Building Community Resilience Across California: A Statewide Analysis of Climate Vulnerability and Resilience Hub Potential

Technical Methods

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About This Document

This report provides the technical methods for a broad set of work on resilience hubs resulting from a collaboration between PSE Healthy Energy, Communities for a Better Environment, and Asian Pacific Environmental Network. The results of this analysis have been incorporated into the California Public Safety Power Shutoff Interactive Mapping Tool, the Candidate Resilience Hub Mapping Tool, multiple blogs and briefs, and the *Building Community Resilience Across California: A Statewide Analysis of Climate Vulnerability and Resilience Hub Potential* report. These materials are all available on PSE's website at: https://www.psehealthyenergy.org/work/california-community-resilience-hubs/

About PSE Healthy Energy

PSE Healthy Energy (PSE) is a scientific research institute generating energy and climate solutions that protect public health and the environment. PSE provides expertise in public health, environmental science, and engineering and brings science to energy policy through actionable research, communications, and advising. **Visit us at psehealthyenergy.org and follow us on X at @PhySciEng.**

About Asian Pacific Environmental Network

Asian Pacific Environmental Network (APEN) is an environmental justice organization with deep roots in California's Asian immigrant and refugee communities. Since 1993, we've built a membership base of Laotian refugees in Richmond, Chinese immigrants in Oakland, and Asian immigrants and refugees in the South Bay region of Los Angeles. Through building an organized movement, we strive to bring fundamental changes to economic and social institutions that will prioritize public good over profits and promote the right of every person to a clean and healthy environment in which their communities can live, work, learn, play, and thrive.

About Communities for a Better Environment

Communities for a Better Environment (CBE) is a statewide Environmental Justice organization building people power in low-income and communities of color in Richmond, East Oakland, Wilmington, and the South East Los Angeles Cities. Using our triad model of Organizing-Research-Legal, we have led successful campaigns and projects that empower CBE youth and adult members to reshape their communities and environment. Visit us at cbecal.org and follow us on Instagram at @cbecal.

1.0 Introduction

The impacts of climate change continue to grow across California, posing a threat to populations statewide but particularly for historically disinvested populations for whom climate impacts compound with ongoing cumulative socioeconomic and environmental health stressors. For example, those who struggle to afford their electricity bills are less likely to have access to air conditioning in the face of a heat wave and people who have asthma are more vulnerable to the impacts of wildfire smoke. In recent years, resilience hubs have emerged as a strategy to support communities both in the face of climate disasters and to provide year-round support to increase everyday resilience.[1] Resilience hubs can take many forms but must be community-trusted and community-led sites that provide year-round programming and services for the communities they serve. These services range from youth services to resilience-building social support as well as emergency services, such as backup power from solar+storage systems, in the case of climate-related or other disasters.

In this study, we seek to identify opportunities and barriers for deploying resilience hubs across the state of California, as well as strategies to support their deployment in the communities that may need them most. This effort is a collaboration between the research institute PSE Healthy Energy (PSE), and two community-based organizations, Asian Pacific Environmental Network (APEN) and Communities for a Better Environment (CBE). The project was supported by California Strategic Growth Council's Climate Change Research Program with funds from California Climate Investments. Under the project, PSE led a statewide analysis of population vulnerability and candidate resilience hub sites while APEN and CBE led case studies and on-the-ground deployment efforts in the Bay Areas' Richmond and Oakland neighborhoods, and in the Wilmington neighborhood in Los Angeles. These combined efforts provide a top-down view of the state, including an assessment of population vulnerabilities as well as solar+storage designs at nearly 20,000 sites; and a bottom-up view of what it takes to actually design a resilience hub reflecting local needs and priorities beyond solar+storage design. Together, these efforts aim to provide guidance at the state, regional, and local levels to policymakers, community-based organizations, government, and other actors to inform both individual hub design as well as broader policies and programs to support resilience hub deployment.

This research aims to answer a series of questions across California to inform resilience hub decision-making. From the top-down vantage point, we first construct a Climate Vulnerability Index (CVI) to identify regions most in need of hubs. The CVI integrates information on adaptive capacity and population sensitivity, including health, environmental, and socioeconomic indicators. Next, we assess nearly 20,000 schools, community centers, libraries, and places of worship across the state as candidate resilience hub sites. For each site, we identify critical electric loads and develop typical solar+storage designs both for everyday use (e.g., to reduce electric utility payments) as well as the design changes needed—and associated costs—to last through multi-day outages. Finally, we identify relevant trends across the state, such as where additional incentives might be needed to scale solar+storage and where climate vulnerability might be the highest. We then develop a series of strategies to support hub design and deployment in communities facing different combinations of socioeconomic, environmental, and climate challenges. We aggregate these into policy recommendations, which are provided in our accompanying recommendations document, Building Community Resilience Across California: A Statewide Analysis of Climate Vulnerability and Resilience Hub Potential.

APEN and CBE have led a series of on-the-ground efforts in the communities where they work to both support resilience hub development and enhance community resilience more broadly. These include community surveys, trainings, toolkit development, and the identification of resilience hub sites in Richmond, Oakland, and Wilmington. Currently, these hubs are in various stages of development, ranging from initial scoping to full solar+storage design and installation. These on-the-ground studies both inform the questions addressed by and the data included in the top-down analysis as well elucidate the limitations that a statewide zoom-out analysis has on capturing local-level information.

This technical document provides the methods used in our research on resilience hubs. This information is integrated into numerous other blogs, policy reports, interactive data tools, and other materials on PSE's website. This centralized report provides the data sources and analytical methods to support this array of materials and publications. While we will describe some of the outreach activities performed by APEN and CBE and how these shaped some of our analyses, we do not seek to comprehensively describe the broad scope of resilience work conducted by these organizations and suggest looking at http://apen4ej.org and https://www.cbecal.org for community toolkits, reports, infographics, and other materials.

This report is divided into the following sections:

- **Section 2** outlines community engagement efforts and case studies in Richmond and Wilmington, led by partners APEN and CBE;
- **Section 3** details the development of the Climate Vulnerability Index;
- **Section 4** describes the climate hazard data included in this work;
- **Section 5** provides an overview of candidate resilience hub site selection and travel distance analysis;
- **Section 6** develops a method for identifying climate zones across California;

- **Section 7** explains the methods used to model solar+storage potential and costs at candidate resilience hub sites;
- **Section 8** provides the approach to estimating greenhouse gas and co-pollutant emissions associated with solar+storage deployment;
- **Section 9** describes a location-allocation model used to prioritize resilience hub deployment based on climate vulnerability. The key take-aways from these analyses are available in *Building Community Resilience Across California: A Statewide Analysis of Climate Vulnerability and Resilience Hub Potential*.

