DEVELOP Technical Report

Coastal South Carolina Water Resources

Isolated Wetlands Risk Assessment using NASA Earth Observations to Support Further Wetland Protections in Coastal South Carolina

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Abstract: Following the 2023 Sackett v. EPA court case, the redefined definition of protected waters of the United States law excludes freshwater wetlands disconnected from navigable waterways. These now "isolated wetlands" are no longer federally protected and are vulnerable to future land cover changes. To understand threats to these newly vulnerable wetlands and potential community impacts, the Coastal Conservation League partnered with NASA DEVELOP to evaluate isolated wetlands in three South Carolina counties (Jasper, Berkley, and Horry). Using Landsat 8 and 9 data, spectral indices including the normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), and normalized difference water index (NDWI) were computed to assess vegetation health, moisture quantities, and water availability, respectively. The team then conducted wetland classification using these indices along with National Wetlands Inventory data. Following the new legal framework, the team categorized wetlands as either protected (connected) or unprotected (isolated) by analyzing their connectivity to navigable waterways from the United States Department of Transportation database and major rivers defined by the Hydrologic Unit Code 10. Lastly, the team derived a 10-year change detection map identifying wetland change from 2015 to 2025. Using Earth observations proved applicable in delineating isolated wetlands, but it can be improved using finer resolution imagery. Results showed that 48% of wetlands in the study area are isolated, with an overall 4-6% wetland decrease over the past decade. These results indicate a negative wetland loss trend that can inform state policy plans for protection.

Key Terms: South Carolina, Coastal Conservation League, isolated wetlands, navigable waterways, remote sensing, random forest classification, change detection, 2023 Sackett v. EPA

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1. Introduction

1.1 Background Information

Wetlands are areas where water is either at or near the surface of the soil and creates conditions for the development of hydric soils and specially adapted hydric plants and animals (U.S. Environmental Protection Agency, 2024). When water fundamentally shapes and influences the landscape, wetland areas can be created. These unique environments influenced by water result in high water tables that saturate the soil, creating highly productive systems (Zedler & Kercher, 2005). They also provide crucial habitats for many plant and animal species (Song et al., 2024; Xu et al., 2015) and vital ecosystem services that account for ~40.6% of the estimated global services (Xu et al., 2020). Such services include water quality improvements, flood mitigation, and carbon sequestering (Zedler & Kercher, 2005). Notably, they house around ~20-30% of Earth's soil carbon while occupying less than ~8% of its surface area (Nahlik & Fennessy, 2016), which is critical to support good air quality. Geographically isolated wetlands, the primary focus of this project, share the same characteristics as typical wetlands, but are set apart from major waterways.

Despite their overall importance to both ecology and the human sector, wetlands have been rapidly disappearing. With a 3.7-fold increase in the rate of wetland loss globally, contributing to 64-71% estimated total loss since the start of the 21st century and 35% loss since 1970, wetland loss translates to a substantial negative impact on global ecosystems (Davidson, 2014; Xu et al., 2020). Although wetlands provide many important services —like improving water quality, reducing heat island effect, and creating diverse recreation activities—urbanization practices, agriculture, habitat loss, and land change can have detrimental effects on wetland conditions (Alikhani et al., 2021). In South Carolina, which includes the projects study area, 2,574 acres are lost annually due to urban expansion (McMaster & Millikin, 2019), putting constant pressure on developing infrastructure across wetland areas (van Asselen et al., 2013).

1.2 Study Area, Project Partners, & Objectives

The team partnered with Coastal Conservation League, a non-profit organization based in Charleston, South Carolina. The Coastal Conservation League works with communities, businesses, and citizen groups to help preserve South Carolina's natural environment while advancing and promoting sustainable policies. Currently, they are working to preserve the health of natural resources within South Carolina's Coastal Plain, centered on isolated freshwater wetlands.

The isolated wetlands are essential for flood mitigation, wildlife habitats, and other ecosystem services, but currently, they only qualify for protection legislation through state laws (Graham, 2023). This is a result of the 2023 United States Supreme Court decision in Sackett v. Environmental Protection Agency, which redefined the scope of 'Waters of the United States' under the Clean Water Act (Sackett v. Environmental Protection Agency, 2023). The case states that isolated freshwater wetlands are excluded from federal protection, and it defines isolated wetlands are those not directly connected to navigable interstate waters that affect commerce (Revised Definition of "Waters of the United States," 2023).

By identifying unprotected freshwater wetlands in the three counties of South Carolina (Horry, Berkeley, Jasper; Figure 1), the Coastal Conservation League can advocate for stronger official protection of these particularly vulnerable ecosystems, especially in areas that are home to a number of at-risk communities. To support the partner's effort, the team pursued three key objectives for this project: identify the isolated wetlands, conduct a 10-year wetland change analysis using remote sensing, and support the partner with geospatial information for outreach and decision making. This analysis will help the partner to understand the rate of change in isolated wetlands and their risk levels. Moreover, incorporating socioeconomic aspects to this study will allow more comprehensive risk assessments, aiding conservation efforts and policy development.

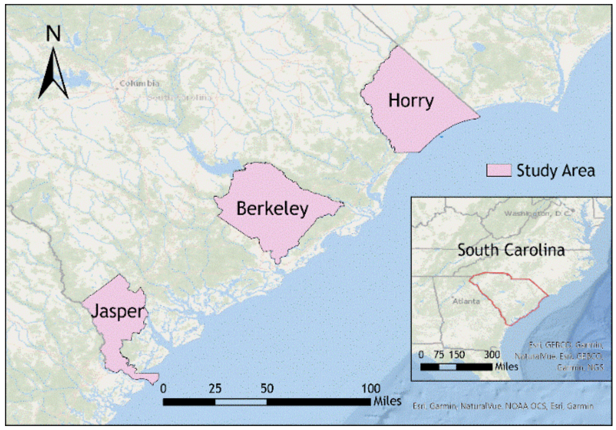

Figure 1. Study area of South Carolina counties Horry, Berkeley, and Jasper, selected for wetland analysis

2. Methodology

2.1 Data Acquisition

To define the study area, the team collected shapefiles of South Carolina county boundaries for Horry, Jasper, and Berkeley Counties, from the United States Census Bureau (U.S. Census Bureau, 2024). Landsat 8 and 9 Collection 2 Level 2 satellite imagery was collected from the United States Geological Survey (USGS) Earth Explorer (U.S. Geological Survey, 2025) for the purpose of creating a 10-year time series of land use and wetland types. Each image was initially collected from October 1, 2024, to February 1, 2025, with cloud cover limited to 10% of the image, while another collection occurred from October 1, 2015, to February 1, 2016. Due to imagery having greater than 10% cloud cover in the southeast corner of Horry County in October 2015, Landsat imagery of the southeast side of Horry was extended from October 1, 2015, to all of 2016. The team collected data from October to February, the optimal wet season for capturing wetland images. Using the National Wetlands Inventory (NWI) data, the team generated a reference wetland map (U.S. Fish & Wildlife Service, 2024). Digital Elevation Model (DEM) data with 10-meter resolution was collected from the USGS National Map that is based on a Light Detection and Ranging dataset. It was utilized to evaluate differences in uplands and lowlands (U.S. Geological Survey, 2024.).

