Looming Deadlines for Coastal Resilience

Rising Seas, Disruptive Tides, and Risks to Coastal Infrastructure

HIGHLIGHTS

The Union of Concerned Scientists report* Looming Deadlines for Coastal Resilience *assesses the risks of disruptive flooding to critical infrastructure in the contiguous United States, Puerto Rico, the US Virgin Islands, and Guam. As detailed below, the analysis combines maps of disruptive flooding with maps of critical infrastructure from a variety of sources. Importantly, this report and the data within it are intended to be a starting point for community and national discussions about the risks of sea level rise and tidal flooding to coastal infrastructure. Where possible, communities should undertake more detailed mapping to better assess their unique risk of disruptive flooding. This document outlines the methods, tools, and data used in this analysis as well as key caveats.

Methodology

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Methodology

Disruptive Flooding Thresholds

We determined the water heights that were reached or exceeded an average of 2, 12, or 26 times per year at each of 119 tide gauges operated by the National Oceanic and Atmospheric Administration (NOAA) along US coastlines. We used 20 years (2001–2020) of hourly, verified water-level data published by NOAA for each gauge, and the analysis was performed on daily maxima to avoid multicounting of short-term events. This means that a "day" of flooding is equivalent to flooding at least 1 hour during the 24-hour period when the threshold was exceeded. These water levels are reported relative to the mean higher high water (MHHW) level—or the average height of highest daily tide—at each gauge. We refer to them as *disruptive flooding water levels*. For future periods, we added gauge-specific sea level rise projections to present-day MHHW levels to yield a projected future disruptive flooding water level.

Elevation Data

Determining the spatial extent of disruptive flooding requires a digital elevation model (DEM). We obtained DEMs for the continental United States from NOAA (NOAA Sea Level Rise Data Download 2024). The resolution of the DEMs varies between 3 m and 5 m, with most having a 3 m resolution. This represents the highest resolution data practicable to analyze at a national scale. The DEMs are based on lidar, a method of determining elevation by sending pulses of light from aircraft toward Earth's surface and measuring their reflectance. The DEMs were conditioned and created specifically for sea level rise mapping and then applied in NOAA's Sea Level Rise Viewer (2024). To ensure that differences between the flooded zones for each future time interval were statistically significant, we used the vertical accuracy of the DEMs along with other sources of uncertainty to calculate a minimum sea level rise interval of 9.3 in. (23.6 cm) for spatial analysis with 68% confidence (Gesch 2018).

Sea Level Rise Scenarios

The analysis utilized five sea level rise scenarios developed by a US interagency task force, which refers to them as low, intermediate-low, intermediate, intermediate-high, and high (Sweet et al. 2022). Here, we chose to focus on three scenarios—intermediate-low, intermediate, and high—and renamed them *low*, *medium*, and *high*. These are calibrated to project 1.6, 3.2, and 6.5 ft. of sea level rise globally in 2100. Because sea level does not change uniformly across geographies and geologies, the task force developed localized projections for 119 tide gauges operated by NOAA. These projections reflect, for example, natural and human-induced vertical land motion that effectively increases or decreases the rate of sea level rise experienced locally.

Changes in Flooding Frequency

The sea level rise scenarios were used following Thompson et al. (2021) to assess changes in flooding frequency associated with each scenario based on local characteristics of storminess and tides, including the 18.6-year nodal tidal cycle—a natural cycle due to the precession of the moon's orbital plane that affects tide levels but is not typically incorporated into assessments of future flooding.

Mapping Disruptive Flooding

Our spatial analysis largely follows methods described by NOAA and employed in subsequent studies (Dahl et al. 2017; NOAA Office for Coastal Management 2017). We began with NOAA's present-day MHHW sea level surface, which was extended during development with the objective of enabling flood analyses to cover all coastal counties (NOAA Inundation Mapping Tidal Surface – Mean Higher High Water 2019). We aimed to develop a set of projected water level (PWL) surfaces based on the sea level rise scenarios: one for each combination of year, sea level rise scenario, and flood frequency. We denote this combination as *forecast parameters* or, simply, a *forecast*. For example, one forecast is for year 2030, high sea level rise scenario, 26 times per year. For each tide gauge and forecast, we computed a PWL. Then, using natural neighbor interpolation, we derived a projected sea level rise (PSLR) surface along each coast. Adding the PSLR surface to the MHHW surface yielded a PWL surface for each forecast.

