DEVELOP Technical Report

Coastal South Carolina Water Resources

Assessing Unprotected Wetlands to Identify Priority Conservation Areas for Community Protection Against Flood Events in South Carolina

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Abstract:
Freshwater wetlands play a critical role in mitigating floods by trapping excess water and reducing the impact of extreme flooding events on surrounding communities. In South Carolina, freshwater wetlands span millions of acres, offering numerous ecosystem services to the state's residents. NASA DEVELOP partnered with the Coastal Conservation League (CCL) to investigate the relationship between isolated wetlands, extreme flooding, and social vulnerability. The CCL's interest in wetland conservation has recently focused on Sackett v. Environmental Protection Agency's (EPA) changes to the legal definition of wetlands, which do not protect isolated wetlands lacking a surface connection to navigable waters. We sought to assess flood resilience and social vulnerability in three South Carolina counties: Jasper, Berkeley, and Horry. Using a combination of remote sensing imagery (Landsat 7, Landsat 8, & Sentinel-1) and hydrological modeling datasets, we generated flood predictions throughout our study region, using data from Hurricane Florence as a reference event. We also conducted a social vulnerability analysis using U.S. Census Bureau data. The team identified isolated freshwater wetlands in medium and high-risk flooding zones that could mitigate flooding risk. Additionally, we produced a bivariate map combining both flooding risk and social vulnerability, highlighting communities of interest to the CCL. While limited by U.S. Census data availability at finer scales and satellite imagery availability during Hurricane Florence (2018), our results will aid the CCL in identifying vulnerable communities, as well as the freshwater wetlands that could promote flooding resilience in these regions.

Key Terms: Coastal Conservation League, remote sensing, isolated wetlands, 2023 Sackett v. EPA, social vulnerability, flood risk analysis

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1. Introduction

Wetlands are diverse ecosystems found at the transition between aquatic and terrestrial environments, often occurring at lower elevations (Jackson & Scaroni, 2022). They are among the most productive ecosystems in the world, offering habitat for wildlife, commercially harvested fish, and a variety of plant species. Additionally, they store large amounts of carbon in plant tissue and peat, a type of soil (Nyman, 2011). Despite their ecological significance, wetlands are rapidly decreasing in areal extent. The long-term global loss of naturally occurring wetlands has been estimated to be between 54-57%, with the rate of loss occurring 3.7x faster during the 20th and early 21st centuries (Davidson, 2014).

Wetlands also provide flood mitigation. They function as natural sponges that control the trapping and releasing of water. A wetland can store around one million gallons of water per acre, making them valuable resources for flood management and prevention (EPA, 2025). A decline in wetlands impacts the human communities surrounding them, leaving them more vulnerable to the negative impacts of flooding events. In South Carolina, there are 229,000 people at risk of coastal flooding, and an additional 56,000 people are projected to be at risk by 2050 (Samadi & Lunt, 2023).

About 9-10% of South Carolina's wetlands are considered at-risk, with the most vulnerable being smaller, isolated wetlands (Sharitz, 2003). Isolated wetlands are wetlands that are surrounded by upland and do not have a surface connection to another body of water (Leibowitz & Nadeau, 2003). The U.S. Supreme Court reinterpreted the definition of protected waters in Sackett v. EPA to only include those that have a surface connection to an existing body of water, excluding isolated wetlands from protection (Marsh, 2024).

For this project, we partnered with the Coastal Conservation League (CCL), a non-profit organization that promotes improved sustainability initiatives and aims to protect the natural environment in South Carolina. They work with different state agencies, local businesses, and citizen groups to engage in community efforts in preserving South Carolina's natural resources (Coastal Conservation League, 2025). Currently, the CCL intends to preserve the natural landscape and assess social vulnerability impacts from natural disasters by focusing on wetlands and their benefits for communities.

We used Hurricane Florence as a baseline for this project, given this severe storm's impacts to coastal South Carolina in September 2018. The storm produced a deluge in both North and South Carolina, causing dozens of fatalities and millions of dollars in damages. Hurricane Florence produced historical flooding in parts of South Carolina, significantly affecting vulnerable communities, particularly in the northern and coastal portions of the state (NOAA-NWS 2018).

In part one of this project, the team delineated connected and isolated wetlands based on the 2023 Sackett v. EPA definitions to determine what percentage of wetlands within three South Carolina counties (Horry, Berkeley, and Jasper; Figure 1) were characterized as unprotected. They found that 48% of the wetlands in the period from October 2024 to February 2025 were isolated, highlighting that nearly half of the freshwater wetlands in the study area were unprotected and could face future land cover changes. To better understand the threat to these freshwater wetlands, the team created a 10-year detection map to detect wetland losses and gains from October 2015 to February 2016 and found a 4-6% decrease in wetlands over the past decade.

Building on the foundational work established during a spring 2025 DEVELOP project, we set out to assess the flood resilience benefits that unprotected isolated wetlands provide. To do this, we identified freshwater isolated wetlands located in high flood risk and socially vulnerable zones in the three South Carolina counties from 2015 to 2025. Using Hurricane Florence (2018) as a basis for precipitation storm data and the previous term's isolated wetland data, we integrated remote sensing imagery and ArcGIS hydrological modeling to create a flood risk assessment. With our assessment, we identified regions where flooding is more likely to occur and determined which isolated wetlands were located in areas of high flood risk. Due to the ability of wetlands to mitigate the impact of flooding during high precipitation events, we identified isolated wetlands located in areas of high flood risk Additionally, we created a bivariate map to assess both the flood risk and social vulnerability of highlighted communities, determined by a variety of physical, social, and environmental factors that increase a community's susceptibility to natural disasters (Singh et al., 2014). These completed maps will help the CCL identify and support further wetland conservation, while protecting vulnerable communities from natural disasters.

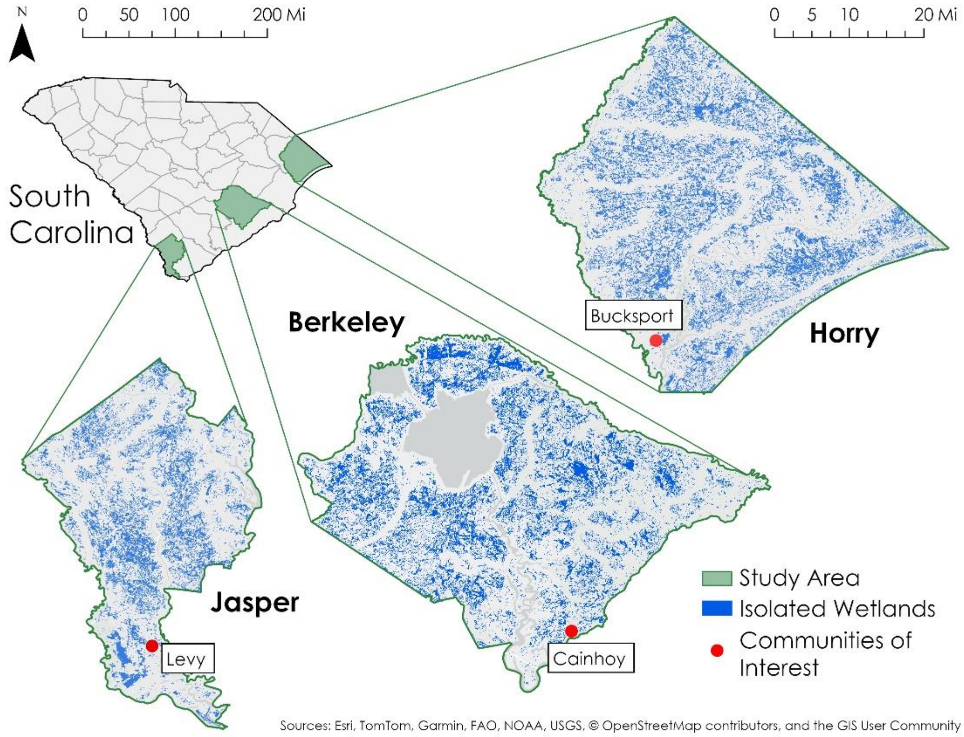

Figure 1. Study area of South Carolina counties Horry, Berkeley, and Jasper, including 2024 to 2025 isolated wetlands and the CCL's identified communities of interest.

