Integrating Bayesian Networks to Forecast Sea-Level Rise Impacts on Barrier Island Characteristics and Habitat Availability

Benjamin T. Gutierrez1,2, Sara L. Ziegler2,3, Erika Lentz4, Emily J. Sturdivant1,5 and Nathaniel G. Plant2

1U.S. Geological Survey Woods Hole Coastal and Marine Science Center, Woods Hole, MA, USA, 2U.S. Geological Survey St. Petersburg Coastal and Marine Science Center, St. Petersburg, FL, USA, 3Now at Woodwell Climate Research Center, Falmouth, MA, USA

Abstract Evaluation of sea-level rise (SLR) impacts on coastal landforms and habitats is a persistent need for informing coastal planning and management, including policy decisions, particularly those that balance human interests and habitat protection throughout the coastal zone. Bayesian networks (BNs) are used to model barrier island change under different SLR scenarios that are relevant to management and policy decisions. BNs utilized here include a shoreline change model and two models of barrier island biogeomorphological evolution at different scales (50 and 5 m). These BNs were then linked to another BN to predict habitat availability for piping plovers (Charadrius melodus), a threatened shorebird reliant on beach habitats. We evaluated the performance of the two linked geomorphology BNs and further examined error rates by generating hindcasts of barrier island geomorphology and habitat availability for 2014 conditions. Geomorphology hindcasts revealed that model error declined with a greater number of known inputs, with error rates reaching 55% when multiple outputs were hindcast simultaneously. We also found that, although error in predictions of piping plover nest presence/absence increased when outputs from the geomorphology BNs were used as inputs in the piping plover habitat BN, the maximum error rate for piping plover habitat suitability in the fully-linked BNs was only 30%. Our findings suggest this approach may be useful for guiding scenario-based evaluations where known inputs can be used to constrain variables that produce higher uncertainty for morphological predictions. Overall, the approach demonstrates a way to assimilate data and model structures with uncertainty to produce forecasts to inform coastal planning and management.

Plain Language Summary Bayesian networks provide a means for estimating the probability of various outcomes that depend on input conditions that also have a range of probabilities. They can, for example, predict the probability that a specific location is a suitable nesting site for shorebirds if provided information about the site. The information required can be obtained from mapping on-the-ground habitat conditions, or as is done here, be predicted from another BN. The methods for doing that, and the additional uncertainties introduced by using multiple networks, are discussed here.

1. Introduction Planning for sea-level rise (SLR) has led to a pressing and persistent need for improved methodologies that explore future coastal change and inform long-term decision making and management (Bindoff et al., 2019; Melillo et al., 2014; Oppenheimer et al., 2019; Reidmiller et al., 2018; Titus et al., 2009). The development of long-term (e.g., multi-decadal) coastal change projections is complicated by the need to integrate a variety of multidisciplinary drivers, processes, and feedbacks across different spatial and temporal scales.

An important consideration in SLR impact studies is the potential for habitat loss, which will have wide-ranging impacts on coastal ecosystems and increase extinction risk for endemic flora and fauna (Couchamp et al., 2014; Mennon et al., 2010; Nicholls & Cazenave, 2010). Although beaches and barrier islands provide key habitat for myriad species including the federally threatened piping plover (Charadrius melodus), few studies have linked SLR-driven coastal change projections to the potential for habitat loss in these settings (but see Chu-Agor et al., 2011, 2012; Galbraith et al., 2014; Seavey et al., 2011; Simms et al., 2013). While these previous studies fill an important need, models used in these works are either largely elevation-based inundation models that do not capture the complexity of dynamic landform change (as in Lentz et al., 2016) or rely on simplified
Characterizations of a beach system's response to SLR (e.g., the Bruun rule; Bruun, 1962). In the species' New York-New Jersey management unit (U.S. Fish and Wildlife Service, 1996), piping plovers nest in beach, dune or washover settings with mixed substrates (i.e., sand width shell cover) and sparse vegetation (<20% cover) within a short distance (<1 km) to foraging habitats (moist substrates along low-energy shorelines, Cohen & Fraser, 2010; Loegering, 1992; Loegering & Fraser, 1995; Maslo et al., 2012; Zeigler et al., 2021). Several modeling approaches have been developed that simulate the evolution of coastal landforms, specifically for barrier islands (Lorenzo-Trueba & Ashton, 2014; McNamara et al., 2011; Passeri et al., 2020; Ranasinghe, 2016; Roelvink et al., 2009; Stolper et al., 2005). Many of these approaches rely on evaluating changes in the geometry and volume of barrier island cross-sections and either do not incorporate variables relevant to habitat for piping plovers and other coastal species (e.g., substrate, vegetation characteristics) or do not consider them in sufficient detail or resolution for such applications. High-resolution models that do capture variability in barrier island conditions and short time-scale forcing (e.g., waves and nearshore currents), such as Delft3D, are difficult to run beyond a decade into the future due to computational limitations and large uncertainties that develop with multi-decadal forecasts (e.g., Passeri et al., 2020). In general, simplified representations of barrier island change (e.g., models relying on the Bruun rule; Bruun, 1962) often do not incorporate detailed habitat characteristics, while models derived for ecological applications often lack a consideration of complicated geological and ecological feedbacks that drive barrier island evolution in the face of SLR and ultimately underpin habitat availability. Consequently, a persistent research need remains for applied models that bridge the crucial “interdisciplinary gap” between geology and ecology in coastal studies (Stallins, 2006).

Bayesian methods and, in the particular focus of this paper, Bayesian networks (BNs), have been increasingly used to investigate problems in ecological and earth sciences (Aspinall et al., 2003; Berger, 2000; Borsuk et al., 2004; Korup, 2021; Marcot, 2012, 2020; McCann et al., 2006; Mount & Stott, 2008; Pawson et al., 2017). Over the last decades, we have been working with collaborators to use Bayesian networks to bridge interdisciplinary gaps in geology and ecology across scales. At the largest scales (e.g., 5 km shoreline segments), BNs have been used to investigate how shoreline change rates (i.e., erosion and accretion) are likely to respond to multi-decadal changes in sea level (Gutierrez et al., 2011, 2014). At moderate spatiotemporal scales (i.e., decadal and 30-m landscapes), BNs have been developed to explore the potential for coastal landscape dynamic response to SLR (Lentz et al., 2016); SLR-driven evolution in barrier island characteristics (e.g., elevation, beach width along shore-normal transects spaced in 50-m intervals; Gutierrez et al., 2015); and storm-driven changes to barrier island characteristics (50-m transects; Plant & Stockdon, 2012; Plant et al., 2016; Wilson et al., 2019). Finally, BNs of seasonal habitat availability given coastal landform conditions (e.g., vegetation density, substrate type) have been developed for species like piping plovers (5-m cells; Zeigler et al., 2021) and beach mice (Peromyscus polionotus) subspecies; 30-m cells; Cronin et al., 2021). In addition to spanning spatial and temporal scales, these BNs are capable of simultaneously incorporating data from a variety of sources (e.g., empirical data and expert opinion) and formats (e.g., continuous and categorical variables), capturing hierarchical and complex correlations among variables, and accommodating incomplete data. Such models also explicitly convey uncertainty in probabilistic outputs and provide a way to quantify outcome uncertainty (McCann et al., 2006; Uusitalo, 2007). As a result, BNs in general and those described above have the potential to forecast barrier island and habitat dynamics at relevant scales and at sufficient detail necessary for multi-decadal planning.

Here, we hypothesize that, by using spatially and temporally varied data inputs, linked BNs can be used to evaluate the probability of (a) future barrier island biogeomorphological states for different SLR, shoreline change, and management scenarios and (b) subsequent nesting habitat availability for piping plovers along the Atlantic coast given this biogeomorphological change. This paper focuses on the development and implementation of an integrated BN modeling framework, with an example application for Fire Island, New York, United States (Figure 1) which is presented in detail in Zeigler et al. (2022). The focus of the present paper is to evaluate the capabilities of a linked BN framework that integrates discipline-specific knowledge to explore an interdisciplinary problem; —understanding the effects of SLR in a barrier island setting with a variety of human use and natural resource management requirements. Section 2 reviews the biogeomorphological setting (i.e., Fire Island) where we conduct the initial model development, the four BNs integrated in the modeling framework, the data used to train and evaluate the BNs, and hindcast performance testing methodology. Section 3 examines BN performance and the impact of linking BNs to hindcast 2014 habitat conditions, highlighting where habitat hindcasts deteriorate as more uncertain information is added to the modeling framework. A companion paper by
Zeigler et al. (2022) focuses on an application of this framework, exploring the nature and implications of forecasted biogeomorphological change at Fire Island on humans and piping plovers.

2. Materials and Methods

2.1. Application Setting

We added to an existing Bayesian framework built for Assateague Island National Seashore (Gieder, 2015; Gutierrez et al., 2015) and extended it spatially using data from Fire Island, New York (Figure 1). Fire Island is centrally located along the south shore of Long Island, New York. Divided by an inlet created in 2012, the Wilderness Breach Inlet, the nearly 50 km of barrier island extends from Moriches Inlet in the east to Fire Island Inlet and Democrat Point to the west. Fire Island has been the focus of many geologic and oceanographic studies aimed at understanding barrier island change and evolution as well as regional sediment management planning as it contains federal, state, and private land holdings maintained for a range of objectives (Brenner et al., 2018; Hapke et al., 2017; Lentz, 2013; Lentz & Hapke, 2011; Schwab et al., 2000, 2013). Fire Island was impacted significantly during Hurricane Sandy in October of 2012, including widespread erosion and breaching of the barrier island (Brenner et al., 2018; Hapke et al., 2013; Sopkin et al., 2014). The 2012 inlet has persisted since initially breaching during the storm (Hapke et al., 2017), and beach and dune restoration has occurred along much of the island via direct emplacement of sediment or sand fencing (Rice, 2017).

Fire Island National Seashore comprises much of Fire Island and, as such, offers valuable recreational and tourism opportunities as well as important habitat for coastal species like piping plovers. Consequently, planning to account for storm and SLR impacts requires consideration of habitat as well as human development and infrastructure on the island. While Hurricane Sandy had adverse impacts to development and infrastructure on Fire Island, high storm water levels resulted in overwash along numerous areas of the island, resulting in new piping plover habitat (Zeigler, Gutierrez, et al., 2019) and subsequent population increases (Robinson et al., 2019).

