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ARTICLE

Delineation of Coastal Marsh Types Along the Central Texas Coast

Michael K. Mitchell · Bart M. Ballard · Jenneke M. Visser · Michael G. Brasher · Eric J. Redeker

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Abstract Tidally influenced wetlands along the Texas coast provide important habitat for wintering waterfowl and myriad other fish and wildlife species. Because habitat values may differ among marsh salinity zones (e.g., waterfowl food resources and use are greatest in fresh and intermediate marsh), the spatial distribution of marsh types is important for understanding the capacity of coastal landscapes to support waterfowl and other wildlife populations and informing coastal restoration priorities. Additionally, documenting spatial patterns of coastal marsh types is necessary for projecting future landscape change and examining impacts of environmental processes (e.g., tropical storms, sea level rise). We used a helicopter-based vegetation survey and remotely sensed imagery to delineate marsh types along the central Texas coast into four categories: fresh, intermediate, brackish, and saline. We recorded vegetation composition at 342 sample points and combined these data with Landsat Thematic Mapper imagery to perform a supervised classification of marsh types throughout our 122,995 ha survey area. Our initial coarse classification delineating coastal marsh from other habitat types was 92 % accurate. Intermediate, brackish, and saline marsh each comprised about 30 % of the coastal marsh in our study area. Freshwater marsh comprised <1 % and may have been underrepresented within the coastal zone due to placement of the inland boundary of our study area. Our final classification of marsh types was 77.2 % accurate which will provide a framework for further delineation efforts. We offer several considerations for future coastal marsh delineation efforts along the Texas coast.

Keywords Brackish marsh · Freshwater marsh · Intermediate marsh · Plant community · Remote sensing · Saline marsh · Coastal marsh · Texas

M. K. Mitchell · B. M. Ballard (✉) · E. J. Redeker
Caesar Kleberg Wildlife Research Institute,
Texas A&M University-Kingsville,
MSC 218 700 University Blvd, Kingsville, TX 78363, USA
e-mail: bart.ballard@tamuk.edu

J. M. Visser
Institute for Coastal Ecology and Engineering and School of Geosciences, University of Louisiana at Lafayette,
PO Box 44650, Lafayette, LA 70504, USA

M. G. Brasher
Gulf Coast Joint Venture, Ducks Unlimited, Inc.,
700 Cajundome Blvd., Lafayette, LA 70506, USA

Present Address:
M. K. Mitchell
Ducks Unlimited, Inc., Southern Regional Office, 193 Business Park Drive, Ridgeland, MS 39157, USA

Coastal marsh consists of several wetland types, each with their own dominant species, salinity, hydrology, and usefulness to waterfowl and other wildlife. Chabreck et al. (1989) identified four distinct marsh types defined by salinity concentration – fresh, intermediate, brackish, and saline – and reported that plant diversity was greatest in freshwater marsh and declined with increasing salinity. Freshwater marsh has the greatest plant species diversity and lowest water salinity (≤0.5 ppt). Spikerush (*Eleocharis* spp.), bulltongue arrowhead (*Sagittaria lancifolia*), and many submerged aquatic and floating-leafed plants can be found in this marsh type (Cowardin et al. 1979). Zwank et al. (1989) found that fresh marsh was the most frequently used marsh type by mottled ducks (*Anas fulvigula*) in Louisiana and is likely the most used coastal marsh type by other waterfowl species. Water salinity in intermediate marsh averages 0.5 to 5 ppt and is only partially influenced by tides (Cowardin et al. 1979). Submerged aquatic species such as southern naiad (*Najas guadalupensis*) and pondweeds (*Potamogeton* spp.) are common and overall vegetation diversity is high. Typical emergent plants found in intermediate marsh include marshhay cordgrass, common reed (*Phragmites australis*), bulltongue arrowhead, and coastal water hyssop (*Bacopa monnieri*) (Cowardin et al. 1979). Brackish marsh is part of the transitional zone between saline and fresh environments with water salinity ranging from 5 to 18 ppt. Vegetation diversity in brackish marsh is greater than in salt marshes, and common species include marshhay cordgrass (*Spartina patens*), seashore saltgrass (*Distichlis spicata*), Olney bulrush (*Scirpus americanus*), and widgeon grass (*Ruppia maritima*) (Cowardin et al. 1979). Brackish marsh provides important foraging habitat for diving ducks and provides year-round habitat for mottled ducks (Breininger and Smith 1990; Erwin 1996). Salt marsh is usually found closest to marine waters and immediately adjacent to the subtidal portions of bays and estuaries. Salinity ranges from 18 to 40 ppt, and is characterized by salt tolerant plant species such as smooth cordgrass (*Spartina alterniflora*), seashore saltgrass, and needlegrass rush (*Juncus roemerianus*) (Cowardin et al. 1979). Salt marsh is believed to offer the least amount of energy to waterfowl among the four types but is important for buffering tides and salinity for marshes further inland (Esslinger and Wilson 2001).

