Vegetation and Habitat Classification of Created and Natural Brackish Marshes via Unoccupied Aerial Systems (UAS): A Case Study of the Lake Hermitage Marsh Creation Project

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ABSTRACT:

Much of Louisiana's coastal wetlands have been lost over the last century, leading to federal and state agencies allocating billions of dollars towards coastal restoration, flood protection, and marsh creation projects. Traditional post-construction monitoring of marshes involves in-situ vegetation sampling and aerial imagery from fixed-wing occupied aircraft, but these methods can be logistically intensive and limited in spatial and temporal resolution. To address these limitations, we evaluated the use of Unoccupied Aerial Systems (UAS) in post-construction monitoring of the Lake Hermitage Marsh Creation Project in Plaquemine Parish, Louisiana as a case study. Specifically, we used UAS-derived habitat classification maps to compare vegetation cover between created and reference (i.e., natural) marsh sites and conducted a power analysis to quantify the number of in-situ plots needed to reliably characterize site-wide vegetation cover. Habitat classification accuracies of UAS-derived maps ranged from 77.9 – 84.5% with slightly lower accuracies at created relative to reference marsh sites due to their more heterogenous vegetation cover. UAS-derived maps discriminated between created and reference marsh sites based on vegetation community similarity, while in-situ vegetation monitoring plots did not. Furthermore, our case study illustrates the ability of UAS-based habitat and vegetation classifications to complement, inform, and optimize plot-based, in-situ vegetation sampling in future post-construction marsh monitoring plans.

KEY WORDS: Coastal monitoring, drones, created wetlands, unoccupied aerial systems, remote sensing

1. INTRODUCTION

Louisiana's coastal wetlands have been disappearing over the last century and will continue to do so unless significant action is taken (Barras et al. 2003). Approximately 5000 km^2 or 25% of coastal wetland has been lost since the 1930s and another 4500 km^2 are projected to be lost over the next 50 years (Couvillion et al. 2016). Federal and state agencies have allocated funds to counteract existing coastal land loss and potentially prevent further losses. For example, the Coastal Wetlands, Planning, Protection and Restoration Act (CWPPRA) is federal legislation that supports wetland restoration and funds selected projects (CWPPRA 1990; LCWCRTF 1993). In addition, the Louisiana Coastal Protection and Restoration Authority (CPRA) has developed a Coastal Master Plan that allocates $50 billion for restoration and risk reduction projects (CPRA 2023). This includes sediment diversions, barrier island restoration, hydrologic restoration, and shoreline protection projects, with the largest funding, $15 billion, directed towards marsh creation (CPRA 2023).

Marsh creation projects commonly uses dredged sediments taken from commercial waterways and places them in project areas where marsh habitats have been previously degraded into open-water systems (CPRA 2023). Post-construction monitoring, including vegetation surveys, is a common component of marsh creation projects which allows managers to assess project success (DWHNRDAT 2017). Post-construction vegetation surveys typically estimate the percent cover of plant taxa in plots along one or multiple transects or distributed in a semi-random fashion. CWPPRA funded projects in Louisiana use an adaptation of the

Coastwide Reference Monitoring System's (CRMS) vegetation sampling methods for post-construction monitoring (Folse et al. 2023).

For example, the post-construction vegetation monitoring plan for the Lake Hermitage Marsh Creation Project in Plaquemine Parish, Louisiana includes twenty 2 m x 2 m monitoring plots across the 322 hectare CWPPRA project area (Richardi 2016). The number of monitoring plots employed in this project was based on the expectations of the site's topographic, hydrologic, and sediment variability (D. Richardi, pers. comm.). Plot locations were then selected in a semi-random fashion informed by topographic surveys and the monitoring budget's constraints that vegetation sampling be completed within a 1–2-day window (Richardi 2016). Vegetation monitoring at the Lake Hermitage Marsh Creation Project is also complemented by aerial imagery captured from fixed-wing aircraft used for vegetation analysis (height and composition estimates) and conducting land/water surveys (Folse et al. 2023).

While in situ vegetation sampling is common, it is also time and labor intensive and can result in vegetation knockdown, soil compression, and ponding resulting from sampling collections and vehicle access to site interiors (Christie et al. 2016; Minchinton et al. 2019). In addition, aircraft-based imagery is expensive and electro-optical satellite imagery is often limited by spatial/temporal resolution and cloud cover obstruction which can hamper their use in post-construction monitoring plans (Christie et al. 2016; Pettorelli et al. 2018). These logistical and financial issues can limit the effectiveness of post-construction monitoring plans that rely on these techniques.

Unoccupied Aerial Systems (UAS) can potentially overcome many challenges faced by traditional in-situ sampling methods. These platforms enable the gathering of visible spectrum, multi-spectral, or hyper-spectral imagery that can be used to produce highly accurate maps for habitat (wetlands, beaches, sea cliffs) and vegetation (marsh, mangrove, aquatic) monitoring (Barlow, Gilham, and Ibarra Cofrã 2017; Cao et al. 2018; Chabot et al. 2018; Jaud et al. 2019; DiGiacomo et al., 2022; Dronova, 2015). In addition, UAS imagery can function as a supplementary tool alongside in -situ vegetation sampling to inform plot selection and expand site characterization (Anderson and Gaston 2013). For example, researchers have used UAS imagery to quantify marsh vegetation height and above-ground biomass (DiGiacomo et al. 2022; Doughty and Cavanaugh 2019), derive land/water area metrics and Normalized Difference Vegetation Indices (NDVI; (C. N. Brooks et al. 2019; Broussard, Suir, and Visser 2018; Sturdivant et al. 2017; Yang et al. 2019)), and evaluate wetland vegetation quality and productivity (Broussard, Visser, and Brooks 2020; Harris 2020). Other studies have applied UAS in coastal erosion, flooding, and storm event assessment both over long timescales and as quick-response data collection (Appeaning Addo et al. 2018; Duo et al. 2018; R. Morgan et al. 2022; Morgan et al. 2023). These studies highlight the ability of UAS approaches to quantify habitat characteristics in coastal systems and indicate their potential to inform post-construction vegetation monitoring.

The goal of this study is to evaluate the use of UAS platforms for post-construction vegetation monitoring using the Lake Hermitage Marsh Creation Project as a case study. Our study had three specific objectives. First, we used UAS imagery in conjunction with in-situ vegetation data to generate and assess high-resolution habitat and vegetation classification maps. Second, we used a combination of UAS imagery and in situ vegetation plots to compare habitat and vegetation cover between created and reference (i.e., natural) marsh sites. Finally, we used UAS-derived vegetation classification maps to conduct a power analysis that evaluates current monitoring plans at these sites and guide restoration managers in the selection of the appropriate number of monitoring plots needed to reliably characterize site-wide vegetation communities using plot-based sampling. We aim to use the products generated from these efforts to evaluate the implementation of UAS platforms as a complement to in-situ methodologies for large-scale/site-wide vegetation monitoring and to inform existing in-situ methods including transect and plot placement for vegetation monitoring.

2. METHODS

2.1 Study Area

Our study focused on the Lake Hermitage Marsh Creation Project (BA-42) located along the eastern side of Barataria Bay, in Plaquemine Parish, Louisiana (Fig. 1). This area of Barataria Bay is characterized by brackish marshes with salinity ranging from 8-15 (Chabreck 1970), with vegetation typically dominated by grasses such as *Spartina alterniflora*, *Spartina patens*, or *Distichlus spicata*, rushes such as *Juncus roemarianus,* reed such as *Phragmites australis*, and shrubs, small trees and other woody vegetation such as *Iva frutescens* (Keppeler et al. 2023).

