Inequities in Coastal Risk and Adaptation: Assessing Exposure and Beach Nourishment Effectiveness in the U.S.

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Abstract

I examine disparities in coastal risk exposure, beach nourishment implementation, and its effectiveness in reducing property damage. I find that high-risk coastal areas are disproportionately inhabited by White populations. Using novel data on precise extents of beach nourishments projects in the states of Connecticut, South Carolina and Florida, I find that they are more likely to be implemented in White communities. Employing a spatial regression discontinuity design and using Hurricane Sandy as a natural experiment, I also show that beach nourishment reduces property damage by 10 percentage points.

1 Introduction

Approximately 40 percent of the U.S. population live in coastal counties producing around 10 trillion dollars in goods and services (National Oceanic and Atmospheric Administration, n.d.). These coastal communities also face increasing risks from rising sea levels and coastal erosion. However, not all populations are equally vulnerable nor do they have equal access to protective measures. Beach nourishments is one of the most widely used shoreline protection strategies that aims to reduce the risk of storm surge by adding sand to beaches. In this paper, I examine which populations are exposed to coastal risk, which populations receive nourishment that is intended to reduce the coastal risk, and finally the extent to which nourishment achieves its intended protective function.

I first provide descriptive evidence on the distribution of coastal risk - physical vulnerability of the coast to rising sea-level - along the United States coast from Maine to Virginia.

I find that irrespective of the risk measure being long-term of short-term, the highest risk areas have the highest percentage of White population.

The coastal adaptation strategies could either mitigate or exacerbate existing inequalities depending on where they are implemented. I provide descriptive evidence on the distribution of beach nourishment in the States of Connecticut, South Carolina and Florida. I obtained the details on precise geographical extents of beach nourishment in the three states above using individual project reports. These exact extents enabled me to correctly identify the block-groups that received nourishment. I find that in Connecticut and Florida, the nourished block-groups have a higher proportion of White population and in Florida, the nourished block-groups also have a higher median household income. In Florida, a one percentage point increase in White population is associated with a 0.4 percentage point increase in probability of receiving nourishment. There is no significant difference in socio-demographic characteristics between nourished and non-nourished block-groups in South Carolina.

Finally, the question that remains is whether these nourishments reduce storm related damage and if so, by how much? Due to geographic variation in coastal slope, wave height, wind speed, and storm intensity—as well as substantial local variation in beach nourishment adoption, often influenced by funding—a simple comparison between nourished and non-nourished beaches would yield biased estimates of damage reduction. To address this, I use a spatial regression discontinuity design, leveraging Hurricane Sandy as a natural experiment, to estimate the local causal impact of nourishment. This design allows me to estimate local effects of beach nourishment on the same beach by comparing properties that are located close to each other. I find that nourished sections reduce property damages by approximately 10 percentage points on average.

Therefore, communities with higher exposure to coastal risk are not necessarily those with a larger minority population. Beach nourishment, however, even after accounting for coastal risk is skewed in favor of White communities. The effectiveness of nourishment in reducing damage coupled with its selective allocation could deepen disparities by shielding some communities while leaving others exposed.

I contribute to several strands of existing studies. First, I add to studies that document the inequality in exposure to environmental hazards between different population groups. These studies have shown that low-income and socially vulnerable sections of the population bear a higher burden of environmental hazards (Banzhaf et al. (2019),Buchanan et al. (2020), Colmer et al. (2020), Hausman and Stolper (2021), Currie et al. (2023)). Another group of studies have also shown that low-income populations experience greater exposure to flood risk and risk from rising sea-level (Bakkensen and Ma (2020), Best et al. (2023), , Qiang

(2019), Wing et al. (2022)). I use a long-term and a newly developed short-term measures of coastal vulnerability from the United States Geological Survey (USGS) to address the first question of who is at risk. Both the long and short-term measures allow for a comprehensive assessment of vulnerability that accounts for both immediate and future risks faced by coastal communities. I add to the existing studies by focusing on the geophysical dimensions of coastal vulnerability.

Another strand of existing studies look at the distribution of adaptation strategies. (Kind et al., 2020) argue that traditional cost-benefit analysis can exacerbate existing inequalities by biasing adaptation strategies towards high-income communities. (Lockwood et al., 2024) find that using income based equity weights can potentially shift mitigation investments towards low-income census tracts. (Siders and Keenan, 2020) use different machine learning models and find mixed evidence on whether low racial composition and high housing value are significant factors in determining beach nourishment in North Carolina. I contribute to these studies by providing additional evidence showing that adaptation strategies are indeed skewed in favor of White communities. Among the main contribution is the use of novel data excavated from detailed project reports, which facilitates the precise calculation of beach nourishment coverage. These granular data allow for a more nuanced analysis of the distribution of adaptation resources across communities with varying demographic and socioeconomic profiles.

Finally, studies also examine the effectiveness of natural geography and adaptation measures in mitigating flood damage (Taylor and Druckenmiller (2022), Sun and Carson (2020), Irish et al. (2013)). (Griffith et al., 2015) provide statistical evidence that damage to property in nourished sections of the coastline was lower than properties in non-nourished sections. They compared the first row structures along all of New Jersey and used all nourishment episodes since 1990 to define nourishment. A few limitations prohibit causal estimation in their analysis. First, the 130 mile coastline of New Jersey exhibits vast differences in shoreline geography. Since local geography can influence the storm-surge, comparing units located in vastly different geographies will give misleading estimates. For example, comparing the damages in sandy beaches to rocky cliffs would be fundamentally incorrect. Second, the density of properties can also vary along the coastline. The variation in building density can change the available pathways to propagate the storm surge blocked by buildings (Loftis, 2014). Third, since beach nourishment loses effectiveness over time due to natural erosion, areas nourished years before the storm may not serve as a correct comparison group. By using a regression discontinuity design of nourishment episodes recently conducted, I am able to circumvent the limitations highlighted above and provide the first causal estimates of the reduction in property damage due to nourishment.

2 Background: Beach Nourishment

Beach nourishment is a soft measure[1] of shore protection. It involves adding sand to a sandy beach to widen the beach width. This helps create a wider buffer between the sea and the built infrastructure on the land. As a result the expanded buffer is supposed to provide additional protection to the built infrastructure behind sandy beaches by reducing the risk of flooding.

An image accessed from Coastal Science & Engineering (n.d.) visually depicts an example of a beach nourishment project area before and after nourishment. As natural forces of the sea continue to erode the beaches, most nourished areas require re-nourishments which are generally carried out periodically based on the erosion rate. Therefore, by design, beach nourishments are a temporary measure of shore protection requiring frequent reinvestments to ensure their effectiveness.

The United States organized its first beach nourishment project in 1923. In 1930, Congress authorized U.S. Army Corps of Engineers to coordinate the federal shore protection initiatives with the state and local jurisdictions (Elko et al., 2021). Till 2024, United States conducted 2570 episodes of nourishment at a cost of approximately $11.28 billion (Program for the Study of Developed Shorelines at Western Carolina University, n.d.). The number of nourishment episodes increased since the early 2000s.

