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A Low-Cost Shoreline Dynamic Simulation Model for Proposed Beach Nourishment and Dune Construction: Introducing a New Feasibility Analysis Tool

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ABSTRACT

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Beach nourishment and dune construction are common coastal risk-management strategies for shoreline erosion in the United States. Federal involvement with such projects relies on cost–benefit analyses, which in turn rely on life-cycle models of shoreline processes, such as the Army Corps of Engineers' Beach-fx event-driven physical and economic coastal model. However, use of these models can be computationally and data intensive. Costs associated with conducting a feasibility analysis for beach nourishment and dune construction may leave a community with few resources to explore other risk-management options. This paper, therefore, presents a first-order, screening-level, low-cost dynamic model that delivers results approximately comparable with those from life-cycle models. Applying the model to three locations in Florida shows that simulated nourishment intervals are within 5 years of those predicted by Beach-fx, leading to a similar number of nourishments over a 50-year project life span. A discussion on how one could apply the model to other areas is also included. It is intended that this model could serve as a first-pass screening tool for communities considering beach nourishment and dune construction before they decide to invest in the more thorough, but costly and data-intensive, life-cycle model simulations.

ADDITIONAL INDEX WORDS: *Shoreline erosion, coastal risk management, sea-level rise, Beach-fx, climate change, adaptation.*

INTRODUCTION

Coastal areas are vulnerable to hazards such as flooding, inundation, and shoreline erosion that are predicted to worsen with climate change, sea-level rise (SLR), and further coastal development (Kron, 2013; Maloney and Preston, 2014; Wong *et al.*, 2014). Therefore, effective coastal storm risk management is becoming increasingly important for coastal communities. One common coastal risk-reduction strategy in the United States is beach nourishment, which consists of adding sand to widen beaches and construct dunes that can counteract shoreline erosion and absorb wave energy to reduce flood damages (National Research Council, 2014; USACE, 2008a). As a traditional strategy for reducing coastal hazards due to tides, waves, and SLR, beach nourishment often receives federal support.

Despite the effectiveness of beach nourishment and dune construction to mitigate coastal storm and SLR impacts, it is not a silver bullet for addressing erosion, nor is there any single hazard mitigation strategy appropriate for all coastal environments (USACE, 2002). Because of the dynamic nature of coastlines, beaches erode over time, making nourishment a temporary solution, and material must be regularly replaced on the beach (Landry, 2011; USACE, 2008b). As a result, beach nourishment projects require periodic input of funding and sand, both of which may be limited resources (Landry, 2011; National Research Council, 2014). Additionally, Armstrong *et al*. (2016) observed the signal of a positive feedback between coastal development and beach nourishment in Florida and argue that this relationship may be the result of a systemic mechanism. The possibility of a persistent positive feedback implies that beach nourishment as a coastal risk-mitigation strategy could rebound or even backfire by incentivizing increased coastal development and that nourishing now could raise demand for nourishment in the future (Armstrong *et al*., 2016). Furthermore, beach nourishment reduces damages for the open coast but does not address back-bay flooding in the low-lying areas behind barrier islands, which are becoming increasingly vulnerable to SLR impacts (National Research Council, 2014). Thus, beach nourishment may have undesirable effects in some contexts at some timescales.

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Some federally supported beach nourishment projects are analyzed using Beach-fx, a life-cycle, event-driven coastal simulation model created and maintained by the U.S. Army Corps of Engineers (USACE) Engineer Research and Development Center's Coastal and Hydraulics Laboratory and the U.S. Army Engineer Institute for Water Resources (Gravens, Males, and Moser, 2007). Beach-fx is a comprehensive physical and economic model that predicts spatially resolved shoreline and economic changes due to inundation, wave attack, and erosion. The model is designed to evaluate life-cycle, event-based project costs and performance for coastal storm risk management (Gravens, Males, and Moser, 2007). However, there are some operational challenges to applying this model. Among these is the data-intensive nature of Beach-fx and similar event-driven life-cycle models, which can drive the cost of modeling to hundreds of thousands of dollars for just the feasibility analysis of beach nourishment projects. This potentially leaves communities with few resources to explore other coastal risk-management options that could be effective. As a result, a low-cost modeling alternative able to serve as a screening-level assessment of beach nourishment projects could help communities decide whether they want to pursue the more-detailed event-driven life-cycle modeling studies. The lower-cost simple model must be able to simulate shoreline response to sea-level change, storms, and nourishment activity with minimal computational and data requirements and should reproduce Beach-fx or similar life-cycle model output with reasonable accuracy.

After providing a short description of Beach-fx, this paper presents a stochastic dynamic model that simulates shoreline response to long-term SLR and storm impacts and that could serve as a simple, screening-level model. The focus is on replicating the nourishment interval (the amount of time that passes between subsequent nourishment episodes) as predicted by Beach-fx and similar life-cycle approaches. Nourishment interval is chosen as the model output of interest because nourishment frequency is one of the main factors that affects the costs of multidecadal nourishment projects. The model is applied to three locations in Florida, two on the Atlantic coast and one on the Gulf of Mexico, and model output is compared with the nourishment interval as predicted by Beach-fx. A sensitivity analysis for model parameters is conducted and possible data sources and techniques for applying the model in other locations are discussed.

This simpler model could serve as a tool for communities to examine the nourishment intervals that may be necessary to maintain a given level of damage reduction. This model is not designed to replace Beach-fx or similar models because the level of detail provided by life-cycle models is critical for making the final decision to pursue large-scale nourishment projects. The intent is, rather, for a simple model that can provide communities with more information before they decide to invest in higher-cost, but more thorough, simulations. For example, on the basis of the results of the simple model, some communities may choose to also consider strategies other than beach renourishment for their adaptation planning.

Short Description of Beach-fx

In Beach-fx, a study location is divided into a set of model reaches, which are segments of beach with relatively uniform dimensions. For each reach, an idealized profile is developed on the basis of observations of current conditions (Gravens, Males, and Moser, 2007). Economic damages due to gradual processes and storm impacts are calculated on the basis of estimated damages to residences, development, and infrastructure subject to erosion, flooding, and waves. The model is calibrated using historic shoreline change rates, and storms are assumed to follow the historic distribution (Gravens, Males, and Moser, 2007). These damages are mitigated by the oceanfront dune and berm, of which height and width are important characteristics (Gravens, Males, and Moser, 2007; USACE Jacksonville District, 2017a,b,c). Users can simulate damages under different nourishment schemes, including a "no action" alternative. To test the effectiveness of a plan, users must specify a dune and berm construction template and thresholds for dune width, dune height, and berm width that trigger nourishment. Together, these specifications affect the frequency of nourishment and quantity of sand necessary to maintain the desired level of risk reduction (Gravens, Males, and Moser, 2007; USACE Jacksonville District, 2017a,b,c).

Output from Beach-fx includes average nourishment interval, sand volume requirements, nourishment costs, and economic damages for each nourishment alternative simulated (Gravens, Males, and Moser, 2007). The model conducts a cost–benefit analysis, comparing nourishment costs and damages avoided relative to a no-action alternative. From this analysis, Beach-fx generates a recommended plan, on the basis of national economic development, that consists of a nourishment template and distance triggers (Council on Environmental Quality, 2013; Gravens, Males, and Moser, 2007; U.S. Water Resources Council, 1983; USACE Jacksonville District, 2017a,b,c).

