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Community-Scale Beach Nourishment and Groin Construction Decisions Along Human-Modified Coasts : The Interplay Between Socioeconomics, Coordination, Tourism, and Shoreline Change

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COMMUNITY-SCALE BEACH NOURISHMENT AND GROIN CONSTRUCTION DECISIONS ALONG HUMAN-MODIFIED COASTS: THE INTERPLAY BETWEEN SOCIOECONOMICS, COORDINATION, TOURISM, AND SHORELINE CHANGE

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ABSTRACT

COMMUNITY-SCALE BEACH NOURISHMENT AND GROIN CONSTRUCTION DECISIONS ALONG HUMAN-MODIFIED COASTS: THE INTERPLAY BETWEEN SOCIOECONOMICS, COORDINATION, TOURISM, AND SHORELINE CHANGE

by Arye M. Janoff

In response to coastal erosion driven by storms, sea-level rise, and local gradients in sediment supply, communities defend their homes and maintain beach recreation by widening beaches via soft engineering (i.e., beach nourishment) or hard engineering (i.e., groins). Past research has found that, at regional scales, the net effect of these interventions has in many cases not only counteracted historically observed beach erosion, but has reversed erosional trends, on average shifting shorelines seaward. While groins trap sediments locally at and upcoast of the structure relative to the direction of alongshore transport, however, they often have adverse downcoast impacts, resulting in heightened erosion and forcing communities to respond with new engineering measures or by abandoning their beachfront properties. This research aims to understand the key drivers of community-scale coastal management decisions. Toward this, I developed a model that couples natural coastal dynamics (i.e., geomorphology) with the economics of beach management, which is used to compare different protection schemes to determine their economic consequences. In the first chapter, I explore the effect of inter-community

beach nourishment coordination, and find that coordination is most important economically for both communities when they have different property values because the less wealthy town tends to nourish more than necessary if they preserve their beach alone. In chapter two, I perform regression analyses with field data on community-scale nourishment, socioeconomics, and geomorphic conditions in New Jersey, and find that both a community's beachfront wealth and its proportion of commercial property value (i.e., a proxy for its level of tourism) help explain its beach nourishment decisions. In chapter three, I employ the geomorphic-economic model in communities downdrift of a groin subject to heightened beach erosion, and find that the community's beachfront property value and its size (a proxy for its tax base) help explain how (i.e., nourishment, groin, both, or neither) and when it will respond. In a scenario in which climate change causes shorelines to retreat more rapidly and the overexploitation of sand/rock resources dramatically increases its cost, less wealthy communities may be unable to keep pace with the changing conditions and instead abandon their properties altogether, leaving only the wealthiest homeowners along the coast. Furthermore, tourism-centric communities facing these threats may respond with different nourishment approaches to meet recreational demand compared to their residential-dominated counterparts. Finally, for communities subject to groin-induced erosion, it is possible that the historical transition away from groins to beach nourishment as the main management response over the last half century could be reversed in the future, and groins could again become the more commonplace approach as communities adapt to sea-level rise. Such divergent outcomes based upon wealth disparity, extent of a local tourism economy, and spatial

proximity to groin-induced erosion should be considered in future policy development at the state and federal levels.

Keywords; coupled natural-human systems, coastal geomorphology, beach nourishment, groin downdrift erosion, spatial-dynamic feedbacks, geo-economics, game theory, coastal tourism, coastal management decisions.

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DEDICATION

I dedicate this dissertation to my paternal grandfather, Dr. Aaron Janoff (January 29, 1930—September 11, 1988), a research pathologist and professor at Stony Brook University, whose groundbreaking discoveries on the link between emphysema and smoking helped inform our understanding of its respiratory consequences. I was unfortunate to have missed his acquaintance but fortunate to have his inherited his scientific constitution, a thirst for knowledge, his deep love for the sea, and most importantly, an unwavering devotion to family. I am inspired by his career and hope my accomplishments will one day match his. I stand on the shoulders of my giant, “Poppy”, with eternal gratitude.

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BACKGROUND AND OBJECTIVES

The New Jersey coast, spanning 127 miles from the northern barrier spit of Sandy Hook and the eroding bluffs of Monmouth County, through the central and southern barrier island complexes, to the headlands of Cape May is almost entirely developed with boardwalks and beachfront communities (Ashley, 1986; Dahlgren, 1977; Newell et al., 1988). Summers at the Jersey Shore have been a mainstay for tourists from all over the state and world, touting some of the oldest seaside resorts in the country (Weiss, 2004). From these seasonal crowds have emerged various cultural landmarks such as the Stone Pony and Convention Hall in Asbury Park, Jenkinson's Boardwalk in Point Pleasant Beach, Casino Pier in Seaside Heights, Steel Pier and the Casino Industry in Atlantic City, Lucy the Elephant in Margate City, Morey's Pier and the tramcar in Wildwood, and the Victorian-style bed and breakfasts and Congress Hall in Cape May (Rosenberg, 2019; Simm, 2019).

These attractions and an increasing demand for beach vacation homes has led to widespread infrastructural development (Crossett et al., 2004). Communities were settled and incorporated to provide public services, and as the densely populated nearby urban centers of New York City and Philadelphia continued to grow in the first half of the 20th century, more people sought refuge from the urban heat in the cool sea breezes and in the waves on the Jersey Shore (Capuzzo, 2003). Eventually, the coastal system became heavily modified, with homes and promenades vying for the best ocean views lining the former foredune environments. Storms and coastal erosion were unplanned for and unmitigated, however, and rather than rethink these beachfront investments after suffering significant property damages, many of New Jersey's communities sought to protect their infrastructure through beach management, eventually requiring help from the State and Federal governments (Psuty and Ofiara, 2002; USACE, 2012).

Over the last half-century, the scale of these human interventions has grown ever larger, creating a unique and unknown system state: the urbanized coast. This effect, coined the “new-jerseyization” of the shoreline by Orrin Pilkey (Pilkey and Neal, 1992), describes a human-adapted system that behaves differently from its natural state, not only due to the loss of various natural components such as the dune, marsh, and maritime forest environments, but also due to the emergent feedbacks between the natural dynamics and human interventions (Nordstrom, 1994; Nordstrom and Jackson, 1995).

Living close to the ocean serves as an amenity, creating the base for local and tourist economies. There is an inherent desire to protect private and public infrastructure, including properties, roads, boardwalks, water and gas lines, sewers, stormwater infrastructure, communications systems, etc. (Johnston et al., 2014). Beaches and oceans have high recreational values, providing public goods and services for surfers, kite-surfers, wind-surfers, swimmers, kayakers, scuba-divers, snorkelers, birders, sunbathers, and others (Ariza et al., 2014; Sano et al., 2011). In addition, many coastal homeowners conserve their properties for future generations, implying high bequest values (Silberman et al., 1992). Without question, humans are attracted to coastal life.

Property owners and coastal managers have utilized soft and hard engineering to protect properties and to sustain beach recreation (Douglass and Krolak, 2008; van Rijn, 2011). Soft engineering involves external sand placement, known as replenishment, nourishment, or beach fill, to widen beaches artificially (Hoagland et al., 2012). This ‘soft’ approach may require regular maintenance as sand spreads alongshore, however, resulting in the need for periodic re-nourishment (Landry, 2004; Smith et al., 2009). Hard engineering involves the construction of immovable objects, such as shore-perpendicular groins, which slow alongshore currents to deposit sediments locally at and updrift of the object (Kraus and Batten, 2007; Mestanza et al., 2018; Valsamidis and Reeve, 2017).

On aggregate, these practices have not only masked regional historical trends in coastal erosion but also led to net shoreline accretion in developed areas along the U.S. East and Gulf coasts, especially in New Jersey (Armstrong and Lazarus, 2019, Hapke et al., 2013). These geomorphic consequences have, in turn, capitalized into the coastal real estate market, which has necessitated further beach management (Armstrong et al., 2016). Additionally, many high tourism zones such as Asbury Park, Long Branch, and Seaside Heights have benefitted in recent years from extensive coastal zone management, providing wider beaches for recreation and more investment in the hospitality and service industries (Psuty and Ofiara, 2002).

Research on the outcomes of heavily developed coasts is still in its infancy and the key drivers of these system dynamics are relatively unexplored. Moreover, the range of feedbacks between private residential properties, commercial development, and natural geomorphological changes along the coast requires a deeper understanding. This dissertation will seek to address the interplay between the natural and human processes of heavily developed coasts, and more fundamentally, to identify the main factors that might help explain the cumulative evolution of such coupled systems.

We focus these efforts on both hard (i.e., groins) and soft (i.e., beach nourishment) engineering practices, on various community types (i.e., residential-dominated vs. commercial-dominated), and on different spatial scales (i.e., single community vs. multi-community interactions). The research proposed in this dissertation can be divided into three main objectives:

I. Objective 1: Explore the role of coordination between neighboring communities in how they choose their beach nourishment programs and the resultant geomorphic and economic consequences of decisions made jointly vs. independently
II. Objective 2: Determine the interplay among socioeconomics, tourism, and geomorphology to understand how commercial vs. residential development controls community-scale beach nourishment decisions differently
III. Objective 3: Couple geomorphology and socioeconomics to account for groin downdrift erosion and explore the key parameters that govern downdrift community responses in sediment-starved locations

Taken together, this work will help to describe how a coupled natural-human system such as the New Jersey coast evolves over decadal to centennial timescales and on sub-regional to regional space scales. This dissertation research will also add to the body of knowledge on the dynamics of developed coasts with an array of human-scale components and intervention types that until now have been unexplored. More broadly, this work will not only benefit our collective scientific understanding of coupled coastal system dynamics, but will also help to inform local managers, state planners, multi-state coalitions, federal policymakers, and flood insurance markets as we face more rapid sea-level-rise rates and changing sand resource economic conditions associated with climate change in the future.

CHAPTER 1 – FROM COASTAL RETREAT TO SEAWARD GROWTH: EMERGENT BEHAVIORS FROM PAIRED COMMUNITY BEACH NOURISHMENT CHOICES

The contents of this chapter appear in:

Janoff, A., Lorenzo-Trueba, J., Hoagland, P., Jin, D., & Ashton, A. D. (2020). From Coastal Retreat to Seaward Growth: Emergent Behaviors from Paired Community Beach Nourishment Choices. *Earth and Space Science Open Archive ESSOAr*.

1.0 Summary

Coastal communities facing shoreline erosion preserve their beaches both for recreation and for property protection. One approach is nourishment, the placement of externally-sourced sand to increase the beach's width, forming an ephemeral protrusion that requires periodic re-nourishment. Nourishments add value to beachfront properties, thereby affecting re-nourishment choices for an individual community. However, the shoreline represents an alongshore-connected system, such that morphodynamics in one community are influenced by actions in neighboring communities. Prior research suggests coordinated nourishment decisions between neighbors were economically optimal, though many real-world communities have failed to coordinate, and the geomorphic consequences of which are unknown. Toward understanding this geomorphic-economic relationship, we develop a coupled model representing two neighboring communities and an adjacent non-managed shoreline. Within this framework, we examine scenarios where communities coordinate nourishment choices to maximize their joint net benefit versus scenarios where decision-making is uncoordinated such that communities aim to maximize their independent net benefits. We examine how community-scale property values affect choices produced by each management scheme and the economic importance of coordinating. The geo-economic model produces four behaviors based on nourishment frequency: seaward growth, hold the line, slow retreat, and full retreat. Under current conditions, coordination is strongly beneficial for wealth-asymmetric systems, where less wealthy communities acting alone risk nourishing more than necessary relative to their optimal frequency under coordination. For a future

scenario, with increased material costs and background erosion due to sea-level rise, less wealthy communities might be unable to afford nourishing their beach independently and thus lose their beachfront properties.

1.1 Introduction

Beach nourishment involves dredging sediment from external sources to deposit locally in order to widen beaches (Hoagland et al., 2012; Lazarus et al., 2011; Smith et al., 2009). As the predominant form of beach maintenance along the U.S. east coast since the 1960's, this practice has not only masked regional historical trends in coastal erosion but also led to net shoreline accretion in developed areas along the U.S. East and Gulf coasts, e.g. New York and New Jersey (Armstrong & Lazarus, 2019; Hapke et al., 2013). While communities or groups of communities often nourish on a local scale, these sudden increases in beach width are subject to heightened erosion due to alongshore and cross-shore sediment transport, thereby diminishing the volume of sand placed by these communities over time and thus, the efficiency (sand lost relative to the sand added) of the nourishment project as well. When combined with neighboring actions, regional nourishment comprises a dynamical system (Ells & Murray, 2012).

Aggregate shoreline trends do not always explain community-scale nourishment choices, however. While many communities have widened their beaches since initiating maintenance activities, some have held their shoreline position (Hapke et al., 2013). In extreme cases, communities have lost individual properties or have abandoned entire municipalities (Kobell, 2014; Tischler, 2006). This range of outcomes highlights the location-specific variability of beach nourishment decisions, potentially influenced by underlying differences in geology and socioeconomics that affect the efficiency or feasibility of nourishment projects, and necessitates a deeper analysis of the dynamic processes by which communities and coastlines interact, accounting for both human and natural components.

Previous work found a positive feedback between coastal development and nourishment effort, whereby widened beaches add value to adjacent properties and compel future beach nourishments (Armstrong et al., 2016; McNamara et al., 2015). There is limited knowledge on what initially triggers this geomorphic-economic feedback, and what role, if any, the distribution of alongshore wealth might play in this feedback. Recent work has suggested that the level of coordination among coastal neighbors could partially explain these emergent outcomes (Gopalakrishnan et al., 2016; Smith et al., 2015).

Many studies have explored the economic effects of coordinated vs. independent behavior (Brandts & Schram, 2001; Cason & Gangadharan, 2015; Gachter et al., 2017; Metzner et al., 2006), but research on its application to coastal dynamics is still in its infancy. Empirical studies in behavioral economics use rule-based games to explore how humans interact (Bohnet & Frey, 1999; Hoffman et al., 1996). In one such example, a public goods game, two players contribute toward a shared good, and enjoy that good regardless of their contribution levels. Each player may choose not to contribute but still enjoy the good, thus benefiting from the other player's effort and maximizing self-utility. Contributors who compare their payoff to the "free-rider" often react by giving less out of spite, resulting in an economically suboptimal outcome in subsequent rounds of the game (Cason et al., 2004).

Beach nourishment interactions among coastal neighboring communities follow these economic dynamics, including feedbacks between human "players" and their natural environment. In response to geomorphic processes and background erosion, coastal communities actively maintain their beaches to protect nearby properties and infrastructure (Johnston et al., 2014), for recreational activities such as surfing, swimming, or sunbathing (Lazarow, 2007; Wagner et al., 2011), for providing ecosystem services including dune and intertidal habitats (Landry & Whitehead, 2015; Pompe & Rinehart, 1995), and for supporting local tourism economies (King, 1999).

Properties adjacent to the beach capitalize these services into their value. A small but growing literature on hedonic pricing has shown that property owners benefit economically from local beach widening due to human intervention (Gopalakrishnan et al., 2011; Landry & Hindsley, 2011; Pompe & Rinehart, 1995). Ocean currents driven by waves redistribute this sand along the coast between neighboring communities, implying that beach nourishment is a quasi-public good where down flow communities cannot be excluded. Where communities border natural coast, tidal inlets, or other sinks for nourishment sand, these currents might also reduce the physical efficiency of nourishment projects by removing sand from the active beach system. Using a simplified game-theoretic framework, we explored how socioeconomic relationships drive nourishment decisions and how these management outcomes and their corresponding nourishment efficiencies might differ if communities coordinate their beach maintenance programs or choose strategies independently.

Historically, coastal communities have not coordinated their nourishment plans (Gopalakrishnan et al., 2016; Lazarus et al., 2011). Records of past beach maintenance projects indicate that local governments and private sponsors fund many such projects, most of which have occurred in New Jersey and Florida (Pilkey & Clayton, 1989; PSDS, 2019). One example is Ocean City, NJ, which pumped sand onto its beaches more than 30 times between 1952 and 1982 using city funds and a city-owned dredge (Pilkey & Clayton, 1987). Similarly, Captiva Island, FL states on their Erosion Prevention District website, "(the) residents and businesses on Captiva Island have successfully managed their beaches for over 50 years" (Captiva Erosion Prevention District, 2020).

This decentralized behavior often has both local and non-local effects (Beasley & Dundas, 2018; Ells & Murray, 2012; Goodrow & Procopio, 2018; Hillyer, 1996), and Gopalakrishnan et al. (2016) suggest this has resulted in narrower beaches due to the effort-reducing feedback described earlier, leading to an economically suboptimal outcome to alongshore coordination. In other words, cooperation amongst communities represents their economically optimal solution. Further, there is no incentive for communities acting alone to increase their nourishment effort because doing so would mean they would lose more sand from their beach due to the higher angle formed by their seaward protrusion, effectively reducing their nourishment project's physical efficiency as well. These historically uncoordinated beach nourishments may have caused accidental geoengineering of the coastal system that differs from the natural dynamics resulting in narrower beaches (Smith et al., 2015). Indeed, Armstrong et al. (2019) and Hapke et al. (2013) detected this anthropogenic signature, finding that beaches along the US east coast have accreted seaward since beach nourishment began in earnest in the 1960s.

While anecdotal evidence indicates that communities have exhibited uncoordinated behavior, intuition from game theory and past research would suggest that this behavior results in narrower beaches. Yet, the outcome of widened beaches is both observable and quantifiable; which suggests the question: is uncoordinated or coordinated beach nourishment the cause of this coastal-anthropic signature? Perhaps it is not mutually exclusive but depends on certain conditions. If so, what are the underlying conditions that drive cooperation?

In this paper, we construct an idealized modeling framework that couples cross-shore and alongshore geodynamics with changes in coastal property values, and we explore how community-scale economic characteristics control beach nourishment decisions. We speculate that the property value distribution between coastal neighbors determines the importance of coordinating nourishment plans, and that alongshore wealth asymmetry could control the emergent system behaviors. These differences could explain the broad array of outcomes along the U.S. East and Gulf coasts, ranging from seaward growth to retreating shorelines, and they could provide insight into the key drivers of past coastal behavior.

It will be especially important to understand the future evolution of these heavily developed coasts under different coordination schemes when faced with more extreme conditions, including more rapid sea-level-rise rates and higher sand resource costs for completing beach nourishment projects. Exploring how these future changes might affect community- and regional-scale behaviors using our geo-economic framework could help address these knowledge gaps, and inform coastal policymakers and managers dealing with unique challenges associated with global climate change.

1.2 Mathematical Framework

We explore beach nourishment decisions for two alongshore-neighboring communities with an idealized geometry as depicted in Figure 1.1. The model domain includes neighboring communities $i=1,2$ that can nourish and an alongshore-adjacent boundary region $i=3$ that cannot nourish, each with alongshore length s_i. Each community has an average shoreline location $x_{S,i}$ and shoreface toe location $x_{T,i}$. The geometric relationship comprising these boundaries along with the depth of closure (shoreface depth) D form the shoreface slope θ_i:

$$\theta_i(t) = \frac{D}{x_{T,i}(t) - x_{S,i}(t)}. \tag{1.1}$$

The property setback $x_{H,i}$ delineates the community's seaward limit, and along with its shoreline, bounds the community's beach width w_i, i.e., $w_i = x_{S,i} - x_{H,i}$. Given this idealized geometry, we can describe the system with two state variables per alongshore community: the location of the shoreline $x_{S,i}$ and the shoreface toe $x_{T,i}$.

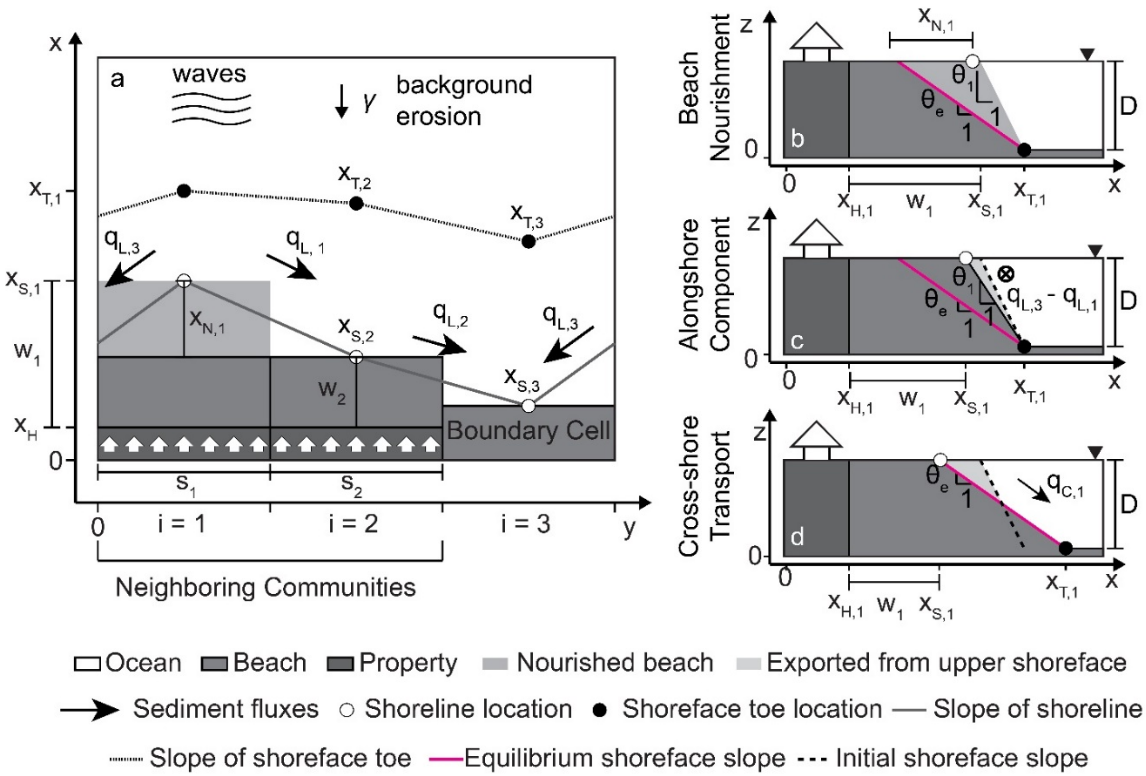

Figure 1.1. (a) Model setup planview, (b) cross-section illustrating beach nourishment, and (c) the alongshore and (d) the cross-shore transport that occurs due to this seaward protrusion.

To describe the dynamics of this system, we account for both natural processes, including cross-shore and alongshore sediment transport, and human processes, including beach nourishment practices. Communities respond to a background erosion rate γ by nourishing their beaches with a fixed nourishment width $x_{N,i}$, with the human intervention thus forming a shoreline protrusion. A low-angle wave climate flattens these beach nourishments via natural processes. Alongshore sediment flux $q_{L,i}$ is directed from seaward-relative communities to landward-relative communities, with an alongshore distance between communities $(s_i + s_{i+1})/2$. We highlight a representative example of the flux direction between communities in Figure 1, but in theory the alongshore transport can occur in either direction depending on the shoreline's configuration.

The boundary cell represents a natural coastline in which no nourishment occurs. A periodic boundary condition at the edges of the system domain means that any sediment leaving the system at one boundary re-enters at the other boundary. When one or both communities nourish, sediment from these protrusions transports alongshore from the communities to the boundary cell, which therefore serves as a sediment sink for nourishment sand. Nourishment events at the shoreline also trigger cross-shore sediment flux $q_{C,i}$ due to the over-steepened shoreface slope, directing sand from the shoreline to the shoreface toe. The balance between the volume of nourishment sand and the sand lost alongshore to the boundary cell, cross-shore to the toe, or removed from the system due to background erosion determine the physical efficiency of the nourishment project.

A two-community system with a boundary cell is analyzed here. The governing equations are presented in general form allowing an extension to *n* communities. We characterize the geometry of each community (and the adjacent boundary coast) with the average shoreline location $x_{S,\mathrm{i}}$ and shoreface toe $x_{T,i}$, which allows us to describe the evolution of the system using six ordinary differential equations.

We present these geodynamics in the first section below, followed by the coupling between physical processes and community behaviors. We then discuss the control problem by which communities choose nourishment actions, and we propose a numerical solution to this problem.

1.2.1 Beach and Shoreface Morphodynamics

We compute the alongshore-averaged component of sediment flux $q_{L,i}$ using the difference in average shoreline locations $x_{s,i} - x_{s,i+1}$ between neighboring communities i and $i+1$:

$$q_{L,i}(t) = K_1 \cdot \frac{(x_{S,i}(t) - x_{S,i+1}(t))}{(s_i + s_{i+1})/2}, \tag{1.2}$$

where K_1 is the alongshore flux coefficient. This equation, which assumes the low-wave-angle case for a standard CERC formula (Coastal Engineering Research Center, 1984), represents an average alongshore flux between each community based on the angle formed by the two shoreline locations. This shoreline angle controls both the magnitude and the direction of alongshore sediment transport, given by equation 1.2.

Widening a beach via nourishment steepens the beach's slope (i.e., shoreface) relative to its equilibrium profile (Dean, 1977, 1991; Miselis & Lorenzo-Trueba, 2017), which triggers cross-shore sediment transport. The shoreface flux $q_{C,i}$ is the cross-shore component of sediment transport based on its slope θ_i relative to its equilibrium profile θ_{eq}:

$$q_{C,i}(t) = K_2 \cdot \left(\theta_i(t) - \theta_{eq}\right), \tag{1.3}$$

where K_2 is the shoreface flux coefficient. When the shoreface is steeper than its equilibrium profile (i.e., $\theta_i > \theta_{eq}$), sand moves from the upper shoreface to the lower shoreface, whereas the opposite is true if the shoreface has a milder slope than its equilibrium profile (i.e., $\theta_i < \theta_{eq}$).

Changes in shoreline position $x_{S,i}$ are computed using the discretized ordinary differential equation $\Delta x_{s,i}/\Delta t$ for each cell:

$$\frac{\Delta x_{S,i}(t)}{\Delta t} = \frac{2 \cdot \left(q_{L,i-1}(t) - q_{L,i}(t)\right)}{s_i} - \frac{4 \cdot q_{C,i}(t)}{D} - \gamma + N_i\left(x_{N,i}, R\right), \tag{1.4}$$

where $q_{L,i}$ and $q_{C,i}$ are given by equations (1.2) and (1.3)[1]. The nourishment term N_i is a function representing intermittent nourishment with a fixed cross-shore width $x_{N,i}$ and rotation length R_i (time interval between periodic nourishment) (Smith et al., 2009).

We assume the nourishment function N_i to be discrete in order to capture the time-specific costs of each sand placement. Nourishment events occur when the time function equals a multiple j of the rotation length R_i with a subsequent cross-shore magnitude $x_{N,i}$:

$$N_i^*(t, R_i) = \begin{cases} x_{N,i}; & if\ t = R_i \cdot \sum_{j=1}^{h_i} j \\ 0; & else \end{cases}, \tag{1.5}$$

where h_i is the number of nourishment episodes per community. We only apply the nourishment term N_i in equation 1.4 for interior communities who nourish. The term N_i is set to zero in the boundary cell $i = 3$, which represents a natural nearby coastline.

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[1] The ordinary differential equation for the shoreline location is based on previous work that has tested the effect of alongshore (Ashton et al., 2006a, 2006b) and cross-shore (Dean, 1977, 1991) dynamics on shoreline changes using field observations. Given that this framework assumes both alongshore and cross-shore mass balance, the numerical solution is grounded in the principles of physics as employed in previous literature (Falqués, 2003; Williams et al., 2013). Finally, the numerical solution for the shoreline was also validated using the analytical solution for a simplified version of this ordinary differential equation for one community (see Kraus and Batten, 2007), and the two solutions were found to be in agreement.

A second discretized ordinary differential equation $\Delta x_{T,i}/\Delta t$ simulates the evolution of the shoreface toe location $x_{T,i}$ as a function of the cross-shore sediment flux $q_{C,i}$, the shoreface depth D, and the background erosion rate γ:

$$\frac{\Delta x_{T,i}(t)}{\Delta t} = \frac{4 \cdot q_{C,i}(t)}{D} - \gamma. \tag{1.6}$$

These geodynamics can then be used to describe the physical efficiency of the nourishment projects, or in other words, the volume of sand retained in the beach system relative to the volume of sand pumped onto the beach via nourishment activities. We track the volume of sediment lost from the nourishment projects q_{Loss} in both communities based on the cross-shore flux q_C, the alongshore flux q_L and the background erosion rate γ:

$$q_{Loss}(t) = (s_1 + s_2) \cdot D_T \cdot \gamma + 4 \cdot \left(s_1 \cdot q_{C,1}(t) + s_2 \cdot q_{C,2}(t)\right) + 2 \cdot D_T \cdot \left(q_{L,3}(t) - q_{L,2}(t)\right). \tag{1.7}$$

The total volume of sand lost over the course of a model run V_{Loss} is the integration of this q_{Loss} through time:

$$V_{Loss} = \int_0^{t_f} q_{Loss}(t) \cdot dt, \tag{1.8}$$

where tf is the planning time horizon.

The total volume of sand added by the nourishment projects $V_{Nourish}$ is the discrete sum of all nourishment volumes based on the cross-shore project widths $x_{N,1}$ and $x_{N,2}$, and the rotation lengths R_1 and R_2 in communities one and two:

$$V_{Nourish} = \frac{D_T}{2} \cdot \left(\frac{t_f \cdot x_{N,1} \cdot s_1}{R_1} + \frac{t_f \cdot x_{N,2} \cdot s_2}{R_2} \right). \tag{1.9}$$

The efficiency of the nourishment project E can then be determined by the balance between the volume nourished $V_{Nourish}$ and the volume lost V_{Loss}:

$$E = \frac{V_{Nourish}}{V_{Nourish} + V_{Loss}}. \tag{1.10}$$

1.2.2 Economic Model

The system's physical components feed into a socioeconomic framework used to compare the outcomes of different nourishment choices (i.e., rotation lengths). Toward this end, beaches are assumed to provide both protective and recreational benefits for coastal communities (Jin et al., 2015; Landry et al., 2003; McNamara & Keeler, 2013; McNamara et al., 2015; Pompe & Rinehart, 1995, Simmons et al., 2002). When analyzing the benefit for the whole community, we assume that an average beach width borders all beachfront homes in the community with an average property value. We assume that each community is the relevant decision-maker.

The value of beach width w_i is capitalized into the benefit function B_i for community i as:

$$B_i(t) = \alpha_i \cdot \rho \cdot \left(\frac{w_i(t)}{w_\alpha} \right)^\beta, \tag{1.11}$$

where α_i is the baseline property value that includes all of a home's amenities except for that of the beach's width (i.e., the number of bedrooms/bathrooms, square footage, lot acreage, etc.) as well as the number of alongshore properties per community, ρ is the discount rate that weights future vs. present values and can be interpreted here as the capitalization rate through time, and w_α is the baseline width beyond which the beach adds value to the front property.

Note that $\alpha_i \cdot \rho$ is the baseline rental value or capital added per unit time for the average home in community i. The positive parameter β describes the effects on B_i of unit changes in beach width. The sum of all property values in a community represents the community's total wealth. Assuming each community has the same number of homes, the difference in average property value reflects the difference in total wealth between neighboring communities. This relationship, therefore, captures how beach morphodynamic processes affect a community's level of wealth.

In addition to the benefits of widening a beach, communities incur a cost for their nourishment project C_i based on the fixed cost c_f (for permitting, equipment, labor, etc.) and the variable cost ϕ_N (i.e., volumetric price of sand resource):

$$C_i(t) = c_f + \phi_N \cdot \frac{1}{2} \cdot x_{N,i} \cdot D \cdot s_i \ , \tag{1.12}$$

where nourishment volume is a triangular prism formed by the cross-shore width $x_{N,i}$, the depth of closure D, and the alongshore project length s_i (Figure 1.1). Non-nourishing communities do not incur any costs, i.e., $C_i = 0$.

1.2.3 Optimization: Nourishment Rotation Length for Coordination and Non-Coordination

We define the net benefit NB_i as the sum of continuous benefits B_i (Equation 1.11) and discrete costs C_i (Equation 1.12) discounted by a representative rate ρ over a planning time horizon t_f:

$$NBi = \int_0^{t_f} B_i(t) \cdot e^{-\rho \cdot t} \cdot dt - \sum_{j=1}^{h_i} \frac{C_{i,j}(t)}{(1+\rho)^t} . \tag{1.13}$$

We simulate two levels of coordination: jointly optimized rotation lengths (coordination), and independently optimized rotation lengths (non-coordination). Under non-coordination, each community i independently maximizes its net benefits NB_i as follows:

$$\max_{R_i} NBi . \tag{1.14}$$

We explore two end-member assumptions and present one as a representative decentralized case. For one end member scenario, a community choosing its nourishment strategy independently assumes its neighbor will not nourish, which is a cautionary assumption. This might cause the community to nourish more frequently than necessary and may be suboptimal, but at least the community can avoid under-nourishing its beach and potentially losing beachfront properties. While this assumes that communities cannot observe what their neighbor is doing, which represents a limited setup that simplifies the problem of non-cooperation, we use this scenario as a baseline analysis because it is the most conservative assumption a community can make. For the other end member scenario, a community assumes its neighbor will nourish with high frequency, which is a risky assumption because it could lead to more instances of beachfront property loss. The risky end member is included in the chapter 1 appendix.

Under coordination, both communities share their management decision by choosing the optimal rotation lengths that maximize the sum of their net benefits:

$$\max_{R_1,R_2} \sum_{i=1}^{2} NBi \qquad (1.15)$$

Coordination implies both communities have full information about their neighbor's behavior, and thus represents the socially optimal solution. There are cases in which communities might find it individually net beneficial to deviate from their socially optimal solution, however, unless a cost-sharing arrangement exists.

In all cases, communities commit to the nourishment rotation lengths yielded by equations (1.14) or (1.15) until the end of the model run, similar to a real-world community's contractual obligation to a dredge company for a fixed period (USACE, 1999). This represents a one-time decision in our framework. While this approach does not allow for dynamic feedbacks between communities through time, this simplifies a difficult problem into a basic decision framework, describing how communities might choose their nourishment strategies initially, and how these first moves might differ based on their coordination scheme.

1.2.4 Numerical Solution

In this section, we explain how we numerically solve the optimization problem described in equations (1.14) and (1.15). First, we compute the evolution of the shoreline location x_S and shoreface toe x_T in each community for a wide range of nourishment rotation lengths between 0-25 years with a spacing of 0.2 years. In particular, we obtain x_S and x_T from equations (1.4) and (1.6) respectively, which we solve numerically using the simplified forward Euler method[2]. We then calculate the benefits and costs for each scenario using equations (1.11) and (1.12) respectively. The discounted difference between the benefits and costs yields the net benefit, which we compare between all options. The rotation lengths R_1* and R_2* provide the maximum net benefit under each scenario (i.e., non-coordination and coordination). All results presented below ensure that neither the resolution nor the boundary limits employed misrepresent the true optimal choice.

[2] The Forward Euler method for the numerical solution is employed here because it is the simplest approach, which is appropriate for the set of first order differential equations with given initial values. In addition, the Forward Euler method was verified using the Modified Euler and the Runge-Kutta methods, all of which returned similar results for the system's dynamics. Finally, the Forward Euler was tested with various model time steps, which did not produce any appreciable differences.

1.2.5 Parameter Estimation

Table 1.1. Economic Input Parameters for Model Simulations

Economic Parameters	Symbol	Feasible range of values	Units	Test value: figs. 2, 5-6, 8	Test value: figs. 9-10
Variable Nourishment Cost[a,b,e,i,m,p,t]	ϕ_N	5—30	$/m^3	15	15—50
Fixed Nourishment Cost[d,j,p]	c_f	-	$1,000,000	1	1
Baseline Property Value[c,f,h,k,n,r,u]	α	-	$1,000	25—550	Community 1: $385 Community 2: $257
Discount Rate[g,q,s,t]	ρ	1—10	%/yr	6	6
Hedonic Parameter (Beach Width)[b,d,l,o,q]	β	0.05—0.8	-	0.4	0.4

Sources. [a]ASBPA (2020). [b]Gopalakrishnan (2010). [c]Gopalakrishnan et al. (2011). [d]Gopalakrishnan et al. (2016). [e]Hillyer (1996). [f]Jin et al. (2015). [g]Landry (2004). [h]Landry and Hindsley (2011). [i]Mcdowell Peek et al. (2016). [j]McNamara et al. (2011). [k]National Association of REALTORS (2020). [l]Pompe and Rinehart (1995). [m]PSDS (2019). [n]Redfin Inc. (2020). [o]Slott (2008). [p]Slott et al. (2010). [q]Smith et al. (2009). [r]Trulia LLC. (2020). [s]USACE (1999). [t]Williams et al. (2013). [u]Zillow Inc. (2020).

