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Submerged aquatic vegetation mapping in coastal Louisiana through development of a spatial likelihood occurrence (SLOO) model

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A R T I C L E I N F O

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Species distribution modeling
Spatial mapping
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A B S T R A C T

Determining the spatial distribution of coastal foundation species is essential to accurately determine restoration goals, predict the ecological effects of climate change, and develop habitat management strategies. Mapping the distribution of submerged aquatic vegetation (SAV) species assemblages, which provide important habitat resource and ecological services in Louisiana, has been difficult due to the dynamic nature of SAV occurrence and the limited water clarity across much of the coast. Species distribution models (SDMs) link ecological conditions species occurrence across landscapes, and can predict the distribution of species across un-sampled or hard to sample areas and support the development of habitat maps. To predict SAV distribution in coastal Louisiana, a SDM was developed and projected across the landscape to create a spatial likelihood of occurrence (SLOO) model describing the probability of SAV presence in aquatic habitats. SAV presence and absence data were examined from over 500 field observations in relation to physical and hydrologic variables, including exposure, turbidity, water level, and salinity. A binary logistic regression model ($p < 0.0001$) identified three significant predictors of SAV presence: mean winter salinity, exposure, and turbidity. As each of these variables increased, the probability of SAV presence in the summer growing season decreased. The spatial application of this SDM helps to predict the likelihood of occurrence across the coastal landscape, creating a valuable tool to describe un-sampled SAV habitat and estimate future changes in habitat availability.

1. Introduction

Submerged aquatic vegetation (SAV) communities occur extensively in shallow coastal waters in the northern Gulf of Mexico (NGOM) (Carter et al., 2011; Merino et al., 2009). SAV is a vital coastal resource for fish and wildlife (Heck et al., 2003; Hitch et al., 2011; Kanouse et al., 2006; La Peyre and Gordon, 2011) and can mitigate the effects of erosion on the adjacent marsh shoreline (Christianen et al., 2013; Gurbisz et al., 2016; Nowacki et al., 2017; Robbins and Bell, 2000). Despite the valuable ecological role SAV plays in coastal landscapes, relatively few studies have examined drivers of presence and distribution across the estuarine gradient (Cho and Biber, 2016; Estes et al., 2015), and this knowledge gap has limited attempts to map and predict SAV distribution across in the NGOM. Distribution mapping is particularly challenging in coastal Louisiana where the use of remote sensing and aerial photography is problematic due to high turbidity (Carter et al., 2009; Merino et al., 2009; Vis et al., 2003), while field surveys remain logistically difficult and expensive.

Species distribution models (SDMs) characterize the distributions of species, and can have strong predictive power when supported by field data (Elith and Leathwick, 2009). SDMs are particularly useful in coastal landscapes where large areas of potential habitat are inaccessible and/or difficult to view remotely (Anderson et al., 2014; Cho and Biber, 2016; Guisan and Thuiller, 2005; Menuz et al., 2015). To identify species distributions, SDMs predict the likelihood of occurrence across potential habitats based on relationships between functionally relevant drivers for presence and the species or assemblage of species of interest (Beale and Lennon, 2012; Peterson and Li, 2015; Mendoza-González et al., 2013). Logistic regression models are often used as the framework through which a SDM is developed, particularly when the desired model outcomes are either presence or absence (Elith and Leathwick, 2009). Linking habitat studies with spatial data via SDMs

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can provide valuable datasets to support maps across large landscapes and inform research, management, and restoration (Adams et al., 2016; Kotta et al., 2014; Wenger and Freeman, 2008).

The primary environmental conditions driving SAV presence or absence are light availability, physical disturbance from wind and waves (exposure), and salinity (Bornette and Puijalon, 2011; Kemp et al., 2004; Koch, 2001; Martin and Valentine, 2012; Santos et al., 2011). Multiple parameters can alter light availability to SAV (including water depth, total suspended solids, turbidity, and epiphytes), and are typically used as the proxy for light penetration. Generally, as light availability decreases or exposure increases, the ability for SAV species to colonize and persist decreases (Barrat-Segretain, 2001; Fonseca and Bell, 1998; Gurbisz et al., 2016; Robbins and Bell, 2000; Strand and Weisner, 2001). For example, Cho and Poirrier (2005a) found that in Lake Pontchartrain the likelihood of successful colonization of two brackish species *(Ruppia maritima* and *Vallisneria americana*) decreased due to reduced light availability with increasing depth. Exposure affects SAV likelihood of occurrence both indirectly, by decreasing light availability by resuspending sediment and increasing turbiditys, and directly, as drag exerted on the plants breaks shoots and leaves (decreasing plant biomass) or tears the plant from the sediments by the roots (Koch, 2001; Martin and Valentin, 2012).

In addition to determining SAV occurrence, salinity also structures SAV assemblages, described as different species that share similar ecological requirements (Burgos-León et al., 2013; Lirman et al., 2008; Rodríguez-Gallego et al., 2015). Wetland vegetation assemblages, along with SAV, are distinctive across salinity gradients in coastal Louisiana, with species composition driven by salinity patterns (Hillmann et al., 2016; Snedden and Steyer, 2013). SAV species assemblages are somewhat predictably organized across Louisiana estuarine gradients (DeMarco, 2018), sorted by fresh marsh zones (0–3.0 ppt; *Hydrilla verticillata*, *Ceratophyllum demersum*, *Cabomba caroliniana,* and floating aquatic vegetation species), intermediate marsh zones (> 3.0-10 ppt; *V. americana*, *Najas guadalupensis*, *Zanichellia palustris, C. demersum*), brackish marsh zones (> 10–20 ppt; *Myriophyllum spicatum*, *R. maritima*), and saline marsh zones (> 20 ppt; *R. maritima* excluding the Chandeleur Islands) (Chabreck, 1970; Hillmann et al., 2016; Penfound and Hathaway, 1938). Extreme conditions (i.e. drought, floods) that alter salinity patterns can influence SAV assemblages (Kinney et al., 2014), changing dominant species in an area or affecting the ability for any SAV species to occur at all. Additionally, light requirements have been found to be lower in fresh and intermediate SAV communities as compared to brackish and saline SAV communities in the Chesapeake Bay, VA (Kemp et al., 2004), suggesting a potential interaction between salinity tolerance and light requirements.

While salinity regimes are typically described by mean values they can be further differentiated by salinity variability, or deviation from mean values. In wetlands, salinity patterns can act as a layer in an “environmental sieve”, preventing the colonization of species unable to adapt to the environmental conditions while creating conditions for species better adapted to those conditions (Snedden and Steyer, 2013; Van der Valk, 1981). However, the effects of salinity variation on the likelihood of SAV occurrence are less clear. Increased salinity fluctuations in a greenhouse setting significantly decreased growth for a key brackish SAV species, *R. maritima* (La Peyre and Rowe, 2003). Similarly, survival and biomass of *R. maritima* seedlings and adults decreased significantly at sites with large salinity fluctuations in the Florida Everglades ecotone (Strazisar et al., 2015), supporting earlier work showing that for every 3% increase in salinity standard deviation, SAV biomass decreased by an order of magnitude (Montague and Ley, 1993). Salinity variability may directly influence SAV presence by essentially acting as a benthic disturbance (van Diggelen and Montagna, 2016), and causing declines in SAV growth.

Understanding SAV occurrence across the estuarine gradient in relation to environmental conditions in coastal Louisiana would help predict future availability of SAV as marsh loss rates remain high (Couvillion et al., 2017). Marsh loss can alter hydrologic and exposure conditions in aquatic habitats, and potentially create new SAV habitat, or, alternatively destroy SAV habitat. Ongoing and planned restoration efforts, including large scale sediment diversions, are predicted to impact coastal isohalines and sediment input (Coastal Protection and Restoration Authority of Louisiana (CPRA), 2017), which will locally affect environmental conditions. Sea-level rise (SLR) and subsidence currently impacts much of the Louisiana coastal zone, altering salinity regimes, and changing the location and extent of shallow open-water areas suitable to SAV (Anderson et al., 2014; Coastal Protection and Restoration Authority of Louisiana (CPRA), 2017; Sheets et al., 2012). As wetland loss occurs, areas maintaining healthy SAV beds can continue to provide benefits to both wildlife and the remaining coastal wetlands (Brasher et al., 2012; Castellanos and Rozas, 2001; Petrie et al., 2011; Wilson et al., 2002), while newly inundated areas may become suitable for SAV establishment (Cho and Poirrier, 2005a). As SAV habitat changes across the coast, predicting the likelihood of SAV occurrence will be increasingly useful, as healthy SAV habitat provides valuable ecosystem services and can mitigate some of the effects of SLR.

To map SAV in coastal Louisiana, we developed a spatial SDM describing the SAV likelihood of occurrence (SLOO), and projected the spatially. The primary objectives of this study were to 1) define the key drivers for SAV presence and absence across the salinity gradient in estuarine coastal Louisiana, 2) develop a predictive occurrence model to determine probability of SAV occurrence given a set of environmental conditions in shallow aquatic habitats, and to 3) project the predictive occurrence model into geographic space, creating a map depicting the probability of SAV occurrence.

2. Methods

2.1. Study area

The study area encompasses the coastal zone of Louisiana as defined by the Coastal Wetland Planning, Protection and Restoration Act (CWPPRA) basins (Louisiana Coastal Wetlands Planning, Protection and Restoration Act Program (LA CWPPRA), 2011). The study area was further restricted to water bodies persistently present during the 2012–2015 period of observation (Couvillion et al., 2017). Additionally, only water bodies that were less than 2 m deep based on 2015 bathymetry data (U.S. Geological Survey (USGS), 2015) were included in the analysis, because SAV species were not typically located at depths greater than 2 m in Louisiana coastal waters (Cho and Poirrier, 2005a; Merino et al., 2009). Offshore, marine areas (i.e., Chandeleur Islands) were excluded from this analysis as field data were not available. The study area included the full range of salinities within the Louisiana coastal zone, with sites stratified across fresh, intermediate, brackish, and saline marsh zones (Table 2; Sasser et al., 2014).