2.0 Community Case Studies: Richmond and Wilmington

The research collaboration between APEN, CBE, and PSE was structured as a Multiple Principal Investigator project with a lead investigator from each organization to ensure research design, goals, processes, and outputs reflected the priorities and approaches core to each organization. As such, the collaboration agreed upon common principles and commitments at the outset of the project. Each organization rotated through facilitator roles for each inter-organizational meeting and shared progress, updates, data, findings, and feedback on work from each group. As part of this collaboration, APEN and CBE provided input on assumptions, data tool needs and designs, and other key inputs and outputs developed by PSE. APEN and CBE shared methods and tools for community outreach in each region with each other, and PSE provided tailored data analysis and trainings relevant to work in each community, among other activities. The work conducted by APEN and CBE for this specific project is part of a much broader suite of resilience-related work each group is leading in their communities. Below, we provide an outline of some of these efforts but direct the reader to each organization for the full scope of their work.

APEN's work for this project focused primarily on community engagement alongside the design and development of a resilience hub at the RYSE youth center in Richmond, California; and in the latter half of the project on the design of a proposed resilience hub at the Lincoln Recreation Center in Oakland's Chinatown. Richmond is home to a largely low-income community of color that has long been exposed to numerous sources of pollution, including major freeways, a refinery, and a coal export terminal.[2] APEN works closely with Asian immigrant and refugee communities in Richmond, including in collaboration with the RYSE Center, to support Richmond youth. In recent years, the community has faced increased heat, smoke from wildfires, and power outages due to public safety power shutoffs. The Lincoln Recreational Center in Oakland has long been a trusted gathering place for Chinatown residents, including many immigrant, elderly, and renter households, and the recent effort with the City of Oakland and other community organizations to redo the Center includes the expansion of its role into a full resilience hub.

Throughout this project, APEN has conducted numerous workshops, trainings, tours, advocacy training days, townhalls, and other resilience-related engagement and educational efforts. These were particularly focused on work with youth at the RYSE Center. Efforts focused on:

1. Community ground-truthing to find out what people identify as barriers to healthy and resilient communities and where there are gaps in knowledge about what to do in climate emergencies.
2. Community visioning to identify what communities want to develop as a place where they feel they can gather safely and build trust.
3. Resilience infrastructure learning to understand how solar and storage works.
4. Scenario planning and prioritization for specific resilience hub sites. Surveys guided the broader phases of this work, and more tailored workshops guided the rest. Among these activities, RYSE youth helped plan a Richmond Our Power Coalition Townhall on resilience hubs, with dozens of community members in attendance.

They also participated in virtual advocacy days educating decision-makers on the concepts of resilience hubs and the importance of supporting environmental justice communities. Youth are also deeply involved in the design of the hub and its governance. Early efforts included the co-development of an outreach survey conducted by Richmond youth to identify needs and priorities for the RYSE resilience hub, which reached 122 participants from ages 14-22 in 11 East Bay cities. The surveys identified primary disaster concerns (e.g., earthquakes, wildfires), resources youth would like to see at a resilience hub (e.g., mental health support, Wi-Fi, phone charging, food, personal protective equipment, supportive staff, activities), resources in the case of emergency (e.g., backup power, first aid kits), training needs (e.g., emergency response training); and other factors, such as feelings about safety, school, and community strategies.

RYSE youth also helped RYSE and APEN identify needs and priorities for solar+storage design at the site. PSE also supported APEN and RYSE in developing a request for proposals (RFP) for solar+storage, including guiding documents on design trade-off considerations; a storage and solar developer was identified and solar+storage installed on-site in 2023; this process has faced long interconnection waits, and while the solar on one building has been connected, the second is awaiting interconnection in spring 2024, and the timeline for the battery interconnection is uncertain. APEN developed a curriculum and outreach strategy for APEN members in Oakland's Chinatown to support the development of a solar+storage resilience hub at the Lincoln Recreational Center. APEN also began developing a field-building guide for resilience hubs for release in early 2024.

CBE has focused its work for this project in Wilmington, a largely low-income community of color, exposed to pollution from the Port of Los Angeles, neighborhood oil drilling, refineries, and significant heavy diesel trucking, among other sources. Following a similar approach to APEN, but tailored to its specific community, CBE has conducted educational, outreach, and training efforts in the Wilmington community throughout this project. Initial project efforts also include a community survey to identify resilience hub needs, including demographics, top community climate concerns, places people typically go in an emergency, and priority resilience efforts. This last category included in-center resources (e.g., solar+storage, Wi-Fi) as well as mutual aid in the community (e.g., food drives, resilience kits, box fan distribution) (available in Appendix A). CBE identified two candidate resilience hub sites and supported the ongoing development of resilience hubs at the Tzu Chi Clinic and the Senior Center in Wilmington. These efforts included measures such as identifying transportation needs, energy needs, and programs and services, including through community visioning exercises. CBE has developed a wide range of educational materials on resilience, including blogs, infographics, an Instagram reel on how to make a box fan air filter, blogs, and a Resilience Hub Toolkit.

These on-the-ground efforts from CBE and APEN have directly built resilience in Richmond, Oakland, and Wilmington communities. The findings from these surveys and outreach efforts, alongside direct feedback from APEN and CBE, were used by PSE to inform various modeling inputs such as climate vulnerability indicators and candidate site identification alongside outputs including the development of a Candidate Resilience Hubs Mapping Tool. APEN, CBE, and PSE also conducted training workshops at the 2022 National Adaptation Forum and the 2023 California Adaptation Forum, and gathered input from these efforts to help shape research inputs and deliverables.

3.0 Climate and Population Vulnerability Indicators

In order to identify areas in California where resilience hubs might be most needed by nearby populations, we developed a Climate Vulnerability Index (CVI). Numerous methods currently exist to identify vulnerable populations in California, but none fully encompassed indicators we believed would be valuable to help identify priority regions for resilience hub deployment.

To inform our approach to CVI development, we adopted the climate vulnerability definition developed in 2017 by California's Integrated Climate Adaptation and Resiliency Program (ICARP) Technical Advisory Council:

"Climate vulnerability describes the degree to which natural, built, and human systems are at risk of exposure to climate change impacts. Vulnerable communities experience heightened risk and increased sensitivity to climate change and have less capacity and fewer resources to cope with, adapt to, or recover from climate impacts. These disproportionate effects are caused by physical (built and environmental), social, political, and/ or economic factor(s), which are exacerbated by climate impacts. These factors include, but are not limited to, race, class, sexual orientation and identification, national origin, and income inequality (Climate Equity and Vulnerable Communities, n.d.)*"*[3]

Based on this definition, three core components characterize climate-vulnerable communities: 1) increased sensitivity to climate change, 2) less capacity to cope, adapt, or recover from climate impacts, and 3) heightened risk to climate-related hazards. We used these three core components as the foundation to develop a Climate Vulnerability Framework (**CVF**) (**Figure 3.1**) and, subsequently, the CVI. The CVF includes three domains that encompass the core components of the climate vulnerability definition:

1. **Population Sensitivity,** which we defined as populations that, due to physiological, medical, or working conditions, have an increased sensitivity to climate stressors (e.g., people with asthma, cardiovascular diseases, people with disabilities, children, elderly, outdoor workers, etc.) and that are already overburden by environmental pollution (e.g., people living in areas with high levels of air pollution, drinking water contamination, traffic-related pollution, etc.).
2. **Adaptive Capacity,** which we defined as the capacity of populations to withstand, recover, and adapt to climate impacts. It encompasses *Socioeconomic Capacity*, that is, the financial capital of communities; *Social and Population Capacity*, which reflects on the capacity of communities to work together effectively and on the value of human resources; and *Infrastructure Climate Capacity*, which refers to the ability of a population's built environment to withstand climate impacts.
3. **Climate Risk,** which is the likelihood a population will face climate hazards.