Remote sensing technology has been employed to study flooding events, enabling social vulnerability analysis at a broader spatial scale (Cutter et al. 2003; Klemas, 2015). Generally, for flood mapping, remotely sensed data are collected before and after flood occurrence (Wang et al., 2002). Optical viewing is often hindered by cloud interference, but Synthetic Aperture Radar (SAR) data can penetrate clouds, lending useful data about flooding events (Tsokas et al., 2022). However, as flooding is a rapid event, both methods encounter temporal constraints on their ability to constantly capture images of the flood event. Existing literature demonstrates the ability of flood modeling using ArcGIS to remedy this. These events can be interpreted, combined with other hazard information, and used to determine what areas are potentially vulnerable to flooding (Samanta & Koloa, 2014).

2. Methodology

2.1 Data Acquisition

We downloaded Landsat 7 (Scan Line Corrector-off) and Landsat 8 Level 2/Collection 2 surface reflectance products in Google Earth Engine (Gorelick et al., 2017; EROS, 2020a; EROS, 2020b). We masked cloud and cloud shadow pixels from all Landsat images using pixel QA values and computed mosaics of Landsat 7 and Landsat 8 data together for the study region and period. We downloaded Sentinel-1 C-band Synthetic Aperture Radar (SAR) data from Google Earth Engine. Additionally, our team downloaded 10 m elevation (USGS, 2020), 10-m slope (USGS, 2020), 1 km precipitation (Thornton et al., 2022), and 30 m USGS land cover data (Dewitz & USGS, 2021) from Google Earth Engine for the desired date ranges (Table 1 & Table

A1). We acquired census data from the US Census Bureau's 2023 American Community Survey and 2020 Decennial Census.

We combined remote sensing imagery with traditional hydrological datasets to compute a flood risk model. It consisted of the Landsat 7, Landsat 8, Sentinel-1, elevation, slope, and land cover datasets. To create our social vulnerability model, we used the data collected from the U.S. Census Bureau, at both the census tract and block group level.

The isolated wetlands raster and shapefiles we used were derived by the previous DEVELOP team in the spring of 2025. The isolated wetland files were derived from a random forest classification and input guidance from the National Wetland Inventory. The raster was compiled in regards to downloaded Landsat 8 and Landsat 9 Level 2 data. Isolated wetlands were used to compare with the flood risk model.

Table 1
Earth observations for before versus after the landfall of Hurricane Florence

Platform & Sensor	Spatial Resolution	Purpose	Date range
Landsat 7 Enhanced Thematic Mapper (ETM+)	30m	Flood extent mapping; input for indices in FLATS+ modeling (2-month period)	Pre-Florence: 06/01/2018 - 09/13/2018 Post-Florence: 09/14/2018 - 12/14/2018
Landsat 8 Operational Land Imager (OLI)	30m	Flood extent mapping; input for indices in FLATS+ modeling (2-month period)	Pre-Florence: 06/01/2018 - 09/13/2018 Post-Florence: 09/14/2018 - 12/14/2018
Sentinel–1 C-SAR	10m	Flood extent mapping during and after 2 weeks of Hurricane Florence	Pre-Florence: 09/01/2018 - 09/14/2018 During Florence: 09/17/2018 - 09/23/2018 Post-Florence: 09/30/2018 - 10/07/2018

2.2 Data Processing
For data processing and analysis, we used ArcGIS 3.5.2 and downloaded the Arc Hydro toolbox for flood modeling. We performed statistics and visualizations in Python (version 3.10.13) and Excel Online.

2.2.1 Flooding: FLATS+
We used a Flooding in Landsat Across Tidal Systems (FLATS+) algorithm to identify flooded regions throughout the study area after Hurricane Florence. The FLATS+ algorithm was originally designed to detect fully or partially flooded pixels in salt marsh ecosystems using Landsat imagery, incorporating both a measure of water (Normalized Difference Water Index, NDWI) and vegetation (Enhanced Vegetation Index, EVI) presence (Narron et al., 2022; Rogers & Kearney, 2004). The formulas for NDWI and EVI are presented in Equations 1 & 2. In the equations, "Red", "NIR" (Near Infrared), and 'Blue" represent bands in the electromagnetic spectrum, as recorded by the sensor.

While not expressly calibrated for freshwater isolated wetlands, the FLATS+ algorithm can detect flooding likelihood in regions that are at the interface between land and water (Narron et al., 2022). As such, we decided that the FLATS+ algorithm could be used as a predictor of flooding, even in inland regions. The algorithm generates a value between 0 (dry) and 1 (flooded) that represents the probability that a given pixel is flooded.

We calculated the FLATS+ value for each pixel in the study area before and after Hurricane Florence (Table 1), using a combination of Landsat 7 and Landsat 8 imagery to augment the number of cloud-free images. We decided on a longer temporal range, approximately 2 months pre- and post- Florence, to capture any potential time lag associated with these large-scale flooding events. We used the median FLATS+ value before Florence, while we used the maximum FLATS+ value after Florence to capture the greatest flooding extent available in the imagery (Figure 2).

Our team then calculated the difference in FLATS+ values between the two time periods, with larger differences indicating an increase in flooding likelihood. We did not employ cutoff values for the logistic regression output, only using the raw probability results. The FLATS+ equation is presented below, in Equation 3.

$$\text{NDWI} = \frac{(\text{Red - SWIR})}{(\text{Red + SWIR})} \tag{1}$$

$$\text{EVI} = \frac{(\text{NIR - Red})}{(\text{NIR+6*Red-7.5*Blue+1})} \tag{2}$$

$$\text{FLATS+} = 1 - \frac{1}{1 + e^{(1.51 + 12.5 * \text{NDWI} - 41.2 * \text{EVI})}} \tag{3}$$

2.2.2 Flooding: SAR Mapping

We also incorporated Sentinel-1 C band Synthetic Aperture Radar (SAR) data into our analysis, due to its ability to penetrate cloud cover, meaning that it was able to collect usable data during Hurricane Florence (NASA Earthdata, n.d.). We sourced SAR imagery from the Google Earth Engine Data Catalog, filtering for data with an interferometric wide swath (IW) mode, ascending orbit pass, and vertical transmit-vertical receive (VV) polarization. We used three distinct date ranges to compute image mosaics (10m resolution) of before, during, and two weeks after Hurricane Florence (Table 1). Random noise, or speckle, can often occur in SAR imagery due to the interference of waves reflected from other surfaces, affecting the accuracy of the data (Lee et al., 1994). To account for specular noise, we applied a focal median filter, replacing the center pixel with the median of all pixels in a window of 100 square meters (Lee et al., 1994). We created a binary change map by subtracting post-flood data from pre-flood data, with '1' indicating flooding and '0' indicating no change. Lastly, we applied a threshold of 1.25 dB to the final flood map using a histogram of VV polarization frequencies, where values above 1.25 dB were considered to be flooded (Figure 2).

