APPENDIX K
CLIMATE VULNERABILITY METRIC

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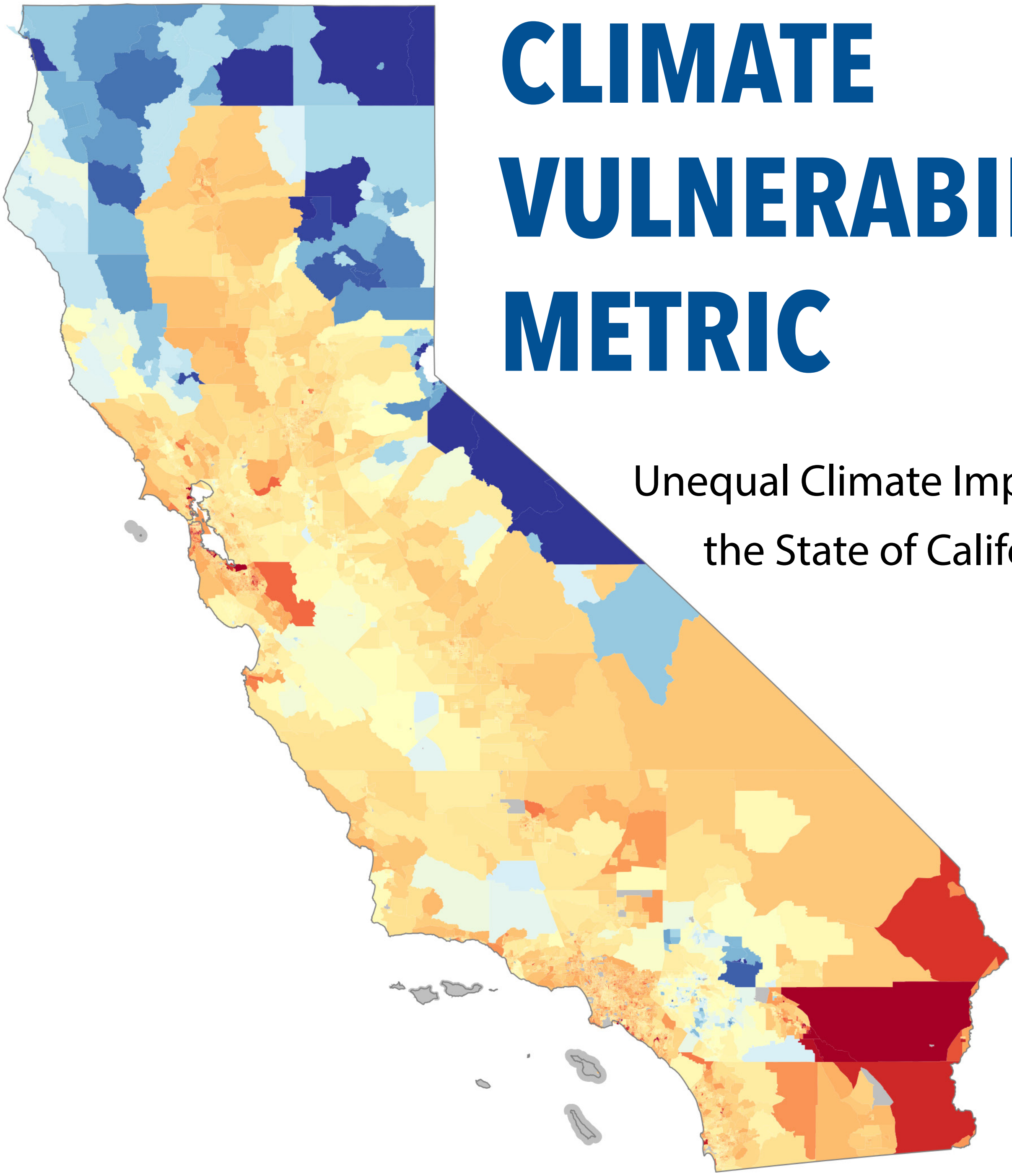
CLIMATE VULNERABILITY METRIC



Unequal Climate Impacts in the State of California

emLab UC SANTA BARBARA

Climate Impact Lab

Rhodium Group

Climate Vulnerability Metric

Unequal Climate Impacts in the State of California

Submitted to California Air Resources Board

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Executive Summary

As California invests in climate mitigation and adaptation, it is essential to understand the relative impact of climate change across the state's diverse communities. This report supports ongoing efforts by the California Air Resources Board (CARB) to better understand the impacts of greenhouse gas emissions on human welfare by introducing the Climate Vulnerability Metric (CVM). The CVM is the first metric in California specifically focused on quantifying the community-level impacts of a warming climate on human welfare.

The CVM is an aggregation of the impacts of climate change that can be quantified at the census tract level using currently available research. The CVM includes the projected impacts of climate change on human welfare across four impact categories through midcentury (2050) under a moderate emissions scenario (RCP 4.5[1]) that is broadly consistent with the world's countries meeting their current emissions reduction pledges under the Paris Climate Agreement. This time horizon has the benefit of capturing the collective effect of current and near-term global greenhouse gas emissions on California's climate system. There are nine components of climate impacts (Figure ES1) that when aggregated, are the total CVM in each

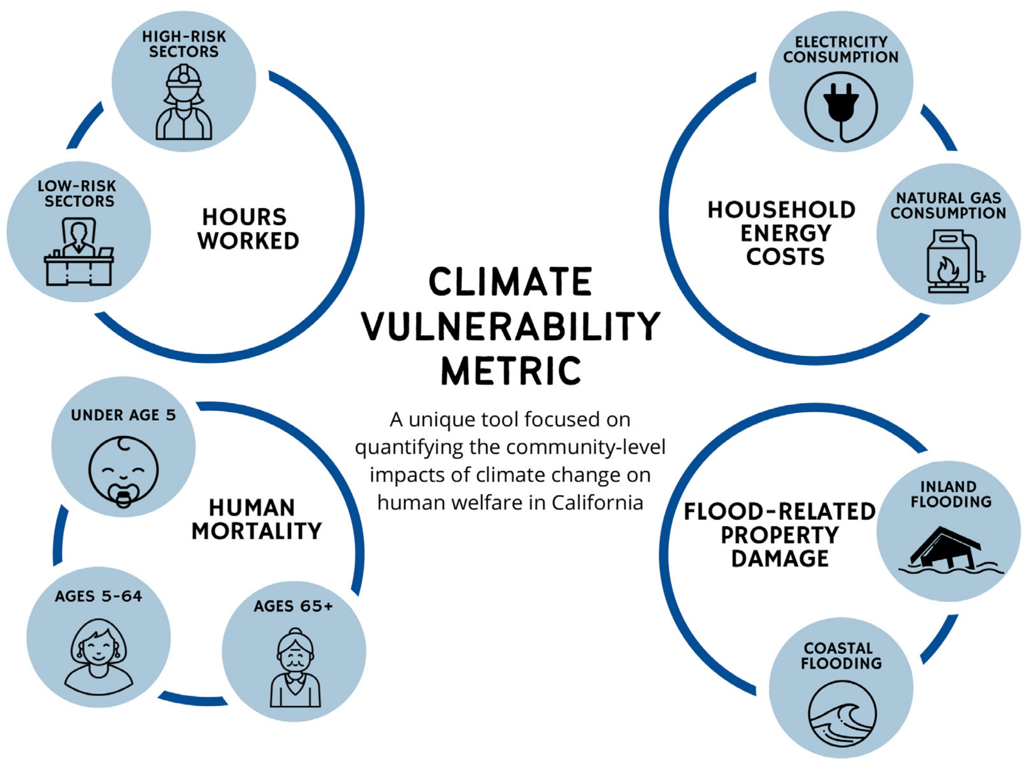


Figure ES1: Categories of climate change impacts on human welfare included in the Climate Vulnerability Metric.

[1] Representative Concentration Pathway (RCP) 4.5.

census tract.

The CVM is constructed by aggregating climate change impact estimates across the nine impact components shown in Figure ES1. In order to ensure that the CVM represents the diversity of California communities, it is reported as the aggregate monetized impact of climate change as a percentage of census tract-specific incomes.[2] This format accounts for current levels of economic inequality across California and captures the impact of a warming climate on fundamental aspects of community well-being such as public health, housing, and our ability to earn a livelihood. The higher the CVM for a given census tract, the more damaging the projected impacts of climate change on human welfare. A lower CVM is associated with lower impacts and/or greater resilience, while a negative CVM value represents a projected beneficial impact of moderate climate change by 2050. Figure ES2 outlines the five-step method used to calculate the CVM.

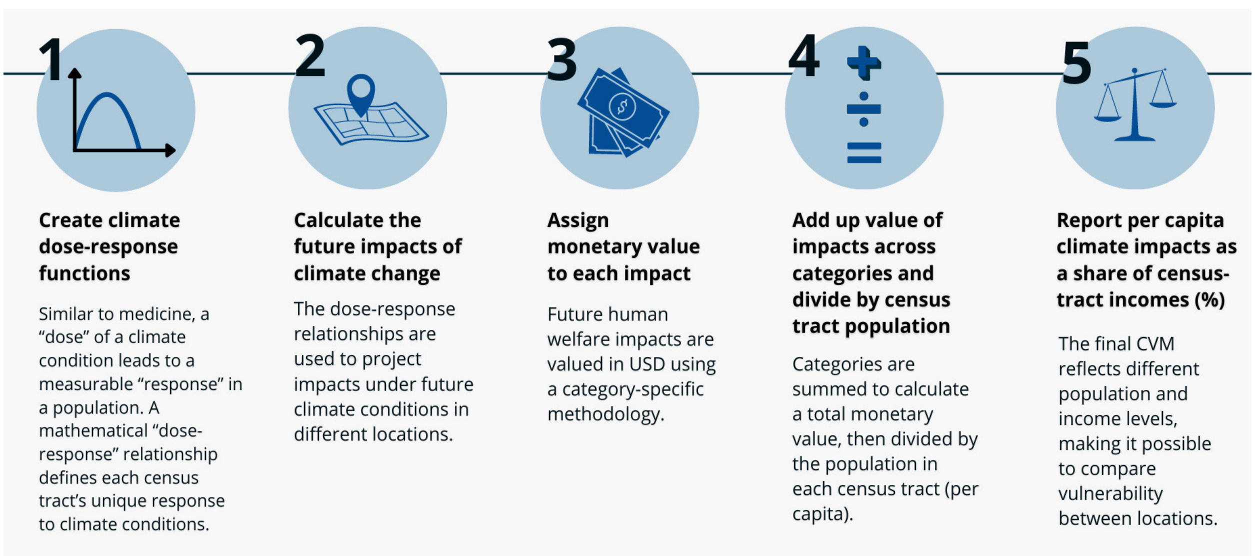


Figure ES2: 5-Step Method for Calculating the CVM. *Constructing the CVM requires five main steps, beginning by quantifying the impacts of climate change on human welfare and ending with aggregating impacts across categories and reporting the CVM as a single metric for each census tract. Figure ES2 overviews these steps.*

[2] Per capita income in 2019 for census tracts across California ranges from $633 to $176,388, with a median of $32,181 ($2019). Source: American Community Survey.

Figure ES3 presents a map of the CVM at the census tract level. Each census tract CVM value is a comprehensive total of the 9 category-specific estimates, calculated using the five-step method described in Figure ES2.

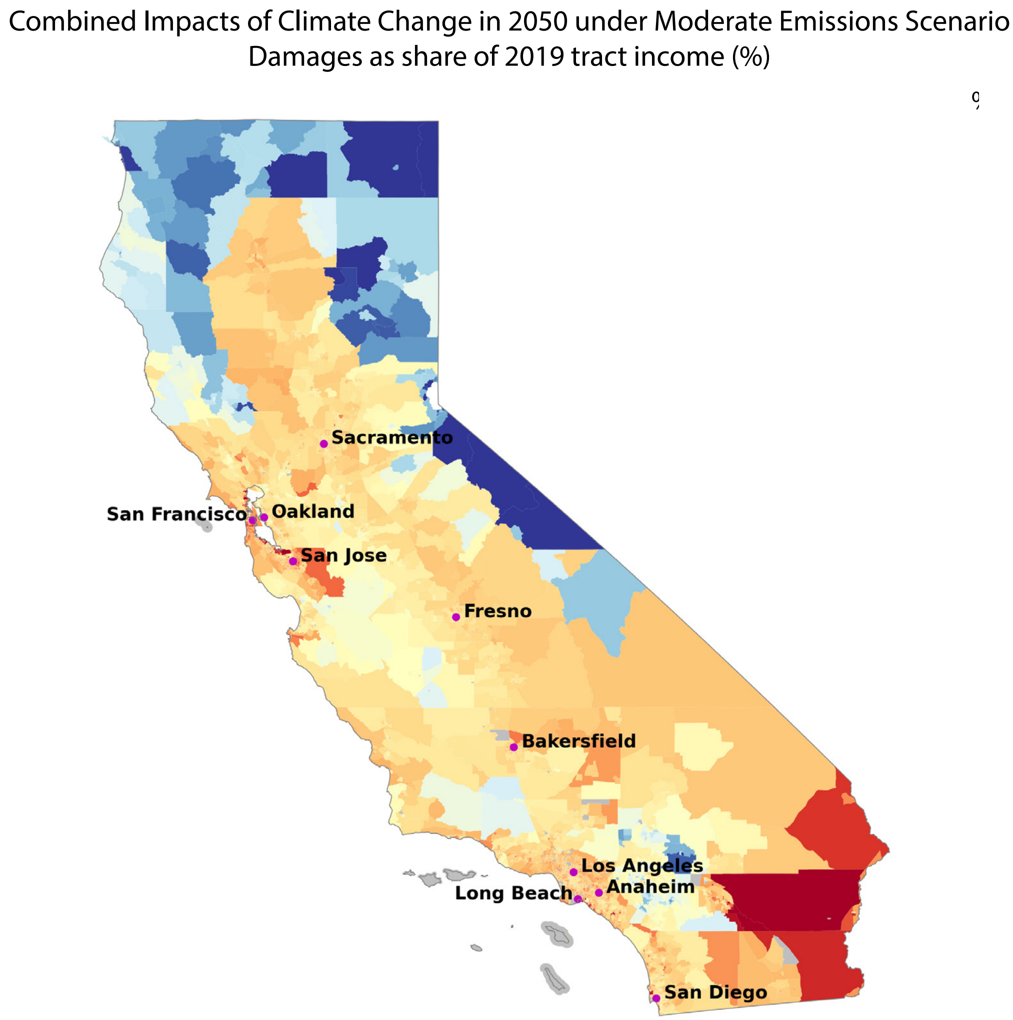


Figure ES3: Climate Vulnerability Metric (CVM). *The map shows combined impacts of climate change in 2050 under a moderate emissions scenario (RCP 4.5), reported as a share of 2019 census tract income. For example, a CVM value of 3 implies that by 2050, a census tract is projected to experience human welfare impacts of climate change that amount to 3% of annual income. Impacts are combined across the categories shown in Figure ES1. The higher the CVM for a given census tract, the more damaging the projected impacts of climate change on human welfare. Census tracts with high CVMs are represented by positive percentages in orange and red. A lower CVM is associated with lower projected impacts of climate change, shown in yellow, while a negative CVM value represents a projected beneficial impact of climate change (e.g., through reductions in deaths caused by extremely cold winter weather). Negative CMVs are represented by negative percentages in blue.*

The CVM shows that climate change will have highly unequal impacts across Californian census tracts. While some regions in the southeast are estimated to suffer damages that exceed 5% of annual income, other high-elevation regions are estimated to see benefits of up to 10%. Some low-lying urban areas are estimated to be particularly vulnerable, while much of the Central Valley suffers at least moderate damages. The wide diversity of projected impacts underscores the importance of estimating climate vulnerability at a community level.

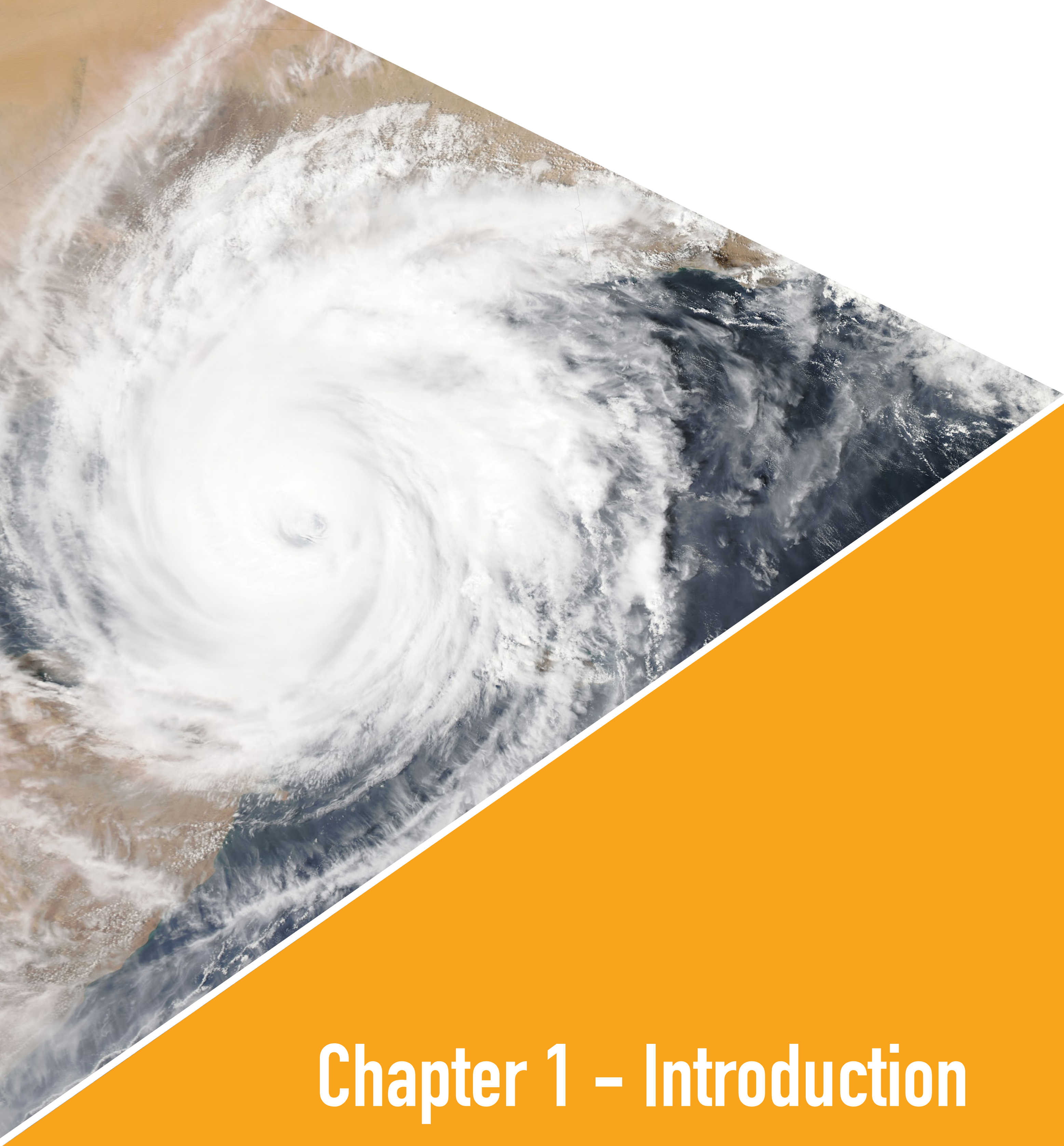
As a tool for California policymakers and communities, the CVM provides information about the relative climate vulnerability that Californians may face in the future. The CVM can direct funding to communities with higher relative climate vulnerability for adaptation and mitigation. In addition, the CVM can direct funding by impact category — census tracts with high energy cost impacts could receive reduced rate plants or targeted funding. The CVM can also be used by policymakers to designate communities as "vulnerable" to climate change or "disadvantaged" similar to the approach in CalEnviroScreen. The CVM can also be used in combination with existing screening tools to identify communities that are vulnerable to the impacts of climate change as well as current environmental and health hazards.