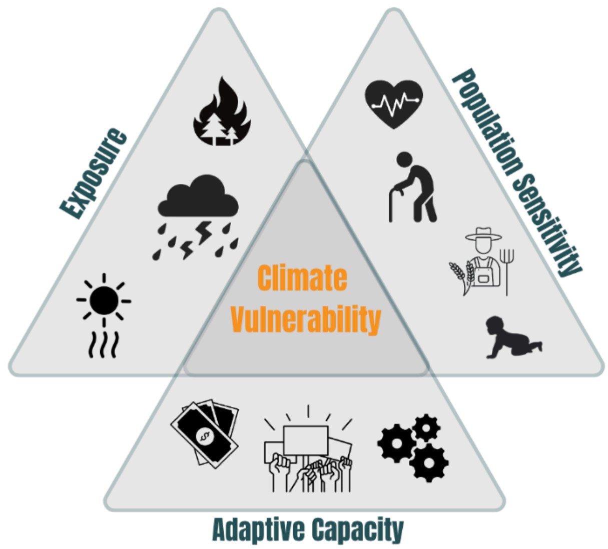

Figure 3.1. Components of Climate Vulnerability. Climate Vulnerability is influenced by the sensitivity of populations, their adaptive capacity, and their risk to face climate-related hazards.

Using this framework, we estimated the CVI leveraging publicly-available data to identify indicators that would capture information about Population Sensitivity and Adaptive Capacity. Due to the vastness of climate-related events, limitations in climate data, uncertainties of projected climate estimates, and an analytical objective to develop a flexible CVI that can be used to assess population's climate vulnerability to a broad array of climate events, the CVI itself does not include data on climate risk (**Figure 4.2**). Excluding climate risk data makes the CVI relevant to *any* extreme weather event or disaster, given that Population Sensitivity and Adaptive Capacity indicators tend to overlap across different climate events. We assess climate risks as part of their own sub-analysis in detail in **Section 4** below.

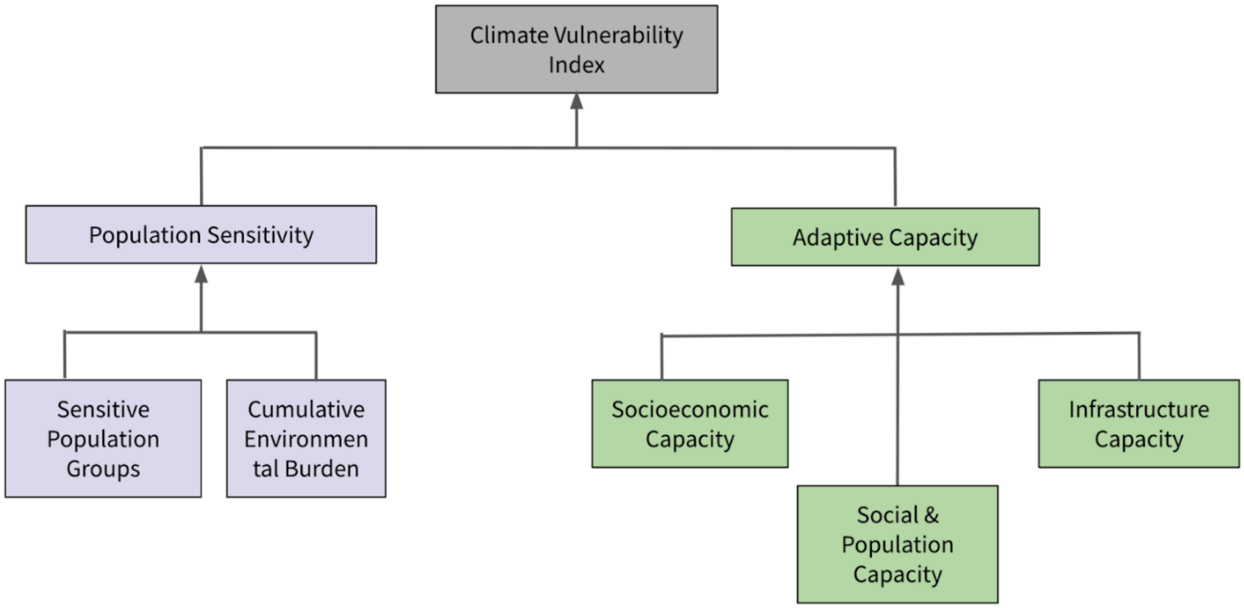

Figure 3.2. Climate Vulnerability Index Diagram. The CVI includes two main domains that align with the definition of climate vulnerability. Each domain is divided into subdomains, which are then composed of various indicators.

The CVI consists of 39 indicators and is estimated at the census tract level. It includes all CalEnviroScreen 4.0 (CES) indicators and 19 additional ones gathered from publicly-available data sources (**Table 3.1**). CES was developed to identify communities facing cumulative socioeconomic and environmental health burdens and histories of environmental injustice;[4] therefore, the indicators included are likely to reflect various measures of population sensitivity and some level of adaptive capacity, as described above. However, CES was not specifically designed to identify climate vulnerable populations and as a result a number of climate vulnerability indicators are excluded from the index. We added additional indicators to try to better capture climate vulnerabilities—adaptive capacity—in particular. Two of the additional indicators are related to healthcare infrastructure. We used hospital and urgent care facility location data from Homeland Infrastructure Foundation-level data[5] and census block group centers of population from the 2010 Decennial Census[6] to calculate the linear distance to the closest hospital or urgent care facility.

We calculated the linear distance from the census block group centers of population to the nearest hospital or urgent care facility. Then, we averaged the distances across all census block groups within a census tract to get the census tract's average linear distance to the closest hospital or urgent care facility. We used these averages as Infrastructure Climate Capacity indicators. We also estimated an indicator to capture infrastructure capacity to cope with extreme heat by multiplying census tract-level projected extreme heat days for

2030-2050 (RCP 4.5) by the percentage of households without air conditioning (See **Table 3.1** for information about data sources). Census tracts with a high number of projected extreme heat days and a high percentage of households without air conditioning have high values for this indicator. The additional 16 indicators included four Sensitive Populations Indicators and 12 Adaptive Capacity Indicators (see **Table 3.1**). Adding these indicators to the list of CES indicators brings important additional climate-relevant information into the CVI.