Beach nourishment projects are classified as federal or state/local based on the primary cost bearer. Federally authorized projects usually follow a 65-35 division of costs with 65 percent being financed by the federal government and 35 percent being provided by the state and local governments (Mercer et al., 2020). Some local governments also design a special tax district to raise tax revenues to cover their share of the cost. The purpose of such special districts is to identify the property owners that would directly benefit from the project and charge them a special rate (Mercer et al., 2020).

3 Data

3.1 Coastal Vulnerability Index

The Coastal Vulnerability Index (CVI), developed by the United States Geological Survey (USGS), is a comprehensive measure designed to assess the vulnerability of coastal regions

[1]Shore protection measures can be hard structures such as breakwaters or seawalls, non-structural measures such as managed retreat or soft measures such as beach nourishments or dune construction. Hard measures use artificial physical structures while soft measures are more natural, considered to be more environmentally friendly and less expensive than hard measures.

to sea-level rise (U.S. Geological Survey, n.d.). This index integrates six key variables: geomorphology, regional coastal slope, tide range, wave height, relative sea-level rise, and shoreline erosion and accretion rates. By combining these variables and analyzing their interrelationships, the CVI provides a broad overview of areas where physical changes are likely to occur due to sea-level rise. Each section of coastline is assigned a risk value for each variable, and the CVI is calculated as the square root of the geometric mean of these values. This relative measure reflects long-term estimates, projecting coastal changes 50 to 100 years into the future, based on data initially developed in 2000. To incorporate this measure into my analysis, I used nearest neighbor matching to align each block group's (in a coastal county) centroid with the corresponding CVI shapefile, ensuring accurate spatial integration of the vulnerability data. The descriptive statistics is shown in A1.

3.2 Coastal Change Likelihood

Coastal Change Likelihood (CCL) is a near-term measure recently developed by the USGS in 2023 (Sterne et al., 2023). Unlike the CVI, which assesses long-term vulnerability, CCL focuses on predicting coastal changes over the next decade. It offers higher resolution and greater accuracy, making it a valuable tool for understanding near-future risks. Currently, CCL data is available for the Northeast region of the U.S., spanning from Maine to Virginia, and extends to inland areas as well. To analyze this data, I employed ArcGIS Pro to calculate zonal statistics for each 2010 block group geometry. This process enabled me to determine the CCL measure for each block group, providing a detailed assessment of near-term coastal vulnerability at a localized level. The descriptive statistics is shown in A1.

3.3 Beach Nourishment

I obtained data on beach nourishments from the database maintained by the Program for the Study of Developed Shorelines (Western Carolina University, 2021). This database provides point locations for each nourishment episode dating back to 1923, with each episode varying in the extent of shoreline coverage. For episodes occurring on or after 1990 in Connecticut, South Carolina, and Florida, I extracted precise nourishment extents from U.S. Army Corps of Engineers (USACE) project reports, state-specific nourishment proposals, and official state websites[2].

To implement the spatial regression discontinuity analysis, I obtained data on beach

[2]U.S. Army Corps of Engineers (2014), U.S. Army Corps of Engineers, New England District (n.d.), South Carolina Department of Health and Environmental Control (n.d.), Florida Department of Environmental Protection (2020), U.S. Army Corps of Engineers, Mobile District (2020)

nourishment episodes in Cape May County, New Jersey between 2000 and 2012 from U.S. Army Corps of Engineers (USACE) project reports and an assessment report prepared by the Richard Stockton College of New Jersey (The Richard Stockton College of New Jersey, Coastal Research Center, n.d.). I cross-verified the information in the above sources with details in the Climate Change Resilience Strategy document prepared by the State of New Jersey. Between 2005 and 2011, two nourishment episodes in Cape May county (one in Avalon and another in Ocean City), had non-nourished areas on the same island. The Avalon project was undertaken in 2010-11 while the Ocean City project was finished in 2011.

I mapped the extents of individual beach nourishment episodes on Google Earth and subsequently converted them into shapefiles. To identify the geographic areas impacted by nourishment, I created a shape-preserving geodesic buffer of 1,000 meters for each nourishment section. I then intersected these buffers with U.S. Census block groups to identify the nourished block-groups.

3.4 Beach

I obtained the data on sandy beaches from two primary sources: (1) the Beaches Environmental Assessment and Coastal Health Act (BEACH Act) of 2000 (U.S. Environmental Protection Agency, 2022) and (2) manual inspection using Google Earth. The BEACH Act requires coastal and Great Lakes states and territories to report beach monitoring, notification, and geospatial data for coastal recreation waters to the Environmental Protection Agency (EPA). The EPA publicly releases beach shapefiles upon approval from the respective jurisdictions. To ensure comprehensive coverage, I cross-verified the above records and supplemented them with manually mapped beaches identified through Google Earth. I finally applied the same methodology used for nourished block groups—creating 1,000-meter buffers and intersecting them with Census block groups—to identify block groups containing sandy beaches.

3.5 Demographics

To examine demographic characteristics, I obtained demographic data from the 2015-2019 American Community Survey and 2000 Decennial Census at the block group level through (Manson et al., 2022). The key variables include the share of White population, share of Black population, the share of college graduates and higher, the share of employed population and the median household income.

3.6 Damage

I obtained detailed building level damage data prepared by Federal Emergency Management Agency's Modeling Task Force's (MOTF) Hurricane Sandy Impact Analysis team. It contains geocoded point level estimates of damaged buildings. FEMA-MOTF uses both satellite imagery and modeled flood depth to estimate damages. I retain the damage data that results from flooding.

3.7 Building Footprint

I obtained the polygon data on building footprint in New Jersey from Microsoft (2025). I take the anti-intersection of the polygon shapefiles of buildings with damage points to obtain the set of buildings that were not damaged.

3.8 Nourishment Boundary

I manually drew the nourishment boundary dividing each project into a nourished and non-nourished section. Both projects nourished selected sections of the beach in question on the same island.

4 Results

4.1 Coastal Risk and Socioeconomic Demographics

This section examines the demographic and socioeconomic characteristics of block-groups across different coastal risk categories, focusing on long-term Risk (CVI) and short-Term Risk (CCL) (Table 1). Only block-groups with measures on both types of risks are included[3].

On both long-term (CVI) and short-term (CCL) risk scales, the proportion of White population is highest in the most risky category. This suggests that White population is disproportionately represented in areas with the greatest coastal risk exposure. For long-term risk, block-groups with moderate risk (5th–90th percentile) tend to have higher income and proportion of education population than those in the extreme risk categories. For short-term risk, block-groups with the lowest risk have the highest incomes and education levels, indicating potential disparities in adaptive capacity. Households with more resources are likely better equipped to tackle environmental hazards by re-locating in a timely manner in the wake of warnings or post-disasters by rebuilding and investing in protective measures.

[3] The short-term measure of risk is available only for the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Virginia.

Employment rates remain relatively stable across all risk categories for both long-term and short-term risk, suggesting that employment levels are not a significant factor in coastal risk exposure.

4.2 Beach Nourishment and Socioeconomic Demographics

All sandy beaches do not receive beach nourishment. In this section, I explore the distribution of beach nourishment across block-groups with varying socio-economic demographics in the states of Connecticut, South Carolina and Florida. In Connecticut there is no significant disparity in the demographic characteristics of nourished versus non-nourished block groups (Table 2, Panel A). Notably, nourished areas have a 8 percentage point higher share of White residents and 5 and 10 percentage points lower shares of Black and Hispanic residents, respectively—all differences that are statistically significant. While employment rates are similar across both groups, the proportion of residents with a bachelor's degree or higher is significantly lower in nourished areas, by 13 percentage points. Median household income does not differ significantly between nourished and non-nourished areas. However, non-nourished areas have significantly higher median house values ($538,776 vs. $281,577).