The recommended plan must be tested for robustness to sea-level change (USACE, 2013, 2014). Precise projections of SLR are notoriously difficult because of unknown future greenhouse gas emissions and limited understanding of ice sheet dynamics (de Winter *et al*., 2017; Jevrejeva *et al*., 2016; Ritz *et al*., 2015). Deep uncertainty regarding the rate and magnitude of future SLR has motivated coastal managers to consider a range of plausible scenarios when planning for climate change impacts (Hall *et al*., 2016). Using this strategy, USACE uses Beach-fx to simulate net benefits and the benefit-to-cost ratio for the recommended plan under three SLR scenarios (USACE Jacksonville District, 2017a,b,c, USACE 2013, 2014).

The effects of SLR are included in Beach-fx through the Bruun Rule, which assumes that shorelines recede to maintain an equilibrium profile as sea level rises (Bruun, 1962). The Bruun Rule is a simple equation that relates shoreline recession to SLR and has been widely used in the scientific literature, despite criticism that it is inaccurate and neglects key processes such as longshore, landward, and aeolian sediment transport (Cooper and Pilkey, 2004; Houston and Dean, 2014; Passeri, Hagent, and Irish, 2014). Studies that modify the Bruun Rule to include additional terms for shoreward sediment transport can better predict shoreline movement (Dean and Houston, 2016; Rosati, Dean, and Walton, 2013)

Modeling coastal morphology with Beach-fx requires data inputs for the study location, including historic shoreline position, projected shoreline change in response to each nourishment strategy simulated, and a shore response database (SRD), which includes shoreline changes for all combinations of anticipated beach profiles and storm events (Gravens, Males, and Moser, 2007). Nourishment-induced shoreline change can be predicted using physical process models that require data such as observations of wave conditions, beach profiles, and local bathymetry. Typically, the SRD is created using SBEACH, a numerical model that takes as input beach profile measurements, sediment grain size, and storm conditions, including wave height, wave period, and water elevation (Rosati *et al*., 1993). Thus, Beach-fx simulations require extensive geophysical, hydrologic, and hydraulic data and modeling.

METHODS

After presenting the basic structure of the dynamic simulation model, methods for calibrating the model and comparing output with Beach-fx are described. Finally, a sensitivity analysis is conducted on model parameters.

Model Structure

The model assumes a straight, homogeneous coastline, typical of the reaches used in more detailed models. The entire cross-shore width of beach is subject to linear erosion, and the nourished portion of beach width erodes exponentially with time since the last nourishment episode. The following state equation for beach width, x, subject to gradual erosion comes from previous geoeconomic shoreline modeling studies (Gopalakrishnan *et al*., 2011; McNamara *et al*., 2015; Smith *et al*., 2009):

$$\frac{\mathrm{d}x}{\mathrm{d}t} = -\hat{x}\theta e^{-\theta\tau} - \gamma \tag{1}$$

where, μ is the nourished portion of the beach, $\hat{x}$ is the width of the nourished beach, θ is the exponential erosion rate of the nourished portion of the beach, τ is years since last nourishment, and γ is the background linear erosion rate.

To capture the effects of SLR on erosion, the background erosion rate, γ, is allowed to vary with time in proportion to SLR, according to the Bruun Rule. Following Rosati, Dean, and Walton (2013) and Dean and Houston (2016), an additive correction term for landward sediment transport and sand sources and sinks elsewhere along the coast is included. That is:

$$\gamma_t = r\Delta S_t - H \tag{2}$$

where, γ_t is linear erosion in year t, r is the slope of the active profile, ΔS_t is the change in relative sea level, S, from year $t-1$ to year t, and H is the correction term, assumed to be constant with time. The Bruun Rule has been criticized in the literature, with some researchers calling for it to be abandoned entirely (Cooper and Pilkey, 2004). Its use here is justified on the basis that this model is not intended to predict shoreline behavior with high accuracy, but rather to approximate output from life-cycle models such as Beach-fx, which relies upon the Bruun Rule to capture SLR effects.

A stochastic term is used to represent storm-induced erosion, assuming that the occurrence of storms is Poisson distributed with rate parameter λ. Thus the probability of n storms in year t can be expressed as:

$$P(n_t) = e^{-\lambda}\frac{\lambda^{n_t}}{n_t!} \tag{3}$$

Shoreline change that results from a given storm follows a generalized extreme value (GEV) distribution and storm-induced erosion, E, in year t is modeled as:

$$E_t = \frac{1}{10}\sum_{i=1}^{n_t}\frac{M}{i} \tag{4}$$

where, n_t is the number of storms in year t, $M \sim \mathrm{GEV}(k, \sigma, m)$, with k, σ, and m the shape, scale, and location parameters for the GEV distribution, respectively, and the factor of 1/10 represents the fact that approximately 90% of storm-induced erosion in the study area recovers within a few weeks (USACE Jacksonville District, 2017a,b,c). Dividing by i accounts for observations that subsequent storms that strike a location in a single year have a smaller-than-expected impact on shoreline change, presumably because much of the easily erodible material has already been removed as a result of previous storm(s) (Sallenger *et al*., 2006). It is helpful to note here that the effect on model output of dividing by i will be minimal because even when assuming an unrealistically high storm frequency parameter of $\lambda = 0.5\ \mathrm{y}^{-1}$, the probability that there will be more than one storm in a given year, according to Equation (3), is less than 0.1.

Finally, it is assumed here that implementation of beach renourishment begins to occur once the beach erodes to a width narrower than some critical width x_{crit}, and the beach is nourished the year after this critical width is reached. Thus, combining Equations (1–4), and discretizing to annual time steps gives the following difference equation for beach width:

$$\Delta x_t = \begin{cases} -\hat{x}\theta e^{-\theta\tau} - r\Delta S_t + H - \frac{1}{10}\sum\limits_{i=1}^{n_t}\frac{M}{i} & \text{if } x_{t-1} \geq x_{\mathrm{crit}} \\ \hat{x} - x_t & \text{if } x_{t-1} < x_{\mathrm{crit}} \end{cases} \tag{5}$$

Model Application

The ability for the above model structure to reproduce Beach-fx output is demonstrated by calibrating the model for three Florida locations: Vilano Beach (VB) and Hutchinson Island (HI) on the Atlantic Coast and Gasparilla Island (GI) on the Gulf Coast (Figures 1 and 2). These three locations were selected as communities that have worked with USACE Jacksonville District within the past 3 years to evaluate beach nourishment projects using Beach-fx. The complete coastal storm risk-management reports with all model input and output are available from the USACE Jacksonville District at http://www.saj.usace.army.mil/About/Divisions-Offices/Planning/Environmental-Branch/Environmental-Documents/. The USACE reports for HI and VB are both feasibility analyses for new projects, whereas the report for GI is a re-evaluation of an ongoing project (USACE Jacksonville District, 2017a,b,c).

Figure 1. Map showing the three Florida study sites: Vilano Beach (VB), Hutchinson Island (HI), and Gasparilla Island (GI). Image produced using Google Earth Pro (Google, 2018). (Color for this figure is available in the online version of this paper.)

(a) Hutchinson Island (b) Vilano Beach (c) Gasparilla Island

Figure 2. Photos of the three study sites. Images courtesy of USACE (USACE Jacksonville District, 2017a,b,c). (Color for this figure is available in the online version of this paper.)

The measurements and observations that served as input for Beach-fx are used to set parameter values, enabling comparison of the average nourishment interval as computed by both models. The dune is excluded from beach width measurements, and therefore the model considers only berm width. This simplification is justified on the grounds that the plans recommended by USACE for all of the selected study sites do not include extension of the dune profile. Additionally, previous studies have defined beach width as the distance from the high-tide line to the base of the dune (Gopalakrishnan *et al.*, 2011).