Wetlands along the Texas coast have been lost to and become degraded by agriculture and development over the past century (Dahl 1990; Moulton et al. 1997). Moulton et al. (1997) estimated that wetland area throughout the Texas Coastal Plain had declined by 85,222 ha from the 1.6 million ha that existed in the mid-1950s, with coastal marsh accounting for about 30 % of this decline (Moulton et al. 1997). These changes have likely reduced the carrying capacity of waterfowl habitats along the Texas coast.

Because vegetation community and diversity vary in response to salinity, abundance of waterfowl foods is also assumed to vary by salinity, with an inverse relationship between food abundance and salinity. The Gulf Coast Joint Venture (GCJV) uses a bioenergetics model to extrapolate dietary energy abundance among the four coastal marsh types (i.e., fresh, intermediate, brackish, and saline) and calculate the capacity of coastal landscapes to satisfy energetic demands of wintering waterfowl populations. Because habitat values differ among marsh types, estimating the capacity of coastal landscapes to support wintering waterfowl, and consequently calculating habitat conservation objectives, requires knowledge of the spatial extent and distribution of different marsh types.

Since 1968, the Louisiana Department of Wildlife and Fisheries has conducted a helicopter-based survey at approximately 7 to 10 year intervals to delineate fresh, intermediate, brackish, and saline coastal marsh types within the Louisiana coastal zone (Visser et al. 1998, 2000). These data have revealed temporal changes in the distribution and extent of marsh types and enabled examination of how they have been affected by anthropogenic activities and natural events, including tropical storms, sea level rise, subsidence, and coastal restoration projects. Additionally, the GCJV has used these data in calculations of waterfowl carrying capacity of the Louisiana coastal marshes. However, extant spatial databases of wetlands and landcover for the Texas coast (e.g., National Wetlands Inventory [NWI], Coastal Change Analysis Program [CCAP]) have classified marsh types only into fresh and estuarine categories, thus limiting the accuracy and precision of landscape-scale carrying capacity estimates. The ability to delineate coastal marsh types in Texas in a repeatable manner is needed to increase confidence in calculations of landscape carrying capacity for waterfowl and other wildlife populations, refine habitat conservation priorities, and enable more detailed examinations of how coastal processes may shape landscapes in the future. Thus, we designed a pilot survey to delineate coastal marsh types along a portion of the central coast of Texas using remote sensing and landcover classification techniques.

Study Area

Our study area encompassed the coastal zone of Matagorda and Brazoria counties along the central coast of Texas (Fig. 1). A series of barrier islands create 7 bays/estuary systems in our study area: Matagorda Bay, East Matagorda Bay, Christmas Bay, Drum Bay, Bastrop Bay, Chocolate Bay, and West Bay. Coastal prairies and marsh cover extensive areas inland from the bays and estuaries (e.g., > 140 km in some areas) (Stutzenbaker and Weller 1989; Griffith et al. 2007). The climate of the region is semi-arid to subtropical, and annual rainfall averages 80 cm (Chen et al. 2002). Precipitation, however, is extremely variable averaging from 60 to 104 cm per year (Hobaugh et al. 1989). Historically, much of our study area consisted of tall grass prairie, post oak savannah, and flooplain forests. Much of the tall grass prairie has been converted to rice agriculture (Stutzenbaker and Weller 1989). Remaining coastal marsh in this area is used primarily for cattle grazing. However, residential and commercial development along the coast is further changing waterfowl foraging habitats and potentially making it more difficult for species to meet their dietary energy demands (Moulton et al. 1997).

