Appendix C. Inputs and Projections

1. Overview of Overall Approach to Estimating Climate Change Risk to Socially Vulnerable Populations

This report uses a standardized approach to estimate risks of climate change to socially vulnerable populations. The details of estimating climate risks vary by sector, and are described more fully in Technical Appendices D through I. All sectors share a common set of input data, however, and a common approach. The general steps in the common approach (Figure 1) are outlined below.

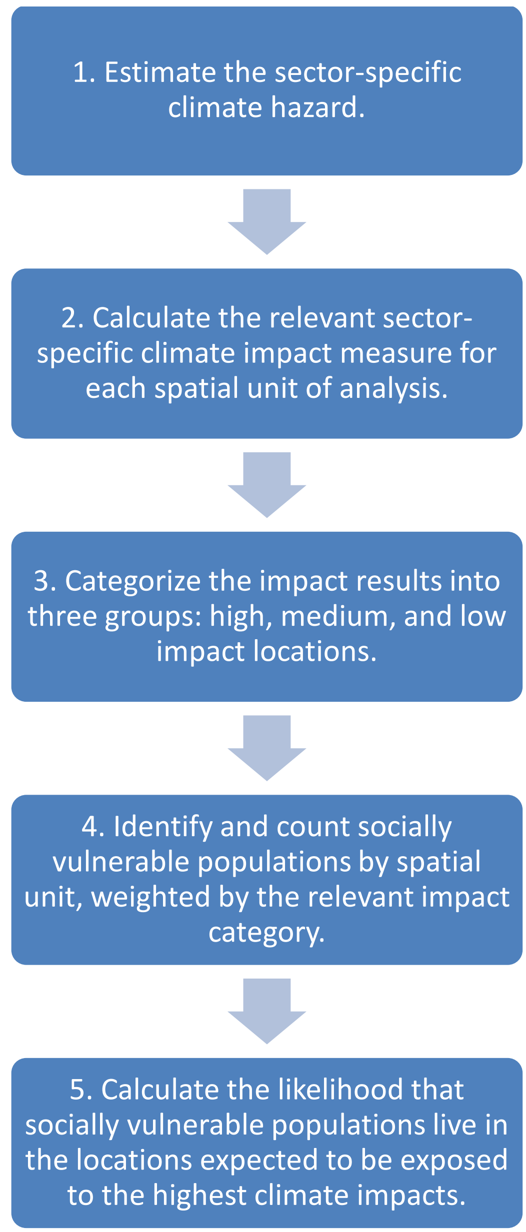
Step 1: Estimate the sector-relevant climate hazard from climate models. Details of the specific climate hazard used for each sector are provided in the relevant chapters and supporting technical appendices. Details on the six downscaled CMIP5 GCMs used to develop local scale climate hazard projections are provided in the next section of this technical appendix. For example, for the labor sector, the relevant climate hazard is the number of degree-days above 90 degrees per year; for the extreme temperature mortality sector, it is the number of days per year above a city-specific temperature threshold; and for the coastal property sector, it is the local level of sea level rise associated with a 25 centimeter increment rise in global mean sea level.

Step 2: Calculate the relevant sector specific impact measure. Details on the specific measure and spatial scale are provided in the sector-specific chapters and supporting technical appendices. For example, for the labor sector, this analysis estimates the labor time lost to high heat at the Census tract level; for heat stress mortality, this analysis estimates excess mortality risk associated with extreme temperature days, at the county level. This step involves accessing the data and results from the relevant underlying sector study – details and citations are provided in the relevant report chapters and supporting material.

Step 3: Categorize the spatial data into three groups: high, medium, and low impact locations. This analysis uses the output from Step 2 to categorize climate impacts by spatial unit (Census tracts, block groups, or counties) into three evenly sized groups, called terciles. The use of terciles is a convenient approach to separate spatial units into high, medium, and low impact categories for analysis, and is used in some literature for this reason.[1] The focus of subsequent analysis is on the composition of populations found in the high impact group – this analysis is attempting to identify cases where high impact areas disproportionately affect socially vulnerable populations.

Step 4: Identify and count socially vulnerable populations by location tract. While it is not possible to observe exactly which individuals are both exposed to the relevant climate hazard and socially vulnerable, this analysis overlays results by location. Data from the American Community Survey (2014-2018) are used at the Census tract, block group, or county level to (1) count the number of individuals in socially vulnerable groups relative to non-socially vulnerable groups then (2) weight the proportions by relevant climate hazard exposed population (which differs by sector). In the absence of projections describing how detailed demographics will shift over the century, this analysis assumes the relative distribution of socially vulnerable to non-socially vulnerable populations is fixed at 2014-2018 levels. The four measures of social vulnerability included in this analysis are: minorities (including racial and ethnic minority categories), over age 65, no high school diploma, and low income. Details of how this analysis defines these populations are provided at the end of this technical appendix.

Figure 1. Five steps for Assessing Impacts on Socially Vulnerable Populations



Step 5: Calculate the likelihood that socially vulnerable climate-exposed populations live in the locations expected to be exposed to the highest climate impacts. 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 climate impacts

[1] We chose terciles based on our analysis of the data, as presented in the sectora; o,[act Technical Appendices and in other analyses conducted for the data; we are not aware of strong precedents in the literature for the choice of terciles versus other groupinogs, although some literature cited in the Labor technical appendices makes similar use of terciles to identify high impact areas (see for example Behrer and Park, 2017, cited in Appendix F). One concern is that finer cuts of the data (e.g., deciles) could result in outsized focus on outlier areas, whereas this analysis provides a broad definition of "high impact." Informal robustness checks on the data suggest that similar results would be obtained with quartiles or quintiles. Data made available with the final report provides researchers the opportunity to explore other analyses.

disproportionately expose socially vulnerable groups relative to non-socially vulnerable groups. An example calculation is included in the last section of this technical appendix.

The next section of this Technical Appendix describes climate information used to estimate the climate hazard degree of warming, and the overall approach. The last section describes the estimation of potentially disproportionate climate impacts on socially vulnerable populations, and the details of the American Community Survey data used to develop those estimates.

2. Overview of Impacts by Degree Approach

As described in the Approach chapter, this report conveys climate risk information using an 'impacts by degree' framework that presents impacts to the U.S. under different levels of future global temperature change. The methods use the same mainstream scenarios and projections used in the climate science community, but instead of estimating an impact at a specific period of time under an explicit greenhouse gas (GHG) emissions scenario, impacts are simulated during the years when future warming thresholds are reached. Such an approach aids in communicating risk information as it can provide a range of estimates expected for a given temperature change. The general steps in this approach are outlined below, with reference to more detailed information in this and other technical appendices that support this report.

Climate Data

Consistent with guidance for the development of the Fourth National Climate Assessment,[2] this report uses representative concentration pathway 8.5 (RCP8.5) representing a higher emission scenario.[3] This selection is not an endorsement of RCP8.5, and does not indicate any judgment regarding the likelihood of that scenario. Given that this report estimates impacts under increasing degrees of future warming, RCP8.5 was chosen to allow for analysis of the widest potential temperature range in the modeling approaches, while limiting the number of total scenarios necessary for running through sectoral impact models. RCP8.5 provides projections for the full range of plausible 21st century temperatures, obviating the need to run multiple scenarios to address low, medium, and high impacts. Using multiple scenarios could provide insights into how the 2 degree warming level for RCP8.5 might differ from the 2 degree level for RCP4.5, but these differences have been shown to be small.[4]

The analyses of this report use climate projections from fifth phase of the Coupled Model Intercomparison Project (CMIP5).[5] For most sectors, six climate models are used: the Geophysical Fluid Dynamics Laboratory coupled general circulation model (GFDL_CM3), the Canadian Earth System Model (CanESM2), the Community Climate System Model (CCSM4), the Goddard Institute for Space Studies

[2] U.S. Global Change Research Program. 2015.. U.S. Global Change Research Program General Decisions Regarding Climate-Related Scenarios for Framing the Fourth National Climate Assessment. USGCRP Scenarios and Interpretive Science Coordinating Group. Available online at https://scenarios.globalchange.gov/accouncement/1158

[3] RCP8.5 and a lower emissions scenario (RCP4.5) were recommended for use in NCA4. The Sixth Assessment of the IPCC, which is scheduled for release in summer 2021, will provide updated scenarios and temperature projections based on the Coupled Model Intercomparison Project Phase 6 (CMIP6).