2.2. SAV Presence/absence data

Presence and absence data for SAV from two sources were used to develop the SDM (Fig. 1). Both sources of data, referred to as (1) survey data, and (2) Wetland Value Assessments (WVA) data, include observations of SAV presence-absence collected during the summer growing season (June 1-September 15th) over a 3 year period (2013–2015), (described by DeMarco, 2018). Due to logistical restrictions (physically accessing site, obtaining landowner permission to access site), there were fewer sites sampled in fresh marsh (n = 73) than the other zones (intermediate = 129, brackish = 168, and saline n = 152).

2.2.1. Survey data

Survey data from 158 sites for a coast-wide survey of SAV across the estuarine salinity gradient were used to inform the SLOO (DeMarco, 2018; Hillmann, 2018; La Peyre et al., 2017). Sites were randomly

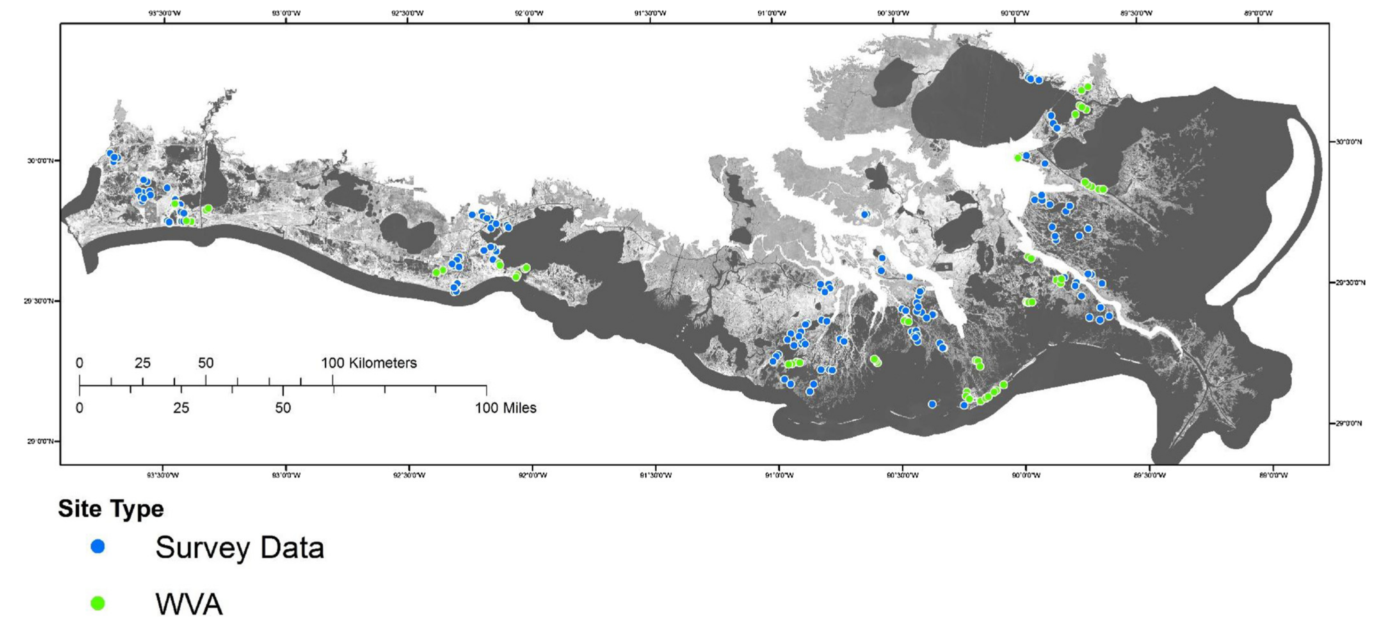

Fig. 1. Map of presence-absence observation sites. Survey data (blue) had 3 observations for each year sampled (2013, 2014 and 2015). Wetland Value Assessment (WVA) sites (green) had 1 observation in the year it was sampled (one year each, between 2013 and 2015), b) seasonal salinity variation, c) mean seasonal depth, and d) seasonal depth variance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Number of sites across marsh zones and salinity values.

	Fresh	Intermediate	Brackish	Saline
N	73	129	168	152
Mean	1.38	3.63	5.58	13.24
Standard Error	0.13	0.13	0.16	0.26
Range	0.02–10.64	0.23–19.39	0.02–25.59	0.53–31.87

selected from shallow aquatic habitats across the coast., brackish, and saline marsh zones (Table 1; Sasser et al., 2014). To determine presence or absence at each site, a quarter meter quadrat was thrown from the boat three times and presence or absence was assessed by collecting SAV from within the quadrat and identified to species. If SAV was present in one quadrat, the site was considered to have SAV present. The same sites were visited in 2013, 2014, and 2015, resulting in 462 individual observations.

2.2.2. *Wetland value assessments (WVA) data*

SAV presence and absence data collected in wetland value assessments (WVA) surveys by the Coastal Wetlands Planning, Protection, and Restoration Act (CWPPRA) Environmental Workgroup (Roy, 2012; Appendix A) were also used for model calibrations. Presence or absence of SAV was determined at 60 sites over the time period by visual assessment or by rake sampling when visual assessment was impossible due to turbidity along transects across the proposed restoration project area.

2.3. *Environmental parameters and spatial layer development*

We compiled, analyzed, and tested spatial datasets of environmental parameters known to be associated with SAV presence-absence. These datasets were developed from multiple sources, including continuous data recorders, remotely sensed satellite imagery, and bathymetry datasets (Couvillion et al., 2017; U.S. Geological Survey (USGS), 2015). The SAV presence/absence data were intersected with the values of the 30 m, Landsat-based, estimates for turbidity, exposure, and salinity (also interpolated to 30 ms), and the resulting spatial model was built off of field observations intersected with remotely sensed data at 30-meter resolution (model: 9,108,251 pixels).

2.3.1. *Salinity, temperature, and water level*

Continuously recorded hydrographic (salinity and water level) data from the Coast-wide Reference Monitoring System (CRMS; https://lacoast.gov/crms2/home.aspx) stations were used to delineate seasons (water temperature) and develop spatial layers for salinity and water levels. These data described spatial and temporal variation in temperature, salinity, and water level trends for the Louisiana coastal zone from October 2012 through October 2016 (Table 2). Daily means were used for the mean values in the analyses, and standard deviations of these daily means were used to assess salinity variability.

To assess potential effects of seasonal conditions on summer SAV presence and growth, we separated hydrologic data into seasons using CRMS water temperature data. Seasons were delineated as: Summer = May 15 – September 14 (daily mean water temperature $\geq$ 25 °C), Fall = September 15 – November 14 (daily mean water temperature range = 24 °C – 16 °C), Winter = November 15 – February 14 (daily mean water temperature $\leq$ 15 °C), and Spring = February 15 – May 14 (daily mean water temperature range = 16 °C – 24 °C). Water temperature was only incorporated to define seasons for this model, and was not included as an environmental parameter elsewhere as temperature did not vary substantially across sites within the study area.

Daily averaged data from approximately 390 CRMS sites were interpolated in ArcGIS to create a raster surface for the salinity and water level using hydrographic barriers to prevent interpolation across boundaries. The resulting interpolated spatial layers were used to calculate seasonal means and standard deviation (hereafter referred to as variance) for salinity and water level.

The interpolation was performed in ArcGIS v. 10.3, using the spline with barriers interpolation technique to create daily datasets. Barriers consisted of levees, impoundments, and basin boundaries that confine hydrologic flow and prevented interpolation across these boundaries. These daily values were used to calculate seasonal averages and standard deviations, on a per-pixel basis (30 m pixels, for approximately 9,000,000 pixels). The spatial resolution of 30 ms was selected as that is the native resolution of the Landsat series of satellites. Landsat data was used in the formulation of the turbidity and exposure layers and as

Table 2
Mean seasonal salinity and standard deviation, calculated using daily interpolated means by pixel, salinity minimum and maximum, mean water level (WL;m) and standard deviation, calculated using daily interpolated means by pixel, exposure index, and reflectance values for observed sites (n = 522) 2013–2015. Seasons were differentiated as follows: Summer = May 15–September 14 (daily mean water temperature $\geq$ 25 °C), Fall = September 15–November 14 (daily mean water temperature range = 24 °C – 16 °C), Winter = November 15–February 14 (daily mean water temperature $\leq$ 15 °C), and Spring = February 15–May 14 (daily mean water temperature range = 16 °C – 24 °C). For the winter season, values were computed from the full winter season (the previous November through the following February) to evaluate influence on the summer growing season. Reflectance and exposure values are not seasonally differentiated due to data limitations, and are represented as a mean value over the period of study.

Explanatory Variable	Winter	Spring	Summer	Fall
Mean Salinity (ppt)	6.1	5.47	6.16	9.22
Salinity Standard Deviation	2.14	1.64	1.85	1.61
Salinity Minimum (ppt)	0.02	0.02	0.04	0.02
Salinity Maximum (ppt)	31.86	26.14	26.96	31.13
Mean WL (m	1.17	1.86	1.98	2.13
Mean WL Standard Deviation	0.38	0.40	0.40	0.35
Mean WL Minimum (m)	−0.79	−0.56	−0.36	−0.34
Mean WL Maximum (m)	6.33	6.19	6.13	6.42
Reflectance Mean*	7059 (20)	7059 (20)	7059 (20)	7059 (20)
Reflectance Minimum	6098	6098	6098	6098
Reflectance Maximum	8557	8557	8557	8557
Exposure Mean*	16.67 (0.27)	16.67 (0.27)	16.67 (0.27)	16.67 (0.27)
Exposure Minimum	15	15	15	15
Exposure Maximum	79	79	79	79

such, this was a natural choice for the resolution of the probability map. Spatial layers were clipped to a 2 m depth, as this was the depth cut off point for the field sampling data.