Methods

We defined our survey area of interest and universe of potential coastal marsh through analyses of existing spatial datasets for land cover and wetland classifications. Specifically, we merged all polygons classified as wetlands in the (1) Texas Ecological Systems Classification Project (Texas Parks and Wildlife Department), (2) CCAP; (National Oceanic and

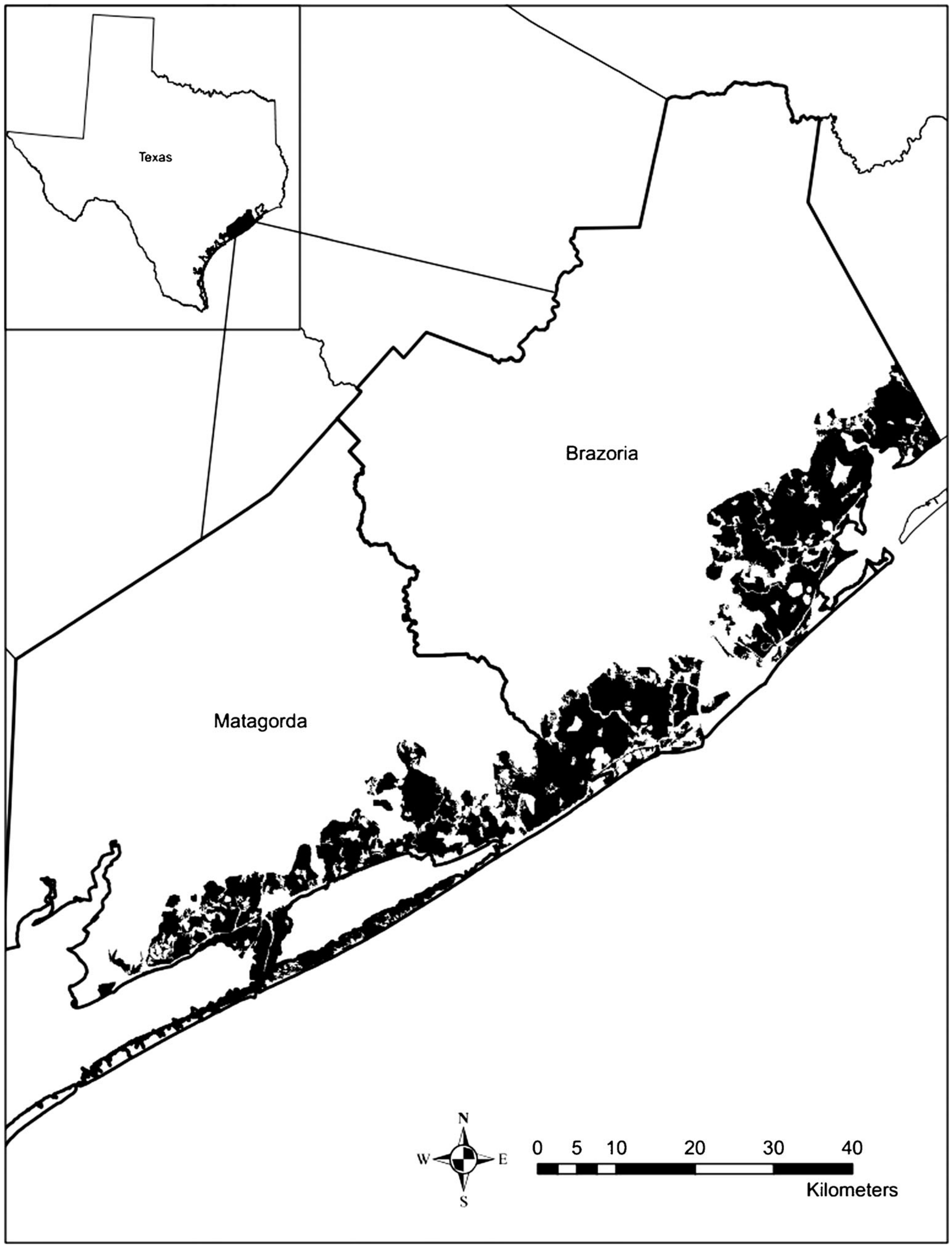

Fig. 1 Extent (*shaded area*) of coastal marsh survey region in Matagorda and Brazoria countries, Texas, October 2011