Table 1.2. Physical Input Parameters for Model Simulations

Physical Parameters	Symbol	Feasible range of Values	Units	Test value: figs. 2, 5-6, 8a	Test value: fig. 7	Test value: fig. 8b	Test value: figs. 9-10
Background Erosion Rate[a,i,k,r,v,w]	γ	0—10	m/yr	5	5	5	5—10
Nourishment Magnitude[b,t]	x_N	0—200	m	50	100	50	50
Rotation Length[b,o,t,u]	R	-	yr	0—25	(g) R_1=6.38 R_2=11.86 (h) R_1=6.92 R_2=7.55	0—25	0—25
Depth of Closure[f,g,j,m,n,s]	D	5—20	m	16	16	16	16
Alongshore Flux Coefficient[c,d,e,h]	K_1	10—1,000	1,000 m^2/yr	600	600	600	600
Cross-shore Flux Coefficient[p,q,s]	K_2	-	m^2/yr	2,000	2,000	2,000	2,000
Shoreface Equilibrium Slope[p,q,s]	θ_{eq}	-	m/m	0.02	0.02	0.02	0.02
Alongshore Community Length (Cell Length)[l]	s	-	m	1,500	(g) s_1=7090 s_2=3670 s_3=5380 (h) s_1=2720 s_2=7780 s_3=5250	10,000	1,500

Sources: [a]Armstrong and Lazarus (2019). [b]ASBPA (2020). [c]Ashton et al. (2001). [d]Ashton and Murray (2006a). [e]Ashton and Murray (2006b). [f]Birkemeier (1985). [g]Brutsché et al. (2014). [h]Falqués (2003). [i]Gopalakrishnan (2010). [j]Hallermeier (1980). [k]Hapke et al. (2013). [l]Inspired by field values observed in New Jersey. [m]Kraus and Batten

(2007). [n]Kraus et al. (1995). [o]Lazarus et al. (2011). [p]Lorenzo-Trueba and Ashton (2014). [q]Miselis and Lorenzo-Trueba (2017). [r]Murray et al. (2013). [s]Ortiz and Ashton (2016). [t]PSDS (2019). [u]Smith et al. (2009). [v]Williams et al. (2013). [w]Zhang et al. (2004).

1.3 Community Behaviors

1.3.1 Single Community

The model produces four primary behaviors based on nourishment choices: seaward growth due to frequent beach nourishment (i.e., short rotation length); hold the line due to moderately frequent nourishment (i.e., medium rotation length); slow retreat due to infrequent nourishment (i.e., long rotation length) and resulting in property abandonment; and full retreat due to a lack of nourishment and resulting in property abandonment (Figure 1.2). We characterize seaward growth behavior as the maximum shoreline position in the final five years greater than the maximum seaward extent of the first nourishment event. Hold the line behavior falls between this threshold and the initial property setback. Whereas, slow retreat and full retreat result in shorelines landward of the initial property setback. The only difference between the latter two scenarios is that slow retreat includes nourishment effort on the part of the community and full retreat does not (Figure 1.2). When considering two communities, each behavioral category that includes beach nourishment can comprise a mix of two primary behaviors.

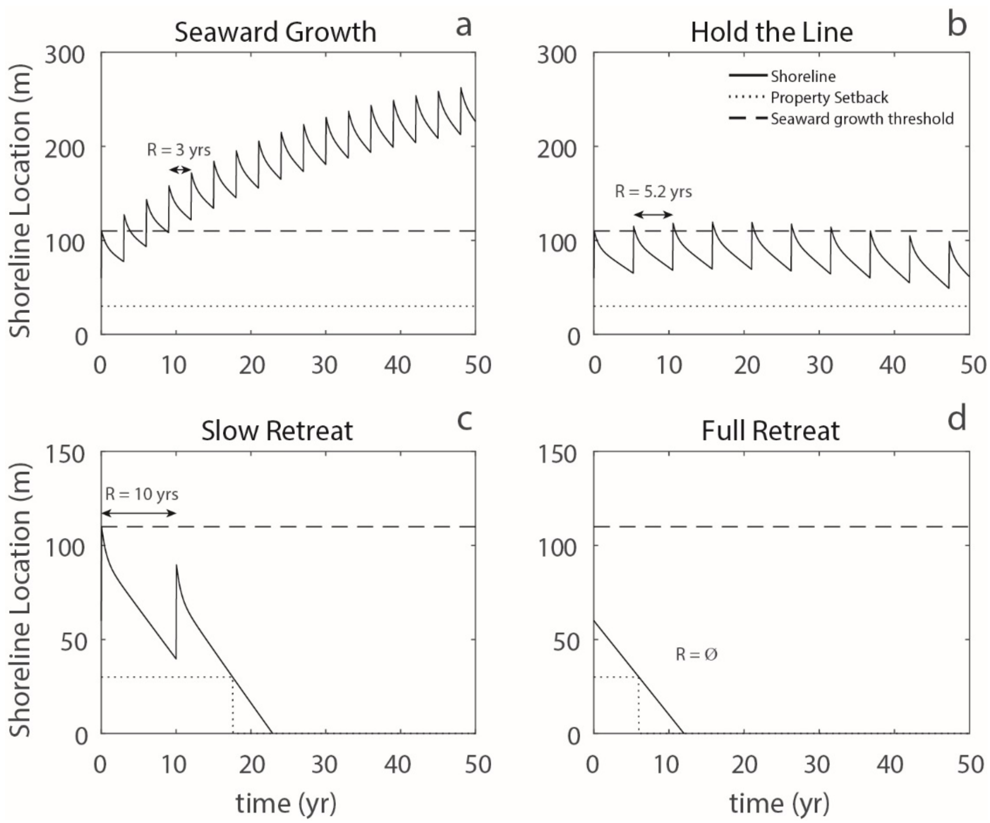

Figure 1.2. Mode behaviors resulting from different beach nourishment frequencies: a) R=3 years b) R=5.2 years c) R=10 years d) R=Ø (no nourishment).

We present an example of each mode behavior observed in the field. Using the beach nourishment databases from the Program for the Study of Developed Shorelines (PSDS) of Western Carolina University (2019) and the American Shore and Beach Preservation Association (ASBPA, 2020), we report the number of nourishment events and year of first/last nourishment event for each example below and show that these mode behaviors likely depend on nourishment decisions (Figure 1.3a-d).

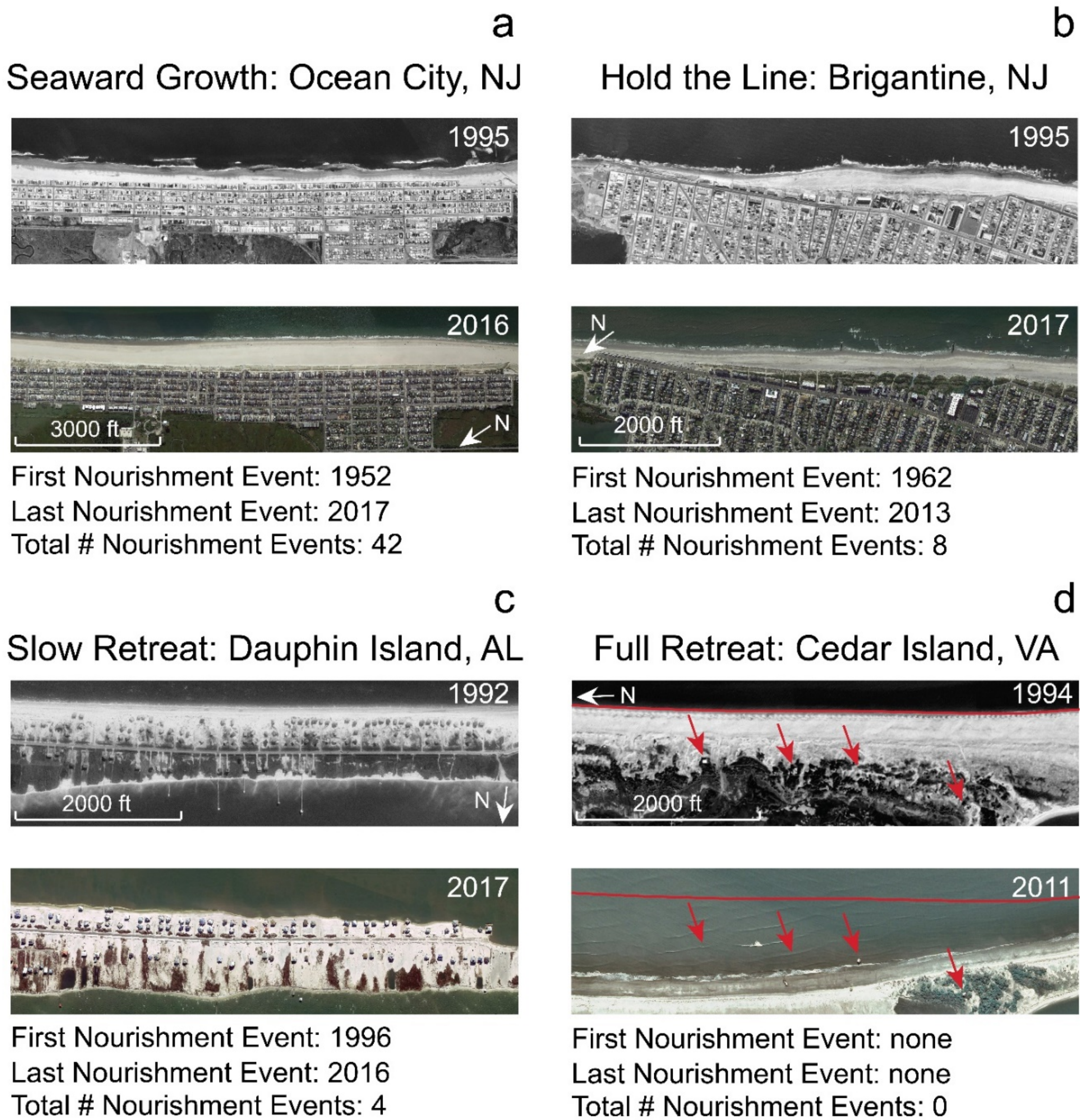

Figure 1.3. Emergent mode behaviors observed in the United States East and Gulf coasts: (a) seaward growth in Ocean City, NJ; (b) hold the line in Brigantine, NJ; (c) slow retreat in Dauphin Island, AL; and (d) full retreat in Cedar Island, VA.

Toward coupling these nourishment decisions and their emergent mode behaviors with community-scale socioeconomics, we present the rotation lengths for coastal New

Jersey communities as a function of their property values (Figure 1.4). We determine a median property value estimate using four real estate search engines (National Association of REALTORS, 2020; Redfin Inc., 2020; Trulia LLC., 2020; Zillow Inc., 2020), and calculate the representative beachfront property value assuming a power law relationship between property value and inland distance from the ocean (Gopalakrishnan et al., 2011; Pompe & Rinehart, 1995). We gather data using spatial analyst tools on alongshore community lengths and representative property sizes. The total wealth of the community is defined here as the summed value of all alongshore properties in a community. We track the number of nourishment events by community, as reported in the PSDS (2019) and the ASBPA (2020) databases, and use the first (1936) and last (2020) completed nourishment event along the New Jersey coast to calculate a representative rotation length for each community.

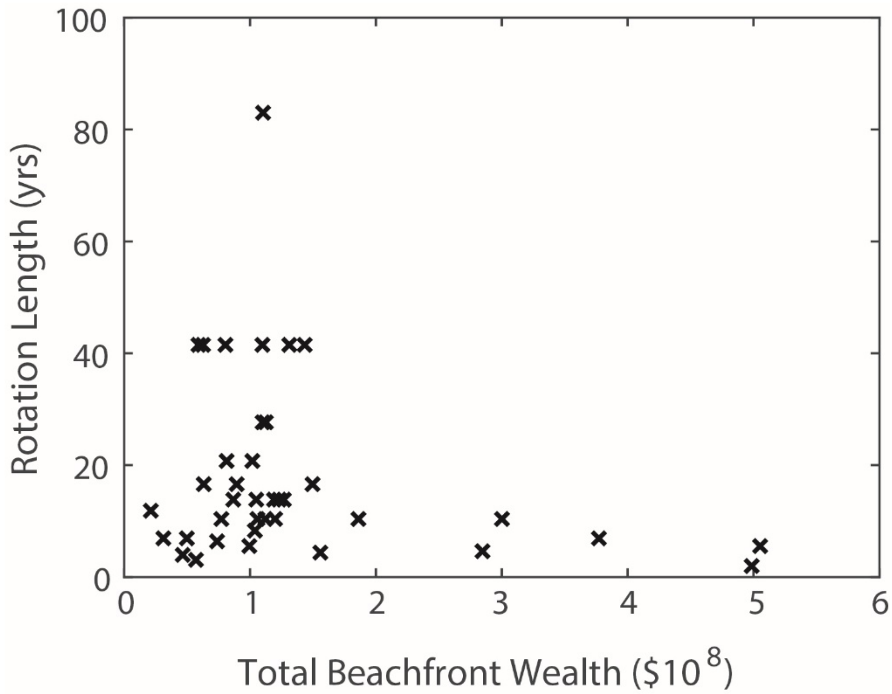

Figure 1.4. Rotation lengths for coastal communities in New Jersey as a function of their total beachfront wealth (alongshore sum of beachfront property values), exhibiting nourishment variability for low-wealth communities and frequent nourishment for high-wealth communities.

While in general, the rotation length decreases as total beachfront wealth increases, there is variability for low-wealth communities. This could be due to commercial real estate exerting control over nourishment frequency (e.g. Atlantic City, Ocean City, Asbury Park, Cape May, Wildwood, Long Branch, etc.), where beach tourism economies are often located in neighborhoods with lower property values (or there is a disamenity associated with proximity to tourism areas). Other variability, however, could be due to alongshore interactions between neighboring communities' nourishment decisions.

In many field cases, mode behaviors realized by a community depend at least in part on their neighbor's actions as well. We account for this alongshore coupling between neighboring nourishment choices in the subsequent section (1.3.2). However, these initial field insights do provide context for our beach nourishment game concerning the range of both property values and rotation lengths used for model explorations.

1.3.2 Two-community Interconnection

In order to capture the alongshore feedbacks between neighboring community nourishment decisions, a two-community model setup was implemented, allowing a comparison of the emergent behaviors produced by coordinated and uncoordinated schemes. The setup comprises a sample array of real-world scenarios in which neighboring communities can be wealth-symmetric or wealth-asymmetric (Figure 1.5). The sensitivity of community nourishment decisions to different baseline property values (Equation 1.7) in each community was explored.

Under coordination, community-specific rotation lengths depend on relative baseline property value balances, but under non-coordination, they depend only on each community's baseline property value (Figure 1.5a-b). This baseline property value regime space encompasses all key behaviors that emerge from the model (Figure 1.2) including instances of mixed behaviors (i.e., seaward growth/hold the line). The thresholds between these behaviors depend upon the level of coordination, and these thresholds demarcate regions in which communities that do not coordinate misallocate their distribution of nourishment effort (rotation length) compared to their economically optimal distribution of effort produced by coordination. This emerges, in particular, when there is a disparity in baseline property values between neighbors (Figure 1.5a-b).

Full retreat arises for the lowest wealth systems regardless of whether or not coordination occurs. Both coordinated and uncoordinated emergent behaviors are sensitive to minor changes in baseline property values for low and moderately wealthy systems, while they are less sensitive for high baseline property values. Neighboring communities with different baseline property values experience many instances of behavioral difference between coordinated and uncoordinated regimes, particularly for moderate baseline property values. By working independently, communities effectively treat all of their neighbors equally; thereby, ignoring the marginal importance of helping a neighbor based on the benefit they might provide the system. Accounting for the alongshore distribution of wealth under coordination represents the economically optimal allocation of nourishment effort, contrasting with the uncoordinated scenario in which communities might either under-nourish (i.e., longer rotation lengths) or over-nourish (i.e., shorter rotation lengths) compared to their rotation length choices under coordinated efforts (Figure 1.5a-b, e).

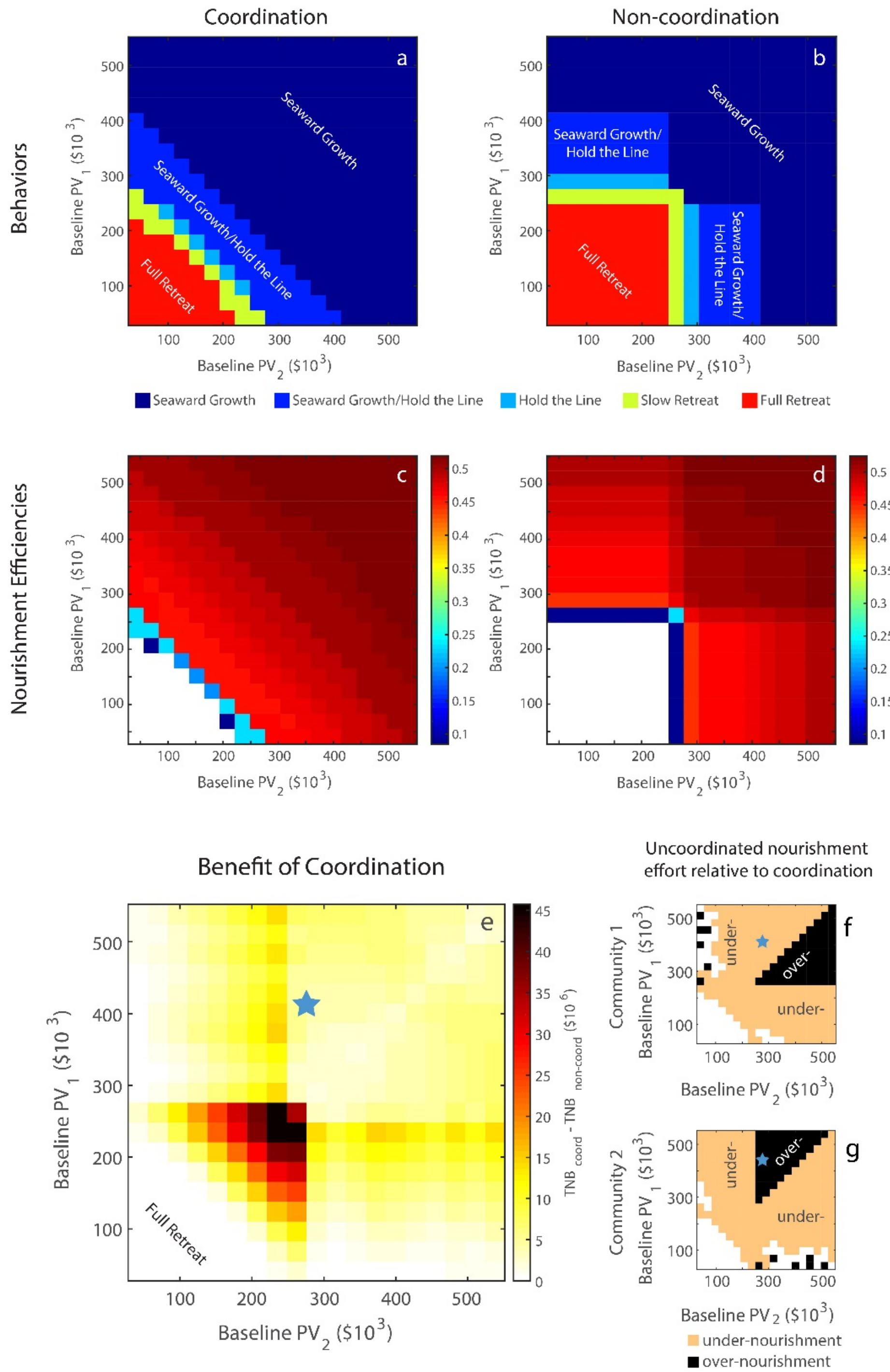

Figure 1.5. Emergent behaviors for coupled systems under (a) coordination and (b) non-coordination and (c-d) the nourishment efficiencies under the respective management schemes. Panel (e), the benefit of coordination relative to non-coordination indicates the economic difference between management scenarios, and the community-specific regions of over- and under-nourishment for (f) community one and (g) community two reveals

how uncoordinated strategies economically compare with their optimal strategies under coordination.

In general, nourishment efficiency increases as the wealth increases corresponding with decreasing rotation lengths (Figure 1.5c-d). While this increase in efficiency can be attributed in part to the larger volume of sand placed by frequent nourishment (Equation 1.9), triggering an increase in the volume of sand lost from the two communities (Equation 1.8), the fraction of volume lost relative to the nourishment volume decreases and the efficiency thus increases (Equation 1.10). These efficiencies differ between coordination schemes primarily in regions of wealth disparity, where coordination results in a higher physical efficiency than non-coordination (Figure 1.5c-d), corresponding with a higher economic efficiency (i.e. optimal solution) produced by coordination in this region as well.

The difference in behavioral outcomes depending on the coordination level highlights the baseline-property-value combinations for which coordination is most important. The benefit of coordination is the smallest (i.e., coordination is least important) for low wealth communities that cannot afford nourishment regardless of their coordination level (Figure 5e). It is also lowest for regions of high wealth disparity between neighbors because the marginal benefits provided by wide beaches in a wealthy community outweigh the marginal costs of frequent nourishment, and their less wealthy neighbor can neither afford nourishment on their own nor provide any appreciable benefit to the system if they work together.

The benefit of coordination is largest (i.e., coordination is most important) for lower-wealth communities that can afford beach nourishment by cooperating but not by acting alone. Coordination is also important for regions with moderate baseline-property-value asymmetry, identified by the blue star as an example (Figure 1.5e). This baseline-property-value combination corresponds with seaward growth behavior for both coordination levels (Figure 1.5a-b), but coordination is more beneficial to the two communities as a whole, assuming that a cost-sharing arrangement or transfer payment exists under coordination, because the less wealthy community over-nourishes and the wealthier community under-nourishes when acting alone (Figure 1.5f-g). This uncoordinated distribution of nourishment effort between the two communities results in a lower nourishment efficiency compared to coordination, meaning that the two communities lose more sand from their beaches relative to the amount they place if they neglect cooperation.

The optimal distribution of nourishment effort between communities for the blue star in figure (1.5e) under coordination, while representing the maximum total net benefit for the entire system, results in an asymmetric share in net benefits between communities (Figure 1.6). In fact, the less wealthy community that nourishes infrequently under coordination receives a larger share of the net benefits than the wealthier community that nourishes frequently (Figure 1.6a). This is due to the large asymmetry in nourishment effort, whereby the wealthier community bears the majority of the nourishment responsibility, and is a function of the level of interconnectivity between communities (i.e., that small alongshore length and the high diffusivity value). In regions where communities are more alongshore disconnected, the distributed nourishment effort and thus the corresponding community-specific breakdown in net benefits might be more comparable. A cost-sharing or transfer payment arrangement from the community nourishing less might be necessary here to ensure the wealthier community remains in a coordinated scheme.

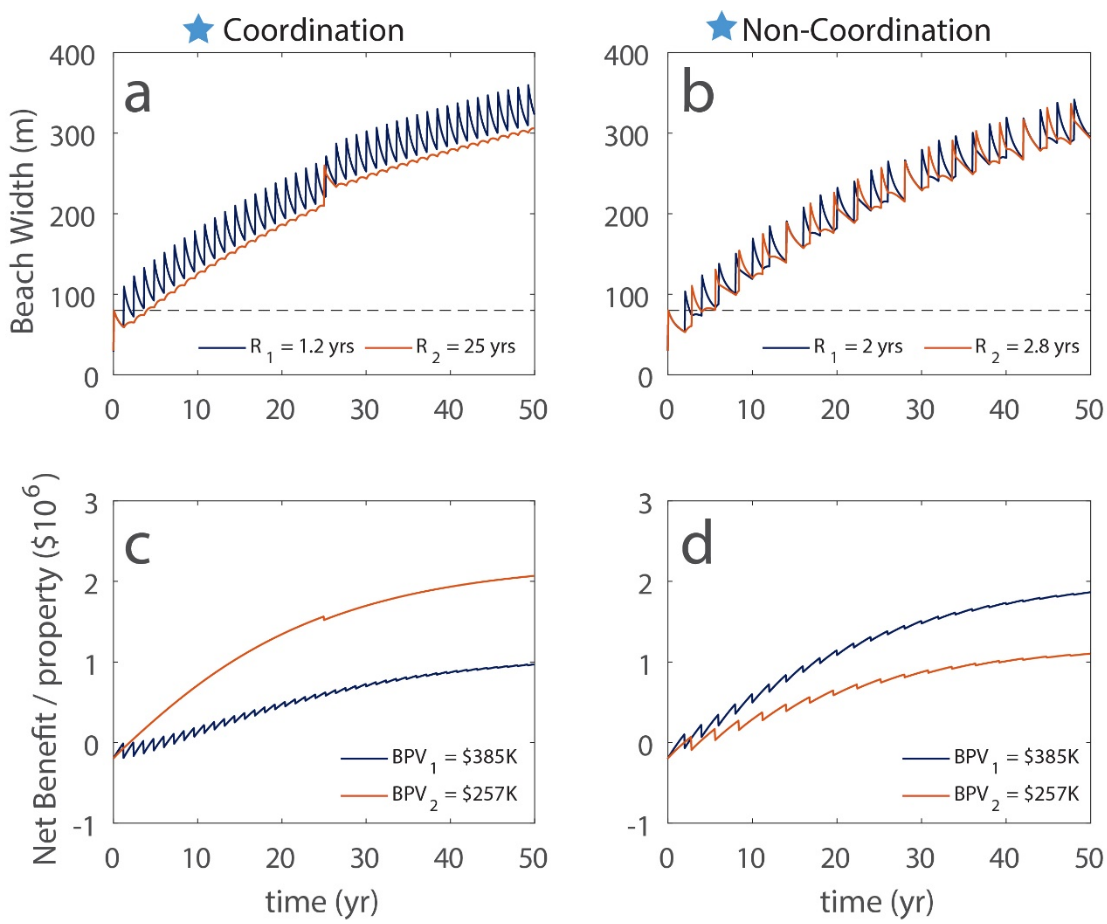

Figure 1.6. Beach widths for communities with baseline property values corresponding to the blue star in figure 1.5e under (a) coordination and (b) non-coordination, and (c-d) the resulting community-specific net benefits for coordination and non-coordination respectively.

If these two communities compare their own payoffs resulting from each coordination level rather than the total net benefit, however, there is an incentive for the less wealthy community to cooperate (i.e., to follow their coordinated nourishment choice) while there is an incentive for the wealthier community to defect (i.e., to follow their uncoordinated nourishment choice) (Figure 1.6c-d). The wealthier community realizes a higher net benefit from acting alone than coordinating because they not only nourish less and incur fewer costs, but their less wealthy neighbor nourishes more than they would have under the coordinated plan (Figure 1.6a-b). This combination of strategies, if followed, would result in reduced nourishment effort system-wide, which would lead to the suboptimal outcome of narrower beaches due to non-coordination as described by Gopalakrishnan et al. (2016). These individual incentives, in the absence of a cost sharing or transfer payment plan, might be a barrier to coordination, which could help explain why communities have historically operated in a decentralized manner.

1.4 Model Comparison with Field Decisions

While the historical level of coordination between real-world communities and their initial property values is unknown, we do see evidence of these two-community mode behaviors in the field. Specifically, we highlight two barrier island systems in southern New Jersey: Avalon/Stone Harbor and Strathmere/Sea Isle City. In both instances, the two communities experience seaward growth behavior due to their distributed nourishment effort. This evolution is evident both in historical aerial imagery (Figure 1.7a-d) and in the modeled shorelines (Figure 1.7e-f).

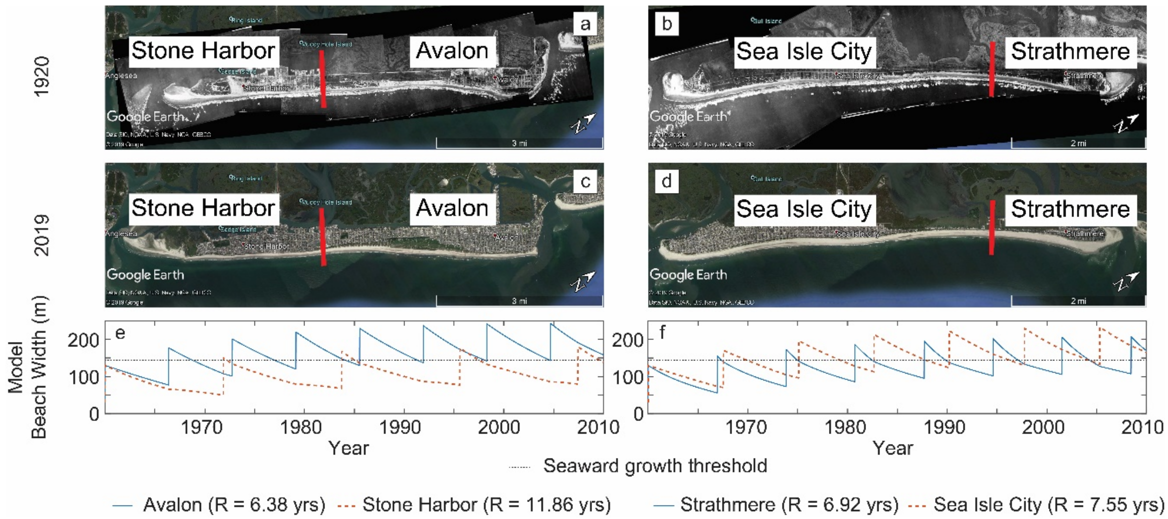

Figure 1.7. Example of dynamic interconnection between neighboring New Jersey communities: (a) Avalon and Stone Harbor and (b) Strathmere (Upper Township) and Sea Isle City. Historical aerial imagery from (a-b) 1920 and (c-d) 2019 illustrate their developmental and morphodynamic evolution. From the PSDS and ASBPA beach nourishment databases, we calculate each community's rotation length, from which seaward growth behavior emerges for (e-f) both barrier island systems.

We group two-community neighbors for all New Jersey community pairs in our database and analyze their distributed nourishment choices (i.e., rotation length ratio) as a function of their distributed beachfront wealth (i.e., wealth ratio). Here, the beachfront wealth is defined as the sum of all beachfront property values in a community, which accounts for the community's alongshore length and number of properties adjacent to its beachfront. Some field community pairs result in a rotation ratio that is larger than one, meaning the less wealthy community nourishes more than the wealthier community nourishes. We find that the commercial real estate influences associated with high tourism areas such as Seaside Heights and Atlantic City could bias these examples.

Similarly, the natural dynamics of shorelines adjacent to fully hardened (i.e. two jetties) tidal inlets and the resultant sediment deficits downdrift of these inlet jetties, for which our model does not account, could be affecting nourishment decisions in communities such as Avon-by-the-Sea and Barnegat Light. For these reasons, we remove the field pairs composed of these communities.

We plot the rotation-length ratios as a function of wealth ratios (relative to the lower-wealth community for each two-community pair) for coordinated and uncoordinated model scenarios and shade each region surrounding the corresponding observations, terming these regions the coordinated and uncoordinated model envelopes. These field-model comparisons include both small communities (Figure 1.8a) and large communities (Figure 1.8b) to cover most New Jersey community sizes. In general, increasing the wealth ratio results in a decreasing rotation-length ratio because when neighboring communities have more wealth disparities (i.e., large wealth ratios) their rotation lengths are more dissimilar (i.e., small rotation-length ratio). If neighboring communities have high wealth disparities but similar rotation lengths, this may indicate that they are misallocating their distributed nourishment effort compared to their economically optimal levels.

The slope of this decreasing rotation ratio for small wealth ratios is steeper under coordination than non-coordination for smaller communities, and the rotation ratios are small for large wealth ratios under coordination (Figure 1.8a), meaning that nourishment decisions are more different between the two communities when they coordinate and more similar between the two communities when they act independently. We then overlay field data from neighboring New Jersey communities to see how two-community pair decisions might compare with the model's output. Given that many field communities have alongshore lengths (median length = 2.68 km) similar to the case presented in Figure 8a, the regions enveloping field pairs in this subplot might serve as an indicator of their underlying decision-making scheme, i.e., whether or not they coordinated their nourishment plans. An example of non-coordination could include Sea Isle City/Avalon, NJ, which is plausible given they are on different barrier islands and separated by a partially hardened (i.e., one jetty) tidal inlet. Whereas, Loveladies/Harvey Cedars could be an example of coordination given they are tightly coupled alongshore and subject to the same USACE regional beach nourishment plan (1999).

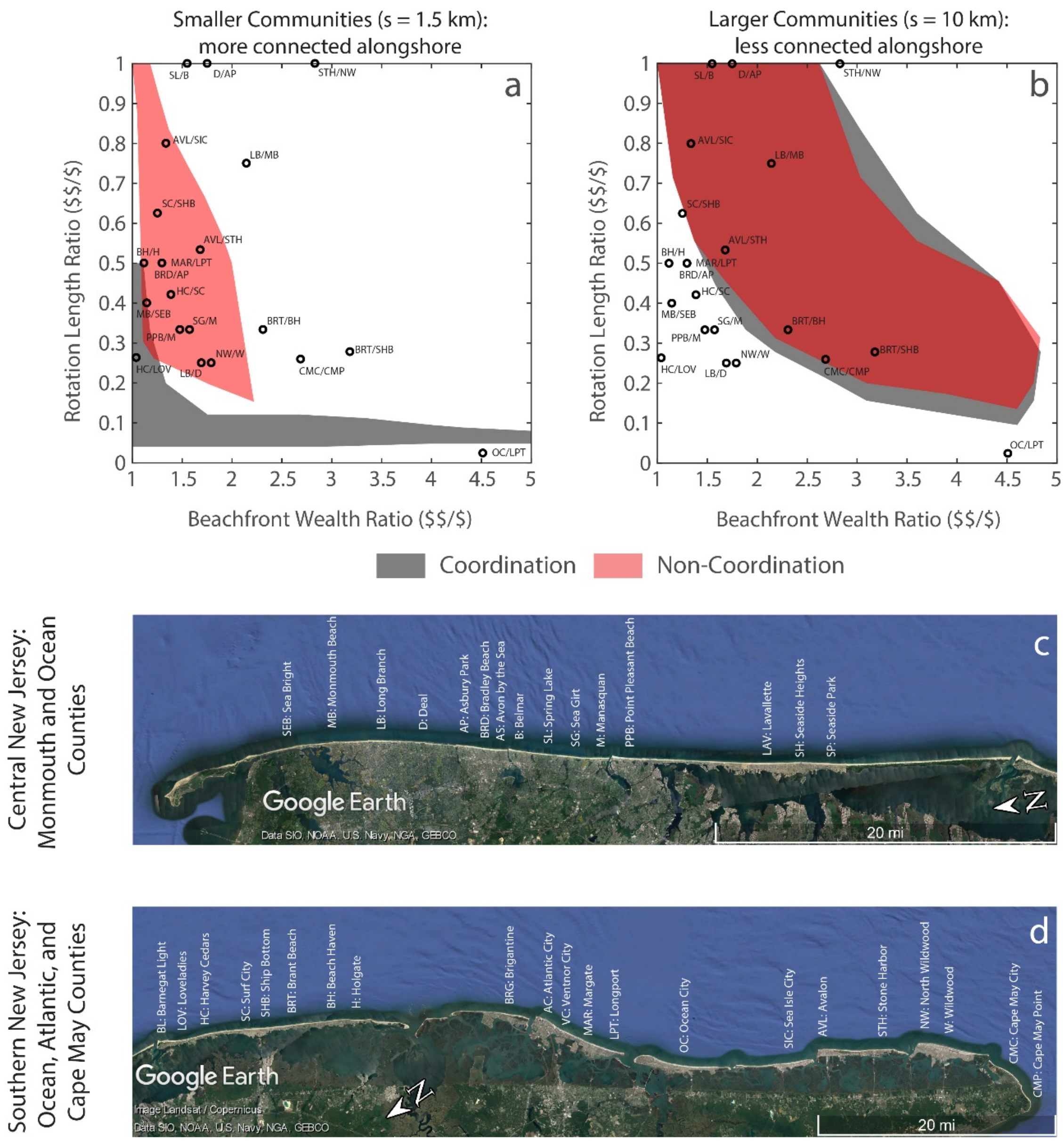

Figure 1.8. Comparison of rotation-length ratio vs. wealth ratio between model (coordination/non-coordination) and field observations for (a) small communities and (b) large communities. Field pair locations identified by the abbreviations used in subplots a-b are shown for the (c) central and (d) southern New Jersey coast regions.