United States Department of Transportation (USDOT) navigable waters of commerce data were downloaded in tandem with South Carolina Hydrologic Unit Code (HUC) 10 boundary shapefiles to determine which rivers in the South Carolina study sites are navigable (U.S. Department of Transportation, 2025; South Carolina Department of Natural Resources, 2024). The navigable waterways provided by USDOT displayed major rivers mostly for large scale shipping, and HUC-10 boundaries were added to identify watersheds and delineate their respective major waterways. Major waterways were considered as the limit of a "navigable waterway for commerce." Detailed spatial resolutions, sources, purposes, and the year published per dataset are indicated (Table 1).

Table 1
Datasets utilized

Dataset	Spatial Resolution	Source	Purpose	Year
U.S. County shapefile	n/a	U.S. Census Bureau	Outline study area	2024

Landsat 8, Landsat 9	30m, Tiff	USGS Earth Explorer	Basemap of the stud area, indices calculation, and 10-year time series of land use and wetland types	Oct 2015 – Feb 2016 Oct 2024 – Feb 2025
Google Earth Pro	0.1m to 15m	Google	Selection of training polygons and accuracy points	Oct 2015 – Feb 2016 Oct 2024 – Feb 2025
NWI	n/a	National Wetlands Inventory	View wetland types and locations	2024
USDOT	n/a	Department of Transportation, Bureau of Transportation Statistics	Denote large-scale Navigable Waters of Commerce	2025
SC Water Boundary HUCS 8, 10, 12	n/a	SCDNR Open Data	Find smaller navigable waters missed in USDOT	2024

2.2 Data Processing

2.2.1 Landsat Imagery

The team utilized ArcGIS Pro 3.4.2 for data processing. First, the team created a study site shapefile from the collected counties shapefile using the "select attributes" feature to select only Jasper, Berkeley, and Horry Counties. After downloading six Tiff Landsat 8 and 9 satellite images from October 1, 2024, to February 1, 2025, with a 10% cloud cover filter, the team derived individual band composites with bands one through seven using the "Band Composite" tool in ArcGIS. Then, using the "Mosaic to New Raster" function, a mosaic was assembled from the six processed composites as a preparatory step to compute three indices (Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Normalized Difference Water Index (NDWI) maps for the study sites. Following the clipping of the new mosaic to the three study site shapefiles, stretch conversions occurred to enhance the visualization of depicted features. This mosaic was compiled for computing indices later in the processing workflow. As an additional reference, the team displayed this mosaic image using two different band combinations: true color and false color RGBs. In the order of red, green, and blue colors on-screen, the images were displayed in true color using bands 4, 3, and 2, and false color with bands 5, 4, and 3.

Additionally, the team collected five Tiff Landsat 8 images from October 1, 2015, to February 1, 2016, from Jasper, Berkeley, and Horry Counties for a 10-year change comparison. Due to the lack of cloud free image availability in the southwest side of Horry County, six separate Landsat 8 images were collected across all of 2016. The "Band Composite" feature and the "Mosaic to New Raster" function were used to create a similar mosaic of the 2015 to 2016 imagery to compare to the 2024 to 2025 Landsat imagery. The mosaic symbology was modified for visualization using the "percent clip" stretch type and gamma adjustments.

3.2.2 Indices

Using the resulting Landsat imagery mosaic, the team ran a series of raster calculations to produce three different indices using unique combinations of Landsat bands. First, the team calculated NDMI to create a map showing vegetation moisture contents (Equation 1; Wilson & Sader, 2002)). Since the team used Landsat 8 and Landsat 9 satellite imagery, band 5 Near Infrared (NIR) refers and band 6 is the Shortwave Infrared

(SWIR). The new NDMI raster map was overlaid with the NWI vector data to compare moisture contents to pre-established wetland delineations.

$$\text{NDMI} = \frac{\text{NIR - SWIR1}}{\text{NIR + SWIR1}} \tag{1}$$

Second, the team calculated NDVI to produce a map layer showing vegetation density and plant health (Equation 2; Rouse et al., 1974). The corresponding Landsat 8 and Landsat 9 bands used were NIR Band 5 and Red (R) Band 4. Applying a NDVI index makes visibility of areas with vegetation outstanding.

$$\text{NDVI} = \frac{\text{NIR - R}}{\text{NIR + R}} \tag{2}$$

Third, the team calculated NDWI to generate a layer displaying surface water content and extent (Equation 3; Gao, 1996). The Landsat 8 and Landsat 9 bands used were Green (G) Band 3 and SWIR Band 6. Applying a NDWI index highlights areas with surface water cover.

$$\text{NDWI} = \frac{\text{G - SWIR}}{\text{G + SWIR}} \tag{3}$$

Fourth, the team processed the elevation data in the ArcGIS Pro resampling tool by converting the layer from 10 m to 30 m resolution. Since the Landsat imagery has a 30 m spatial resolution, the team resampled the elevation data to correspond appropriately. To prepare for data analysis and classification, the team created a composite using the composite bands function to compile the NDVI, NDMI, and NDWI indices so they could be layered into the classification program.

Finally, to capture the navigable waterways in the three study areas, major rivers and tributaries within each HUC 10 watershed boundary and polygon layer from USDOT were selected and digitized using ArcGIS Pro. This digitization contributed to adding more polylines to the main layer to USDOT, creating a more complete vector map of navigable waterway network. The team did not digitize canals since they were mostly used for irrigation purposes. This provided a conservative estimate of the major possible navigable waterways of commerce to denote whether a wetland is isolated or not.

2.3 Data Analysis

The team used the ArcGIS Pro Training Samples Manager in the Classification Tools to create 1,553 training points for the supervised classification by Random Forest model. The NWI shapefile was overlaid with the composite of the NDMI, NDVI, and NDWI raster files to create training points of the different pre-established classifications of wetlands to each respected spectral signature (Peng et al., 2023). Elevation data were initially used as part of the composite of indices to improve the classification of wetlands to differentiate types of wetlands. However, upon analysis and trial and error, the team deduced that the DEM was not differentiated well enough to use in the classification and opted to remove it as a classification input.