Atmospheric Administration), and (3) NWI (U.S. Fish and Wildlife Service) within Matagorda and Brazoria counties, Texas. Once the desired wetland types were merged we clipped the combined wetland area to the Texas General Land Office coastal management zone. We then converted the 30-m raster image to a point file using ESRI ArcMap 10× (ESRI 2011). We used a kernel estimator to depict spatial density of wetlands in our study area; we defined our study area as those regions whose wetland density fell within the top 45 % of the density estimation (ESRI 2011; Fig. 2). We clipped this area from Landsat 5 Thematic Mapper imagery (date: 15 October 2011, path: 26, row: 40) and performed an unsupervised classification in ERDAS Imagine to produce 5 generic land cover classes. We used these generic classes to guide placement of sample points from which we collected image classification training and validation data. We established a series of transects, spaced 2,000 m apart and oriented north to south across the full extent of our study area which was approximately 2,115 km^2. Along transects, we initially established sample points every 2,000 m, but altered this in an attempt to achieve an even distribution of points among the 5 generic land-cover classes. On 2–3 October 2011, we sampled each point from a helicopter following protocol of Visser et al. (1998, 2000). While the helicopter hovered at about 10-m above ground level at each sample point, an experienced observer recorded all plant species within a 30-m radius of the sample point, along with an index of their coverage (i.e., <5 %, 6–25 %, 26–50 %, 51–75 %, >75 %). This technique has proven to be accurate and effective in delineating coastal marsh plant communities (Chabreck 1970).

We classified vegetation from 342 sample points within the coastal zone of Brazoria and Matagorda counties. Fifty-five percent of the points from each habitat class (totaling 185 points) were used in the supervised classification of coastal marsh types (Fig. 2), and we used the remaining 45 % of classified sample points within each habitat class (154 points) to assess our classification accuracy.

Statistical Analyses We analyzed vegetation data using a two-way indicator-species analysis (TWINSPAN) to assign them to clusters of stations with similar species composition. Based on this analysis, each sample point was assigned to one of the four marsh types (Hill 1979). We conducted this analysis because it more accurately predicts vegetation types compared to other cluster analysis algorithms (Dale 1995). The TWINSPAN output resulted in each sample point being classified as fresh, intermediate (oligohaline), brackish (mesohaline), or saline (polyhaline or euhaline) based on dominant vegetation types and coverage. We used the resulting categories for marsh classification and accuracy assessment.

We used Landsat 5 Thematic Mapper imagery from 15 October 2011 to remotely classify coastal marsh types within the 2 county study area. We first classified the survey area into three types: marsh, open water, and non-marsh using unsupervised and supervised classification tools and a cluster busting technique in ERDAS Imagine (ERDAS 2011). Cluster busting is a technique that separates mixed classes by systematically differentiating classes based on reference points. We performed an unsupervised classification and identified the pixel classifications as successful or unsuccessful based on known reference points. We then masked out the pixels that were classified successfully and reclassified pixels that were classified unsuccessfully. We reevaluated the new cluster and repeated the process until all pixels were classified or until no additional classification could be achieved. We used ancillary data (previous supervised and unsupervised classifications, surrounding classification types, aerial photography, and Soil Survey Geographic database [SSURGO, Natural Resources Conservation Service]) to classify pixels that remained unclassified after the cluster busting procedure. This resulted in manually editing <1 % of all pixels. We used a minimum mapping unit of 0.405 ha for classification purposes. Areas initially classified as marsh were further delineated into fresh, intermediate, brackish, or saline using the same process of cluster busting. We then conducted an accuracy assessment on the final coastal marsh classification using the 45 % of unused sample points and with the default values in the accuracy assessment tool in ERDAS Imagine.

