RESPONSE TO REVIEWERS – *nhess-2019-159*

13 September 2019

Dear Editors –

We thank you and the two reviewers for your time, and for the opportunity to revise this submission. Here we offer detailed responses to the comments made by both reviewers (whose remarks are *italicised*).

Sincerely –

Eli Lazarus (E.D.Lazarus@soton.ac.uk)
Scott Armstrong

REVIEWER #1 (Anon) Comments

(1) Introduction speaks very broadly about risk and vulnerability, when the model is based on shoreline change and vulnerability that is defined by beach width and re-nourishment. Although this paper does contribute to the discussion about coastal risk, it is a very narrow framing of this problem (for example, your vulnerability measure does not include things like social vulnerability or built environment vulnerability). I think you need to reframe the introduction to talk about what this does do well – investigate geomorphic risk and the impacts of renourishment - rather than what it doesn't.

We have sought to clarify our vantage and framing of the problem in the Abstract and Introduction (detailed replies below).

2) Results need to be rewritten to talk about the major findings and not just describe the figures.

We respectfully disagree with this characterisation of the Results section. However, in addressing R1's specific comments, we have also tried to improve the clarity of the text throughout, with an eye toward emphasising the major findings.

3) Data analysis is unclear at times (for example, how many counties are in the analysis? Do figures 7 and 9 show a count of counties or transects?). Please make sure the main details are discussed in the methods (like the statistical analysis in Figures 8 and 10).

We address these issues in detail where they appear, below.

4) To really hit home the interesting interactions between risk and renourishment, I think you need to add a spatial component – how does risk change in the model over the coastline, regionally (a color-coded map would be a great way to show this).

We suggest that this is what Figs. 1 & 2 show, albeit in a matrix rather than a spatially explicit map. (We revisit this point below.) The relationship between risk intensification in nourishment zones comes out most clearly in the shape of the statistical distributions (now Figs. 7 & 8), not in a "heat map" of their own – they are embedded in Figs. 1 & 2, but not easily seen in that format. Their collective statistical distributions are their signature.

Title: I would reframe coastal risk throughout the paper as geomorphic or shoreline erosion risk.

Noted – and see our reply, below, to the related comment on P2/Introduction.

We hew close to the formal definitions of hazard, exposure, and risk used by the US National Research Council. Those definitions are generic inasmuch as hazard, exposure, and vulnerability *types* can be substituted in. It is therefore unclear to us what "geomorphic risk" is. We can imagine geomorphic *hazard*, which is the role of shoreline change in this work. Or, because the definition of "vulnerability" is not always mutually exclusive from other components of risk, we can imagine geomorphic *vulnerability* where the susceptibility of exposed assets/people is a function of, for example, the recurrence interval of a geomorphic/natural event (e.g., hurricanes, floods, landslides). We treat vulnerability as a kind of buffer between hazard and exposure. But "geomorphic risk" is an entanglement of the three separate components (hazard, exposure, vulnerability), which we take pains to differentiate and not double-count in our analysis.

In that context, "coastal risk" is both generic and a readily accepted term. We agree with R1 that how coastal risk is then defined is essential. We have made amendments to the Abstract (see related comments below) to help make our framing/definition more readily accessible from the outset.

Abstract: Overall: The abstract does not give any description of what kind of data goes into the model or major findings. If you reframed the abstract and intro around geomorphic hazard and beach renourishment, this abstract could be a lot more specific and interesting. At the moment it is way too broad and says little about the actual study.

We have amended the Abstract (blue text) to read as follows:

"…But risk may also increase because of interactions, or feedbacks, between hazard, exposure, and vulnerability. Using empirical records of shoreline change, valuation of owner-occupied housing, and beach nourishment projects to represent hazard, exposure, and vulnerability, respectively, here we present a data-driven model that describes trajectories of risk at the county scale along the US Atlantic Coast over the past five decades. We also investigate quantitative relationships between risk components that help explain these trajectories. We find higher property exposure in counties where hazard from shoreline change has appeared to reverse from high historical rates of shoreline erosion to low rates in recent decades. Moreover, exposure has increased more in places that have practiced beach nourishment intensively. The spatio-temporal relationships that we show between exposure and hazard, and between exposure and vulnerability, indicate a feedback between coastal development and beach nourishment that exemplifies the "safe development paradox", in which hazard protections encourage further development in places prone to hazard impacts. Our findings suggest that spatially explicit modelling efforts to predict future coastal risk need to address feedbacks between hazard, exposure, and vulnerability to capture emergent patterns of risk in space and time."

Line 12: What do you mean by "indications of feedbacks"?

For clarity, corrected (P1, L14) to read "quantitative relationships" between risk components.

Page 2: Introduction generally: It is good to start out broad with risk analysis, but the introduction does not really address geomorphic risk or beach renourishment. I think you could reframe in along these lines and set the reader up much better for what is coming. At the moment it stays too broad.

We have addressed this with added text (blue) at the end of the Introduction (P2, L36):

"Here, we develop a data-driven model to investigate how hazard, exposure, and vulnerability may describe trajectories of risk in space and time along the US Atlantic Coast, from Massachusetts to South Florida, at the county-level for the past 47 years (Fig. 1). We restrict our analysis of risk to three specific components: shoreline change (hazard), valuation of owner-occupied housing units (exposure), and beach nourishment – the active, and typically repeated, placement of sand on a beach to counteract chronic erosion (vulnerability). We do not address socioeconomic or demographic exposure or vulnerability (Cutter and Emrich, 2006; Cutter and Finch, 2008; Cutter et al., 2006, 2008), nor the exposure of infrastructural aspects of the built environment beyond owner-occupied housing value. Neither do we address other types of coastal hazard, such as storm strikes or flooding, or types of hazard mitigation other than beach nourishment. Despite this tightly defined framing, our analysis captures underlying quantitative relationships between risk components. Our findings suggest that spatially explicit modelling efforts to predict future coastal risk need to address feedbacks between hazard, exposure, and vulnerability to capture emergent patterns of risk in space and time."

Lines 4-7: Add citations to these sentences

We have amended P2, L3, to emphasise that all of these definitions are those used by the US National Research Council.

Lines 14-18: I think you can elaborate on this paragraph more and perhaps make it more about geomorphic change.

We have fixed this issue by removing the paragraph break (P2, L19). Our discussion of geomorphic change is more appropriate later in the manuscript, as we move into specifics types of hazard.

Line 24: Put the parenthetical and the citation in the same parentheses

Amended for clarity.

Line 25: This paragraph needs more connective tissue and elaboration. Also needs to be focused more on geomorphic hazard. Could also talk about "levee effects" as another example of safe development paradox.

We have addressed this comment by amending the final paragraph of the Introduction (P2, L36) (excerpted above). We have also added references to the land-use-management and/or levee paradox (P2, L26): White, 1945; Burby & French, 1981; and Di Baldassare *et al.*, 2016.

Lines 30-36: This paragraph still doesn't tell the reader what to expect going forward. Need to add objectives and specify that you are looking at shoreline change and beach renourishment as a subset of coastal risk.

Changes to the final paragraph of the Introduction (P2, L36) likewise address this comment.

Page 3: Line 7: How many counties?

Amended (P3, L13) to state that we examine 51 coastal (ocean-facing) counties.

Line 20: Are there different points in time for the first survey?

We have amended this line (blue text), at P3, L29, to read:

"Because the dates of shoreline surveys vary by location, following Armstrong and Lazarus (2019) we calculate shoreline-change rates using the available surveys at each transect that are closest to the start- and end-date of each period. We calculated…"

Page 4: Lines 20-28: The exposure you define here is capital exposure. Could you add in number of structures as a way to estimate count or some variable related to population number. Additionally, you are using the whole county as a way to get at the value of just beach front properties. This assumption could be wrong in places where there is less of a beach front community or tourism. You are assuming that the whole county is exposed to beachfront erosion.

We agree that parcel-scale granularity of the housing stock would be optimal, especially because waterfront properties tend to be more expensive than inland ones. But using the county-scale data is not the same as assuming the whole county is directly exposed to erosion. It is simply an indicator of relative exposure. Because three factors contribute to risk, a hypothetical county like the one R1 is imagining – with high county-scale exposure but little beach-front development – may return a low risk index if its erosion rates are low and/or it doesn't nourish.

Still, in the context of beach nourishment (and hazard mitigation more broadly), oceanfront landowners are not the only people involved in mitigation actions. "Local governance" can include decision-making at the county scale, and governance processes vary by state. With the Census data available (which we use because they offer maximum spatial and temporal coverage of the domain), there is neither a perfect metric for exposure, nor an alternative metric that is unequivocally better than the one we choose (total value divided by length of county oceanfront).

Line 23: How are you dealing with uncertainty in this dataset? If there are whole counties missing, how much of other counties is missing? Would it be valuable to only use counties with low missingness?

We use the Census data with the most complete coverage available. The other areas of uncertainty in this analysis – the shoreline change measurements, our treatment of vulnerability – mean that whatever vagaries exist in the Census data are no more extreme than those inherent in the other components.

We do test the sensitivity of the analysis to those elements with the greatest potential to systematically affect our results. We present the various trajectories defined by different treatments of shoreline change rates, and by different parameters in our representation of temporal dynamics of beach nourishment. Through these tests, we understand what the model is doing – and that is perhaps the best way we can deal with uncertainty in this exploratory context.

Line 31: The vulnerability you are talking about here is just geomorphic vulnerability. These terms do not capture social vulnerability or built environment vulnerability. You should be clear about this from the beginning of the paper.

Now addressed by clarifications in the Introduction and Discussion.

Page 5: Lines 7: What dataset is the beach width coming from?

We do not use a dataset for beach width. At P5, L11, we state that "because real measurements are unavailable, we assumed that in 1970 all counties had the same beach width." There are no annual surveys of beach width for the US Atlantic Coast; this aspect of our model is parameterized based on best-available references.

Line 13: What about places that have a beach shoreline and then an interior shoreline (i.e. coastal lagoons)?

We now state at P5, L18, that we do not consider back-bay (interior) shorelines.

Line 18: Does the size of the renourishment play a role in the vulnerability change? Seems like the size would determine the change in vulnerability across the county.

We agree, but the nourishment dataset does not include volume for all projects over time (especially for projects farther back in time). We use total number of projects as a way to at least represent relative volume and/or renourishment activity over time. Indeed, not all nourishment projects involve the same volume of sediment, but the US does not (yet) use singular, Dutch-style "mega-nourishments" either.

Page 6: Result Overall: The results section needs to be rewritten. At the moment, much of it just describing figures without much narrative. Start your paragraphs out with a verbal description of the main finding for the paragraph and then get into the details. Additionally, there are results described here that are not discussed in the methods section (statistical analyses). Also some paragraphs are very short – two sentences in not a paragraph.