2.3.2. Exposure and turbidity spatial layer development

2.3.2.1. Exposure index. Exposure and turbidity are unitless parameters associated with an average over the study period at each location that were not separated by seasons due to data limitations. Exposure values are an index reflecting maximum fetch, and reflectance values are a proxy for turbidity

Relative exposure is a function of potential wind driven wave energy at a site. This exposure index was developed using an average 2013–2015 landscape configuration (Couvillion et al., 2017), and the maximum potential wind-driven fetch across the waterbodies was used as a proxy for exposure. To quantify the exposure index, maximum potential fetch for 16 compass directions (every 22.5 degrees) was calculated in ArcGIS (v. 10.3) and an omni-directional, maximum fetch raster spatial layer was developed. This spatial raster layer described maximum potential wind driven fetch from all directions at a given pixel. To interpolate across pixels the fetch raster was reclassified on a scale of 0–100 based upon a 2 standard deviation stretch of all values in coastal Louisiana. This measure did not account for directionality of dominant winds or waves and is essentially a measure of the relative “open-ness” of the water body.

2.3.2.2. Turbidity. The turbidity layer was developed using reflectance values from the Landsat 8 Operational Land Imagery (OLI). In this imagery, the red wavelengths of visible light, covered by Band 4 (0.636–0.673 μm) of the sensor are highly correlated with turbidity and/or total suspended solids (TSS) in studies around the world (Chen et al., 2007; Fritz et al., 2017; Hadjimitsis et al., 2006; Misbari and Hashim, 2016; Quang et al., 2017). The reflectance values in this layer are the average of all cloud-free dates of imagery from 2012 to 2015 and provide relative measure of the average turbidity over the time period. Cloudy conditions in coastal Louisiana often lead to cloud-contaminated images and an inability to observe turbidity for long periods of time (sometime more than 3 months). As such, we were unable to differentiate turbidity into seasons, and the resulting layer represents average turbidity conditions over the 3 year period. There are currently insufficient field data to correlate the reflectance values to TSS, so this measure is unitless. Reflectance is hereafter referred to as turbidity.

2.4. Model development

A generalized linear model (GLM) was selected as the statistical modeling method most appropriate for the presence-absence dataset (n = 522). The model was developed using field data sites with observations of SAV presence and absence. Field observations of presence and absence were intersected with the spatial layers (seasonal mean salinity, seasonal salinity variability, seasonal water level mean, seasonal water level variability, exposure to wind, and reflectance as a proxy for turbidity) at each geographic location (Table 2). Potential environmental variables were evaluated for model inclusion using stepwise analysis in both directions of the binomial regression model including all possible variables and post-hoc Tukey HSD tests to determine significant differences. ANOVA tests were used to compare environmental variables among seasons for descriptive purposes. All statistical analyses were conducted in R (The R Core Team, 2016).

To choose the most appropriate model we compared Akaike’s Information Criterion (AIC) scores, Wald tests, and likelihood ratio tests to assess the predictive power of the full model, a reduced model, and a null model. A probability threshold of 50% likelihood of occurrence was selected as presence (SAV = 1), and anything below that threshold was considered absence (SAV = 0). The GLM for the final SLOO Model generated a logit function to predict the probability of presence spatially for each cell in the 2017 land/water USGS coastal map (Couvillion et al., 2017) The model development tool in ArcGIS version 10.4 (Environmental Systems Research Institute (ESRI), 2015) spatially projected the logit function in each pixel, creating continuous spatial layer that quantified the probability of SAV occurrence across the Louisiana coastal landscape.

A confusion matrix to evaluate model performance was generated predicting presence or absence at each individual site based on the rest of the observations, comparing the actual observations versus predicted SAV presence or absence (Lewis and Brown, 2010). From the confusion matrix, we were able to evaluate model performance by calculating Cohen’s Kappa statistic (a measure of how well the model performed based on environmental drivers versus how well it would have performed by chance), and a correct classification rate, as well as calculate model sensitivity, specificity, and precision.

3. Results

3.1. SAV presence/absence

SAV species observed included *C. demersum, H. verticillata, C. caroliniana, M. spicatum, V. americana, Potamogeton pusillus, N. guadalupensis, Stuckenia pectinata, and R. maritima*, across the fresh to saline marsh zones (described in Table 1). All species are submerged and rooted, except *C. demersum*, which is rootless and primarily found floating at the top of the water column. Although other species of floating aquatic vegetation were observed, they were not included in this analysis. According to ANOVA tests comparing years, there was no significant difference (F value = 0.846, p = 0.358) in presence or absence in all field collected data (both survey and WVA sites) among years across this spatial scale; SAV was present at 109 sites (n = 179) in 2013, 96 sites in 2014 (n = 170), and 97 sites in 2015 (n = 173).

3.2. Salinity, water level

Salinity ranged from 0 to 31.9 across all sites and seasons (Table 2). Mean seasonal salinity in the fall was higher ($p < 0.0001$) than the other seasons, which were similar. Mean water level was significantly different across all seasons with lowest levels in the winter. Water level data were ultimately removed from the model as attempts to spatially reconcile the CRMS recorded depth and bathymetric elevation data were unsuccessful due to high error rates in coastal Louisiana bathymetry data (i.e., > 2 m, which was the depth limit for this study, Couvillion, personal communication). Moreover, the distance between the actual site and the CRMS recorder in some cases resulted in water levels that were not representative of each unique site, and interpolation of water level across pixels would have required making significant, and potentially inaccurate, assumptions.

3.3. Exposure index and turbidity

Exposure index values ranged from 15 to 79, with a mean value of 16.7 (SE = 0.27), with the majority of exposure values between 15 and 18 (Table 2). There were very few instances of exposure values above 50 (n = 9); highest exposure index value incorporated into the model was 79. Higher exposure numbers reflect potentially higher wave/wind energy at the site. Turbidity values ranged from 6098 to 8557, with a mean value of 7061 (SE = 20). The highest turbidity values were located near freshwater outflows of large rivers, indicating low water clarity.

3.4. Model

Both the AIC scores and ANOVA comparing models indicated that the reduced model was better for this analysis (Supplemental Table S1; Full model AIC = 575.87; Reduced model AIC = 567.01; df = 521). The ANOVA tests for the full model showed that winter mean salinity and turbidity were significant (Supplemental Table S2; $p < 0.001$) predictors of SAV presence. Exposure was included in a stepwise (both directions) reduced model from all of the evaluated predictor variables ($p < 0.07$). Interactions were examined, but the improvements to the goodness of fit were limited, and following Occam's razor principle, we restricted the model to single effects. Model comparison tests indicate that there were no significant difference between the reduced and the full models so the reduced model was selected. Significant predictors were winter mean salinity ($p < 0.00001$), and reflectance ($p = 0.002129$), with exposure included in the final model ($p = 0.068871$).

The binomial logistic regression equation for the final SLOO Model is:

$$Logit\,(Presence) = 6.6330{-}0.2068(WinterM){-}0.0007(REFL){-}0.0277(EPO)$$

Where Logit (Presence) is the logit function for the likelihood of presence, *WinterM* is mean winter salinity, *REFL* is reflectance, and *EPO* is exposure.

The corresponding logit function for the SLOO is:

$$P(SAV = 1) = \frac{[\exp(6.6630{-}0.2068(WinterM){-}0.0007(REFL){-}0.0277(EPO)]}{[1 + exp(6.6630{-}0.2068(WinterM){-}0.0007(REFL){-}0.0277(EPO)]}$$

The logit function was attached to each values for the spatially interpolated environmental data (mean winter salinity, exposure, and turbidity) at each pixel was plugged into the spatial model to develop a continuous layer describing probability of SAV occurrence across the Louisiana coastal landscape (Fig. 2).

The SLOO model performed satisfactorily to predict the presence of SAV in the Louisiana coastal zone, according to the confusion matrix (Table 3) predicting presence more correctly than absence. The Kappa statistic suggests moderate agreement between the model classifiers and the predictions, 0.55, and the correct classification rate of 0.74 indicates good to moderate model performance (Table 4) as indicated by a very high sensitivity rate (or true positive) of 0.86, and a moderate specificity rate (true negative) of 0.564.

The model is strongly influenced by changes in winter mean salinity, turbidity, and exposure with varying degrees of certainty (Fig. 3). Model sensitivity to variables was tested by analyzing the probability of presence given a range of possible salinity, turbidity, and exposure. Mean winter salinity had the strongest effect with an almost linear reduction in probability of presence and high confidence of this effect across the full range of values (Fig. 3a). The impact of turbidity was less pronounced (although still significant) on SAV probability of presence, and confidence in the effect of turbidity was decreased towards the high and low turbidity values (Fig. 3b). The effect of exposure was the most uncertain of the 3 variables included in the model, as indicated by very wide range of confidence around the mean (Fig. 3c), which increased as potential relative exposure values increased.

4. Discussion

The model accurately predicts SAV presence 74% of the time across the Louisiana study area and identifies three primary drivers for SAV occurrence, mean winter salinity, turbidity, and exposure. As values for these key drivers increased, the likelihood for SAV presence during the summer growing season decreased coast-wide. These results indicate that SAV occurrence across large landscapes can be predicted based on a few key environmental parameters, providing a means to estimate current SAV occurrence as well as to predict future changes to SAV habitat availability. Moreover, the use of imagery data to approximate turbidity as a proxy for light availability is the first application of this method in coastal Louisiana, and has wide ranging research applications.