2.2. Bayesian Networks

Bayesian networks provide a way to implement Bayes theorem of conditional probability (Bayes, 1763; Gelman et al., 1995). In Bayes theorem, one can compute the conditional probability \( R \) given the occurrence of some event \( O \) according to Equation 1:

\[
p(R_j | O_i) = \frac{p(O_i | R_j) \cdot p(R_j)}{p(O_i)}
\]
In this Equation 1, the left-hand side represents the conditional probability of a particular response, $R_j$, given a set of observations ($O_j$), which are assumed to influence $R$. For example, $R$ could represent the joint probability of a specific shoreline change rate where $O$ represents a forcing such as incoming wave height or rate of relative SLR (Gutierrez et al., 2014). The subscripts $i$ and $j$ represent one of a finite set of scenarios that can be observed and the potential number of sets of observations, respectively. The right-hand side of the equation contains two terms. The first is the likelihood of the observations if the response is known and indicates the strength of the correlation between observation and response. The second term is the prior probability of the response, which is integrated over all expected observation scenarios. The denominator is a normalization factor that accounts for the likelihood of the observations.

BNs combine Bayes' rule with graphical models of a system, such as a physical or biological system (Korb & Nicholson, 2004). In a BN, nodes represent variables describing relevant system components. Nodes are further broken down into discrete characteristics or, for continuous variables, discretized into bins. Edges connect nodes to convey dependencies, correlations, or causal influences among those nodes, ultimately illustrating the manner by which all input nodes are directly or indirectly connected to one or more output nodes (Korb & Nicholson, 2004). BNs are typically trained with empirical or observational datasets containing cases that show how values for each individual input node are associated with a given value for the output node(s). Together, cases determine the conditional probability distributions for each node according to Bayes Theorem, and the set of all possible node-value combinations forms a conditional probability table that underlies a “trained” BN.

In this study, we integrated four BNs to forecast future conditions (Figure 2). Although we use Fire Island as a case study location, these methods could be applied to a variety of barrier island settings. Two of the BNs were developed in previous research efforts to forecast (a) shoreline change due to SLR (Gutierrez et al., 2014) and (b) piping plover nesting habitat availability (Zeigler et al., 2021). Two additional BNs were developed as part of the present study to forecast barrier island conditions under future shoreline changes; these BNs were substantially modified from a previous version developed for Assateague Island (Gutierrez et al., 2015). Each of the four BNs addresses a different aspect of a SLR-driven response over a different spatiotemporal scale. The BNs were developed separately using the Netica software package (Netica, 2016). BNs were trained using an expectation maximization algorithm (EM) to compute the posterior probability of each variable in question (Dempster et al., 1977; Lauritzen, 1995). Once trained, data analysis was conducted using Matlab codes (Matlab, 2018) based on those developed in Python by Fienen and Plant (2015). Individual BNs were also integrated using the Matlab-based framework (Text S1 in Supporting Information S1; Gutierrez & Plant, 2022). The BNs can be used independently to predict shoreline change (i.e., erosion or accretion), barrier island characteristics, or piping plover habitat availability. Alternatively, BNs can be linked by passing predicted probability distributions generated as outputs from one BN to identical nodes used as inputs in another. When linked, predicted SLR rates can be propagated through the geomorphology and piping plover BNs to forecast barrier island biogeomorphological characteristics and/or piping plover habitat availability. We describe the structure and training data used to parameterize individual BNs in the next three sub-sections.

2.2.1. Shoreline Change BN

The Shoreline Change BN (SCBN) was developed to evaluate the probability of shoreline erosion or accretion (henceforth, “shoreline change”) given rates of historical relative SLR (Figure 2; Figure S1 in Supporting Information S1) and is described in detail in Gutierrez et al. (2014). The BN consists of six nodes: five of the nodes serve as inputs of forcing conditions (rate of relative SLR, mean tidal range, and mean significant wave height) and physical characteristics (coastal slope and geomorphology; Table 1). The remaining node, shoreline change rate, serves as a response or output node. To apply this to Fire Island for hindcast and performance testing, we used data from Gutierrez et al. (2014) to train and parameterize the BN (Table 1). At Fire Island, long-term shoreline changes are likely the result of the combined effects of long-shore transport gradients, SLR, erosion management efforts and interaction with the underlying geological framework (Brenner et al., 2018; Hapke et al., 2010; Lentz & Hapke, 2011; Lentz et al., 2013; Schwab et al., 2000). The data used in this BN, from Thieler and Hammar-Klose (1999), include factors that attempt to account for the range of factors influencing long-term shoreline changes (geomorphology, coastal slope, tidal range, and wave height).
2.2.2. Barrier Island Geomorphology Bayesian Networks

We developed two BNs to capture barrier island geomorphology characteristics, which are best described across different spatial scales (Figures 2 and 3; Figures S2 and S3 in Supporting Information S1). In previous iterations of this research (Gieder, 2015), we used a large suite of variables representing two different spatial scales in a single BN in a “megamodel” approach. A limitation of the prior approach was that the predicted value for transect-level variables (e.g., beach width) could differ for every 5-m cell along a single transect, resulting in inconsistent predictions from one cell to the next along a transect. Dividing the barrier island BN into two separate BNs in our current study allowed for a clearer separation of spatial scales (50 vs. 5 m), ensured more consistency in predictions at transect scales, and improved computational efficiency.

The first BN, henceforth referred to as the “Coarse-scale Geomorphology BN” (CSBN), was modified from Gutierrez et al. (2015) and considers barrier island attributes best measured across a barrier island's cross-section (here, along shore-normal transects spaced 50-m apart). Nodes in this BN include distance to inlet, dune crest height, beach width, beach height, mean transect elevation, and distance to dune crest (from the mean high water (MHW) shoreline). We also incorporated three nodes to capture anthropogenic modification to the barrier island across each cross-section: the presence of (a) beach nourishment (“nourishment”), (b) erosion management structures (“construction”), and (c) development (Table 2, Figure 3, Text S2 in Supporting Information S1). In the network structure, each geomorphic characteristic is interlinked because we assumed that all characteristics influenced or were correlated each other. Here, the forcing variables (shoreline change rate, distance to inlet, nourishment, development, construction) are parent nodes to variables that describe basic characteristics of a
barrier island cross-section (barrier width, mean transect elevation, distance to dune crest, dune crest height, beach width, beach height).

The second BN, henceforth referred to as the “Fine-scale Geomorphology BN” (FSBN), considers variables that are more accurately measured at a higher resolution; here, at 5-m intervals along each barrier island cross-section (or transect). Parent nodes in this BN are equivalent to child variables considered in the CSBN and include dune crest height, distance to dune crest, barrier island width, mean transect elevation, and beach height. Because these variables are considered along each barrier island transect, 5-m points along a single transect share the same value. Parent nodes are then used to predict distance to the MHW shoreline, elevation, geomorphic setting, substrate type, vegetation type, and vegetation density—the values of which can vary by point along the transect (Table 3, Figure 3; Figure S3 in Supporting Information S1).

Table 1

| Variable                          | Description and data source                                                                                                                                 |
|-----------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Relative sea-level rise (mm/yr)   | Rate of sea-level rise recorded at NOAA tide gauge stations. These were computed by fitting a linear trend to National Ocean Service long-term (50–100+ years) tide gauge measurements and interpolating alongshore between stations. |
| Mean wave height                  | The long-term mean offshore wave height computed from U.S. Army Corps of Engineers Wave Information Studies (WIS) hindcast data (Hubertz et al., 1996). For each WIS station nearest to the coastline, the mean wave height for a 20-to-24-year period was computed and associated with the nearest shoreline point. |
| Tidal range                       | The long-term mean range of the tidal water level variations computed from National Ocean Service tide gauges (National Ocean Service, 2013) and interpolated alongshore between stations. These tidal datum values for mean high water (MHW) and mean low water (MLW) were associated with each shoreline data point used to approximate the tidal range at that location (Hammar-Klose & Thieler, 2001; Thieler & Hammar-Klose, 1999). |
| Coastal slope                     | The coastal slope is used to distinguish differences in geologic and tectonic settings. Computed from gridded National Geophysical Data Center and U.S. Navy topographic and bathymetric elevation data extending approximately 50 km landward and seaward of the local shoreline for the Atlantic Coast and approximately 10 km landward and seaward of the local shoreline for the Gulf and Pacific coasts (Thieler & Hammar-Klose, 1999). |
| Geomorphology                     | A classification of the geomorphic and related geologic and oceanographic processes that might control shoreline change. We simplified the Thieler and Hammar-Klose (1999) definitions such that geomorphic settings convey only morphologic conditions without explicit reference to levels of vulnerability (Gutierrez et al., 2014). |
| Shoreline change rate (m/yr)      | For the U.S. Atlantic, Gulf, and Pacific coasts, decadal- to centennial-scale shoreline-change rates were based on data compiled by May et al. (1983) and Dolan et al. (1988), as presented in the Coastal Erosion Information System (CEIS) (May et al., 1982). Data in CEIS are drawn from a wide variety of sources, including published reports, historical shoreline-change maps, field surveys, and aerial photo analyses. Shoreline-change rate data along the southern shore of Delaware Bay and the northern Chesapeake Bay were updated with shoreline-change rates from Dolan and Peatross (1992) because of possible gridding errors in the original (Hammar-Klose & Thieler, 2001) data set, which included an older shoreline-change rate data set (Dolan et al., 1988). |

Note. Data that support the Shoreline Change Bayesian Network are published in Gutierrez et al. (2014).
in biogeomorphological states found on Fire Island. Data from 2010 to 2014 represent more typical Fire Island conditions, which may include remnants of other, less extensive storm impacts. Data from 2012 capture conditions shortly after Hurricane Sandy made landfall in this region. Data sampling to parameterize the BNs was accomplished via Matlab.