The team generated a schema by which to classify the training points and run the Random Forest model, a machine learning algorithm that combines the output of multiple decision trees to reach a single result (IBM, n.d.; Peng et al., 2023). The schema was based on spectral signatures, in combination with observed visual patterns and cross-comparison with the NWI, the base map of World Imagery in ArcGIS, and the false color Landsat RGB imagery. The schema was chosen carefully based on partner goals, spectral visibility, and feasibility (Table 2). Amongst the class scheme, 1,553 training polygons were collected, with each class having more than 150 training polygons.

Table 2

Classification schema

01	DEVELOPED	Urban and residential landscapes characterized by human development
02	WATER	Water features such as rivers, lakes, and estuaries
03	BARE SOIL	Landscape primarily covered in soil typically associated with future development and agriculture
04	UPLAND FOREST	Forested areas without hydric soils
05	UPLAND GRASSLAND	Grassland areas without hydric soils
06	EMERGENT WETLAND	Wetlands that are submerged by water in different seasons of the year with hydric soils and hydric-adapted vegetation growth
07	WETLAND FOREST	Forested areas with hydric soils and hydric-adapted trees
08	AQUATIC WETLAND	Water features where vegetation is prominently growing in, around, or on surface water, including aquatic beds and unconsolidated beds

Random Forest supervised classification was used to classify wetland areas because of its high accuracy and flexibility when dealing with missing values (Mahdavi et al., 2017). We ran the classifier with 100 trees, 50 tree depths, and 1,000 samples per class, as it gave a conservative classification of the training points without using unnecessary processing power. Then it was classified through the "Classify Raster" function, and the team integrated the composite of the indices with the spectral bands to increase the accuracy of the classification. The classification was clipped to the study sites and underwent a "Majority Filter" to smooth out the salt and pepper pixelated noise in the classification. In the Majority Filter, we set the number of neighbors to "four" and the replacement threshold to "half", which led to the most accurate classification shown within the confusion matrix (Table A1 – A2). On top of the Random Forest built-in accuracy assessment, we created confusion matrix using the "Compute Confusion Matrix" function as an additional assessment to check the accuracy of the classification. The "Create Accuracy Assessment Points" feature generated a total of 150 accuracy assessment points per class and that were manually checked using imagery of high spatial resolution viewed in Google Earth Pro, the NDVI layer, and false color Landsat images to create reference data as a substitute for ground truth data.

To prepare the final generated classification layer for analysis with the navigable waterways layer, we processed the classification layer from Random Forest by converting the raster data to vector data using the "Raster to Polygon" function. Then, all non-wetland classes were excluded by "Select by Attribute" in the attribute table to include only the three wetland categories (emergent, forested, and aquatic)—this created a final total wetland distribution map. To determine which wetlands qualified as isolated, the "Select by Location" tool detected all wetlands intersecting the navigable waterways within a distance of 0.5 km of the digitized line. To account for varying waterway widths, we applied a 0.5 km intersect distance on the waterways. This was used as a conservative estimate because the largest observed navigable waterway in the study area was 500 m wide. All wetlands within this intersect were designated as "connected", or, in the case of the most recent 2024-2025 data (post-Sackett vs. EPA case), "protected." The "Select by Location" tool provided more accurate connected wetland results than excluding wetlands beyond a buffer distance of the navigable waterways. This tool included continuous wetlands and their corresponding adjoining features. Using the "Select by Attributes" tool again, the "isolated" wetlands were separated, and we repeated this process for the earlier 2015 to 2016 data.

For the 10-year land cover change analysis, the raster classifications for 2015 to 2016 and 2024 to 2025 were simplified into 3 classes: wetlands, uplands, and fixed landscapes (developed land and water features). Then, we used the "Change Detection Wizard" to create a 10-year change raster containing categorical changes. We denoted any change leading to an increase of wetland cover in blue and any change leading to the removal of wetlands in red.

3. Results

3.1 Analysis of Results

3.1.1 Classification Results

The land use land cover (LULC) classification of the three study sites revealed slight changes across the decade. From 2015 to 2016 (October to February), wetland forests and upland forests covered most of the land at 61% coverage, with wetland forest covering 35% and upland forests covering 26%, respectively. In contrast, from 2024 to 2025 (October to February) wetland forests decreased by 2%, covering 33% of the land coverage, while upland forests remained the same at 26%. This decrease in wetland forest may be the result of a 2.3% increase in developed land within those 10 years, covering 7.1% in 2015 to 2016 and 9.4% in 2024 to 2025 (Figure 2).

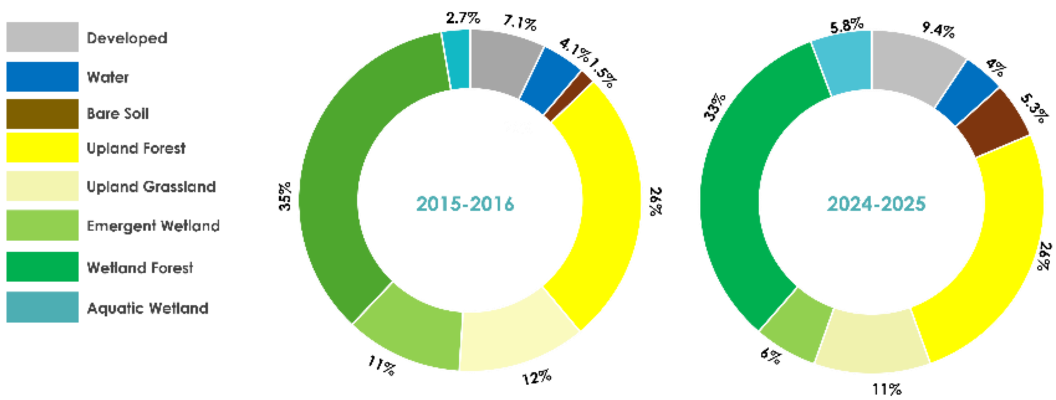

Figure 2. Pie chart of the land use land cover classification change between 2015-2016 and 2024-2025

Within the decade, the most significant changes occurred in bare soil, aquatic wetlands, and emergent wetlands. Bare soil increased by 3.8% over the 10 years, primarily due to deforestation and changes in agricultural land use throughout the years. Aquatic wetlands increased by 3.1%, while emergent wetlands decreased by 5%. These changes can be attributed to differences in land use near rivers, the water regime of the imagery time period, and potential errors in the random forest model, as some emergent wetlands were confused with some aquatic bed wetlands. Overall wetlands decreased by 3.9% in land cover, based on the difference of 48.7% wetland coverage in 2015 to 2016 and 44.8% coverage in 2024 to 2025.