It is important to note that the impacts included in the CVM do not represent the total cost climate change will likely impose on individual and household welfare across California. For example, currently available research is not robust enough for us to include a quantification of the impact of climate change-driven changes in wildfires on human welfare at a census tract level.

There are also areas of California, including rural and tribal communities, that are not accurately reflected through a census tract level tool. Additionally, the CVM can be expanded to include additional socio-demographic data that better reflects the under-represented regions of California.

As climate economics research continues to mature, the CVM can be expanded to include additional categories and improve the coverage and granularity of communities, offering a more comprehensive assessment of vulnerability.

While these are important limitations, the CVM represents the only census tract-level analysis of climate vulnerability across California. Critically, the CVM is built from community-specific estimates of vulnerability to climate change, and it will be straightforward to build upon these estimates as future research evolves.



Chapter 1 - Introduction

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Evidence continues to mount that California's climate is rapidly changing. Past greenhouse gas emissions from fossil fuels have already increased temperatures, altered precipitation patterns, and raised sea levels. The resulting climate hazards—floods, heat waves, droughts, intense storm activity, and wildfires—threaten communities across the state. Both these extreme events and chronic, slower shifts in temperature, precipitation, and sea level rise impact human welfare in ways that Californians can feel today. Climate change will continue to affect California, but the implications of climate change will not be the same across all communities, each with unique populations and geographic characteristics.

Over the last decade, advances in data and economic research have dramatically expanded knowledge of the links between changing climate conditions and human welfare. A number of these new, empirically grounded studies make it possible to quantify current and anticipated climate impacts locally, accounting for disparities in how populations respond to climate change. This climate economics research can provide insight into the relative vulnerability of each of California's diverse communities to climate change's impacts on human welfare.

A wide array of California climate change assessments exists, with varying approaches to assessing impacts on human welfare. While no single study has captured the large and complex universe of potential costs that California may face, the research community has made great strides over the last two decades in measuring the potential risks of specific climate hazards and documenting them in an array of state climate assessments.[i] This report contributes to this body of work by quantifying the relative risks facing California's diverse communities, accounting for the fact that vulnerable populations have less capacity to anticipate, cope with, and respond to changing climate conditions, as well as fewer resources to recover and adapt to be better protected from future events.[ii]

Essential to this effort is a body of climate economic research that uses cloud computing and increasingly available empirical data to identify the effects of changing climate conditions on social and economic conditions at a *local* scale. This research shows that while a ton of carbon emitted anywhere will have the same impact on the atmosphere, it is inaccurate to assume that increased physical hazards, such as more frequent extreme heat and damaging coastal storms, will impact all California communities in the same way. Instead, climate change's impact on human welfare is shaped by existing socioeconomic, demographic, and climatic conditions. Quantifying the impacts of climate change with an approach that accounts for these local differences makes it possible to estimate who is most vulnerable in today's climate and in the future as climate conditions evolve.

Purpose of the report

This report supports ongoing efforts by the California Air Resources Board (CARB) to better understand the impacts of greenhouse gas emissions on human welfare by introducing the Climate Vulnerability Metric (CVM). The CVM provides an aggregation of the quantifiable impacts of near-term climate change for each California census tract under moderate levels of projected global greenhouse gas emissions. It is the first metric in California specifically focused on quantifying the community-level impacts of a warming climate on human welfare.

As California invests in climate mitigation and adaptation, it is essential to understand the relative impact of climate change across communities. Identifying the difference in impacts across communities can be used to direct resources and avoid increasing inequities resulting from climate change. The CVM also provides information on the impact of reducing greenhouse gas emissions on California communities.

The CVM is intended to augment California's existing resources for understanding physical hazards by quantifying the impact of changing climate conditions on human welfare at the census tract level. While a handful of statewide mapping platforms are available for assessing vulnerability, no centralized set of indicators exists. This has made it very challenging to develop a comprehensive view of the communities that are most at risk.[iii] Policy experts have also suggested that relying on more local data—at the census tract—could provide the correct scale for analysis of climate impacts on disadvantaged populations at the community level.[iv] The CVM is the first comprehensive tool to identify the impact of climate change on human welfare at the census tract or community level.

Interpreting CVM results

CVM AT A GLANCE

Timing: The CVM is calculated through 2050, or a midcentury time horizon.

Emissions scenario: The CVM is based on an emissions scenario that is consistent with nations meeting their Paris Climate Agreement pledges.

Output: The CVM is reported as a percentage of monetized impacts, a format that accounts for current economic inequalities across California and is intuitive to read. A higher CVM value in a census tract indicates more predicted damages.

The CVM considers projected impacts of climate change on human welfare across four categories, composed of nine components, through midcentury (2050). This time horizon has the benefit of capturing the collective effect of current and near-term global greenhouse gas emissions on California's climate system. Driven by assumptions about currently available technologies and near-term political will, future climate conditions are modeled under a moderate emissions scenario (RCP 4.5[3]) that is consistent with the world's

[3] Representative Concentration Pathway (RCP) 4.5, a moderate forcing path.

countries meeting their current emissions reduction pledges under the Paris Climate Agreement. Under this scenario, carbon dioxide emissions stabilize close to their current levels through midcentury and decline after that, reflecting moderate mitigation action.

In order to ensure that the CVM represents the diversity of California communities, the CVM is reported as the combined monetized impacts as a percentage of census tract-specific incomes. This format, a percentage, accounts for current levels of economic inequality[4] across California and captures the impact of a warming climate on fundamental aspects of community well-being such as public health, housing, and our ability to earn a livelihood in a common format. The higher the CVM for a given census tract, the more damaging the projected impacts of climate change on human welfare. A lower CVM is associated with greater resilience, while a negative CVM value represents a projected beneficial impact.

The CVM captures the potential for climate change to exacerbate income-driven disparity. Notably, while the CVM is a monetized metric, it includes impacts on non-market outcomes, such as health risks and the discomfort of outdoor laborers. Included in the aggregate CVM for each census tract are four categories for which a robust body of evidence demonstrates the relationships between daily climate variables and human welfare impacts affecting California while accounting for differential vulnerability across the state (see Technical Appendix for citations and methodology). These are:

- the impact of daily temperature on all-cause mortality rates across three different age groups;
- the impact of hourly temperature on household electricity and heating fuels consumption, and resulting changes in energy costs;
- the impact of daily temperature on the number of hours people work in both "high-risk" outdoor sectors (agriculture, mining, forestry, construction) and "low-risk" sectors (all other sectors); and
- the impact of sea-level rise and changes in precipitation on flood-related property and structural damage, both for coastal and inland properties.

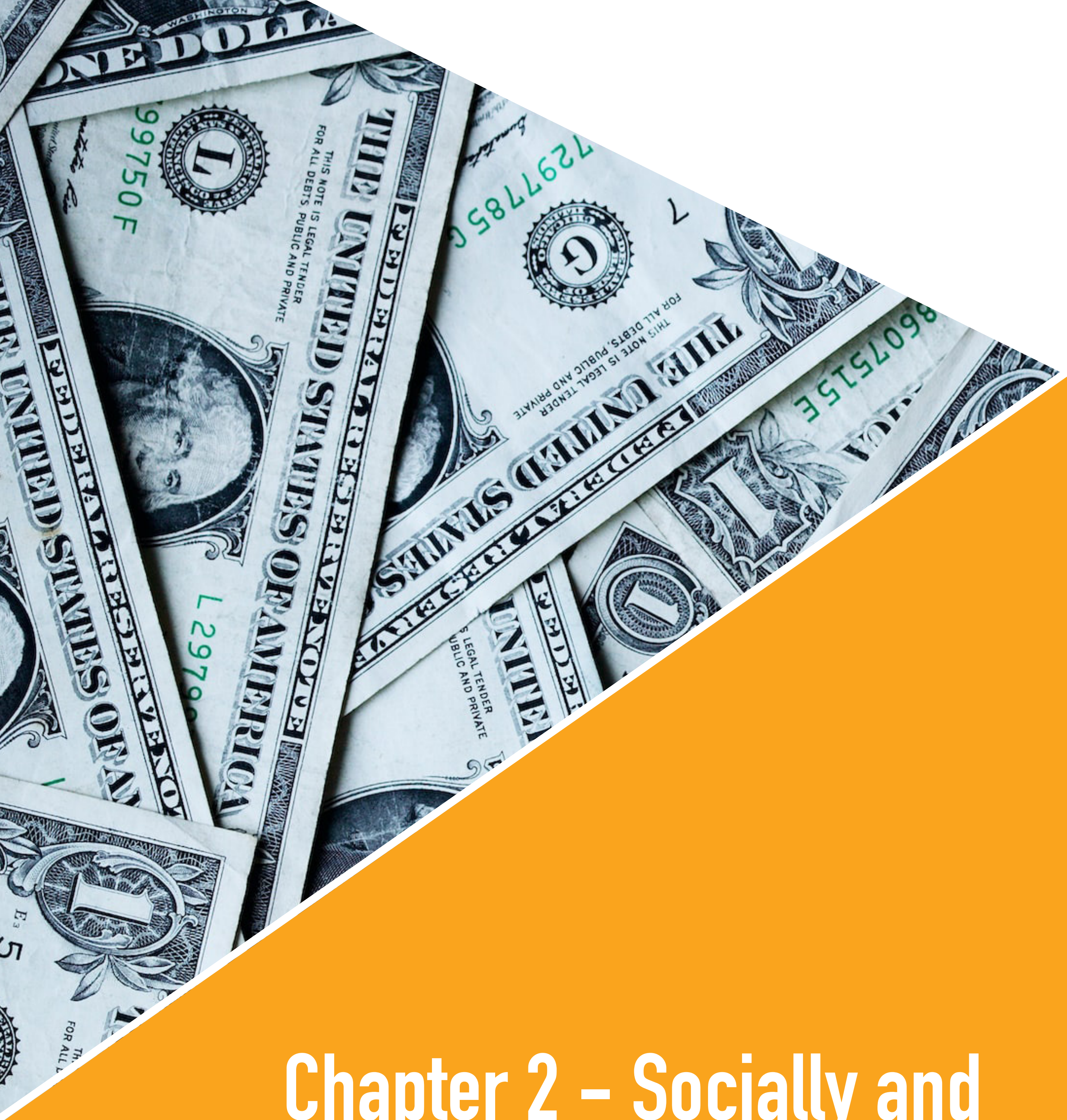
The relative vulnerability of each census tract is quantified by:

1. Summing monetized damages from climate change across all impact categories in each census tract; and
2. Reporting each census tract's combined projected damages in 2050 as a share of their current income (% of census tract-specific income in the present day, as obtained by the Census[v]).

Importantly, the CVM calculation accounts for uncertainty in how the global climate responds to greenhouse gas emissions by simulating a range of future climate projections. For each census tract, the median outcome and the 25th and 75th percentiles are estimated, showing the spread of the middle half of the CVM distribution.[5]

[4] Per capita income in 2019 for census tracts across California ranges from $633 to $176,388, with a median of $32,181 ($2019). Source: American Community Survey.

[5] The 25th and 75th percentiles each have 1-in-4 odds.



Chapter 2 – Socially and Economically Significant Impacts of Climate Change

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The CVM aims to capture socially and economically significant climate impacts that can be quantified in a manner that accounts for disproportionate impacts across diverse populations.

The CVM aims to capture socially and economically significant climate impacts that can be quantified in a manner that accounts for disproportionate impacts across diverse populations. California's existing frameworks for assessing climate vulnerability offer a granular set of physical hazard indicators (e.g., extreme heat days, wildfire risk) overlayed with social vulnerability indicators (e.g., nutritional status, educational attainment) and particular forms of adaptive capacity (e.g., air conditioning) at the county or census tract level.[vi] In addition, there are visualization tools that identify the exposure of disaster response facilities or California residents to physical hazards such as coastal flooding[vii] and wildfires.[viii]

Defining vulnerability in this report.

Prior approaches to estimating climate vulnerability implicitly assume that social vulnerability indicators, such as lack of a high school diploma, indicate climate vulnerability. For instance, the approach used in the U.S. EPA's recent assessment of climate change and social vulnerability assumes every human has the same uniform response to a given physical hazard, then estimates the likelihood that socially vulnerable humans live in those regions exposed to the highest physical hazards.[ix] This approach fails to incorporate the fact that individuals and communities differ in their capacity to respond to the same physical hazard. In contrast, the research underlying the CVM uncovers how populations respond and adapt to climate change through empirical estimation using large-scale, comprehensive data.[x] Throughout this report, we distinguish between "vulnerability," which reflects this empirical measure of the varying ability to adapt and cope, and "exposure," which does not reflect these differences and instead relies on static assumptions of uniform ability to respond and adapt to climate change.

While these frameworks can increase understanding of physical hazard projections at a local level, they do not quantify the impacts on human welfare. The CVM quantifies these impacts with an approach rooted in peer-reviewed literature that has recovered the factors influencing vulnerability. For example, recent climate economic research on human mortality finds that people in regions with lower incomes and older populations fare worse on extremely hot days than do younger people in wealthier locations.[xi] These disparities can be measured using socioeconomic and demographic data disaggregated to the census tract level to highlight the difference in climate vulnerabilities across the state.

The CVM takes a detailed approach that follows frontier advances in the scientific literature on climate impacts. In estimating climate impacts, the CVM allows varying responses to changing climate conditions based on differences between populations. For each category included in the CVM, a robust body of evidence demonstrates the relationships between climate conditions and socially or economically significant impacts in California.

Human mortality

The impact of daily temperature on mortality risk has been widely studied globally, as well as in the United States and California. Extreme heat events have been shown to cause heat-related illnesses, like heat exhaustion or heat stroke. Heat stroke occurs when a person's body temperature rises faster than it can cool itself down, causing damage to the brain and vital organs. This can be especially dangerous for older adults and young children.[xii] Similarly, extreme cold raises mortality rates due to pneumonia, flu, and other illnesses triggered under cold conditions. Warming temperatures are projected to lead to an increase in heat-related deaths and a smaller decline in cold-related deaths in most regions of the U.S.[xiii] Importantly, vulnerability to these health risks has been documented to vary substantially across diverse populations, depending on many non-climate factors such as age, housing, and access to protective technology like air conditioning.[xiv] Recent research enables us to capture differential exposure to health-threatening temperatures and to account for differences in the ability to adapt across communities in California. Prior research in the U.S. suggests that these mortality-related impacts of warming may be the single most significant driver of human welfare losses under climate change over the next century.[xv]

Household energy costs

Warmer temperatures are projected to raise Californian households' electricity expenditures as demand for cooling steadily grows.[xvi] These higher energy bills will be particularly burdensome in regions of California where temperatures are already high enough to lead to pervasive air conditioning use. However, warmer winters also decrease the use of heating fuels, particularly in colder regions of the state.[xvii] This means that climate change will cause very different energy-related costs across the diverse regions of California. However, switching from heating to cooling will likely result in a net increase in spending on energy bills for most households.[xviii]

Energy equity research suggests that

assessing the share of household income spent on energy may miss energy-limiting behavior in low-income households, such as keeping the thermostat set higher during periods of extreme heat to avoid an unaffordable increase in energy spending.[xix] This hidden form of energy poverty means poorer households, including those who rely on less electricity-intensive cooling technology like swamp coolers and fans, are more exposed to higher indoor temperatures and associated health risks.

Hours worked in both high-risk and low-risk sectors

More frequent and severe temperature extremes can cause people to spend less time working, as they spend more time indoors to beat the heat or take more frequent breaks during outdoor labor to cool off.[xx] This is especially relevant for the nearly one-in-four workers in the U.S. labor force who work in high-risk sectors like agriculture or construction.[xxi] Heat strain can also affect workers in low-risk sectors who spend their days in retail stores or offices.[xxii] When the temperature inside commercial buildings is uncomfortable for workers, their productivity and performance are negatively impacted.[xxiii] More frequent and severe temperature Workers who are elderly, overweight, or have high blood pressure or heart disease are at a greater risk of heat stress.[xxiv] To reduce exposure to heat, workers may choose to work fewer hours overall, work during a different time of day, or drop out of the labor force altogether.[xxv] Emerging evidence on the link between temperature and the workforce enables a calculation of these impacts at the local level across California.

Flood-related property damage

Globally, sea levels have risen by 7 to 8 inches since 1900—at a rate greater than during any similar period in at least the last 3,000 years—posing growing threats to coastal communities and economies.[xxvi] Even a small amount of sea-level rise can harm coastal habitats through destructive erosion, wetland flooding, and soil contamination. As the California coast erodes and waters rise, so do the number of properties at risk of tidal flooding or inundation caused by offshore storms. In addition to increasing the risk of property damage along coastlines, climate change is increasing flood risk inland as warming increases the atmosphere's capacity to store more water vapor, resulting in heavier rain and powerful storms.[xxvii] Flooding has disproportionately harmed urban areas with economically disadvantaged and minority populations.[xxviii] Low-income, Black, and Hispanic people are more likely to move into high-risk flood zones compared to homebuyers and renters who can afford to live in less exposed areas.[xxix] Additionally, rising flood insurance premiums may leave low-income households priced out of flood insurance, shifting the financial burden onto remaining ratepayers and putting others at greater risk of uninsured losses.

Gaps the CVM aims to fill

Existing research on the human welfare impacts of climate change is limited in geographic granularity—some reports estimate impacts in 10 U.S. regions,[xxx] while others conduct state- or county-level climate damage estimates.[xxxi] However, even at the county level, environmental and socioeconomic conditions between communities may vary drastically (Figure 1). This means there are no existing estimates indicative of the lived experiences on the ground in highly impacted communities within California's 58 counties. The CVM fills this gap, providing a geographically comprehensive and granular assessment that makes it possible to assess which communities face disproportionate impacts.

There are also diverse physical climate hazards that impact specific California regions. Changes in the severity and frequency of winter storms in the Sierra Nevada mountains will impact human welfare in the region. More severe drought conditions and reduced water availability will impact communities in the Central Valley. While these impacts are part of the lived experience in these communities, there is no comprehensive statewide data on their impact on human welfare. Therefore, these regional impacts are not included in the CVM.