2.2.3. Piping Plover Habitat Bayesian Network

The Piping Plover Habitat BN (PIPLBN) includes input nodes for beach width, distance to ocean, elevation, geomorphic setting, vegetation type, vegetation density, and substrate type—which are equivalent to child (or output) nodes found in the FSBN (Figure 3, Figure S4 in Supporting Information S1). These nodes are directly or indirectly connected to the output node “habitat availability.” Probability distributions in this network were derived from piping plover presence/absence data and associated landcover characteristics observed in 2014 and 2015 (Sturdivant et al., 2016, 2018; Thieler et al., 2016). Network structure was derived from correlations present in the presence/absence data set using a hill-climb algorithm in the R package bnlearn (Scutari, 2010), as described in Zeigler et al. (2021). For the Fire Island example, we used BN structure and probability distributions derived from presence/absence points collected at sites in New York and New Jersey, which included 177 presence and 159 absence points. Landscape characteristics associated with these points were either determined by field observation (geomorphic setting, substrate type, vegetation type, and vegetation density) or supplemented with remotely sensed information (beach width, distance to ocean, elevation) according to Zeigler, Sturdivant, & Gutierrez, 2019. This BN had an 18% error rate based on 10-fold cross-validation (Zeigler et al., 2021). In addition, the original model configuration included a node for distance to foraging habitat (referred to as moist substrate habitat or MOSH in Zeigler et al., 2022). Although this variable is an important driver of piping plover habitat selection in the New York—New Jersey region, the CSBN and FSBN used to forecast future barrier island conditions, which drive forecasts in the PIPLBN, are not currently designed to predict long-term availability of back-barrier, low energy shorelines that serve as important piping plover foraging habitats. As a result, we removed this node from the PIPLBN in the linked modeling framework.
Table 2
Summary of Variables Included in the Coarse-Scale Geomorphology Bayesian Network

| Variable                 | Description and derivation |
|--------------------------|-----------------------------|
| Shoreline change rate (m/yr) | Obtained from the U.S. Geological Survey National Assessment of Shoreline Change (Himmelstoss et al., 2010) analysis. Represents the rate of change of shoreline positions over the past ~150 years. We used the linear regression rates of long-term shoreline change calculated from a set of 6-10 historical shorelines spanning 1845–2000. |
| Distance to inlet (m)    | Computed as the alongshore distance of each sampling transect from the nearest tidal inlet. This distance includes changes in the path of the shoreline rather than just a straight-line distance between each transect and the inlet and reflects sediment transport pathways. In these cases, the inlets were either Moriches inlet, Fire Island inlet, or the Wilderness Inlet (present in 2012 and 2014). |
| Development              | Indicates if there is no development, light development, moderate development, or heavy development along a transect. |
| Nourishment              | Indicates if a site has been not nourished, occasionally nourished (>5 years), or frequently (1–5 years) nourished to mitigate shoreline erosion. |
| Construction             | Indicates the presence of structures put in place to mitigate erosion or prevent high water from encroaching on the landscape. These included no constructed features present, soft structures (sand fencing, constructed berms or dunes), hard structures (seawalls, rip-rap), or both hard and soft structures. |
| Barrier island width (m) | The distance between the ocean side mean high water (MHW) shoreline and bay-side mean tide line (MTL) as defined for each year’s data set. Barrier width includes only the footprint of the barrier above the MHW and MTL levels and did not extend into any of the sinuous or intervening back-barrier waterways and islands. |
| Mean transect elevation (m) | Calculated by averaging elevations sampled at 5-m points along each shore-normal transect. The averaging process filtered short-scale features and observational noise. Mean transect elevations were calculated for only those transects for which at least 80% of the 5-m points had a value for elevation. Transects that did not meet this threshold were considered to have missing data for this variable. |
| Distance to dune crest (m) | The distance between the oceanside MHW shoreline and the dune crest on a given transect. |
| Dune crest height (m)    | Influences whether a barrier island is eroded, overwashed, or inundated by storm surge and wave runup position along a transect (Plant & Stockdon, 2012; Sallenger, 2000; Stockdon et al., 2007). Heights are referenced to local MHW (Weber et al., 2005). |
| Beach width (m)          | Calculated as the horizontal distance between the dune toe location and the MHW shoreline. Where manmade structures were present in place of dunes or seaward of the dunes, beach width was calculated as the distance from MHW to these structures. |
| Beach height (m)         | Defined as the vertical difference between the dune toe elevation and the elevation of the shoreline, referenced to local MHW. |

Note: Additional variable descriptions, their derivation, and examples are available in Zeigler, Gutierrez, et al. (2019), Zeigler, Sturdivant, & Gutierrez (2019). For the Fire Island example presented here, variable values were sampled from spatial datasets in Sturdivant et al. (2019).

Variables are measured as barrier island cross-sections, or transects, spaced in 50-m intervals perpendicular to the shoreline.

2.3. Bayesian Network Performance Testing

Validations of the SCBN and PIPLBN were described in each network’s representative publication (Gutierrez et al., 2014; Zeigler et al., 2021). In this paper, we evaluate the performance of the geomorphology BNs and the fully linked BN framework. By evaluating both individual and linked framework performance, we explore the propagation of uncertainty through the framework and its impact on habitat predictions.

We implemented 5-fold cross-validation, a method that provides a comprehensive measure of BN performance using the entire training/testing data set (Fienen & Plant, 2015; Marcot, 2012). We used 5-folds instead of the 10-fold cross-validation employed in Fienen and Plant (2015) due to computational limitations imposed by the BNs presented here. We believe that we were unable to attain successful training using the 10-fold ensemble-calibration validation tests due to the larger number of nodes, bins within some nodes, and connections in the CSBN and FSBN in comparison to our previous experience (Gutierrez et al., 2015). Geomorphology data to support 5-fold cross-validation was sampled at points occurring in 5-m intervals for transects spaced at 50-m intervals across Fire Island for the years 2010, 2012 and 2014 as described in Section 2.2.2 (Sturdivant et al., 2019).
A fifth of this data set (i.e., a fifth of the transects, their 5-m points, and associated attributes; also known as a “fold”) was randomly selected, without replacement, using the Matlab function “randperm.m” and designated as a “testing set” for validation purposes (Matlab ver. 2018). The remainder of the data set (or the remaining four folds) was then used as calibration data to train each of the geomorphology BNs in Netica (Norsys, 2016). For each combination of calibration and validation data, a calibration performance measure—where the same four folds of the data were used for both training and testing—and a validation performance measure—where the fifth fold of the data was used for testing—were calculated. Here, we report the mean ensemble performance measure for each calibration and validation score, which averages the performance measure across each of the five folds. In this way, we can evaluate model skill and the potential for over-fitting and selection bias (Cawley & Talbot, 2010).

For both the CSBN and FSBN, we calculated mean ensemble calibration and validation performance measures where (a) all output nodes were predicted simultaneously and (b) only one output node was predicted at a time (and the value of all other nodes was specified). This was done to evaluate separately how much error or uncertainty a single variable introduces to overall BN performance as well as the magnitude of error introduced when several variables are unknown. Variables considered as output nodes included distance to dune crest, beach width, mean transect elevation, beach height, and dune crest height in the CSBN. Geomorphic setting, substrate type, vegetation type, and vegetation density were considered output nodes in the FSBN. All other nodes were always specified as input nodes in performance testing.

We used three separate measures of BN performance (Marcot, 2012) to evaluate the geomorphology BNs. We used an error rate, where we compared the most likely outcome predicted for a given node against the observed value for that point or transect. Reported error rate reflects the percentage of transects or points for which the most likely predicted outcome differed from the actual value in the testing data set. We also calculated spherical payoff and quadratic loss (or the Brier score), which are recommended metrics for models like BNs where the full output probability distribution is also considered in the scoring metric as opposed to an error rate which relies on classifying an output according to the most probable value (Marcot, 2012; Morgan & Henrion, 1990; Pearl, 1978). Spherical payoff (SP) was calculated according to Equation 2:

$$SP = MOAC \times \left( \frac{P_i}{\sqrt{\sum_{j=1}^{n} (P_j^2)}} \right)$$ (2)
where mean probability over all cases refers to the mean probability of an outcome over all possible input cases with data, \( P_r \) is the predicted probability of the correct state, \( P_i \) is the predicted probability of state \( j \), and \( n \) is the number of states. Scores vary between 0 and 1, with 1 indicating perfect model performance (Marcot, 2012; Morgan & Henrion, 1990; Pearl, 1978). Quadratic-loss (or the Brier score; \( QL \)) was calculated using the same variables as spherical payoff according to Equation 3:

\[
QL = MOAC = \left( 1 - 2 \left( P_r + \sum_{j=1}^{n} P_i^2 \right) \right). \tag{3}
\]

Quadratic loss scores vary from 0–2, with 0 indicating perfect model performance (Morgan & Henrion, 1990; Pearl, 1978).

Finally, we evaluated the performance of the entire linked model framework through 5-fold cross-validation, where performance was measured as the error rate in predictions of piping plover habitat availability outcomes. Here, a correct prediction occurs when the PIPLBN assigns a probability \( \geq 66\% \) of being habitat to a combination of landscape values that are associated with a nest (or presence point) in the training data set or, conversely, a \( p \leq 33\% \) of being habitat to values associated with an absence point. Error occurs when the BN assigns a \( p \geq 66\% \) to an absence point (i.e., a false positive) or a \( p \leq 33\% \) to a nest point (i.e., a false negative). These thresholds coincide with the Intergovernmental Panel on Climate Change’s (IPCC) definition for “likely” outcomes (Mastrandrea et al., 2010), as used in Zeigler et al. (2021, 2017); Zeigler, Gutierrez, et al. (2019); Zeigler, Sturdivant, and Gutierrez (2019). We report the percentage of erroneous predictions, partitioned as false positives and negatives.

The calibration-validation data set used here in performance testing consists of 2014 biogeomorphological characteristics sampled along 5-m points and 50-m transects across Fire Island (Sturdivant et al., 2019) and piping plover nest presence/absence points collected in 2014 (Sturdivant et al., 2016). Piping plover presence/absence points were associated with the nearest transect and 5-m transect point. We repeated error testing in four performance “scenarios,” which represent increasing model complexity (Table 4). This was done to evaluate how error and uncertainty are propagated and enhanced with the addition of each BN. Although a network error rate (18%) was determined in Zeigler et al. (2021), we retested the error rate of the PIPLBN here because, in the present study, we (a) removed a variable (distance to foraging), (b) used a different testing/training data set (Fire Island only), and (c) associated each presence/absence point with the biogeomorphological characteristics at the nearest point on 50-m transects used for sampling barrier island data. The error rate of the PIPLBN alone offers the minimum error rate expected in predictions of piping plover habitat availability, and additional error that occurs can be attributed to increasing model complexity as the BNs are linked.