The nourished beach width and trigger for nourishment are taken from the recommended plans according to the USACE reports for each study location. For HI and VB, nourished beach width, $\hat{x}$, is set equal to the nourished berm width, whereas x_{crit} is set equal to the product of the nourished berm width and the berm width distance trigger, as it is in Beach-fx. These beach dimensions are assumed to be constant within each study site (USACE Jacksonville District, 2017a,b). For GI, the recommended plan consists of a berm extension relative to the current project baseline. The current baseline and berm distance trigger vary by model reach. Thus x_{crit} is taken to be the average, over all model reaches, of the product of the berm extension and the berm distance trigger. The nourished beach width parameter, $\hat{x}$, is calculated as the average over all model reaches of the recommended nourishment template, which is equal to the sum of the original authorized berm width and the 60-foot berm extension (USACE Jacksonville District, 2017c). At all sites, the parameter μ, which is the proportion of beach width nourished, is calculated as $\frac{\hat{x}-x_{\mathrm{crit}}}{\hat{x}}$.

SLR scenarios are the same as those used by USACE, calculated according to Engineer Regulation 1100-2-8162 and Engineering Technical Letter 1100-2-1 (USACE, 2013, 2014). This gives the following equation for relative sea level:

$$S_t = at + b\left(t^2 + 2t[T_i - 1992]\right) \qquad (6)$$

where, t is years since the start of the simulation, S_t is local sea level relative to the start of the simulation, T_i is the start year for the simulation, a is a site-specific parameter equal to the historic rate of sea-level change, accounting for eustatic and local effects, and b is the predicted acceleration in SLR. To account for uncertainty in future SLR, three values of b are considered, producing low-, intermediate-, and high-SLR scenarios (USACE Jacksonville District, 2017a,b,c, USACE, 2013, 2014).

Determining shoreline response to sea-level change, according to a modified Bruun Rule, requires values for r, the slope of the active profile, and H, the constant additive correction term. The USACE reports include measurements of the width and height of the active profiles, which are used to calculate r (USACE Jacksonville District, 2017a,b,c). These reports also provide observed historic shoreline change rates, which are used to obtain the average shoreline change rate $\overline{\Delta x}$. For each study site, the observed long-term shoreline change rate used to calibrate Beach-fx is averaged over all model reaches. The years included in the long-term average are 1972–2015 for VB, 1970–2008 for HI, and 1979–2006 for GI. For HI, the model is also run using the pre-2004 shoreline change rate to exclude the unusually severe erosion that occurred in this location during the 2004 hurricane season (USACE Jacksonville District, 2017a,b,c). From this, assuming that the long-term erosion rate is equal to the linear background erosion rate, given the observed historic SLR rate a, H is calculated according to:

$$H = \overline{\Delta x} + ra \qquad (7)$$

The initial beach width, x_0, at VB and HI is taken to be the berm width for the existing/future without-project conditions (USACE Jacksonville District, 2017a,b). At GI, the average berm width from observed 2016 profiles is used, which, unlike the without-project conditions, includes the nourishment that occurred in 2013 as part of the initial authorized project (USACE Jacksonville District, 2017c).

The storm frequency parameter λ is the historical annual average number of hurricanes and tropical storms to pass within a 50-mile radius of the study location given in the USACE reports (USACE Jacksonville District, 2017a,b,c). The shoreline response to hurricanes is calculated using a GEV distribution. Parameters for this distribution are fit to observations of shoreline changes after Hurricanes Charley, Frances, Ivan, and Jeanne, all of which made landfall in Florida in 2004 (Sallenger *et al.*, 2006). For each storm, Sallenger *et al.* (2006) provide the mean shoreline position change immediately after the storm. With only four data points, a maximum likelihood estimation does not converge. Thus, recognizing that the data are severely limited, the mean (6.223 m), median (2.795 m), and variance (91.43 m^2) of the four averages are determined, and shape, scale, and location

Table 1. *Estimated parameter values used to calculate mean nourishment intervals.*

Parameter	Parameter Description	Vilano Beach	Hutchinson Island	Gasparilla Island
$\hat{x}$ (m)	Nourished beach width	18.3	6.10	74.0
x_{crit} (m)	Beach width, triggering nourishment	0	0	13.2
μ	Proportion of beach width that is nourished, defined as $(\hat{x} - x_{crit})/\hat{x}$	1	1	0.821
r	Slope of active profile	50.0	70.0	53.3
H (m/y) (pre-2004 value)	Bruun Rule correction term	−0.239	0.0857 (0.153)	−0.113
a (m/y^2)	Historic rate of SLR	2.40×10^{-3}	2.36×10^{-3}	2.40×10^{-3}
b (m/y^2)				
Low	SLR acceleration	0	0	0
Mid		0.0271×10^{-3}	0.0271×10^{-3}	0.0271×10^{-3}
High		0.113×10^{-3}	0.113×10^{-3}	0.113×10^{-3}
x_0 (m)	Initial beach width	0	0	42.2
θ	Exponential erosion rate	0.1	0.1	0.1
λ (1/y)	Storm frequency	0.41	0.35	0.31
k	Storm-induced erosion GEV distribution shape parameter	0.277	0.277	0.277
σ (m)	Storm-induced erosion GEV distribution scale parameter	4.24	4.24	4.24
m (m)	Storm-induced erosion GEV distribution location parameter	1.68	1.68	1.68
τ_0 (y)	Initial time since last nourishment	∞	15	3
T_i	Initial year of simulation	2020	2020	2016
T_f	Final year of simulation	2070	2070	2056

parameters for a GEV distribution with similar mean, median, and variance are found. This is done using the lsqnonlin() function from the Matlab optimization toolbox, which solves nonlinear least-squares curve-fitting problems. Lacking additional data, it is assumed that these parameters are the same for all locations. The impact of this assumption is tested using a global sensitivity analysis (see below).

Finally, the start year, T_i, and end year, T_f, for each location are taken directly from the USACE studies, and following Smith *et al*. (2009) and Gopalakrishnan *et al*. (2011), $\theta = 0.1$. All parameter values for the three study locations are given in Table 1. Using these parameter values, the model is run 1000 times for each location and SLR scenario, and the nourishment interval, after the first nourishing event, is compared with the nourishment interval reported by USACE. Note that, given the parameter values used for GI, it is possible that, for some model runs, the nourishment interval will be long enough, relative to the simulation run time, that only one nourishment event occurs before the end of the simulation. Any model runs in which this is the case are excluded from further analysis, as they do not contain information regarding the time between successive nourishment events, which is the model output of interest. Given that this occurs in fewer than 1% of model runs, this exclusion is not expected to appreciably change the results. Over a 50-year simulation, this is not an issue for VB or HI.

Sensitivity Analysis

A sensitivity analysis is conducted to determine which parameters, if changed, have the largest effect on predicted nourishment interval. Assuming that there is a range of plausible values for each parameter, there is a corresponding range of possible model outputs (*i.e*. mean nourishment intervals). There is, thus, a multidimensional parameter space, consisting of all plausible parameter values, and the goal of the sensitivity analysis is to determine which parameters, if fixed at a single value, would lead to the largest reduction in the variance of possible nourishment intervals (Saltelli *et al*., 2008).