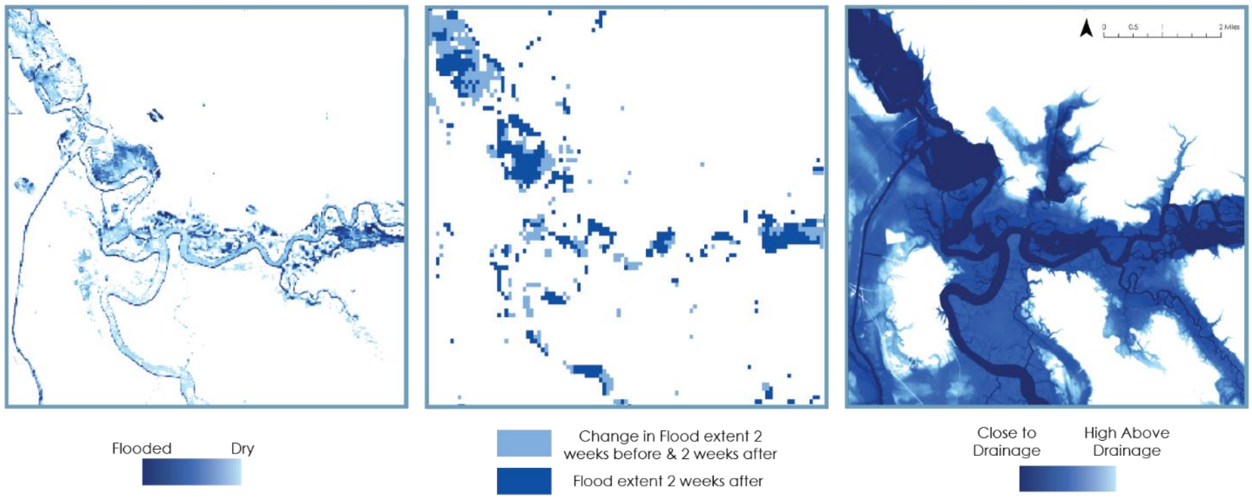

Figure 2. FLATS+ (left), SAR (middle), and HAND (right) flood extents showing inundation of Berkeley County's Cooper River, represented in blue. In the SAR extent, dark blue represents flooding 2 weeks after Florence and light blue shows the extent during Florence.

2.2.3 Flooding: Arc Hydro

In the Arc Hydro toolbox, our team produced multiple outputs to create a weighted sum flood vulnerability assessment. First, we used the "Fill Sinks" function to correct depression errors in the 10 m DEM and slope data. Then, we estimated flow direction by utilizing the "Flow Direction" tool, inputting D8 as a direction type, assigning flow in 8 cardinal directions for efficient surface flow delineation (ESRI, 2025). Following the creation of the flow direction, we derived flow accumulation from the "Flow Accumulation" tool to determine where most water will gather across the study area. With flow accumulation as the input, we utilized the "Stream Definition" tool to identify stream networks and create a stream raster, using a threshold of 1% (Zhang et al., 2021). The team used the newly established streams to generate distance to streams from the "Euclidean Distance" function, which calculates the shortest distance from each waterway.

Using DEM-derived flow accumulation, flow direction, and stream definition rasters, we utilized a Height Above Nearest Drainage (HAND) model, generating a flood depth raster at 4 meters to simulate a 4-meter flood scenario at the study site. The HAND inundation mapping approach estimates the vertical distance for each cell above the nearest stream channel, allowing for flood mapping based on elevation data alone (Nobre et al., 2011). Then, with the created stream definition and flow direction rasters, we used the "Stream Segmentation" tool to create a stream link raster, breaking down the defined streams into individual segments or links. Using the stream link and flow direction rasters, we created a catchment grid with the "Catchment Grid Delineation" tool, defined as the incremental drainage area for a single stream segment (Johnston et al., 2009). In this grid, each cell is assigned a value corresponding to the stream segment that drains that area, as defined in the stream link raster. Using the catchment and stream link rasters, we then built a HAND raster using the "Create HAND Based on Distance with Catchment Raster" tool. Finally, we generated a flood depth raster at 4 meters using the "Define HAND Based Flood Depth and Extent" tool to visualize potential flooding under a 4 meter flood scenario (Figure 2).

2.2.4 Flooding: Reclassification

To weigh each variable in the weighted sum function, we reclassified 8 variables using the "reclassify" tool. We chose the scheme shown in Table A1 as a criterion for impact based on the standard 1-5 flood risk (Chen et al., 2024 & Rincon et al., 2018). We classified precipitation based on the severity of precipitation events across previous storms in South Carolina (South Carolina DNR). Slope and Elevation were reclassified using Natural Breaks/Jenks because the Jenks method reduces variance across the range and is useful at identifying statistically significant separations (Gui et al., 2025). We manually reclassified the Euclidean distance to streams through our visual approximations on river width and scale. The flood extent HAND model was reclassified in intervals based on severity scales of flooding events in South Carolina (South Carolina DNR). SAR imagery and the FLATS+ data were already in a usable reclassified state, allowing us to include them with minimal changes. The Land Use Land Cover was classified as unique classes, with classes in or around water labeled as higher risk for flooding (Diribal et al., 2024).

2.2.5 Social Vulnerability

The Census Bureau datasets were already ready for analysis; no additional processing was needed. We used the following variables: income, education level, minority status, poverty status, heirs' property likelihood, insurance coverage, vehicle access, and age. More details can be found below in Section 2.3.2 and Table C1.

2.3 Data Analysis

2.3.1 Weighted Flood Risk Assessment

To compute the weighted flood vulnerability map, we input each of the eight variables into the "weighted sum" function in ArcGIS. Our original weights for each variable were equal to each other, all weighed at 12.5. However, precipitation was too coarse, with a resolution of 1-km. Also, the precipitation arc of Hurricane Florence heavily skewed the impact of flooding, favoring Horry County. To compensate, we removed precipitation and recalculated the flood risk weighted sum. We made a new weighted sum where Distance to Streams, HAND modeling, and SAR were weighted at 20%, while FLATS+ Modeling, Elevation, Slope, and LULC were weighed at 10% (Table B1). This scale was derived from a combination of academic literature, the CCL's emphasis on flood extent, and our own derived estimations (Rincon et al., 2018).

We reclassified both variants of the weighted sum, with and without precipitation, to analyze flood risk in terms of low, medium, and high levels. Then, we used the weighted sum without precipitation and overlaid previously derived isolated wetlands using the "Extract by Mask" tool. With that, we were able to derive isolated wetlands and their corresponding flood risk zones. Also, we removed water bodies classified by the LULC for greater accuracy in flood risk, as locations with permanent surface water like rivers and lakes are not flooded land and would skew the statistics for flooded land.