### 2.4. Geomorphology BN Sensitivity Testing

We also conducted sensitivity tests for the CSBN and FSBN to determine the importance of each variable on predicted outcomes. To perform these tests, we used a variation reduction scheme included with the Netica software (Fienen et al., 2013). Sensitivity was calculated according to Equation 4 as the percent of variance reduction (\( V_r \)) in a response variable after updating the finding for the input variable of interest:

\[
V_r = \frac{V(F) - V(F|O)}{V(F)} \times 100 \tag{4}
\]

where \( V(F) \) is the variance of a forecast prior to the update in an observed finding, and \( V(F|O) \) is the variance of the forecast after updating with the observations. \( V(F) \) and \( V(F|O) \) are calculated according to Equations 5 and 6, respectively:

\[
V(F) = \sum_{j=1}^{N} p(f_j) (f_j - E(f_j))^2 \tag{5}
\]

\[
V(F|O) = \sum_{i=1}^{M} \sum_{j=1}^{N} p(f_j|o_i) (f_j - E(f_j|o_i))^2 \tag{6}
\]

where \( p(f_j) \) is the prior probability of the \( j \)th forecast; \( f_j \) is the actual value of the \( j \)th forecast; \( E(f_j) \) is the expected value of the \( j \)th forecast (determined by the BN); \( p(f_j|o_i) \) is the updated probability (posterior) of the \( j \)th forecast.
Table 4: Error Rates Associated With Combinations of Linked Bayesian Networks (BNs)

| “Scenario” name | BNs used                                                                 | Description                                                                                                                                   | Error rate (%) |
|-----------------|--------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|----------------|
| PIPLBN          | Piping Plover Habitat BN                                                 | Biogeomorphic characteristics at 5-m transect points were input directly into the Piping Plover Habitat BN to make predictions for habitat availability for that combination of landscape values. Actual nest presence/absence points were associated with the nearest transect point, and only these points were used for error testing. | 20 17.5 2.5 27.4% |
| FSBN-PIPLBN     | Piping Plover Habitat BN + Fine-scale Geomorphology BN                   | Values for dune crest height, barrier island width, distance to dune crest, mean transect elevation, beach height, and beach width were specified as inputs to predict output PDFs for each 5-m transect point for distance to shoreline, geomorphic setting, elevation, substrate type, vegetation type, and vegetation density in the Fine-scale Geomorphology BN. These PDFs were passed to the Piping Plover Habitat BN to act as inputs to predict probability of habitat availability for each 5-m transect point. Transect points that were associated with an actual nest presence/absence point were used for error testing. | 30 12.5 17.5 21.3% |
| CSBN-FSBN-PIPLBN| Piping Plover Habitat BN + Fine-scale Geomorphology BN                  | Values for shoreline change rate, distance to inlet, nourishment, development, and construction were specified as inputs to predict PDFs for dune crest height, barrier island width, distance to dune crest, mean transect elevation, and beach height for each transect in the Coarse-scale Geomorphology BN. These PDFs were passed to the Fine-scale Geomorphology BN to act as inputs for corresponding nodes. Output PDFs were generated for each 5-m transect point and ultimately passed to the Piping Plover Habitat BN as in FSBN-PIPLBN. | 27.5 10 17.5 21.6% |
| SCBN-CSBN-FSBN-PIPLBN | Piping Plover Habitat BN + Fine-scale Geomorphology BN + Coarse-scale Geomorphology BN + Shoreline Change BN | Values for relative sea-level rise, tidal range, coastal slope, geomorphic setting, and mean wave height were specified in the Shoreline Change BN to generate a shoreline change rate PDF for each shore-normal transect. This PDF was passed to the Coarse-scale Geomorphology BN, where the shoreline change rate PDF and specified values for distance to inlet, nourishment, development, and construction acted as inputs. Output PDFs were passed through the Fine-scale Geomorphology BN and Piping Plover Habitat BNs as in CSBN-FSBN-PIPLBN. | 27.5 10 17.5 22% |

Note. See Table S3.3 in Supporting Information S1 for Associated Confusion Matrices.

Given the $i$th evidence datum, $E(f/o_i)$ is the expected value of the $j$th forecast given the $i$th evidence datum; $M$ is the number of discrete evidence data; and $N$ is the number of discrete forecasts. The percent variance reduction is calculated as the variance calculated by using observations $O$ from an input node divided by the variance calculated by updating the response variable with findings of itself. Consequently, $V_r$ for the forecast node is 100% while $V_r$ for all other nodes is less than or equal to 100%. A $V_r$ approaching 100% for a given node indicates that the BN output is sensitive to the value of that node. Conversely, a $V_r$ approaching 0% indicates that the BN output is insensitive to the value of that node.
3. Results

3.1. Performance Analysis of the Geomorphology BNs

To evaluate the performance of the geomorphology BNs, we conducted performance tests where one outcome variable at a time was computed and where multiple output variables were computed simultaneously. This was done to evaluate the decline in model performance when fewer input variables were known. Because trends in error rate, spherical payoff, and quadratic loss for variables in the CSBN and FSBN mirrored each other (Figure 4; Tables S3.1 and S3.2 in Supporting Information S1), we discuss only error rates in this section for simplicity. For predictions made by the CSBN where multiple variables were predicted simultaneously, error was 24%–51% in calibration tests and 23%–55% in validation tests (Table S3.1 in Supporting Information S1). When only a single variable was predicted (i.e., values for all other variables were known), error rates were 11%–24% in calibration tests, increasing to 29%–37% in validation tests (Table S3.1 in Supporting Information S1). Ranking metrics by variable from highest to lowest in error rate shows a consistent pattern, with distance to dune crest and beach width associated with the lowest error rates and beach height and dune crest height associated with the highest error rates.

In the FSBN, error rates were 27%–47% in calibration tests and 27%–45% in validation tests when all five output variables were predicted simultaneously (Table S3.2 in Supporting Information S1). The best performance scores were associated with geomorphic setting, and the worst scores were associated with vegetation type (Table S3.2 in Supporting Information S1). When a single variable was predicted at a time, the lowest error rates were

![Figure 4. Performance metrics for coarse-scale (a, c, e) and fine-scale Bayesian networks (BNs) (b, d, f) showing calibration (gray circles) and validation (black squares) for single (filled squares or circles) and multi-variable (unfilled squares or circles) BN outputs. Error rates are shown in boxes a and b, spherical payoff in boxes b and d, and quadratic loss in (e and f).](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2022EA002286)
associated with substrate type, vegetation type, and vegetation density, and highest error rates were associated with geomorphic setting and elevation. Error rates for elevation were largely consistent whether predicted as a single or simultaneous variable, with error rates differing between 6% and 7% when calibration and validation scores were compared for single and multivariable hindcasts (Table S3.2 in Supporting Information S1).

### 3.2. Performance Analysis of Linked BNs

To evaluate the impact of linking BNs on predicted outcomes, we calculated error rates for four different hindcasts using data representing observed piping plover nest locations and random point locations. When error rates were determined for piping plover habitat availability hindcasts, we found that they increased modestly with increasing model complexity in the linked BN framework (Table 4). For reference, the error rate of the PIPLBN (trained with biogeomorphic and piping plover nest presence/absence data for Fire Island) was 20%. The highest error rate (30%) was associated with FSBN-PIPLBN, where the FSBN was used to predict biogeomorphic conditions used in the PIPLBN. The error rate decreased slightly to 27.5% for both the CSBN-FSBN-PIPLBN and the most complicated SCBN-CSBN-FSBN-PIPLBN linked model frameworks, where predictions generated by the CSBN and the SCBN, respectively, were propagated through the networks to predict piping plover habitat availability (Table 4). In the simplest versions of the framework (PIPLBN, FSBN-PIPLBN), the majority of the error was associated with false positives, where the models predicted habitat availability for biogeomorphic conditions in locations where no nest was present (Table 4). Conversely, in the most complex versions of the framework (CSBN-FSBN-PIPLBN, SCBN-CSBN-FSBN-PIPLBN; Table 4), the majority of error was associated with false negatives where models predicted no habitat availability for biogeomorphic conditions associated with a nest.

Figure 5 shows examples of predicted habitat for the different combinations of linked models (brown, orange, and green transect points). We plot model predictions for specific nests and random points (black and gray points; Table 4) over mapped habitat predictions. Here, examples of hindcasts can be seen showing nest and random point locations where there is agreement (black dots with green centers or gray dots with brown centers) and disagreement (gray markers with green centers indicating false positives) between observations and model hindcasts. In these comparisons there is general agreement for the different combinations of linked models with habitat hindcast to occur along beach areas. However, the maps show that the variability in the amount of habitat along each transect decreases with the addition of additional BNs to predict geomorphic conditions. One observation to note in these maps, is that the width of the barrier island in “c” and “d” differs in comparison to “a” and “b.” This occurs since the CSBN calculates the barrier width and uses a mean barrier width value for the predictions, often resulting in a barrier width that varies from the 2014 training data.