The Lake Hermitage Marsh Creation Project constructed ~322 hectares of land using hydraulically dredged Mississippi River sediments (Richardi 2016) with support from the Coastal

Wetlands Planning, Protection and Restoration Act (CWPPRA) between 2012 and 215 (Fig. 1). An additional ~42 acres of marsh area was created using excess dredged materials with Natural Resource Damage Assessment (NRDA) support (DHNMP 2015). We examined two created and two reference (i.e., natural) marsh sites in and adjacent to the project area for this study. We sampled created marsh sites within two of the project’s primary fill areas in this study: Marsh Creation Areas A and B, referred to hereafter as Lake Hermitage A (LHA) and Lake Hermitage B (LHB; Fig. 1). LHA was constructed from August 2012 to October 2013 and was approximately 8.5 years old at the time of this study, and LHB was constructed between December 2013 to May 2014 and was approximately 8 years old at the time of this study. Due to logistical constraints, only the western half of LHA was surveyed in this study (Fig. 1). In addition, we sampled two reference marshes adjacent to the Lake Hermitage Marsh Creation Project: Lake Hermitage Control (LHC) and the Coastwide Reference Monitoring System (CRMS) site CRMS-3680 (Fig. 1).

2.2 Imagery Collection

Imagery used in this study was collected on a single day May 3, 2022, between 10:00. – 17:00 CST, using a Trinity F90+ fixed-wing UAS equipped with a MicaSense RedEdge-MX Dual camera system (Fig. 2). Conditions during the image collection were sunny with occasional clouds with mild winds. This fixed-wing UAS is noteworthy for its vertical takeoff and landing capabilities while being a fixed-wing UAS, its integrated autopilot system, long flight times (90+ minutes), and high wind tolerance during flights (12 m/s). The MicaSense RedEdge-MX Dual camera system integrates two five-band sensors as well as a Downwelling Light Sensor to output 10 reflectance bands: coastal blue at 444 nm, blue at 475 nm, green at 531 and 560 nm, red at 650 and 668 nm, red edge at 705, 717, and 740 nm, and near-infrared at 842 nm. Facing downward, the sensor's maximum field of view was 34.5 degrees. The drone platform includes an internal GNSS receiver that communicated with the closest available reference station to produce georeferenced imagery with 8 mm horizontal RMS and 15 mm vertical RMS.

We planned flights using the Quantum Systems QBase 3D mission planning software (Fig. 2). Flights were conducted at ~122 m altitude, the U.S. Federal Aviation Administration's legal high limit for small UAS operations, to output high resolution imagery while maximizing area coverage. Side and front overlap of the imagery ranged from 70 – 75 percent on each of the sites and flight speed was variable as the UAS compensates for changes in wind speed. Flight times over our selected sites ranged from 50 – 90 minutes totaling flight time for this study at ~5 hours. These parameters allowed for < 8.4 cm pixel resolution in the final maps used in this study.

2.3 Imagery Processing

Imagery obtained during UAS flights was mosaicked within the Pix4D Mapper software to create orthomosaics and 3D digital surface models (DSMs) using Structure from Motion (SfM) algorithms. Orthomosaics are high-resolution, georeferenced photo representations of a ground area generated from, in this study's case, 4500 to 15000 images per site (Fig. 2). Digital Surface Models are digital elevation models that represent the tallest point of surfaces and objects such as vegetation. The SfM technique to generate surface models provides an affordable yet effective alternative to producing elevation data compared to LiDAR (Forsmoo et al. 2019).

Pix4D evaluated imagery metadata to determine the image coordinate system, altitude, and location details for each picture. The coordinate system for output orthomosaics was NAD 1983 StatePlane Louisiana South FIPS 1702 (US Feet). Image scale used for processing was one half. A maximum number of five images were used per manual tie point and orthomosaics were generated with 10000 keypoints (Fig. 2). Processing was performed on a computer with 128 GB of RAM, an Intel Xeon CPU E5-1603 v3 @ 2.80GHz, and an NVIDIA GeForce RTX 2080 Ti GPU.

2.4 Object-Based Imagery Analysis (OBIA)

We used an object-based image analysis method to perform vegetation analysis of our sites using eCognition Developer v 10.3 (Trimble Inc. 2023; Fig. 2). Orthomosaics and Digital Surface Models (DSMs) output from Pix4D were uploaded into eCognition for each site and provided 11 layers for use in imagery analysis: two blue, two red, two green, one near-infrared, three red-edge, and one elevation surface model bands. Using these 11 available layers, we performed a multi-stage image segmentation to group pixels together into larger distinct image "objects" (Dronova 2015).

From these created objects, we developed an object classifier to distinguish among habitat classes at each site (Fig. 2). Habitat classes included water and four terrestrial vegetation types. Water was chosen as it is both spectrally and functionally distinct from terrestrial habitat classes (Broussard, Suir, and Visser 2018) and the four terrestrial feature classes were selected to best characterize the dominant vegetation at each site. First, a “reeds” class, reflecting the dominance of *Phragmites australis*. This species occurs in tall (1-6 m), dense stands and stabilizes marsh platform due to its extensive root systems (Knight et al. 2018). Second, a “shrubs/trees” class, reflecting a dominance of woody vegetation that is visually distinct from the herbaceous species present on these sites. Third, a “grasses” class reflecting a combination of the three dominant marsh grass species found on these sites - *Spartina alterniflora*, *Spartina patens*, and *Distichlus spicat*a. Some prior studies using aerial imagery have had success in classifying *S. alterniflora* separately from *S. patens* and *D. spicata* (Harris 2020), as *S. alterniflora* is functionally distinct (food source, habitat, biogeochemistry) from *S. patens* and *D. spicata,* while others have not (Correll et al. 2019). We chose to group these three taxa into a single class in this study as a preliminary analysis indicated that on these four sites senesced patches of *S. alterniflora* had broadly similar spectral characteristics relative to *S. patens* and *D. spicata* making distinct classification among these grasses beyond the capacity of this project. Fourth, a “rushes” class reflecting a dominance of *Juncus roemarianus* which occur on these sites as tightly packed, spiky, dark green patches.

We adopted a fully supervised method to configure our object classifier, starting by choosing a set of known objects from each habitat/vegetation category (such as water, reeds, shrubs/trees, grasses, and rushes) at every site. We used these selected objects to determine which features (reflectance bands, elevation, brightness, NDVI, etc.) were most effective at distinguishing our specified habitat/vegetation classes, detailed further in our Supplementary Methodology. This approach allowed us to tailor the object features for each site, which were then applied to classify objects into the five predetermined habitat/vegetation classes at each location using eCognition, as documented in Supplementary Tables 1-5. Finally, the fully classified habitat/vegetation maps for each site were exported from eCognition for additional analysis.

2.5 Classification Accuracy Analysis

We conducted an accuracy assessment based on a comparison of the classified maps and base imagery at select points within each site using a stratified random approach in ArcGIS Pro (Congalton 1988). Accuracy assessment points at each site were standardized to three points per hectare of site area or a minimum of 50 points per site whichever was larger. The classification of accuracy points was compared to site orthomosaics to create an Error Matrix that contained the Producer’s, User’s, and Total accuracies of each site. Producer's accuracy assesses errors of omission made by the classification map (i.e., a measure of false negatives). An example of an error of omission is when a point on the base imagery is water, but the classification map misclassified the point as reeds. User’s accuracy assesses errors of commission made by the classification map (i.e., a measure of false positives). An example of an error of commission is when the classification map says a point is water, but the base imagery shows it as reeds. Total accuracy describes how often the accuracy points were correctly classified across all habitat classes by a classification map. The Kappa coefficient was also calculated at each site. This is a statistical evaluation of the accuracy of a classification that can range from -1 to 1, with values near -1 being worse than randomly assigned classifications, 0 being no better than randomly assigned classifications, and values near 1 being significantly better.

