nature climate change

SUPPLEMENTARY INFORMATION

DOI: 10.1038/NCLIMATE1944

Coastal habitats shield people and property from sea-level rise and storms

1. **Supplementary Methods and Definitions**
2. **Supplementary Acknowledgements**
3. **Supplementary Tables**
4. **Supplementary Figures**
5. **Supplementary References**

DOI: 10.1038/NCLIMATE1944

1. Supplementary Methods

Summary

We assessed the role of coastal habitats in reducing the relative vulnerability of people and property to erosion and flooding from storms and five sea-level rise (SLR) scenarios in 1 km^2 segments along the entire coast of the United States. We quantified exposure to coastal hazards on a nationwide scale, and based our SLR scenarios on those used in the 2013 National Climate Assessment[24]. We calculated a coastal hazard index that incorporates seven physical and biological variables: shoreline type (which includes geomorphology and physical structures), habitats, relief, SLR, wind exposure, wave exposure, and surge potential (Supplementary Table 1)[21]. Five years (2006-2010) of the US Census Bureau's American Community Survey (ACS)[22] data and Zillow's Home Value Index (ZHVI), which is the median market value of residential properties in each U.S. 2010 Census block group[23], allowed us to identify where habitats provide protection for the most vulnerable people and highest value properties.

Our analysis followed a four step process, summarized here and illustrated in Supplementary Fig. 1. First, we designed the SLR, storm and habitat scenarios. To assess the effect of SLR we developed four scenarios for 2100 and one current scenario (Supplementary Fig. 2) using the 2013 National Climate Assessment guidance[24]: trend, B1 and A2 (based on emission scenarios), high (incorporates maximum glacier and ice sheet contributions), and current (observed rise from 1992 to 2006). Because of uncertainty among models and studies about the relationship between waves and climate change[29], we made the simplifying assumption that storm intensity and frequency in 2100 will be the same as the current scenario. We estimated current wave and wind exposure based on six years of NOAA WAVEWATCH III model hindcast reanalysis results for 2005-2010 (see Wind and Wave Data descriptions below for more information)[28]. To determine where habitats play an important role in providing protection from erosion and flooding with SLR, we contrasted a scenario including nine habitats in the index (coastal forests, coral reefs, emergent marsh, oyster reefs, low and high dunes, seagrass beds, kelp forests, additional intertidal aquatic vegetation, Supplementary Fig. 4) with the exclusion of all habitats for a total of ten climate by habitat scenarios.

Second, we collected data for each of the seven variables in the coastal hazard index and ran the model for the ten habitat/climate scenarios. For the six physical variables we used nationwide datasets. For the habitat data we used nationwide datasets if they were available for certain habitat types (e.g., coral) and supplemented with regionally collected data for habitats lacking a single dataset for the whole country (e.g., seagrass beds). The methods sections of Arkema et al. contains further details on the index, which is a part of the InVEST software and is freely available for downloading and application to other locations at www.naturalcapitalproject.org. Note that each variable in our analysis was weighted equally, after several previously developed coastal vulnerability indices[16,17] (see Table 4 in ref [31] for review of indices). However, our approach is flexible for future studies; variables can be weighted more or less heavily than others and/or excluded from the analysis entirely if appropriate (see section below on wind and wave data).

The resulting index measures the relative exposure to coastal hazard of each 1 km^2 segment compared to all other segments nation-wide and across the ten habitat/climate scenarios (Supplementary Fig. 3). To map hazard we classified the

DOI: 10.1038/NCLIMATE1944

distribution of index values for all segments and scenarios (ranging from 1-5) into quartiles to indicate areas of highest hazard (>3.36 = top 25% of the distribution), intermediate hazard (2.36-3.36 = central 50% of the distribution) and lowest hazard (<2.36= bottom 25% of the distribution, Supplementary Fig. 3).

Third, we drew on two sources of socio-economic data, the US Census Bureau's ACS 5-year summary reported at the census block group scale[22] and ZHVI[23], which we used to determine where habitats provide protection for the most vulnerable people and highest value properties. From the ACS data we extracted four metrics per census block group: total population, number of people older than 65, number of families with total income below the poverty line, and total number of residential properties. From Zillow we received the median home value for all census block groups with greater than 30 properties on 08 May 2012. We distributed the data for people and properties throughout the census block group at a resolution of 30 m with a dasymetric mapping approach[30] that uses land-use, land-cover and land stewardship data (indicating uninhabited public lands) to identify where people are most likely to live.

Fourth, we estimated the total human population, number of people older than 65 years, number of families under the poverty line, number of properties, and median value of properties in each 1 km^2 segment exposed to the highest coastal hazard (index value >3.36) for the ten habitat/climate scenarios for the entire U.S. coastline. To ground our results, which are based in part on a relative coastal hazard index, we compared our estimates for number of people exposed to the greatest coastal hazard to observed data on hazard events and losses for the coastal U.S.[25].

All open-access data and code for the coastal hazard index is available at [address].

Definitions

The terms hazard, risk, exposure and vulnerability (both social and physical) are often used differently by scientists from different fields. For clarity, we define these terms:.

Coastal hazard refers to flooding and erosion caused by storms and sea level rise acting upon shorelines. Even though erosion and flooding are natural processes they may incur negative consequences for people and property so we refer to them as hazards. Results from the hazard index encompass both the relative magnitude of erosion and/or flooding, and the probability that these hazards may occur based on the distribution of the index across scenarios.

Risk refers to the potential societal consequences of erosion and flooding (e.g., mortality or economic damages).

Vulnerability refers to both social and physical vulnerability. For example, socially vulnerable populations, such as poor families or elderly, may be more likely to suffer adverse effects from hazards. Physically vulnerable populations and property are highly exposed to coastal hazards. In this paper, we use "coastal vulnerability" to represent the numbers of people, their demographics and the total value of property with the highest exposure to coastal hazards.

Exposure refers to the location of people and property where hazards may occur.

Data and models for all variables in the hazard index and vulnerability mapping

Habitat Data

 DOI: 10.1038/NCLIMATE1944

We identified nine types of habitats that occur along the coast of the U.S. that may provide varying levels of coastal protection: coral reefs, coastal forests (e.g., mangroves and other coastal trees and shrubs), emergent marsh, seagrass beds, kelp forests, additional intertidal aquatic vegetation, oyster reefs, and high and low dunes. The hazard index ranks the habitats based on differences in their morphology and observed ability to provide protection from erosion and flooding by dissipating wave energy, attenuating storm surge, or anchoring sediments, for example (Supplementary Table S1). The index also accounts for greater protection provided by co-occurring multiple habitats and assigns a distance over which different categories of habitats will provide protection for coastlines[21] (see below).

For the "with habitat" scenario, we used a two-part approach to amass data nationwide. Where possible we used national scale habitat datasets. If unavailable, we pieced together habitat data on a state-by-state basis. Given the scarcity and inaccuracy of national scale datasets for some important habitats (e.g., oyster reefs, seagrass beds, kelp forests, and dunes), we felt it was important to pursue the piecemeal approach. For the "without habitat" scenario we assigned a rank of 5 for the habitat variable (Supplementary Table 1) to all coastal segments when running the model.

We used ArcGIS to measure a habitat-specific distance (Supplementary Table 2) from all borders of each habitat patch, based on expert judgment, natural history, and the peer-reviewed literature. These distances are essentially a technical shortcut, rather than an ecological or hydrodynamic parameter. They allow us to designate which coastline segments are protected by patches of habitats located at different distances from the grid cells, given that the model does not take into account the numerous factors (depth, channel configuration etc.) that could influence the distance over which effects of these habitats could be felt. For example, oysters generally exist close to shore, so their protective distance is small. In contrast, coral reefs sometimes exist much farther from shore and evidence from the literature suggests that they can attenuate waves and surge over large distances to protect more distant shorelines[32]. Thus, for corals, the protective distance is larger. If the "protective distance" buffer from a patch of habitat overlapped a coastline segment then we considered it protected by that particular habitat.

Lastly, we included in the index the protection provided to coastal segments by more than one habitat type. For example, some shorelines may have just coral reefs, while other areas are fringed by mangroves and seagrass, as well as corals. To account for multiple habitats we ranked the habitat(s) protecting a particular segment of coastline using the *integers* in Supplementary Table 1. Next we combined these one or more values into an overall habitat rank (*decimal*) using the equation below

$$R_{Hab} = 4.8 - 0.5\sqrt{(1.5\max_{k=1}^{N}(5-R_k))^2 + (\sum_{k=1}^{N}(5-R_k)^2 - \max_{k=1}^{N}(5-R_k))^2)}$$

where k keeps track of the multiple habitats. The outcome of this equation is that multiple high-ranking habitats (e.g., seagrass and kelp) perform better with a combined rank of 3.899 than either one alone (i.e., final rank of kelp = 4.050 and final rank of seagrass = 4.050). But kelp and seagrass together do not perform as well as a coral reef alone (final rank coral = 1.80). Our ranking approach is a first attempt to incorporate the role of multiple habitats in reducing coastal vulnerability over such a large geographic scale and is flexible enough to be refined as future research in this field emerges. Please

DOI: 10.1038/NCLIMATE1944

see ref [21] for a full listing of the final ranks of all habitats individually and in combination.

Coastal forests, emergent marsh, additional intertidal aquatic vegetation

We used the National Wetland Inventory Wetlands Data[33] to create habitat layers for three habitat categories: coastal forests, emergent marsh, and additional intertidal aquatic vegetation. This dataset delineates the areal extent, approximate location and type of wetlands and deepwater habitats in the conterminous U.S.[33,34]. Compiled since 1977 by the U.S. Fish and Wildlife Service, the NWI data cover the lower 48, Hawaii and Alaska. The maps were prepared from analysis of high altitude imagery. Wetlands were identified based on vegetation, visible hydrology, and geography and classified using alpha-numeric codes for the wetland and deepwater classifications[34].

We used the alpha-numeric map codes to extract the polygons from the NWI that were classified as estuarine intertidal forests and scrub shrub (coastal forests -- including mangroves and other coastal tree and shrub taxa), emergent wetland (emergent marsh), marine and estuarine aquatic vegetation (additional intertidal aquatic vegetation). We created shapefiles for each habitat. To reduce model run-time we resampled these data to a resolution of 50 m. For the coastal hazard analysis we classified coastal forests, emergent marsh and aquatic vegetation as rank “1”, “2” and “4” and assigned protective distances of 2000, 1000 and 500 m, respectively (Supplementary Table 2).

The NWI data exclude certain habitats because of the limitations of aerial imagery. These habitats include seagrass beds, kelp forests and coral. We gathered seagrass bed and kelp forest data state-by-state and used a separate global dataset for coral.