Paramount to developing the CVM is

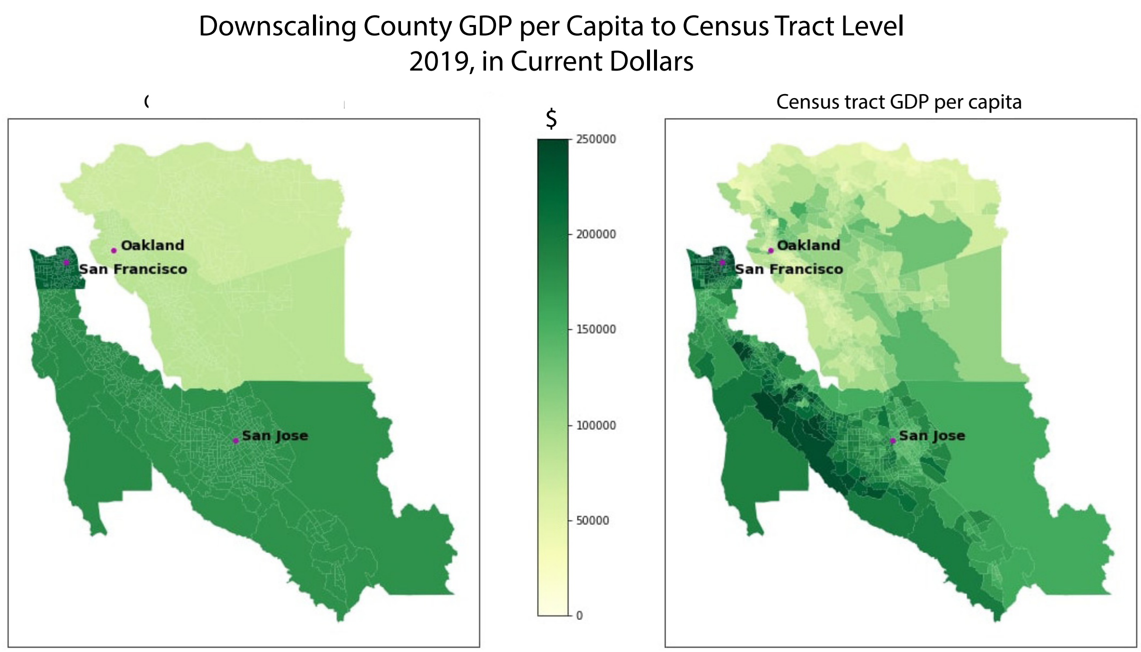


Figure 1: Census tract-level data makes it possible to assess economic and demographic conditions at a localized scale that is obscured with county-level data. *The left panel of this figure shows 2019 county Gross Domestic Product (GDP) per capita as reported by the Bureau of Economic Analysis. The right panel shows the same dataset scaled to the census tract level using per capita income data from the American Community Survey. Income is a key factor in estimating how communities will respond to changing climate conditions.*

assessing the relative vulnerability of Californians to climate impacts by exploring a full range of potential changes in temperature and precipitation at a daily, local level using methods that account for different responses across populations. For example, Long Beach and Fresno have roughly the same annual average temperature. But households in Fresno experience more cold days and hot days throughout the year, causing them to face higher energy bills for heating and cooling. Capturing this response to daily conditions, rather than annual averages or hazards (e.g., days above 95 degrees), also makes it possible to pick up on the effects of seasonal variation.

By capturing the effects of the full distribution of daily weather events, we account for the fact that individuals experience their climate one day at a time and make decisions about their actions based on the daily events they experience. The method for quantifying climate impacts employed by the CVM relies on constructing mathematical functions that describe the relationship between climate conditions that a population experiences and the corresponding response that the population shows in terms of social or economic outcomes. For more information on these functions, see Chapter 3.

Importantly, the CVM is focused on climate impacts that have documented human welfare impacts at the individual and household levels. Welfare encompasses market impacts that have an observable change in expenditures and non-market impacts whose value is measured in people's perceived willingness to pay for an increased amount of risk (Figure 2). Some existing tools take a purely financial or economic assessment of climate impacts and focus on changes to a region's economy rather than quantifying the impacts on human welfare.[xxxii]

Because the CVM is focused on climate change impacts (i.e., impacts caused by greenhouse gas emissions that alter the

Category	Market	Non-market
Human mortality		X
Hours worked in high- and low-risk sectors		X
Household energy costs	X	
Flood related property damage	X	

Figure 2: Breakdown of "market" vs. non-market impacts on human welfare. *The CVM encompasses four categories of climate change impacts on human welfare, encompassing both market impacts that can be directly observed in markets via changes in prices or quantities of goods exchanged, and non-market impacts, whose value is measured in people's willingness to pay for a decreased amount of climate risk. While working hours are observed in labor markets, the CVM uses the response of hours worked to changes in the climate to measure the discomfort workers face when working under extreme conditions. As this discomfort is not itself a market good, this impact category is indicated as "non-market".*

global climate), it does not include any impacts related to changes in localized air pollutants. However, the CVM can be combined with other census tract level metrics for pollution burden and population vulnerability characteristics, including CalEnviroScreen, to provide a more comprehensive assessment of community vulnerability to environmental conditions.

Chapter 3 - The Five Step Method For Calculating the CVM

Chapter 3 – The Five-Step Method for Calculating the CVM

Constructing the CVM as a single metric capturing the effects of climate change across impact categories and communities requires five main steps, beginning by quantifying the impacts of climate change on human welfare and ending with aggregating impacts across categories and reporting the CVM for each census tract in California as combined monetized impacts per capita as a percentage of census tract-specific incomes. These steps result in the first census tract measure of the quantifiable impacts of climate change, combining both market and non-market impacts of climate change in monetized terms and accounting for differences in vulnerability across communities.

Step One: Create climate dose-response functions

The first step in calculating a CVM is constructing dose-response functions, which describe the mathematical relationship between the "dose" of a particular climate condition that a population experiences and the corresponding "response" that the population or local economy shows in terms of key social or economic outcomes. The CVM takes a detailed approach that considers the full probabilistic distribution of climate sensitivity and allows varying responses to climate conditions based on differences between populations.

Following frontier advances in scientific literature on climate impacts,[xxxiii] the CVM shows that the impacts of changing climatic conditions on human welfare are not uniform and do not scale linearly with increased warming. Instead, those outcomes are shaped by existing socioeconomic and climate conditions, which vary across communities, and dose-response functions are highly nonlinear (Figure 3). Quantifying the impacts of climate change with an approach that accounts for these local differences and assesses daily climate conditions makes it possible to estimate who is most vulnerable in today's climate and in the future as physical hazards evolve.

Primarily, the CVM relies on research that measures responses to a complete distribution of daily temperature or rainfall measures, rather than average conditions, to more accurately characterize how populations respond to local changes in those distributions. Using historical data on social and economic outcomes matched to historical climate data, dose-response functions can relate future climate conditions to projected outcomes (Step Two, next page). When controlling for other factors, such as social services, average population health conditions, and trends in energy infrastructure, these statistical models can isolate the role of climate change in individual components of human welfare in historical data.[xxxiv] This approach ensures that future projections are based

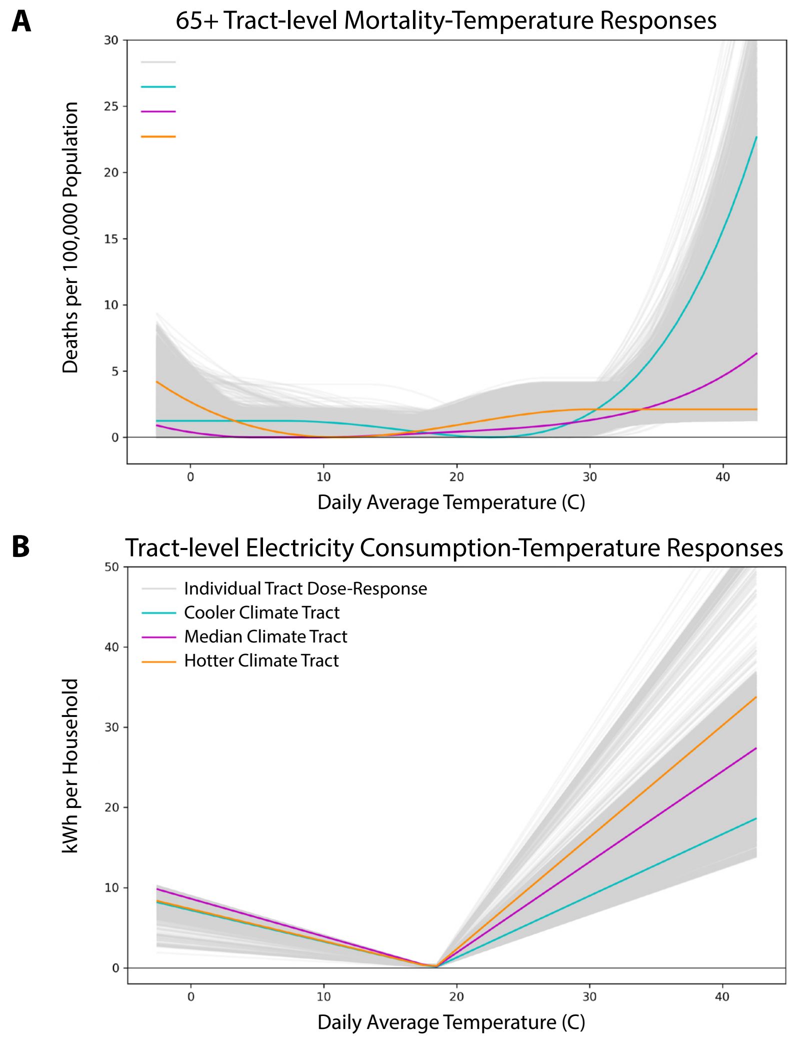


Figure 3: Dose-response functions for two components of the CVM. *These figures show census tract-level dose-response functions for two example components of the CVM. Each dose-response function shown in grey relates a key human welfare outcome (e.g., mortality rates) to daily average temperature. Select census tract dose-response functions are shown in colors to illustrate how vulnerability is influenced by long-run average climate conditions and by levels of income, among other factors. Panel A shows this dose-response relationship for changes in human mortality (deaths per 100,000 people) for populations over 65 with the teal line representing a lower-income tract, the pink line representing a median income tract, and the gold line representing a high-income tract. This shows that communities with higher incomes are far less vulnerable to the mortality risks of extreme heat than are communities with lower incomes. Panel B shows this dose-response relationship for changes in household electricity consumption (kWh) with the teal line representing a cooler census tract, the pink line representing a median climate census tract, and the gold line representing a hotter census tract. This shows that in hotter communities, increased penetration of air conditioning and other cooling technologies leads to larger electricity expenditures under higher temperatures than in cooler communities. In both panels, the grey lines represent dose-response functions for all 8,057 individual census tracts across California.*

on the best available estimates of how populations and economies have responded to historical fluctuations in climate conditions.

Step Two: Calculate the future impacts of climate change

Next, this set of category-specific dose-response functions is applied to present-day climate data and projected climate data for a midcentury time horizon.[6] Here, the “dose” of climate conditions a population is projected to experience in 2020 and 2050 generates corresponding “responses” based on today’s population characteristics. The difference between today’s dose-response and the future dose-response represents the impacts of climate change. Current demographic data is used because long-term projections for population changes are highly uncertain and currently unavailable at the census tract level. Moreover, this approach ensures that the CVM reflects differential vulnerability as reflected in today’s populations without imposing additional assumptions about how the demographics or socioeconomics of individual locations may evolve in the future.

This approach to modeling future climate is consistent with the approach developed as part of the Intergovernmental Panel on Climate Change’s (IPCC) 5th Coupled Model Intercomparison Project, which compares data generated by climate modeling research programs around the globe. Through a computationally intensive process called “downscaling,” these climate model outputs are transformed, bridging the gap between large-scale climate change and local or regional effects. This makes the downscaled, local California climate projections employed by the CVM consistent with the best available scientific estimates of how temperature change will evolve over the next three decades (Figure 4).

A moderate emissions scenario, RCP 4.5, is used to project future climate conditions. This scenario is consistent with the world’s countries meeting their current emissions reduction pledges under the Paris Climate Agreement. The CVM’s 2050 time horizon has the benefit of capturing the cumulative effect of current and near-term global greenhouse gas emissions on California’s climate system, driven by assumptions about currently available technologies and near-term political will. Under these parameters, the dose-response functions are used to quantify the effect of specific daily weather events on outcomes in each census tract. The results are annual impacts for the 2020 and 2050 time periods, expressed in physical units (e.g., mortality risk in units of deaths per 100,000 population or electricity consumption in kilowatt-hours). The difference between these physical units from 2020 to 2050, or the sector-specific impact of climate change, is monetized in Step Three.

[6] “Present-day climate data” refers to the long-run average of 2010-2030 climate conditions, while the “midcentury time horizon” is based on projected conditions in 2040-2060. For simplicity, we refer to these time horizons as “2020” and “2050,” respectively.

Change in annual average temperature from 2020 to 2050 under moderate emissions
degrees C

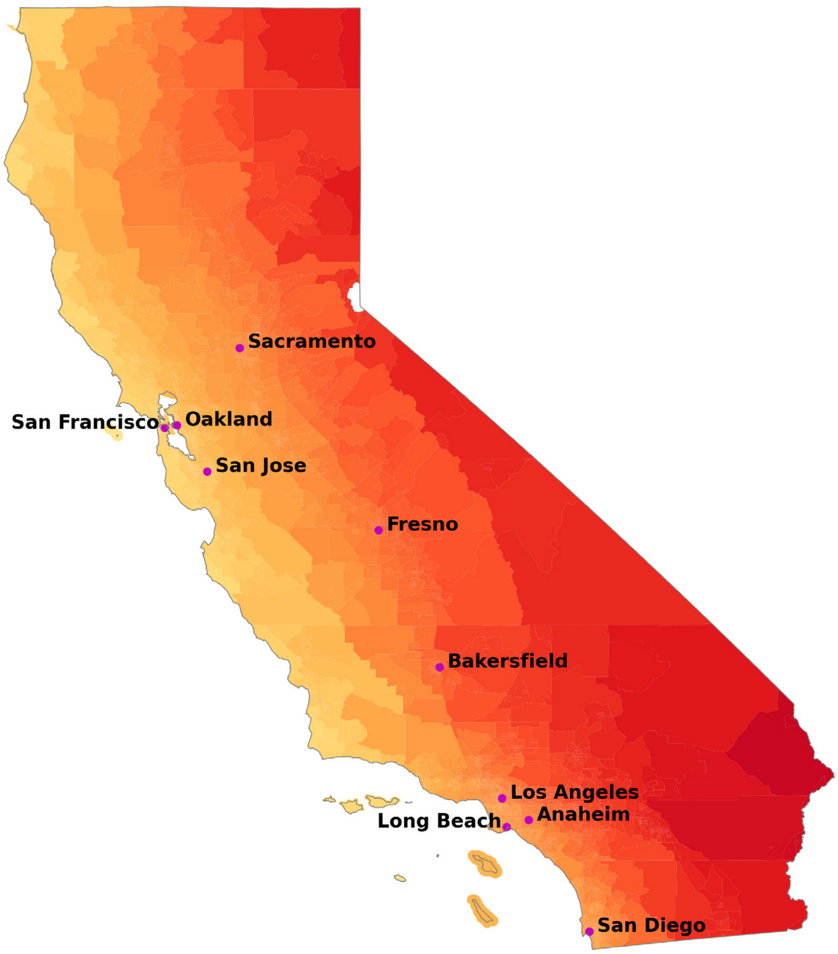


Figure 4: The CVM is estimated using downscaled California climate projections that are consistent with the best available scientific assessments of how warming will evolve in the future. *This map shows the projected annual average change in temperature by midcentury under a moderate emissions scenario (RCP 4.5) relative to current annual average temperatures. The difference between each census tract's response to future climate conditions (2040-2060) and current climate conditions (2010-2030) represents the projected impacts of climate change on human welfare in each category of the CVM. These values show median values across an ensemble of climate models that together account for uncertainty in projected warming (see Technical Appendix for details).*

3 Step Three: Assign monetary value to each impact

These census tract impacts are then valued in dollars using a category-specific methodology that captures economic impacts and human welfare effects. For example, changes in mortality rates are valued in dollars using a widely used, well-established federal measure of the value of statistical life.[7] Expressing impacts across categories in the same unit (dollars) allows us to account for the magnitude of each category's effect when summing across categories in later stages of the analysis (Step Four).

This approach captures both economic impacts and the potentially substantial non-market impacts of climate change on communities across California. For instance, impacts of warming temperatures on the number of hours worked by laborers are represented as the monetized value of labor disutility—measuring the discomfort workers experience when laboring under extreme climate conditions. By doing so, the CVM accounts for important welfare components of communities' vulnerability to climate change instead of only counting direct financial implications.

Monetization relies on assumptions regarding how to value both market and non-market impacts. In some categories, this is straightforward (e.g., the total change in monthly energy bills). Other categories require a set of critical assumptions, described in the Technical Appendix, such as computing labor disutility.

Converting climate change's impact on sectors of the economy to dollar values, such as increases in energy expenditures or mortality risk, is a technique used throughout the economics literature as part of the research underlying estimates of the social cost of carbon (SCC) and other greenhouse gases. The SCC is defined as the total monetary value of the damages imposed by the release of one additional ton of carbon dioxide, and it is used to compare the costs of emissions mitigation policies against their benefits. Like the CVM, the SCC relies on converting impacts to dollar values in order to aggregate climate change impacts across impact categories. However, unlike the CVM, the SCC combines the monetized damages of climate change from regions around the world into a single global metric, obscuring localized information on how damages vary from place to place. The CVM is designed to capture this local variation in the costs of climate change within a single region, the state of California.

While both are built from aggregations of category-specific estimates of climate change damages, the SCC and CVM differ in other important ways. For example, the CVM for each census tract is composed of near-term (2050) combined projected damages from climate change along a path of global emissions (RCP4.5). The SCC, on the other hand, is computed as the present discounted value of the long-term combined projected damages caused by emitting one marginal ton of CO_2, including damages starting in the present and continuing centuries into the future through the year 2300).

[7] For more details on the Value of Statistical Life, vetted and endorsed by the U.S. EPA since 2000, see the Technical Appendix methodology for estimating climate change's impact on human mortality.

Step Four: Add up values of impacts across categories and divide by census tract population

Valuing the impacts in monetary terms (Step Three) across all CVM categories of climate impacts allows for summing across categories to estimate a combined total. These combined monetized impacts are then reported per capita as a share of census tract-specific incomes (percent), ensuring that impacts in wealthy, high-population census tracts do not dwarf impacts in low-income, low-population census tracts by construction.

To implement this approach, total census tract monetized impacts are first divided by census tract populations to calculate monetized impacts per capita. This approach helps to normalize the CVM across various levels of the population in each of California's census tracts, ranging from 1,200 to 8,000 people. Each census tract's combined projected damages in 2050 are then reported as a share of their current income (% of census tract-specific per-capita income in 2019). This format accounts for current levels of economic inequality,[8] reflecting that the same dollar value of monetized impacts would be a more significant loss to a low-income household than a wealthy household.

Notably, the calculation of combined monetized impacts in each census tract accounts for uncertainty in how the climate will respond to increased concentrations of greenhouse gases, known as "climate sensitivity." Low-probability, high-impact climate change matters just as much, if not more, than those futures that are most likely to occur due to the greater risk of catastrophic impacts. An approach that ignores the probability of these catastrophic outcomes and focuses only on the average impact would fall short in assessing the vulnerability of California's communities, leaving them unprepared for these low-probability but costly impacts.

Probabilistic future climate projections are used to construct estimates of the median, or 50th percentile, impact across climate uncertainty.[xxxv] We provide the median rather than the mean because it avoids overly representing any outliers and represents a CVM that is "as likely as not." Additionally, the CVM includes estimates in each census tract of the monetized impacts under the less likely 75th percentile high impact future climates and 25th percentile low impact future climates, showing the spread of the middle half of the CVM distribution.[9]

[8] Per capita income in 2019 for census tracts across California ranges from $633 to $176,388, with a median of $32,181 ($2019). Source: American Community Survey.

[9] The 25th and 75th percentiles each have 1-in-4 odds.

5

Step Five: Report per capita climate impacts as a share of census-tract incomes (%)

The final CVM is the first metric in California specifically focused on quantifying the community-level impacts of a warming climate on human welfare. The CVM quantifies how vulnerable each California community is to the impacts of climate change and makes it possible to assess which communities benefit most from efforts to mitigate climate change to avoid the range of impacts on human welfare.