[4] Sarofim MC, Martinich J, Neumann JE, Willwerth J, Kerrich Z, Kolian M, Fant C, Hartin C. 2021. A temperature-binning approach for multi-sector climate impact analysis. *Climatic Change*, 165(1):1-18.

[5] Taylor KE, Stouffer RJ, and Meehl GA. 2012. An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93, 485-498.

model (GISS_E2_R), the Hadley Centre Global Environmental Model (HadGEM2_ES), and the Model for Interdisciplinary Research on Climate (MIROC5). These six GCMs are listed in Table 1 below.

Table 1. CMIP5 GCMs Used in the Analyses of this Technical Report

CENTER (MODELING GROUP)	MODEL ACRONYM	REFERENCES
Canadian Centre for Climate Modeling and Analysis	CanESM2	Von Salzen et al. 2013[6]
Geophysical Fluid Dynamics Laboratory	GFDL-CM3	Donner et al. 2011[7]
National Center for Atmospheric Research	CCSM4	Gent et al. 2011[8] Neale et al. 2013[9]
NASA Goddard Institute for Space Studies	GISS-E2-R	Schmidt et al. 2006[10]
Met Office Hadley Centre	HadGEM2-ES	Collins et al., 2011[11] Davies et al. 2005[12]
Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	Watanabe et al. 2010[13]

Five of these GCMs (all but GFDL_CM3) were used in the second modeling phase of the CIRA project.[14] These five GCMS were chosen based on a consideration of independence, skill at matching historical observed U.S. climate, and coverage of a wide range of future precipitation and temperature outcomes (see Figure 2 showing the range of temperature and precipitation outcomes across the CMIP5 ensemble). GFDL_CM3 was added to that set with the most important criteria being the inclusion of an additional high temperature model that was different from other models already included, as evaluated by estimates of inter-model distance.[15] Other warm models considered included CESM1_CAM5 which

[6] von Salzen K, Scinocca JF, McFarlane NA, Li J, Cole JN, Plummer D, Verseghy D, Reader MC, Ma X, Lazare M, and Solheim L. 2013. The Canadian fourth generation atmospheric global climate model (CanAM4). Part I: representation of physical processes. *Atmosphere-Ocean*, **51**, 104-125.

[7] Donner LJ, Wyman B, Hemler RS, et al. 2011. The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL Global Coupled Model CM3. *Journal of Climate*, 24, 3484–3519.

[8] Gent PR, Danabasoglu G, Donner LJ, Holland MM, Hunke E, Jayne S, Lawrence D, Neale RB, Rasch PJ, Vertenstein M, and Worley PH. 2011. The community climate system model version 4. *Journal of Climate*, 24, 4973-4991.

[9] Neale RB, Richter J, Park S, Lauritzen PH, Vavrus SJ, Rasch P, and Zhang M. 2013. The mean climate of the community Atmosphere Model (CAM4) in forced SST and fully coupled experiments. *Journal of Climate*, 26, 5150-5168.

[10] Schmidt GA, Ruedy R, Hansen JE, Aleinnov I, Bell N, Bauer M, Bauer S, Cairns B, Canuto V, Cheng Y, and Del Genio A. 2006. Present-day atmospheric simulations using GISS ModelE: Comparison to in situ, satellite, and reanalysis data. *Journal of Climate*, 19, 153-192.

[11] Collins WJ, Bellouin N, Doutriaux-Boucher M, Gedney N, Halloran P, Hinton T, Hughes J, Jones CD, Joshi M, Liddicoat S, Martin G, O'Connor F, Rae J, Senior C, Sitch S, Totterdell I, Wiltshire A, and Woodward S. 2011. Development and evaluation of an Earth system model–HadGEM2. *Geoscience Model Development*, 4, 1051-1075.

[12] Davies T, Cullen MJP, Malcolm AJ, Mawson MH, Staniforth A, White AA, Wood N. 2005. A new dynamical core for the Met Office's global and regional modelling of the atmosphere. *Quarterly Journal of the Royal Meteorological Society*, 131, 1759-1782.

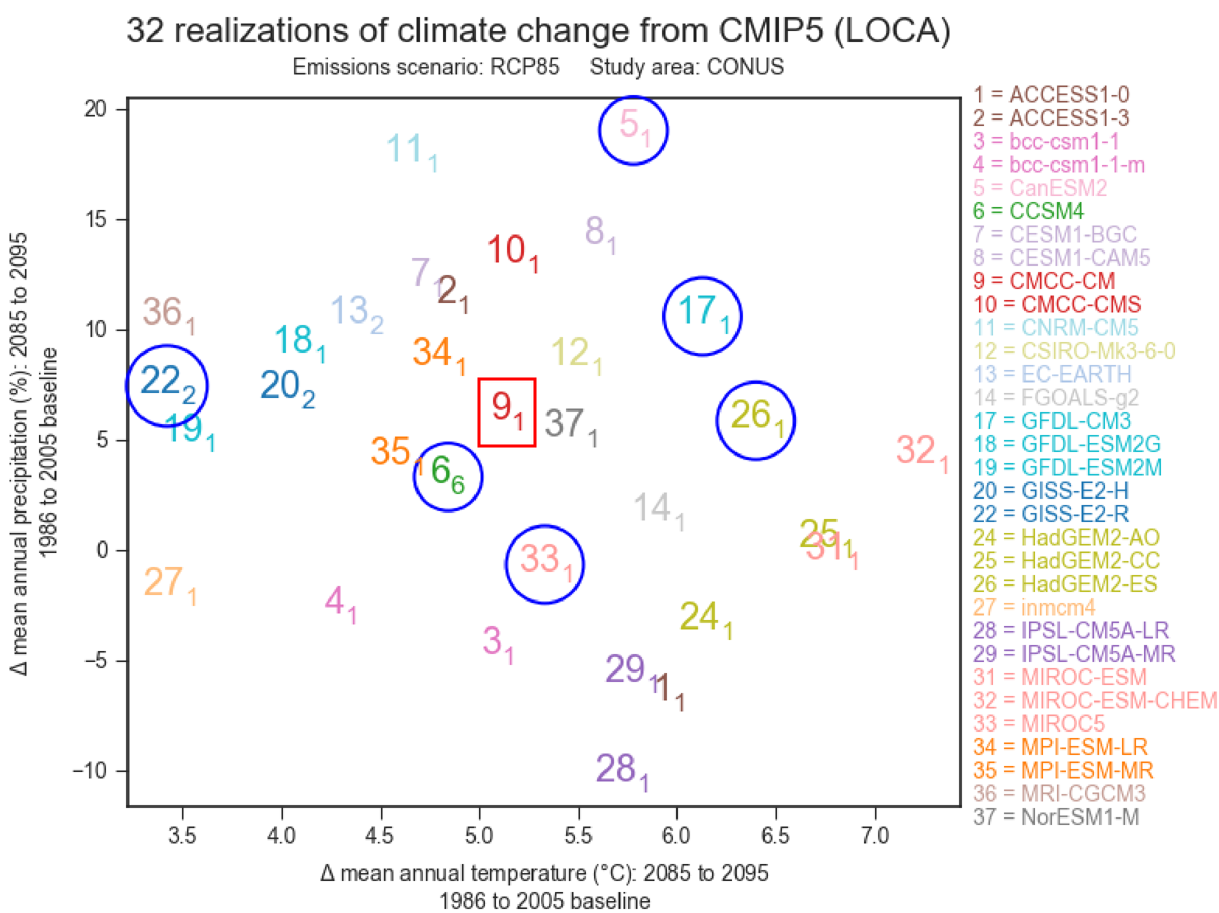
[13] Watanabe M, Suzuki T, O'ishi R, Komuro Y, Watanabe S, Emori S, Takemura T, Chikira M, Ogura T, Sekiguchi M, and Takata K. 2010. Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity. *Journal of Climate*, 23, 6312-6335.