2.6 In Situ Vegetation Sampling

The post-construction vegetation monitoring plan for the Lake Hermitage Marsh Creation Project includes 20 sampling plots that was last sampled in 2018 and will be sampled again in 2025 and 2034 (Richardi 2016). This includes 4 plots at LHB and 2 plots in the western portion of LHA surveyed in this study. Given the timing between the last vegetation survey (2018) and this study (2022), and because the monitoring plan does not include plots at the LHC reference marsh site, we conducted independent vegetation sampling at the three Lake Hermitage sites (LHA, LHB, and LHC) on May 12, 2022. Aboveground vegetation (clipped at the sediment surface) was collected from replicate (1 m apart) 0.25m x 0.25m plots at five distances (1, 10, 25, 50, and 100 m) from the marsh edge along a transect at each site. The vegetation was sorted by species, and rinsed free of sediment and epiphytes, and then dried to constant mass at 70°C to determine aerial aboveground biomass (in grams) by species for each quadrat (Hill and Roberts 2017).

Vegetation sampling data from one additional reference marsh, CRMS-3680, was retrieved from the Coastal Information Management System (CIMS) database (http://cims.coastal.louisiana.gov). CRMS site sampling occurs between August 1 and September 30 (end of growing season) of each year and is conducted along a 282.8-m transect at ten 2 m x 2 m vegetation plots. CRMS-3680 was sampled on July 28, 2022. Specifically, we retrieved data on the percent cover of vegetative species for each plot collected using visual estimates. Aboveground biomass (LHA, LHB, LHC) and percent cover (CRMS-3680) data was then used to identify the dominant vegetation type found in each sampled plot.

2.7 Created vs. Reference Marsh Sites

As a secondary accuracy assessment, we compared the vegetation classes predicted by UAS-classified maps (such as trees/shrubs, reeds, rushes, or grasses) against the dominant vegetation types actually observed in the in-situ vegetation plots sampled at each site. This comparison enabled us to verify whether the dominant vegetation predicted by UAS maps aligned with what was physically observed in each sample plot. Additionally, this process provided a measure of how accurately our maps reflected the real-world conditions of both created and reference sites, in relation to direct, on-the-ground observations. Next, we assessed the similarity of vegetation communities between created and reference sites by creating Bray–Curtis resemblance matrices using the vegan package in R (Oksanen et al., 2018). We created two resemblance matrices: one using classified UAS map data and a second using in situ plot data. To allow for direct comparisons between methods we used percent vegetation class data (i.e., reeds, shrubs/trees, grasses, and rushes) to create both UAS and in-situ resemblance matrices and square-root transformed percentage data prior to analyses. To visualize similarity among created and reference marshes, we then calculated the centroids for each site and constructed separate hierarchical clustering dendrograms using ward.D's algorithm (Murtagh & Legendre, 2014). These dendrograms were then cut into two clusters based on calculated similarity to assess the degree to which UAS classified maps and in-situ plot data identified differences in vegetation communities between created and reference marshes.

2.8 Power Analysis

We used UAS-derived vegetation classification maps to conduct a power analysis to evaluate the degree to which the current, plot-based vegetation monitoring efforts at our sampling sites are representative and identify the required sampling intensity (i.e., number of monitoring plots) needed to reliably characterize site-wide vegetation. We used a probabilistic approach to our power analysis, by generating between 1 to 200 random points (i.e. vegetation plots) within each marsh site's terrestrial area without replacement, iterated 1000 times per number of plots at each site. Randomly generated plots were structured to be no closer than 2 meters together to simulate the average size of CRMS vegetation plots (2 m x 2 m). We then assigned a dominant vegetation class (i.e., reeds, shrubs/trees, grasses, and rushes) to each randomly generated plot using the UAS-derived vegetation classification maps from each site and calculated the proportional occurrence of each vegetation class for each iteration. We then calculated the percentage of iterations that resulted in predicted proportional occurrence of the four vegetation classes that fell within 10% of the actual site-wide vegetation cover seen in the UAS-derived vegetation classification maps.

We then used binomial regressions between the number of sample plots (1-200) and the probability of the resulting predicted proportional occurrence falling within 10% of the actual site-wide vegetation cover. The resulting statistical relationship allowed us to evaluate the reliability of current monitoring plans at three of our sites by calculating the probability that plot-based sampling accurately reflects site-wide vegetation cover given the 2, 4, and 10 vegetation monitoring plots currently in place at sites LHA, LHB, and CRMS-3680 respectively. In addition, we also used this relationship to assess the expected degree reliability if plot-based sampling at LHA and LHB was increased to 10 plots per site similar to CRMS-3680 and other CRMS monitored sites. Finally, we calculated the minimum number of vegetation plots needed to reliably characterize site-wide vegetation at each site by determining when the 95% confidence interval around each binomial regression lines overlapped with 100% (i.e., the number of plots needed for the predicted proportional occurrence of each vegetation class to consistently fall within 10% of the actual site-wide values).

3. RESULTS

3.1 Habitat Classifications

Total landscape area for the sites ranged from 5.7 to 83.3 hectares (CRMS-3680 and LHB respectively; Table 1). The proportion of total landscape area that was land ranged between 69.0 – 77.8% (Table 1). The created sites generally had higher proportions of land area than our reference sites (Table 1). Classified maps indicated that the terrestrial habitat of the four study sites were dominated by the grasses class at all four sites (Table 2; Fig. 3; Fig. 4). The percentage of terrestrial habitat classified (i.e., excluding area classified as water) as grasses ranged from a low of 74.6% at LHB to a high of 97.6% coverage at CRMS-3680. Rushes comprised the second most abundant class at three of the sites (LHA, LHC, and CRMS-3680) with Reeds being the second most abundant at the final site (LHB). Shrubs/trees abundance ranged from 2.5% at LHA to 7.2% at LHB and were not present on the classification maps of LHC and CRMS-3680.

3.2 Classification Accuracy

Producer's Accuracy, a measure of false negatives, ranged from 44.1% to 100% across taxa and sites (Table 2), averaging 78.0 ± 15.3%. Producer's Accuracy averaged slightly lower across all habitat classes at the two created marsh sites (LHA: 73.5 ± 18.2%.; LHB: 68.6 ± 15.6%.) relative to the two reference marsh sites (LHC: 82.6 ± 6.4%.; CRMS-3680: 83.7 ± 18.5%). User's Accuracy, a measure of false positives, ranged from 54.8% to 100% across taxa and sites (Table 2), averaging 78.6 ± 14.1%. User's Accuracy averaged slightly lower cross all habitat classes at the two created marsh sites (LHA: 79.3 ± 12.7%.; LHB: 72.6 ± 15.5%.) relative to the two reference marsh sites (LHC: 81.0 ± 16.4%.; CRMS-3680: 84.1 ± 15.1%). Total Accuracy ranged from 77.9 – 84.5% across taxa and sites (Table 2), averaging 81.2 ± 3.2%. Kappa values, measures showing how well a classification performed against random assignment, were 0.65, 0.68, 0.76, and 0.74 at sites LHA, LHB, LHC, and CRMS-3680 respectively. Total accuracies and Kappa values averaged slightly lower at the two created marsh sites relative to the two reference marsh sites.

3.3 In-situ Vegetation Sampling

Grasses were the dominant vegetation class recorded during in situ vegetation sampling at all four sites, ranging from 63 to 98% of plot biomass (LHA, LHC, and LHB) or cover (CRMS-3680; Fig. 4). Four grass taxa were recorded in plots including: *Distichlis spicata, Paspalum sp., Spartina alterniflora*, and *Spartina patens*. *Spartina alterniflora* comprised the highest percentage of plots by biomass at LHA (35.6%), LHB (44.4%), and LHC (35.8%) and *Spartina patens* comprised the highest percentage of plots by coverage at CRMS-3680 (32.3%; Fig. 4).