Field examples that do not fall in either model envelope in figure (1.8a) could be influenced by other underlying factors. One such factor could be the shoreline orientation effects whereby one community protrudes farther seaward than its landward neighbor thus necessitating more frequent nourishment than expected due to its reduced nourishment efficiency (e.g. Stone Harbor/North Wildwood). Another factor could be an asymmetry in how the neighboring communities value their beach for recreational purposes where wealthier communities value these amenities less than poorer communities do (e.g. Deal/Asbury Park and Monmouth Beach/Long Branch). This relates to the beach amenity value β in equation (1.11). Such factors are not considered here, although future work will be necessary to explore these dynamics further.

A simple test within the model's framework, however, is increasing the alongshore community length (Figure 1.8b). This serves to reduce the connectivity between communities and results in nourishment decisions that are less dependent on the dynamics of neighboring communities. The coordinated scheme for large communities, especially, yields rotation lengths that are more similar (i.e., rotation ratio that is closer to one) than the same scheme for smaller communities. The model envelopes for large communities (Figure 1.8b) cover nearly all remaining data points not covered by the model envelopes for small communities (Figure 8a), including larger field communities such as Long Branch (length = 6.95 km). One data point that remains uncovered by the large community envelopes, Ocean City/Longport, could be a result of the disparity in community lengths (Ocean City = 11.47 km; Longport = 2.27 km) or their separation by a large tidal inlet (Great Egg Harbor Inlet) that is partially hardened, which could be disrupting alongshore flow between communities.

Furthermore, when we include community-average nourishment volumes as well as frequencies in our analysis, presented below as nourishment flux, we find that community pairs might be allocating their nourishment effort in an economically inefficient manner. For instance, in figure 9a, poorer communities in a moderate wealth-disparate pair tend to nourish with larger fluxes than wealthier neighbors do, on average, indicating that these poorer communities are likely over-nourishing or that their wealthier neighbors are under-nourishing compared to their economically optimal levels in the context of a two-community framework. In addition, these emergent flux differences result in quantitative differences in beach width, such that poorer communities often realize wider beaches than their wealthier neighbors (Figure 1.9b).

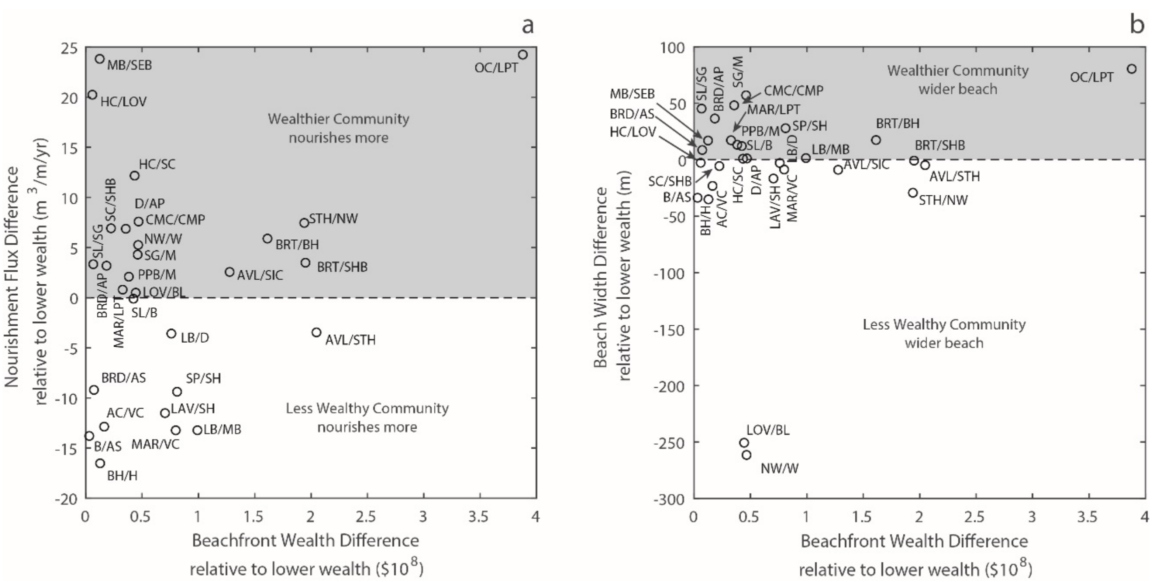

Figure 1.9. (a) Nourishment flux differences and (b) beach width differences for each two-community pair as a function of their beachfront wealth differences revealing that poorer communities often nourish more than wealthier communities do and supporting the model's result that poorer communities might be over-nourishing compared to their economically optimal level of effort under coordination. This over-nourishment, in many

cases, yields wider beaches for poorer communities compared to their wealthier counterparts.

While it is unclear whether each two-community pair actually coordinated their nourishment plans or chose their strategies alone in the past, these field observations compared with our model's results do suggest that neighboring communities with large wealth disparities may have foregone benefits by failing to coordinate regional nourishment strategies. In the face of climate change impacts on coastal New Jersey communities and worldwide, it will be important to understand how these neighboring community interactions might change in the future and the potential paths of coupled coastal behavior based on the different coordination schemes they might undertake.

1.5 Future Conditions: Effect of a Higher Sand Cost and Background Erosion Rate

Subsequent nourishment decisions might rely on a different suite of underlying physical and economic conditions. A likely future scenario involves higher background erosion associated with sea-level rise and increases in the cost of sand. The prevalence of beach nourishment on regional scales increases the demand for sand (Brauchle, 2013). Additionally, reductions in near-shore-sediment supply shift dredge operations further offshore, implying that sand is a non-renewable resource (McNamara et al., 2011). Both expanding demand and diminishing supply drive up the price of sand for beach nourishment.

Under the asymmetric wealth scenario represented by the blue star in Figures (1.5-1.6), behavioral sensitivities to increasing background erosion rate and increasing sand cost for both coordination levels are depicted in Figure (1.10).

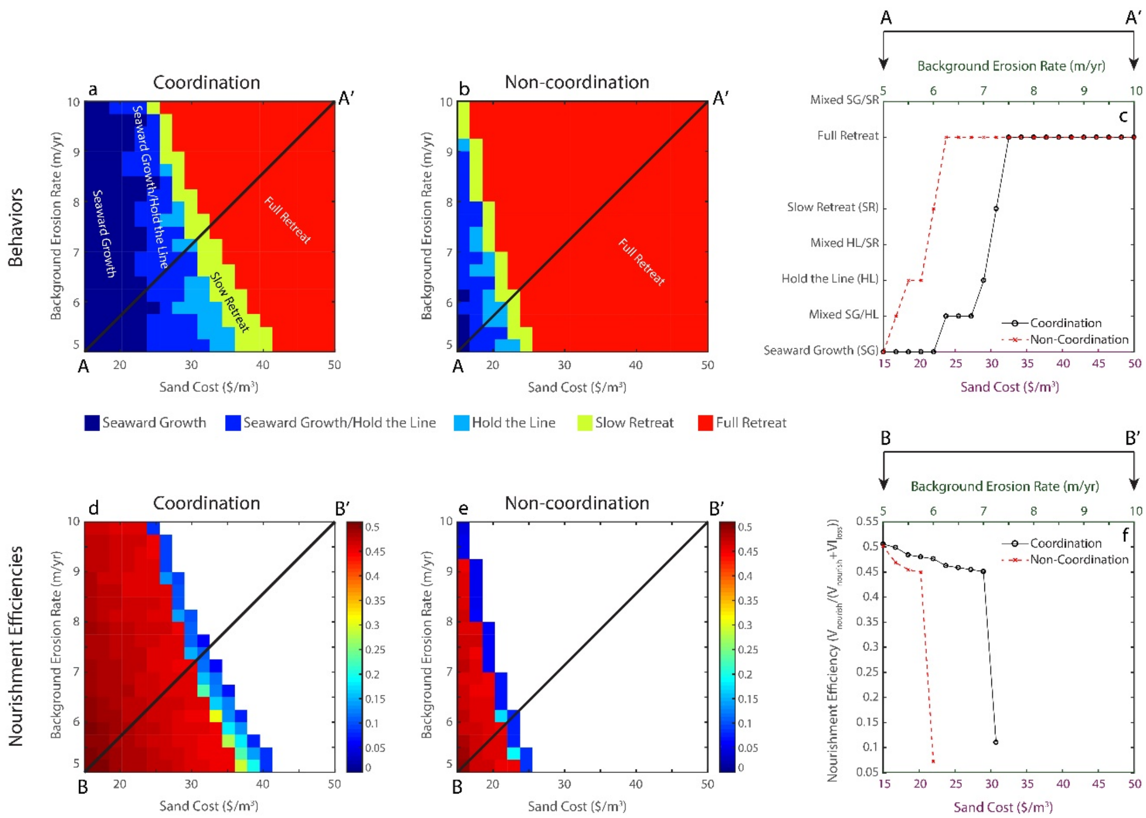

Figure 1.10. Emergent behaviors under (a) coordination and (b) non-coordination based on the background erosion rate and the sand resource cost, a diagonal transect (A-A') through the regime space showing (c) the behavioral transgression from seaward growth to full retreat, the corresponding nourishment efficiencies for (d) coordinated and (e) uncoordinated regime spaces, and (f) the decreasing nourishment efficiency along the diagonal transect (B-B').

Communities that coordinate will experience a progression from seaward growth to seaward growth/hold the line to slow retreat to full retreat, highlighting their added difficulty in maintaining beaches when faced with more extreme geo-economic forcings (Figure 1.10a). In contrast, uncoordinated communities will experience this shift from seaward growth to full retreat much sooner, i.e., for lower sand costs and lower erosion rates (Figure 1.10b-c). This drives a threshold switch for uncoordinated systems from over-nourishment in the less wealthy community to under-nourishment system-wide, as evidenced by the loss of property sooner than had the communities coordinated. The switch from over-nourishment to under-nourishment occurs because, when choosing a nourishment strategy alone, the less wealthy community can no longer justify over-nourishing, or in other words, the cost of nourishment inefficiency (Figure 1.10e) outweighs the benefit of protecting beachfront properties. Ultimately, the less wealthy community acting alone will be unable to nourish at all and will abandon properties sooner than if it had cooperated with its wealthier neighbor (Figure 1.10a-c). Together, the uncoordinated communities will reduce their nourishment efforts due to the increased marginal cost of nourishment inefficiency compared to the benefit provided by frequent nourishment. These decisions correspond with lower nourishment efficiencies and a more rapid decline in efficiency than coordinated communities might experience (Figure 1.10d-f).

The vulnerability to property loss for uncoordinated systems in the future mirrors what is already happening in many communities across the United States, both wealthy and not, who are struggling to protect their beachfront properties in the face of eroding beaches and rising seas. Wealthy homeowners in Nantucket, Massachusetts are self-funding their protection efforts (Keneally & Simon, 2020). Likewise, upscale neighborhoods in Nags Head, North Carolina, and Malibu, California who both lose approximately 5-6 feet of beach width per year plan to spend $48 million and $55-60 million respectively to restore their beaches and keep their homes from falling into the sea (McMullen, 2018). Especially at risk, however, are property owners with fewer means such as those in Manistee, Michigan whose homes have begun tumbling into Lake Michigan due to coastal bluff erosion following record-high lake levels in recent years (Reynolds, 2020). These homeowners often either abandon their properties after their property values depreciate or sell to developers, which results in bigger homes and thus more wealth in the most vulnerable locations (Capuzzo, 2017; Lazarus et al., 2018).

These instances and many more around the world will undoubtedly become commonplace under more extreme conditions in the future. Property-value disparities might amplify these risks, triggering a sharp transition from seaward growth to property abandonment for communities that neglect to coordinate their management plans with their neighbors.

1.6 Discussion and Future Work

A geomorphic-economic model to understand the key drivers influencing a dynamically coupled-coastal system with two communities was developed. The model predicted a broad array of emergent-behavioral pathways based on nourishment rotation length as the control variable. For instance, communities might choose to nourish their beaches so frequently that their shorelines grow seaward. Conversely, communities might choose to nourish their beaches infrequently or not at all, such that they lose nearshore properties as a result.

Whether this dynamical system can produce the observed coastal anthropic signatures typically ascribed to uncoordinated management was examined. The model predicted that communities might accidentally nourish more frequently than is optimal under a coordinated management program, although this is not a blanket result. Instead, this behavior persists mainly when neighboring communities have different property values, and in particular, less wealthy communities in such situations tend to over-nourish.

Irrespective of the coordination scheme, neighboring communities with high baseline property values are predisposed to nourishing frequently, leading ultimately to seaward growth. These outcomes shed light on how coastal communities might have behaved in the past; specifically, they might have misallocated nourishment efforts when the underlying socioeconomic conditions such as alongshore wealth asymmetry between coastal neighbors was large.

Preliminary evidence of these model trends appears in New Jersey beach communities. Other local factors that distinguish these systems could affect a comparison, however. First, groin fields are widespread along the New Jersey coast, thereby limiting the interconnection between neighboring communities. Second, barrier islands, comprising most of the southern New Jersey coast, experience washover (i.e., the transport of sediment from the shoreface to the top or back of the barrier), a process for which the model does not account at present. Future work should explore how groin fields and barrier processes interact with the coupled model by extending it to include hard structures (Janoff et al., 2019; Kraus & Batten, 2006) and overwash dynamics (Lorenzo-Trueba & Ashton, 2014).

Third, high recreational values associated with beaches in tourism-centric zones, where commercial beachfront real estate likely controls nourishment decisions more than residential properties do, could add complexity to this inter-community relationship. In particular, potential asymmetries in these beach amenities between neighboring communities could play a role in determining how they plan their beach nourishments and whether or not they coordinate such plans. New Jersey is a perfect example of variability in beach recreational values as evidenced by the wide distribution of beach badge (use fee) revenues by community, especially from one community to the next (Hoover, 2017). We plan to explore how these community-scale economic differences dictate how communities interact with each other when forming their management plans.

Finally, the efficiency of these nourishment projects could differ by community, namely for those in regions with cross-shore or alongshore sediment deficits. Sand supply limitations could be due to local effects such as inlets or inlet jetties, which trap sand updrift, or underlying geologic characteristics on a regional scale. Similarly, communities that protrude seaward might experience limited alongshore supply. All of these conditions might decrease the efficiency of nourishment projects for certain communities, which would force more frequent nourishment than the model predicts. Building off the efficiency approximation (Equation 1.10) presented in this paper, future work will explore how the amount of sand lost from nourishment projects to nearby sediment sinks over time, and community perceptions about the sustainability of such projects, could affect community nourishment decisions.

These analyses would help clarify some of the behavioral variability observed in New Jersey (Figure 1.8). Nonetheless, the comparison between field data and model results presented in this paper suggests that many neighboring communities in New Jersey may have adopted an uncoordinated approach, which is also consistent with anecdotal evidence (Gopalakrishnan et al., 2016; Lazarus et al., 2011; Pilkey & Clayton, 1989).

If these communities have benefited economically from their past nourishment decisions, however, and the consequence of their beachfront property vulnerability (i.e., property damage) is largely subsidized by external sources (i.e., federal disaster relief, federally-/state-funded beach maintenance, flood insurance policy discounts, etc.), perhaps there is little incentive to overcome potential barriers to coordination and change behavior in the future. If this is indeed the case, the model suggests that decentralized communities might experience a rapid switch from over-nourishment to under-nourishment in the face of rising sea levels and increasing sand resource costs, and less wealthy communities are at particularly high risk of losing coastal properties. This underscores that communities that choose not to coordinate might realize disparities in the distribution of wealth along the coast, leading eventually to the persistence only of wealthier communities there.

As sand resources dwindle and sea levels rise, costs will continue to increase, beaches will erode more rapidly, and fewer communities will be able to afford beach nourishment. Using a coordinated scheme, communities could dampen their vulnerability, but they cannot prevent the eventual loss of properties. Managed retreat is a topic of growing interest for the scientific community (Rott, 2019), and it has already become a reality for some homeowners from the heavily developed shores of New York City (Binder et al., 2015) to the remote coasts of Alaska (Agyeman et al., 2009; Mach et al., 2019).

While managed retreat approaches focus largely on buyouts as a mechanism for property removal, the model explored here revealed a different but possibly complementary strategy of slowing the rate of retreat via infrequent beach nourishment to incorporate near-term benefits of property preservation in conjunction with relocation. Interestingly, the model suggests that this behavior of slow retreat is a viable strategy even without including the incentives comprising buyout programs. If such incentives are included in our modeling framework, slow retreat could be an even more attractive solution looking to the future.

It will be difficult to balance the private benefits provided for beachfront properties, resulting in tax revenues for small coastal municipalities, and the broader public benefits of beach access for all (Fallon et al., 2017). A framework that accounts for all stakeholder components is most likely to succeed, perhaps requiring a mix of incentives for property owners (buyouts), subsidies for coastal community welfare (beach nourishment), and reducing coastal development in the most vulnerable areas.

Ultimately, efforts to coordinate climate change adaptation plans such as beach nourishment might prove to be inadequate against the risks associated with coastal life on centennial scales. Subsidizing a neighboring community’s beach maintenance might not avoid the vulnerabilities associated with coastal life, amplified by rapid sea-level rise rates in the future. Instead, top-down master plans, including planned region-scale migration from the coast, may be inescapable.

CHAPTER 2 – DETERMING THE INTERPLAY BETWEEN SOCIOECONOMICS, TOURISM, AND GEOMORPHOLOGY IN BEACH NOURISHMENT DECISIONS

2.0 Summary

Coastal communities facing erosion maintain their beaches for recreation and property protection. One form of maintenance is nourishment, the placement of externally sourced sand to increase cross-shore beach width, forming an ephemeral seaward protrusion that requires periodic re-nourishment. Nourishment projects add value to beachfront properties, thus affecting future management choices through feedbacks between nourishment decisions and the benefits provided to coastal communities. Previous work explored this socioeconomic control on beach nourishment choice, but many New Jersey community decisions indicate that other factors may help explain management patterns. We surmise this is due to the high beach tourism demand experienced along this heavily developed coast in close proximity to major US cities (New York City, Philadelphia, Baltimore, and Washington D.C.). To understand how communities in New Jersey decide their management strategies, we compiled community-scale data on nourishment projects and estimated their nourishment fluxes, and combined this information with socioeconomic, tourism, and geomorphologic data. We run a multiple linear regression under various model specifications and find that both a community's beachfront wealth and its proportion of commercial property value (i.e., a proxy for its level of tourism) help explain its beach nourishment decision. This suggests that the interplay between socioeconomics and tourism can help us to understand how communities have managed their beaches, and thus, how coupled natural-human coastlines have evolved in the past. While most of New Jersey's coast has been held in position or even accreted seaward, as sea-level rises and material costs increase, beach

maintenance may become more difficult over the long-term, requiring expanded subsidies from federal and state governments. With the viability of increased expenditures for beach maintenance in question, local governments may experience difficulty protecting their properties and planned relocation of vulnerable infrastructure may be required. Tourism-centric communities facing these threats may respond with different nourishment approaches to meet recreational demand compared to their residential-dominated counterparts. This paper highlights the added complexity in coastal policy development within a high tourism, human-modified zone such as New Jersey, which must be included in deterministic modeling frameworks moving forward.

2.1 Introduction

Coastal communities nourish their beaches for recreational and protective purposes. Previous literature and empirical evidence from hedonic modeling (i.e., quantifying housing, environmental, and neighborhood effects on a property's value) found that socioeconomic factors, such as the beachfront property value, likely control how communities make nourishment decisions (Gopalakrishnan et al., 2011; McNamara et al., 2015; Smith et al. 2009). In general, the higher a community's beachfront property value, the more frequently the community will nourish, or, the shorter the return period between re-nourishments (i.e. rotation length). However, the frequency is not the only important metric in distinguishing a community's nourishment effort; the volume per nourishment episode is equally as important. A community's nourishment rate (volume/year) therefore captures both of these components, providing information on how much sand communities are placing on their beaches each year.

Past work found that a community's nourishment effort depends in part on its own beachfront property value, but also in part on its neighbor's property value given their spatial interconnection (Gopalakrishnan et al., 2016; Janoff et al., in review; Jin et al., 2013; Smith et al., 2015; Williams et al., 2013). The underlying assumption in this work is that wealthier communities will nourish more while poorer communities will nourish less. Homing in on New Jersey communities, however, it is not clear that beachfront wealth is the only determinant of nourishment output and in some cases, communities with lower wealth might even nourish more than wealthier communities (Janoff et al., in review).

In fact, Qiu et al. (2020) point out that other factors such as underlying geophysical conditions could play a role in a community's nourishment choice as well. They show that a community's distance from the nearest tidal inlet, a proxy for its access to sand resources and thus its realized project cost for beach nourishment, will dictate how frequently and with how much volume they replenish their beaches.

Other factors in addition to geomorphic site characteristics likely explain this nourishment variation, however. In coastal regions with an emphasis on seasonal tourism, such as New Jersey, the value that tourism-dominated communities (i.e., those with a high proportion of commercial properties) place on their beach is likely different from residential-dominated communities (i.e., those comprised mostly of residential properties), which might play a role in how they nourish their beaches.

Moreover, previous work found that beach amenity values differ by state (Dundas, 2017; Gopalakrishnan et al., 2011; Parsons et al., 1999; Pompe and Rinehart, 1995), and even by community type, i.e. gated vs. non-gated (Pompe, 2008). There is also anecdotal evidence of this difference in beach recreational values by municipality in New Jersey. Deal, NJ, one of the wealthiest coastal communities in the state, opted out of the countywide nourishment project in 1999, citing concerns over the possible degradation of fishing/surfing quality at local spots (B. Rosenblatt, personal communication, January 13, 2017). Furthermore, restrictive parking ordinances and reductions in public beach access points have led the municipality to multiple court battles over the past two decades, creating a reputation for attempting to make their beaches private (Strunsky, 2019). As a result, Deal's beaches are noticeably narrower (Figure 2.1a) than neighboring Asbury Park's beaches, a lower-wealth community with dense commercial development and a robust tourism-centric economy.

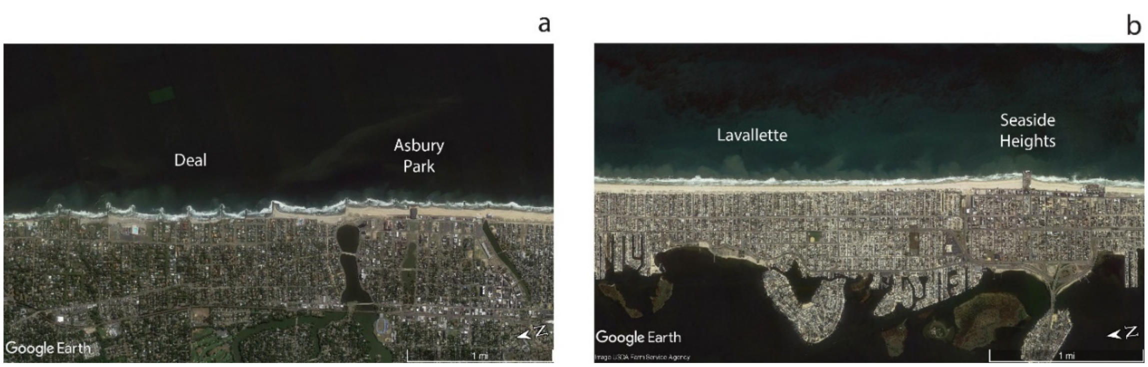

Figure 2.1. Examples of differential hedonic beach values: Asbury Park/Deal (a), and Seaside Heights/Lavallette (b).

While intuition suggests that beaches provide more value to wealthier homeowners in the form of protection, the intentional reduction in recreational benefits by wealthy homeowners could mean that their beach's amenity value is lower than expected. Only recently, in 2016, did the community of Deal begin participating in nourishment projects, largely due to the flood damages associated with Super Storm Sandy and the expanded funding availability as a result of the consequent federal disaster relief package (Gladden, 2015).

Similarly, in Lavallette/Seaside Heights (Figure 2.1b), wealthier Lavallette is a residential beach community whereas the lower-wealth community, Seaside Heights is a boardwalk hub replete with rides, Ferris Wheels, concessions, and games on their pier and beachfront facilities. Seaside Heights nourishes more frequently and with larger volumes of sand, resulting in wider beaches than Lavallette and higher recreational revenues.

Beach revenues and the tourism industry linked to these physical beach characteristics (i.e. beach widths) are directly affected by preceding nourishment decisions, which depend on past tourism-related revenues, thus describing a recreation-driven feedback. This could translate into a difference in nourishment policies for high-wealth and low-wealth communities based on their respective levels of tourism.

While previous work has explored the relationship between wealth and beach nourishment frequency (Gopalakrishnan et al., 2011; McNamara et al., 2015; Smith et al., 2009), few to no studies have explored a complete portfolio of other possible drivers of these management decisions, which could include both economic and geophysical factors. We seek to test the interactions among socioeconomics, tourism, and geomorphology in controlling community-scale beach nourishment decisions. Our main socioeconomic variable of interest is the value of beachfront properties in a community, which is the primary determinant tested in other coupled geo-economic studies on beach nourishment (McNamara et al., 2011; Murray et al., 2011; Smith et al., 2009). We expand on this analysis to include other components that might help explain why communities nourish as they do, particularly in the tourism-dominated region of the New Jersey coast.

Tourism variables of interest include the revenue generated by beach recreation, the ratio between the aggregate assessed values of commercial and residential properties, and the community's distance from the nearest tourism-concentrated zone. These variables could help explain why communities with lower property values might choose nourishment policies different from expected if oceanfront wealth is the only predictor of beach nourishment considered.

Underlying site geomorphology might also help explain these nourishment decisions, due either to differences in local sediment supply or to coastline orientation effects such as alongshore or cross-shore gradients in sediment fluxes. One geomorphic variable of interest is a community's distance downdrift of the nearest tidal inlet, which could serve as a sediment sink that limits downdrift availability or as a sediment source that supplies immediately adjacent beaches with sand via ebb-tidal delta attachment bars (Kraus, 2000; Kraus, 2002; Nienhuis and Ashton, 2016; Nienhuis and Lorenzo-Trueba, 2019a; Nienhuis and Lorenzo-Trueba, 2019b).

A second geomorphic variable we would like to test as a potential nourishment predictor is the underlying efficiency of nourishment projects, or, the rate at which the nourishment sand erodes from its placement location. This efficiency is a common research topic for coastal engineers (Benedet and Dobrochinski, 2017; Kuang et al., 2011; Roberts and Wang, 2012; Tonnon et al., 2018), though its connection as a control on nourishment policy has not been explored, to our knowledge. We estimate nourishment efficiency via the half-life of a nourishment project.

In this chapter, we broaden the understanding of what drives community-scale nourishment decisions. We test an array of predictors including socioeconomic factors such as a community's level of wealth; its level of local tourism/recreation; its regional proximity to beach tourism economies; and its geophysical site characteristics such as its supply or deficit of natural sand resources. From our analysis, we implement the key drivers of nourishment policy into the geo-economic modeling framework described by Janoff et al. (in review) that accounts both for the natural and for the economic evolution of a heavily developed coastal system. This analysis provides information on how the key predictors of community-scale nourishment policies manifest in the morphodynamics of a community's beach to help describe the past geomorphic outcomes observed at New Jersey field sites, and how these drivers will interact with future climate change effects such as heightened erosion rates due to sea-level rise.

Insights from this work and other literature expanding the envelope of explanatory predictors of coastal management decisions must be taken into account in deterministic modeling frameworks in the future, not only to understand how these systems might change, but also to supply regional and local managers with the tools necessary to make hyperopic and sustainable decisions moving forward.

2.2 Methods

In order to test the relationship between socioeconomics/tourism/geomorphology and community-scale nourishment choices, we run a multiple linear regression using Statistical Analysis System (SAS) software with the set of variables outlined above that we predict will help explain community-scale management decisions. We build a statewide dataset for all New Jersey communities with a history of beach nourishment practices (Figure 2.2).

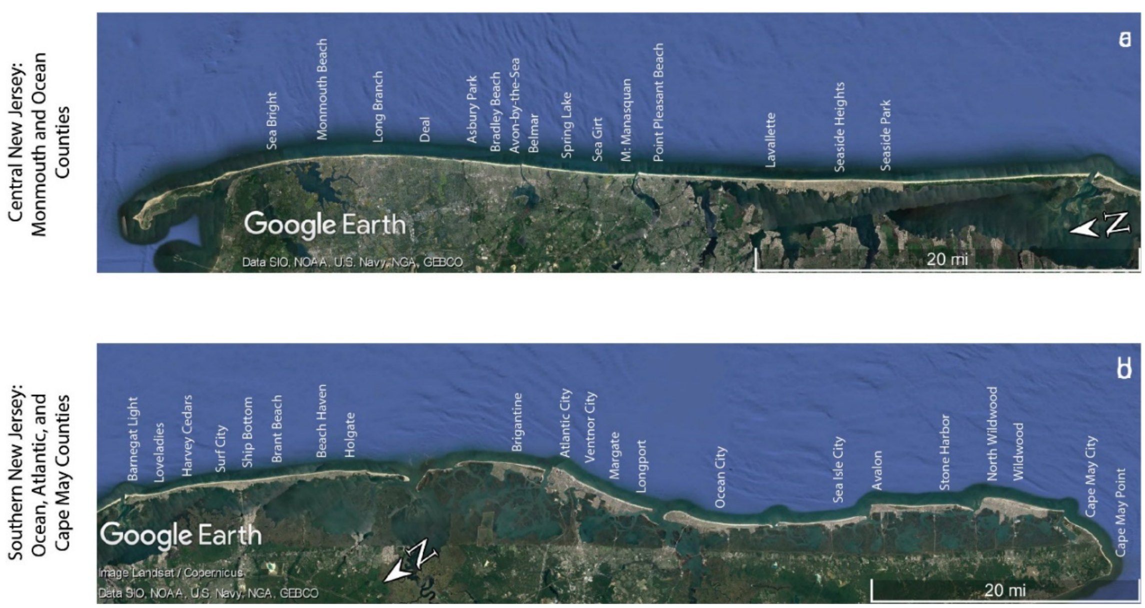

Figure 2.2. Regional locations of New Jersey communities for the northern (a) and southern coasts (b).

Below, we present each variable that is used in our analysis, split by category: 1) socioeconomics (i.e., beachfront wealth); 2) tourism (i.e., beach recreational revenues, local proportion of tourism, and proximity to tourism centers); and 3) geomorphology (i.e., site and regional characteristics affecting sediment availability and beach erosion). The general form of the nourishment regression is thus: *Nourishment = f(socioeconomics, tourism, geomorphology).* Methods of data collection/processing are listed in the appendix (Table A2.1).

We hypothesize that these three broader categories and the corresponding explanatory variables within these categories determine a community's nourishment choice as follows:

- Increasing a community's beachfront property value/wealth will increase the rate at which the community nourishes its beach (i.e., nourishment rate) because the community will have higher tax revenues from which they can fund nourishment projects and larger demand for private property protection from damaging storm surges.
- Increasing a community's beach recreational revenues will increase its nourishment rate because the community will not only have a larger operational balance for appropriating funds to management projects but they also have a higher recreational demand for which they must supply a sufficiently wide beach.
- Increasing a community's proportion of aggregate commercial value will increase its nourishment rate because communities must not only protect private residential properties from storm surge, but also cater to the influx of non-local beach users

who are recreating on their municipal beaches and patronizing their local businesses.

- Increasing a community's distance from the nearest tourism center (i.e., community with a high proportion of commercial real estate) will decrease its nourishment rate because it places less importance on maintaining a wide beach for the potential spatial recreational spillover from the tourism center should its beach reach capacity. Conversely, we could also expect that communities immediately adjacent to tourism centers might nourish less than communities further from tourism centers in the hopes of free riding off the tourism center's nourishment efforts.
- Increasing a community's distance downdrift of the nearest tidal inlet updrift will decrease its nourishment rate because it will not be starved of sand by the ebb-tidal delta that might serve as a sediment sink which thus would limit sand availability to downdrift beaches. Increased distance downdrift likely dampens this effect.
- Increasing the nourishment efficiency (i.e., increasing the nourishment project's half-life) in a community will decrease its nourishment rate because the longer that artificially-added beach sand remains on a community's beach, the less frequently and with smaller magnitude they must re-nourish in the future.

We test the effect of these independent variables listed above on the dependent variable, nourishment rate, using a multiple linear regression analysis for an array of model specifications and combinations of independent variables. We also test how the interaction between the geomorphic variables and the socioeconomic variables listed above, and discuss in more detail in subsequent sections. We present the normal regression as the base model in this paper because it corresponds with the highest adjusted R-square value of our initial regression analyses, and provides direct insight into the key drivers of nourishment policy without possible endogeneity associated with any of our independent variables listed above. To elaborate, while we predict that nourishment efficiency will help to determine a community's nourishment rate, the amount of sand communities add to their beaches could re-orient alongshore gradients or re-position the shoreline in deeper water, such that more sand could be lost via alongshore or cross-shore transport. The nourishment efficiency, therefore, could actually depend on the nourishment rate as well. This endogeneity could introduce bias, and so we avoid any model that includes nourishment efficiency as a significant independent variable.

The other two specifications we test are the lognormal and log-log regression models, which are listed in appendix A2.2. In addition, we provide a more detailed justification for why we use the normal regression as the representative empirical relationship in appendix A2.3. To determine the relative importance of each variable x in predicting the nourishment rate, we calculate the standardized value X_{st} of the vector of independent variables using its mean value μ_x and its standard deviation σ_x:

$$X_{st} = \frac{x-\mu_x}{\sigma_x}. \tag{2.1}$$

The dependent variable, nourishment rate, is standardized in the same fashion. In this way, the estimated parameters for the independent variables have equal ranges between zero and one, and thus, their orders of magnitude are comparable. We run this standardized normal model with the forward, backward, and stepwise processes to determine the set of significant parameters that best explains the nourishment rate. We also test all model combinations and isolate the model with the lowest root mean square error (RMSE), which represents the most accurate model fit of all possible models with the vector of independent variables X.

While this regression model provides information on the main factors controlling community-scale beach nourishment decisions, however, these empirical relationships do not provide explicit information on the physical morphology of the coast. We implement these empirical relationships found in our regression analysis that govern the rate at which communities nourish their beaches into the coupled geomorphic-economic modeling framework described in Janoff et al. (2019) and Janoff et al. (in review).

This model accounts for alongshore and cross-shore dynamics of shoreline change, assuming that seaward protrusions are diffusive and that beach nourishment sand is redistributed to adjacent shorelines and offshore to the shoreface toe when the shoreface is steepened beyond its equilibrium slope (Figure 2.3). Resultant changes in beach width are then capitalized into beachfront property values, and when combined with the costs of these nourishment projects, provide information on the net benefit of these management policies.