We then subtracted the DEM from the PWL surface to create an inundation depth surface for each forecast. To ensure that the areas considered inundated were hydrologically connected to the ocean and not merely low-lying areas disconnected from the ocean by higher-elevation barriers, we "clumped" the data and excluded disconnected areas. Consistent with NOAA's Sea Level Rise Viewer (2024), we excluded areas protected by federal levees as well as zones in the San Francisco Bay Area categorized by the Federal Emergency Management Agency as having reduced flood risk due to levees (FEMA Flood Data Viewers and Geospatial Data 2024; USACE National Levee Database 2024). These refinements yielded a map of the depth of ocean-connected flooding and a more compact map of Boolean values indicating whether a given point was flooded. The latter was used in the next step of identifying infrastructure at risk of disruptive flooding.

We excluded Alaska from the analysis because of a lack of high-resolution DEMs. We excluded Hawaii and American Samoa because available MHHW data were not compatible with the vertical datums for the other coastlines in the study.

The key differences between our work and NOAA's sea level rise mapping work were accounting for the nodal tidal cycle and computing for many more sets of forecast parameters, including different flooding frequencies.

Infrastructure Datasets

We overlaid these forecast maps of disruptive flooding with a dataset we compiled of critical infrastructure in coastal counties. The dataset included twenty different types of infrastructure in six broad categories: public and affordable housing (HUD Public Housing Buildings 2024; National Housing Preservation Database 2023); educational institutions (USGS National Structures Dataset 2024); industrial contamination sites (EPA NPL Superfund Site Boundaries 2024; EPA TRI Basic Data Files 2023; EPA Geospatial Data Download 2021); energy infrastructure (EIA Electricity 2023; NOAA Electric Power Substations 2017); government facilities (USGS National Structures Dataset 2024); and public safety and health facilities (HIFLD 2024; USGS National Structures Dataset 2024).

Note that this is not an exhaustive list of critical infrastructure important to communities, and what may be categorized as critical to one community (e.g., Dollar General stores, Target stores, churches, burial grounds, playgrounds, care facilities for older adults, etc.) may not be considered critical to another. In developing our list of critical infrastructure to include, we consulted with several frontline community groups in coastal locations. Among those important assets not included were

- underground spaces (e.g., metro stations), because our elevation models capture only surface elevations;
- roads, because in spatial datasets they are often broken into many individual segments, which makes quantifying and reporting the number of roads at risk challenging and potentially misleading;
- drinking water treatment plants, because of a lack of standardized, nationally available data; and
- bridges, because their span location (i.e., over a waterway) risks them being identified as flooded when they may be elevated, and because the locations, materials, and resilience of their foundations would need to be ascertained on an asset-by-asset basis.

By excluding areas protected by federal levees or that are known to have reduced flood risk (see previous section), we assume that existing protections will remain effective through 2100 (FEMA Flood Data Viewers and Geospatial Data 2024; NOAA Sea Level Rise Viewer 2024; USACE National Levee Database 2024).

Definition of Assets as *at Risk*

With the exception of Superfund sites, which were represented in our data as polygons, all categories of infrastructure were represented as points. We marked an asset *at risk* of disruptive flooding if it fell at least partially within the flooded area. Because most of the critical infrastructure data consist of point data that are, ideally, located at asset centroids, this method may underestimate flood risk to the property on which an asset lies.

Population, Socioeconomic, and Demographic Data and Statistics

Finally, we analyzed the human population potentially affected by inundated infrastructure and the exposure of disadvantaged versus nondisadvantaged communities to disruptive flooding using the White House Council on Environmental Quality's screening tool and the data therein (CEQ Climate and Economic Justice Screening Tool 2022). These data are provided for each census tract. Our accounting includes the entire population of a census tract if one or more critical infrastructure assets in that tract were projected to be flooded. It is important to note, however, that people could be affected by flooding even if their tract does not contain any at-risk critical infrastructure.