We appreciate the suggestion, but perhaps do not see the same issue. None of the topic sentences in our Results, as written, simply introduce figures. R1 notes, "Start your paragraphs out with a verbal description of the main finding for the paragraph and then get into the details," but by our reading, we do that. (Where there is perhaps more "narrative", R1 suggests in a comment below that the text be moved to the Discussion.)

We have added a statistical analysis section to the Methods, as recommended.

With our amendments to the framing of the argument and analysis, we have tried to more clearly motivate the Results overall.

Page 7: Line 18: Table 1 is a great example of why this risk analysis needs to be reframed. Although Miami-Dade is subject to high probably of hurricane and king tides and high social vulnerability, it has a coastal risk of 0.08. This shows how this analysis is not a full reflection of total coastal risk, but more of geomorphic or shoreline erosion risks.

We do not claim that this work is a "full reflection" of total coastal risk. We have aimed to better align readers' expectations with our changes to the Introduction.

Lines 35-37: Your findings would be more realistic if you only included parts of the county that were most at risk of hazards from the coast and not the whole county.

We agree – but see related comment above.

Page 8: Line 11: Could you add some numbers about the peak of mode or the skew- ness to add some quantitative metrics to this description?

We have added summary statistics in a supplementary table (Table S5.)

Lines 13-15: Add these statistical steps to the methods section.

Amended as suggested at P7, L8.

Lines 25-27: Again add numbers about modes and skewness to add quantitative metrics to the description.

As above.

Lines 28-34: Much of this paragraph seems like discussion.

Noted. As written, this paragraph ties off the findings and what they mean, setting up the wider implications in the Discussion. Given its technical detail, we have opted to leave it in the Results (P9, L18), rather than move it into the less technical Discussion.

Page 9: Discussion overall: Again, this goes very broad and general for a study that is on geomorphic risk. I think you should really find those 2-3 results you want to highlight and talk about them here without taking it too broad. Would also consider making the analysis explicitly spatial (see comment below).

We appreciate the suggestion – but again perhaps this comes down to a difference of stylistic preference. With the amended framing of the Introduction, the broader scope we consider in the Discussion should now be better anchored.

Lines 7-9: This is a great finding! And should be highlighted in the abstract.

We have amended the Abstract as suggested (excerpted above).

Line 20: Also no measures of social or built environment vulnerability. . ..

Amended (blue text) to read:

"…thus excluding other potential measures of exposure, such as socio-economic indices (e.g., Cutter et al., 2006, 2008; Neumann et al., 2015; NRC, 2014; Samuels and Gouldby, 2009; Strauss et al., 2012), and requiring that we spatially aggregate our analysis to county scales. Finally, our measure of vulnerability – intended to represent "susceptibility" (NRC, 2014; Samuels and Gouldby, 2009) without double-counting exposure or hazard – includes no method of shoreline protection other than beach nourishment, and no explicit inclusion of storm recurrence or severity…."

Line 29: I think you could really hit this out of the park with some spatial discussion. What are the regional trends? What types of counties seems to be most at risk? A map color coded for risk would also be a great addition.

We offer that these are the color-coded patterns shown in Figs. 1 & 2. We have opted not to include a spatially explicit map in part because the trajectories of risk become more difficult to render, as opposed to in the matrix format we use. (Secondarily, the matrices also help reinforce that these results, though interesting and robust, are exploratory.)

Figure 1: Why does it seem that some counties have more rows than others? Are you just labelling some of them? Or do some counties have multiple rows?

This scaling is explained at the very start of the Results (P7, L18), but we have added this explanation to the caption.

Figure 5: How are these rates calculated? What is the difference between historical and long-term?

Explanation of these trajectories (and the relative differences in their calculation) are provided on P3, L28.

Figures 7 and 9: How are the counts so high in these figures? If you only have 51 counties, shouldn't they be lower? Otherwise you are applying the same county level exposure number across multiple shoreline transects? I would suggest making these figures over counties and not transects. Additionally, is exposure normalized by area? Because otherwise this just shows that bigger counties with more resources for nourishment are adding more property, if I am reading this correctly (not sure if I am reading it correctly because of the count issue I brought up above).

We have amended the captions to specify that the distributions are transect-level, and have added the following text (in blue) to the beginning of Section 3.2, on "Component relationships" (P8, L26):

Finally, we compared the statistical distributions of exposure in high- and low-hazard counties, and in high- and low-intensity nourishing counties (as an aspect of vulnerability), to examine whether the three components of risk, as we represent them, reflect temporal interrelationships. In keeping with the scaled stripes in Figures 1, 2, and 4, we present these distributions (Figs. 7, 8) at the transect scale rather than the county scale to better represent the contributions of counties by their coastal extents. For example, Queens County, NY, hosts a high density of exposure per alongshore kilometere – very high exposure and a short coastline – and contributes only four transects to the total (Fig. 2). Likewise, because of its size, Dare County, NC, has both high exposure and a longer shoreline, resulting in a lower value of exposure per alongshore kilometre that accounts for over 100 transects of the domain. Overall, Dare County is less densely developed than Queens County. However, our treatment of exposure does overlook concentrated areas of high-density development within otherwise low-density counties – hotspots at which hazard, exposure, and vulnerability (i.e. nourishment activity) may be closely related.

Figure 8 and 10: The p-value part of the figures is a bit unnecessary. I think you could use words in the results section to describe this. Also the y-axes, particularly in Figure 8, are misleading. It makes it look like the difference in exposure is huge, when in reality it is less than 0.1. Please make axes consistent (across historical and recent) and bigger range on the figure to better represent what is actually happening.

We have amended these figures for clarity, but also shifted them to the Supplement, given their supportive roles for Figs 7 & 8 (formerly Fig. 9), respectively.

REVIEWER #2 (JLT) Comments

Page 4-Line31: . . . that tracks the vulnerability associated with beach width (Vbw) and beach nourishment (Vbn)...

Corrected.

Page 5-Lines 5-10: Equation (3) suggests that Vbw is equal to 1 when x=xo. Is 1 just an arbitrary value? If this is the case, I suggest the authors clarify this in the text. Additionally, the authors normalize Vbw by the min and max of Vbw (as we can see in Figure 3 and 6, for instance). Being this the case, would it be easier to write the normalized expression as Vbw = 1-x/xo?

We have corrected Eq. (3), and clarified that V_{bw} is a normalised value.

Page 5-Line 7: . . . in 1970 all counties had the same beach width (x). . .. The use of "x" in this case might be misleading. I believe "x" is the beach width at any point in time, not just in 1970.

Corrected (by deleting reference to *x*).

Line 15-20: I suggest the authors include the equation used to calculate Vbn. Including this expression will also help to better understand lines 20-32 in the results section (page 7).

We have added a new Eq. 4 (P5, L25) to show the expression we describe.

Additionally, I suggest the authors better explaining why as beach nourishment volume and frequency increases, the vulnerability of a coastal community increases. I can see why this is the case, but it might not be intuitive. Is it perhaps due to the community becoming dependent on such practices, which in turn depend on the availability of a limited resource?

Addressed with new text and citations at P7, L1.

The new text (in blue) reads:

"Like a ratchet, the cumulative beach-nourishment factor (V_{bn}) increases each time a county nourishes. This assumption represents the fact that nourishment projects for shoreline protection (as opposed to reactionary projects for emergency storm response) are cyclical within multi-decadal programmes (NRC 1995, 2014). Nourishment at a given site rarely occurs only once. A community that initiates a nourishment programme will likely depend on periodic nourishment into the future. By comparison, the beach-width factor (V_{bw}) is more dynamic, reflecting the oscillatory behaviour of a nourishment cycle at multi-annual time scales by dropping to a minimum after a nourishment project (as the wide beach buffers property from hazard) and then increasing as the nourished beach erodes and coastal properties become more susceptible to hazard."

Page 7 – Line 15: Would it be useful to mention here that the shoreline erosion rate predicted by bathtub models often underestimates the natural rate of erosion? This is particularly the case in barrier island environments, which are quite common in the region of study included in this manuscript.

We have added this caveat and an appropriate reference at P4, L15, and at P7, L31:

Our estimation is effectively a "bathtub model" of change, controlled only by topography with no incorporation of wave-driven sediment transport or other shoreline dynamics. Bathtub models tend to underpredict shoreline erosion rates in wave-dominated, sandy barrier settings, such as those of the US Mid-Atlantic (Lorenzo-Trueba and Ashton, 2014; Wolinsky and Murray, 2009).

The alongshore mean rate derived from sea-level rise shows close agreement with the mean "recent" shoreline-change rate, suggesting that our simplified "bathtub" representation of hazard is a reasonable proxy on a multi-decadal time scale (Fig. 5), even though bathtub models tend to underestimate shoreline erosion rates along barrier coastlines (Lorenzo-Trueba and Ashton, 2014; Wolinsky and Murray, 2009).

Page 7 – Line 18: . . .we ranked each county by its risk. . .

Corrected.

Reconstructing patterns of coastal risk in space and time along the US Atlantic Coast, 1970–2016

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Abstract. Despite interventions intended to reduce impacts of coastal hazards, the risk of damage along the US Atlantic Coast continues to rise. This reflects a long-standing paradox in disaster science: even as physical and social insights into disaster events improve, the economic costs of disasters keep growing. Risk can be expressed as a function of three components: hazard, exposure, and vulnerability. Risk may be driven up by coastal hazards intensifying with climate change, or by increased exposure of people and infrastructure in hazard zones. But risk may also increase because of interactions, or feedbacks, between hazard, exposure, and vulnerability. Using empirical records of shoreline change, valuation of owner-occupied housing, and beach nourishment projects to represent hazard, exposure, and vulnerability, respectively, here we present a data-driven model that describes trajectories of risk at the county scale along the US Atlantic Coast over the past five decades. We also investigate quantitative relationships between risk components that help explain these trajectories. We find higher property exposure in counties where hazard from shoreline change has appeared to reverse from high historical rates of shoreline erosion to low rates in recent decades. Moreover, exposure has increased more in counties that have practiced beach nourishment intensively. The spatio-temporal relationships that we show between exposure and hazard, and between exposure and vulnerability, indicate a feedback between coastal development and beach nourishment that exemplifies the "safe development paradox", in which hazard protections encourage further development in places prone to hazard impacts. Our findings suggest that spatially explicit modelling efforts to predict future coastal risk need to address feedbacks between hazard, exposure, and vulnerability to capture emergent patterns of risk in space and time.

