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ARTICLE

Using Bayesian multispecies models to evaluate fish and invertebrate detection probability and distribution in the hypersaline Bahia Grande tidal basin

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Abstract

Objective: In 2000, the Laguna Atascosa National Wildlife Refuge acquired the Bahia Grande (Texas) management unit, a space that had lain barren and arid for 70 years. A large cooperative partnership launched a restoration project to replenish the basin and recover its original tidal hydrology. In 2005, the construction of a pilot channel successfully restored water throughout the basin, and plans to eventually widen the channel were developed. Our study aims to evaluate an estuarine habitat restoration by assessing ecological drivers and the impacts on species diversity.

Methods: We evaluated species richness, detection/occupancy rates, and species–habitat relationships, and we estimated the sampling effort required to achieve a given level of relative precision if relative abundance was used instead of occupancy to inform future sampling. Sampling gear included bag seines for juvenile life stages and gill nets for capturing subadult and adult life stages. For analysis, we used a Bayesian negative binomial linear mixed-effects model to evaluate richness–habitat relationships and a hierarchical Bayesian multispecies model to evaluate individual species–habitat relationships, and we calculated the total number of fish captured and relative standard error by gear and sample year to produce a precise estimate of relative abundance.

Result: Overall, 29 species were caught between 2018 and 2021. Salinity emerged as a clear driver in the Bahia Grande, as both species richness and individual-level responses were negatively associated with high salinity values. We found that catch estimated as relative abundance had much variability, as is typical of most survey programs assuming constant detectability, and the number of net sets or seine hauls required to achieve a given level of relative precision varied considerably depending on the species, season, year, and gear type. The most collected species were found in the upper extremes of their salinity tolerances—potentially a unique adaptation to this hypersaline system.

Conclusion: Baseline data suggest that for the channel widening to be successful, there must be a noticeable increase in suitable habitat characteristics throughout the basin.

KEYWORDS

Bahia Grande, Bayesian, Bayesian models, detection probabilities, fisheries, hypersaline, management, species distribution

INTRODUCTION

Coastal marine habitats require freshwater inputs to maintain their unique and diverse habitats (Pritchard 1967). Unfortunately, many of these habitats have been degraded, filled, or destroyed in various parts of the world (Zedler et al. 2001), leading to decreased freshwater flow, altered nutrient cycling, habitat loss, and reductions in estuarine-associated populations (Kennish 2002; Russell et al. 2006). In Texas, the Bahia Grande tidal basin was once a thriving nursery for fish and other aquatic life on the southern coast (Hicks et al. 2010). However, the dredging of the Brownsville Ship Channel in 1934–1936 caused the estuary to dry up due to the placement of dredge material, which blocked all tidal flows. Over the next 70 years, the Bahia Grande basin remained dry and unproductive, posing a significant health risk to nearby communities through dust storms.

In 2000, the Laguna Atascosa National Wildlife Refuge (LANWR) acquired the Bahia Grande management unit. A large partnership was formed, and one of the largest restoration efforts in Texas was launched, with the goal of refilling the basin and restoring its original tidal hydrology as well as providing subsequent watering to two other basins. The first phase of the project began in 2005, which involved constructing a pilot channel (4.5 × 695.5 m [15 × 1250 ft]) to reconnect the main interior basin (i.e., Bahia Grande) to the Brownsville Ship Channel. Two additional interior channels were built in 2007, linking the Bahia Grande to two smaller basins: Little Laguna Madre and Laguna Larga. The pilot channel and interior channels were effective in restoring water flow throughout the basins (Hicks et al. 2010). In 2021, the next phase started, which aimed to widen the pilot channel to 45.5 m (150 ft) to enhance water circulation and reduce salinity levels in the Bahia Grande basin.

Despite the construction of the pilot channel in 2005, the Bahia Grande remains a hypersaline environment (>35‰), with salinity levels reaching 150‰ in the northern half of the basin. The basin's shallow morphology, arid climate, low tidal exchange, and lack of freshwater inflow all contribute to its high salinity levels. Salinity gradients are a reliable predictor of fish distribution in hypersaline environments: the higher the salinity, the lower the species diversity and abundance (Gunter 1961). With the majority of the basin reaching extreme hypersaline conditions (>75‰), habitat for most fish and invertebrates is reduced to just half the wetted area. Estuarine fish are influenced by salinity gradients, which can be a major physical barrier to habitat use and organism survival (Baggett et al. 2015). Upon completion of the pilot channel bridge in 2008, the Texas Department of Transportation reported a tidal exchange rate of 1.7%, which increased to 9.7% by 2011 (Coast and Harbor Engineering [CHE] 2011). Tidal exchange is limited to the southern half of the Bahia Grande due to an old railroad trestle, which is a porous barrier that splits the basin in two halves. The planned widening of the pilot channel in 2021 was expected to substantially increase tidal exchange, improve water circulation, and reduce salinity ranges throughout the basin, thereby creating more suitable habitat for aquatic species.

Impact statement

Habitat restoration is a unique opportunity to assess changes in aquatic communities. We used hierarchical Bayesian models to describe prerestoration community relationships for one of the largest coastal restorations in Texas. This flexible framework can be applied to other complex habitat restorations.

The Bahia Grande restoration project aims to reestablish a nursery habitat for native species and to provide wetland habitat for birds. This project offers a unique opportunity to observe species changes in a transitioning environment. To evaluate the restoration, we collected 3 years of baseline data using fisheries-independent monitoring to assess changes in the habitat and aquatic communities. These data are essential for understanding the effectiveness of the 2021 channel widening project, providing a baseline against which to measure the project's effectiveness in restoring tidal exchange to the basin. Our objectives were to (1) evaluate species richness; (2) estimate the effect of drivers (salinity, season, water temperature, and water depth) on detection probability and occupancy rates using hierarchical Bayesian multispecies models; and (3) determine the number of seine hauls and gill-net sets required to attain a relative precision in relative abundance of 80% and 95% to inform future sampling.

METHODS

Study area

The Bahia Grande is a management unit within the LANWR (U.S. Fish and Wildlife Service [USFWS]) in south Texas along the Gulf Coast. Our study area encompassed the entire main bay system of Bahia Grande (Figure 1). The area also contained bird islands where numerous species of colonial waterbirds nest, including the reddish egret *Egretta rufescens* (listed as threatened in the state of Texas), black skimmer *Rynchops niger*, and gull-billed tern *Gelochelidon nilotica*. Therefore, a 200-m buffer was implemented during sampling to protect these nesting areas (as shown in Figure 1).

