12-2023

The development of strategies for coastal wetland conservation prioritization in Virginia under climate change

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Recommended Citation

Mitchell, M., Z. Lv, K. Angstadt, D. Stanhope, C.H. Hines, L. S. Duval, B. D. Watts, K. Havens, D.M. Bilkovic, and K. Nunez. 2023. Enhancing development of strategies for coastal wetland conservation prioritization in Virginia under climate change: Final Report. Virginia Institute of Marine Science, William & Mary.

Enhancing development of strategies for coastal wetland conservation prioritization in Virginia under climate change

EPA final report CD96390801

Virginia Institute of Marine Science
Center for Coastal Resources Management

Grant Title: Enhancing development of strategies for coastal wetland conservation prioritization in Virginia under climate change.

EPA Assistance # CD-96390801

Report *#:* Final

Report Date: Dec 31, 2023

Reporting Period Dates*:* 01-Oct-2021 to 30-Sep-2023

Budget/Project Period Dates: 01-Oct-2021 to 30-Sep-2023

Grantee's Contact Name and Phone number: Molly Mitchell, 804-684-7931

Total Federal Funding: $292,324 (+ match $97,440)

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Executive summary

This project focuses on developing strategies to improve our understanding and strengthen the sustainability of Virginia's coastal wetlands to climate change impacts. Marsh migration under sea level rise is a primary pathway for marsh persistence. However, the resulting extent and habitat function of the newly migrated marsh is still being explored. In addition, accelerating sea level rise suggests that coastal wetlands need frequent monitoring to assess change. This project addresses Virginia regional priority 1, to develop a framework to overcome barriers to use existing wetland assessment methodologies and studies for restoration/compensatory mitigation projects to improve functional performance of aquatic resources by creating a method to readily update tidal marsh status, evaluate trends under sea level rise, and understand shifts in habitat function.

This project expands the tidal wetlands assessment and monitoring programs to include consideration of climate stressors. It also extends outcomes and lessons learned from previous EPA project (CD96347001-0, CD963819-01-1) that identified tidal marsh vulnerability to loss or community change from sea level rise. Key products are *i)* development of a remote tidal marsh monitoring protocol, *ii)* an analysis of newly migrated marsh habitat function for a sentinel marsh obligate species, and *iii)* a framework for anticipating and incorporating climate change impacts into management options for sustaining coastal wetland acreage. These outcomes can inform strategies for long-term protection of wetland resources in Virginia.

The research done for this project suggests that drone imagery is a reasonable tool for plant community identification; however, it is still a time-consuming process. Therefore, it is best suited for long-term monitoring of sentinel sites or creation of a validation data set rather than a technique for replacing field visits in the state-wide TMI. Satellite imagery is a promising technology for marsh community identification; however, the methodology needs further development and refinement. Advances in the resolution of satellite imagery will make this a more useful tool in the future. Under the current technology, it is hard to replace the accuracy associated with a field visit but including drone footage in the field visit highly improves precision of plant community identification and will allow long-term monitoring of shifts in the plant community locations.

Saltmarsh loss and creation are occurring at an increasingly rapid rate due to the rapid rate of sea level rise. Given the speed of this process over the past decades, a greater portion of the current marsh is relatively young, but it is not clear how a change in the proportion of young and old marsh might affect animal and plant communities. We compared bird richness, plant cover, and soil carbon between recently established marshes and those that have remained relatively stable since the early-mid 20th century on the Eastern Shore of Virginia, USA. We found that the plant species composition, soil carbon, and bird communities differed between recently formed marshes and those that have been relatively stable since the early-mid 20th century. Plant cover was greater for *J. roemerianus*, *Phragmites australis* in newly formed marshes while *Sporobolus alterniflorus*/*Spartina alterniflora*, *S. pumilus*/*Spartina patens*, and *Distichlis spicata* cover was greater in marshes that remained relatively unchanged. The bird community in recently formed marshes included fewer saltmarsh obligates but more bird species that also breed in uplands and freshwater marshes. In addition to whether the marsh was recently created, species-specific bird occupancy was frequently affected by presence of past agricultural use, latitude, whether the marsh occurred on the bayside or seaside of the Delmarva peninsula and *J. roemerianus cover*. The percentage of organic matter in marsh soils was affected by predictors that were commonly included in bird occupancy models including whether the marsh was recently created, past agricultural use, latitude, and whether the marsh occurred on the bayside or seaside of the Delmarva peninsula. Organic matter comprised the greatest percentage of soils in the northernmost bayside marshes that exhibited evidence of past agricultural use. We believe that our observed trends in bird occupancy, plant cover, and organic matter are driven by the duration and frequency of tidal flooding which may be affected by berms and ditches erected around former agricultural fields. We expect that the bird community will support fewer saltmarsh obligates as a greater proportion of the marsh becomes younger and occurs in areas formerly used for agriculture.

Accomplishments And Achieved Environmental Results

Task 1: Develop a remote sensing protocol for enhancing the frequency of Virginia Tidal Marsh Inventory updates. Outputs: Literature review of remote marsh community identification techniques, a comparison of results from different attempted survey techniques, and a recommended direction for the development of a remote monitoring protocol to enhance the Virginia Tidal Marsh Inventory. **Outcomes:** Improved data and models to assist robust decision making under sea level rise, and increased understanding of opportunities to achieve no net loss of wetland acreage, and function, improve water quality, and enhance long-term restoration success in Virginia.

This task will be an exploration of Tidal Marsh Inventory techniques (such as such satellite photography, drones and machine learning, and the traditional field survey methods) and an assessment of the pros and cons associated with each technique identified. Combined, these survey techniques provide valuable monitoring data and capacity of early change detection that can result in improved wetland management under climate change.

Activity 1: Literature Review

The intention of the literature review was to understand the current state of the technology related to remote sensing techniques for identifying vegetation. **The literature review (an annotated bibliography) is included as Appendix A of this report.** 24 of the 30 papers reviewed specifically included marsh vegetation and some of the papers addressed biomass quantification or species identification. Broad lessons from the literature review were 1) both lidar/RTK and multi-spectral imagery are useful, although they have different strengths; 2) drone imagery has been successfully used in individual sites for the identification of plant species and quantification of biomass.

Drone imagery shows promise for the long-term monitoring and identification of changes in marsh vegetation. Structure-from-Motion (SfM) allows the creation of 3-dimensional salt marsh surfaces. Since these 3-D surfaces can be used to identify some plant communities (e.g. where *Spartina patens* becomes *Phragmites australis*), annual drone images can elucidate areas of change in invasive species. Lidar and RTK allow the creation of digital elevation models and measurement of plant heights. Spectral indices (such as the Normalized Difference Vegetation Index (NVDI), Excess Green (ExG) and Vegetative Index Green (VIg)) have been successfully used in marshes. Studies have found a strong positive correlation between SfM-computed NDVI and field-derived above ground biomass. One study found different spectral signatures between species, with *Phragmites* having a high NIR response late in the growing season, *Typha* spp. Having a high red/green ratio and *S. patens* had a unique green/blue ratio. It is not clear how transferable these results are between marshes. NDVI values can vary between sensors and data sources (e.g., different satellites and drones). The values need to be atmospherically corrected and can become saturated at high levels of biomass, both of which can limit their transferability. Calibration of drone cameras is recommended if indices are going to be used. Orthomoasics and digital models from drone photography have higher spatial resolution than ones created from drone lidar. However, the photography results in large files that require long processing times, relative to the lidar, limiting its usability.

Activity 2: Examination of drone capabilities

Drone imagery was examined for its ability to replace or augment field visits for plant community identification. We selected 7 sites with different plant communities to fly. Since the beginning of the project, we have acquired a new drone (funded by VIMS) capable of multi-spectral and RTK imagery. The new drone is a DJI Phantom 4 RTK Multispectral drone. The sensors are visible, blue (450nm), green (560nm), red (650nm), red edge (730nm) and near infrared (840nm). We have also acquired PIX4D software for processing data. Drone imagery was processed using Pix4Dmapper to create Structure-from-Motion (SfM) models of each site. Imagery was geolocated using GPS on the drone, which allowed georectification of the images.

Four sentinel sites with diverse plant communities were selected for multi-season drone surveys. These include the Guinea marshes (2 sites, salt marshes), Taskinas marsh (1 site, brackish/oligohaline marshes), and Chickahominy marshes (1 site, tidal freshwater marshes). At each marsh plant communities were noted in the field at the time of the site visit, using the current Tidal Marsh Inventory (TMI) protocol. This involves the listing of species observed in the marsh with identification of the primary community type (DWE 1993). Drone images were processed using Pix4D and plant communities were delineated by hand. Drone imagery was assessed for the potential to use machine learning to delineate plant communities using a combination of RTK and multi-spectral data. Drone flights are listed in Table 1 and the processed data with plant community identification is archived on ScholarWorks (DOI https://doi.org/10.25773/3t1n-ss33).

Table 1. Drone flight details.

Marsh Name	Latitude	Longitude	Community Type (TMI)	Dates Flown	Species Observed	Altitude	Type of Camera
Maryus Rd	37.280132	-76.392142	Type XII – Brackish mix	11/14/2022, 02/15/2023	Juncus, Spartina alt., Spatina patens, Phrag	90	Multispectral/RTK
Capt. Sinclair	37.324537	-76.429135	Type XII – Brackish mix	11/14/2022, 02/15/2023	Juncus, Spartina alt., Spatina patens, Phrag	90	Multispectral/RTK
Taskinas	37.415622	-76.715468	Type I – Saltmarsh Cordgrass / low marsh, Type XII – Brackish mix	10/26/2022, 3/28/2023	Spartina alt., Spartina patens, Spartina cyno., Phrag	90	Multispectral/RTK
Chickahominy	37.270171	-76.864561	Type VII – Arrow Arum – Pickerel Weed	10/26/2022, 3/28/2023	It was hard to ID, most of the site was submerged at low tide during both flights	90	Multispectral/RTK
Browns Bay	37.29906	-76.395694	Type XII – Brackish mix	6/15/2023	Juncus, Spartina alt., Spatina patens, Phrag	100	Multispectral/RTK
Cherry Row Marsh	37.475306	-76.705687	Type I – Saltmarsh Cordgrass / low marsh	7/7/2023	Spartina alt., Spartina cyno., Scirpus americanus, Typha latifolia (in the upper reaches)	100	Multispectral
Saxis	37.906466	-75.682061	Type III – Black Needlerush	10/11/2022	Juncus, Spartina alt., Spatina patens, Phrag	90	Multispectral

Drone imagery shows high potential for remote identification of vegetation. The resolution of the imagery is good enough to distinguish between very similar species (such as *Peltandra virginica* and *Sagittaria latifolia*) when the image is zoomed in and between similar species (such as *J. roemerianus* and *Spartina alterniflora*) from the zoomed out image. The drone imagery has significant improvements over the current TMI field visit methodology because it allows delineation of each plant community within the marsh, rather than just identification of a plant community type. Since the current TMI methodology required 9 years to assess all the marshes in Virginia, a field methodology of the same precision as the drone survey (e.g., GPS delineation of plant communities) is prohibitively time-intensive. The delineation of plant communities is important because it enhances our ability to detect signs of climate change over short time scales.

Despite the precision of the drone imagery analysis, the drawback is that it still requires significant time to collect and process the data. Flight times range from 15-30 mins per marsh (depending on the size) and the delineation of plant communities from the imagery takes an additional 1-2 hours and requires a person with plant identification expertise. Using a computer-assisted classification scheme with occasional verification would reduce some of the effort, although the collection time (flight time) is still significant. Our explorations of using a computer-assisted classification highlighted some issues. First, since the lighting is different for every flight, you need to compensate for that before you can use a classification scheme across different marshes. However, you can use the multi-spectral data to compute indices—one of these indices, NDVI showed some promise in distinguishing *J. roemerianus* and *Spartina alterniflora*. The RTK is very promising for distinguishing between certain communities, such as the fringing *Phragmities asutralis* around a salt marsh. However, to use RTK elevations across sites, you ideally want to optimize the elevation measurements using ground point controls with elevations determined via GPS. We have used arrow points in some locations for highly accurate RTK. These are time consuming to set up and require that you access the marsh surface. In conclusion, we see significant potential in drone imagery for enhancing the precision of the TMI. Preliminary exploration of machine-learning and classification of drone imagery as a method of reducing the time required for image analysis is promising and we recommend continuing to explore these techniques. At this time, remote sensing via drones does not resolve the issues related to the time required to acquire field data.

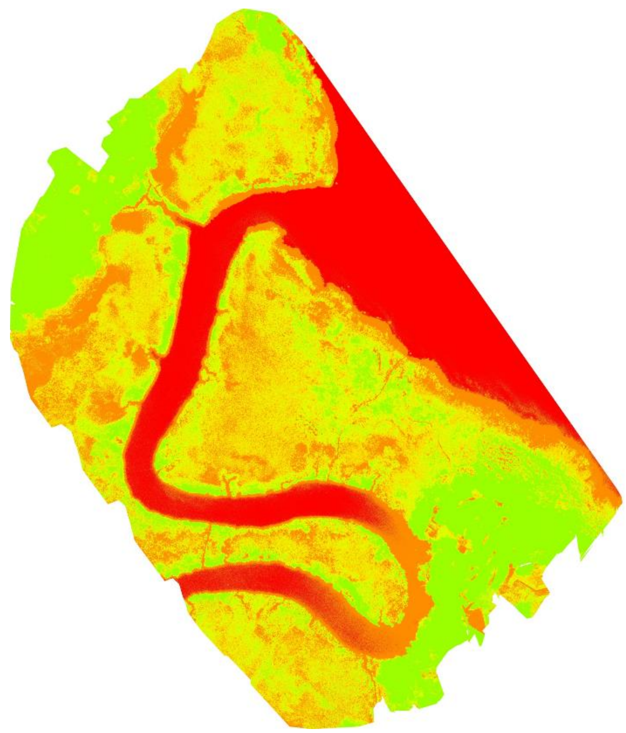


Figure 1. Example of processed drone imagery.

Activity 3: Examination of satellite capabilities

Prior to the awarding of the grant, PI Mitchell formed a collaborative relationship with Brian Lamb (USGS), Stephanie Schollaert Uz (NASA) and Helen Amos (NASA) to explore the capabilities of satellite data in identify plant communities and verifying the communities using Tidal Marsh Inventory data. Brian Lamb is an author of the most up-to-date satellite surveys of Chesapeake Bay marsh vegetation (Lamb et al. 2019 and Lamb et al. 2020). This collaboration showed that the satellite data (30m pixel) could identify several different plant communities, assuming that the patches of vegetation were large enough, using a combination of SARS data (radar—primarily identifying plant height and persistence) and multispectral satellite imagery. The processes need refinement to identify other plant communities or species-level discrimination. Data, such as spectral signatures of particular plant communities (e.g. *J. roemerianus*, *Spartina cynosuroides*), which are 1) persistent, 2) co-located with and/or of similar height to other dominant vegetation (*Spartina alterniflora*, *Phragmites australis* respectively), and 3) frequently found on the edge of larger marshes or as small communities within the marshes, make it difficult to use satellite data to establish the signature.

