Appendix I. Inland Flooding

1. Introduction

Extreme precipitation events have intensified in recent decades across most of the U.S., and this trend is projected to continue.[1] Flood risk from high excessive riverine flow has been documented to be widespread in the contiguous U.S., and as a result of climate change, is growing either as a result of changes in housing and population density over time (Wing et al. 2018),[2] as a result of climatic changes in the frequency and intensity of precipitation patterns (Davenport et al. 2021; Wobus et al. 2019),[3,4] or both. Riverine flooding, also known as fluvial flooding, occurs when excessive rainfall over an extended period of time collects across a watershed and causes a river to exceed its capacity.[5]

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[1] Hayhoe K, Wuebbles DJ, Easterling DR, Fahey DW, Doherty S, Kossin J, Sweet W, Vose R, and Wehner M. 2018. Our Changing Climate. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller DR, Avery CW, Easterling ER, Kunkel KE, Lewis KLM, Maycock TK, and Stewart BC, (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 72–144. doi: 10.7930/NCA4.2018.CH2

[2] Wing, Oliver EJ, Bates PD, Smith AM, Sampson CC, Johnson KA, Fargione J, and Morefield P. 2018. Estimates of Present and Future High-End River Flood Risk at Present Levels in the Conterminus United States. *Environmental Research Letters* 13(3):1–7

[3] Davenport FV, Burke M, Diffenbaugh MS. 2021. Contribution of historical precipitation change to US flood damages. *Proceedings of the National Academy of Sciences* 118 (4) e2017524118; doi:10.1073/pnas.2017524118.

[4] Wobus C, Zheng P, Stein J, Lay C, Mahoney C, Lorie M, et al. 2019. Projecting changes in expected annual damages from riverine flooding in the United States. *Earth's Future*, 7, 516–527. https://doi.org/10.1029/2018EF001119. Riverine flooding can also be caused by heavy snow melt (which is also considered in this appendix) and ice jams (which is not considered here).

[5] A second type of freshwater flooding, known as pluvial flooding, is caused by the excessive rainfall itself, and is often associated with urban drainage systems reaching a state of over-capacity, rather than rain causing a river system to exceed its capacity. Pluvial flooding is also expected to grow worse as a result of climate change (see Price J, Wright L, Fant C, and Strzepek K. 2014. Calibrated Methodology for

Heavier downpours can result in more extreme flooding, affecting human health and safety, property, infrastructure, and natural resources. In the U.S., inland flooding caused over 600 deaths between 1980 and 2020 and flood-related damages (e.g., to property and crops) averaged nearly $3.7 billion per year during this period (NWS, 2021).[6]

The 2016 Climate and Health Assessment found that people living in floodplains are more vulnerable not only to extreme weather, but also to social and economic stressors that can occur simultaneously or consecutively and accumulate over time.[7] Concerns for socially vulnerable populations in inland floodplains include that these groups are disproportionately located in areas that are most vulnerable to damaging flooding. This analysis projects changes in river flooding from climate change-driven changes in precipitation; assesses exposure of properties to flooding; connects these physical vulnerabilities to measures of social vulnerability; and estimates the extent to which socially vulnerable individuals may be more likely to currently live in areas with the highest projected impacts.

In the remainder of this appendix, evidence is presented of the potential for climate change to exacerbate existing social inequities in inland floodplains. Section 2 describes the motivation and background for investigating these factors, and Section 3 provides more detail on the relevant hazards from climate change-driven flooding. Sections 4 and 5 lay out the methods employed to perform the inland flooding analysis and the mapping of coastal risks to socially vulnerable populations. Sections 6 and 7 provide the results of the flooding risk analysis and the implications for disproportionate impacts on socially vulnerable populations, respectively. Sections 8 and 9 summarize conclusions from the findings and describe important limitations, while Section 10 provides a summary of data sources.

2. Social Vulnerability and Flooding

In the U.S., some minority communities, low-income groups, people with limited English proficiency, and certain immigrant groups are at increased risk of exposure given their higher likelihood of living in risk-prone areas and locations with poorly maintained infrastructure (Gamble et al. 2016). A number of studies document that socially vulnerable groups often inhabit flood-prone areas due to societal barriers related to social stratification. Exposure of these communities has been well-examined in the U.S. (e.g., Lee and Jung 2014: Adeola and Picou 2012).[8,9] Previous studies have evaluated different components of climate-driven effects on inland flooding and socially vulnerable communities.

Assessing Climate Change Adaptation Costs for Urban Drainage Systems. *Urban Water Journal*, **13**, doi:10.1080/1573062X.2014.991740), but is not considered in this analysis.

[6] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters. 2021. https://www.ncdc.noaa.gov/billions/, DOI: 10.25921/stkw-7w73

[7] Gamble JL, Balbus J., Berger M, Bouye K, Campbell V, Chief K, Conlon K, Crimmins A, Flanagan B, Gonzalez-Maddux C, Hallisey E, Hutchins S, Jantarasami L, Khoury S, Kiefer M, Kolling J, Lynn K, Manangan A, McDonald M, Morello-Frosch R, Redsteer MH, Sheffield P, Thigpen Tart K, Watson J, Whyte KP, and Wolkin AF. 2016. Ch. 9: Populations of Concern. *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment.* U.S. Global Change Research Program, Washington, DC, 247–286. http://dx.doi.org/10.7930/J0Q81B0T

[8] Lee D, Jung J. 2014. The growth of low-income population in floodplains: a case study of Austin, TX. *KSCE J Civ Eng* 18:683–693. https://doi.org/10.1007/s1220 5-014-0205-z

[9] Adeola FO, Picou JS. 2012. Race, social capital, and the health impacts of Katrina: evidence from the Louisiana and Mississippi gulf coast. *Human Ecological Review* 19:10–24.

Using geospatial analysis, Finch et al. (2010)[10] and Emrich and Cutter (2011)[11] identify locations highly vulnerable to flood hazards that are inhabited by socially vulnerable populations. Lu (2017) finds that for Houston, TX and other areas, socioeconomic status and racial characteristics correlate with low elevation above coastal and inland water bodies.[12] Other studies develop composite indices to identify which measures of social vulnerability are the most predominant in flood-prone areas (Qiang, 2019; Rufat et al. 2015).[13,14] Similarly, a recent analysis overlays hotspots of high flood exposure and high social vulnerability to identify dominant indicators of social vulnerability (Tate et al. 2021).[15]

Recent events such as Hurricane Harvey have reinforced the social inequities associated with flood risk and impacts, particularly identifying racial and income inequities. Chakraborty et al. (2019) analyzed whether the spatial distribution of flooding effects were distributed inequitably with respect to race, ethnicity, and socioeconomic status, after controlling for relevant explanatory factors.[16] A similar study found that Hispanic, Black and other racial/ethnic minority households were subject to more extensive flooding than households occupied by White individuals, and that households who experience lower income faced more extensive flooding than higher income households (Collins et al. 2019).[17]

Measures of Social Vulnerability

This analysis quantifies whether socially vulnerable populations face disproportionate risks of experiencing the largest flooding-related damages to their properties. The determinants of social vulnerability examined in this analysis include the following:

- ***Low Income:*** Individuals with low income may only be able to afford to rent or purchase properties in less desirable areas across the country, including those located in floodplains.[18] Also, these individuals may not be able to take on additional expenses from climate impacts, such as repeated

[10] Finch C, Emrich CT, Cutter SL. 2010. Disaster disparities and differential recovery in New Orleans. *Population and Environment* 31:179–202. doi:10.1007/s11111-009-0099-8

[11] Emrich CT, Cutter SL. 2011. Social vulnerability to climate-sensitive hazards in the southern United States. *Weather, Climate, and Society* 3:193–208.

[12] Lu Y. 2017. Hurricane flooding and environmental inequality: do disadvantaged neighborhoods have lower elevations? *Socius* **3** 1–3. Table 2 reports the average marginal effects of the disadvantage dummies in the 80 regressions. In 11 out of the 20 MSAs, tracts in the bottom income quartile have lower ($p < .05$) elevations compared to other tracts. In 15 out of 20 MSAs, tracts in the top poverty quartile have lower elevations ($p < .05$). Tracts with highest racial/ethnic minority concentration and non-citizen concentration have lower elevations ($p < .05$) in 13 of the MSAs. In 9 of the MSAs, elevation is negatively associated with all four measures of neighborhood disadvantage.

[13] Qiang Y. 2019. Disparities of population exposed to flood hazards in the United States. *Journal of Environmental Management* 232:295–304

[14] Rufat S, Tate E, Burton CG, and Maroof AS. 2015. Social vulnerability to floods: Review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction*. 14:470–486, doi:10.1016/j.ijdrr.2015.09.013.