The following parameters are included as inputs for the sensitivity analysis: $\hat{x}$, x_{crit}, H, θ, r, λ, k, σ, and m. This results in a nine-dimensional parameter space in which each of the input parameters is allowed to vary from 80 to 120% of the estimated value. At HI and VB, x_{crit} is estimated to be 0 m, so instead of allowing this parameter at these locations to vary from 80 to 120% of 0, its minimum is set to 0 and its maximum is taken to be 0.4 $\hat{x}^*$, where $\hat{x}^*$ is the original estimate for $\hat{x}$, the nourished beach width.

A Monte Carlo simulation, in which a point in this parameter space is randomly selected and the model run 1000 times to estimate the mean nourishment interval for this combination of parameters, is used to find the distribution of possible mean nourishment intervals. Model runs in which the nourishment interval is too long for a second nourishment event to occur before the end of the simulation are excluded from further analysis. The expected number of model runs excluded for each location and SLR scenario is reported below. The stopping criteria for the Monte Carlo simulation are taken to be when an additional 500 parameter combinations change the total variance of possible nourishment intervals by less than 0.005 y^2 and the mean by less than 0.01 y. At this point, it is assumed that the parameter space for a given location and SLR scenario has been sufficiently sampled.

To determine sensitivity to the i^{th} input parameter P_i, the conditional variance of the expected nourishment interval given a small range of values for P_i is calculated. As an example, suppose P_i has a minimum possible value v_{min} and maximum possible value v_{max}. The mean nourishment interval, as predicted by the Monte Carlo simulation, is calculated given a "slice" of values of P_i, that is, all outputs for $v_j \leq P_i < v_{j+1}$ are considered. The v_j are defined such that $v_0 = v_{min}$ and there are

Table 2. *Mean nourishment interval, 90% confidence interval (CI), range, and expected number of nourishment episodes over a 50-year project life span for the simple dynamic model (1000 iterations) and Beach-fx for Vilano Beach. In all scenarios, nourishment interval is overestimated by 2–3 years, resulting in 0–2 fewer nourishment episodes over 50 years. The USACE study did not report confidence intervals or a minimum and maximum for average nourishment frequencies. Expected episodes per 50 years for Beach-fx are calculated here as 50 divided by the mean nourishment interval, rounded down to the nearest whole number. Fifty-year error is the difference in number of nourishments estimated by the simpler model, rounded to the nearest whole number, and the number of nourishments predicted by Beach-fx over 50 years. Beach-fx results are obtained from USACE Jacksonville District (2017b).*

	Simplified Model				Beach-fx			
	Mean Interval (y)	90% CI (y)	Full Range (y)	Expected Episodes per 50 y	Mean Interval (y)	Expected Episodes per 50 y	Interval Error (y)	50-y Error
Low SLR	13.9	13.9–14.0	10.8–17.0	4.0	12	4	2	0
Mid SLR	12.7	12.7–12.8	10.0–14.7	4.2	10	5	3	−1
High SLR	10.3	10.3–10.3	8.6–11.3	5.1	7	7	3	−2

25 data points in each interval (v_j, v_{j+1}). The first-order sensitivity of the nourishment interval to input parameter P_i is defined as the variance of the mean nourishment interval over all 25-data-point slices normalized by the total variance of the output. See Saltelli *et al*. (2008) for a more thorough discussion on this variance-based sensitivity analysis technique.

RESULTS

Tables 2–4 compare the nourishment intervals predicted by the simple dynamic model with those predicted by Beach-fx for each study location and SLR scenario. Note that the nourishment interval for a single simulation is the average time between renourishments based upon 1000 simulations. Tables 2–4 report the mean, 90% confidence interval (CI), and range of this average, as well as the expected number of nourishments over a 50-year project life span. For the Monte Carlo simulation at each location and SLR scenario, the stopping criteria were reached after 1000–4000-parameter combinations. For VB and HI under all SLR scenarios, 1000 model runs are used to calculate expected nourishment interval for each parameter combination (*i.e*. all model runs have at least two nourishments, so none is excluded from analysis). For GI, with low SLR, on average, 54 runs were excluded per parameter combination because of no second nourishment occurring, giving an expected value of 946 runs included in the mean interval calculation. For the intermediate and high scenarios, the expected value of simulations included for each parameter combination is 1000, with no model runs excluded. Figures 3–11 show scatter plots of the mean nourishment interval as a function of each input parameter. The black lines show the mean over each 25-data-point slice of the input parameter. Sensitivity to each input parameter, s, defined as the conditional variance of the expected nourishment interval normalized by the total variance, is presented in Table 5.

Vilano Beach

At VB, the dynamic model consistently overestimates the nourishment interval by 2–3 years. It calculates expected nourishment intervals of 13.9, 12.7, and 10.3 years for the low-, intermediate-, and high-SLR scenarios, respectively, whereas Beach-fx predicts 12, 10, and 7 years for the same scenarios (USACE Jacksonville District, 2017b). Over a 50-year life, the nourishment intervals estimated for the simpler model result in the same number of nourishments as Beach-fx at low SLR, one fewer nourishment at intermediate SLR, and two fewer at the high-SLR scenario. So the simpler model could underestimate costs by zero to two nourishments compared with Beach-fx, depending on the rate of SLR (Table 2).

For all SLR scenarios, nourishment interval at VB is most sensitive to $\hat{x}$ and x_{crit} ($s > 0.3$). This implies that nourishment interval is most strongly controlled by the user-specified nourishment width and trigger, rather than beach or storm characteristics. Model output is also sensitive to θ, the exponential erosion rate in the low scenario ($s > 0.2$). Nourishment interval is mildly sensitive to this parameter and r, the slope of the active profile, for the intermediate and high scenarios and H, the Bruun Rule correction term in the low-SLR scenario ($s > 0.1$) (Table 5).

Table 3. *Mean nourishment interval, 90% confidence interval (CI), range, and expected number of nourishment episodes over a 50-year project life span for the simple dynamic model (1000 iterations) and Beach-fx for Hutchinson Island. Results in parentheses are calculated using the pre-2004 value for* $\overline{\Delta x}$. *Nourishment interval is underestimated for the low-SLR scenario and overestimated for the intermediate and high scenarios. The difference in number of nourishments over 50 years ranges from two more than predicted by Beach-fx at low SLR, to four fewer than Beach-fx at high SLR, with roughly the same number predicted at intermediate SLR. Excluding the impacts of the 2004 hurricane season produces slightly longer intervals. The USACE study did not report the minimum and maximum for their average nourishment frequencies. Expected episodes per 50 years for Beach-fx are calculated here as 50 divided by the mean nourishment interval, rounded down to the nearest whole number. Fifty-year error is the difference in number of nourishments estimated by the simpler model, rounded to the nearest whole number, and the number of nourishments predicted by Beach-fx over 50 years. Beach-fx results are obtained from USACE Jacksonville District (2017a).*

	Simplified Model				Beach-fx				
	Mean Interval (y)	90% CI (y)	Full Range (y)	Expected Episodes per 50 y	Mean Interval (y)	90% CI (y)	Expected Episodes per 50 y	Interval Error (y)	50-y Error
Low SLR	12.7 (15.1)	12.6–12.8 (15.0–15.3)	8.0–19.0 (7.0–45)	4.3 (3.8)	18	17–19	2	−5 (−3)	2 (2)
Mid SLR	9.6 (10.5)	9.6–9.7 (10.4–10.5)	6.7–12.0 (6.9–14.0)	5.6 (5.3)	8	7–8	6	2 (3)	0 (−1)
High SLR	6.4 (6.6)	6.4–6.4 (6.6–6.6)	5.4–7.2 (5.4–7.5)	8.1 (8.0)	4	4–4	12	2 (2)	−4 (−4)