[14] EPA. 2017. Multi-model framework for quantitative sectoral impacts analysis: a technical report for the Fourth National Climate Assessment. U.S. Environmental Protection Agency, EPA 430-R-17-001.

[15] Sanderson BM, Wehner M, Knutti R. 2017. Skill and independence weighting for multi-model assessments, *Geoscientific Model Development*, 10, 2379–2395.

was excluded based on similarity to CCSM4, ACCESS1_3 which has similarities to HadGEM2_ES, and CNRM_CM5 which was slightly cooler and slightly less skillful by the empirical metrics than GFDL_CM3.[16]

Figure 2. Variability of Projected Annual Temperature and Precipitation Change across the CMIP5 Ensemble for the Continental U.S.



To aid in the selection of GCMs, the LASSO[17] tool was used to produce scatter plots showing the variability across the CMIP5 ensemble for projected changes (2085-2095 compared to the 1986-2005 reference period) in annual (first plot) and summertime (second plot) temperature and precipitation. The GCMs used in the climate projections for this report are displayed with blue circles around them to highlight their location within the scatter plots. The model identified as the double median across temperature/precipitation outcomes is shown in a red rectangle.

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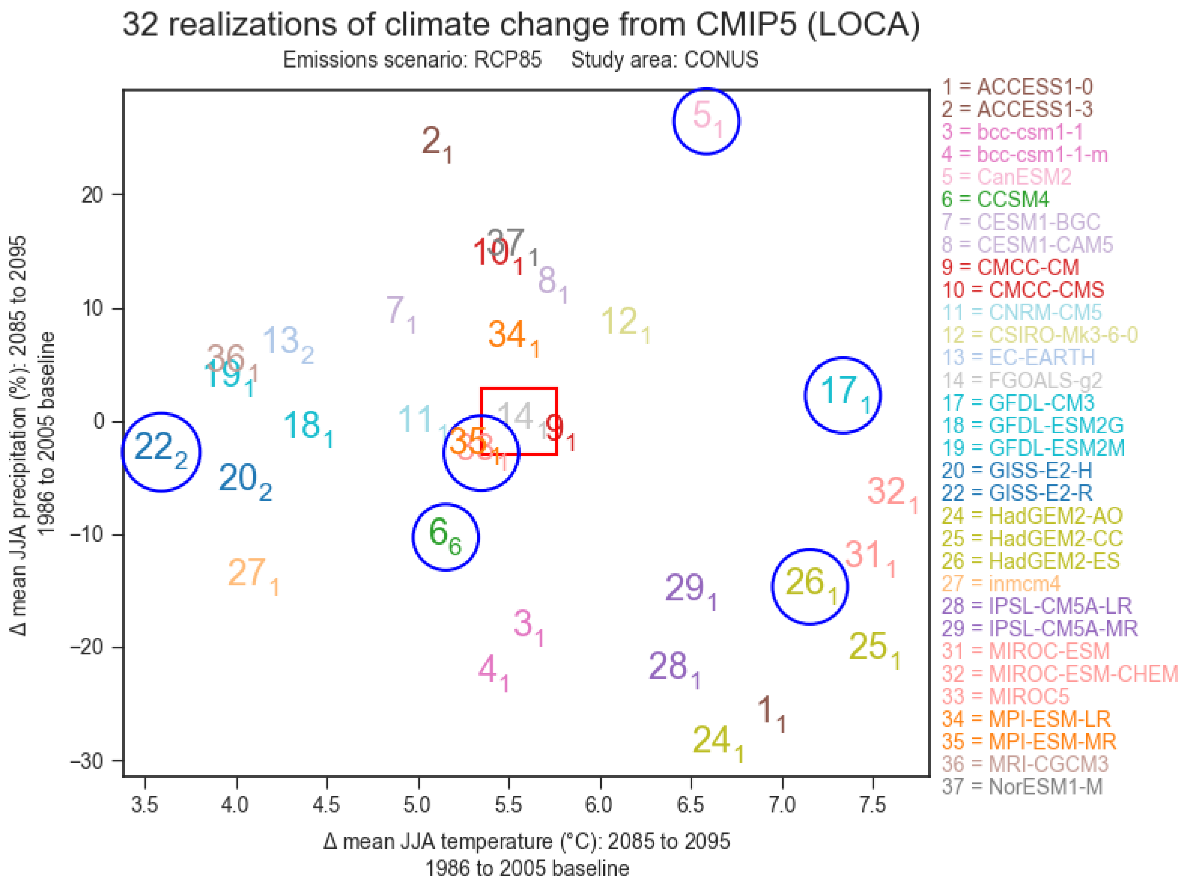
[16] Sanderson BM, Wehner M, Knutti R. 2017. Skill and independence weighting for multi-model assessments, *Geoscientific Model Development*, 10, 2379–2395.

[17] U.S. Environmental Protection Agency. 2019. Locating and Selecting Scenarios Online, https://lasso.epa.gov/



In the case of the air quality analysis, only two of the six GCMs (GFDL_CM3 and CCSM4) were used due to computational constraints of the dynamic downscaling and atmospheric chemistry modeling steps. See the Air Quality section of the main report and Technical Appendix D for additional details. Also, the Inland Flooding analysis used the 14 GCMs from CMIP5 that reach 5°C of warming by the end of the century. See the Inland Flooding section of the main report and Technical Appendix I for additional details.

Most sectoral analyses of this report require downscaled climate projections to reduce model bias and provide finer resolution. The approach presented here relies primarily on the LOCA (Localized Constructed Analog)[18,19] approach to produce daily temperature (maximum and minimum) and precipitation data at a 1/16 degree scale (approximately 6.25 km). Sectors of this report that did not use the LOCA data include Coastal Property and the coastal component of Roads, both of which use sea level

[18] U.S. Bureau of Reclamation, Climate Analytics Group, Climate Central, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, U.S. Army Corps of Engineers, and U.S. Geological Survey, 2016: Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs. Available online at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/downscaled_climate.pdf. Data available at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/.

[19] University of California San Diego, cited 2017: LOCA statistical downscaling. Scripps Institution of Oceanography. Available online at http://loca.ucsd.edu/

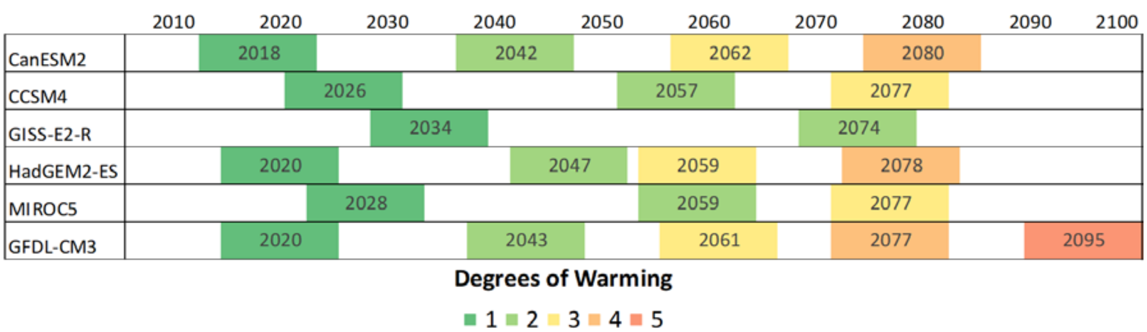
rise projections that are described below. The Air Quality analysis utilized dynamically downscaled climate projections that are described in Technical Appendix D.