2.3.2 Weighted Social Vulnerability Assessment

We used the U.S. Census Bureau data to perform a social vulnerability analysis at the census tract-level throughout our study area. With input from the CCL, we selected the following variables to assess social vulnerability in South Carolina: income (median), poverty status (percent), adults graduated from high school (percent), minority status (percent), age (median), health insurance (percent), and vehicle availability (percent).

We employed the U.S. Department of Agriculture's technique for identifying regions that are likely to have a high proportion of heirs' properties present (Pippin et al. 2017). Heirs' property is defined as land that has passed through generations without a legally designated owner. The CCL expressed a strong interest in using heirs' property to assess social vulnerability, and while we did not have access to parcel-level tax data, we were able to use several of our social datasets as proxies for heirs' property likelihood. These included: income, poverty status, education level, and minority status (Pippin et al., 2017). We reclassified each variable using quantiles to separate the data into high, medium, and low classes.

We performed a weighted overlay analysis, using all of the social vulnerability datasets at the census tract-level. The weights are shown below in Table C1. We performed a similar analysis at the census block groups-level, focusing on three communities of interest to our partner: Levy, Cainhoy Peninsula, and Bucksport. At the census block group level, there are fewer datasets available; therefore, we only used data that could serve as a proxy for heirs' property likelihood for this targeted analysis (income, poverty status, education level, and minority status).

2.3.3 Bivariate Map: Flood Risk and Social Vulnerability

Once we selected the weightings for each variable (Table C1), our team combined the social vulnerability analysis with our flood risk mapping to create a bivariate map. For each dataset, we reclassified flood risk and social vulnerability into 'low', 'medium', and 'high' groups based on the output of the weighted overlay analyses. The low, medium, and high groups were based on even splits of the output of the weighted overlay analysis. For example, the flood risk ranged from 1-9 after the weights were applied; it was classified as low (1-3), medium (4-6), and high (7-9). The team overlaid the two datasets to compile a bivariate map.

2.3.4 Carolina Bay Mapping

The CCL expressed interest in identifying and mapping Carolina Bays, freshwater wetlands that have a characteristic elliptical shape and are of uncertain origins. They are common in the southeastern U.S., mostly clustered along the Atlantic Coastal Plain (Prouty, 1962). We used a geographic dataset based on the output of an elevation-based neural network model that identified Carolina Bays in South Carolina (Lundine & Trembanis, 2021). While examining the data in our study region, however, we noticed that the model performed poorly in areas with a gradual slope, often failing to identify Carolina Bays at low elevations. We decided to digitize Carolina Bays that we could identify in the ArcGIS Pro World Imagery basemap (true color). We digitized clusters in each of the three counties, selecting those that clearly bore the following hallmarks of Carolina Bays: elliptical in shape; axial elongation from northwest to southeast; and sand-rimmed edges (Prouty, 1962). The digitized clusters were added to the model-derived output.

3. Results

3.1 Analysis of Results

3.1.1 Flood Risk

Our flood model, derived from the weighted flood vulnerability assessment, is shown in Figure 3. Dark Red colors indicate high flood risk, while light gray indicates low flood risk. Horry had the largest concentration of high flood risk areas, with 9% of its pixels classified as high risk, while also having the highest concentration of low flood risk areas at 48%. On the other hand, Jasper has the highest concentration of medium risk areas at 60% of its pixels, while also having 8% of its pixels in the high-risk category. Although Horry County has the highest concentration of high flood risk vulnerability, Jasper County has the highest overall amount of risk, with 68% of its area constituting as medium to high risk. Berkeley County has 2.3% of its pixels that constitute high risk, and 51% of its pixels are classified as medium risk. Overall, the highest flood risk areas in the study area follow major water bodies: marshes in Jasper, the Cooper River in Berkeley, and the Waccamaw River in Horry.

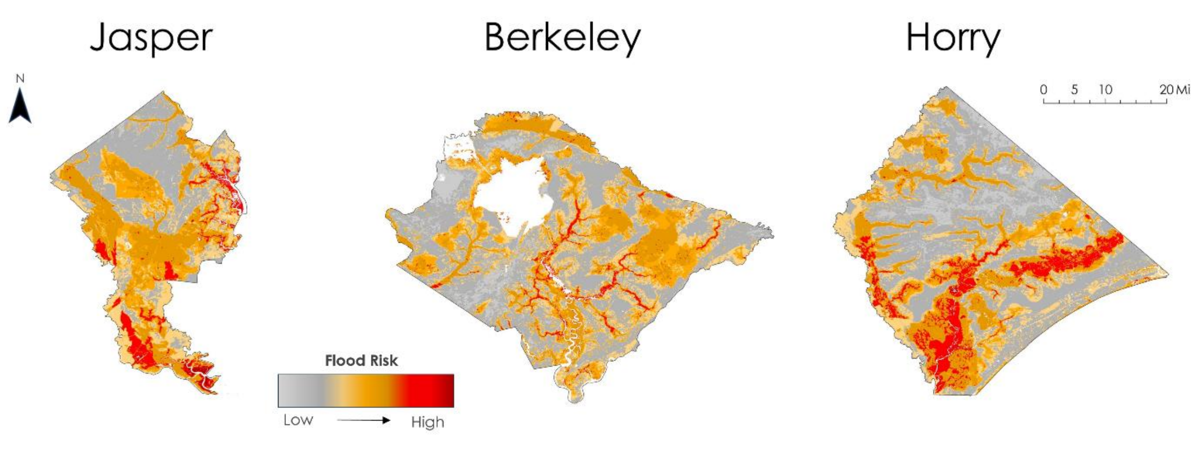

Figure 3. Weighted overlay of flood risk without considering precipitation data in Jasper, Berkeley, and Horry counties. The same map with precipitation included is shown in Figure B1.

The output of our flood model, combined with the previously identified isolated freshwater wetlands, is shown in Figure 4. In this figure, red pixels indicate isolated freshwater wetlands in areas of high flood risk. The inset maps show isolated wetlands in areas of high flood risk near the CCL's identified communities of interest. We estimated that 43% of the freshwater isolated wetlands in our study site were in such areas. Specifically, isolated wetlands in high flood risk areas make up 4% of all the isolated wetlands in the counties, while 39% make up medium flood risk areas. This reflects the current definition of isolated wetlands as regions of high flood risk that occur most frequently near major rivers and bodies of water and thus are more likely to be connected (protected) wetlands.

Berkeley had the most isolated freshwater wetlands at 657 km², with 412 km² (63%) located in regions of low flood risk. It is important to note that Berkeley has 2 km² (less than 1%) of its isolated wetlands in high-risk areas. Most of the isolated wetlands in Jasper were characterized by a medium flood risk, at 285 km² (57%). Horry had the highest number of high-risk wetlands at 34 km² (6%) (Figures B2-B3).