Coral reefs

The Reefs at Risk Base Dataset[35] was developed by World Resources Institute and its partners, United Nations Environmental Program –World Conservation Monitoring Centre (UNEP-WCMC) and the WorldFish Center, to assess the status of and threats to the world's coral reefs. The original sources for the data include the 1) Institute for Marine Remote Sensing, University of South Florida and Institut de Recherche pour le Développement's "Millennium Coral Reef Mapping Project," 2009 (30 m Landsat data classified and converted to shapefile), 2) UNEP-WCMC "Coral Reef Map," 2002 and 3) additional data that were acquired or digitized from a variety of sources. Scales typically range from 1:60,000 to 1:1,000,000. To standardize these data for the purposes of the Reefs at Risk Revisited project, data were converted to raster format (ESRI GRID) at 500-m resolution. We created shapefiles for coral reefs for Hawaii and the Gulf Coast (including Florida) and projected the layers in meters. We ranked coral reefs as "1" and assigned them a protective distance of 2000 m (Supplementary Table 2).

Seagrass beds

Data for seagrass beds were compiled on a state-by-state basis from a variety of sources (Supplementary Table 3). We are confident that our analysis includes all existing datasets at a state or regional scale, but we did not attempt to amass all datasets on a local scale (i.e., less than a few kilometers). Although our maps may be missing some seagrass coverage, due to lack of data, timing of most recent survey, or another source of error, we feel our state-by-state approach is preferable to excluding seagrass beds altogether, given

DOI: 10.1038/NCLIMATE1944

that much spatial data are available at a state or regional level. To address the issue that the disparate datasets were collected during different years and over different time periods, we created composite layers for each state and then merged the layers for four of our five regions: Alaska, West Coast, East Coast, Gulf Coast. We included seagrass beds for each state except Hawaii, South Carolina, Georgia and Delaware. After much searching and discussions with local experts, we decided not to include seagrass data for Hawaii, as the coverage of *Halophilia hawiiana* is quite sparse. Seagrass beds do not exist in South Carolina or Georgia, and we were unable to find spatial data for seagrass beds in Delaware. Seagrass data were rasterized at a 50 m resolution. We assigned seagrass beds a rank "4" and protective distance of 500 m (Supplementary Table 2).

Kelp forests

Like seagrass beds, no national scale dataset exists for kelp forests. To address this problem we amassed data for canopy-forming kelps (e.g., *Macrocystis pyrifera* and *Nereocystis leutkeana*) that line the West Coast of the U.S. and Alaska using comprehensive datasets that exist for California, Oregon, Washington and Alaska (Supplementary Table 4). We focused on kelp forests and so did not include data for understory kelps in the northeast. Unfortunately, we lacked digitalized spatial data for large areas of Alaska (Supplementary Fig. 4) where we know from the ecological literature that canopy kelps exist[36]. Because we lack kelp data, we may underestimate the difference in coastal hazard between with and without habitat scenarios. For data rich areas on the West Coast like California, we incorporated a range of surveys to generate a single kelp forest composite spanning multiple years which was rasterizing at 50 m resolution. We assigned kelp forests a rank "4" and protective distance of 1500 m (Supplementary Table 2).

Oyster reefs

We compiled data for oyster reefs on a state-by-state basis for the Gulf Coast and the East Coast south of Delaware (Supplementary Table 5). Along the East Coast we chose to include oyster reefs south of Delaware, as oyster populations in the northeast U.S. have been decimated over the last century to a point of functional extinction[37]. Thus our dataset does not include reefs in the northeast where restoration has recently begun (e.g., sites funded by NOAA through the American Recovery and Reinvestment Act of 2009[38]) and which will hopefully provide protection in the near future. We chose to exclude West Coast oyster populations as these occur in much smaller clumps and do not form reef-like structures. We merged the layers for the East Coast and Gulf Coast by projecting all layers in meters and dissolving the borders between polygons. For certain high resolution datasets (e.g., those for SC and GA), we filtered out all patches less than 50 m resolution. Oyster reefs were assigned rank "4" and a protective distance of 100 m (Supplementary Table 2).

Dunes

Coastal dunes data were obtained from three different sources, covering the Pacific Northwest, California from Santa Barbara north, the Gulf of Mexico and half of the eastern seaboard. Data for the Pacific Northwest (Oregon and Washington[39]) and California[40] were obtained from LiDAR records collected between 1998 and 2000. Dune data for the Gulf of Mexico and part of the eastern seaboard (from Texas through North Carolina) were obtained from the US Geological Survey (USGS) Coastal Classification

DOI: 10.1038/NCLIMATE1944

Mapping Project[16,41]. Dunes were classified as "high dune" if their crest was higher than 5 m. High dunes are less likely to lead to overwash and inundation when impacted by typical surge elevations that would occur during a large hurricane[42,43]. High dunes were assigned rank "2" and low dunes rank "3." Both were assigned a protective distance of 100 m (Supplementary Table 2).

Physical data

Coastal region

The coastal hazard index requires an outline of the region of interest. We used the Global Self-consistent, Hierarchical, High-resolution Shoreline (GSHHS) provided by NOAA[44].

Shoreline Type

Shoreline classification information for the continental U.S. is available from NOAA's Office of Response and Restoration Environmental Sensitivity Index (ESI) Maps[45] at state and/or regional levels. We extracted polylines from the state and regional ESI geodatabases, except for Maine, where classification data were only available as polygons; we converted those to polylines. State and regional polylines were merged into a national dataset . We classified shoreline type for each state or region based on the associated ESI data for geomorphology or physical structures. Each shoreline segment was then assigned a relative ranking from 1 to 5 based on its classification (Supplementary Table 1[16,21]).

The ESI dataset gives information about the type of physical structures present along the shore. However, for some states it lumps geomorphic features (e.g., vertical rocky shore) and physical structure type (e.g., seawall) present at a shoreline into one category (e.g., Category "1" in Florida) and doesn't indicate the type of feature (geomorphology or physical structure). This makes any differentiation between hardened and natural shorelines impossible at a nationwide scale. Further, for the states that do differentiate between hardened and natural shorelines, the ESI dataset does not include information about the geomorphic classification of the coastal region protected by the structure. Thus, for simplification, we assumed that where physical structures were present, they replaced the natural geomorphology. As a result our analysis combines physical structures and geomorphology into a single variable. Segments backed by seawalls were assigned a rank of 1 because they protect shores against erosion and inundation. Note that this is the same ranking as that for rocky shores and high cliffs. Segments with a revetment or riprap wall were assigned a rank of 3 because they protect the shore against erosion, but have the potential to fail during storms, and do not reduce inundation level. We also assigned a rank of 3 to segments with undefined types of shoreline hardening. Because ESI datasets are not updated regularly (some maps were created more than 15 years ago), our shoreline classification layer may underestimate the amount of armored shoreline in the U.S.

Our approach of combining physical structures and geomorphology may underestimate hazard where physical structures are present because we do not account for geomorphology (which is often sand or cobble beach and mudflat where physical structures are built). Moreover, because we combine physical structures and geomorphology, our analysis is not appropriate for comparing the coastal defense provided by physical structures versus habitats nor for comparing differences in hazard with combinations of habitats and physical structures that are similarly ranked to natural

 DOI: 10.1038/NCLIMATE1944

geomorphologies. Note however, that our open access tool and approach is flexible and with more detailed, local data and information, a user could create a separate variable and ranking system for physical structures and use the index to begin to get at these comparisons. We do caution, however, that a full cost-benefit analysis will require quantitative ecological, storm surge and wave models coupled with valuation of a full suite of ecosystem services.

Relief

To generate a relief rank for each coastline segment, we utilized the World Wildlife Fund's Hydrosheds digital elevation model (DEM) available globally at 90 m resolution[46]. The coastal hazard index tool summarizes neighborhood relief on a cell-by-cell basis using a focal radius of 3000 m x 3000 m for each coastline segment. The tool determines the average elevation (height in meters) of all DEM cells on land within this 3000 m search window. The resulting distribution is classified using percentile breaks (20, 40, 60, and 80) to produce relative ranks of 5 through 1 respectively. The rationale for this 3000 m search radius is to best approximate variance in coastal relief at local and regional scales and still allow for coarse DEMs as inputs. Through sensitivity testing, we determined no significant change in the U.S. relief rankings when providing a finer DEM than the 90 m input used for this analysis.

Wind exposure

Strong winds can generate high storm surges and/or high waves if they blow over an area for a long period of time. These high surges and waves increase the relative exposure of a particular segment of coastline to flooding and erosion. We computed relative wind exposure for each coastline segment using time series data of wind speeds and associated direction, above the 90th percentile value, and fetch distance. Wind speed and direction were estimated from wind data compiled from six years (2005-2010) of NOAA WAVEWATCH III (WWIII) model hindcast reanalysis results[28]. Fetch distance was estimated with an accuracy of 1 km[47].

Wave exposure

The relative exposure of a segment of coastline to storm waves is a qualitative indicator of the potential for shoreline erosion. A given stretch of shoreline is generally exposed to long period swells generated by distant storms or locally-generated wind-waves. For a given wave height, waves that have a longer period have more power than shorter waves[48,49]. We computed relative wave exposure for each coastline segment. The hazard index tool ranks wave exposure for each 1 km^2 coastline segment based on its orientation with respect to the average of the time series of wave power above the 90th percentile value in each of 16 cardinal directions. This wave power value is the maximum between wave power values computed using observed wave information from WWIII outputs[28], and wave power computed from wind speed values obtained from the same source cited above and fetch distances. We found that, in sheltered areas where oceanic waves have little influence and most waves are locally generated, wave power values directly from WWIII were equal to the wave power values obtained from fetch and wind data. However, in areas exposed to the open ocean, wave power values obtained from WWIII were higher than those obtained from wind and fetch data because the former intrinsically contain the signature of waves generated by local storms, long distance storms (swells) and wind-generated waves.

DOI: 10.1038/NCLIMATE1944

Although wave exposure was, in part, calculated from wind data, wind and wave exposure outputs are not duplicative as winds have distinct effects on coastal areas. Higher winds speed values lead to a higher wave-induced water level[50], which can in turn be modified by coastal habitats[51]. In addition to waves, wind generates surge. By including wind speed and direction, in addition to the variable for distance to continental shelf, we were able to represent surge potential more thoroughly in the index. Wind is also important to include as an independent variable because it can damage structures directly. The 'roughness' of wetlands and coastal forests may provide protection for coastal communities by reducing wind speed[52,53]. Finally, for this particular nation-wide analysis, we found that including or excluding wind did not change the overall results. Outputs from the model with and without wind were highly correlated ($r^2 = 0.9$) across regions and scenarios. In spite of this justification to include both wind and wave data, there are indeed some locations where it may be more appropriate to include just wave data. Our approach is flexible and the online open source tool used in this analysis allows the user to choose to exclude variables from the index.