Arrival Times of Integer Warming

As part of the impacts by degree framework, the arrival times of global average temperature increases compared to the 1986-2005 baseline were identified from the GCMs described above. These arrival times represent the first 11-year period to have an average temperature equal to that of the warming degree. Figure 3 shows the year at which the 11-year moving average for each of the GCMs first reached each degree above the baseline, and the 11-year window around that year. It is important to note that the 1986-2005 baseline is 0.61 degrees warmer than preindustrial (1850-1900) temperatures at the global scale.[20]

Figure 3. Arrival Years of Global Increases in Temperature

This graphic shows the 11-year windows assigned to each integer temperature by GCM under a higher emission scenario (RCP8.5). Values calculated using a 1986-2005 baseline. Arrival years, or the year at which the 11-year moving average reaches the given integer, are listed in each bin.



Sea Level Rise Projections

This report projects impacts using future increases in global mean sea level in increments of 25 cm up to 150 cm relative to Global Mean Sea Level (GMSL) in 2000. Results in the main sectoral sections of the report convey impacts under 50 cm and 100 cm of global rise. The underlying economic impact literature provides results for each year up to 2100, using six GMSL trajectories developed for the USGCRP's fourth National Climate Assessment. The scenarios are categorized according to the future change in GMSL in 2100 relative to the year 2000 (e.g., 100 cm, 200 cm). Projections of location-specific differences in relative (or local) sea level change[21] account for land uplift or subsidence, oceanographic effects, and responses of the geoid and the lithosphere to shrinking land ice. Mean values for each tide gauge location are used. A distance weighting procedure for interpolating between tide gauge locations

[20] Oppenheimer M, Campos M, Warren R, Birkmann J, Luber G, O'Neill B, and Takahashi K. 2014. Emergent risks and key vulnerabilities. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TD, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, and White LL, (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1039-1099.

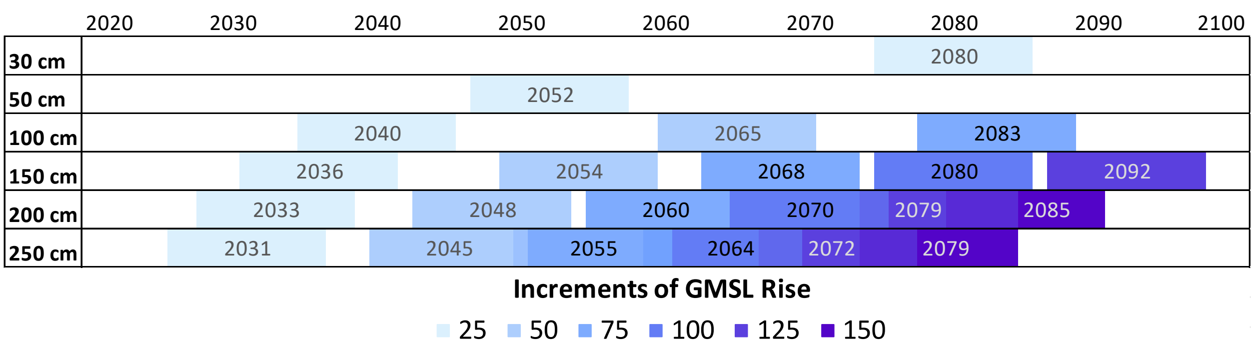
[21] National Oceanographic and Atmospheric Administration. 2017. Global and regional sea level rise scenarios for the United States. NOAA Center for Operational Oceanographic Products and Services, Technical Report NOS CO-OPS 083.

is employed to attribute tide gauge-level results to each coastal county. This procedure allows us to connect changes in GMSL with county-scale relative SLR that considers these local scale factors, and in turn to data on the economic impacts of each increment in SLR for those localities.

Figure 4 shows the specific 11-year bins used to connect the underlying economic impact literature to GMSL increments in the NCA4 SLR trajectories. The SLR bins are based on the published NCA SLR trajectories and calculated using the using the temperature binning "arrival time" method used in supporting literature, adapted for GMSL arrival timing.[22]

Figure 4. Arrival Years of Global Mean Sea Level Rise

This graphic shows the 11-year windows assigned to each 25 cm increment for results from each of the National Climate Scenario GMSL scenarios. Values calculated using a year 2000 baseline. Arrival years, or the year at which the 11-year moving average reaches the given integer, are listed in each bin.



Aligning the Timing of the Climate Stressor and the Resulting Physical and Economic Impacts

Underpinning the approach is an implicit assertion that the temperature or sea level rise stress during an 11-year bin triggers damages that are manifest within that same 11-year period. For sectors such as extreme temperature mortality or labor productivity, the effects of temperature are effectively contemporaneous. Further, in other sectors, such as coastal property and road infrastructure, damages under a "no adaptation" response assumption also align reasonably well, in a temporal sense, with the temperature or sea level rise stressor. These infrastructure sectors, however, are also characterized by a high level of demonstrated cost-effectiveness of investments in adaptive capacity – and in some cases, the investment involves one-time or periodic capital investments, with "payoffs" to the investment (in the form of avoided damages) realized after a delay. In these cases, it is possible that the trajectory of estimated adaptation costs may not align temporally with an 11-year arrival year. To improve the alignment, this analysis performs a "financial smoothing" of capital costs, essentially annualizing capital costs over the useful life of the adaptation investment, using a discount rate of 3%.

[22] Sarofim MC, Martinich J, Neumann JE, Willwerth J, Kerrich Z, Kolian M, Fant C, Hartin C. 2021. A temperature-binning approach for multi-sector climate impact analysis. *Climatic Change*, 165(1):1-18.

Other Sector-Specific Climate Projections

Some analyses in this report utilize additional projections of climate or other physical variables that are described in the method descriptions of those sectors. While binning damages by a primary stressor (temperature or sea level rise) may obscure the relationship between damages and other climate variables, the use of GCMs that capture a range of variability in climate sensitivity ensures that uncertainty in the relationship between primary and secondary stressors is included in the analysis.

3. Estimating Potentially Disproportionate Effects on Socially Vulnerable Populations

Assumptions about Socioeconomic Change

This report isolates the effects of climate change on socially vulnerable populations by projecting effects imposed upon society as it is today (i.e., using current demographics). In other words, the results of this report are intended to convey how different levels of future warming would impact human health and welfare as known today. The primary rationale for this approach is that long-term projections for changes in demographics, particularly for socially vulnerable populations, are highly uncertain, and therefore generally unavailable at the level of detail necessary for the sectoral analyses described in this report. However, shifting demographics and socioeconomic change will affect the spatial distribution and magnitude of vulnerability to climate change. Multi-sector assessments have demonstrated the compounding effects of population growth and climate change impacts, particularly with regards to health-related effects.[23] Therefore, the results of this report should be interpreted with this limitation in mind, as actual impacts could be larger or smaller based on potentially changing demographics.

Determining Disproportionality

This report relies on a standardized method for assessing disproportionality of climate change impacts on socially vulnerably populations. Across all sectors, this analysis uses a standard set of four socially vulnerable populations: minority, 65 and older, no high school diploma, and low income. The specific data used to define each of these populations is identified below. For each sector, populations that meet the definition of socially vulnerable are first identified and are located within the spatial domain considered to be vulnerable to impacts for the sector. For example, for coastal properties, only consider populations that live in coastal areas and are exposed to the coastal hazards of sea level rise or storm surge during the 21st century projection period are considered – inland areas are not included.