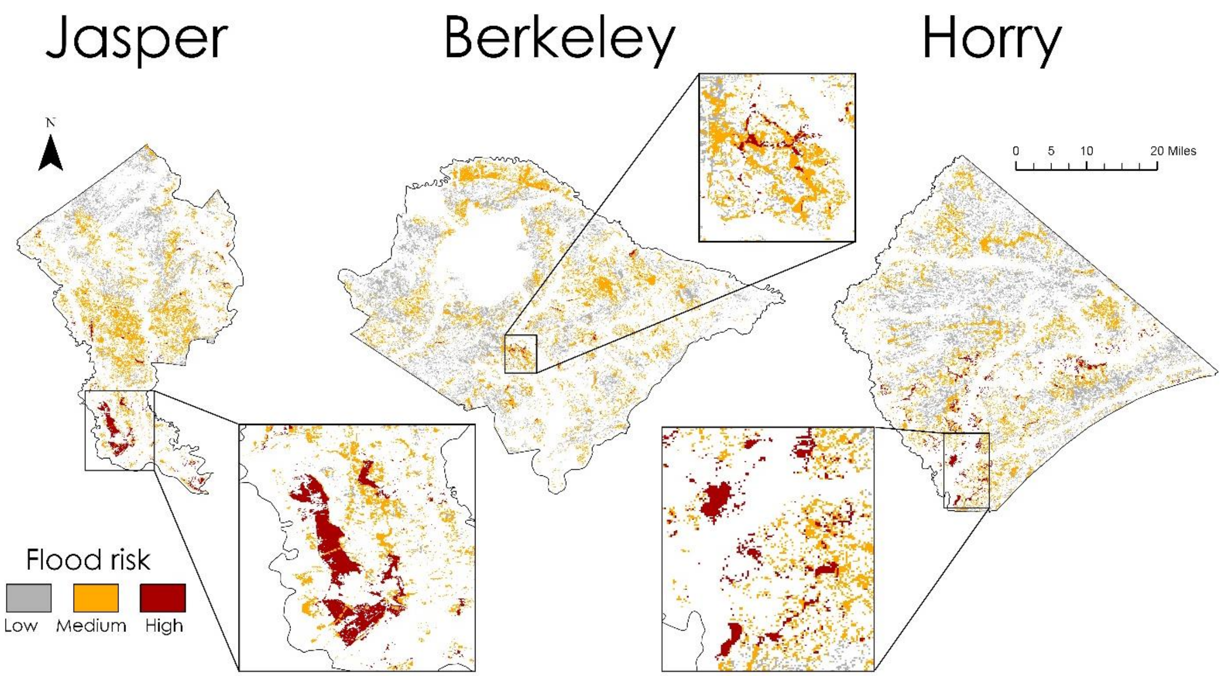

Figure 4. Isolated wetlands located in low, medium, and high flood risk areas in Jasper, Berkeley, and Horry counties.

3.1.2 Bivariate Map Output

Figure 5 shows the bivariate map at the census tract-level, combining both flood risk and social vulnerability into an integrated, wholistic map. Regions of increased flood risk and social vulnerability (depicted in purple) occurred within each county throughout the study area. In Jasper, higher risk regions were located closer to the Savannah River and the coast. In both Berkeley and Horry counties, higher risk regions were largely associated with the Cooper River and Waccamaw River watersheds, respectively. Across all three counties, over 80% of census tracts had an elevated social vulnerability, while over 50% had an elevated flood risk ('medium' or 'high'). Approximately 10% had either a 'high' social vulnerability or flood risk.

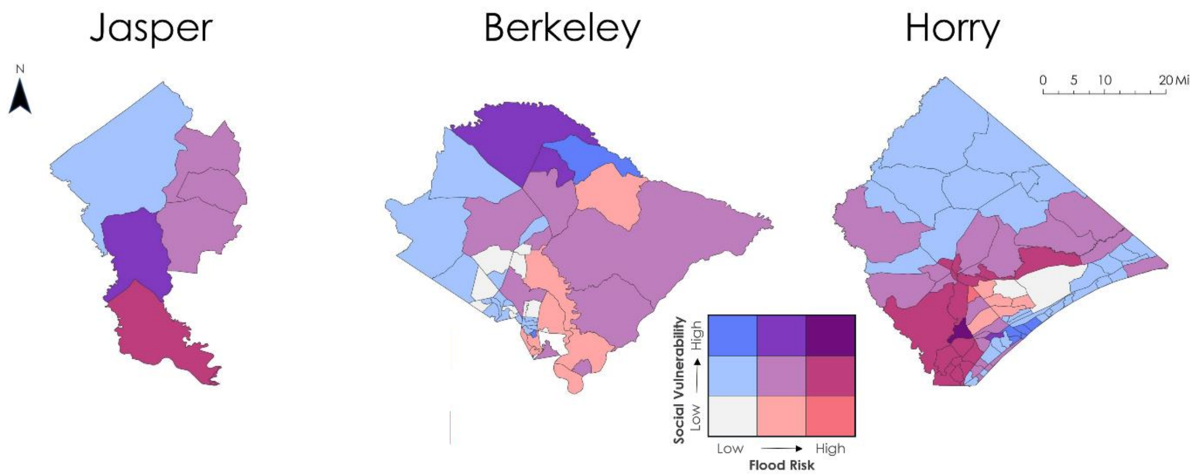

Figure 5. Social vulnerability compared to flood risk in Jasper, Berkeley, and Horry counties at the census tract level.

3.1.3 Highlighted Community Risk

Our finer-scale analysis for the three communities of interest is shown in Figure 6. Again, we only used heirs' property likelihood for this analysis, given the constraints associated with census block groups. Both communities of interest in Jasper and Horry were in regions of high flood risk and high social vulnerability (Levy and Bucksport, respectively). Levy and Bucksport are both located near major rivers and intertidal regions, increasing their risk of flooding. In Berkeley County, the Cainhoy Peninsula was characterized by an elevated flood risk, though social vulnerability was not particularly high – potentially due to its proximity to the city of Charleston, SC, and its surroundings.

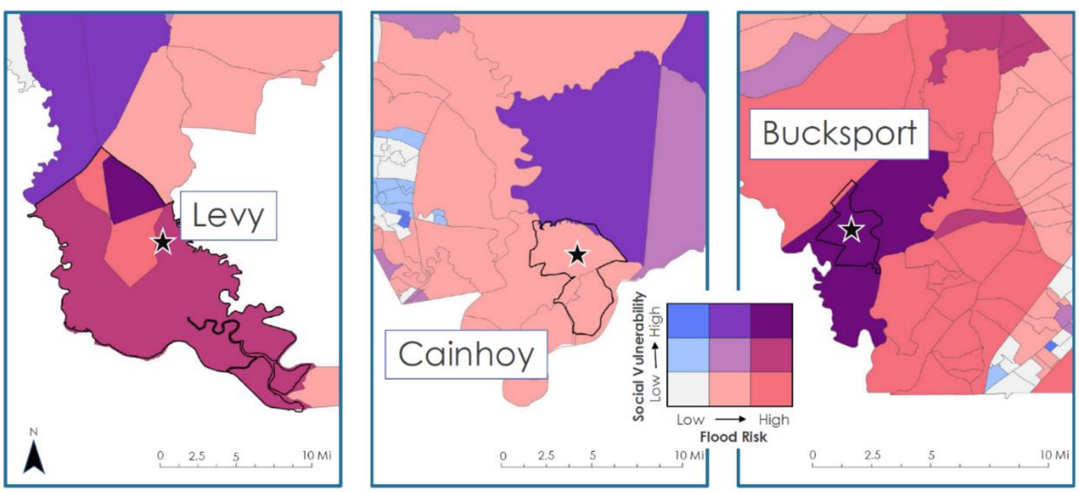

Figure 6. Bivariate map of social vulnerability compared to flood risk at the Block Group level, zooming in on the partner-identified communities of interest of Levy (Jasper), the Cainhoy Peninsula (Berkeley), and Bucksport (Horry).