Methodology

In this project, we focused on the potential to identify plant communities using hyperspectral signatures. To enhance the potential for remote identification of plant species, we utilized PlanetLabs satellite data (PlanetLabs, 2022) acquired under a different funding source. This data was hyperspectral and available at a 3m pixel resolution.

Study area and reference data

Plant community delineation from the drone imagery was used to train the machine learning models, focusing on salt marsh communities. We started by trying to distinguish *J. roemerianus* and *Spartina alterniflora* communities from satellite data. To do this, we used drone imagery and resulting plant communities were manually digitized from three of the sites, Maryus, Captain Sinclair, and Taskinas. Each of these aerial images comprises four bands: red, yellow, blue, and near-infrared, from which a variety of indices can be calculated. The digitized polygons from the drone imagery representing *Spartina alterniflora* and *Juncus roemerianus* were used as a ground truth dataset.

In the regions identified as *S. alterniflora* and *J. roemerianus*, a set of random points was generated, resulting in 691 of *S. alterniflora* and 504 of *J. roemerianus* points, respectively. Subsequently, these points were further randomly subdivided into both training and validation sets, employing a 70% and 30% splitting strategy.

High-resolution imagery

Our analysis utilized globally available 8-bands multi-spectral (Coastal Blue, Blue, Green I, Green, Yellow, Red, RedEdge, NIR) high-resolution satellite images from Planet Labs (PlanetLabs, 2022), with a spatial resolution of 3 meters (Table 1 summarizes the wavelength range of each band). In this research, seven spectral bands from Level-3B data were chosen[1] These bands underwent orthorectification and comprehensive correction processes, encompassing radiometric, geometric, and atmospheric corrections, resulting in surface reflectance values.

[1] Excluding coastal blue band due to its common usage in atmosphere correct.

One of the difficulties associated with using hyperspectral data in tidal marshes is the signature of the water which is present at high tide and not present at low tide. To avoid any complications that the signature of the water might present in the classification of vegetation, we opted to only use satellite data taken during low tide. We downloaded tide data from the closest NOAA tide gauge to our salt marsh sites (8637689 Yorktown USCG Training Center, VA, https://tidesandcurrents.noaa.gov/stationhome.html?id=8637689) over a 1-year period in 2022. We used this data to identify the hours of low tide (when water levels were below mean sea level) for each day. This information was used to constrain the potential satellite data to only low tide events. Satellite data was further constrained by weather (cloudy days were excluded) and time of day (nights were excluded). A total of 33 image tiles, captured throughout 2022, were carefully selected for further processing, resulting in the creation of four seasonal mosaic images.

Table 2. Planet Scope Imagery Wavelength

Spectral Bands	Wave Length (nm)
Coastal Blue	431 - 452
Blue	465 – 515
Green I	513 - 549
Green	547 – 583
Yellow	600 - 620
Red	650 – 680
RedEdge	697 – 713
NIR	845 – 885

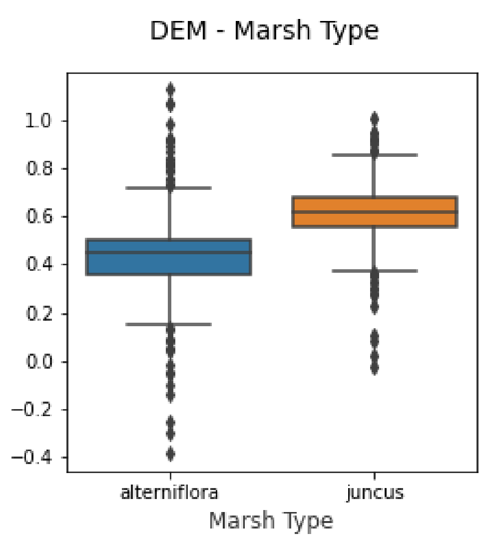


Figure 2. The distribution of DEM between two marsh types

Beyond the visual band information, we also incorporated five satellite indices - green/blue, red/green, NIR/red, the Normalized Difference Vegetation Index (NDVI

= (NIR - red)/(NIR + red)), and the Normalized Difference Water Index (NDWI

= (green - NIR)/(NIR + green)) - into the analysis, acknowledging their historical significance in wetland classification (Gilmore et al., 2008; Sun, Fagherazzi, & Liu, 2018).

In addition to the spectral bands and satellite indices, this study incorporated a high-resolution coastal elevation dataset, specifically a 1-meter topobathymetric elevation model (TBDEM), obtained from the U.S. Geological Survey (USGS) Coastal and Marine Geology Program (USGS, 2021). The TBDEM represents a comprehensive compilation of the most reliable multi-source topographic and bathymetric elevation data available for the Chesapeake Bay region. It seamlessly integrates data from over 261 diverse sources, including topographic and bathymetric LiDAR point clouds, hydrographic surveys, side-scan sonar surveys, and multi-beam surveys, all sourced from the USGS. Figure 2 illustrates the distribution of the DEM within the sampled *S. alterniflora* and *J. roemerianus* areas.

This process yields 49 predictive variables retrieved from various seasons for further data analysis.

Table 3. Accuracy assessment with Random Forest including all 49 prediction features.

	Precision	Recall	F1-score	Count
J. roemerianus	0.86	0.88	0.87	136
S. alterniflora	0.92	0.91	0.92	223
Overall Accuracy	0.90			

Table 4. Accuracy assessment with Support Vector Machine (SVM) with all 49 predicting variables.

	Precision	Recall	F1-score	Count
J. roemerianus	0.83	0.91	0.87	136
S. alterniflora	0.94	0.89	0.91	223
Overall Accuracy	0.90			

Classification

Two increasingly employed supervised machine learning approaches for classifying remote sensing images are support vector machine (SVM) and random forest (RF) classification. RF is an established ensemble learning algorithm in classification and regression tasks (Ho, 1995). It operates by constructing a multitude of decision trees during the training phase and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees (Ho, 1995). The strength of RF lies in its ability to mitigate overfitting, handle high-dimension data, and provide robust predictions.

The Support Vector Machine (SVM) algorithm is a versatile and widely adopted machine learning technique designed for both classification and regression tasks (Cortes & Vapnik, 1995). Rooted in statistical learning theory, SVM aims to construct an optimal hyperplane that maximally separates data points belonging to different classes in the feature space. Leveraging the kernel functions, SVM accommodates non-linear decision boundaries, rendering it effective in capturing intricate patterns and relationships within diverse datasets, thereby contributing to its prominence in various scientific research domains and applications.

Both RF and SVM are prominent machine learning algorithms with distinct characteristics suitable for diverse applications incorporating remote sensing and geospatial data, including land cover classification (Gislason, Benediktsson, & Sveinsson, 2006; Wang et al., 2019), coastal vegetation mapping (Juel, Groom, Svenning, & Ejrnæs, 2015; Morgan, Wang, Li, Schill, & Morgan, 2022), crop types classification (Neetu & Ray, 2019), and more (Belgiu & Drˇagut, 2016; Sheykhmousa et al., 2020). In this analysis, both SVM and RF are applied to get the optimal performance output for marsh community classification.

Results

Table 3 and table 4summarize the classification outputs from RF and SVM utilizing the 30% testing data withheld. Both tables show results after including all 49 predicting variables.

Both Random Forest and Support Vector Machine models demonstrate high accuracy, achieving an overall accuracy of 90% in predicting the presence of *J. roemerianus* and *S. alterniflora*. Specifically, RF achieves 86% and 92% precision in predicting *J. roemerianus* and *S. alterniflora*, respectively. In contrast, SVM achieves slightly lower precision in predicting *J. roemerianus* at 83% but excels in predicting *S. alterniflora* with a precision of 94%.

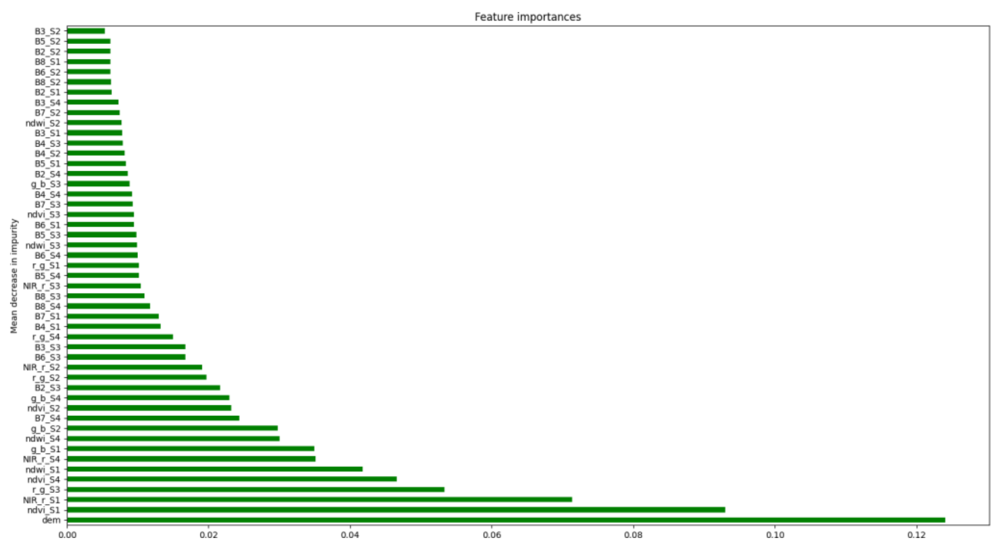


Figure 3. Important features that contribute to the model performance in making classification. Note: S1, S2, S3, and S4 appendix are abbreviations meaning data from spring, summer, fall, and winter.

To gain deeper insights into the crucial predictors influencing model outcomes, we examined the variable importance using the Random Forest (RF) algorithm. Figure 3 provides a comprehensive overview of each variable's significance in predicting results. Among the top ten influential variables, key contributors comprise DEM, NDVI, NIR/red, red/green, green/blue, and NDWI. It's noteworthy that certain variables appear multiple times (from different seasons) within the top ten rankings, underscoring their consistent impact on the predictive performance. Figure 4 shows the rank of the top ten variables.

A new set of experiments was conducted using both RF and SVM models, incorporating only the six selected features along with the RedEdge band, acknowledging its significance in various vegetation analyses (Delegido, Verrelst, Alonso, & Moreno, 2011). The summarized results are presented in Tables 5 and 6. While the overall accuracy slightly decreased by 1% with the filtered variables in the RF model, the SVM model demonstrated superior performance, surpassing other model prediction results by 1%. Particularly noteworthy is the SVM's achievement of 0.88 and 0.93 F1-score in predicting *J. roemerianus* and *S. alterniflora*, respectively, surpassing the performance of the other three model results in predicting each plant category.

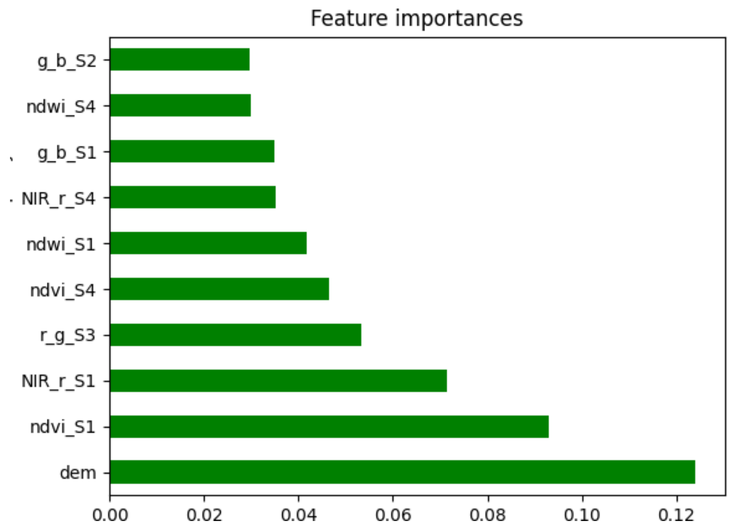


Figure 4. Top ten features that contribute to the model performance in making classification. Note: S1, S2, S3, and S4 appendix are abbreviations meaning data from spring, summer, fall, and winter.

Table 5. Accuracy assessment with Random Forest

	Precision	Recall	F1-score	Count
J. roemerianus	0.85	0.87	0.86	136
S. alterniflora	0.92	0.91	0.91	223
Overall Accuracy	0.89			

Table 6. Accuracy assessment with Support Vector Machine (SVM)

	Precision	Recall	F1-score	Count
J. roemerianus	0.88	0.89	0.88	136
S. alterniflora	0.93	0.92	0.93	223
Overall Accuracy	0.91			

Conclusions

High-resolution satellite imagery shows promise for identifying marsh plant communities at a precision equivalent to the community types from the last TMI survey. The advantages of the satellite methodology over the field visits lie in its capacity to map the locations of the marsh communities within the marsh and its ability to provide broad and consistent spatial and temporal coverage for surveys. Disadvantages are the inability to identify communities smaller than the resolution of the satellite data and potential challenges related to vegetation heterogeneity caused by mixed plant communities, which are common in high marshes and freshwater tidal marshes. In the last TMI, plant species were listed for every marsh. Many of these species were trace presence, but changes in their extent may herald climate impacts and should be tracked.

The satellite remote sensing of vegetation needs to be extended to other community types and needs to be tested in additional marshes before it is ready to be incorporated into the TMI. However, we think that this is an avenue worth pursuing, given the advantages offered of being able to update the TMI more frequently.

<u>Recommendations for future iterations of the TMI</u>

There are three methodologies for updating the TMI: field visits, drone imagery, and satellite imagery. We recommend that all 3 methods should be strategically employed to create a balance between intensity of efforts and precision and accuracy of the data.

1. Sentinel sites, consisting of marshes considered to be highly sensitive to sea level rise, should be targeted for joint drone/field surveys at regular (e.g. 5-year intervals). The drone imagery will be used to map the locations of plant communities and monitor changes in their extent. It may also be useful for monitoring changes in plant biomass, which could indicate a stressed plant community. The field surveys will verify the plant communities identified in the drone imagery and add the identification of plants that are sparsely distributed through the marsh.
2. Once the satellite capabilities are extended, an annual classification of marsh plant communities will be added to the TMI. This classification can be used to monitor changes in marshes and add sites to the sentinel survey if significant changes in vegetation are identified.

Task 2: Assess changes in ecosystem function (habitat provision) in marshes impacted by rapid rates of sea level rise. Outputs: survey results from newly migrated marsh habitats, vegetative composition, and a comparison of the marsh sediment organic matter availability. Linkage of avian marsh-obligate breeders use to inundation period to allow for the extension of results from this survey to other marshes in Virginia and allow for the prediction of changes in the potential habitat under sea level rise. **Outcomes:** Increased understanding of the relationship between marsh migration and marsh function.