1 Introduction

Risk reduction in developed coastal zones is a global challenge (Parris et al., 2012; Sallenger et al., 2012; Witze, 2018; Wong et al., 2014). Risk can be expressed as a function of hazard, exposure, and vulnerability. In the terminology of the US National Research Council (NRC, 2014; Samuels and Gouldby, 2009), hazard is typically expressed as the likelihood that a natural hazard event will occur (e.g., a recurrence interval for a storm of a given magnitude) or as a chronic rate of environmental forcing (e.g., a rate of sea-level rise). Exposure tends to capture either the economic value of property and infrastructure that a hazard could negatively impact, or the number of people a hazard could affect. Vulnerability can reflect a wide variety of dimensions, but in physical terms (relative to social metrics) vulnerability generally represents the susceptibility of exposed property to potential damage by a hazard event (NRC, 2014). Although the reduction of disaster risk – across all environments, not only coastal settings – is an intergovernmental priority (UNISDR, 2015), a paradox has troubled disaster research for decades. Even as scientific insight into physical and societal dimensions of disaster events get clearer and more nuanced, the economic cost of disasters keeps rising (Blake et al., 2011; Mileti, 1999; Pielke Jr. et al., 2008; Union of Concerned Scientists, 2018).

There are a number of possible explanations for this trend. Economic costs could be rising because natural hazards, exacerbated by climate change, are getting worse (Estrada et al., 2015; Sallenger et al., 2012); because with migration and population growth more people are living in hazard zones (NOAA, 2013); or because more infrastructure of economic value, from highways to houses, now exists in hazard zones (AIR Worldwide, 2013; Desilver, 2015; Union of Concerned Scientists, 2018). These drivers are typically addressed separately – but they are not mutually exclusive. A parallel explanation for the disaster paradox is that environmental, population, and infrastructural drivers are systemically intertwined, resulting in "disasters by design" (Mileti, 1999) – unintended consequences of coupled interactions, or feedbacks, between natural forcing and societal shaping of the built environment. An example of one such feedback is when infrastructure development in hazard zones destroys natural features that would otherwise buffer hazard impacts, such as the loss of coastal wetlands that would have absorbed storm surge (Barbier et al., 2011; Arkema et al., 2013; Temmerman et al., 2013). An example of another feedback is when hazard defences stimulate further infrastructure development behind them – a phenomenon called the "land-use-management paradox", "levee effect" or "levee paradox", or the "safe development paradox" (Armstrong et al., 2016; Burby and French, 1981; Burby, 2006; Di Baldassarre et al., 2016; Keeler et al., 2018; McNamara and Lazarus, 2018; Werner and McNamara, 2007; White, 1945). While both feedbacks can increase hazard impacts without any change in natural forcing, climate change accelerates them.

Investigations of coastal risk tend to focus on case studies of hazard, exposure, and/or vulnerability (Smallegan et al., 2016; Taylor et al., 2015), or on projections of future risk (e.g., Brown et al., 2016; Hinkel et al., 2010; Neumann et al., 2015). Few examine patterns of risk across large spatial scales (~10^2–10^3 km) or retrospectively over longer time scales (>10^1 yrs). Here, we develop a data-driven model to investigate how hazard, exposure, and vulnerability may describe trajectories of risk in space and time along the US Atlantic Coast, from Massachusetts to South Florida, at the county-level for the past 47 years (Fig. 1). We restrict our analysis of risk to three specific components: shoreline change (hazard), valuation of owner-occupied housing units (exposure), and beach nourishment – the active, and typically repeated, placement of sand on a beach to counteract chronic erosion (vulnerability). We do not address socioeconomic or demographic exposure or vulnerability (Cutter and Emrich, 2006; Cutter and Finch, 2008; Cutter et al., 2006, 2008), nor the exposure of infrastructural aspects of the built environment beyond owner-occupied housing value. Neither do we address other types of coastal hazard, such as storm strikes or flooding, or types of hazard mitigation other than beach nourishment. Despite this tightly defined framing, our analysis captures underlying quantitative relationships between risk components. Our findings suggest that spatially explicit modelling efforts to predict future coastal risk need to address feedbacks between hazard, exposure, and vulnerability to capture emergent patterns of risk in space and time.

2 Methods

Using the components of risk broadly defined by the US National Research Council (NRC, 2014; Samuels and Gouldby, 2009), we represent coastal risk as a function of time (t) with the expression:

$$\boldsymbol{R(t)} = \boldsymbol{H\,E\,V} \tag{1}$$

where R is coastal risk, H is natural hazard, E is exposure, and V is vulnerability. We define hazard (H) in terms of chronic shoreline erosion (as opposed to the likelihood of a hazard event). We define exposure (E) in terms of the total property value of owner-occupied housing units in 51 US Atlantic coastal (ocean-facing) counties. We address vulnerability (V) as a function of beach width, modulated by beach nourishment, which functions as a buffer between hazard and exposure (Armstrong and Lazarus, 2019; Armstrong et al., 2016).

2.1 Hazard

We calculated rates of shoreline change in two different ways to compare their respective effects on risk over time.

2.1.1 Shoreline-change rates from shoreline surveys

First, we calculated "end-point" rates of change from surveys of shoreline position published by the US Geological Survey (USGS) (Himmelstoss et al., 2010; Miller et al., 2005). An end-point rate is the cross-shore distance between two surveyed shoreline positions, divided by the time interval between the surveys. Using the Digital Shoreline Analysis System (DSAS) tool for Arc GIS (Thieler et al., 2008), we cast cross-shore transects every 1 km alongshore to intersect the surveyed shorelines, and at each transect calculated the end-point rate for three time periods (Armstrong and Lazarus, 2019): "historical", from the first survey to 1960; "recent", from 1960 to the most recent survey; and "long-term", from the first survey to most recent (Fig. 2a, e, i; Fig. 3a). Because the dates of shoreline surveys vary by location, following Armstrong and Lazarus (2019) we calculate shoreline-change rates using the available surveys at each transect that are closest to the start- and end-date of each period. We calculated the median historical, recent, and long-term rates of shoreline change for each county alongshore.

We used 1960 to differentiate between historical and recent shoreline-change rates because during that decade, beach nourishment overtook shoreline hardening to become the predominant form of coastal protection in the United States (NRC, 1995, 2014). Cumulative, diffuse effects of nourishment are therefore embedded in recent and long-term rates of shoreline change (Hapke et al., 2013; Johnson et al., 2015). We report long-term end-point rates for context, because they are common in other shoreline-change studies, particularly for the US Mid-Atlantic region (Hapke et al. 2013). However, a historical rate calculated from shorelines surveyed prior to 1960 may better reflect environmental forcing in the effective absence of beach nourishment (Armstrong and Lazarus, 2019). Historical rates are not "natural" rates: human alterations to the US Atlantic Coast began long before 1960, with engineered protection, including seawalls, groyne fields, and limited beach-nourishment projects (Hapke et al., 2013). Here, we consider them a pre-nourishment "background" rate of chronic forcing.

2.1.2 Shoreline-change rates from sea-level change rates

To test an independent measure of chronic shoreline-change hazard, we also derived rates of shoreline change (Fig. 4a, e) from recorded rates of sea-level change (Holgate et al., 2013; PSMSL, 2018) and a USGS dataset of cross-shore slope for the US Atlantic Coast (Doran et al., 2017). We calculated spatially distributed rates of sea-level rise from annual tide-gauge records maintained by the Permanent Service for Mean Sea Level (PSMSL) (Holgate et al., 2013; PSMSL, 2018). For each tide-gauge record, we linearly interpolated across gaps in the annual data. We smoothed the resulting continuous record with a 10-year moving average, and calculated the annual rate of sea-level change (Table S1). Because the tide-gauge locations are not evenly distributed alongshore, to find rates of sea-level change for the full extent of the US Atlantic Coast we linearly interpolated rates of sea-level change between tide-gauge stations, and calculated the median annual rate of sea-level change at each coastal county. To convert a vertical change in sea level to a horizontal change in shoreline position, we shifted shoreline position at each transect up (or down) cross-shore slope from USGS coastal lidar surveys (Doran et al., 2017) (Table S2). Linking the slope measurements to county shapefiles with a spatial join, we calculated median slope per county and then the horizontal distance that each annual vertical change in sea level moved the shoreline (Fig. 4a).

The relationship between sea-level change and shoreline position is more complicated than the one abstracted in our deliberate simplification (Cooper and Pilkey, 2004; Lentz et al., 2016; Nicholls and Cazenave, 2010). Our estimation is effectively a "bathtub model" of change, controlled only by topography with no incorporation of wave-driven sediment transport or other shoreline dynamics. Bathtub models tend to underpredict shoreline erosion rates in wave-dominated, sandy barrier settings, such as those of the US Mid-Atlantic (Lorenzo-Trueba and Ashton, 2014; Wolinsky and Murray, 2009). However, for this exercise, our method is useful for its simplicity – especially given the spatial scales under consideration – and for the independent estimation of shoreline change that it provides.

2.1.3 Sign convention

By the sign convention in our calculations, a negative rate of shoreline change denotes accretion (reducing hazard), and a positive rate denotes erosion (increasing hazard) (Fig. 2a, e, i). Hazard magnitudes are normalized by the minimum and maximum rates to range between 0–1.

2.2 Exposure

To represent exposure along the US Atlantic Coast, we used county-level Census data for the total value (adjusted to 2018 $USD) of owner-occupied housing units in 51 coastal (ocean-facing) counties for each decade from 1970 (Table S3) (Minnesota Population Center, 2011). Because property value data are sparse for the 2010 Census community survey (16 Atlantic coastal counties are missing), we instead used the 2009–2013 Census five-year survey. Several five-year Census surveys incorporate 2010, but we chose the 2009–2013 survey because it provides full overage of all the Atlantic coastal counties, and its mean of total values is closest to the 2010 Census community survey (for those Atlantic coastal counties surveyed in 2010). We adjusted the county-total values of owner-occupied housing units to 2018 $USD and divided by the number of transects in each county to yield a proxy for property value per alongshore kilometre. Because of the range of values along the coast, we took a log-transform and normalized the results to fall between 0–1 (Fig. 2 b, f, j; Fig. 3 b).

2.3 Vulnerability

We represented vulnerability (V) with a two-part relationship based on beach width (V_{bw}) and beach nourishment (V_{bn}) over time:

$$V = 0.5V_{bn} + 0.5V_{bw} \tag{2}$$

Because the value of exposed property is not included in V_{bw} or V_{bn}, this formulation disentangles vulnerability from exposure – a subtle but important conceptual departure from the definition used by the National Research Council (NRC, 2014; Samuels and Gouldby, 2009), which includes property values in vulnerability.

We made the beach-width component (V_{bw}) inversely related to beach width, such that vulnerability increases as beach width decreases. We express the normalised beach-width component as:

$$V_{bw} = \frac{x_0 - x}{x_0 - x_{min}} \tag{3}$$

where x_0 is maximum beach width, x_{min} is minimum beach width, and x is beach width. Because real measurements are unavailable, we assumed that in 1970 all counties had the same initial beach width. (In the results presented here, x_{min} = 10 m and x_0 = 50 m; see also Table S4). From this baseline, the county-scale shoreline erodes or accretes according to the linear rate determined by the hazard condition (historical, recent, long-term, or sea-level derived). Because we used counties as the smallest spatial unit of comparison, our assumption implies that each county is fronted by beach. The physical geography of the real coastline is, of course, more spatially heterogeneous. Our analysis is too coarse to capture, for example, change at isolated pocket beaches in a predominantly rocky coastline, but counties with rocky coastlines will reflect very low or null rates of shoreline change. We consider only oceanfront shoreline, and do not account for back-bay or estuarine shoreline.