Rushes, predominately *Juncus roemerianus* but also *Schoenoplectus spp.* and *Bolboschoenus robustus*, were the second most abundant vegetation class, ranging from 2 to 33% by biomass (LHA, LHC, and LHB) or cover (CRMS-3860; Fig. 4). Shrub/tree (*Iva frutescens*) and reed (*Typha latifolia* and *Phragmites australis*) species were present in low abundance in LHA plots only, with 7% and 3% of total plot biomass, respectively (Fig. 4). Shrubs/trees were observed in areas outside of plots at LHB (but not LHC and CRMS-3860), and reeds were observed in areas outside of plots at both LHB and LHC (but not CRMS-3860). Other herbaceous plant species observed in plots at low abundance (<2% by biomass or cover) include *Cynanchum angustifolium, Ipomea sp., Lythrum salicaria, Solidago sempervirens*, and *Symphyotrichum tenuifolium* (Fig. 4).

3.4 Created vs. Reference Marshes

At the two created marsh sites (LHA and LHB) the predicted dominant vegetation from UAS classified maps agreed with the observed dominant vegetation on the ground in four out of five plots (80%) at each site. We obtained a similar result, with agreement in 8 out of 10 plots (80%) at the CRMS-3680 reference marsh site, while 100% of plots (four out of four) were in agreement at the LHC reference marsh site. Three of the incorrectly classified in-situ vegetation plots were misclassified as the Grasses class, when in situ sampling indicated these plots were dominated by Rushes. In addition, one incorrectly classified vegetation plot at CRMS-3680 was classified as Grasses when in situ sampling noted that this plot was shallow water just adjacent to the vegetated marsh edge.

The comparison of vegetation community patterns showed distinct differences between UAS-derived data and field plot observations at the vegetation class level. Specifically, a dendrogram based on UAS-derived data revealed two primary clusters that separated the created marsh sites (LHA and LHB) from the reference sites (LHC and CRMS-3680; Fig. 5). This separation was primarily due to the higher presence of Reeds and Shrubs/trees in the UAS-classified maps at LHA and LHB, in contrast to the reference sites where these vegetation classes were either significantly less common or completely absent (Fig. 4). On the other hand, a dendrogram based on in-situ plot data grouped the sites into two clusters without distinguishing between created and reference marshes: one cluster included LHC, and the other combined LHA, LHB, and CRMS-3680 (Fig. 5).

3.5 Power Analysis

At the three marsh sites with existing monitoring plans our regression model indicated that their current levels of monitoring predicted a 50.6% (LHA: 2 plots), 51.5% (LHB: 4 plots), and 99.9% (CRMS-3680: 10 plots) chance of the resulting vegetation cover estimates being within 10% of the actual site-wide vegetation cover, respectively (Fig. 6). If our three Lake Hermitage marsh sites (LHA, LHB, and, LHC) had monitoring efforts similar to CRMS-3680 and other CRMS stations (i.e., 10 plots per site) our regression model predicted that it would result in a 59.9%, 57.9%, and 89.3% chance of the resulting vegetation cover estimates being within 10% of the actual site-wide vegetation cover (Fig. 6). Finally, our regression models predicted that it would require 70, 79, 108, and 31 in situ plots at sites LHA, LHB, LHC, and CRMS-3680, respectively to provide vegetation cover estimates that would consistently (i.e. 100% of iterations) be within 10% of the actual site-wide vegetation cover (Fig 6).

4. DISCUSSION AND CONCLUSIONS

Our case study highlights the utility of UAS-based imagery for post-construction monitoring of coastal marsh restoration projects. Habitat classification map accuracies were slightly higher on the two reference sites relative to the two created sites and both UAS-based and in situ plot sampling identified greater habitat and vegetation heterogeneity at the created marsh sites. In addition, UAS-derived data discriminated between created and reference marsh sites based on vegetation class community similarity, while in-situ plot data did not likely due to differences in the innate spatial scales of the two sampling methods. The greater habitat and vegetation heterogeneity seen at created sites led to their slightly lower UAS classification accuracies and higher number of in situ plots needed to reliably characterize site-wide vegetation cover as predicted by our power analysis. In addition, our power analysis also indicates that all four sites examined in our study sites require increased sampling effort (i.e., a higher number of in situ plots per site) than what is currently implemented for these monitoring plans to consistently (i.e. 100% of the time) provide vegetation cover estimates that are within 10% of the actual site-wide vegetation cover at each site.

4.1 UAS-based Habitat and Vegetation Classification

The generation of accurate habitat and vegetation classifications using UAS-based imagery can be challenging in heterogeneous environments such as coastal marshes. Even so, classification total accuracies in our study ranged from 77.9 – 84.5% which is similar to the levels of classification accuracy observed in several prior UAS-based studies in coastal regions (C. Brooks et al. 2022; Broussard, Visser, and Brooks 2020; Cao et al. 2018; Harris 2020). In these prior studies and ours, homogenous marsh sites were more easily/accurately classified compared to heterogeneous sites (Broussard, Visser, and Brooks 2020; Harris 2020). However, while the created sites in our study were more heterogenous and difficult to classify relative to reference sites, the created sites studied by Harris (2020) were more homogenous and easier to classify than adjacent reference sites.

Our study encountered some of the challenges reported by other UAS-based marsh and coastal system studies (DiGiacomo et al. 2022; Dronova 2015; Manfreda et al. 2018). For example, our study required site-specific habitat classification algorithms due to differences in spectral baselines between sites that were likely due in part to differences in time of day when imagery was collected. Prior studies have also found that the OBIA methodologies we used in our study can be limited by their site-specificity and often require trial and error when parametrizing classifiers to tailor them for sites (Dronova 2015). In addition, prior studies have noted how the use of DSMs in UAS-based habitat classifications can be heavily affected by variable ground elevations (DiGiacomo et al. 2022; Manfreda et al. 2018). Ground elevation survey conducted by a prior study at the three Lake Hermitages sites indicates much more variable average ground elevations at the two created sites (LHA: 0.18 ± 0.13 m; LHB: 0.07 ± 0.11 m) relative to the reference site (LHC: 0.09 ± 0.04 m; Keppeler et al. 2023). The more variable ground elevation may have led to greater misclassification of tall vegetation classes such as Reeds and Shrubs/trees which relied on DSMs for classification. We found that the presences of senesced *S. alterniflora* at our sites with similar spectral similarity to other vegetation types prevented our ability to classify specific grass taxa and likely contributed to the lower classification accuracies obtained for Rushes. In addition, *Phragmites australis*, the dominant plant within our Reeds category, was undergoing a die-back period on our sites at the time of image collection, creating large spectral value overlap with senesced marsh grasses and leading to a reliance on DSM values for distinguishing between the two classes. Doughty and Cavanaugh (2019) employed the use of a handheld spectrometer during their in-situ vegetation sampling to measure canopy reflectance and inform their later UAS classification. In retrospect, we find that this method could have improved our classification parameters by providing expected spectral values for each target class and recommend implementing the method in future monitoring efforts if within logistical constraints.

Our case study also highlights several of the logistical benefits related to the application of UAS coastal marsh monitoring. First, this technology allows for mostly noninvasive monitoring compared to traditional in-situ methodology as exemplified in our study where the only site impact from our UAS collection occurred at the edge of the sites where our boat was moored (DiGiacomo et al. 2022; Manfreda et al. 2018). In addition, we were able to collect aerial imagery for ~170 hectares of marsh in a single day of flights. This demonstrates the potential for UAS-based imagery to expand the spatial coverage of monitoring projects in a manner that is not logistically feasible using solely in-situ methods. However, while time efficient in the field, collecting imagery over a single day was likely a contributing factor for the need for site-specific habitat classification algorithms due to differences in spectral baselines between sites. While the framework for UAS analysis applied in our case study (i.e., imagery collection, processing, and classification algorithm development) can serve as a model, future studies will need to similarly balance the likely tradeoffs between rapid (e.g., flights conducted throughout the day) vs. systematic (e.g., flights conducted at consistent times and conditions) imagery collection.