Climate change impacts are modeled using the methods described in the sectoral chapters, to identify high impact areas. "High impact" are defined as areas in the highest tercile of impacts. Note that the spatial resolution of analysis varies by sector (e.g., county, Census tract, Census block group), but is consistent within each analysis. Once high impact areas are identified, the number of socially vulnerable people, and the "reference" non-socially vulnerable population in those areas are tabulated (see details below on definitions of both socially vulnerable and reference populations for each specific population). From this, the likelihood of living in a high impact location is calculated, relative to the reference domain, for both populations that are and are not socially vulnerable. The relative likelihoods this report

[23] EPA. 2017. Multi-Model Framework for Quantitative Sectoral Impacts Analysis: A Technical Report for the Fourth National Climate Assessment. U.S. Environmental Protection Agency, EPA 430-R-17-001.

describes are then the result of comparing likelihoods of living in high impact areas for populations that are and are not socially vulnerable. This standardized approach allows us to present relative likelihoods of high impacts at both national and regional scales; regional-level relative likelihoods are based on regional spatial domains and populations. As an example, the details of the calculation for the impact of traffic delays from weather damage on roads for people 65 and older are presented in Table 2.

Table 2. Example Calculation of Disproportionate Impacts on a Socially Vulnerable Population – Road Sector Impacts on Population Aged 65 and Older

STEP	VALUES
1. Identify populations that are or are not socially vulnerable	Socially Vulnerable: 49 million people 65 years of age and older Not Socially Vulnerable: 272 million people less than 65 years old
2. Identify high impact areas	Within high impact Census tracts: 17 million people are socially vulnerable; 86 million are not socially vulnerable
3. Calculate the likelihood of living in a high impact area	Likelihood of high impact: Vulnerable population: 17/49 = 0.35 Population not vulnerable: 86/272 = 0.32
4. Compare likelihoods	Vulnerable likelihood / Non-vulnerable likelihood = 0.35/0.32 = 1.09 (9% more risk for the socially vulnerable population)

In standardized form, the difference in risk is calculated as:

$$\Delta R = \left(\frac{\sum P_{vh}}{\sum P_v}\right) / \left(\frac{\sum P_{rh}}{\sum P_r}\right) - 1$$

where ΔR is the difference in risk (expressed as %); P_{vh} is the sum of the socially vulnerable population in all high hazard areas; P_v is the total socially vulnerable population; P_{rh} is the sum of the reference population in high hazard areas; P_r is the total reference population.

For two sectors that only apply to a specific population (labor – for the weather-exposed worker population - and air quality – for individuals over 65 susceptible to premature mortality, or individuals 18 and younger susceptible to asthma emergency department visits), the procedure is modified to weight the populations by the proportion, E, that is exposed to the hazard. For example, for labor, the proportion of the total population that are workers in high-risk industries in each Census tract is used to apply a weight to the population, P. The same approach for air quality is applied where premature death only applies to those 65 and older and childhood asthma only applies to those 18 and younger. For the other sectors, where all or the majority of the population is exposed, no weighting is applied.

$$\Delta R = \left(\frac{\sum(P_{vh}E_{vh})}{\sum(P_v E_v)}\right) / \left(\frac{\sum(P_{rh}E_{rh})}{\sum(P_r E_r)}\right) - 1$$

Note that some may interpret that this equation as implying that information exists on the number of high-risk workers that are also in a socially vulnerable population (e.g., high-risk workers who are also in a low-income household). As stated earlier, data limitations prevent linking the specific susceptible population with status in a socially vulnerable population. Absent the ability to cross-reference this type of population information, the proportion of the exposed population, E, is a second-best approach based on the population exposed (e.g., high-risk workers) in each Census tract divided by the total population.

Demographic Data

Analyses in this report rely on demographic data from the five-year American Community Survey 2014-2018 (ACS). Where available, data are collected at the block group level, or if necessary, at the Census tract level. This analysis relied on the IPUMS[24] platform to download ACS data through its National Historical Geographic Information System (NHGIS). The NGHIS codes for data this report relies upon are provided in Table 3.[25]

Demographics Presented

- Minority: The ACS provides race and ethnicity information at the block group level. Racial and ethnic minority is defined as all racial and ethnic groups except white, non-Hispanic individuals. This report relies on total population and white, non-Hispanic population to calculate minority population at the block group spatial scale. For calculations of disproportionate effects on socially vulnerable populations, the white non-Hispanic population is used as the reference population (see details on disproportionality calculations above).

- 65 and Older: This report identifies people aged 65 or older as socially vulnerable. This analysis uses age demographic information from the ACS to determine 65 and older populations at the block group level by aggregating population estimates for age groups provided by the ACS counting people 65 or older. The reference population is all individuals younger than 65 years.

- No High School Diploma: The ACS tracks information on educational attainment – in this analysis populations without a high school diploma are considered to be a socially vulnerable demographic. To estimate the number of people per block group with an educational credential of less than a high school diploma or equivalent, this analysis relies on educational attainment data for the population 25 years or older. The reference population is the number of individuals 25 years or older with educational attainment of a high school diploma (or equivalent) or higher.

- Low Income: "Low income" is defined as populations living in households that have an aggregate income that is at most, twice the poverty threshold. ACS definitions for poverty thresholds are not geographically differentiated but do vary by household composition. Additional information on the definition of poverty thresholds can be found on the Census

[24] IPUMS had previously been an acronym for Integrated Public Use Microdata Series, but not all of the data it accesses is public, or is microdata, so since 2016 it has been known only by its acronym.

[25] Manson S, Schroeder J, Van Riper D, Kugler T, and Ruggles S. IPUMS National Historical Geographic Information System: Version 15.0 American Community Survey 2014-2018a. Minneapolis, MN: IPUMS. 2020. http://doi.org/10.18128/D050.V15.0. Note that the NHGIS field codes in Table 3 are unique to IPUMS – ACS table numbers differ from the field codes shown here, but the data are identical.

website.[26] In this report the estimates of population living in those households that fall into income to poverty threshold ratios below two are aggregated. The reference population is individuals living in households with income greater than two times the poverty threshold.

These four variables were chosen primarily because the literature suggests individuals in these categories have been shown to be disproportionately vulnerable to the specific climate impacts analyzed, or because there are plausible reasons to suggest they might be disproportionately vulnerable. Introductory sections of each chapter and supporting technical appendix summarize the literature and/or the conceptual links between sector impacts and vulnerability of these populations. There are additional dimensions of social vulnerability not considered in this report, and therefore warrant further analysis. Further, additional disproportionate risks may be present when evaluating the interconnections between social vulnerability measures, connections that are not explored in this report. It is also true that, as illustrated in Figure 4 of the Approach chapter, the four demographic groups are spatially correlated with each other, in particular the minority, no high school diploma, and low-income variables. The key disproportionality results, however, do not necessarily exhibit the same degree of correlation nationally or by region that could be seen in the full ACS dataset, because each impact examines a different spatial domain based on the specific locations of the higher impact terciles. Many individuals also may meet the ACS definition for inclusion in multiple categories from among the four we have chosen. While supplemental analysis was considered of disproportionate effects for individuals included in multiple categories of social vulnerability, ACS data supports only limited versions of these types of analyses (for example, available low income cross-tabulations are focused on individuals with income below the poverty line, rather than below twice the poverty line).

