Surviving and Thriving in the Face of Rising Seas

Building Resilience for Communities on the Front Lines of Climate Change
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Technical Appendix

Union of Concerned Scientists

1. Data Sources

We applied the climate equity tool to 35 counties along the east and Gulf coasts (see Figure 2 in the main report for a list of counties). County-level data were collected for the following categories of information:

Socioeconomic data for profiles of the counties that reflect some measure of vulnerability from this perspective
Projected risks from climate change especially related to sea levels and associated tidal flooding for 2030 and 2045
Historical weather and climate-related dollar damages and fatalities for the 35 coastal counties over 30 years (1985–2014)

The main sources of data used in the analysis in this report are outlined below.

1.1 SOCIOECONOMIC DATA

We used the **U.S. Census QuickFacts**[1] application to pull together consistent data profiles for the 35 counties, the states in which the counties are located, and for the United States as a whole (U.S. Census Bureau 2015). Each downloaded profile included more than 70 variables,[2] from which a subset was used to analyze and contrast the counties.

We used four variables to construct the socioeconomic risk indicator:

Per-capita income (over the previous 12 months, in 2013 dollars)
Poverty rate (percentage of people living below the federal poverty level)
Education (percentage of people aged 25 or above with an educational attainment of less than a high school graduation)
The percentage of minority population (the percentage of the population that is Hispanic or Latino, Black or African American, Asian American, Native Hawaiian and Other Pacific Islander, and American Indian and Alaska Native)

Data for the first two variables came directly from the census data. The third variable, on education, was calculated by subtracting from 100 percent the "high school graduate or higher, percent of persons age 25 years+, 2009-2013" available in the census data.[3] Similarly, the fourth variable was calculated by subtracting from 100 percent the available "white alone, not Hispanic or Latino, percent, July 1, 2013, (V2013)." This number is different than simply the sum of percentages of African American and Hispanic or Latino shares of the population because the ethnic Hispanic/Latino category includes both whites and African Americans.

The following figures show the population of the counties included in this report and the underlying profiles used in our socioeconomic risk indicator.

[1] QuickFacts is an easy to use online application that allows users to access Census data for the nation, all 50 states plus the District of Columbia and Puerto Rico, counties, and places with populations of 5,000 or more. See *www.census.gov/quickfacts*.
[2] We accessed the database in February 2015. In some cases, depending on the geographic level, there were fewer variables for which data were available or could be disclosed.
[3] The Census QuickFacts definitions are as follows: "high school graduates" include people whose highest degree was a high school diploma or its equivalent, people who attended college but did not receive a degree, and people who received an associate's, bachelor's, master's, or professional or doctorate degree. People who reported completing the 12th grade but not receiving a diploma are not included. "Persons with a bachelor's degree or higher" are those who have received a bachelor's degree from a college or university, or a master's, professional, or doctorate degree. For the complete definitions, see American Community Survey subject definitions for "Educational Attainment" at *https://www.census.gov/programs-surveys/acs/*