4.2 Created vs. Reference Marsh Vegetation Communities

Marsh restoration is enacted in the attempt to return systems to their original states prior to environmental impacts. Our study is not the first to assess if vegetation communities within the Lake Hermitage Marsh Creation Project are similar to those found in nearby reference marshes. Keppeler et al. (2023) performed a comprehensive analysis of vegetation communities at six marsh sites, including LHA, LHB, and LHC, in 2018 using in-situ, plot-based sampling. They reported these three sites as each being dominated first by marsh grasses followed by rushes. Using Bray–Curtis resemblance matrices and hierarchical clustering of biomass data at the species level Keppeler et al. (2023) also found that vegetation communities varied among marshes. Specifically, the created marsh site LHB clustering with three of reference marsh sites and differed from created marsh site LHA and reference marsh site LHC which clustered together.

Our UAS and in situ-based vegetation class data agree with Keppeler et al.'s (2023) findings in that LHA, LHB, and LHC were primarily dominated by marsh grasses followed by rushes. However, the results of our vegetation community similarity analyses differed from Keppeler et al.'s (2023) as well differing between our two data sources (i.e., UAS and in-situ plots). Specifically, UAS-derived data clustered our two created marshes (LHA and LHB) together as being different from the two reference marshes (LHC and CRMS-3680) which clustered together. In contrast, in-situ-derived data clustered LHA, LHB and CRMS-3680 together as having similar vegetation communities that differed from LHC. These contrasting results may be attributable to the inherent strengths and biases of each method. For example, UAS-derived vegetation data provides site-wide coverage but can be limited to estimating percent coverage of the dominant vegetation at lower taxonomic resolution. In contrast, in-situ derived vegetation data provides higher taxonomic resolution within the plot area but may not accurately reflect site-wide vegetation cover due to sampling biases related to the number and placement of plots. For example, the in-situ vegetation plots employed by Keppeler et al.'s (2023) and our case study were taken within 100 m of the edge of the sites, limiting the likelihood of data from these plots reflecting vegetation communities found within the interior of each site. Even so, there are past studies that have successfully used UAS for vegetation mapping with higher taxonomic resolution, especially where projects were targeting a specific species of vegetation. The efforts of Brooks et al. (2022) highlight their ability to classify Eurasian Watermilfoil separately from other submerged vegetation in the Great Lakes primarily due to significant spectral differences among their vegetation species. A separate study conducted along the banks of Lake Erie was able to accurately map *Phragmites australis* in the efforts to control the plant’s presence as an invasive species wherein they highlight NDVI and a canopy height model being features useful in separating *Phragmites* from other vegetation (Abeysinghe et al. 2019).

4.3 Power Analysis of Plot-Based Sampling

Plot sampling is a common vegetation monitoring method. However, care should be taken when designing monitoring studies to ensure that the number and/or size of plots employed can reliably characterize vegetation communities and/or detect change within or between sites over time (Hao et al. 2021; Hoffmann et al. 2019; James-Pirri, Roman, and Heltshe 2007; Steyer et al. 2003). For example, James-Pirri et al. (2007) conducted a power analysis to determine the number of $1m^2$ plots needed for in-situ monitoring vegetation community change in New England salt marshes. They found that 20 plots were required to detect subtle changes over time, though in some cases between 5 to 15 plots were adequate to detect major shifts in vegetation communities.

In our study, we sought to evaluate the ability of the current, plot-based vegetation monitoring plan at the Lake Hermitage Mash Creation Project and adjacent reference sites to characterize site-wide vegetation cover. The monitoring plan employed within this CWPPRA project is heavily based on the methods used at CRMS sites (Folse et al. 2023) as the goal of CRMS is to provide a network of regularly monitored reference sites that can be compared to CWPPRA restoration projects (Steyer et al. 2003). Past power analyses of CRMS have focused on the number and distribution of reference sites required to identify trends in vegetation communities across coastal Louisiana (Steyer et al. 2003). However, to our knowledge no prior study has assessed the number of plots required to accurately reflect site-wide vegetation cover within CRMS or CWPPRA marsh sites.

Our analysis suggests that the current number of monitoring plots at Lake Hermitage Marsh Creation Project sites LHB (4) and the portion of LHA surveyed here (2) are insufficient to reflect site-wide vegetation cover. Specifically, we found that approximately 50% of the time the current level of plot sampling at these two sites is likely to result in estimates that fall outside 10% of the actual site-wide vegetation cover. In contrast, the current number of monitoring plots at CRMS-3680 (10) is 99.9% likely to result in estimates that fall within 10% of the actual site-wide vegetation cover. Furthermore, our results indicate the effort needed to reliably characterize site-wide vegetation cover using plot-based sampling is site dependent, with larger more heterogenous sites (e.g., LHA and LHB) requiring a higher number of monitoring plots than smaller more homogeneous sites (e.g., CRMS-3680). Our conclusions support the recommendation made by prior researchers who suggests that heterogeneous sites require more accuracy sampling points than homogenous sites for statistically valid assessments to be performed (Congalton and Green 2019).

We also found that the predicted number of sampling plots needed to reliably characterize site-wide vegetation cover at our four study sites (31-108 plots per site) is well outside of what would be likely logistically or financially feasible for CRMS or CWPPRA projects. As such, UAS-based vegetation surveys represent a more effective and cost-efficient method for characterization of site-wide vegetation cover at these sites. However, it is important to note that the primary goal of plot-based vegetation monitoring at CRMS sites and CWPPRA projects is not site-wide vegetation assessment *per se*, instead it is to generate floristic quality and productivity indices that can be used to track changes in vegetation assemblage over time associated with either natural variation (i.e., CRMS sites) or restoration activities (i.e., CWPPRA projects; Cretini et al. 2011). Furthermore, it is important to recognize that the UAS-based analysis employed in our case study only identifies the single dominant vegetation class in a discrete area, and not the relative cover of multiple vegetation taxa within plots as in-situ sampling. Even so, our results suggest the potential for the indices and trends derived from in-situ plots at CRMS sites and CWPPRA projects to not necessarily be reflective of site-wide vegetation conditions. Given the differing spatial and taxonomic resolutions, using UAS and plot-based methods in combination is likely to provide a more accurate and comprehensive assessment view of vegetation communities than either method can provide in isolation. As such, we recommend that restoration managers in Louisiana embrace the potential for UAS-based surveys to optimize the number and placement of monitoring plots at CWPPRA and CRMS sites to ensure they are reflective of the vegetation communities present, similar to how UAS-based approaches have been integrated into studies of other systems (Hao et al. 2021; Hoffmann et al. 2019).

4.4 Conclusions and Recommendations

This case study highlights the ability of high-resolution, multispectral UAS-based imagery to create accurate habitat and vegetation classification maps in brackish coastal marshes in Louisiana. It also illustrates the ability of UAS-based vegetation classification maps to compare site-wide vegetation communities among created and reference marsh sites in a manner not logistically feasible using traditional plot-based sampling. Furthermore, we found that unlike UAS-based surveys, the current, plot-based vegetation monitoring at the Lake Hermitage Marsh Creation Project does not accurately represent site-wide vegetation cover at both created and reference sites. Moreover, our case study illustrates the potential for UAS-based methods to complement traditional plot-based sampling and aid restoration managers in optimizing the number and placement of plots to reliably characterize vegetation communities and assess the success of marsh creation projects intended to offset coastal land loss.