Sampling

Biannual sampling trips were initiated in 2018 and completed before the start of the Bahia Grande channel widening construction in summer 2021. Five preconstruction sampling trips were conducted, with no sampling taking place in 2020 due to COVID-19 restrictions. Fish and invertebrates were sampled using bag seines and gill nets. Bag seines were used to sample shorelines and capture juvenile life stages, while gill nets were used to sample subadult (age 1) and adult (age > 1) life stages, providing a comprehensive understanding of species utilization in the Bahia Grande. Bag seines measured 18.3 m long × 1.8 m deep (60 × 6 ft), with 19-mm (0.75-in) mesh in the wings and 13-mm (0.50-in) mesh in the bag. Gill nets measured 61 m long × 0.9 m deep (200 × 3 ft), with 15.2-m (50-ft) sections of 76-, 102-, 127-, and 152-mm mesh (3, 4, 5, and 6 in). Both gears were used to sample fish and invertebrate

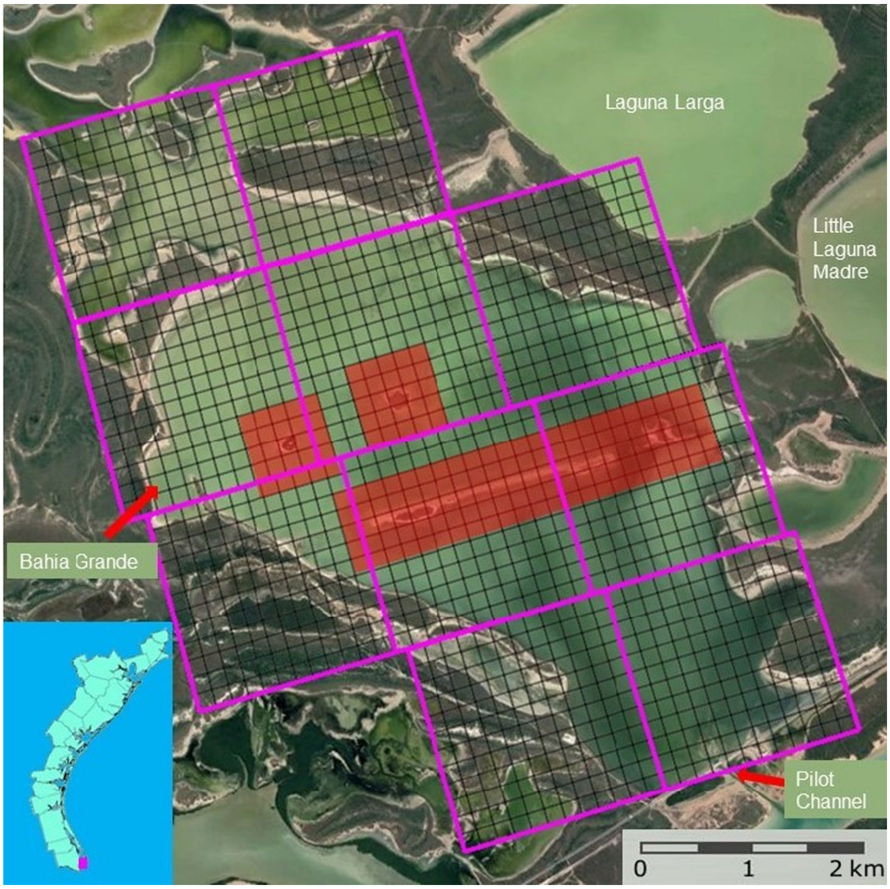

FIGURE 1 Large pink grids on the Bahia Grande tidal basin indicate 60 × 60 arcseconds; small black gridlets indicate 5 × 5 arcseconds. The red highlighted regions indicate sensitive bird nesting areas that were avoided. Grids were labeled 1–10 from left to right and from top to bottom. Inset depicts the location of the Bahia Grande along the Texas coastline.

numbers (catch per unit effort [CPUE]) and sizes. The shallow depth of the system (0.025–1.000 m) prevented the use of trawls.

Survey framework

The Bahia Grande was sampled using a stratified random sampling design. The basin was divided into 10 large grids (60 × 60 arcseconds or 1.86 × 1.86 km in size), each containing 144 smaller gridlets (5 × 5 arcseconds or 0.15 × 0.15 km; Martinez-Andrade 2015). The 10 grids were numbered sequentially and sampled systematically from west to east and from north to south. Odd-numbered grids were sampled with bag seines (five grids, each gridlet sampled with four replicate seine hauls), and even-numbered grids were sampled with gill nets (five grids, each gridlet sampled with three replicate 4-h soaks). Each grid that was selected for bag seine sampling had five randomly chosen gridlets for a total of 25 gridlet sample sites, each with four seine hauls repeated at the same location, resulting in 100 total seine hauls. Each grid that was selected for gill netting had one randomly chosen gridlet, which was sampled three times for a total of 12 h of soak time per gridlet; sampling of the five gridlets (one gridlet per grid) resulted in 60 h of total gill-net soak time. Water depth (m), water temperature (°C), dissolved oxygen (mg/L), and salinity (‰) were measured at every bag seine haul and gill-net set using a YSI Professional Plus meter.

Salinity gradient mapping

Salinity measurements were taken on July 23, 2019, at 71 sites in the Bahia Grande (34 sites in the southern area and 37 sites in the northern area) under typical conditions for the estuary (i.e., no recent rainfall events and no large tidal swings; Figure 2). Salinity sampling occurred 2 months after spring fish sampling and 2 months before fall fish sampling. A Hydrolab Compact DS5 multi-parameter probe (Hydrotech ZS) was used to measure salinity (from specific conductivity), water temperature, and dissolved oxygen at each site. Where the salinity was too high to be determined with the data sonde, water samples were collected, diluted 1:1 with deionized water, and then analyzed with a refractometer. The Global Positioning System (GPS) coordinates at each site were recorded using a Trimble Juno 3B and were differentially corrected using GPS Pathfinder Office software to improve accuracy. The corrected GPS locations and salinity values were mapped using kriging in ArcMap's Geostatistical Analyst toolbox, with values assigned to classes based on natural breaks in the data (e.g., 0–20‰, 20–40‰, and 40–60‰).

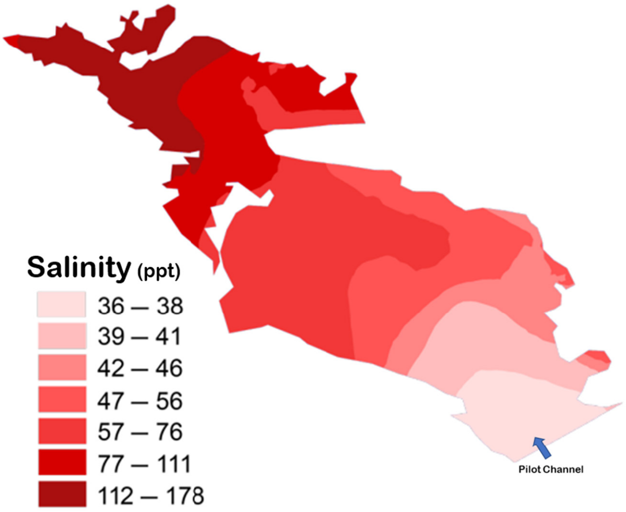

FIGURE 2 Salinity (‰ [parts per thousand, ppt]) gradient map for the Bahia Grande tidal basin based on salinity values measured at 71 sites during a single event under typical conditions. Salinity ranges are shown. The blue arrow indicates the pilot channel opening location.