The strong response of SAV occurrence to winter salinity is likely driven by the species specific adaptations and the competitive abilities of dominant species. In the study area, species occurrence was dominated by *H. verticillata*, *C. demersum*, and *M. spicatum*, with other species (*N. guadalupensis*, *V. americana*, and *R. maritima*) found much less frequently. Each of these dominant SAV species are known for being "winter-hardy" as they overwinter in the benthos as roots, tubers, or winter buds (or turions) and regenerate vegetatively instead of from seed (Cho and Poirrier, 2005b; Cronk and Fennessy, 2001; Nichols and Shaw, 1986; Van den Berg et al., 2003). In this region, as soon as mean water temperatures increase above 15 °C plants can begin to germinate, and SAV shoots are able to grow rapidly to form canopies (Haller et al., 1976; Jarvis and Moore, 2008; Rybicki and Carter, 2002). These early growing SAV species are dominant in shallow aquatic habitats in the fresh marsh zones of coastal Louisiana (Hillmann et al., 2016) but are sensitive to increased salinities. Consequently, increased salinities during early growth season (i.e. winter) stages can negatively impact their likelihood of occurrence.

The absence of SAV during all 3 years in the saline coastal marsh zones of Louisiana may be due to the inability of the salt-tolerant species (i.e., *R. maritima*) to colonize and grow under exposure to high wave and wind energy (Cho et al., 2009). SAV species found in lower salinities, while unable to persist in high current or wave conditions, may be more tolerant to lower light levels as compared to more salt tolerant SAV (Koch, 2001, and references therein), an artifact of the evolutionary trade-off between stress tolerance and competitive ability. Declines of SAV as the result of physical disturbances have been well documented in other locations (Fonseca and Bell, 1998; Gurbisz et al., 2016; Pulich and White, 1991; Robbins and Bell, 200; Santos et al., 2011) and in specific species (Barrat-Segretain, 2001; Martin and Valentine, 2012; Strand and Weisner, 2001). In particular, SAV species in Louisiana that are able to persist in brackish salinities and high turbidities (*R. maritima* and *M. spicatum*) have a low tolerance to

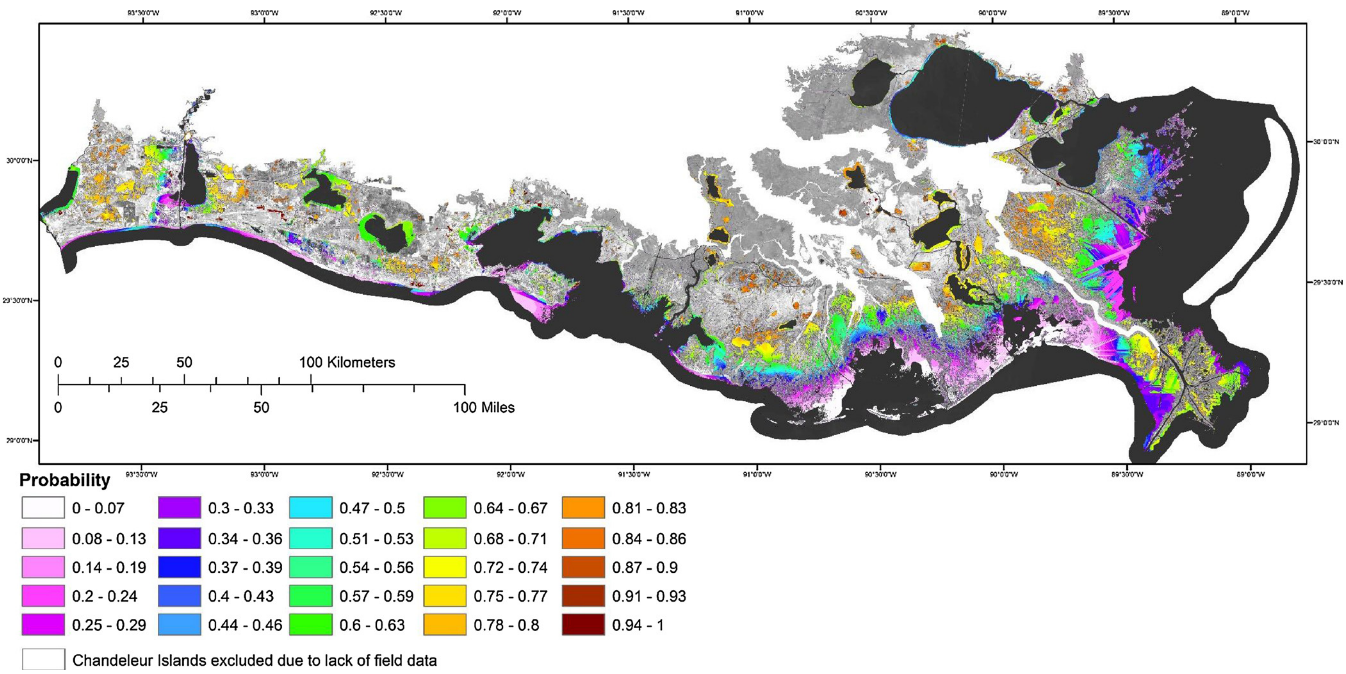

Fig. 2. Probability of submerged aquatic vegetation (SAV) occurrence across coastal Louisiana (2013–2015). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Confusion Matrix for Reduced Model. A confusion matrix was designed with presence/SAV = 1 and absence/no SAV = 0. If a cell was given a probability of 50% or greater likelihood of presence, it was coded as present = 1.

		Predicted		
		Present	Absent	Total
Actual	Present	260	42	302
	Absent	96	124	220
	Total	256	166	522

Table 4
Performance and error measures for the submerged aquatic vegetation (SAV) likelihood of occurrence model (SLOO).

Measure	Error Rate
Kappa Statistic	0.546
Correct Classification Rate	0.736
Misclassification Rate	0.264
Sensitivity (true positive rate)	0.861
Specificity (true negative rate)	0.564
False Positive Rate	0.436
False Negative Rate	0.139

physical disturbance (Cho and Poirrier, 2005b; Martin and Valentine, 2012).

Although the relationship between exposure and presence is the most uncertain of the significant environmental drivers identified, it is likely due to the coarseness of the exposure index itself. An exposure index with a finer resolution that accounts for wave and wind orientation may improve model predictions by more accurately capturing the linkage between SAV presence-absence and exposure, particularly if seasonal exposure can be calculated based on dominant wind direction and speed.

Past work on SAV has identified light to be the dominant factor influencing SAV occurrence (Koch, 2001; Kemp et al., 2004; Cho and Poirrier, 2005). The SLOO model corroborates this work, as the probability of SAV presence decreased linearly as turbidity increased. Turbidity would have a stronger effect on SAV occurrence if seasonal turbidity was identified, as light availability can have a greater impact on seedling plants than adults (Cho and Poirrier, 2005a, b; Fourqurean et al., 2003). The light requirements of many SAV species can vary according to growth stage, and the effect of turbidity on SAV occurrence could be seasonal. However, the seasonal growth of SAV in Louisiana has not been fully described, so these linkages remain less clear. The importance of turbidity to SAV may be further related to water levels, as seasonally driven changes in water depth can affect light penetration through the water column even if turbidity remains constant. It is possible that in the winter season when water levels are lowest, higher turbidity values may not have as significant an effect on growing plants.

The SLOO model tended to over-predict presence and under-predict absence. The errors in prediction are concentrated in areas (1) where brackish and saline marsh zones converge, (2) with high freshwater outflow, and (3) with potentially intensive human management activities affecting water level and salinity (Fig. 4). There are several possible reasons for these errors: 1) the timing of sampling fails to capture the full growing season and thus probability of presence, 2) the lack of directionality and seasonality in exposure and turbidity does not accurately reflect field conditions, 3) anthropogenic activities which significantly impact local conditions are not represented at the scale evaluated, and/or 4) there is an interaction effect missing in the model. Moreover, the absence of an extreme event (tropical storm or hurricane) over the study period may similarly fail to capture the response of SAV assemblages to rapid ecological changes. Despite these limitations, the SLOO model provides a means to estimate current SAV habitat and predict future changes in SAV habitat availability based on the drivers identified. Potential changes in salinity, turbidity and exposure are likely both as the landscape is subjected to accelerated sea-level rise, and as restoration projects are constructed. While SLR will increase salinity, river diversions may simultaneously decrease salinity and increase turbidity as fresh and turbid Mississippi River water flows over shallow aquatic habitats. Similarly, while increased SLR will increase the potential for SAV habitat, by creating aquatic areas, it may also increase exposure and/or fetch.

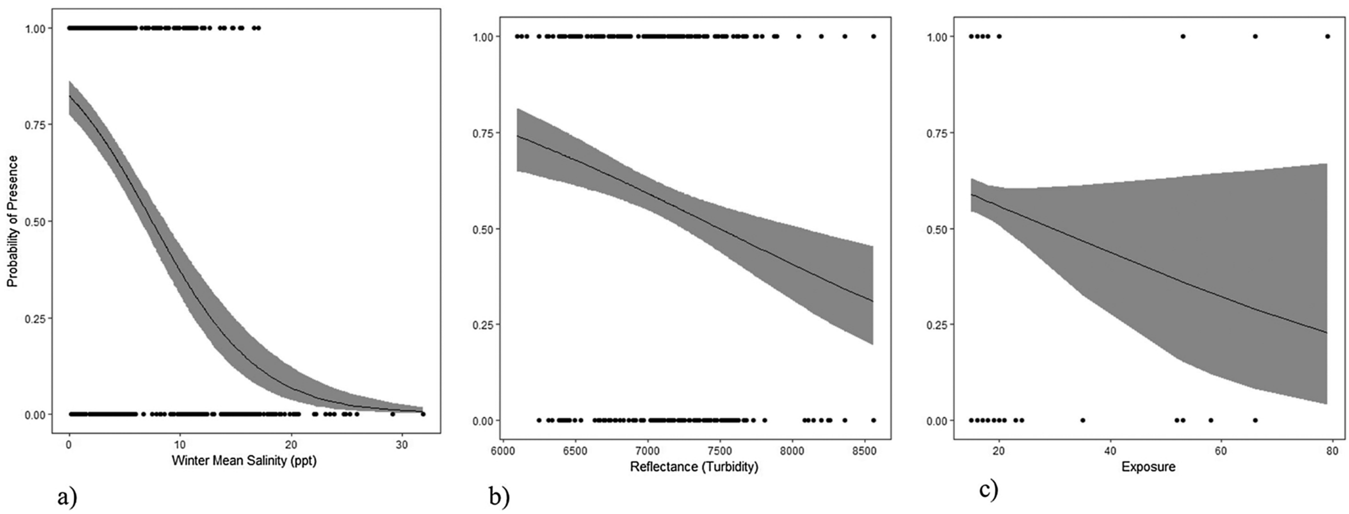

Fig. 3. Contour plots for effect of significant predictors on the likelihood of submerged aquatic vegetation (SAV) presence in the spatial likelihood of occurrence (SLOO) model. a) Winter Mean Salinity vs probability of presence, b) Reflectance vs. probability of presence, and c) Exposure vs. probability of presence. The steepness of the slope represents the strength of the parameter effect on SAV presence and the gray area is the uncertainty surrounding each parameters ability to influence SAV presence based on 95% confidence intervals.