We followed the CES methodology[7] with a few modifications to integrate all the indicators into a single index. Most notably, to estimate the CVI, we incorporate a climate vulnerability narrative; thus, the domains into which indicators are aggregated differ from those in CES. Based on our CVF described above, in the CVI, we aggregated indicators into two main domains: Population Sensitivity and Adaptive Capacity. Population Sensitivity has two subdomains: Sensitive Population Groups and Cumulative Environmental Burden. Adaptive Capacity has three subdomains: Socioeconomic Capacity, Social and Population Capacity, and Infrastructure Capacity (**Figure 3.2**). Additionally, in CES, several environmental exposure indicators are given lower weights, but in CVI, all indicators are weighted equally as there is not enough information available to decide the importance of each indicator. After assigning indicators to subdomains, we ranked each indicator by percentile and then averaged the rankings within subdomains to calculate a subdomain score. Then, we summed and scaled the subdomain scores within each domain to obtain a domain score (Population Sensitivity and Adaptive Capacity) ranging from 1-10 (following CES methodology). Lastly, we multiplied the Population Sensitivity score by the Adaptive Capacity score to get the CVI, which ranges from 1–100 (**Figure 3.3**), where higher values indicate higher climate vulnerability. We estimated a CVI for each census tract. To more easily compare Census tracts, we estimated percentile ranks of the CVI index. Census tract spatial geometries are from the 2010 Decennial Census and the data spans multiple years (**Table 3.1**).

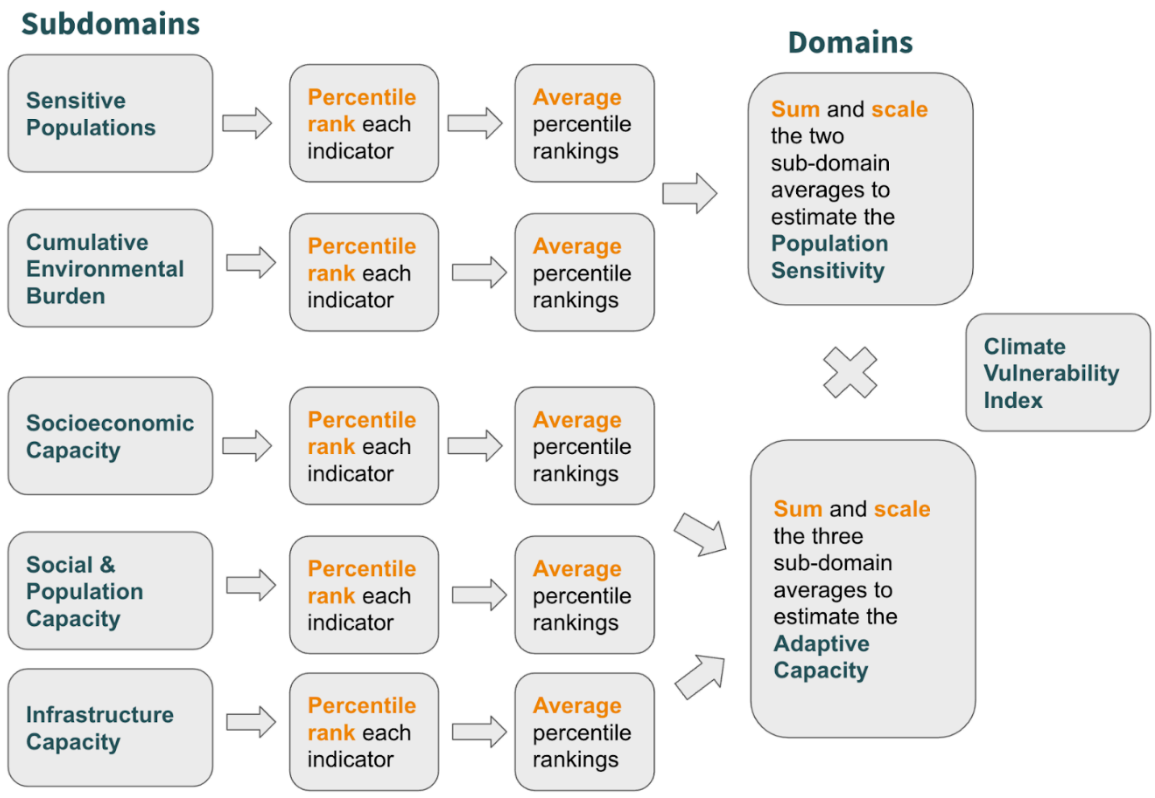

Figure 3.3. Climate Vulnerability Index Methods Flow Chart. Indicators are classified into subdomains, percentile ranked, and averaged to produce a subdomain value. The subdomain values are scaled and integrated into a domain score. Lastly, the domain scores are multiplied to generate the final CVI score.

There were a few census tracts with missing data. If a census tract was missing 50 percent or more of the indicators in a subdomain, we assigned an NA to that census tract and didn't estimate a CVI for it. We calculated a CVI for 7,983 census tracts out of the 8,035 existing census tracts in California based on the 2010 Decennial Census tracts divisions. The census tracts with missing CVI were missing information for more than 50 percent of the socioeconomic indicators; thus, we didn't have enough data to calculate a reliable CVI. The population for the census tracts with missing CVI ranged from 0 to 11,977, with a population median of 27 and a mean of 1,881. The census tract with the largest population and missing CVI covers one of the University of California Los Angeles campuses, and the census tract with the second largest population (9,035) covers the California Substance Abuse Treatment Facility and State Prison.

Table 3.1. Cumulative Vulnerability Index Indicators			
Indicator	**Definition**	**Source**	**Data Year(s)**
Domain: Population Sensitivity			
Sub-Domain 1: Sensitive Populations			
Asthma	Age-adjusted rate of emergency department visits for asthma per 10,000	CalEnviroScreen 4.0	2015–2017 average
Cardiovascular diseases	Age-adjusted rate of emergency department visits for acute myocardial infarction per 10,000	CalEnviroScreen 4.0	2015–2018 average
Low birth weight	Percent population with low birth weight	CalEnviroScreen 4.0	2009–2011 average
Population with disabilities	Percent population with a disability	American Community Survey	2015–2019
Population under 5 years	Percent population less than 5 years	American Community Survey	2015–2019
Population above 64 years	Percent population older than 64 years	American Community Survey	2015–2019
Outdoor workers	Percent of population employed and aged >15 years working outdoors	American Community Survey via CCHVIz/CalBrace	2011–2015
Sub-Domain 2: Cumulative Environmental Burden			
Clean up sites	Sum of weighted EnviroStor cleanup sites within buffered distances to populated blocks of census tracts	CalEnviroScreen 4.0	2021
Diesel $PM_{2.5}$	Diesel PM emissions from on-road and non-road sources	CalEnviroScreen 4.0	2016
$PM_{2.5}$	Annual mean concentration of $PM_{2.5}$ (weighted average of measured monitor concentrations and satellite observations, $\mu g/m^3$), over three years	CalEnviroScreen 4.0	2015–2017
Ozone	Mean of summer months (May-October) of the daily maximum 8-hour ozone concentration (ppm), averaged over three years	CalEnviroScreen 4.0	2017–2019
Traffic	Sum of traffic volumes adjusted by road segment length (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of the census tract	CalEnviroScreen 4.0	2017
Drinking Water	Drinking water contaminant index for selected contaminants	CalEnviroScreen 4.0	2011–2019
Groundwater Threats	Sum of weighted GeoTracker leaking underground storage tank sites within buffered distances to populated blocks of census tracts	CalEnviroScreen 4.0	2021