Surge potential

Surge height at the coast can be related to the length of the continental shelf and storm characteristics[54]. To estimate surge potential we calculated the distance between a segment of coastline and the edge of the continental shelf. We used a contour polygon that depicts the edge of the continental margin, prepared by the Continental Margins Ecosystem (COMARGE) effort in conjunction with the Census of Marine Life. The same global dataset is included with the hazard index tool download. It represents an estimate of continental margins worldwide based on bathymetry and expert opinion.

Socio-economic data

Population metrics

Historically, vulnerability to natural hazards (e.g., drought, floods etc.) was measured in terms of natural and physical environmental variables, akin to our coastal hazard index[18]. Over the last few decades, the approach has evolved and been adapted to assess social vulnerability to climate hazards[18]. Studies have shown conceptually and through applications that vulnerability to natural hazards depends on the social, political and economic characteristics of individuals and populations[18,55]. This in turn constrains their responses and abilities to cope with disasters[55]. For example, the burden of Hurricane Katrina depended on a community's physical exposure to the hazard and socioeconomic factors such as disposable income for coping with the consequences of the hazard. In this study, we were interested in identifying where coastal habitats provide protection from flooding and erosion caused by SLR and storms for the greatest number of people and those subsets of the population that are least capable of avoiding or preventing hazards. We assessed the vulnerability of U.S. populations to storms and SLR using three population metrics: total population, number of families below the poverty line and number of people above age 65. We chose these three metrics, rather than a social vulnerability index because 1) they are meaningful to people, 2) there is not yet general consensus on the variables that should be used to measure social vulnerability to climate change[18] and 3) the data for these metrics are publically available from the American Community Survey (ACS) conducted by the U.S. Census Bureau.

The ACS is a household survey that currently samples about 3.5 million addresses annually. Through the ACS, the U.S. Census Bureau collects data on demographic,

 DOI: 10.1038/NCLIMATE1944

social, economic, and housing variables such as gender, ethnicity, age, citizenship, and birthplace. Each year the survey produces data that include 1-year, 3-year, and 5-year estimates of these variables for geographic areas in the United States and Puerto Rico, ranging from neighborhoods to Congressional districts to the entire nation. We used the most recent 5-year estimates for the period 2006-2010 summarized by census block-group. Block-groups are geographical units nested within larger units called tracts, which are nested within counties. For each block-group we mapped total population, population over 65, and number of families whose total income is under the poverty line using the ACS data provided in table B00003, B01001, and B17001, respectively[22].

Dasymetric mapping of ACS data and density of properties

To create a more precise map of where people live on the landscape, we employed a dasymetric mapping technique available as a tool for ArcGIS from the USGS[30]. Dasymetric mapping makes use of areal interpolation to convert aggregated population units (e.g., census block-groups) into homogenous zones. The mapping technique uses empirical sampling and areal weighting to represent population densities within a standard unit of area. The USGS dasymetric mapping tool requires a land-use raster input layer that has been reclassified into groups representing inhabited and uninhabited areas based on density stratification. This hierarchy serves to distribute more people into the higher density classes as well as determine cells where no people reside. We used the 2006 National Land Cover Database (NLCD)[56] and reclassified 20 land-use/land-cover (LULC) classes into four population density classes required by the tool: 1) high-density residential, 2) low-density residential, 3) non-urban inhabited and 4) uninhabited. Since the NLCD land-use categories for low, medium and high development do not always differentiate the built environment from where people are permitted to live, we also utilized land stewardship information from the USGS Gap Analysis Program[57] which identifies uninhabited public lands. By performing raster overlays we were able to mark all the development LULC cells found on public lands. As shown in Supplementary Table 6, LULC cells originally categorized as "developed" that occur on public lands were changed to a value of "4" indicating uninhabited, and no people were distributed in these cells. Ultimately, the areal interpolation performed by this tool allows for the disaggregation of any demographic data in a geospatial format that has one population value represented as a unit (polygon). Using LULC and land stewardship information we were able to produce more detailed information on population density and where people reside on the landscape, for each of the three population metrics.

Property values

The value of coastal properties was estimated using the ZHVI, which is the median market value of housing units in each U.S. 2010 Census block-group[23]. The ZHVI is similar to two other popular housing-price metrics – the Federal Housing Finance Agency's House Price Index (HPI) and Standard & Poor's Case-Shiller Index (CSI) – in that it is designed to track the changing value of residential real estate. While the HPI and CSI do so by observing changes in value between sales of the same home (repeat sales), the ZHVI uses a newer methodology known as hedonic imputation which tracks the movement in the estimated value of every unit in the housing stock, thereby adjusting for differences between the composition of sales versus the composition of the overall housing stock. The ZHVI is the preferred estimate for this application for several

DOI: 10.1038/NCLIMATE1944

reasons. First, because the ZHVI is based currently on over 100 million of the 131,704,730 homes (76%) from across the country[23], it can be computed for any location in the U.S., while the HPI and CSI are available only for select metropolitan areas. This is advantageous for our analyses of property values within each 1 km^2 coastline segment both in and outside of metropolitan centers. Second, Zillow uses all residential properties to compute an area's ZHVI, while the HPI includes only those properties with mortgages held by Fannie Mae and Freddie Mac. Furthermore, unlike the HPI and CSI, the ZHVI incorporates physical attributes of the lot and structures (such as square footage), assessed value, and prices of comparable properties. The ZHVI estimates the value of residential dwellings. It does not include commercial properties.

On May 08, 2012, Zillow provided ZHVI estimates for each U.S. Census 2010 block-group in every coastal state in the U.S. for which they had more than 30 valued properties. 115,571 of 134,723 block-groups contained a ZHVI. Missing ZHVI values were replaced with the ZHVI from the closest block-group with data that was in the same census tract (the U.S. Census arranges tracts to encompass areas of similar socio-economic characteristics). If no block-groups within a tract contained ZHVI data, we replaced all missing values of the block-group with the average ZHVI from block-groups in adjacent census tracts. We calculated property values for each 30 m raster cell in the dasymetric map of housing units by multiplying the number of units by the median home value for the census block-group. The number of residential housing units per U.S. Census 2010 block-group was taken from ACS table B25001. This value estimates the number of dwellings including apartments and condominiums which can be greater than the number of properties and structures in some places.

Vulnerability of people and property to coastal hazards

To assess the vulnerability of the people and property of the U.S. to coastal hazards, we analyzed the overlap between the coastal segments with the highest exposure to coastal hazards (Supplementary Fig. 3) and the data for the social metrics and property values produced from the dasymetric mapping. We used the ArcGIS Focal Statistics tool to determine the average number of people, average number of families below poverty line, average number of individuals over 65, and average number of properties at a 30 m resolution (the native resolution of the NLCD that went into the dasymetric model) within a 3 km search radius from the center of each segment. To produce estimates for total number of people, families below poverty line, individuals above 65, and number of properties for each 1 km^2 of coastline segment, we scaled-up the average of each 30 m x 30 m by multiplying by 1111 (1,000,000 m^2 / 900 m^2).

Comparison of vulnerability outputs to observed coastal hazard data

To assess the ability of the hazard index to capture risk, we compared the outputs from our analysis to observed data on hazard events and losses for the coastal U.S. We used data from the Spatial Hazards Events and Losses Database for the United States (SHELDUS[25]). SHELDUS is a county-level hazard data set for 18 different natural hazard event types such thunderstorms, hurricanes, floods, wildfires, and tornados from 1960 to 2010. The data are derived from several existing national data sources such as the National Climatic Data Center's monthly Storm Data publications.

We compared our estimates for total population of people most exposed to coastal hazards to the observed number of fatalities per state due to coastal hazard events that occurred between 1995 and 2010. We chose this time period because it is both current

DOI: 10.1038/NCLIMATE1944

(in this paper we used our index to assess current exposure to coastal hazards) and because the SHELDUS data from the previous time period (1985 to 1995) only includes events with greater than $50,000 in property or crop damages. Our coastal hazard index is designed to quantify exposure to hazards of all magnitudes, not just large events. We used state as the unit of analysis where hazard events per state during the 1995 to 2010 time period ranged from 3 in Connecticut to 390 in Florida, and fatalities ranged from zero in New Hampshire to 241 in Florida. We chose state as a unit of analysis rather than county for two reasons. One, several counties within coastal states experienced geographic changes (e.g. absorption of a county or the creation of a new county), but counties did not change states. Second, SHELDUS divides fatalities from events that affected multiple regions equally among counties because often the sources that SHELDUS draws on list causalities without sufficient spatial resolution[25]. Thus, we had the most confidence in the state level data.

For the comparison to SHELDUS data, we used estimates of total population exposed to the greatest coastal hazard based on a cut-off value derived from the distribution of hazard values for the current sea level rise and habitat scenario *only* (upper quartile of hazard index are values >3.14). We found a significant relationship between our estimates of total population exposed to the greatest coastal hazard and number of fatalities (N = 21 states, $R^2 = 0.70$, $P<0.0001$). Including the recent fatalities from Hurricane Sandy improved the ability of our index to explain variation among states in coastal hazard-related fatalities (N = 21 states, $R^2 = 0.75$, $P<0.0001$, total coastal hazards = 1271, total coastal hazard related fatalities = 600, Supplementary Fig. 9), suggesting that our hazard index indicated higher vulnerability for the northeastern states than had been observed until Hurricane Sandy. Even excluding Florida (the state with the greatest number of fatalities and vulnerability of people to hazards), the relationship is still significant, although the amount of variance explained by our modeling and mapping is lower (N = 20 states, $R^2 = 0.25$, $P<0.03$ for just SHELDUS data). These comparisons suggest that fatalities per state per year are proportional to the number of people most exposed to coastal hazards as estimated by our hazard index and population mapping. Note that because we lacked the dasymetric mapping outputs for the ACS data for Hawaii and Alaska, the modeled versus observed analysis excludes those two states.

We also compared the relationships between the version of our model that includes habitat as an explanatory variable and a version excluding habitat as an explanatory variable. We found that a model including habitat as an explanatory variable explains 15% more of the variance than a model without habitat, which further supports our case for the importance of including natural habitats in analyses of vulnerability and hazard planning. Note that excluding habitat as an explanatory variable is different than our "without habitat" scenario in the manuscript. For the "without habitat" scenario we keep habitat in as an explanatory variable but set its rank to 5 which means buffering habitats are absent.