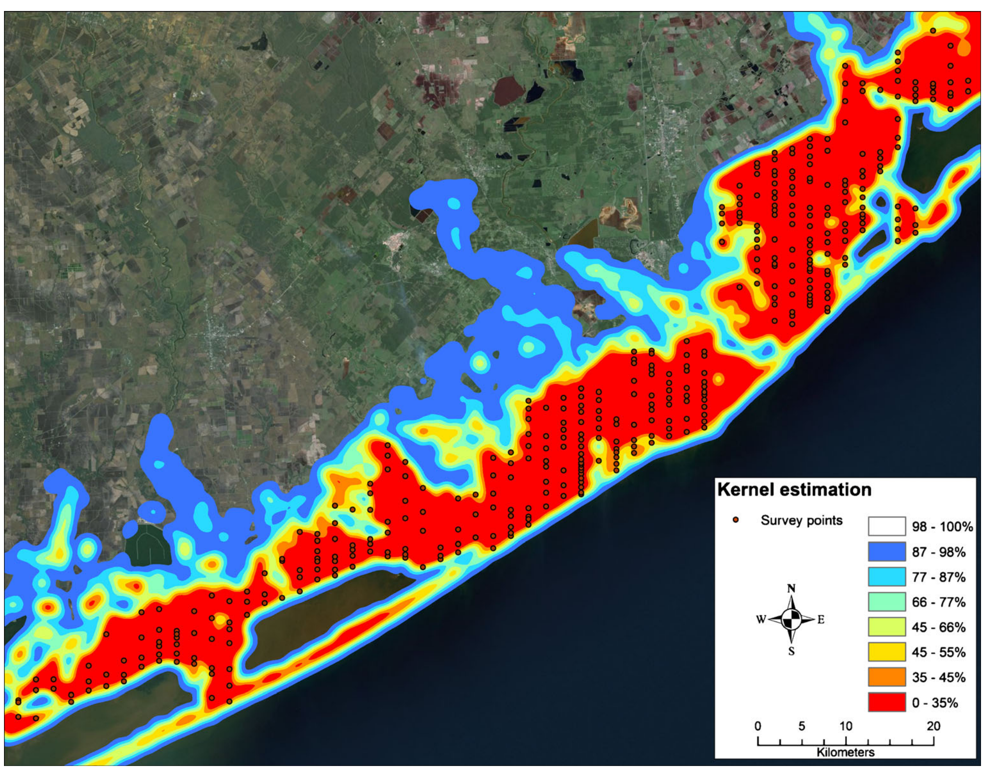

Fig. 2 Kernel density estimation, consisting of wetlands falling within our study area, and displayed using a standard deviation of 0.5. All pre-flight survey points are shown in this figure, but not all were visited during the survey. The finalized wetland survey area included the portions of the map with kernel estimation from 0 to 45 % (The bottom two estimation colors - red and dark orange)

Results

Seventy-two percent of the sampled points were classified as coastal marsh with the remaining classified as open water or non-marsh habitats (e.g., forested, agriculture, developed, etc.). Three sampled points were on a corrupted edge of the Landsat image and were excluded from analysis.

Total classified survey area was 122,995 ha, of which 86,324 ha were classified as marsh (Fig. 3). Our initial coarse classification delineating coastal marsh from other landcover types was 92 % accurate (i.e., 92 % of points were correctly classified). Subsequent classification of the four marsh types was 77.2 % (95 % CI=74.6–79.8 %) accurate with an overall kappa statistic of 0.708 (95 % CI=0.691–0.725), suggesting there was 70.8 % better agreement than by chance alone. This classification resulted in intermediate, brackish, and salt marsh each accounting for about 30 % of the coastal marsh area, and fresh marsh <1 % (Fig. 3). Accuracy for classification of fresh marsh was relatively low (20 %) compared to the other marsh types (all >66.7 %; Table 1). This resulted from the limited abundance of fresh marsh in our survey area and the corresponding low number of reference points available (i.e., n=4).

A few spatial distribution patterns were evident in our final classification scheme. As expected, salt marsh was located closer to the coast compared to the other marsh types. However, in the central and northern parts of the study area, saline marsh extended inland 2–7 times further than in the southern portion of the study area (Fig. 3). Saline and brackish marshes were prevalent along channels entering the bays and extended about 60 % further inland in these situations (Fig. 3). Intermediate and fresh marshes occurred inland from saline marsh and generally surrounded forested patches and freshwater streams. A salinity gradient was distinct in most areas, as salinity decreased with increasing distance from the coastline.