For the beach-nourishment factor (V_{bn}), we collated beach-nourishment projects since 1970 by county from the beach-nourishment database maintained by the Program for the Study of Developed Shorelines (PSDS, 2017). We took V_{bn} as the running total number of nourishment projects per county (n_c) over time (t, summed annually), and normalized V_{bn} by the maximum number of projects among counties as of 2016 (n_c^*), such that the county that nourished the most has V_{bn} = 1 in 2016. Each county starts with V_{bn} = 0 in 1970, and V_{bn} increases incrementally with every nourishment project within the county boundary:

$$V_{bn} = \frac{\sum_{1970}^{1970+t} n_c}{max(n_c^*)} \tag{4}$$

We initiated V_{bn} in 1970 to match the Census data for exposure (E). Because 80% of beach nourishment projects on the US Atlantic Coast have occurred since 1970, we excluded a relatively small number of events. To test the sensitivity of our vulnerability and risk results to the 1970 start date, we examined the relative effects of (1) initiating V_{bn} from the first nourishment project in our record (in 1930), and (2) excluding the V_{bn} term altogether (Fig. S1). Although the risk patterns resulting from these sensitivity tests changed in detail, their general characteristics did not.

In our routine, until a county nourishes for the first time, beach width (x) changes according to the county median linear erosion rate (γ):

$$\boldsymbol{x(t) = x_{t-1} + \gamma_t} \quad (5)$$

The linear erosion rate (γ) applied to each county is either the (pre-normalised) historical, recent, or long-term shoreline change rate, or the rate derived from sea-level change, depending on the hazard scenario. The sign convention for γ is negative for erosion, and positive for accretion.

Once a county has nourished – as determined by the empirical dataset of nourishment projects (PSDS, 2017) – beach width becomes a function of a linear erosion rate (γ), as in Eq. (5), and a nonlinear erosion rate (θ), which is applied to the nourished fraction of the total beach width (μ) to capture cross-shore and alongshore diffusion of nourishment deposition across and along the shoreface (Dean and Dalrymple, 2001; Lazarus et al., 2011; Smith et al., 2009):

$$\boldsymbol{x(t) = (1-\mu)x_0 + \mu e^{-\theta t} x_0 + \textstyle\sum_1^t \gamma_t} \quad (6)$$

where x_0 is maximum beach width, θ is nonlinear erosion rate, μ is the fraction of the total beach width that the nonlinear rate applies to, γ is linear erosion rate, and t is the number of years since the last nourishment project. If a county nourishes at least once in a given year, its beach is restored to a maximum width in that year before it begins to erode. (Our minimum temporal increment was 1 year, and we assumed that nourishment always occurs at the end of a given year.) Maximum beach width (x_0), nonlinear erosion rate (θ), and the fraction of beach width affected by the nonlinear rate (μ) are variables applied to the full spatial domain. Beach width (at the county scale) thus changes at a linear rate (γ), where a negative value is erosion and a positive value is accretion, with an additional nonlinear erosion rate (θ) over a fraction of the beach (μ) when nourishment occurs, until the beach is restored to maximum width by a subsequent nourishment project or reaches a specified minimum width (here, 10 m). The V_{bn} term is ultimately normalised by the maximum and minimum beach width.

Because vulnerability is normalised, the minimum beach width that we specify (x_{min} = 10 m) affects the length of time it takes to reach maximum V_{bw}, but does not affect the overall magnitude of V. A wider minimum threshold means that V_{bw} reaches a maximum faster, and vice versa. We used a minimum width of 10 m to avoid the numerical instabilities in V_{bw} that arise with a minimum width equal to or less than 0 m. The minimum width threshold does not affect the cumulative beach-nourishment factor.

We test the effect of altering x_0, θ, and μ on both vulnerability and risk, under historical hazard and linear erosion rates (Fig. S1; Table S4). Sensitivity testing shows that vulnerability over time is highest in the case of a narrow beach (x_0 = 25 m) with a high nonlinear erosion rate (θ = 0.75) affecting a large fraction of the beach (μ = 0.75). Vulnerability over time is lowest in the opposite case (x_0 = 100 m, θ = 0.05, μ = 0.25) (Fig S1). In calculating our results, we used a case in the middle of these extremes (x_0 = 50 m, θ = 0.5, μ = 0.33), applying a value of μ similar to the value (μ = 0.35) used by Smith et al. (2009) and Lazarus et al. (2011).

Like a ratchet, the cumulative beach-nourishment factor (V_{bn}) increases each time a county nourishes. This assumption represents the fact that nourishment projects for shoreline protection (as opposed to reactionary projects for emergency storm response) are cyclical within multi-decadal programmes (NRC 1995, 2014). Nourishment at a given site rarely occurs only once. A community that initiates a nourishment programme will likely depend on periodic nourishment into the future. By comparison, the beach-width factor (V_{bw}) is more dynamic, reflecting the oscillatory behaviour of a nourishment cycle at multi-annual time scales by dropping to a minimum after a nourishment project (as the wide beach buffers property from hazard) and then increasing as the nourished beach erodes and coastal properties become more susceptible to hazard.

2.4 Statistical tests

We examine relationships between the resulting spatial distributions of hazard, exposure, and vulnerability over time using a Kolmogorov-Smirnov test that quantifies, to 95% confidence, relative differences between pairs of distributions. A Kolmogorov-Smirnov test does not require parametric distributions, and evaluates the null hypothesis that a given pair of distributions are sampled from the same parent distribution. Rejection of the null hypothesis thus means the distributions are significantly different.

3 Results

3.1 Risk trajectories

Our data-driven model generates a pattern of coastal risk that varies in space and time at county scale along the US Atlantic Coast (Fig. 1). From 1970, each county generates its own risk trajectory that represents the interaction of hazard, exposure, and vulnerability in that county (Fig. 1 a). For visualisation and analysis, we scaled each county by the number of 1 km transects they comprise (Fig. 1 a). The result is a matrix of 2386 km over 47 years, in which each of the 2386 (1 km) rows is associated with a county. Alongshore mean values for the whole US Atlantic Coast are taken from the full matrix so that they reflect the relative alongshore scale of each county (Fig. 1 b).

We find that the collective trajectory of risk increases from 1970 to 2016 for all hazard scenarios – despite the occurrence of 998 beach-nourishment projects, ostensibly intended to reduce risk, during the same period (Figs., 2, 3). The influence of beach-nourishment projects on vulnerability means that county-scale risk varies over time even if hazard forcing remains constant. Because hazard based on measured shoreline change (historical, recent, and long-term) is spatially variable but temporally static (Figs. 2, 3), changes in risk over time under this model condition are driven by either exposure or vulnerability.

The overall risk trajectory also increases with the spatio-temporally variable hazard condition derived from rates of sea-level rise (Fig. 4). The alongshore mean rate derived from sea-level rise shows close agreement with the mean "recent" shoreline-change rate, suggesting that our simplified "bathtub" representation of hazard is a reasonable proxy on a multi-decadal time scale (Fig. 5), even though bathtub models tend to underestimate shoreline erosion rates along barrier coastlines (Lorenzo-Trueba and Ashton, 2014; Wolinsky and Murray, 2009).

Individually, not all counties register rising risk trajectories over time. To compare how individual counties contribute to mean risk, we ranked each county by its risk index in 2016 (Table 1). We also examined in detail two examples of how individual counties responded to different hazards and beach-nourishment cycles (Fig. 6). Plymouth County, Massachusetts, demonstrates how vulnerability may respond to linear erosion rates (γ) that vary from eroding (negative, under the "historical" condition), to static (under the "long-term" and sea-level derived conditions), to accreting (positive, under the "recent" condition) (Fig. 6 a-d). Ocean County, New Jersey, demonstrates how the cumulative beach-nourishment factor (V_{bn}) can drive up risk (Fig. 6 e-h). There, V_{bn} causes the local maxima and minima in vulnerability to increase over time (Fig. 6 g), such that even when beaches are at full width, exposed property is still subject to vulnerability $V > 0$. Ocean County highlights how the cumulative beach-nourishment factor functions as a ratchet that forces vulnerability to only increase over time. Because not every county practices beach nourishment, it is possible for a county to have $V = 0$ if its shoreline is accreting (e.g., Camden and McIntosh Counties, Georgia). A county that never nourishes will have a $V_{bn} = 0$, and if a county nourishes only once or twice then their V_{bn} will remain negligible (but not negative). However, mean vulnerability is greater – and therefore mean risk is greater – when V_{bn} is left out ($V = V_{bw}$) (Fig. S1 c, d), because its inclusion makes vulnerability less sensitive to changes in beach width. For example, a county that does not nourish could have a narrow beach but a low V_{bn}, and therefore a lower vulnerability score than if its vulnerability were only a function of beach width.

Alongshore mean risk in our model also increases because of a well-documented national trend in exposure (NOAA, 2013). Exposure in an individual county may increase or decrease from one decade to the next, but mean exposure along the full span of the coast increases over time (NOAA, 2013; Union of Concerned Scientists, 2018). The 51 coastal counties in this analysis represent 1.6% of all US counties, but since 1970 have constituted 6.9–9.25% of the total value of all owner-occupied housing units in the country (Fig. S2). Thus, while our data-driven model includes simplifying assumptions, we suggest that the increasing risk trends in our findings represent a real phenomenon, since exposure has risen at the coast decade on decade in real terms, and our cumulative beach-nourishment factor both dampens mean vulnerability and highlights the reality of long-term risk in counties that nourish continually.

3.2 Component relationships

Finally, we compared the statistical distributions of exposure in high- and low-hazard counties, and in high- and low-intensity nourishing counties (as an aspect of vulnerability), to examine whether the three components of risk, as we represent them, reflect temporal interrelationships. In keeping with the scaled stripes in Figures 1, 2, and 4, we present these distributions (Figs. 7, 8) at the transect scale rather than the county scale to better represent the contributions of counties by their coastal extents. For example, Queens County, NY, hosts a high density of exposure per alongshore kilometere – very high exposure and a short coastline – and contributes only four transects to the total (Fig. 2). Likewise, because of its size, Dare County, NC, has both high exposure and a longer shoreline, resulting in a lower value of exposure per alongshore kilometre that accounts for over 100 transects of the domain. Overall, Dare County is less densely developed than Queens County. However, our treatment of exposure does overlook concentrated areas of high-density development within otherwise low-density counties – hotspots at which hazard, exposure, and vulnerability (i.e. nourishment activity) may be closely related.