We also evaluated habitat hindcasts with increasing model complexity to determine if linking models would result in over-or-under predicting the percentage of habitat on Fire Island (Table 4). The percentage of 5-m transect points that were likely (p ≥ 66% using IPCC likelihood terminology; Mastrandrea et al., 2010) to support piping plover nesting habitat decreased with the addition of other BNs, from 27.4% of transect points based on the PIPLBN alone to 21.3% for the FSBN-PIPLBN framework (Table 4). The percentage of transect points that supported habitat increased slightly to 21.6% and 22% in the CSBN-FSBN-PIPLBN and the SCBN-CSBN-FSBN-PIPLBN frameworks, respectively (Table 4). Overall, these results show fewer transect points were associated with a high certainty of being habitat (i.e., uncertainty increased) in predictions made through a linked framework compared to predictions made by the PIPLBN alone. This trend was also observed when we compared the percentage of likely nesting habitat (p ≥ 66%) on Fire Island based on the PIPLBN alone compared to versions of the linked model framework (Figure 6). The largest loss of agreement in predicted locations of habitat occurred when we used the CSBN to predict the transect- and point-scale biogeomorphological characteristics on the island (CSBN-FSBN-PIPLBN). For the linked model frameworks containing the CSBN, predictions tended to be more congruent with those of the PIPLBN alone in areas with less habitat (e.g., the central, more developed portion of Fire Island; Figure 6). To determine the degree to which linking BNs resulted in a decrease in certainty for predictions, we compared the absolute differences in habitat probability for each transect point for predictions made by the PIPLBN alone (2014 habitat hindcast) versus those made by the linked model framework. Results showed that the simplest version of the framework (FSBN-PIPLBN) tended to have the lowest absolute differences (Figure 7). For the transect points likely to support habitat as predicted by the PIPLBN alone, more than half of all transect points had a small absolute difference (0.01–0.05; Figure 7a). Cumulative proportions did not converge for the FSBN-PIPLBN, CSBN-FSBN-PIPLBN, and SCBN-CSBN-FSBN-PIPLBN frameworks until
there was an absolute difference of approximately 0.75 (Figure 7a). We observed a similar trend for transect points predicted to have a low probability of being habitat by the PIPLBN alone (i.e., all points where \( p \leq 33\% \)). Over half of these transect points had an absolute difference <0.15 for predictions made by the FSBN-PIPLBN.
framework and those made by the PIPLBN alone, and cumulative proportions in absolute differences converged for all versions of the linked framework around an absolute difference of 0.75 (Figure 7c). Versions of the linked BN framework converged at a lower absolute difference (0.35) for transect points that were predicted to be as likely as not habitat (i.e., all points where 33% < p < 66%; Figure 7b).

3.3. Sensitivity Analysis for the Geomorphology BNs

Sensitivity tests were conducted to determine the importance of each variable in the geomorphology BNs on predicted outcomes. Results for the CSBN showed that the output variables, when specified as inputs, tended to have a greater influence on other output variables compared to the variables that were always utilized as known inputs (Figure 8; input-only variables shown by gray bars). Of the input variables, distance to inlet had the largest influence on output variables except in the case of distance to dune crest. The presence of development had the largest influence on mean transect elevation, and whether a transect had been nourished impacted beach width. For the output variables, three pairs showed a strong correspondence: barrier width and mean transect elevation, distance to dune crest and beach width, and dune crest height and beach height.

Like the CSBN, output variables in the FSBN tended to have a greater influence on other output variables when their values were specified compared to the variables that were always utilized as known inputs (Figure 9; input-only variables shown by gray bars). For the input variables, distance from MHW shoreline consistently had the largest influence on all output nodes, followed by mean transect elevation and barrier island width (Figure 9). Substrate type, vegetation type, and vegetation density had the strongest influence on one another, but geographic setting also had a consistent influence for all other output variables.
4. Discussion

We established a methodology for linking multiple BNs to answer questions in barrier island environments that cross disciplines, spatial footprints, and temporal scales. In this way, researchers can evaluate the impacts of multi-decadal processes, such as SLR, on nesting habitat availability, an important management consideration for species like the piping plover. An important aspect of this approach is that each BN incorporates variables that are relevant to the subdiscipline represented by a given network at the appropriate spatial scale. This approach also fills a knowledge and utility gap in modeling barrier island evolution. Process models can provide higher resolution and a more fully prescribed physics-based calculations of barrier evolution, but these approaches are computationally expensive and have large uncertainties beyond a decade (Passeri et al., 2020). On the other hand, simplified morphokinematic barrier island models (e.g., Lorenzo-Trueba & Ashton, 2014; Stolper et al., 2005) capture fundamental aspects of barrier island evolution but are based on idealized barrier island cross-section geometries and applied at time scales of a century and beyond. In our approach, we bridge the gap between computationally expensive process models and simplified morphokinematic models with BNs trained using on-the-ground observations to provide multi-decadal forecasts that directly incorporate variables at a sufficient spatial resolution important for habitat availability.

The modular approach described here is similar to that defined as a “metamodel,” where a suite of discipline-specific models representing system components are linked to reveal emergent properties of multidimensional interactions (Lacy et al., 2013; Nicholson et al., 2002; Sparks et al., 2011). A metamodel is in contrast to a “mega-model” wherein all system components are represented in a single model structure. Although there is utility in megamodels, a metamodel offers a number of important advantages. Individual models can be developed with a high degree of disciplinary confidence using variables and spatiotemporal scales most relevant to the process of interest. For example, the SCBN was developed to capture broad geomorphological changes in shoreline position (over 5-km increments) due to multi-decadal oceanographic processes. The PIPLBN, on the other hand, describes

---

**Figure 8.** Sensitivity and correlations for variables in the Coarse-scale Geomorphology Bayesian Network: Sensitivity of output variables (panels a–f) to input variable values (gray bars) and correlations among output variables (black bars) were measured according to percent variance reduction, where a high value indicates high sensitivity or correlation.
finer-scale ecological conditions over a 25-m² area that reflect seasonal piping plover nesting habitat selection patterns. Developing separate models that can be linked through shared variables allows us to cross disciplines and scales while also enhancing communication among scientists from different fields of expertise. Metamodels also allow the user to explore alternative configurations to better understand error, uncertainty propagation, and variable sensitivity, which we further discuss in the next section. Finally, the modular nature of our linked BN metamodel framework allows for the use of alternative models when necessary or beneficial. For example, a more data-intensive numerical model of coastal evolution (e.g., Passeri et al., 2018) could replace the SCBN, CSBN, and FSBN if available for a site of interest, and outputs from that model could be used to explore habitat availability within the PIPLBN under storm and SLR scenarios. Alternatively, the PIPLBN could be replaced by a BN developed for another species, such as sea turtles, to explore scenarios of habitat availability for a species that relies on different coastal habitat conditions. In addition, BNs that capture other aspects of physical systems, such as coastal groundwater (e.g., Fienen et al., 2013), could be integrated into the modeling framework to address a range of end user needs.

4.1. BN Error, Sensitivity, and Uncertainty

The performance evaluation shows that, with a larger number of linked networks and a greater number of variables specified as outputs, there is an increase in prediction error. For each geomorphology BN, we observed large increases in error with an increasing number of outcomes predicted (i.e., a greater number of unknown variables). For applications where the maximum number of output variables were unknown (6 for the CSBN and 5 for the FSBN), error rates ranged from 23% to 55%, indicating high uncertainty associated with model applications where a greater number of variables are hindcasted. We also observed that, when more variables were specified as outputs, differences between calibration and validation scores were small, indicating very little overfitting of the calibrated model. This, in turn, indicated that sufficient data were used in model calibration and that the BNs were constructed with appropriate complexity and resolution.

![Figure 9. Sensitivity and correlations for variables in the Fine-scale Geomorphology Bayesian Network: Sensitivity of output variables (panels a–e) to input variable values (gray bars) and correlations among output variables (black bars) were measured according to percent variance reduction, where a high value indicates high sensitivity or correlation.](image-url)
We observed different impacts of individual variables depending on the geomorphology BN considered and whether single or multiple outputs were generated. For variables in the CSBN, distance to dune crest and beach width had the lowest error rates for both single and multivariate predictions. Field-based studies have indicated that these variables are associated with piping plover nesting habitat selection; narrow beaches in Virginia and Maryland are inconsistently used by nesting shorebirds (Boeticher et al., 2007; Patterson, 1988). These variables are also important for understanding vulnerability to storm-surge overwash and erosion (Stockdon et al., 2009). In contrast, beach height and dune crest height introduced the greatest uncertainty (34%–55% error rate) to overall BN performance.

In the FSBN, geomorphic setting produced the lowest error rates for multivariate predictions and the second highest (next to elevation) for single variable predictions. Substrate type, vegetation type, and vegetation density had a strong influence on one another as indicated in sensitivity scores. Elevation produced higher error rates compared to other variables but had fairly consistent performance scores between single and multivariate hindcasts.

We hypothesize that several factors may contribute to high error rates in dune crest height and elevation variables. First, the geomorphology BNs were trained using data from three datasets acquired at different points in time. The 2012 data set was collected immediately following Hurricane Sandy and reflects extensive reshaping of the Fire Island barrier island (Sopkin et al., 2014). Consequently, dune crest heights and elevations for the same transect can differ widely when the three datasets are compared (Sturdivant et al., 2019). Second, Fire Island encompasses a range of development types from public land holdings with no development to densely developed regions where the dune systems are managed to prevent inundation and erosion during flood events. This results in greater variability in along-island elevations compared to undeveloped barrier islands. We hypothesize that additional datasets for both Fire Island (temporal variability) and from other settings (spatial variability) would help to better capture the variability of barrier island characteristics and may help reduce model error and improve prediction confidence.

The linked BN framework performed well in predicting piping plover nest presence/absence (or habitat availability), with error remaining relatively low in comparison to error rates associated with outputs of the geomorphology BNs (Table 4; Figures 4 and 5; Tables S3.1 and S3.2 in Supporting Information S1). We hypothesize that the PIPLBN had lower error rates because of the binary nature of the single output variable, whereas the geomorphology BNs could have 5 to 6 possible values for each of the 11 barrier island output variables. We also initially hypothesized that error would increase with increasing framework complexity, with lowest error associated with the PIPLBN alone and highest error with the fully linked framework. Instead, the largest increase in error rate occurred when the FSBN was linked to the PIPLBN (30% error); error declined slightly to 27.5% with the addition of the CSBN and SCBN. When we examined the results further, the difference in error (30%–27.5%) was associated with a single observation site where the probability density function (PDF) for elevation was uniform (i.e., equal probability for all bins) in the FSBN-PIPLBN framework; however, the PDF for this variable became more certain with the addition of the CSBN. As a result, the uniform PDF in the FSBN-PIPLBN led to an additional false positive for that framework compared to the fully linked 5-BN framework. Even with this small discrepancy, our results indicated that error remains relatively constant once morphological predictions, which are inherently more uncertain, are added to the framework.

We also observed a change in the relative percentage of false positives and negatives as additional BNs were linked to the PIPLBN. The majority of error (88% of the total error) associated with the PIPLBN alone was due to false positives (i.e., the model predicted nesting habitat for conditions associated with a random point). False positives are expected in absence presence models for territorial species of conservation concern, like piping plovers, because available habitat may not be fully occupied (Fielding & Bell, 1997).