Table 4. *Mean nourishment interval, 90% confidence interval (CI), range, and expected number of nourishment episodes over a 50-year project life span for the simple dynamic model (1000 iterations) and Beach-fx for Gasparilla Island. In all scenarios, nourishment interval is overestimated by 1–3 years, but both models predict the same number of nourishments over 50 years. The USACE study did not report confidence intervals for their nourishment frequencies. Expected episodes per 50 years for Beach-fx are calculated here as 50 divided by the mean nourishment interval, rounded down to the nearest whole number. Fifty-year error is the difference in number of nourishments estimated by the simpler model, rounded to the nearest whole number, and the number of nourishments predicted by Beach-fx over 50 years. Beach-fx results are obtained from USACE Jacksonville District (2017c).*

	Simplified Model				Beach-fx				
	Mean Interval (y)	90% CI (y)	Full Range (y)	Expected Episodes per 50 y	Mean Interval (y)	Full Range (y)	Expected Episodes per 50 y	Interval Error (y)	50-y Error
Low SLR	25.1	24.9–25.2	16.0–30.0	2.0	22	15–29	2	3	0
Mid SLR	22.7	22.6–22.8	12.0–26.0	2.0	21	14–28	2	2	0
High SLR	18.6	18.6–18.7	14.0–20.0	2.0	18	10–26	2	1	0

Hutchinson Island

As shown in Table 3, at HI, using shoreline change data from 1970 to 2008 to calculate $\overline{\Delta x}$ the model predicts an expected mean nourishment of 12.7 years for the low-SLR scenario compared with 18 years predicted by Beach-fx. For the intermediate and high scenarios, the model predicts, respectively, that nourishing would be necessary, on average, every 9.6 and 6.4 years, compared with 8 and 4 years predicted by Beach-fx (USACE Jacksonville District, 2017a). However, 2004 was an especially severe hurricane season for this area, with two hurricanes making landfall on HI, causing significant beach impacts (Sallenger *et al*., 2006; USACE Jacksonville District, 2017a). Therefore, the model is also run using only shoreline change data from before the 2004 hurricane season, as this may present conditions more representative of the historical erosion and accretion patterns used to calibrate life-cycle models. With this change, the low-SLR scenario nourishment interval increases to 15.1 years, that for the intermediate scenario is raised to 10.5 years, and that for the high scenario increases slightly to 6.6 years. Thus, this modification shifts all of the predicted intervals to be within 3 years of the Beach-fx intervals. Over a 50-year project life, the nourishment intervals estimated for the simpler model result in two more nourishments than the Beach-fx model at the low-SLR scenario, the same number at intermediate SLR, and four fewer at the high-SLR scenario. Here, the simpler model is roughly the same as Beach-fx under intermediate SLR, but could slightly overestimate costs under low SLR and significantly underestimate renourishments under a high-SLR scenario (Table 3).

The sensitivity analysis for HI reveals that the model is most sensitive to $\hat{x}$ and x_{crit} in all SLR scenarios ($s > 0.2$). Thus, as with VB, the user-specified inputs are key for determining nourishment interval. For the intermediate and high scenarios, the model is also sensitive to r, the slope of the active profile ($s > 0.2$). The model also shows slight sensitivity to θ in the low and intermediate scenarios and H, r, and λ in the low-SLR scenario ($s > 0.1$) (Table 5).

Gasparilla Island

At GI, the model consistently overestimates the nourishment interval by 1–3 years, predicting an expected 25.1, 22.7, and 18.6 years for the low-, intermediate-, and high-SLR scenarios, respectively, whereas Beach-fx predicts 22, 21, and 18 years for the same scenarios (USACE Jacksonville District, 2017c). Over a 50-year life, the nourishment intervals estimated for the simpler model result in the same number of nourishments as

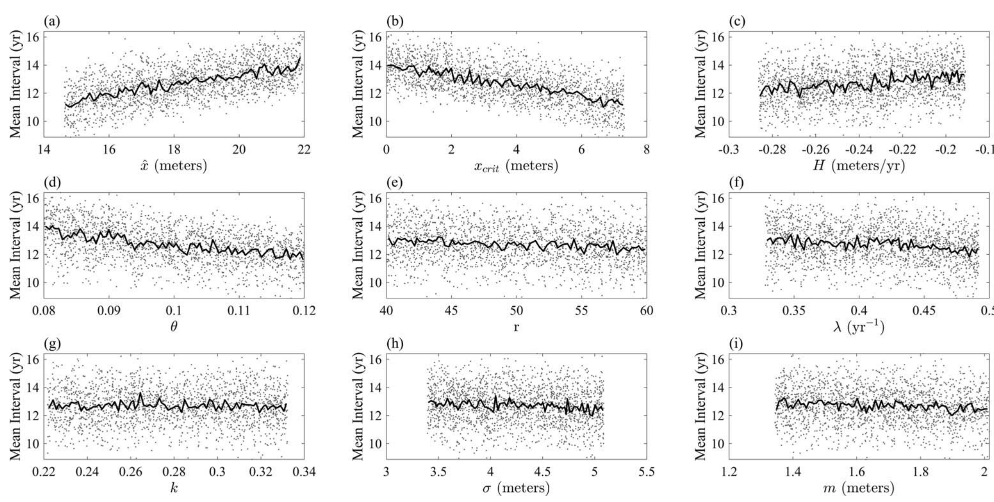

Figure 3. Monte Carlo simulation for low-SLR scenario at VB. Mean nourishment is most sensitive to (a) $\hat{x}$, (b) x_{crit}, and (d) θ. The model is slightly sensitive to (c) H and is relatively insensitive to all other input parameters (e–i).

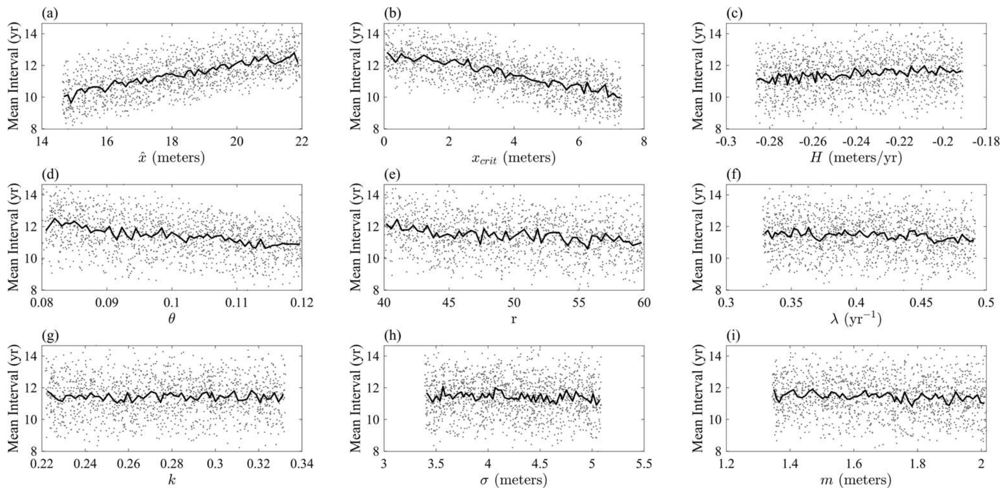

Figure 4. Monte Carlo simulation for intermediate-SLR scenario at VB. Mean nourishment is most sensitive to (a) $\hat{x}$ and (b) x_{crit}. The model is slightly sensitive to (d) θ and (e) r and is relatively insensitive to all other input parameters (c, f–i).

predicted by the Beach-fx model at low-, intermediate-, and high-SLR scenarios (Table 4).