To explore potential relationships between exposure and hazard, we sorted the exposure time series (Fig. 2) into counties associated with "high hazard" (eroding shorelines) and "low hazard" (accreting shorelines) for historical and recent shoreline change (Figs. 7 and S3). We find that exposure increases each decade in zones of high and low hazard, alike, for both historical and recent shoreline change. Under “historical” shoreline-change hazard, exposure of property value is greatest in zones of high hazard (Fig. 7 a-h, Fig. S3 a). Conversely, exposure to high hazard is relatively low for "recent" shoreline-change rates (Fig. 7 i-p, Fig S3 d), in part because recent shoreline-change rates tend to be less erosional than their historical counterparts (Fig. 3 a). The difference between relative distributions of exposure in high and low hazard zones for historical shoreline-change rates increases in significance decade on decade, with a decreasing Kolmogorov-Smirnov p-value that reflects the significance of their divergence (Fig. S3 c). There is no such temporal divergence of exposure in high and low hazard zones for recent shoreline-change rates (Fig. S3 f).

To explore, in parallel, potential relationships between exposure and vulnerability, we sorted the exposure time series into nourishing and non-nourishing counties, and then by the intensity of beach nourishment (high or low) according to whether counties fell above or below the 2016 median value of cumulative V_{bn} (Figs. 8, S4). We find that although exposure increases each decade in nourishing and non-nourishing counties, alike, more property is ultimately exposed in nourishing counties. Moreover, the mean value of that exposed property increases at a greater rate than in non-nourishing counties (Figs. 8 a-h, S4 a-c). Initially, all property is exposed in counties where nourishment intensity is present but low (their V_{bn} sits below the 2016 median) – which we expect, because for counties to accrue enough nourishment events to match the 2016 median cumulative-nourishment factor requires time (Fig. 8 i, m). Exposure in intensively nourished counties (counties that accrue enough nourishment projects to have V_{bn} above the 2016 median) shows a marked increase in the 1980s (Fig. S4 d). Total exposure in intensively nourished counties overtakes total exposure in sparsely nourished counties by the 2010s (Fig. S4 e), such that more property ends up exposed in counties where nourishment intensity is high (Figs. 8 i-p, S4 d-f).

Both of these temporal relationships in spatial patterns of exposure and hazard (Fig. 7) and exposure and vulnerability (Fig. 8) are likely two vantages of same feedback, catalysed by beach nourishment. Higher property value is exposed where historical shoreline-change hazard was high (Fig. 7, a–d) and recent shoreline-change hazard is low (Fig. 7, m–p) because those places also practice relatively intensive use of beach nourishment (Fig. 9). The cumulative effect of beach nourishment may be sufficiently strong to mask "true" rates of shoreline change (Armstrong and Lazarus, 2019) – a defensive intervention that, by reducing apparent hazard, may spur further development (Fig. 8), increasing exposure and creating demand for additional protection (Armstrong et al., 2016).

4 Discussion and implications

Our data-driven, spatio-temporal model of risk along the US Atlantic Coast produces trajectories that vary in space and, on average, rise over time for all four chronic hazard scenarios that we test (Fig. 5). We know from the underlying data that real exposure increases over time, but we suggest that our modelled risk trajectories also reflect intrinsic feedbacks between hazard, exposure, and vulnerability (Mileti, 1999). We find higher property exposure in counties with "high hazard" historical shoreline-change rates and "low hazard" recent shoreline-change rates (Fig. 7), and that exposure has increased more in places that have practiced beach nourishment intensively (Fig. 8). The spatio-temporal relationships that we show between exposure and hazard (Fig. 7) and exposure and vulnerability (Fig. 8) may reflect a feedback between coastal development and beach nourishment (Fig. 9) (Armstrong et al., 2016; Armstrong and Lazarus, 2019) – a manifestation of the "safe development paradox" (Burby, 2006), in which hazard protections encourage further development in places prone to hazard impacts (Armstrong et al., 2016; Burby and French, 1981; Burby, 2006; Di Baldassarre et al., 2013, 2016; Keeler et al., 2018; Lazarus et al., 2016; McNamara and Lazarus, 2018; McNamara et al., 2015; Mileti, 1999; Smith et al., 2009; Werner and McNamara, 2007; White, 1945).

Our model is exploratory, and we reiterate its main caveats. Although there are many kinds of coastal hazard (e.g., storm impacts, flooding), we represented "chronic" hazard with shoreline-change rates that are spatially heterogeneous but temporally static. An alternative derivation of shoreline change, from sea-level rise rates and simplified shore slopes, varies in both space and time, and yielded overall results similar to those returned by the "recent" shoreline-change scenario. Exposure in our model only accounts for the monetary value of owner-occupied properties in coastal counties, as captured by the US Census, thus excluding other potential measures of exposure, such as socio-economic indices (e.g., Cutter et al., 2006, 2008; Neumann et al., 2015; NRC, 2014; Samuels and Gouldby, 2009; Strauss et al., 2012), and requires that we spatially aggregate our analysis to county scales. Finally, our measure of vulnerability – intended to represent "susceptibility" (NRC, 2014; Samuels and Gouldby, 2009) without double-counting exposure or hazard – includes no method of shoreline protection other than beach nourishment, and no explicit inclusion of storm recurrence or severity. Furthermore, our treatment of dynamic vulnerability is underpinned by a set of broad assumptions: that beaches comprise shorelines at the county scale; that in 1970, all counties have the same initial beach width; that a beach-nourishment project always restores a beach to its full width; and that counties with intensive nourishment programmes may render themselves more vulnerable over time by masking a chronic erosion problem (Armstrong and Lazarus, 2019; Pilkey and Cooper, 2014; Woodruff et al., 2018). We do not directly address alongshore spatial interactions within or between counties (Lazarus et al., 2011; Ells and Murray, 2012; Lazarus et al., 2016). Despite these assumptions, our model captures temporal interactions among the components of risk that ultimately yield large-scale spatial patterns similar to those identified in recent, fully empirical studies (Armstrong and Lazarus, 2019; Armstrong et al., 2016).

We suggest that models intended to test different coastal management policies, interventions, and scenarios should aim to include feedbacks between hazard, exposure and vulnerability. In our data-driven model, traces of these feedbacks – and perhaps others – are likely embedded in the data we use. More detailed work at the intersection of theory and empiricism is necessary to resolve how feedbacks between hazard, exposure, and vulnerability dynamically affect each component of risk, and to explore how different management interventions may mitigate – or exacerbate – the "safe development paradox".

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Figures

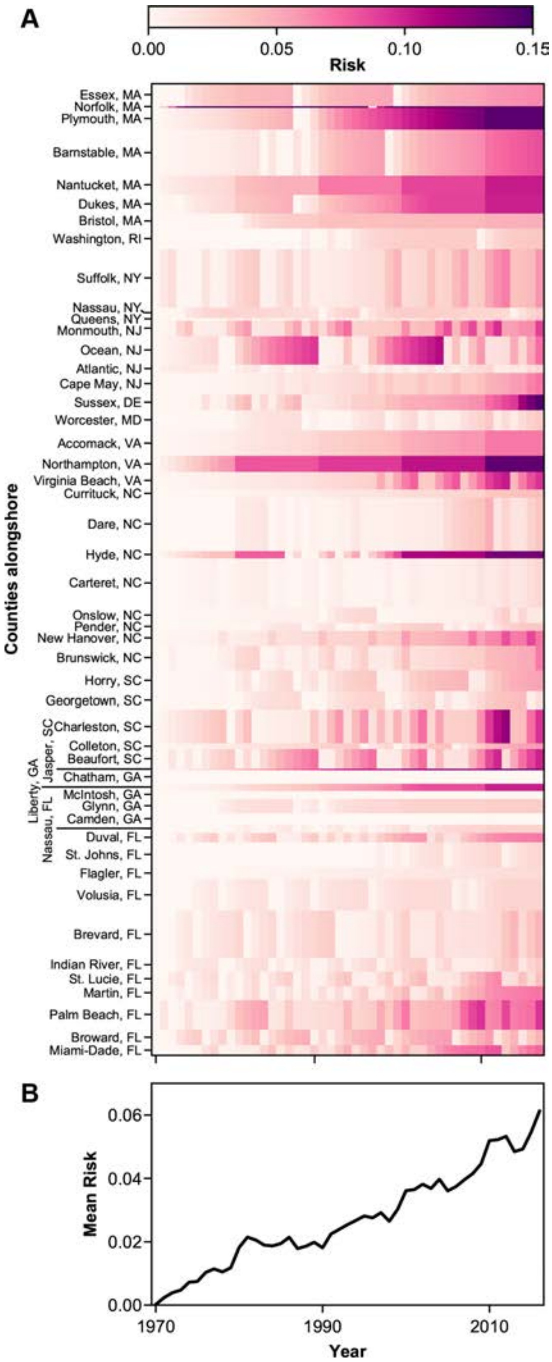

Figure 1: Evolution of (a) county-level risk (a function of hazard, exposure, and vulnerability) modelled for the US Atlantic Coast, from 1970–2016. Hazard in this simulation reflects historical erosion rates. For visualisation and analysis, each county is scaled by the number of 1 km transects it comprises. The result is a matrix of 2386 km over 47 years, in which each of the 2386 (1 km) rows is associated with a county. Note that risk in Norfolk County, MA, exceeds the maximum scale bar value of 0.15 (2016 risk = 0.418; see Table 1). **(b)** Alongshore mean values through time for the whole US Atlantic Coast are taken from the full matrix (a), reflecting the relative alongshore scale of each county.