As noted, the four categories of climate change impacts included in the CVM estimates were chosen because of the availability of robust methods and data to quantify outcomes at the census tract level across California. Importantly, categories were only selected if existing methods and data enabled characterization of an individual census tract's differential vulnerability to the same climate hazard. Therefore, the impacts included in the CVM do not represent the total cost that climate change is likely to impose on individual and household welfare across California because some critical categories, such as the health effects of exposure to smoke from climate-driven wildfires and income losses due to agricultural productivity declines, cannot be feasibly quantified at census tract scale with existing research (see Chapter 4 for more discussion).

Chapter 4 – Categories of CVM Climate Impacts

Chapter 4 – Categories of CVM Climate Impacts

Climate change affects the health, well-being, and economic security of Californians. These impacts are uneven and localized. The CVM improves understanding of how socioeconomic characteristics and physical climate conditions within each census tract interact to create climate change vulnerability and quantifies future impacts to each census tract across four categories. The CVM is built from methods and data, detailed below, that make it possible to account for the differential capacity of each census tract to respond to climate shocks and stresses when quantifying outcomes under climate change. By combining these projected category-specific impacts and reporting total impacts in a format that accounts for existing economic inequalities, the CVM can provide context on the magnitude of risks facing Californians with a statewide scope and community-level resolution.

The CVM can provide context on the magnitude of risks facing Californians with a statewide scope and community-level resolution.

To determine the categories included in the CVM, the first phase of this project involved surveying the existing academic literature for categories of climate impacts to human welfare that are significant and quantifiable at the community level across the state. The categories identified as possibly able to meet these criteria were:

1. **the impact of daily temperature on all-cause mortality rates across different age groups;**
2. the impact of daily temperature on learning/educational attainment;
3. the impact of smoke exposure from climate-driven wildfires on morbidity;
4. **the impact of daily temperature on household electricity and heating fuels consumption, and resulting changes in energy costs;**
5. **the impact of daily temperature on the number of hours people work, especially in "high-risk" outdoor sectors;**
6. the impact of daily temperature and precipitation on agricultural crop yields, and resulting changes in food supply;
7. **the impact of sea-level rise on expected future coastal flood-related property damage;**
8. **the impact of changes in precipitation on expected future inland flood-related property damage; and**
9. the impact of climate-driven wildfire burn risk on property damage.

From there, the scope was narrowed to categories that can be measured, based on existing scientific research, in a way that accounts for differential vulnerability to climate conditions. For example, a heat wave's effect on health at the census tract level depends on the existing socio-demographic characteristics of that census tract—geographic location, starting temperature, and income—not just the intensity of the heat wave. Those categories fitting the criteria are in **bold** above. For other (non-bolded) categories, prior research indicates that climate change is likely to have important consequences, but there is insufficient research available to characterize climate vulnerability and change impacts at a census tract level.

Below, the methodology for estimating impacts in each category is overviewed. More detailed methods can be found in the Technical Appendix.

Impact of daily temperature on all-cause mortality rates across different age groups

Hot and cold temperatures are deadly, with heat waves and cold spells worsening underlying conditions. Those most vulnerable during periods of extreme temperatures are people who have pre-existing respiratory and cardiovascular conditions, like high blood pressure, asthma, or lung problems. Climate warming is anticipated to bring a reduction in cold-related mortality, but an increase in heat-related mortality. Excessively hot nights have been shown to interrupt sleep, leading to immune system damage and a higher risk of chronic disease. Heat places the body under a lot of stress and is particularly dangerous to very young children, those over 65, people experiencing homelessness, and those who cannot afford air conditioning.

The risks that extreme temperatures pose to human health are often misreported, since individual deaths are rarely attributed to temperature surges. Therefore, public health officials and policymakers have historically had insufficient information about the mortality risks of climate change. The level of vulnerability of populations to the emerging heat stress brought about by climate warming will depend on the severity of the temperature extremes, the age distribution of the underlying population, and on society's adaptive response, all of which must be measured at a very local scale. To account for the many investments and behaviors that compose society's adaptive response, we empirically estimate how different climates and different incomes, which are proxies for adaptive investments like air conditioning penetration and emergency preparedness, translate into differential vulnerability to weather shocks in historical data. For example, people living in temperate climates (e.g., the San Francisco Bay Area) do not have the technologies, institutions, or behavioral patterns that enable them to cope well with extreme heat, while populations living in hot climates (e.g., the Central Valley) are better prepared for heat wave events.

Historical estimates of the mortality-temperature relationship across locations can help shed light on whether resilience measures can mitigate the risk of heat-related mortality. Studying the potential effects of future climate change on both heat-related and cold-related mortality can help the public health community in California assess where risks will be the most severe and mobilize resources in local communities to improve resilience.

The CVM analysis of the mortality impacts of climate change across California relies on estimates from Carleton et al. (2022)[xxxvi] in combination with data collection and methods adaptations that are specific to the state of California. Specifically, the CVM uses the empirical estimates in Carleton et al. along with data on demographic and income information from the Census to calculate climate change's effect on future age-specific, all-cause mortality rates across the state.

Carleton et al. provides a globally representative assessment of mortality impacts of climate change, econometrically estimating the effects that extreme cold and extreme heat have on death rates separately for each of three age groups (<5, 5-64, >64). The analysis uses comprehensive historical mortality records from the largest sub-national vital statistics database in the world, detailing 232.9 million deaths across 40 countries accounting for 38 percent of the global population, combined with decades of detailed daily and local temperature observations, which account for both daytime and nighttime temperatures. The authors find a U-shaped relationship in which both extreme heat and cold increase mortality rates, particularly for those over the age of 64. A single hot day (35C/95F) increases annual mortality rates by 4 deaths per 1 million people relative to a moderate (20C/68F) day, while cold days (-5C/23F) increase the annual mortality rate by 3 deaths per 1 million people.

However, Carleton et al. shows that these relationships are strongly modified by the climate and income levels of the affected population, demonstrating that adaptation decisions have an important influence over the sensitivity of a population to extreme temperatures. This leads to substantial differences in climate vulnerability between places, depending on how wealthy the population is and how warm the average climate is. This modeling of differential vulnerability enables us to use these estimates, in combination with custom climate, demographics and socioeconomic data collection for California, to characterize the differential effects of climate change on communities across the state.

To calculate mortality impacts in the CVM, these empirical mortality-temperature relationships are used to generate projections of the future impacts of climate change on mortality rates at the census tract level. The CVM analysis based on Carleton et al. proceeds in four steps:

1. **Collect and harmonize socioeconomic and demographic data for all census tracts in California.** Since the model in Carleton et al. shows that income, average climate, and demographics shape the dose-response function for mortality, the CVM analysis needs measures of these variables at the census tract level to determine the community-level vulnerability of mortality risk to heat and cold. Furthermore, the variables used at the census tract level must be defined in the same way as those used to estimate the response functions in Carleton et al., or a close proxy. For example, GDP (Gross Domestic Product) per capita is the measure of income used by Carleton et al. However, the highest attainable resolution of this measure is provided at the county level.[xxxvii] Given the CVM aims to capture income differences within a county, per capita income, a close proxy to GDP,[xxxviii] is used at the census tract level.[xxxix] Per capita income is then scaled to the tract level using the

county-level GDP per capita data. Other series are more straightforward to recreate at the census tract level. Census tract level population counts[xl] in 5-year bins construct the 0-4, 5-64, and 65+ age groups needed to estimate the age-specific response functions in Carleton et al. (2022). Census tract level long-run climate variables are constructed by taking a population-weighted 30-year Bartlett kernel of daily average temperatures, following Carleton et al. (2022).[xli]

2. **Construct census tract-level dose-response functions.** Each tract-level dose-response function shows a community's unique relationship between age-specific mortality rates and daily temperature (precipitation is used as a control in Carleton et al. but is not shown to be a quantitatively important driver of mortality). This analysis uses regression coefficients directly from Carleton et al. and uses data on the average GDP per capita and average long-run climate for each census tract as described above to construct tract-level dose-response functions.
3. **Project future changes in mortality rates due to climate change.** Dose-response functions from Step Two are then combined with a set of 32 climate model projections[10] to generate a probabilistic set of projected impacts of climate change on mortality rates at tract level.[xlii] These estimates correspond to the year 2050 and emissions follow the RCP 4.5 scenario.
4. **Monetize mortality risk changes.** Projected impacts of climate change on mortality rates are then monetized to determine the costs of excess mortality risk in 2050. This monetization uses the U.S. EPA value of a statistical life (VSL).[11] EPA takes an approach to estimating the VSL that has been vetted and endorsed by the agency since 2000 (see Technical Appendix for further detail).

Impact of daily temperature on household electricity and heating fuels consumption, and resulting changes in energy costs

Energy for cooling and heating plays a crucial role in the ability of Californians to cope with extreme temperatures. Demand for heating and cooling fluctuates hourly, daily, and seasonally in response to outdoor

[10] We use a set of 21 high-resolution, bias-corrected global climate projections that provide daily temperature and precipitation to the year 2099 from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP). As this set of 21 climate models systematically underestimates tail risks of future climate change, we assign probabilistic weights to climate projections and use 11 surrogate models that describe local climate outcomes in the tails of the climate-sensitivity distribution.

[11] The VSL used in the CVM is of $10.95 million, which is from the 2012 U.S. EPA Regulatory Impact Analysis (RIA) for the Clean Power Plan Final Rule. This RIA provides a 2020 income-adjusted VSL in 2011 USD, which we convert to 2019 USD.

ambient temperatures. How people alter their energy use in response to heat waves and cold spells is shaped by access to technology, such as heaters, fans, and air conditioning units. Californians also make decisions about their energy use based on what they can afford to budget for energy bills. In other words, the relationship between temperature and energy use looks very different depending upon household income and on the average climate conditions.

Hotter temperatures will increase the demand for residential and commercial air -conditioning powered by electricity. As the climate warms gradually, air conditioning will become increasingly critical in more temperate areas of the state, such as the Bay Area. At the same time, in colder climates, warmer winter temperatures as a result of climate change will reduce the demand for heating fueled by natural gas.

The CVM relies on estimates from Auffhammer (2022)[xliii] to analyze how changing climate conditions will impact household energy expenditures at the census tract level. Auffhammer uses two independent sets of proprietary household billing data at the zip code level across California to measure household-level expenditures on both electricity (used for heating and cooling) and natural gas (primarily used for heating). This analysis links energy expenditures from nearly 2 billion energy bills to daily temperatures in a regression analysis that models differential vulnerability to heat and cold events based on household income and average climate conditions. As such, it represents the highest resolution and most comprehensive assessment of energy consumption responses to climate change in California, while also capturing differential vulnerability to weather events at zip code level.

For the CVM, a set of results from Auffhammer's analysis is adapted to (a) estimate impacts at census tract level, as opposed to zip code level; and (b) estimate impacts for all tracts in California, as opposed to only the subset of zip codes for which billing data were available. Because multiple modifications of Auffhammer's analysis are required to meet these two goals and to ensure consistency with the rest of the CVM, some components of this method are under development and are noted as such below.

In our analysis, electricity and natural gas are modeled independently, as they are in the original publication by Auffhammer. Expenditures on electricity and expenditures on natural gas are likely to respond very differently to climate change, impacting different communities unevenly, given highly heterogeneous baseline climates, incomes, and demands for heating and cooling. However, because our process for adapting results from Auffhammer's work to the CVM is similar across these two outcomes, we describe our methodology for both electricity and natural gas jointly.

Expenditures on electricity and expenditures on natural gas are likely to respond very differently to climate change.

The CVM analysis based on Auffhammer (2022) proceeds in four steps:

1. **Collect and harmonize socioeconomic, energy expenditure, and climate data for all census tracts in California.**

Auffhammer's analysis shows that income and average climate shape the dose-response function for both electricity and natural gas expenditures. Therefore, measures of these variables at census tract level are used to determine the community-level vulnerability of energy expenditures to both heat and cold. For income, the same household income series[xliv] from Auffhammer's analysis is used but at the higher resolution census tract level. For climate data, Auffhammer uses the PRISM climate dataset. In this analysis, PRISM is used to construct climate variables at the census tract level, matching the definitions used in Auffhammer precisely.

2. **Construct census tract-level dose-response functions.** Each tract-level dose-response function shows a community's unique relationship between the level of household electricity consumption (kWh) and daily temperature, as well as between the level of household natural gas consumption (therms) and daily temperature (precipitation is used as a control in Auffhammer's work but is shown to not be quantitatively important). This analysis uses regression coefficients directly from Auffhammer's estimates of average income per capita and average long-run climate for each census tract as described above to construct tract-level dose-response functions.
3. **Project changes in future electricity and natural gas expenditures due to climate change.** Dose-response functions from Step Two are then combined with a set of 32 climate model projections to generate a probabilistic set of projected impacts of climate change on energy consumption at tract level. xlv These estimates correspond to the year 2050 and emissions follow the RCP 4.5 scenario.
4. **Monetize changes in electricity and natural gas consumption.** To translate those impacts into absolute changes in expenditures, we use 2020 state-level average residential prices from the Energy Information Administration (EIA) to convert into dollars.[12] For consistency with other categories, we converted the 2020 EIA values to $2019.

Impact of daily temperature on the number of hours people work, in both "high-risk" outdoor sectors and "low-risk" sectors

Rising average temperatures will make it harder to sustain optimal working conditions for outdoor and indoor labor. Higher temperatures can change the amount of time allocated to various types of work as individuals spend more time indoors to beat the heat, or as outdoor laborers take more frequent breaks to cool off. Climate-related factors can also affect worker performance, affecting cognitive capacity and endurance. Increased use of

[12] Specific EIA data used to estimate energy costs can be found in the Technical Appendix.

air conditioning for indoor labor and schedule changes for outdoor labor can mitigate some, but not all, of the effects.

Not all workers will be equally affected as the impact of climate differs across sectors of the economy. Workers in agriculture, construction, utilities, and manufacturing are among the most exposed. Workers in these "high-risk" sectors are at particular risk of heat stress because of the internal body heat produced during physical labor. Extreme heat stress, brought on by more intense or extended days of exposure to high temperatures, can induce heat exhaustion or heat stroke and can significantly reduce ability to carry out daily tasks. According to Center for Disease Control records, from 1992–2006 there were 423 worker deaths attributed to heat exposure in the US, nearly a quarter from the agriculture, forestry, fishing, and hunting industries.[xlvi]

Higher temperatures and heat strain, however, can also impact workers in stores and offices as well. Thermal conditions inside commercial buildings are often not well-controlled and can vary considerably over time as outdoor conditions change, making it difficult to ensure optimum temperatures for worker comfort and safety.

The CVM analysis of the labor impacts of climate change across California relies on the estimates from Rode et al. (in prep)[xlvii] to calculate climate change's effect on the number of hours that people work. Rode et al. provides a globally representative assessment of labor force impacts of climate change, systematically evaluating the nonlinear response of labor supply to daily temperature separately for workers in "high-risk" sectors (i.e., weather-exposed sectors—agriculture, mining, construction, and manufacturing) and "low-risk" sectors (all others). The analysis uses daily and weekly worker-level labor supply data from time use and labor force surveys in seven countries (USA, Mexico, Brazil, France, UK, Spain, and India), combined with decades of detailed daily and local temperature observations.

To calculate labor impacts in the CVM, we use these sector-specific labor supply-temperature responses to generate projections of the future impacts of climate change on the number of hours people work at the census tract level (see Figure 5).

The CVM analysis based on Rode et al. proceeds in four steps:

1. **Collect and harmonize sectoral employment data for all census tracts in California.** Since the model in Rode et al. shows that the sector of employment shapes the dose-response function for labor supply for the working age population, the CVM analysis needs a measure of the share of the workforce employed in high-risk versus low-risk work for each census tract. Specifically, census tract data on civilian population employment by industry and occupation following the sector definitions in the analysis by Rode et al., is used to create counts of high-risk and low-risk workers in each census tract.[xlviii] Individuals in the agriculture, forestry, fishing and hunting, and mining; construction; manufacturing; and transportation and warehousing, and utilities sectors are considered high-risk workers while all others are categorized as low-risk.

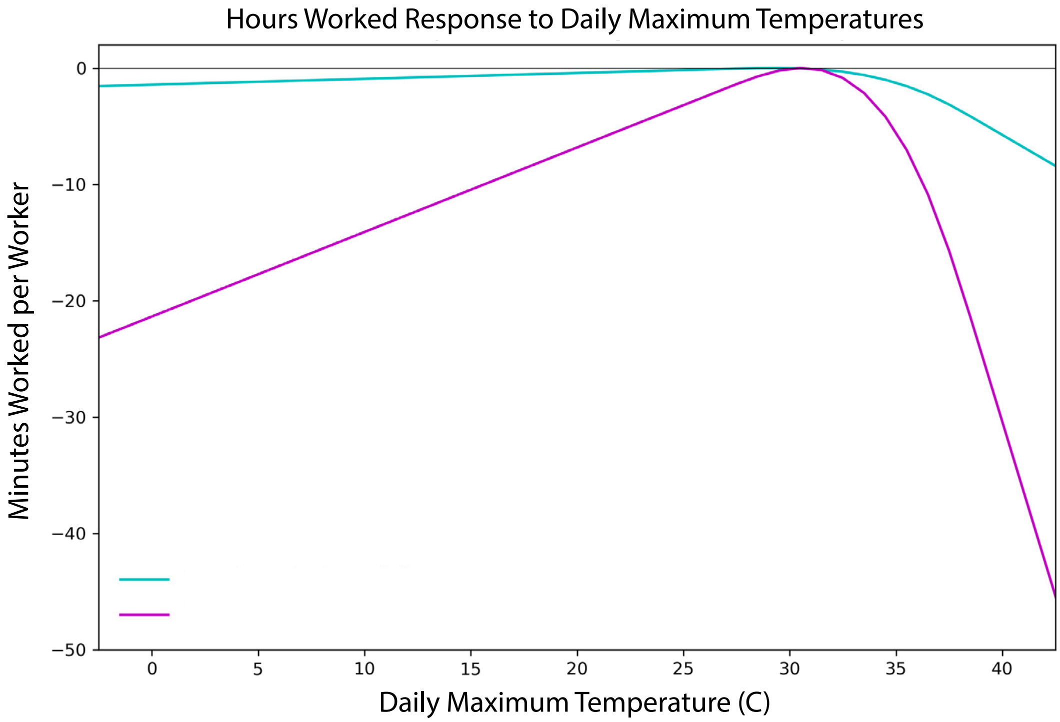


Figure 5: The dose-response relationships between daily maximum temperature and hours worked in high-risk and low-risk sectors. *This figure shows the sector-specific temperature dose-response functions quantifying how minutes worked per day by laborers changes with daily maximum temperatures. These dose-response functions are used to generate projections of the future impacts on climate change on the number of hours people work. Individuals working in jobs in weather-exposed sectors including agriculture, construction, utilities, and manufacturing are designated "high risk" and the relationship between work time and daily maximum temperature for these workers is represented by the magenta line. All other jobs are designated "low risk" and the relationship between work time in these sectors and daily maximum temperature is represented by the teal line. The plot shows that workers in "high risk" sectors are much more sensitive to both extremely hot and extremely cold days than workers in "low risk" sectors.*

2. **Construct dose-response functions.** Each dose-response function shows a community's relationship between labor supply for the working age population and daily maximum temperature (precipitation is used as a control in Rode et al., but not shown to be quantitatively important). This analysis uses regression coefficients directly from Rode et al. and

1. estimates of workforce composition across high- and low-risk sectors as described above to construct dose-response functions. Following Rode et al., the two dose-response functions—a high-risk and a low-risk response function—are shared across all census tracts, but workforce composition across these two employment sectors is accounted for at the tract level.