Across all scenarios, at GI, the model is most sensitive to $\hat{x}$ and θ ($s > 0.3$). Thus, at GI, nourishment interval is most strongly determined by the amount of fill placed on the beach during each nourishment episode and the exponential erosion rate of the nourished portion of the beach. The model also shows sensitivity to r in the intermediate and high scenarios ($s > 0.1$).

DISCUSSION

With the exception of the low-SLR scenario at HI, the model estimates nourishment intervals that are several years longer than those predicted by Beach-fx. Despite this, the actual number of nourishments over a 50-year project life is approximately the same for low and intermediate SLR for VB, intermediate SLR for HI, and all SLR scenarios for GI. The simpler model predicted slightly fewer nourishments at high SLR for VB and slightly more nourishments at low SLR for HI. The only scenario where this model was substantially different from Beach-fx was high SLR at HI, where it estimated 8 nourishments compared with 12 predicted by Beach-fx. Therefore, this simple dynamic model shows promise for estimating number of nourishments, which drives cost, and at all locations, it has captured the effect of SLR on nourishment interval as predicted by Beach-fx. Thus, this low-cost, computationally fast tool with minimal data requirements can give communities an approximate estimate for future renourishment costs and the potential variability in nourishment interval due to SLR.

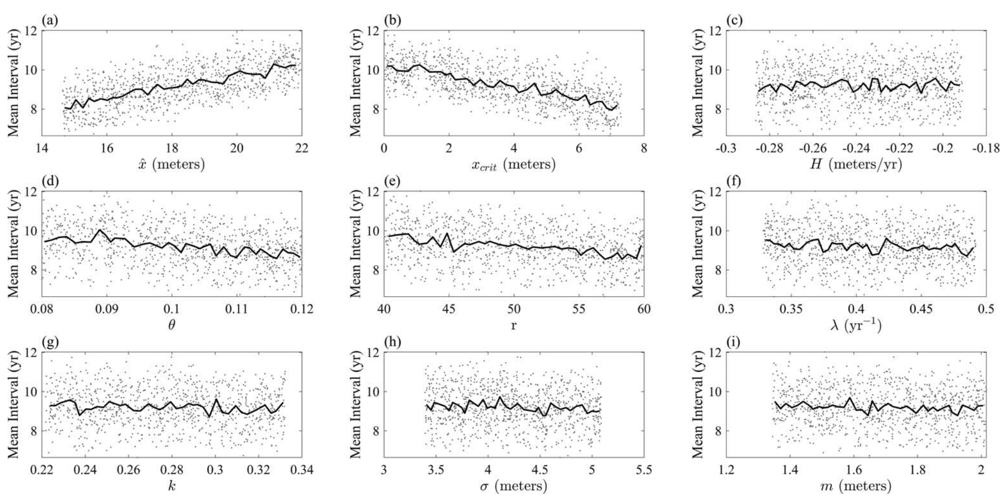

Figure 5. Monte Carlo simulation for high-SLR scenario at VB. Mean nourishment is most sensitive to (a) $\hat{x}$ and (b) $x_{\text{crit.}}$ The model is slightly sensitive to (d) θ and (e) r and is relatively insensitive to all other input parameters (c, f–i).

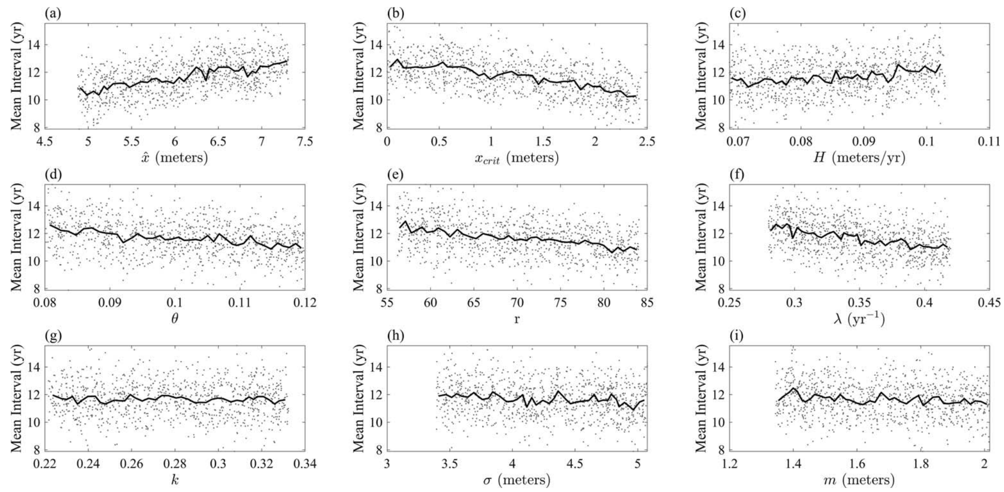

Figure 6. Monte Carlo simulation for low-SLR scenario at HI. Mean nourishment is most sensitive to (a) $\hat{x}$ and (b) x_{crit}. The model is moderately sensitive to (c) H, (d) θ, (e) r, and (f) λ. The model is relatively insensitive to all other input parameters (g–i).

Predicted nourishment interval appears to be most sensitive to $\hat{x}$, x_{crit}, and θ, with some locations and SLR scenarios showing sensitivity to r. H and λ also appear to be moderately important in some scenarios. The dependence on $\hat{x}$ and x_{crit} is reasonable because, together, these user-defined parameters determine the quantity of sand placed on the beach during each nourishment episode. The importance of θ is also not surprising, as this exponential erosion rate controls how quickly the nourished portion of the beach is removed. Sensitivity to r, H, and λ can be interpreted as the relative importance of gradual SLR-induced erosion *vs*. storm-induced erosion for each location and SLR scenario.

The ability for this simpler model to produce approximately the same results as Beach-fx suggests that it is capturing the most important dynamic processes governing shoreline behavior. Although changes in beach morphology are heterogeneous in space and time and the result of many interacting variables (Rosati, Dean, and Walton, 2013), this model distills these complex dynamics into the most fundamental processes. Additionally, when possible, this model was calibrated with the same data used for Beach-fx analyses, which undoubtedly contributes to the closeness in output. Also, despite the substantial structural differences, both models use the Bruun Rule to simulate the effects of SLR and use the same SLR scenarios. It is, therefore, not surprising that variations in output across SLR scenarios are similar between the two models.

It is important to stress that although the models produce similar output for the three sites presented here, many aspects of this model are based on statistics. Thus, it could be

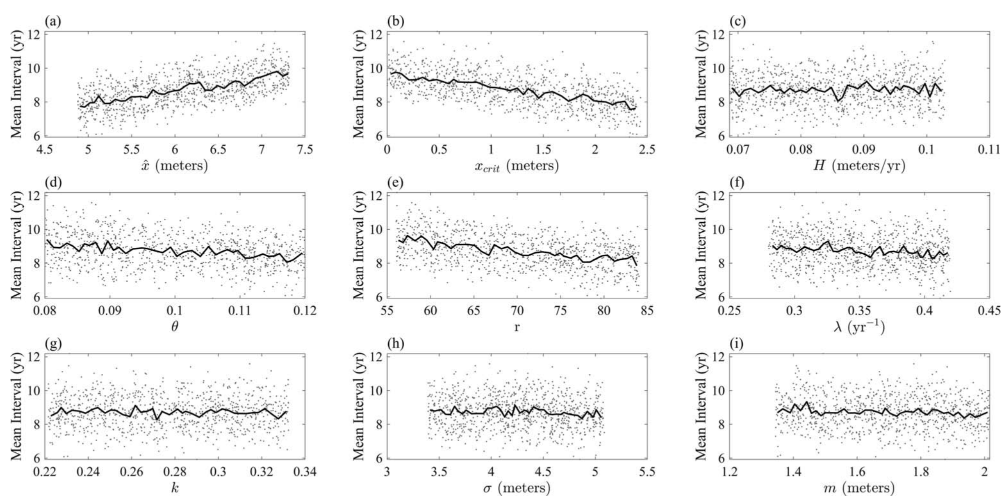

Figure 7. Monte Carlo simulation for intermediate-SLR scenario at HI. Mean nourishment is most sensitive to (a) $\hat{x}$, (b) x_{crit}, and (e) r. The model is slightly sensitive to (d) θ and relatively insensitive to all other input parameters (c, f–i).