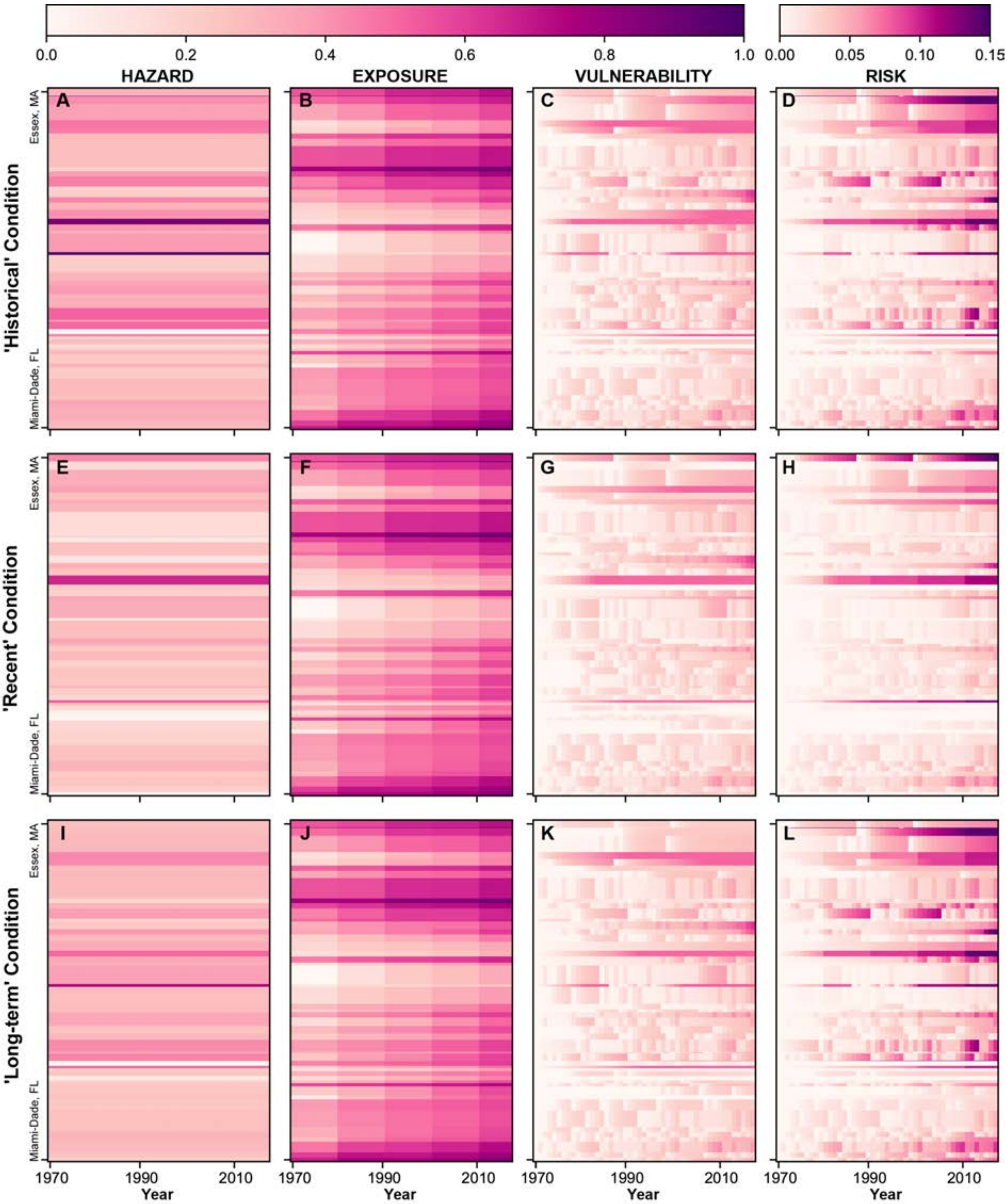

Figure 2. Columns show hazard, exposure, and vulnerability components and resulting risk. Each row of panels illustrates a different rate of shoreline change (i.e., hazard condition): **(a–d)** historical, **(e–h)** recent, and **(i–l)** long-term. Risk in Norfolk County, MA, exceeds the maximum scale bar value of 0.15 (2016 risk = 0.418; see Table 1). Each county is scaled by the number of 1 km transects it comprises; the northern- and southern-most counties are labelled.

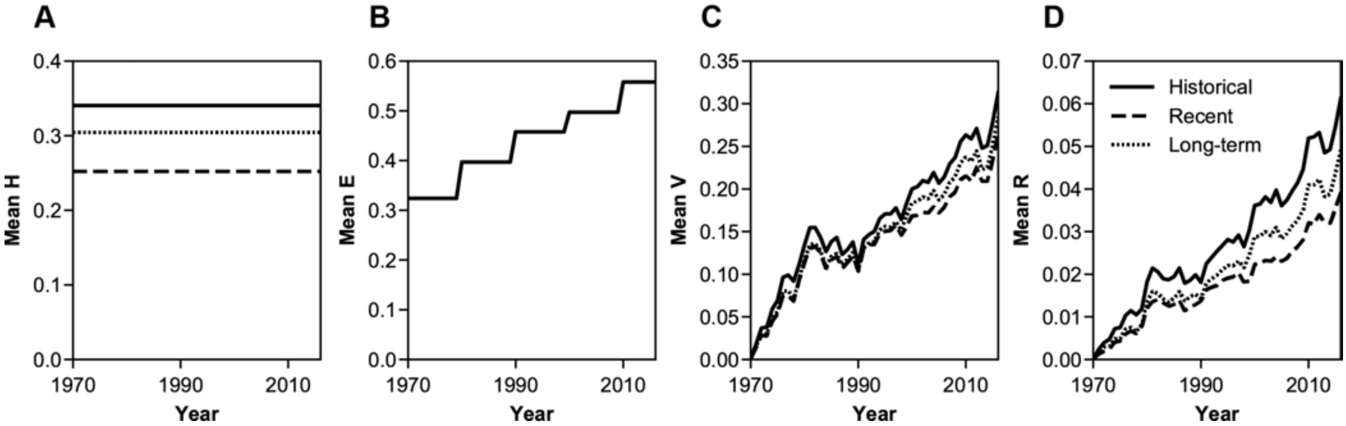

Figure 3. Evolution over time of alongshore mean risk components – **(a)** hazard, **(b)** exposure, and **(c)** vulnerability – and the resulting **(d)** mean risk, given historical (solid black), recent (dashed black), and long-term (dotted black) shoreline-change rates as hazard conditions.

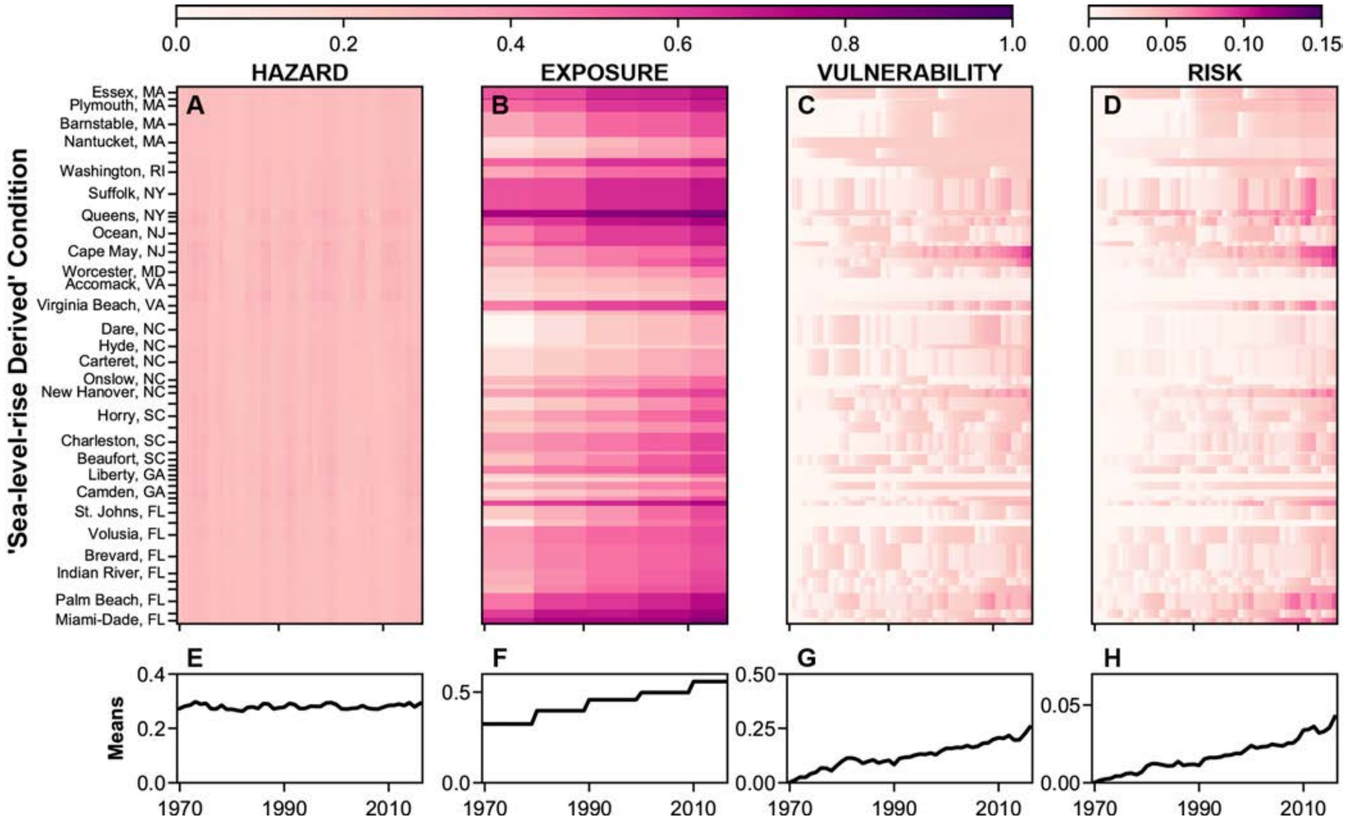

Figure 4. County-scale component **(a)** hazard, **(b)** exposure, **(c)** vulnerability and **(d)** overall risk evolution over time, and **(e–h)** corresponding means, using shoreline-change rates derived from sea-level change as the hazard condition. Each county is scaled by the number of 1 km transects it comprises; not all counties are labelled.

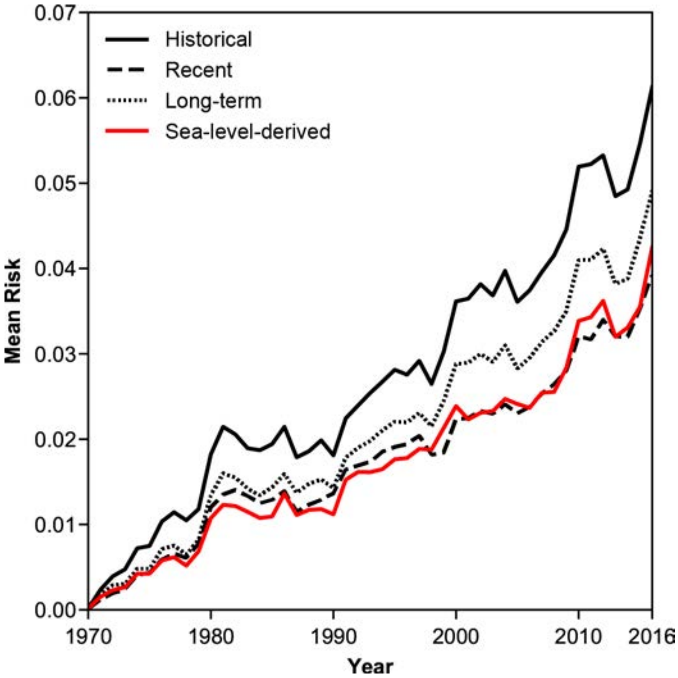

Figure 5. Comparative evolution of mean risk over time under different representations of shoreline-change rate (hazard condition): historical (solid black), recent (dashed black), long-term (dotted black), and sea-level-derived (red).