3. **Project future labor supply under climate change.** Dose-response functions from Step Two are then combined with a set of 32 climate model projections to generate a probabilistic set of projected impacts of climate change on labor supply at tract level, accounting for differences in workforce composition and climate across census tracts. These estimates correspond to the year 2050 and emissions will follow the RCP 4.5 scenario.
4. **Monetize welfare effects of labor supply changes.** Projected impacts of climate change on labor supply are then monetized to determine the welfare costs of excess heat to laborers in 2050. Specifically, a simple labor market model is used to translate minutes of labor supply lost into a measure of the monetary value of the disutility of working under extreme climate conditions. To implement this, the CVM analysis follows Rode et al. by multiplying the time lost due to climate change by the wage rate and by the Frisch elasticity of labor supply, a coefficient that describes how workers alter their labor supply when the wage rate changes.[xlix] The wage rate used is census tract specific.[l]

Impact of climate change on expected future coastal and inland flood-related property damage

Flood risk is increasing in the state of California. Higher average sea levels due to climate change are leading to elevated risk of tidal flooding and higher storm surges in coastal communities. Inland communities also see increased risk of flooding, with climate change altering precipitation patterns. Wet Pacific storm patterns bring heavy rain that can trigger debris flows and property damage. In particular, plumes of moisture known as atmospheric rivers, notorious for deluges of rain, are increasing in frequency and intensity as heat increases the atmosphere's capacity to hold moisture.

Our analysis of the flooding impacts of climate change across California relies on the estimates from the First Street Foundation (FSF) Flood Model (FSF-FM).[li,lii] The FSF-FM finds that over the next 30 years, the number of properties with the risk of flooding will increase by 5.5%, bringing the total number of properties with substantial risk to more than 1.15 million compared to 1.09 million properties currently.[liii] Central Valley cities, including Sacramento, see riverine and stormwater flood risk in FSF's modeling, as the dams and levees designed to protect the city often fail, and drainage issues cause flooding in some areas during storms.[liv] FSF's data also shows that 20% of properties in the city of Los Angeles are at some risk of flooding, while 100% of properties in Yuba City are at risk of flooding.[lv]

The FSF property-level flood damage estimates are developed in Armal et al. (2020)[lvi] and Porter (2021).[lvii] Unlike other categories in which we calculated census tract level impacts, monetized data was provided at this aggregation. Below, we overview their methodology for estimating flood hazards under climate change and their methodology for estimating annual average monetary losses due to flood hazards. FSF-FM estimates property and structural damage from coastal flooding due to storm surge and tides and from inland flooding due to overtopping of riverbeds (fluvial flooding) and rainfall (pluvial flooding), taking into account adaptive measures such as levees, and incorporating changing rainfall and tropical cyclones, as well as rising sea levels due to climate change in the future. Damage estimates from flooding depend on information about aggregate flood depths from each of these physical hazards and on estimates of the damage incurred at different flood depths.

Flood hazard data

Flood depth hazard data for the RCP 4.5 moderate emissions scenario is from the First Street Foundation (FSF) FloodFactor database, which relies on the FSF-FM. This dataset represents a joint modeling effort between FSF, Rhodium Group, Fathom Global, and WindRiskTech and is documented in Bates et al. (2020)[lviii] and FSF-FM Technical Documentation[lix] and is briefly described here. Changes in future climate are derived from the IPCC's 5th Coupled Model Intercomparison Project (CMIP5) global climate models under emissions pathway RCP 4.5, and from the Global Daily Downscaled Projections from NASA Earth Exchange (NASA/NEX-GDDP; Thrasher et al. (2012)[lx] statistically bias corrected and downscaled CMIP5 global climate models under RCP 4.5).[13] The flood depth modeling approach incorporates the following additional methods and data sources:

1. Changes in tropical cyclone activity (including associated rainfall and wind fields) from WindRiskTech, methodology published in Emanuel (2021),[lxi] and based on climate change from CMIP5 global climate models;
2. Changes in tropical cyclone precipitation fields modeled by Rhodium Group using WindRiskTech's changes in tropical cyclones and rain field model;[lxii]
3. Changes in water levels from storm surge modeled by a modified version of GeoCLAW[lxiii] operated by the Rhodium Group;[lxiv] and
4. Changes in river overtopping (otherwise known as "riverine" or "fluvial flooding") and rain-caused (otherwise known as "pluvial") flooding due to changes in CMIP5 precipitation patterns, modeled by Fathom Global.[lxv]

Damage data

For each return period frequency and time period in the flood hazard data set described above, FSF estimated losses based on depth-damage functions compiled and estimated from several sources. These include the publicly available Hazus-MH Flood Model[lxvi] and internal FSF estimates based on historical National Flood Insurance Program claims data from Armal et al. (2020)[lxvii] and Porter (2021).[lxviii] These depth-damage functions distinguish vulnerability based on a number of structure characteristics and were applied at the structure level, using building exposure data compiled from Hazus-MH, Attom, and other sources. Building values were estimated using the FSF Automated Valuation Model (AVM) (see Armal et al. 2020, Porter 2021). The per-structure losses for each return period

[13] This makes the flooding category impacts completely consistent with the global climate model projections used in all other categories.

frequency were then interpolated into an extreme value distribution, resampled to estimate average annual losses (AAL), and aggregated to California census tracts for incorporation into the CVM.

Limitations of the CVM

The categories of impacts included in the CVM do not represent the total cost that climate change is likely to impose on individual and household welfare across California, because some important categories cannot be feasibly quantified at the census tract level across the state with existing research. Unquantified climate impacts have material impacts on California's communities and may vary across regions and communities, highlighting the need for new analyses to identify their local impact.

Outreach to environmental justice advocates and community groups has highlighted physical climate damages that are not included in the CVM but represent material impacts to the lived experience of California communities. Specifically, the CVM does not capture any impacts related to:

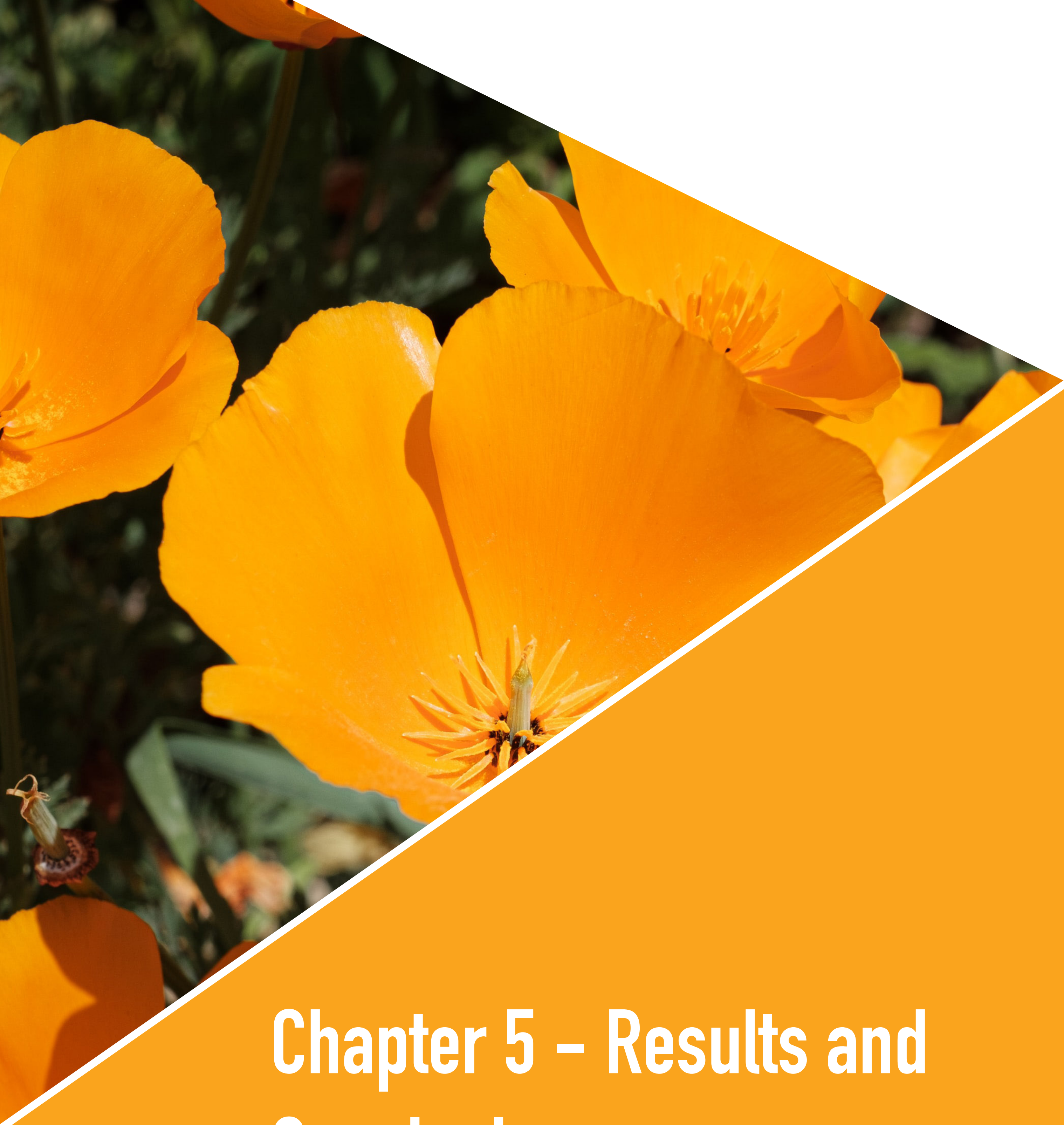
- water scarcity or drought;
- winter storm activity;
- wildfire activity or smoke exposure;
- urban heat islands;
- ozone increases associated with increased temperatures;
- food scarcity; and
- Tribal land impacts.

We acknowledge that these unquantified impacts could alter the CVM's magnitude and the distribution of impacts to human welfare across the state. For instance, wildfire activity and smoke could affect the number of hours worked, mortality, and electricity used for indoor air purifiers and air conditioners. Urban heat islands—metropolitan areas that are hotter than surrounding rural areas due to less tree cover and impervious dark surfaces, such as parking lots and roads that radiate more heat—could prevent water from soaking into the ground during storm events, leading to more inland flooding. While this list of unquantified impacts is not exhaustive, additional research will be needed to identify their differential impact on California's diverse communities.

The CVM is also limited by geographic resolution. While identified physical climate damages at the census tract level is a research advancement, it may obfuscate the differential impact to communities with vastly different socio-demographic characteristics that are located within the same census tract. Continuing to increase the geographic granularity of climate impact research and data will only improve the understanding of how climate change impacts local communities. In addition, the geographic footprint of census tracts can be quite large in rural areas, where census block-level information may provide more meaningful, real-world assessment of climate impacts. The CVM is also limited by the availability of socioeconomic data even on geographies of similar scale to census tracts, resulting in a gap in understanding of the impacts of climate change on human welfare within the many Tribal communities in California. Additional research and data are needed to ensure that every California community is appropriately represented, especially historically underserved communities.

Finally, there are impacts that may be

significant to specific geographic regions—including the impact of changes in water quality on fishing in Indigenous communities—that have not yet been scientifically evaluated at scale across the state of California. As climate economics research continues to mature, the CVM can be expanded to include additional categories and improve the coverage and granularity of communities, offering a more comprehensive assessment of vulnerability.



Chapter 5 – Results and Conclusions

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The CVM's goal is to quantify the costs of climate change on society in terms of human welfare, making it possible to assess the magnitude of damage to California's communities and the relative vulnerability of each census tract. This chapter presents a summary of the statewide results from each category of climate change impacts analyzed, and a summary of CVM findings, concluding with recommendations for application of the CVM and future research priorities to expand the scope of the metric.

Effects across key categories of climate change's impact on human welfare

Figure 6 shows census tract level maps of the median estimated annual effects of climate change in 2050 for each of the components of the CVM under a moderate emissions scenario. Overall, mortality risk is likely to be the dominant factor in the CVM, given that the impacts of climate change on death rates are more damaging to human welfare (panel A) than the effects in other categories (panels B-F). Human mortality risk is projected to increase the most in the San Francisco Bay Area, in the greater Los Angeles area, and throughout the Central Valley and southeastern regions of the state. Some colder regions at higher elevations are projected to experience reductions in mortality risk due to climate change, as the frequency of extreme cold declines.

Looking across the categories of climate change impacts in Figure 6, it becomes clear that vulnerability to climate change is closely tied to the climate, demographic, and socioeconomic conditions in each census tract. In other words, drivers of vulnerability are category-specific and can differ substantially across categories of climate change impacts.

Drivers of vulnerability are category-specific and can differ substantially across categories of climate change impacts.

Human mortality impacts of climate change, the most significant category of CVM by magnitude, are strongly associated with census tract-level demographics. Because the dose-response functions in this category show older individuals are more susceptible to heat stress, in part due to the higher prevalence of pre-existing conditions relative to other age groups, census tracts with a greater share of the population aged 65 and up are estimated to have higher CVMs on average. Figure 7 demonstrates that tract-level climate change impacts are strongly tied to the proportion of the census tract's population that is over 64 years of age. While children under age 5 are also more vulnerable to heat, they make up a small share of California's overall population and therefore do not drive overall human mortality impacts. The income level[14] of a tract also influences the human mortality dose-response functions, with wealthier areas estimated to have greater adaptive capacity to extreme heat.

[14] Measured in Gross Domestic Product (GDP) per capita.

A Human Mortality Impacts, Change in Annual Deaths per 100,000 Population

B Hours Worked, High-risk Sectors, Change in Average Annual Hours per Worker

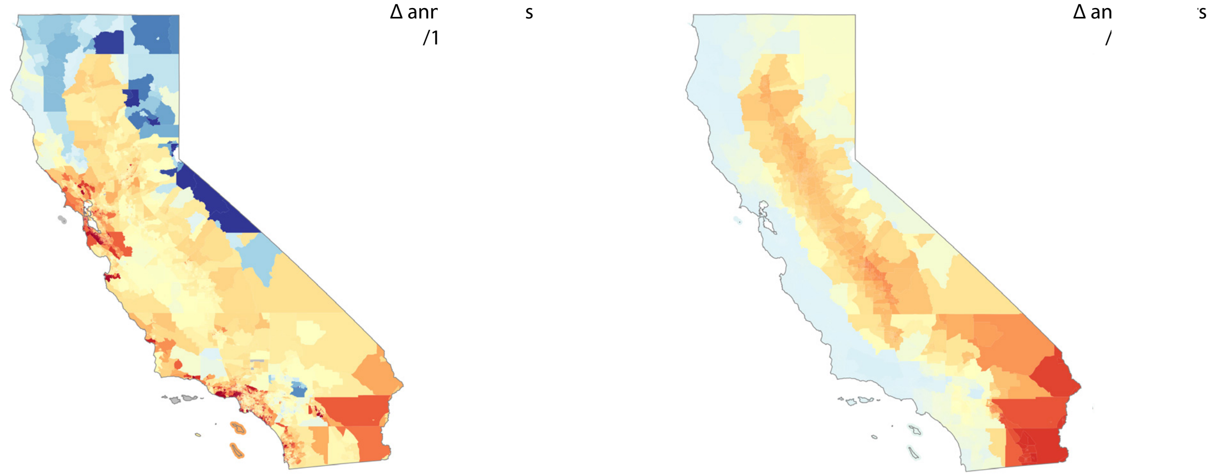

Figure 6: Climate change impacts on human welfare that are considered in the Climate Vulnerability Metric. *Maps show median estimates of the annual effects of climate change in 2050 under a moderate emissions scenario (RCP 4.5) for all categories composing the CVM. Units vary across impact categories. For example, impacts of climate change are reported for mortality as a change in annual deaths per 100,000, while impacts for natural gas consumption are reported as a change in household annual expenditure on natural gas. The maps show spatial variation of vulnerability to climate change across census tract and category, which is driven by differences in climate, demographic, and socioeconomic conditions. In all maps, shades of orange and red indicate detrimental outcomes due to climate change (e.g. higher mortality risk, lower hours worked), whereas shades of blue indicate beneficial outcomes. Detrimental impacts are visible across the majority of the state for all categories except natural gas consumption, as consumption of heating fuels is decreased due to climate change. Other exceptions to this are regions of decreased mortality risk in northern and northeastern California and increased hours worked along the coastline for high-risk sectors.*

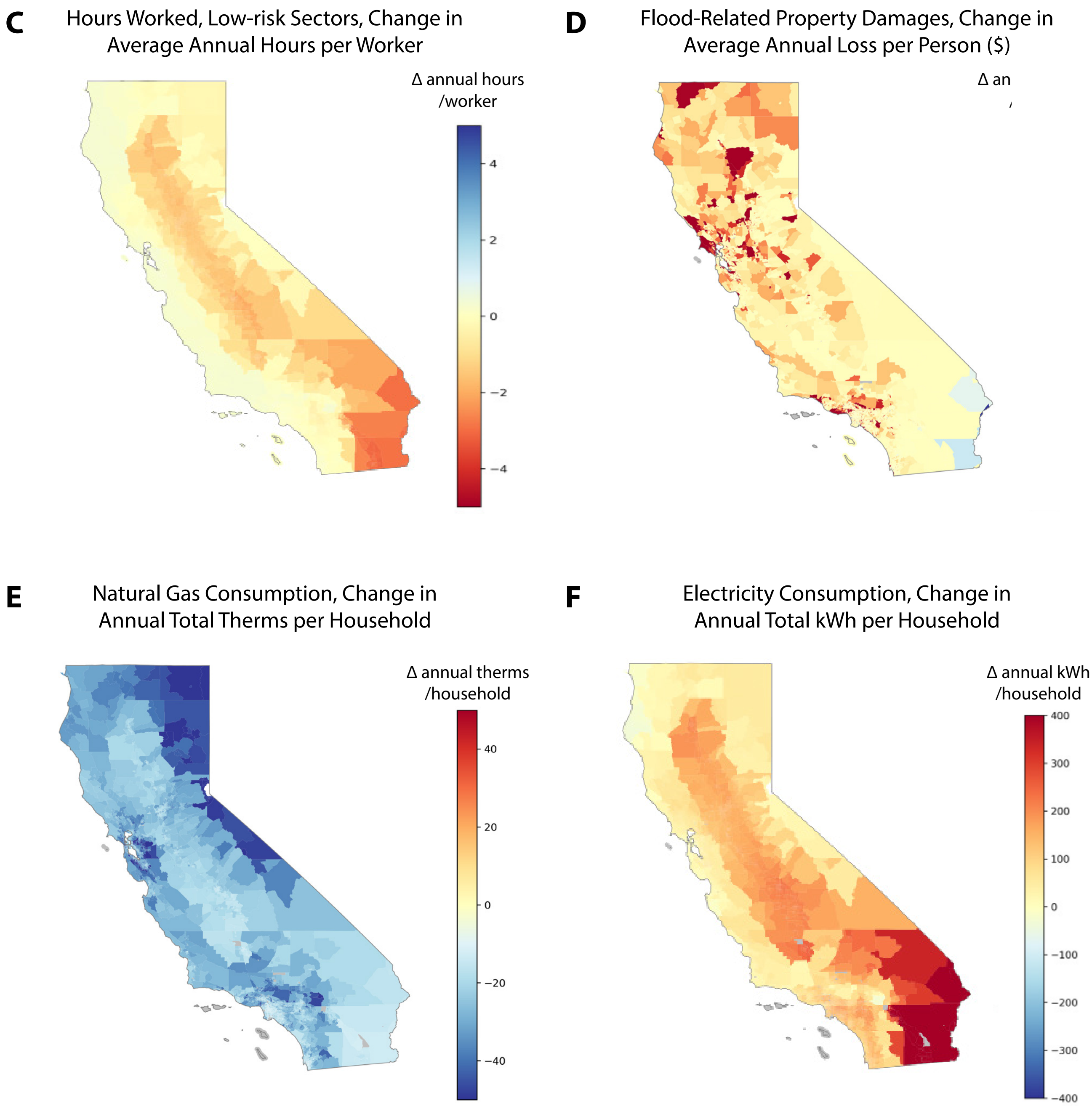

Figure 6 continued.