2. Supplementary Acknowledgments: We thank the Gordon and Betty Moore Foundation for financial support and for hosting the National Climate Assessment Biodiversity, Ecosystems and Ecosystem Services Technical Chapter working group. We also thank the many individuals and institutions that provided data. Svenja Gudell and Zillow provided property value data. Thanks to the United States Fish and Wildlife

 DOI: 10.1038/NCLIMATE1944

Service for providing the National Wetlands Inventory data, David Revell and Bob Batallio at ESA PWA for California dune data, Hillary Stockdon at United States Geological Survey for gulf and east coast dune data, the Center for Remote Sensing and Spatial Analysis at Rutgers University for New Jersey eelgrass data, Patrick J. Clinton at the United States Environmental Protection Agency for providing Oregon eelgrass data, Brian Corley, Daniel Harris, Douglas S. Atkinson, and Randall Walker at the University of Georgia Marine Extension Service for providing Georgia oyster data, Mark Luckenbach, PG Ross, Marcia Berman and Sharon Killeen at Virginia Institute of Marine Science for providing oyster data, Brian Conrad at North Carolina Division of Marine Fisheries for providing North Carolina oyster data, Christine Addison and Don Field at the United States National Oceanographic and Atmospheric Administration's Beaufort Laboratory for seagrass and oyster data for various states, John Harper and Kalen Morrow at Coastal and Oceans Inc. for providing the Alaska Shorezone data, Fred Short at University of New Hampshire for providing New Hamphsire eelgrass data, Chris Shepard at The Nature Conservancy for providing oyster and seagrass data for the Gulf of Mexico, Arlene Merems at Oregon Department of Fish and Wildlife for help with Oregon kelp and seagrass data, CK Kim for unpacking the Wave Watch III data, and all the institutions listed in Supplementary Tables 2, 3, and 4 that amassed habitat data and made it publicly available so seamlessly. We also thank Jen Burke, Guy Gelfenbaum, Rob Griffin, CK Kim, Josh Lawler, Mark Plummer, Peter Ruggiero, Jameal Samhouri, Heather Tallis, Jodie Toft, and Guy Ziv for helpful discussions during this research.

Links for downloading the coastal hazard index and visualizing and downloading results are available at www.naturalcapitalproject.org.

3. Supplementary Tables

Supplementary Table 1. Coastal hazard index variables and ranking system. Ranks for the last five variables are based on the distribution of values for these variables for all 1 km^2 segments of the U.S. coastline across all five SLR scenarios.

Rank Variable	Very low 1	Low 2	Moderate 3	High 4	Very high 5
Natural habitats	coral reef; coastal forest	high dune; emergent marsh; oyster reef	low dune	seagrass bed; canopy kelp forest; aquatic vegetation	No habitat
Shoreline type	Rocky; high cliffs; fiord; fiard; seawalls	Medium cliff; indented coast;	Low cliff; glacial drift; alluvial plain; revetments; rip-rap walls	Cobble beach; estuary; lagoon; bluff	Barrier beach; sand beach; mud flat; delta
Relief	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile
Sea-level change	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile
Wind exposure	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile
Wave exposure	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile
Surge potential	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile

DOI: 10.1038/NCLIMATE1944

Supplementary Table 2. Habitat rank and distance of effect for coastal vulnerability analysis.

Habitat	Rank	Protective distance (m)
Coral reefs	1	2000
Coastal forests	1	2000
Emergent marsh	2	1000
Oyster reefs	2	100
High dunes	2	300
Low dunes	3	300
Submerged aquatic vegetation	4	500
Kelp forests	4	1500
Seagrass beds	4	500

Supplementary Table 3. Seagrass data and source. NOAA C-CAP stands for National Oceanographic and Atmospheric Administration Coastal Change Analysis Program.

State	Source	Description	URL for data or data contact
Maine	NOAA C-CAP	Data were mapped by ME's Department of Marine Resources from aerial imagery acquired between 1993 and 1997. The data set is a composite of the distribution during these two years. We created an ArcGIS shapefile consisting of all polygons with attribute "Class" = submerged aquatic vegetation.	http://www.csc.noaa.gov/digitalcoast/data/benthiccover/download.html
New Hampshire	Dr. F.T. Short Seagrass Ecology Group, Univ. of New Hampshire (UNH); NH Dept. of Environmental Services	Data were mapped in the Great Bay Estuary based on aerial photographs taken in 2004, 2005, 2006, and 2007. We created a composite dataset for all polygons with eelgrass present during these 4 years.	http://www.granit.unh.edu/data/downloadfreedata/downloaddata.html
Massachusetts	MA Department of Environmental Protection	Data were mapped by MA's Department of Environment Protection from aerial imagery acquired in 2001 and 2006-7. We created a composite dataset of the distribution during these years.	http://www.mass.gov
Rhode Island	Rhode Island Geographic Information System (RIGIS)	Data were mapped by the Narragansett Bay Estuary Program based on aerial imagery collected in 2000 and classified according to the USFWS system. We created a layer made up of all polygons and line segments with "Aquatic beds (eelgrass)" in the attribute table.	http://www.edc.uri.edu/RIGIS/data/data.aspx?ISO=biota
Connecticut	CT Department of Energy and Environmental Protection	Data were created by the USFWS National Wetlands Inventory, Region 5. Delineations of eelgrass beds were completed based on aerial imagery collected in 2002 and 2006. We created a composite layer for these two years.	http://www.ct.gov/dep/cwp/view.asp?a=2698&q=322898&depNav_GID=1707#CoastalHabitat
New York	NOAA C-CAP	Data were mapped by New York State Department of Coastal Resources from aerial imagery acquired between 2002.	http://www.csc.noaa.gov/digitalcoast/data/benthiccover/download.html
New Jersey	Center for Remote Sensing and Spatial Analysis (CRSSA), Rutgers University.	Data were mapped by CRSSA from aerial imagery acquired in 2009 for the Barnegat Bay-Little Egg Harbor Estuary.	http://crssa.rutgers.edu/projects/coastal/sav/downloads.htm
Chesapeake Bay (Maryland, Virginia)	Virginia Institute of Marine Science	Data were mapped baywide by the Virginia Institute of Marine Science from aerial imagery collected annually during 2000-2010. We created a composite data set of all years using any regions with eelgrass density classes 1-4. We excluded density class 0 which indicates no eelgrass.	http://web.vims.edu/bio/sav/gis_data.html (*56*)
North Carolina	Albemarle-Pamlico National Estuary Program	Data were mapped by NOAA-Beaufort and Atkins North America, Inc for the entire North Carolina coast, as well as the Virginia	http://portal.ncdenr.org/web/apnep/resources/maps

DOI: 10.1038/NCLIMATE1944

		portion of the Albemarle-Pamlico Estuary from aerial imagery collected during 2006, 2007, and 2008.	
Florida	Florida Fish and Wildlife Conservation Commission (FWC), Fish and Wildlife Research Institute (FWRI), NOAA, Dade County; Southwest Florida Water Management District (SWFWMD)	The first seagrass dataset for FL includes benthic data for Florida Bay, Biscayne Bay and the Florida Keys National Marine Sanctuary created from aerial imagery collected in 2001-2002 by FWC-FWRI, NOAA and Dade County. The second dataset was mapped by SWFWMD from aerial imagery collected for St. Joseph's Sound and Clearwater Harbor, Charlotte Harbor, Tampa Bay, Sarasota Bay, Lemon Bay in 2006. We created a composite layer for seagrass from these two layers.	N/A – received data from NOAA Center for Coastal Fisheries and Habitat Research
Alabama	Mobile Bay Estuary Program	Data were mapped from aerial imagery collected in 2009 for Mississippi Sound (AL), Mobile Bay, Mobile-Tensaw Delta, Little Lagoon, Bay La Launch, Perdido Bay, and their communicating tributaries.	N/A – received data from TNC Gulf of MX Coastal Resilience http://gulfmex.coastalresilience.org/
Mississippi	The Nature Conservancy Northern Gulf of Mexico Ecoregion (2000)	Data were collected from a variety of sources which mapped the distribution of seagrass from aerial imagery (*57*)	N/A – received data from TNC Gulf of MX Coastal Resilience http://gulfmex.coastalresilience.org/
Louisiana	The Nature Conservancy Northern Gulf of Mexico Ecoregion (2000)	Data were collected from a variety of sources which mapped the distribution of seagrass from aerial imagery (*57*)	N/A – received data from TNC Gulf of MX Coastal Resilience http://gulfmex.coastalresilience.org/
Texas	The Nature Conservancy Northern Gulf of Mexico Ecoregion (2000); NOAA C-CAP	Data were collected from a variety of sources which mapped the distribution of seagrass from aerial imagery (*57*); data are also available for different bays in TX from NOAA C-CAP	N/A – received data from TNC Gulf of MX Coastal Resilience http://gulfmex.coastalresilience.org/
California	Pacific States Marine Fisheries Commission	Data are a compilation of currently available seagrass GIS data sets for the west coast of the United States. The source data were acquired over a large range of time periods (1987-2003), at many different spatial resolutions using a variety of methods, including aerial photography, videography, multispectral sensors, sonar, and field surveys.	http://marinehabitat.psmfc.org/pacific-coast-groundfish-efh-gis-data.html
Oregon	Pacific Marine Fisheries Commission (coastal); Environmental Protection Agency (EPA, bays)	Coastal data are a compilation of currently available seagrass GIS data sets for the west coast of the United States. The source data were acquired over a large range of time periods (1987-2003), at many different spatial resolutions using a variety of methods, including aerial photography, videography, multispectral sensors, sonar, and field surveys.	http://marinehabitat.psmfc.org/pacific-coast-groundfish-efh-gis-data.html

		Bay data were mapped from aerial imagery collected in Alsea, Coos, Nestucca, Salmon, Tillamook, Umpqua and Yaquina estuaries from 2004 to 2007.	N/A received from EPA
Washington	Washington Department of Natural Resources;	The first dataset was created using the ShoreZone Mapping System with aerial videos collected between 1994 and 2000. We created a data for seagrass by selecting all coastal segments classified as Zostera (ZOS_UNIT = patchy or continuous) or surfgrass (SURF_UNIT = patchy or continuous).	http://fortress.wa.gov/dnr/app1/dataweb/dmmatrix.html
	Pacific Marine Fisheries Commission	The second dataset is a compilation of currently available seagrass GIS data sets for the west coast of the United States. The source data were acquired over a large range of time periods (1987-2003), at many different spatial resolutions using a variety of methods, including aerial photography, videography, multispectral sensors, sonar, and field surveys.	http://marinehabitat.psmfc.org/pacific-coast-groundfish-efh-gis-data.html
Alaska	NOAA Alaska Fisheries; Coastal and Oceans Inc. ShoreZone	Data were created using the ShoreZone Mapping System with aerial videos collected for more than 47,000 km of shoreline, from Bristol Bay to southern Southeast Alaska at the US-Canada border in 2001-2003. We created a dataset for just seagrass by selecting all coastal segments classified as Zostera (ZOS_UNIT = patchy or continuous) or surfgrass (SURF_UNIT = patchy or continuous).	N/A – we received the data from Coastal and Oceans Inc. http://alaskafisheries.noaa.gov/shorezone/

DOI: 10.1038/NCLIMATE1944

Supplementary Table 4. Kelp forest data and source.