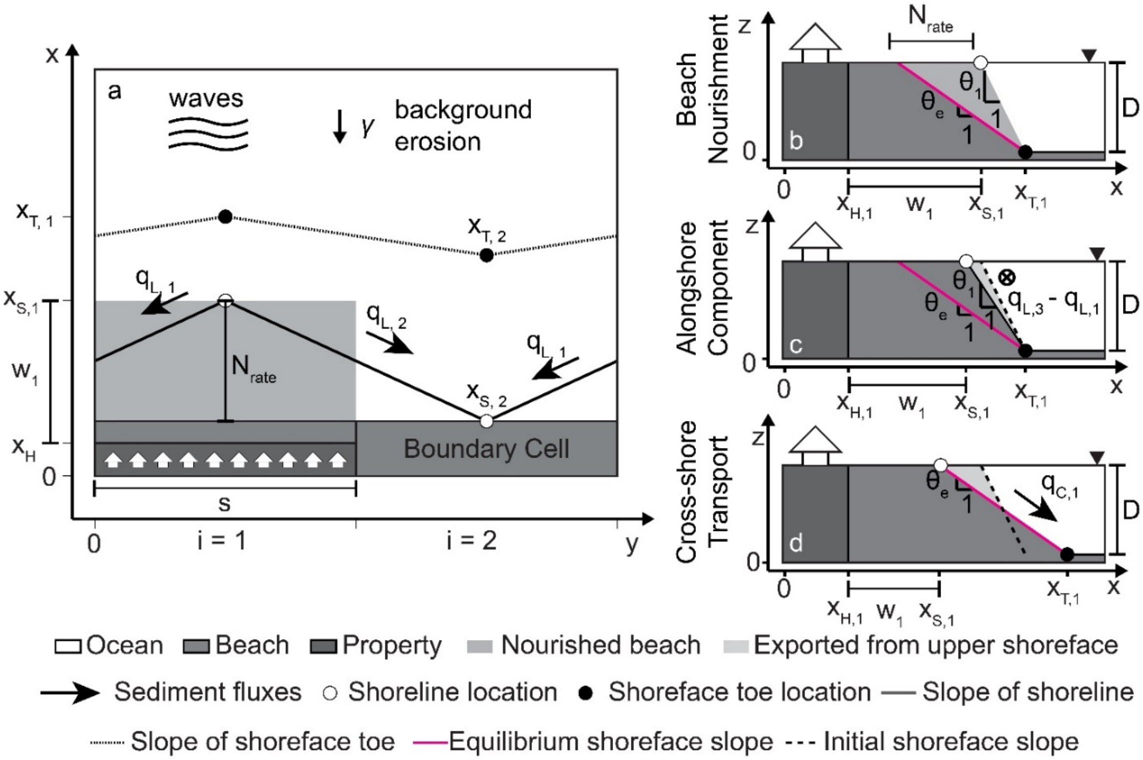

Figure 2.3. Idealized deterministic modeling framework described in Janoff et al. (in review) that accounts for both alongshore/cross-shore dynamics and socioeconomic effects on beachfront properties due to this physical morphology.

We modify this coupled geo-economic model (Janoff et al., 2019; Janoff et al., in review) that accounts for nourishment as periodic events and implement a continuous nourishment rate, which is consistent with our field data and the regression model's output. Changes in shoreline position $x_{S,i}$ are computed using the discretized ordinary differential equation $\Delta x_{S,i}/\Delta t$ for each cell:

$$\frac{\Delta x_{S,i}(t)}{\Delta t} = \frac{2 \cdot \left(q_{L,i-1}(t) - q_{L,i}(t)\right)}{s_i} - \frac{4 \cdot q_{C,i}(t)}{D} - \gamma + N_i \, , \tag{2.2}$$

where $q_{L,i}$ and $q_{C,i}$ are given by the slopes of the alongshore gradient and the shoreface respectively. Here, the nourishment term N_i is the nourishment rate as determined by the regression model and implemented as the volume of external sand added to the subaerial beach per year. This nourishment rate is based on the empirical relationship with the significant independent variables from the normal regression model, i.e., the beachfront wealth and the commercial-residential value ratio, which will be discussed in section 2.3.1. Using this model as a baseline, we test geomorphic variable (i.e., the nourishment half-life and the inlet distance) interactions with these two socioeconomic variables for the following specifications: the economic variables multiplied/divided by the geomorphic variables; the economic variables multiplied/divided by the natural log of the geomorphic variables; and the economic variables multiplied/divided by the geomorphic variables squared. All input parameters used in this geo-economic modeling framework are listed in appendix A2.4 (Table A2.8).

2.3 Results

2.3.1 Empirical Regression Model

All regression selection processes for the normal model suggest the same set of independent variables best predicts the nourishment rate: 1) the total beachfront wealth, and 2) the commercial-residential assessment value ratio. We find that each parameter estimate is significant at the 95% confidence level (Table 2.1).

Table 2.1. Parameter estimates for the normal model (total beachfront wealth and commercial-residential ratio) showing the effect of each independent variable on the nourishment rate.

Parameter Estimates					
Variable	df	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-7800.23	17556.00	-0.44	0.66
Total Beachfront Wealth	1	$1.51 \cdot 10^{-4}$	$4.03 \cdot 10^{-5}$	3.74	< 0.01
Commercial-Residential Ratio	1	223965.00	85407.00	2.62	0.01

In general, as a community's total beachfront wealth increases or as its share of commercial real estate value increases, the community will nourish more per year. This suggests that both socioeconomics and tourism have a positive linear impact on nourishment policy decisions, and that residential property values are not the only determinant of how a community will manage its beach. The standardized version of this model also indicates that a community's total beachfront wealth has a larger effect on its nourishment rate than the commercial-residential assessment value ratio (Table 2.2). This supports previous literature's assumption that property value is the primary driver of a community's nourishment decision (Gopalakrishnan et al., 2011; McNamara et al., 2015; Smith et al., 2009), but highlights that a community's proportion of commercial development, a proxy for its level of tourism, is also an important control on beach management.

Table 2.2. Parameter estimates for the standardized normal model (total beachfront wealth and commercial-residential ratio) showing the relative importance (i.e., magnitude of parameter estimate) of each independent variable on the nourishment rate.

Parameter Estimates					
Variable	df	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	$-1.70 \cdot 10^{-16}$	0.14	0	1.00
Total Beachfront Wealth	1	0.54	0.14	3.74	< 0.01
Commercial-Residential Ratio	1	0.38	0.14	2.62	0.01

Nourishment rates observed in the field align moderately with predicted nourishment rates, although much of the variability cannot be explained by the model and is thus assigned to regression error in the absence of other explanatory variables (adjusted R-square = 0.32, Figure 2.4). This model that includes the commercial-residential ratio, however, explains approximately 13% of the remaining variability that cannot be explained by a linear regression for beachfront wealth alone (adjusted R-square = 0.19). It is therefore reasonable to assume that the level of commercial development is an important characteristic of a community in determining its beach management strategy as well. We integrate both the significant predictors and the corresponding nourishment rate into the geo-economic modeling framework constructed in Janoff et al. (in review).

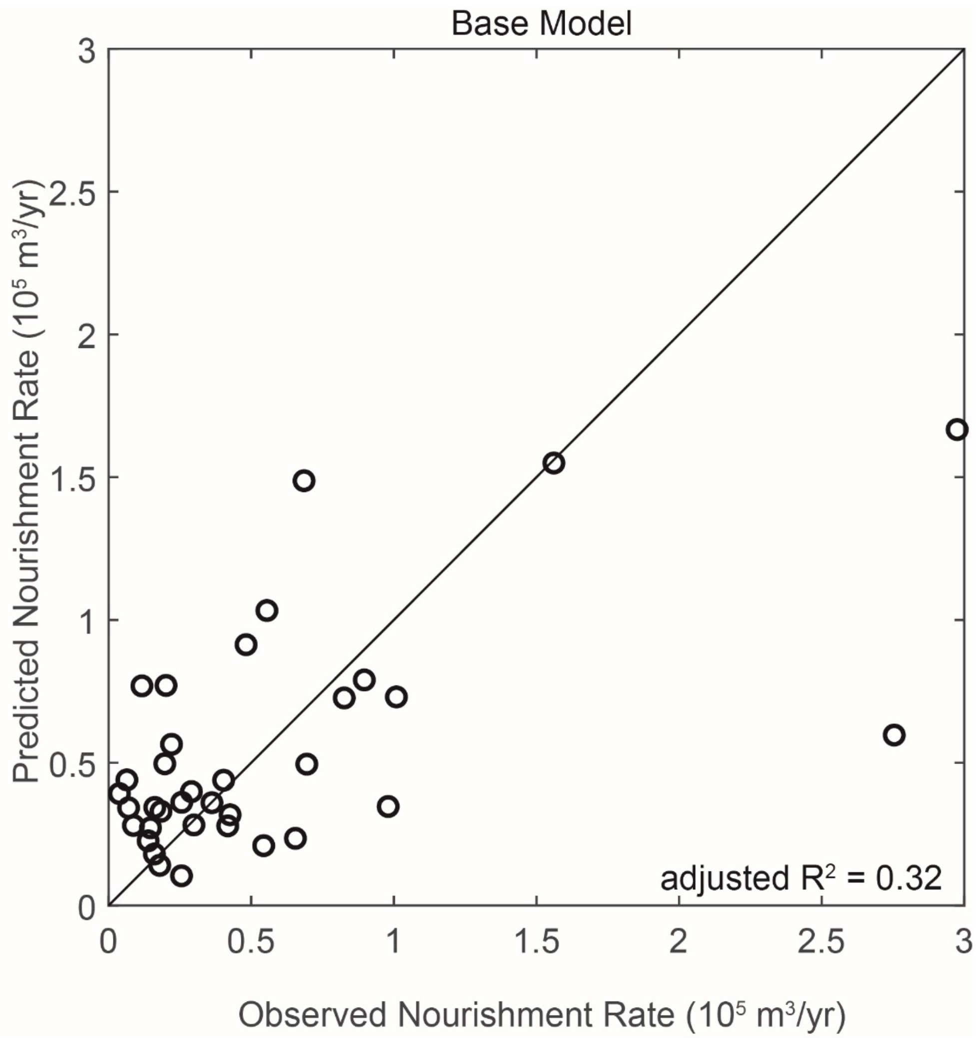

Figure 2.4. Observed vs. predicted nourishment rates for the normal regression model that includes a community's beachfront wealth and its proportion of commercial real estate as predictors.

2.3.2 Geomorphic-economic Interaction Regressions

The normal regression model presented in the previous section highlights the importance of including other socioeconomic variables as predictors of nourishment decisions, such as the extent of commercial real estate development within a community. While these variables help explain approximately 1/3rd of the variation in nourishment rates (adjusted R-square = 0.32; Figure 2.4), it should be noted that the importance of socioeconomic conditions relative to the coast's physical conditions might be specific to New Jersey (Silberman and Klock, 1988). The high tourism and property values along this stretch coast, which is in close proximity to major urban centers such as New York City and Philadelphia, could be out-competing the underlying geomorphic conditions of the region.

Building off of the main components in the base model, we explore how the model's two socioeconomic variables (i.e., wealth and tourism) interact with the geomorphic variables (i.e., the nourishment half-life and the distance downdrift of a tidal inlet). We run various interaction scenarios: economic variable multiplication/division by geomorphic variable, economic variable multiplication/division by natural log of geomorphic variable; and economic variable multiplication/division by the square of the geomorphic variable. Similar to the model selection process outlined in previous sections (2.2-2.3.1), we present the geo-interaction models for half-life and inlet distance that result in the lowest RMSE and the highest adjusted R-square value.

The geo-interaction model that includes a community's nourishment half-life, i.e., a metric of its physical efficiency, is comprised of the total beachfront wealth and the commercial-residential ratio divided by the half-life (i.e., the geo-interaction variable). Both the wealth and the geo-interaction variable have positive parameter estimates, such that increasing the wealth or the commercial-residential ratio results in higher nourishment rates, and increasing the half-life results in lower nourishment rates (Table 2.3). This relationship aligns with the base model presented in section 3.1 and our sub-hypothesis for half-life, in which we expected that higher efficiency nourishments (i.e., longer half-lives) allow communities to nourish less frequently, or with less volume, both of which correspond with a lower nourishment rate.

Table 2.3. Parameter estimates for the geomorphic-economic interaction regression models that includes (1) a community's beachfront wealth and the commercial-residential ratio divided by the nourishment half-life, and (2) the commercial-residential ratio and the product of the beachfront wealth the natural log of the inlet distance.

Parameter Estimates: Geo-interaction Model 1 (Half-life)					
Variable	df	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3637.95	15265	0.24	0.81
Total Beachfront Wealth	1	$1.38 \cdot 10^{-4}$	$3.88 \cdot 10^{-5}$	3.55	< 0.01
Commercial-Residential Ratio / Half-life	1	89970	30513	2.95	< 0.01
Parameter Estimates: Geo-interaction Model 2 (Inlet Distance)					
Variable	df	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-12648	18185	-0.70	0.49
Commercial-Residential Ratio	1	235722	85224	2.77	< 0.01
Total Beachfront Wealth · ln(Inlet Distance)	1	$1.88 \cdot 10^{-5}$	$4.90 \cdot 10^{-6}$	3.85	< 0.01

The geo-interaction model that includes the community's distance downdrift of a tidal inlet, i.e., a proxy for its natural sediment availability, is comprised of the commercial-residential ratio and the product of the total beachfront wealth and the natural log of the inlet distance (Table 2.3). Both parameters have a positive estimate, such that increasing the extent of commercial development, increasing the beachfront wealth, and increasing the distance downdrift of an inlet results in a higher nourishment rate. This is consistent with the base model and one of our sub-hypotheses for inlet distance, in which inlets serve as a sediment source for downdrift communities, supplying immediately adjacent beaches with sand and thus resulting in lower nourishment rates closer to inlets. Communities further downdrift do not benefit as much from this natural sediment supply and respond with higher nourishment rates, though the relationship between increasing distance downdrift and increasing nourishment rate is nonlinear. It is important to note, however, that this result could differ by region due to differences in net vs. gross alongshore sediment transport, the influence of partially/fully-jettied inlets vs. natural inlets, and differences in ebb-shoal delta dynamics between the central New Jersey coast (Monmouth/Ocean Counties) and the southern New Jersey coast (Atlantic/Cape May Counties).

Both of these geo-interaction models help explain more of the variation in observed nourishment rates, with adjusted R-square values of 0.35 and 0.33 for the half-life and inlet distance models respectively (Figure 2.5). This result highlights that while socioeconomics plays a primary role in determining how New Jersey communities choose their beach management strategies, natural characteristics of a site such as its sediment availability or deficit are also important components. These models add information on community-scale nourishment and highlight that the interplay between socioeconomics and geomorphology is key to understanding how communities choose to intervene in the coastal environment.

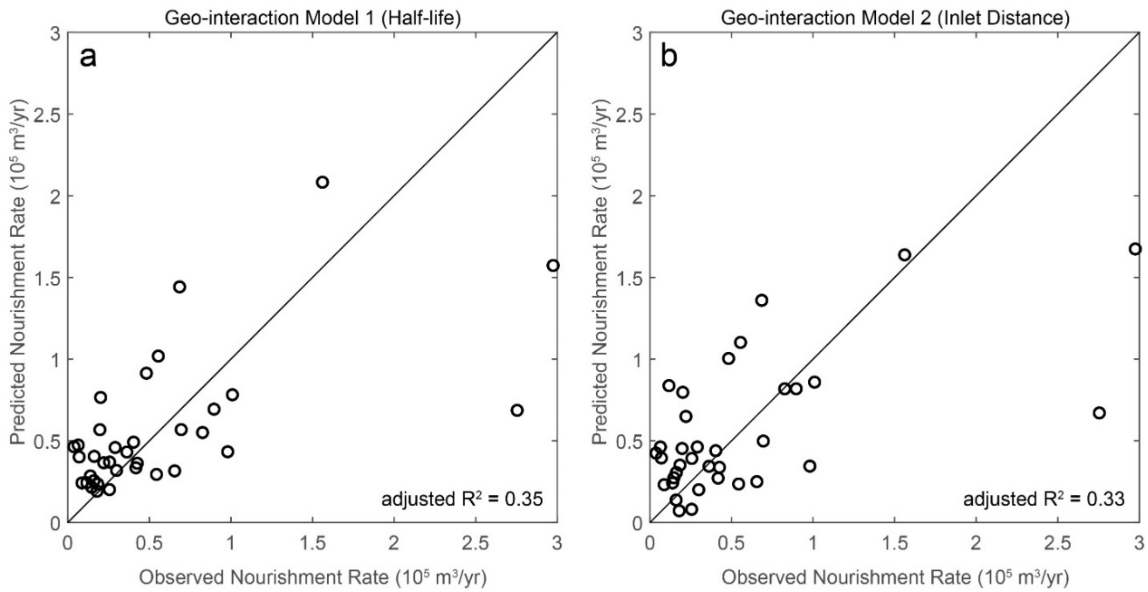

Figure 2.5. Observed vs. predicted nourishment rates for the geomorphic-economic interaction regression models that includes (a) a community's beachfront wealth and the commercial-residential ratio divided by the nourishment half-life and (b) the commercial-residential ratio and the product of the beachfront wealth the natural log of the inlet distance.

2.3.3 Geo-economic Model Behaviors and Future Vulnerability

We implement the base regression model (Section 2.3.1) into the numerical geo-economic model framework (Janoff et al. in review), and test the model's sensitivity to the beachfront wealth and the commercial-residential ratio, specifically focusing on the emergent mode behaviors. Communities can experience seaward growth, in which their beach widens over time (Figure 2.6a); hold the line, in which their beach does not widen but beachfront properties are maintained (Figure 2.6b); slow retreat, in which nourishment projects delay but ultimately accept beachfront property loss (Figure 2.6c); and full retreat, in which the community does not nourish and their beachfront properties are lost at the rate of background erosion (Figure 2.6d).

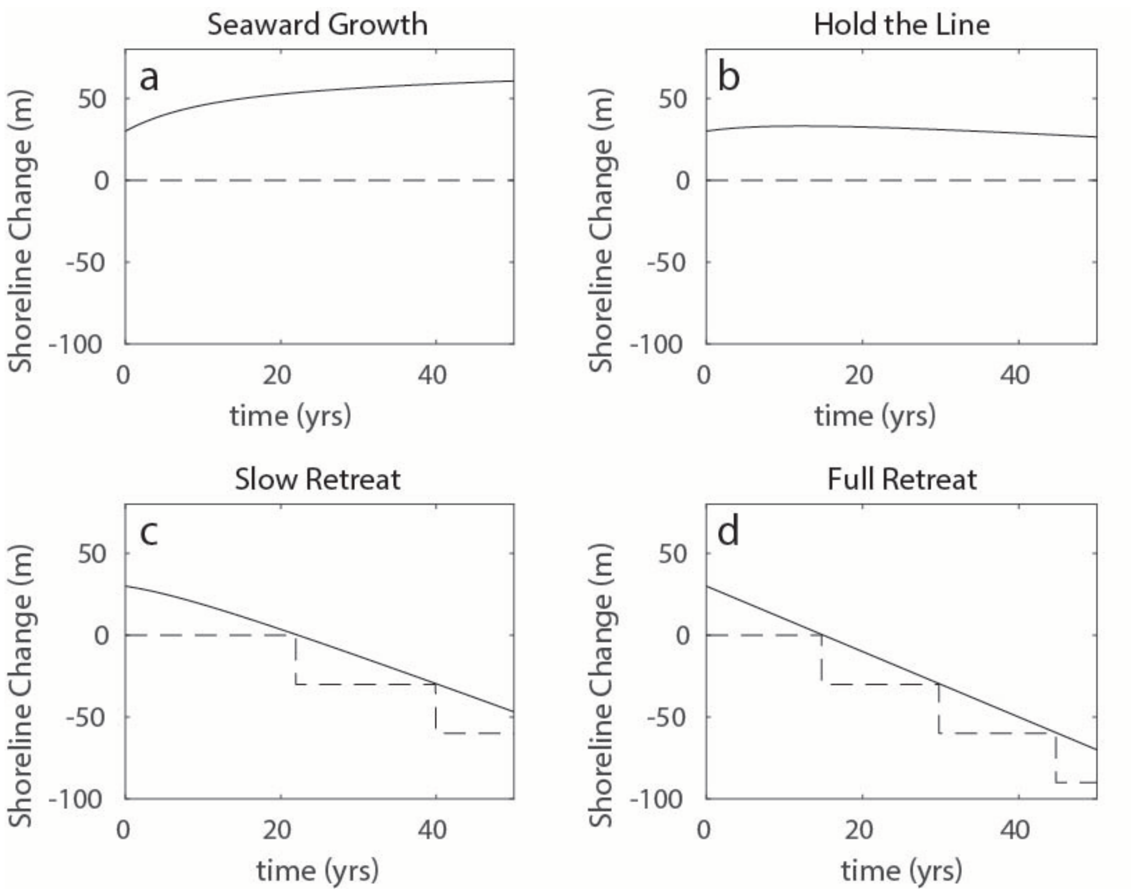

Figure 2.6. Example mode behaviors produced by the modified geo-economic model: seaward growth (a); hold the line (b); slow retreat with nourishment (c); and full retreat without nourishment (d).

Low-wealth communities with mostly residential properties will nourish enough to maintain their beach width, while wealthier communities or those with a larger proportion of commercial real estate will widen their beaches (Figure 2.7a). Superimposed on this regime space is each New Jersey community color-coded by its categorical mode behavior. This behavior is determined by the difference in shoreline locations between 1899 and 2012 for each community, where >50% seaward shoreline change corresponds to seaward growth, <50% shoreline change maintenance is classified as hold the line, and >50% landward shoreline change corresponds to retreat (slow retreat in nourishing communities; full retreat in non-nourishing communities). Red circles indicate communities that have prograded their shorelines seaward, while blue circles indicate communities that have held their shorelines in place (Figure 2.7a).

Approximately 65% of the model's behavioral predictions match the categorical field behaviors, and more importantly, both the model and field support our hypothesis that low wealth communities with a high proportion of commercial real estate can nourish with large rates, and thus, result in seaward growing shorelines. In addition, nearly all of the field observations that comprise hold the line behavior are residential-dominated communities. This indicates that the distinction between tourism-dominated and residential-dominated communities can help explain some of the counterintuitive geomorphic-economic trends we have observed along the U.S. east coast (i.e., less wealthy communities nourishing more and resulting in wider beaches than wealthier communities) and should be included when determining the future of developed coastlines more broadly.

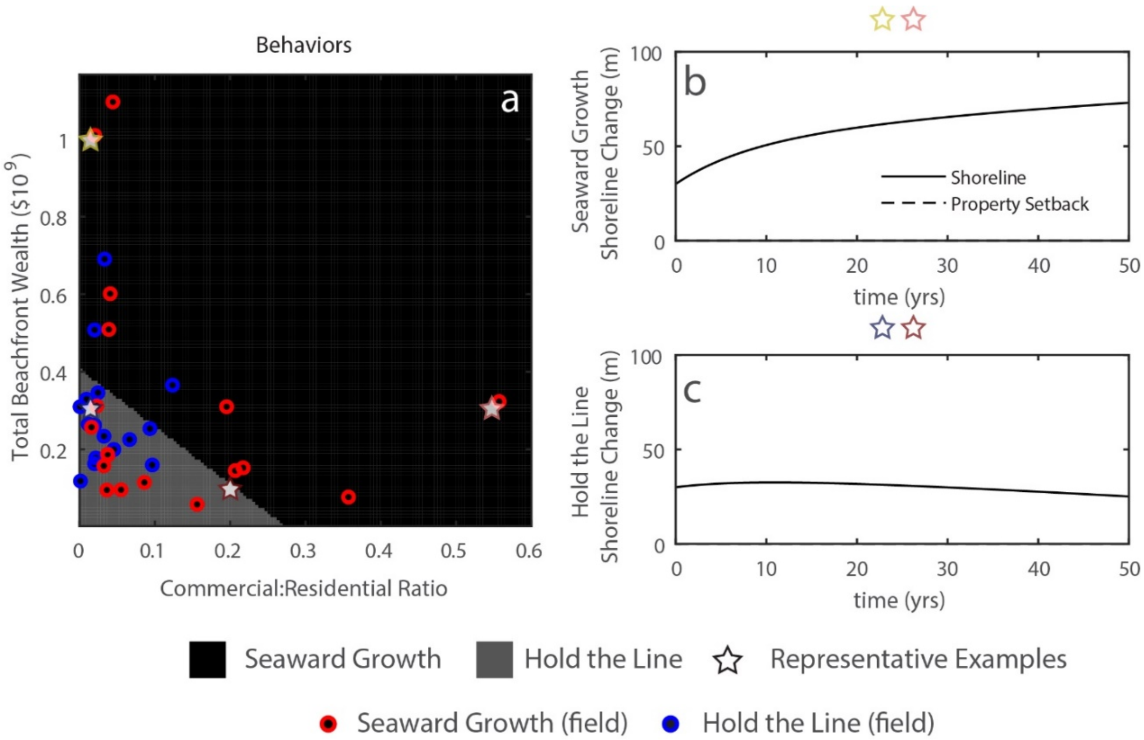

Figure 2.7. Emergent mode behaviors (a) based on the nourishment rates determined by its relationship with total beachfront wealth and the commercial-residential assessment value ratio from the normal regression model. New Jersey field observations are included in the regime space and color-coded by their field behaviors (red: seaward growth; blue: hold the line) to show how many communities experience each mode behavior and whether the nourishment projects result in a positive or negative net benefit for the local residential community. Also included are shoreline evolution subplots for each behavior (b-c) through time for both residential-dominant and commercial-dominant communities experiencing seaward growth and hold the line behaviors respectively.

In the future, expected increases in erosion rates associated with sea-level-rise rates will make it more difficult for communities to maintain their beachfront properties. Should communities continue nourishing at the same rate in the future, compared to the baseline behaviors under current conditions (Figure 2.7a), fewer communities will experience seaward growth, and more communities will experience hold the line or slow retreat (Figure 2.8a). Eventually, more extreme erosion rates will force most (Figure

2.8b) or all communities to abandon beachfront properties (Figure 2.8c-d) even with nourishment action in place. In addition to enhanced erosion rates, nearshore sand supply will decrease due to continued, expansive nourishment programs, forcing dredging operations further offshore, thus driving the price of sand up. Should communities experience increases in sand cost, erosion rate , or likely both , it may become more difficult for communities to maintain their nourishment policies in the future, highlighting the added economic difficulty for coastal communities facing the effects of climate change as well.

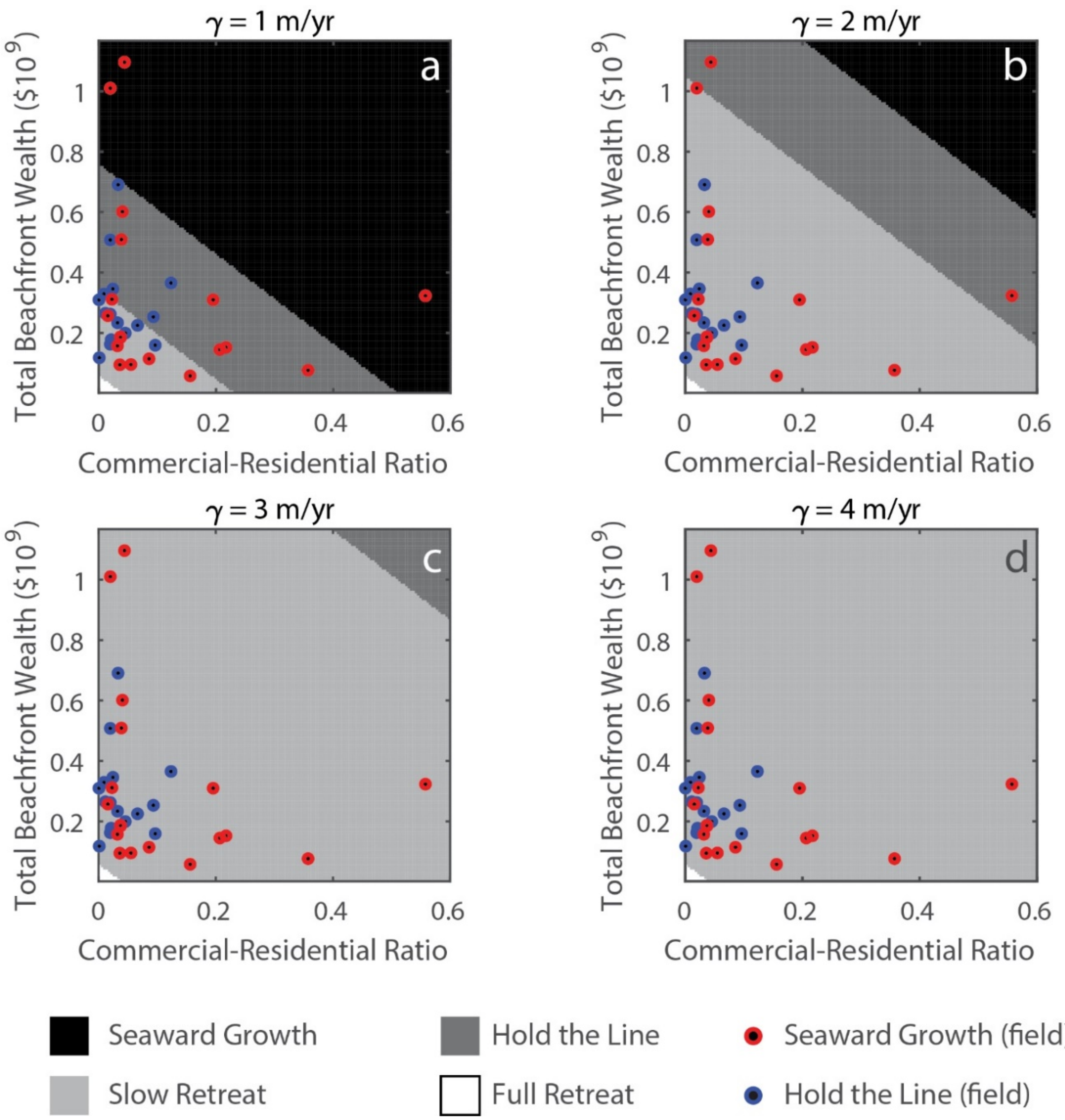

Figure 2.8. Emergent mode behaviors based on the nourishment rates determined by its relationship with total beachfront wealth and the commercial-residential assessment value ratio from the normal regression model for an increasing background erosion rate: $\gamma = 1$ m/yr (a); $\gamma = 2$ m/yr (b); $\gamma = 3$ m/yr (c); $\gamma = 4$ m/yr (d). Field observations color-coded by current behavior (red: seaward growth; blue: hold the line) are included to show their behavioral transition in the future if they maintain their status quo nourishment policy.

2.4 Discussion

While under current climate and economic conditions, most all coastal communities have been able to maintain or even widen their beaches over the last half century due to extensive artificial beach nourishment policies (Armstrong and Lazarus, 2019; Janoff et al., in review), the future sustainability of these communities is less clear. It is even more uncertain how communities comprised primarily of residential properties might choose management strategies differently from communities focused on beach recreation and a commercial tourism industry. In addition, the extent of rental properties, full-time homes, and secondary homes within a residential-dominant community could affect the community's nourishment choices. These differences in socioeconomic structure by community type and even a community's proximity to nearby tourism-dominated communities will likely leave a categorically distinct signature on the evolution of developed coasts. In addition, local geomorphological impacts will also interact with and feedback on these human-scale components in unknown ways under future conditions associated with climate change such as sea-level rise and diminished resource availability.

The level of intervention required of these communities will not remain static; instead, a regional re-analysis of our management approach is likely required. This impending choice centers on whether to increase beach nourishment efforts to keep pace with increasing rates of erosion, thus further fueling the positive feedback that has increased both wealth and the magnitude of beach nourishment interventions on decadal timescales (Armstrong et al., 2016); or, disband current management frameworks with state and local governments, remove vulnerable infrastructure, and accept property relocation in high risk zones toward developing a more hyperopic management view.

This paper adds to the growing body of developed coast literature in highlighting that a community's beachfront property value is not the sole predictor on its current or future beach management decisions. Instead, the economic extent of the local tourism industry and the interplay between socioeconomics and geomorphology are important, and must be considered when analyzing how communities will respond to increased erosion.

The New Jersey coast's proximity to New York City and Philadelphia promotes steady demand for beach recreation and beachfront property ownership (Silberman and Klock, 1988), which will likely serve to entrench our current management mentality toward holding the line and protecting our vulnerable infrastructure. This may be especially true for communities whose economies rely heavily on hospitality and recreational services. It is unlikely that communities will consent to moving away from the coast voluntarily, thereby giving up their prime real estate, reducing their municipal property tax revenues, and losing their local businesses that anchor their seasonal tourism economies. It is possible that tourism-dominant communities will demand even more protection than residential-dominant communities in the future, possibly serving to focus state and federal subsidy programs on such areas with high recreational values.

The complex sociopolitical dynamics between neighboring communities fighting for limited and likely more expensive sand resources coupled with a potentially apprehensive federal government will only exacerbate these existing challenges to coastal management, whose weight is often felt most by environmental justice and low-income communities.

Furthermore, while our analysis supports the theory that the proportion of commercial real estate in a community might make up for its lower property values in explaining its high rates of nourishment and thus its wide beaches, we find evidence from the field that suggest some lower-wealth communities may be nourishing with large magnitudes even in the absence of an extensive local tourism economy. This harkens back to findings from Janoff et al. (in review) who suggest that low-wealth communities may be over-nourishing, or nourishing more than they otherwise would have had they coordinated their nourishment plans on regional scales with neighboring communities. This highlighting not only the interconnectivity of these coastal systems but also the socioeconomic and geomorphic consequences that might result from community-scale differences in wealth or tourism-related benefits.

In order to understand how heavily developed coastlines, such as New Jersey, and how communities in particular might adapt in economically/environmentally sustainable ways, deterministic models must be developed that account for shifts in the decision-making process and for the various changes to both natural and human components within this coupled system. These will not only include changes to coastal real estate markets but also disruptions to local tourism economies and to the value of beaches as recreational amenities.

Previous work highlighted property value as a primary determinant of how communities have interacted with shoreline dynamics in the past and how these interactions might change in the future (Armstrong et al., 2016; Smith et al., 2009; Lazarus et al., 2011). Recent work has built on these findings, considering the interconnected dynamics of neighboring communities making different nourishment decisions based on their level of coordination (Gopalakrishnan et al., 2016; Janoff et al., in review; Jin et al., 2013; Smith et al., 2015). Further, Qiu et al. (2020) suggested that underlying geophysical conditions in the coastal environment can also help explain why communities have managed their beaches in specific ways depending on their spatial proximity to sand resources.

Our empirical analysis here adds to this growing list of nourishment predictors, highlighting the importance of tourism within a community. Additionally, our initial attempt at incorporating these relationships into a semi-empirical, geo-economic modeling framework features the importance of including tourism as a control on the regional geomorphic trends we observe in the field, such as seaward prograding shorelines (Armstrong and Lazarus, 2019; Hapke et al., 2013). Further, natural geomorphologic conditions, such as sediment delivery and sand retention at nourishment sites are important components of nourishment choices, though further work is needed to understand the effect of tidal inlets based on regionally distinct characteristics between central (Monmouth/Ocean Counties) and southern (Atlantic/Cape May Counties) New Jersey.

We use the geo-economic framework based on the normal regression model's parameter estimates to predict how community-scale decisions will interact with higher erosion rates associated with sea-level rise in the future, and show that communities might not only have a harder time maintaining wide beaches, but they will also be susceptible to property loss.

It will be important within future deterministic modeling frameworks and/or the continued development of these existing frameworks, however, to account for a wider suite of community-scale differences, including the interactions between socioeconomics, tourism, and geomorphology, and to find ways in which we can analyze the socioeconomic evolution of communities dominated by commercial real estate. This paper provides a potential avenue toward addressing this goal, but more work is required to fully understand how beach morphodynamic changes are capitalized into a tourism economy. This information will not only further our intrinsic understanding of the evolution of coupled natural-human systems such as urbanized coasts with variable community types, but also will be critical for local governments faced with the expanding challenges associated with climate change and the federal and state governments helping to facilitate these difficult management decisions in order to maximize social welfare.

CHAPTER 3 – A GEO-ECONOMIC MODEL TO EXPLORE COMMUNITY RESPONSES TO DOWNDRIFT GROIN-INDUCED EROSION

The contents of this chapter partially appear in:

Janoff, A., Lorenzo-Trueba, J., Hoagland, P., Jin, D., & Ashton, A. (2019). Coupling Geomorphology and Socioeconomics to Account for Groin Downdrift Erosion. In P. Wang, J. D. Rosati, M. Vallee (Eds.), *Proceedings of the 9th International Conference*, (pp. 1826–1839). Tampa/St. Petersburg, FL: International Conference on Coastal Sediments 2019. https://doi.org/10.1142/9789811204487_0158

3.0 Summary

Coastal communities use hard and soft engineering to sustain beach recreation and to protect physical properties and infrastructure. Soft engineering involves external sand placement to widen beaches artificially; this placement is typically termed ‘nourishment’. Hard engineering involves the construction of immovable objects, such as shore-perpendicular groins, which slow alongshore currents and deposit sediments locally at and updrift of the objects. While groins accrete sediment updrift, they also limit downdrift sediment supply, exacerbating erosion and often forcing downdrift communities to respond with new engineering measures. We have developed a coupled geo-economic model to explore how communities make relevant management decisions. The model identifies a set of factors that could help explain the geo-economic condition and timing of a community’s responses to groin-induced erosion as observed in New Jersey. These include the community’s beachfront property value and its size (a proxy for its tax base), both of which determine its ability to finance groin construction or beach nourishment projects. Results of model simulations for future conditions, such as higher background erosion rates and higher rock material costs, suggest that management interventions will likely be economically infeasible, resulting in beachfront property loss and retreat from the coast. Depending on the balance between erosion rates and economic conditions, the model also highlights the possibility that the historical transition away from groins to beach nourishment as the main management response could be reversed

in the future, and groins could again become the more commonplace intervention as communities adapt to sea-level rise.