[15] Tate E, Rahman MA, Emrich CT, et al. Flood exposure and social vulnerability in the United States. *Natural Hazards* 106, 435–457 (2021). https://doi.org/10.1007/s11069-020-04470-2

[16]Chakraborty J, Collins TW, and Grineski SE. 2019. Exploring the environmental justice implications of Hurricane Harvey flooding in greater Houston, Texas. *American Journal of Public Health* 109**,** 244–50.

[17] Collins TW, Grineski SE, Chakraborty J, and Flores AB. 2019. Environmental injustice and Hurricane Harvey: a household-level study of socially disparate flood exposures in Greater Houston, Texas, USA. *Environmental Research* 179 108772

[18] Bakkensen L, and Ma L. 2020. Sorting over flood risk and implications for policy reform*. Journal of Environmental Economics and Management*, 104:102362. https://doi.org/10.1016/j.jeem.2020.102362

home repair, flood-proofing, or other adaptation costs. Low-income populations have been shown to be less likely to evacuate in response to warning systems (Fothergill and Peek, 2004).[19]

- ***Minority: Black and African American, Asian, Pacific Islander, Native American, and Hispanic/Latino racial and ethnic groups:*** Individuals from these groups may have limited access to information and resources publicly offered because of language or cultural differences.[20] Also, nature-based infrastructure projects, such as those designed to protect against flooding, often exclude socially vulnerable groups and instead end up displacing lower income residents.[21]
- ***No High School Diploma:*** Lower educational attainment can result in less awareness regarding environmental and natural hazards when choosing where to live, as well as insufficient understanding of emergency preparedness information for floodplain risks. Individuals with no high school diploma are also more likely to receive lower hourly wages and have less wealth. As a result, individuals with no high school diploma may be forced to rent or purchase properties in less desirable locations, such as floodplains.[22]
- ***Older age:*** Since older individuals have lived longer than the younger population, they are more likely to have greater ties to the community or home. Even the process of moving to another home can be daunting, especially for those with physical or mental ailments, or other health-related factors such as proximity to health facilities. Some evidence indicates that those over 65 could see increased riverine flood frequency and magnitude by 2050 as a result of climate change.[23]

3. Climate Change and Flooding Hazards

Floods are among the most damaging natural disasters in the U.S., causing billions of dollars in monetary damages each year (NWS, 2021; Smith & Matthews, 2015).[24] Relative to other extreme hazards, floods are omnipresent across the country and manifest in many ways, including large watershed floods, localized flash floods, and overflows of urban drainage systems. Flooding events can be frequent or rare and be of short or long durations (Rufat et al. 2015). Because a warmer atmosphere can hold more moisture than a cooler atmosphere, climate change is expected to change the frequency and magnitude

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[19] Fothergill A, and Peek A. 2004. Poverty and disasters in the United States: A review of recent sociological findings. *Natural Hazards*, 32, 89-110. doi:10.1023/B:NHAZ.0000026792.76181.d9

[20] Gamble JL, Balbus J, Berger M, Bouye K, Campbell V, Chief K, Conlon K, Crimmins A, Flanagan B, Gonzalez-Maddux C, Hallisey S, Hutchins S, Jantarasami L, Khoury S, Kiefer M, Kolling J, Lynn K, Manangan A, McDonald M, Morello-Frosch R, Redsteer MH, Sheffield P, Thigpen Tart K, Watson J, Whyte KP, and Wolkin AF. 2016. Ch. 9: Populations of Concern. *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment*. U.S. Global Change Research Program, Washington, DC, 247–286. http://dx.doi.org/10.7930/J0Q81B0T

[21] Anguelovski I, Connolly JJT, Pearsall H, Shokry G, Checker M, Maantay J, Gould K, Lewis T, Maroko A, and Roberts JT. 2019. Why green "climate gentrification" threatens poor and vulnerable populations. *PNAS* 116(52): 26139–26143. https://www.pnas.org/cgi/doi/10.1073/pnas.1920490117

[22] Bakkensen and Ma 2020.

[23] Mills D, Jones R, Wobus C, Ekstrom J, Jantarasami L, St. Juliana A, Crimmins A. 2018. Projecting Age-Stratified Risk of Exposure to Inland Flooding and Wildfire Smoke in the United States under Two Climate Scenarios. *Environmental Health Perspectives* 126(4). https://doi.org/10.1289/EHP2594

[24] Smith AB, and Matthews JL. 2015. Quantifying uncertainty and variable sensitivity within the US billion-dollar weather and climate disaster cost estimates. *Natural Hazards*, 77(3), 1829–1851. doi:10.1007/s11069-015-1678-x

of flooding across the country, with important implications for flood damages (Dottori et al., 2018).[25] Multiple extreme floods in the U.S. over recent years have heightened attention on the role of climate change in exacerbating damages from both inland and coastal flooding (Trenberth et al., 2018; van der Wiel et al., 2017).[26,27]

A number of recent studies have estimated future changes in flood risk and damages in the U.S. (Davenport et al. 2021; First Street, 2021; Wobus et al. 2019; AECOM, 2013).[28,29,30] These studies find that inland flood damages have increased over the past several decades, and are projected to continue increasing as the climate further warms. Climate-driven changes in flood risk can also amplify risks from non-climate factors such as expanded development in floodplains, urbanization, and land-use changes.[31] These human processes can have large effects on the extent and severity of flooding, ameliorating impacts in some instances, but amplifying damages in others (Rufat et al. 2015). Adaptive measures to mitigate flood risk are known to be effective, however, in addition to the costs associated with these investments, widescale implementation and effectiveness remains uncertain due to a variety of social, economic, and institutional challenges (Ward et al. 2017).[32]

4. Methods for Estimating Climate Risk

To simulate physical effects from climate-driven changes in flood risk, this analysis uses site-specific characteristics of properties located in floodplains across the country in a multi-step flood modeling framework described in Wobus et al. (2021)[33] and Wobus et al. 2019. The analysis follows four overall steps, which are described here.

1. **Calculate baseline period damages for a portfolio of specific flood events:** Estimating baseline damage (referred to as expected annual damage, or EAD) is the backbone of the analysis as the

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[25] Dottori F, Szewczyk W, Ciscar W, Zhao JC, Alfieri F, Hirabayashi L, Bianchi Y, Mongelli A, Frieler I, Betts K, and Feyen L. 2018. Increased human and economic losses from river flooding with anthropogenic warming. *Nature Climate Change*, 8(September), 781–786. doi: 10.1038/s41558-018-0257-z

[26] Trenberth KE, Cheng L, Jacobs P, Zhang P, Fasullo J. 2018. Hurricane Harvey links to ocean heat content and climate change adaptation. *Earth's Future*, 6(5), 730–744. doi:10.1029/2018EF000825

[27] van derWiel K, Kapnick SB, vanOldenborgh GJ, Whan K, Philip S, Vecchi GA, Singh RK, Arrighi J, and Cullen H. 2017. Rapid attribution of the August 2016 flood-inducing extreme precipitation in south Louisiana to climate change. *Hydrology and Earth System Sciences*, 21(2), 897–921. https://doi.org/10.5194/hess-21-897-2017.

[28] First Street Foundation. 2021. The Cost of Climate America's Growing Flood Risk. Brooklyn, NY. https://assets.firststreet.org/uploads/2021/02/The_Cost_of_Climate_FSF20210219-1.pdf

[29] Wobus C, Zheng P, Stein J, Lay C, Lorie M, Mills D, Spies R, Szafranski B, and Martinich J. 2019. Projecting changes in expected annual damages from inland flooding in the United States. *Earth's Future*, 7. doi:10.1029/2018EF001119

[30] AECOM. 2013. The impact of climate change and population growth on the National Flood Insurance Program through 2100. Retrieved from http://www.adaptationclearinghouse.org/resources/the-impact-of-climate-change-and-population-growth-on-the-national-flood-insurance-program-through-2100.html

[31] Bell JE, Herring SC, Jantarasami L, Adrianopoli C, Benedict K, Conlon V, Escobar J, Hess J, Luvall CP, Garcia-Pando D, Quattrochi J, Runkle J, and Schreck CJ, III. 2016. Ch. 4: Impacts of Extreme Events on Human Health. *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment*. U.S. Global Change Research Program, Washington, DC, 99–128.