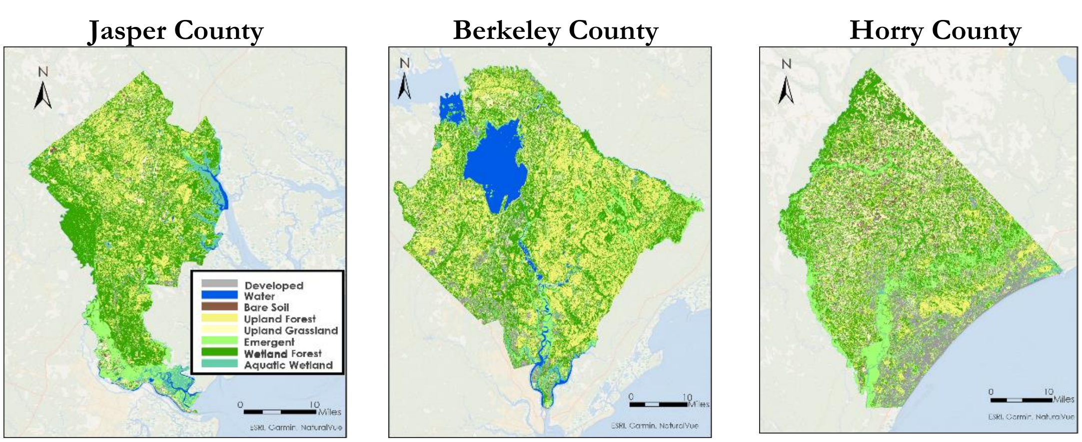

Figure 3. Land use land cover classification map of 2015 to 2016

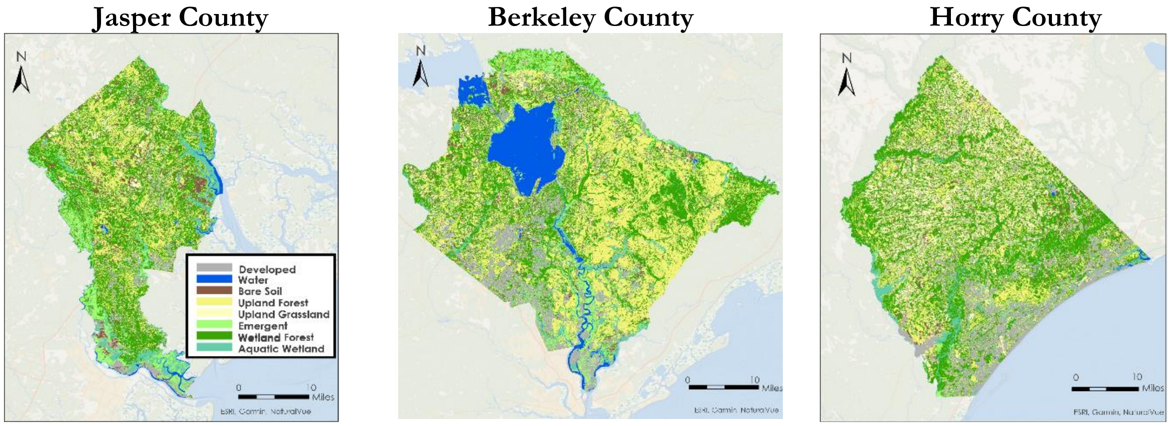

Figure 4. Land use land cover classification map of 2024 to 2025

Comparing the two dates of land cover maps, each county changed in unique ways (Figures 3 & 4). In Jasper County, developed areas increased from 1.8% to 5.1% over a 10-year period, and wetland forest areas decreased from 46% to 37%. Key changes in Berkeley County include a 5.8% increase in developed areas and a total loss of 7% in wetland forest areas, mainly showing a difference along the west side of the Cooper River. Horry County experienced a 6% increase in wetland forest areas, but a 13.5% decrease in emergent wetland areas. According to the classification accuracy assessment, the user accuracy of the LULC classification was approximately 63% for the study period 2015-2016 and approximately 59% for 2024-2025 (Appendix B).

3.1.2 Isolation of Wetlands

The total isolated wetland area has decreased by approximately 6% across all three counties for the current versus historic dates. Connected wetlands have decreased by 4% and isolated wetlands have decreased by 2%. When considering the proportion of all the wetlands in the three counties, there has not been much change in the percentage of connected and isolated wetlands. In 2015, connected wetlands were approximately 53% and decreased to 52% in 2025, and isolated wetlands were at 47% and increased to 48% by 2025 (Figure 5).

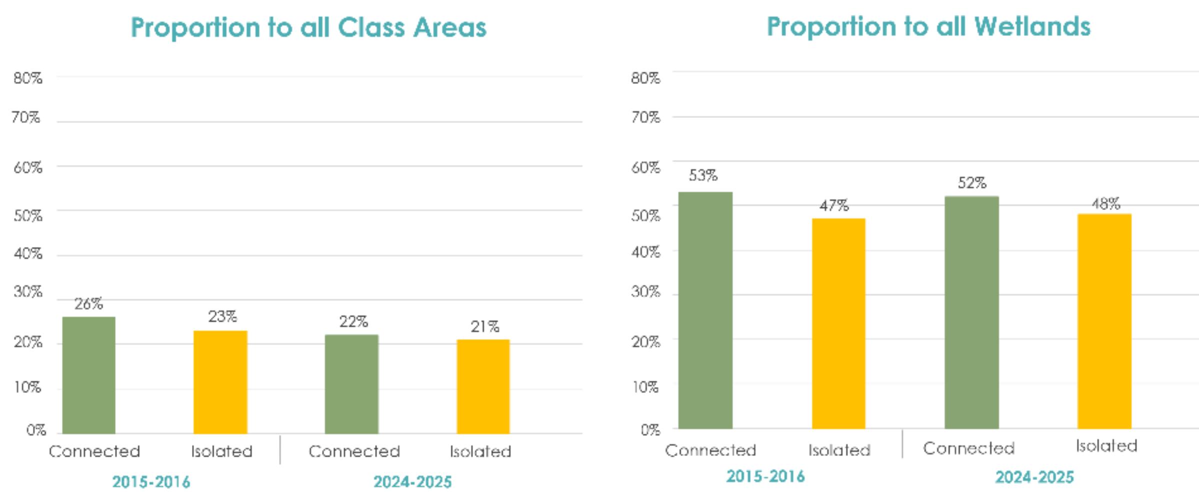

Figure 5. Bar charts of wetlands proportional to all classes and all wetlands across three counties

Examining wetland isolation results by county, Jasper County showed a significant change during the 10 years (Figures 6 & 7). The map of Jasper County's isolated wetland changes map in the study period of 2015 to 2016 shows that the connected wetlands are more prominent around the southern coastal region, as well as around the west side of the county. A noticeable change took place in the study period of 2024 to 2025, where the inland, eastern, and southern coastal regions experienced major protected wetland loss. In total, Jasper County faced a 14% decrease in connected wetlands paired with an 8% increase in isolated wetlands. (Figure B1). This increase in isolated wetlands can be seen through increased agriculture use along the Great Swamp River severing the connection of the adjoining wetlands.