Hazardous Waste	Sum of weighted hazardous waste facilities and large quantity generators within buffered distance to populated census tracts' blocks	CalEnviroScreen 4.0	2018–2022
Impaired Water Bodies	Sum of number of pollutants across all impaired water bodies within buffered distances to populated blocks of census tracts	CalEnviroScreen 4.0	2018
Solid Waste Sites	Sum of weighted solid waste sites and facilities	CalEnviroScreen 4.0	As of July 2021
Toxic Release	Toxicity-weighted concentrations of modeled chemical releases to air from facility emissions and off-site incineration; includes releases from Mexican facilities	CalEnviroScreen 4.0	2014–2016, 2017–2019
Lead	Percentage of households within a census tract with likelihood of lead-based paint hazards from the age of housing combined with the percentage of households that are both low-income (household income less than 80% of the county median family income) and have children under 6 years old	CalEnviroScreen 4.0	2017, 2015–2019, and 2013–2017
Pesticides	Total pounds of 132 selected active pesticide ingredients (filtered for hazard and volatility) used in production-agriculture per square mile, averaged over three years	CalEnviroScreen 4.0	2017 to 2019
DOMAIN: ADAPTIVE CAPACITY			
Sub-Domain 1: Socioeconomic Capacity			
Housing Burden	Percent of households in a census tract that are both low income (making less than 80% of the HUD Area Median Family Income) and severely burdened by housing costs (paying greater than 50% of their income to housing costs)	American Community Survey via CalEnviroScreen 4.0	2013–2017
Education	Percent of population over 25 with less than a high school education	American Community Survey via CalEnviroScreen 4.0	2015–2019
Limited English Proficiency	Percentage of limited English-speaking households	American Community Survey	2015–2019
Population w/o Health Insurance	Percent population without health insurance (all ages)	American Community Survey	2015–2019
Poverty	Percent of the population living below 200% of the federal poverty level	American Community Survey via CalEnviroScreen 4.0	2015–2019
Energy Burden	Percent of household income spent on energy bills	DOE LEAD map tool	Data download 1/31/23
No Vehicle Access	Percent households without vehicle access	American Community Survey	2015-2019

No Internet Access	Percent households without internet access	American Community Survey	2015-2019
Unemployment	Percent unemployed out of the total in labor force	American Community Survey	2015-2019
Sub-Domain 2: Social and Population Capacity			
Voting Indifference	Percent of registered voters who did NOT voted in the 2020 general election	California Healthy Places	2020 general elections
Census Indifference	Percent of households who did NOT completed the 2020 decennial census	Decennial Census	2020
Crime	Number of violent crimes per 1000 residents	Uniform crime reports from US Federal Bureau of Investigation via CCHVIz/CalBrace	2013
Population Decrease	Percent population change over time. Population difference between 2010 Decennial Census and 2015-2019 American Community Survey divided by 2010 population times 100. Negative refers to population decrease	American Community Survey and Decennial Census	2010, 2016-2019
Health Professional Shortage	Health Professional Shortage Areas (HPSA) designations for primary care. Scores range from 0-25; 0 means no shortage	Health Resources & Services Administration	Designations from 2017-2020 (varies by region)
Sub-Domain 3: Infrastructure Climate Capacity			
Hospital Accessibility	Closest linear distance to a hospital or urgent care facility (miles)	Decennial Census block groups population; health facility locations from the Homeland Infrastructure Foundation-level data	Population 2010; infrastructure 2012-2021
Impervious Surfaces	Population-weighted percent of area covered by impervious surfaces	National Land Cover Database via CCHVIz/CalBrace	2011, 2016 (NLCD) & 2010 population
Canopy Coverage	Population-weighted percent of area not covered by tree canopy	National Land Cover Database via CCHVIz/CalBrace	2011, 2016 (NLCD) & 2010 decennial census
Urban Heat Island	Sum of 182 day temperature differences (degree-hr) between urban and rural reference. Available only for urban areas	CalEPA via California Healthy Places website	2015
Air Conditioning Access	Percent of households without air conditioning × number of projected extreme heat days 2030-2050 (RCP 4.5)	Residential Appliance Saturation Survey via CCHVIz/CalBrace; extreme heat projections from CalAdapt	2010 Decennial Census population; 2009 AC data

4.0 Climate Hazards

Climate-induced weather extremes are increasing the frequency and duration of power outages, driving the need for local energy resilience in California.[8,9] Millions of people have already lost power during public safety power shutoffs (PSPS), where during drought and high wind conditions a utility will turn off power to parts of the grid to lower the risk of their infrastructure sparking a fire. The need for clean air and cooling is also often highest while wildfires and extreme heat stress the electric grid, heightening the risk of power outages. For this analysis, we focused on five climate and air quality hazards that indicated a need for resilient energy, using data at the census-tract level to correspond to climate and population vulnerabilities. These include PSPS, projected extreme heat days, ozone and $PM_{2.5}$ nonattainment areas, wildfire-related $PM_{2.5}$, and wildfire hazard zones.

While earthquakes are a significant concern in California, they are not a climate hazard and this analysis did not include them in its evaluation of possible resilience hub locations.[10, 11] Although resilience hubs can support disaster recovery efforts, this analysis focused on hubs for outages and wrap-around services rather than disaster response.

4.1 Public Safety Power Shutoffs (PSPS)

Public Safety Power Shutoffs (PSPS) are proactive utility power outages to reduce the risk of wildfire. While intentional, PSPS events can have significant impacts, particularly for those reliant on electricity for health and safety. Because these outages are transparently reported, we use PSPS data as a proxy for outage duration to inform solar+storage hub design. Other resilience-oriented policies, such as the Self-Generation Incentive Program and the Microgrid Incentive Program, also use past PSPS events as part of their funding eligibility criteria.