[32] Ward PJ, Jongman B, Aerts JC, Bates JH, Botzen PD, Diaz Loaiza WJW, Hallegatte A, Kind S, Kwadijk JM, Scussolini J, and Winsemius HC. 2017. A global framework for future costs and benefits of river-flood protection in urban areas. *Nature Climate Change*, 7(9), 642–646. doi:10.1038/nclimate3350

[33] Wobus CW, Porter J, Lorie M, Martinich J, and Bash R. 2021. Climate change, riverine flood risk and adaptation for the conterminous United States. *Environmental Research Letters* in press https://doi.org/10.1088/1748-9326/ac1bd7

projected damages from climate change will shift damages in the future compared to the baseline. This step is data driven and relies primarily on a property-level flood risk dataset and model for the U.S. (First Street Foundation, 2020[34]; Bates et al., 2021).[35] For each property in the CONUS, this dataset includes the primary driver of flood risk (i.e., coastal, fluvial or pluvial), as well as the projected depth of flooding for return intervals of 2 years (50% annual exceedance probability, or AEP) through 500 years (0.2% AEP) based on climate models projecting conditions out to the year 2050 under RCP4.5.[36] The dataset also includes an estimate of the first-floor elevation for each building, the building type, the square footage, the replacement cost, and the market value for each property. Details regarding the development of this dataset are available in First Street (2020) and Armal (2020).[37]

Following steps described in Wobus et al. (2021), baseline damages are estimated for each property using unique depth-damage curves for each occupancy class (FEMA, 2016)[38] and a portfolio of flood events identified by recurrence intervals ranging from the 2-year (or 50% annual exceedance probability (AEP)) event to the 500-year (0.2% AEP) event. The first step subtracts the first-floor elevation from each flood depth value, to obtain the depth of flooding relative to the first floor at each recurrence interval. Using each of the resulting flood depths, the analysis calculates the fractional loss that would be incurred to the property due to a flood with that recurrence interval. These fractional losses were estimated by matching the occupancy class for each property with the appropriate depth-damage curve, following the guidelines in the HAZUS manual to select a unique depth-damage curve for each occupancy class (FEMA, 2016). Using the combination of fractional loss, building replacement value, and recurrence interval, a frequency-loss curve is calculated for each property and numerically integrated under this curve between flood frequencies of 0.001 and 0.10 to calculate the EAD.[39]

2. **Historical and projected river flows:** River flows are estimated using topography and other ground surface and sub-surface characteristics, climatic variables like precipitation and temperature, and river-routing. This analysis uses a downscaled hydrology dataset developed by a consortium of federal agencies including the U.S. Army Corps of Engineers, the U.S. Bureau of Reclamation, and other federal agencies (Reclamation 2014).[40] This dataset includes daily

[34] First Street Foundation. 2020. First Street Foundation Flood Model (FSF-FM): Technical Documentation. Brooklyn, NY. Published 06/17/2020. https://assets.firststreet.org/uploads/2020/06/FSF_Flood_Model_Technical_Documentation.pdf

[35] Bates PD, Quinn N, Sampson C, Smith A, Wing O, Sosa J, Savage J, Olcese G, Neal J, Schumann G, and Giustarini L. 2020. Combined modelling of US fluvial, pluvial and coastal flood hazard under current and future climates. *Water Resources Research*, p.e2020WR028673.

[36] The flood risk dataset and model use RCP4.5 in the underlying climate projections, while the hydraulic projections use RCP8.5. Given that this analysis looks across long time horizons (i.e., decades) to estimate changes in flood risk, the use of these two concentration pathways is reasonable as they have overlapping uncertainty ranges across climate model projections.

[37] Armal S, Porter JR, Lingle B, Chu Z, Marston ML, and Wing OE. 2020. Assessing Property Level Economic Impacts of Climate in the US, New Insights and Evidence from a Comprehensive Flood Risk Assessment Tool. *Climate*, 8(10), 116.

[38] Federal Emergency Management Agency. 2016. Multi-hazard Loss Estimation Methodology Flood Model HAZUS®MH MR3 Technical Manual. Developed by: Department of Homeland Security, Federal Emergency Management Agency -Mitigation Division. Washington, D.C. Under a contract with: National Institute of Building Sciences Washington, D.C.

[39] 2 yr through 500-yr flood depth grids are available in the First Street data product. EAD is calculated between 10 and 1000 yr flood intervals/events to put consistent bounds on the area under the curve.

[40] Reclamation: Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Hydrology Projections, Comparison with Preceding Information, and Summary of User Needs, Prepared by the US Department of the Interior, Bureau of Reclamation, Technical Services

routed flows at approximately 57,000 stream reaches across the CONUS for an ensemble of global climate models (or GCMs) downscaled using the bias correction and spatial disaggregation method. The analysis for this report uses 14 climate models from this ensemble whose temperature trajectories under RCP8.5 reach a CONUS-averaged temperature of 5°C above baseline by 2100.[41] Table 1 summarizes these 14 GCMs, along with the year that each of these models reaches each of the specified temperature thresholds. Note that these GCMs and their respective arrival years for each integer of warming are different compared to the other sectors of this report. See Wobus et al. (2019) for additional details about the selection of these 14 models.

Using the projected hydrology for each climate model, an annual maximum flow timeseries is extracted at each stream reach for a 20-year window centered on the year that the model reaches temperature thresholds of 1°C through 5°C above the 2001-2020 baseline.[42]

Table 1. List of 14 models included in the hydrologic analysis, as well as the year that each model reaches a CONUS-averaged temperature threshold of 1°, 2°, 3°, 4°, and 5°C above the 2001-2020 baseline period.

MODEL ID	1ºC	2ºC	3ºC	4ºC	5ºC
access1-0	2027	2045	2058	2073	2088
canesm2	2033	2048	2065	2074	2091
cesm1-cam5	2032	2045	2063	2078	2090
cmcc-cm	2031	2052	2064	2074	2093
csiro-mk3-6-0	2041	2058	2066	2080	2093
fgoals-g2	2032	2052	2066	2078	2095
gfdl-cm3	2029	2049	2061	2070	2087
hadgem2-ao	2036	2048	2058	2067	2082
hadgem2-cc	2029	2041	2057	2063	2073
hadgem2-es	2028	2043	2056	2065	2079
ipsl-cm5a-mr	2029	2043	2057	2068	2086
miroc-esm-chem	2026	2037	2047	2064	2073
miroc-esm	2026	2034	2047	2060	2073
noresm1-m	2032	2050	2065	2080	2093

Center, Denver, CO, 2014. Documentation and VIC hydrology data are available at ftp://gdo-dcp.ucllnl.org/pub/dcp/archive/cmip5/hydro/BCSD_daily_VIC_nc/

[41] The only scenario used is RCP8.5, which represents a pathway with relatively high greenhouse gas concentrations, leading to substantial warming by 2100. RCP8.5 was chosen to assess a wide range of future temperatures, and the selection of a higher emissions scenario ensures that this approach evaluates sectoral impacts at higher levels of warming (e.g., 4 or 5ºC) in addition to smaller levels (i.e., an RCP with considerably lower forcing may not reach higher degree bins, therefore leading to data gaps on the sectoral impact response to higher levels of warming).

[42] Note that these results are for changes in temperature across CONUS. For subsequent steps, these were converted for this analysis to integer global temperature changes, using an interpolation between the decimal global temperature changes equivalent to integer CONUS temperature changes.

3. **Estimate distributions of extreme flow events:** Changes in flooding damage are driven by changes in the recurrence interval of extreme flooding events. As these rare events are difficult to discern in the historical record, it is necessary to use a statistical technique to identify the flow associated with the return periods of interest. The method is driven by changes in frequency for the flood events provided in the baseline data (step number 1) using extreme-value distributions. Using 20 years of historical flow data, the generalized extreme value distribution is fit to the flow data to estimate the flows for each storm event (2-year to 500-year). Using the same distribution to the 20-year future flow series, the analysis estimates the recurrence intervals for the flows of each historical storm event. Baseline damages for that event would then occur more or less frequently in the future based on the differences in statistical properties, which is how the process estimates the change in expected annual impacts. For example, if a flow event in the historical period is a 1-percent flood event, and these same flows occur with 2-percent per year frequency in the future projection, the contribution to expected annual damages from that event would be double the baseline annual expected damages. Similarly, if the 1-percent event occurs with a 0.5-percent frequency in the future, the contribution to expected annual damages from that event would be half of baseline.

   Each future period is represented by 20-year eras centered on degrees of warming thresholds at 1 to 5°C above the 20-year baseline (2001-2020). Each temperature threshold thus has a set of 280 annual maxima (20 years x 14 GCMs), to which the method fits a generalized extreme value (GEV) distribution. For each future temperature warming threshold (see step 4), the future recurrence interval is calculated for the flow corresponding to each of these baseline events. Future recurrence intervals are then averaged for all of the stream reaches in each HUC10 basin, allowing the EAD curve for each property to be shifted.[43] Finally, average changes by HUC10 are applied to each property's EAD curve, with the property-level results being aggregated to the Census block group level. Additional details on the methods used for extracting future return intervals can be found in Wobus et al. (2017)[44] and Wobus et al. (2019).