This task was a field survey of marsh-obligate bird species in marshes migrating into upland regions. In Virginia, there are several avian marsh-obligate breeders (i.e., Seaside Sparrow, Saltmarsh sparrow, Marsh Wren, Virginia Rail, Clapper Rail) that have been used as a sentinel species for marsh habitat quality. Surveys of avian marsh-obligate breeders in reference and newly created marsh migration areas will be done to see if these areas are being used by marsh obligates and if their use may offset expected declines due to the loss of other marshes around the region.

We selected locations on the Virginia portion of the Delmarva Peninsula for the marsh surveys. We selected points that represent current high and low marsh and that have different habitat origins including marsh, forest and agriculture (about half of the previous forest was agriculture before it was forest), as show in Table 2. The "past habitat" was based on the two historic photo series. We also have built in variable distances to upland edge. This configuration should allow us to evaluate the influence of marsh creation via upland conversion on bird use. A subset of Ag→High marsh, Forest → High marsh, and High marsh → High marsh sites have been selected for soil organic matter sampling. Characteristics of the sites are archived on ScholarWorks (DOI https://doi.org/10.25773/3t1n-ss33).

We compared bird richness, plant cover, and soil carbon between recently established marshes and those that have remained relatively stable since the early-mid 20th century on the Eastern Shore of Virginia, USA. We found that the plant species composition, soil carbon, and bird communities differed between recently formed marshes and those that have been relatively stable since the early-mid 20th century. Plant cover was greater for *J. roemerianus, Phragmites australis* in newly formed marshes while *Sporobolus alterniflorus* / *Spartina alterniflora*), *S. pumilus* / *Spartina patens*), and *Distichlis spicata* cover was greater in marshes that remained relatively unchanged. The bird community in recently formed marshes included fewer saltmarsh obligates but more bird species that also breed in uplands and freshwater marshes. In addition to whether the marsh was recently created, species-specific bird occupancy was frequently affected by presence of past agricultural use, latitude, whether the marsh occurred on the bayside or seaside of the Delmarva peninsula and *J. roemerianus* cover.

The percentage of organic matter in marsh soils was affected by predictors that were commonly included in bird occupancy models including whether the marsh was recently created, past agricultural use, latitude, and whether the marsh occurred on the bayside or seaside of the Delmarva peninsula. Organic matter comprised the greatest percentage of soils in the northernmost bayside marshes that exhibited evidence of past agricultural use.

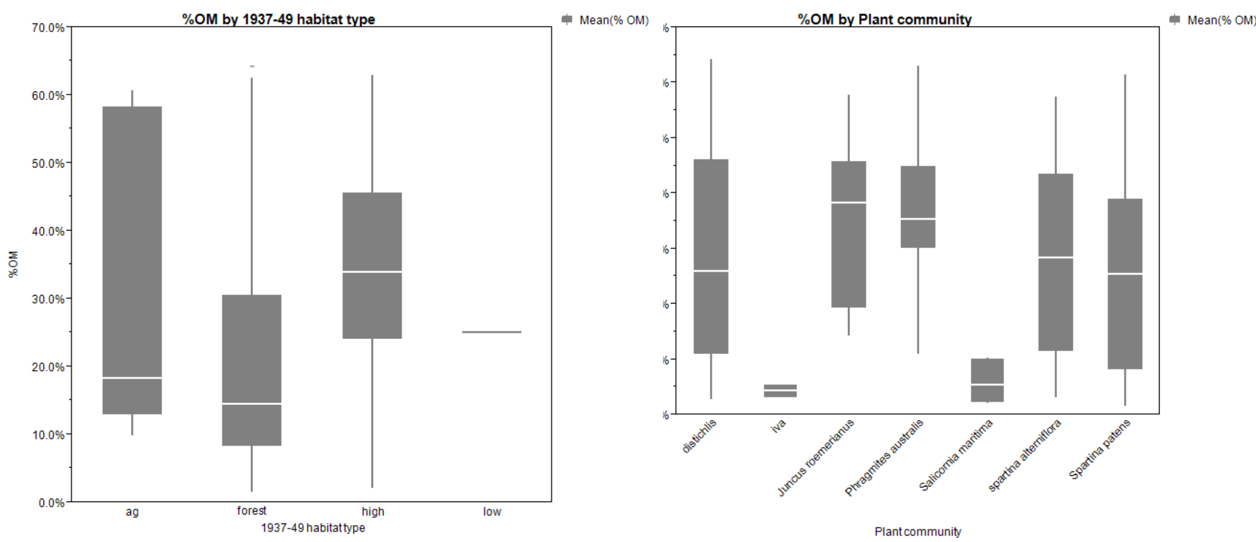
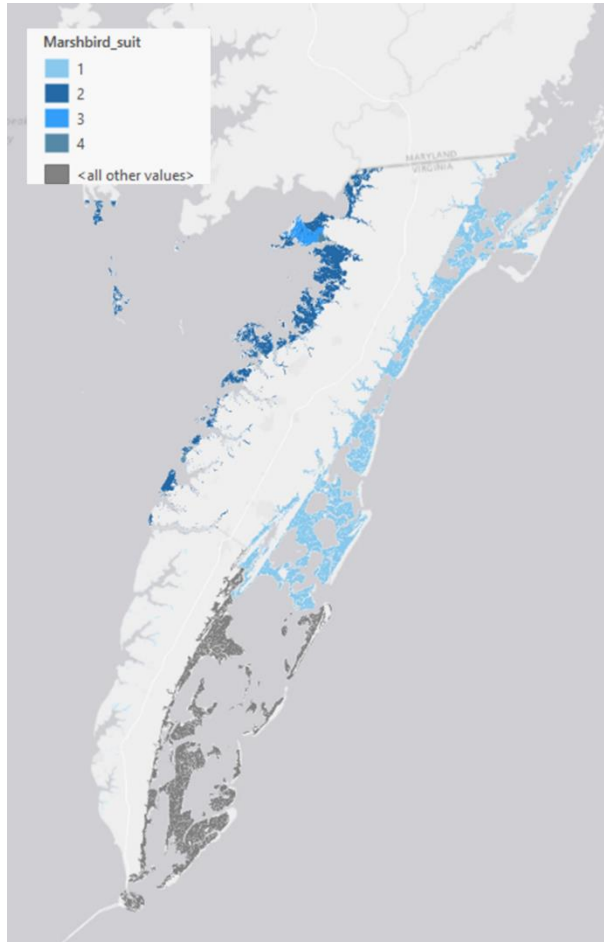


Figure 5. Distribution of %OM across different original habitat types and different current plant communities.

We believe that our observed trends in bird occupancy, plant cover, and organic matter are driven by the duration and frequency of tidal flooding which may be affected by berms and ditches erected around former agricultural fields. We expect that the bird community will support fewer saltmarsh obligates as a greater proportion of the marsh becomes younger and occurs in areas formerly used for agriculture. **A detailed report is included in Appendix B**.

Task 3: Outreach. Outputs: the addition of a new functional assessment metric into WetCat for the Eastern Shore of Virginia and educational talks and newsletters. **Outcomes:** Increased use of Virginia wetland planning tools, such as WetCAT to identify sustainable restoration areas and conservation targets under sea level rise.



This project is designed to provide information that is both accessible and useful to a diverse group of scientists, managers, policy makers, and the public. CCRM also provides training on-request to state agencies that wish to use WetCat in their permitting and/or planning efforts. Information from this project was broadly disseminated through locality and scientific/management meetings.

Activities

A ranking of the potential for Eastern Shore marshes to provide good habitat for avian marsh-obligate breeders was developed using the results from the bird survey. Marshes were ranked by their location (North = 1, South =0) and (Bay = 1, Ocean = 0); and vegetative community type (*J. roemerianus* = 2, *Spartina patens* and Mixed Brackish = 1). Community types were extracted from the Virginia TMI (Berman et al, 2011 & 2016). On the Eastern Shore of Virginia, a number of these marshes are classified as "unknown" so this dataset may be missing some of the J. roemerianus dominated marshes. Higher values indicate that marsh obligate species had shown a higher association with this characteristic. Rankings were summed to create a composite index of marshes where obligate marsh birds are likely to find the most suitable habitat. The best habitat had a ranking of 4, while marshes without any of the highly correlative qualities had a ranking of 0. These rankings can be used to inform monitoring and conservation efforts. The resulting geodatabase is archived on ScholarWorks (DOI https://doi.org/10.25773/3t1n-ss33).

Public and scientific outreach

- M. Mitchell gave a talk at the VIMS CCRM Wetlands Workshop entitled "Tidal Wetland Project Updates & Marsh Migration" which informed tidal marsh regulators and managers about EPA-funded data included in WetCat and the goals for the current project.
- M. Mitchell also discussed the value of data in WetCat for decision-making in a talk to locality leaders at the Middle Peninsula Raft Resilience Education Workshop entitled "Predicted sea level rise in Virginia: Risks to wells, septic systems, roads, buildings, shorelines".

- A article about the research entitled “CCB and Saltmarsh Bird Surveys” was sent out by The Center for Conservation Biology newsletter, which has a diverse and broad readership https://ccbbirds.org/2023/06/01/ccb-and-saltmarsh-bird-surveys/
- M. Mitchell gave a talk at the 2023 MAWWG-NEBAWWG Webinar Series #1 Coastal Conservation Highlights entitled “Enhancing Development of Strategies for Coastal Wetland Conservation Prioritization in Virginia Under Climate Change”. There were approximately 85 attendees.
- C. Hines gave a talk at the Mid-Atlantic Wetlands Workgroup (MAWWG) 2023 Annual Meeting, November 14th-16th, in Lancaster, PA in the Climate Change Sea Level Rise and Coastal Wetlands session entitled ‘Bird use in Recently Created Marshes”.

QA/QC report

There were two issues caught and resolved in the QA/QC process.

1. Data from one day during the bird survey was reviewed and it was determined that the GPS locations did not match the marsh that the survey was supposed to take place in. This survey was done by a new employee. The discrepancy was noticed within a couple days of the data collection. Corrective action: the data was deleted, and the bird survey was re-done in the correct location by an experienced employee. The new employee was no longer engaged in the bird surveys.

2. A spreadsheet containing the soil organic matter data had 2 sites with the same ID number, but different GPS locations. Corrective action: One of the ID numbers was verified using data and photos collected during the field visit. The second data point could not be verified—since there weren’t any missing sites, the unverified data point was deleted.

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Acknowledgements

We would like to thank C-StREAM intern Joseph Rivera-Lopez for his work on the literature review and Sean Gregory for his help in the field.

Appendix A. Literature Review

Search terms used:

Multispectral remote sensing, UAV, Photogrammetry, LiDAR, NDVI, Remote Sensing, UAS, SfM, salt marsh, LiDAR, Tidal marsh remote sensing methods, UAV tidal marsh, tidal marsh remote sensing methods drone, UAV vegetation, UAV tidal marsh biomass, UAS coastal vegetation, drone marsh imagery, drone imagery marsh identification

Synopsis of literature:

Abeysinghe, T.; Simic Milas, A.; Arend, K.; Hohman, B.; Reil, P.; Gregory, A.; Vázquez-Ortega, A. Mapping Invasive Phragmites australis in the Old Woman Creek Estuary Using UAV Remote Sensing and Machine Learning Classifiers. Remote Sens. 2019, 11, 1380. https://doi.org/10.3390/rs11111380

> Lake Erie
>
> RGB/Infrared/spectral
>
> The research was using UAV to identify an invasive marsh plant in a Lake Erie wetland using machine learning (ML) algorithms: Neural network (NN), support vector machine (SVM), and k-nearest neighbor (kNN)

Broussard, W.P., Visser, J.M. and Brooks, R.P., 2020. Quantifying Vegetation and Landscape Metrics with Hyperspatial Unmanned Aircraft System Imagery in a Coastal Oligohaline Marsh. Estuaries and Coasts, pp.1-12. https://doi.org/10.1007/s12237-020-00828-8

> Terrebonne Parish, LA
>
> RGB/Infrared/spectral, Multispectral, object-based image analysis (OBIA)
>
> Utilized UAS to collect hyperspatial, multispectral aerial images in a coastal wetland in order to produce very-high-resolution orthomosaics and DEMs. Applied object-based image analysis (OBIA) techniques to delineate the land-water interface, classify composition by dominant species, and quantify average plant height by species. Found land-water interface model accurate and reliable, resolving complex smaller pockets of open water in the interior marsh; accurately predicted dominant vegetation (although low sample size); shows promise in ability to estimate plant height at the landscape scale.

Buffington, K.J., Dugger, B.D., Thorne, K.M. and Takekawa, J.Y., 2016. Statistical correction of lidar-derived digital elevation models with multispectral airborne imagery in tidal marshes. Remote Sensing of Environment, 186, pp.616-625. https://www.sciencedirect.com/science/article/am/pii/S0034425716303637

Pacific Northwest, San Francisco Bay, and Southern California

Lidar

Although LIDAR is a great method for capturing elevation data in a broad area, it has its obstacles especially when penetrating dense vegetation. This hinders its usefulness in marshes. Therefore, this report seeks a method of correcting this obstacle that doesn't imply exaggerated field work. It finds the "the Lidar Elevation Adjustment with NDVI (LEAN), to correct lidar digital elevation models (DEMs) with vegetation indices from freely available multispectral airborne imagery (NAIP) and RTK-GPS surveys". With this, the study proved its increased effectiveness.

Curcio, A.C., Peralta, G., Aranda, M. and Barbero, L., 2022. Evaluating the performance of high spatial resolution UAV-photogrammetry and UAV-LiDAR for salt marshes: the cádiz bay study case. Remote Sensing, 14(15), p.3582. https://www.mdpi.com/2072-4292/14/15/3582

Cádiz Bay, Spain

Lidar, RGB/Infrared/spectral, Pix4Dmapper (SfM)

The purpose of the study by Curcio et. al, 2022, was to establish a baseline using UAV technology of mapping a wetland, which could be used for future modeling to explore potential climate change scenarios. The location of the study was on the southwestern Atlantic coast of Spain, specifically Cádiz Bay, a tidal marsh near the Mediterranean. Vegetation types in the marsh include Sarcocornia fruticose and Sarcocornia perennis, Sporobolus maritimus, Zostera noltei, Cymodocea nodosa, and Zostera marina. The author's intent was to create DEM and DSM using both UAV-LiDAR and UAV photogrammetry, exploring both performance and precision, as well as classify habitats using multispectral data.

Dai, W., Li, H., Gong, Z., Zhou, Z., Li, Y., Wang, L., Zhang, C. and Pei, H., 2021. Self-organization of salt marsh patches on mudflats: Field evidence using the UAV technique. Estuarine, Coastal and Shelf Science, 262, p.107608. https://doi.org/10.1016/j.ecss.2021.107608

Jiangsu Doulong harbor, China

RGB/Infrared/spectral

Examined the relationship between vegetation patch size and size-frequency distributions of Spartina alterniflora in a salt marsh using UAV- and satellite-derived orthoimages and DEMS. Observed the growth and expansion of the S. alterniflora edge patches, with patch area determined by the UAV images being the smallest and most accurate due to image resolution.