DATA ANALYSIS

Objective 1: Site-specific correlates of species richness

We used a Bayesian negative binomial linear mixed-effects model to describe the relationship between species richness (the number of different species encountered in each gear at a site) and environmental covariates. The observed elements of species richness consist of the number of species encountered y at each site $i = 1, \dots I$. The observed data y_i were denoted by the vector of visits at each site $Y = \{y_i : i = 1, \dots, I\}$ and regarded as a negative binomial outcome $h(y_i | \lambda_i, \theta)$:

$$P(y_i = l | \lambda_i, \theta) = \binom{l+\theta-1}{l}\left(\frac{\lambda_i}{\lambda_i+\theta}\right)^{l}\left(\frac{\theta}{\lambda_i+\theta}\right)^{\theta},$$

where λ_i is the underlying negative binomial mean of y_i and θ is the inverse parameter that controls the overdispersion, the scaled square of the mean. A generalized linear random-effects model was assumed between the mean count λ_i and predictor variables X_i:

$$\log(\lambda_i) = \alpha_0 + \sum_{v=1}^{w} \alpha_v X_{v,i} + \gamma_j,$$

where the X_i are the predictors (e.g., salinity, water temperature, and water depth) $v = 1, \dots, w$ measured at location i throughout the study period. The α_0 and α_v are the intercept and slope fixed-effect coefficients, and γ_j is the random effect for the jth year and is assumed to be distributed as $\gamma_j \sim N\left(0, \sigma_j^2\right)$ with the prior of $\sigma_j^2 \sim \text{Cauchy}(0, 3.5)$.

Predictor variables were standardized with a mean of zero and a standard deviation of 1. To reduce multicollinearity, only predictor variables with a correlation coefficient r less than 0.60 were used in the same model (Dormann et al. 2013). This resulted in two models—one containing depth (m) and the other containing gear (1 = gill net; 0 = beach seine)—due to correlation. Models were fitted simultaneously in Stan (Carpenter et al. 2017) with the RStan interface (Stan Development Team 2021) in R (R Core Team 2021) using a Hamiltonian Monte Carlo algorithm to estimate parameters with the No-U-Turn sampler (Hoffman and Gelman 2011). We ran four chains for each model, with a warm-up phase of 2000 iterations (analogous to the burn-in phase in other software) and an additional 7000 iterations that were retained for each chain. We did not apply thinning to the posteriors, as computational memory was not a limiting factor for model runs (Link and Eaton 2012; Annis et al. 2017) and estimates of bulk and tail effective sample sizes were sufficiently large (Gelman et al. 2013). Inspection of trace plots for chains and the potential scale reduction factor ($\hat{r}$; Gelman and Rubin 1992) indicated that all parameters converged (i.e., $\hat{r} < 1.10$). If the 95% credible interval (CRI) of a coefficient estimate had any overlap with zero, the estimate was considered unsupported and insufficient evidence of a statistical difference (Oleson 2010; Murtaugh 2014). We compared the two models with the Watanabe–Akaike information criterion (WAIC), a fully Bayesian information criterion that works particularly well with hierarchical models (Hooten and Hobbs 2015). We considered the top model to be the one with the lowest WAIC value.

Objective 2: Site-specific correlates of species detection and occupancy

To quantify species-specific detection and true local occupancy estimates at a site within a grid, we developed a hierarchical Bayesian multispecies framework that links the subset of individuals collected from temporally replicated samples to a latent occupancy state of animals present at a site within each grid. This model estimates species-specific parameters from spatially replicated observations by assuming that terms among species and location-level random effects are independent and exchangeable. The approach accounts for the variability in visit number across space (individual grid location) and time. The observed elements consist of species-specific visits y from each survey occasion $j = 1, \dots, J$ within each set of $i = 1, \dots, I$ sites for the $k = 1, \dots, K$ species and gear type. The observed data y_{ijk} are denoted by the matrix of visits for each species as $Y = \left\{y_{ijk}; i = 1, \dots, I; j = 1, \dots, J; k = 1, \dots, K\right\}$ and regarded as a Bernoulli outcome $h\left(y_{ijk} \mid \psi_{ik}, p_{ijk}\right)$. The integrated likelihood representing the survey design is denoted as

$$\begin{aligned}\left[y_{ijk} \mid \psi_{ik}, p_{ijk}\right] = {} & I_{\left\{\sum_{j=1}^{J} y_{ijk} > 0\right\}} \left[\psi_{ik} \prod_{j=1}^{J} p_{ijk}^{y_{ijk}} \left(1 - p_{ijk}\right)^{1 - y_{ijk}}\right] \\ & + \left(1 - I_{\left\{\sum_{j=1}^{J} y_{ijk} > 0\right\}}\right) \\ & \times \left[\left(1 - \psi_{ik}\right) + \psi_{ik} \prod_{j=1}^{J} \left(1 - p_{ijk}\right)\right].\end{aligned}$$

The true occupancy probability ψ_{ik} of species k at site i arises as a Bernoulli random variable and is represented as a logit-linear model of environmental variables:

$$\text{logit}\left(\psi_{ik}\right) = \beta_{0,k} + \sum_{v=1}^{w} \beta_{v,k} X_{v,i} + \gamma_j,$$

where $X_{v,i}$ are the predictor variables $v = 1, \dots, w$ measured at site i; $\beta_{0,k}$ and $\beta_{v,k}$ are species-specific parameter estimates that arise from a normal distribution; and γ_j is the random effect for the jth year and is assumed to be distributed as $\gamma_j \sim N\left(0, \sigma^2\right)$ with a prior of $\sigma_j^2 \sim \text{Cauchy}(0, 3.5)$. We modeled p_{ijk} (the probability that a species is detected given that it is present; i.e., detectability) as a logit-linear model of predictor variables:

$$\text{logit}\left(p_{ijk}\right) = \alpha_{0,k} + \sum_{v=1}^{w} \alpha_{v,k} X_{v,i},$$

where $\alpha_{0,k}$ and $\alpha_{v,k}$ represent species-specific parameter estimates. Predictor variables were standardized with mean of zero and a standard deviation of 1. Only predictor variables with r less than 0.60 were used in the same model to reduce intercorrelation (Dormann et al. 2013; Christensen 2020). Given that the WAIC was unstable, we calculated the conditional deviance information criterion (DIC) proposed by Celeux et al. (2006), with DIC determined based on the conditional likelihood. Similarly, for other model selection procedures, the top model among the four models (developed from a priori hypotheses) with a DIC less than 4 was considered to be plausible, and the degree of evidence supporting one model over another was calculated from deviance weights (i.e., Akaike weights based on DIC statistics; Burnham and Anderson 2002).