3.1 Introduction

More than two-thirds of the world's largest cities are located on coastlines (Uzun and Celik, 2014). As of 2003, coastal counties in the United States comprised 53% of the national population but only 17% of the coterminous land area (Crossett et al., 2004). Dense coastal development led to engineering activities to protect assets and maintain beaches. Living close to the ocean serves as an amenity, creating the base for local and tourist economies, and there is an inherent desire to protect private and public infrastructure associated with them, including residential/commercial properties, roads, boardwalks, water and gas lines, sewers, stormwater infrastructure, communications systems, etc. (Johnston et al., 2014). Beaches and oceans have high recreational values as well, providing public goods and services for surfers, anglers, swimmers, scuba-divers, birders, sunbathers, and other beach/ocean users (Ariza et al., 2014; Sano et al., 2011). In addition, many coastal homeowners conserve their properties for future generations, implying high bequest values (Silberman et al., 1992). Taken altogether, the coastal zone encompasses a variety of amenities that humans seek to preserve.

Property owners and coastal managers have utilized soft and hard engineering to protect properties and to sustain beach recreation (Douglass and Krolak, 2008; van Rijn, 2011). Soft engineering involves external sand placement, known as replenishment, nourishment, or beach fill, to widen beaches artificially (Hoagland et al., 2012). This 'soft' approach may require regular maintenance as sand spreads alongshore, however, resulting in the need for periodic re-nourishment (Landry, 2004; Smith et al., 2009). Hard engineering involves the construction of immovable objects, such as shore-perpendicular groins, which slow alongshore currents to deposit sediments locally at and updrift of the object (Kraus and Batten, 2007; Mestanza et al., 2018; Valsamidis and Reeve, 2017).

A small but growing literature on hedonic pricing has shown that properties benefit economically from local beach widening caused by both beach nourishment and the emplacement of groins (Gopalakrishnan et al., 2011; Landry and Hindsley, 2011; Pompe and Rinehart, 1995). Rational communities will choose their most efficient protective option, providing the most benefit for the least cost. Beach maintenance in updrift communities may encourage "free-riding" behavior in downdrift communities, where the downdrift communities benefit without being required to contribute to the cost of protection (Williams et al., 2013). Depending upon local coastal dynamics, the alongshore extent of groin-stabilized updrift shorelines can even lead to free-riding by communities in the updrift direction.

While groins stabilize updrift beaches, they also limit downdrift sediment supply, exacerbating erosion and often forcing vulnerable communities to respond with new engineering measures (Brown et al., 2016; Bruun, 1995; Ells and Murray, 2012). If these communities have the necessary resources, they will be able to stabilize their shorelines, an example of which can be seen in southern Long Beach Island, NJ, where Holgate built groins and nourished their beaches after a certain amount of time, resulting in a downdrift-hardened coast with a significant shoreline offset relative to the updrift community, Beach Haven (Figure 3.1a).

Where groins or beach nourishment are economically difficult to justify, downdrift communities might abandon properties altogether (Tischler, 2006). An example of a multi-property abandonment occurred in coastal New Jersey during the early 20th century when the town of South Cape May experienced accelerated rates of beach erosion as a consequence of updrift development and the construction of groins in Cape May City (Tischler, 2006; Figure 3.1b). Cape May City properties were more highly valued than those in South Cape May, and the community chose to invest in the emplacement of coastal protections, thereby accelerating beach erosion in the downdrift community. Along with storm surge damages, the loss of South Cape May properties to accelerated beach erosion forced the town into bankruptcy (Tischler, 2006).

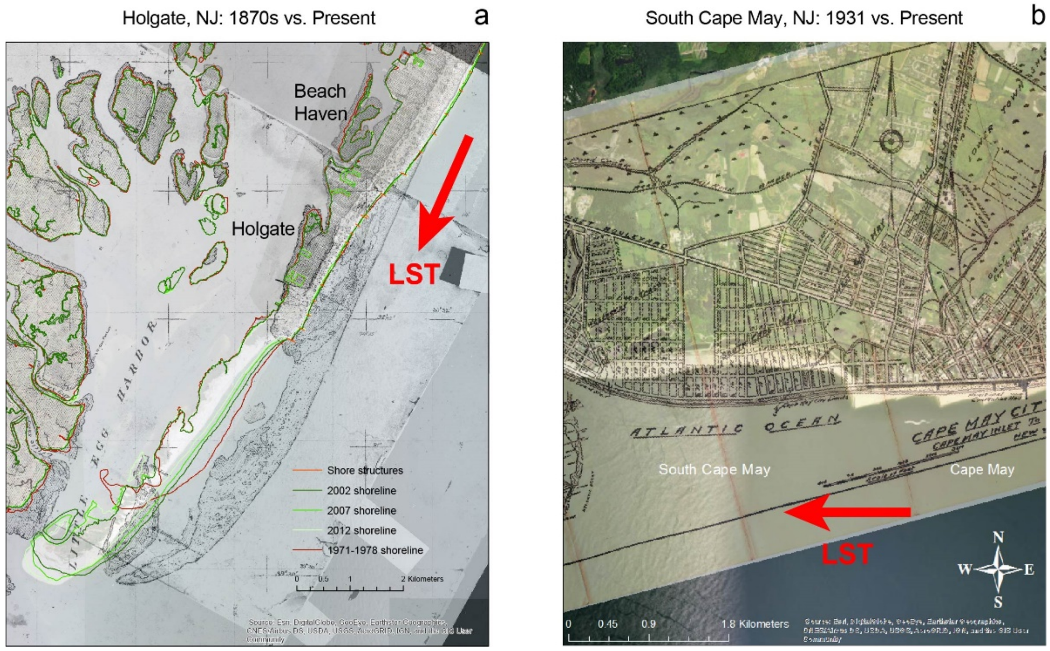

Figure 3.1. 1870s map of southern Long Beach Island, NJ (a) and 1931 map of South Cape May, NJ (b) superimposed on current aerial imagery showing the shoreline offsets that result from updrfit groin constructions. In one case, the downdrift community responded with subsequent groin constructions and beach nourishment (Holgate), while in another, the downdrift community filed for bankruptcy and abandoned their properties/community altogether.

Here, our objective is to present a simple model coupling geomorphology and socioeconomics along developed coasts to help understand strategy selection behavior for a community downdrift of a neighbor that built a groin updrift. Our research differs from the earlier literature exploring developed coast behavior in that we model the interaction between hard structures (groins) and soft structures (nourishment) to examine the role of groin-induced downdrift abandonment vs. management intervention while also analyzing the benefits and costs of these decisions. The model compares different protective strategies (i.e., soft engineering, hard engineering, a combination of the two, time-delayed intervention, and 'do nothing' resulting in property abandonment) to maximize economic efficiency, encompassing the feedback between natural coastal morphodynamics and human-scale modifications to the system. We will explore how different system characteristics (i.e., parameter values) might affect management choices in sediment-starved communities downdrift of a groin.

3.2 Methods

3.2.1 Beach Morphodynamics

We use an idealized geometry modified from previous work (Janoff et al., in review 2021; Janoff et al., 2019) to predict shoreline change averaged across a community (Figure 3.2). We assume an average number of cross-shore property rows *n*. Alongshore input sediment transport $Q_{L,1}$ is calculated using the CERC formula, and is a function of the wave climate (i.e., fixed wave angle χ and the wave height *H*) and the alongshore flux coefficient K_1:

$$Q_{L,1}(\mathrm{t}) = \mathrm{K}_1 \cdot H^{5/2} \cdot \cos(\chi - \mu(t)) \cdot \sin(\chi - \mu(t)) \tag{3.1}$$

$Q_{L,2}$ represents the bypass sediment flux around the groin with length *L* placed between communities *i*=1 and *i*=2 (Figure 3.2, Kraus and Batten, 1994). Bypass is governed by the input sediment flux into the updrift cell $Q_{L,1}$ and the ratio between the beach width w_i and the groin length *L*:

$$Q_{L,2}(t) = Q_{L,1}(t) \cdot \frac{w_i(t)}{L}\,. \tag{3.2}$$

For the case in which the system's shorelines are beyond the groin's seaward limit, the beach morphodynamics are governed by the alongshore transport equation (3.1) where the shoreline gradient μ is determined by their shoreline positions $x_{S,1}$ and $x_{S,2}$ as:

$$\mu(t) = \frac{(x_{S,i}(t) - x_{S,i+1}(t))}{(s_i + s_{i+1})/2} \tag{3.3}$$

We assume a flat updrift shoreline (i.e., μ=0) such that input sediment flux to the model domain is a function of the system's wave climate only, rather than any localized shoreline perturbations.

Using the cross-shore and alongshore dynamics presented in Janoff et al. (in review 2021), we can describe the system at any point in time with two variables, the shoreline location $x_{s,i}$ and the shoreface toe $x_{T,i}$ (Figure 3.2).

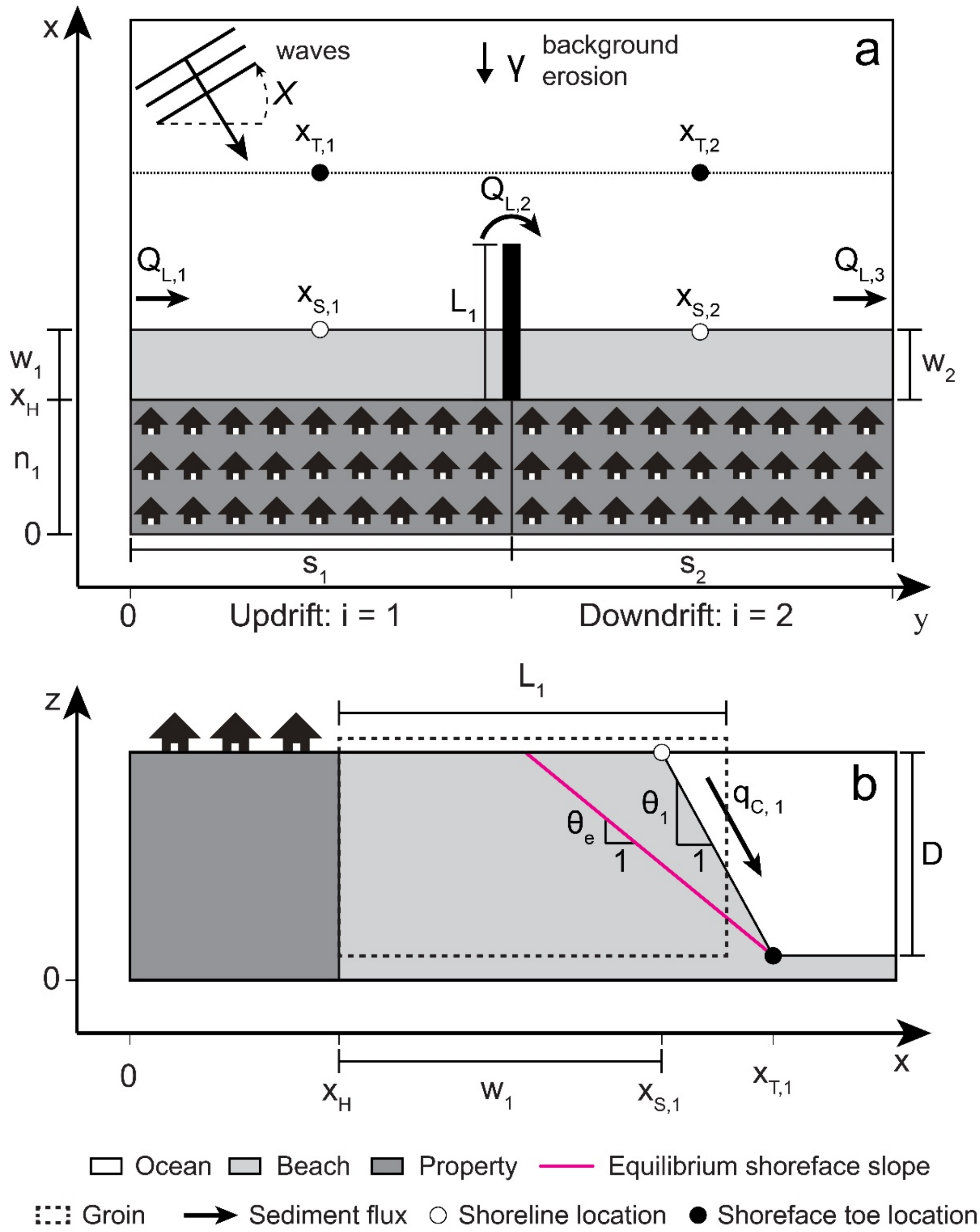

Figure 3.2. Model setup planview (a) with modified sediment flux between communities using the bypass equation (2). Cross-section (b) illustrates the depth of closure and equilibrium condition governing shoreface dynamics in the vicinity of a groin.

In contrast with the model framework originally presented by Janoff et al. (in review), which implements nourishment as discrete and periodic events, we implement nourishment in a community with a continuous rate. In this way, the model results for this study depend more on the comparison between nourishment and groin construction and the timing of each implementation, rather than the timing of specific re-nourishment events. This is the same approach utilized by Gopalakrishnan et al. (2016) and Janoff et al. (in prep).

3.2.2 Welfare Analysis

We calculate the net benefit for different management decisions (i.e., initial/delayed groin construction, initial/delayed beach nourishment, a combination of the two, and no intervention). The net benefit for each strategy is unique, providing a metric to compare options. The net benefit NB_i for community i is the sum of net benefits over a planning horizon ($0 \leq t \leq T$):

$$NB_i = \int_0^T (B_i(t) - C_i(t)) \cdot e^{-\rho \cdot t} \cdot dt \, , \tag{3.4}$$

where B_i = the benefits, C_i = the costs, ρ = the discount factor ($0 \leq \rho \leq 1$), t = time, and T = the model time horizon. Net benefits appreciate proportional to the discount factor, thus describing the community's effective time horizon of interest.

3.2.3 Benefits

Beach width provides both a protective and a recreational value to coastal communities (Jin et al., 2015; Landry et al., 2003; McNamara and Keeler, 2013; McNamara et al., 2015; Pompe and Rinehart, 1995; Simmons et al., 2002). We extend previous formulations to account for a community's size, modeled as the number of homes in cross-shore. This captures a community-scale perspective rather than that of only the beachfront homes. The benefit B_i for community i is defined as:

$$B_i(t) = \alpha_i \cdot \rho \cdot \left(\frac{w_i(t)}{w_\alpha}\right)^{\beta} \cdot (n_i(t))^{\psi}\ , \tag{3.5}$$

where α_i = the beachfront property value and w_α = a reference beach width. Note that $\alpha_i\rho$ = the baseline rental value, which encompasses a home's structural and neighborhood characteristics excluding the beach width. The above specification assumes that benefits of shoreline protection are positively related to the number of homes in a community. Two positive parameters β and ψ describe the effects on B_i of unit changes in beach width and the number of rows in the community, respectively. This relationship captures how dynamic changes in beach width affect a property's value, and ultimately a community's total wealth.

The parameter ψ also captures the effect of declining value of property as its distance from the beach increases. Typically beachfront properties are most valuable, and properties in each subsequent row inland are less valuable (Figure 3.3). This relationship is due to diminished viewership, increased travel cost, and decreased recreational amenity with distance from the beach (Jin et al., 2015; Landry and Hindsley, 2011; Pompe and Rinehart, 1995). Our model formulation allows for the migration of beachfront benefit if property rows are lost to erosion.

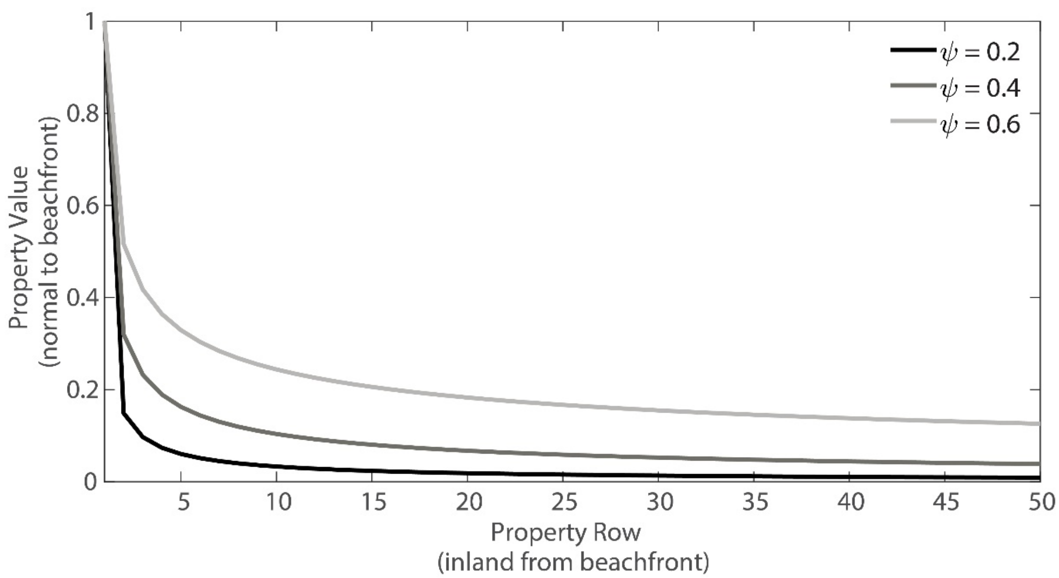

Figure 3.3. Property value (PV) distribution as a function of increased distance from the beach (property row). Normalized values illustrate proportional decrease in price for each row inland.

3.2.4 Costs

The total cost of shoreline management C_i for community i is a sum of engineering-related activities:

$$C_i(t) = C_{G,i}(t) + C_{N,i}(t, N_i) \ , \tag{3.6}$$

where $C_{G,i}$ = the cost of groin construction; $C_{N,i}$ = the cost of nourishment; and N_i = the nourishment rate. In turn, we describe the groin construction cost $C_{G,i}$ as:

$$C_{G,i}(t) = \phi_G \cdot L \ , \tag{3.7}$$

where ϕ_G = the variable cost coefficient for rock (\$/m) and L = the groin's length (m). This cost is a discrete event at the time of groin construction. The cost of nourishment $C_{N,i}$ is:

$$C_{N,i}(t) = \phi_N \cdot N_i, \tag{3.8}$$

where ϕ_N = the variable sand cost coefficient, and N_i = the nourishment rate. Nourishment costs are continuous across the model's time horizon and starting at the time of nourishment intervention.

3.2.5 Optimization

Similar to the optimal control problem presented in Janoff et al. (in review), we compare the welfare analysis equation (3.4) for different strategies that a community can take in response to heightened erosion due to the updrift community's groin. These strategies include combinations of initial groin construction/beach nourishment, time-delayed beach nourishment/groin construction, or no intervention. Each strategy's corresponding effect on the system's natural and human components are implemented into the morphodynamic and socioeconomic frameworks respectively, and the timing of strategic implementation that maximizes the downdrift community's net benefit is considered their rational response. This net benefit maximization also includes the optimal time at which a community will choose to nourish, build a groin, or pursue a combination of strategies. In sum, this corresponds to an optimal control problem, with the times of groin construction and nourishment intervention as the control variables t_g and t_n respectively, and the net benefit NB (Equation 3.4) as the functional to be optimized:

$$\max_{t_g, t_n} NB. \tag{3.9}$$

We utilize a time range between zero (i.e., initial intervention) and 100 years (i.e., the model's time horizon) for both the groin timing and the nourishment timing variables, with temporal resolution of one year. Neither the range nor the resolution affect the optimal solution. We employ a brute force approach to solve this optimal control problem, such that we calculate the net benefit of each combination of intervention timings and identify the combination that produces the maximum net benefit for the downdrift community.

3.2.6 Parameter Estimation

Table 3.1. Economic input parameters including the symbol, feasible range of values, representative test values, units, and references.

Economic Parameters	Symbol	Feasible Range of Values	Units	Test Value: Fig. 6, 8b	Test Value: Fig. 9
Sand Cost Coefficient[a,d,j,m,o,r,s]	ϕ_N	2—30	\$/m^3	5	5
Groin Cost Coefficient[d,j,r]	ϕ_G	0.8—290	\$10^3/m	100	1—1,000
Baseline Property Value[b,f,h,k]	α	100—650	\$10^3	6: 0.1—650 8b: 80—110	277.519
Number of Cross-shore Property Rows[e]	n_i	8—140	-	6: 1—120 8b: 38	38
Discount Factor[g,p,s]	ρ	0.01—0.2	yr^{-1}	0.15	(a-b) 0.15 (c-d) 0.03
Hedonic Parameter (Beach Width)[a,c,l,n,p]	β	0.05—0.8	-	0.5	0.5
Hedonic Parameter (Property Rows)[a,b,h,i]	ψ	0.0001—0.8	-	0.2	0.2

References: [a]Gopalakrishnan, 2010; [b]Gopalakrishnan et al., 2011; [c]Gopalakrishnan et al., 2016; [d]Hillyer, 1996; [e]Inspired by field values observed in New Jersey; [f]Jin et al., 2015; [g]Landry, 2004; [h]Landry and Hindsley, 2011; [i]Landry et al., 2003; [j]Mcdowell Peek et al., 2016; [k]Municipal financial documents; [l]Pompe and Rinehart, 1995; [m]PSDS, 2019; [n]Slott, 2008; [o]Slott et al., 2010; [p]Smith et al., 2009; [q]USACE, 1999; [r]USACE, 2015; [s]Williams et al., 2013.

Table 3.2. Physical input parameters including the symbol, feasible range of values, representative test values, units, and references.

Physical Parameters	Symbol	Feasible Range of Values	Units	Test Value: Figs. 5—6, 8b	Test Value: Fig. 9
Background Erosion Rate[a,g]	γ	0—??	m/yr	2	0.5—10
Nourishment Rate[b,m]	N_i	2—130	10^3 m^3/yr	Updrift: 8.415 Downdrift: 18.614	Updrift: 8.415 Downdrift: 18.614
Groin Length[h,i]	L_i	20—240	m	Updrift: 135 Downdrift: 100	Updrift: 135 Downdrift: 100
Depth of Closure[d,f,l]	D	5—20	m	16	16
Alongshore Flux Coefficient[c,e]	K_1	10—1,000	10^3 m^2/yr	500	500
Cross-shore Flux Coefficient[j,k]	K_2	2—10	10^3 m^2/yr	2	2
Shoreface Equilibrium Slope[j,k]	θ_{eq}	-	m/m	0.025	0.025
Alongshore cell length[h]	s	185—630	m	300	300
Property size[h]	*lot*	20—60	m	30	30
Deep Water Wave Angle[h]	χ	0—90	°	75	75
Deep Water Wave Height[h]	H	0.5—5	m	1	1

References: [a]Armstrong and Lazarus, 2019; [b]ASBPA, 2020; [c]Ashton et al., 2001; [d]Birkemeier, 1985; [e]Falqués, 2003; [f]Hallermeier, 1980; [g]Hapke et al., 2013; [h]Inspired by field values observed in New Jersey; [i]Kraus and Batten, 2007; [j]Lorenzo-Trueba and Ashton, 2014; [k]Miselis and Lorenzo-Trueba, 2017; [l]Ortiz and Ashton, 2016; [m]PSDS, 2019.

3.3 Downdrift Community Responses

We compare four primary strategy responses by the downdrift community (Figure 3.4): no groin or nourishment (a), groin without nourishment (b), nourishment without groin (c), and groin with nourishment (d). In this case, the updrift community's strategy is independent of the downdrift community but the downdrift community's strategy is conditioned upon the choice of groin construction in the updrift community. For this analysis, we assume that the updrift community has chosen to build a groin, and thus, we focus only on the downdrift community's response to that groin.

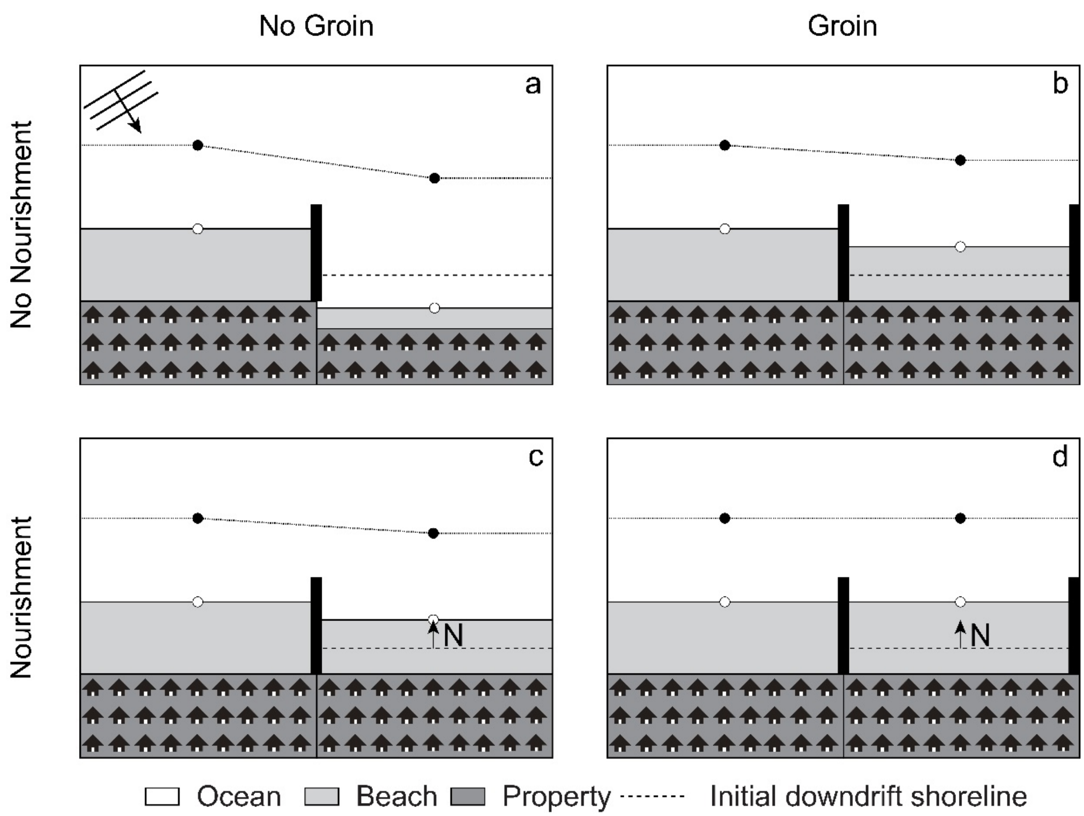

Figure 3.4. Four primary responses a downdrift community can take: no nourishment or groin (a), groin without nourishment (b), nourishment without groin (c), and nourish with groin (d).

If we consider delayed downdrift responses, communities might choose to nourish and/or build a groin at any point during the model run (i.e., time-delayed intervention). Including all possible combinations of strategies, this amounts to nine possible responses. We include a sample shoreline time-series for each strategy combination as well as the resultant loss of properties depending on the strategy and/or timing of intervention (Figure 3.5).

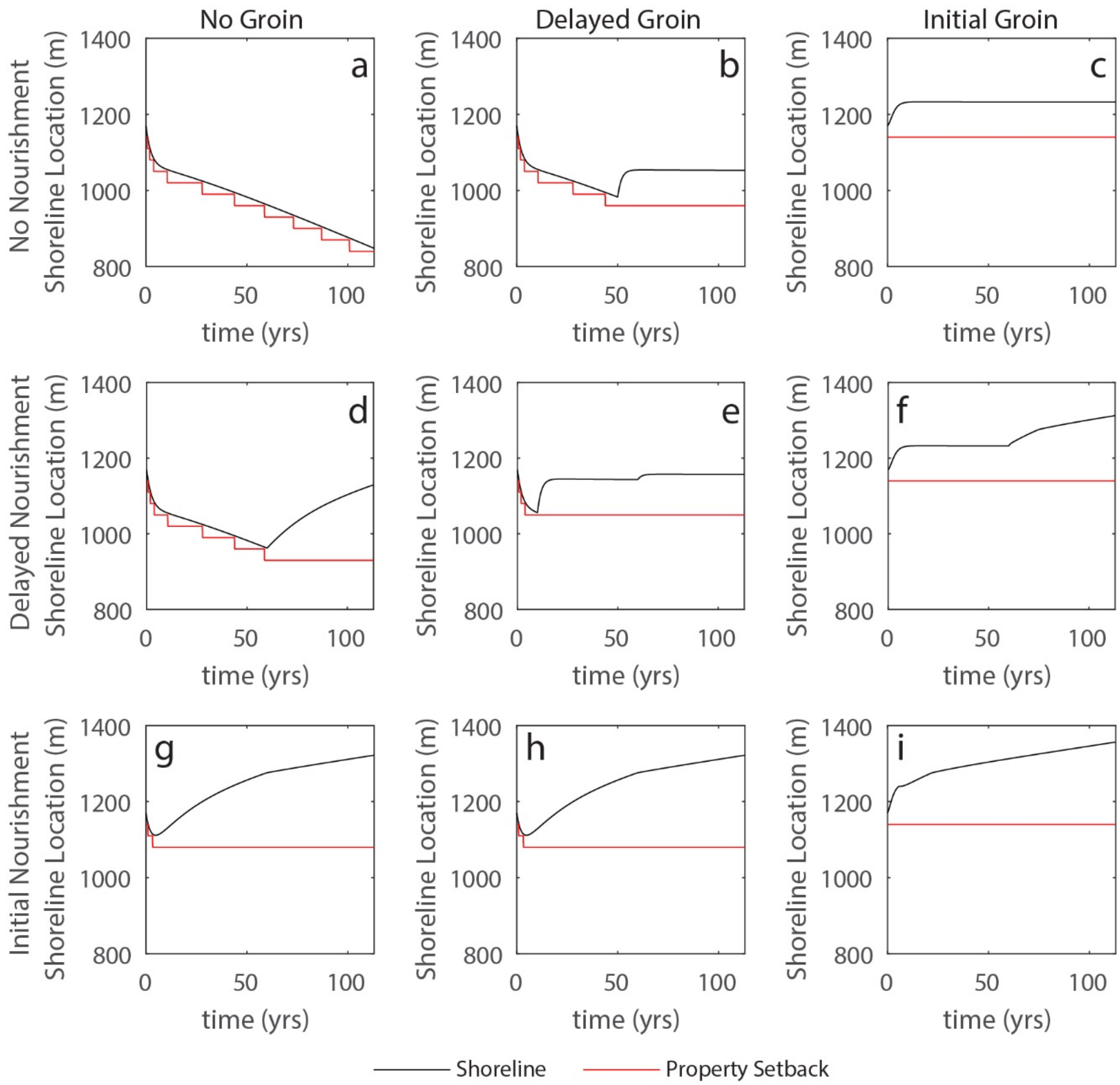

Figure 3.5. Decision matrix for downdrift community with all combinations of initial/delayed/no beach nourishment and/or groin construction.

Using these options given to the downdrift community, we explore the model's predicted downdrift responses for a range of beachfront property values (a proxy for the community's level of wealth) and community sizes (proxied by the number of property rows in cross-shore). We assume average updrift and downdrift groin lengths and nourishment rates based on field observations for this initial analysis in Figure 3.6 (as listed in Table 3.2).

From literature, furthermore, the common assumption is that storm events have been the main cause of intervention timing, where many field communities built groins after damaging storms such as the one in 1920, the Great Atlantic Hurricane of 1944, and the Ash Wednesday Storm of 1962 (Rankin, 1952; Rayner, 1952; Stauble et al., 2005; Farrell et al., 2004b; Pilkey and Wright III, 1988; Rice, 2015; Miller, 1980; Everts et al., 1980; Donahue et al., 2004). These observations indicate that communities have historically responded in a very myopic manner, meaning that they likely did not consider future storm impacts or damages associated with chronic erosion when choosing to intervene in order to stabilize their beaches. This decision-making dynamic corresponds with a high discount rate, which effectively shortens the time horizon across which a community might make a management decision. Based on this qualitative evidence, we assume a relatively high discount rate in the following analysis (Figure 3.6).

When property value is low, regardless of community size, downdrift communities can neither build a groin nor nourish because they don’t have the adequate financial means to do so, thus resulting in property abandonment, i.e., no groin; no nourishment (Figure 3.6). If a community has a low property value and has a moderate amount of property rows, it builds a groin after a time delay but does not nourish, i.e., delayed groin; no nourishment. Downdrift communities with moderate property values or few cross-shore property rows respond to updrift-induced erosion by constructing a groin at the start of the model run but without complementary nourishment, i.e., initial groin;

no nourishment. If the community has a higher property value and is large, it is able to build a groin initially but nourish after a time delay, i.e., initial groin; delayed nourishment. If a community is large, wealthy, or both, it will choose both to nourish and to build a groin as soon as possible, i.e., initial groin; initial nourishment.

This result highlights that building a groin is more easily achieved for communities with fewer economic resources available, but that nourishing is also achievable if community resources (i.e., higher wealth or larger tax base) are even more readily available. Irrespective of their intervention type, however, by intervening instantaneously, communities are able to avoid property loss associated with downdrift-enhanced erosion, and instead, stabilize their shorelines over the long-run.

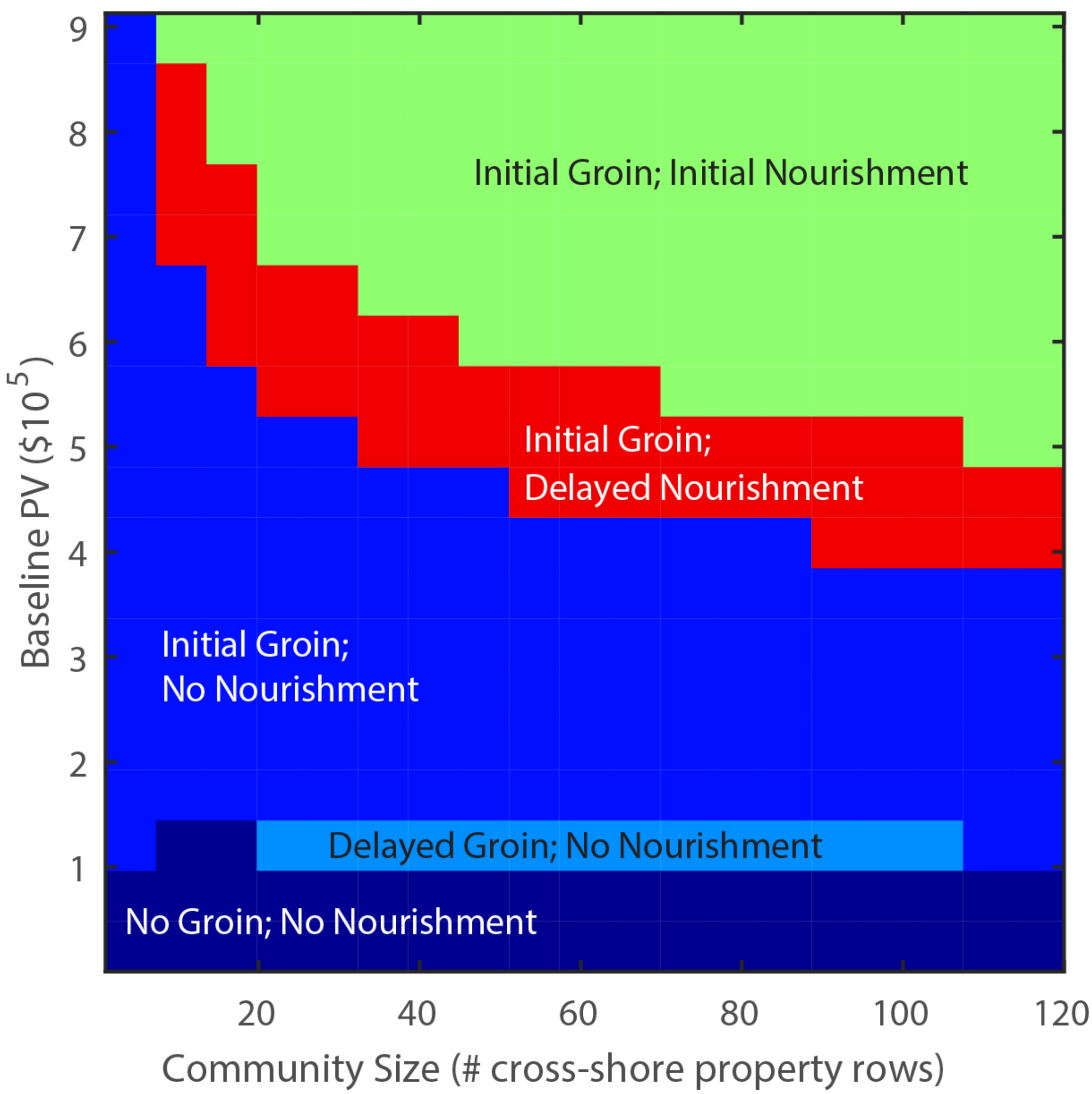

Figure 3.6. Downdrift community responses as a function of baseline property values and community sizes.