However, when additional BNs were included in the model framework, false negatives (i.e., the model predicted unsuitable conditions associated with a nest point) comprised the majority of error. With further investigation, we found that all seven false negatives corresponded to a location where a washover feature occurred on the observed landscape, which is known to be a key component of piping plover habitat selection (Zeigler et al., 2021). In these locations, the BNs predicted that the most likely geomorphic setting was barrier interior, a setting selected less often by nesting piping plovers (Zeigler et al., 2021). As a result, the BNs predicted lower probabilities of habitat availability at these locations that were actually high-quality nesting sites. To confirm this, we re-ran the analysis and specified the original geomorphic setting (washover) for the points that were false negatives. As long as
we also set the vegetation characteristics as identical to the observed data to be consistent with washover settings, the hindcasts no longer resulted in false negatives.

As uncertainty in the value of morphological variables increased with model complexity, so too did uncertainty in the probability that the associated combination of landscape conditions would support piping plover nesting habitat in our linked BN framework. In some instances, the PIPLBN alone predicted that an area was likely (≥66% probability) to be habitat, given known landscape conditions. However, the same area was predicted as likely as not to support habitat (33% < p < 66%) in the linked framework as the value of landscape conditions became more uncertain (Figure 5). This trend can be seen in discrepancies in the percentage of transect points predicted to be habitat; the PIPLBN alone predicted that 27.4% of points would support habitat while the linked BN framework predicted a total of 22% (Table 4). The difference indicates a decline in the certainty of predictions with increasing model complexity, not a physical loss of habitat. Furthermore, as discussed in the previous paragraph, washover features are relatively rare settings in the training data. They are also among the most highly selected nesting areas (Zeigler et al., 2021). Therefore, a reduced probability of washover presence as predicted by the FSBN would automatically reduce the probability that a given area is piping plover habitat. Classifications of aerial imagery captured in 2015 (Sturdivant et al., 2019) indicated that the washover geomorphic setting comprised 5.9% of Fire Island, which is approximately equal to the difference in estimates of predicted habitat availability as made by the PIPLBN and the linked BN framework (Table 4). Thus, the linked model framework may underpredict piping plover nesting habitat availability as morphological predictions become more uncertain and as relatively rare but important features are predicted with lower probabilities.

4.2. Limitations and Applications

While the linked BN framework can provide useful predictions, there are several limitations to highlight. First, our ability to accurately predict the location and availability of washover features was limited, which hinders the framework’s ability to forecast the highest quality nesting sites for piping plovers (Cohen et al., 2008, 2009; Maslo et al., 2011; Zeigler et al., 2021). As mentioned in the previous section, washovers were relatively sparse in the 2010 and 2014 training data sets; therefore, they made up a small proportion of the geomorphic settings. Incorporating a wider range of barrier island settings in the training data (i.e., at sites beyond Fire Island), particularly those that include unmanaged barrier islands, are likely to increase the number of observations of recent washover environments in our training data. As a result, we would expect to hindcast/forecast these environments more accurately.

Additionally, the habitat model applied here does not explicitly incorporate a variable for access to low-energy shorelines with MOSH; e.g., bay and inlet shorelines, ephemeral pools). These areas offer important foraging habitats for piping plovers and their chicks prior to fledging (Cohen & Fraser, 2010; Loegering, 1992; Maslo et al., 2012) and have been shown to be an important factor in piping plover habitat selection patterns in certain regions (Zeigler et al., 2021). Because on-the-ground observations of distance to MOSH were not made for nest and random points in the training data set, there was a concern that important foraging habitats (e.g., ephemeral pools not appearing in the aerial photographs) were not adequately considered in models of habitat selection patterns. Furthermore, as discussed in the next paragraph, the geomorphology BNs do not currently model forecasted changes to the back-barrier shoreline or smaller ephemeral water bodies. To further examine the impact of not including this variable, we analyzed the amount of habitat as predicted by the PIPLBN with and without the variable “distance to MOSH” (which was contained in the original habitat model; Zeigler et al., 2021). The BN with consideration of access to MOSH predicted that 23.8% of Fire Island would support piping plover habitat compared to 27.4% predicted by the model without the MOSH variable (results not shown). Therefore, without a variable for access to foraging habitat, BNs may slightly over-predict habitat availability.

Another potential limitation of the framework is that the geomorphology BNs do not explicitly include back-barrier shoreline changes. While elevation, substrate, vegetation, and barrier width can be used to forecast back-barrier conditions, there are important additional characteristics that are not considered by these BNs that influence back-barrier shoreline conditions. For example, overwash processes, longshore transport, and marsh accretion can have substantial impacts on the position of the back-barrier shoreline (Davis jr, 1994; Leatherman, 1979; Oertel, 1985; Riggs & Ames, 2006). Additional variables or BNs could be added to the framework in the future to more adequately address back-barrier processes (Plant et al., 2018). This will be particularly important when modeling barrier islands with less human management and limited, if any, stabilization structures. For a full
discussion of this, see our companion paper (Zeigler et al., 2022). As we expand this framework to other barrier island settings, future work can examine how and where incorporating these parameters may have the greatest impact.

Despite these limitations, a linked BN model approach can be applied to address a variety of management challenges where detailed environmental observations or information might be limited. For example, with what is known regarding piping plover habitat preferences represented in the PIPLBN, we can use the FSBN-CSBN to evaluate the probability of those preferred settings occurring at specific barrier island locations where plover management is a concern. Because these BNs can be used to provide us with generalized information about barrier island evolution, this approach is applicable to regional evaluations of morphologic change and habitat availability that can help managers identify and prioritize prime locations for conservation efforts or the need for more detailed study. In one specific case on Assateague Island National Seashore, it was observed that a protective berm constructed to protect the island from overwash, degraded piping plover habitat over time. In that case, on-the-ground management experience informed the decision to create washover pathways which improved habitat (Gieder et al., 2014; Schupp et al., 2013). In the future, a BN framework such as this can be used to explore the impacts of management activity to inform similar decisions.

Finally, scenarios based on informed assumptions can be used as a way to explore model outcomes when uncertainties are considerable (Moss et al., 2010), especially when few inputs are specified with the linked BN framework. Aside from uncertainty arising in our BNs, there are major sources of uncertainty regarding the future of barrier island systems, including our case study system at Fire Island. First, with higher probabilities of SLR (Sweet et al., 2022), there is a higher probability of rapid coastal erosion over the 21st century. Second, a significant portion of the coast has undergone and will likely continue to undergo restoration in response to erosion and storm damage. These efforts, which often include beach nourishment and dune building, can alter the morphology of barrier island settings in ways that differ from unmanaged sites (e.g., Dolan, 1972; Godfrey & Godfrey, 1976; Psuty & Ofiara, 2002; Riggs & Ames, 2003; Smith et al., 2008) and have large impacts on the long-term morphologies of islands and implementation of management actions to mitigate erosion, flooding, and landloss. Consequently, future island morphology will also depend on human actions, introducing uncertainty regarding the path of future management decisions. With a scenario-based approach, we can use defined assumptions to evaluate the impact of different barrier island morphologies (e.g., low-elevation vs. high-elevation islands) on habitat suitability resulting from different management scenarios as a way to constrain these uncertainties. This is explored in detail in a companion paper (Zeigler et al., 2022).

5. Summary

This study demonstrates the ability of a linked probabilistic modeling framework to provide morphological and habitat forecasts at decadal to century timescales given the potential for SLR, shoreline change, and barrier island impacts. In doing so, the resulting linked BNs provide a means of considering high uncertainty in forecasts while still allowing forecasts to be used to evaluate the potential for landscape changes at time scales that exceed numerical model prediction time scales. The described methodology also provides more detailed resolution for biogeo-morphological characteristics compared to long-term barrier island evolution models that have been developed to date. Although we found that predicting multiple variables simultaneously can lead to more uncertain predictions, this uncertainty can be handled using a scenario-based approach with user-constrained assumptions about the value of otherwise unknown variables. When constrained in this manner, error rates for morphological variables in the CSBN ranged from 11% to 37%, with distance to dune crest having the lowest error and dune crest height having the highest. Error for variables in the FSBN was 0.02%–38%, with vegetation type producing the lowest error rate and elevation the highest. When multiple variables are forecasted simultaneously, error rates were 23%–55% in the CSBN, with the lowest error occurring for distance to dune crest and the highest for dune crest height. For the FSBN, error rates were 27%–47% for multivariate predictions, with the lowest error occurring for geomorphic setting and the highest for vegetation type. Error rates for the fully linked BN framework reached a maximum of 30% in predictions of piping plover nest presence/absence.
Data Availability Statement

Data that were used in this study are reported and available in Zeigler, Sturdivant, & Gutiérrez (2019) and Sturdivant et al. (2019). The Bayesian networks used in this study are shown in the supplemental material where network structures and bin discretization can be viewed. The Matlab codes used to conduct our analysis can be obtained via Gutiérrez and Plant (2022).

Acknowledgments

Funding for this work was provided by the U.S. Geological Survey (USGS) Coastal and Marine Geology Program and the U.S. Fish and Wildlife Service with supplemental funding from the Disaster Relief Appropriations Act of 2013. We thank Anne Hecht of the U.S. Fish and Wildlife Service for providing the impetus for this study. This work grew out of the collaboration with Sarah Karpany, Katy Geider, Jim Fraser, and Dan Catlin of the Virginia Tech Department of Wildlife Conservation. We also thank colleagues in the piping plover breeding range research and management community for their perspectives on piping plover habitat. We are also grateful to E. Robert Thieler of the US Geological Survey Coastal and Marine Science Center who was involved in the early phases of this work. The work by Emily J. Sturdivant was done while serving as a Geographer with the U.S. Geological Survey. We thank Chris Sherwood of the US Geological Survey and two anonymous reviewers, as well as the editorial staff of Earth and Space Science for their comments on this manuscript. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. Although these data have been processed successfully on a computer system at the U.S. Geological Survey (USGS), no warranty expressed or implied is made regarding the display as a computer system at the U.S. Geological Survey data have been processed successfully on a computer system at the U.S. Geological Survey.

References

Aspinall, W. P., Woo, G., Vought, B., & Baxter, P. J. (2003). Evidence-based volcanology: Application to eruption crises. Journal of Volcanology and Geothermal Research, 128(1–3), 273–285. https://doi.org/10.1016/S0377-0273(03)00260-9

Bayes, T. (1763). An essay towards solving a problem in the doctrine of chances. Philosophical Transactions of the Royal Society of London, 53, 370–418.