We developed hierarchical Bayesian multispecies occupancy and detection models and implemented them in R using NIMBLE, which combines the advantages of the BUGS and JAGS programming languages while offering a new user-adaptable Metropolis–Hastings sampling method (de Valpine et al. 2021; R Core Team 2021). To improve Bayesian computation, we ran four independent parallel chains using the "parallel" package in R to facilitate parallel Markov chain–Monte Carlo sampling in NIMBLE (de Valpine et al. 2021; R Core Team 2021). We used diffuse priors and simulated models for 75,000 iterations, with the first 20,000 iterations used as burn-in. The required number of iterations was estimated using the global model and testing for convergence via the Gelman–Rubin statistic $\hat{r}$, examination of chain histories, and inspection of posterior density plots (Gelman and Rubin 1992).

Objective 3: Minimum effective sampling effort

We calculated the total number of fish captured and the relative standard error (RSE) from the survey data set for the species that were consistently captured annually by gear and by sample year to determine the degree of precision in catch indices (CPUE; Stewart and Long 2016). We determined precision and the minimum effective number of gill-net and beach seine sets needed to attain an RSE no greater than 15% (RSE15) and an RSE no greater than 25% (RSE25) for each species, season, and gear as part of a stochastic resampling procedure (Dumont and Schlechte 2004; Stewart and Long 2016). We chose target levels of RSE15 and RSE25 to reflect the amount of effort needed to inform research and management objectives based on recommendations by Robson and Regier (1964) and Hardin and Conner (1992). The resampling technique involved randomly sampling two nets from the empirical data for each site and species 3000 times with replacement. Next, the proportion of the 3000 samples achieving an RSE15 or RSE25 was calculated (Stewart and Long 2016). If the proportion was less than 0.80, then the number of nets was increased from two to three and continued to increase by an additional net until the proportion of the 3000 samples from the resampling routine achieving the desired precision (RSE15 and RSE25) was at least 0.80 (Stewart and Long 2016).

RESULTS

Salinity gradient mapping

Salinity gradient mapping of the Bahia Grande revealed that the environment became more hypersaline as the distance from the pilot channel increased (Figures 2 and 3). Salinities were lowest (36–45‰) in the southernmost areas of the Bahia Grande and highest (91–178‰) in the northernmost areas. Based on the salinity data collected for gradient mapping (i.e., on a single event under typical conditions), the southern area of the basin had an average salinity of 39.7‰, while the northern area of the basin had an average salinity of 73.4‰. Further, the northeastern area had an average salinity of 67.5‰, while the northwestern area had an average salinity of 80.3‰.

Species composition and richness

Overall, 29 species were caught from 150 gridlets in 10 grids between 2018 and 2021 (Table 1). Of the 29 species caught, 24 (83%) were fish and 5 (17%) were invertebrates (Table 2). Sixteen fish families and four invertebrate families were represented. Sciaenidae was the most dominant family (5 fish species out of 29 species). The most commonly collected fish species were the Sheepshead Minnow (350 detections), silverside *Menidia* sp. (88 detections), Gulf Killifish (78 detections), and Striped Mullet (77 detections). The most commonly collected invertebrate species were the brown shrimp (128 detections), blue crab (91 detections), and lesser blue crab (24 detections).

From the set of two models fitted to the data relating species richness to site-level environmental variables, a single model was assigned the full WAIC weight. This model estimated a fixed effect for gear. The second model was 4.5 points worse than the first model and received none of the WAIC weight. Salinity, season, water temperature, and water depth were the four strongly supported variables (i.e., 95% CRIs did not overlap with zero) in the top model, which also included temporal random effects. Season and water depth were both related to species richness, while species richness was negatively related to salinity and water temperature (Figures 2 and 3). Dissolved oxygen was not strongly supported.

Species detection and occupancy

Detection probabilities (p) estimated from an unconditional model were different among species (Table 2). Overall, detection probabilities were highest for Sheepshead Minnow (85%), Black Drum (69%), brown shrimp (59%), Striped Mullet (44%), silverside (42%), blue crab (40%), and Pinfish (34%). Estimated detection probabilities were lowest for Atlantic Needlefish (2%), grass shrimp (5%), Spotted Seatrout (5%), and lesser blue