Discussion

We successfully used remotely sensed imagery and spectral classification techniques to classify four marsh types along the Texas coast. This is a promising start for future delineation efforts and demonstrates the potential for classification of large areas of coastal marsh. However, our assignment of marsh types to field reference points was based on associations between salinity concentrations and vegetation

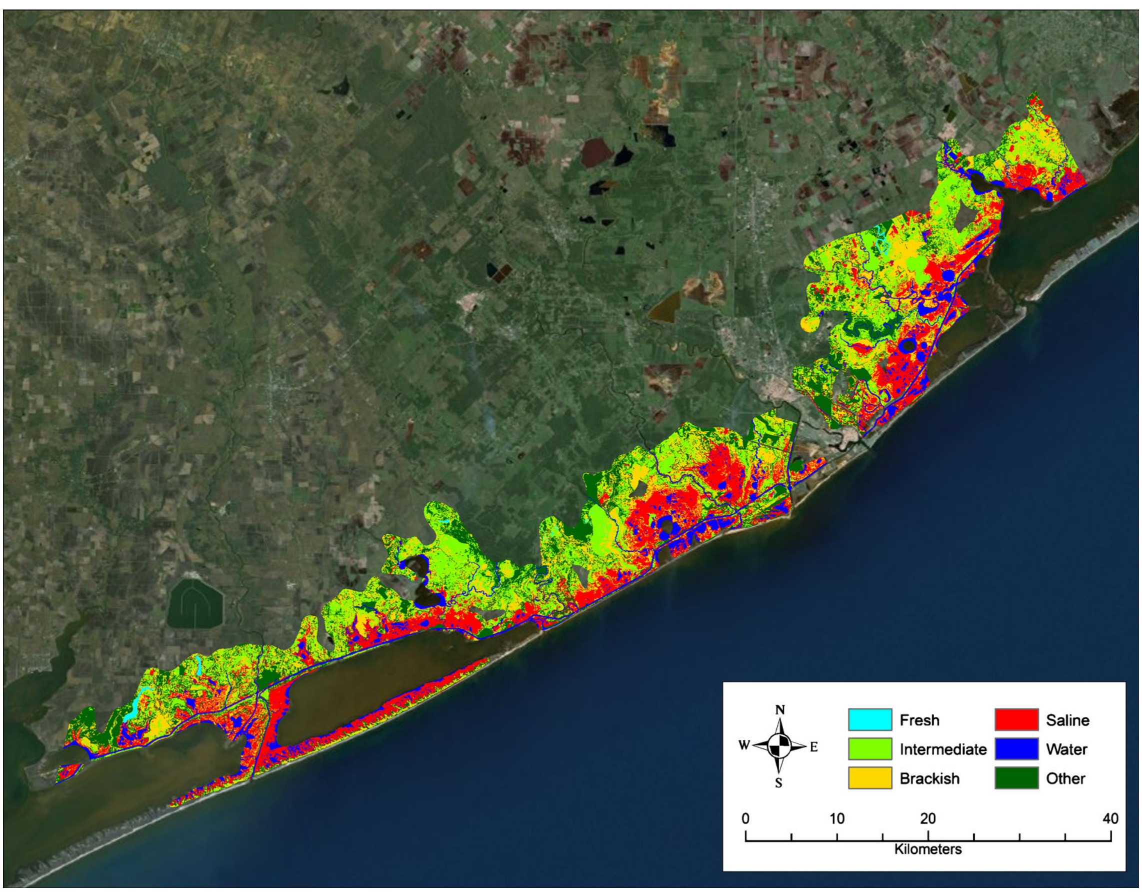

Fig. 3 Final classification scheme showing the separation of surveyed area into freshwater marsh, intermediate marsh, brackish marsh, saline marsh, open water, and other non-marsh habitat types within the coastal marsh zone in Brazoria and Matagorda counties, Texas

Table 1 Estimates of accuracy of supervised classification of coastal marsh types derived from 342 sampled points in Brazoria and Matagorda counties, Texas in October 2011. Reference totals are sample sizes of ground reference points taken from each class (154 total). Classified totals are the number of sample points classified by our assessment. Number correct refers to the number of points that reference and classified are in agreement. Producer's accuracy (error of exclusion) refers to the probability of an actual on the ground classification being classified as such. User's accuracy (error of inclusion) refers to the probability that a pixel classified by our classification is actually what is found on the ground

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (SE)	Users Accuracy (SE)
Fresh	5	1	1	20.0 % (0.019)	100 % (0.00)
Intermediate	27	25	19	70.4 % (<0.001)	76.0 % (0.031)
Brackish	29	30	20	69.0 % (<0.001)	66.7 % (0.034)
Saline	50	55	43	86.0 % (<0.001)	78.2 % (0.030)
Water	22	26	22	100 % (<0.001)	84.6 % (0.026)
Other	21	17	14	66.7 % (<0.001)	82.4 % (0.027)

community composition as documented in Louisiana (Visser et al. 1998, 2000). Field observations during this study provided anecdotal evidence that dominant vegetation associations with salinity zones in Texas may differ from those in Louisiana. Thus, a refined understanding of vegetation-salinity associations in Texas may improve the accuracy of future classifications.