However, within California, census tracts with relatively older census populations tend to be relatively wealthier. This implies that overall, lower-income tracts have lower adaptive capacity to extreme heat but are not necessarily more vulnerable to the human mortality impacts because they tend to be younger. to extreme heat but are not necessarily more vulnerable to the human mortality impacts because they tend to be younger.

Figure 8 shows analogous results to Figure 7, but for hours worked, electricity expenditures, and natural gas expenditures. Figure 8, panel A shows that for hours worked (which is used to estimate the discomfort workers face while working under extreme conditions), census tract vulnerability to climate change is associated with workforce composition. Specifically, vulnerability is highest where the proportion of the workforce that is employed in high-exposure sectors, such as agriculture and forestry, is also highest. In tracts where most of the workforce is protected from the elements, risks of climate change to worker discomfort are low and indistinguishable from zero. As seen in Figure 6, average climate is also important for projected impacts on hours worked, as many coastal regions are not projected to reach temperatures sufficiently high to lead to lost working time.

In Figure 8, panels B and C show that for electricity and natural gas, today's climate conditions are strong determinants of vulnerability to future climate change. Locations that are hot and getting hotter face the largest projected impacts on electricity expenditures, while locations that are cold and getting warmer benefit the most from savings on their natural gas bills. Income is also a factor for these categories, as wealthier individuals tend to be able to afford cooling and heating services and therefore see larger expenditure responses to temperature. However, when we account for the fact that energy is a small share of a wealthy household's income by measuring impacts as a percent of tract-level income, we see that climate is a more important determinant of vulnerability. Flooding damages across California are heavily concentrated in a small proportion of census tracts. Most tracts have close to $0 estimated change in annual average losses driven by sea-level rise and changes in precipitation. Vulnerability in this category is in part determined by individual and community-level investment in infrastructure, such as sea walls, levees, pump stations, and tide gates, that are shown to make a property less exposed to potential flood damage. These structures, as well as adaptation projects (i.e., beach nourishment, coral and oyster reefs, property buyouts) are accounted for in the model used to estimate this category of impacts. Thus, properties that have not invested in these adaptation strategies are more vulnerable to climate change's impact on property damage. Overall, the correlation of census tract flooding damages with census tract income is not significant.

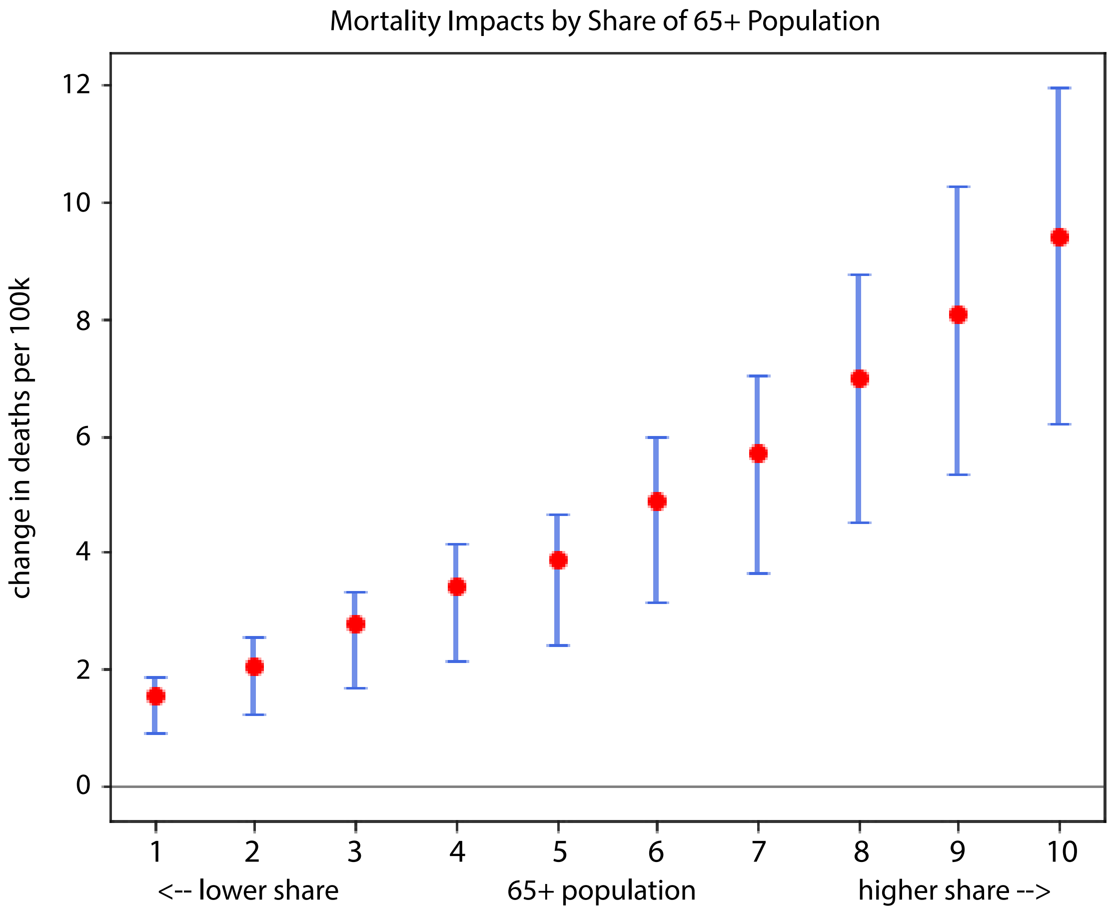

Figure 7: Vulnerability to climate change impacts on mortality risk is driven by census tract age demographics. *This figure shows that the estimated mortality damages from climate change are strongly correlated with the age demographics of a census tract's population. Whiskers on the left represent impacts for census tracts with the smallest share of people ages 65+, representing tracts with a younger age distribution. Whiskers on the right represent impacts for census tracts with the greatest share of people ages 65+, representing tracts with an older age distribution. This figure is made by dividing all census tracts into ten groups based on their share of the population 65 years and older. For each group, the blue bar represents the 25th to 75th percentile range of mortality impacts and the red dot represents the median mortality impact. Census tracts with a higher share of population that is 65 years or older are far more vulnerable to the mortality risks of climate change. While not shown, other factors can influence vulnerability to mortality risk, such as average climate and income within a tract.*

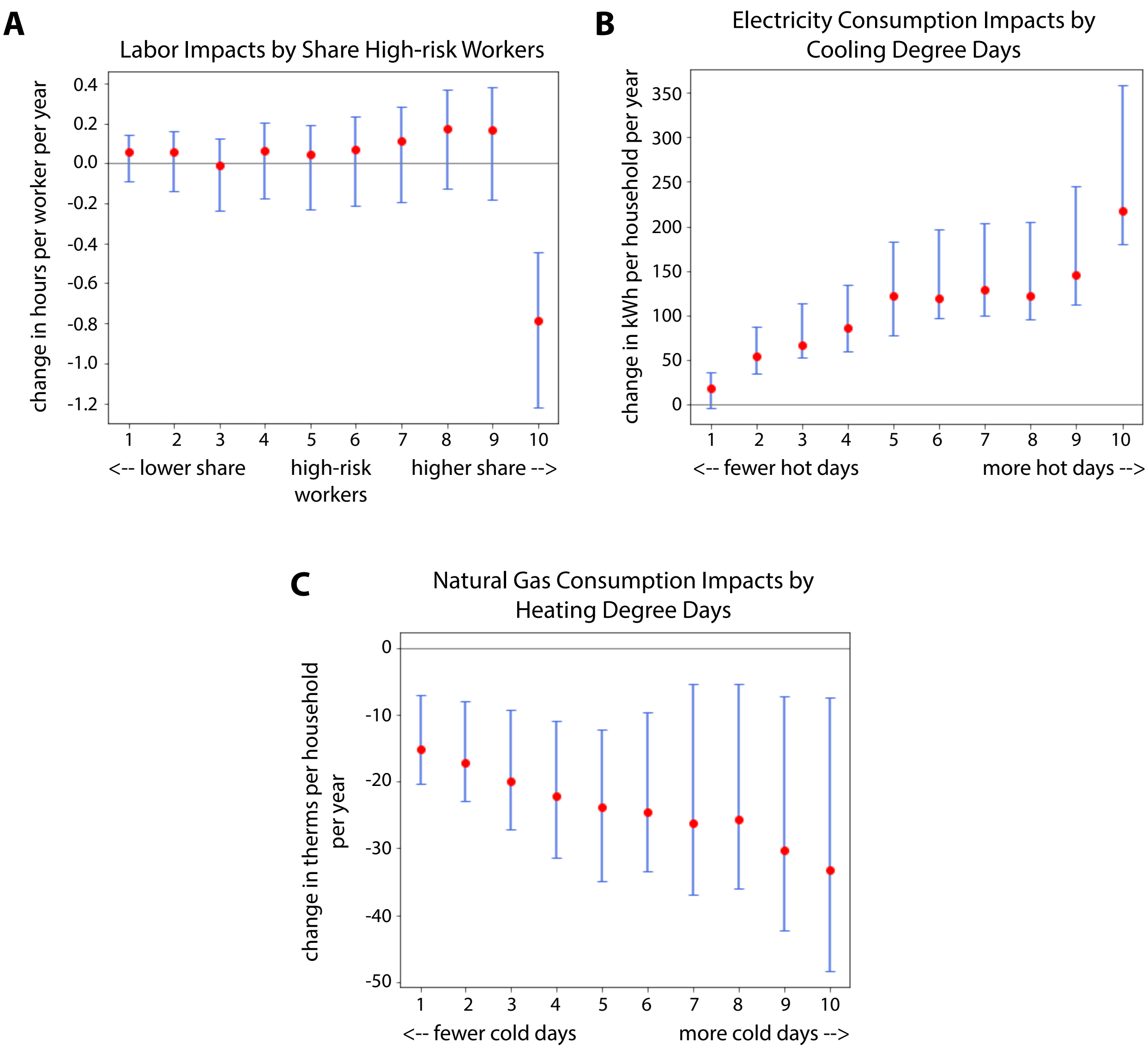

Figure 8: Drivers of vulnerability to climate change for hours worked, electricity expenditures, and natural gas expenditures. *This figure shows that the magnitude of estimated change in hours worked, electricity consumed, and natural gas consumed (per household) from climate change are driven by different determinants of vulnerability. Red circles and whiskers are constructed analogously to Figure 7. For hours worked, the sector of employment is critical: tracts with the highest share of the population working in high-risk sectors (such as agriculture and forestry) face the largest impacts on hours worked. For energy expenditures, today's average climate drives vulnerability: climate change impacts on electricity expenditures are larger for tracts that are hotter today, while climate change causes larger natural gas expenditure savings in tracts that are colder today. While not shown, other factors can influence vulnerability to damages in these three sectors, such as income and population density.*

The Climate Vulnerability Metric (CVM)

Figure 9 presents a map of the Climate Vulnerability Metric (CVM) at the census tract scale. As detailed in previous sections, the CVM is presented as damages of climate change as a share of 2019 census tract level income. That is, a value of 6 (solid red color on the map) indicates that the median climate change projection estimates a census tract will suffer annual damages in 2050 that amount to 6% of annual income. This figure is the sum of all category-specific estimates shown in Figure 6.

Figure 9 shows that climate change will have highly unequal impacts across Californian census tracts. While some regions in the southeast are estimated to suffer damages that exceed 5.7% of annual income, other high-elevation regions are estimated to see benefits of up to 10%. Some low-lying urban areas are estimated to be particularly vulnerable, while much of the central valley suffers at least moderate damages. The wide diversity of projected impacts underscores the importance of estimating climate vulnerability at a community level.

The wide diversity of projected impacts underscores the importance of estimating climate vulnerability at a community level.

Figure 10 again maps the CVM, but additionally highlights the contrast between census tracts that are designated as Disadvantaged Communities ("DAC", following the designation by the California Environmental Protection Agency (CalEPA),[lxix] for the purpose of SB 535[lxx]) versus those that are not. DAC tracts are outlined in black and have full color saturation in Figure 10, while all other counties are semi-transparent. This figure makes clear that most DAC tracts suffer negative impacts from climate change, unlike the many non-DAC tracts where climate change brings benefits from reductions in extreme cold. Moreover, DAC tracts are some of the most severely impacted, such as tract 06081606100 in central Riverside County, where damages reach 5.7% of annual income. In general, DAC tracts are projected to see larger impacts on hours worked and on electricity expenditures than non-DAC tracts, and to enjoy larger natural gas savings. However, flooding impacts are larger in non-DAC tracts, as are projected mortality impacts. The wide range of CVM values in DAC tracts is explained, in part, by the fact that CalEPA's designations are based on current environmental conditions, while the CVM is based on future climate conditions. Thus, as environmental conditions continue to evolve into the future, DAC designations will also evolve.

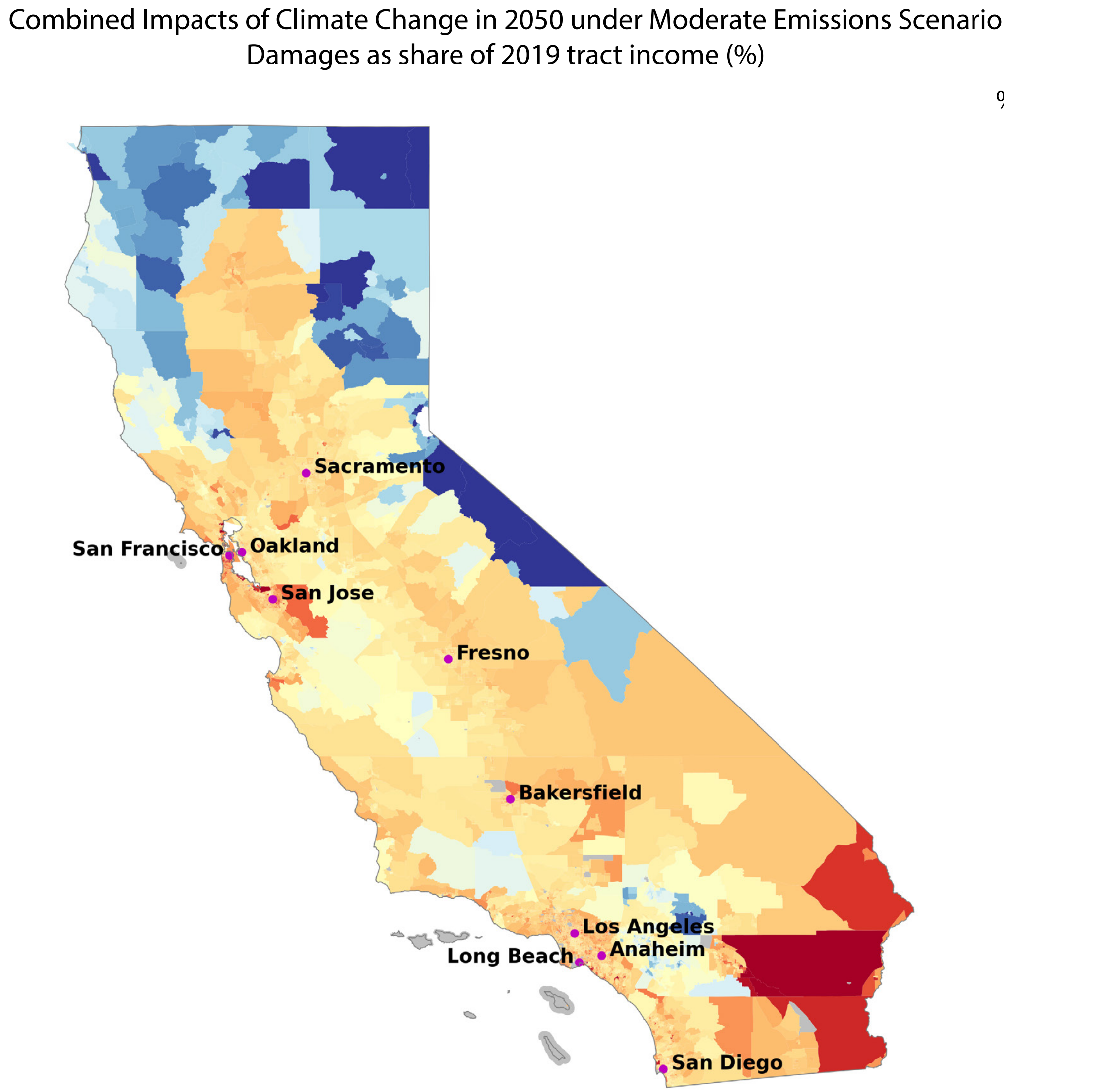

Figure 9: Climate Vulnerability Metric (CVM), median outcome. *The CVM is computed as the median estimate of aggregated climate damages in 2050, relative to 2020, under a moderate emissions scenario (RCP 4.5) and represented as a share of 2019 income. A value of 4 indicates the annual damage to human welfare from climate change across categories is equivalent to 4% of tract-level income, while a value of –3.5 indicates a benefit to human welfare that is equivalent to 3.5% of tract-level income. The map shows a wide diversity of vulnerability to the combined impacts of climate change across the state, with the largest damages in southeastern California and the San Francisco Bay area, and benefits in northern California outside of the Central Valley.*

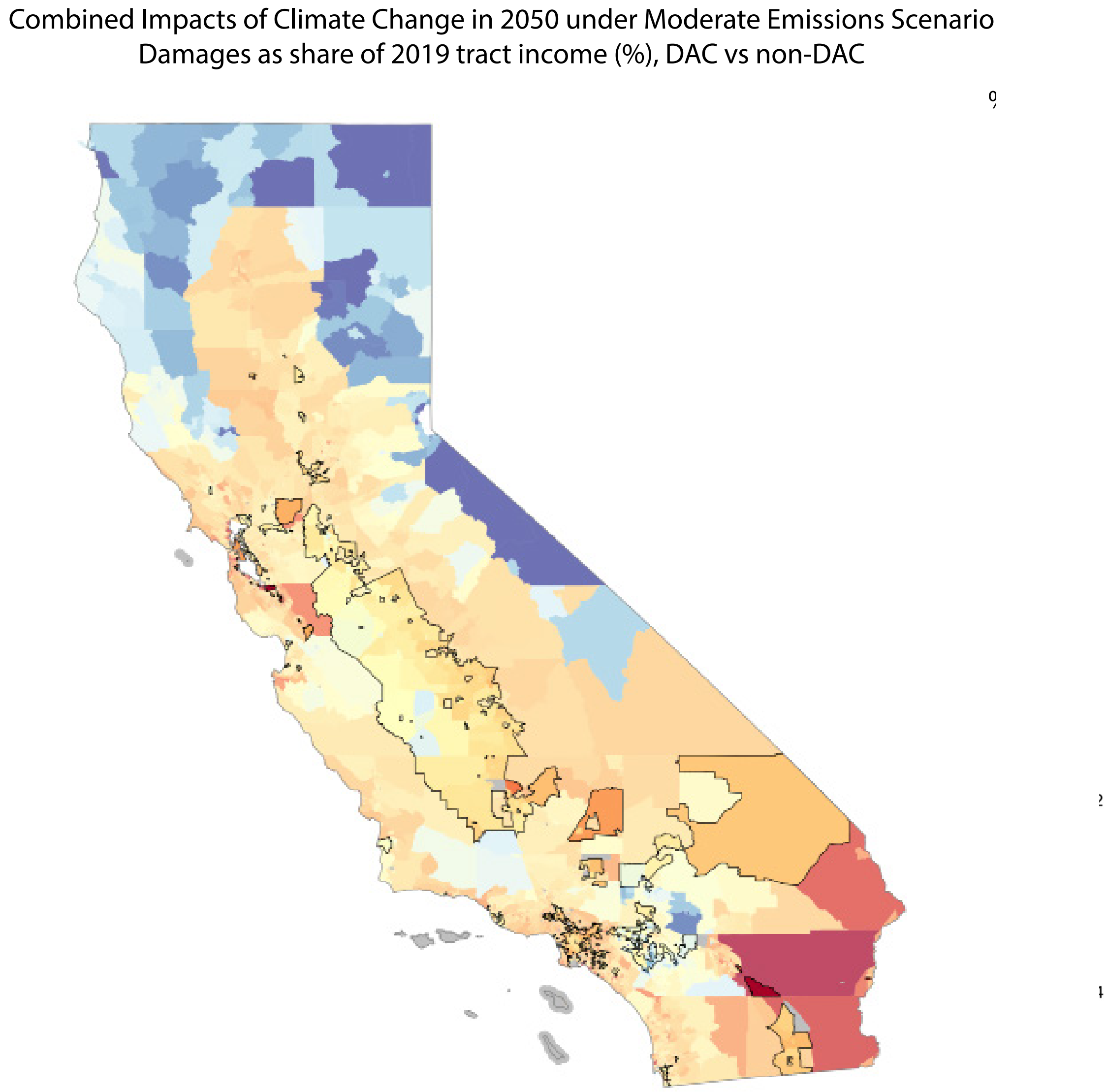

Figure 10: Climate Vulnerability Metric (CVM) in Disadvantaged Communities (DACs). *The CVM is computed as the median estimate of aggregated climate damages in 2050 under the moderate RCP 4.5 emissions scenario, represented as a share of 2019 income. Census tracts determined to be disadvantaged (DAC) under CalEPA's updated CalEnviroScreen 4.0 designations[lxxi] are in solid colors and outlined, while non-DAC census tracts are semi-transparent. The majority of DAC tracts are estimated to experience negative impacts of climate change in 2050, and DAC tracts include some of the worst affected tracts in the state (e.g., Riverside in southeastern California). The imperfect alignment between DAC tracts and those with high CVM values can be explained in part by the fact that DAC designations are based on current social and environmental conditions and not on vulnerability to future impacts of climate change, as in the CVM.*

Regional analysis of the Climate Vulnerability Metric

While the maps in Figures 9 and 10 give an overall picture of geographic differences in projected climate change impacts across California, it can be difficult to discern regional patterns without additional analysis. In Figures 11 and 12, we show category-specific and overall CVM results at the regional level, using boundaries which were defined in the state's Fourth Climate Change Assessment.[lxxii] These figures show the patterns across regions of California that share similar climate conditions and highlight how each climate region is likely to face impacts on human welfare that differ strongly across categories.