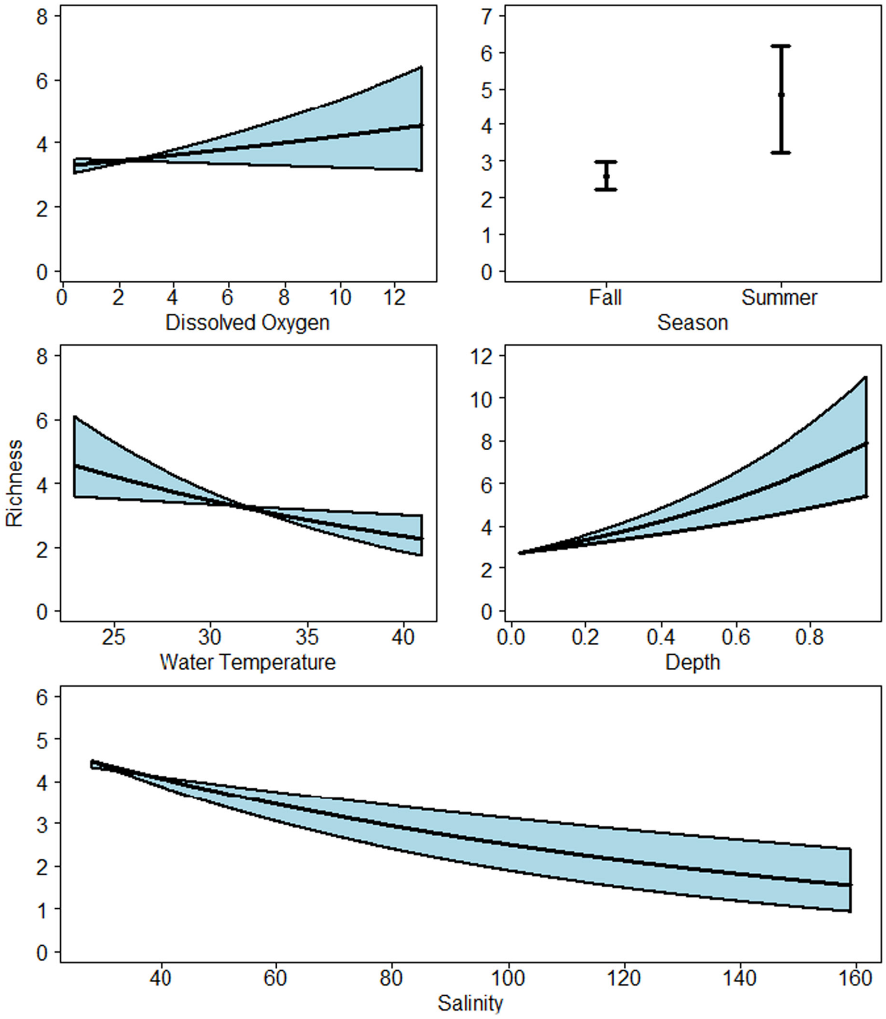

FIGURE 3 Estimated species richness response (with 95% credible intervals) to dissolved oxygen (mg/L), season, water temperature (°C), water depth (m), and salinity (‰) from the best supported Bayesian negative binomial random-effects model for the Bahia Grande tidal basin.

crab (9%). The model selection procedure identified one of four models showing that the detection and occupancy of fish and invertebrates were strongly related to salinity, dissolved oxygen, water temperature, water depth, season, and gear type (Table 3). The best overall model included salinity, water temperature, water depth, season, and gear type (Figure 4). Detection probabilities for brown shrimp, Ladyfish, Longnose Killifish, and White Mullet were higher in spring/summer sampling than in fall (Figure 5). Brown shrimp, Gulf Killifish, Pinfish, Sheepshead Minnow, and silverside had the highest detection rates in bag seines, whereas Hardhead Catfish, Red Drum, and Spotted Seatrout had the highest detection rates in gill nets (Figures 4 and 5). Furthermore, occupancy for some species had a strong negative relationship with salinity and water temperature, whereas the occupancy of most species showing a strongly supported effect was positively related to water depth (Figure 5).

Minimum effective number of traps

The estimated number of seine sets or gill-net sets that were required to achieve an RSE15 or RSE25 varied considerably depending on the species, season, year, and gear type (Table 4). On average, the number of gill-net sets required to describe CPUE with a precision of RSE25 at 80% and 95% for Striped Mullet (range = 6–25) and Red Drum (range = 12–20) was 12–16, which was less than the number of gill-net sets required to describe CPUE for Ladyfish (mean = 21.5; range = 11–35), Black Drum (mean = 22.9; range = 4–45), Hardhead Catfish (mean = 30.6; range = 18–48), and Spotted Seatrout (mean = 37.5; range = 26–48). The number of seine sets required to describe CPUE with a precision of RSE25 at 80% and 95% was, on average, higher than the estimates reported for gill nets. For example, the lowest required number of seine sets was observed for Sheepshead Minnow (mean = 16.8; range = 4–40),

TABLE 1 Seasonal total capture counts of fish and invertebrates in the Bahia Grande tidal basin, Texas (2018, 2019, and 2021), from the replicate surveys using bag seines and gill nets. Blank cells represent zero captures. White rows indicate data from the spring/summer survey period (May/June), and gray rows correspond to the fall survey period (October/November).

	Bag seine			Gill net		
Species	**2018**	**2019**	**2021**	**2018**	**2019**	**2021**
Atlantic Croaker *Micropogonias undulatus*					1	
					2	
Bay Whiff *Citharichthys spilopterus*						
		2				
Black Drum *Pogonias cromis*		503		126	87	64
				91	64	
Blue crab *Callinectes sapidus*	23	17	71			1
	1	17				
Brown shrimp *Farfantepenaeus aztecus*	149	685	161			
	18	90				
Crevalle Jack *Caranx hippos*	3				3	
Grass shrimp (also known as daggerblade grass shrimp) *Palaemonetes pugio*	7					
	7	5	9			
Gulf Killifish *Fundulus grandis*	63	166	21			
	4	91				
Gulf Menhaden *Brevoortia patronus*		179				
Gulf Pipefish *Syngnathus scovelli*	2		2			
Hardhead Catfish *Ariopsis felis*				18	26	30
				24	10	
Ladyfish *Elops saurus*			84	8	3	13
				2	3	
Least Puffer *Sphoeroides parvus*		5				
Lesser blue crab *Callinectes similis*	13	3	7	1		
	2					
Longnose Killifish *Fundulus similis*	116	21				
	9					
Atlantic Needlefish *Strongylura marina*		6		1		
Pinfish *Lagodon rhomboides*	89	430	27	2	1	
	2	25				
Pink shrimp *Farfantepenaeus duorarum*	12					
Red Drum *Sciaenops ocellatus*				3	12	5
				4	12	
Sheepshead *Archosargus probatocephalus*				1	2	3
Sheepshead Minnow *Cyprinodon variegatus*	1940	1441	542			
	776	634				
Silverside *Menidia* sp.	77	286	41			
	14	59				
Common Snook *Centropomus undecimalis*					1	
Spot *Leiostomus xanthurus*	22					
Spotfin Mojarra *Eucinostomus argenteus*	45					

TABLE 1 (Continued)

Species	Bag seine			Gill net		
	2018	2019	2021	2018	2019	2021
	3	19	14			
Spotted Seatrout *Cynoscion nebulosus*				2	9	3
					3	
Striped Mullet *Mugil cephalus*	142		104	4		4
	7	3		7	13	
White Mullet *Mugil curema*	140	194				
		1				

TABLE 2 Names of the 27 fish and invertebrate species selected for modeling, sample characteristics, and mean conditional detection probabilities (p ± 95% credible intervals) observed within the Bahia Grande tidal basin.

Species	Sites (%)	Bag seine (%)	Gill net (%)	p
Atlantic Croaker	0.67	–	0.67	
Bay Whiff	0.67	0.67	–	
Black Drum	17.33	4.67	12.66	0.69 (0.55, 0.80)
Blue crab	18.00	17.33	0.67	0.40 (0.31, 0.49)
Brown shrimp	23.33	23.33	–	0.59 (0.52, 0.67)
Crevalle Jack	1.33	0.67	0.66	
Grass shrimp	6.67	6.67	–	0.05 (0.03, 0.08)
Gulf Killifish	17.33	17.33	–	0.39 (0.30, 0.50)
Gulf Menhaden	0.67	0.67	–	
Gulf Pipefish	1.33	1.33	–	
Hardhead Catfish	8.67	–	8.67	0.15 (0.10, 0.21)
Ladyfish	12.67	6.67	6.00	0.18 (0.12, 0.25)
Least Puffer	2.67	2.67	–	
Lesser blue crab	10.00	9.33	0.67	0.09 (0.06, 0.13)
Longnose Killifish	12.67	12.67	–	0.21 (0.15, 0.29)
Atlantic Needlefish	2.67	2.00	0.67	0.02 (0.01, 0.04)
Pinfish	16.00	14.67	1.33	0.34 (0.24, 0.45)
Pink shrimp	2.00	2.00	–	
Red Drum	9.33	–	9.33	0.10 (0.06, 0.14)
Sheepshead Minnow	38.00	35.33	2.67	0.85 (0.82, 0.89)
Silverside	20.00	20.00	–	0.42 (0.33, 0.51)
Common Snook	0.67	–	0.67	
Spot	8.00	4.00	4.00	
Spotfin Mojarra	11.33	11.33	–	0.14 (0.10, 0.19)
Spotted Seatrout	4.00	–	4.00	0.05 (0.03, 0.08)
Striped Mullet	24.00	14.67	9.33	0.44 (0.34, 0.56)
White Mullet	12.00	12.00	–	0.19 (0.13, 0.27)