DiGiacomo, A.E., Bird, C.N., Pan, V.G., Dobroski, K., Atkins-Davis, C., Johnston, D.W. and Ridge, J.T., 2020. Modeling salt marsh vegetation height using unoccupied aircraft systems and structure from motion. Remote Sensing, 12(14), p.2333. https://doi.org/10.3390/rs12142333

Beaufort, NC

Lidar, RGB/Infrared/spectral

Utilized a UAS-SfM photogrammetry approach combining DSMs with DTMs to extract salt marsh vegetation height. Vegetation height, combined with imagery of lateral vegetation area, were used to assess above ground biomass. DSM was constructed by connecting RGB point cloud points, while DTMS were constructed using three different methods: NDVI, manual identification, and LiDAR-derived terrain points. All three computed vegetation height methodologies demonstrated significant linear relationships between predicted and observed vegetation height, but under-predicted vegetation height proportionally, missing more absolute vegetation at higher stem heights.

Doughty, C.L. and Cavanaugh, K.C., 2019. Mapping coastal wetland biomass from high resolution unmanned aerial vehicle (UAV) imagery. Remote Sensing, 11(5), p.540. https://doi.org/10.3390/rs11050540

Carpinteria Salt Marsh Reserve, Santa Barbara, CA

RGB/Infrared/spectral, Multispectral

UAV with multispectral camera used to capture imagery for biomass estimation in salt marsh across 4 seasons and compared with in situ canopy reflectance measurements, in situ biomass measurements and vegetation indices to validate data collection and processing. Reflectance measurements pooled for all seasons indicated a strong correlation with spring presenting the strongest model. Amount of seasonal aboveground biomass, tidal inundation, etc. alters the effectiveness of UAV imagery modeling purposes.

Doughty, C.L., Ambrose, R.F., Okin, G.S. and Cavanaugh, K.C., 2021. Characterizing spatial variability in coastal wetland biomass across multiple scales using UAV and satellite imagery. Remote Sensing in Ecology and Conservation, 7(3), pp.411-429. https://doi.org/10.1002/rse2.198

Southwest coast of CA

RGB/Infrared/spectral, Multispectral

Tested the feasibility of using UAV-based approaches to map coastal wetland biomass across spatial scales and compared how the spatial resolution of high- and moderate-resolution imagery can influence biomass estimation by comparing UAV and Landsat approaches. Also tested impacts of dominant vegetation cover type on the ability to model AGB. Combining UAV-derived AGB maps and Landsat NDVI imagery provided the strongest AGB estimation for the wetland sites overall.

Durgan, S.D., Zhang, C., Duecaster, A., Fourney, F. and Su, H., 2020. Unmanned aircraft system photogrammetry for mapping diverse vegetation species in a heterogeneous coastal wetland. Wetlands, 40(6), pp.2621-2633. https://doi.org/10.1007/s13157-020-01373-7

Biscayne Bay, FL

RGB/Infrared/spectral

Objective was to map a large number of plant species (~17) found in a heterogeneous coastal wetland using UAS-derived (RGB) orthoimagery and 3D products to assist an ongoing wetland restoration project. Fusing UAS 4.23-cm orthoimagery with the simultaneously generated DSM showed the best performance for wetland species classification (although there was variability between certain species). While Random Forest and Support Vector Machine processes achieved similar classification accuracies, the uncertainty map displayed a fair amount of disagreement over the study area.

Farris, A.S., Defne, Z. and Ganju, N.K., 2019. Identifying salt marsh shorelines from remotely sensed elevation data and imagery. Remote Sensing, 11(15), p.1795. https://www.mdpi.com/2072-4292/11/15/1795/htm

Coastal marshes from Massachussetts

Lidar, Structure from motion (SfM) aerial photogrammetry collected by UAS, image classification techniques

This study explores remote sensing techniques to track the seaward edge of salt marsh shorelines. It introduces methods that can be applied to high resolution datasets of elevation and imagery, better them digitizing from imagery. These methods are marsh edge from elevation data (MEED) and marsh edge by image processing (MEIP), and the report also discusses their advantages and disadvantages. It concludes that both methods are effective and efficient for the purpose mentioned.

Ganju, N.K., Couvillion, B.R., Defne, Z. et al. Development and Application of Landsat-Based Wetland Vegetation Cover and UnVegetated-Vegetated Marsh Ratio (UVVR) for the Conterminous United States. Estuaries and Coasts 45, 1861–1878 (2022). https://doi.org/10.1007/s12237-022-01081-x

Conterminous US

RGB/Infrared/spectral

This article developed unvegetated-vegetated marsh ratio using Landsat imagery to quantify vegetated wetland in the US. They use the methodology to track wetland changes and forecast upcoming changes in the near future.

Gillan, J.K., Karl, J.W. & van Leeuwen, W.J. Integrating drone imagery with existing rangeland monitoring programs. Environ Monit Assess 192, 269 (2020). https://doi.org/10.1007/s10661-020-8216-3

Northern California

UAS

Field identifications were compared to UAS drone images collected to identify rangeland vegetation in Northern CA. Authors found promising correlation and suggest an online photo resource to share data among researchers.

Huang, S., Tang, L., Hupy, J.P., Wang, Y. and Shao, G., 2021. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. Journal of Forestry Research, 32(1), pp.1-6. https://link.springer.com/article/10.1007/s11676-020-01155-1

N/A

RGB/Infrared/spectral

This comments on the usefulness of NDVI in Vegetation remotes sensing analysis and the inherent risks with some of the sensors. This article summarizes the progress of NDVI acquisition, highlights the areas of NDVI application, and addresses the critical problems and considerations in using NDVI. Detailed discussion mainly covers three aspects: atmospheric effect, saturation phenomenon, and sensor factors.

Haskins, J., Endris, C., Thomsen, A.S., Gerbl, F., Fountain, M.C. and Wasson, K., 2021. UAV to inform restoration: a case study from a California tidal marsh. Frontiers in Environmental Science, 9, p.642906. https://doi.org/10.3389/fenvs.2021.642906

Monterey Bay, CA

RGB/Infrared/spectral, NIR

Evaluated the utility of UAVs as a tool for monitoring tidal marsh restoration. Experimented with different flight elevations, imagery data methods, concentration of ground control points (GCPs), etc. and compared to data collected in field to evaluate elevation profiling and vegetation cover estimates from UAV imagery. Lower flight altitude (30 m) was more ideal for capturing patchy early plant cover. Reduced detail overall was evident in the inability to distinguish between species, upland vs marsh plants, native vs. non-native plants in classification of UAV imagery. Vegetation cover estimates improved when NIR and RGB data were collected/utilized together.

Kalacska, M., Chmura, G.L., Lucanus, O., Bérubé, D. and Arroyo-Mora, J.P., 2017. Structure from motion will revolutionize analyses of tidal wetland landscapes. Remote Sensing of Environment, 199, pp.14-24. https://www.sciencedirect.com/science/article/am/pii/S003442571730281X

Three salt 150 marshes on the New Brunswick coast of the Gulf of St. Lawrence

LiDAR, RGB/Infrared/spectral

"The study emphasizes that UAV-based SfM photogrammetry is particularly useful in environments with distinct seasons. In regions where, herbaceous vegetation becomes dormant during winter and is affected by ice and snow cover, spring is the most suitable time to map geomorphological features accurately.

The low cost of SfM photogrammetry combined with its ability to target specific wetlands makes it a valuable tool. The method can be used during the growing season to map vegetation and assess species distribution in relation to elevation and drainage features.

Characteristics captured by SfM photogrammetry, such as elevation, vegetation, and channel networks, are important inputs for predictive models concerning marsh response to sea-level rise and water quality. The use of SfM photogrammetry improves the accuracy of such assessments.

SfM photogrammetry outperforms other methods like LiDAR or aerial photography in terms of resolution and detail. It provides a more comprehensive depiction of features important for estuarine and tidal marsh ecology, conservation, and management.

The affordability of SfM photogrammetry makes it suitable for monitoring changes in elevation, vegetation (especially during the growing season), and channel networks in response to wetland restoration efforts.

Accurate Digital Elevation Models (DEMs) developed through SfM photogrammetry aid in the creation of hydrodynamic models that better predict hydroperiod and associated stresses. The high vertical resolution is beneficial for process studies, as small-scale variations in topography can impact various ecological factors such as hydroperiod, soil conditions, vegetation growth, species composition, and greenhouse gas emissions."

Kedia, A.C., Kapos, B., Liao, S., Draper, J., Eddinger, J., Updike, C. and Frazier, A.E., 2021. An integrated spectral–structural workflow for invasive vegetation mapping in an arid region using drones. Drones, 5(1), p.19. https://doi.org/10.3390/drones5010019

Lower Salt River, Tonto National Forest, AZ

RGB/Infrared/spectral, Multispectral

Study developed a spectral-structural workflow for classifying invasive species in a region prone to fire and flooding. UAS images were processed into spectral orthomosaics and structural DEMs, including a DTM and a CHM. The spectral mosaics were used to derive a suite of vegetation indices, while the DTM was used to derive a hydrological flow accumulation model of the site. The spectral data layers, which included five multispectral bands and six vegetation indices, were used to develop a spectral-only random forest classification model to distinguish vegetation species. The full set of spectral and structural layers were combined into a spectral-structural model for the same purpose.

Kimball, M.E., Connolly, R.M., Alford, S.B., Colombano, D.D., James, W.R., Kenworthy, M.D., Norris, G.S., Ollerhead, J., Ramsden, S., Rehage, J.S. and Sparks, E.L., 2021. Novel applications of technology for advancing tidal marsh ecology. Estuaries and Coasts, 44(6), pp.1568-1578. https://link.springer.com/content/pdf/10.1007/s12237-021-00939-w.pdf

N/A

RGB/Infrared/spectral, Optical or refractive light imagery (thermal and hyper-spectral; satellite to submersible); usage of drones for unmanned aerial systems structure-from-motion (UAS-SfM) photogrammetry methods; hyper- and multi-spectral imaging; optical and acoustic underwater imaging to study tidal marshes; tidal marsh animal tracking; biotracers; and machine learning.

This paper discusses the innovations in technology for research of tidal marshes. It also discusses the ways to analyze and combine the different and large amount of data compiled with this technology. "While the power of individual approaches is obvious, it is the synergies of these approaches that have significant potential for sparking transformative research and supporting ecosystem-based management of tidal marshes" (p. 1574). These technological advances can help with science support for management. However, these new methods still need a little ground-truthing.

Kimball, M.E., Connolly, R.M., Alford, S.B. et al. Novel Applications of Technology for Advancing Tidal Marsh Ecology. Estuaries and Coasts 44, 1568–1578 (2021). https://doi.org/10.1007/s12237-021-00939-w

n/a

Lidar, RGB/Infrared/spectral

Authors reviewed several types of technological advances in tidal marsh research including drones, satellites, and biotracers.

Klemas, V., 2013. Remote sensing of coastal wetland biomass: An overview. Journal of Coastal Research, 29(5), pp.1016-1028. file:///C:/Users/river/Downloads/JCOASTRES-D-12-00237.1.pdf

U. S. Eastern Coast

SAR, Lidar, RGB/Infrared/spectral, Landsat TM, IKONOS, QuickBird, NDVI

"This article is an overview of the known data related to mapping wetland biomass and the use of aboveground biomass by using different remote-sensing techniques. It encompasses the U.S. Eastern Coast including the Chesapeake Bay and Florida. It analyses many techniques and concludes that key biophysical characteristics of wetlands…can be measured with high resolution remote sensors and extrapolated over large coastal areas"

Lin, Y.C., Cheng, Y.T., Zhou, T., Ravi, R., Hasheminasab, S.M., Flatt, J.E., Troy, C. and Habib, A., 2019. Evaluation of UAV LiDAR for mapping coastal environments. Remote Sensing, 11(24), p.2893. https://www.mdpi.com/2072-4292/11/24/2893

Dana Island, Turkey, and along the Indiana beaches of southern Lake Michigan, USA

LiDAR, RGB/Infrared/spectral

"The quality of the UAV LiDAR point cloud is compared with an image-based point cloud across a 1.7 km coastal area containing both bare ground and heavily vegetated areas. Results show that both UAV LiDAR and image-based techniques produce point clouds with a high degree of agreement, with an overall precision of ±5-10 cm. UAV LiDAR offers advantages such as extensive and uniform ground coverage, higher point density, and the ability to capture ground points through vegetation. Image-based reconstruction is more sensitive to technical and environmental factors.

The authors plan to automate the detection of eroding areas and ridge points. Additionally, they intend to integrate UAV LiDAR data with airborne or satellite-borne LiDAR data to establish baseline information for long-term change quantification and bathymetric data collection. This integration will support the development of a high-temporal-resolution hydrologic model and aid decision-making in coastal management."

Monteiro, J.G., Jiménez, J.L., Gizzi, F. et al. Novel approach to enhance coastal habitat and biotope mapping with drone aerial imagery analysis. Sci Rep 11, 574 (2021). https://doi.org/10.1038/s41598-020-80612-7

Madeira Island

Lidar

This article uses Drone Imagery to map marsh habitats and identify and classify marsh biotopes. The data is combined to determine likely distribution patterns.

Morgan, G.R., Wang, C. and Morris, J.T., 2021. RGB indices and canopy height modelling for mapping tidal marsh biomass from a small unmanned aerial system. Remote Sensing, 13(17), p.3406. https://doi.org/10.3390/rs13173406

North Inlet Winyah Bay, SC

Lidar, RGB/Infrared/spectral

Tested the concepts of using RGB-indices (derived from sUAS imagery) for s. alterniflora biomass modelling. RGB imagery used to generate a DSM and LiDAR data downloaded from NOAA digital coast website used to generate a DTM; DSM and DTM were used to create a canopy height model (CHM) to assess its utility for adding merit to biomass modelling with RGB indices. Distance-based RGB indices perform better than the common ratio-based indices for biomass estimation and the drone-extracted CHM were not effective in modelling biomass.

Nolte, S., Koppenaal, E.C., Esselink, P., Dijkema, K.S., Schuerch, M., De Groot, A.V., Bakker, J.P. and Temmerman, S., 2013. Measuring sedimentation in tidal marshes: a review on methods and their applicability in biogeomorphological studies. Journal of Coastal Conservation, 17(3), pp.301-325. https://link.springer.com/content/pdf/10.1007/s11852-013-0238-3.pdf

N/A

Lidar

This is an overview of the different methods, with their advantages and disadvantages, to use remote sensing in salt marshes specifically for biogeomorphological research. "This review gives an inventory of the available methods to quantify sedimentation, vertical accretion and erosion processes in coastal marshes for researchers from different fields". Its purpose is to organize and let the reader choose the best method depending on the research project; the article also explains the recommended process of choosing it. The only remote sensing method mentioned was LIDAR.