Specifically, Figure 11 shows that the San Francisco Bay region is projected to suffer the largest impacts from climate change, with median projected damages of 1.4% of 2019 tract level income. In contrast, the North Coast region is projected to experience benefits amounting to 1.5% of 2019 tract level income.

These results are decomposed further in Figure 12, where impacts are shown within each category for each climate region. This figure shows that while mortality damages dominate in most regions, impacts on the workforce are important drivers of climate vulnerability in the Inland South, Sacramento Valley, San Joaquin Valley, and the Sierra Nevada Mountains, while flooding is substantial in San Francisco Bay Area. The North Coast region is the only region with net benefits, which come primarily through avoided deaths due to extreme cold, but also are due to increases in hours worked and decreases in natural gas spending.

Combined Impacts of Climate Change in 2050 under Moderate Emissions Scenario
CalAdapt Regions, Median Damages as share of 2019 tract income (%)

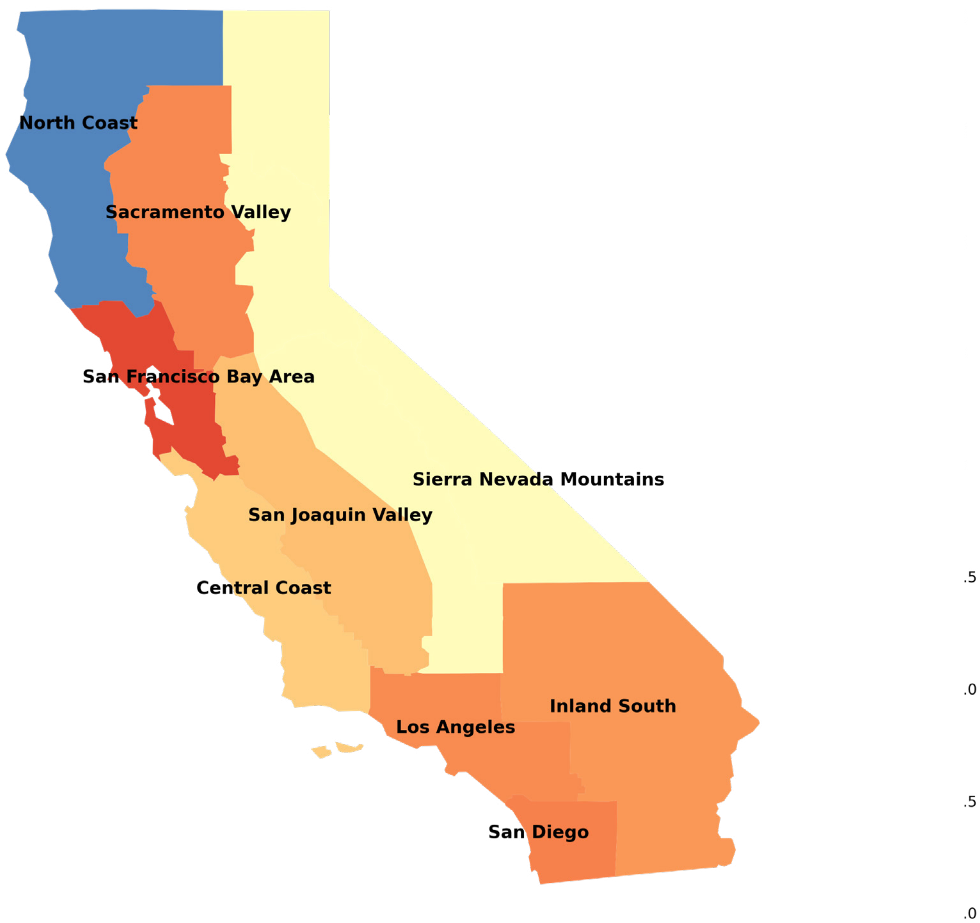

Figure 11: Climate Vulnerability Metric (CVM) across California climate regions. *The CVM is shown at the level of the state's nine climate regions, as defined by the Fourth Climate Change Assessment. Regional CVM metrics were computed by taking the population-weighted mean across CVM values for all census tracts within a region. Moderate to high vulnerability to climate change in 2050 is estimated for the majority of the state. The San Francisco Bay Area is estimated to have the greatest vulnerability, while the North Coast is the only region estimated to have decreased vulnerability to climate change by 2050, relative to 2020.*

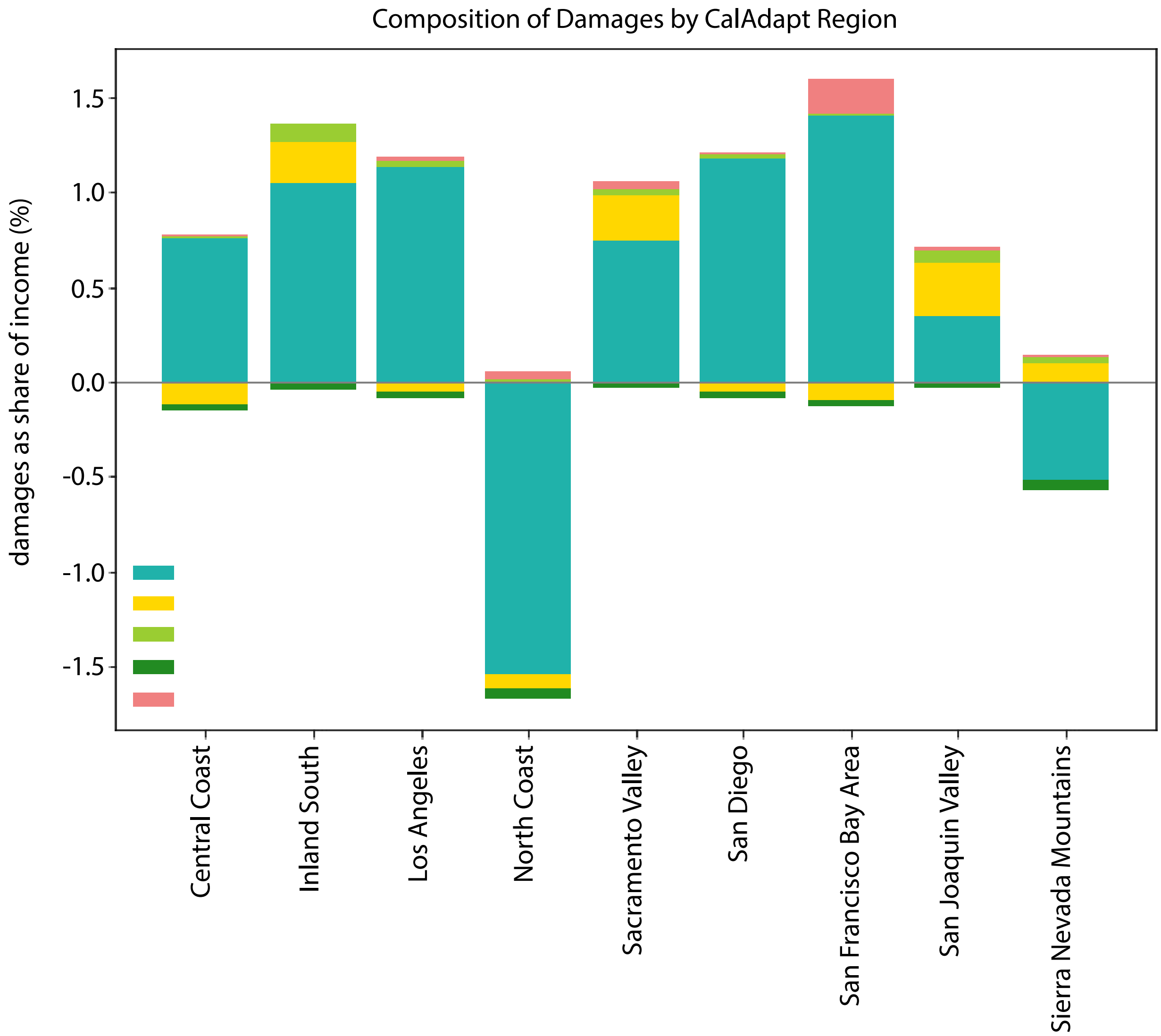

Figure 12: Climate change impacts across California climate regions. *This chart shows projected impacts of climate change by impact category for each of the state's nine climate regions defined by the Fourth Climate Change Assessment. The units shown match the CVM, and are the projected damages from climate change as a share of a region's income. The main driver of most regions' CVM value is mortality damages, followed by labor damages. The San Fransisco Bay region is estimated to have the largest damages due in large part to increased mortality and flood damages, whereas the North Coast is estimated to have benefits due primarily to decreased mortality damages in the form of decreased cold-related deaths. Labor damages are substantial in the San Joaquin Valley, Sacramento Valley, and Inland South.*

Potential policy application of the CVM

The CVM provides California communities and policy makers with information about the relative climate vulnerability Californians may face in the future. The CVM can be used to direct funding to communities that will be disproportionately impacted by climate change and can be targeted based on impact category. For instance, census tracts with high energy cost impacts could receive targeted funds or rate plans to reduce energy costs. Policy makers and advocates could also use the CVM to identify a threshold of vulnerability that could be used to designate communities as "climate vulnerable" or "disadvantaged," similar to the approach laid out in CalEnviroScreen. Mitigation and adaptation funding could then be directed to communities that are most classified as vulnerable to climate impacts to reduce the inequality of climate impacts that may be faced in the future.

The CVM can also be used in combination with other screening tools to identify communities that are vulnerable to current environmental and health hazards and may also be vulnerable to the future impacts of climate change. For instance, the CVM can be used to support the efforts of the Integrated Climate Adaptation and Resiliency Program (ICARP) or can be combined with census tract data from CalEnviroScreen to identify communities that are and will be disadvantaged by climate change and environmental hazards. In addition to a comprehensive estimate of the future impacts of climate change, the CVM can be broken down by physical hazard to identify the most significant drivers of climate damage in each California community which can be used to direct targeted funding based on specific damages and help communities implement policies and programs to best adapt to the future impacts of climate change.

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Technical Appendix – Climate Vulnerability Metric

Technical Appendix Table of Contents

I. Constructing Dose-Response Functions

a. Collect dose-response functions from previous literature

To construct category-specific relationships between climatological factors and physical impacts, we draw from existing peer reviewed literature that uses big data and robust econometric methods to estimate dose-response functions over a geographically and temporally diverse sample. Most of these category-specific models quantify differential vulnerability by identifying and using social, economic, and climate variables that are found to drive differential vulnerability to climate events in the historical record. For example, lower income populations may face higher mortality risks under extreme heat, while locations that are on average hot have larger energy demand responses on hot days. We use these published dose-response functions as inputs into the CVM pipeline, adapting them to measure differential vulnerability at the scale of each California census tract by gathering relevant data on drivers of vulnerability at a census tract level. Combining this novel data collection effort with published dose-response function relationships, we are able to construct differential dose-response functions at the census tract level. The research we rely on is as follows:

Mortality: Carleton et al. (2022)[i] separately estimates mortality-temperature response functions for the under 5, 5-64, and 65+ age groups conditional on an area's GDP per capita and long run average climate.

Labor: Rode et al. (2022)[ii] separately estimates the worker disutility-temperature response functions for high-risk and low-risk sector workers.

Energy: Auffhammer (2022)[iii] estimates household electricity consumption-cooling degree day (CDD) and household natural gas consumption-heating degree day (HDD) response functions. We use a variant on the model presented in Auffhammer (2022) that is conditional on an area's median household income and on its long run average climate.

Flooding: We obtained from First Street Foundation already projected and monetized census tract damages due to flooding. The projections are based on depth-damage functions, which relate water depths to property damage and are developed in Armal et al. (2020)[iv] and Porter (2021)[v].

b. Harmonize response functions across categories

The dose-response functions taken from existing research differ in important ways across different categories. For example, nonlinear relationships are modeled using different functional forms, and vulnerability is modeled based on different social, economic, and climatological factors relevant to each category. We harmonize these different dose-response functions as much as possible across categories to construct a set of comparable functions across diverse outcomes. While the harmonization process differs based on the category, for all categories besides coastal (where the dose-response function is not explicitly modeled by us), we end with a tract-specific "binned" dose-response function, where the response of the outcome (e.g., energy demand or mortality rate) is estimated for each 1 degree C temperature bin. We detail the process for each category below:

Mortality: Carleton et al. estimate age cohort-specific fourth order polynomial dose-response functions linking mortality rates to temperature, where the shape of the polynomials for each age group depends on income (log of GDP per capita) and on the long-run average temperature (see Carleton et al. for details). That is, these two variables determine differential vulnerability to temperature within each age group. To construct age cohort-specific dose-response functions for each of the 8,057 census tracts in California, we use tract-level values of log GDP per capita and long-run average temperature (as described below) to determine the shape of the dose-response function in that location.

Following Carleton et al., each tract's dose-response function is re-centered around its minimum mortality temperature (MMT) between 10 and 30 °C so that the mortality response is 0 at that temperature and relative to the MMT at all other points. Also following the authors, a weak monotonicity restriction is also applied that ensures the response function maintains a U-shaped curve (i.e., hotter temperatures cannot result in lower mortality rates above the MMT—see Appendix E.2 in Carleton et al). Finally, we then evaluate these tract-specific dose-response functions at each 1-degree C value between –45 °C to 65 °C. We plot these dose-response functions on an X-Y plane to generate Figure 3A in the main report. This results in a set of 8,057 tract-specific dose-response functions where predicted mortality rates in each age group vary with each 1-degree C bin of daily average temperature.

Labor: Rode et al. estimate sector-specific restricted cubic spline dose-response functions. In this case, no other variables determine differential vulnerability to temperature besides sector of employment. Therefore, we evaluate both the "low risk" and "high risk" sector dose-response functions at each 1-degree C bin between –45 °C and 65 °C, and assign these two binned dose-response functions to each tract within California. Differential vulnerability to climate change is then determined based on different realized temperatures in each tract and different shares of employment in low versus high-risk labor sectors.

Energy: We construct our household electricity consumption and natural gas consumption dose-response functions using a model adapted from Auffhammer (2022). Specifically, we use household-level electricity and natural gas billing data observed at roughly monthly intervals over the years 1999-2009 for electricity and 2004-2015 for natural gas, data obtained through a confidential data sharing agreement with California's Invester Owned Utilities (see Auffhammer (2022) for details). We estimate the following econometric model:

$$
\begin{aligned}
(1)\quad q_{it} &= \beta_1 HDD_{jt} + \beta_2 CDD_{jt} \\
&+ \beta_3\left(HDD_{jt} \cdot HDDmean_j\right) \\
&+ \beta_4\left(CDD_{jt} \cdot CDDmean_j\right) \\
&+ \beta_5\left(HDD_{jt} \cdot Y_j\right) + \beta_6\left(CDD_{jt} \cdot Y_j\right) \\
&+ Z_{jt} + \alpha_j + \phi_m \\
&+ \psi_y + \varepsilon_{it}
\end{aligned}
$$

where q_{it} is household *i*'s average daily electricity or natural gas expenditure during billing period *t*. HDD_{jt}, CDD_{jt} are average daily heating and cooling degree days based off a 65 °F threshold calculated as described in Section II in zip code *j* over billing period *t*. $HDDmean_j$, $CDDmean_j$ are zip code specific long-run averages of daily heating and cooling degree days from 1998 - 2015, and are interacted with (or multiplied by) the respective time-varying HDD and CDD terms to capture differential sensitivity of expenditures to heat and cold driven by different levels of climate adaptation. Y_j is the zip code level time invariant 2015 median household income, and is interacted with both the HDD and CDD terms to capture differential sensitivity of expenditures to heat and cold driven by different levels of income.

Z_{jt} is an array of two terms which control for precipitation, α_j are zip code fixed effects, φ_m are month of year fixed effects, ψ_y are year fixed effects, and ε_{it} is a stochastic error term.

Energy dose-response functions differ from the impact categories above in that they are functions of heating and cooling degree days, rather than a distribution of daily average temperatures experienced throughout the year. Heating and cooling degree days exploit hourly variation in temperature and are standard in the energy literature. However, like Carleton et al. (2022), Auffhammer's dose-response functions vary based on location-specific income (median household income) and climate (long-run average annual cooling and heating degree days). We therefore follow the procedure outlined for mortality where we determine a tract-specific sensitivity to both heating and cooling degree days for both electricity and natural gas, based on the income and long-run average climate of each census tract. However, we do not "bin" this response function based on daily average temperature; instead, we generate estimated climate change impacts using cooling and heating degree days directly.

c. Assemble tract-level covariate data

Mortality: Differential vulnerability in the mortality-temperature relationship is based upon tract income and long-run average climate.

Generally, regions with higher incomes or historically hotter climates have lower mortality responses to extremely high temperature occurrences. To match the variables used in the model specified in Carleton et al., we construct tract-level variables for GDP per capita and a 30-year average historical climate, while tract-level population by age data allows us to compute total mortality impacts from age-specific dose-response functions.

