperatures, and proximity to tidal inlets. Although overall accuracy of the ANN model was slightly lower than the BRT spatially tested model, the ANN correctly predicted a 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 models both displayed good predictive performance of spatial predictions to an independent data set. The ANN consisted of a similar number of observed and predicted occurrences than did the BRT. However, the BRT had a higher predictive performance for the training set compared with the ANN model and a higher percentage correct for the prediction of presence–absence of juvenile Southern Flounder. The ANN and BRT models were similar with regard to the number of observed and predicted fish. The primary difference between the overall percentage correct between the two models for the training and testing sets was the number of fish predicted and not observed, suggesting that the ANN model and possibly the BRT could be overfitting, a common feature of correlation-based

predictive models including ANN (Zuur et al. 2007). Despite this limitation, ANN remains a powerful tool 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 approach for a particular application, which is difficult or impossible to identify a priori 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 spatiotemporal context, which is essential for ecosystem based management approaches (Pikitch et al. 2004). Predicted distribution patterns were very similar between the spatiotemporal models. 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, suggesting that the high predicted frequency of occurrence determined from the ANN is consistent with salinity preference seen among juvenile Southern Flounder (Hickman 1968; Stickney and White 1974; Froeschke et al., in press).

Despite the utility of our modeling approaches, there are some limitations to both methodologies. While model evaluation indicated good performance of both the BRT and ANN at predicting the independent testing cases, substantial unexplained deviance remained in the models. This suggests that some important variables in the habitat usage of these species were available in the study data set. For example, biotic components such as spawning location, prey and predator density, and movement patterns of individuals were not considered in this study. The methods used in this study allowed the consideration of several variables simultaneously and provided timely information for conservation and management of Southern Flounder. 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 spatiotemporal 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. Our results provide tools for fisheries managers to promote sustainability of the Southern Flounder fishery. For example, the effect of increased salinity due to changes in precipitation or urban water diversion could be evaluated in this context as grids of environmental conditions were developed for predictive purposes. A range of scenarios could be explored and the change in occurrence or distribution of Southern Flounder could be evaluated. This study provides a predictive framework for proactive approaches to ecosystem management where the effects on environmental conditions on a population can be considered and incorporated into harvest strategies. Hidalgo et al. (2011) demonstrated that stock depletion can enhance the impact on environmental forcing on fish populations. These data suggest that this species is present even if the best biotic habitat (e.g., seagrass meadow) is available and

if the physical environment (e.g., temperature, salinity) is not within the tolerable range for that species. Thus, decreases in freshwater inflow could have a major impact on the distribution of juvenile Southern Flounder. 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.

## ACKNOWLEDGMENTS

We thank Texas Parks and Wildlife Department, especially Science Director M. Fisher and F. Martinez-Andrade, for providing access and insight into the Southern Flounder monitoring data. Additionally, we thank the Mission–Aransas National Estuarine Research Reserve Fellowship Program, and the Harte Research Institute for the Gulf of Mexico Studies for funding and support. Furthermore, we thank B. Sterba-Boatwright, J. Fox, and L. McKinney for their assistance with and comments on the manuscript.

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