FIGURE A-1. **Population of Selected Counties**

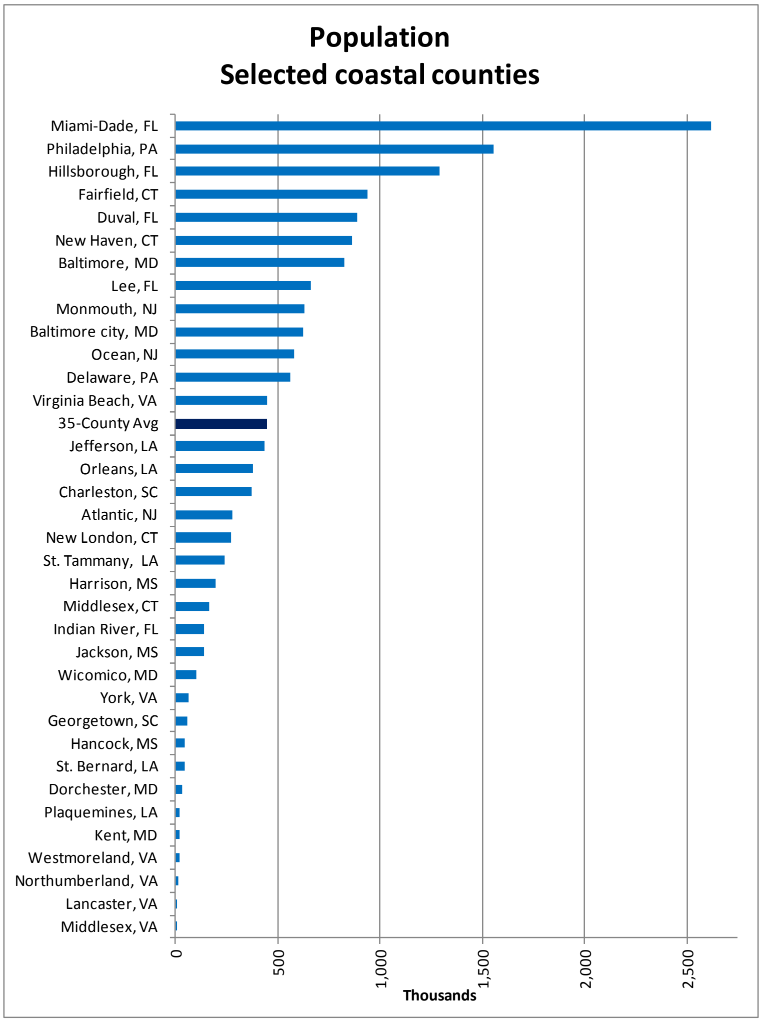


FIGURE A-2. **Annual Per-Capita Income of Selected Counties**

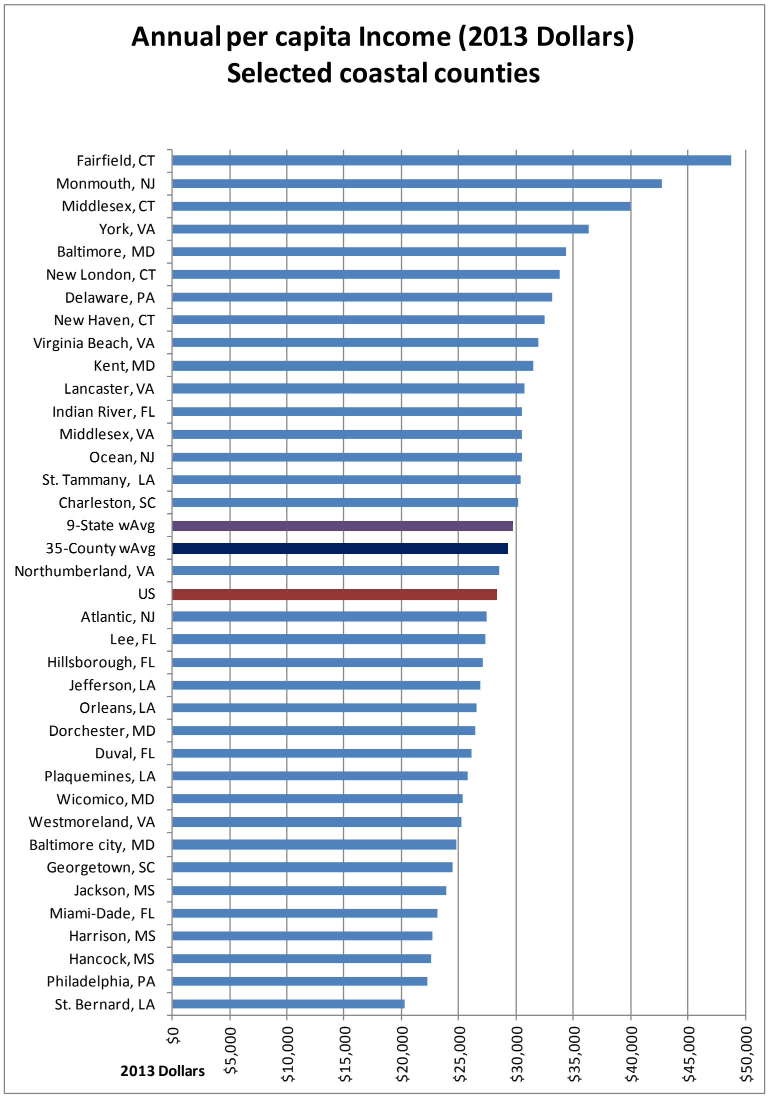