Berger, J. O. (2000). Bayesian analysis: A look at today and thoughts of tomorrow. Journal of the American Statistical Association, 95(452), 1269–1276. https://doi.org/10.2307/2669788

Bindoff, N., Cheung, W., Kairo, J., Ariegi, J., Guindier, V., Hallberg, R., et al. (2019). Chapter 5: Changing Ocean, marine ecosystems, and dependent communities. In H.-O. Pörtner, D. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, et al. (Eds.), IPCC special report on the ocean and cryosphere in a changing climate. Intergovernmental Panel on Climate Change.

Boehtler, R., Penn, T., Cross, R. R., Terrilligier, K. T., & Beck, R. A. (2007). An overview of the status and distribution of piping plovers in Virginia. Waterbirds, 30(1), 138–151. https://doi.org/10.1675/1524-4895(2007)030[0138:atosoa]2.0.co;2

Borsuk, M. E., Stow, C. A., & Reckhow, K. H. (2004). A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecological Modelling, 174(2–3), 219–239. https://doi.org/10.1016/j.ecolmodel.2003.08.020

Brenner, O., Lenz, E., Hapke, C., Henderson, R., Wilson, K., & Nelson, T. (2018). Characterizing storm response and recovery using the beach change envelope: Fire Island, New York. https://doi.org/10.1016/j.geomorph.2017.08.004

Bruun, P. (1962). Sea-level rise as a cause of shore erosion. Journal of the Waterways and Harbors Division, 88(1), 117–130. https://doi.org/10.1061/joh.0000252

Cawley, G., & Talbott, N. (2010). On over-fitting in model selection and subsequent selection bias in performance evaluation. Journal of Machine Learning Research, 11, 2079–2107.

Chu-Agor, M., Muñoz-Carpena, R., Kiker, G., Aiello-Lammens, M., Ackakahy, H., Convertino, M., & Linkov, I. (2012). Simulating the fate of biodiversity afloat. Ecological Modelling, 393, 127–130. https://doi.org/10.1016/j.ecolmodel.2011.10.021

Cohens, M., Muñoz-Carp..., R., Kiker, G., Aiello-Lammens, M., Ackakahy, H., Convertino, M., & Linkov, I. (2011). Exploring vulnerability of coastal habitats to sea level rise through global sensitivity and uncertainty analyses. Environmental Modelling & Software, 26(5), 593–604. https://doi.org/10.1016/j.envsoft.2010.12.003

Cohn, J., & Fraser, J. (2010). Piping plover foraging distribution and prey abundance in the pre-laying period. The Wilson Journal of Ornithology, 122(3), 578–582. https://doi.org/10.1676/09-145.1

Cohn, J., Houghton, L., & Fraser, J. (2009). Nesting density and reproductive success of piping plovers in response to storm- and human-created habitat changes. Wildlife Monographs, 173(1), 1–24. https://doi.org/10.2193/2007-553

Cohens, J., Wunkir, E., & Fraser, J. (2008). Substrate and vegetation selection by nesting piping plovers. The Wilson Journal of Ornithology, 120(2), 404–407. https://doi.org/10.1676/06-1691

Costan, F., Hofmann, B., Russell, J., Leclerc, C., & Bellard, C. (2014). Climate change, Sea-Level rise, and conservation: Keeping island biodiversity afloat. Trends in Ecology & Evolution, 29(3), 127–130. https://doi.org/10.1016/j.tree.2014.01.001

Cronin, J., Tippak, D., Luke, E., Robensky, V., Tippak, J., & Marcot, B. (2021). Strategic habitat conservation for beach mice: Estimating management scenario efficiencies. Journal of Wildlife Management, 85(2), 324–339. https://doi.org/10.1002/jwmg.21983

Davis, J. R. (Ed.) (1994). Geology of holocene barrier island systems. Springer-Verlag.

Deposit, A., Laird, N., & Rubin, D. (1977). Maximum likelihoods from incomplete data via the EM algorithm. Journal of the Royal Statistical Society: Series B, 53(1), 1–22. https://doi.org/10.1111/j.2517-6161.1977.tb01600.x

Dolan, R. (1972). Man’s impact on the outer banks of North Carolina, dune stabilization study, natural resource report No. 3, U.S. Department of Interior, National Park Service, Office of Natural Science. (p. 16).

Dolan, R., Anders, F., & Kimball, S. (1988). Coastal erosion and accretion - national atlas of the United States of America, U.S. Geological Survey Sheet 1-sheet.

Dolan, R., & Petross, J. (2007). Data supplement to the U.S. Geological Survey 1/2,000,000-scale map of shoreline erosion and accretion of the mid-Atlantic coast. U.S. Geological Survey Open-File Report (pp. 92–377).

Doran, K., Long, J., Birchler, J., Brenner, O., Hardy, M., Morgan, K., et al. (2017). Lidar-derived beach morphology (dune crest, dune toe, shoreline) for U.S. sandy coastlines. U.S. Geological Survey data release. https://doi.org/10.5066/F7GF0G5Z

Esri. (2021). ArcGIS Pro ver. 2.0. Environmental Systems Research Institute, [Mapping and Computing Software]. https://pro.arcgis.com/en/pro-app/latest/get-started/whats-new-in-arcgis-pro.htm

Fielding, A. H., & Bell, J. F. (1997). A review of methods for assessment of prediction errors in conservation presence/absence models. Environmental Conservation, 24(1), 38–49. https://doi.org/10.1017/S0376892997000088

Fienen, M., Masterson, J., Plant, N., Gutiérrez, B., & Thieler, E. (2013). Bridging groundwater models and decision support with a Bayesian network. Water Resources Research, 49(10), 6459–6473. https://doi.org/10.1002/wrcr.20496

Fienen, M., & Plant, N. (2015). A cross-validation package driving Netica with python. Environmental Modelling & Software, 63, 14–23. https://doi.org/10.1016/j.envsoft.2014.09.007

Galbraith, H., DesRochers, D., Brown, S., & Reed, J. (2014). Predicting vulnerabilities of North American shorebirds to climate change. PLoS One, 9, e108899. https://doi.org/10.1371/journal.pone.0108899

Gelman, A., Carlin, J., Stern, H., & Rubin, D. (1995). Bayesian data analysis. Chapman & Hall.

Gieder, K. (2015). Assessing the effects of sea-level rise on piping plover (Charadrius melodus) nesting habitat and the ecology of a key mammal shorebird predator on Assateague Island. (PhD). Virginia Tech.
Gieder, K., Karpanty, S., Fraser, J., Catlin, D., Gutierrez, B., Plant, N., et al. (2014). A Bayesian network approach to predicting nest presence of the federally-threatened piping plover (Charadrius melodus) using barrier island features. Ecological Modelling, 276, 38–50. https://doi.org/10.1016/j.ecolmodel.2014.01.005

Godfrey, P. J., & Godfrey, M. F. M. (1976). Barrier island ecology of cape lookout national Seashore and vicinity, National Park Service Scientific Monograph Series. (Vol. 9, p. 160).

Gutierrez, B., Plant, N., Pendleton, E., & Thieler, E. (2014). Using a Bayesian network to predict shoreline-change vulnerability to sea-level rise for the coasts of the United States. United States Geological Survey open file report 2014-1083. https://doi.org/10.13130/20141083

Gutierrez, B., Plant, N., & Thieler, E. (2011). A Bayesian network to predict coastal vulnerability to sea level rise. Journal of Geophysical Research, 116(F2), F02009. https://doi.org/10.1029/2010j001891

Gutierrez, B., Plant, N., Thieler, E., & Turecek, A. (2015). Using a Bayesian network to predict barrier island geomorphic characteristics. Journal of Geophysical Research: Earth Surface, 120(12), 2451–2475. https://doi.org/10.1002/2015jf003671

Gutierrez, B. T., & Plant, N. G. (2022). LinkedBNs4Habitat. U.S. Geological Survey software code. https://doi.org/10.5066/P9R63EMY

Hammar-Klose, E., & Thieler, E. (2001). Coastal vulnerability to sea-level rise—a preliminary database for the U.S. Atlantic, Pacific, and Gulf of Mexico coasts. U.S. Geological Survey Digital Data Series DDS-68. Retrieved from http://pubs.usgs.gov/ds/ds68/

Hapke, C., Brenner, O., Hehre, R., & Reynolds, B. (2013). Coastal change from Hurricane sandy and the 2012-2013 winter storm season: Fire Island, U.S. Geological Survey Open-File Report 2013-1231. Retrieved from https://pubs.usgs.gov/of/2013/1231/

Hapke, C., Lentz, E., Gayes, P., McCoy, C., Hehre, R., Schwab, W., & Williams, S. (2010). A review of sediment budget balances along Fire Island, New York. Can nearshore geologic framework and patterns of shoreline change explain deficit? Journal of Coastal Research, 26(3), 510–522. https://doi.org/10.2112/08-1140.1

Hapke, C., Nelson, T., Henderson, R., Brenner, O., & Miesel, J. (2017). Morphologic evolution of the wilderness area breach at Fire Island, New York—2012–2015. U.S.Geological Survey open-file report 2017-1116. https://doi.org/10.3133/ofr20171116

Himmelstoss, E., Kratzmann, M., Hapke, C., Thieler, E., & List, J. (2010). The national assessment of shoreline change: A GIS compilation of vector shorelines and associated shoreline change data for the new England and mid-atlantic coasts. U.S. Geological Survey open-file report 2010-1119. Retrieved from https://pubs.usgs.gov/of/2010/1119

Hubertz, J., Thompson, E., & Wang, H. (1996). Wave information studies of U.S. Coastlines—annotated bibliography on coastal and ocean data assimilation: WIS report 36.

Korb, K., & Nicholson, A. (2004). Bayesian artificial intelligence. Chapman & Hall/CRC.

Korup, O. (2021). Bayesian geomorphology. Earth Surface Processes and Landforms, 46(1), 151–172. https://doi.org/10.1002/esp.4995

Lacy, R., Miller, P., Nyhus, P., Pollak, J., Raboy, B., & Zeigler, S. (2013). Metamodels for transdisciplinary analysis of wildlife population dynamics. PLoS One, 8(12), e84211. https://doi.org/10.1371/journal.pone.0084211

Lauritzen, S. (1995). The EM algorithm for graphical association models with missing data. Computational Statistics & Data Analysis, 19(2), 191–201. https://doi.org/10.1016/0167-9473(93)ee0056-a

Leatherman, S. (Ed.) (1979). Barrier islands: From the Gulf of St. Lawrence to the Gulf of Mexico. Academic Press.