Tooling for Disruptive Flooding Analysis

To generate the disruptive flooding maps, we used open-source software, including Python, Fiona (Gillies 2023), GDAL (Rouault et al. 2024), NumPy (Harris et al. 2020), Rasterio (Gillies 2019), and Shapely (Gillies et al. 2021). For natural-neighbor interpolation, we used C++ and CGAL (Fogel and Teillaud 2015); for clumping connected regions, we used GRASS (Neteler et al. 2012). While our report discusses only a subset, we computed forecasts at 3 m resolution for eight decades (2030–2100), five sea level rise scenarios, three flood frequencies, and four regions—West; East, including the Atlantic and Gulf coasts; Puerto Rico and US Virgin Islands;

and Guam. Computation required approximately 60 hours using 24 virtual machines, each with eight dual-thread 2.6 GHz AMD Genoa cores and 3.2 TB of remote SSD.

To save time, cost, energy, and carbon emissions, for some steps in our computation, we decomposed large rectangular (but not oblique) rasters into tiles. Because of the shape of the coastline, many tiles did not cover land, so we omitted their computation.

We validated results for selected forecasts against an alternative implementation using ArcGIS Pro (Esri n.d.); the results of flooded land area agreed within less than 0.25%. ArcGIS Pro also handled spatial joins with critical infrastructure datasets and subsequent processing.

Tooling for Infrastructure Analysis

Disruptive flooding maps and critical infrastructure data were processed in R (R Core Team 2021), RStudio (Posit Team 2023), and QGIS (QGIS.org n.d.). Public web maps were developed in ArcGIS Online (Esri n.d.). We used the following R packages:

- aws.s3 (Leeper 2020)
- data.table (Barrett et al. 2023)
- doParallel (Folashade, Microsoft, and Weston 2022a)
- dplyr (Wickham et al. 2023)
- foreach (Folashade, Microsoft, and Weston 2022b)
- foreign (R Core Team 2022)
- ggplot2 (Wickham 2016)
- ggradar (Bion 2024)
- logr (Bosak 2023)
- openxlsx (Schauberger and Walker 2023)
- readxl (Wickham and Bryan 2023)
- stringr (Wickham 2023)
- terra (Hijmans 2023)
- tictoc (Izrailev 2023)
- tidyr (Wickham, Vaughan, and Girlich 2023)
- tidyterra (Hernangómez 2023)

For geospatial data processing, we reprojected datasets separately as follows: NAD 1983 Albers North America (continental United States), NAD 1983 Puerto Rico and US Virgin Islands (Puerto Rico and the US Virgin Islands), and NAD 1983 SPCS Zone Guam (Guam). Because of the large size of the flooding rasters, we first clipped them to county subdivisions to obtain smaller rasters to process.

We eliminated critical infrastructure cases with invalid or missing latitude-longitude coordinates.

We conducted geospatial join operations to spatially select critical infrastructure inside of coastal counties.

For each forecast, we conducted spatial join analysis to determine if a critical infrastructure asset will be inundated. We used the st_within predicate in the st_join instruction in the *sf* R library.

Tooling for Population and Socioeconomic Vulnerability Analysis

We carried out the population and disadvantaged community analysis in Python and ArcGIS Pro using the following libraries:

- arcpy (Esri n.d.)
- pandas (Pandas Development Team 2024)
- osgeo/gdal (Rouault et al. 2024)
- other packages in the Python Standard Library (Python 2024)

Ancillary Data

To define the geographic boundaries of coastal counties and county subdivisions (used to identify named communities with infrastructure at risk), we used datasets from NOAA (Marine Cadastre 2024) and the US Census Bureau (2023).

Caveats

Each community has a distinct profile, defined by its unique location, topography, population, financial resources, and coastal development patterns, among other characteristics. Communities may find that their risks differ from those outlined here, particularly communities with important relevant features, such as locally controlled coastal defenses, geographic areas with complex tidal dynamics, and rapidly changing economies or populations. Therefore, there are important caveats to bear in mind when applying our results:

1. Population, demographics, number of assets, and disadvantaged status are assumed to remain constant at present-day levels. Studies incorporating future population growth into analyses of sea level rise tend to show greater population impacts, which suggests our results may be conservative (Hauer 2017).