FIGURE A-3. **Poverty Rate in Selected Counties**

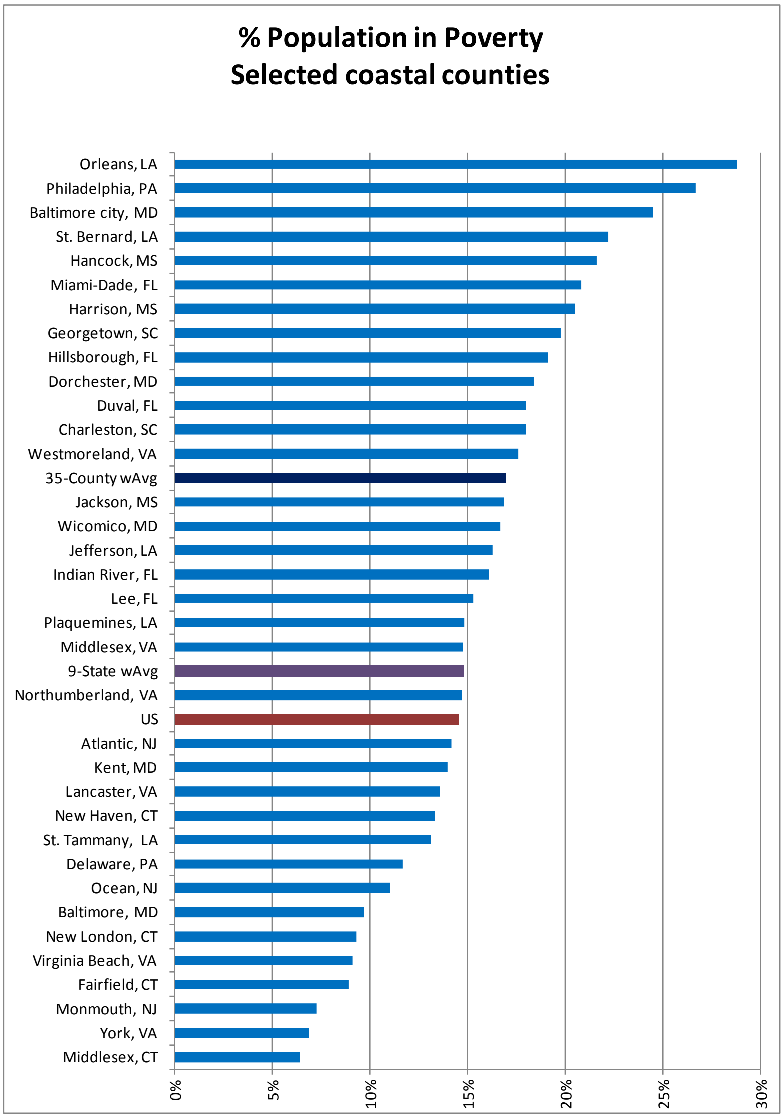


FIGURE A-4. **Educational Achievement in Selected Counties**

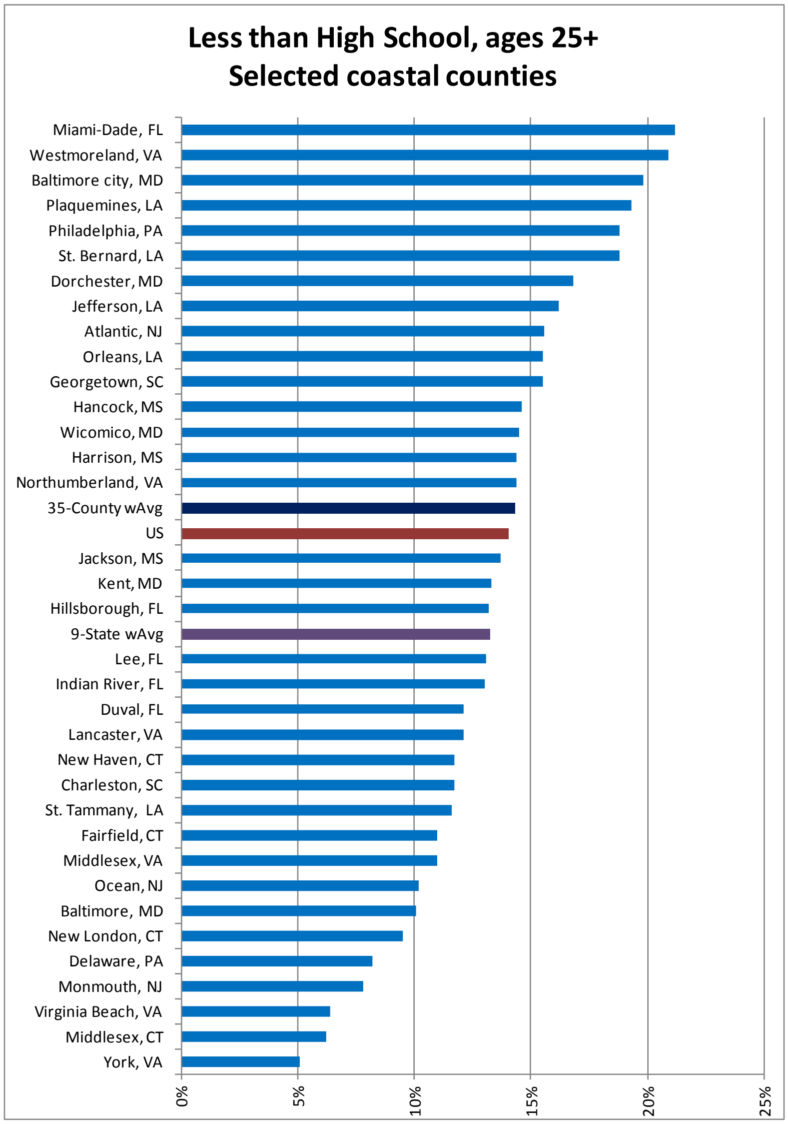
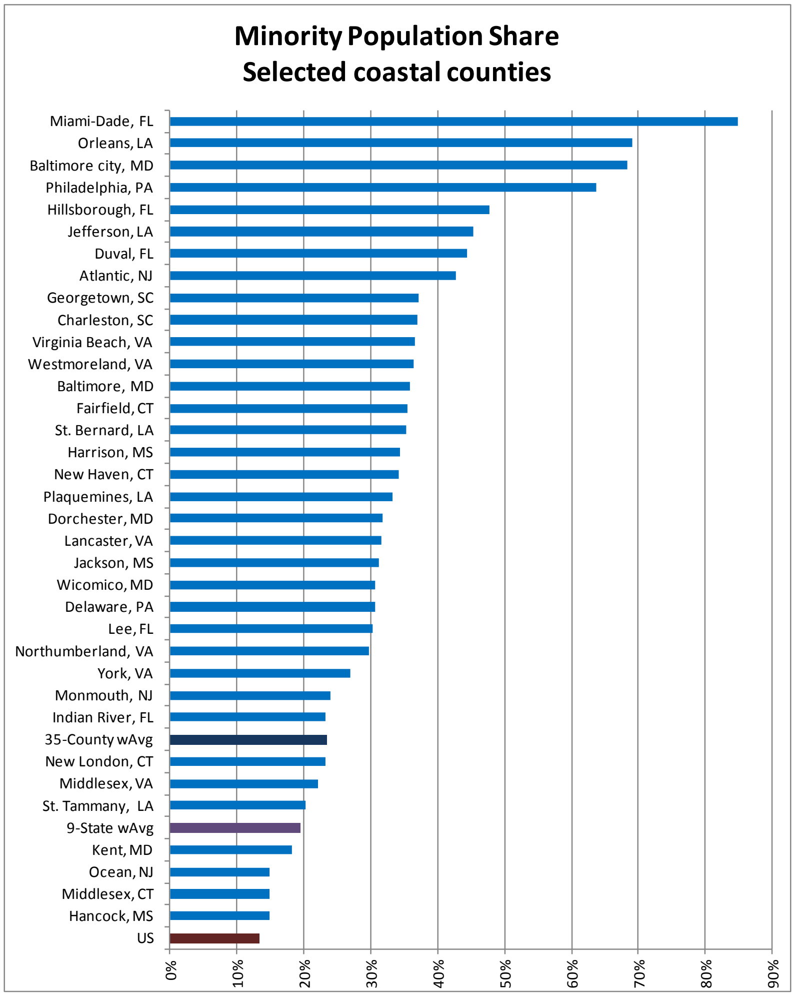