[43] The USGS has developed Hydrologic Unit Codes (HUCs) to describe a standardized set of basins of the U.S. at several spatial scales. The number in the code indicates the number of digits in the code, from 2 to 12 digits, with higher numbers of digits corresponding to increasing spatial detail, in a nested system. HUC10 is one of the finer spatial scales available. See https://water.usgs.gov/GIS/huc.html for more detail.

[44] Wobus C, Gutmann R, Jones M, Rissing N, Mizukami M, Lorie M, Mahoney H, Wood AW, Mills D, and Martinich J. 2017. Modeled changes in 100 year flood risk and asset damages within mapped floodplains of the contiguous United States. *Natural Hazards and Earth System Sciences*. doi: 10.5194/nhess-2017-152.

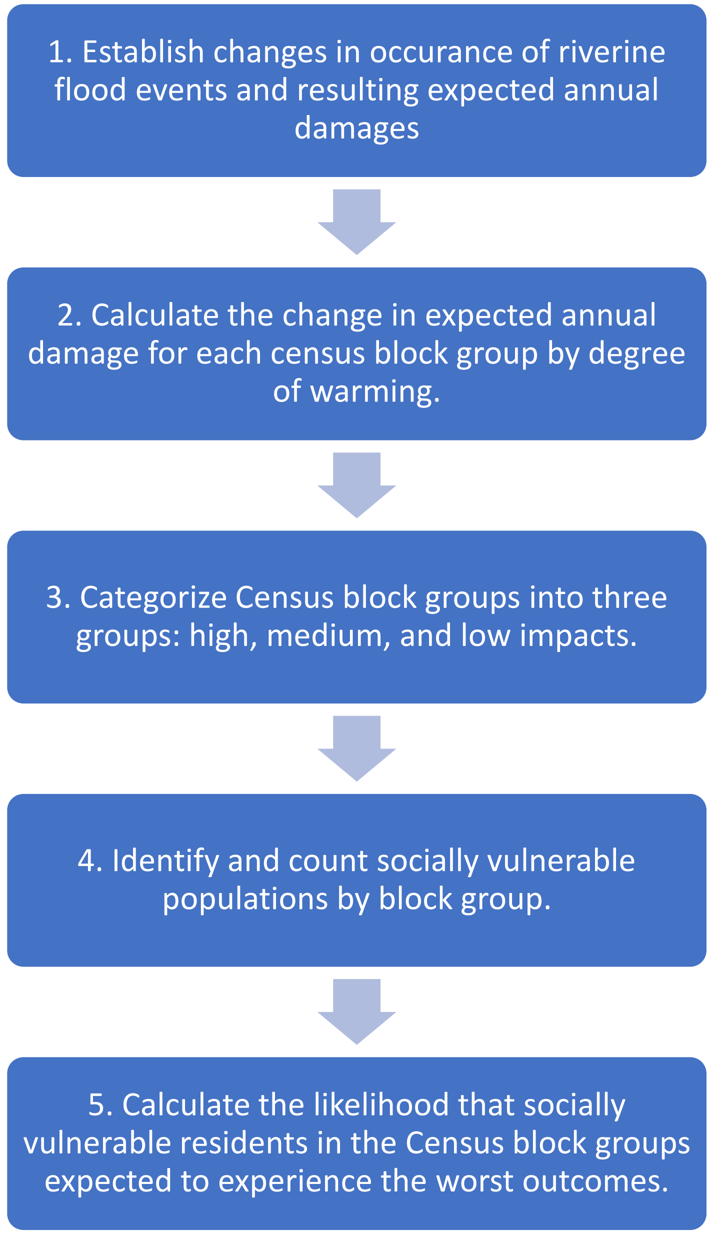
4. **Project changes in future expected annual damages:** This step uses the estimates of changes in riverine flooding occurrence (#2-3) and the baseline damages (#1) to estimate future expected annual damages for all climate projections and each degree of warming above the baseline (see Table 1 for arrival years that are the centroid of each 20-year era).

5. Methods for Assessing Social Vulnerability Dimensions

This study further investigates if socially vulnerable communities are disproportionately more likely to experience the worst outcomes from riverine flood damage compared to the baseline. The analysis uses the Census block group as the unit of analysis, and the annual expected damage ratio as a metric of hazard impact for each Census block group. The expected annual damage ratio is an estimate of the change in the proportion of property value that would be necessary to repair damages on average, per year, as a result of changes in riverine flooding occurrence in the future.

To explore the risks of changes in expected annual damages from riverine flooding on socially vulnerable populations, the approach follows the five steps outlined in Figure 2 and described in further detail below.

Figure 2. Five steps for Assessing Impacts on Socially Vulnerable Populations.



Step 1: Estimate the changes in annual expected damage ratio. This step follows the process outlined in Section 4.

Step 2: Calculate the change in expected annual damage for each Census block group by degree of warming. This process follows the steps outlined in Section 4.

Step 3: Categorize block groups into three groups: high, medium, and low impacts. The output from Step 2 is used to categorize Census block groups into three evenly sized groups. The high impact group comprises block groups with the largest expected annual damage ratios while the low impact group includes geographies with the smallest expected annual damage ratios. The focus of the analysis is on the composition of populations found in the high impact group.

Step 4: Identify and count socially vulnerable populations by Census block group. The approach does not observe exactly which individuals are both impacted and socially vulnerable. Instead, the method relies on data from the American Community Survey (2014-2018) at the block group level to count the number of individuals in socially vulnerable groups relative to non-socially vulnerable groups. In the absence of projections describing how detailed demographics will shift over the century, it is assumed that the relative distribution of socially vulnerable to non-socially vulnerable populations is fixed at 2014-2018 levels. The four determinants of social vulnerability included in this analysis are: Low Income, Minority, no high school diploma, and 65 or older.

Step 5: Calculate the likelihood that socially vulnerable residents in the Census block groups are projected to experience the worst outcomes. These likelihoods are expressed relative to the non-socially vulnerable population and are calculated at the national and regional level. The likelihood measures are separately calculated for each social vulnerability metric. These likelihood metrics can be interpreted as the degree to which the worst outcomes of increasing levels of flooding affect socially vulnerable groups relative to non-socially vulnerable groups. For more details, see Appendix C.

6. Results for Changes in Inland Flooding Damages

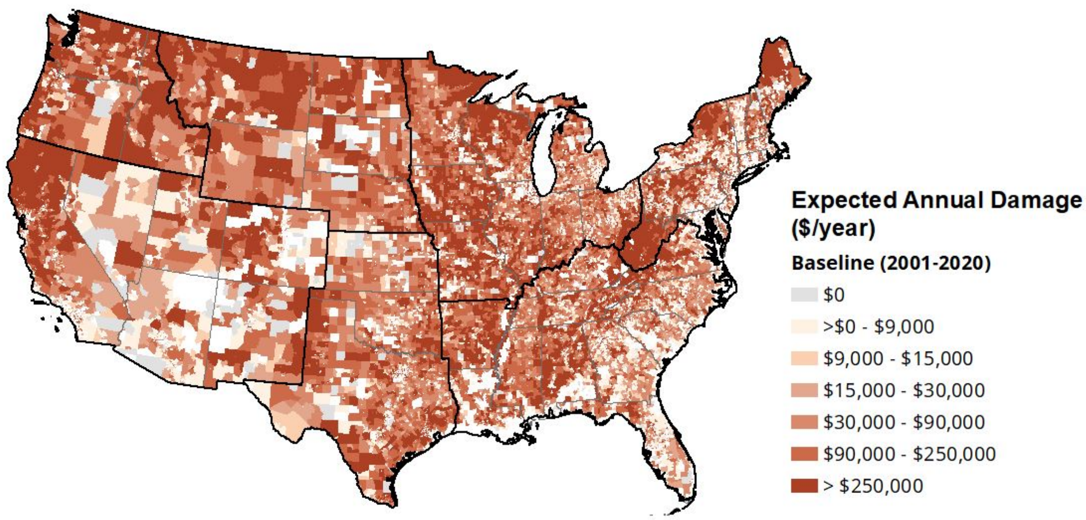
This section describes the results of the analytic methods described in Sections 4 and 5. The first set of figures show the geographic distribution of impacts across regions. The next charts depict national level likelihood of impact by social vulnerability factors. Finally, regional level likelihoods of riverine flood-related impacts by social vulnerability factors are presented. In general, this analysis finds the greatest total impacts are projected to occur in the Northwest and Northern Great Plains, but that socially vulnerable populations do not experience a significant disproportionate risk of living in areas with the highest impacts.