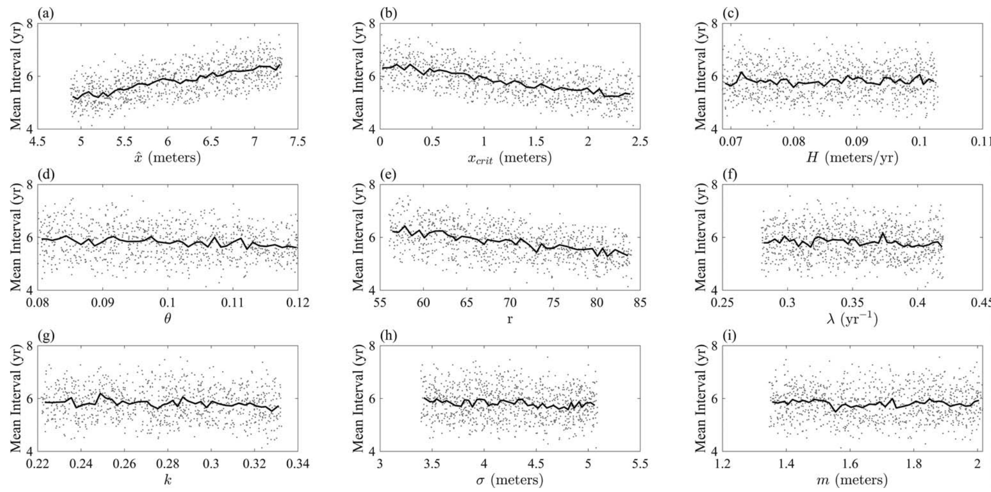

Figure 8. Monte Carlo simulation for high-SLR scenario at HI. Mean nourishment interval is most sensitive to (a) $\hat{x}$, (b) x_{crit}, and (e) r The model is relatively insensitive to all other input parameters (b, c, f–i).

dangerous to apply this model to beaches with an entirely different morphology, tidal regime, or wave climate without first verifying that the model is appropriate for such locations.

The structural differences between these models result in dramatically different computational requirements. Beach-fx results are generally reported as the average over 100 simulations. This full life-cycle analysis takes approximately 8 hours, and USACE therefore considers 100 simulations to be a reasonable trade-off between achieving stable results and time required to complete all runs (USACE Jacksonville District, 2017a,b,c). In contrast, running the simpler model presented here 1000 times and calculating the minimum, maximum, and mean nourishment intervals with a 90% CI takes approximately 1 second on a 2014 MacBook Pro.

Using the Tool

The model presented here is available as open-source code from the shoreline-dynamics GitHub repository available at https://github.com/emcutler/shoreline-dynamics. A community interested in using this tool would need to specify x_{crit} and $\hat{x}$, which together determine the level of risk reduction a project imparts. To select x_{crit} and $\hat{x}$, a community could rely on historic beach profiles pre- and postnourishment at or near their location. If profile data are not available, the Program for the Study of Developed Shorelines (PSDS) at Western Carolina University maintains a comprehensive database of beach nourishment projects undertaken since 1923 in the United States (Program for the Study of Developed Shorelines at Western Carolina University, 2019). This database provides

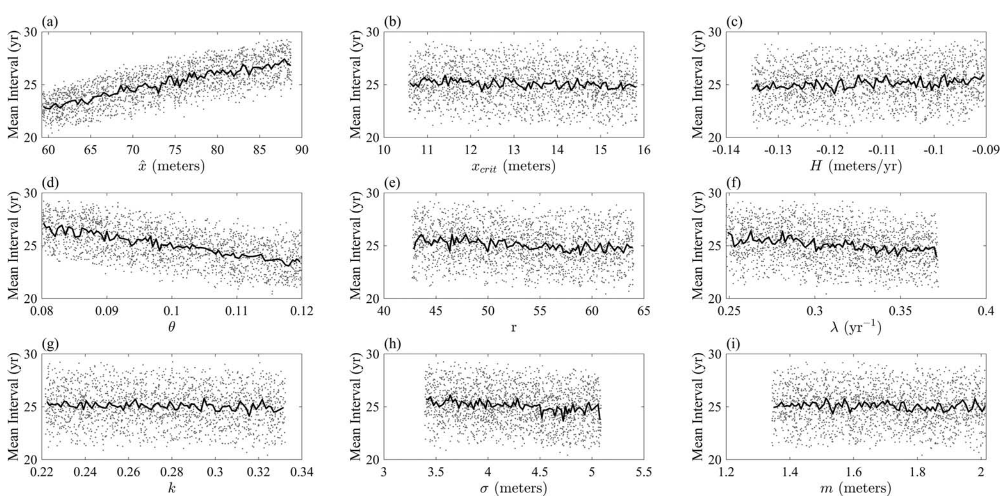

Figure 9. Monte Carlo simulation for low-SLR scenario at GI. Mean nourishment is most sensitive to (a) $\hat{x}$ and (d) θ. The model is relatively insensitive to all other input parameters (b, c, e–i).

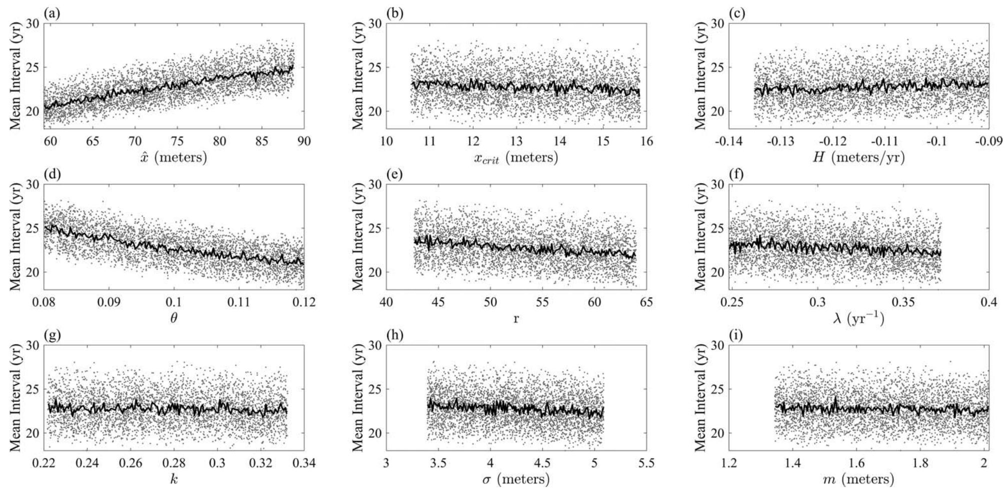

Figure 10. Monte Carlo simulation for intermediate-SLR scenario at GI. Mean nourishment is most sensitive to (a) $\hat{x}$ and (d) θ. The model is also moderately sensitive (e) r. The model is relatively insensitive to all other input parameters (b, c, f–i).

nourishment length and volume, which could be used to estimate width, assuming an appropriate value for the height of the construction template. From this, users could model their choices of x_{crit} and $\hat{x}$ after what similar communities have done in the past. Because of the high sensitivity of model output to $\hat{x}$ and x_{crit}, users may wish to test the model for several combinations of $\hat{x}$ and x_{crit} and use the product of the nourishment interval and $\hat{x} - x_{\text{crit}}$ to estimate relative costs of nourishment. The PSDS database could also help communities determine an appropriate value of τ_0 on the basis of the last time the beach of interest was nourished (if ever).