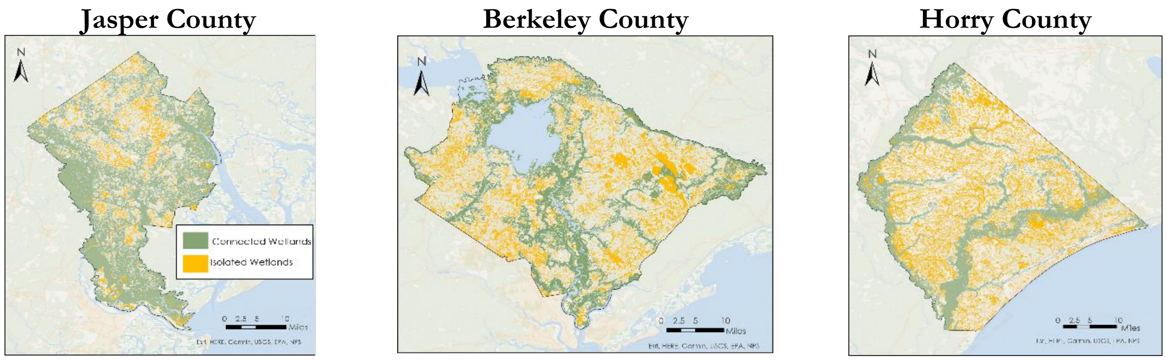

Figure 6. Isolated wetlands change maps of 2015 to 2016

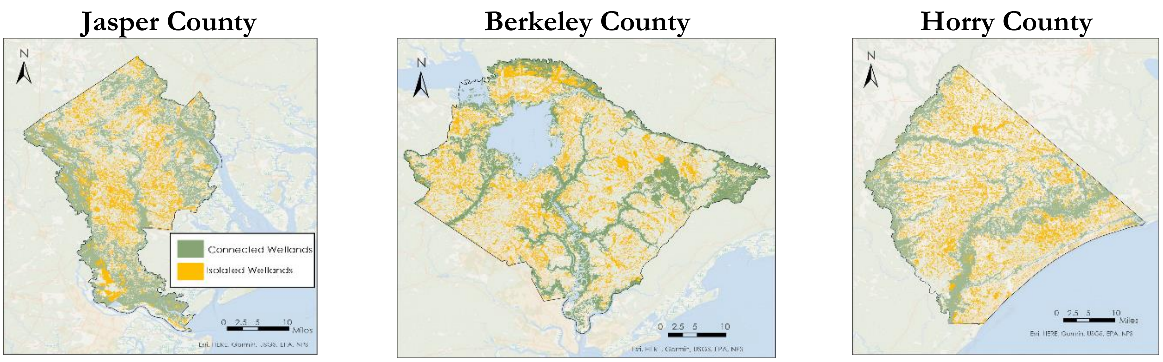

Figure 7. Isolated wetlands change maps of 2024 to 2025

Berkeley County showed ~ 2% loss in connected wetlands over a decade, from 22% wetland cover in 2015-2016 to 20% wetland cover from 2024-2025. The decline in protected wetlands was seen in conjunction with the urban expansion along the west side of Coopers River. Overall, Berkeley County had a 3% decrease in isolated wetlands, ranging from 22% land cover in 2015-2016 to 19% land cover from 2024-2025 (Figure B2).

Horry County experienced no change in connected wetlands, and a 6% decrease in isolated wetlands from 29% in 2015 to 23% in 2025. (Figure B3) The Waccamaw River, which flows through southern Horry County shows the longest stretch of connected wetlands in the county. In the map for 2024-2025, more connected wetlands are shown in the far eastern side of the wetland stretch (Figure 7). This change could be due to water regimes between the years, potential high flooding in 2025, and how the land along the river is used.

3.1.3 10-Year Change Detection

A 10-year change detection map was created for the different counties studied, through class-based detection wizard (Figure 8). The blue colors represent wetlands that have increased over 10 years. This can be due to different uses of land for agricultural practices over the years. Finally, the red is wetlands that have decreased over the 10 years. This could be from different uses of the land like agriculture and urban expansion.

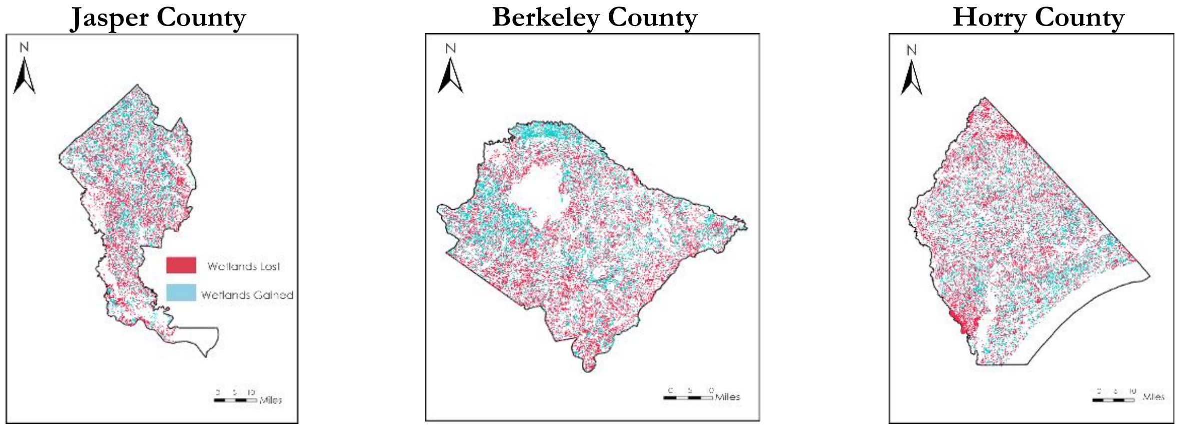

Figure 8. 10-year change detection map (2015-2016 to 2024-2025) in Jasper, Berkeley, and Horry counties

Overall, there has been a 35% change in wetlands over 10 years, with a 15% increase in wetlands due to differences in land use and a 20% decrease in wetlands due to urban expansion and increase in agricultural practices (Figure 9). This led to an overall 5% decrease in wetlands based on the 10-year detection. Also, there is around 1% difference in the amount of wetland loss detected by the 10-year change detection and the calculated change through the classification.