Figure 3 shows expected annual damages by census tract for the baseline period (2001-2020), both as a total damage value (top panel) and as a percent of property value (bottom panel).[45] In the baseline period, expected annual damage is spread across regions (top panel), with a greater percentage of impacts concentrated in parts of the Northwest region, and in the east around Appalachia, as well as parts of West Texas and the confluence of the lower Missouri River valley with the mid- to lower Mississippi River valley, in the state of Missouri (bottom panel).

[45] Results are mapped at the Census tract level for visual clarity in a national map, but analysis was performed at the Census block group level.

Figure 3. Map of Expected Annual Damages for the Baseline Period (2001-2020) by Census Tract

EAD ($/year)



EAD (% of value/year)

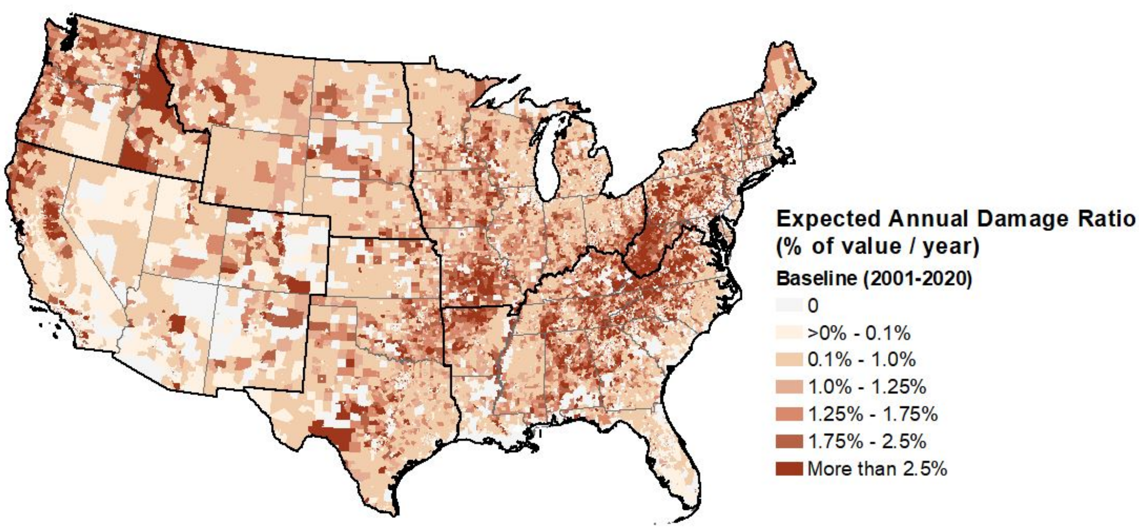
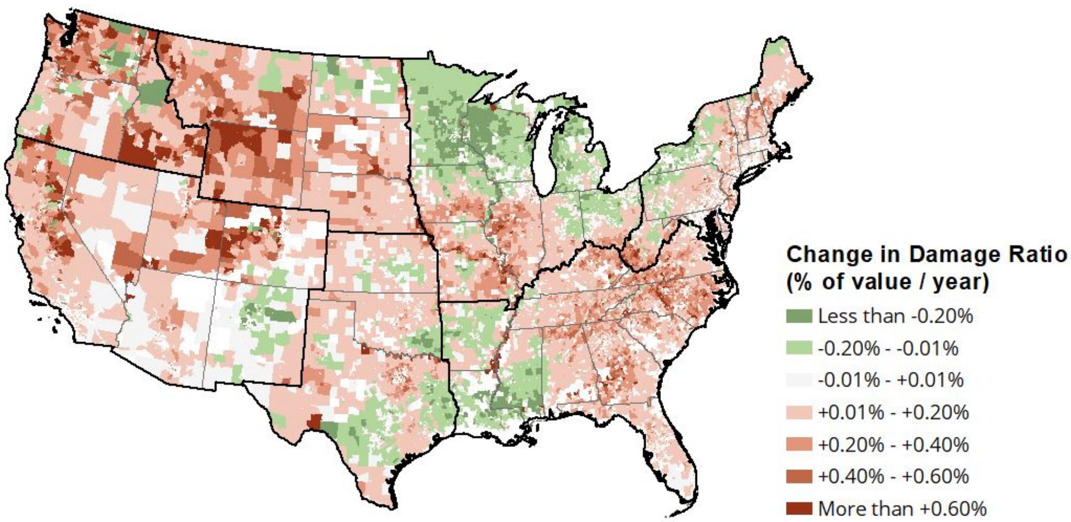


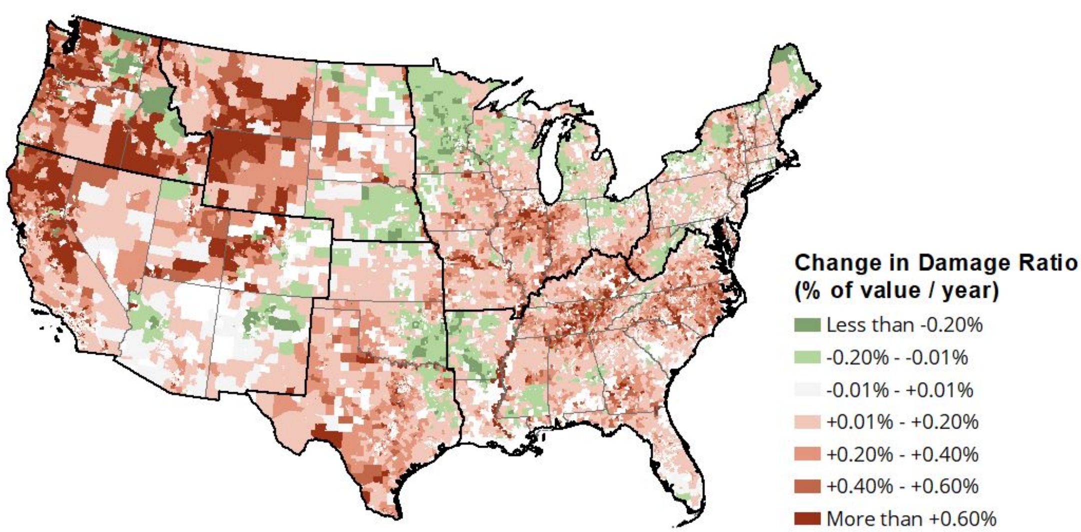
Figure 4 shows the change in damage ratio by Census tract associated with 2°C and 4°C increases in global mean temperature. The units are percent of property value per year.

Figure 4. Map of Projected Change In Expected Annual Damages at 2°C and 4°C Increase in Global Mean Temperature by Census Tract

2°C of Global Warming



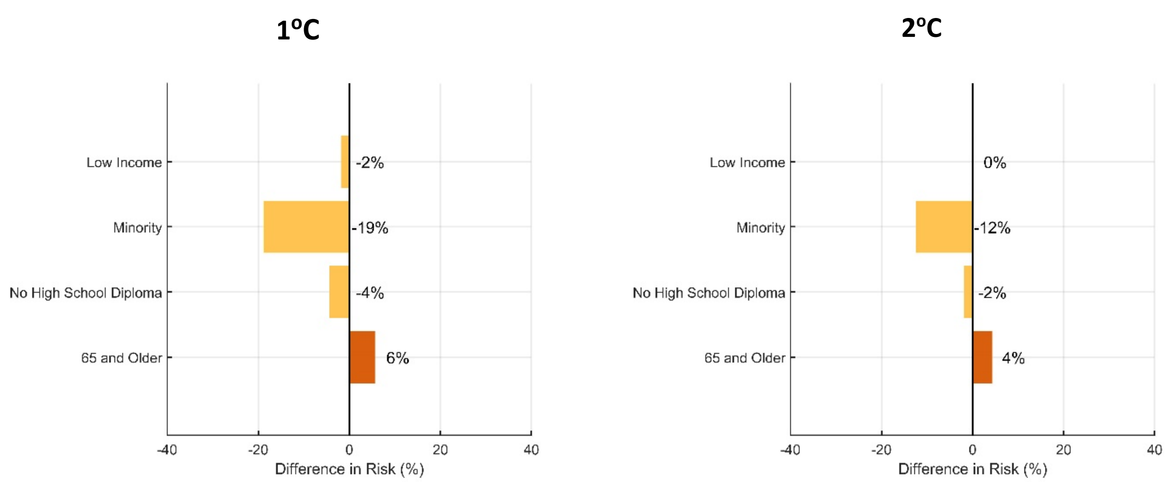
4°C of Global Warming



The greatest impacts are projected to occur in the Northern Great Plains and Northwest regions. Other regions projected to experience a disproportionate burden of damage are the Southwest and Southeast. From 2°C to 4°C increases in warming, the damage ratio (percent of property value per year) is projected to increase, especially in parts of the Southwest and Southern Great Plains. The northernmost tracts of the Midwest are projected to experience less damage relative to the baseline, as well as western Arkansas, eastern Oklahoma, and northeast Texas. Details about change in property damage ratio within regions only tells part of the story; the other important consideration is the proportion of socially vulnerable individuals living in these areas.