State	**Source**	**Description**	**URL for data or data contact**
California	California Department of Fish and Game	Data were mapped by CA DFG from aerial imagery collected annually from 2000-2010. We created a composite dataset for these years.	http://www.dfg.ca.gov/marine/gis/naturalresource.asp
Oregon	Oregon Department of Fish and Wildlife	Data were mapped by ODFW and Ecoscan Resources Data from aerial imagery collected during 1990, 1996, 1999.	http://www.oregonocean.info/index.php?option=com_content&view=article&id=338&Itemid=134
Washington	Washington State Department of Natural Resources	Data for WA's saltwater shorelines were created using the ShoreZone Mapping System with aerial videos collected between 1994 and 2000. We created a kelp layer by selecting all coastal segments classified as Nereocystis (NER_UNIT = patchy or continuous) or Macrocystis (MAC_UNIT = patchy or continuous). Data for the outer coast and Straight de Juan de Fuca were mapped by WDNR Nearshore Habitat Program and NOAA Olympic Coast NMS using aerial imagery collected annually from 1989-1992 and 1994-2004. These data include two species of floating kelp, Nereocystis luetkeana and Macrocystis integrifolia.	http://fortress.wa.gov/dnr/app1/dataweb/dmmatrix.html
Alaska	NOAA Alaska Fisheries; Coastal and Oceans Inc. Shorezone	Data were created using the ShoreZone Mapping System with aerial videos collected for more than 47,000 km of shoreline, from Bristol Bay to southern Southeast Alaska at the US-Canada border in 2001-2003. We selected coastal segments classified as Nereocystis (NER_UNIT), Macrocystis (MAC_UNIT) and Alaria (ALF_UNIT) were classified as "patchy" or "continuous."	N/A – we received the data from Coastal and Oceans Inc. http://alaskafisheries.noaa.gov/shorezone/

Supplementary Table 5. Oyster reef data and source.

State	Source	Description	URL for data or contact
Maryland	Maryland Department of National Resources	Dataset indicates areas where oyster repletion activities have taken place between 1992 and 2009. Data were delineated from coordinates collected in the field.	http://dnrweb.dnr.state.md.us/gis/data/
Virginia	Center for Coastal Resources Management; Eastern Shore Laboratory Virginia Institute of Marine Science	The first dataset designates areas within Chesapeake Bay where oyster reefs have been restored. The second dataset reflects the location of natural reefs on the seaside of Virginia's Eastern Shore in 2007-2008.	N/A - received data directly from VIMS
North Carolina	Shellfish and Benthic Mapping Program, Resource Enhance-ment Section, North Carolina Division of Marine Fisheries	Data were mapped from benthic surveys of intertidal and subtidal shellfish habitat conducted by the NC DMF Shellfish Mapping program from 1989-2012.	http://portal.ncdenr.org/web/mf/contact-dmf
South Carolina	South Carolina Department of Natural Resources (SCDNR)	Data for intertidal oyster reefs were mapped from aerial photographs taken between 2003-2006 by Photo Science Inc. and SCDNR.	http://www.dnr.sc.gov/GIS/descoysterbed.html
Georgia	University of Georgia Marine Extension; Service; Sapelo Island National Estuarine Research Reserve; Georgia Department of Natural Resources	Data for intertidal oyster reefs were mapped from field surveys conducted in Duplin River, Sapelo Island, Chatham, Bryan, Liberty and McIntosh Counties during 2008-2011.	N/A – received the data from MAREX http://www.marex.uga.edu/
Florida	Florida Fish and Wildlife Conservation Commission-Fish and Wildlife Research Institute	Data represent oyster coverage at study areas available to Florida Fish and Wildlife Institute (FWRI) as of 2011. Source collection methods and dates (1992 to 2007) vary.	N/A – received data from TNC Gulf of MX Coastal Resilience http://gulfmex.coastalresilience.org/
Alabama	Alabama Dept. of Conservation, Marine Resources Division	Data show locations of oyster reefs in 1995.	Same as FL
Mississippi	Mississippi Department of Marine Resources	Data delineate location of natural reefs and areas enhanced via cultch plants. Data were updated as of 2010.	Same as FL
Louisiana	N/A	N/A	N/A
Texas	Texas A&M University; Texas Parks and Wildlife; Lower Texas Coast Oil Spill Response Mapping Project	Composite of five datasets indicating locations of oyster reefs in Galveston Bay, Corpus Bay, Copano Bay, Lavaca Bay and Matagorda Bay at various times between the mid-1990s and present day. Data were amassed via field mapping techniques, acoustic techniques, and hand drawn based on known locations of reefs.	Same as FL

DOI: 10.1038/NCLIMATE1944

Supplementary Table 6. Linking NLCD2006 LULC and USGS Dasymetric Mapping Tool.

NLCD2006 LULC	USGS Dasymetric Mapping Density Class
Developed, High Intensity	(1) high-density residential
Developed, Medium Intensity	(2) low-density residential
Developed, Low Intensity	(3) non-urban inhabited
Developed, Open Space	(4) uninhabited
All other LULC classes (e.g. water, forest, wetlands, etc.)	(4) uninhabited
Developed LULC cells occurring on public lands	(4) uninhabited

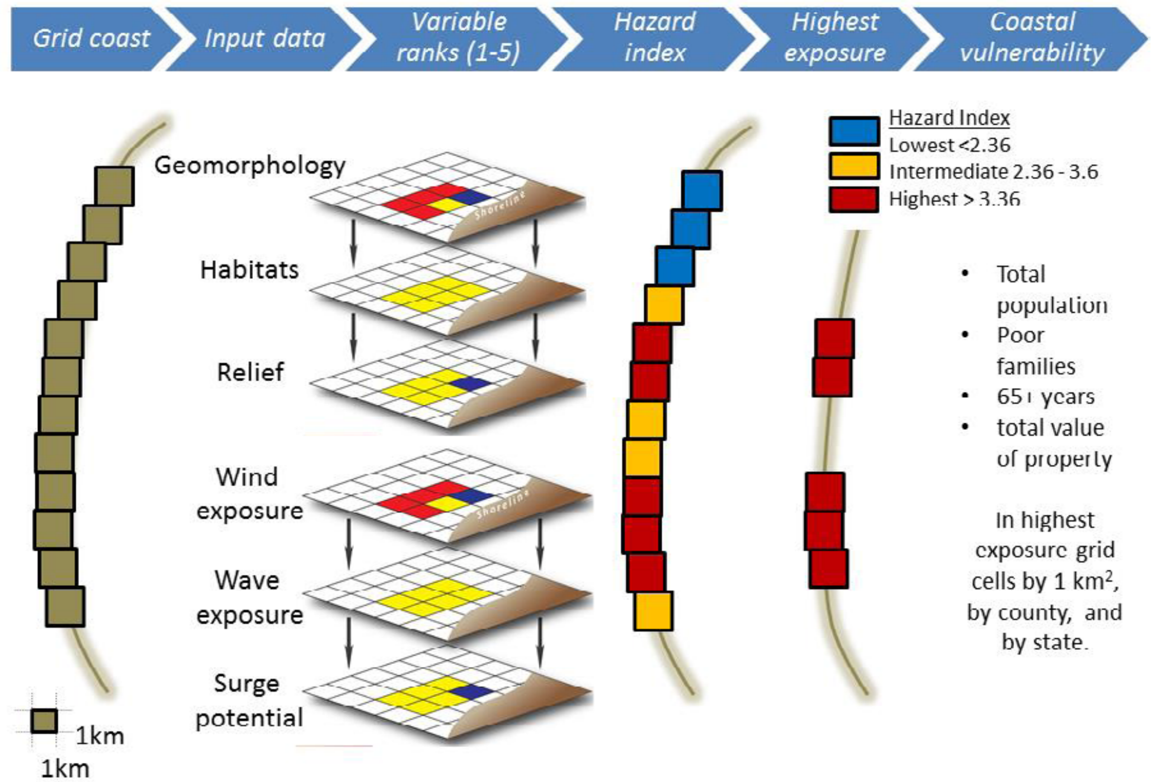
upplementary Table 7. Protection of total people and property from storms and SLR in 2100 (A2) for the highest coastal hazard segments in ich state. Data are the difference in the number of people and value of property protected with and without habitats included in the model.

State	Protected coastline (km)	Protected people (thousands)	Protect poor families	Protected elderly (thousands)	Protected property value (billions $)
HI	180	NA	NA	NA	12.1
AK	1736	NA	NA	NA	0.8
WA	233	25.5	476	4.6	2.9
OR	229	12.1	377	3.0	2.5
CA	250	108.9	1753	12.4	24.7
TX	723	30.7	1038	4.5	2.4
LA	666	1.7	42	0.4	0.3
MS	61	11.7	411	1.7	0.5
AL	132	9.1	249	1.9	1.8
FL	1526	356.0	6139	97.7	80.7
GA	149	1.5	23	0.6	0.5
SC	249	14.4	135	3.0	7.2
NC	1602	70.1	1170	12.7	21.4
VA	789	55.1	1075	7.2	5.0
MD	989	68.3	684	11.6	12.3
DE	94	16.8	236	2.9	2.5
NJ	244	96.0	2458	16.2	22.3
NY	457	326.6	7345	59.3	79.1
CT	87	55.4	698	9.6	10.9
RI	95	31.1	384	5.2	5.0
MA	182	93.3	1707	16.0	18.1
NH	2	0.3	3	0.1	0.1
ME	536	30.4	578	6.3	3.7