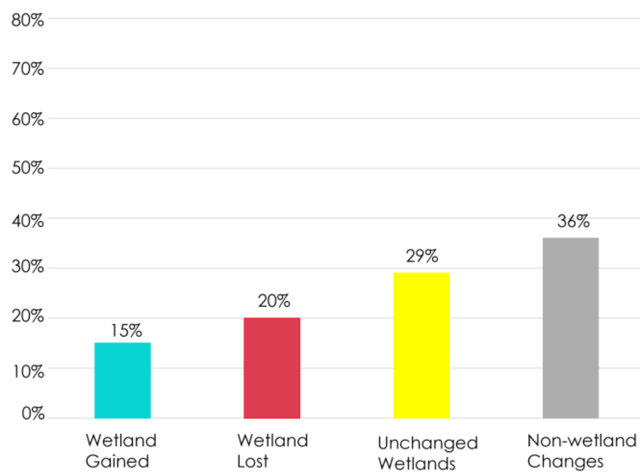

Figure 9. 10-year wetland change analysis across three counties (2015-2016 to 2024-2025). In acres the numerical values of these sections include Wetland Gained: 287293.4226, Wetland Loss: 386212.0587, Unchanged Wetlands: 565902.4996, Non-Wetland Changes: 712892.0191

3.2 Errors & Uncertainties

There were uncertainties and limitations on our project using the methodologies explained above. One of the uncertainties is the variability of the Landsat satellite imaging. The team used the Landsat image source from the whole period of 2016 for the small part of southwest Horry instead of October 2015 to February 2016; this was because the satellite imagery for that specific area during our study period contained cloud cover. The team used images from only part of the year, from October to February, which is the wet, winter season. Thus, there is inevitably some fluctuation in vegetation cover and patterns, as well as moisture and water flows, compared to the imageries ranging the whole year.

Furthermore, since we lacked discrete ground truth data of the study areas, we solely relied on visual interpretation of high spatial resolution imagery to create training points for the Landsat classifications. Our reference imagery included the ArcGIS base map of World Imagery, Google Earth Pro imagery, and the Landsat mosaic images of our study areas, along with the National Wetlands Inventory as a reference. This potentially could have reduced the accuracy of our wetland classifications and the accuracy assessment results.

Additionally, the data layers and classification results were filtered and adjusted throughout the data processing through the Majority Filter function in the ArcGIS Pro to create a more aesthetically cohesive image. Consequently, the surrounding pixel groups consumed some smaller pixels, resulting in losses of individual pixels (land areas) when smoothing. This process might have omitted some areas with accurate classification results.

Lastly, the project is based on the court case legislative document in which isolated wetlands are given a somewhat vague definition regarding their proximity and adjacency to "navigable waterways." In response, we created custom parameters for "navigable waterways", which were left up to an interpretation of the team and partners. Thus, this definition is subjective and uncertain, and some isolated wetlands may have been omitted or erroneously included.

4. Conclusions

4.1 Interpretation of Results

Overall, nearly half of all wetlands in the three counties are isolated and are not currently federally protected. This is concerning as wetlands decreased across the three counties from 2015 to 2025. This decrease is estimated to be from the increase in developed land and agricultural use, seen in the increase in bare soil coverage. The increase of isolated wetlands compared to the total wetland coverage can be seen through increased fragmentation of the landscapes, which may be isolating wetlands from their adjoining waterways.

When analyzing per county, Berkeley County showed slight variation between isolated and protected wetlands, while Horry County showed a decrease in protected and isolated wetlands. Jasper County was unique and showed a mix of decreasing and increasing wetlands. The reason for a wetland's classification as isolated and protected is based on the environment studied and the human influence on the area. Therefore, future studies need to consider the land use changes as well as landscape dynamics for a more accurate assessment of wetland vulnerability.

4.2 Feasibility & Partner Implementation

Upon completing the project, the team found the use of NASA Earth observations to be practical in assessing land cover and classification, identifying and isolating wetlands, identifying federally protected regions surrounding navigable waterways, and conducting change analysis. However, wetland identification with GIS classification tools could be more feasible and accurate by using finer resolution spectral imagery and increasing the amount of ground truth data. The results will be advantageous for the partners for regional analysis, through identification of legally defined and protected areas surrounding navigable waterways. Final products could be beneficial for bridging the gap between Earth science and public communication and awareness. The partners may use the results to distribute to government officials to aid in conservation efforts and outreach. This could be useful at the local, state, or federal levels. Because the legislation limiting the protection of isolated wetlands is established at the federal level, this could have implications for lower-level government and their ability to develop and apply appropriate legislation in these adjoining and overlapping communities. Therefore, not only can the results of this project be used to advocate for change to existing policies established by the federal government, but they can also be utilized to inform new policies or community efforts in and surrounding the study area. The project will be continued for a second term and will utilize current project results to evaluate flood risk and potential community impact.

5. Acknowledgements

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6. Glossary

Change Detection – A process that measures how the attributes of a particular area have changed between two or more time periods
Composite Bands – A technique in ArcGIS to create a single raster dataset from multiple bands
Digitizing – The process of converting the geographic features on an analog map into digital x, y coordinates, or spatial data
Digital Elevation Model (DEM) – A 3-D representation of a terrain's surface, created by storing elevation data
Earth Observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
Freshwater Wetlands – Areas where soils (hydric) are saturated with water seasonally or permanently, and vegetation is adapted to be water tolerant
Hydrologic Unit Code (HUC) – Hierarchical watershed classification system created by the United States Geological Survey based on surface hydrologic features in a standard, uniform geographical framework
Isolated Wetlands – Areas defined by the 2023 Sackett v. EPA legislation; they have many of the same characteristics as non-isolated wetlands, but differ in distance from and connectivity with major waterways
Mosaic – A raster dataset composed of two or more merged raster datasets
Normalized Difference Moisture Index (NDMI) – A remote sensing index detecting moisture levels in vegetation using a combination of near-infrared (NIR) and short-wave infrared (SWIR) spectral bands
Normalized Difference Vegetation Index (NDVI) – A remote sensing index that measures vegetation health based on the difference between near-infrared and red-light reflectance
Normalized Difference Water Index (NDWI) – An index focused on identifying water bodies by measuring the difference in reflectance between the near-infrared and shortwave infrared bands of light
Near Infrared (NIR) – A band of the electromagnetic spectrum that has wavelengths from 0.75 to 1.4 µm, varying slightly based on the technology and application
National Wetlands Inventory (NWI) – Wetland mapping and classification system developed by the United States Fish and Wildlife Service
Light Detection and Ranging (LiDAR) – An active, optical remote sensing technique that uses rapid pulses of laser light to measure distances and to densely sample the surface of the Earth, objects on the Earth, and physical infrastructure
Protected Wetlands – Wetlands adjoining navigable waters from federal protection under the Clean Water Act according to the 2023 Sackett v. EPA legislation
Random Forest Classification (Random Forest Model) – A machine learning technique using multiple decision trees to classify data. Each tree provides a "vote", and the most common outcome is chosen.
Short Wave Infrared (SWIR) – A band of the electromagnetic spectrum that has wavelengths in the 1.2 to 2.5 µm range.
Watershed – A basin-like terrestrial region consisting of all the land that drains water into a common terminus.