FIGURE A-5. **Minority Share of the Population in Selected Counties**



1.2 CLIMATE RISK DATA

Climate risks for the coastal counties in this report are expressed in terms of projected sea level rise and tidal flood frequency projections for 2045. Both these factors were evaluated in the UCS report published in 2014 *Encroaching Tides: How Sea Level Rise and Tidal Flooding Threaten U.S. East and Gulf Coast Communities over the Next 30 Years* (Spanger-Siegfried, Fitzpatrick, and Dahl 2014a). The present report used a similar methodology to the one used in *Encroaching Tides*, although the subset of counties analyzed was not the same. Please see the appendix of that report for more details about the methodology (Spanger-Siegfried, Fitzpatrick, and Dahl 2014b).

The appendix of *Encroaching Tides* includes a table of **Projections for Flooding Frequency in 52 Communities** which lists the following data for the locations of 52 of the tide gauges maintained and monitored by the National Oceanic and Atmospheric Administration (NOAA) National Ocean Service:

Sea level rise projections for 2030 and 2045. Localized, tide-gauge specific sea level rise projections were provided by Climate Central. Projections are based on NOAA's Intermediate-High scenario and adjusted to account for local variation using historical tide-gauge data. For some counties the SLR projection from the nearest available tide gauge was used (Climate Central 2015).

Tidal flooding frequency, measured as the average number of flooding events per year, between 2009 and 2013 and projections for 2030 and 2045 based on sea level rise-induced lowering of the presently-defined flooding threshold.

From that appendix, data for NOAA's Intermediate-High scenario were available for roughly half of the 35 counties analyzed in this report (see table 4 in Spanger-Siegfried, Fitzpatrick, and Dahl 2014b). For the rest of the counties we identified the nearest tide gauge for each county and evaluated the correspondence between that tide gauge's flooding events and the issuance of coastal flood advisories (or other coastal flood statements) for the county of interest for the 2012–2013 period. When the correspondence was two-thirds or greater (i.e., two-thirds of flood events as defined by tide-gauge water levels were associated with a coastal flood advisory), we applied flood-frequency data from the tide gauge to the county. We also used the corresponding localized sea level rise projection. This methodology for assessing the relevance of a tide gauge flooding threshold to the surrounding counties was applied in *Encroaching Tides* (Spanger-Siegfried, Fitzpatrick, and Dahl 2014a).

For 10 of the 35 counties in our sample no reliable tidal-flood-frequency data were available. These were:

Louisiana: Jefferson, Orleans, Plaquemines, St. Tammany, and St. Bernard parishes
Mississippi: Harrison and Jackson counties
Florida: Indian River and Lee counties
Virginia: Westmoreland County

For these counties, we relied solely on the sea level rise projections for 2045 to construct the climate risk indicator.
Table A-1 summarizes the sea level rise and tidal flooding data for the 35 counties in our sample.

TABLE A-1. **Sea Level Rise and Tidal Flooding Projections for Selected Counties**

County	Tide Gauge for tidal flooding assessment	Gauge #	Events Today	Intermediate-High Scenario SLR 2030 (in)	Events 2030	SLR 2045 (in)	Events 2045	Nearest Sea Level Rise (SLR) Projection	Miles to Nearest Proj.
New London, CT	New London	8461490	2.2	5.2	7.2	11.4	36.6	New London	
Middlesex, CT	New London	8461490	2.2	5.2	7.2	11.4	36.6	New London	
New Haven, CT	New Haven *	8465705	7.2	5.1	25.2	11.3	86.4	Bridgeport	27
Fairfield, CT	Bridgeport	8467150	21.6	5.1	62.0	11.3	162.4	Bridgeport	
Monmouth, NJ	Sandy Hook *	8531680	33.0	5.4	87.8	11.7	210.6	The Battery (NYC)	16
Ocean, NJ	Sandy Hook *	8531680	33.0	5.4	87.8	11.7	210.6	The Battery (NYC)	16
Atlantic, NJ	Atlantic City	8534720	31.8	6.4	92.0	13.7	244.2	Atlantic City	
Philadelphia, PA	Philadelphia *	8545240	19.0	5.9	66.0	12.8	206.2	Reedy Point	35
Delaware, PA	Philadelphia *	8545240	19.0	5.9	66.0	12.8	206.2	Reedy Point	35
Wicomico, MD	Cambridge	8571892	10.0	5.9	45.8	12.7	242.4	Cambridge	
Dorchester, MD	Cambridge	8571892	10.0	5.9	45.8	12.7	242.4	Cambridge	
Kent, MD	Tolchester Beach *	8573364	4.4	5.4	16.2	11.8	78.4	Baltimore	45
Baltimore, MD	Baltimore	8574680	17.0	5.4	63.2	11.8	226.8	Baltimore	
Baltimore city, MD	Baltimore	8574680	17.0	5.4	63.2	11.8	226.8	Baltimore	
Westmoreland County, VA				7.1		14.9		Lewisetta	20
Northumberland, VA	Lewisetta	8635750	14.0	7.1	87.6	14.9	386.0	Lewisetta	
Lancaster, VA	Windmill Point *	8636580	7.8	7.1	54.0	14.9	303.8	Lewisetta	28
Middlesex, VA	Windmill Point *	8636580	7.8	7.1	54.0	14.9	303.8	Lewisetta	28
York, VA	Windmill Point *	8636580	7.8	7.1	54.0	14.9	303.8	Lewisetta	28
Virginia Beach, VA	Kiptopeke	8632200	9.6	5.7	36.0	12.4	140.4	Kiptopeke	
Charleston, SC	Charleston	8665530	24.2	5.2	78.2	11.5	187.4	Charleston	
Georgetown, SC	Springmaid Pier	8661070	3.6	5.8	14.6	12.4	65.6	Springmaid Pier	
Duval, FL	Mayport *	8720218	6.6	4.7	25.2	10.5	101.2	Fernandina Beach	19
Indian River, FL				5.4		11.8		Vaca key	209
Miami-Dade, FL	Virginia Key *	8723214	5.8	5.4	47.6	11.8	237.2	Vaca Key	92
Lee, FL				4.7		10.6		Naples	31
Hillsborough, FL	Clearwater Beach	8726724	0.2	5.0	1.4	11.1	5.2	Clearwater Beach	
Jackson, MS				4.7		10.5		Pensacola	84
Harrison, MS				9.6		19.4		Grand isle	96
Hancock, MS	Bay Waveland Yacht Club*	8747437	12.8	4.7	37.4	10.5	110.4	Pensacola	83
St. Tammany, LA				9.6		19.4		Grand isle	79
Orleans, LA				9.6		19.4		Grand isle	56
St. Bernard, LA				9.6		19.4		Grand isle	59
Plaquemines, LA				9.6		19.4		Grand isle	30
Jefferson, LA				9.6		19.4		Grand isle	50