Table 3. Underlying Demographic data from Census Bureau's American Community Survey 2014-2018

DATA TABLE	NHGIS FIELD CODE	SPATIAL SCALE	DESCRIPTION	USE
Race	AJWNE001	Block Group	Total	Minority
Race	AJWNE002	Block Group	White alone	Minority
Race	AJWNE003	Block Group	Black or African American alone	Minority
Race	AJWNE004	Block Group	American Indian and Alaska Native alone	Minority
Race	AJWNE005	Block Group	Asian alone	Minority
Race	AJWNE006	Block Group	Native Hawaiian and Other Pacific Islander alone	Minority
Race	AJWNE007	Block Group	Some other race alone	Minority
Race	AJWNE008	Block Group	Two or more races	Minority
Race	AJWNE009	Block Group	Two or more races: Two races including Some other race	Minority
Race	AJWNE010	Block Group	Two or more races: Two races excluding Some other race, and three or more races	Minority
Hispanic or Latino Origin by Race	AJWVE001	Block group	Total Population	Minority

[26] https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html

DATA TABLE	NHGIS FIELD CODE	SPATIAL SCALE	DESCRIPTION	USE
Hispanic or Latino Origin by Race	AJWVE003	Block group	Not Hispanic or Latino: White alone	Minority
Sex by Age	AJWBE020	Block group	Male: 65 and 66 years	65 and Older
Sex by Age	AJWBE021	Block group	Male: 67 to 69 years	65 and Older
Sex by Age	AJWBE022	Block group	Male: 70 to 74 years	65 and Older
Sex by Age	AJWBE023	Block group	Male: 75 to 79 years	65 and Older
Sex by Age	AJWBE024	Block group	Male: 80 to 84 years	65 and Older
Sex by Age	AJWBE025	Block group	Male: 85 years and over	65 and Older
Sex by Age	AJWBE044	Block group	Female: 65 and 66 years	65 and Older
Sex by Age	AJWBE045	Block group	Female: 67 to 69 years	65 and Older
Sex by Age	AJWBE046	Block group	Female: 70 to 74 years	65 and Older
Sex by Age	AJWBE047	Block group	Female: 75 to 79 years	65 and Older
Sex by Age	AJWBE048	Block group	Female: 80 to 84 years	65 and Older
Sex by Age	AJWBE049	Block group	Female: 85 years and over	65 and Older
Educational Attainment for the Population 25 Years and Over	AJYPE002	Block group	No schooling completed	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE003	Block group	Nursery school	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE004	Block group	Kindergarten	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE005	Block group	1st grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE006	Block group	2nd grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE007	Block group	3rd grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE008	Block group	4th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE009	Block group	5th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE010	Block group	6th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE011	Block group	7th grade	No High School Diploma

DATA TABLE	NHGIS FIELD CODE	SPATIAL SCALE	DESCRIPTION	USE
Educational Attainment for the Population 25 Years and Over	AJYPE012	Block group	8th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE013	Block group	9th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE014	Block group	10th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE015	Block group	11th grade	No High School Diploma
Educational Attainment for the Population 25 Years and Over	AJYPE016	Block group	12th grade, no diploma	No High School Diploma
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E002	Block group	Under .50	Low Income
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E003	Block group	.50 to .99	Low Income
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E004	Block group	1.00 to 1.24	Low Income
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E005	Block group	1.25 to 1.49	Low Income
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E006	Block group	1.50 to 1.84	Low Income
Ratio of Income to Poverty Level in the Past 12 Months	AJY4E007	Block group	1.85 to 1.99	Low Income

4. Sources of Uncertainty

The modeling framework for analyses underlying this report is designed to evaluate how climate change impacts affect socially vulnerable populations within the U.S. As with any study, there are sources of uncertainty that are important to consider, several of which are described below. Future work to address these will further strengthen confidence in the estimates presented in this report. Limitations specific to the individual sectoral analyses are described in those sections of this report, as well as in the peer-reviewed literature underlying the analyses.

Projections of Future Climate

With the goal of presenting a consistent set of climate change impact analyses across sectors, this report presents results using an impacts by degree approach. Arrival windows for integral levels of future warming were identified from each climate model, and these years were used in the simulations for each sectoral impact analysis. Due to the level of effort necessary to run each scenario through the sectoral models of this report, only six climate models were chosen. While these models were chosen to capture a large range of the variability observed across the entire ensemble, this subset is not a perfect representation. However, even the full set of GCMs is not likely to span the entire range of potential physical responses of the climate system to changes in the concentration of atmospheric GHGs. Previous literature has demonstrated the importance of climate sensitivity assumptions in understanding a wide range of potential changes to the climate system,[27,28] as well as the effect of natural variability on timing and magnitude of impacts.[29,30] The Sixth Assessment of the IPCC, which is scheduled for release in summer 2021, will provide updated scenarios and temperature projections based on the CMIP6 project. However, these newer projections were not available in time for use in this report.

Coverage of Sectors and Impacts

The analyses presented in this report cover just a handful of potential climate change impacts in the U.S. The six included were chosen because of the availability of robust methods and data for analysis, the demonstrated economic importance of these sectors, and because disproportionate impacts to socially vulnerable populations were hypothesized. There are likely a large number of additional sectoral impacts of climate change that will have disproportionate effects on socially vulnerable populations. Examples of omitted impacts include health effects (e.g., mortality due to extreme events other than temperature; mental health and behavioral outcomes) and social impacts (e.g. violence). Other potentially important omissions are those on wild and managed ecosystems, such as those on water resources, agriculture, forestry, and fisheries, which are known to be particularly salient for the well-being of Native American populations.

Without information on these impacts, this report provides only partial insight into the effects of climate change on socially vulnerable populations.[31]

Unlike previous CIRA reports that primarily focused on the presentation of economic results across sectors, the monetization of future impacts is provided in select sections of this report to provide context regarding the magnitude of disproportionate risks facing socially vulnerable populations. In cases where economic estimates are provided, it is important to note that some impacts are only

[27] Paltsev S, Monier E, Scott J, Sokolov A, and Reilly J. 2013. Integrated economic and climate projections for impact assessment. *Climatic Change*, doi:10.1007/s10584-013-0892-3.

[28] Monier E, Gao X, Scott JR, Sokolov AP, and Schlosser CA. 2014. A framework for modeling uncertainty in regional climate change. *Climatic Change*, doi:10.1007/s10584-014-1112-5.

[29] Monier E, and Gao X. 2014. Climate change impacts on extreme events in the United States: an uncertainty analysis. *Climatic Change*, doi:10.1007/s10584-013-1048-1.

[30] Mills D, Jones R, Carney K, St Juliana A, Ready R, Crimmins A, Martinich J, Shouse K, DeAngelo B, and Monier B. 2014. Quantifying and Monetizing Potential Climate Change Policy Impacts on Terrestrial Ecosystem Carbon Storage and Wildfires in the United States. *Climatic Change*, doi:10.1007/s10584-014-1118-z.

[31] Importantly, this report does not assume that socially vulnerable populations will always face disproportionately larger risks from climate change. In fact, sectoral results are shown throughout the report where risks to the reference population may be greater than specific categories of socially vulnerable people.

partially valued. For example, a wide range of morbidity health effects are omitted in either the Air Quality, Heat Stress, or Labor analyses. Therefore, the damages described in this report are likely an undervaluation of the actual climate impacts that would occur under any given scenario.

Sectoral Impacts Modeling

The impact estimates presented in each section of this report were developed using a single sectoral impact model. These models are complex analytical tools, and choices regarding the structure and parameter values of the model can create important assumptions that affect the estimation of impacts. Ongoing studies, such as the Inter-sectoral Impact Model Intercomparison Project (ISI-MIP), are investigating the influence of structural uncertainties across sectoral impact models.[32] The use of additional models for each sector of this report would help improve the understanding of potential impacts in the future.

The results presented in each sector were primarily developed independently of one another. As a result, the estimated impacts may omit important interactive effects. For example, the Air Quality and Heat Stress analyses do not examine the compounding health risks that individuals could suffer during heat waves with high ozone concentrations in the air. Although first order connectivity was achieved in limited cases (e.g., projected installation of coastal defenses in the Coastal Flooding analysis provides information on location and timing to inform where coastal roads may receive ancillary protection), improved connectivity between sectoral models would aid in gaining a more complete understanding of climate change impacts on socially vulnerable populations of the U.S.