In South Carolina, again, there are no significant disparities in demographic or socioeconomic characteristics between nourished and non-nourished block groups (Table 2, Panel B). Differences in racial composition, education, employment, income, and housing values are minimal and statistically insignificant, suggesting a more uniform distribution of nourishment activity across demographic lines in this state. It is also worth noting that nourishment is a widely used adaptation strategy in South Carolina, with approximately 78% of block groups having received nourishment.

Finally, I observe significant disparities in the demographic and socioeconomic characteristics of nourished versus non-nourished block groups in Florida (Table 2, Panel C). Nourished areas have a 6 percentage point higher share of White residents and 3 percentage point lower share of Black residents. The proportion of Hispanic population is 50% lower in nourished block-groups as opposed to non-nourished block-groups. Median household income is approximately 22% higher in nourished areas than non-nourished areas while the median house value is 31.6% higher.

I estimate a simple regression model to examine the correlation between beach nourishment and population characteristics:

$$Nourished_i = \beta_0 + \mathbf{X}'\theta + \mathbb{1}(NourishedPre1965) + \epsilon_i \qquad (1)$$

where $Nourished_i$ is an indicator of whether a block-group received nourishment post

1990. X is a vector of controls including share of White population, Hispanic population, log of median household income, log of median house value, rate of employment, share of population with a bachelors degree or higher, erosion rate, relative rate of sea-level rise and wave height. $NourishedPre1965$ is an indicator of whether a block-group received nourishment prior to 1965. I also specify it to be a pre-1965 county indicator. The results are reported in Table 3. I find that even after accounting for environmental vulnerability (erosion rates, sea-level rise, and wave height), areas with a higher share of white population are more likely to have been nourished (columns (1)-(3)). Having received nourishment prior to 1965, when most projects were initially planned and implemented, is a strong predictor of recent nourishment episodes (columns (4) and (5)). Many projects are executed in phases, with some beach sections receiving nourishment in the early 1960s and others in later years. Additionally, a significant number of nourishment episodes are repeat efforts in previously nourished areas (Figure 2).

4.3 Effectiveness of Beach Nourishment in Storm Damage Reduction

4.3.1 Background: Hurricane Sandy

Hurricane Sandy is one of the largest storms to hit the Atlantic basin. It made a landfall in southern New Jersey in October 2012. It particularly affected New York, New Jersey and Connecticut with record storm surges (FEMA, 2013). Sandy destroyed at least 650,000 houses (Sullivan and Uccellini, 2013). It resulted in over \$60 billion of economic damages (U.S. Global Change Research Program, 2023).

Sandy clearly demonstrated the vulnerability of coastal population and infrastructure to coastal flooding and the importance of investing in coastal resilience. The post-Hurricane Sandy aid package included over \$5 billion for U.S. Army Corps of Engineers repairs, with a significant portion allocated to beach re-nourishment (Song and Shaw, 2018).

4.3.2 Empirical Framework

I employ a sharp spatial regression discontinuity design to estimate the effect of beach nourishment in reducing damage to built infrastructure in the event of a hurricane. There are a few reasons why ordinary least squares will fail to provide causal estimates. The local geography and structure of the coast can influence the storm-surge, comparing units located in vastly different geographies will give misleading estimates. The density of properties can also vary along the coastline. The variation in building density can change the available pathways to propagate the storm surge blocked by buildings (Loftis, 2014). By using a spatial regression discontinuity design of nourishment episodes recently conducted, I am able to circumvent both the limitations highlighted above.

I use the nourishment boundary for each area to assign damaged and non-damaged buildings to nourishment and non-nourishment. I then calculate the distance of each building to the nourishment boundary. I convert the distance to negative for buildings behind the non-nourished sections. The cut-off point is 0 meters. Those with positive distances are treated (i.e. receive enhanced protection from nourishment) and those with negative distance are not treated. Regression takes the following form:

$$Damaged_i = \alpha + \beta_1 Nourished_i + \beta_2 f(distance_i) + \beta_3 Nourished_i * f(distance_i) + \epsilon_i \quad (2)$$

where $Damaged_i$ is the outcome variable of interest. It is assigned a value of 1 if it was damaged due to flooding and 0 otherwise. $Nourished_i$ is also an indicator taking a value 1 if the structure is behind the nourished section and 0 otherwise. $f(distance_i)$ is the RD polynomial which controls for flexible functions of distance. The interaction term $Nourished_i * f(distance_i)$ allows the effect of distance on damage to differ between nourished and non-nourished sections. The model does not include any other covariates. β_1 is the treatment effect of lying behind a nourished section of the beach.

The key identifying assumption is that all relevant factors beside treatment exhibit no discontinuity at the border. This assumption is needed to argue that buildings located on the non-nourished section is no different from those in the nourished section. Given the hyper local geography under consideration, this assumption is plausible[4]. Each county implements county level policies. Therefore, any building related mandate would be applicable uniformly to both nourished and non-nourished sections. Furthermore, the areas not nourished between 2005 and 2011 in both Avalon and Ocean City act as good counterfactuals because they are a part of bigger nourishment projects and were set to receive re-nourishments after 2011. So, any remaining concern around the properties being different between the two sections because one is currently treated can be alleviated. Furthermore, the long-term rates of mean wave height, erosion and relative sea-level change is the same across both the sections (Table 4, Panel B).

[4]In section 4.2, I find that areas with a higher proportion of White population is more likely to be nourished. The analysis in section 4.2 is based on block-group geography. In this section, I am able to use point data of the built environment allowing me to circumvent the large geography problem. Essentially, when using block-groups to identify nourishment vs. non-nourishment, the entire block-group is classified as nourished even if only one portion of the beach in it was nourished. However, the same block-group can have other non-nourished sections. Since, I restrict my study area to one beach, assuming the buildings are not too different from each other at the immediate boundary is highly likely.

An additional assumption is that there is absence of selective sorting around the cut-off. This assumption would be violated if the number of constructions increased in response to nourishment behind the nourished region. I use the McCrary density to test for a discontinuity in the number of buildings on either side of the cut-off. The result of the test is shown in Figure 3.

4.3.3 Results

I estimate the likelihood of sustaining damage as outlined in Equation 2. The main results are in Table 5 and visually represented in Figure 4.

The point estimates indicate that in Avalon, the probability of sustaining damage is 9.4–13.1 percentage points significantly lower in the nourished section compared to the non-nourished section. Given that the overall damage rate in Avalon is 14.2%, this reduction represents more than 65% of the mean probability of damage. In Ocean City, the probability of sustaining damage is reduced by 10–10.6 percentage points in the nourished section relative to the non-nourished section. With an overall damage rate of 87.3–90.2% in Ocean City, this decline accounts for approximately 11% of the mean probability of damage.