whereas the number of seine sets needed for attaining a precise CPUE estimate was significantly higher for blue crab (mean = 67.6; range = 19–116), brown shrimp (mean = 58.5; range = 26–115), Gulf Killifish (mean = 68.8; range = 33–124), Longnose Killifish (mean = 117; range = 62–216), Pinfish (mean = 109; range = 38–234), silverside (mean = 61.2; range = 25–127), Spotfin Mojarra (mean = 72.3; range = 28–108), Striped Mullet (mean = 140; range = 17–257), and White Mullet (mean = 132.5; range = 109–155). The number of

TABLE 3 Results of the hierarchical Bayesian multispecies models predicting species occupancy and detection in relation to environmental variables in the Bahia Grande tidal basin. DIC, deviance information criterion; ΔDIC, difference in DIC between the given model and the best model; oxy, dissolved oxygen; temp, temperature; w_i, Akaike weight based on DIC statistics.

Occupancy	Detection	DIC	ΔDIC	w_i
ψ(salinity; temp; depth)	*p*(salinity; season; gear)	4167	0	1.00
ψ(salinity; season; temp; depth)	*p*(oxy; gear)	4203	36	0.00
ψ(salinity; temp; season)	*p*(season; oxy; gear)	4280	113	0.00
ψ(salinity; gear; oxy; season)	*p*(season)	4296	129	0.00

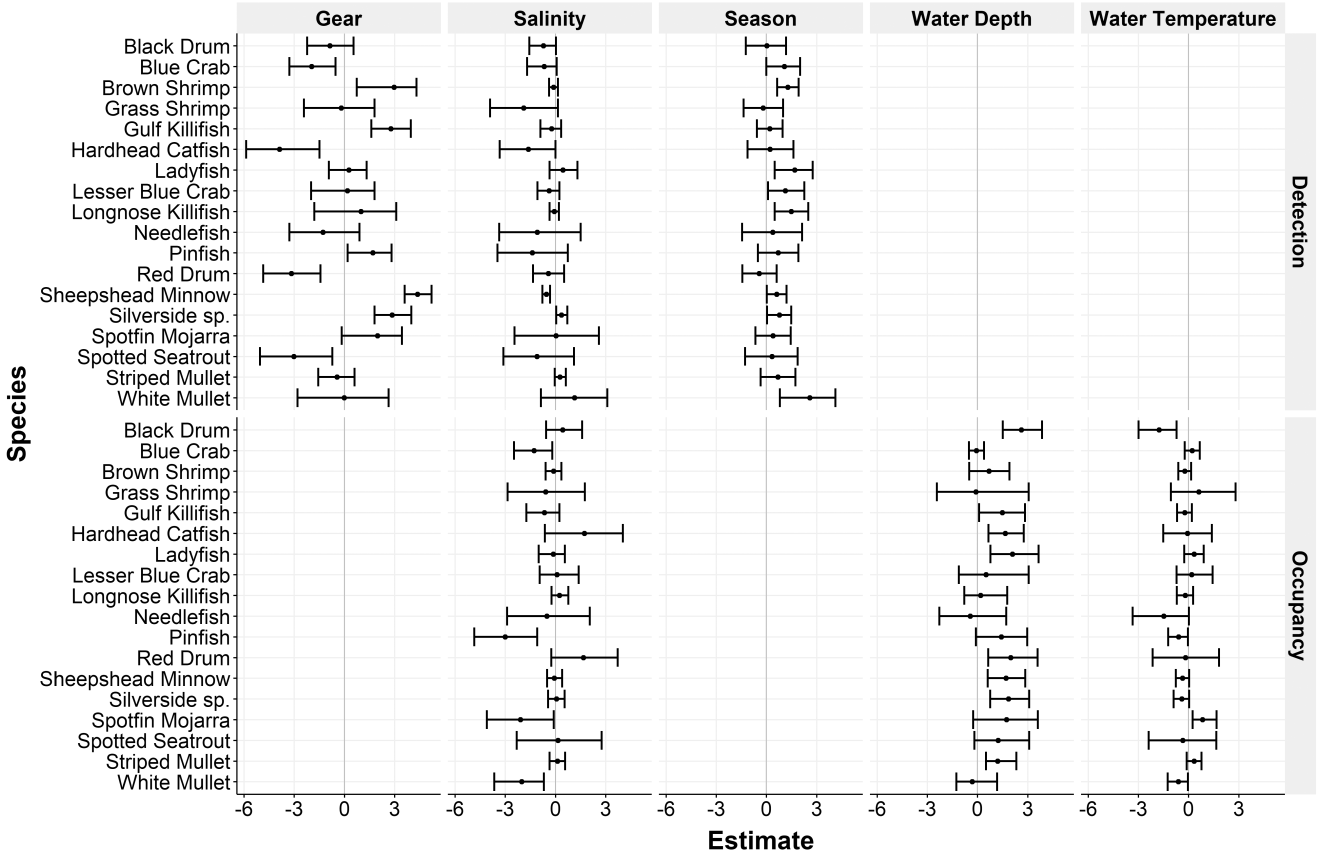

FIGURE 4 Species-specific parameter estimates from the best supported hierarchical multispecies Bayesian model relating environmental variables (gear, salinity, season, water depth, and water temperature) to conditional detection probability and occupancy for 18 marine species in the Bahia Grande tidal basin. The bars represent the 5% and 95% values for the parameter estimate. Overlap with zero indicates that the variable was not strongly supported for that species and parameter.

gill-net or bag-seine sets required to attain a precise estimate of CPUE with RSE15 at 80% or 95% was more than two to three times the effort needed to achieve an RSE25 with 80% or 95% confidence.