The focus of the field sampling on a summer growing season in coastal Louisiana may not capture the full influence of seasonal environmental conditions on the probability of presence throughout the year. In the continental United States, the growing season of SAV is loosely defined as the summer months, when temperatures and light availability are high enough for growth (Dennison et al., 1993; Rybicki and Landwehr, 2007; Stevenson et al., 1993; Vis et al., 2003). However, the subtropical climate of Louisiana is characterized by mild winters (https://www.ncdc.noaa.gov/climatenormals/clim60/states/Clim_LA_01.pdf), with average air temperature in January (the coldest month) at 7 °C, and even milder water temperatures averaging 15 °C. Further, Cho and Poirrier (2005b) identified two separate growing seasons for SAV in Lake Pontchartrain, Louisiana, observing the highest percent cover of SAV species in the summer and fall seasons. An intra-annual study in one Louisiana basin identified high SAV biomass in May and July, with a low in December (Hillmann, 2018) In Louisiana, SAV occurs year round (DeMarco, 2018) and tighter seasonal coupling between occurrence and conditions could increase model accuracy both spatially and temporally.

The incorporation of orientation into exposure to capture dominant winds, and the identification of seasonal trends in both exposure and turbidity have the potential to provide significantly greater predictive

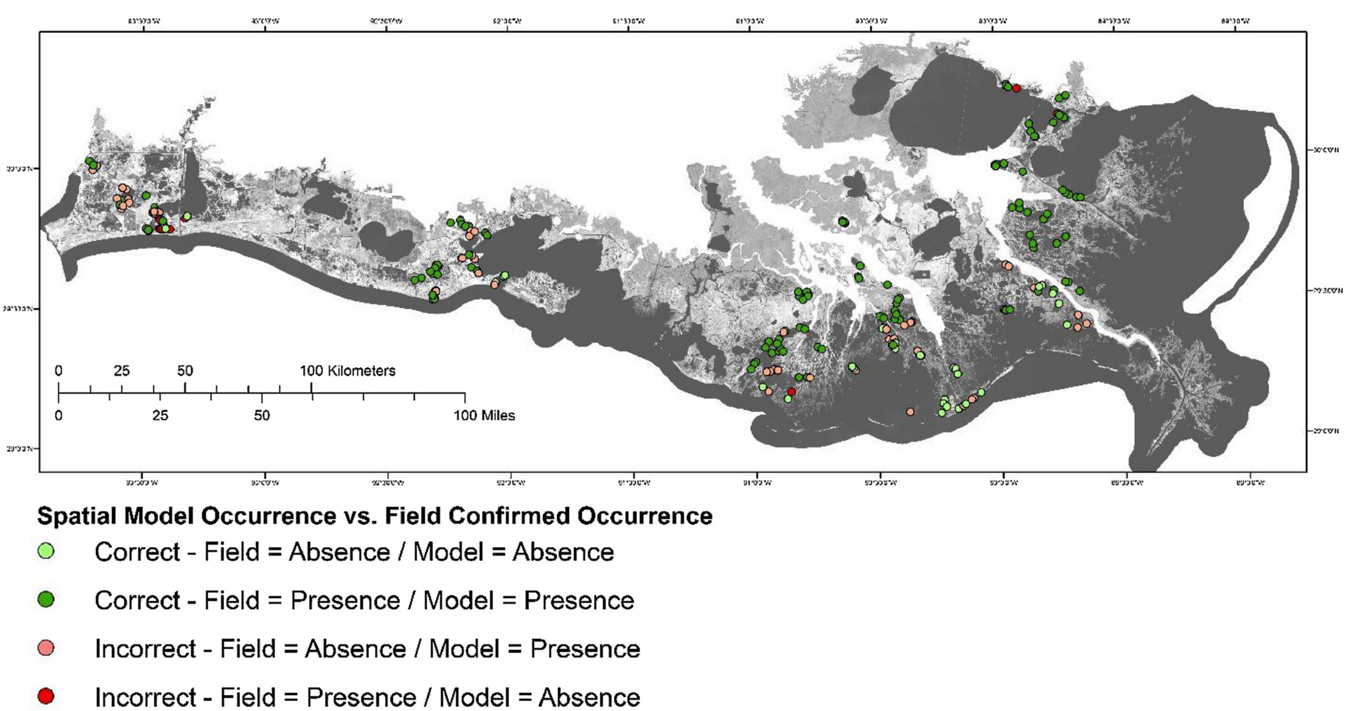

Fig. 4. Areas of error between observed and predicted presence-absence at sampled sites. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

capacity. SAV in the northern Gulf of Mexico are known to persist in sheltered areas of open bays and in areas protected from wind/waves in relatively large water bodies (Hillmann et al., 2016). Including directionality and orientation spatially as well as seasonally into the exposure index would more accurately reflect existing seasonal wind patterns in the field (Allison et al., 2016; Feng and Li, 2010; Walker and Hammack, 2000). Turbidity patterns are similarly seasonal as they are influenced by seasonal (spring) riverine flooding, winter cold fronts, and summer storm events (hurricanes). For example, cold fronts and dominant north winds in Louisiana push water out of interior marshes (Feng and Li, 2010), lowering depth and, as a result, potentially increasing light availability to benthic organisms, while spring flooding may decrease light availability by increasing turbidity (Alison and Meselhe, 2010).The effects of increased exposure and/or turbidity could have a greater influence on SAV species during the seedling stage (Doyle and Smart, 2001; Jarvis and Moore, 2008; Strasizar et al., 2015) as seedlings are generally more sensitive than adult plants to fluctuating salinity, decreased light in the water column, and water movement. The effects of and interactions among exposure and turbidity may be seasonally significant, and a better resolution of these drivers would improve model performance and representation of SAV occurrence. Moreover, the ability to capture SAV response to temporary events (i.e. storms) that can affect multiple drivers would provide insight into planning under future climate change scenarios.

Louisiana's coast is largely privately owned and managed for various uses, creating dynamic and variable environmental conditions (Merino et al., 2005; Snedden and Steyer, 2013; Syvitski et al., 2009) that can in turn have abrupt and localized effects on the SAV community. Anthropogenic influences are inherently difficult to parameterize for model applications and include commercial and recreational boating, commercial fishing, chemical industries, navigation, and water level management activities – all of which can significantly influence the ability for SAV to colonize and germinate in the immediate vicinity. In fact, high error between predicted and observed occurrence in western Louisiana, may reflect high amounts of management activities in this area, although the exact mechanisms and outcomes of these efforts remain unclear (https://www.fws.gov/refuge/Sabine/what_we_do/resource_management.html). This influence of human management coupled with the active natural processes in the coast complicate our ability to model and predict environmental conditions (Coastal Protection and Restoration Authority of Louisiana (CPRA), 2012; Keddy et al., 2006; Snedden and Steyer, 2013; White and Visser, 2016). Incorporating the regional activities and natural processes may improve model accuracy in certain areas, and although this may be difficult to evaluate on a large scale, may be testable as a local, site specific study.

Although the inclusion of an interaction effect was not reported in this effort, future improvements might incorporate the interaction of salinity with exposure and turbidity, once these measures can be seasonally described. The strong salinity response is spatially distinctive, and marsh vegetation zones (Sasser et al., 2014) and SAV may respond uniquely to these interactions. The individual species physiological tolerances to stressors could be dictating the presence of SAV across large landscapes (Koch, 2001; Patrick and Weller, 2015). The creation of submerged habitat zones based on salinity patterns and exposure and the development of models specific to these spatial zones will reflect natural separations between species assemblages, resulting in more accurate predictive models.

5. Conclusion

Across the NGOM coast, SAV communities are known to exist across a wide range of salinity, water clarity, and exposure conditions (DeMarco et al., 2016; Hillmann et al., 2016; Merino et al., 2009). However, this large-scale analysis identified potential hotspots for SAV and areas less likely to support SAV communities. Specifically, there was marked SAV absence in the saline and brackish marsh areas located in the more exposed, down-estuary regions in the Louisiana coastal landscape. In contrast, interior estuarine habitats with lower salinity, turbidity, and/or exposure were found to have a high likelihood of SAV occurrence. It is probable that the combined salinity and turbidity patterns in these areas are only suitable for SAV species that, while tolerant of brackish to saline salinities and low water clarity, are unable to colonize or persist in high exposure habitats, preventing the occurrence of any SAV in down-estuary coastal waters.