3.4 Model Comparison with Field Observations

To compare the field and model, we collect community-specific data on groin construction and beach nourishment characteristics for two-community couplets along the New Jersey coast, including the times of groin construction (Table A3.1) and first nourishment intervention (ASBPA, 2020; PSDS, 2019) in the updrift and downdrift communities. This analysis, for the purposes of determining the updrift community, assumes a net alongshore sediment transport direction by region, i.e., northerly transport in central New Jersey and southerly transport in southern New Jersey (Ashley et al., 1986).

We arrange these times of groin and nourishment interventions for each downdrift community, listed from north to south (from left to right), and grouped by coastal county in New Jersey (Figure 3.7). Also included are the times and names of prominent storms that struck or affected these communities to show the relative importance of storms in how communities have made their management decisions.

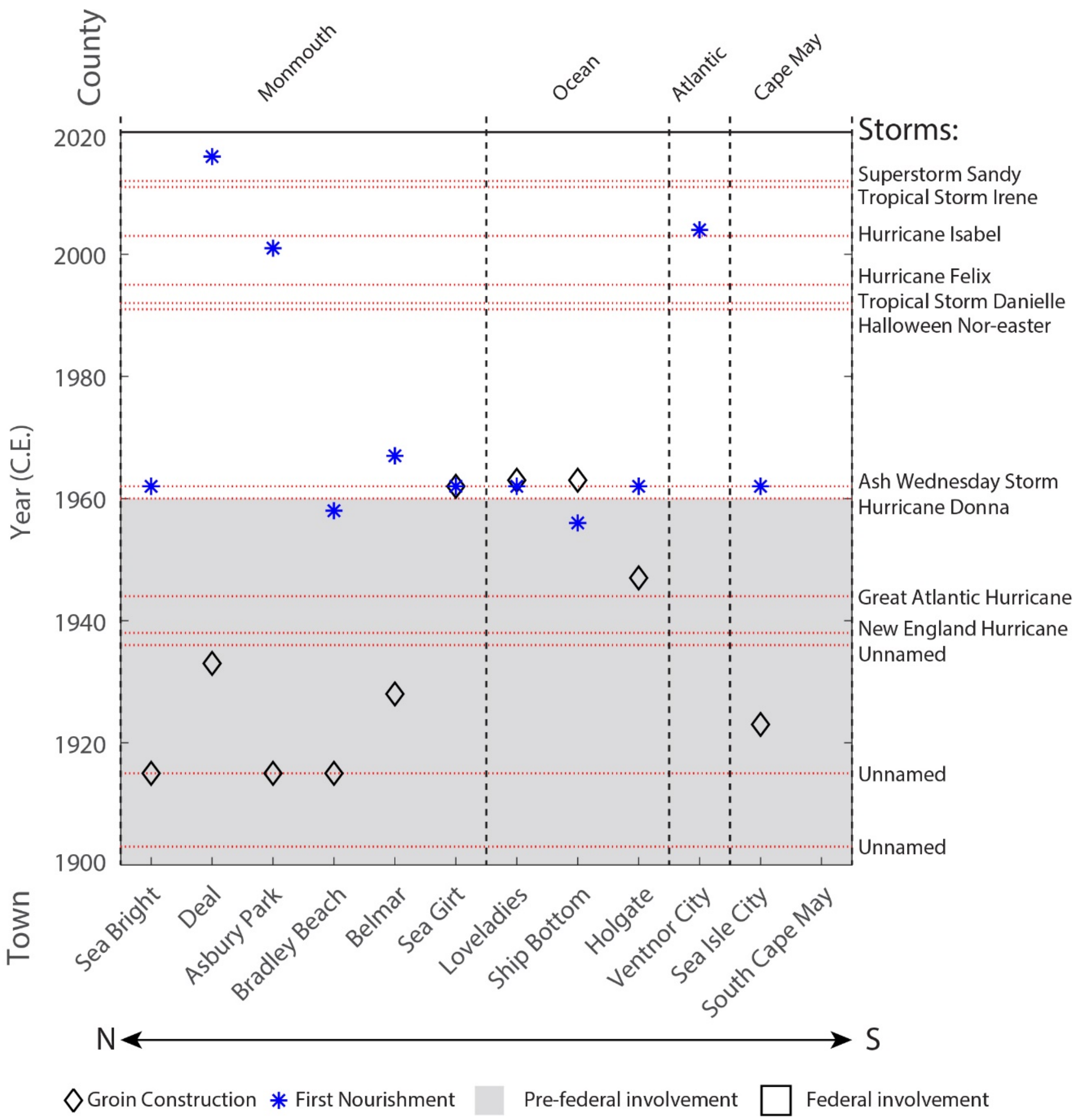

Figure 3.7. A general timeline of groin construction and the timing of first nourishment in downdrift New Jersey communities relative to the storms causing beach erosion and the transition from locally-managed to federally-managed/-subsidized projects after approximately 1960.

The model is community-centric and does not analyze the effect of federal or state involvement (i.e., externally subsidized or planned groin/nourishment projects). After a series of storms in the 1950s-1960s, culminating in the Ash Wednesday storm of 1962, The US Army Corps of Engineers responded to significant storm damages along the New Jersey coast with emergency measures such as new groin constructions, modified existing wooden groins with rock and cement reinforcements, and beach nourishments (Hillyer, 1996).

Following passage of the Water Resources Development Act in 1986, the federal government has taken the leading role in designing, managing, and subsidizing many regional beach nourishment interventions (Hillyer, 1996). This top-down policy response plays a key role in how and when observed downdrift nourishment responses were implemented. As such, we assume that the switch from locally-driven to federally-driven management occurred in approximately 1960 (Hillyer, 1996). Focusing only on the period of time prior to federal involvement, therefore, provides information on how communities made groin management decisions isolated from the influence of external agencies.

Most downdrift communities built groins in response to large storm events in order to stabilize their beaches as an emergency adaptation measure, but some built groins at points in time not closely succeeding major storms, e.g., Deal, Belmar, and Sea Isle City (Figure 3.7). Furthermore, cases such as Deal and Belmar are particularly interesting because they did not respond to the unnamed 1915 storm in the same way that their fellow Monmouth County communities such as Sea Bright, Asbury Park, and Bradley Beach did (i.e., with groin construction). Instead, Deal and Belmar waited until 1933 and 1928 respectively to construct their groins (Table A3.1). Similarly, Sea Girt did not build groins after any of the storms during the pre-federal period, and waited until

1962 to intervene, at which point the federal government's role likely influenced their decision. Altogether, this suggests that storms are not the only driver of groin construction policy.

In fact, New Jersey's coastal communities were at various stages of development at the beginning of the 20th century (US Census Bureau, 2010), with the most densely populated (i.e., many residents per meter alongshore) communities such as Asbury Park and Bradley Beach constructing groins immediately after the 1915 storm, and less densely populated communities such as Belmar, Deal, and Sea Girt opting to delay groin construction (Figures 3.7, 3.8a). However, we are interested in the time at which downdrift communities built groins relative to the date of groin construction in the updrift community to understand how communities responded to groin-induced erosion, in particular.

We plot the time delay in downdrift groin construction as a function of the population density at the time of the management implementation, i.e., the preceding decadal Census count (Figure 3.8b). These data are superimposed on the envelope of model predictions for downdrift groin time delays based on the same population density metric. We proxy the population density in the model by multiplying the number of cross-shore property rows with the number of people per property (assuming two taxpaying residents in a home) and dividing by the alongshore property length (Table 3.2). This envelope is constructed with a series of sensitivity analyses for different baseline property values (Table 3.1), and encompasses all time-delay data points produced by the model for each combination of baseline property value and population density (Figure 3.8b).

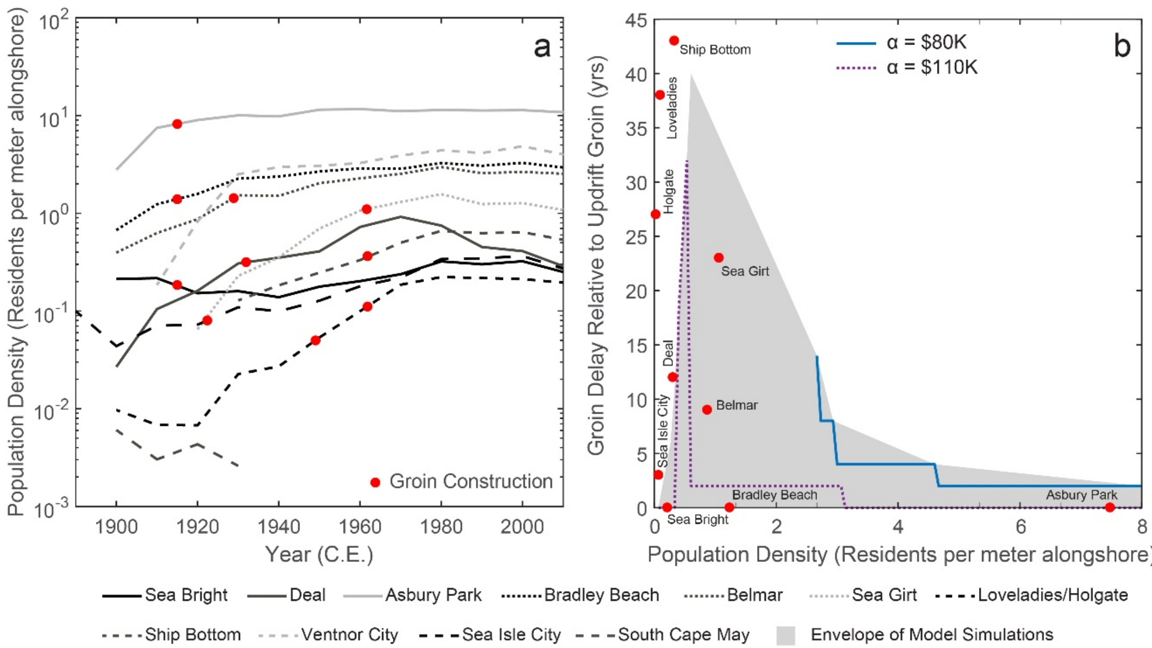

Figure 3.8. (a) Population density changes through time for each downdrift community in New Jersey collected from the 2010 US Census counts, and (b) the comparison between predicted time delays in downdrift groin construction relative to updrift groin construction and observed time delays for field communities in New Jersey. Results provide evidence that the extent of coastal development plays a role in how communities respond to groin-induced erosion.

Field observations and model predictions both indicate that the downdrift delay in groin construction decreases as the population density increases, highlighting that the extent of community development is important in determining when the community decides to intervene in the coastal zone. Furthermore, the model is capable of capturing this population density dynamic observed in the field, and suggests that while exogenous environmental forcings such as storms are important drivers of groin construction, the human component of these developed systems also serves an important role in coastal management timing.

How these communities might respond differently in the future is of utmost importance given the often fragmented, community-by-community management approach that has resulted from hard structural interventions historically and the possibility of a return to local financing of adaptation measures (Coburn, 2009). Changing physical and economic conditions will undoubtedly force communities to respond to groin-heightened erosion differently, the full range of which we explore in the subsequent section, below.

3.5 Future Conditions: Effect of Higher Erosion Rates and Rock Material Costs

In the future, increased sea-level-rise rates and reductions in groin-quality rock supplies due to the potential over-exploitation of common-pool rock resources may lead to increased erosion rates and material costs (Hudson et al., 2015; Rich 2014). Should these downdrift communities face such challenges in addition to the already enhanced erosion rates they experience due to updrift groins, communities will find management interventions more difficult to justify economically.

The model indicates that for low erosion rates and groin costs, myopic downdrift communities respond by building a groin initially and nourishing their beach after a time delay (Figure 3.9a). Increasing the groin cost results in delayed nourishment without a groin for these communities because groins are too expensive to justify their marginal benefit, and the erosion rate is low enough that delayed intervention is appropriate because enough properties can be preserved. Increasing only the erosion rate results in initial groin construction without nourishment, suggesting that groins could be a more effective approach toward stabilizing beaches compared to nourishment under higher sea-level-rise rates, given that the marginal costs are low enough to justify groin intervention. And while this result depends on the relative balance between unit rock and sand costs, which govern the total costs of groin construction vs. beach nourishment, the sand costs used here ($5/m^3) are relatively low, thus reinforcing the key point that groins are likely to be the more effective management option in the future.

High erosion rates and moderate groin costs result in delayed groin construction without nourishment in myopic communities because groins are economically infeasible in the near term, but property preservation (and community preservation more generally) is still feasible in the longer term. If both the groin cost and the erosion rate are too high, however, the community can neither nourish nor build a groin at any point because it is either too costly or too ineffective to produce any appreciable benefit for the community (Figure 3.9a).

These community responses correspond with a progression of system behaviors from seaward growth (i.e., property preservation due to widened beaches) for low groin costs and/or erosion rates, slow retreat (i.e., initial property loss due to shoreline transgression with delayed intervention) for moderate erosion rates and sand costs, and full retreat (i.e., extensive property loss due to shoreline transgression without intervention) for high erosion rates and sand costs (Figure 3.9b). The higher the groin costs or erosion rates are, the more likely the downdrift community responds with either a groin or nourishment later and thus lose more properties in the long term.

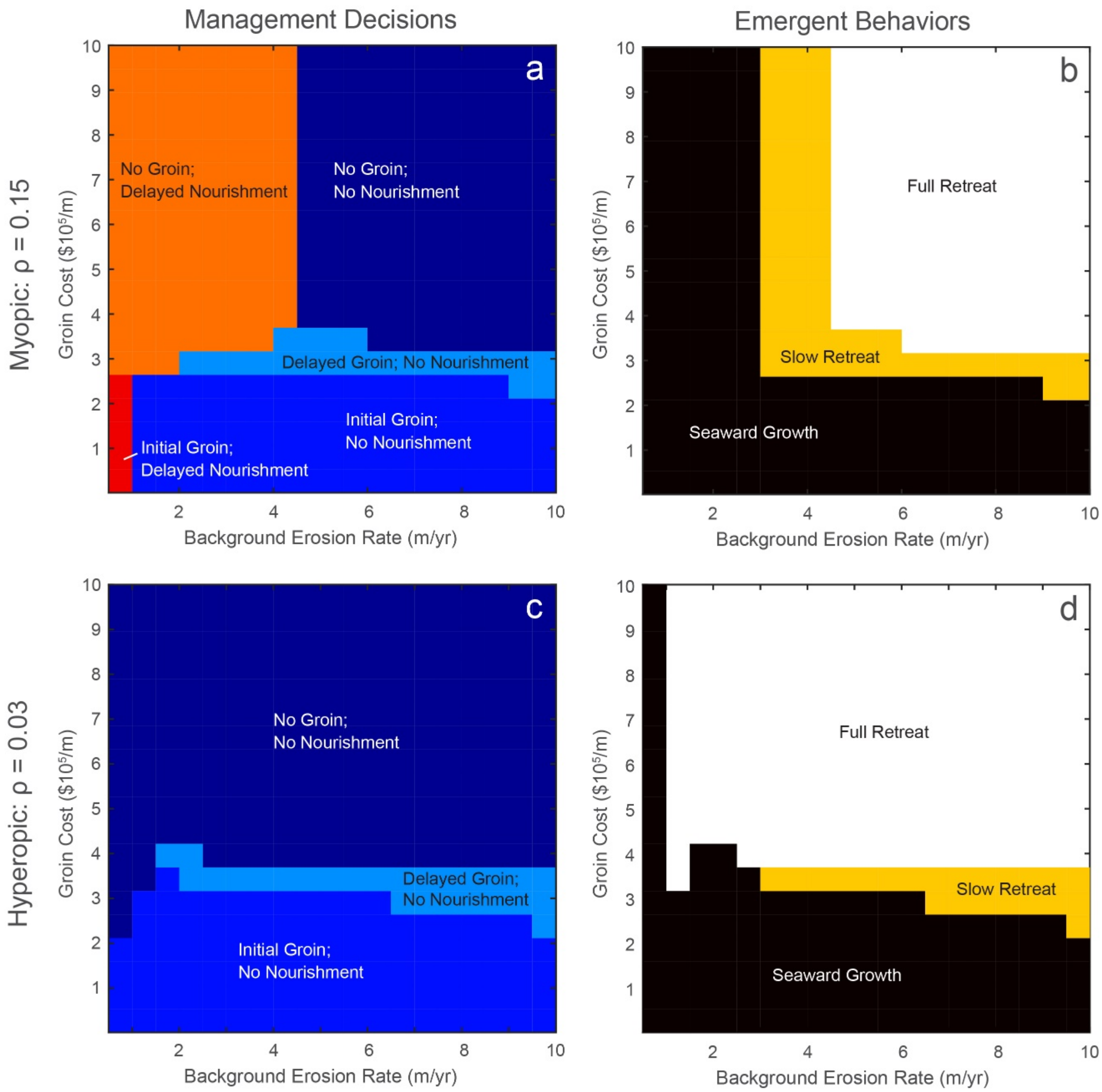

Figure 3.9. Downdrift community responses to updrift groin-induced erosion for myopic communities (a) and for hyperopic communities (c), and geomorphic behavioral responses for myopic communities (b) and for hyperopic communities (d) for future increases in groin material costs and background erosion rates.

While communities have historically made management decisions in a myopic manner, especially when constructing groins, there is support for lower social discounting when adapting to sea-level rise in the future (Lincke and Hinkel, 2018; Weisbach and Sunstein, 2009). Should downdrift communities follow a more hyperopic planning approach, they respond to future climate change and socioeconomic conditions with only an initial groin (no nourishment) for low rock costs, a delayed groin (no nourishment) for moderate rock costs, and no groin or nourishment for high rock costs (Figure 3.9c). These decisions correspond with more instances of full retreat and thus, property abandonment, for higher rock costs than for the myopic scenario (Figure 3.9b). These results underscore not only that how communities value the future in their planning process determines the decisions they make and their corresponding geomorphic behaviors, but also that groins may be a more attractive adaptation solution than beach nourishment irrespective of the community's discounting scheme.

In summary, under future conditions, we can expect communities downdrift of a groin to respond in possibly different ways than we see currently, depending on the relative balance between the physical forcing associated with sea-level rise (i.e., the background erosion rate) and the economic forcing of resource dynamics (i.e., the rock material cost), as well as how they plan for the future. These changes may make the current trend of complementary hard and soft management interventions more difficult. Furthermore, the model indicates a potential switch from soft engineering practices such as beach nourishment (prevalent in the modern day) toward hard engineering practices such as groins in the future due to higher erosion rates, leading to a pervasive hardening of the coast until a threshold beyond which communities can no longer justify any management intervention without help from the federal or state government. Which decision these communities make will ultimately dictate how many properties are lost and what the physical re-orientation of the coast will look like.

3.6 Discussion

We have developed a simple model coupling coastal geomorphology and community-scale socioeconomics to account for emergent management decisions, addressing the groin-induced erosion problem. Assuming that beaches provide erosion protection and recreational value and that community size/property value serves as a proxy for wealth, our model predicts a community's decision (i.e., initial vs. delayed beach nourishment and/or groin construction, or doing nothing) based on its most rational option (i.e., most economically beneficial).

Downdrift communities have often responded to one-time storm events with groin and nourishment interventions, suggesting that most decisions have historically been myopic. While stochastic conditions such as storminess might help explain the specific timing of groin or nourishment interventions, how communities decide to respond (i.e., with initial or delayed nourishment/groin construction) also depends on the underlying socioeconomic and resource economic conditions at the community scale.

The model presented in this paper highlights the key parameter controls on downdrift community responses to updrift-groin-induced erosion. These include a community's size (a proxy for population density) and a community's baseline property value. In fact, both field observations and model predictions suggest that population density is an important factor that helps determine when communities have built groins in the past, which may also provide clues into how communities will respond in the future. We find that how the community weights future vs. present benefits and costs (i.e., the discount rate) is also an important factor in predicting downdrift community responses, indicating that implementing a myopic vs. hyperopic decision-making scheme could determine the evolution of developed coasts.

Looking toward the future, it will be important to incorporate the influence of state and federal government cost-sharing agreements, coupled with behavioral controls associated with tourism in highly commercialized regions such as New Jersey. These additional factors likely play a role in how downdrift communities choose to respond based on their location along the coast, their proximity to nearby tourism-concentrated zones, and their underlying geomorphic conditions such as the physical efficiency of nourishment or groin projects.

All of these dynamics should be explored in future work to fully understand community-scale responses historically, and how they might change in the future due to climate change. Our understanding of how these systems might behave in the future is integral to the development of sustainable management policies at local, state, and federal levels of government. For example, our model simulations suggest that the historical transition from groins to beach nourishment as the main management response during the late 20th century could be reversed in the future, suggesting that hard structures such as groins could again become more commonplace as communities adapt to sea-level rise.

Information gained from this modeling framework and scientific findings built off these coupled geomorphic-economic explorations can provide coastal managers and policymakers the foresight necessary to make more informed and comprehensive decisions in the future.

In sum, this simple model replicates the observed field responses to groin-induced erosion in downdrift communities, shedding light on the anthropogenic role in coastal morphologic evolution. Importantly, coordination across communities is gaining recognition as a way to incorporate unintended consequences and to redistribute risk to avoid situations such as heightened erosion downdrift of groins. Exploring the range of spatial relationships and behaviors requires a larger scale approach. Future work will extend the model to account for more community and inter-community dynamics, whether communities will maintain their status quo policies, and how external funding will affect strategy decisions for coupled natural-human coastal systems faced with climate change impacts such as sea-level rise and changing resource economic conditions.

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APPENDICES

Chapter 1 Appendix

We present the alternative end-member assumption that uncoordinated communities make about their neighbor when choosing strategies independently, as discussed in section (1.2.3). In contrast with the representative non-coordination assumption presented previously, communities assume their neighbor nourishes with high frequency here, which we consider a risky assumption. Given this expectation, communities nourish less than they would have under coordination, resulting in full retreat for most baseline-property-value-combinations and slow retreat when one or both communities are wealthy (Figure A1.1b). This extreme behavioral difference results in a maximum benefit of coordination that is an order of magnitude larger than our representative non-coordination (Figures A1.1c, 1.7a) and corresponds with under-nourishment in both communities for most of the regime space (Figure A1.1d-e).

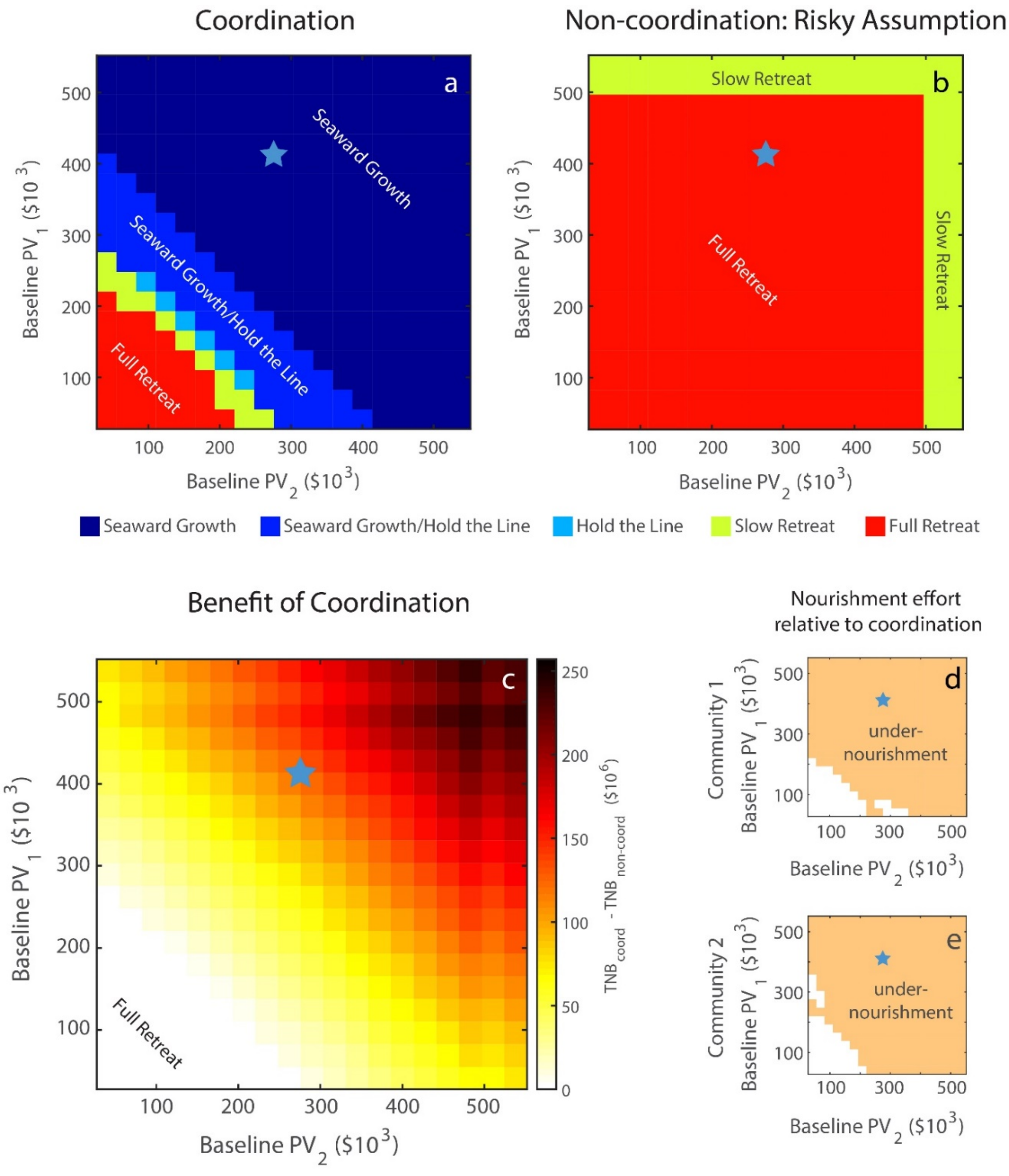

Figure A1.1. Emergent behaviors from (a) coordinated and (b) uncoordinated management schemes, (c) the benefit of coordination between the two, and regions of over-/under-nourishment in (d) community one and (e) community two. We highlight the same baseline-property-value combination as Figure 1.7 (blue star) for sensitivity analyses to future conditions.

We test how these coordination regimes using the same baseline-property-value distribution presented in figure (1.7) and represented by the blue star in figure (A1.1) will differ under increases in background erosion rate and sand resource cost. Unsurprisingly, uncoordinated communities operating under a risky assumption will never choose to nourish, thereby experiencing full retreat behavior under all future conditions (Figure A1.2b). This results in a large benefit of coordination in the near future and no benefit in the distant future when both coordination schemes result in full retreat (Figure A1.2c).

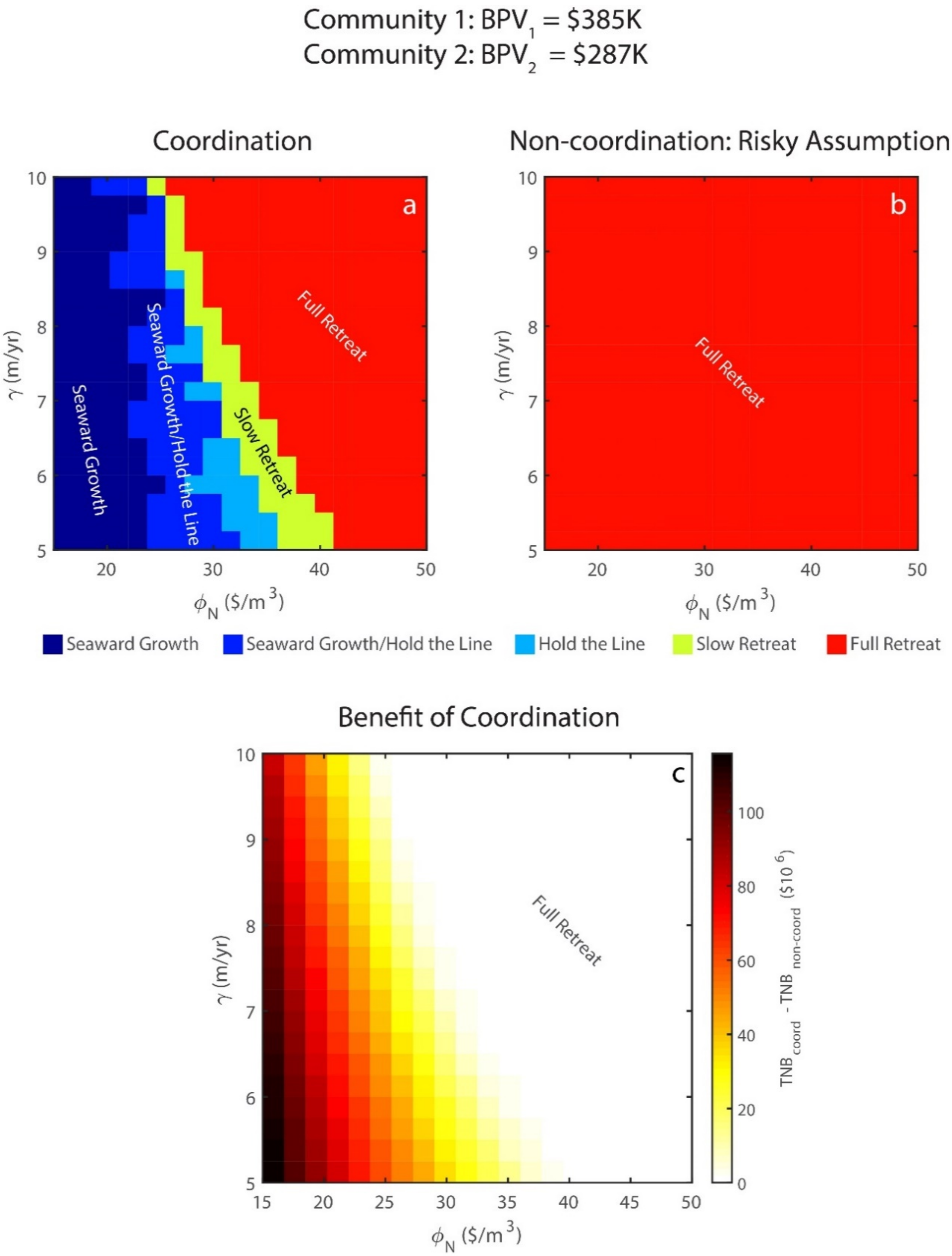

Figure A1.2. Emergent behaviors under future increases in background erosion rate and sand resource cost for (a) coordinated and (b) uncoordinated communities, and (c) the benefit of coordination between these two schemes.

Overall, risky non-coordination results in systematic under-nourishment and thus property abandonment under both current and future conditions. Given that many communities along U.S. coastlines and worldwide have not behaved in this way, this uncoordinated scheme (i.e., the risky assumption) is less common than our representative uncoordinated scheme (i.e., the cautionary assumption). Nevertheless, we present this end-member case to show the two boundaries between which communities might operate when choosing beach maintenance independently, highlighting the variation of response based on the assumptions communities make about their neighbors' behaviors.

Chapter 2 Appendix

A2.1. Information on Data Collection for Regression Variables

A2.1.1. Beach Nourishment Decisions

We collect historical data on beach nourishment projects for each community that has nourished their beach in New Jersey from Western Carolina University's Program for the Study of Developed Shorelines and the American Shore and Beach Preservation Association's beach nourishment databases. From these data, we calculate the average nourishment volume per event and combine with re-nourishment frequency to determine the average volume each community places on its beach per year, termed the nourishment rate. This variable will be our dependent variable, or each community's nourishment decision (Table A2.1).

Table A2.1. Data for dependent variable (Nourishment Rate) and independent variables (Average Total Beachfront Wealth—Distance to nearest inlet) for regression analyses and descriptive statistics (i.e., minimum, maximum, mean, median, and standard deviation) for each variable.

Beach Location	Nourishment Rate (m^3/yr)	Average Total Beachfront Wealth ($)	Average Beach Revenue ($)	Commercial-Residential Ratio	Distance to Tourism Center (m)	Nourishment Half-life (yrs)	Distance to nearest inlet (m)
Sea Bright	275653.74	151042100.71	466097.08	0.22	1.00	0.45	19693.00
Monmouth Beach	65697.41	176474574.98	1074446.25	0.02	3037.00	0.58	16231.00
Long Branch	82800.68	364186558.96	1621443.58	0.12	1.00	10.23	12990.00
Deal	40530.63	327935601.94	2012662.64	0.01	2353.00	5.22	6286.00
Asbury Park	11872.84	75526858.36	3761387.86	0.36	1.00	3.20	4182.00
Bradley Beach	16239.54	94366573.29	1591114.22	0.06	2590.00	0.57	1567.00
Avon by the Sea	18113.98	93642948.93	1705041.94	0.04	3730.00	1.38	494.00
Belmar	14883.17	113284048.85	3391369.06	0.09	5295.00	3.75	8585.00
Spring Lake	20321.39	507908530.10	2546260.53	0.04	6955.00	1.27	5717.00
Sea Girt	16387.05	255854128.83	1063304.09	0.02	4672.00	1.05	3347.00

Manasquan	8909.67	138712427.62	1821710.23	0.07	2634.00	4.99	1245.00
Point Pleasant	22253.88	143708162.06	2170550.40	0.21	1.00	1.44	37180.00
Lavallette	7184.97	232551547.86	903038.40	0.03	3030.00	0.70	23753.00
Seaside Heights	18566.34	56755726.12	3062188.83	0.16	1.00	1.19	20754.00
Seaside Park	14045.32	156113234.65	2062806.96	0.03	1924.00	0.93	18773.00
Barnegat Light	30100.88	186061150.31	249294.29	0.04	20900.00	1.41	827.00
Loveladies	36410.70	261131127.19	1669343.01	0.02	25264.00	0.55	5122.00
Harvey Cedars	98213.31	263791947.23	240557.63	0.01	27150.00	0.35	7090.00
Surf City	42779.50	198374781.21	604863.09	0.05	32860.00	0.82	12655.00
Ship Bottom	25827.10	158246738.31	731240.99	0.10	35190.00	0.77	15299.00
Brant Beach	101101.27	506810708.39	1669343.01	0.02	35222.00	0.41	17847.00
Beach Haven	29225.17	223980865.46	567008.43	0.07	27440.00	0.54	25755.00
Holgate	54567.97	161468655.57	1669343.01	0.02	25540.00	0.55	28111.00
Brigantine	69688.88	344656768.45	1226638.72	0.03	7600.00	0.41	5885.00
Atlantic City	156308.56	321989746.17	1087542.78	0.56	1.00	0.31	1606.00
Ventnor	41974.62	183697813.87	341249.37	0.04	5308.00	0.79	6909.00
Margate	6595.27	310248403.33	372142.27	0.02	7928.00	2.50	8856.00
Longport	3968.64	308564359.65	240089.47	0.00	10273.00	1.37	11955.00
Ocean City	297715.09	1094929077.27	6486481.29	0.04	16354.00	1.49	3656.00
Sea Isle City	55704.98	689434843.20	2024539.93	0.03	22840.00	0.99	6808.00
Avalon	68726.67	1008771169.10	1199899.71	0.02	15915.00	1.26	1904.00
Stone Harbor	48396.22	600117161.76	1150186.64	0.04	8624.00	0.76	9105.00
North Wildwood	19890.35	252069155.62	1135611.60	0.09	1858.00	0.46	1785.00
Cape May City	89845.81	308602653.23	4637839.47	0.20	1.00	0.77	3915.00
Cape May Point	25751.90	116868953.73	171115.97	0.00	6010.00	0.77	9136.00
Descriptive Stats							
Min	3968.64	56755726.12	171115.97	0.00	1.00	0.31	494.00
Max	297715.09	1094929077.27	6486481.29	0.56	35222.00	10.23	37180.00
Mean	55321.53	296796545.78	1620792.94	0.08	10528.66	1.55	10429.23
Median	30100.88	232551547.86	1226638.72	0.04	5308.00	0.82	7090.00
Standard Deviation	66853.51	238512484.84	1347699.71	0.11	11453.77	1.94	8943.65

A2.1.2. Socioeconomics: Beachfront Wealth

Most previous literature assumes that beachfront property value is a singular control on nourishment decisions. We build off this assumption and extend this variable to include beachfront wealth, or the sum of all beachfront property values alongshore in a community. This scale is consistent with our dependent variable, the nourishment rate, which includes the alongshore length of these nourishment projects. Furthermore, the beachfront wealth serves as a proxy for the tax base, such that communities with more beachfront properties will have larger revenues with which to fund such beach nourishments.