The Avalon beach nourishment was funded entirely by the state and local governments. It cost 6.8 million dollars. The Ocean City beach nourishment is estimated to have cost the federal government 11.6 million dollars i.e. 65 percent of the total project cost. The damage estimates by FEMA range from affected ($0 to $5000), minor ($5000 to $17000), major (more than $17000) and destroyed. More than 99% of the damages in Avalon were either of type “affected” or “minor”. Using the estimated 9.4-13.1 percentage reduction in damage for all 1432 properties behind the nourished section, the maximum potential damage loss prevention ranges from $2,228,336 to $3,189,064, resulting in a property damage reduction benefit of 32.8% to 46.9% relative to the cost[5]. In Ocean City, 31.3% of the damages were of type “affected” and 67.5% were of type “minor”. Using the estimated 10-10.6 percentage reduction in damage for all 4821 properties behind the nourished section, the maximum potential damage loss prevention ranges between $8,195,700-$8,687,422, resulting in a property damage reduction benefit of 70.65% to 74.89% relative to the cost to the federal government. Relative to the cost of the entire project ($17.8 million), the maximum benefit of directly avoided storm damages is 45.9%-48.7%.

The results are robust to a donut regression discontinuity design (Tables A2 and A3). They are also robust to choice of different MSE-optimal bandwidths (Tables A4 and A5).

[5]These prevented damages are a lower bound. There is also significant reconstruction costs to repair the damages. These repair costs can vary greatly depending on the type and size of property and level of flood depth. The average cost of repair could range from $3.75 to $7 depending on water depth and extent of damage (AOA Cleaning and Restoration, 2023)

5 Conclusion

I provide an integrated analyses of coastal risk exposure, access to adaptation through beach nourishment, and the effectiveness of that adaptation to provide a comprehensive view of how coastal communities are responding to climate risks. I find that both long and short-term coastal risk are disproportionately borne by White populations. For long-term risk, areas with moderate exposure tend to have higher incomes than those at the extremes, while for short-term risk, the least risky area is also the richest. This suggests that households with more resources are better positioned to avoid or adapt to risk. I also find clear disparities in who receives beach nourishment with block-groups with a higher share of White population having a higher probability of nourishment. I also find that nourishment reduces storm-related damage by about 10 percentage points.

Several limitations pertain to the analysis of these results. First, I rely on block-group level data, which may mask important within-area variation and individual-level mechanisms that shape both exposure and adaptation outcomes. Second, data availability also varies across states—short-term risk data is limited to a subset of the states. Third, some historical nourishment records may be incomplete. Finally, demographic shifts subsequent to adaptation interventions are not documented, and it is thus difficult to determine if nourished sites were initially more advantaged or became so over time due to investment in coastal defense. I recommend that future research assesses how community characteristics evolve subsequent to nourishment in order to better understand the long-term distributional impacts of adaptation policies.

Given the high and repeated costs of beach nourishment, policymakers can use the estimated reduction in damage to assess the cost-benefit ratio of nourishment projects and evaluate their long-term effectiveness. With federal funding for beach nourishment becoming increasingly constrained, local and state governments must carefully determine whether nourishment is the most effective strategy for mitigating storm-related damage in their specific contexts. Based on my estimates, the benefit-cost ratio of nourishment is less than one when considering only the reduction in storm damage to properties. This suggests that, on its own, property protection may not justify the high and recurring costs of nourishment. Unless nourishment also boosts tourism, protects public infrastructure such as highways, or generates other forms of local revenue, it may be difficult to make a strong case for continued public investment in this strategy.

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6 Tables

Table 1: Population Characteristics by Coastal Risk Category

Risk Category	White (%)	Median Household Income	Education (%)	Employed (%)	Count
Long-Term Risk (Coastal Vulnerability Index)					
>= 99th Percentile	84.07	75680.10	38.22	95.14	51
95th - 99th Percentile	71.68	71322.28	39.91	94.36	199
90th - 95th Percentile	79.98	80503.75	39.71	95.06	127
5th - 90th Percentile	75.12	88683.47	43.15	94.41	2660
<= 5th Percentile	64.18	71689.15	39.79	93.71	334
Short-Term Risk (Coastal Change Likelihood)					
>= 99th Percentile	88.38	87442.01	45.54	95.27	111
95th - 99th Percentile	84.86	84319.21	41.05	93.89	327
90th - 95th Percentile	78.50	89950.11	41.27	94.43	282
5th - 90th Percentile	71.76	84924.98	42.38	94.38	2596
<= 5th Percentile	71.60	94375.32	52.69	94.89	55

Note: The unit of observation is a block-group. Block-groups with both a short-term and long-term measure of risk have been used. States included are Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Virginia. Block-groups were partitioned into different risk categories. Demographic data has been obtained using ACS 2015–2019.

Table 2: Differences Between Nourished and Non-Nourished Block Groups

Variable	Nourished	Not Nourished	p-value
A. Connecticut			
Proportion of White	0.92	0.84	0.01
Proportion of Black	0.04	0.09	0.01
Proportion of Hispanic	0.04	0.14	0.00
Employment Rate	0.94	0.94	0.80
Proportion with Higher Education	0.35	0.48	0.02
Median Household Income	102667.30	102412.00	0.98
Median House Value	281576.90	538776.30	0.00
B. South Carolina			
Proportion of White	0.90	0.89	0.92
Proportion of Black	0.07	0.06	0.80
Proportion of Hispanic	0.05	0.05	0.89
Employment Rate	0.96	0.95	0.51
Proportion with Higher Education	0.49	0.48	0.89
Median Household Income	81112.23	80831.84	0.97
Median House Value	441728.00	496456.30	0.45
C. Florida			
Proportion of White	0.95	0.89	0.00
Proportion of Black	0.02	0.05	0.00
Proportion of Hispanic	0.08	0.16	0.00
Employment Rate	0.96	0.96	0.65
Proportion with Higher Education	0.51	0.43	0.00
Median Household Income	90683.95	74152.05	0.00
Median House Value	564748.10	428965.60	0.00

Note: Nourishment episodes post 2010 have been used to identify the nourished block groups. Demographics have been obtained using ACS 2015–2019. Unit of analysis for nourishment status is a block-group.

Table 3:

	Dependent variable:				
	Nourished				
	(1)	(2)	(3)	(4)	(5)
White (%)	0.005	0.005	0.004	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Hispanic (%)	−0.004	−0.003	−0.002	−0.003	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
log(Median Household Income)	−0.069	−0.067	−0.028	−0.022	0.011
	(0.072)	(0.067)	(0.050)	(0.056)	(0.035)
log(Median Household Value)	0.056	0.032	0.078	0.086	−0.029
	(0.064)	(0.065)	(0.070)	(0.069)	(0.043)
Employed (%)	−0.001	−0.003	−0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
College Degree (%)	0.006	0.006	0.004	0.004	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Erosion Rate		0.012	−0.015		
		(0.021)	(0.024)		
Sea-level Rise Rate		0.387	0.307		
		(0.174)	(0.218)		
Wave Height		0.072	−0.063		
		(0.151)	(0.134)		
Nourished before 1965			0.497	0.506	
			(0.093)	(0.087)	
County Nourished before 1965					0.826
					(0.071)
Constant			−1.508	−1.008	0.102
			(0.894)	(0.858)	(0.544)
Mean	0.4	0.4	0.39	0.39	0.39
State FE	Yes	Yes	No	No	No
Only Florida	No	No	Yes	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes
Observations	1,127	1,127	942	942	942
R^2	0.161	0.189	0.275	0.249	0.612
Adjusted R^2	0.155	0.181	0.267	0.244	0.609

Note: Nourishment episodes post 1990 have been used to identify the nourished block groups. Demographics have been captured using ACS 2015-2019. The dependent variable is a categorical variable taking a value of 1 for a nourished block-group and 0 for non-nourished. Standard errors are clustered at the county level and reported in parentheses. Columns (1) and (2) include observations from Connecticut, South Carolina and Florida. Column (1) includes only demographic predictors. Column (2) adds long term measures of coastal risk. Columns (3)-(5) are based only on the observations from Florida. Column (3) adds an indicator for pre-1965 nourishment of a block-group. Column (5) replaces the block-group-level pre-1965 nourishment indicator with a county-level measure.