*Local sea level rise projections were unavailable for these tide gauges therefore projections from the nearest tide gauge were used in these cases.

SOURCES: SEA LEVEL RISE PROJECTIONS FROM CLIMATE CENTRAL 2015; TIDAL FLOODING PROJECTIONS BASED ON UCS ANALYSIS FOLLOWING SPANGER-SIEGFRIED, FITZPATRICK, AND DAHL 2014B.

1.3 HISTORICAL DATA ON CLIMATE DAMAGES

For weather or climate damages in the United States, we looked at NOAA's Storm Events Database, maintained by its National Climatic Data Center, and the Spatial Hazard Events and Losses Database for the United States (SHELDUS), developed and maintained at the University of South Carolina's Hazards and Vulnerability Research Institute (Hazards and Vulnerability Research Institute 2015; National Climatic Data Center 2015).

We examined the data in both sources and chose to use the SHELDUS data (v. 14.0) for this climate analysis because applicable coastal data (on flooding, storm surge/tide, hurricanes and tropical storms, etc.)[4] were available for a longer time period.[5] We used SHELDUS data for the 30 years between 1985 and 2014. The data extracts included injuries, fatalities, crop and property damage estimates (damages inflation-adjusted to 2014 dollars), and records counts of each query, based on hazard type. We selected the following four highlighted "hazard types" from the list of 18 in SHELDUS: Coastal, Flooding, Hurricane/Tropical Storm and Wind:

SHELDUS (18 hazard types, chosen categories highlighted)

Avalanche	Landslide
Coastal	Lightning
Drought	Severe storm/thunder storm
Earthquake	Tornado
Flooding	Tsunami/seiche
Fog	Volcano
Hail	Wildfire
Heat	Wind
Hurricane/tropical storm	Winter weather

After preliminary analysis, consultations with SHELDUS technical experts, and selected testing we concluded that these would capture the essential scales of impacts and damages in coastal counties that reasonably relate to sea levels and associated tidal flooding, and will likely be impacted by changes in both. We also included hurricane- and tropical storm–related categories because there is some scientific evidence that climate change could contribute to more intense storms in the future, with higher rainfall rates than in present-day storms (NOAA 2015).

We focused on crop and property damage estimates and fatalities for the 35 counties in our sample and for the states in which these counties are located. All data entering SHELDUS that impacted more than one county were first allocated evenly to the impacted counties. This means that aggregation to the county level will not lead to any double-counting of damages. Data on impacts within a county must be interpreted carefully. Within each county, we did not aggregate damages individually for each of the four selected hazard types. Rather, we aggregated to the sum of the four hazard types. All records in SHELDUS are associated with some non-zero loss or damages; therefore our queries' record counts could be used as a proxy for hazard frequency. That is, the record counts effectively measure of the number of loss-causing events or loss event days recorded by SHELDUS (for the group of hazards we selected, as a whole). However, given that some events are of a multi-hazard nature and span more than one hazard category, the raw data should *not* be aggregated to individual hazard type to ensure that such events are counted only once.[6]

2. Methodology for Risk Scoring and Ranking

There is a wide literature covering different ways to measure varying degrees of socioeconomic vulnerability. Both the Social Vulnerability Index (SoVI) (Hazards and Vulnerability Research Institute 2013), which we describe below, and the NOAA coastal Well-Being Assessment (Dillard et al. 2013) are based on in-depth research and analysis of a broad range of population and other characteristics having to do with the complex relationship between communities and their environment. Indicators based on these

[4] The NOAA Storm Events Database has contents on 48 event types from 1996 onward; prior to that it included only tornado events from 1950 to 1954 and thunderstorms, wind, and hail from 1955 to 1995. See *www.ncdc.noaa.gov/stormevents/details.jsp*.

[5] For additional information about differences between the SHELDUS dataset and the National Climatic Data Center's dataset here, visit *http://hvri.geog.sc.edu/SHELDUS/index.cfm?page=faq*.