 DOI: 10.1038/NCLIMATE1944

4. Supplementary Figures and Legends

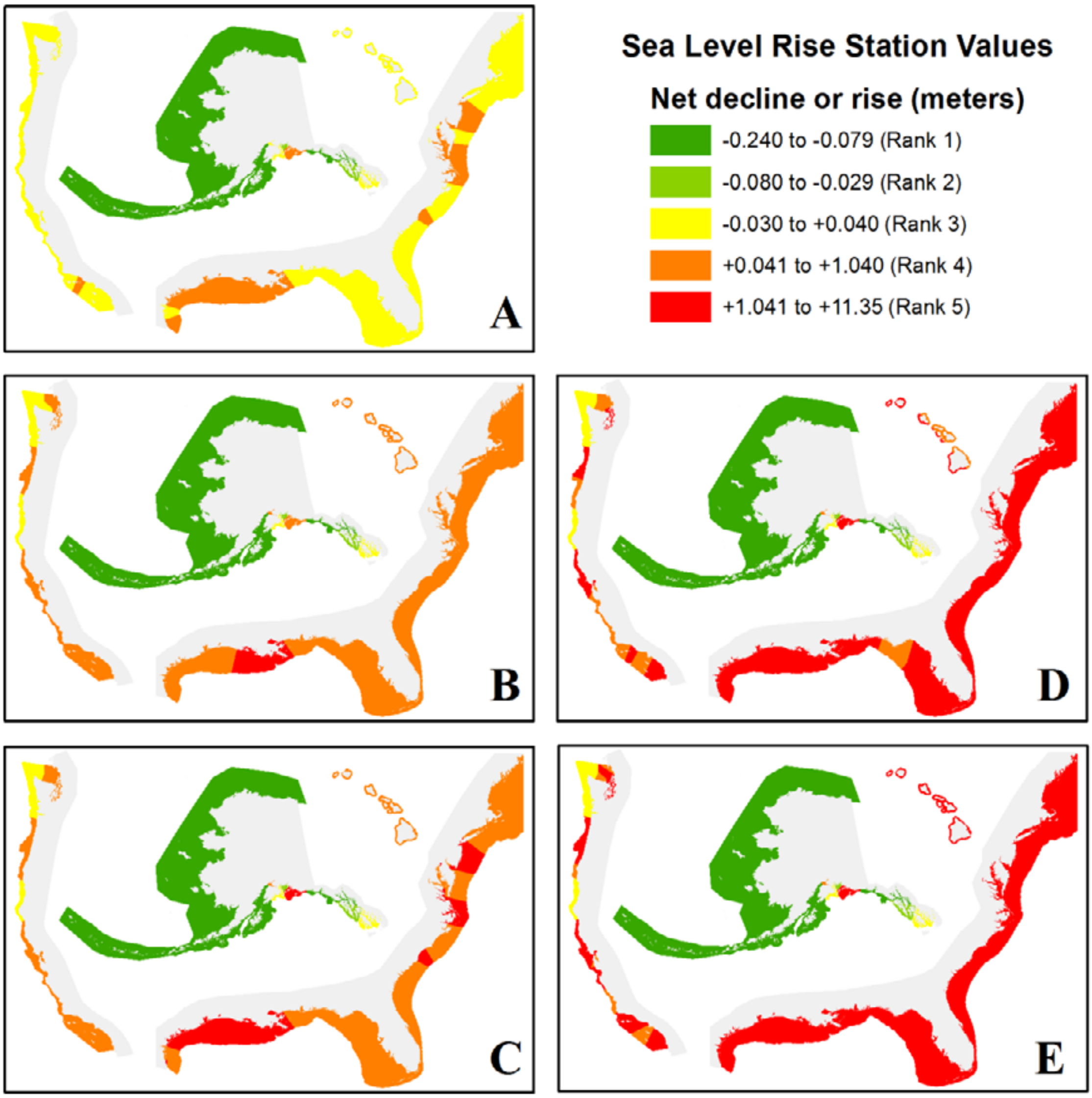
A.



B.

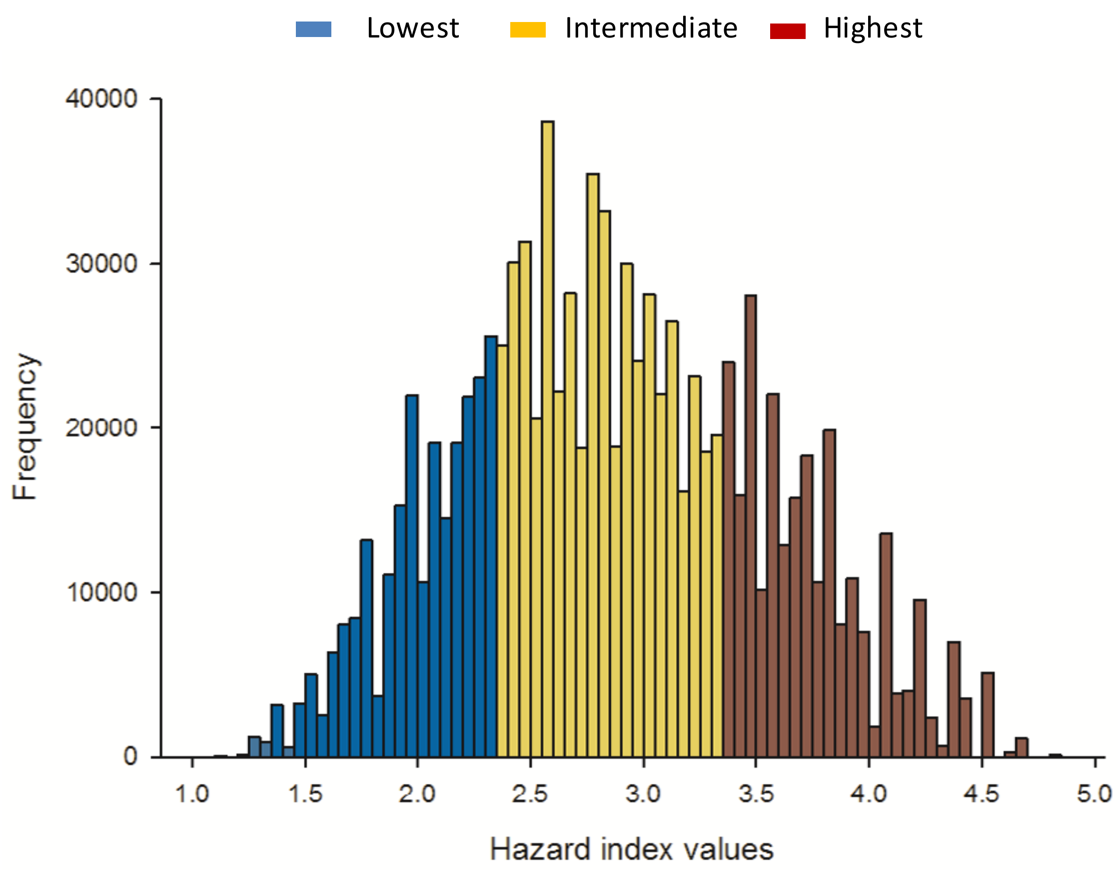
Climate scenarios	Habitat scenarios	Range of hazard index values	Coastal vulnerability
High	Habitat No habitat	1.05 - 4.69 1.26 - 4.84	• Total population • Poor families • 65+ years • total value of property In highest exposure grid cells (>3.36) by 1 km^2, by county, and by state.
Medium	Habitat No habitat	1.05 -4.69 1.26 - 4.84	
Low	Habitat No habitat	1.05 - 4.69 1.26 - 4.84	
Trend	Habitat No habitat	1.05 - 4.69 1.26 - 4.69	
Current	Habitat No habitat	1.05 - 4.50 1.26 - 4.69	

Supplementary Figure 1. Conceptual diagram showing A) steps in coastal vulnerability analysis for a single scenario and B) a list of the ten climate by habitat scenarios and range of hazard values for the whole country for each scenario.

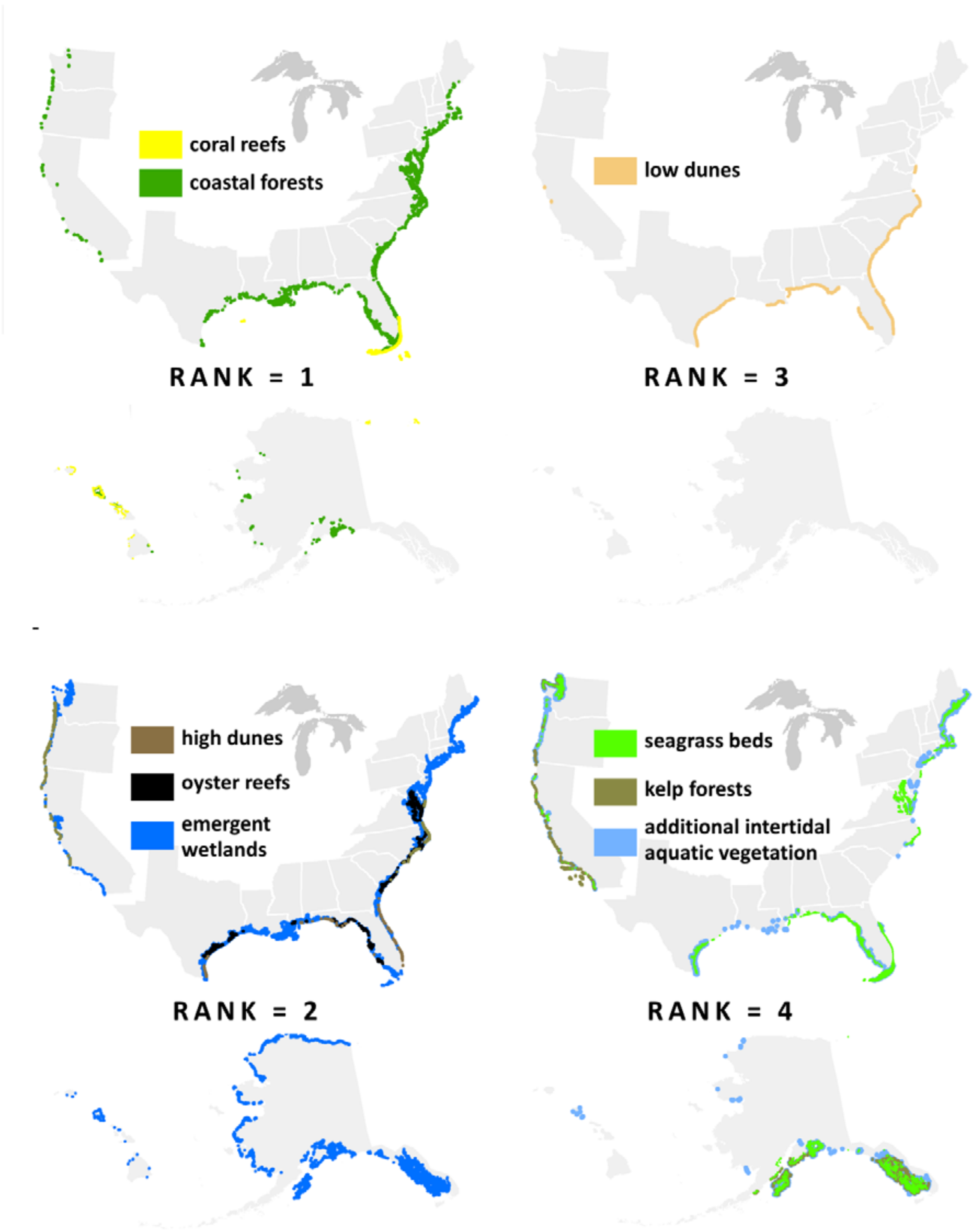


Supplementary Figure 2. Rise in sea level for the A) current, B) trend, C) B1, D) A2, and E) high scenarios.