3.1.4 Comparisons to the National Risk Index

To validate our bivariate map, we compared our results to the Federal Emergency Management Agency's (FEMA) National Risk Index (NRI) (Figure 7). The NRI serves as an index for both natural disaster risk and community resilience (FEMA 2023). Both our bivariate output and the NRI identified vulnerable areas throughout Jasper County, as well as sections along the Cooper and Waccamaw Rivers, though there were differences in risk at the census tract-level. Notably, the NRI predicted that almost every census tract was either at a 'Relatively High' or 'Very High' risk level.

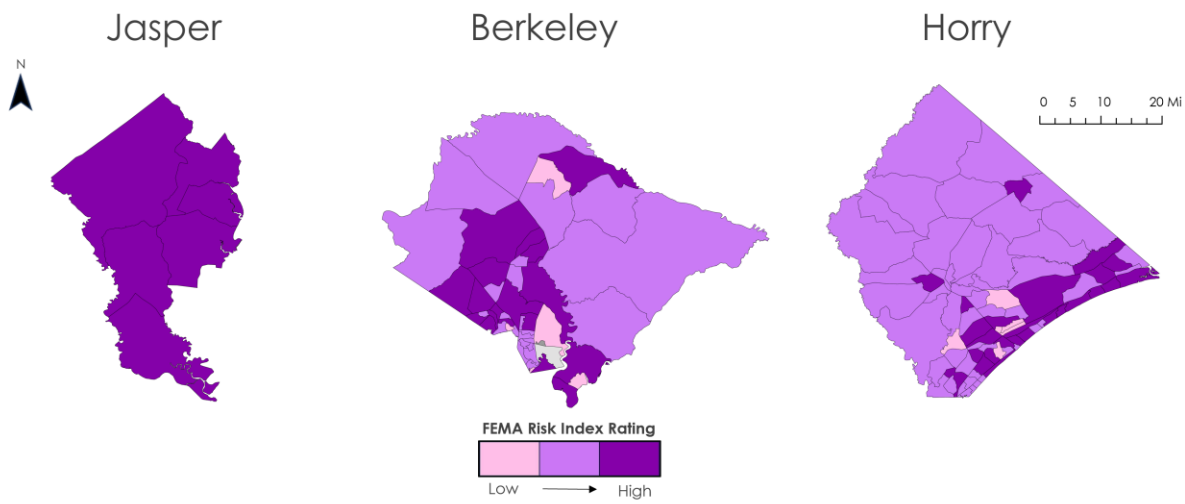

Figure 7. FEMA NRI ratings at the census tract level for Jasper, Berkeley, and Horry counties.

3.1.5 Carolina Bay Mapping

We identified clusters of Carolina Bays in both Berkeley and Horry counties, adding them to the map provided by Lundine & Trembanis (2021) (Figure D1). We did not identify any additional Carolina Bays in Jasper County; this is consistent with the observations of the CCL. The additional Carolina Bays were typically located in areas with a gradual slope; while many were identified using true-color satellite imagery, they did not appear clearly in the DEM.

3.2 Errors & Uncertainties

Throughout our methodology, there were errors, uncertainties, and limitations relating to the project. During data acquisition, there was no widespread ground-truth data used for our Earth observations. The accuracy of both SAR and optical data would be improved by the inclusion of ground-truth data. In addition, we were limited by the temporal resolution of the Earth observation data, causing time gaps in our flood extent. We addressed this by incorporating a time lag after the hurricane made landfall (2 weeks for SAR, 2 months for optical) and using multiple sensors to acquire imagery, but there were still gaps in data availability. For radar data, VV polarization often has trouble penetrating tree cover, meaning that flooding in wooded areas, which cover a considerable amount of the study area, may not have been detected.

Furthermore, the subjective nature of the flood risk and social vulnerability weighted overlays may be a limitation for our study. The weighted scales relied on estimated weights based on observations and previous literature instead of mathematical equations. Scale mismatch between demographic variables (census tract, or even census block) and flooding maps can affect map utility in a sub-optimal way. The Modifiable Areal Unit Problem (MAUP) causes different outcomes based on the scale of mapping (Jelinski & Wu, 1996). The socio-demographic data showed different results when mapping at the census tract and census block groups. Additionally, by largely focusing on one hurricane event (Florence), we may have underestimated the flooding risk in regions of SC that were not in its immediate path and received less precipitation. Removing precipitation as an input to the flood risk map was a conscious choice due to the lack of other precipitation events that were considered. In future studies, acquiring data from multiple events is advised.

4. Conclusion

4.1 Interpretation of Results

Our team identified that 43% of isolated freshwater wetlands were in areas with medium-to-high-risk flood zones. Wetlands in these regions likely play an important role during flooding events, having high potential to mitigate floods for the communities that surround them. Levy, Cainhoy, and Bucksport, communities of interest to the CCL, would all benefit from the flood mitigation provided by isolated wetlands, as we found that they had medium to high flood risk and social vulnerability.

This project emphasized the importance of heirs' property for our social vulnerability analysis at the suggestion of the CCL. Heirs' property is correlated with demographic factors that can render a community less resilient to the effects of flooding (e.g., higher rates of poverty) (Pippin et al., 2017). We originally intended to analyze several other socio-demographic datasets in our analysis, including flood insurance, hospital access, and food access. Due to constraints in our methodology, mostly related to scale differences and data availability, we were unable to include these data in our final product. Nevertheless, we feel as though our social vulnerability analysis was useful for assessing flood resiliency in South Carolina.

We provided a tool that can be used to identify flood-prone areas with communities characterized by a reduced capacity to recover from extreme precipitation events. The CCL can use our products to prioritize communities of interest, as well as associated isolated freshwater wetlands. While our results differed from FEMA's NRI, these discrepancies may be due in part to its scale: the NRI is based on national averages and is not specific to South Carolina. In the NRI, almost every census tract in each of the counties was either 'Relatively High' or 'Very High' risk; this most likely reflects South Carolina's vulnerability relative to the national average, particularly with regard to social risk. Furthermore, the NRI considers a variety of natural disasters in its assessment, not only flooding. We believe our results, as shown in our bivariate maps, are of greater use to the CCL due to their specificity to the study region.

South Carolina is susceptible to flooding from severe weather events like Hurricane Florence. Building flood resilience is a broad-scale problem, so combining multiple datasets such as optical and active radar data allows our partner to quickly prioritize wetland conservation in specific locations. These results will help the Coastal Conservation League assimilate a large amount of information and prioritize wetlands in areas with increased flood risk, allowing them to more effectively understand where to concentrate their conservation efforts and advocate for isolated wetland protection.