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Table 1. Class area statistics for the habitat and vegetation classes found on each site calculated from UAS-based classification maps.

Site	Class	Area (ha)	Total area (%)	Land area (%)
LHA	Water	14.8	22.2	-
	Land	52	77.8	-
	Reeds	3.2	4.8	6.2
	Trees/Shrubs	1.3	1.9	2.5
	Grasses	40.6	60.8	78.1
	Rushes	6.9	10.3	13.3
LHB	Water	22.6	27.1	-
	Land	60.7	72.9	-
	Reeds	9.4	11.3	15.5
	Trees/Shrubs	4.4	5.3	7.2
	Grasses	45.3	54.4	74.6
	Rushes	1.6	1.9	2.6
LHC	Water	4.8	31	-
	Land	10.7	69	-
	Reeds	0.1	0.6	0.9
	Trees/Shrubs	0	-	-
	Grasses	9.7	62.6	90.7
	Rushes	0.9	5.8	8.4
CRMS-3680	Water	1.6	28.1	-
	Land	4.1	71.9	-
	Reeds	0	-	-
	Trees/Shrubs	0	-	-
	Grasses	4	70.2	97.6
	Rushes	0.1	1.8	2.4

Table 2. The accuracy metrics of the imagery-based accuracy assessment performed for this project including Producer's, User's, and Total Accuracies. Producer's accuracy is a measure of errors of omission/false negatives for each habitat class. User's accuracy is a measure of errors of commission/false positives for each habitat class. Total accuracy describes how much of the target area/points were correctly classified by a classification map.

Site	Accuracy Metric	Habitat Classes (%)					
		Water	Shrubs/Trees	Reeds	Grasses	Rushes	Total
LHA	Producer's	70.4	83.3	77.8	91.7	44.1	-
	User's	80.9	100.0	70.0	77.3	68.2	-
	Total	-	-	-	-	-	77.9
LHB	Producer's	79.5	64.3	65.4	87.0	46.7	-
	User's	95.9	64.3	54.8	78.1	70.0	-
	Total	-	-	-	-	-	79.2
LHC	Producer's	75.0	-	80.0	89.7	85.7	-
	User's	100.0	-	80.0	83.9	60.0	-
	Total	-	-	-	-	-	83.3
CRMS-3680	Producer's	63.6	-	-	100.0	87.5	-
	User's	100.0	-	-	82.4	70.0	-
	Total	-	-	-	-	-	84.5

Figure Captions

Figure 1. Location map of the four marsh areas used in this study. The dashed outline denotes the eastern half of LHA that was not surveyed during this study due to logistical constraints.

Figure 2. Detailed UAS workflow performed in this project. Bold text below each step indicates the software used for each step of planning, processing, and analysis. Modified from Harris (2020).

Figure 3. UAS-derived habitat classification maps of the created (a,b) and reference (c,d) marsh sites examined in this study.

Figure 4. Vegetation class composition of each site using UAS data (a) and in-situ vegetation composition (b,c) at both the class and taxa level. In-situ vegetation composition reflects percent by biomass at LHA, LHB, and LHC and percent cover at CRMS-3680.

Figure 5. Similarity analyses of created (blue) and reference (green) marsh sites vegetation community composition at the class level using UAS (a) and in-situ (b) data.

Figure 6. Power analysis with binomial regression curves indicating the probability of being within 10% of the true of site-wide vegetation cover with increasing number of in-situ sampling points (1-200 plots) at the created (a, b) and reference (b,c) marsh sites examined in this study.

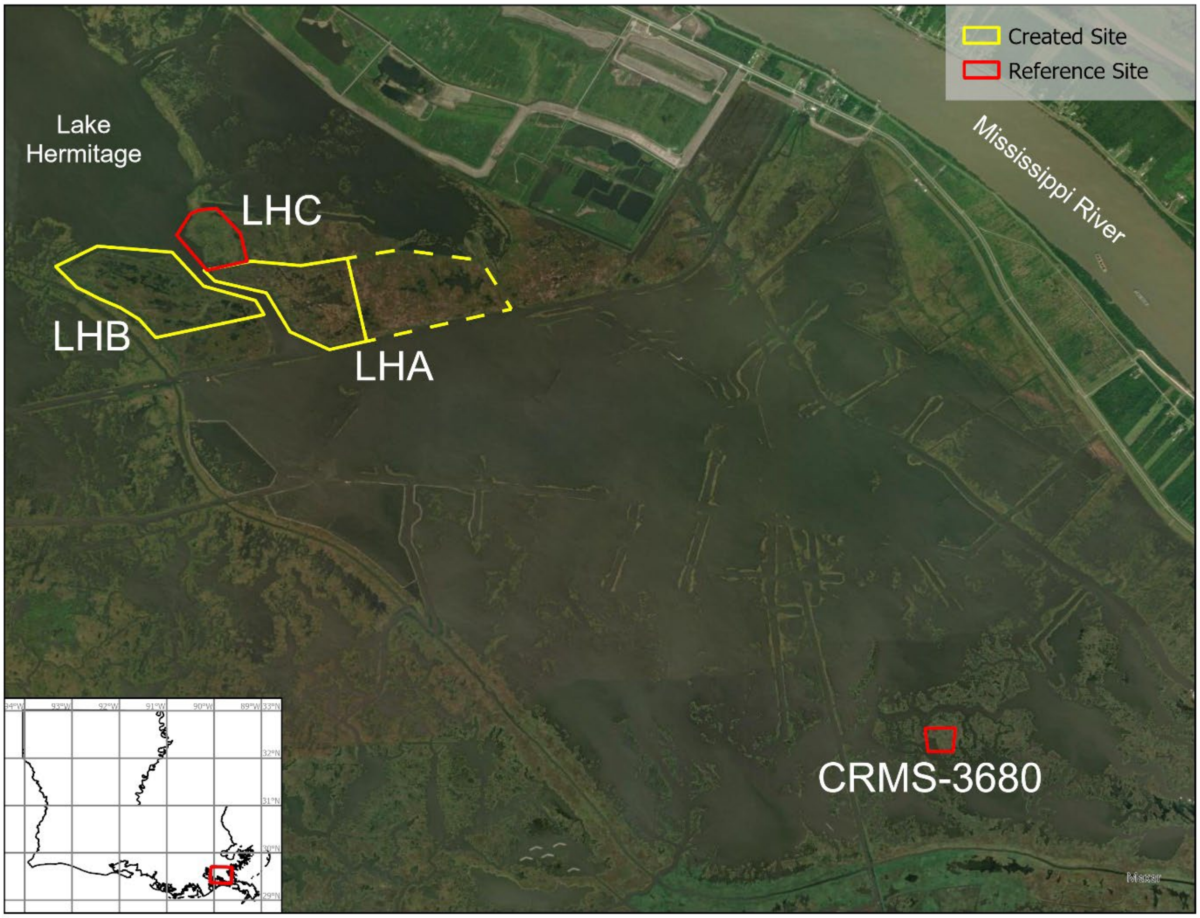
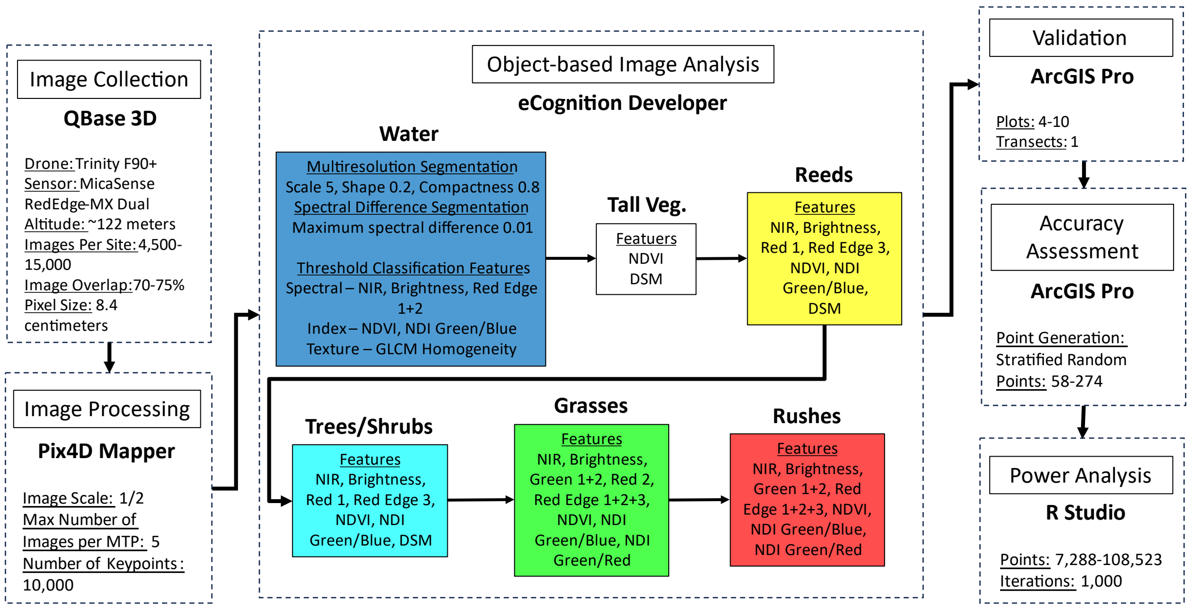