Socioeconomic and Demographic Change

This report isolates the effects of climate change on socially vulnerable populations by projecting effects imposed upon society as it is today (i.e., using current demographics). The primary rationale for this approach is that long-term projections for national changes in demographics are highly uncertain, and therefore currently unavailable. However, shifting demographics and socioeconomic change will affect the spatial distribution and magnitude of vulnerability to climate change. Therefore, the results of this report should be interpreted with this limitation in mind, as actual impacts could be larger or smaller based on these changing demographics.

Treatment of Adaptation

Populations will adapt to climate change in many ways, with some actions limiting the impact of climatic exposure, and other actions likely exacerbating impacts. Many of the same factors that contribute to exposure to impacts also influence the ability of both individuals and communities to adapt to climate variability and change. Socioeconomic status, the condition and accessibility of infrastructure, the accessibility of health care, specific demographic characteristics, and other institutional resources all contribute to the timeliness and effectiveness of adaptive capacity.[33]

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[32] Huber V, Schellnhuber HJ, Arnell NW, Frieler K, Friend AD, Gerten D, Haddeland I, Kabat P, Lotze-Campen H, Lucht W, Parry M, Piontek F, Rosenzweig C, Schewe J, and Warszawski L. 2014. Climate impact research: beyond patchwork. *Earth System Dynamics*,

[33] 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.

The sectoral analyses of this report treat adaptation in unique ways, with some sectors directly modeling the implications of adaptation responses, and others implicitly incorporating well-established pathways for adapting to climate stress. For example, the air quality, extreme temperature mortality, and labor sectors all incorporate empirical analyses of individual, community, and infrastructure adaptation in estimating a climate stressor-response function, and so they reflect historical responses to these stressors. As climate stress worsens and expands geographically, wider adoption of historical adaptation actions (e.g., wider adoption of air conditioning as a response to extreme heat) therefore is implicitly incorporated in the estimated response function, and by extension in the estimates presented here. The roads and coastal flooding analyses employ a simulation modeling approach which allows for incorporation of baseline adaptation actions (e.g., in high-tide flooding a set of "reasonably anticipated actions" such as traffic re-routing are incorporated in the baseline – and continuation and expansion of existing beach nourishment at locations where it is currently practiced is incorporated in the coastal flooding analysis). These simulation modeling approaches also facilitate future adoption of more complex and extensive adaptive actions, such as changing maintenance practices and extending seawall and beach nourishment protections, which constitute new adaptation scenarios.

Adaptation actions that go beyond historically implemented practices, however, require planning, potentially complex financing, and evaluation of efficacy with consideration of the specific human and natural environment contexts. Adaptation plans therefore are typically developed and implemented at local scales. As such, the general adaptation scenarios considered in the analyses of this report will not capture the complex issues that drive adaptation decision-making at regional and local scales. For example, the Coastal Flooding section considers the cost effectiveness of adaptive responses to sea level rise inundation and storm surge damages by comparing the costs of protection to the value of those properties at risk. While many factors at the property, community, region, and national levels will determine adaptive responses to coastal risks, this sectoral analysis uses the simplistic cost/benefit metric to enable consistent comparisons for the entire coastline. However, the adaptation scenarios and estimates presented in all sections of this report should not be construed as recommending any specific policy or adaptive action.

Geographic Coverage

This report does not examine impacts and damages occurring outside of U.S. borders. Aside from the inherent value of people and ecosystems around the world, these impacts could also affect the U.S. through, for example, changes in migration, impacts on trade, and concerns for conflict and national security.

In addition, the geographic focus of this report is on the contiguous U.S., with the sectoral analyses excluding Hawai'i, Alaska, and the U.S. territories. This omission may be particularly important given the unique climate change vulnerabilities of these high-latitude and/or island locales, and the subsequent effects on their populations. Finally, the Temperature Mortality analysis quantifies impacts in a limited set of major U.S. cities; incorporation of additional locales would gain a more comprehensive understanding of likely effects on socially vulnerable populations.

Summary

The influence of these sources of uncertainty on the estimates of disproportionate climate exposure for socially vulnerable populations is difficult to estimate. In theory, a quantitative estimate of the influence of different GCMs in the climate impact step can be performed to estimate the sensitivity of results to this source of variation in climate outcomes. In addition, the influence of different socioeconomic inputs, sampling margins of error for the ACS data, or statistical measurement error from certain exposure-response relationships, or perhaps other sources of uncertainty as well, might be estimated quantitatively, and many of the underlying peer-reviewed studies relied on for this report perform these types of analyses to inform readers of the uncertainty associated with each estimate presented. For this analysis, however, attempting to combine any quantitative results on uncertainty across analytic steps would necessarily involve mixing estimates of variability (e.g., across GCMs) with estimate of statistical uncertainty (e.g., for ACS margins of error or the sector impacts that rely on statistically estimated exposure-response relationships). In addition, a combined estimate of uncertainty would necessarily ignore other sources of uncertainty that cannot be quantified (e.g., structural uncertainty associated with the choice of a single sector impacts model) and potential correlation in sources of uncertainty that may not be fully independent (e.g., many GCMs share a common structural foundation). As a result, this report relies on an approach of identifying the key sources of uncertainty, and attempting to qualitatively characterize the potential influence of each source of uncertainty on the overall disproportionality results. Table 4 below provides a summary of this qualitative assessment of uncertainty associated with data sources and modeling and analytic choices made in the development of this report's results.

Table 4: Summary of Estimated Influence of Key Sources of Uncertainty on Overall Results

SOURCE OF UNCERTAINTY	ANALYTIC STEP	COMMENTS AND ESTIMATE OF INFLUENCE OF UNCERTAINTY ON DISPROPORTIONALITY RESULTS
Geographic coverage	All steps	**Possible underestimate, impact may be minor.** Due to data and modeling constraints, the analyses presented in this report do not assess impacts of climate change that occur outside of the contiguous U.S., such as those in Hawai'i, Alaska, and the U.S. territories, or the rest of the world. Limitations in coverage possibly result in omission of high impact areas in some impact categories, which if included might increase estimates of disproportionality – especially considering that Alaska (see Melvin et al. 2016[34] for one of many examples) has been shown to be particularly sensitive to climate change and/or have limited adaptative capacity. Incorporation of additional locales could increase or decrease disproportionality results.
Use of six climate models to assess variability in climate outcomes in the "impacts by	Climate Hazard Projections	**Likely minor impact on central estimates, potentially major impact on variability**. The six GCMs for climate forecasts were chosen based mostly on the variation in outcome across their results for the full CONUS domain, as well as other considerations (see Figure 2 of this appendix, and associated text). They do not represent the full range of

[34] Melvin AM, Larsen P, Boehlert B, Neumann JE, Chinowsky P, Espinet X, Martinich J, Baumann MS, Rennels L, Bothner A, Nicolsky DJ, Marchenko SS. 2016. Climate change damages to Alaska public infrastructure and the economics of proactive adaptation. *Proceedings of the National Academy of Sciences*.