4.2 Feasibility & Partner Implementation

4.2.1 Flood Vulnerability Assessment of Isolated Wetlands Feasibility & Partner Implementation

We found it feasible to analyze flood vulnerability in relation to isolated wetlands by utilizing NASA Earth observation data. With the methods employed in this study, the CCL will be able to determine which isolated wetlands need to be prioritized more easily than collecting in-the-field data and more accurately than observations on Google Earth Pro. Although the CCL doesn't primarily use Google Earth Engine and ArcGIS Pro software, the methodology described in this paper could greatly reduce needed analysis time and improve output map utility at various spatial scales.

4.2.2 Highlighted Community Risk Feasibility & Partner Implementation

Similarly, we found that using this methodology is an effective way to highlight communities vulnerable to flooding that could benefit from flood mitigation provided by surrounding isolated wetlands. Our comparison of social vulnerability data and flood risk through GIS bivariate mapping is simpler to use than interpreting the input map variables individually. However, for smaller communities of interest, the CCL may consider acquiring higher resolution parcel data that our methodology does not address.

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6. Glossary

Arc Hydro – Esri toolbox designed for GIS analysis of water resources
Bivariate Map – Illustrates the relationship between two different variables and how they relate on a map
Block Group – The Census Bureau's statistical clustering of blocks within census tracts between populations of 600 to 3,000 people
Census Tract – The Census Bureau's statistical subdivisions of counties between populations of 1,200 to 8,000 people
Digital Elevation Model (DEM) – A 3-D representation of a terrain's surface as elevation
Earth Observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
Euclidean Distance – Measured shortest path between two points within a map
Enhanced Vegetation Index (EVI) – A calculation that corrects for atmospheric and canopy noise, while increasing sensitivity of dense vegetation that the Normalized Difference Vegetation Index (NDVI) does not
Federal Emergency Management Agency (FEMA) – US government agency that coordinates disaster response and recovery
Flooding In Landsat Across Tidal Systems (FLATS) – algorithm designed to detect fully or partially flooded pixels in salt marsh ecosystems using Landsat imagery, incorporating both NDWI and EVI
Freshwater Wetlands – Ecosystems where soils (hydric) are saturated with water seasonally or permanently, and vegetation is adapted to be water tolerant
Height Above Nearest Drainage (HAND) Model – Normalizes heights through topography drainages representing vertical distance between each drainage
Heirs' Property – Property that has passed through generations without a clear deed, leaving ownership of a parcel uncertain; correlated with social vulnerability
Interferometric Wide Swath Mode (IW) – Main acquisition mode of Sentinel-1 satellites over land
Isolated Wetlands – Areas defined by the 2023 Sackett v. EPA legislation; wetlands that do not have a continuous surface connection to navigable waters of the United States.
Land Use Land Cover (LULC) – Maps describing landscape utilizations and types in the form of classes
Modified Areal Unit Problem (MAUP) – Statistical problem where changing the shape and scale of areal units alters the results
National Risk Index (NRI) – equation created by FEMA using natural disasters, social vulnerability, and community resilience to provide a holistic view of community risk
Normalized Difference Water Index (NDWI) – A calculation to delineate surface water features through measured moisture content
Synthetic Aperture Radar (SAR) – An active collection radar system attached to ESA's Sentinel-1 satellite that records amount of pluses energy reflected from physical structures
Weighted Sum Overlay – Multiplies several rasters together from their given weights and sums them together out of 1
Vertical Transmit-Vertical Receive (VV) Polarization – A radar polarization in which pulses are received vertically (perpendicular) to the Earth; useful for analyzing ground features

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8. Appendices

Appendix A: Datasets Used

Table A1
Ancillary Datasets

Dataset	Spatial Resolution	Purpose	Date Range
USGS Digital Elevation Model (DEM; Elevation & Slope)	10 m	Input for Arc Hydro flood modeling	1998 - 2020 (mosaic)
Daymet precipitation	1 km	Precipitation data from Hurricane Florence for flood modeling	09/14/2018 - 09/19/2018
National Land Cover Database (NLCD)	30 m	Input for weighted flood risk assessment	2019
U.S State and County Shapefiles	polygon	Creation of the Study Area	2020
Social Vulnerability Data (Income, Education, Minority Status, Poverty Level, Age, Vehicle Access, Insurance)	census tract, block group	Input for weighted social vulnerability assessment	2020 (decennial census); 2023 (American Community Survey)
Isolated Wetlands	30 m & polygon	Used for isolated wetlands and flood risk map	2024 - 2025

Appendix B: Weighted Flood Assessment

Table B1

Weights of Flood Risk

Variable	Method	Reclassification Low – High Flood Risk		Overall Weight WO - Without Precipitation W – with Precipitation
Precipitation	Manual Interval	0 - 5 m 5 - 25.4 mm 25.4 - 127 mm 127 - 254 mm >254 mm	(Low Risk) (High Risk)	W – 12.5% WO – 0%
Slope	Natural Jenks	1.0 - 0.65 0.65 - 2.17 2.17 - 4.76 4.76 - 10.40 10.40 - 55.22	(Low Risk) (High Risk)	W – 12.5% WO – 10%
Elevation	Natural Jenks	-1.41 - 7.03 7.03 - 15.50 15.50 - 24.14 24.14 - 35.95 35.95 - 60.06	(High Risk) (Low Risk)	W – 12.5% WO – 10%
Distance to Streams	Manual Interval	0 - 0.02 m 0.02 - 0.05 m 0.05 - 0.0 8m 0.08 - 0.14 m 0.14 - 0.355 m	(High Risk) (Low Risk)	W – 12.5% WO – 20%
HAND	Manual Interval	0 - 0.05 m 0.5 - 1 m 1 - 2 m 2 - 3 m 3 - 4 m	(Low Risk) (High Risk)	W – 12.5% WO – 20%
SAR	Manual Interval	0 No Flood Change 1 Flood Change	(Low Risk) (High Risk)	W – 12.5% WO – 20%
FLATS	Manual Interval	1. -1 - -0.5 2. -0.05 - 0 3. 0 - 0.5 4. 0.5 - 1 5. > 1	(Low Risk) (High Risk)	W – 12.5% WO – 20%
LULC	Unique Classes	Developed Land Forest Open Land & Agriculture Wetlands Open water	(Low Risk) (High Risk)	W – 12.5% WO – 10%

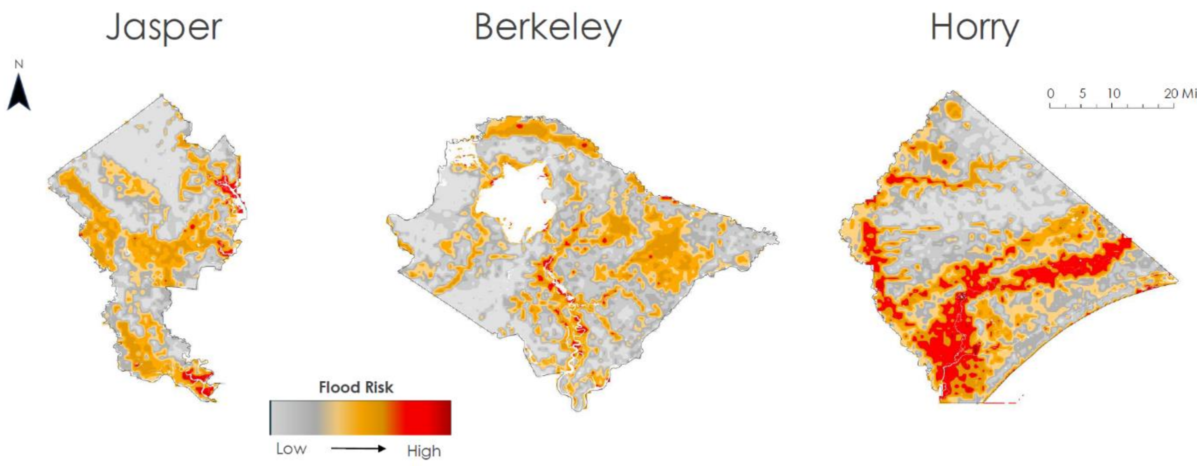

Figure B1. Weighted Overlay of Flood Risk with Precipitation.