[6] We offer special thanks for helpful informational and clarifying discussions and assistance to Melanie Gall, research scientist, Department of Geography, University of South Carolina, and to Stuart Hinson, meteorologist, NOAA National Centers for Environmental Information Center for Weather and Climate.

data can be tracked over time and provide useful information to communities, their representatives, and other people with planning responsibilities.[7] The SoVI is also now available at a sub-county level.

While such a resource-intensive effort was outside the scope of this report, we utilized insights from previous research to create and implement a simplified screening methodology adapted to our focus on coastal climate equity. To better grasp and portray the combined vulnerabilities facing coastal communities in the counties, we opted for a simple approach that can be explained in a straightforward and understandable way, using data that are readily available at the county level and clearly related to rising seas.

We assembled data profiles for the 35 coastal counties for each of our criteria of interest. We selected a few key variables for each criterion and normalized them into a common metric using the linear scaling technique (Dillard et al. 2013; Salzman 2003). Indicators of relative socioeconomic and climate risks among the counties provide a view of their vulnerability from both perspectives.

Two key elements of the linear scaling technique allow for different kinds of variables to be combined toward a shared goal:

The direction of the variables is aligned to indicate vulnerability along the same scale.
The values of the variables are normalized to the same scale (0 to 1) for comparability and aggregation.

The first element called for two different equations to implement the second one, depending on how a variable was related to the vulnerability being measured. Equation 1 below was used for variables whose *higher* values contributed to greater vulnerability and equation 2 for variables whose *lower* values contributed to greater vulnerability. Both were normalized to a common 0-1 scale by dividing by the range of values of a variable across the sample of 35 counties.

Equation 1: measures that increase vulnerability $(\mathbf{x} - \min) / (\max - \min)$
Equation 2: measures that reduce vulnerability $(\max - \mathbf{x}) / (\max - \min)$

where **x** is the value of a given variable, **min** is the minimum value in the distribution of counties and **max** is the maximum value.

Once each of the variables was normalized using this linear scaling method, they were combined into a composite indicator transformed to a percentage of its total possible score: a county's scores for its variables were summed and averaged[8] (over the count of variables included in the composite indicator), and then expressed as a percentage of possible maximum aggregate scores among all counties in the sample.

Composite percentage score = 100 * [sum of variables normalized via linear scaling] / [count of variables in composite]

Note: It is important to keep in mind that the risk vulnerability indicators created with this method measure how these counties compare *in relation to one another*, among this particular set of 35 coastal counties. All of the rankings are simply that; they are not measures or rankings on a wider regional or national context. With a different selection and composition of counties, the results for any given county could change.

2.1 CONSTRUCTING THE CLIMATE RISK INDICATOR USING THE LINEAR SCALING TECHNIQUE

[7] For example, the NOAA Gulf counties' Well-Being Assessment generated nine composite indicators in the following areas: access to social services, basic needs, economic security, education, governance, health, safety, social connectedness, and environmental condition. Each indicator, in turn, is the result of combining several underlying variables. The 2006–2012 county-level SoVI is derived from 29 variables across seven major components: race (black), ethnicity (Hispanic), ethnicity (Native American), class (poverty), wealth, age (old), residence in a nursing home, and employment in service industries.

[8] A simple, un-weighted average was used.

The climate risk indicator was constructed from sea level rise and tidal flooding projections for 2045 for the counties in our sample. We first converted the two variables individually to a 0-1 scale using the linear scaling technique. This technique normalized each data point based on its distance from the minimum value for that variable across the 35 counties in the study, as a fraction of the range (minimum to maximum) for that variable across the 35-county sample.[9] (Distance from the minimum value was used because a higher value for each of these variables indicates a higher risk). Because this normalization technique was based on the range of values within the sample of counties selected, the resulting scores are only comparable across the counties selected and are not absolute scores that allow a universal comparison. For each county, the linearized scores of the two variables were then summed and averaged, and expressed as a percentage, giving equal weight to each variable. This percentage score for each county served as the climate risk indicator for that county in our analysis. It reflects a county's overall percentage of possible maximum scores of its two component variables across the 35-county sample.

Ten of the 35 counties did not have associated tidal flooding projections, but this method still included their sea level rise projections; their percentage scores reflect their fewer variables via their count in the formula denominator (one in their case, two for all of the other counties).

For example, according to our methodology, Miami-Dade County is projected to experience 11.8 inches of sea level rise and 237.2 annual tidal flooding events in 2045. The selected 35 counties are projected to have a range of sea level rise of 10.5 to 19.4 inches and a range of 5.2 to 386 tidal flooding events. On a 0-1 scale this translates into a score for Miami-Dade County of 0.146 = (11.8 – 10.5)/(19.4 – 10.5) for sea level rise and 0.609 = (237.2 – 5.2)/(386 – 5.2) for tidal flooding frequency, adding to a combined value of 0.755 for the county. The climate risk indicator percentage score for Miami-Dade is then 37.8 (=100*.755/2). This climate risk score places the county in the middle of the 35 counties in the sample, in 17th place.

2.2 SOCIOECONOMIC RISK SCORING AND RANKING

The above linear scaling method was applied to the four socioeconomic variables introduced above: per-capita income, poverty rate, education (percentage of adults without a high school diploma), and the percentage of minorities in the population (of any race or ethnicity). We selected these four variables to provide a simple perspective on socioeconomic risk and vulnerability among the counties.