Lentz, E., & Hapke, C. (2011). Geologic framework influences on the geomorphology of an anthropogenically modified barrier island: Assessment of dune/beach changes on Fire Island, New York. Geomorphology, 126(1–2), 82–96. https://doi.org/10.1016/j.geomorph.2010.10.032

Lentz, E., Hapke, C., Stockdon, H., & Hehre, R. (2013). Improving understanding of near-term barrier island evolution through multi-decadal assessment of morphologic change. Marine Geology, 337, 125–139. https://doi.org/10.1016/j.margeo.2012.02.004

Lentz, E., Thieler, E., Plant, N., Stippa, S., Horton, R., & Gesch, D. (2016). Evaluation of dynamic coastal response to sea-level rise modifies inundation likelihood. Nature Climate Change, 6(7), 1–6. https://doi.org/10.1038/nclimate2957

Loegering, J. (1992). Piping plover breeding biology, foraging ecology, and behavior as Assateague Island National Seashore (MS Thesis). Maryland: Virginia Tech.

Loegering, J., & Fraser, J. (1995). Factors affecting piping plover chick survival in different brood-rearing habitats. Journal of Wildlife Management, 59(4), 646–655. https://doi.org/10.2307/3801940

Lorenzo-Trueba, J., & Ashton, A. (2014). Rollover, drowning, and discontinuous retreat: Distinct modes of barrier response to Sea-Level rise arising from a simple morphodynamic model. Journal of Geophysical Research, 119(4), 779–801. https://doi.org/10.1002/2013jgrd11941

Marcot, B. (2012). Metrics for evaluating performance and uncertainty of Bayesian network models. Ecological Modelling, 230, 50–62. https://doi.org/10.1016/j.ecolmodel.2012.01.013

Marcot, B. G., Woo, I., Thorne, K. M., Freeman, C. M., & Guntenpergen, G. R. (2020). Habitat of the endangered salt marsh harvest most (Reithrotomys ravnvinteri) in San Francisco Bay. Ecology and Evolution, 10(2), 662–677. https://doi.org/10.1002/eece.5860

Maslo, B., Burger, J., & Handel, S. (2012). Modeling foraging behavior of piping plovers to evaluate habitat restoration success. Journal of Wildlife Management, 76(1), 181–188. https://doi.org/10.1002/jwmg.210

Maslo, B., Handel, S., & Pover, T. (2011). Restoring beaches for Atlantic coast piping plovers (Charadrius melodus): A classification and regression tree analysis. Restoration Ecology, 19(2), 194–203. https://doi.org/10.1111/j.1526-100x.2010.00709.x

Mastrandrea, M., Field, C., Stocker, T., Edenhofer, O., Ebi, K., Frame, D., et al. (2010). Guidance note for lead authors of the IPCC Fifth Assessment report on consistent treatment of uncertainties. Retrieved from http://www.ipcc.ch

Matlab. (2018). Mapping toolbox. The Mathworks, Inc. [Scientific computing software]. https://www.mathworks.com

May, S., Dolan, R., & Hayden, B. (1983). Erosion of U.S. shorelines. EOS Transactions of the American Geophysical Union, 64(35), 521–523. https://doi.org/10.1029/edo64035p0521

May, S., Kimball, W., Grady, N., & Dolan, R. (1982). CEIS-The coastal erosion information system. Shore and Beach, 50, 19–26.

McCann, R., Marcot, B., & Ellis, R. (2006). Bayesian belief networks: Applications in ecology and natural resource management. Canadian Journal of Forest Research, 36(12), 3053–3062. https://doi.org/10.1139/j06-238

McNamara, D., Murray, A., & Smith, M. (2011). Coastal sustainability depends on how economic and coastline responses to climate change affect each other. Geophysical Research Letters, 38(7), 1–5. https://doi.org/10.1029/2011gl047207

Melillo, J., Richmond, T., & Yohe, G. (Eds.) (2014). Climate change impacts in the United States: The third national climate assessment. U.S. Global Change Research Program.

Mennan, S., Soberón, J., Li, X., & Peterson, A. (2010). Preliminary global assessment of terrestrial biodiversity consequences of sea-level rise mediated by climate change. Biodiversity & Conservation, 19(6), 1599–1609. https://doi.org/10.1007/s10531-010-9790-4

Morgan, M., & Henrion, M. (1990). Uncertainty: A guide for dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press.

Moss, R., Edmonds, J., Hibbard, K., Manning, M., Rose, S., van Vuuren, D., et al. (2010). The next generation of scenarios for climate change research and assessment. Nature, 463(7282), 747–756. https://doi.org/10.1038/nature0823
Stockdon, H., Sallenger, A., Holman, R., & Howd, P. (2007). A simple model for the spatially variable response to hurricanes. *Marine Geology*, 238(1–4), 1–20. https://doi.org/10.1016/j.margeo.2006.11.004

Stockdon, H. F., Doran, K. S., & Sallenger, A. H. (2009). Extraction of lidar based dune crest heights for use in examining the vulnerability of beaches to inundation during hurricanes. *Journal of Coastal Research*, 53, 59–65. https://doi.org/10.2112/s05-007.1

Stolper, D., List, J., & Thieler, E. (2005). Simulating the evolution of coastal morphology and stratigraphy with a new morphological-behaviour model (GEOMBEST). *Marine Geology*, 218(1–4), 17–36. https://doi.org/10.1016/j.margeo.2005.02.019

Sturdivant, E., Thieler, E., Zeigler, S., Winslow, L., Hines, M., Read, J., & Walker, J. (2016). Biogeomorphic classification and images of shorebird nesting sites on the U.S. Atlantic coast. U.S. Geological Survey data release. https://doi.org/10.5066/F70V89X3

Sturdivant, E., Thieler, E., Zeigler, S., Winslow, L., Hines, M., Read, J., & Walker, J. (2018). Table and accompanying photographs for biogeomorphic classification of shorebird nesting sites on the U.S. Atlantic coast from March to September, 2016. U.S. Geological Survey data release. https://doi.org/10.5066/P998M9DC5

Thieler, E., Zeigler, S., Gutierrez, B., & Weber, K. (2019). *Barrier island geomorphology and shorebird habitat metrics—Four sites in New York*. U.S. Geological Survey. Retrieved from https://www.sciencebase.gov/catalog/item/5d0fc949e4b0941bde4fc630

Sweet, W. V., Hamlington, B. D., Kopp, R. E., Weaver, C. P., Barnard, P. L., Bekait, D., et al. (2022). Global and regional sea level rise scenarios for the United States: Up-dated mean projections and extreme water level probabilities along U.S. coastlines. In *NOAA technical report NOS 01*. National Ocean Service.

Thieler, E., & Hammar-Klose, E. (1999). National assessment of coastal vulnerability to future Sea-Level rise: Preliminary results for US Atlantic coast (pp. 99–93). U.S. Geological Survey Open-File Report. Retrieved from https://pubs.usgs.gov/of/1999/of99-593

Thieler, E., Winslow, L., Hines, M., Read, J., Walker, J., & Zeigler, S. (2016). Smartphone-based distributed data collection enables rapid assessment of shorebird habitat suitability. *PLoS One*, 11(11), e0164979. https://doi.org/10.1371/journal.pone.0164979

Titus, J., Anderson, K., Cahoon, D., Gesch, D., Gill, S., Gutierrez, B., et al. (2009). Coastal sensitivity to Sea-Level rise: A focus on the mid-Atlantic region. U.S. Climate change science Program synthesis and assessment product (Vol. 4, p. 1).

U.S. Fish and Wildlife Service. (1996). *Piping plover (Charadrius melodus) atlantic coast population revised recovery plan*. U.S. Fish and Wildlife Service. (p. 245).

Uusitalo, L. (2007). Advantages and challenges of Bayesian networks in environmental modelling. *Ecological Modelling*, 203(3–4), 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033

Weber, K., List, J., & Morgan, K. (2005). An operational mean high water datum for determination of shoreline position from topographic Lidar data. U.S. Geological Survey Open-File Report 2005-1027. Retrieved from http://pubs.usgs.gov/of/2005/1027/

Wilson, K., Lentz, E. E., Miselis, J. L., Safak, I., & Brenner, O. T. (2019). A Bayesian approach to predict sub-annual beach change and recovery. *Estuaries and Coasts*, 42(1), 112–131. https://doi.org/10.1007/s12237-018-0444-1

Zeigler, S., Gutierrez, B., Hecht, A., Plant, N., & Sturdivant, E. (2021). Piping plovers demonstrate regional differences in nesting habitat selection patterns along the U.S. Atlantic coast. *Ecosphere*, 12(3), e03418. https://doi.org/10.1002/ecs2.3418

Zeigler, S., Gutierrez, B., Sturdivant, E., Catlin, D., Fraser, J., Hecht, A., et al. (2019). Using a Bayesian network to understand the importance of coastal storms and undeveloped landscapes for the creation and maintenance of early successional habitat. *PLoS One*, 14(7), e0209986. https://doi.org/10.1371/journal.pone.0209986

Zeigler, S., Sturdivant, E., & Gutierrez, B. (2019). Evaluating barrier island characteristics and piping plover (Charadrius melodus) habitat availability along the U.S. Atlantic coast—geospatial approaches and methodology. https://doi.org/10.13133/6f220191071

Zeigler, S., Thieler, E., Gutierrez, B., Plant, N., Hines, M., Fraser, J., et al. (2017). Smartphone technologies and Bayesian networks to assess shorebird habitat selection. *Wildlife Society Bulletin*, 41(4), 666–677. https://doi.org/10.1002/wsb.820

Zeigler, S. L., Gutierrez, B. T., Lentz, E. E., Plant, N. G., Sturdivant, E. J., & Doran, K. S. (2022). Predicted sea-level rise-driven biogeomorphic changes on Fire Island, New York: Implications for people and plovers. *Earth’s Future*, 10(4), e2021EF002436. https://doi.org/10.1029/2021EF002436