7. References

Alikhani, S., Nummi, P., & Ojala, A. (2021). Urban wetlands: A review on ecological and cultural values. *Water, 13*(22). https://doi.org/10.3390/w13223301

Davidson, N.C. (2014). How much wetland has the world lost? Long-term and recent trends in global wetland area. *Marine and Freshwater Research*, *65*(10), 934-941. https://doi.org/10.1071/MF14173

EOS Data Analytics (2023, July 11). *Normalized Difference Water Index (NDWI)*. EOS Data Analytics. https://eos.com/make-an-analysis/ndwi/

EOS Data Analytics (2023, June 11). *Normalized Difference Moisture Index (NDMI)*. EOS Data Analytics. https://eos.com/make-an-analysis/ndmi/

Esri (n.d.). *Composite Bands (Data Management)*. Esri. https://pro.arcgis.com/en/pro-app/latest/tool-reference/data-management/composite-bands.htm

Esri (n.d.). *GIS Dictionary*. Esri. https://support.esri.com/en-us/gis-dictionary/

Gao, B. C. (1996). *NDWI*—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment, 58(3),* 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Graham, L. (2023, June 28). *A Patchwork of Differing State Laws to Protect Wetlands*. Circle of Blue. https://www.circleofblue.org/2023/world/a-patchwork-of-differing-state-laws-to-protect-wetlands/

IBM (n.d.). *What is random forest?*. IBM. https://www.ibm.com/think/topics/random-forest

Kringen, D. (2022, March 22). *What is a Hydrologic Unit Code (HUC)?*. South Dakota State University Extension. https://extension.sdstate.edu/what-hydrologic-unit-code-huc

Landsat Missions (n.d.). *Normalized Difference Moisture Index*. U.S. Geological Survey. https://www.usgs.gov/landsat-missions/normalized-difference-moisture-index

Landsat Missions (n.d.). *Normalized Difference Vegetation Index*. U.S. Geological Survey. https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index

Mahdavi, S., Salehi, B., Granger, J., Amani, M., Brisco, B., & Huang, W. (2017). Remote sensing for wetland classification: A comprehensive review. *GIScience & Remote Sensing, 55*(5), 623-648. https://doi.org/10.1080/15481603.2017.1419602

McMaster, H., & Millikin, T. (2019, November). *South Carolina Floodwater Commission Report*. South Carolina Floodwater Commission. https://governor.sc.gov/sites/governor/files/Documents/Floodwater%20Commission/SCFWC%20Report.pdf

Nahlik, A. M., & Fennessy, M. S. (2016). Carbon storage in US wetlands. *Nature Communications*, *7*. https://doi.org/10.1038/ncomms13835

Peng, K., Jiang, W., Hou, P., Wu, Z., & Cui, T. (2023). Detailed wetland-type classification using Landsat-8 time-series images: a pixel- and object-based algorithm with knowledge (POK). *GIScience & Remote Sensing, 61*(1). https://doi.org/10.1080/15481603.2023.2293525

Revised Definition of "Waters of the United States", 88 Fed. Reg. 3004(Jan. 18, 2023) (to be codified at 40 CFR Part 120). https://www.federalregister.gov/documents/2023/01/18/2022-28595/revised-definition-of-waters-of-the-united-states

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publication*, *351*, 309–317. https://ntrs.nasa.gov/api/citations/19740022614/downloads/19740022614.pdf

Sackett v. Environmental Protection Agency, Volume 598 U.S. Page 21 –545 (2023). https://www.supremecourt.gov/opinions/22pdf/21-454_4g15.pdf

Song, A., Liang, S., Li, H., & Yan, B. (2024). Effects of biodiversity on functional stability of freshwater wetlands: A systematic review. *Frontiers in Microbiology, 15*. https://doi.org/10.3389/fmicb.2024.1397683

South Carolina Department of Natural Resources (2024). *South Carolina HUCS 8 12*. https://data-scdnr.opendata.arcgis.com/maps/26e00a148f8b4338a97d20eda2705cdf/about

U.S. Census Bureau (2024). *U.S. county boundaries* [Data set]. U.S. Census Bureau. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html

U.S. Department of Transportation (2025). *Navigable Waterway Network Lines* [Data set]. U.S. Department of Transportation Bureau of Transportation Statistics. https://geodata.bts.gov/datasets/usdot::navigable-waterway-network-lines/about

U.S. Environmental Protection Agency (2024, April 25). *What is a Wetland?*. EPA. https://www.epa.gov/wetlands/what-wetland

U.S. Fish & Wildlife Service (2024). *National Wetlands Inventory* [Data set]. U.S. Fish & Wildlife Service. https://www.fws.gov/program/national-wetlands-inventory

U.S. Geological Survey (2024). *1/3 arc-second DEM* [Data set]. U.S. Geological Survey National Map. https://apps.nationalmap.gov/downloader/

U.S. Geological Survey (2025). *Landsat 8-9 OLI/TIRS C2 L2* [Data set]. Earth Explorer. https://earthexplorer.usgs.gov/

van Asselen, S., Verburg, P. H., Vermaat, J. E., & Janse, J. H. (2013). Drivers of wetland conversion: A global meta-analysis. *PLoS ONE, 8*(11). https://doi.org/10.1371/journal.pone.0081292

Wilson, E.H. and Sader, S.A., 2002, "Detection of forest harvest type using multiple dates of Landsat TM imagery." Remote Sensing of Environment, *80*, pp. 385-396. https://doi.org/10.1016/S0034-4257(01)00318-2

Xu, X., Chen, M., Yang, G., Jiang, Bo., & Zhang, Ji. (2020). Wetland ecosystem services research: A critical review. *Global Ecology and Conservation, 22*. https://doi.org/10.1016/j.gecco.2020.e01027

Xu, X., Zhang, Q., Tan, Z., Li, Y., & Wang, X. (2015). Effects of water-table depth and soil moisture on plant biomass, diversity, and distribution at a seasonally flooded wetland of Poyang Lake, China. *Chinese Geographical Science, 25*(6), 739–756. https://doi.org/10.1007/s11769-015-0774-x

Zedler, J.B., & Kercher, S. (2005). WETLAND RESOURCES: Status, trends, ecosystem services, and restorability. *Annual Review of Environment and Resources*, *30*, 39-74. https://doi.org/10.1146/annurev.energy.30.050504.144248