Development of the SLOO model relied heavily on the field collection of presence absence data to create a SDM modeling tool that can quantify drivers of SAV occurrence, represent these potential drivers spatially, and inform coastal restoration and management. Coastal restoration projects in Louisiana wetlands may significantly alter environmental and hydrologic conditions (Allison and Meselhe, 2010; Coastal Protection and Restoration Authority of Louisiana (CPRA), 2017; Kemp et al., 2016; Snedden et al., 2007; White and Visser, 2016) and ultimately the extent and location of SAV communities by changing salinity, water clarity, and exposure patterns. It may be advantageous to consider both changes in the annual and the seasonal patterns to predict SAV response to restoration efforts. Incorporation of the SLOO model and map into coastal management and restoration strategies provides a useful predictive tool to help create healthy aquatic ecosystems and SAV habitat in future coastal landscapes.

Conflicts of interest

The authors declare that we have no significant competing financial, professional, or personal interests that may have influenced the performance or presentation of the work contained in this manuscript.

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Appendix A

Table A1

Table A1
Wetland Valuation Assessment (WVA) Survey Data. PA = Presence/Absence; LAT = Latitude; LON = Longitude (LAT/LON in decimal degrees).

Location Name	PA	Date	WVA_Notes	Year	LAT	LON
SW Pass	0	6/4/2013	0%	2013	29.61509	−92.0249
SW Pass	0	6/4/2013	0%	2013	29.59399	−92.0562
SW Pass	0	6/4/2013	0%	2013	29.58511	−92.061
SW Pass	0	6/4/2013	0%	2013	29.61886	−92.0179
WestCove	0	6/5/2013	1%. per personal comm w/ R.Gosnell (FWS), most years there is little/no SAV in the open water area	2013	29.84356	−93.4539
WestCove	0	6/5/2013	1%. per personal comm w/ R.Gosnell (FWS), most years there is little/no SAV in the open water area	2013	29.84848	−93.454
NOLB	1	6/12/2013	50%	2013	30.12806	−89.7603
NOLB	1	6/12/2013	50%	2013	30.14415	−89.7159
NOLB	1	6/12/2013	50%	2013	30.15826	−89.7423
NOLB	1	6/12/2013	50%	2013	30.1538	−89.7336
Wilk	0	6/13/2013	2% SAV Coverage	2013	29.62638	−89.9701
Wilk	0	6/13/2013	2% SAV Coverage	2013	29.61974	−89.9583
BGC	0	6/13/2013	11% total. "dense SAV in the SE portion of the S cell. That's the only area of dense SAV cover"	2013	29.54054	−89.8566
BGC	1	6/13/2013	11% total. "dense SAV in the SE portion of the S cell. That's the only area of dense SAV cover"	2013	29.52791	−89.8407
BGC	0	6/13/2013	11% total. "dense SAV in the SE portion of the S cell. That's the only area of dense SAV cover"	2013	29.54452	−89.8366
Cam BB	0	6/18/2013	0%	2013	29.11623	−90.1775
Cam BB	0	6/18/2013	0%	2013	29.12664	−90.1561
Cam BB	0	6/18/2013	0%	2013	29.13226	−90.1471
Island Rd	0	6/19/2013	0%	2013	29.41306	−90.4759
Island Rd	0	6/19/2013	0%	2013	29.40905	−90.4804
Island Rd	0	6/19/2013	0%	2013	29.40533	−90.4635
E Leeville	0	6/3/2014	0%	2014	29.26175	−90.1934
E Leeville	0	6/3/2014	0%	2014	29.25859	−90.1849
E Leeville	0	6/3/2014	0%	2014	29.23992	−90.1778
Dularge	0	6/4/2014	1%. 0% observed 2014, traces of milfoin obseved in past years	2014	29.2701	−90.9229
Dularge	0	6/4/2014	1%. 0% observed 2014, traces of milfoin obseved in past years	2014	29.26283	−90.941
Dularge	0	6/4/2014	1%. 0% observed 2014, traces of milfoin obseved in past years	2014	29.26166	−90.9548
Dularge	0	6/4/2014	1%. 0% observed 2014, traces of milfoin obseved in past years	2014	29.26703	−90.909
BBienvenue	1	6/10/2014	90%	2014	29.98467	−89.9976
BBienvenue	1	6/10/2014	90%	2014	29.98155	−90.0051
BBienvenue	1	6/10/2014	90%	2014	29.9783	−90.001
Shell1	1	6/11/2014	80%. Watermilfoil (Myriophyllum spp.) was prevalent throughout the open water areas of the site.	2014	29.85882	−89.6646
Shell1	1	6/11/2014	80%. Watermilfoil (Myriophyllum spp.) was prevalent throughout the open water areas of the site.	2014	29.85867	−89.6736
Shell1	1	6/11/2014	80%. Watermilfoil (Myriophyllum spp.) was prevalent throughout the open water areas of the site.	2014	29.85867	−89.6569
W. Fourchon	0	6/12/2014	0%	2014	29.15017	−90.2327
W. Fourchon	0	6/12/2014	0%	2014	29.13629	−90.2366
W. Fourchon	0	6/12/2014	0%	2014	29.12488	−90.2242
No Name	0	6/18/2014	1%. Small patch of widgeon grass observed on south shoreline but nothing else	2014	29.82623	−93.3268
No Name	0	6/18/2014	1%. Small patch of widgeon grass observed on south shoreline but nothing else	2014	29.83272	−93.318
SE Pecan	1	6/18/2014	40% SAV in the existing terrace field. 20% in other interior water areas.	2014	29.61161	−92.3595
SE Pecan	1	6/18/2014	40% SAV in the existing terrace field. 20% in other interior water areas.	2014	29.60333	−92.387
Fritchie	1	5/27/2015	42% of depth measurements had SAV present	2015	30.21297	−89.7333
Fritchie	1	5/27/2015	42% of depth measurements had SAV present	2015	30.22418	−89.7067
N. Shell Beach	1	5/28/2015	70%	2015	29.86937	−89.704
N. Shell Beach	1	5/28/2015	70%	2015	29.87615	−89.7197
N. Shell Beach	1	5/28/2015	70%	2015	29.88584	−89.7295
BarBay Rim	0	6/2/2015	large open water areas were notably absent of SAV. smaller ponds appeared 10 to 20% SAV	2015	29.46682	−89.9823
BarBay Rim	0	6/2/2015	large open water areas were notably absent of SAV. smaller ponds appeared 10 to 20% SAV	2015	29.46402	−89.976
BarBay Rim	1	6/2/2015	large open water areas were notably absent of SAV. smaller ponds appeared 10 to 20% SAV	2015	29.46425	−89.9732
BarBay Rim	1	6/2/2015	large open water areas were notably absent of SAV. smaller ponds appeared 10 to 20% SAV	2015	29.46475	−89.9584
Cam BB 2	0	6/3/2015	0%	2015	29.15319	−90.1137
Cam BB2	0	6/3/2015	0%	2015	29.14828	−90.1222
Cam BB2	0	6/3/2015	0%	2015	29.17242	−90.0838
Ter Ridge	0	6/4/2015	0%	2015	29.26155	−90.5937
Ter Ridge	0	6/4/2015	0%	2015	29.2696	−90.6006
Ter Ridge	0	6/4/2015	0%	2015	29.27519	−90.6064
W. Vermilion Bay	9999	6/24/2015	5%. VERY shallow water/mudflat. probably muscrats/nutria.likely not representative.	2015	29.63542	−92.1309
W. Vermilion Bay	9999	6/24/2015	5%. VERY shallow water/mudflat. probably muscrats/nutria.likely not representative.	2015	29.62729	−92.1257
OysterLake	9999	6/25/2015	10%. cover was sporadic in the open water areas. only Ruppia was observed.	2015	29.78591	−93.388
OysterLake	9999	6/25/2015	10%. cover was sporadic in the open water areas. only Ruppia was observed.	2015	29.78844	−93.4072

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aquabot.2018.08.007.

References

Adams, M.P., Saunders, M.I., Maxwell, P.S., Tuazon, D., Roelfsema, C.M., Callaghan, D.P., Leon, J., Grinam, A.R., O'Brien, K.R., 2016. Prioritizing localized management actions for seagrass conservation and restoration using a species distribution model. Aquat. Conserv. Mar. Freshw. Ecosyst. 26, 639–659.

Allison, M.A., Meselhe, E.A., 2010. The use of large water and sediment diversions in the lower Mississippi River (Louisiana) for coastal restoration. J. Hydrol. (Amst.) 387, 346–360.

Anderson, J.B., Wallace, D.J., Simms, A.R., Rodriguez, A.B., Milken, K.T., 2014. Variable response of coastal environments of the northwestern Gulf of Mexico to sea-level rise and climate change: implications for future change. Mar. Geol. 352, 348–366.

Barrat-Segretain, M., 2001. Biomass allocation in three macrophyte species in relation to the disturbance level of their habitat. Freshw. Biol. 46, 935–945.

Beale, C.M., Lennon, J.J., 2012. Incorporating uncertainty in predictive species distribution modelling. Philos. Trans. Biol. Sci. 367, 247–258.

Bornette, G., Puijalon, S., 2011. Response of aquatic plants to abiotic factors: a review. Aquat. Sci. 73, 1–14.

Brasher, M.G., James, J.D., Wilson, B.C., 2012. Gulf Coast Joint Venture Priority Waterfowl Science Needs. Gulf Coast Joint Venture, Lafayette, LA, USA 54 pp.

Burgos-León, A.M., Valdés, D., Vega, M.A.E., O, Defeo, 2013. Spatial structuring of submerged aquatic vegetation in and estuarine habitat of the Gulf of Mexico. J. Mar. Biol. Assoc. UK 93 (4), 855–866.

Carter, J., Merino, J.H., Merino, S.L., 2009. Mesohaline submerged aquatic vegetation survey along the US Gulf of Mexico coast, 2000: a stratified random approach. Gulf Mex. Sci. (1), 1–8.