Pastore, V.P., Zimmerman, T.G., Biswas, S.K. et al. Annotation-free learning of plankton for classification and anomaly detection. Sci Rep 10, 12142 (2020). https://doi.org/10.1038/s41598-020-68662-3

unknown

Machine learning

This article used machine learning to identify plankton from photographs and compare to lab data. (Similar methods but in different field of study.) The authors developed an algorithm to recognize and classify species as well as detect anomalies. They used artificial neural networks with Random Forest classifier in the machine learning algorithm.

Peciña, M.V., Bergamo, T.F., Ward, R.D., Joyce, C.B. and Sepp, K., 2021. A novel UAV-based approach for biomass prediction and grassland structure assessment in coastal meadows. Ecological Indicators, 122, p.107227. https://doi.org/10.1016/j.ecolind.2020.107227

Western coast of Estonia

RGB/Infrared/spectral, Multispectral

UAV-based multispectral imagery and aerial photogrammetry (RGB) were used to produce high spatial resolution maps of standing biomass in coastal meadows to assess grassland sward structure and the effects of the duration and type of management regime. Multispectral orthomosaics were used to compute 13 vegetation indices and were combined with microtopography models (DTMs) obtained through SfM. Demonstrates that wetland and grassland habitats characterized by high spatial heterogeneity at micro scales can be surveyed following this approach.

Pinton, D., Canestrelli, A., Wilkinson, B., Ifju, P. and Ortega, A., 2021. Estimating ground elevation and vegetation characteristics in coastal salt marshes using UAV-based LiDAR and digital aerial photogrammetry. Remote Sensing, 13(22), p.4506. https://doi.org/10.3390/rs13224506

Little Sapelo Island, GA

Lidar, RGB/Infrared/spectral, Digital Aerial Photogrammetry (DAP), Structure from Motion (SfM)

Compared spatial distribution of ground elevation and vegetation characteristics obtained from a LiDAR- and a DAP-UAV dataset collected on a salt marsh system and applied a machine learning algorithm (genetic algorithm) to obtain distributions. Results underlined the superiority of LiDAR-UAV over DAP-UAV in computing bed elevation and vegetation characteristics in a salt marsh due to low penetration of the DAP-UAV point cloud in dense vegetation layers. Results confirmed that adding a point-cloud dataset to an imagery dataset (such as RGB data) is beneficial for vegetation classification purposes only if its resolution is similar or higher than the resolution of the initial dataset.

Sankey, T.T., McVay, J., Swetnam, T.L., McClaran, M.P., Heilman, P. and Nichols, M., 2018. UAV hyperspectral and lidar data and their fusion for arid and semi-arid land vegetation monitoring. Remote Sensing in Ecology and Conservation, 4(1), pp.20-33 https://doi.org/10.1002/rse2.44

Walnut Gulch Experimental Watershed, AZ

Lidar, RGB/Infrared/spectral, Hyperspectral

Utilized hyperspectral imagery to estimate presence and subpixel abundance of plant species, lidar data to estimate individual canopy heights and herbaceous vegetation patch heights, and fused the hyperspectral classification and lidar-derived vegetation canopy height estimates to produce a final land-cover type map. Plants were shrubs (20-225 cm) in arid environmenst. Compared to the classification of hyperspectral data alone, the fusion of lidar and hyperspectral data provides >30% improvement in species identification by leveraging differences in plant height.

Yeo, S., Lafon, V., Alard, D., Curti, C., Dehouck, A. and Benot, M.L., 2020. Classification and mapping of saltmarsh vegetation combining multispectral images with field data. Estuarine, Coastal and Shelf Science, 236, p.106643.
https://www.sciencedirect.com/science/article/pii/S027277141930232X

Southwest France

Lidar, RGB/Infrared/spectral

A study from southwest France by Yeo et al., 2020, sought to develop maps of salt marsh topology in a nature reserve lagoon by combining field data and multispectral images. Summertime field sampling included GPS point locations, as well as plant abundance and cover in each of the 832 locations, which were grouped by vegetative species. The authors obtained 2-m resolution multispectral satellite images which they indexed into 8 bands to detect water and vegetation, and a DEM taken from LiDAR data. Yeo et al. 2020 used a technique called Maximum Likelihood Classification to classify pixels into different vegetation groups. The authors found their approach to be effective at creating marsh topology as compared to field data, with variations in accuracy among the different plant types. The upper and lower marshes were more accurately mapped than the intermediate marsh was. It was interesting that the authors found adding the LiDAR data acquired DEM actually decreased the accuracy of their results, which was different than other studies which recommended using LiDAR data. The results from Yeo et al., 2020, are transferrable to larger areas and useful for spatial analysis over time of marshland changes.

Zheng, Z., Zhou, Y., Tian, B. and Ding, X., 2016. The spatial relationship between salt marsh vegetation patterns, soil elevation and tidal channels using remote sensing at Chongming Dongtan Nature Reserve, China. Acta Oceanologica Sinica, 35(4), pp.26-34. https://link.springer.com/content/pdf/10.1007/s13131-016-0831-z.pdf

Chongming Dongtan Nature Reserve, in the Changjiang (Yangtze) River Estuary, China

RGB/Infrared/spectral, QuickBird

This article explores the different environmental factors (soil elevation, tidal channels density, vegetation classification, and fractional vegetation cover) could affect the distribution of marsh vegetation. The vegetation studied was the native Scirpus mariqueter and the invasive Spartina alterniflora, specifically seeing how the invasive species affected in the native. The study also studied the effectiveness of remote sensing, and "it was shown to be a reliable dynamic observation technique, providing access to the wide range of temporal and spatial scales of interest in tidal environments" (p. 7).

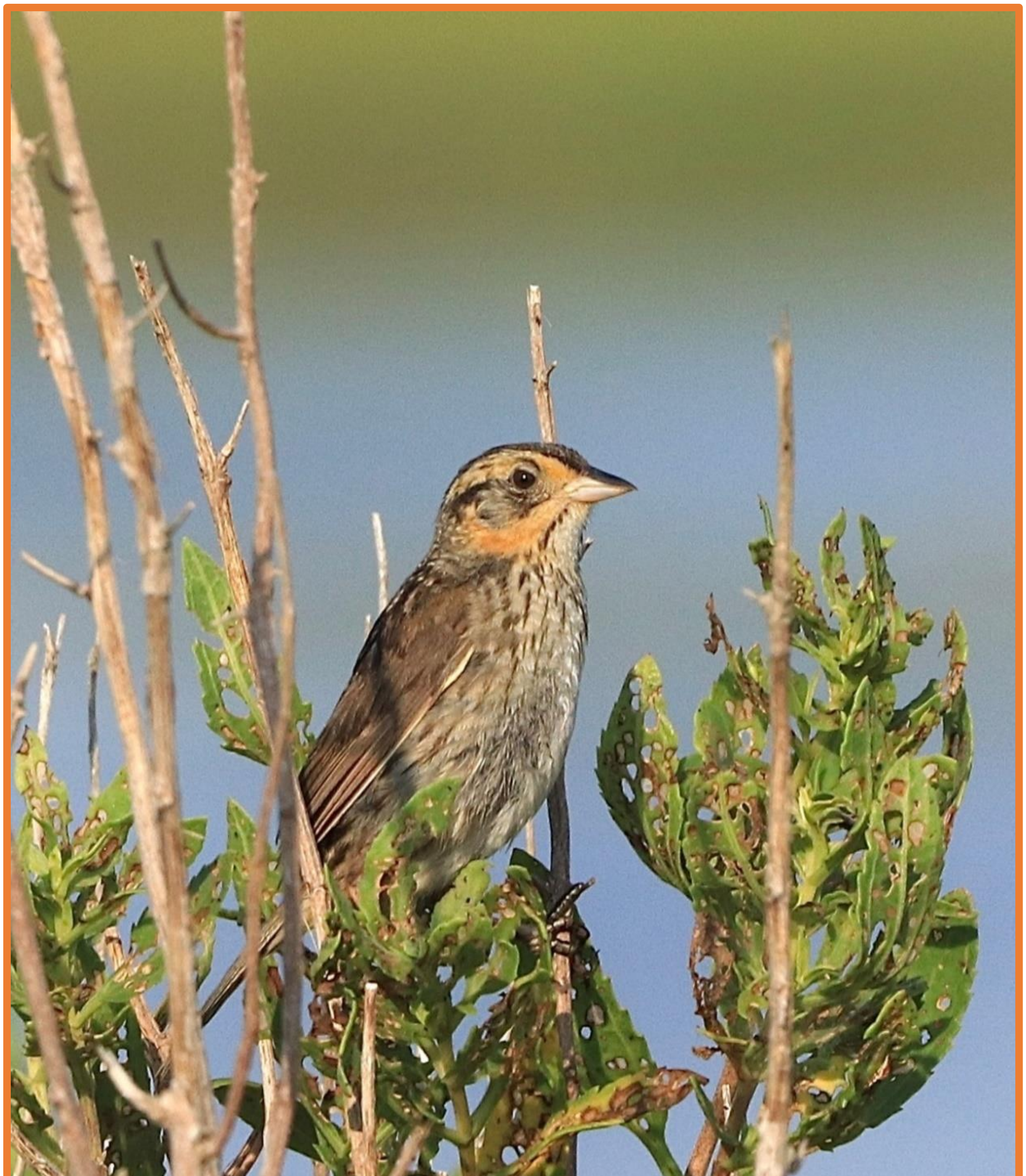
Zhou, Z., Yang, Y. and Chen, B., 2018. Estimating Spartina alterniflora fractional vegetation cover and aboveground biomass in a coastal wetland using SPOT6 satellite and UAV data. Aquatic Botany, 144, pp.38-45. http://dx.doi.org/10.1016/j.aquabot.2017.10.004

Sansha Bay, China

RGB/Infrared/spectral, Multispectral

Fractional vegetation cover (FVC) and aboveground biomass (AGB) were estimated based on SPOT6 satellite images and UAV images. FVC obtained from UAV high spatial resolution imaging and AGB acquired from in situ field data collection compared to VIs with SPOT6 satellite imagery. Relationships between SPOT6 spectral signals and in situ measured AGB were poor, while the correlation between VIs and the field-data AGB was promising. FVC obtained from UAV imagery was effective though certain deficiencies are still present.

Appendix B. Evaluating Wildlife Values of Newly Created Marshes Via Marsh Migration: Final Report



Evaluating wildlife values of newly created marshes via marsh migration: final report

THE CENTER FOR CONSERVATION BIOLOGY

WILLIAM & MARY

EVALUATING WILDLIFE VALUES OF NEWLY CREATED MARSHES VIA MARSH MIGRATION: FINAL REPORT

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Recommended Citation:

Hines, C. H., L. S. Duval, B. D. Watts and M. Mitchell. 2023. Evaluating Wildlife Values of Newly Created Marshes via Marsh Migration: Final Report. Center for Conservation Biology Technical Report Series, CCBTR-23-20. William & Mary, Williamsburg, VA. 22 pp.

Project Partners:
United States Environmental Protection Agency
Virginia Institute for Marine Science
Virginia Department of Wildlife Resources
United States Fish & Wildlife Service
The Nature Conservancy
The Center for Conservation Biology

Front Cover Image: A saltmarsh sparrow perched on a marsh elder branch in a marsh at Wallops Island. Photograph by Will Burgoyne.

THE CENTER FOR CONSERVATION BIOLOGY

The Center for Conservation Biology is an organization dedicated to discovering innovative solutions to environmental problems that are both scientifically sound and practical within today's social context. Our philosophy has been to use a general systems approach to locate critical information needs and to plot a deliberate course of action to reach what we believe are essential information endpoints.

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EXECUTIVE SUMMARY

Saltmarsh loss and creation are occurring at an increasingly rapid rate due to the rapid rate of sea level rise. Given the speed of this process over the past decades, a greater portion of the current marsh is relatively young but it is not clear how a change in the proportion of young and old marsh might affect animal and plant communities. We compared bird richness, plant cover, and soil carbon between recently established marshes and those that have remained relatively stable since the early-mid 20th century on the Eastern Shore of Virginia, USA. We found that the plant species composition, soil carbon, and bird communities differed between recently formed marshes and those that have been relatively stable since the early-mid 20th century. Plant cover was greater for *J. roemerianus roemerianus*, *Phragmites australis* in newly formed marshes while *Sporobolus alterniflorus (Spartina alterniflora)*, *S. pumilus (Spartina patens)*, and *Distichlis spicata* cover was greater in marshes that remained relatively unchanged. The bird community in recently formed marshes included fewer saltmarsh obligates but more bird species that also breed in uplands and freshwater marshes. In addition to whether the marsh was recently created, species-specific bird occupancy was frequently affected by presence of past agricultural use, latitude, whether the marsh occurred on the bayside or seaside of the Delmarva peninsula and *J. roemerianus* cover. The percentage of organic matter in marsh soils was affected by predictors that were commonly included in bird occupancy models including whether the marsh was recently created, past agricultural use, latitude, and whether the marsh occurred on the bayside or seaside of the Delmarva peninsula. Organic matter comprised the greatest percentage of soils in the northernmost bayside marshes that exhibited evidence of past agricultural use. We believe that our observed trends in bird occupancy, plant cover, and organic matter are driven by the duration and frequency of tidal flooding which may be affected by berms and ditches erected around former agricultural fields. We expect that the bird community will support fewer saltmarsh obligates as a greater proportion of the marsh becomes younger and occurs in areas formerly used for agriculture.

BACKGROUND

Context

Tidal wetlands (hereafter saltmarsh) are being subjected to an increasingly more rapid rate of marsh loss and marsh creation associated with sea level rise (Ezer and Corlettt 2012). Marsh loss occurs via several processes but the most important, relative to area lost over the past decades, is edge erosion (Wasson et al 2019, Marriotti 2020). The area of saltmarsh lost to erosion can be compensated via marsh transgression into adjacent uplands if available space exists for existing saltmarsh to migrate into (Kirwan and Meganigal 2013, Schieder et al 2018). Given the increased speed of this process over the past decades, a greater portion of the current marsh is relatively young compared to historical marshes that experienced lower rates of sea level change (Ablain et al 2019, Fagherazzi et al 2020). In some areas, like the Chesapeake Bay, nearly a third of the existing marsh has been created within the last 100 years (Schieder et al 2018).

It is not clear how a change in the proportion of young and old marsh might affect the animal and plant communities found there. Generally, the saltmarsh plant communities are driven by the duration and frequency of tidal flooding with the most salt tolerant plants found nearest the outer edge of the marsh and less salt-tolerant plants found nearer the upland boundary (Sharpe and Baldwin 2012, Pelligrini et al 2019). The animal community within the saltmarsh can be associated with specific plant communities but can also be directly driven by the duration and frequency of tidal flooding, which can limit nest success, reduce foraging opportunities, and alter the frequency of predator-prey interactions (Plaschke et al 2019, Thorne et al 2019, Houpt et al 2020). Research has found a variety of ways that plants and animals have responded to the relatively rapid rate of sea level rise as well as anthropomorphic activities in adjacent uplands, like pesticide and nutrient application to agricultural fields, installation of impervious surfaces that affect rainwater runoff and subsidence, and establishment of invasive species (Johnson et al 2016, Geedicke et al 2018, Boorman 2019, Gedan and Fernández-Pascual 2019).