Figure 5 shows the likelihood that individuals in the four socially vulnerable groups analyzed currently live in areas that are projected to have the highest inland flooding damages with 1°C through 4°C global mean temperature increase, relative to their reference populations. At the national level, impacts are not projected to be largely disproportionate across low income populations, individuals with no high school diploma, or those age 65 and older. These groups are about equally likely, compared to their respective reference populations, to live in high impact areas at 1°C through 4°C increases of global mean temperature. Black and African American, Native American, Pacific Islander, Asian, and Hispanic/Latino individuals collectively have a lower relative risk at 1°C through 4°C of warming, which ranges from -4% to -19%. The underlying data used in this analysis excludes flooding events associated with urban drainage, quantifying only riverine floods instead (see Wobus et al. 2021; First Street Foundation 2021).[46] The focus on riverine flooding, as a result, may not account for flooding events in cities and other urban areas, such as Hurricane Harvey in Houston, where large populations of socially vulnerable individuals reside. As shown in Figure 3 above, riverine floods tend to occur in more rural areas.

Figure 5. Likelihood that Those in Socially Vulnerable Groups Currently Live in Areas with the Highest Projected Inland Flooding Damages, Relative to Those in Reference Populations



[46] See https://firststreet.org/flood-lab/published-research/flood-model-methodology_overview/ for an explanation of the First Street Foundation's flood risk modeling approach.

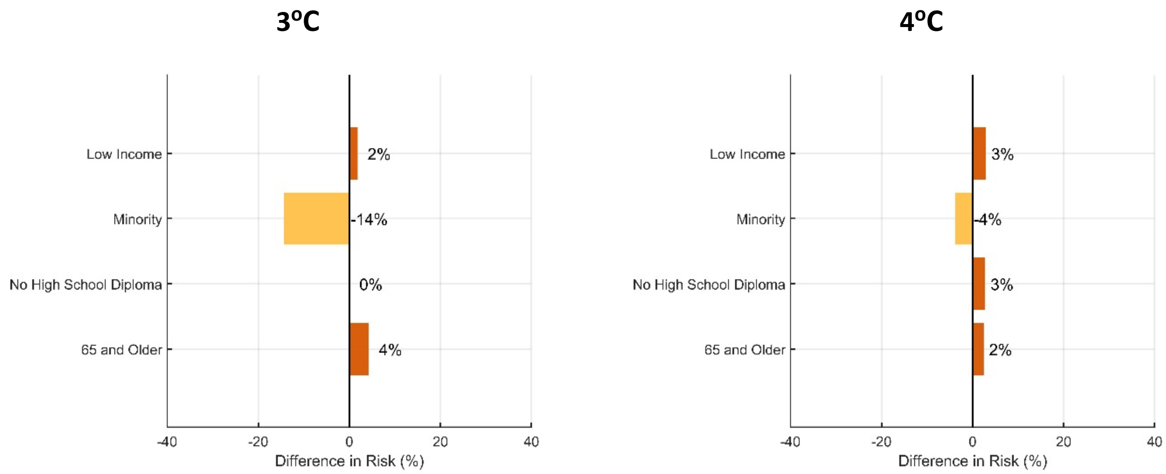
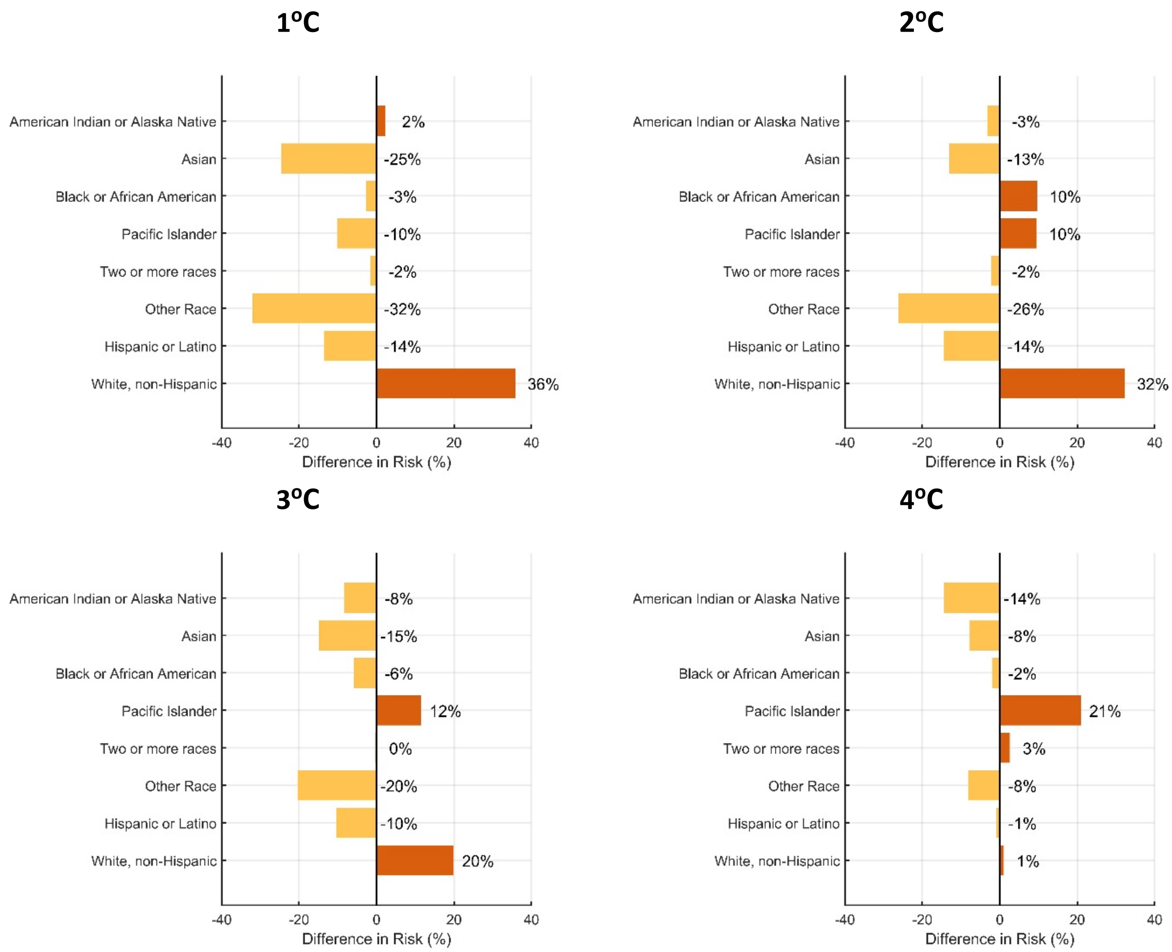


Figure 6 presents results for individual racial and ethnic groups regarding the likelihood that individuals in each group live in high-impact areas, relative to their reference populations. Generally, individuals who identify as American Indian and Alaska Native, Asian, and Hispanic or Latino are projected to be less likely to live in areas that are projected to experience the worst outcomes of riverine flooding at 1°C through 4°C of warming, relative to their reference populations. Pacific Islander individuals are approximately 10% more likely and 21% more likely to live in high-impact areas relative to non-Pacific Islander individuals at 2°C and 4°C of warming, respectively. Black and African American individuals are 10% more likely to live in high-impact areas with 2°C of global warming, but are slightly less likely than non-Black or African American individuals to live in high-impact areas with 1°C, 3°C, and 4°C of warming.