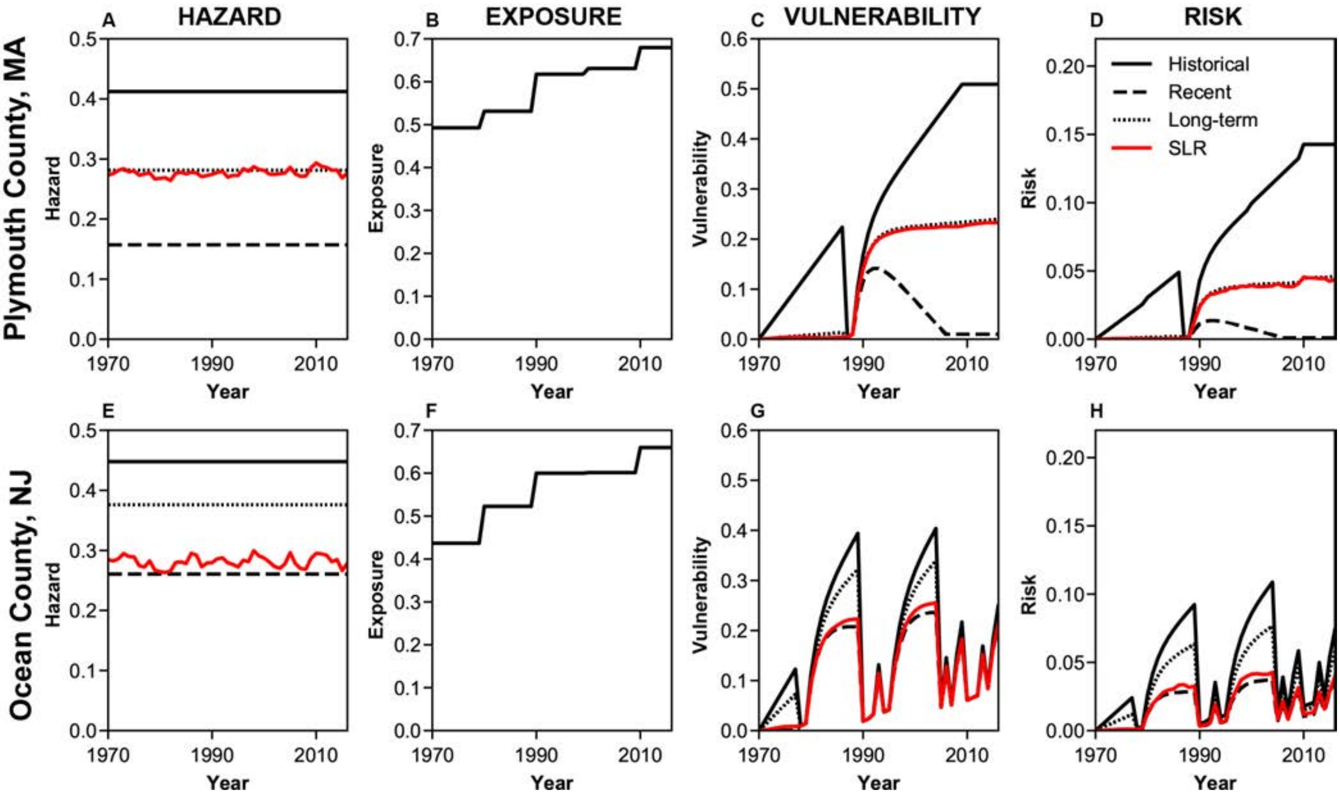

Figure 6. Evolution of **(a–c)** mean components and **(d)** risk for Plymouth County, Massachusetts, and **(e–h)** Ocean County, New Jersey. Line type indicates results under a given hazard condition. Note that the vulnerability time series for Ocean County (panel g) shows the "ratchet effect" of cumulative vulnerability from repeated beach nourishment episodes.

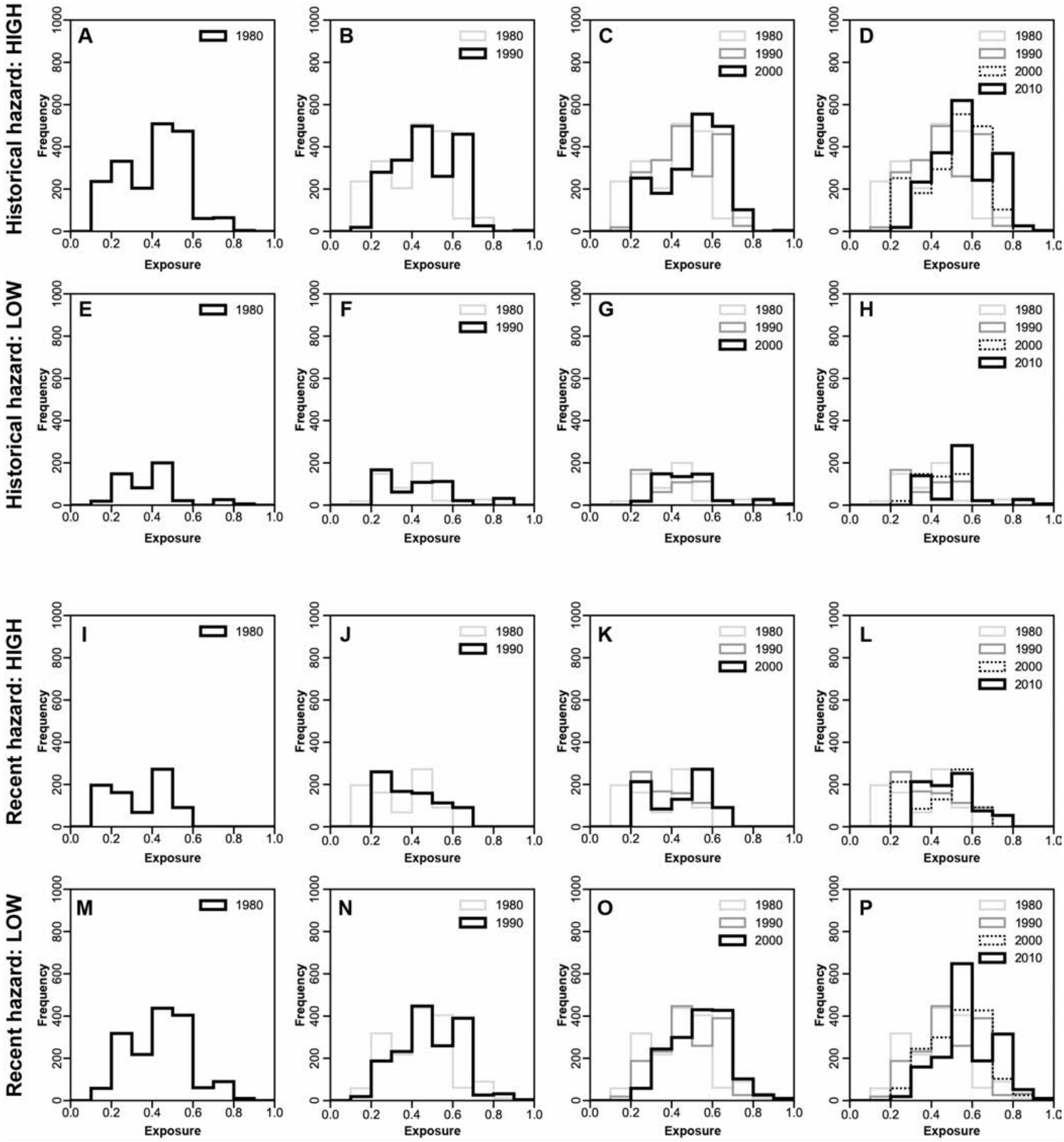

Figure 7. Transect-level distribution of exposure per coastal kilometre, by decade, under **(a–h)** high and low historical and **(i–p)** high and low recent shoreline-change hazard. "High" hazard here is a value greater than 0.272 (the normalised value for a shoreline-change rate of zero); "low" hazard is a value greater than 0.272. High hazard therefore indicates erosion, and low hazard indicates accretion. Summary statistics for these distributions are provided in Table S5.

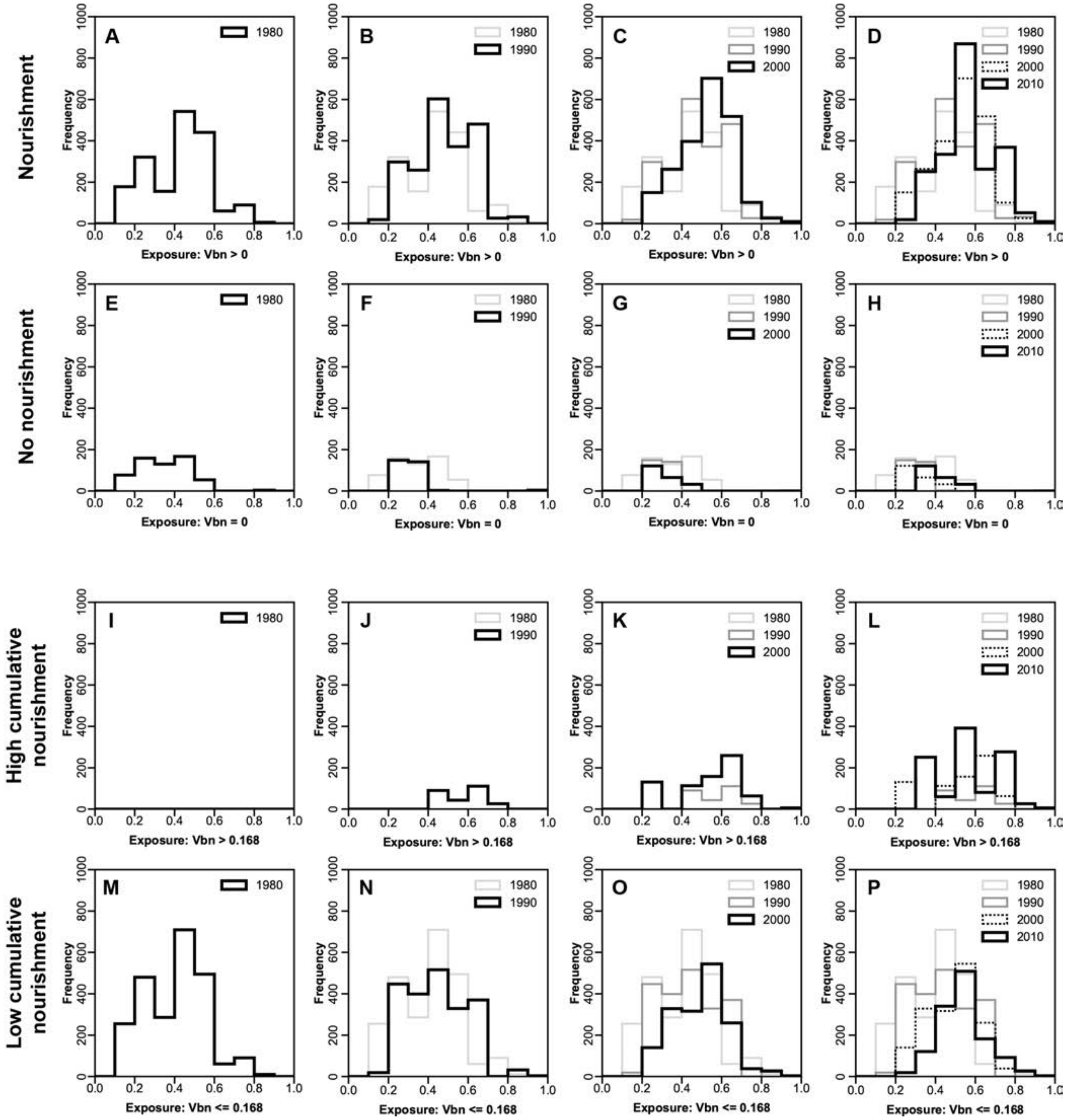

Figure 8. Transect-level distribution of exposure per coastal kilometre, by decade, **(a–h)** in counties that have and have not nourished, and **(i–p)** in counties that have nourished above and below the 2016 median cumulative beach-nourishment index (V_{bn} = 0.168). The 2016 median V_{bn} denotes the normalised value of the overall median cumulative number of nourishments across the domain. Summary statistics for these distributions are provided in Table S5.