Table 4: Descriptive Statistics

A. Built Environment	Avalon (249.254 m)	Avalon (606.525 m)	Ocean City (625.049 m)	Ocean City (928.770 m)
Observations	514	1084	1330	1916
Nourished	278	623	734	1083
Non-nourished	236	461	596	833
Damaged Behind Nourished	47	123	640	908
Damaged Behind Non-nourished	26	33	559	765
B. Coastal Vulnerability	Avalon		Ocean City	
	Nourished	Non-nourished	Nourished	Non-nourished
Mean Wave Height (m)	1.2	1.2	1.2	1.2
Erosion (m/year)	-0.2	-0.2	0.5	0.5
Relative Sea-level Change (m/year)	3.3	3.3	3.85	3.8

Note: Panel A contains the descriptive data related to the built environment. The numbers in parenthesis corresponds to the optimal bandwidth for polynomials of degree one and two. Each observation is a building. Panel B contains the descriptive data related to coastal vulnerability.

Table 5: Regression Discontinuity Estimation

	Dependent variable: Damaged			
	Avalon		Ocean City	
	p=1	p=2	p=1	p=2
Nourished	-0.094	-0.131	-0.100	-0.106
	(0.042)	(0.041)	(0.038)	(0.047)
Observations	514	1084	1330	1916
MSE-bandwidth (m)	249.254	606.525	625.049	928.770
Mean	0.142	0.144	0.873	0.902

Note: The unit of analysis is an individual building. First two columns contain the results for the Avalon community nourishment and the last two columns contain the results for the Ocean City community. Estimates for first-degree polynomials are in columns 1 and 3 while those for second-degree polynomials are in columns 2 and 4. The optimal bandwidth was determined non-parametrically using the mean squared error. Robust standard errors are reported in parentheses.

7 Figures

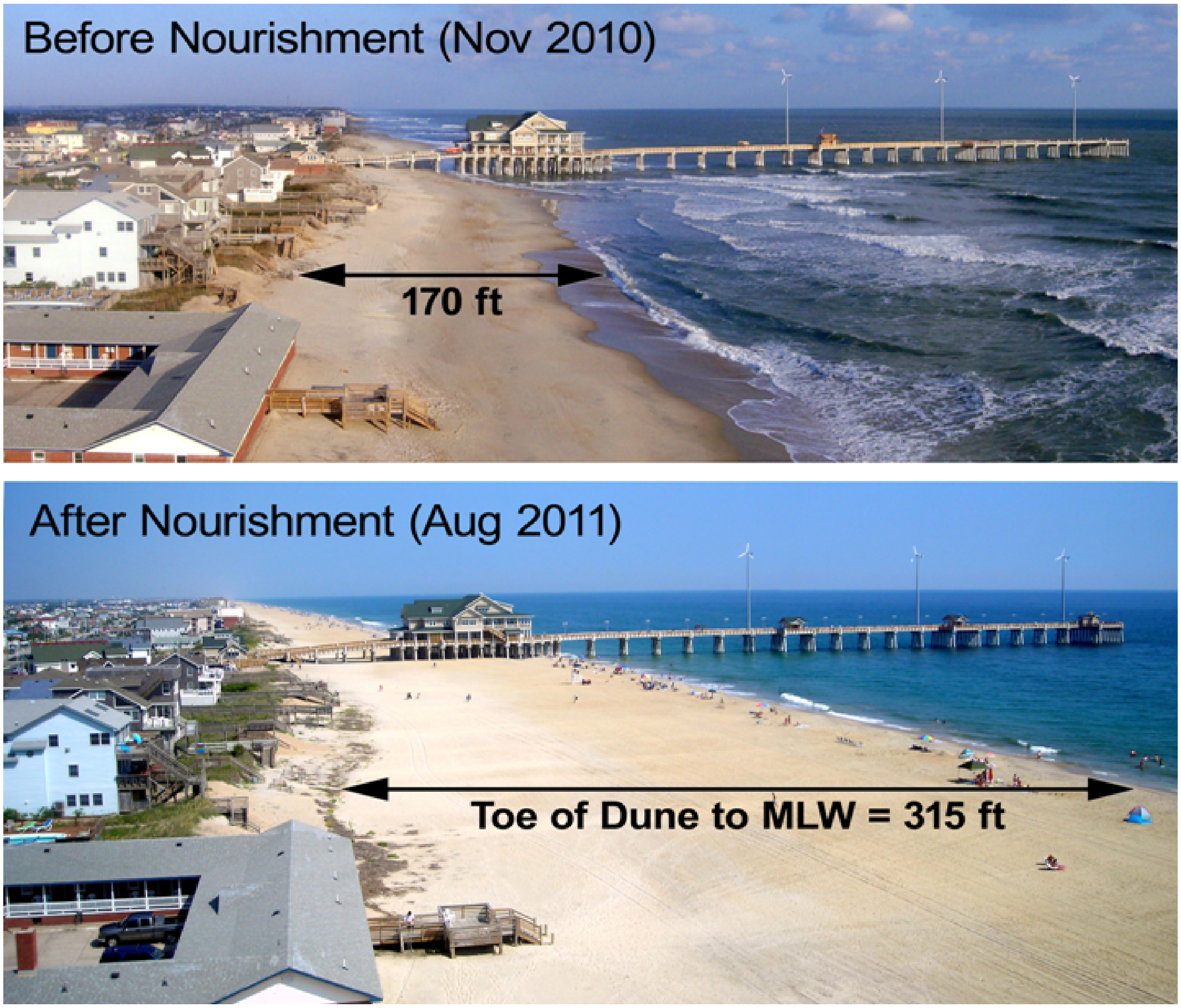


Figure 1: An Example of Beach Nourishment
Note: This image illustrates a beach nourishment project before and after implementation. **Source:** (Coastal Science & Engineering, n.d.).