We approximate beachfront wealth from each municipality's publicly available financial documents on their respective government websites, including their annual budgets and audits. Each year, communities report their aggregate assessment value for the entire community. From the United States Census Bureau (2010), we collect land areas and number of housing units for each community, which provides an estimate of the average lot size, i.e., land area / # housing units = mean property square footage. The square root of this square footage then provides us with one dimension of the lot size, termed the average property length.

Dividing the land area by the alongshore length of the community, collected with Google Earth Pro, provides a representative cross-shore community width, or the landward extent of the community. We can then divide this cross-shore width by the average property length to determine the number of properties in cross-shore (i.e., inland extent of development). We then assume a power law relationship between total cross-shore property value (TPV) and a property's distance from the ocean, such that $TPV=\alpha \cdot n^{\psi}$, which treats beachfront property value α as the highest value in the cross-section, and each successive landward row n declines in value based on the hedonic parameter ψ.

If we divide the aggregate assessment value by the community's alongshore length, this gives us a cross-sectional total assessment value, and divided by the number of rows gives us the average assessment value per house per meter alongshore. We can then back-calculate the beachfront property value α using the number of cross-shore property rows (i.e., n = cross-shore width / average property length), the cross-sectional total property value *TPV*, and a representative ψ value (e.g., psi = 0.7).

Given that we have inferred the beachfront property value per meter alongshore and that the alongshore community length is known, we can determine the total beachfront wealth that encompasses all beachfront property values. We gather these data for as many years as are publicly available on each municipality's website, correct for dollar value changes through time (i.e., inflation), and take the average of all years collected. This average beachfront wealth serves as the representative socioeconomic metric in our regression analysis.

A2.1.3. Tourism

New Jersey's beaches generate approximately $12.1 billion annually in revenue (Klein et al., 2004). As such, the amount of revenue realized by communities likely factors into their beach management decisions, both directly and indirectly. We test this metric directly using information on each community's annual beach revenue, but also test how the extent of local tourism or the proximity to nearby tourism-concentrated towns indirectly affects their consequent nourishment decisions.

Beach Revenue from Recreation

We gather data on the recreational revenues each community collects on its beach from annual financial documents including audits and budgets found on each municipality's website. From these documents, we gather revenue generated within the beach utility budget from various sources, including beach badge (access fee) sales, parking meter receipts, concession rents, boardwalk tramcar leases, and local tourism taxes. Together, these revenues represent the amount of money that users spend at the beach over the course of each summer, providing an implicit willingness to pay for beach recreation.

We gather these data for a wide time range as determined by the availability of financial documents on each municipality's website, which in some cases includes up to 20 years. These annual data are time-corrected for inflation such that all revenues are converted to a single year's dollar value. To correct for any bias introduced by weather-related variation from one summer to the next, we take the average beach revenue for all years, which provides a representative value of their beach recreation.

Commercial vs. Residential Value Ratio

From the New Jersey MODIV database encompassed within the State's Open Public Records System (Monmouth County Clerk, 2020), we collect parcel-level property information for each community including assessment values and property classes.[3] From these data, we group properties by class and sum all assessed values for commercial and residential classes respectively. The ratio of the total commercial to residential assessment values is between zero and one, and serves as a metric for the proportion of local tourism in a town. We assume that since many of a New Jersey's beach communities are seasonal, most or all businesses are affected by or dependent on the influx of summer tourists, and thus, the total commercial assessment value serves as a proxy for the relative importance of the local tourism economy.

[3] Data collected on assessed property values are in year 2020 dollar values (Monmouth County Clerk, 2020)

Proximity to Tourism Centers

Using the commercial-residential ratio above, we define a community to be tourism-dominated, termed a tourism center, if their ratio is greater than 0.1, or 10% commercial value of residential value. All communities below this threshold are considered residential-dominated. We calculate the distance from the center of each residential-dominated community to the nearest tourism center. This metric provides information on the spatial extent of tourism's impact on non-local beach management decisions, including any alongshore spillover from tourism-related beach visits in cases in which residential-dominated communities are adjacent or in close proximity to tourism-dominated communities.

A2.1.4. Geomorphology: Site and Regional Characteristics

In addition to the various economic factors listed in the previous sections (A2.1.2-A2.1.3), other site- and region-specific physical characteristics interact with and reshape management interventions in the coastal environment. These underlying conditions can limit or supply sediment to the beach and nearshore environment, thereby affecting and possibly controlling future management decisions. To test this effect, we gather data on the following two metrics: beach nourishment efficiency (i.e., a nourishment project's half-life); and a community's downdrift distance from the nearest tidal inlet updrift (a proxy for the natural sediment supply or deficit as a result of ebb-tidal delta dynamics and wave refraction/shadowing).

Beach Nourishment Efficiency

We collect data on beach nourishment efficiency using CoastSat, a shoreline extraction tool that gathers imagery from publicly available satellite data (Vos et al., 2019). This tool employs a machine-learning algorithm that automatically detects ocean and terrestrial pixels from Landsat 5, 7, and 8 and Sentinel 2 satellite imagery and estimates the shoreline location as the land-sea boundary between these classes. Casting transects provides information on shoreline evolution through time. We average these position changes across all transects to dampen any meter-scale patterns or perturbations in shoreline change.

We then correct these position changes relative to a representative beach width calculated using Google Earth Pro for a specific date in our time-series, i.e., beach area for date X / alongshore community length = beach width for date X. We can then track the change in average beach width through time, and plot the 50-point moving mean to dampen day-scale wave climate effects on beach morphodynamics (Figure A2.1). Combined with the years in which communities nourished, known from the ASBPA/PSDS datasets, we can pinpoint the seaward extent of a community's nourishment project and track the decay of this nourishment sand through time.

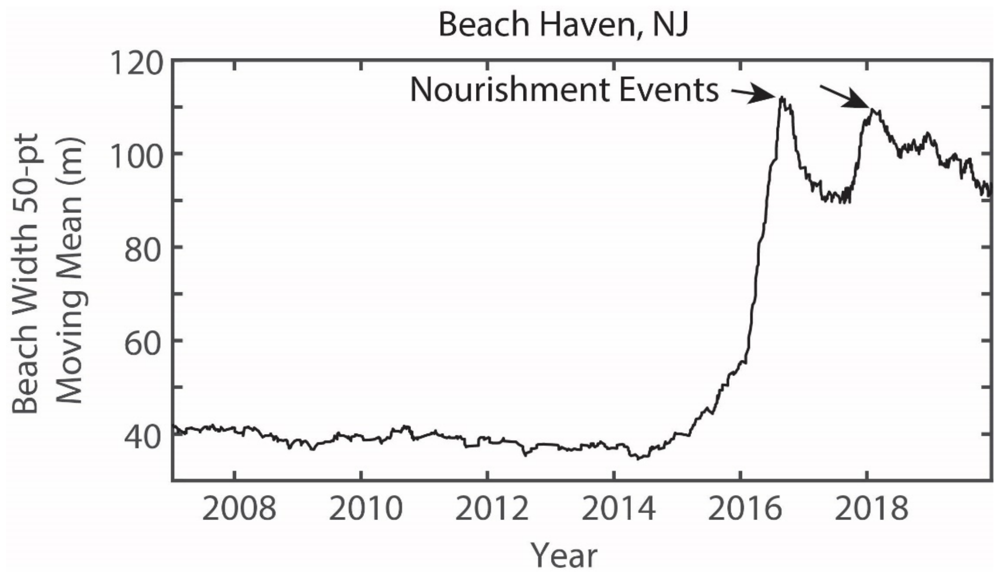

Figure A2.1. 50-point beach width moving mean time-series for a representative community, Beach Haven.

This information from multiple beach nourishments can then be used to determine a representative decay rate, and thus, the half-life of a nourishment project in a community (Figure A2.2). We assume this metric is a proxy for the nourishment efficiency because it provides information on how long a community can expect to retain its artificially added beach sand, which will inform their future actions in terms of the volume it should place and frequency of re-nourishment to adequately maintain its beach over the long-term.

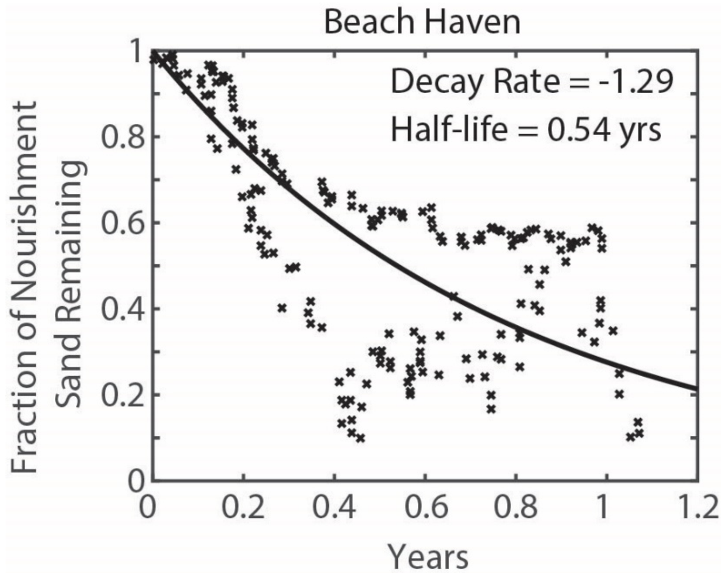

Figure A2.2. Fraction of volume remaining through time with decay rate and half-life information.

We use this approach to calculate the nourishment project's half-life for each community in our dataset.

Natural Alongshore Sediment Supply: Downdrift Distance from Nearest Tidal Inlet

While previous work tested a community's distance from tidal inlets to understand its access to sediment resources as an economic effect on the decision-making process (Qiu et al., 2020), here, we explore the morphodynamic effects of inlet proximity, and specifically, the natural supply or limitation of sediments to the beach system via alongshore fluxes. Toward this, we calculate each community's distance downdrift of its nearest updrift tidal inlet, assuming that communities closer to tidal inlets will be more affected by inlet dynamics and the consequent sediment flux variability, while communities further downdrift of tidal inlets will be more isolated from the hydro/morphodynamics. This serves not only as a metric of sediment availability but also of both local and non-local geophysical characteristics.

A2.2. Regression Results for Lognormal and Log-log Model Specifications

A2.2.1. Lognormal Regression

The second model specification we test is the lognormal regression. We run this model with the forward, backward, and stepwise process to determine the set of significant parameters that best explain the nourishment rate. We also test all model combinations and isolate the model with the lowest root mean square error (RMSE), which represents the most accurate model fit of all possible models with our vector of independent variables X.

All regression selection processes suggest the same set of parameters can predict the log of the nourishment output, producing similar qualitative results as the normal model: 1) the total beachfront wealth; 2) the commercial-residential assessment value ratio; and 3) the distance from the nearest tourism center (i.e., nearest community with commercial-residential ratio > 0.1). We find that this model is statistically significant using the ANOVA test and that each parameter estimate is significant at the 95% confidence level (Table A2.2).

Table A2.2. ANOVA results and parameter estimates for lognormal model (beachfront wealth, com-res ratio, tourism center distance).

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	12.12593	4.04198	5.61	0.0034
Error	31	22.34586	0.72083		
Corrected Total	34	34.47178			

Parameter Estimates							Heteroscedasticity Consistent			
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standard Error	t Value	Pr > |t|	Type II SS
Intercept	Intercept	1	9.31673	0.30884	30.17	<.0001	0.25398	36.68	<.0001	655.96535
Average_Total_Bfrnt_Wealth	Average Total Bfrnt Wealth	1	1.95284E-9	6.31992E-10	3.09	0.0042	4.25347E-10	4.59	<.0001	6.88248
Com_Res_Ratio	Com-Res Ratio	1	3.54402	1.39791	2.54	0.0165	1.24889	2.84	0.0079	4.63308
Distance_to_Tourism_Center	Distance to Tourism Center	1	0.00002195	0.00001392	1.58	0.1249	0.00000961	2.28	0.0293	1.79302

In general, as a community's total beachfront wealth increases, as its share of commercial real estate value increases, or as the community's distance from the nearest tourism center increases, the community will nourish more per year. This suggests that socioeconomics and local tourism both have a positive linear impact on nourishment policy, while proximity to tourism has an inverse relationship with beach nourishment. This latter result could be indicative of the free riding effect whereby communities immediately adjacent to tourism centers require less nourishment since neighboring tourism-dominated community nourishment rates are so high. This also implies that tourism can play a significant role in how a community manages its beach in multiple ways and that these various effects likely interact with beachfront wealth differently in driving nourishment choices.

We test the model's collinearity among parameters and find that the beachfront wealth and the distance from the nearest tourism center are collinear, indicating that some of the variation in response could be explained by both variables (Table A2.3). In general, as the distance from high tourism zones increases, so too does the beachfront wealth, which suggests that tourism might be a disamenity to residential property values, and reinforces the theory that tourism-dominant and residential-dominant communities are categorically different and likely behave differently.

Table A2.3. Collinearity diagnostics for lognormal model with beachfront wealth and com-res ratio.

Collinearity Diagnostics						
			Proportion of Variation			
Number	Eigenvalue	Condition Index	Intercept	Average_Total_Bfrnt_Wealth	Com_Res_Ratio	Distance_to_Tourism_Center
1	2.68674	1.00000	0.02690	0.03873	0.02964	0.03858
2	0.84225	1.78605	0.00115	0.01510	0.45256	0.14443
3	0.32425	2.87856	0.00020812	0.58627	0.09958	0.56808
4	0.14677	4.27856	0.97175	0.35990	0.41822	0.24892

Observed nourishment rates for the lognormal model do not align as well with predicted nourishment rates as the normal model, and more variability can only be explained by the regression error (Adjusted R-square = 0.29, Figure A2.3).

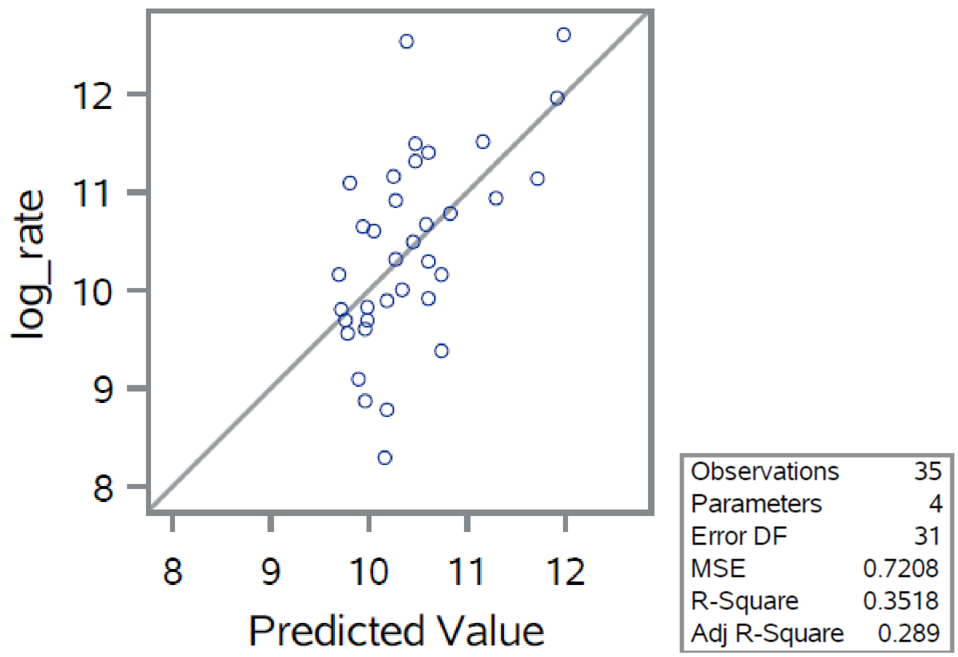

Figure A2.3. Observed vs. predicted nourishment rates for lognormal model with adjusted R-square statistics.

Using the same approach described in equation (2.5), the standardized lognormal model indicates that the order of variable importance is: 1) total beachfront wealth; 2) commercial-residential assessment value ratio; and 3) distance from the nearest tourism center (Table A2.4). These results complement the standardized normal model's outcome that while socioeconomics is still the primary control on nourishment policies, tourism also plays a significant role.

Table A2.4. Parameter estimates for the standardized lognormal model, where the total beachfront wealth is most important, the commercial-residential ratio is second most important, and the tourism distance is third most important.

Parameter Estimates										
							Heteroscedasticity Consistent			
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standard Error	t Value	Pr > |t|	Type II SS
Intercept	Intercept	1	3.98815E-15	0.14253	0.00	1.0000	0.13413	0.00	1.0000	5.56688E-28
Standard_Wealth	Standard Wealth	1	0.46258	0.14970	3.09	0.0042	0.10075	4.59	<.0001	6.78829
Standard_CR_Ratio	Standard CR Ratio	1	0.39583	0.15613	2.54	0.0165	0.13949	2.84	0.0079	4.56968
Standard_Tourism_Distance	Standard Tourism Distance	1	0.24974	0.15835	1.58	0.1249	0.10929	2.28	0.0293	1.76848

A2.2.2. Log-log Regression

The third model specification we test is the log-log regression. We run this model with the forward, backward, and stepwise process to determine the set of significant parameters that best explain the nourishment rate. We also test all model combinations and isolate the model with the lowest root mean square error (RMSE), which represents the most accurate model fit of all possible models with our vector of independent variables X.

All regression processes suggest the same set of parameters can predict the log of nourishment output: the log of total beachfront wealth, the log of tourism distance, and the log of nourishment half-life. We find that this model is statistically significant using the ANOVA test and that each parameter estimate is significant at the 95% confidence level (Table A2.5).

Table A2.5. ANOVA results and parameter estimates for the log-log model (log wealth, log tourism distance, log half-life).

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	3	14.92957	4.97652	7.89	0.0005
Error	31	19.54221	0.63039		
Corrected Total	34	34.47178			

Parameter Estimates										
							Heteroscedasticity Consistent			
Variable	**Label**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Standard Error**	**t Value**	**Pr > |t|**	**Type II SS**
Intercept	Intercept	1	-4.20813	3.96680	-1.06	0.2970	3.23646	-1.30	0.2031	0.70943
log_wealth		1	0.80028	0.20985	3.81	0.0006	0.17106	4.68	<.0001	9.16797
log_tourdist		1	-0.10774	0.03869	-2.78	0.0091	0.03151	-3.42	0.0018	4.88848
log_halflife		1	-0.47432	0.16910	-2.80	0.0086	0.15487	-3.06	0.0045	4.95989

In general, as a community's total beachfront wealth increases, its nourishment rate increases. It's nourishment rate also increases as it's distance from a tourism center or as its half-life increases. This suggests that communities in close proximity to tourism centers or those that are tourism centers will nourish more than communities further from these recreation-centric locations.

This model is also the first indication of our various model specifications that underlying nourishment efficiency is a significant determinant of nourishment policy, such that more efficient projects allow communities to nourish less, and reduced efficiency could drive communities to nourish more than they otherwise would have. Of note, however, there is likely a feedback between nourishment efficiency and rate whereby higher rates shift shorelines further seaward into deeper water, thus steepening the shoreface and alongshore gradients in sediment transport, which would increase cross-shore and alongshore fluxes, reduce nourishment efficiency, and necessitate higher re-nourishment rates in the future. Alas, the relationship between nourishment half-life and nourishment rate might be endogenous by nature.

The two site-specific variables that are significant in this model (i.e., the tourism distance and the nourishment half-life) suggest that spatial variation is important in how communities interact with their natural environment.

We test the model's collinearity among parameters and find that none of the parameters are collinear, meaning that no independent variables are correlated (Table A2.6).

Table A2.6. Collinearity diagnostics for log-log model with log wealth, log tourism distance, and log half-life.

Collinearity Diagnostics						
			Proportion of Variation			
Number	Eigenvalue	Condition Index	Intercept	log_wealth	log_tourdist	log_halflife
1	2.85605	1.00000	0.00013691	0.00013201	0.02003	0.00000309
2	1.00656	1.68447	0.00000132	0.00000109	0.00097638	0.94686
3	0.13682	4.56884	0.00140	0.00118	0.89892	0.05311
4	0.00056167	71.30900	0.99846	0.99869	0.08007	0.00002433

Observed nourishment rates for the log-log model align the best of all model specifications with predicted nourishment rates, and less of the nourishment rate variation can be explained by the model' error term (Adjusted R-square = 0.38, Figure A2.4).

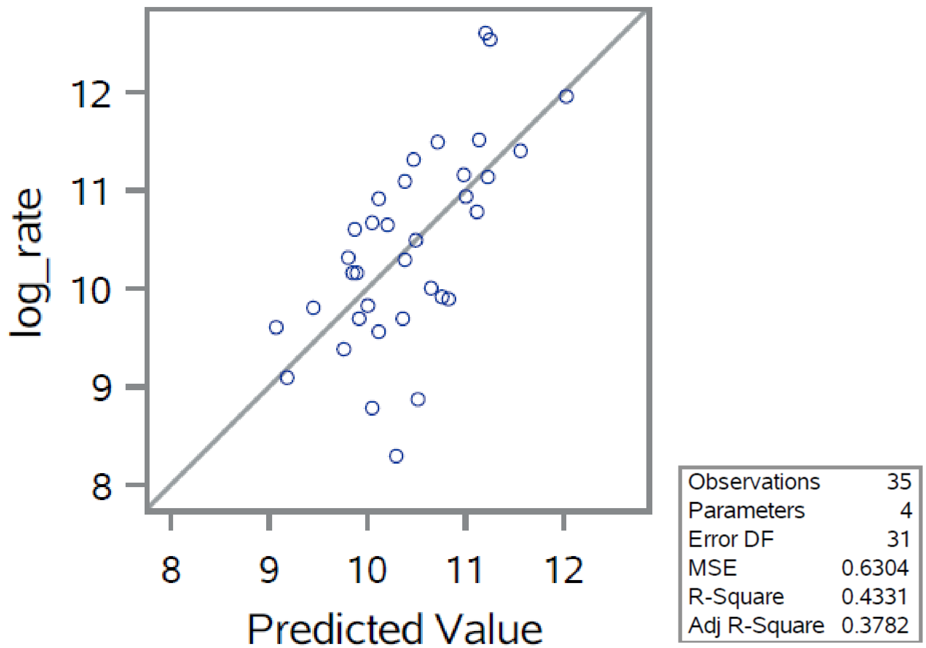

Figure A2.4. Observed vs. predicted nourishment rates for log-log model with adjusted R-square statistics.

Finally, applying equation (2.1), the standardized log-log model indicates that the order of variable importance is: 1) total beachfront wealth; 2) distance from the nearest tourism center; and 3) nourishment half-life (Table A2.7). These results highlight that while socioeconomics and tourism help explain nourishment decisions, so too do underlying geomorphic conditions that affect nourishment project efficiency.

Table A2.7. Parameter estimates for the standardized log-log model, where the total beachfront wealth is most important, the tourism distance is second most important, and the nourishment half-life is third most important.

Parameter Estimates										
							Heteroscedasticity Consistent			
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standard Error	t Value	Pr > |t|	Type II SS
Intercept	Intercept	1	4.04253E-15	0.13445	0.00	1.0000	0.12654	0.00	1.0000	5.71972E-28
Standard_Wealthln	Standard Wealthln	1	0.50055	0.14002	3.57	0.0012	0.12103	4.14	0.0003	8.08550
Standard_CR_Ratioln	Standard CR Ratioln	1	0.37249	0.13996	2.66	0.0122	0.16196	2.30	0.0284	4.48164
Standard_Half_lifeln	Standard Half-lifeln	1	-0.32982	0.13678	-2.41	0.0220	0.15265	-2.16	0.0386	3.67875

A2.3. Justification for using the Normal Regression as the Representative Model

We choose the normal regression as the representative model because it has the highest adjusted R-square value of the three model specifications while only including explanatory variables that are independent of the nourishment rate. While the log-log model has a higher adjusted R-square value than the normal model, this regression include the nourishment half-life as an explanatory variable, which is difficult to implement into the geo-economic model given that we do not have information on why the sand is eroding from the beach or where it is depositing. Within the deterministic model framework, a nourishment project's efficiency can be affected by the diffusivity (which governs alongshore sediment transport), the shoreface response rate (which governs cross-shore sediment transport), or the background erosion rate associated with the sea-level-rise rate and wave climate. All of these processes/forcings can affect the nourishment half-life, and without information on the key controls on efficiency, we cannot estimate where the nourishment sand will deposit within/outside of the system.

In addition, the half-life likely is not only a predictor of nourishment rate, but could also be dependent upon nourishment rate. As communities place more sand on their beaches per year, shorelines would prograde seaward rapidly and into deeper water, and given the intrinsic time lag between shoreline and shoreface toe evolutions, these effects would steepen the shoreface and potentially reduce the emergent efficiency. Furthermore, the rapid growth of the shoreline in one location relative to the adjacent coastline would increase the alongshore gradient, thereby increasing sediment transport rates from the nourishment site and reducing the nourishment efficiency. In both scenarios, the nourishment half-life might depend, in part, on the nourishment rate, thus describing an endogenous feedback between the two system components. As such, we avoid any regression models with nourishment half-life as a significant predictor of nourishment response.

While the log-log model produces the highest adjusted R-square value, it includes the variable for nourishment efficiency, so we instead implement the regression model with the second highest adjusted R-square value, the normal regression model, which includes the beachfront wealth and the commercial-residential ratio as predictors of nourishment rate.

A2.4. Table of Input Parameters used in Geo-economic Model

Table A2.8. Physical and economic input parameters including the symbol, feasible range of values, representative test values, units, and references.

Parameters	**Symbol**	**Feasible Range of Values**	**Test Value: Fig. 18**	**Test Value: Figs. 19—21**	**Units**	**References**
Variable Nourishment Cost	ϕ_N	5—30	5	5—20	$/m³	Gopalakrishnan et al., 2010; Hillyer, 1996; Mcdowell Peek et al., 2016; PSDS, 2019; Slott et al., 2010; Williams et al., 2013
Discount Rate	ρ	1—10	3	3	%/yr	Landry, 2004; Smith et al., 2009; USACE, 1999; Williams et al., 2013
Hedonic Parameter (Beach Width)	β	0.05—0.8	0.6	0.6	-	Gopalakrishnan et al., 2010; Gopalakrishnan et al., 2016; Pompe and Rinehart, 1995; Slott, 2008; Smith et al., 2009
Hedonic Parameter (# cross-shore properties)	ψ	0.0001—0.8	0.2	0.2	-	Gopalakrishnan et al., 2010; Gopalakrishnan et al., 2011; Landry and Hindsley, 2011; Landry et al., 2003
Background Erosion Rate	γ	0—10	0.5	0.5—4	m/yr	Armstrong et al., 2019; Gopalakrishnan et al., 2010; Hapke et al., 2013; Murray et al., 2013; Williams et al. 2013; Zhang et al., 2004
Depth of Closure	D	5—20	16	16	M	Birkemeier, 1985; Brutsché et al., 2014; Hallermeier, 1981; Kraus and Batten, 2007; Kraus et al., 1995; Ortiz and Ashton, 2016
Alongshore Flux Coefficient	K_1	10 — 1,000	500	500	1,000 m^2/yr	Ashton et al., 2001; Ashton and Murray, 2006a; Ashton and Murray, 2006b; Falqués, 2003
Cross-shore Flux Coefficient	K_2	-	2,000	2,000	m^2/yr	Lorenzo-Trueba and Ashton, 2014; Miselis and Lorenzo-Trueba, 2017; Ortiz and Ashton, 2016
Shoreface Equilibrium Slope	θ_{eq}	-	0.02	0.02	m/m	Lorenzo-Trueba and Ashton, 2014; Miselis and Lorenzo-Trueba, 2017; Ortiz and Ashton, 2016
Alongshore Community Length (Cell Length)	s	-	5,000	5,000	m	Inspired by field values observed in New Jersey
Number of cross-shore property rows	n	-	10	10	-	Inspired by field values observed in New Jersey

Chapter 3 Appendix

Table A1. Field observations from New Jersey communities downdrift of groins that respond with either contemporaneous or delayed groin/nourishment interventions of their own. These data include the year the interventions occurred, the timing relative to the updrift community's groin construction, the groin lengths and nourishment rates normalized to a 300-meter alongshore cell length (as employed by the model), socioeconomic parameters such as the baseline property value and the community size, and the resultant shoreline behavior observed between 1899 and 2012.

Community: Downdrift (Updrift)	*Groin Construction Year: Downdrift (Updrift)*	*First Nourishment Year: Downdrift (Updrift)*	*Groin Length* [m]: Downdrift (Updrift)*	*Nourish Rate* [m^3/yr]: Downdrift (Updrift)*	*Downdrift Baseline PV* [$]*	*Downdrift # Property Rows*	*Groin Delay [yrs]*	*Nourish Delay [yrs]*	*References*
Sea Bright (Monmouth Beach)	1915 (1915)	1962 (1963)	46 (32)	21388 (11192)	104577	9	0	47	ASBPA, 2020; Dallas et al., 2013; Donohue et al., 2004; NJDEP, n.d.; Pilkey and Wright III, 1988; PSDS, 2019; Rankin, 1952; Rice, 2015; US Census Bureau 2010
Deal (Allenhurst)	1933 (1921)	2016 (-)	157 (102)	128891 (-)	489775	21	12	95	ASBPA, 2020; Messaros et al., 2018; NJDEP, n.d.; PSDS, 2019; USACE, 1988; US Census Bureau, 2010
Asbury Park (Ocean Grove)	1915 (1915)	2001 (-)	172 (203)	11023 (-)	197589	116	0	86	ASBPA, 2020, Farrell et al., 2004b; NJDEP, n.d.; PSDS, 2019; Rankin, 1952; Rice, 2015; Stauble et al., 2005; US Census Bureau, 2010
Bradley Beach (Avon by the Sea)	1915 (1915)	1958 (1947)	131 (239)	4540 (7040)	251950	49	0	43	ASBPA, 2020; Donahue et al., 2004; Farrell et al., 2004b; NJDEP, n.d.; PSDS, 2019; Rice, 2015; Stauble et al., 2005; US Census Bureau, 2010
Belmar (Spring Lake)	1928 (1919)	1967 (1959)	105 (173)	3126 (2652)	193679	45	9	48	ASBPA, 2020; Farrell et al., 2004b; NJDEP, n.d.; PSDS, 2019; Rayner, 1952; USACE, 1995; US Census Bureau, 2010
Sea Girt (Manasquan)	1962 (1939)	1962 (1999)	123 (131)	4236 (6764)	590139	35	23	23	ASBPA, 2020; Farrell et al., 2004b; NJDEP, n.d.; PSDS, 2019; Rayner, 1952; Stauble et al., 2005; US Census Bureau, 2010
Loveladies (Harvey Cedars)	1963 (1925)	1962 (1954)	97 (96)	4706 (11869)	301155	23	38	37	ASBPA, 2020, Miller 1980, NJDEP n.d., PSDS 2019, Rice 2015, USACE 1999, US Census Bureau 2010
Ship Bottom (Surf City)	1963 (1920)	1956 (1962)	76 (69)	4726 (8233)	285581	29	43	36	ASBPA 2020, Miller 1980, NJDEP n.d., PSDS 2019, Rice 2015, USACE 1999, US Census Bureau 2010
Holgate (Beach Haven)	1947 (1920)	1962 (1962)	119 (66)	11406 (4172)	301155	23	27	42	ASBPA 2020; Miller, 1980; NJDEP, n.d.; PSDS, 2019; Rice, 2015; USACE,

									1999; US Census Bureau, 2010
Ventnor City (Atlantic City)	- (1948)	2004 (1936)	- (200)	26195 (8604)	269197	75	-	56	ASBPA, 2020; NJDEP, n.d.; PSDS, 2019; Rankin, 1952; US Census Bureau, 2010
Sea Isle City (Strathmere)	1923 (1920)	1962 (1950)	130 (136)	3128 (13145)	345432	25	3	42	ASBPA, 2020; Everts et al., 1980; NJDEP, n.d.; PSDS, 2019; USACE, 1978; USACE, 2001; US Census Bureau, 2010
South Cape May (Cape May City)	- (1924)	- (1967)	- (114)	- (10478)	-	-	-	-	NJDEP, n.d.; Tischler, 2006

*Value normalized to a 300-meter compartment size for comparison amongst communities.

Codes

A4.1 Chapter 1

All field observations, model codes, data produced by model experiments, and scripts used to generate manuscript figures are available at our Github repository page https://github.com/aryejanoff/Nourishment-Coordination.