For variables where a higher value indicates a higher socioeconomic risk (poverty rate, education level, and minority percentage), we normalized the variable based on its distance from the minimum value for that variable across the 35 counties and expressed it as a fraction of the range (maximum to minimum) for that variable across the 35 counties.[10] For per-capita income, where a higher value indicates a lower socioeconomic risk, we normalized the variable based on its distance from the *maximum* value for that variable across the 35 counties in the study and expressed it as a fraction of the range (maximum to minimum) for that variable across the sample.[11] As with the climate risk indicator, the resulting scores are comparable only across the counties selected and are not absolute scores that allow a universal comparison.

The linear scaling method was used to create a composite indicator for each county for this dimension of vulnerability. Each composite indicator was normalized to a common 0-1 scale based on its distance between the minimum and maximum values across the 35 counties in the study. It is important to note that income has the opposite direction from the others in terms of contribution to vulnerability; therefore, equation 2 was used for income, while equation 1 was applied for the rest of these variables.

Because the African American and Hispanic/Latino shares of the population are not strictly additive categories (because one person can be a member of both), we derived the minority share of the population from the census variable "white alone, not Hispanic or Latino". Our measure of the minority share of the population is simply the remaining share of the population that does not fall in this category.

Each county's socioeconomic risk indicator was calculated as the sum of the scores of the variables divided by the count of its components (four), and expressed as a percentage ranking of the possible maximum score among all 35 counties. This percentage score was a composite indicator that reflected a county's score as a percentage of possible maximum linearized scores of

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[9] The normalization equation was: (**x** – min) / (max – min), where x was the variable being normalized.
[10] In other words, the normalization equation was: (**x** – min) / (max – min), where x is the variable being normalized.
[11] In other words, the normalization equation was: (max – **x**) / (max – min), where x is the variable being normalized.

the component variables (which in this case is four, since there were four variables: per-capita income, poverty, education, and percentage of minorities).

To continue with the example of Miami-Dade county, its poverty rate (20.8%), adult population without a high-school diploma (21.2% = 100% - 78.8% of persons aged 25 years+ high school graduate or higher), and minority share of the population of 84.8% = (100% - 15.2% white alone, not Hispanic or Latino) were re-scaled to a 0-1 value based on their distance from their minimum values among the 35-county sample—each in proportion to the range of values of these variables over the sample. Across the 35 counties, poverty rates ranged from 6.4% to 28.8%, adults not completing high-school ranged from 5.1% to 21.2%, and minority population shares ranged from 14.8% to 84.8%. For Miami-Dade this resulted in 0-1 values of 0.643 for poverty, 1.0 for education, and 1.0 for minority population. Since higher per-capita income indicates less vulnerability, the county's per-capital income of $23,174 was measured against the maximum income in the sample of counties and in proportion to the range among them, $20,316 to $48,721, for a 0-1 value of 0.899. The sum of the four scores is 3.542, which divided by 4 (the number of variables) and converted to a percent gives a socioeconomic risk score of 88.56 for Miami-Dade, the highest such score among the 35 counties.

3. Joint Vulnerability: Combined Climate Socioeconomic Risk

We did not calculate a single overall indicator of combined risk or vulnerability for each of the 35 counties. There were too many limitations in county-level data even when considering separately the current socioeconomic and future climate risks a given county might face. As the report illustrates, the interplay between socioeconomic and climate vulnerabilities is a complex one that resists simplification. Both composite indicators are relatively straightforward depictions of more intricate phenomena. To show joint vulnerability we used a combined scatter plot of counties' rankings along both of these dimensions as a way to visually display the results. This was not meant to imply any inherent relationship between the two types of risk factors for a county, and especially not for areas within a county.

3.1 HOW TO INTERPRET OUR RISK INDICATORS APPROPRIATELY

Our analytic framework uses climate and socioeconomic risk indicators to help identify "climate equity hotspots." These risk indicators (and the component climate and socioeconomic variables) are not meant to be interpreted as determinants of specific outcomes—rather, they are proxies for factors that contribute to a county's vulnerability.

For example, the tide gauge data we used provided a reasonable approximation of projected sea level rise and the risk of tidal flooding in a county given a certain level of local sea level rise. However, tide gauge data are not always an accurate predictor of actual outcomes in nearby counties, or even for every location within a county. Differences in topography, the presence or absence of human-made and natural flood defenses, distance from the coast, and other local factors mean that there can be considerable variation in whether and how much flooding might actually occur in given place. Nevertheless, as a practical matter, many local weather forecasting offices rely on nearby tide gauge data in issuing coastal flood advisories that cover one, or even several, nearby counties; therefore, it was a reasonable assumption for this report.[12]

We were not able to take into account the impact of storm-surge flooding in our climate risk indicator; therefore, it is likely to be a conservative estimate of the risks of sea level rise to some coastal communities (see section 3.2 of the report). The socioeconomic variables we used were chosen to represent a relevant subset of factors identified in the risk assessment literature as contributing to a community's vulnerability to environmental hazards or disasters (see section in report, Measuring Socioeconomic Risk). Additional factors such as the average age in a county (or share of the youngest and oldest segments), the health status of the population, and the number of female-headed households may also be important. There can also be considerable variation within a

[12] These county-level flood advisories indicate the potential for flooding somewhere within—not necessarily throughout—a county. Similarly, our climate risk indicator merely signals the relative potential risk among the counties in the examined sample.

county in the socioeconomic profile of the population, which can lead to very different levels of vulnerability for different communities (see the Box 6 in the report on Fairfield, Connecticut).

For our purposes, within a risk assessment framework, the climate and socioeconomic risk indicators we developed provide a useful, transparent, easily replicable method by which to make an initial assessment of a county's vulnerability to sea level rise.