When simulating extreme events such as riverine floods decades into the future, it is possible to see discontinuities across degrees of warming, as a river flood requires a combination of high rainfall over multiple days in specific locations - a set of circumstances that can vary tremendously across future climate simulations and be sensitive to relatively small daily shifts in extreme rainfall amounts and location. It is also important to note that less vulnerable populations are typically more knowledgeable of their flood risk, and generally have the capital and capacity to prepare adequately. Socially vulnerable populations, on the other hand, are less likely to know their risk and may not be prepared for the damages that their properties could face.[47]

[47] Gamble JL, Balbus J, Berger M, Bouye K, Campbell V, Chief K, Conlon K, Crimmins A, Flanagan B, Gonzalez-Maddux C, Hallisey E, Hutchins S, Jantarasami L, Khoury S, Kiefer M, Kolling J, Lynn K, Manangan M, McDonald M, Morello-Frosch M, Redsteer MH, Sheffield P, Thigpen Tart K, Watson J, Whyte KP, and Wolkin AF. 2016. Ch. 9: Populations of Concern. The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment. U.S. Global Change Research Program, Washington, DC, 247–286. http://dx.doi.org/10.7930/J0Q81B0T

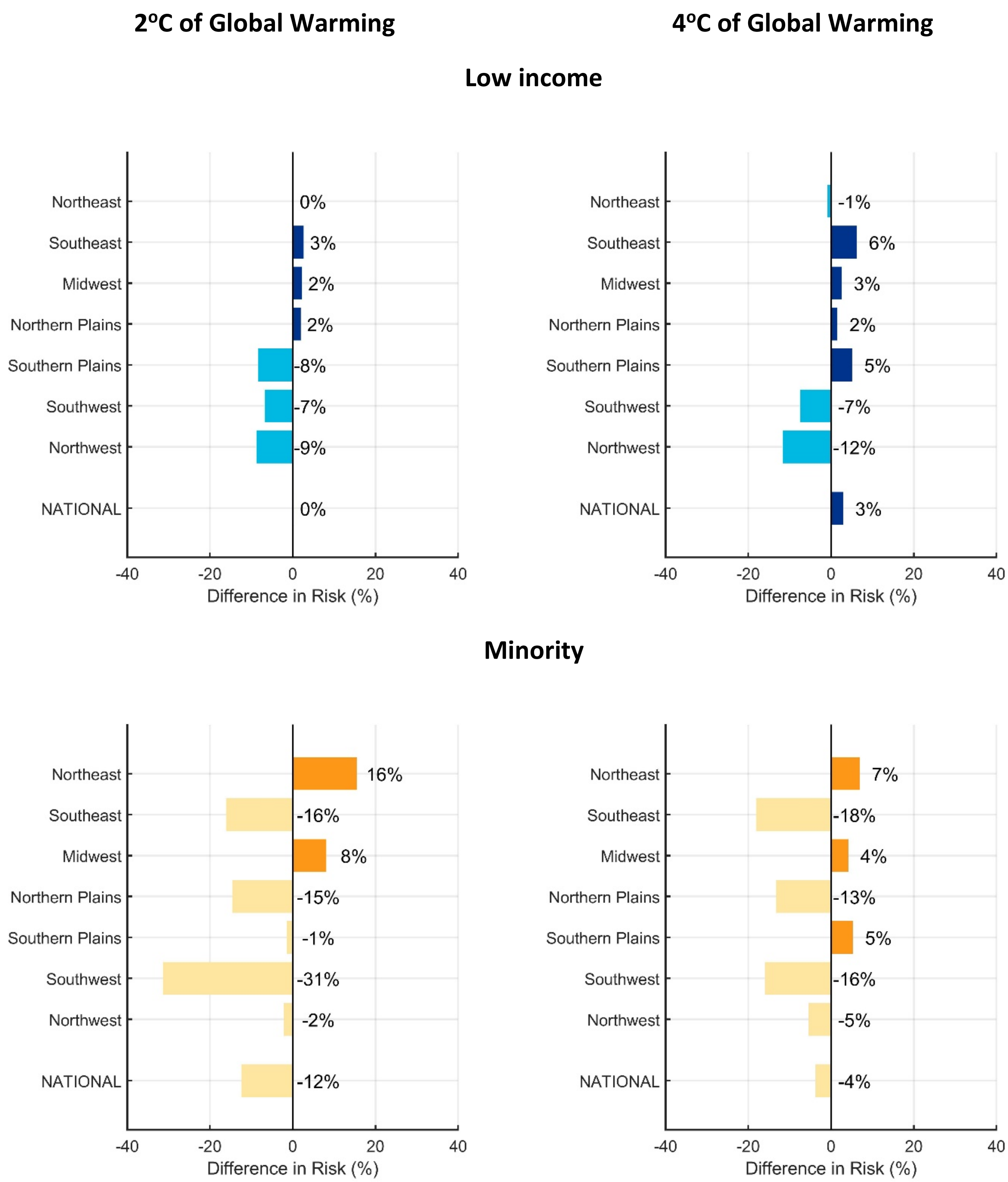
Figure 6. Likelihood that Those in Individual Racial and Ethnic Groups Currently Live in Areas with the Highest Projected Inland Flooding Damages, Relative to Those in Reference Populations



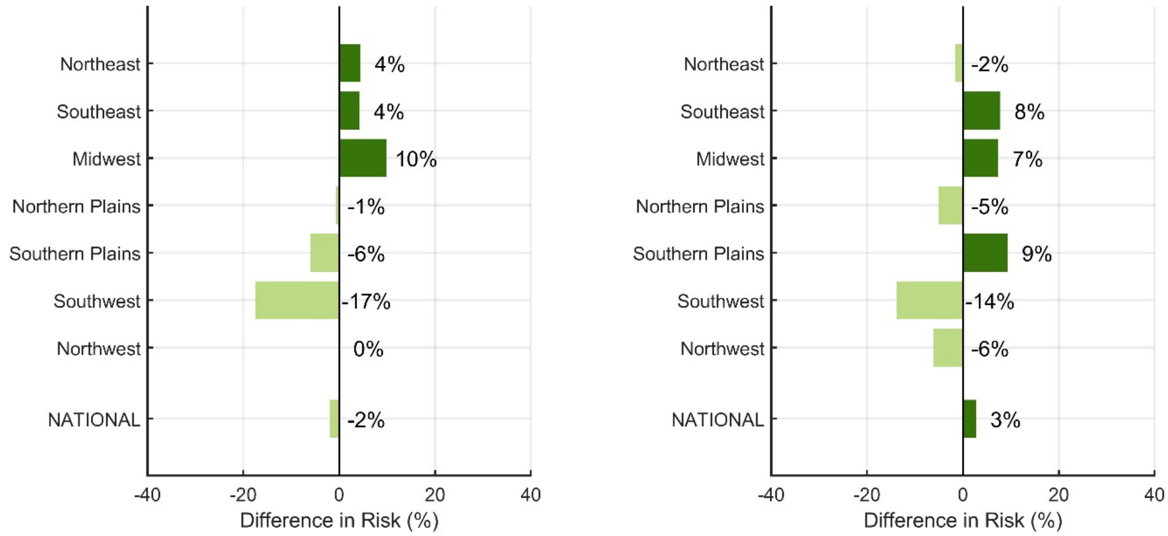
It is important to consider the distribution of socially vulnerable populations in addition to the total damages shown in Figure 4 of this Appendix to understand the regional differences in likelihood outlined in the following figures. Regionally, low income populations and minority populations are concentrated in the central Southwest (e.g., Navajo Region), along the southern border of the Southern Great Plains, and the southern half of the Southeast (see Chapter 2, Figure 4). Figure 4 of this Appendix shows that these areas experience lower inland flooding impacts at both 2°C and 4°C warming than areas with lower populations of low income and minority populations. Similarly, areas that are projected to experience more substantial damages, including much of the Northwest and parts of California, have lower percentages of low income and minority populations.

This pattern is less pronounced for individuals with no high school diploma and those age 65 and older, whose populations are more heterogeneously distributed across CONUS. Nonetheless, the Northern Great Plains has lower percentages of individuals with no high school diploma, but significant impacts projected at 4°C of warming (Figure 4). Areas in the Southwest that are projected to experience greater impacts overlap in many cases with areas of lower percentages of individuals with no high school diploma. In contrast, parts of the Northern Great Plains and the Southwest that experience high impacts related to riverine flooding also have higher percentages of individuals who are age 65 and older, which demonstrates a slightly larger correlation between vulnerability and impacts in these regions. Regional patterns of vulnerability are further investigated in Figure 7.