As saltmarsh continues to transgress upslope, a greater proportion of these newly formed marshes occur in areas influenced by human activities that can have a variety of effects on the ecosystem (Gedan et al 2009). Generally, birds are good indicators of ecosystem health because they predictably respond to environmental change, tend to be near the top of the food chain, and survey methods have been reasonably well-developed so they may serve as a useful indicator for saltmarsh quality (Koskimies 1989, Fraaixeda et al 2020). Included among bird species that breed within saltmarsh are those that only breed in tidal saltmarsh, those that nest only in fresh and salt marshes, and those that nest in upland and marsh habitats. Among these marsh-nesting birds, saltmarsh specialists appear to be facing the most precipitous population declines and are the focus of management efforts throughout coastal North America (Sauer and Link 2011, ACJV 2020). These population changes suggest that either the quality of habitat or the total amount of habitat available to these birds has declined.

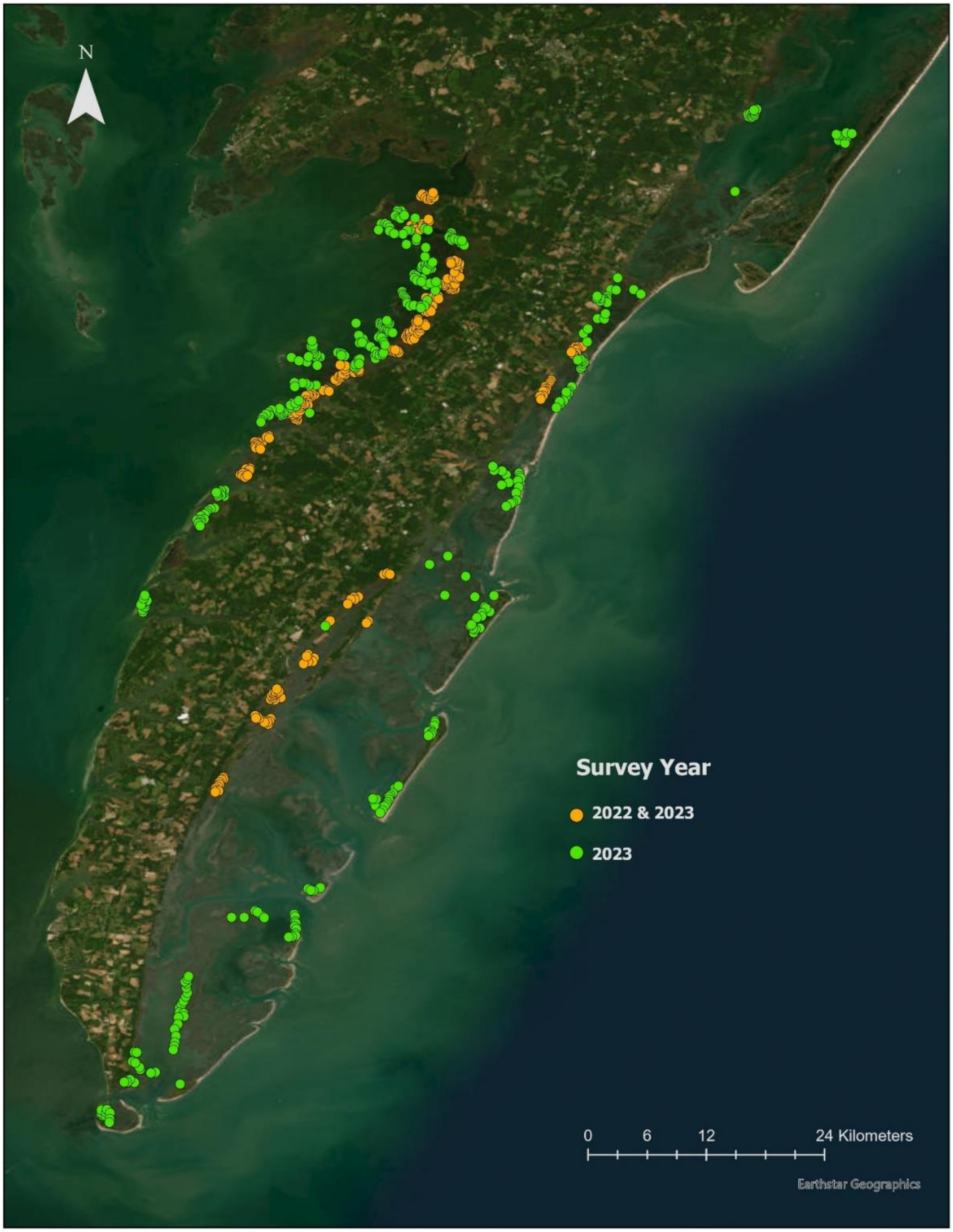
The goal of this study is to compare bird richness between recently established marshes and those that have remained relatively stable since the early-mid 20th century. Though our focus is on birds, we also compare plant cover and soil carbon in marshes that have been created since the early-mid 20th century with those that have remained relatively stable.

METHODS

Survey Network

The survey network included 615 points in Accomack and Northampton Counties on Virginia's Eastern Shore. Of the 615 points, 238 were surveyed in 2022 and 2023 and an additional 377 points were surveyed only in 2023 (Figure 1). During 2022 all marshes were accessed by land and the distribution of points was primarily in Accomack County. During 2023, we leveraged a Virginia DWR grant to survey saltmarsh sparrows to expand the footprint of the study and used boats to access marshes further from the mainland edge. The resulting survey point network covered all large marshes on the bayside of the peninsula, portions of the leeward side of all barrier islands and large marshes on the mainland edge of the peninsula's seaside. We surveyed all portions of marshes including high outer marsh fringes, low marsh, and the marsh-upland transition zones.

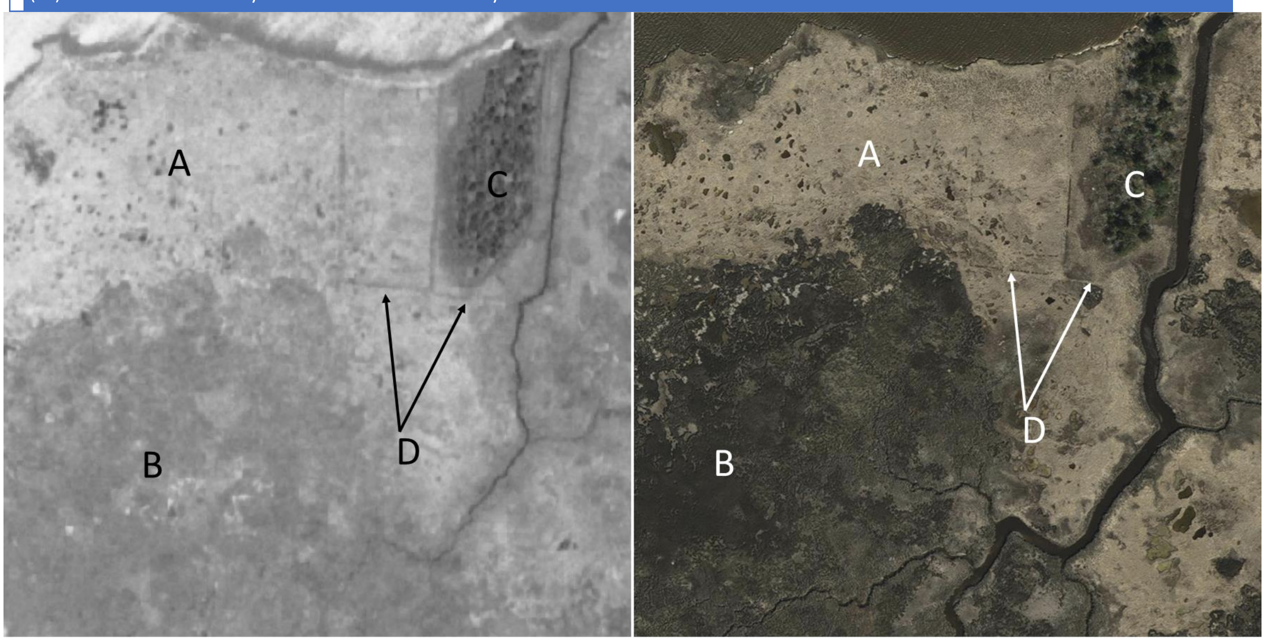
Figure 1. Point network for marshbird surveys conducted during 2022 and 2023 on the eastern shore of Virginia, USA. Points surveyed only in 2022 & 2023 are orange and points surveyed during 2023 only, are green.



Marsh Characteristics

Desktop review – We used the Virginia Institute for Marine Science shoreline change viewer (Hardaway et al 2021), which includes aerial photography from 1937 on the bayside and 1949 on the seaside, to determine whether the historic habitat was high marsh, low marsh, upland, or water (Figure 2). We used imagery hosted on the VIIMS shoreline change viewer from 2021 to classify the current habitat. We considered high marsh habitat to be dominated by short form of *Sporobolus pumilus* (*Spartina patens*) and *Distichlis spicata* which were represented by light gray tones in historic imagery and tan tones in modern imagery (A, Figure 2). We considered low marsh to be dominated by tall *S. alterniflorus* (*Spartina alterniflora*) and *J. roemerianus roemerianus* which was represented by darker tones in historic and modern imagery (B, Figure 2). Upland habitat was delineated by the presence of trees and shrubs which are dark in historic imagery and green in modern and can also be identified by their shape in both historic and modern imagery (C, Figure 2). We also classified each point as a former agricultural field if berms or ditches surrounded a survey point (D, Figure 2).

Figure 2. Historic (1937) and current (2021) imagery of a marsh on the bayside of Accomack County, VA. Features on this image include high marsh (A), low marsh (B), forest (C), and two agricultural fields (D) that had already been abandoned by 1937.



Field protocol – We also collected finer scale habitat parameters between 10 Jun and 31 July at all points. We visually estimated % cover for all plant species that comprised ≥5% cover within 50 m of each survey point, % cover for each habitat type (low marsh, high marsh, saltmarsh/terrestrial border, upland, creeks/pans/pools, and open water) within 50 m, the number of living trees and snags within a 50 m of each survey point and recorded the horizon angle in each cardinal direction using a clinometer. We quantified the % organic matter in soils by extracting three 6" diameter, 3" deep soil cores at 133 locations. % Soil Organic Matter (SOM) was determined using a Loss-on-ignition protocol. All cores were dried at 60°C until their weights became stable and then muffled at 450°C for 7 hours.

Bird Survey Protocol

Surveys were conducted between sunrise and four hours after sunrise from 17 April to 28 July. We attempted to survey each point four times during this window with ≥10 days between surveys at each point but tides and weather prevented access to some points throughout the 2023 season. The surveys were 10 minutes in length including 5 minutes of silence followed by five one-minute audio playback tracks for black rail, Virginia rail, king rail, clapper rail, and least bittern. We recorded all birds observed between 0-50 m from the observer.

Statistical Analyses

We used the package 'unmarked' (Fisk and Chandler 2011) to construct occupancy models in program R (R Core Team 2023) for all species detected at ≥10% of our survey points. We initially used only an intercept in the occupancy function and constructed models that included day of year, time of day, wind speed, cloud cover, and temperature in the detection function. We also included a model with a polynomial factor for day of year to account for species that may be more easily detected during the middle of the breeding season than during either the end or beginning. We then used AIC score to select the most parsimonious model. If two competing were within two AIC points of each other we created an additional model with both parameters resulted in a lower AIC score. After selecting our predictors for the detection function we found the most parsimonious submodel among four groups of predictors including 1.) geographical: all single and additive combinations of latitude, whether a marsh was on the bayside or seaside, and an interaction between the two predictors, 2.) historical: all single and additive combinations of whether the marsh was recently created, whether site had been an agricultural field in the past, and an interaction between the two, 3.) single predictors including % cover for broad habitat type (low marsh, high marsh, upland, saltmarsh-terrestrial border, pools and creeks, open water, and invasive species), the number of small living trees, the number of large living trees, the number of snags, and mean horizon angle, and 4.) single predictors for % cover of each individual plant species. If any models were within 2 AIC points from each other, we included both models in our final model selection process. We then created a model including all predictors within our top submodels and used backwards selection to remove uninformative parameters (Leroux 2019) one at a time, starting with the predictor that was insignificant ($p>0.05$) with the smallest effect size. We did not remove predictors that were insignificant with small effect size if an interaction included the predictor and had a significant effect. We then extracted best unbiased predictors for each species and summed the total number of species at each point to get predicted species richness.

We used a beta regression to evaluate the effect of geographical and historical effects on % SOM. We constructed models using all additive combinations of whether a marsh was on the bayside or seaside, latitude, an interaction between latitude and bayside/seaside, whether the marsh was recently created, whether site had been an agricultural field in the past, and an interaction between recency of marsh creation and presence of past agriculture. We then used model results to predict % SOM at all sites. We used a Poisson regression to determine whether predicted % SOM was related to predicted bird richness.

RESULTS

Marsh Characteristics

Recently formed marsh habitat represented 230 of the 615 survey sites and included 123 survey points that had converted from upland habitat or open water to high marsh and 107 points that converted from upland habitats, high marsh, or open water to low marsh. Of the areas classified as recently created marsh, 73 of 230 (31.7%) exhibited evidence of past agricultural use compared to 45 of 385 (11.7%) that had not changed since the early-mid 20th century.

Upland habitat (shrub and forest) comprised a greater percentage of cover in newly created high marsh than existing high marsh ($t_{155.5}$=-4.83, p <0.001) but was relatively the same in newly created and existing low marsh habitats ($t_{175.5}$=-1.72, p =0.087). We encountered more living trees within 50 m of survey points in recently converted high ($t_{176.2}$=-5.03, p <0.001) and low ($t_{134.1}$=-2.16, p =0.033) marshes compared to existing marshes. We also encountered more snags in recently converted high ($t_{147.2}$=-7.94, p <0.001) and low ($t_{107.3}$=-2.88, p =0.005) marshes compared to existing marshes.