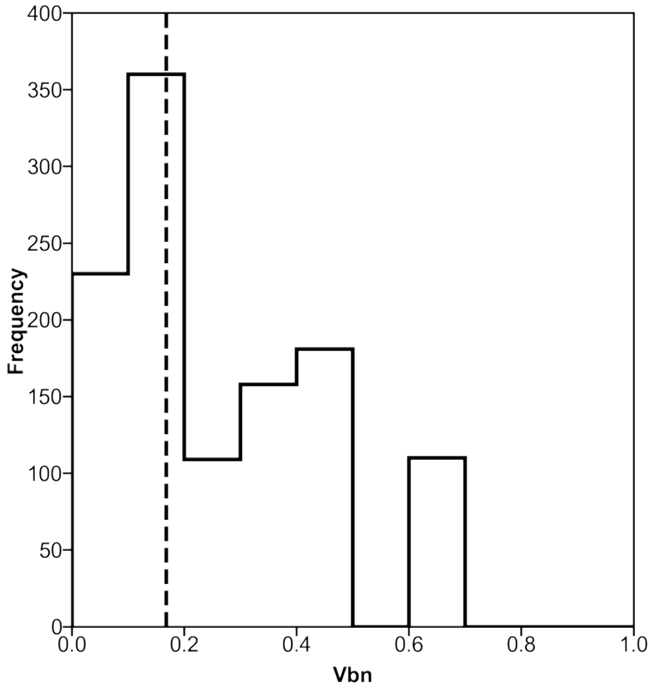

Figure 9. Cumulative beach-nourishment index (V_{bn}), as of 2016, at transects (across all counties) that express both high "historical" and low "recent" rates of shoreline erosion (see Fig. 7, a–d and m–p). Dotted line indicates the overall median V_{bn} = 0.168 in 2016 for the full domain. For this component distribution, median V_{bn} = 0.178 (mean = 0.251). This spatial correspondence between a major reversal in shoreline-change trend (from erosion to accretion) and above-average nourishment intensity is an indication of a coupling between chronic erosion (hazard) and defensive intervention (vulnerability).

Tables

Table 1. Counties ranked by risk in 2016, calculated with historic, long-term, recent, and sea-level-derived shoreline-change rates.

	Historical			*Long-term*			*Recent*			*Sea-level-derived*		
Rank	*County*	*State*	*2016 Risk*	*County*	*State*	*2016 Risk*	*County*	*State*	*2016 Risk*	*County*	*State*	*2016 Risk*
1	Norfolk	MA	0.4176	Sussex	DE	0.1303	Essex	MA	0.1451	Cape May	NJ	0.0995
2	Sussex	DE	0.1456	Jasper	SC	0.1176	Liberty	GA	0.1304	Sussex	DE	0.0899
3	Plymouth	MA	0.1427	Liberty	GA	0.1171	Accomack	VA	0.1130	Miami-Dade	FL	0.0809
4	Northampton	VA	0.1400	Hyde	NC	0.0999	Sussex	DE	0.1010	Palm Beach	FL	0.0807
5	Jasper	SC	0.1382	Dukes	MA	0.0946	Bristol	MA	0.0867	Queens	NY	0.0763
6	Hyde	NC	0.1328	Nantucket	MA	0.0924	Nantucket	MA	0.0790	Duval	FL	0.0661
7	Nantucket	MA	0.1026	Beaufort	SC	0.0828	Palm Beach	FL	0.0696	Monmouth	NJ	0.0647
8	Liberty	GA	0.1009	Virginia Beach	VA	0.0808	Currituck	NC	0.0682	Virginia Beach	VA	0.0640
9	Dukes	MA	0.1008	Palm Beach	FL	0.0806	Queens	NY	0.0642	Norfolk	MA	0.0637
10	Beaufort	SC	0.1002	Northampton	VA	0.0798	Barnstable	MA	0.0634	New Hanover	NC	0.0621
11	Charleston	SC	0.0953	Cape May	NJ	0.0787	Brunswick	NC	0.0497	Suffolk	NY	0.0613
12	Virginia Beach	VA	0.0949	Charleston	SC	0.0732	New Hanover	NC	0.0488	Brunswick	NC	0.0529
13	Palm Beach	FL	0.0940	Monmouth	NJ	0.0700	Atlantic	NJ	0.0435	Martin	FL	0.0512
14	Monmouth	NJ	0.0895	New Hanover	NC	0.0700	Brevard	FL	0.0420	Beaufort	SC	0.0495
15	Barnstable	MA	0.0841	Suffolk	NY	0.0618	Washington	RI	0.0419	Charleston	SC	0.0490
16	Miami-Dade	FL	0.0758	Brunswick	NC	0.0610	Indian River	FL	0.0412	Atlantic	NJ	0.0484
17	Ocean	NJ	0.0737	Ocean	NJ	0.0583	Virginia Beach	VA	0.0405	Horry	SC	0.0483
18	New Hanover	NC	0.0711	Martin	FL	0.0549	Colleton	SC	0.0403	Nassau	FL	0.0467
19	Cape May	NJ	0.0711	Norfolk	MA	0.0542	Charleston	SC	0.0389	Essex	MA	0.0463
20	Martin	FL	0.0708	Queens	NY	0.0514	Cape May	NJ	0.0366	Nassau	NY	0.0461
21	Accomack	VA	0.0694	Miami-Dade	FL	0.0497	Ocean	NJ	0.0365	Brevard	FL	0.0456
22	Duval	FL	0.0692	Colleton	SC	0.0481	St. Lucie	FL	0.0350	Broward	FL	0.0453
23	Brunswick	NC	0.0690	Barnstable	MA	0.0460	Pender	NC	0.0350	Bristol	MA	0.0444
24	Essex	MA	0.0639	Plymouth	MA	0.0457	Martin	FL	0.0330	Volusia	FL	0.0439
25	Suffolk	NY	0.0596	Duval	FL	0.0437	Carteret	NC	0.0328	Plymouth	MA	0.0438
26	Colleton	SC	0.0578	Essex	MA	0.0427	Suffolk	NY	0.0308	Ocean	NJ	0.0395
27	Horry	SC	0.0545	Brevard	FL	0.0419	Dare	NC	0.0302	Washington	RI	0.0382
28	Bristol	MA	0.0484	Washington	RI	0.0411	Norfolk	MA	0.0296	Barnstable	MA	0.0380
29	Broward	FL	0.0468	Bristol	MA	0.0397	Beaufort	SC	0.0287	St. Johns	FL	0.0376
30	Brevard	FL	0.0455	Horry	SC	0.0377	Broward	FL	0.0282	Indian River	FL	0.0372
31	Queens	NY	0.0415	Broward	FL	0.0377	Worcester	MD	0.0271	Glynn	GA	0.0371
32	Currituck	NC	0.0408	St. Lucie	FL	0.0354	Horry	SC	0.0252	Carteret	NC	0.0369
33	St. Lucie	FL	0.0402	Indian River	FL	0.0350	Monmouth	NJ	0.0225	Pender	NC	0.0360
34	Pender	NC	0.0370	Dare	NC	0.0348	Dukes	MA	0.0223	Colleton	SC	0.0321
35	Washington	RI	0.0364	Accomack	VA	0.0346	Volusia	FL	0.0190	Chatham	GA	0.0321
36	Dare	NC	0.0364	Carteret	NC	0.0333	Nassau	NY	0.0161	St. Lucie	FL	0.0318
37	Worcester	MD	0.0346	Worcester	MD	0.0323	Onslow	NC	0.0157	Worcester	MD	0.0312
38	Indian River	FL	0.0344	Pender	NC	0.0317	St. Johns	FL	0.0156	Dukes	MA	0.0275
39	Nassau	NY	0.0314	Currituck	NC	0.0315	Georgetown	SC	0.0155	Nantucket	MA	0.0274
40	Glynn	GA	0.0311	Atlantic	NJ	0.0303	Chatham	GA	0.0143	Dare	NC	0.0253
41	Nassau	FL	0.0276	Volusia	FL	0.0299	Miami-Dade	FL	0.0079	Hyde	NC	0.0190
42	Volusia	FL	0.0271	St. Johns	FL	0.0287	McIntosh	GA	0.0057	Georgetown	SC	0.0188
43	Atlantic	NJ	0.0268	Nassau	NY	0.0222	Glynn	GA	0.0011	Onslow	NC	0.0132
44	St. Johns	FL	0.0260	Glynn	GA	0.0184	Plymouth	MA	0.0010	Camden	GA	0.0083

Rank	Historical County	State	2016 Risk	Long-term County	State	2016 Risk	Recent County	State	2016 Risk	Sea-level-derived County	State	2016 Risk
45	Carteret	NC	0.0248	Georgetown	SC	0.0182	Nassau	FL	0.0008	Northampton	VA	0.0078
46	Flagler	FL	0.0223	Nassau	FL	0.0170	Hyde	NC	0.0006	Jasper	SC	0.0069
47	Georgetown	SC	0.0206	Onslow	NC	0.0128	Flagler	FL	0	Liberty	GA	0.0061
48	Onslow	NC	0.0136	Chatham	GA	0.0007	Duval	FL	0	Accomack	VA	0.0058
49	Chatham	GA	0.0005	Flagler	FL	0	Camden	GA	0	McIntosh	GA	0.0053
50	Camden	GA	0	Camden	GA	0	Jasper	SC	0	Currituck	NC	0.0050
51	McIntosh	GA	0	McIntosh	GA	0	Northampton	VA	0	Flagler	FL	0.0021