We documented relatively even distribution among three estuarine marsh types (intermediate 35 %, brackish 30 %, and saline 35 %), while fresh marsh made up <1 % of our surveyed area. Sasser et al. (2008) also reported a rather even distribution among all 4 marsh types along the Louisiana coast (fresh 27 %, intermediate 29 %, brackish, 21 %, and saline 23 %). Most of the historic coastal fresh marsh in our study area has been converted to rice agriculture and pasture. Six percent of the stations that we sampled were classified as upland, reflecting this conversion. Indeed, we observed fresh marsh outside of our survey area; however, these areas were not mapped because they were not within the coastal marsh zone as defined in this study. Though nearby wetlands may be similar in appearance and plant communities, they may not be tidally influenced and therefore not considered coastal marsh. One way to distinguish between tidally influenced and non-tidally influenced wetlands would be to analyze elevation data to help with classification.

Based on our results and experiences from this study, we provide the following recommendations for an expanded coastal marsh delineation survey for Texas: 1) convene a meeting among stakeholders of Texas coastal marsh management and conservation to collaboratively identify the spatial extent for delineating coastal marsh, 2) consider adoption of survey methodologies applied in this pilot study, 3) explore alternative classification techniques and incorporation of ancillary data to improve the accuracy of the classification, and 4) ensure appropriate number of reference points are collected. We used a combination of the Texas Government Land Office Coastal Management Zone and kernel estimation to define the spatial extent of classification in our study, but this represents only one of many possible coastal zone depictions. There are many potential applications and objectives for an operational, repeatable coastal marsh survey; thus, these should be carefully considered when defining the spatial extent of a coastal marsh survey zone.

We suggest the use of a helicopter to survey sample points across the Texas coast as a virtual necessity. Use of a helicopter enabled our survey crew to move quickly among sample points without the need to gain access permission from a large number of landowners. Due to the expanse and inaccessibility of the coastal marsh in Texas, as well as the myriad of landowners that would be involved, we suggest this is likely the most efficient and effective way to collect the necessary reference data. Additionally, pre-processing available spatial data to discriminate between marsh and non-marsh areas will ensure greater efficiency in locating sample points within areas that will produce relevant reference data (i.e., will reduce placement of sample locations in non-marsh habitats). For example, of the 342 points we sampled, 95 were located in non-marsh categories, which were not useful to our classification of coastal marsh types. Using a Normalized Difference Vegetation Index tool, much of the unwanted categories can be removed and more survey time spent concentrating on the categories of interest.

The spatial resolution of Landsat imagery used in this study was 30-m, but higher resolution imagery is available from other sensors. However, cost-benefit analyses may be warranted for future efforts that consider more sophisticated classification techniques or imagery of greater spatial and spectral resolution. One aspect that may increase classification accuracy but would require more survey points would be to create a finer classification. In our study we combined vegetation communities together into the four desired marsh types. Some of these vegetation communities may not fall into one marsh type or the other, but may indicate an intermediate type between the more coarsely defined classifications we used. Following a classification scheme similar to the Louisiana's Comprehensive Master Plan for a Sustainable Coast (Visser et al. 2013) may yield more informative and ecologically relevant results.