2. Our determination of the extent of flooding in this analysis is dependent upon the quality of the underlying elevation data, which were provided by NOAA's Sea Level Rise Data Download (2024). These data vary in horizontal resolution and accuracy; communities are encouraged to work with the highest-resolution elevation data available to conduct more detailed mapping. In addition, any structures developed after the elevation data were collected—such as the installation of levees or bulkheads—are not reflected.

3. By excluding areas protected by federal levees or deemed by FEMA to have reduced flood risk because of protective structures, we assume infrastructure within such areas will be sufficiently protected by existing structures through 2100. If these systems fail or are damaged, however, such areas may actually experience flooding in the future.

4. Even the highest-resolution elevation data used in this study do not adequately capture most local coastal defenses, such as seawalls. Areas with such structures in place may not experience as much flooding as suggested by our analysis.

5. Tidal dynamics and storm surge vary greatly depending on local coastal morphology. Features such as bays, inlets, barrier islands, and wetlands can attenuate or amplify tide and surge relative to their levels at the open ocean-facing tide gauges that determined water levels. Run-up and swash due to ocean waves, which are not included in the analysis, can contribute to flooding as well. As a result, some areas may experience more or less flooding than we estimate.

6. All the infrastructure asset location data we used were free and publicly available, largely from federal sources. While we attempted to ensure that locations were reasonable—for example, regeolocating or removing assets geocoded in bodies of water—we did not systematically or independently verify each asset's location or current purpose. Nor did we assess the ground-floor elevations of assets. As such, there may be instances in which an asset identified as at risk of disruptive flooding is improperly located or identified, or is elevated in such a way that mitigates flood risk.

7. This analysis makes no assumptions about adaptation measures communities may implement in the future, such as building flood-control structures or restoring wetlands. Several factors affect the range of adaptation options available to any given community, including its geography and financial resources.

8. The water levels we identified as being reached or exceeded 2, 12, or 26 times per year at each tide gauge could be caused by high tides, storm surge, or a combination of the two. This analysis does not distinguish between those mechanisms.

9. Our sea level rise projections reflect subsidence (vertical land motion), because it is incorporated into NOAA's tide gauge measurements, which are relative to land. However, improved estimates of current subsidence in local areas along the coast or increased future subsidence rates would change how much critical infrastructure is exposed to disruptive flooding under each scenario (Ohenhen et al. 2024).

10. The screening tool that we used to identify disadvantaged communities has limitations and imperfections, including that it does not consider race as a factor in its methodology. Some of these limitations have been identified in comments on the beta

version of the tool from the White House Environmental Justice Advisory Council (WHEJAC 2021). As such, the screening likely excludes communities that are undoubtedly disadvantaged because of the legacy of past and ongoing racism and inequities. Nevertheless, it is a useful tool that relies on publicly available, nationally consistent data to create a nationally comparable dataset. We also chose it because it is the preferred federal tool, whose development has been led by the White House Council on Environmental Quality (CEQ) with the intent for annual updates. CEQ has directed all federal agencies to use this tool in identifying disadvantaged communities for the purposes of implementing the Justice40 Initiative (CEQ 2023). We recognize that other federal and state tools exist, such as EJScreen (EPA EJScreen 2023) and CalEnviroScreen (August et al. 2021).

Disclaimer

This research is intended to help individuals and communities appreciate when sea level rise may place existing infrastructure assets at risk of disruptive flooding. It captures the current locations and types of infrastructure and is not intended to project changes in the locations or types of property. The projections herein are made to the best of our scientific knowledge and comport with our scientific and peer review standards. They are limited by a range of factors, including but not limited to the quality of asset-level data, the resolution of coastal elevation models, the potential installment of defensive measures not captured by those models, and uncertainty around the future pace of sea level rise. Neither the authors nor the Union of Concerned Scientists are responsible or liable for financial or reputational implications or damages to asset holders, insurers, investors, mortgage holders, municipalities, or any other entities. The content of this analysis should not be relied on to make business, real estate, or other real-world decisions without independent consultation with professional experts with relevant experience.

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