To estimate census-tract level impacts from PSPS events—which have historically been reported by circuit rather than census tract—we used the California Public Utilities Commission (CPUC) PSPS Rollup as our starting database.[12] The Rollup is a spreadsheet with the names of circuits that have been partially or fully de-energized during a PSPS event, their outage and restoration times, and the numbers of customers impacted since 2013. These data can be inconsistent and incomplete, so we verified against, and supplemented with, information from utility Post Event Reports and electronic data requests, focusing on outages with customer impacts. Each utility reports its data slightly differently and reporting standards have changed over time. Because of this, we then standardized the data between utilities, with a separate geospatial circuits dataset and over the course of reporting. Additionally, we created a unique identifier for each circuit-level outage and assigned each to a larger PSPS event, noting where circuits had had power cut and restored multiple times during the same event. These data only exist for investor-owned utilities, meaning we do not have coverage for places with municipal utilities such as Los Angeles and Sacramento.

We then matched PSPS-impacted circuits from the investor-owned utilities (PG&E, SCE, and SDG&E) to their geospatial coordinates from each utility's Integration Capacity Analysis map and allocated outage impacts to census tracts by calculating what percentage of each circuit was in each census tract. For example, if a circuit was 40 percent in census tract A, 60 percent in census tract B, and a PSPS outage on that circuit impacted 100 customers, 40 customers were allocated to tract A and 60 to tract B. Allocating customers this way assumes that outages always impact the full circuit and that customers are evenly distributed along that circuit. Early PSPS outages likely did impact full circuits, though for more recent outages, utilities may have only de-energized the most at-risk segment of a given circuit. However, we do not have data on the location of circuit segments. Customers are also not evenly distributed across circuits, so some customers were likely allocated to the wrong census tracts. However, we also lack census-tract specific customer allocations from utilities. PacifiCorp does not publish geospatial circuit data, so we approximated the locations of their circuits using data from Post Event Reports.

Non-investor-owned utilities are not required to report on PSPS events to the CPUC, so we used a similar approach as described above to assign utilities to census tracts, which enabled us to note which census tracts had not experienced any PSPS outages and which census tracts were primarily served by utilities for which we had no data.

To calculate the average annual frequency of PSPS events, we found the total number of PSPS events that a census tract had experienced and divided it by the number of years the utility responsible for those outages had been reporting on PSPS events. This was necessary to normalize the frequency of outages, because each utility started reporting PSPS in different years. We also calculated the average customer-weighted outage duration for each census tract, based on how many customers in each tract were without power for various durations.

These data were presented alongside socio-economic and demographic data in the California Public Safety Power Shutoff Interactive Map, a web-based and publicly-available mapping tool specific to PSPS events.[13] The annual frequency of outages in each census tract was also used to represent PSPS outage risk in the candidate resilience hub mapping tool. For further detail on the methods and data sources used to generate the PSPS dataset, see "Public Safety Power Shutoff Maps: Methodology & Data Sources"[14] online.

4.2 Extreme Heat

The number of extreme heat days has increased in California since 1950 and heat events are expected to become more frequent with climate change.[15,16] Extreme heat can have severe health consequences and strain the power grid, particularly in areas that are not prepared for these higher temperatures. As typical temperatures vary across the state, the projected extreme heat data used in our analyses is a measure of how many more extremely hot days an area will have in the future. Specifically, it refers to the average projected annual number of extreme heat days above the 98th percentile of historical maximum temperature for each census tract.[17] Projections are for the time period 2030-2050 and were estimated by averaging the results of four different climate models (HadGEM2-ES, CNRM-CM5, CanESM2, and MIROC5) to capture the range of possible projections. The models relied on historic temperature data from 1961-1990 and the Representative Concentration Pathway (RCP) 4.5 scenario. The RCP 4.5 scenario is reflective of current clean energy transition efforts, as it assumes some emissions reductions. We selected the 2030-2050 time period to evaluate near future increases in temperature within which resilience hubs can both be built and provide community benefits.

The projected extreme heat data was downloaded from CalAdapt.[18] You can find more information about the climate models and underlying data on the CalAdapt website and in the Climate, Drought, and Sea Level Rise Scenarios for California's Fourth Climate Change Assessment report.[17,19]

4.3 Air Quality Nonattainment Areas

Fine particulate matter known as $PM_{2.5}$ is emitted from gas and diesel cars, as well as wildfires and other sources, and is associated with asthma attacks, bronchitis, increased hospital admissions, and premature death.[20,21] Ozone forms when volatile organic compounds (VOCs) and nitrogen oxides (NO_x)—emitted from cars, trucks, and other sources—interact with heat and sunlight, and can cause health problems such as aggravating asthma and making breathing difficult.[22] Climate change may increase concentrations of both pollutants, as wildfires exacerbate existing $PM_{2.5}$ levels and increasing temperatures increase ozone formation. In the absence of air filtration systems at home, resilience hubs may provide the best place for community members experiencing chronically poor air quality. $PM_{2.5}$ and ozone nonattainment areas were drawn from the EPA nonattainment area classifications based on 2019-2020 data, with data downloaded from the EPA Green Book.[23]

Ozone nonattainment areas are census tracts that did not meet the eight-hour national air quality standards for ozone concentrations of less than 0.07 ppm. These nonattainment areas are also classified into six levels: Marginal (0.071 - 0.081 ppm), Moderate (0.081 - 0.093 ppm), Serious (0.093 - 0.105 ppm), Severe-15 (0.105 - 0.111 pm), Severe-17 (0.111 - 0.163 ppm), and Extreme (0.163 ppm and above).[24] For the Candidate Resilience Hub Mapping tool, tracts with a Severe-15 and Severe-17 classifications were grouped together into a single 'Severe' designation and any tracts that were not in nonattainment areas were classified as 'Meets Standard.' $PM_{2.5}$ nonattainment areas are census tracts that did not meet the 2020 annual national air quality standards for $PM_{2.5}$ concentrations of 12 micrograms per cubic meter ($\mu g/m^3$).[25] At the time of this work, the EPA had proposed updating the primary, health-based annual $PM_{2.5}$ standard to between 9.0 and 10.0 $\mu g/m^3$, but the change had not yet been made.[1]

Nonattainment areas are also classified into "Moderate" and "Serious." Moderate areas are not in attainment when the rules are updated and Serious for areas unable to reach attainment within six years.[26,27] Additional classification of "Meets Standards" was added to the Candidate Resilience Hubs Mapping Tool to indicate census tracts that are meeting the $PM_{2.5}$ air quality standards. $PM_{2.5}$ nonattainment designations typically exclude so-called "exceptional events,"[28] including wildfires, so we include wildfire-related $PM_{2.5}$ as a separate measurement.

4.4 Wildfire-Related $PM_{2.5}$

As noted above, wildfires emit $PM_{2.5}$ and can worsen health impacts in areas with already-poor air quality. Wildfire-related $PM_{2.5}$ concentrations for each census tract were provided by Dr. Tarik Benmarhnia at Scripps Institution of Oceanography. These data were estimated using a variety of machine learning techniques that integrated remote-sensing data, $PM_{2.5}$ measurements from EPA Air Quality System monitors, meteorological data, and other relevant variables. For a description of these methods, see Aguilera et al. (2023).[29]

As the distribution of wildfires across California can change from year to year, for the Candidate Resilience Hub Mapping tool we averaged all available data, which runs from 2006 to 2020.