Figure 7. Likelihood that Those in Socially Vulnerable Groups Currently Live in Areas with the Highest Projected Inland Flooding Damages, Relative to Those in Reference Populations, by Region



No High School Diploma



65 and Older

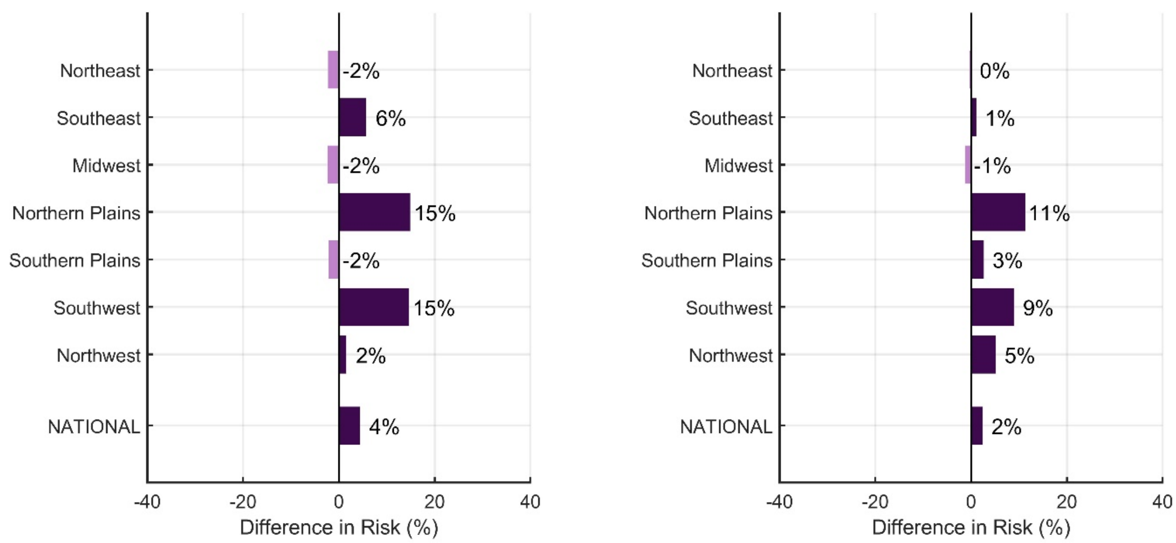


Figure 7 shows the likelihood that socially vulnerable individuals experience the worst outcomes of riverine flooding relative to non-vulnerable individuals by region. Individuals who experience low income are slightly more likely to live in high-impact areas relative to those with higher income in the Southeast, Midwest, and Northern Great Plains, up to 6% in the Southeast at 4ºC of warming. Those living in the Southern Great Plains experience a slight decrease in likelihood at 2ºC and a slight increase at 4ºC, but the projected effect is less than 10% in both cases. The finding is nonetheless consistent with the high variability of total impacts seen in the Southern Great Plains across degrees of warming in Figure 4. Those living in the Northeast experience minimal or no difference in likelihood of impacts based on their income status. As briefly summarized above with reference to the spatial distribution of socially vulnerable populations, which is mapped in Figure 4 of Chapter 2 of the main report, individuals who experience low income in the Northwest and Southwest are less likely to experience the highest impacts relative to non-vulnerable individuals, even though both regions are projected to experience substantial overall impacts.

Individuals who identify as Black and African American, Native American, Pacific Islander, Asian, or Hispanic/Latino are projected to live in high-impact areas in the Northeast (16% at 2°C; 7% at 4°C) and the Midwest (8% at 2°C; 4% at 4°C). Those in the Southeast, Northern Great Plains, Southwest, and Northwest experience a decrease in likelihood of living in the most impacted areas relative to non-vulnerable populations, with the most significant effect of -31% in the Southwest at 2°C of warming. Again, these regions are projected to have the greatest impacts as temperature increases, but the distribution of Black and African American, Native American, Pacific Islander, Asian, and Hispanic/Latino individuals is not correlated with geographies experiencing greater impacts.

Individuals who have received an education lower than a high school diploma or its equivalent are projected to experience an increased likelihood of living in an area with the worst riverine flooding-related impacts in the Midwest (10% 2°C), Northeast (4% at 2°C), and Southeast (4% at 2°C). In contrast, individuals with no high school diploma in the Northern Great Plains, Southwest, and Northwest experience either a decrease in likelihood or no difference compared to individuals who received a high school diploma. This effect is the greatest at -17% in the Southwest at 2°C of warming.

People who are age 65 or older are projected to experience an increased likelihood of living in the most impacted areas in the Northern Great Plains (15% at 2°C; 11% at 4°C) and Southwest (15% at 2°C; 9% at 4°C), with slight increases in the Southeast and Northwest as well (less than 6%). The regions with more significant disproportionality align with regions experiencing the greatest total impacts for those individuals of this age category. Other regions do not experience much disproportionality in risk between those age 65 and older and those younger than 65.

7. Main Findings

- The greatest impacts are projected to occur in the Northern Great Plains and Northwest regions, however there are high impact areas in every region. The highest impacts of inland flooding are projected to generally occur in areas with lower percentages of socially vulnerable populations.
- At a national level, impacts are not largely disproportionate across low income populations, individuals with no high school diploma, or those age 65 and older. Black and African American, Native American, Pacific Islander, Asian, and Hispanic/Latino individuals are estimated to be less likely to currently live in high flood risk areas compared to white, non-Hispanic individuals.
- In most regions, the difference in likelihood for vulnerable populations is relatively small. In many regions, individuals who identify as Black and African American, Native American, Pacific Islander, Asian, or Hispanic/Latino experience a decreased likelihood of living in the most impacted areas. However, individuals age 65 and older have a greater risk of experiencing worse impacts in multiple regions.

8. Limitations

The analysis above represents a high-level analysis of how socially vulnerable populations may disproportionately experience inland flooding damages to their properties. The findings, however, are subject to several key limitations that are summarized here. See Wobus et al. (2021), Wobus et al. (2019), and Wobus et al. (2017) for additional details on assumptions and limitations of the methods.

- The analysis presented in this section does not evaluate the potential for adaptation measures to mitigate flood risk at the property or community levels. As such, the risks presented here may be overestimated, however, adaptation measures typically require careful planning and capital to pay for the investments. A detailed adaptation analysis could model prioritization of future investments as a function of avoided damages and socioeconomic factors (e.g., income), but such an analysis is beyond the scope of this report.
- The distribution of demographics within the Census block groups are not considered because that information is not available. However, there are likely differences in demographics between, for example, river-front property-owners and property-owners several streets away from the river. These differences in relative risk are not captured in this analysis.
- This analysis does not account for changes in population and development within flood risk zones. Future demographic changes could either increase or decrease damages from flooding in the future, but without reasonable means of predicting future floodplain development or policies governing development, this analysis holds these factors constant.
- Climate projections using models from the CMIP5 archive remain limited in their ability to resolve tropical and extratropical storms that drive large-scale flooding in some regions of the U.S. GCMs also do not simulate the smaller-scale convective storms that can lead to localized flooding in some locations. To the extent that tropical and convective storms are projected to become more severe in a warming climate, results in this report will underestimate future changes in inland flooding risk, particularly in regions where these events dominate hydrologic extremes. In addition, the routed hydrology used in this study was derived from statistical downscaling, which requires an assumption that the underlying spatial patterns in precipitation variability remain consistent as temperatures rise.

9. Data Sources

DATA TYPE	DESCRIPTION	DATA DOCUMENTATION AND AVAILABILITY
Downscaled Hydrology Dataset	Daily routed flows at approximately 57,000 stream reaches across the CONUS for an ensemble of global climate models (or GCMs) downscaled using the bias correction and spatial disaggregation method.	Reclamation: Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Hydrology Projections, Comparison with Preceding Information, and Summary of User Needs, Prepared by the US Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, CO, 2014. Documentation and VIC hydrology data are available at ftp://gdo-dcp.ucllnl.org/pub/dcp/archive/cmip5/hydro/BCSD_daily_VIC_nc/
Property Flood Risk Data	Property-level flood risk dataset and model for the United States	First Street Foundation, 2020. First Street Foundation Flood Model (FSF-FM): Technical Documentation. Brooklyn, NY. Published 06/17/2020.https://assets.firststreet.org/uploads/2020/06/FSF_Flood_Model_Technical_Documentation.pdf Bates, P.D., Quinn, N., Sampson, C., Smith, A., Wing, O., Sosa, J., Savage, J., Olcese, G., Neal, J., Schumann, G. and Giustarini, L., 2020. Combined modelling of US fluvial, pluvial and coastal flood hazard under current and future climates. Water Resources Research, p.e2020WR028673. Armal, S., Porter, J. R., Lingle, B., Chu, Z., Marston, M. L., & Wing, O. E. (2020). Assessing Property Level Economic Impacts of Climate in the US, New Insights and Evidence from a Comprehensive Flood Risk Assessment Tool. Climate, 8(10), 116. First Street data can be accessed on the Foundation's website: https://firststreet.org/flood-factor/
Depth-damage curves	Depth-damage curves for different occupancy classes of properties	Federal Emergency Management Agency. 2016. Multi-hazard Loss Estimation Methodology Flood Model HAZUS®MH MR3 Technical Manual. Developed by: Department of Homeland Security, Federal Emergency Management Agency -Mitigation Division. Washington, D.C. Under a contract with: National Institute of Building Sciences Washington, D.C. https://www.hsdl.org/?abstract&did=480580