Carter, G.A., Lucas, K.L., Biber, P.D., Criss, G.A., Blossom, G.A., 2011. Historical changes in seagrass coverage on the Mississippi barrier islands, northern Gulf of Mexico, determined from vertical aerial imagery (1940–2007). Geocarto Int. 26 (8), 663–673.

Castellanos, D.L., Rozas, L.P., 2001. Nekton use of submerged aquatic veg- etation, marsh and shallow unvegetated bottom in the Atchafalaya River Delta, a Louisiana tidal freshwater ecosystem. Estuaries 24 (2), 184–197.

Chabreck, R.H., 1970. Marsh Zones and Vegetative Types in the Louisiana Coastal Marshes. LSU Historical Dissertation and Thesis 1773. http://digitalcommons.lsu.edu/gradschool_disstheses/1773.

Chen, Z., Hu, C., Muller-Karger, F., 2007. Monitoring turbidity in Tampa Bay using MODIS/Aqua 25. Remote Sens. Environ. 109, 207–220.

Cho, H.J., Biber, P.D., 2016. Habitat characterization for submerged and floating-leaved aquatic vegetation in coastal river deltas of Mississippi and Alabama. Southeast. Geogr. 54 (4), 454–472.

Cho, H.J., Poirrier, M.A., 2005a. A model to estimate potential submersed aquatic vegetation habitat based on studies in Lake Pontchartrain, Louisiana. Restorat. Ecol. 13 (4), 623–629.

Cho, H.J., Poirrier, M.A., 2005b. Seasonal growth and reproduction of *Ruppia maritima* L. s.l. In Lake Pontchartrain, Louisiana, USA. Aquat. Bot. 81, 37–49.

Cho, H.J., Biber, P., Nica, C., 2009. The rise of Ruppia in seagrass beds: changes in coastal environment and research needs. In: Drury, E.K., Pridgen, T.S. (Eds.), Handbook of Environmental Quality. NOVA Science Publisher, pp. 1–15.

Christianen, M.J.A., van Belzen, J., Herman, P.M.J., van Katwijk, M.M., Lamers, L.P.M., van Leent, P.J.M., Bouma, T.J., 2013. Low-canopy seagrass beds still provide important coastal protection services. PLoS One 8 (5), e62413. https://doi.org/10.1371/journal.pone.0062413.

Coastal Protection and Restoration Authority of Louisiana (CPRA), 2012. Mid-Barataria Sediment Diversion Final Draft Executive Summary Report 30% Basis of Design. Coastal Protection and Restoration Authority of Louisiana, Baton Rouge, LA.

Coastal Protection and Restoration Authority of Louisiana (CPRA), 2017. Louisiana's Comprehensive Master Plan for a Sustainable Coast. Coastal Protection and Restoration Authority of Louisiana, Baton Rouge, LA.

Couvillion, B.R., Beck, H., Schoolmaster, D., Fischer, M., 2017. Land Area Change in Coastal Louisiana 1932 to 2016: U.S. Geological Survey Scientific Investigations Map 3381. 16 p. pamphlet. https://doi.org/10.3133/sim3381.

Cronk, J.K., Fennessy, M.S., 2001. Wetland Plants: Biology and Ecology. CRC Press/Lewis Publishers, Boca Raton, FL 440 pp.

DeMarco, K.E., 2018. Shifting Niche Space in Coastal Landscapes: Spatio-temporal Patterns Driving Submerged Aquatic Vegetation Across the Northern Gulf of Mexico. Dissertation. Louisiana State University 119 pp.

DeMarco, K.E., Hillmann, E.R., Brasher, M.G., La Peyre, M., 2016. Brackish marsh zones as a waterfowl habitat resource in submerged aquatic vegetation beds in the Northern Gulf of Mexico. J. Southeast. Assoc. Fish Wildl. Agents 3, 261–269.

Dennison, W.C., Orth, R.J.T., Moore, K.A., Stevenson, J.C., 1993. Assessing water quality with submersed aquatic vegetation. BioScience 43 (2), 86–94.

Doyle, R.D., Smart, R.M., 2001. Impacts of water column turbidity on the survival and growth of *Vallisneria americana* winterbuds and seedlings. Lake Reserv. Manag. 17 (1), 17–28.

Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Ann. Rev. Ecol. 40, 677–697.

Environmental Systems Research Institute (ESRI), 2015. ArcGIS Release 10.4. Redlands, CA. .

Estes, M.G., Al-Hamdan, M.Z., Ellis, J.T., Judd, C., Woodruff, D., Thorn, R.M., Quattrochi, D., Watson, B., Rodriguez, H., Johnson III, H., Herder, T., 2015. A modeling system to assess land cover/land use change effects on SAV habitat in the Mobile Bay estuary. J. Am. Water Resour. Assoc. 51 (2), 513–536.

Feng, Z., Li, C., 2010. Cold-front induced flushing of Louisiana Bays. J. Mar. Syst. 82, 252–264.

Fonseca, M., Bell, S., 1998. Influence of physical setting on seagrass landscapes near beaufort, North Carolina. Marine Ecology Progress Series 121. pp. 109–121.

Fourqurean, J.W., Boyer, J.N., Durako, M.J., Hefty, L.N., Peterson, B.J., 2003. Forecasting responses of seagrass distributions to changing water quality using monitoring data. Ecol. Appl. 13 (2), 474–489.

Fritz, C., Dörnhöfer, K., Schneider, T., Geist, J., Oppelt, N., 2017. Mapping submerged aquatic vegetation using RapidEye Satellite data; the example of Lake Kummerow (Germany). Water 9 (510). https://doi.org/10.3390/w9070510.

Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. 8, 993–1009.

Gurbisz, C., Kemp, W.M., Sanford, L.P., Orth, R.J., 2016. Mechanisms of storm-related loss and resilience in a large submersed plant bed. Estuaries Coasts 39, 951–966.

Haller, W.T., Miller, J.L., Gerrard, L.A., 1976. Seasonal production and germination of hydrilla vegetative propagules. J. Aquat. Plant Manag. 14, 26–29.

Heck Jr, K.L., Hays, G., Orth, R.J., 2003. Critical evaluation of the nursery role hypothesis for seagrass meadows. Mar. Ecol. Prog. Ser. 253, 123–136.

Hillmann, E.R., 2018. Analysis of Submerged Aquatic Vegetation Across the Northern Gulf of Mexico: communities and Biomass. Dissertation. Louisiana State University 166 pp.

Hillmann, E.R., DeMarco, K.E., La Peyre, M., 2016. Establishing a baseline of estuarine submerged aquatic vegetation resources across salinity zones within coastal areas of the northern Gulf of Mexico. J. Southeast. Assoc. Fish Wildl. Agencies 3, 25–32.

Hitch, A.T., Pucrell, K.M., Martin, S.B., Klerks, P.L., Leberg, P.L., 2011. Interactions of salinity, marsh fragmentation and submerged aquatic vegetation on resident nekton assemblages of coastal marsh ponds. Estuaries Coasts 34, 653–662.

Jarvis, J.C., Moore, K.A., 2008. Influence of environmental factors on *Vallisneria americana* seed germination. Aquat. Bot. 88, 283–294.

Kanouse, S., La Peyre, M.K., Nyman, J.A., 2006. Nekton use of *Ruppia maritima* and non-vegetated bottom habitat types within brackish marsh ponds. Mar. Ecol. Prog. Ser. 327, 61–69.

Keddy, P.A., Campbell, D., McFalls, T., Shaffer, G.P., Moreau, R., Draguet, C., Heleniak, R., 2006. The wetlands of Lakes Pontchartrain and Maurepas: past, present, and future. Environ. Rev. 15, 43–77.

Kemp, W.M., Batiuk, R., Bartleson, R., Bergstrom, P., Carter, V., Gallegos, C.L., Hunley, W., Karrh, L., Koch, E., Landwehr, J.M., Moore, K.A., Murray, L., Naylor, M., Rybicki, N.B., Stevenson, J.C., Wilcox, D.J., 2004. Habitat requirements for submerged aquatic vegetation in Chesapeake Bay: water quality, light regime and physical-chemical factors. Estuaries 27 (3), 363–377.

Kemp, G.C., Day, J.W., Rogers, J.D., Giosan, L., Peyronnin, N., 2016. Enhancing mud supply from the Lower Missouri River to the Mississippi River Delta USA: dam bypassing and coastal restoration. Estuar. Coast. Shelf Sci. 183, 304–313.

Kinney, E.L., Quigg, A., Armitage, A.R., 2014. Acute effects of drought on emergent and aquatic communities in a brackish marsh. Estuaries Coasts 37, 636–645.

Koch, E.W., 2001. Beyond light: physical, geological, and geochemical parameters as possible submersed aquatic vegetation habitat requirements. Estuaries 24, 1–17.

Kotta, J., Möller, T., Orav-Kotta, H., Pärnoja, M., 2014. Realized niche width of a brackish water submerged aquatic vegetation under current environmental conditions and projected influences of climate change. Mar. Environ. Res. 102, 88–101.

La Peyre, M.K., Gordon, J., 2011. Nekton density patterns and hurricane recovery in submerged aquatic vegetation, and along non-vegetated natural and created edge habitats. Estuar. Coast. Shelf Sci. 98, 108–118.

La Peyre, M.K., Rowe, S., 2003. Effects of salinity changes on growth of *Ruppia maritima* L. Aquat. Bot. 77, 235–241.

La Peyre, M., DeMarco, K., Hillmann, E.R., 2017. Submerged Aquatic Vegetation and Environmental Data for Coastal Areas From Texas Through Alabama, 2013-2015: U.S. Geological Survey Data Release. https://doi.org/10.5066/F7GH9G44.

Lewis, H.G., Brown, M., 2010. A generalized confusion matrix for assessing estimates from remotely sensed data. Int. J. Remote Sens. 22 (16), 3223–3235.