4.5 Wildland Fire Hazard Severity Zones

Wildland Fire Hazard Severity Zones (FHSZ) illustrate fire hazard in areas where the California Department of Forestry and Fire Protection (CAL FIRE) is primarily responsible for fire prevention and suppression. Designated by CAL FIRE and classified as Moderate, High, or Very High hazard, these zones are based on quantities of woody debris that could serve as fuel, weather-related variables such as wind, and other relevant factors.[30] For the Candidate Resilience Hubs Mapping Tool we used the recently updated 2022 maps available from the California Office of the State Fire Marshal.[30]

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[1] In February 2024, the EPA updated the primary annual PM2.5 standard to 9.0 $\mu g/m^3$.

The FHSZs only cover areas where CAL FIRE is responsible for fire services, known as State Responsibility Areas. As a result, a significant portion of the Central Valley and many city and town centers are not included in fire hazard classifications.[31] These data are also significantly more granular than census tracts. Because of these factors, these data are not assigned to census tracts and instead are presented as a separate layer in the Candidate Resilience Hub Mapping tool.

5.0 Candidate Resilience Hub Site Identification

Resilience hubs strengthen human adaptive capacity year-round with community-driven programs and resources, including information sharing, social support, and health services. Additionally, resilience hubs serve as community resources during and after disasters by providing support before, in, and during recovery from emergencies.[1,32] Resilience hubs must be built on trust, strong relationships, and communication during everyday operations in order to strengthen communities year-round and improve response capacity during emergencies.[33,34]

Numerous sites, ranging from libraries to multifamily apartment buildings, hold the potential to serve as resilience hubs. However, certain sites are more conducive to serving communities' needs than others due to factors such as capacity, proximity to disadvantaged populations, and existing relationships with the surrounding communities. Moreover, not all sites are capable of providing the full range of resilience services.[35] Roode and Martinac, (2020) in their case study of resilience hub design for Maui, Hawaii, argue that in addition to providing year-round critical community services, a site should be in good structural condition, located outside of natural hazard zones, and accessible by all members of the community.[36]

For the purpose of this analysis, we faced data limitations regarding which sites might make reasonable resilience hub candidates. Below we first outline the advantages and disadvantages of different types of sites, then describe the methods we followed to identify the buildings we included in our analysis and the methods for assessing the average travel distances required for a community to reach a hub.

5.1 Advantages and Disadvantages of Different Site Types

We collected data for community centers (including libraries and clubs), schools, and places of worship as potential resilience hub sites. Other potential locations were not considered in this study, including government buildings, stadiums, and multi-family housing. The excluded sites face considerable staffing and programming challenges, and comprehensive statewide datasets for them are lacking. If the sites analyzed here cannot provide sufficient space or energy for resilience hub services, either statewide or in particularly high-risk or vulnerable communities, additional site categories may need to be considered. Ultimately, a viable resilience hub should be chosen and led by the community, and local leaders can leverage almost any trusted site to host the day-to-day and emergency services of a hub.[1] As such, we leave it to communities to select the location and develop the necessary programming. Below, we discuss some of the advantages and disadvantages of each of the site types we included in our analysis for the purpose of serving as resilience hubs.

Community centers are common candidates for resilience hubs, especially given their existing local constituencies. Libraries already serve as public community centers, providing internet access and assistance in emergency relief applications.[35] Oakland, California is currently piloting a resilience hub at the West Oakland Branch of the Oakland Public Library, focused on heat and smoke relief.[37] However, libraries and many community centers lack showers and bed space for long-term disaster housing.[35]

Places of worship also have long-standing relationships with existing communities and so are included as potential candidate sites for resilience hubs. A Lawrence Berkeley National Lab report suggests that rooftop solar+storage on places of worship can provide energy for resilience hubs, and can also raise local awareness and acceptance of solar energy in communities where adoption has lagged.[38] Some places of worship, as exemplified by Glad Tidings International in Hayward, California, have already initiated green energy solutions to support their communities during power outages. Similarly, Stillmeadow Community Fellowship in Baltimore Maryland has demonstrated the ability to work with local, state, and federal governments to provide food, water, and supplies during disasters along with additional services, like job training, to a broad constituency during everyday operations.[39-41]

Schools, from elementary through college, can provide different scales of services given the wide range of sizes. However, schools pose challenges for managing student safety if long-term events require ongoing resilience hub services and education functions simultaneously.[41] Elementary schools are deeply embedded in their local communities and can offer resources that are often within walking distance of constituents. Secondary schools offer more space but typically cover larger (not necessarily walkable) service areas. Community colleges may be even farther from constituents but often have space that could be reserved for resilience services during disasters. Most schools have showers, kitchens, and large spaces like gyms that can be outfitted for emergency housing when required. Multiple organizations are considering schools as hubs, but peer-reviewed analyses and reviews of outcomes are lacking.[42-44]

5.2 Site Identification and Footprint Estimates

We identified candidate resilience hub sites from multiple databases and online sources. We considered community centers (including libraries and clubs), schools, and places of worship as potential sites for resilience hubs. Ultimately, we identified over 18,000 potential sites across California. We obtained place of worship and community college data through Open Street Maps (OSM) inquiries. We obtained community center data through OSM, the California State Library website database,[45] and the National Shelter System Facilities data set.[46] We found school data from the California State Schools data set[47] and OSM. To our knowledge, there are no complete, centralized, and publicly available databases of community centers and houses of worship in California. We therefore leveraged OSM, an open-source dataset detailing geospatial information around the world. The OSM database is freely available for public use and includes crowd-sourced, digitized building footprints tagged with relevant attributes such as building name and type. It is divided into several component datasets, including places, buildings, roads, and land uses. To build a candidate site dataset, we relied primarily on the building and land use datasets for Northern and Southern California, as downloaded on August 24, 2021.

We queried the buildings and land use datasets by feature type and name. Buildings tagged as relevant feature types, such as school, community center, church, temple, and mosque were retained as potential sites. Land use types were similarly queried and the spatial intersection of buildings falling within these land use categories was taken to capture buildings lacking the appropriate tags. To further capture buildings that may not have received the appropriate tags, we queried buildings and land uses by name. For example, buildings containing the words “Elementary School” or “Youth Center” in their name were retained as potential sites. This methodology was iteratively refined as nuances in the dataset requiring additional processing were identified. For example, ground-mount solar panels and baseball dugouts on school campuses were sometimes identified as buildings via these methods. Buildings within above-ground parking lots were accordingly removed, as were buildings with a footprint of less than 100 square feet. Additionally, duplicate buildings identified via more than one of the above methods were removed from the dataset to avoid double counting their square footage.