8. Appendices

Appendix A: *Confusion Matrix of Wetland Classification Maps*

Table A1

Confusion matric of wetland classification map of 2015-2016

Metric/Year	2015-16
P accuracy	**0.63**
Kappa	**0.54**

Classification (2015-16)	Developed	Water	Bare Soil	Upland Forest	Upland Grass	Emergent Wetland	Wetland Forest	Aquatic Wetland	Total	U_Accuracy
Developed	0	9	0	0	0	0	0	1	10	**0.9**
Water	0	0	0	28	1	1	9	0	39	**0.72**
Bare Soil	0	0	0	2	16	1	0	0	19	**0.84**
Upland Forest	1	0	0	23	2	1	26	0	53	**0.49**
Upland Grass	7	1	0	0	3	0	0	0	11	**0.64**
Emergent wetland	0	0	10	0	0	0	0	0	10	**1**
Wetland Forest	0	0	0	1	1	6	5	3	16	**0.375**
Aquatic Wetland	0	3	0	1	0	3	0	3	10	**0.3**
Total	8	13	10	55	23	12	40	7	168	**0**
P_Accuracy	**0.86**	**0.69**	**1**	**0.51**	**0.70**	**0.50**	**0.65**	**0.43**	**0**	**0.63**

Table A2

Confusion matrix of wetland classification map of 2024-2025

Metric/Year	2024-25
P accuracy	**0. 59**
Kappa	**0.49**

Classification (2024-25)	Developed	Water	Bare Soil	Upland Forest	Upland Grass	Emergent Wetland	Wetland Forest	Aquatic Wetland	Total	U_Accuracy
Developed	7	0	3	3	1	0	0	0	14	**0.5**
Water	0	10	0	0	0	0	0	0	10	**1**
Bare Soil	0	0	3	1	5	0	1	0	10	**0.3**
Upland Forest	0	0	0	28	0	1	10	0	39	**0.72**
Upland Grass	0	0	2	0	11	0	3	0	16	**0.69**
Emergent wetland	0	0	0	0	0	5	5	0	10	**0.5**
Wetland Forest	0	0	1	16	2	0	29	1	49	**0.59**
Aquatic Wetland	1	1	0	3	0	4	0	1	10	**0.1**
Total	8	11	9	51	19	10	48	2	158	**0**
P_Accuracy	**0.88**	**0.91**	**0.33**	**0.55**	**0.58**	**0.50**	**0.60**	**0.50**	**0.00**	**0.59**

Appendix B: *Statistics of Wetlands Proportional to All Classes and Wetlands by County*

Figure B1. Bar charts of wetlands proportional to all classes and all wetlands across Jasper County

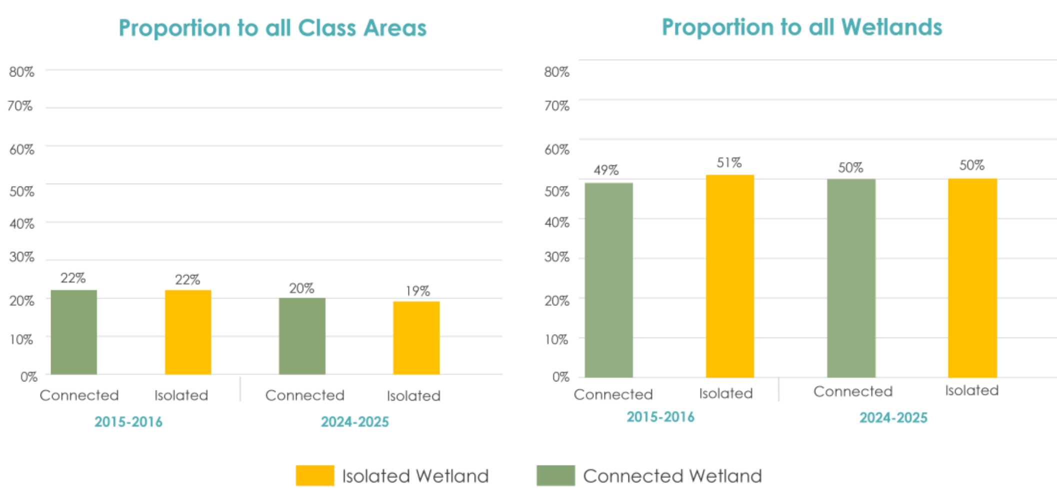

Figure B2. Bar charts of wetlands proportional to all classes and all wetlands across Berkeley County

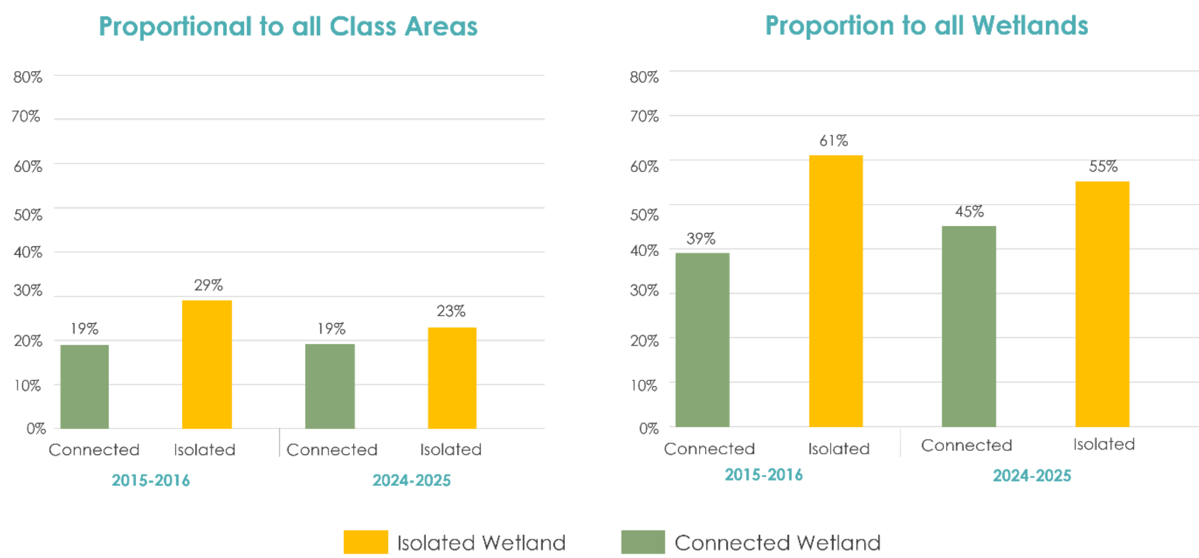

Figure B3. Bar charts of wetlands proportional to all classes and all wetlands across Horry County