SLR scenarios are available from the Climate Preparedness and Resilience program of USACE (USACE, 2017). The active profile slope, r, can be inferred from beach profile data or nearby beaches. Historic average shoreline change rate data may be available from previous studies, such as USACE feasibility analyses. Also, some state and local agencies maintain records of shoreline position. For example, the Florida Department of Environmental Protection maintains a database with historic beach profile and shoreline position data (Florida Department of Environmental Protection, 2018). If that is not available for the area of interest, the U.S. Geological Survey (USGS) Coastal Change Hazards Portal has long- and short-term shoreline change rates and historic shoreline positions for most of the continental United States and parts of Alaska and Hawaii (Kratzmann, Himmelstoss, and Thieler, 2017). Using the historic shoreline change rate, rate of SLR, and active profile slope, the Bruun Rule correction term, H, can be calculated according to Equation (7).

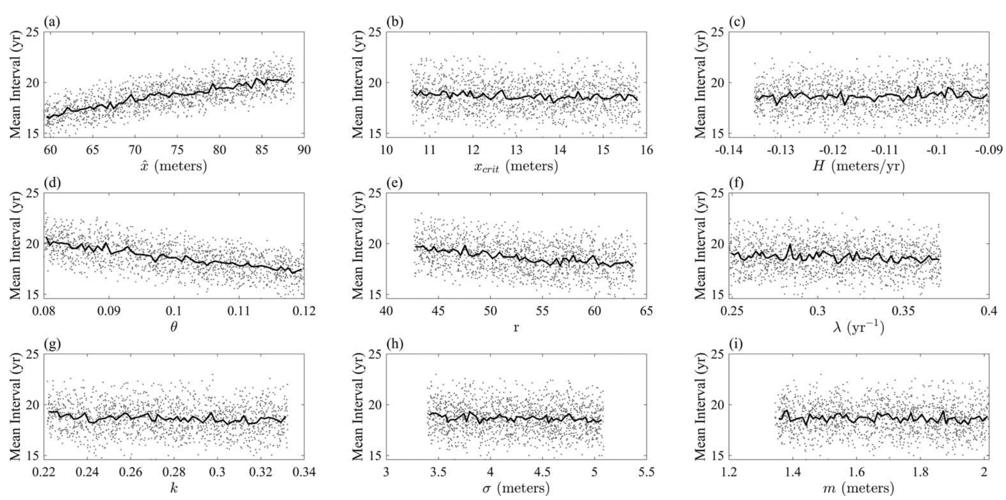

Figure 11. Monte Carlo simulation for high-SLR scenario at GI. Mean nourishment is most sensitive to (a) $\hat{x}$ and (d) θ. The model is also moderately sensitive (e) r. The model is relatively insensitive to all other input parameters (b, c, f–i).

Table 5. *First-order sensitivity of each input parameter. See text for description of sensitivity calculations using conditional variances normalized by total variance. All sensitivity scores greater than 0.2 have been bolded. "Low," "Mid," and "High" refer to the three SLR scenarios.*

	Vilano Beach			Hutchinson Island			Gasparilla Island		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
$\hat{x}$	**0.36**	**0.39**	**0.42**	**0.28**	**0.38**	**0.40**	**0.58**	**0.50**	**0.54**
x_{crit}	**0.41**	**0.45**	**0.45**	**0.33**	**0.38**	**0.38**	0.04	0.05	0.04
H	0.12	0.06	0.05	0.10	0.06	0.04	0.05	0.05	0.05
θ	**0.22**	0.16	0.12	0.12	0.10	0.05	**0.36**	**0.45**	**0.37**
r	0.05	0.10	0.12	0.16	**0.22**	**0.24**	0.07	0.10	0.14
λ	0.07	0.04	0.05	0.17	0.06	0.04	0.09	0.07	0.06
k	0.04	0.03	0.05	0.02	0.03	0.05	0.03	0.05	0.05
σ	0.05	0.05	0.05	0.06	0.04	0.04	0.07	0.06	0.03
m	0.04	0.04	0.04	0.05	0.04	0.03	0.04	0.04	0.05

Using data from the National Hurricane Center, the Coastal Services Center at the National Oceanic and Atmospheric Administration maintains a database of historic tropical storms and hurricanes that can be used to calculate the expected number of storms per year ($1/\lambda$) to pass within 50 miles of the desired study area (National Oceanic and Atmospheric Administration, 2017). Shoreline response to storms may be available from previous studies focusing on the area of interest or from the USGS Coastal Change Hazards Portal (Kratzmann, Himmelstoss, and Thieler, 2017). Alternatively, the sensitivity analysis revealed that the model is minimally sensitive to the GEV parameters (Table 5), and thus, it may be acceptable for communities to use the values of k, σ, and m given in Table 1.

Gopalakrishnan *et al*. (2011) and Smith *et al*. (2009) set $\theta = 0.1$ for a generic North Carolina beach. Lacking better data, the same value was used for the three Florida locations and produced acceptable results. However, the sensitivity analysis revealed that the model is sensitive to changes in this parameter, particularly at GI for all SLR scenarios and at VB for the low-SLR scenario. Thus, although communities could use $\theta = 0.1$, as has been done here, it may be beneficial to invest in studies to measure the exponential erosion rate of nourished beaches.

Finally, communities must select T_i and T_f according to the time frame over which they wish to predict nourishment intervals. Having determined appropriate parameter values, a community could then use the model presented here to estimate the necessary nourishment frequency under low, medium, and high SLR, to maintain a desired beach width.

Future Work

This paper has shown that a simple model can approximate the number of renourishments predicted by Beach-fx for three Florida locations. Future work could include verifying the model for other coastal locations. Additionally, as explained above, model application relied upon the representative value of 0.1 for θ, which is not supported by data. Thus, this model could potentially be improved by incorporating measurements of the exponential erosion rate of nourished beaches. Additionally, future research could investigate the validity of model assumptions, such as 90% of storm damage recovering within several weeks and a constant Bruun Rule correction term, under the different SLR scenarios.

CONCLUSION

This paper presents a low-cost stochastic dynamic model that simulates the beach nourishment interval, which largely determines renourishment costs over the life of a project. The model is applied to three locations in Florida, and a sensitivity analysis identified input parameters that have the largest effect on model output. Results indicate that this simple dynamic model requiring minimal data inputs can reasonably well approximate the renourishment costs on the basis of the intervals predicted by Beach-fx. This model is not intended to replace Beach-fx simulations but rather to serve as a first-pass screening process. This could help communities decide whether they wish to proceed with the more money-, time-, and data-intensive life-cycle simulations or if they would prefer to explore other coastal risk-management options.

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