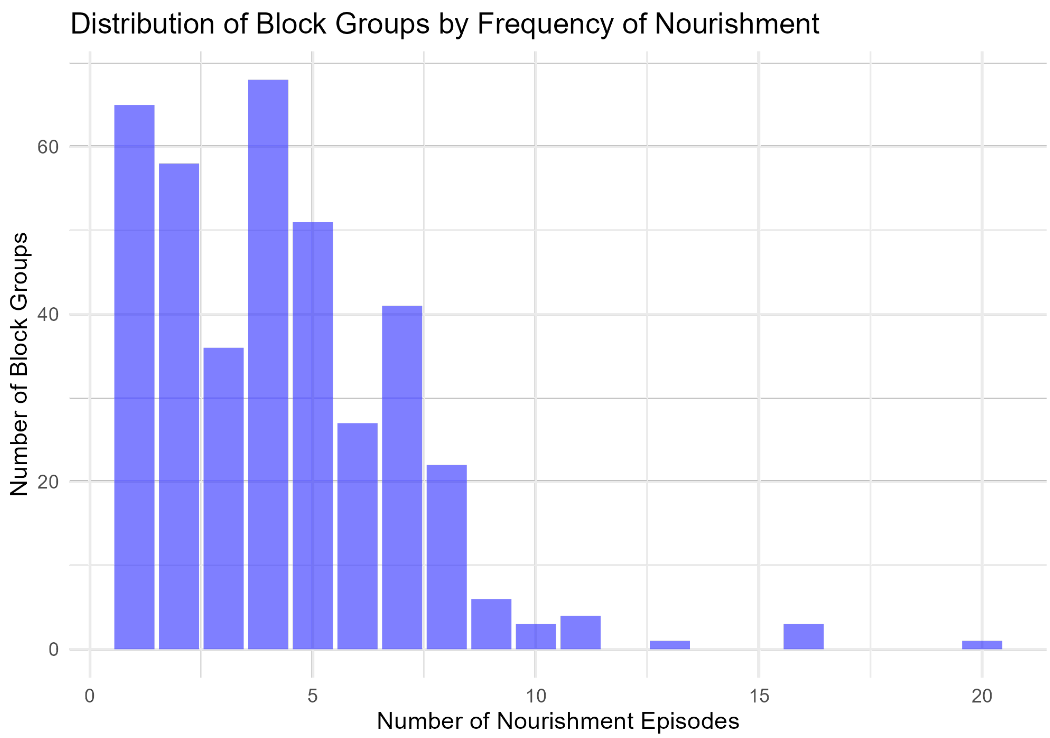


Figure 2: Distribution of Nourishment Episodes in Florida 1990-2022
Note: The figure shows the distribution of nourishment frequency in Florida from 1990 to 2022. The x-axis represents the number of nourishment episodes, while the y-axis represents the number of block groups.

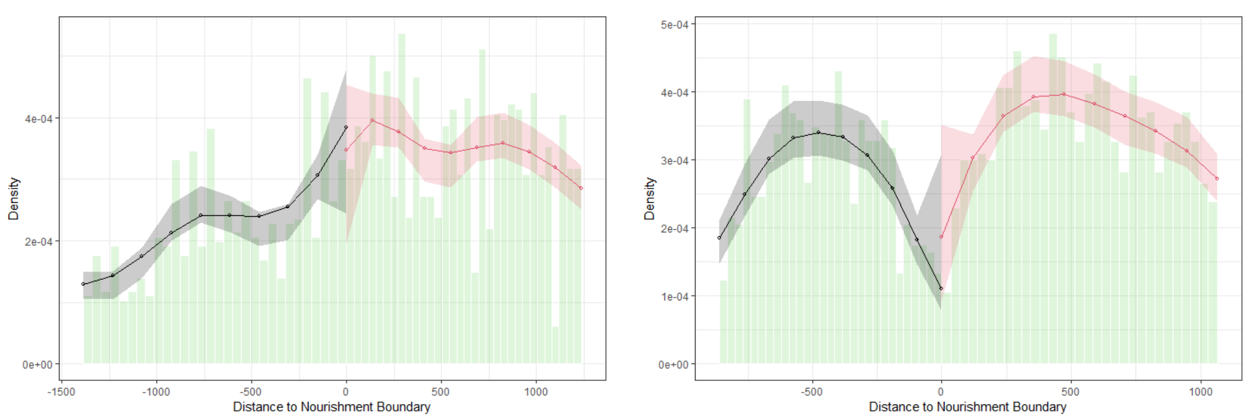


Figure 3: McCrary Density Test Plots
Note: The figure presents the results of the McCrary density test, which evaluates potential manipulation around the cutoff. The results show no evidence of a discontinuity in the density at the cutoff. Figure on the left is for Avalon and that on the right is for Ocean City.

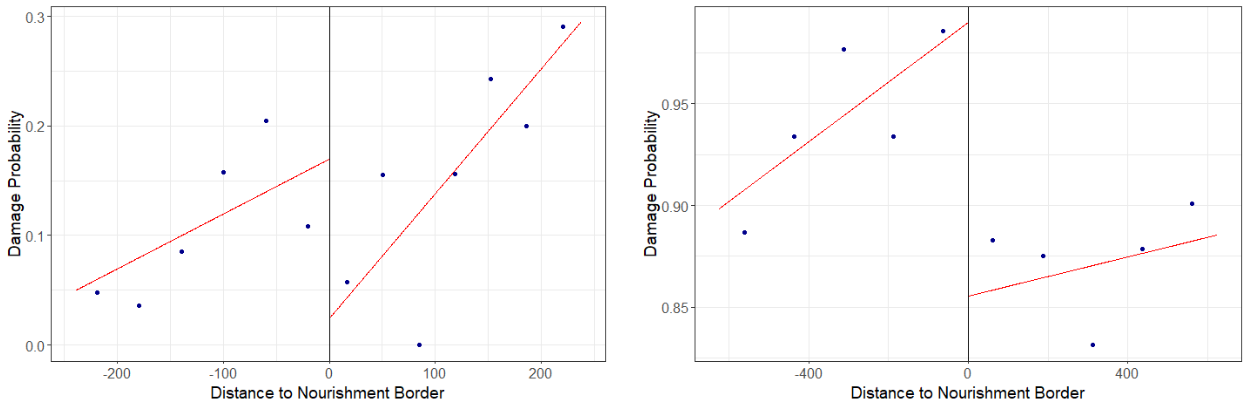


Figure 4: First-Degree Polynomial Regression Discontinuity Plots

Note: The figure depicts the first-degree polynomial fit in the optimal bandwidth. The optimal bandwidth was selected using the mean squared error optimal bandwidth selection method. The bins are based on the ISME-optimal evenly spaced method. Figure on the left is for Avalon and that on the right is for Ocean City.