4. Storm Surge Maps for the Case Studies

Sea level rise and tidal flooding are poised to increasingly encroach upon coastal communities. Many of the coastal counties we analyzed, however, are also at risk of catastrophic flooding during hurricanes. This flooding can be exacerbated by local factors that can prevent drainage of the heavy rains often associated with hurricanes or of the storm surge itself. While hurricanes occur much less frequently than minor floods associated with high tides, flooding associated with hurricanes extends much farther inland, tends to be deeper, and poses a greater threat to life and property.

Storm surge is caused when hurricane winds cause seawater to pile up offshore as the storm approaches land. As evidenced by the damage wrought by Hurricanes Katrina and Sandy in 2005 and 2012 respectively, storm surge can be even more devastating to coastal communities than hurricane-force winds. Hurricanes can bring significant amounts of rain that also induce flooding as well. For four of the counties in our study—Plaquemines Parish, Louisiana; Dorchester County, Maryland; Harrison County, Mississippi; and Charleston County, South Carolina—we analyzed the present-day exposure to storm surge from different categories of hurricanes. The National Hurricane Center classifies hurricanes into five categories based on wind speed, with category 1 hurricanes having the weakest winds and category 5 the strongest. Storm surge depth and extent are not incorporated into the classifications; however, storm surge tends to be deeper and reach farther inland as the storm category increases.

To determine how exposed these counties are to storm surge, we mapped the output from NOAA's storm surge model, the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model, for each category of storm (NWS 2015). Specifically, we mapped the high tide maximum of the Maximum (MOM), which show worst-case scenario flooding for each location given each storm category. No single storm would produce the pattern of flooding indicated by the MOM. Rather, our map indicates the worst potential flooding at every location.

For Miami-Dade County, Florida, we took a different approach for evaluating flood risk because the Biscayne aquifer underlying the land has a strong influence on flooding in the region. Within the aquifer, groundwater lies very close to the land surface, which prevents rapid drainage of flood waters from either storm surge or rainfall-induced flooding. To capture these multiple flood stressors, we relied on NOAA's Coastal Flood Exposure Mapper.[13] This tool tallies how many potential flood hazards exist in a given area and includes storm-surge inundation, the Federal Emergency Management Agency's high- and moderate-risk flood zones, and tidal flooding zones.

[13] *www.coast.noaa.gov/floodexposure/#/splash*

[REFERENCES]

Climate Central. 2015. Climate Central surging seas risk finder. Princeton, NJ, and New York, NY. Online at *http://sealevel.climatecentral.org/* , accessed on October 22, 2015.

Dillard, M.K., T.L. Goedeke, S. Lovelace, and A. Orthmeyer. 2013. Monitoring well-being and changing environmental conditions in coastal communities: Development of an assessment method. NOAA technical memorandum NOS NCCOS 174. Washington, DC: National Oceanic and Atmospheric Administration. Online at *www2.coastalscience.noaa.gov/publications/detail.aspx?resource=vEJnl8tRMtte2uSEyRGtPk33w24iNAPwSRAf9Pp6iYM=*, accessed September 17, 2015.

Hazards and Vulnerability Research Institute. 2015. The Spatial Hazard Events and Losses Database for the United States, version 14.0. Columbia, SC: University of South Carolina. Online at *www.sheldus.org*, accessed September 17, 2015.

Hazards and Vulnerability Research Institute. 2013. Social Vulnerability Index for the United States, 2006-2010. Columbia, SC: University of South Carolina. Online at *http://webra.cas.sc.edu/hvri/products/sovi.aspx*, accessed October 20, 2015.

National Climatic Data Center. 2015. Storm events database. Washington, DC: National Oceanic and Atmospheric Administration. Online at *www.ncdc.noaa.gov/stormevents/*, accessed October 20, 2015.

National Oceanic and Atmospheric Administration (NOAA). 2015. Global warming and hurricanes. Online at *www.gfdl.noaa.gov/global-warming-and-hurricanes*, accessed October 20, 2015.

National Weather Service (NWS). 2015. Sea, lake, and overland surges from hurricanes (SLOSH). Washington, DC: National Hurricane Center, National Oceanic and Atmospheric Administration. Online at *www.nhc.noaa.gov/surge/slosh.php*, accessed October 20, 2015.

Salzman, J. 2003. Methodological choices encountered in the construction of composite indices of economic and social well-being. Ottawa, Ontario, Canada: Center for the Study of Living Standards. Online at *www.csls.ca/events/cea2003/salzman-typol-cea2003.pdf*, accessed September 17, 2015.

Spanger-Siegfried, E., M. Fitzpatrick, and K. Dahl. 2014a. *Encroaching tides: How sea level rise and tidal flooding threaten U.S. East and Gulf coast communities over the next 30 years*. Cambridge, MA: Union of Concerned Scientists. Online at *www.ucsusa.org/sites/default/files/attach/2014/10/encroaching-tides-full-report.pdf*, accessed September 17, 2015.

Spanger-Siegfried, E., M. Fitzpatrick, and K. Dahl. 2014b. *Encroaching tides: How sea level rise and tidal flooding threaten U.S. east and Gulf coast communities over the next 30 years*. *Appendix: Technical background document*. Cambridge, MA: Union of Concerned Scientists. Online at *www.ucsusa.org/sites/default/files/attach/2014/10/encroaching-tides-technical-appendix.pdf*, accessed October 20, 2015.

U.S. Census Bureau. 2015. Census quick facts data tool. Online at *http://quickfacts.census.gov*, accessed September 27, 2015.