We observed that marsh types generally do not have well-defined borders, but rather are characterized by a gradient of vegetation change. Thus, alternative image classification techniques, such as fuzzy classification and accuracy assessment, should be explored for their potential to increase classification accuracy (Foody 1994, 1995; Kumar et al. 2007). Also, the use of ancillary data such as high vertical and horizontal point density of airborne Light Detection and Ranging (LIDAR) could be used for determining changes in vegetation communities. LIDAR is a remote sensing technology used to measure the distance to other objects by collecting a 3-dimensional point cloud of laser return data from an aerial platform. Rosso et al. (2005) used LIDAR to study vegetation changes associated with *Spartina* invasion in San Francisco Bay marshes. They found that the accuracy of LIDAR was high enough to differentiate *Spartina foliosa* from a co-occurring *Spartina* hybrid. Rosso et al. (2005) also used LIDAR to determine the rate of expansion of *Spartina* patches within the coastal marsh. Because *Spartina* species are common in Texas coastal marshes, alternative methods to refine the mapping of these vegetation communities may help marsh classification models. Use of hyperspectral data may also increase the accuracy of marsh type delineation. Hyperspectral imagery includes many more bands (100 – 200) with narrow bandwidths from 5 to 10 nm, compared to multispectral imagery as used in this study, which often has ≤10 bands with bandwidths between 70 and 400 nm. Clark and Swayze (1995) and Clark et al. (2003) used hyperspectral imagery to identify and map water, snow, vegetation, and man-made objects. However, hyperspectral imagery is more costly than most multispectral data sources and may increase analysis time and data storage needs. Additionally, use of multi-temporal imagery should be explored because it has been demonstrated to improve classification accuracy (Yuan et al. 2005).

The number of reference points is a key determinant of the resulting accuracy of a remotely sensed vegetation classification (Congalton 1991; Jensen 2007). Jensen (2007) suggests that the number of reference points used for the classification should be 10 times the number of bands used to achieve highest accuracy possible. Similarly, Congalton (1988) advises the use of at least 50 reference points per class for areas <405,000 ha or when there are <12 classes, and suggests between 75 and 100 reference points per class for all other studies for sufficient accuracy assessment. Due to constraints on helicopter time in our study, we were unable to sample the number of reference points recommended by Jensen (2007) and Congalton (1988). Ideally, we would have visited 550 points comprised of 300 training points (6 bands × 10 reference points × 5 classes) and 250 points used for accuracy assessment (50 reference points × 5 classes). We suggest future surveys follow these recommendations to yield higher classification accuracy. Increasing the number of reference points sampled will likely result in an increase in sampling the spectral differences available within each class. This will facilitate detection of available variation in spectral signatures and increase accuracy of the classification. Additionally, sampling more reference points will help to curb problems related to low sample sizes in less available habitat types, such as fresh marsh in our study.

We provide a repeatable framework for delineating coastal marsh types in Texas. When expanded to relevant portions of the entire Texas coast, this dataset should provide substantial benefits to numerous landscape-scale conservation planning and management efforts. For example, the GCJV assumes waterfowl food resources differ in quality and abundance among the different marsh types, with fresh marsh providing the greatest density of waterfowl foods and salt marsh the lowest. The GCJV uses a bioenergetics model to combine estimates of waterfowl food abundance for each marsh type with data on their spatial abundance and configuration to calculate landscape-scale carrying capacity for wintering waterfowl. Estimates of landscape carrying capacity are subsequently compared to habitat needs for target waterfowl populations to help identify conservation needs and priorities. Spatial mapping of Texas coastal marsh types at a level of detail previously unavailable will enable the GCJV to refine assessments of landscape carrying capacity for wintering waterfowl and refine conservation priorities as appropriate. Ultimately, refinements to conservation priorities will increase the efficiency with which conservation resources are allocated. However, our study addressed only a small portion of the central Texas coast; a comprehensive delineation of marsh types along the Texas coast is needed.

Additionally, this survey and the resulting spatial dataset will enable examination of temporal changes in distribution of Texas marsh types and how they may impact populations of other fish and wildlife and the coastal economies that depend upon them. This will become a growing need as concerns about climate change and sea level rise intensify. Indeed, the Intergovernmental Panel on Climate Change (IPCC) suggests that global sea levels will increase between 30 and 100 cm by 2,100. Other reports, such as Rahmstorf (2007), propose that the IPCC is providing a conservative estimate and that sea level rise will be between 50 and 140 cm by 2,100. In either scenario, rising sea level will cause marsh to migrate inland, become submerged, or both, resulting in substantial changes to habitat values for fish and wildlife populations along the Texas coast (Moorhead and Brinson 1995). The increased availability of remotely sensed imagery and advancements in spectral classification techniques provide tremendous opportunities to efficiently monitor temporal changes in coastal marsh distribution and their impacts on fish, wildlife, and coastal economies. Coastal change models, combined with further marsh delineation, will be useful tools allowing coastal managers to involve the public in discussions concerning sea level rise and to make more educated management decisions.

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