8 Maps

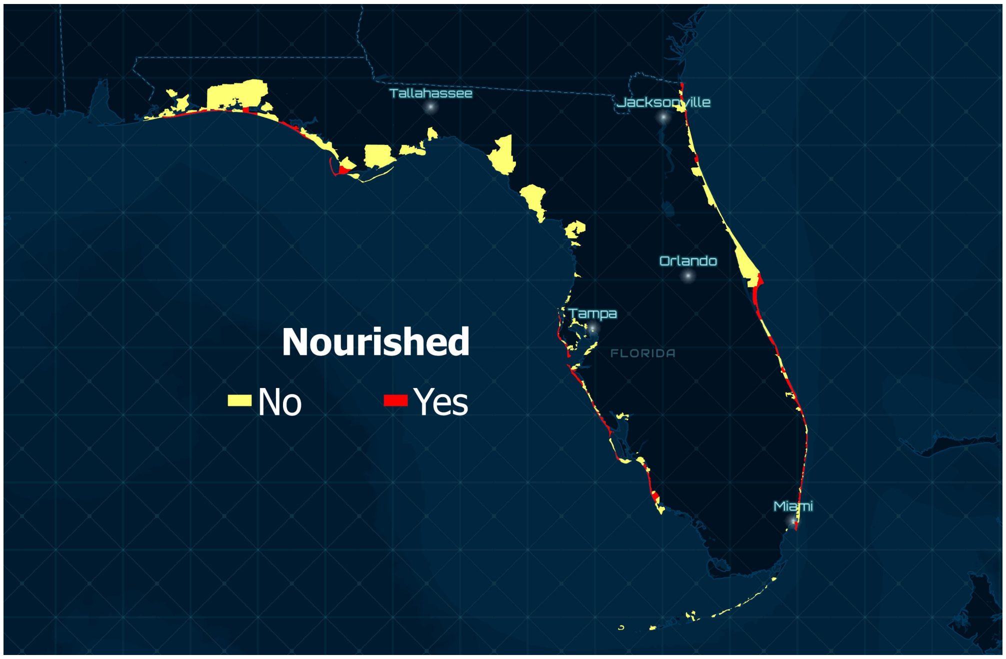
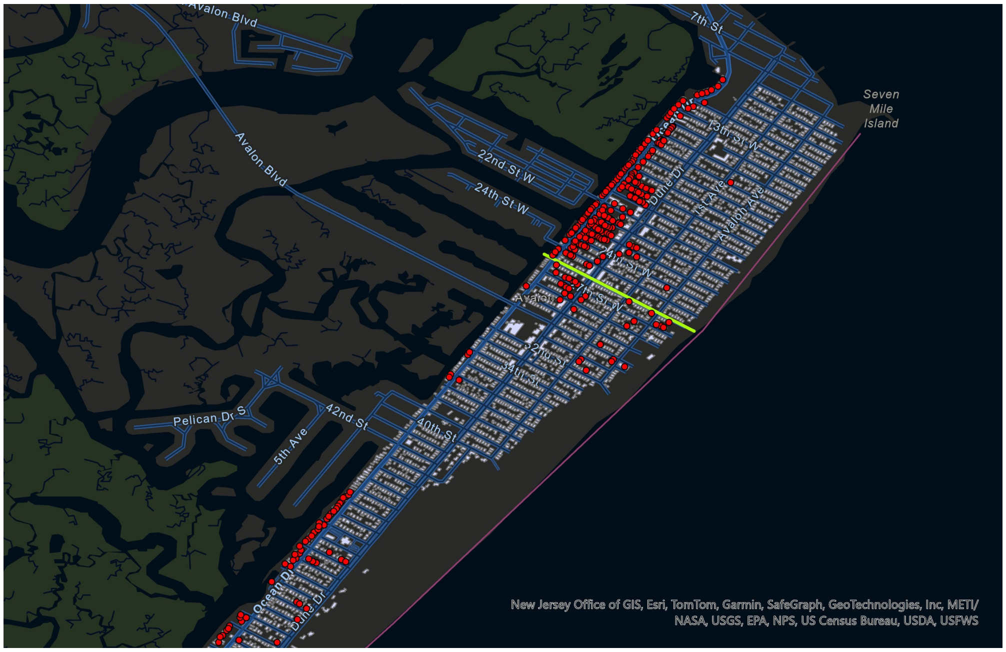
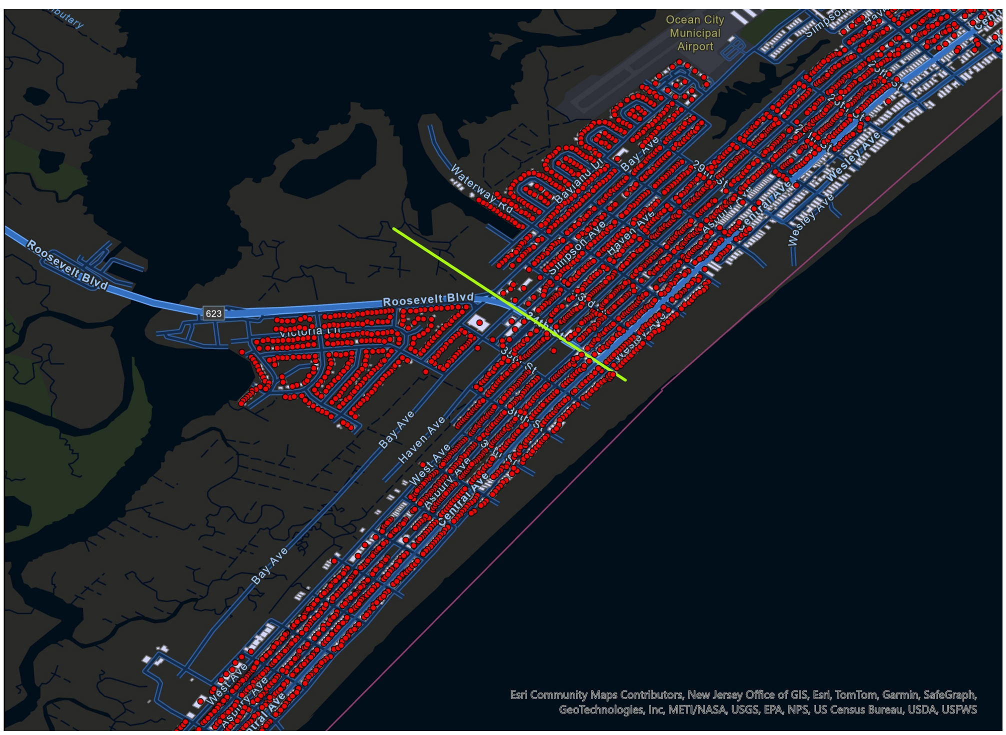


Figure 5: Map of Nourished and Non-Nourished Areas in Florida

Note: All block-groups that received nourishment between 1990 and 2023 are represented in red. The remaining block-groups with sandy beaches are in yellow. The count of nourished block-groups is 387 and the count of non-nourished block-groups is 636. Block-groups within 1000m from the beach line geometry have been considered.



Avalon Community



Ocean City Community

Figure 6: Study Areas for Effectiveness of Beach Nourishment

Note: The nourished section in both images is the area on the right of the nourishment discontinuity boundary, which is highlighted in green. The red points depict damages while the polygons show all the buildings in the area.

A Appendix

A.1 Out-of-Sample Prediction: South Carolina and Connecticut

Using data from Florida, I estimated the following logistic regression model predicting the likelihood of nourishment:

$$Nourished_i = \beta_0 + \beta_1 WhiteShare_i + \beta_2 ln(HouseholdIncome)_i + \beta_3 SLR_i + \epsilon_i \quad (3)$$

where $Nourished_i$ is a binary indicator on whether or not a block group received nourishment. $WhiteShare_i$ is the proportion of population that is White in the block-group and SLR_i is the rate of sea-level rise. i is a block-group.

I made out-of-sample predictions for block groups in Connecticut and South Carolina using the model estimates. The distribution of these probabilities are represented in Figure A1. The range of predicted probability is 0.0004-0.005 in Connecticut and 0.003-0.033 in South Carolina. The mean predicted probability is 0.002 in Connecticut and 0.011 in South Carolina.