I. Log of GDP per capita: The income series used to estimate dose-response functions in Carleton et al. is the log of the US county equivalent-level (ADM2) constant GDP per capita in 2005$. They construct this series by downscaling state-level GDP per capita data from Penn World Tables (see Appendix B.3 in Carleton et al. for more details). The standard source for US GDP data is the Bureau of Economic Analysis' (BEA) Gross Domestic Product by County[vi] series, however the highest resolution this is made available is at the county level. Given we want to capture the differential vulnerability in the mortality-temperature relationship stemming from differential incomes between tracts within counties, we use the distribution of another measure of income, the American Community Survey's (ACS) Per Capita Income[vii] (PCI) series, to downscale BEA GDP per capita data to the census tract level. Our downscaling method is only an approximation however, since while GDP per capita and PCI are similar measures of income, GDP measures all economic activity generated within a given geographic area including that of businesses, while PCI only accounts for the income brought in by individuals whose residency is in that area. Generally, GDP per capita is larger than CPI due to the inclusion of categories such as business income and government spending.

Using the logic that these investments and expenditures may provide benefits to individuals who reside in the area without it being reflected in their incomes, we downscale GDP to the tract level by adding tract PCI to a county-specific value which is the residual of county GDP and county PCI equally split by the number of people in the county. This ensures that the sum of our downscaled tract GDP equals BEA county-level GDP, but allows us to capture some of the within-county disparities of the PCI series. Replicating Carleton et al., to construct our final income covariate, we take the 10-year average of our tract-level GDP per capita series between 2010-2019, convert it to 2005$, then take the natural log.

II. Long Run Average Climate: We project mortality with a 2020 climatology derived from daily surface air temperature as described in Section II below, but with daily temperature fields averaged into simple arithmetic annual means before regionalization. The annual regional values are then averaged into a climatology using a 30-year half-Bartlett kernel—averaging from 1990 to 2020 with the greatest weights on the later years.

III. Age-Specific Population: Once we generate mortality impacts per 100,000 for the under 5, 5-64, and 65 + age groups for each tract, we multiply this rate by the number of individuals in each age group to calculate total tract mortality impacts. We construct a series of the number of people in each age group by tract using ACS Age by Sex[viii] data, which provides us a total count for various age bins (we sum across male and female) for each tract.

Labor: We use the worker disutility-temperature dose-response functions defined in Rode et al., which separately estimate the relationship for high-risk and low-risk sectors of labor. Unlike mortality and energy which have tract-specific dose-response functions based on measures of tract income and long run climate, the shape of the labor dose-response functions are fixed for each labor risk group. Rather, differential vulnerability in the labor category is determined by the share of workers in the high-risk sector, who are forced to work fewer hours in response to hotter conditions compared to low-risk workers, causing them higher disutility. Additionally, tracts with a higher percentage of the population employed have a higher share of individuals exposed to the labor impacts of climate change. Similar to the interpretation of the MMT in the mortality category, there is an optimal working temperature (at which the least amount of time working is lost), and all other points along the dose-response curve represent hours lost per worker at that given daily maximum temperature (see Figure 5 in main text). The optimal working temperature for low-risk workers in Rode et al. Is 29 °C and for high-risk workers it is 30 °C.

I. High-risk and low-risk workers: Following the distinction made in Rode et al., workers in the Construction, Manufacturing, Farming, Mining, Hunting, Forestry, Transportation, Warehousing, and Utility sectors are considered high-risk in the context of the worker disutility-temperature relationship. Workers in all other sectors are classified as low-risk.

We use ACS's 2019 Industry by Occupation for the Civilian Population table[ix] which provides a count of persons over 16 employed in each industry to aggregate the number of high-risk and low-risk workers in each census tract.

Energy: Differential responses in cooling and heating use are driven by a tract's median household income as well as the long-run average annual number of heating and cooling degree days. Higher income households tend to increase their energy use more on hot and cold days, presumably due to either larger spaces heat/cool or a lower marginal utility of income. Tracts in hotter climates increase their electricity use more on hot days while tracts in colder climates increase their natural gas use more on cold days, reflecting the prevalence of residential cooling and heating systems in these areas respectively. Dose-response functions are interpreted as the change in annual household electricity and natural gas consumption in kilowatt hours (kWh) and therms, respectively, due to annual cooling and heating degree days.

I. Household Income: To match the specification of the income variable used in Auffhammer, we use census tract level 2015 median household income from ACS[x].

II. Annual Average HDDs and CDDs: Using the method to calculate degree days outlined in Section II below, daily average HDD and CDD values are taken at the tract level from 1998-2015 PRISM data.

III. Households per tract: In order to convert from impacts per household to total tract impacts, we require the household count in each tract. We use the 2019 Total Households series from the ACS Households and Families tables[xi].

II. Projecting Future Climate

a. Climate data transformation and aggregation

We project the impacts of climate change on mortality, labor, and energy with an ensemble of daily 0.25° grid resolution downscaled climate projection fields from NASA Earth Exchange Global Daily Downscaled Projections (NASA NEX-GDDP) per Thrasher et al. 2012[xii] under representative concentration pathway 4.5 (RCP4.5) and "historical" scenario simulations. We standardized all ensemble members to a 365-day calendar, removing leap years. The NEX-GDDP global climate models (GCM) do not represent a probability space across climate uncertainty. In order to ensure the tails of climate uncertainty are properly represented, the NEX-GDDP ensemble is supplemented with synthetic GCMs, called surrogates, that fill in the tails of the distribution. The final ensemble is called the surrogate mixed model ensemble (SMME) and is described in detail in Rasmussen et al. 2016[xiii].

We used daily average surface air temperature and maximum surface air temperature fields for mortality and labor projections, respectively. For both fields, we first transformed each year of daily values, at each grid point into an annual histogram with regular 1 degree Kelvin bins from 230 Kelvin to 340 Kelvin.

We then regionalized the histograms into 2010 US Census tracts (from 2019 US TIGER polygons[xiv]), weighing each grid point histogram with its estimated population (from 2019 GPWv4r10[xv]) and averaging to estimate an annual histogram for each census tract. Finally, we estimated average histograms for 2020 and 2050 with the 21-year arithmetic mean of the annual census tract histograms, averaging the annual census tract histograms from 2010 to 2030 and 2040 to 2060, respectively.

Our energy category projection follows Auffhammer, adapting similar methods to estimate warming and cooling degree-day variables. We interpolated daily minimum and maximum air temperature fields to estimate hourly air temperature following Schlenker & Roberts (2009)[xvi]. We then used the hourly air temperature fields to calculate the annual sum of cooling degree days for 65 °F and 80 °F thresholds, and annual sum of heating degree days at the 65 °F threshold. We then regionalized these annual degree-day fields to US census tracts using the same population-weighting scheme described above. We estimated degree day climatologies for 2020 and 2050 with the 21-year arithmetic mean for each of the annual census tract degree-days, computing the average for each tract from 2010 to 2030 and 2040 to 2060, respectively. Finally, we adjusted each of these climatologies with a "delta-shift".

First, we calculated a "delta" which is the difference between the GCM simulation's average degree day for each tract from 1998 to 2015 and comparable values computed from a reference product—here, 2.5 minute grid resolution PRISM daily minimum and maximum air temperature fields[xvii]. This delta is then added to each of the 2020 and 2050 degree-day climatologies by GCM, in order to ensure the projected degree days are consistent with the dose response function reference data used in Auffhammer (2022).

III. Calculating Impacts of Climate Change

For each impact category, we calculate the impacts of climate change by combining tract-level dose-response functions with impact category-specific historical and future temperature distributions under a moderate emissions scenario (RCP4.5). However, due to the uniquely specified dose-response functions (described above in Section I.b) and the nonuniform data structures of the necessary components, the process of calculating climate change impacts is slightly different for each impact category. The details are as follows.

Mortality: The mortality dose-response functions represent the age-specific increase in the mortality rate (deaths per 100,000) caused by a single day at a given daily average temperature, relative to a day at each tract's minimum mortality temperature (MMT). The historical and projected climate variable used is the annual average number of days with a daily average temperature in a given 1-degree C bin. To compute climate change impacts for mortality, we apply the following calculation:

(2) $\Delta M_{i,\,2050} = \sum_{a\,\epsilon\,\{<5,\,5-64,\,>64\}} \sum_{b=-44.5}^{64.5} \beta_{aib} \cdot \Delta D_{ib} \cdot P_{ai}$

where ΔM_i is the annual change in total deaths caused by climate change in 2050 within census tract i, β_{aib} is the age and tract specific mortality response at a given temperature bin *b* (measured as the change in deaths per 100,000), ΔD_{ib} is the tract specific change in the number of days in a year for a given 1-degree C temperature bin between 2020 and 2050, and P_{ai} is the population of a given age group in each tract, measured in units of 100,000. Note that temperature bins *b* are of width 1 degree C and are centered at 0.5 degree C intervals, starting at –44.5C and ending at 64.5C.

Mechanically speaking, we first compute ΔD_{ib} for all tracts *i* and all temperature bins *b*. This is the difference between the binned temperature distributions of the historical and projected climates so that the result can be interpreted as the number of additional days in a year that a tract experiences daily average temperature in a given 1-degree bin in 2050 relative to 2020. For example, the number of days per year falling between 32 and 33 degrees C is likely to increase in most census tracts by 2050, while the number of days per year falling between 0 and 1 degrees C is likely to decrease in most census tracts by 2050. Then, we multiply this tract-specific change in temperature distribution by the tract-specific response at each 1-degree bin, β_{aib}. We then sum across the temperature bins to get the age-specific annual mortality impacts of climate change in 2050 per 100,000 for each tract and each age group. In order to combine across age groups and calculate total mortality impacts, we multiply age-specific mortality rates by the population in each tract in each age group, then sum across age groups to get total deaths in 2050 due to climate change for each tract.

Labor: The labor dose-response functions represent the worker hours lost from a single day at a given daily maximum temperature, relative to a day with a maximum temperature of 29°C for low-risk workers and 30°C for high-risk workers. There are two dose-response functions, one for high-risk workers and another for low-risk workers, following Rode et al. (2022). The historical and projected climate variable used is the annual average number of days with a daily maximum temperature in a given 1-degree C bin. To compute climate change impacts, we apply the following calculation:

(3) $\Delta L_{i,\,2050} = \sum_{s\,\epsilon\,\{low,\,high\}} \sum_{b=-44.5}^{64.5} \beta_{sb} \cdot \Delta D_{ib} \cdot P_{si}$

where ΔL_i is the annual change in the number of worker hours due to climate change within census tract i, β_{sb} is the sector specific labor response at a given temperature bin b, ΔD_{ib} is the tract specific change in the number of days in a year for a given 1-degree C temperature bin between 2020 and 2050, and P_{si} is the number of workers in a given risk-share sector group in each tract.

To compute this object, we first multiply the difference in the number of days in each temperature bin (ΔD_{ib}) by the risk category-specific response at that temperature (β_{sb}). We then sum across temperatures to get the risk category-specific labor hours lost impact of climate change in 2050 per worker. These risk category-specific impacts are then multiplied by the number of workers in each tract in each sector of employment to get the number of expected labor hours lost in for high and low-risk sectors of work. These are then summed to get total labor hours lost per tract in 2050 due to climate change.

Energy: The energy dose-response functions represent the change in household electricity and natural gas consumption levels due to the number of heating degree days (HDDs) and cooling degree days (CDDs) experienced. We construct census tract level sensitivities to HDDs and CDDs using the above empirical specification, as follows:

(4) $\gamma_{fi} = \beta_1 + \beta_3 HDDmean_i + \beta_5 Y_i,$

Where γ_{fi} represents the change in energy consumption for a one unit change in HDDs for tract i and fuel *f*. Similarly, τ_{fi} represents the tract and fuel-specific change in energy consumption (in kWh for electricity and therms for natural gas) for a one unit change in CDDs:

(5) $\tau_{fi} = \beta_2 + \beta_4 CDDmean_i + \beta_6 Y_i$

We then use these two sets of dose-response functions to calculate the total change in fuel-specific energy consumption due to climate change with the following formula:

(6) $\Delta E_{fi,\,2050} = \gamma_{fi} \cdot \Delta HDD_i + \tau_{fi} \cdot \Delta CDD_i$

where ΔE_{fi} is the change in energy consumption due to climate change for a given fuel source (electricity or natural gas) in a given census tract, γ_{fi} and τ_{fi} are the tract specific heating and cooling degree day responses for fuel source f, and ΔHDD_i and ΔCDD_i are the difference in annual heating and cooling degree days in a given tract between 2020 and 2050.

IV. Valuing Impacts in Dollars

In order to combine impacts measured in physical units across impact categories, we first value climate change impacts in each category in dollars using a category-specific methodology that captures economic impacts and human welfare effects.

Mortality: Deaths are monetized equally across age groups and tracts using the U.S. EPA value of a statistical life (VSL), which is $7.4 million in 2006$[xviii]. Converted to 2019$ using the St. Louis Federal Reserve's implicit price deflator series, this value equals $9.15 million per life lost. In each tract, we multiply the total number of deaths by the VSL to calculate total monetized value of the deaths due to climate change, measured in 2019$.

Labor: Impacts on worker hours are monetized by estimating the disutility workers experience under extreme working conditions and turning such wellbeing losses into dollars using average local wages, following the approach outlined in Rode et al. First, we take the sum of the 2019 ACS Aggregate Wage or Salary Income for Households[xix] and Aggregate Self Employment Income for Household[xx] series and divide by the count of total workers to estimate the average annual wage per worker. We then follow the methodology used in Rode et al. to calculate the worker disutility from an hour unable to work, first using 1500 working hours a year to convert from annual to hourly wages, then dividing the result by a Frisch Elasticity of labor supply coefficient of 0.5 to obtain the value of disutility from working, given the observed labor supply response (see Rode et al. for details on this calculation). Total worker hours lost to climate change are then multiplied by this tract-specific measure of hourly worker disutility.

Energy: Change in household electricity and natural gas consumption is valued using average residential prices paid per unit of demand of each energy source. While consumers across the state pay different prices based on location, use, source, or enrollment status for various programs, this heterogeneity is difficult to comprehensively and accurately capture at a census tract level. Hence, we use 2020 EIA statewide average prices of 20.45 cents per kWh for electricity[xxi] and $14.14 per thousand cubic feet of natural gas[xxii]. We convert these to 2019$ and convert thousands of cubic feet to therms to get our final values of 20.21 cents per kWh and $1.35 per therm of natural gas. For each tract, prices are multiplied by total change in consumption to calculate the annual cost of changed energy consumption under climate change in 2050.

Flooding: The unit of measure for the flooding impacts is average annual property loss, a metric which is already measured in dollars. However, the damage data provided to us by the First Street Foundation is in 2020$. We use the FRED implicit price deflator to convert from 2020$ to 2019$ to be consistent with the other impact categories. The data provided by First Street Foundation was also pre-aggregated to 2020 census tracts. To ensure consistency across categories for their combination into the CVM, we used the National Historical Geographic Information System Crosswalk to transform 2020 tract damages to 2010 tract damages.

V. Constructing the CVM

Once we have all our individual category-specific impacts valued in 2019$, we sum across them to calculate combined climate change damages per tract. While these combined monetized damages can be a useful measure for certain situations, inevitably tracts with higher populations will tend to have higher damages. We take a two-step approach in normalizing tract damages to better portray how individuals living in each tract will experience the costs of climate change.

Calculate Damages per Capita: We begin by dividing each tract's combined damages by the number of people living in that tract, using the ACS Population by Tract series described above in the mortality covariates section. The following gives us the average damages per person in each tract:

(7) $$CVM_i^{percapita} = \frac{1}{pop_i} \sum_{c \in C} D_{ci}$$

where D_{ci} are category-specific monetized total tract-level damages (in 2019$) and pop_i is the tract-specific population.

Calculate Damages as a Share of Tract Incomes: Recognizing that the relative burden of a given level of damages imposed differs based on a person's income, we ultimately express the CVM as a percentage of average tract income per capita. To construct this variable, we divide tract damages per capita (in 2019$) by the 2019 ACS tract-specific Per Capita Income series[xxiii], then multiply by 100. The equation is:

(8) $$CVM_i^{shareincome} = \frac{1}{income_i} \sum_{c \in C} D_{ci} \cdot 100$$

where D_{ci} are category specific damages monetized total tract damages of a tract and $income_i$ is total tract income.

a. Assessing climate uncertainty

We construct the CVM under a set of 21 high-resolution, bias-corrected global climate projections and 11 surrogate models that provide daily temperature and precipitation to the year 2099 from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP). Probabilistic weights are assigned to each to represent the full probability distribution, as described in section II, "Projecting Future Climate," allowing for calculation of a probability distribution for each census tract.

The interquartile range across the GCMs within each census tract is computed as the SMME probability-weighted 0.25 and 0.75 quantiles. We also compute the median. Note that we sum the category-specific census tract damages for each GCM, giving us a distribution across climate uncertainty of census tract level combined damages that we then convert to a CVM and quantile. Because quantiles in the flooding damage data are already calculated when we receive them, we simply sum the 0.25, 0.50, and 0.75 quantiles of flooding damages to the respective quantiles of the combined value across the remaining categories. This assumes that there is perfect correlation between the flooding damage and the sum of other categories (i.e., flooding damage will be at the 75th percentile at the same time as the sum of other categories). We expect that error to be small.

We present the median scenario as our primary CVM, with the weighted interquartile range to illustrate the range of potential damages coming from uncertainty in projecting future climate.

b. CVM decompositions

In Figure 10, we overlay California's disadvantaged communities (DAC) tracts over our CVM results. For a DAC vs non-DAC designation, we use CalEnviroScreen version 4.0[xxiv] from the California Office of Environmental Health Hazard Assessment, which has been recently updated for 2022. CalEnviroScreen is utilized to indicate regions of California most prone to various sources of pollution. It includes several population characteristics, such as the identification of disadvantaged communities based on their higher levels of pollution and lower population sizes. Specifically, it takes the top 25% tracts with the greatest scores in these categories and calls these disadvantaged communities (DACs). Regions outside of this top 25% are considered non-DAC.

In Figures 11 and 12, we show the CVM and its components by the 9 regions defined by CalAdapt's 2018 California's Fourth Climate Change Assessment report[xxv]. We use CalAdapt's regional shapefile to assign census tracts to the region in which they sit. In cases where a census tract falls within more than one region, we assign it to the one where the majority of its area lies. We then use tract populations to take a weighted mean of damages as well as incomes to generate a CVM at the regional level. In Figure 12, we do this for each impact category to show how the drivers of the combined CVM differ by region.

In Figures 7 and 8, we show how impact-category effects of climate change vary based on category-specific drivers of vulnerability. These are proportion of population over 65 for mortality damages, share of high-risk sector workers for labor damages, number of annual CDDs for electricity consumption damages, and number of annual HDDs for natural gas consumption damages. We first divide up tracts into 10 groups, or "deciles based on their values for these vulnerability drivers. We then average category-specific impacts in their respective physical units across the tracts in each decile group for each climate model. In the final chart, we plot the GCM-weighted median and interquartile range of category-specific impacts (Y-axis) for each decile of the variable of differential vulnerability (X-axis).

To identify the 10 most populous cities in California highlighted in our headline CVM map (Figures ES3/9), we use the GeoNames database[xxvi]. As of the latest data, the 10 most populous cities in California are Los Angeles, San Diego, San Jose, San Francisco, Fresno, Sacramento, Long Beach, Oakland, Bakersfield, and Anaheim. Coordinates to plot these cities are also taken from this database.

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