Figure 1. Location map of the four marsh areas used in this study. The dashed outline denotes the eastern half of LHA that was not surveyed during this study due to logistical constraints.



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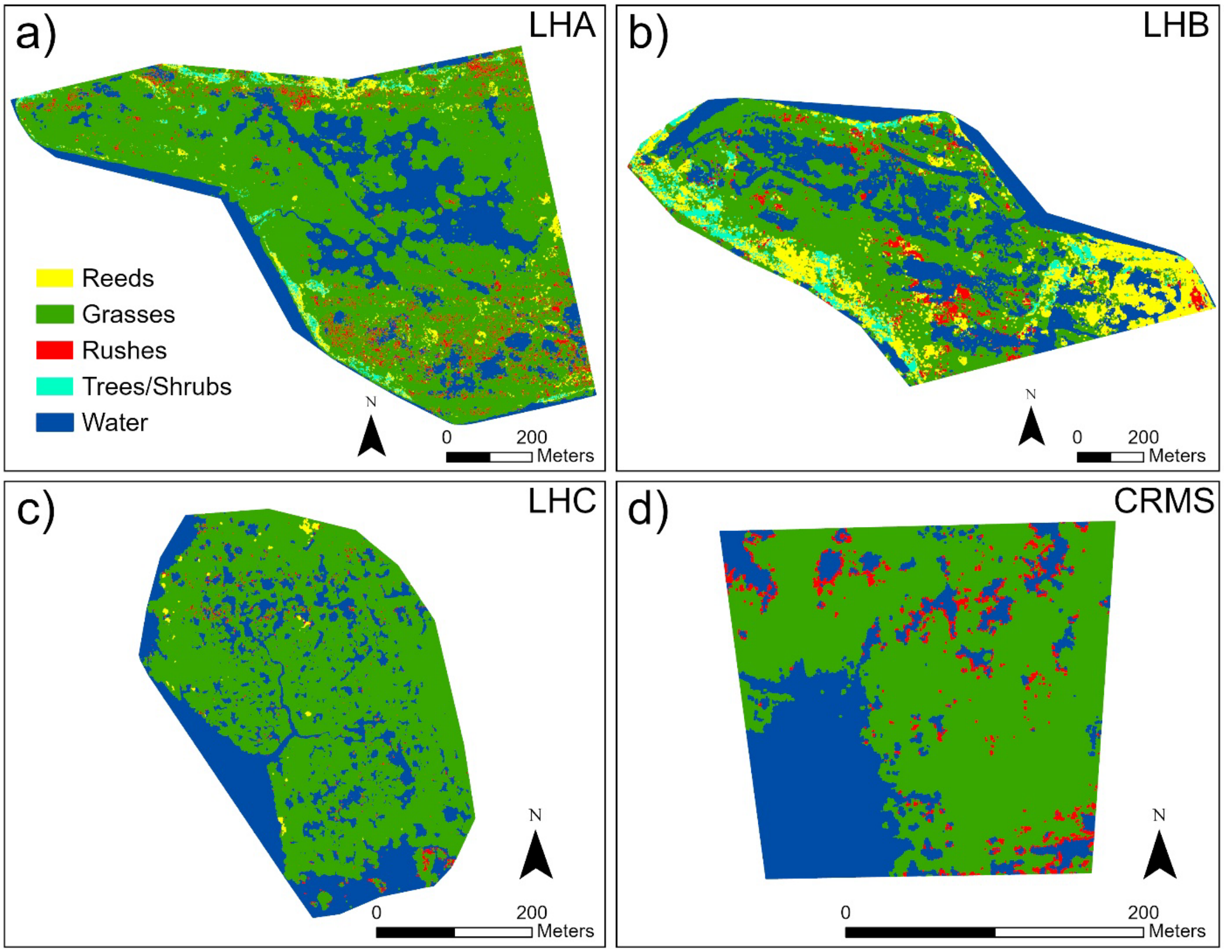

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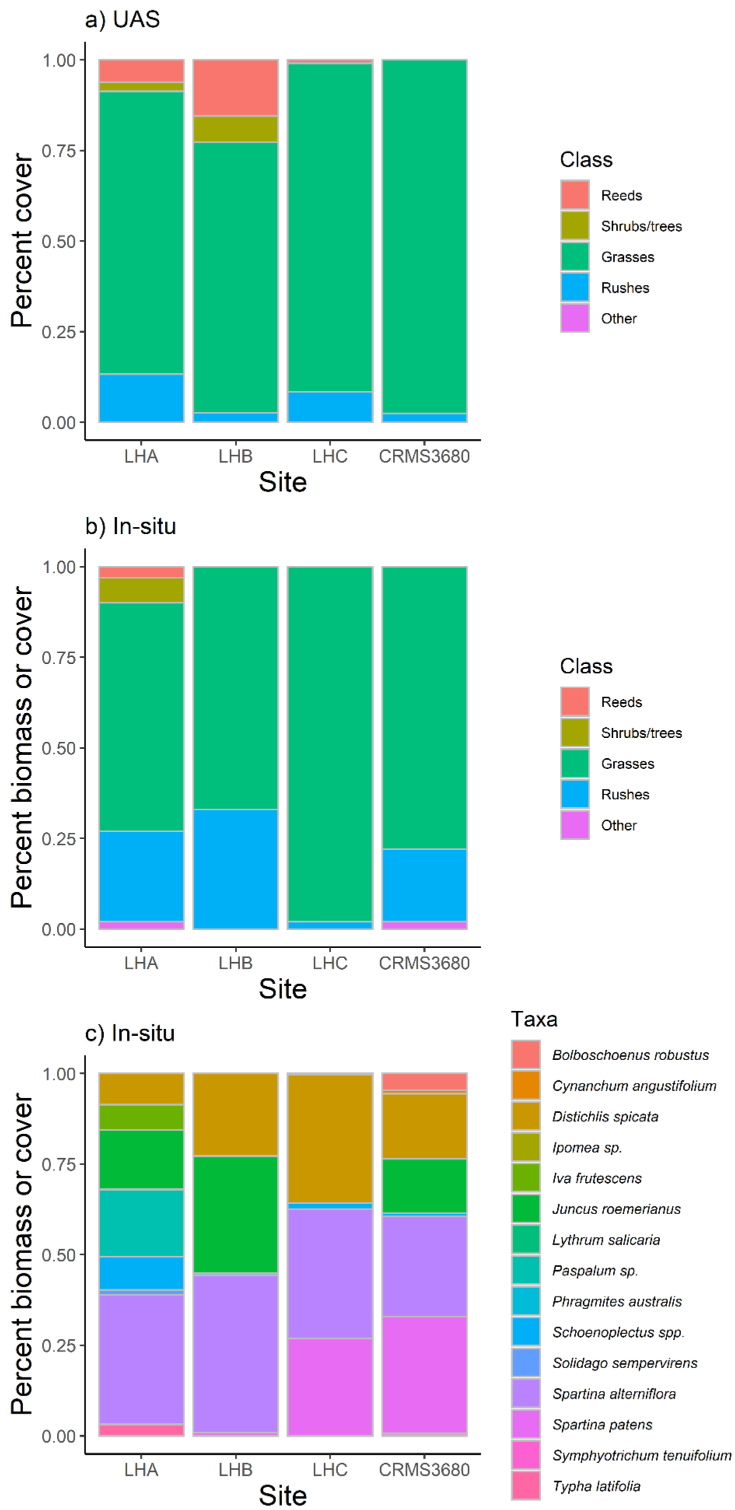