Actual data on nourishment reveals that 13 out of 95 block-groups have been nourished in Connecticut while 73 out of 93 block-groups received nourishment in South Carolina. The predicted probabilities do not adequately capture the likelihood of nourishment in both the states. This suggests that factors beyond socio-demographics and long term rate of sea-level rise play a role in determining nourishment. These factors could be related to individual state level policies regarding funding coupled with local variation in demand for nourishment. It could also be related to the availability of off-shore sand sources, the distance and cost to obtain them (Qiu et al., 2020).

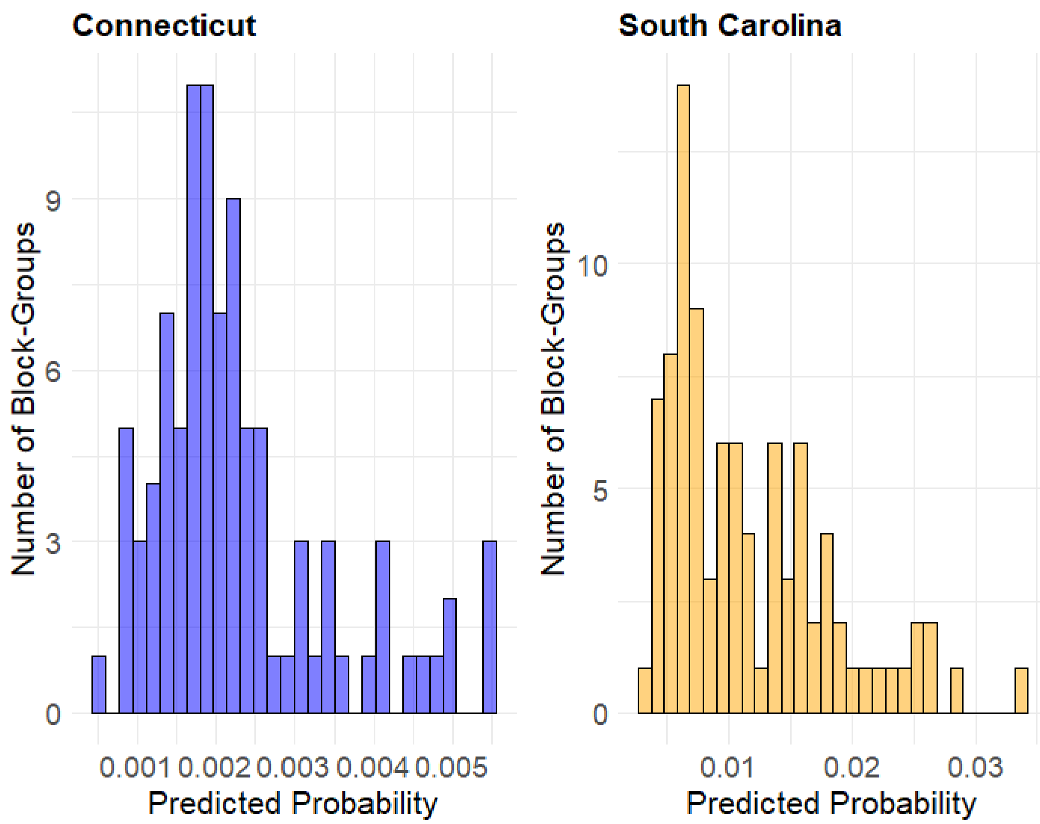


Figure A1: Distribution of Predicted Probabilities

Note: The figure plots the histogram of predicted nourishment probabilities for Connecticut (left) and South Carolina (right). The predicted probabilities were calculated using estimates from Equation 3 that was run on data from Florida.

A.2 Additional Tables

Table A1: Descriptive Statistics for Coastal Risk

Statistic	Coastal Vulnerability	Coastal Change
Mean	10.93	4.18
Min	1.22	0.00
Max	35.36	8.26
99th Percentile	28.28	6.52
95th Percentile	23.09	5.64
90th Percentile	20.00	5.23
5th Percentile	2.45	3.00

Note: This table contains the descriptive statistics for (1) long-term coastal vulnerability and (2) short-term coastal change likelihood. The coastal vulnerability uses data for the Atlantic coast. The statistics were calculated based the values assigned to block-groups within 1000m for (1). The short-term data are spatial polygons, so, all block-groups that intersected with it were included.

Table A2: Robustness Check: Donut Regression Discontinuity - Avalon

	Dependent variable:			
	Damaged			
	Avalon			
	(1)	(2)	(3)	(4)
Nourished	-0.094	-0.088	-0.131	-0.207
	(0.042)	(0.044)	(0.079)	(0.086)
Observations	514	510	402	357
MSE-bandwidth (m)	249.254	247.648	219.810	195.925
Excluded Radius (m)	5	10	15	20

Note: The unit of analysis is an individual building. Each column creates a donut ring in 5 meter increments up to 20 meters. The optimal bandwidth was determined non-parametrically using the mean squared error. Robust standard errors are reported in parentheses.

Table A3: Robustness Check: Donut Regression Discontinuity - Ocean City

	Dependent variable:			
	Damaged			
	Ocean City			
	(1)	(2)	(3)	(4)
Nourished	-0.085	-0.088	-0.091	-0.096
	(0.039)	(0.042)	(0.044)	(0.048)
Observations	1375	1326	1299	1269
MSE-bandwidth (m)	249.254	632.744	625.970	617.726
Excluded Radius (m)	20	30	40	50

Note: The unit of analysis is an individual building. Each column creates a donut ring in 10 meter increments up to 50 meters. The optimal bandwidth was determined non-parametrically using the mean squared error. Robust standard errors are reported in parentheses.

Table A4: Robustness Check: Different Bandwidths - Avalon

	Dependent variable:			
	Damaged			
	Avalon			
	(1)	(2)	(3)	(4)
Nourished	-0.094	-0.099	-0.094	-0.097
	(0.041)	(0.042)	(0.042)	(0.042)
Observations	720	514	514	514
Bandwidth Type	MSETWO	MSESUM	MSECOMB1	MSECOMB2

Note: The unit of analysis is an individual building. The optimal bandwidth was determined non-parametrically. All four bandwidths are MSE-optimal. Column (1) is the MSETWO bandwidth which allows different bandwidths to the left and right of the cut-off. Column (2) is the MSESUM bandwidth that minimizes the sum of the regression coefficients. Columns (3) contains the bandwidth corresponding to the minimum between MSE and MSESUM. Column (4) is the median of MSETWO, MSE, and MSESUM. Robust standard errors are reported in parentheses.

Table A5: Robustness Check: Different Bandwidths - Ocean City

	Dependent variable: Damaged			
	Ocean City			
	(1)	(2)	(3)	(4)
Nourished	-0.102	-0.083	-0.083	-0.099
	(0.037)	(0.041)	(0.041)	(0.039)
Observations	1359	1056	1056	1319
Bandwidth Type	MSETWO	MSESUM	MSECOMB1	MSECOMB2

Note: The unit of analysis is an individual building. The optimal bandwidth was determined non-parametrically. All four bandwidths are MSE-optimal. Column (1) is the MSETWO bandwidth which allows different bandwidths to the left and right of the cut-off. Column (2) is the MSESUM bandwidth that minimizes the sum of the regression coefficients. Columns (3) contains the bandwidth corresponding to the minimum between MSE and MSESUM. Column (4) is the median of MSETWO, MSE, and MSESUM. Robust standard errors are reported in parentheses.