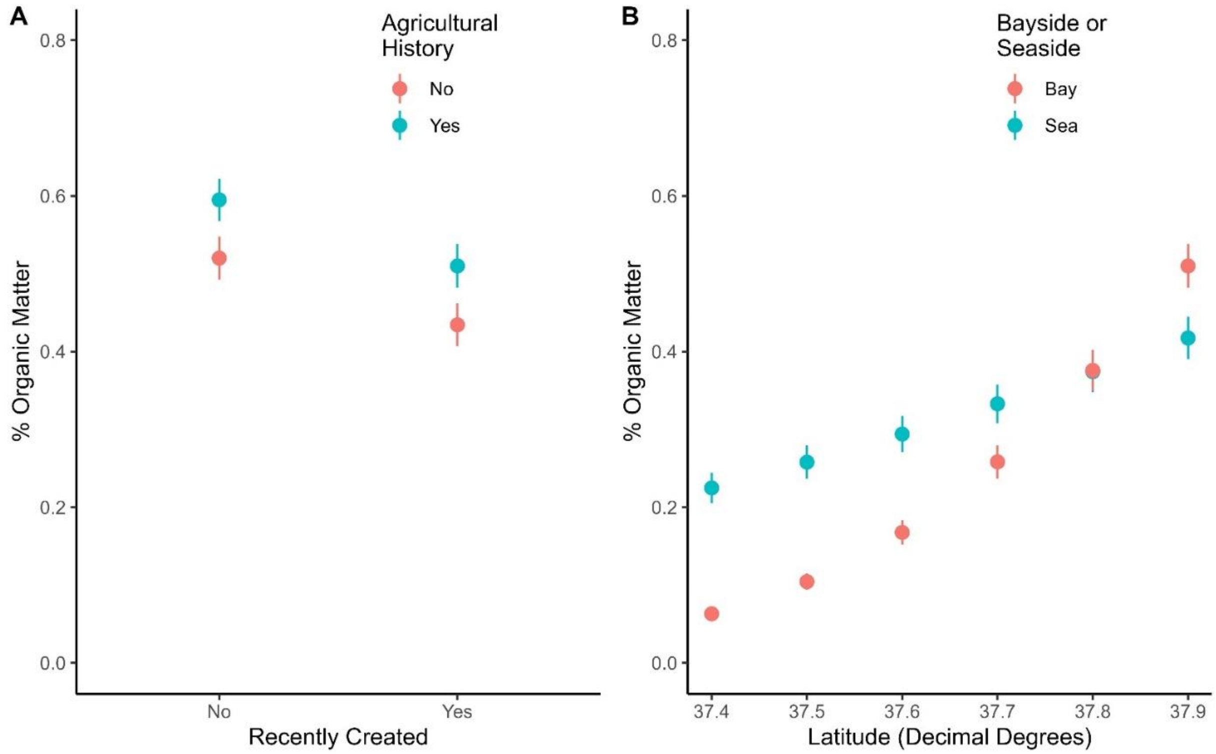
The composition of marsh vegetation also differed between recently formed and existing marshes. The most common types of herbaceous plant species recorded within 50 m of each survey point included short and tall forms of *Sporobolus alterniflorus*, *S. pumulis*, *Distichlis spicata*, *J. roemerianus roemerianus, Phragmites australis*, *and Salicornia spp*. Both forms of *S. alterniflorus* were more common in existing high and low marshes, while *D. spicata, J. roemarianus, Salicornia spp,* and *P. australis* were all more common in newly formed high and low marshes. *S. pumilus* was more common in existing high marsh than recently converted high marsh but less common in existing low marsh than recently formed low marsh (Table 1).

Table 1. Comparison of mean percent cover for most commonly occurring plant species found in high and low marsh habitats on the Eastern Shore of Virginia, USA during 2022-2023.

	High marsh % Cover			Low Marsh % Cover		
Species	Existing	Recently Converted	p-value	Existing	Recently Converted	p-value
Short *S. alterniflorus*	20.0	7.9	<0.001	25.0	19.5	0.116
Tall *S. alterniflorus*	15.0	9.7	0.010	38.4	28.4	0.008
S. pumilus	26.8	20.9	0.014	2.7	5.9	0.016
D. spicata	14.0	25.5	<0.001	2.9	4.9	0.062
J. roemerianus	9.3	14.9	0.009	22.6	34.4	0.006
P. australis	4.8	9.5	0.020	0.3	3.2	0.017
Salicornia spp.	3.4	4.7	0.401	1.8	2.9	0.406

Overall, mean organic matter was 28.8% ± 0.02 SE. Mean organic matter was lower in recently created marshes (23.4% ± 2.0) than marshes that existing (35.2%±2.4, $t = 3.889$, $p < 0.001$). Our modeling effort indicated that the same factors that influenced marsh-nesting bird richness also influenced percentage organic matter in marsh soil. The top model used to predict organic matter (R^2=0.36) included whether the marsh was recently created (β_{recent} = -0.34 ± 0.13 SE, p =0.010), whether the marsh was formerly an agricultural field (β_{ag}= 0.30 ± 0.14, p <0.029), whether the marsh was on the seaside or bayside ($\beta_{seaside}$= 0.54± 0.21, p =0.008, latitude (β= 0.94±0.16, p < 0.001) and an interaction between latitude and whether the marsh was on the seaside or bayside ($\beta_{seaside\ X\ latitude}$=-0.63±0.20, p = 0.001). Organic matter was predicted to be greatest in the northernmost marshes that were once agricultural fields and have remained relatively unchanged over the past 80+ years (Figure 3).

Figure 3. Predicted % organic matter in soil samples collected at marshes on the Eastern Shore of Virginia, USA during 2022-2023 for A.) recently created and existing marshes with and without an agricultural land use history and B.) marshes on the bayside and seaside at 0.1 decimal degree latitude increments. For plot A, predictions were obtained using a latitude of 37.9 and bayside marsh. For plot B, predictions were obtained using a recently created marsh with evidence of past agricultural history. Error bars represent standard error.



Bird Occupancy

We conducted 952 point count surveys at 238 points in 2022 and 2,340 surveys at 615 points in 2023. Eleven saltmarsh nesting species were observed at >10% of survey locations including: 1.) four species that breed exclusively in saltmarsh (saltmarsh obligates)– clapper rail (*Rallus crepitans*), willet (*Tringa semipalmata*), saltmarsh sparrow (*Ammodramus caudacutus*) and seaside sparrow (*A. maritimus*), 2.) three species that breed exclusively in saltmarsh and freshwater marshes (marsh obligates) – Virginia rail (*R. limicola),* marsh wren (*C. palustris*) and red-winged blackbird (*Agelaius phoeniceus*), and 3.) four species that breed in upland and marsh habitats (facultative marsh breeders) – common yellowthroat (*Geothlypis trichas*), song sparrow (*melospiza melodia*), boat-tailed grackle (*Quiscalus major*), and common grackle (*Q. quiscula*).

Table 2. Parameters included in detection (ρ) and occupancy (ψ) functions of final occupancy models for saltmarsh obligates ($_s$), marsh obligates ($_m$), and facultative marsh breeders ($_f$) observed at ≥10% of marsh bird survey locations on the Eastern Shore of Virginia, USA during 2022 and 2023.

Species	Model Parameters

Clapper Rail$_s$	ρ(day of year + day of year^2) ψ(recently created + agricultural history + recently created X agricultural history + bayside/seaside + saltmarsh terrestrial cover + *J. roemerianus roemerianus* cover)
Willet$_s$	ρ(day of year + day of year^2) ψ(recently created + agricultural history + recently created X agricultural history + bayside/seaside + latitude + bayside/seaside X latitude + mean horizon angle + *J. roemerianus roemerianus* cover)
Seaside Sparrow$_s$	ρ(temperature) ψ(recently created + agricultural history + bayside/seaside + latitude + bayside/seaside X latitude + number of large trees)
Saltmarsh Sparrow$_s$	ρ(temperature) ψ(agricultural history + latitude + mean horizon angle + *Sporobolus pumilus* cover)
Virginia Rail$_m$	ρ(.) ψ(recently created + bayside/seaside + latitude + bayside/seaside X latitude + Year + *J. roemerianus roemerianus* cover)
Marsh Wren$_m$	ρ(time + temperature) ψ(bayside/seaside + latitude + number of large trees + *J. roemerianus roemerianus* cover)
Red-winged Blackbird$_m$	ρ(day of year + day of year^2) ψ(bayside/seaside + latitude + bayside/seaside X latitude + *Phragmites australis* cover + *Salicornia spp* cover)
Common Yellowthroat$_f$	ρ(time of day) ψ(recently created + bayside/seaside + latitude + bayside/seaside X latitude + *Phragmites australis* cover+ *Iva frutescens* cover)
Song Sparrow$_f$	ρ(.) ψ(recently created + agricultural history + bayside/seaside + latitude + bayside/seaside X latitude + mean horizon angle + tall form *Sporobolus alterniflorus* cover)
Boat-tailed Grackle$_f$	ρ(.) ψ(recently created + agricultural history + recently created X agricultural history + saltmarsh terrestrial border cover + *J. roemerianus roemerianus* cover)
Common Grackle$_f$	ρ(day of year) ψ(saltmarsh terrestrial border cover + *J. roemerianus roemerianus* cover)

Saltmarsh Obligates – Whether a marsh was recently created or not was included within the top model for three out of four saltmarsh obligates and the effect size was negative for all three (see below for species-specific effect size estimates). Agricultural history was included in the top model for all four species and the effect was negative for all four. Whether a marsh was on the bayside or seaside was included in three out of four species and all three species were more likely to occupy marshes on the bayside. Latitude was included in the final model for three out of four species and all three were more likely to occupy marshes further north. *J. roemerianus* cover was included in three out of four top models and the effect was positive for two out of three species. Mean horizon angle and *S. pumilus* was included in final model for one species and the effects were negative for horizon angle and positive for *S. pumilus* cover.

Clapper Rail – The final clapper rail model (Table 2) included day of year (β= 3.48 ± 0.64, p<0.001) as well as a polynomial term for day of year (β= -3.81±0.65, p < 0.001) in the detection function, whether the marsh was located on seaside or bayside ($\beta_{seaside}$= -0.54 ± 0.26, p <0.035), whether the marsh was recently created (β_{recent} = -0.81 ± 0.25 SE, p =0.001), whether the marsh was formerly an agricultural field(β_{ag}= -1.47 ± 0.37, p <0.001), an interaction between marsh creation recency and past agricultural use ($\beta_{ag\ X\ recent}$=0.96±0.48, p = 0.041), percent cover for saltmarsh-terrestrial border, and percent cover *J. roemerianus* (β= -0.60 ± 0.19, p =0.002).

Willet – The final willet model (Table 2) included day of year (10.08 ± 1.34, p<0.001) as well as a polynomial term for day of year (-10.40±1.34, p < 0.001) in the detection function. Predictors within the occupancy function included whether the marsh was located on seaside or bayside ($\beta_{seaside}$= -0.75 ± 0.40, p =0.062), latitude (β= -0.31 ± 0.43, p =0.473), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=1.00±0.47, p = 0.030), whether the marsh was recently created (β_{recent} = -0.98 ± 0.30 SE, p =0.002), whether the marsh was formerly an agricultural field(β_{ag}= -1.22 ± 0.52, p =0.019), an interaction between marsh creation recency and past agricultural use ($\beta_{ag\ X\ recent}$=1.98±0.66, p = 0.003), and percent cover *J. roemerianus* (β= -0.70 ± 0.17, p<0.001).

Seaside sparrow – The final seaside sparrow model (Table 2) included temperature (-0.11±0.05, p = 0.031) in the detection function. Predictors within the occupancy function included whether the marsh was located on seaside or bayside ($\beta_{seaside}$= -1.34 ± 0.32, p <0.001), latitude (β= 2.34 ± 0.39, p<0.001), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=-1.30±0.42, p = 0.002), whether the marsh was recently created (β_{recent} = -0.63 ± 0.25 SE, p =0.010), whether the marsh was formerly an agricultural field(β_{ag}= -1.11 ± 0.27, p <0.001), the number of nearby large trees (β= -1.26 ± 0.22, p <0.001), and percent cover *J. roemerianus* (β= -0.48 ± 0.16, p<0.003).

Saltmarsh sparrow – The final saltmarsh sparrow model (Table 2) included temperature (0.29±0.12, p = 0.013) in the detection function. Predictors within the occupancy function included latitude (β= 1.13 ± 0.25, p<0.001), whether the marsh was formerly an agricultural field (β_{ag}= -0.83 ± 0.47, p = 0.08), mean horizon angle (β= -2.26 ± 0.45, p<0.001), and percent cover *S. pumilus* (β= -0.51 ± 0.17, p=0.002).

Marsh Obligates – Whether a marsh was recently created was included within the top model for one of three marsh obligates and the effect was positive. Year was included within two of three top models and fewer sites were occupied in 2023 for both species. Whether a marsh was on the bayside or seaside was included in top models for two out of three species with one species more likely to occur on the bayside and the other was more likely to occur on the seaside. Latitude was included in the final model for all three species and two of the three were more likely to occur further north. *J. roemerianus* cover was included in two out of three top models and the effect was positive for both. The number of nearby large trees was included in one top model and the effect was negative. Percent cover for *P. autralis* and *Salicornia spp.* were inlcuded in a single top model and the effect was positive for P. australis and negative for *Salicornia spp*.

Virginia Rail – The final Virginia rail model (Table 2) included zero predictors in the detection function. Predictors within the occupancy function included whether the marsh was recently created (β_{recent} = 0.62 ± 0.27 SE, p =0.022), whether the marsh was located on seaside or bayside ($\beta_{seaside}$= 0.21 ± 0.55, p =0.709), latitude (β= 2.76 ± 0.47, p<0.001), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=-1.8±0.61, p = 0.004), survey year (β_{2023} = -0.66 ± 0.28 SE, p =0.017), and percent cover *J. roemerianus* (β= 0.78 ± 0.13, p <0.001).

Marsh Wren – The final marsh wren model (Table 2) included time of day (β= -0.22 ± 0.09, p=0.016) and temperature (β= 0.20±0.08, p =0.011) in the detection function. Predictors within the occupancy function included whether the marsh was located on seaside or bayside ($\beta_{seaside}$= -2.05 ± 0.55, p <0.001), survey year (β_{2023} = -0.53 ± 0.26 SE, p =0.045), the number of nearby large trees (β= -0.58 ± 0.12, p =0.023), and percent cover *J. roemerianus* (β= 0.65 ± 0.12, p<0.001).

Red-winged blackbird – The final marsh wren model (Table 2) included day of year (β= 4.84 ± 0.57, p<0.001) as well as a polynomial term for day of year (β= -5.07±0.57, p < 0.001) in the detection function. Predictors within the occupancy function included whether the marsh was located on seaside or bayside ($\beta_{seaside}$= -2.44 ± 0.40, p <0.001), latitude (β= -1.44 ± 0.53, p=0.006), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=-1.66±0.54, p = 0.002), percent cover of P. australis (β= 1.84 ± 0.57, p =0.001), and percent cover *Salicornia spp* (β= -0.25 ± 0.11, p=0.018).

Facultative – Whether a marsh was recently created was included within the top model for three of four facultative breeders and the effect was negative for two of the three. Agricultural history was included in the top model for two species and the direction of the effect was positive for one and negative for the other. Year was included within the top model of one species and fewer sites were occupied in 2023. Whether a marsh was on the bayside or seaside was included in top models for two out of four species, and both were more likely to occur on the seaside. Latitude was included in the final model for two of four species, and both were more likely to occur further north. Mean horizon angle was included in the top model for one species and the effect was negative. Percent cover for saltmarsh-terrestrial border was included in the top model for two species and the effect was positive for both species. *J. roemerianus* cover was included in two out of four top models and the effect was positive for one and negative for the other. Percent cover for *I. frutesens* was included in the top model for two species and the effect was positive for both.