Figure 4. Vegetation class composition of each site using UAS data (a) and in-situ vegetation composition (b,c) at both the class and taxa level. In-situ vegetation composition reflects percent by biomass at LHA, LHB, and LHC and percent cover at CRMS-3680.

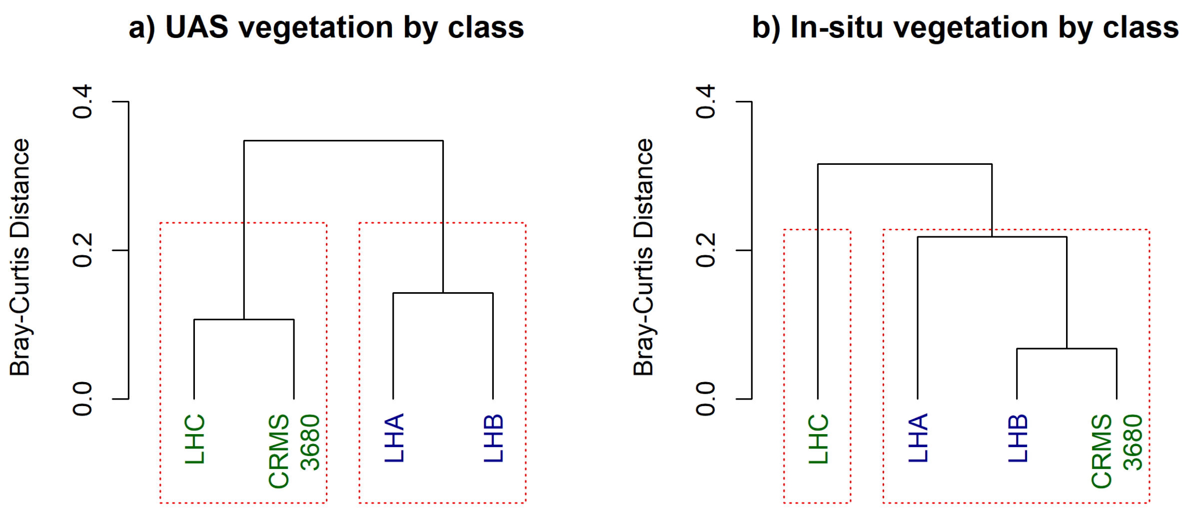

Figure 5. Similarity analyses of created (blue) and reference (green) marsh sites vegetation community composition at the class level using UAS (a) and in-situ (b) data.

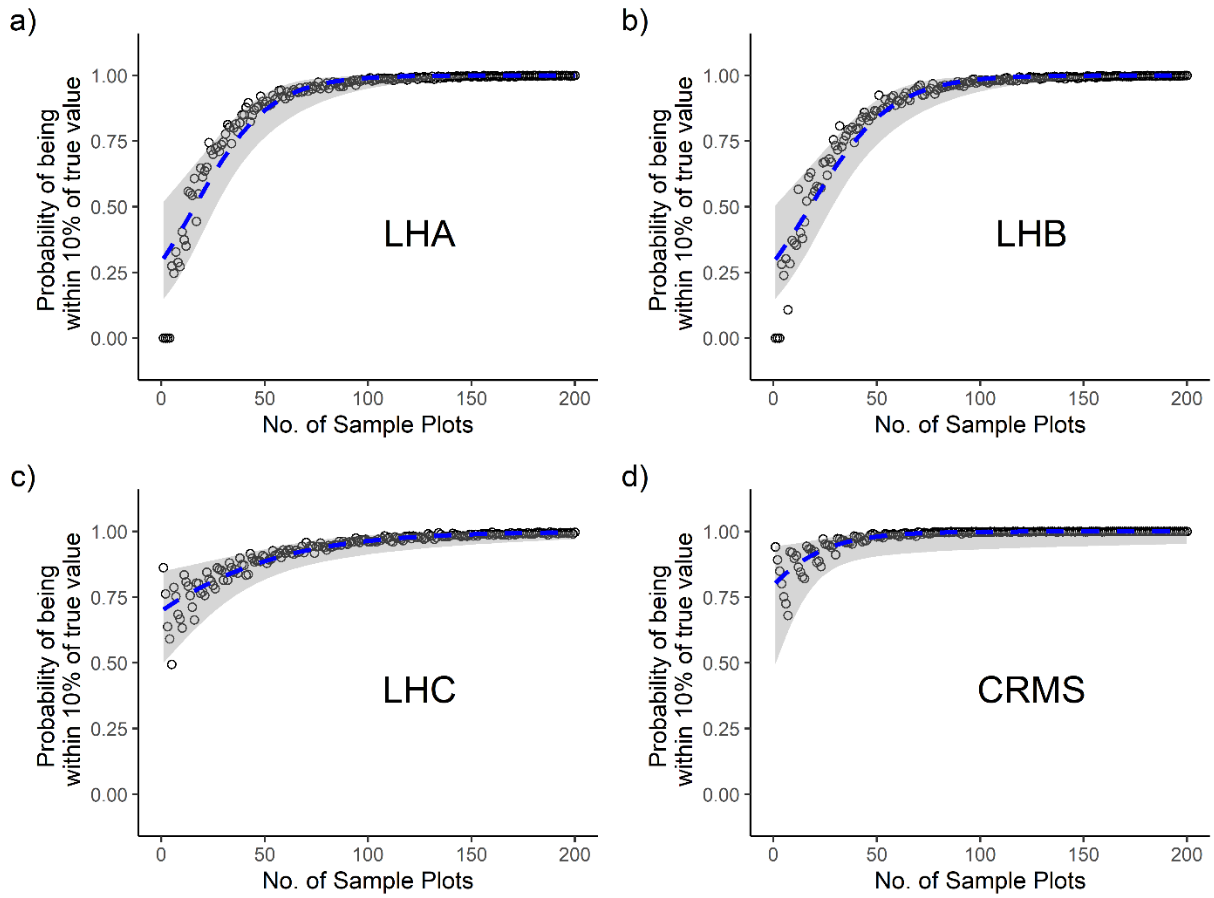

Figure 6. Power analysis with binomial regression curves indicating the probability of being within 10% of the true of site-wide vegetation cover with increasing number of in-situ sampling points (1-200 plots) at the created (a, b) and reference (b,c) marsh sites examined in this study.