SOURCE OF UNCERTAINTY	ANALYTIC STEP	COMMENTS AND ESTIMATE OF INFLUENCE OF UNCERTAINTY ON DISPROPORTIONALITY RESULTS
degree" approach		outcomes that could be considered for temperature and precipitation. The temperature binning/indexing approach effectively standardizes results for downstream temperature-based impact estimates, but the coincident precipitation outcomes for each degree of temperature vary widely. As a result, wide variability across GCMs might be expected for precipitation-dependent outcomes. Variability across GCMs at the local scale, in particular, for both temperature and precipitation can be substantial but was not quantified here.
Socioeconomic and demographic change over time	Climate Impact Estimation	**Unknown impact**. This report estimates climate change impacts to socially vulnerable populations based on current demographic distributions, as long-term and robust projections for national changes in demographics are currently unavailable. As noted in the main text, impacts could be larger or smaller based on future changes in U.S. demographics.
Coverage of impacts	Climate Impact Estimation	**Unknown impact**. The six impacts analyzed in this report were selected due to the availability of robust methods and data, the demonstrated economic importance of these impacts, and the potential for disproportionate risks to socially vulnerable populations. However, there are many other human health and economic impacts of climate change that could disproportionately affect socially vulnerable populations. The impact of limited coverage is unknown.
Structural uncertainty associated with specific impact sector modeling approaches	Climate Impact Estimation	**Unknown impact, probably minor**. Each analysis was developed using a single impact model. These models are complex analytical tools, and choices regarding their structure and parameter values can influence the estimation of impacts. The use of additional models would help improve the understanding of potential impacts, but because so few impact models are currently available for use, the impact of adding new models is uncertain. The impact may be minor because the models applied represent the best available information and the sectors chosen reflect the best understood climate change impacts, and most of the models applied have been recently refined to reflect more recent data and improved understanding of impacts through peer review and other methods improvement processes.
Missing analysis of interactive or correlative effects	Climate Impact Estimation	**Likely underestimate, unknown magnitude.** The impact analyses were developed independently of one another and, as a result, the estimated impacts may omit important interactive or correlative effects. Cross-sectoral impacts, particularly in infrastructure sectors, have been shown to

SOURCE OF UNCERTAINTY	ANALYTIC STEP	COMMENTS AND ESTIMATE OF INFLUENCE OF UNCERTAINTY ON DISPROPORTIONALITY RESULTS
		amplify effects,[35] and reduced adaptive capacity in areas with higher proportions of socially vulnerable capacity could disproportionately impact those areas, which could result in underestimation of the disproportionality of impacts presented in this report.
Estimation uncertainty for impact sector modeling	Climate Impact Estimation	**Impact represented by statistical uncertainty around mean estimates presented, or unknown impact, depending on sector.** Each of the sectoral impact models applied for this report estimates impacts with associated uncertainty. For sector models with econometric or epidemiological origins (air quality, extreme temperature, and labor), this uncertainty can be characterized at least partially by statistical uncertainty around relevant parameter estimates. The report presents mean values, and statistical significance has been established for each model, so no underestimation or overestimation bias is implied, but the estimates are uncertain with varying levels of confidence. For sector models that rely on simulation approaches (coastal flooding and roads, coastal flooding and property, and inland flooding), the results are also uncertain but are generally not characterized by statistical methods. Estimates are either calibrated by or compared to current historical/baseline results, where possible, which increases confidence in the results, but they remain uncertain with mostly unknown impact on the results presented here.
Treatment of adaptation to climate impacts and consideration of adaptative capacity of socially vulnerable groups	Climate Impact Estimation	**Likely underestimate of disproportionality of impact on socially vulnerable populations, potentially major**. Populations will adapt to climate change in many ways, with some actions reducing impacts, and other potentially exacerbating impacts. To the extent socially vulnerable populations have a diminished adaptive capacity compared to reference populations, as established in much of the literature reviewed in each of the impact category chapters and Technical Appendices, estimates of disproportionality of impact would be underestimated.

[35] See both Maxwell, K., S. Julius, A. Grambsch, A. Kosmal, L. Larson, and N. Sonti, 2018: Built Environment, Urban Systems, and Cities. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 438–478. doi: 10.7930/NCA4.2018.CH11 and Jacobs, J.M., M. Culp, L. Cattaneo, P. Chinowsky, A. Choate, S. DesRoches, S. Douglass, and R. Miller, 2018a: Transportation. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 479–511. doi: 10.7930/NCA4.2018.CH12.

SOURCE OF UNCERTAINTY	ANALYTIC STEP	COMMENTS AND ESTIMATE OF INFLUENCE OF UNCERTAINTY ON DISPROPORTIONALITY RESULTS
Attribution of climate impact risk to socially vulnerable populations by location	Disproportionality Estimation	**Unknown impact**. The analyses of this report are not designed to project impacts or risks for specific individuals and are instead intended to explore disproportionate risks based on current demographic distributions in areas with higher projected impacts. As a result, the analyses assume uniform and equal exposure to risks by everybody living in these tracts. Estimation of specific individual-level risk could yield higher or lower estimates of disproportionality.
Uncertainty in population counts from ACS data at tract and block group level	Disproportionality Estimation	**Unknown impact, likely minor**. As discussed elsewhere in this Technical Appendix, the Census Bureau assigns margins of error for ACS population subgroup estimates, for tracts and block groups. These margins of error increase for smaller spatial units, such as the block groups used in the coastal and inland flooding analyses. To the extent that margins of error are randomly distributed across the tracts and block groups identified as exposed to high climatic impact, no bias would result in estimates of disproportionality, but any correlation between socially vulnerable population measurement uncertainty and estimates of high climatic impact are unknown.
Impact of historical and projected future urbanization trends on overall results	Disproportionality Estimation	**Possible underestimate, unknown impact**. Recent demographic and migration trends reflect increasing urbanization in the U.S. For the extreme temperature health analysis in particular, urban areas display a pronounced heat island effect, which has been shown to be greater in neighborhoods with high densities of socially vulnerable populations. As a result, increased urbanization could lead to increased estimates of disproportionality. For other sectors, urbanization could concentrate populations, which could worsen traffic delays in one sector, while also facilitating more cost-effective adaptation from climate hazards such as riverine, coastal, or high-tide flooding.

The American Community Survey (ACS) population data used to estimate the proportion of socially vulnerable subgroups within Census tracts or block groups are a critical input to the results in this report. The ACS relies on a survey of between 3 and 3.5 million households, from among the more than 120 million households in the U.S. Response rates for the ACS are relatively high, and for the years of data used in this report range from 92.0 to 96.7 percent.[36] Nonetheless, every survey is subject to sampling error, which can affect the results of using those data. Table 5 below provides an illustrative summary of reported margins of error for ACS data, for five of the many variables used in this report, at

[36] For more information see the ACS website: https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/response-rates/

two spatial scales (tracts and block groups). A general observation in all surveys is that the statistically estimated margins of error associated with sampling increase for population groups or spatial units of smaller size – this result is seen in Table 5, where for example the margin of error for the low-income, white individual, Black or African American individual, and American Indian and Alaska Native individual subgroups are larger than for the total population, and margins of error at the block group level are larger than for tracts.

This outcome suggests that the disproportionality results for smaller subgroups, or in analyses that rely on ACS estimates at the block group level (the coastal and inland flooding sectors), are relatively more uncertain than for other estimates in the report. However, it is important to keep in mind that all of the disproportionality results rely on broad groups of tracts and block groups (that is the highest impact tercile of spatial units) to draw inferences about disproportionality, rather than individual block groups or tracts. If the survey margins of error are randomly distributed across spatial units, we do not necessarily expect that results based on multiple groups of tracts and block groups are likely to be systematically biased. While no specific statistical robustness tests were performed for this analysis, the method of relying on broad groups of areas for results is likely to reduce the overall uncertainty or any systematic bias in the results presented.

Table 5: Illustrative Reported Average Margins of Error for American Community Survey (ACS) Results at Tract and Block Group Level

VARIABLE	ACS REPORTED MARGIN OF ERROR	
	TRACTS	BLOCK GROUPS
Total Population	8.4%	22%
Low Income Households	13%	27%
White Individuals	8.8%	25%
Black or African American Individuals	11%	55%
American Indian and Alaska Native Individuals	92%	163%