DISCUSSION

Our study aimed to highlight and document a transitioning estuarine environment by evaluating species richness and the effect of environmental drivers (salinity, season, water temperature, and water depth) prior to a large restoration to increase tidal exchange. In this section, we will first explain the use of Bayesian models to account for species-specific patterns and how occupancy and the probability of detection were influenced by habitat variables. Next, we will discuss some of the unique ecology of the system, the life histories of the species caught, and how they contrast with the results from the study. We will end with the importance of the restoration and management implications.

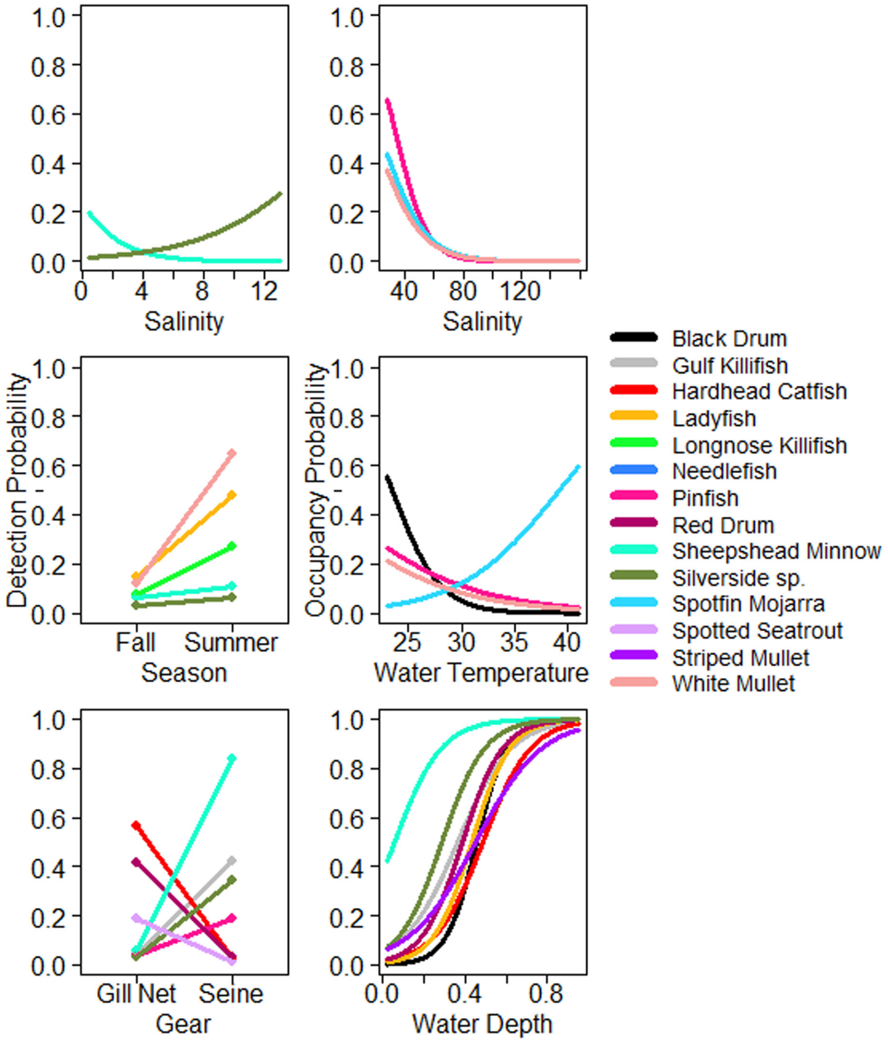

FIGURE 5 Detection and occurrence probability of each species with strongly supported effects under the best supported hierarchical multispecies Bayesian model in response to environmental variables (gear, salinity [‰], season, water depth [m], and water temperature [°C]) in the Bahia Grande tidal basin.

We used a sampling design paired with hierarchical Bayesian models to effectively describe the relationships (1) between species richness and habitat and (2) between occupancy/detection probability and habitat. These models provided a flexible framework for incorporating multiple sources of uncertainty and considering complex data structures, such as dependence between different sampling locations and multiple species (Kirsch and Peterson 2014; Stewart and Long 2016; Stewart et al. 2018). By using hierarchical Bayesian models, we were able to account for individual species-specific patterns and simultaneously describe how occupancy and the probability of detection were influenced by multiple habitat variables (Stewart et al. 2018; Porta et al. 2020). The results obtained from these models provided robust and meaningful estimates of the relationships, which was crucial in understanding the impact of habitat variables on species richness. By accounting for detection probability, we were able to address false negatives (i.e., failing to detect an individual due to habitat and species behavior despite the individual being present and alive at a study site during sampling) that commonly plague surveys based on CPUE (Stewart et al. 2017). This was done because whether species will return and which species will return after the channel widening are unknown. Therefore, this approach allowed for a more accurate assessment of the relationships between habitat variables and species richness in the study area.

We found that the aquatic community in the Bahia Grande consisted of 29 species (as listed in Table 1). The presence and detection probability of some species were significantly influenced by environmental factors, including salinity, water temperature, water depth, season, and gear type (Table 3; Figures 4 and 5). Salinity is widely recognized as a key factor shaping the structure of fish communities in estuarine systems (Rakocinski

TABLE 4 Number of net sets required to achieve a relative standard error (RSE) no greater than 15% or 25% (RSE = [100 × standard error of estimate]/estimate) for the catch per unit effort of fish and invertebrate species collected with gill nets and beach seines in the Bahia Grande tidal basin.

				Effort (net sets)			
Species	**Gear**	**Season**	**Year**	**RSE25, 80%**	**RSE25, 95%**	**RSE15, 80%**	**RSE15, 95%**
Black Drum	Gill net	Spring	2018	43	45	120	122
			2019	9	10	24	25
			2021	38	40	105	107
	Gill net	Fall	2018	4	5	13	14
			2019	17	18	48	49
Blue crab	Bag seine	Spring	2018	90	92	253	258
			2019	45	47	125	128
			2021	19	20	51	53
	Bag seine	Fall	2018	–	–	–	–
			2019	112	116	>300	>300
Brown shrimp	Bag seine	Spring	2018	70	73	197	202
			2019	38	39	105	107
			2021	26	27	72	74
	Bag seine	Fall	2018	111	115	>300	>300
			2019	42	44	116	119
Gulf Killifish	Bag seine	Spring	2018	73	76	205	210
			2019	33	34	90	92
			2021	45	46	125	127
	Bag seine	Fall	2018	120	124	>300	>300
			2019	67	70	187	190
Hardhead Catfish	Gill net	Spring	2018	47	48	130	133
			2019	27	28	74	75
			2021	26	27	72	74
	Gill net	Fall	2018	33	34	90	92
			2019	18	18	48	50
Ladyfish	Gill net	Spring	2018	33	35	93	95
			2019	20	20	54	55
			2021	17	17	47	48
	Gill net	Fall	2018	24	25	66	67
			2019	11	11	29	30
Longnose Killifish	Bag seine	Spring	2018	76	80	215	220
			2019	206	216	>300	>300
			2021	–	–	–	–
	Bag seine	Fall	2018	62	64	173	176
			2019	–	–	–	–
Pinfish	Bag seine	Spring	2018	95	97	265	270
			2019	68	71	191	195
			2021	38	39	106	108
	Bag seine	Fall	2018	–	–	–	–
			2019	229	234	>300	>300
Red Drum	Gill net	Spring	2018	20	20	54	55
			2019	16	17	44	45