DOI: 10.1038/NCLIMATE1944

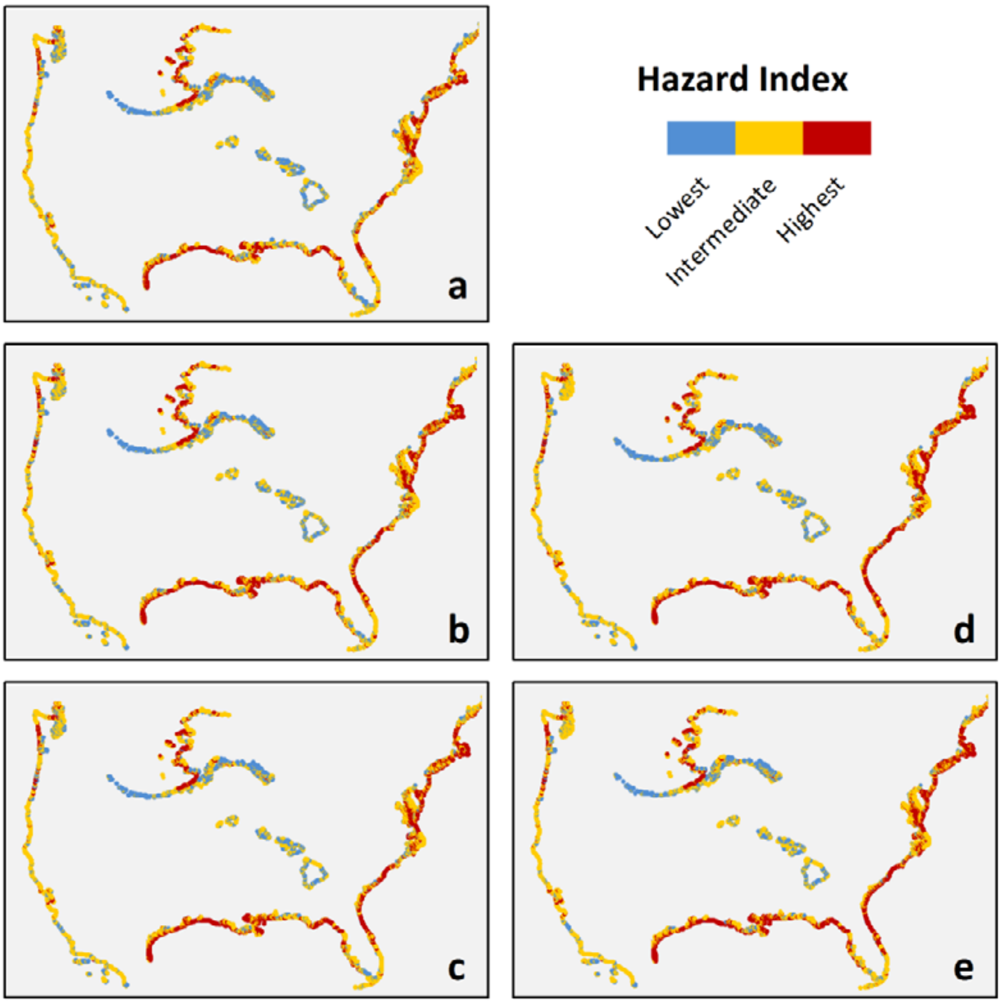


Supplementary Figure 3. Frequency distribution of results from the coastal hazard index for all SLR and habitat scenarios for each of the 5 regions. Lowest 25% < 2.36; highest 25 % > 3.36. Today 16% of the United States coastline is exposed to 'high hazard' (greater than 3.36), and these high hazard coastal areas harbor 1.3 million people, 250,000 elderly, 30,000 families below the poverty line, and $300 billion in property value (Fig. 1). Fifty-three percent of today's coastline and 4.8 million people currently fall in the intermediate coastal hazard class (2.36 to 3.36). The remaining 31% of the coastline (index < 2.36) and 2.3 million people are least exposed to coastal hazards relative to all other locations and scenarios.

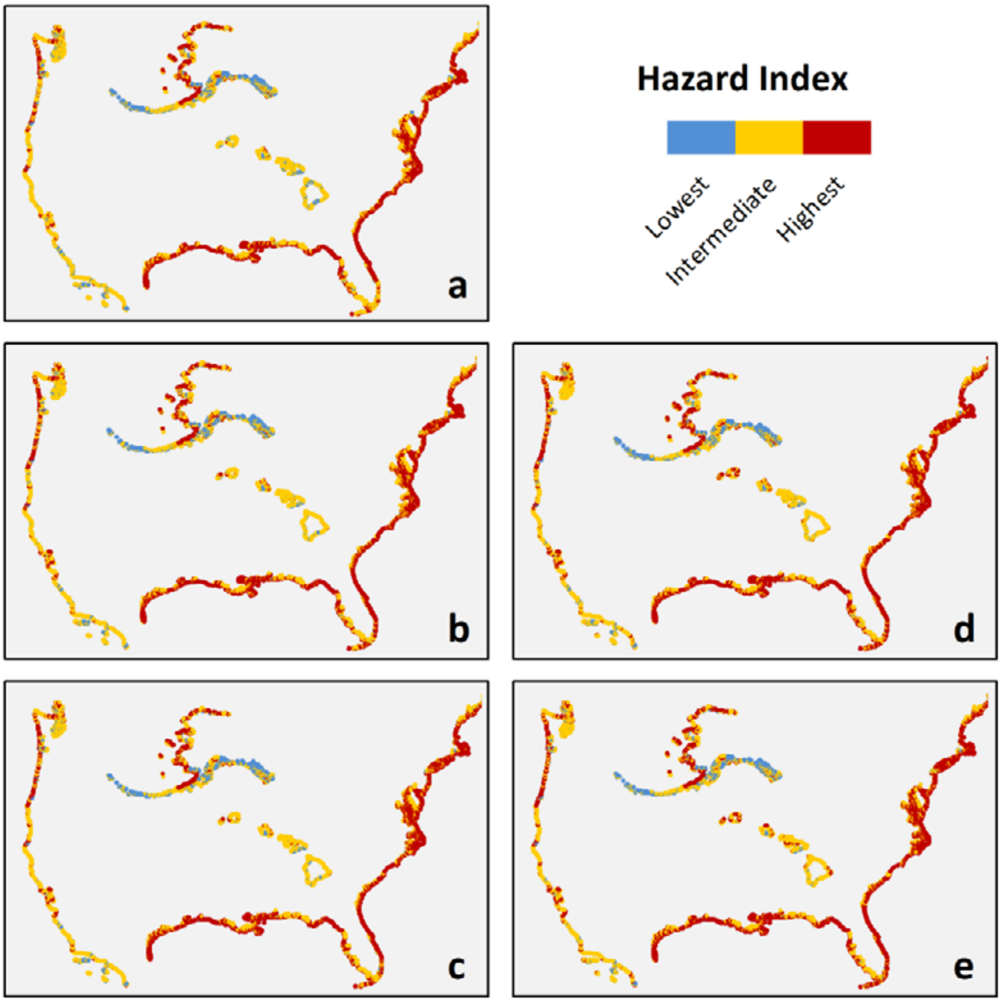


Supplementary Figure 4. Distribution of the nine coastal habitat types and ranks for the United States.

DOI: 10.1038/NCLIMATE1944

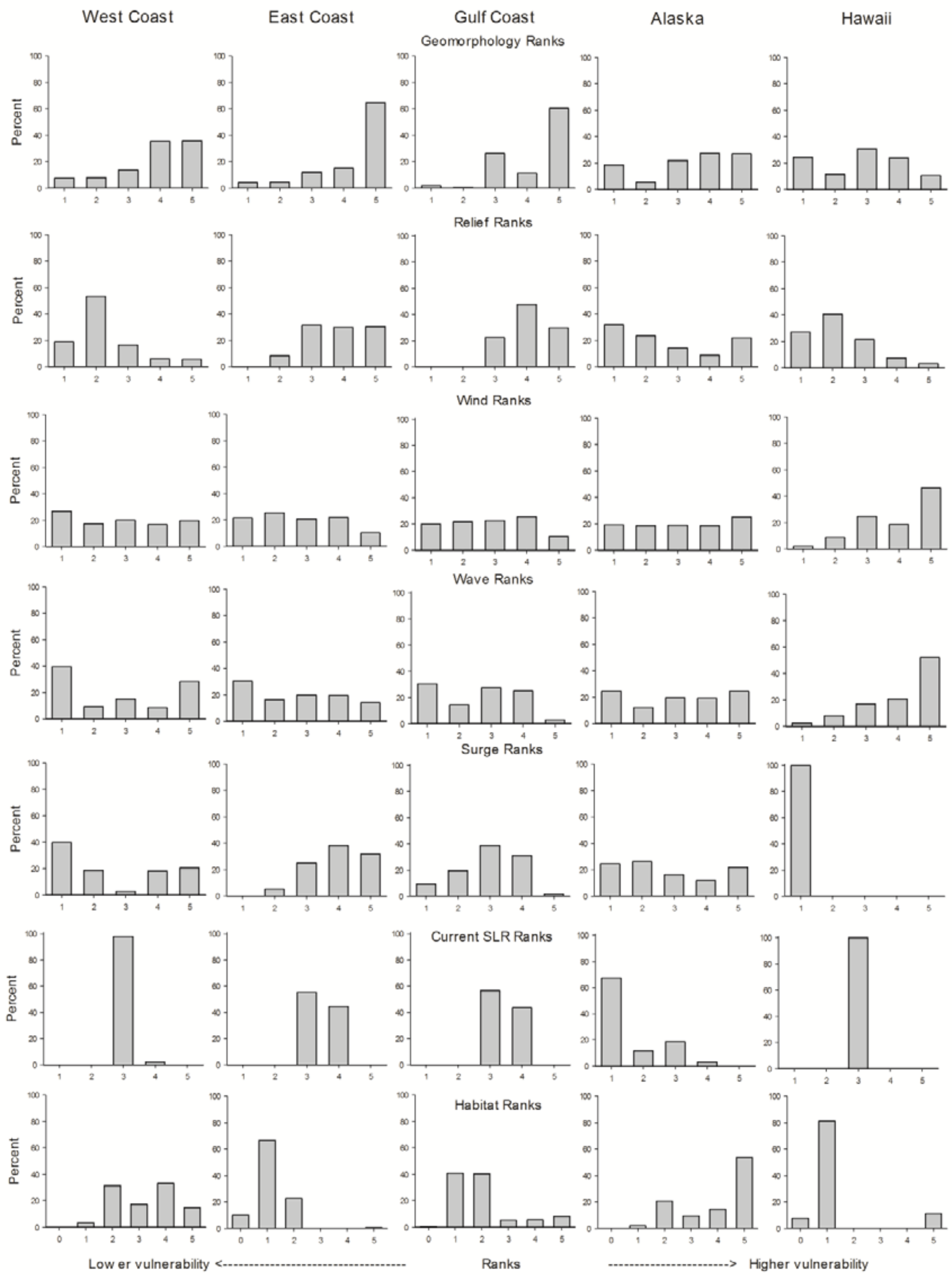


Supplementary Figure 5. Coastal hazard index categories with habitats for each 1 km^2 segment for all five regions for A) current, B) trend, C) B1, D) A2, and E) high SLR scenarios.