Common yellowthroat – The final common yellowthroat model (Table 2) included time of day (-0.13 ± 0.06, p<0.049) in the detection function. Predictors within the occupancy function included whether the marsh was recently created (β_{recent} = 0.46 ± 0.24 SE, p =0.056), located on seaside or bayside ($\beta_{seaside}$= 0.04 ± 0.37, p =0.907), latitude (β= 1.29 ± 0.43, p =0.028), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=-1.37±0.47, p = 0.004), percent cover *P. australis* (β= 5.6 ± 1.38, p<0.001) and percent cover *I. frutescens* (β= 0.69± 0.16, p<0.001).

Song sparrow – The final song sparrow model (Table 2) included zero predictors in the detection function. Predictors within the occupancy function included whether the marsh was recently created (β_{recent} = -0.86 ± 0.36 SE, p =0.016), whether the marsh was formerly an agricultural field(β_{ag}= 1.05 ± 0.38, p =0.006), whether the marsh was located on seaside or bayside ($\beta_{seaside}$= 0.29 ± 0.59 p =0.621), latitude (β= 2.16 ± 0.59, p<0.001), an interaction between seaside/bayside and latitude($\beta_{seaside\ X\ latitude}$=-2.47±0.63, p

<0.001), survey year (β_{2023} = 2.16 ± 0.59 SE, p =0.011), mean horizon (β=-0.88±0.32, p = 0.005), and percent cover tall *S. alterniflorus* (β= -0.81 ± 0.26, p=0.002).

Boat-tailed grackle – The final boat-tailed grackle model (Table 2) included zero predictors in the detection function. Predictors within the occupancy function included whether the marsh was recently created (β_{recent} = -1.07 ± 0.47 SE, p =0.022), whether the marsh was formerly an agricultural field(β_{ag}= -2.46 ± 1.1, p =0.026), an interaction between marsh creation recency and past agricultural use ($\beta_{ag\ X\ recent}$=2.96±1.23, p = 0.017), percent cover saltmarsh-terrestrial border (β=-0.67±0.25, p = 0.006), and percent cover *J. roemerianus* (β= -0.50 ± 0.23, p=0.031).

Common grackle – The final common grackle model (Table 2) included day of year (-0.31 ± 0.14, p<0.028) in the detection function. Predictors within the occupancy function included percent cover saltmarsh-terrestrial border (β= 2.45 ± 1.00, p=0.014) and percent cover *J. roemerianus* (β= -1.29± 0.57, p<0.023).

Bird Occupancy and Organic Matter – Organic matter was a significant predictor for overall marsh-nesting bird richness (β=2.28±0.25, p<0.001) as well as each group of marsh nesting birds and the effect was approximately 2.4 and three times as great for marsh and saltmarsh obligates as facultative nesters (Table 3).

Table 3. Effect size, se, and p-value for Poisson regressions including the % soil organic Matter (%SOM) as the predictor and bird richness as the response variable for saltmarsh obligates, marsh obligates, marsh facultative and all marsh nesting birds.

Bird Response Group	%OM Effect Size±se	p
Salt-marsh Obligates	3.00±0.37	<0.001
Marsh Obligates	2.39±0.47	<0.001
Facultative	0.99±0.49	0.043
All Marsh-nesting Birds	2.28±0.25	<0.001

DISCUSSION

The parameters that affected occupancy for marsh-nesting birds on the eastern shore of Virginia differed among and between marsh-nesting species at our study area. Not only did the predictors included in top occupancy models vary by species, but the direction and magnitude of effect size varied as well. Despite this, there were some parameters that were consistent among species and bird guilds (i.e, saltmarsh obligates, marsh obligates, facultative breeders).

Geographical parameters, including latitude and whether a marsh was located on the seaside or bayside were included among the most species-specific occupancy models and we believe the effects of both geographical parameters are related to coastal flooding dynamics. The latitudinal gradient observed was included for eight out of eleven species and the direction of this effect was among the most consistent with seven of the eight species being more likely to occupy marshes further north. Nest success is often limited by coastal flooding for many marsh-nesting birds and the greater tidal range is generally observed further south on the Delmarva peninsula which may result in more frequent nest flooding and failure (NOAA, Reinert et al 2006). Tidal range in our northernmost seaside study sites is further muted by relatively small inlets that limit the tidal flow into and out of Chincoteague Bay (Allen et al 2007), while many of the marshes we surveyed on the southernmost portion of the peninsula were associated with the seaside lagoons and barrier islands that are prone to increased tidal flooding driven by greater wind-induced wave heights (i.e., fetch). On the bayside, the north south gradient is also affected by a gradual difference in overall size of the marsh with much more expansive marshes further north. Marshes become less extensive towards the southern portion of Accomack County and are practically non-existent in Northampton Conty where most of the shoreline consists of bluffs rather than the gentle slope associated with most of Accomack County.

Whether a species was located on the bayside or seaside was the second most frequently included parameter (7 out of 11 models) and also may have been related to coastal flooding dynamics. The direction of this effect was more mixed than that of latitude with five of nine species more likely to occupy bayside marshes, but there was consistency among nesting guilds. Saltmarsh obligates were all more likely to occupy marshes on the bayside while the two facultative nesters that were affected were more likely to occupy seaside marshes. All of the saltmarsh obligates nest in relatively low-lying herbaceous vegetation that is susceptible to tidal flooding, while the two facultative species nest in taller shrubs or taller herbaceous vegetation (i.e., *P. australis*). Exceptional tidal flooding can lead to nest failure for species that nest in lower-lying vegetation and is believed to contribute toward population declines for saltmarsh-nesting birds (Greenberg et al. 2006, Reinert et al 2006). Saltmarsh obligates may have been more likely to occupy marshes on the bayside because coastal flooding occurs less frequently than on the seaside of the peninsula where tidal range and fetch are both greater. The two marsh obligates which included this parmaters in their final model also nest in low-lying herbaceous vegetation; one of these (marsh wren) was affected similarly to the saltmarsh obligates while the other (Virginia rail) was relatively unaffected (small effect size and insignificant) by seaside/bayside directly but the term was included within the top model because the significant interaction with latitude was significant.

Whether a marsh had been created since the early-mid 20th century was also frequently included among top models. Saltmarsh obligates, in particular, were negatively affected. Newly created high marsh habitat is most often formed when existing marsh transgresses into upland habitats (Scheider et al. 2018). Much of this marsh migration occurs adjacent to forest and the presence of remnant trees and snags in these marshes may deter some bird species, like saltmarsh obligates that prefer the surrounding landscape to be as open as possible with few trees (Marshall et al 2020), from using the area. Marshes that have persisted since the early-mid 20th century were less likely to support trees. The species that were more likely to occur in recently converted fields were Virginia rail and common yellowthroat. Virginia rails are more commonly associated with freshwater marshes where they prefer habitat in the early stages of succession (Pospichal and Marshall 1954) so it is not surprising that they would also occupy saltmarsh in early stages of succession. Common yellowthroats typically nest in shrubby portions of upland and marsh habitats which were also more common in recently converted marshes.

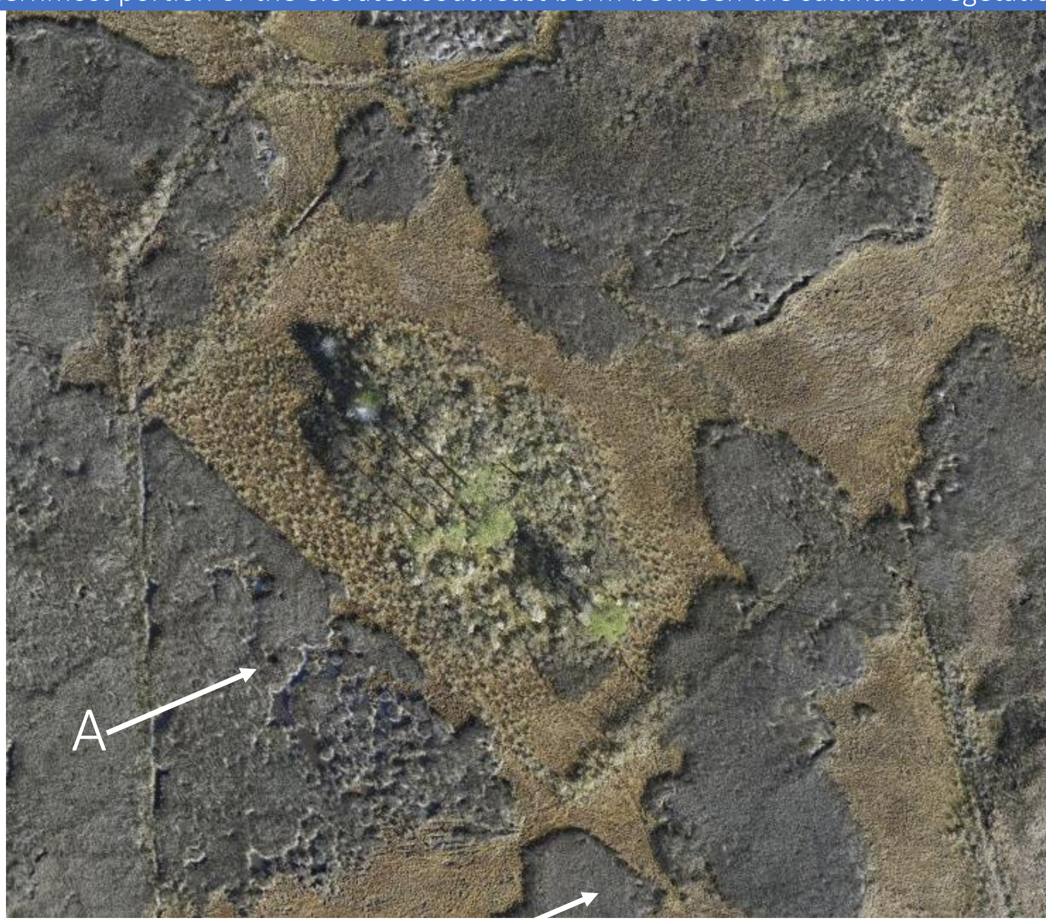
The presence of past agricultural use was also included in several top models and had similar effects as recency of marsh establishment. Saltmarsh obligates were negatively affected by the presence of past agriculture, likely for many of the same reasons they were less likely to occur in recently converted marshes. Just like many of the recently converted marshes were more likely to support trees, these ag fields likely support trees for a longer period of time due to the presence of berms surrounding the perimeter of the form ag field. The berms associated with some of these fields allow less saltwater tolerant plants like these trees to persist by providing elevational refugia from regular tidal flooding (Grossinger et al. 1998). Song sparrows were the only species to have a positive association with ag fields and this is likely explained by the preference this species exhibits for shrubby habitat like that found on berms as well as an avoidance for the mainland edge as evidenced by the inclusion and negative association of mean horizon in the species final model.

The organic component of soil was influenced by the same predictors that were important to predicting bird abundance for many of the marsh nesting species in our study. This may be because tidal flooding, which influences nest success for saltmarsh obligates, can result in greater deposition of sediment into marshes (Butzeck et al. 2015). A potential source of much of the inorganic sediment is a southerly longshore drift along the Delmarva Peninsula that deposits sand along the southern portion of the peninsula on the seaside before drifting into the bay where the sand forms shoals along the southernmost bayside (Colman et al 1988). The marshes that are flooded most frequently and for the longest likely receive a greater input of sediment that is suspended in water from this process. The longshore drift and resulting deposits of inorganic sediment help explain the seaside and bayside geographical distribution of organic material in soil.

The berms surrounding former agricultural fields may be a barrier to tidal flow, which could provide an explanation for the higher proportion of organic material in samples taken from agricultural fields. If the primary inorganic sediment input is from suspended sediment in the water column and the tide is prevented from reaching some of these areas, the proportion of inorganic sediments reaching the area should be lower than areas without barriers to tidal flow. Soil and water table salinity would also be lower if tidal flow was obstructed by berms due to less frequent saltwater inundation (Holt et al. 2017, Taylor and Krüger 2019) and our finding that the less tolerant plant species like *P. australis* and *J. roemerianus* (Rozema and Blom 1977, Touchette et al 2009) were more common in former agricultural fields supports the notion that these fields are less saline than those without berms or ditches.

The barrier effect associated with agricultural berms may not be limited to saltwater flow and suspended sediments or to modern timescales. The berms and ditches associated with the agricultural fields often form a perimeter around the field. After agriculture is abandoned, an upland forest is often established and persists for decades. Rainwater runoff typically carries terrestrial carbon and other nutrients that contribute to saltmarsh accretion and plant growth but may be intercepted and trapped by bermed abandoned agricultural fields prior to reaching the saltmarsh (Ember et al 1987, Fitch et al 2009, Van de Broek 2019). Carbon trapped within these fields may contribute toward the higher percentages of organic matter we observed in former ag fields, especially the wide discrepancy between recently formed marshes that did and did not exhibit evidence of past agricultural use.

Figure 4. Aerial imagery of an abandoned agricultural field converting to saltmarsh in Accomack County, Virginia, USA. The middle of the field still supports shrubs and a handful of trees. The field is surrounded by berms and ditches that have inhibited colonization within the abandoned field by *J. roemerianus roemerianus*, most noticeably along the southwest border (A). Shrubs can also be seen growing along the berm, most noticeably on the southernmost portion of the elevated southeast berm between the saltmarsh vegetation (B).



In conclusion, the marsh-nesting bird community was less rich in recently converted marsh than marsh that has existed since before the early-mid 20th century, but species richness was also dependent on several other factors that were specific to individual bird species or in some cases groups of birds. The presence of past agriculture was an element that was important to predicting occupancy for several bird species, especially those that are saltmarsh obligates. As the marsh continues transgressing upland, a greater proportion of newly created marsh will comprise former agricultural fields and the bird community is likely to shift away from saltmarsh obligates. In addition to the effects on the bird community, this shift will also affect carbon stocks in the area, though it is not clear whether the resulting marsh will be more or less effective at storing carbon. Breaching or removing berms may provide an opportunity to counteract the potential shift away from saltmarsh obligates but further research is necessary to quantify the effect restoring natural freshwater and tidal flow though former ag fields that could have on carbon stocks.

ACKNOWLEDGMENTS

Funding for this project was provided by a grant through the Untied States Environmental Protection Act. We thank Ruth Boetcher, Pam Denmon, Kevin Holcomb, and Shannon Alexander for providing assistance with permitting. We thank the numerous private landowners that granted us permission to survey their marshes. We thank Caitlin Dimarria, Jess Formento, Maddie Was, Emma Purinton, Rylie Strasbaugh, Will Burgoyne, and Erik Martin for assisting with field surveys; David Stanhope, Kory Angstadt, and Sean Gregory for collecting and processing sediment cores. Marie Pitts provided administrative and logistical support. Finally, we thank Erica Lawler from the William & Mary Office of Sponsored Programs who provided contracting assistance.

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