Lirman, D., Deangelo, G., Serafy, J., Hazra, A., Smith Hazra, D., Herlan, J., Luo, J., Bellmund, S., Wang, J., Clausing, R., 2008. Seasonal changes in the abundance and distribution of submerged aquatic vegetation in a highly managed coastal lagoon. Hydrobiologia 596, 105–120.

Louisiana Coastal Wetlands Planning, Protection and Restoration Act Program (LA CWPPRA), 2011. Coastal Louisiana basins: Louisiana Coastal Wetlands Planning, Protection and Restoration Act Program. Accessed May 5, 2011:. http://lacoast.gov/new/About/Basins.aspx.

Martin, C.W., Valentine, J.F., 2012. Eurasion milfoil invasion in estuaries: physical disturbance can reduce the proliferation of an aquatic nuisance species. Mar. Ecol. Prog. Ser. 449, 109–119.

Mendoza-González, G., Martínez, M.L., Rojas-Soto, O.R., Vázquez, G., Gallego-Fernández, J.B., 2013. Ecological niche modeling of coastal dune plants and future potential distribution in response to climate change and sea level rise. Glob. Chang. Biol. 19, 2524–2535.

Menuz, D.R., Kettenring, K.M., Hawkins, C.P., Cutler, D.R., 2015. Non-equiplibrium in plant distribution models – only an issue for introduced or dispersal limited species? Ecography 38, 231–240.

Merino, J.H., Nyman, J.A., Michot, T., 2005. Effect of season and marsh management on submerged aquatic vegetation in coastal Louisiana brackish marsh ponds. Ecol. Restor. 23 (4), 235–243.

Merino, J.H., Carter, J., Merino, S.L., 2009. Mesohaline submerged aquatic vegetation survey along the US Gulf of Mexico coast, 2001 and 2002: a salinity gradient approach. Gulf Mex. Sci. 1, 9–20.

Misbari, S., Hashim, M., 2016. Light penetration ability assessment of satellite band for seagrass detection using landsat 8 OLI satellite data. In: In: Gervasi, O. (Ed.), Computational Science and Its Applications – ICCSA 2016. ICCSA 2016. Lecture Notes in Computer Science, vol 9788 Springer, Cham.

Montague, C.L., Ley, J.A., 1993. A possible effect of salinity fluctuation on abundance of

benthic vegetation and associated fauna in northeastern Florida bay. Estuaries 16 (4), 703–717.
Nichols, S.A., Shaw, B.H., 1986. Ecological life histories of three aquatic nuisance plants, *Myriophyllum spicatum*, *Potamogeon crispus*, and *Elodea canadensis*. Hydrobiologia 131, 3–21.
Nowacki, D.J., Beudin, A., Ganju, N.K., 2017. Spectral wave dissipation by submerged aquatic vegetation in a back-barrier estuary. Limnol. Oceanogr. https://doi.org/10.1002/lno.10456.
Patrick, C.J., Weller, D.E., 2015. Interannual variation in submerged aquatic vegetation and its relationship to water quality in subestuaries of Chesapeake Bay. Mar. Ecol. Prog. Ser. 537, 121–135.
Penfound, W.T., Hathaway, E.S., 1938. Plant communities in the marshlands of southeastern Louisiana. Ecol. Monogr. 8 (1), 1–56.
Peterson, A.T., Li, X., 2015. Niche-based projections of wetlands shifts with marine intrusion from sea level rise: an example analysis for North Carolina. Environ. Earth Sci. 73, 1479–1490.
Petrie, M.J., Brasher, M.G., Soulliere, G.J., Tirpak, J.M., Pool, D.B., Reker, R.R., 2011. Guidelines for Establishing Joint Ventures Waterfowl Population Abundance Objectives. North American Waterfowl Management Plan Science Support Team, Technical Report No. 2011-1.
Pulich, W.M., White, W.A., 1991. Decline of submerged vegetation in the Galveston Bay system: chronology and relationships to physical processes. J. Coast. Res. 7 (4), 1125–1138.
Quang, N.H., Sasaki, J., Higa, H., Huan, N.H., 2017. Spatiotemporal variation of turbidity based on landsat 8 OLI in Cam Ranh Bay and Thuy Trieu Lagoon. Vietnam. Water 9 (270). https://doi.org/10.3390/w9080570.
Robbins, B.D., Bell, S.S., 2000. Dynamics of a subtidal seagrass landscape: seasonal and annual change in relation to water depth. Ecology 81 (5), 1193–1205.
Rodríguez-Gallego, L., Sabaj, V., Masciadri, S., Kruk, C., Arocena, R., Conde, D., 2015. Salinity as a major driver for submerged aquatic vegetation in coastal lagoonsL a multi-year analysis in the subtropical Laguna de Rocha. Estuaries Coasts 38, 451–465.
Roy, K., 2012. Coastal Wetlands Planning, Protection and Restoration Act Wetland Value Assessment Methodology Coastal Marsh Community Model. . https://www.lacoast.gov/reports/wva/WVA%20Procedural%20Manual.,pdf.
Rybicki, N.B., Carter, V., 2002. Light and temperature effects on the growth of wild celery and hydrilla. J. Aquat. Plant Manage. 40, 92–99.
Rybicki, N.B., Landwehr, J.M., 2007. Submerged aquatic vegetation and water clarity. In: Phillips, S.W. (Ed.), Synthesis of U.S. Geological Survey Science for the Chesapeake Bay Ecosystem and Implications for Environmental Management: U.S. Geological Survey Circular 1316, pp. 46–49.
Santos, R.O., Lirman, D., Serafy, J.E., 2011. Quantifying freshwater-induced fragmentation of submerged aquatic vegetation communities using a multi-scale landscape ecology approach. Mar. Ecol. Prog. Ser. 427, 233–246.
Sasser, C.E., Visser, J.M., Mouton, E., Linscombe, J., Hartle, S.B., 2014. Vegetation Types in Coastal Louisiana in 2013. U.S. Geological Survey Scientific Investigations Map 3290, 1 Sheet, Scale 1:550,000. https://doi.org/10.3133/sim3290.
Sheets, J., Brenner, J., Gilmer, B., 2012. Assessing the Potential Impact of Sea-Level Rise and Climatic Hazards on Ecological and Human Communities Within the Northern Gulf of Mexico The Nature Conservancy, Texas Chapter, Corpus Christi, Texas.
Snedden, G.A., Steyer, G.D., 2013. Predictive occurrence models for coastal wetland plant communities: delineating hydrologic response surfaces with multinomial logistic regression. Estuar. Coast. Shelf Sci. 118, 11–23.
Snedden, G.A., Cable, J.E., Swarzenski, C., Swenson, E., 2007. Sediment discharge into a subsiding Louisiana deltaic estuary through a Mississippi River diversion. Estuar. Coast. Shelf Sci. 71, 181–193.
Stevenson, J.C., Staver, L.W., Staver, K.W., 1993. Water quality associated with survival of submersed aquatic vegetation along an estuarine gradient. Estuaries 16 (2), 346–361.
Strand, J.A., Weisner, S.E.B., 2001. Morphological plastic responses to water depth and wave exposure in an aquatic plant (Myriophyllum spicatum). J. Ecol. 89, 166–175.
Strasizar, T., Koch, M.S., Madden, C.J., Filina, J., Lara, P.U., Mattair, A., 2015. Salinity effects on *Ruppia maritima* L. Seed germination and seedling survival at the Everglades-Florida Bay ecotone. J. Exp. Mar. Biol. Ecol. 445, 129–139.
Strazisar, T., Koch, M.S., Madden, C.J., 2015. Seagrass (*Ruppia maritima* L.) life history transitions in response to salinity dynamics along the Everglades-Florida Bay ecotone. Estuaries Coasts 38, 337–352.
Syvitski, J.P.M., Kettner, A.J., Overeem, I., Hutton, E.W.H., Hannon, M.T., Brakenridge, G.R., Day, J., Vörösmarty, C., Saito, Y., Giosan, L., Nicholls, R.J., 2009. Sinking deltas due to human activities. Nat. Geosci. https://www.nature.com/ngeo/journal/v2/n10/full/ngeo629.html.
The R Core Team, 2016. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.
U.S. Geological Survey (USGS), 2015. CoNED TOPOBATHY Data for Entity ID: TBDEMNGOM00034. Retrieved from:. U.S. Geological Survey (USGS), Earth Resources Observation System (EROS) Center, Sioux Falls, SD USA. https://lta.cr.usgs.gov/coned_tbdem.
van den Berg, M.S., Joosse, W., Coops, H., 2003. A statistical model predicting the occurrence and dynamics of submerged macrophytes in shallow lakes in the Netherlands. Hydrobiologia 506-509, 611–623.
van der Valk, A.G., 1981. Succession in wetlands: a Gleasonian approach. Ecology 62 (3), 688–696.
van Diggelen, A.D., Montagna, P.A., 2016. Is salinity variability a benthic disturbance in estuaries? Estuaries Coasts 39, 967–980.
Vis, C., Hudon, C., Carigan, R., 2003. An evaluation of approaches used to determine the distribution and biomass of emergent and submerged aquatic macrophytes over large spatial scales. Aquat. Bot. 77, 187–201.
Walker, N.D., Hammack, A.B., 2000. Impacts of winter storms on circulation and sediment transport: Atchafalaya-Vermilion Bay region, Louisiana, U.S.A. J. Coast. Res. 16 (4), 996–1010.
Wenger, S.J., Freeman, M.C., 2008. Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. Ecology 89 (10), 2953–2959.
White, D.A., Visser, J.M., 2016. Water quality change in the Mississippi River, including a warming river, explains decades of wetland plant biomass change within its Balize delta. Aquat. Bot. 132, 5–11.
Wilson, B.C., Manlove, C.A., Esslinger, C.G., 2002. North American Waterfowl Management Plan, Gulf Coast Joint Venture: Mississippi River Coastal Wetlands Initiative. North American Waterfowl Management Plan. Albuquerque, New Mexico.