A4.2 Chapter 2

A4.2.1 SAS Codes

NJ_nourishmentrate.sas (Normal Regression Model)

```
/*Nourishment Rate*/

libname NJ '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJ.nrate
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJ.nrate;
log_rate=log(Nourishment_Rate);
log_BR=log(Average_Beach_Revenue);
log_wealth=log(Average_Total_Bfrnt_Wealth);
log_tourdist=log(Distance_to_Tourism_Center);
log_inletdist=log(Distance_to_nearest_inlet);
log_halflife=log(Nourishment_Half_life);
proc contents;
proc print;
proc corr data=a;
        var Nourishment_Rate log_rate Nourishment_Half_life log_halflife;
run;
proc reg outest=est1;
        model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        *model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        *model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        output out=out1 p=p r=r; run; quit;
```

```
proc reg outest=est2;
	model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=backward ss2 sse aic;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=backward ss2 sse aic;
	*model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=backward ss2 sse aic;
	output out=out2 p=p r=r; run; quit;

proc reg outest=est3;
	model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	*model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	output out=out3 p=p r=r; run; quit;

proc reg outest=est4;
	model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	*model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	output out=out p=p r=r; run; quit;
```

```
proc reg outest=est5;
	model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
	*model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
	output out=out p=p r=r; run; quit;

data both; set est4 est5;  run;
proc sort data=both; by _rmse_; run;
proc print data=both(obs=10); run;
```

NJ_lognourishmentrate.sas (Semilog Regression Model)

```
/*Nourishment Rate*/

libname NJln '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJln.nrateln
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJln.nrateln;
log_rate=log(Nourishment_Rate);
log_BR=log(Average_Beach_Revenue);
log_wealth=log(Average_Total_Bfrnt_Wealth);
log_tourdist=log(Distance_to_Tourism_Center);
log_inletdist=log(Distance_to_nearest_inlet);
log_halflife=log(Nourishment_Half_life);
proc contents;
proc print;
proc reg outest=est1;
        *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        *model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        output out=out1 p=p r=r; run; quit;

proc reg outest=est2;
        *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=backward ss2 sse aic;
```

```
model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    selection=backward ss2 sse aic;
    *model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
    selection=backward ss2 sse aic;
    output out=out2 p=p r=r; run; quit;

proc reg outest=est3;
    *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    selection=stepwise ss2 sse aic;
    model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    selection=stepwise ss2 sse aic;
    *model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
    selection=stepwise ss2 sse aic;
    output out=out3 p=p r=r; run; quit;

proc reg outest=est4;
    *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    selection=adjrsq sse aic adjrsq;
    model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    selection=adjrsq sse aic adjrsq;
    *model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
    selection=adjrsq sse aic adjrsq;
    output out=out p=p r=r; run; quit;

proc reg outest=est5;
    *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    noint selection=adjrsq sse aic adjrsq;
```

```
	model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
	*model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
	output out=out p=p r=r; run; quit;

data both; set est4 est5;  run;
proc sort data=both; by _rmse_; run;
proc print data=both(obs=10); run;
```

NJ_lognourishmentrate_logparams.sas (Log-log Regression Model)

```
/*Nourishment Rate*/

libname NJlnln '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJlnln.nratelnln
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJlnln.nratelnln;
log_rate=log(Nourishment_Rate);
log_BR=log(Average_Beach_Revenue);
log_wealth=log(Average_Total_Bfrnt_Wealth);
log_tourdist=log(Distance_to_Tourism_Center);
log_inletdist=log(Distance_to_nearest_inlet);
log_halflife=log(Nourishment_Half_life);
proc contents;
proc print;
proc reg outest=est1;
        *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        *model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        output out=out1 p=p r=r; run; quit;

proc reg outest=est2;
        *model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
        selection=backward ss2 sse aic;
```

```
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=backward ss2 sse aic;
	model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=backward ss2 sse aic;
	output out=out2 p=p r=r; run; quit;

proc reg outest=est3;
	*model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=stepwise ss2 sse aic;
	output out=out3 p=p r=r; run; quit;

proc reg outest=est4;
	*model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	*model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
	selection=adjrsq sse aic adjrsq;
	output out=out p=p r=r; run; quit;

proc reg outest=est5;
	*model Nourishment_Rate = Average_Beach_Revenue
Average_Total_Bfrnt_Wealth Com_Res_Ratio Distance_to_Tourism_Center
Distance_to_nearest_inlet Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
	noint selection=adjrsq sse aic adjrsq;
```

```
    *model log_rate = Average_Beach_Revenue Average_Total_Bfrnt_Wealth
Com_Res_Ratio Distance_to_Tourism_Center Distance_to_nearest_inlet
Nourishment_Half_life / white collin slstay=0.15 slentry=0.15
    noint selection=adjrsq sse aic adjrsq;
    model log_rate = log_BR log_wealth Com_Res_Ratio log_tourdist log_inletdist
log_halflife / white collin slstay=0.15 slentry=0.15
    noint selection=adjrsq sse aic adjrsq;
    output out=out p=p r=r; run; quit;

data both; set est4 est5;  run;
proc sort data=both; by _rmse_; run;
proc print data=both(obs=10); run;
```

NJ_nourishmentdischarge_standardized.sas (Standard Normal Regression Model)

```
/*Nourishment Discharge*/

libname NJst '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJst.ndischargest
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs_standardln.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJst.ndischargest;
proc contents;
proc print;
proc corr data=a;
        var Standard_Dischargeln Standard_Half_life;
run;

proc reg outest=est3;
        model Standard_Discharge = Standard_BR Standard_Wealth Standard_CR_Ratio
Standard_Tourism_Distance Standard_Inlet_Distance Standard_Half_life / white collin
slstay=0.15 slentry=0.15
        selection=stepwise ss2 sse aic;
        output out=out3 p=p r=r; run; quit;

proc reg outest=est4;
        model Standard_Discharge = Standard_BR Standard_Wealth Standard_CR_Ratio
Standard_Tourism_Distance Standard_Inlet_Distance Standard_Half_life / white collin
slstay=0.15 slentry=0.15
        selection=adjrsq sse aic adjrsq;
        output out=out p=p r=r; run; quit;

data both; set est4;  run;
proc sort data=both; by _rmse_; run;
proc print data=both(obs=10); run;
```

NJ_geointeractions_sppcombos.sas (Half-life Geo-interaction)

```
/*Nourishment Rate*/

libname NJ '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJ.geointeract
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJ.geointeract;
proc contents;
proc print;
run;
proc reg outest=est1;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
CR_Half_life_Div / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        output out=out1 p=p r=r; run; quit;

proc reg outest=est2;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
CR_Half_life_Div / white collin slstay=0.15 slentry=0.15
        selection=backward ss2 sse aic;
        output out=out2 p=p r=r; run; quit;

proc reg outest=est4;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
CR_Half_life_Div / white collin slstay=0.15 slentry=0.15
        selection=adjrsq sse aic adjrsq;
        output out=out p=p r=r; run; quit;

proc reg outest=est5;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
CR_Half_life_Div / white collin slstay=0.15 slentry=0.15
        noint selection=adjrsq sse aic adjrsq;
        output out=out p=p r=r; run; quit;

data both; set est4 est5;  run;
proc sort data=both; by _rmse_; run;
```

```
proc print data=both(obs=10); run;
```

NJ_geointeractions_sppcombos.sas (Inlet Distance Geo-interaction)

```
/*Nourishment Rate*/

libname NJ '/folders/myfolders/Projects';

/***State***/
PROC IMPORT OUT= NJ.geointeract
        DATAFILE= "/folders/myfolders/Projects/NJ_SAS_inputs.xlsx"
        DBMS=XLSX REPLACE;
SHEET="Sheet1";

data a;
set NJ.geointeract;
proc contents;
proc print;
run;
proc reg outest=est1;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
Wealth_logInlet_Mult / white collin slstay=0.15 slentry=0.15
        selection=forward ss2 sse aic;
        output out=out1 p=p r=r; run; quit;

proc reg outest=est2;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
Wealth_logInlet_Mult / white collin slstay=0.15 slentry=0.15
        selection=backward ss2 sse aic;
        output out=out2 p=p r=r; run; quit;

proc reg outest=est4;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
Wealth_logInlet_Mult / white collin slstay=0.15 slentry=0.15
        selection=adjrsq sse aic adjrsq;
        output out=out p=p r=r; run; quit;

proc reg outest=est5;
        model Nourishment_Rate = Average_Total_Bfrnt_Wealth Com_Res_Ratio
Wealth_logInlet_Mult / white collin slstay=0.15 slentry=0.15
        noint selection=adjrsq sse aic adjrsq;
        output out=out p=p r=r; run; quit;

data both; set est4 est5;  run;
proc sort data=both; by _rmse_; run;
```

```
proc print data=both(obs=10); run;
```

A4.2.2 Matlab Codes

maincode.m

```
function [behavior,NB2,W,Eff,Nrate]=maincode(PV,comres)

% %Nourishment Rate Sensitivities
% Nrate_min=0;
% Nrate_max=300000;
% dN=100;
% Nrate_vector=Nrate_min:dN:Nrate_max;
% nr=length(Nrate_vector);
% NB_storage=NaN(1,nr);
% behavior_storage=NaN(1,nr);
% N_efficiency_storage=NaN(1,nr);
%
% parfor iN=1:numel(Nrate_vector)
    %% Input Physical Pmarameters %%
    lot_size=30;
    w_init=30;
    beta=0.6; %beach width hedonic parameter
%     PV=0.01e6;
%     comres=0.0;
    alpha2=PV/(w_init^beta); %385000; %
    s=[2500 5000 2500]; %alongshore compartment length (m)
    rows_along=s(2)/lot_size;
    rows_cross=10; %# of cross-shore proeprty rows
    properties_total=rows_cross*rows_along;
    comm_width=rows_cross*lot_size; %initial Community Width (m)
    psi=0.2;
    D=16; %depth of closure (m)
    gamma=1; %erosion rate (m/yr)
    d=500000; %alongshore flux coeff
    K=2000; %cross-shore flux coeff
    phi=20; %sand cost ($/m^3)
    rho=0.03; %discount rate
    TBW=PV*rows_along;
    Nrate=max(0,-7800.23119+0.00015081*TBW+223965*comres); %Nourishment
Rate Nrate_vector(iN); %
    nu=0; %beach width decline beyond max threshold
    theta_eq=0.02; %equilibrium shoreface slope
    k2=0;
    k3=0;
```

```
%% Computational Parameters %%
tmax=50; dt=0.01; t=0:dt:tmax; n=length(t);
Smax=3; ds=1; S=1:ds:Smax; m=length(S);
A2=alpha2*rho;
theta=zeros(n,m); qL=zeros(n,m); qC=zeros(n,m); q_loss=zeros(1,n);
fS=zeros(n,m); fT=zeros(n,m);
xS=zeros(n,m); xT=zeros(n,m); xH=zeros(n,m); w=zeros(n,m);
B=zeros(n,m); B_disc=zeros(n,m); TB=zeros(n,m);
C=zeros(n,m); TC=zeros(n,m);
nb=NaN(n,m); N_h=zeros(n,m);
volume=zeros(n,m);
V_nourish=zeros(1,n); V_loss=zeros(1,n); efficiency=zeros(1,n);
TQL_out=zeros(1,n); TQC_out=zeros(1,n); TQ_out=zeros(1,n);
nb2=NaN(1); nb3=NaN(1); behavior=NaN(1); NB2=NaN(1); NB3=NaN(1);
TNB=NaN(1);

%% Initial Conditions %%
xS(1,:)=comm_width+w_init;
xT(1,:)=xS(1,:)+(D/theta_eq);
xH(1,:)=comm_width;
N_h(1,:)=rows_cross;
w(1,:)=xS(1,:)-xH(1,:);
volume(:,2)=Nrate;

%% Main Code %%
for i=1:n-1
  for j=2:m-1
    %% Nourishment Initiation + Volume
    V_nourish(i+1)=V_nourish(i)+(2*(volume(i,2))/(s(2)*D));

    %% Fluxes (Along/Cross-shore) and Shoreface Dynamics
    qL(i,j)=d*((xS(i,j-1)-xS(i,j))/((s(j-1)+s(j))/2)); qL(i,1)=d*((xS(i,m)-
xS(i,1))/((s(j-1)+s(j))/2)); qL(i,m)=d*((xS(i,m-1)-xS(i,m))/((s(m-1)+s(m))/2));
    theta(i,j)=D/(xT(i,j)-xS(i,j)); theta(i,1)=D/(xT(i,1)-xS(i,1));
theta(i,m)=D/(xT(i,m)-xS(i,m));
    qC(i,j)=K*(theta(i,j)-theta_eq); qC(i,1)=K*(theta(i,1)-theta_eq);
qC(i,m)=K*(theta(i,m)-theta_eq);
    q_loss(i)=((2*(qL(i,1)-qL(i,2)))/s(j))+((4*(qC(i,2)+qC(i,3)))/D)+gamma; %

V_loss(i)=(dt/3)*(q_loss(1)+4*(sum(q_loss(2:2:end)))+2*sum(q_loss(2:1:end))+q_loss(e
nd));
    efficiency(i)=100*(1-V_loss(i)./V_nourish(i));
```

```
        %% ODE's ((2*d/(s^2))*(xS(i,m)-2*xS(i,1)+xS(i,2)))-(4*K*(theta(i,1)-
theta_eq)/D)
        fT(i,j)=(4*K*(theta(i,j)-theta_eq)/D)-gamma; fT(i,1)=(4*K*(theta(i,1)-
theta_eq)/D)-gamma; fT(i,m)=(4*K*(theta(i,m)-theta_eq)/D)-gamma;
        fS(i,j)=((2*d/(((s(j-1)+s(j))/2)*((s(j)+s(j+1))/2)))*(xS(i,j-1)-
2*xS(i,j)+xS(i,j+1)))-(4*K*(theta(i,j)-theta_eq)/D)-gamma+((2*volume(i,2))/(D*s(2)));
fS(i,1)=((2*d/(((s(m)+s(1))/2)*((s(1)+s(2))/2)))*(xS(i,m)-2*xS(i,1)+xS(i,2)))-
(4*K*(theta(i,1)-theta_eq)/D)-gamma; fS(i,m)=((2*d/(((s(m-
1)+s(m))/2)*((s(m)+s(1))/2)))*(xS(i,m-1)-2*xS(i,m)+xS(i,1)))-(4*K*(theta(i,m)-
theta_eq)/D)-gamma;

        %% Numerical Approximations

        xT(i+1,j)=xT(i,j)+dt*fT(i,j); xT(i+1,1)=xT(i,1)+dt*fT(i,1);
xT(i+1,m)=xT(i,m)+dt*fT(i,m);
        xS(i+1,1)=xS(i,1)+dt*fS(i,1); xS(i+1,j)=xS(i,j)+dt*fS(i,j);
xS(i+1,m)=xS(i,m)+dt*fS(i,m);
        if xS(i,j)<=lot_size
          volume(i,j)=0; volume(i+1,j)=0; N_h(i,j)=0; xH(i,j)=0; N_h(i+1,j)=0;
xH(i+1,j)=0; %xS(i,j)=0; xS(i+1,j)=0;
        elseif xS(i,j)<=xH(i,j)+0.5
          xH(i+1,j)=xH(i,j)-lot_size; N_h(i+1,j)=N_h(i,j)-1;
        else
          xH(i+1,j)=xH(i,j);
        end
        w(i,j)=xS(i,j)-xH(i,j); w(i,1)=xS(i,1)-xH(i,1);

        %% Housing Lines
        N_h(i,j)=xH(i,j)/lot_size; N_h(i,1)=xH(i,1)/lot_size;
N_h(i,m)=xH(i,m)/lot_size;

        %% Benefit
        B(i,2)=rows_along*A2*((w(i,2)).^beta)*((N_h(i,2)).^psi)-(nu*(w(i,2).^2));
        B_disc(i,j)=B(i,j)*exp(-rho*t(i));

TB(i,j)=(dt/3)*(B_disc(1,j)+4*(sum(B_disc(2:2:end,j)))+2*sum(B_disc(2:1:end,j))+B_di
sc(end,j));

        %% Cost
        C(i,j)=volume(i,j)*phi*exp(-rho*t(i));
        if N_h(i,j)==0
          C(i,j)=0;
        end
```

```
            TC(i,j)=sum(C(:,j));

            %% marginal net benefit
            nb(i,j)=TB(i,j)-TC(i,j);

            %% Net Benefit
            NB2=nb(i,2);
        end
    end

    %% Identify Behavior
    if max(xS(end-1,2))>comm_width+w_init
        behavior=0; %seaward growth
    elseif max(xS(end-1,2))<=comm_width+w_init && xH(end-1,2)-xH(1,2)==0
        behavior=3; %hold the line
    elseif  (xH(end-1,2)-xH(1,2)<0) && Nrate~=0
        behavior=6; %slow retreat
    elseif (xH(end-1,2)-xH(1,2)<0) && Nrate==0
        behavior=9; %retreat
    end

    %% Nourishment Efficiency
    if Nrate~=0
        Eff=efficiency(end-1);
    elseif Nrate==0
        Eff=NaN;
    end
%       ind=find(w(2:end-1,2)-w_init<=0.5*(w(2,2)-w_init));
%       halflife=min(t(ind));

    %% Shoreline Change
    W=xS(end-1,2)-xS(1,2);

%       %% Output Storage
%       N_efficiency_storage(iN)=Eff;
%       NB_storage(iN)=NB2;
%       behavior_storage(iN)=behavior;
% end
% %% find optimum
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% % coordinated
% maxNB=max(NB_storage(:));
% index=find(NB_storage==maxNB);
```

```
% Nrate_star=Nrate_vector(index);
% NB_star=NB_storage(index);
% behavior_star=behavior_storage(index);
% Neff_star=N_efficiency_storage(index);
% PV=5e6;
% comres=0.02;
% rows_along=5000/30;
% TBW=PV*rows_along;
% Nrate_emp=max(0,-7800.23119+0.00015081*TBW+223965*comres);
```

PV_comres_sensitivities.m

```
PV_vec=linspace(1e4,7e6,150);
TBW_vec=PV_vec*5000/30;
comres_vec=linspace(0,0.6,150);
nn=length(PV_vec);
mm=length(comres_vec);
behavior_storage=zeros(nn,mm);
NB2_storage=zeros(nn,mm);
W_storage=zeros(nn,mm);
Eff_storage=zeros(nn,mm);
Nrate_storage=zeros(nn,mm);
%% Main code %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
parfor ii=1:numel(PV_vec)
   behavior_vector=zeros(1,mm);
   NB2_vector=zeros(1,mm);
   W_vector=zeros(1,mm);
   Eff_vector=zeros(1,mm);
   Nrate_vector=zeros(1,mm);
   for jj=1:numel(comres_vec)
      PV=PV_vec(ii);
      comres=comres_vec(jj);
      [behavior,NB2,W,Eff,Nrate]=maincode(PV,comres);
      %% Storage %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
      behavior_vector(jj)=behavior;
      NB2_vector(jj)=NB2;
      W_vector(jj)=W;
      Eff_vector(jj)=Eff;
      Nrate_vector(jj)=Nrate;
   end
   behavior_storage(ii,:)=behavior_vector;
   NB2_storage(ii,:)=NB2_vector;
   W_storage(ii,:)=W_vector;
   Eff_storage(ii,:)=Eff_vector;
   Nrate_storage(ii,:)=Nrate_vector;
end
```

A4.3 Chapter 3

base_code_timesens.m

```
% function
[NB_star,tcritg_star,behavior_star,decision_star,shoreline_change_star]=base_code_time
sens(alpha2,rows_cross,Nrate1,Nrate2,L1,L2,t_crit_n_up,t_crit_n_down,t_crit_g_up)
function
[NB_star,tcritg_star,tcritn_star,behavior_star,decision_star,shoreline_change_star]=base_
code_timesens(phi_g,gamma)
% function
[NB_star,tcritg_star,tcritn_star,behavior_star,decision_star,shoreline_change_star]=base_
code_timesens(alpha2,rows_cross)
% function
[NB_star,tcritg_star,behavior_star,decision_star,shoreline_change_star]=base_code_time
sens(rows_cross)
tt=linspace(0,99,100); %197
tcritg_vec=[tt NaN];
mm=numel(tcritg_vec);
tcritn_vector=linspace(0,99,100); %197
tcritn_vec=[tcritn_vector NaN];
kk=numel(tcritn_vec);
NB_storage=NaN(mm,kk); %(1,mm);
behavior_storage=NaN(mm,kk); %(1,mm);
decision_storage=NaN(mm,kk); %(1,mm);
shorelinechange_storage=NaN(mm,kk); %(1,mm);
parfor ii=1:numel(tcritg_vec)
  NB_vec=zeros(1,kk);
  behavior_vec=zeros(1,kk);
  decision_vec=zeros(1,kk);
  shorelinechange_vec=zeros(1,kk);
  Nh_final_vec=zeros(1,kk);
  for in=1:numel(tcritn_vec)
    %% Input Physical Parameters %%
    lot_size=30;
    w_init=30;
    beta=0.5; %beach width hedonic parameter
    alpha1=1e6/(w_init^beta);
    alpha2=277519; %0.1e6/(w_init^beta);
    s=[300 300]; %alongshore compartment length (m)
    rows_along=s(2)/lot_size;
    rows_cross=38; %# of cross-shore proeprty rows
```

```
        properties_total=rows_cross*rows_along;
        comm_width=rows_cross*lot_size; %initial Community Width (m)
        psi=0.2;
        D=16; %depth of closure (m)
%       gamma=2; %erosion rate (m/yr)
        d=500000; %alongshore flux coeff (m^2/yr)
        K=2000; %cross-shore flux coeff (m^2/yr)
        phi_n=5; %sand cost ($/m^3)
        Nrate1=8415; %Nourishment Rate (m^3/yr)
        Nrate2=18614; %Nourishment Rate (m^3/yr)
%       phi_g=100000; %groin cost ($/m)
        rho=0.03; %discount rate
        nu=0; %beach width decline beyond max threshold
        theta_eq=0.025; %equilibrium shoreface slope
        deg=75; %breaking wave angle
        rad=deg*pi/180;
        H=1; %Wave Height (m)
%       T=10; %Wave Period (s)
        qin=d*(H^(5/2))*cos(rad)*sin(rad);
        k1=0;
        k2=0;
        L1=135;
        L2=100;
        t_crit_g_up=0; %24;
        t_crit_g_down=tcritg_vec(ii); %time of groin construction downdrift
        t_crit_n_up=0; %61; %time of first nourishment downdrift
        t_crit_n_down=tcritn_vec(in); %time of first nourishment downdrift

        %% Computational Parameters %%
        tmax=100; dt=0.05; t=0:dt:tmax; n=length(t);
        Smax=2; ds=1; S=1:ds:Smax; m=length(S);
        A1=alpha1*rho; A2=alpha2*rho;

        L=zeros(1,m); theta=zeros(n,m); qL=NaN(n,m); qC=zeros(n,m); fS=zeros(n,m);
fT=zeros(n,m);
        xS=zeros(n,m); xT=zeros(n,m); xH=zeros(n,m); w=zeros(n,m);
        B=zeros(n,m); B_disc=zeros(n,m); TB=zeros(n,m);
        C=zeros(n,m); TC=zeros(n,m);
        nb=NaN(n,m); N_h=zeros(n,m);
        volume=zeros(n,m); nE=zeros(n,m); Vtotal=zeros(n,m);
        TQL_out=zeros(1,n); TQC_out=zeros(1,n); TQ_out=zeros(1,n);
        share1=NaN(1); share2=NaN(1);
        behavior=NaN(1);  decision=NaN(1);
```

```
    NB1=NaN(1); NB2=NaN(1); TNB=NaN(1);
    time_groin=NaN(1); time_drown=NaN(1); w_crit_g=NaN(1); Nh_crit=NaN(1);
shoreline_change=NaN(1);

    %% Initial Conditions %%
    xS(1,:)=comm_width+w_init;
    xT(1,:)=xS(1,:)+(D/theta_eq);
    xH(1,:)=comm_width;
    N_h(1,:)=rows_cross;
    w(1,:)=xS(1,:)-xH(1,:);
    C(1,1)=phi_g*L1;

    %% Main Code %%
    for i=1:n-1
      for j=1:m
        %% Groin Lengths
%         L(:,1)=L1;
        %% Nourishment Initiation + Volume
        if t(i)>=t_crit_n_up
          volume(i,1)=Nrate1;
        else
          volume(i,1)=0;
        end
        if t(i)>=t_crit_n_down
          volume(i,2)=Nrate2;
        else
          volume(i,2)=0;
        end
        Vtotal(i+1,2)=Vtotal(i,2)+volume(i,2);

        %% Fluxes (Along/Cross-shore) and Shoreface Dynamics
        if xS(i,2)<=comm_width+L(1) && xS(i,1)<=comm_width+L(1) && L(1)~=0
          qL(i,1)=qin*((xS(i,1)-xH(i,1))./L(1));
        elseif xS(i,2)>comm_width+L(1) || xS(i,1)>comm_width+L(1) || L(1)==0
          qL(i,1)=d*(H^(5/2))*cos(rad-atan((xS(i,1)-
xS(i,2))/(0.5*s(1)+0.5*s(2))))*sin(rad-atan((xS(i,1)-xS(i,2))/(0.5*s(1)+0.5*s(2))));
        end
        if xS(i,2)<=comm_width+L(2) && L(2)~=0 %(xS(i,2)-xH(i,2))<=L(2) &&
(xS(i,3)-xH(i,3))<=L(2) && L(2)~=0
          qL(i,2)=qL(i,1)*((xS(i,2)-xH(i,2))./L(2));
        elseif xS(i,2)>comm_width+L(2) || L(2)==0 %(xS(i,2)-xH(i,2))>L(2) ||
(xS(i,3)-xH(i,3))>L(2) || L(2)==0
```

```
        qL(i,2)=qin; %d*cos(rad-atan((xS(i,2)-
xS(i,3))/(0.5*s(2)+0.5*s(3))))*sin(rad-atan((xS(i,2)-xS(i,3))/(0.5*s(2)+0.5*s(3))));
      end
      theta(i,j)=D/(xT(i,j)-xS(i,j)); %theta(i,1)=D/(xT(i,1)-xS(i,1));
theta(i,m)=D/(xT(i,m)-xS(i,m));
      qC(i,j)=4*s(j)*K*(theta(i,j)-theta_eq); %qC(i,1)=4*s*K*(theta(i,1)-theta_eq);
qC(i,m)=4*s*K*(theta(i,m)-theta_eq);

      %% ODE's ((2*d/(s^2))*(xS(i,m)-2*xS(i,1)+xS(i,2)))-(4*K*(theta(i,1)-
theta_eq)/D)
      fT(i,j)=(4*K*(theta(i,j)-theta_eq)/D)-gamma; %fT(i,1)=(4*K*(theta(i,1)-
theta_eq)/D)-gamma; fT(i,m)=(4*K*(theta(i,m)-theta_eq)/D)-gamma;
      fS(i,1)=((2/(D*s(1)))*(qin-qL(i,1)))-(4*K*(theta(i,1)-theta_eq)/D)-
gamma+((2*volume(i,1))/(D*s(1)));  %((2/(D*s(1)))*(qL(i,3)-qL(i,1)))-(4*K*(theta(i,1)-
theta_eq)/D)-gamma;  %
      fS(i,2)=((2/(D*s(2)))*(qL(i,1)-qL(i,2)))-(4*K*(theta(i,2)-theta_eq)/D)-
gamma+((2*volume(i,2))/(D*s(2)));

      %% Numerical Approximations

      xT(i+1,j)=xT(i,j)+dt*fT(i,j); %xT(i+1,m)=xT(i,m)+dt*fT(i,m);
      if xS(i,j)<=lot_size
        volume(i,j)=0; volume(i+1,j)=0; N_h(i,j)=0; xH(i,j)=0; N_h(i+1,j)=0;
xH(i+1,j)=0; %xS(i,j)=0; xS(i+1,j)=0;
      elseif xS(i,j)<=xH(i,j)+5
        xH(i+1,j)=xH(i,j)-lot_size; N_h(i+1,j)=N_h(i,j)-1;
      else
        xH(i+1,j)=xH(i,j);
      end
%         if volume(i,1)~=0
%           xS(i+1,1)=xS(i,1)+xN1;
%         elseif volume(i,1)==0
%           xS(i+1,1)=xS(i,1)+dt*fS(i,1);
%         end
%         if volume(i,2)~=0
%           xS(i+1,2)=xS(i,2)+xN2;
%         elseif volume(i,2)==0
%           xS(i+1,2)=xS(i,2)+dt*fS(i,2);
%         end
%         xS(i+1,3)=xS(i,3)+dt*fS(i,3);
      xS(i+1,j)=xS(i,j)+dt*fS(i,j);
      w(i,j)=xS(i,j)-xH(i,j); w(i,m)=xS(i,m)-xH(i,m);
      %% Housing Lines
```

```
            N_h(i,j)=xH(i,j)/lot_size; N_h(i,m)=xH(i,m)/lot_size;

            %% Groin Construction
            if t(i)>=t_crit_g_up
               L(1)=L1;
            end
            if t(i)>=t_crit_g_down
               L(2)=L2;
            end
            if t(i)==t_crit_g_down && L2~=0 && volume(i,2)==0
               C(i,2)=phi_g*L(2)*exp(-rho*t(i));
            elseif t(i)~=t_crit_g_down && volume(i,2)~=0
               C(i,2)=(volume(i,2)*phi_n)*exp(-rho*t(i));
            elseif t(i)~=t_crit_g_down && volume(i,2)==0
               C(i,2)=0;
            elseif t(i)==t_crit_g_down && L2~=0 && volume(i,2)~=0
               C(i,2)=(phi_g*L(2)+volume(i,j)*phi_n)*exp(-rho*t(i));
            elseif t(i)~=t_crit_g_down && L2~=0 && volume(i,2)==0
               C(i,2)=0;
            end
            if isnan(t_crit_g_down)==0 && t_crit_g_down>0
               w_crit_g=w(t_crit_g_down/dt,2);
               Nh_crit=rows_cross-N_h(t_crit_g_down/dt,2);
            elseif t_crit_g_down==0
               w_crit_g=w(1,2);
               Nh_crit=rows_cross-N_h(1,2);
            elseif isnan(t_crit_g_down)==1
               w_crit_g=NaN;
               Nh_crit=NaN;
             end

            %% Benefit
            B(i,1)=rows_along.*A1.*((w(i,1)).^beta)*((N_h(i,1)).^psi);
B(i,2)=rows_along.*A2.*((w(i,2)).^beta)*((N_h(i,2)).^psi);
%              if xS(i,2)>2
%                 B(i,2)=rows_along.*A2.*((w(i,2)).^beta);
%              elseif xS(i,2)<=2
%                 B(i,2)=0;
%              end
            B_disc(i,j)=B(i,j)*exp(-rho*t(i)); %B_disc(i,m)=B(i,m)*exp(-rho*t(i));

TB(i,j)=(dt/3)*(B_disc(1,j)+4*(sum(B_disc(2:2:end,j)))+2*sum(B_disc(2:1:end,j))+B_di
sc(end,j));
```

```
%TB(i,m)=(dt/3)*(B_disc(1,m)+4*(sum(B_disc(2:2:end,m)))+2*sum(B_disc(2:1:end,m)
)+B_disc(end,m));

            %% Cost
%              C(i,j)=(c+volume(i,j)*phi_n)*exp(-rho*t(i));
%              C(i,m)=(c+volume(i,m)*phi_n)*exp(-rho*t(i));
%              if volume(i,j)==0
%                 C(i,j)=0;
%              end
%              if volume(i,m)==0
%                 C(i,m)=0;
%              end
%              if N_h(i,j)==0
%                 C(i,j)=0;
%              end
%              if N_h(i,m)==0
%                 C(i,m)=0;
%              end
            TC(i,j)=sum(C(:,j)); %TC(i,m)=sum(C(:,m));

            %% marginal net benefit
            nb(i,j)=TB(i,j)-TC(i,j); %nb(i,m)=TB(i,m)-TC(i,m);
%              if w_crit_g>L(2)
%                 nb(i,2)=NaN;
%              end

            %% Net Benefit
            NB1=nb(end-1,1); NB2=nb(end-1,2); TNB=NB1+NB2;
            share1=NB1/TNB; share2=NB2/TNB;

            %% behavior determination
            if xS(end-1,2)>xS(1,2) && (Nrate2~=0 || L(2)~=0)
               behavior=0;
            elseif xS(end-1,2)<=xS(1,2) && N_h(end-1,2)==N_h(1,2) && (Nrate2~=0 ||
L(2)~=0)
               behavior=1;
            elseif N_h(end-1,2)<N_h(1,2) && (isnan(t_crit_g_down)==0 ||
isnan(t_crit_n_down)==0)
               behavior=2;
            elseif N_h(end-1,2)<N_h(1,2) && isnan(t_crit_g_down)==1 &&
isnan(t_crit_n_down)==1
               behavior=3;
            end
```

```
            %% decision determination
            if isnan(t_crit_g_down)==1 && isnan(t_crit_n_down)==1
               decision=0; %no groin; no nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down==0 &&
isnan(t_crit_n_down)==1
               decision=1; %initial groin; no nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down~=0 &&
isnan(t_crit_n_down)==1
               decision=2; %delayed groin; no nourishment
            elseif isnan(t_crit_g_down)==1 && isnan(t_crit_n_down)==0 &&
t_crit_n_down==0
               decision=3;  %no groin; initial nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down==0 &&
isnan(t_crit_n_down)==0 && t_crit_n_down==0
               decision=4; %initial groin; initial nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down~=0 &&
isnan(t_crit_n_down)==0 && t_crit_n_down==0
               decision=5; %delayed groin; initial nourishment
            elseif isnan(t_crit_g_down)==1 && isnan(t_crit_n_down)==0 &&
t_crit_n_down~=0
               decision=6; %no groin; delayed nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down==0 &&
isnan(t_crit_n_down)==0 && t_crit_n_down~=0
               decision=7; %initial groin; delayed nourishment
            elseif isnan(t_crit_g_down)==0 && t_crit_g_down~=0 &&
isnan(t_crit_n_down)==0 && t_crit_n_down~=0
               decision=8; %delayed groin; delayed nourishment
            end
            shoreline_change=(xS(end-1,2)-xS(1,2))./tmax;
         end
      end
      NB_vec(in)=nb(end-1,2);
      behavior_vec(in)=behavior;
      decision_vec(in)=decision;
      shorelinechange_vec(in)=shoreline_change;
      Nh_final_vec(in)=N_h(end-1,2);
   end
   NB_storage(ii,:)=NB_vec; %NB_storage(ii)=nb(end-1,2);
   behavior_storage(ii,:)=behavior_vec; %behavior_storage(ii)=behavior;
   decision_storage(ii,:)=decision_vec; %decision_storage(ii)=decision;
   shorelinechange_storage(ii,:)=shorelinechange_vec;
%shorelinechange_storage(ii)=shoreline_change;
```

```
end
NB_star=max(NB_storage(:));
[row,col]=find(NB_storage==NB_star); %ind=find(NB_storage==NB_star);

% if max(col)~=101 || max(row)~=101
   tcritg_star=tcritg_vec(row); %tcritg_star=tcritg_vec(ind);
   tcritn_star=tcritn_vec(col);
   behavior_star=behavior_storage(row,col); %behavior_star=behavior_storage(ind);
   decision_star=decision_storage(row,col); %decision_star=decision_storage(ind);
   shoreline_change_star=shorelinechange_storage(row,col);
%shoreline_change_star=shorelinechange_storage(ind);
% elseif max(col)==101 && max(row)==101
%    Nh_final_star=0;
%    tcritg_star=NaN;
%    tcritn_star=NaN;
%    behavior_star=max(max(behavior_storage(row,col)));
%    decision_star=min(min(decision_storage(row,col)));
%    shoreline_change_star=shorelinechange_storage(max(row),max(col));
% end
```

alpha2_Nh2_sensitivities.m

```
tic
alpha2_vec=linspace((1e3)/(30^0.5),(5e6)/(30^0.5),20);
Nh2_vec=linspace(1,120,20);
nn=length(alpha2_vec);
mm=length(Nh2_vec);
NBmax_storage=zeros(nn,mm);
tcritg_storage=zeros(nn,mm);
tcritn_storage=zeros(nn,mm);
behavior_storage=zeros(nn,mm);
decision_storage=zeros(nn,mm);
shoreline_change_storage=zeros(nn,mm);

%% Main code %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for ii=1:numel(alpha2_vec)
  NBmax_vector=zeros(1,mm);
  tcritg_vector=zeros(1,mm);
  tcritn_vector=zeros(1,mm);
  behavior_vector=zeros(1,mm);
  decision_vector=zeros(1,mm);
  shoreline_change_vector=zeros(1,mm);
  for jj=1:numel(Nh2_vec)
    alpha2=alpha2_vec(ii);
    rows_cross=Nh2_vec(jj);

[NB_star,tcritg_star,tcritn_star,behavior_star,decision_star,shoreline_change_star]=base_
code_timesens(alpha2,rows_cross);
    %% Storage %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    NBmax_vector(jj)=NB_star(end);
    tcritg_vector(jj)=tcritg_star(end);
    tcritn_vector(jj)=tcritn_star(end);
    behavior_vector(jj)=behavior_star(end);
    decision_vector(jj)=decision_star(end);
    shoreline_change_vector(jj)=shoreline_change_star(end);
  end
  NBmax_storage(ii,:)=NBmax_vector;
  tcritg_storage(ii,:)=tcritg_vector;
  tcritn_storage(ii,:)=tcritn_vector;
  behavior_storage(ii,:)=behavior_vector;
  decision_storage(ii,:)=decision_vector;
  shoreline_change_storage(ii,:)=shoreline_change_vector;
end
```

```
%% figures

%% save data
time_elapsed=toc;
```

Nh2_sensitivites.m

```
tic
Nh2_vec=linspace(1,120,120);
nn=length(Nh2_vec);
NBmax_storage=zeros(1,nn);
tcritg_storage=zeros(1,nn);
behavior_storage=zeros(1,nn);
decision_storage=zeros(1,nn);
shoreline_change_storage=zeros(1,nn);

%% Main code %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for jj=1:numel(Nh2_vec)
   rows_cross=Nh2_vec(jj);

[NB_star,tcritg_star,behavior_star,decision_star,shoreline_change_star]=base_code_time
sens(rows_cross);
   %% Storage %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
   NBmax_storage(jj)=NB_star(end);
   tcritg_storage(jj)=tcritg_star(end);
   behavior_storage(jj)=behavior_star(end);
   decision_storage(jj)=decision_star(end);
   shoreline_change_storage(jj)=shoreline_change_star(end);
end

%% save data
time_elapsed=toc;
```

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