TABLE 4 (Continued)

Species	Gear	Season	Year	Effort (net sets)			
				RSE25, 80%	RSE25, 95%	RSE15, 80%	RSE15, 95%
			2021	17	18	48	48
	Gill net	Fall	2018	14	15	39	40
			2019	12	12	33	33
Sheepshead Minnow	Bag seine	Spring	2018	38	40	106	108
			2019	9	10	26	27
			2021	4	5	12	13
	Bag seine	Fall	2018	16	17	43	44
			2019	14	15	40	41
Silverside	Bag seine	Spring	2018	49	51	136	139
			2019	25	26	68	70
			2021	36	37	100	102
	Bag seine	Fall	2018	68	70	188	192
			2019	123	127	>300	>300
Spotted Seatrout	Gill net	Spring	2018	47	48	130	133
			2019	26	27	71	73
			2021	47	48	130	133
	Gill net	Fall	2018	–	–	–	–
			2019	28	29	78	80
Spotfin Mojarra	Bag seine	Spring	2018	81	84	228	233
			2019	–	–	–	–
			2021	28	29	78	79
	Bag seine	Fall	2018	–	–	–	–
			2019	104	108	296	300
Striped Mullet	Bag seine	Spring	2018	112	116	>300	>300
			2019	–	–	–	–
			2021	17	18	46	47
	Bag seine	Fall	2018	250	257	–	–
			2019	173	178	>300	>300
	Gill net	Spring	2018	24	25	66	67
			2019	–	–	–	–
			2021	8	8	22	23
	Gill net	Fall	2018	6	6	17	18
			2019	8	9	23	23
White Mullet	Bag seine	Spring	2018	152	155	>300	>300
			2019	109	114	>300	>300
			2021	–	–	–	–
	Bag seine	Fall	2018	–	–	–	–
			2019	–	–	–	–

et al. 1992; Akin et al. 2003; Martino and Able 2003; Boucek and Rehage 2014; Zhou et al. 2019). Our findings indicated that the number of species decreased as salinity and water temperature increased, whereas the number of species increased with increasing water depth. The deeper areas in the Bahia Grande near the pilot channel opening offer a wider range of habitats for a variety of species due to greater water exchange, lower salinities, and lower water temperatures. Conversely, with increasing distance from the pilot channel, barriers to water exchange result in shallower depths and higher water temperature and salinity, likely due to evaporation in the arid environments.

Several studies have found strong negative relationships between salinity and fish species abundance and richness in hypersaline estuarine environments (Simier et al. 2004; Sosa-Lopez et al. 2007; Cyrus et al. 2011; Almeida-Silva et al. 2015; Mickle et al. 2018). Our results confirm this relationship but are also novel because the most commonly collected species were found at the upper extremes of their salinity tolerances. Salinities in estuaries along the Gulf coast of Texas vary, but they average between 27‰ and 36‰ (Orlando 1993). However, our most frequently caught species were found at a salinity range of 36–76‰. The previously documented salinity ranges for these species were 0–142‰ for Sheepshead Minnow, 0–76‰ for Gulf Killifish, 0–75‰ for silverside, 0–75‰ for Striped Mullet, 0–45‰ for brown shrimp, and 0–37‰ for blue crab (Simpson and Gunter 1956; Simmons 1957; Holland et al. 1971; Collins 1981; Longly 1994). The salinity ranges for all these species typically have a maximum of 75‰, except for the Sheepshead Minnow. However, in the present study, these species occupied salinities at—if not above—their reported salinity limits. This could represent a unique adaptation to the hypersaline systems that are found in secondary and tertiary bays of south Texas, similar to species like the Black Drum, which has shown high tolerances and adaptations for hypersaline conditions (Oleson 2010).

The species composition of the Bahia Grande has significant implications for fishery management in the Rio Grande Valley. Sportfishing is a popular activity in the area and is part of the resource management plan of the LANWR. Changes in habitat and fish populations could impact the level of fishing that is permitted, as the need to protect nursery areas must be balanced against the potential benefits of a more productive fishery. Habitat restoration is crucial in combatting species decline and habitat loss (Feist et al. 2003). Lower salinity levels may improve the fishery and provide additional nursery habitat for native species and sport fish in the lower Laguna Madre. Furthermore, the Bahia Grande features a crucial string of islands that are home to threatened and endangered bird species. Enhancing the habitat and the fishery could result in increased food availability for these species. Monitoring the effects of habitat restoration will provide a better understanding of changes in fish populations and will help to inform future management decisions. Employing the same monitoring and statistical modeling analysis after restoration will allow us to fully evaluate the ecological responses from a large and complex restoration effort. Such consistency can be applicable to other coastal restoration efforts that have unique or re-establishing environments.

The large effort to restore this former wetland habitat has been a tremendous endeavor by all partners involved. Projects that restore wetlands of this size—especially in such a unique hypersaline environment—are limited. The initial pilot channel was successful in rewetting the Bahia Grande, thus providing more aquatic habitats for returning fish species. Currently, tidal exchange in the Bahia Grande is estimated at 9.7% of its total volume, with a higher percentage in the southern half and a considerably lower percentage in the northern half (CHE 2011). Widening of the pilot channel that connects the Bahia Grande to the Gulf of Mexico may increase tidal exchange, potentially decreasing salinity in the northern half of the basin, which could result in increased species use. The continuation of data gathering over the next 3 years after channel widening will help to identify the level of success in terms of aquatic habitat.

Continued collaboration among stakeholders and adaptive management will be vital in ensuring the success of the Bahia Grande restoration project. Lessons learned from the initial stages of the project will be invaluable in identifying areas for improvement and adjusting management strategies accordingly. As more data are collected and analyzed, it will be crucial to communicate these findings among partners and to use this information to inform future restoration efforts, not only in the Bahia Grande but also in similar hypersaline environments. This iterative process will help to maximize the success of habitat restoration, ultimately leading to a healthier ecosystem that supports a diverse array of aquatic and avian species as well as providing recreational and economic benefits to the local community.

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CONFLICT OF INTEREST STATEMENT

The authors state that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data is available upon request from the USFWS.

ETHICS STATEMENT

This study meets the ethical guidelines outlined by the American Fisheries Society.

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