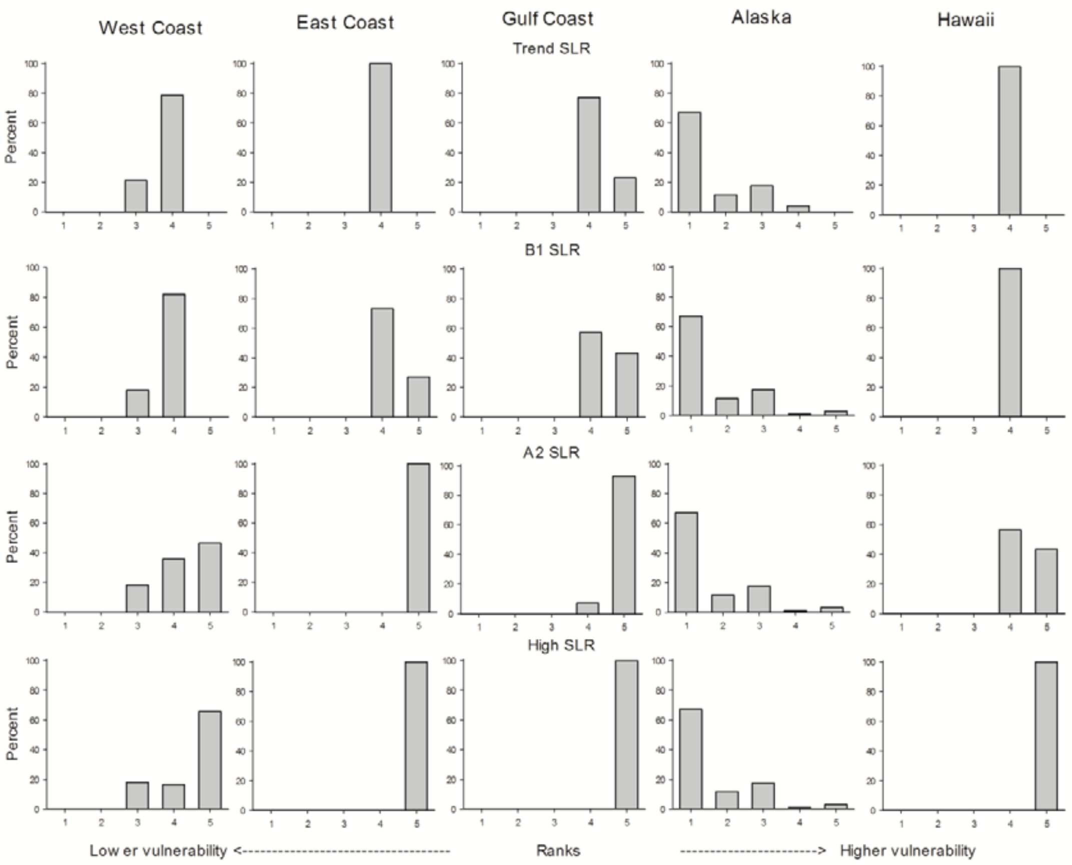


Supplementary Figure 6. Coastal hazard index categories without habitats for each 1 km^2 segment for all five regions for A) current, B) trend, C) B1, D) A2, and E) high SLR scenarios.

DOI: 10.1038/NCLIMATE1944

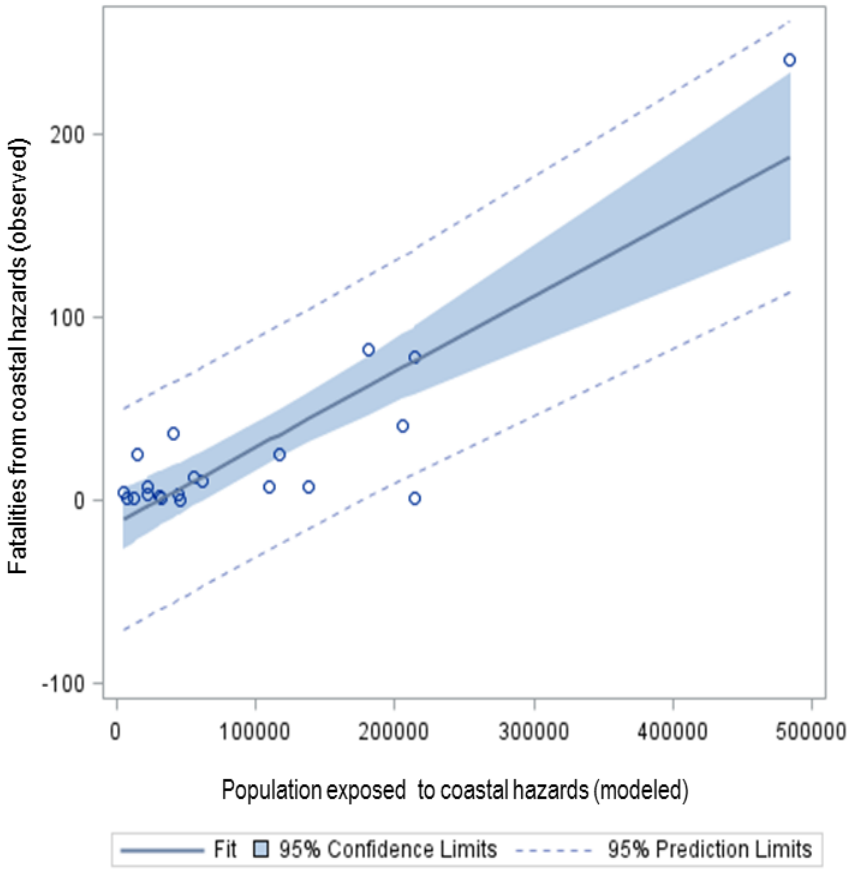


Supplementary Figure 7. Distribution of ranks for each of the seven variables in the coastal hazard index for each 1 km^2 segment of the five regions.



Supplementary Figure 8. Distribution of SLR ranks for the four future SLR scenarios (Trend, B1, A2, High) for all 1 km^2 segments in each of the five regions.

 DOI: 10.1038/NCLIMATE1944



Supplementary Figure 9. Scatterplot of linear regression between observed fatalities from coastal hazards (SHELDUS and Hurricane Sandy fatalities) and modeled number of people most exposed to coastal hazards in the current scenario (upper quantile of index value > 3.14). N = 21 states, $R^2 = 0.75$ $P < 0.0001$. Point in the upper right is Florida.

6. Supplementary References

31. Abuodha, P. A. & Woodroffe, C. D. International assessments of the vulnerability of the coastal zone to climate change, including an Australian perspective. (Department of the Environment and Heritage Australian Greenhouse Office, Australian Government, 2006).

32. Ferrario, F. et al. Coral reefs are effective for coastal hazard risk reduction. *Proc. Nat. Acad. Sci.* In review.

33. U.S. Fish and Wildlife Service CONUS_wet_poly. (U.S. Fish and Wildlife Service, Division of Habiat and Resource Conservation, 2012).

34. Cowardin, L. M., Carter, V., Golet, F. C. & LaRoe, E. T. Classification of Wetlands and Deepwater Habitats of the United States. (U.S. Department of the Interior, Fish and Wildlife Service, 1979).

35. Institute for Marine Remote Sensing, University of South Florida (IMaRS/USF), Institut de Recherche pour le Développement (IRD), UNEP-WCMC, The WorldFish Center, and WRI, Global Coral Reefs composite dataset compiled from multiple sources for use in the Reefs at Risk Revisited project incorporating products from the Millennium Coral Reef Mapping Project prepared by IMaRS/USF and IRD. (2011).

36. Estes, J. A. & Duggins, D. O. Sea otters and kelp forests in Alaska: generality and variation in a community ecological paradigm. *Ecol. Mono.* **65**, 75–100 (1995).

37. Beck, M. W. et al. Oyster reefs at risk and recommendations for conservation, restoration, and management. *BioScience* **61**, 107–116 (2011).

38. NOAA Recovery Projects. Restoration Atlas (2012), http://www.nmfs.noaa.gov/habitat/restoration/restorationatlas/recovery_map.html

DOI: 10.1038/NCLIMATE1944

39. Mull, J. M. Coastal sand dunes in the U.S. Pacific Northwest: regional variability in foredune geomorphology and associated physical vulnerability to hazards. (Oregon State University Master's Thesis, 2010).

40. Revell, D. L., Battalio, R., Spear, B., Ruggiero, P. & Vandever, J. A methodology for predicting future coastal hazards due to sea-level rise on the California Coast. *Climatic Change* **109**, 251–276 (2011).

41. USGS Coastal classification mapping project. at <http://coastal.er.usgs.gov/coastal-classification/index.html>

42. Army Core of Engineers Economic Guidance Memorandum (EGM) 04-01, Generic Depth Damage Relationships. (2003).

43. Sallenger, A. H. Storm impact scale for barrier islands. *J. Coast. Res.* **16**, 890–895 (2000).

44. Wessel, P. & Smith, W. H. F. A global, self-consistent, hierarchical, high-resolution shoreline database. *J. Geophys. Res.* **101**, 8741–8743 (1996).

45. NOAA Environmental Sensitivity Index (ESI) Maps. at <http://response.restoration.noaa.gov>

46. USGS HydroSHEDS (2012), http://hydrosheds.cr.usgs.gov/index.php

47. Finlayson, D. Fetch Program. (2005).

48. U.S. Army Corps of Engineers Coastal Engineering Manual. (U.S. Army Corps of Engineers, 2002).

49. Dean, R. G. & Dalrymple, R. A. *Water wave mechanics for engineers and scientists*. (World Scientific Publishing Co. Pte. Ltd., 1991).

50. Svendsen, I. A. (2006). *Introduction to nearshore hydrodynamics* (World Scientific, 2006).

51. Dean, R. G. & Bender, C. J. Static wave setup with emphasis on damping effects by vegetation and bottom friction. *Coastal Engineering* **53**, 149–156 (2006).

52. Charnock, H. Wind stress on a water surface. *Quarterly Journal of the Royal Meteorological Society* **81**, 639–640 (1955).

53. Hsu, S.A. *Coastal meteorology* (Academic Press, 1998).

54. Irish, J. L. & Resio, D. T. A hydrodynamics-based surge scale for hurricanes. *Ocean Eng*. **37**, 69–81 (2010).

55. Cutter, S. L. & Emrich, C. T. Moral hazard, social catastrophe: the changing face of vulnerability along the hurricane coasts. *Ann. Amer. Acad. Pol. Soc. S.* **604**, 102–112 (2006).

56. Fry, J. et al. Completion of the 2006 National Land Cover Database for the Conterminous United States, *Photogram Eng Rem S* **77**, 858-864 (2011).

57. USGS National Gap Analysis Program. (U.S. Department of the Interior, U.S. Geological Survey).