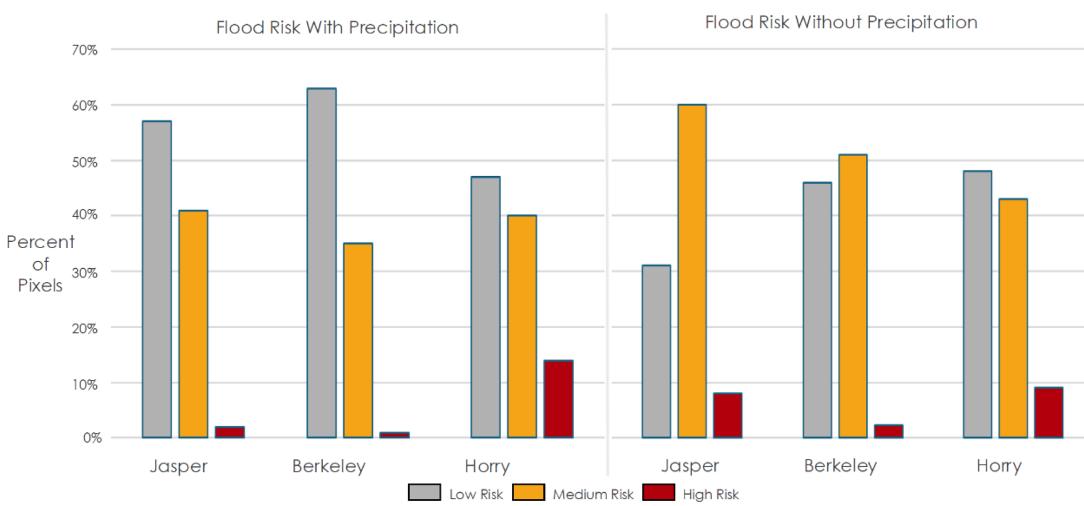

Figure B2. Weighted Overlay of Flood Risk with and without Precipitation.

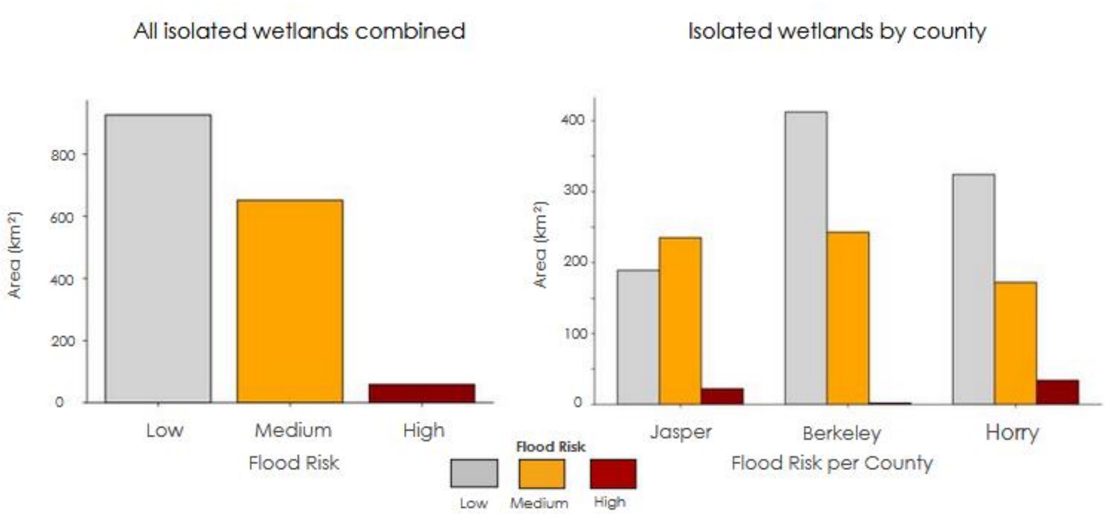

Figure B3. Total area of isolated freshwater wetlands (in square kilometers), grouped by flood risk (low, medium, high) and by county (Jasper, Berkeley, Horry).

Appendix C: Weighted Social Vulnerability

Table C1. *Class weightings for social vulnerability variables. Greater weightings indicate an increased importance in overlay analysis.*

Variable	Overall weight	Subclasses	Subclass weight
Heirs' property likelihood (includes income, poverty status, minority status, and education)	40	0 (lower likelihood) 1 2 3 4 (higher likelihood)	1 3 5 7 9
Health insurance coverage	30	1 (greater coverage) 2 3 4 5 6 7 8 9 (lower coverage)	1 3 3 5 5 7 7 9 9
Median age	20	1 (younger) 2 3 4 5 (older)	1 1 3 7 9
Vehicle availability	10	1 (greater availability) 2 3 4 5 (lower availability)	1 1 3 5 9

Appendix D: Carolina Bays

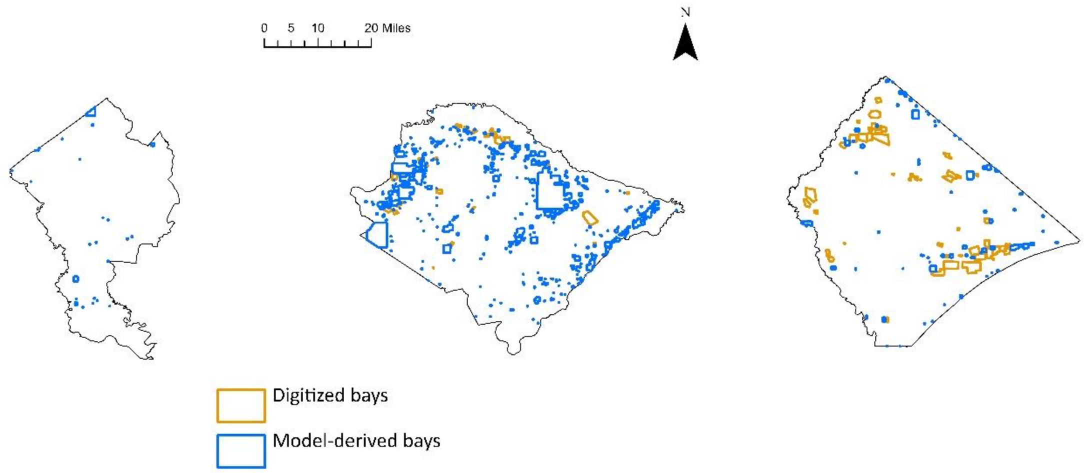

Figure D1. Locations of Carolina Bays in Jasper, Berkeley, and Horry counties, SC. The blue regions indicate model-derived bays, while the gold regions indicate digitized additions.