Building footprints are important to estimate the potential for rooftop solar at each site. For school footprints that were not found and cleaned in the OSM database, we developed a random forest regression model using cleaned school data, including population density of school neighborhoods and the school enrollments to estimate the building’s footprints. We stress that these estimates of rooftop area are only rough estimates and that other essential features, such as the fraction of available space on the roof for solar, are not included.

All spatial data analysis and processing were performed in either ArcGIS Pro or using Python with the Geopandas package. Prior to processing, all data were projected into NAD83 California Teale Albers (US Ft). This projection was selected to facilitate statewide, area-based calculations. Building footprints were spatially joined with utility service area spatial data to assign the most probable electric utility from a subset of utilities under consideration.

5.3 Travel Distance Estimation

Resilience hubs most often serve the communities living nearby. As such, to quantify the potential of resilience hubs to serve community needs and to identify areas with limited to no access to existing hub infrastructure, we found it necessary to measure the driving distance between the potential hub sites and neighborhoods.

While direct or "as the crow flies" distance is a much easier calculation, it overlooks real-world physical challenges. For example, a hub may be physically within less than a mile from a community. However, due to barriers such as highways or rivers, the true travel distance may be much greater. These differences between direct and driving distance can be substantial for studies at short distances. The ideal method would be to find the distance between each home and each potential hub, however, this is not possible due to data and computational limitations. Thus, we choose census block groups as our geospatial unit for neighborhoods. Block groups are smaller than census tracts but larger than census blocks. We found tracts to be too large to approximate a single point where people live, while census blocks were too numerous to measure distances and perform calculations. Still, block groups can often cover large areas, especially in rural areas, and their geographical centroid may be far from where people live or even in water. To minimize these errors, we used the population-weighted centroid calculated from block-level population data to estimate a population center within each block group from which we could calculate the travel distance to the nearest hubs.

Once we identified the population centroids, we calculated the driving distance between each hub and all the block groups within a reasonable distance. Calculation of the minimum driving distance between hubs and block groups was performed using OSM road data in Python using the freely available OSMnx and NetworkX packages. While driving time may be a more important consideration than distance, it is difficult to estimate because traffic data is not freely available and changes throughout the day. Specifically, we calculated the driving distance between each block group and the nearest 10 hubs and all hubs within a three-mile direct distance of that block group's population-weighted centroid. These two criteria ensured each block group had hubs to choose from but not too many to add to computation time. In dense urban areas, often 10 hubs could exist within just a single mile, so finding all hubs within three miles ensured all reasonable hubs were included. In rural areas, often no hubs were found within three miles, so finding the nearest 10 ensured multiple choices were available, even though they may be far away. To calculate the travel distance, we used the nearest node on the OSM road network to both the block group centroid and the site's centroid.

6.0 Estimating Energy Load Profiles from Climate and Building Category

Accurate building simulations to develop solar+storage designs for a specific site require hourly weather data, including temperature, humidity, and solar radiation; and detailed building characteristics, including heating, ventilation, air conditioning systems, building materials, and occupancy.[48] Rather than perform detailed hardware and structural analysis of 20,000 sites, we made simplifications and approximations. To generate load profiles for all building categories, we built a regression model from hourly load profiles in example cities, where EPRI or NREL datasets provide load profiles for building categories in these cities, against hourly average temperature profiles in these cities. We then used this model to generate load profiles for every potential resilience hub site based on its building categories and the temperature profile from the closest weather station. This approach offers a locally-specific load profile, built off of data from more than 400 weather stations across California. These steps are described below. Further details and discussion of these methods will be published in a forthcoming peer-reviewed study from PSE Healthy Energy entitled *Modeling and design of solar+storage-powered community resilience hubs across California*.

6.1 Inadequacy of Climate Zone Proxies

We use REopt, a tool developed by the National Renewable Energy Lab, to model solar+storage for normal operations and outage scenarios. REopt is a techno-economic decision support model designed to optimize behind-the-meter energy assets whose outputs include optimal system design given input constraints and objectives, economics (system cost, net present value), and environmental metrics (CO_2 and other air pollutant emissions).[49]

REopt includes built-in load profiles for various building categories, adjusted to representative cities in each International Energy Conservation Code (IECC) climate zone. Similarly, the Electric Power Research Institute (EPRI) has developed load profiles with data across multiple representative cities for additional building categories.[50] Wang et al. show that analyses based on IECC climate zone or representative city load profiles inadequately account for climate impacts on building energy, as the variability of temperature, humidity, solar radiation, and wind vary widely within climate zones.[51] Similarly, Huang & Gurney show that the variation in energy use within climate zones can be larger than the variation between climate zones.[48] In

California in particular, climate zones fail to account for microclimates, but energy use data can be used to infer microclimate zones.[52]

IECC breaks down geographic regions by climate zones ranging from warmest to coldest on a 1-8 scale and by moisture regime (moist, dry, marine) on an A-C scale.[53] California contains IECC climate zones 2 through 6, as shown in **Figure 6.1**, with zone 2 corresponding to the hot, dry region bordering Arizona and Mexico and zone 6 in the Sierra Mountains and Northern California. Los Angeles is used to represent the climate zone 3B region within California, while Las Vegas is used to represent the 3B region outside of California.[48]

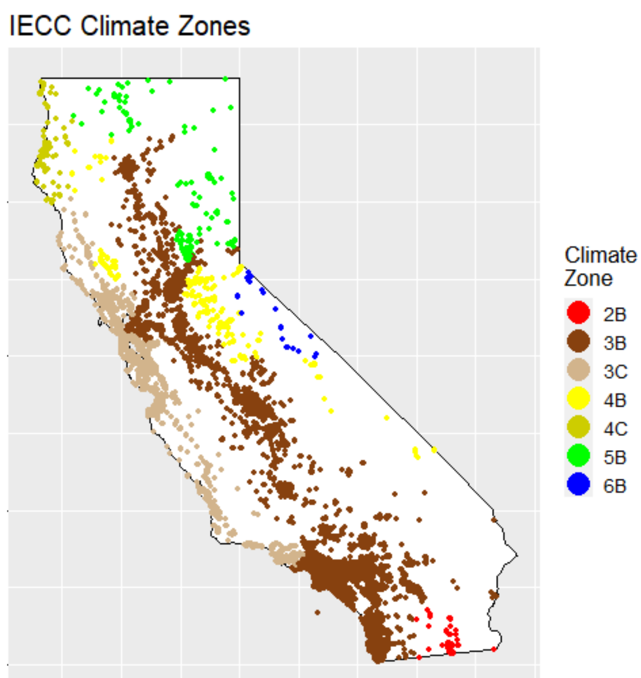

Figure 6.1 Candidate Resilience Hub Sites in California. Hubs are coded to their International Energy Conservation Code (IECC) Climate Zone.

Figure 6.2 illustrates the temperature variability within IECC Climate Regions. The figure gives the average high temperature (°F) experienced in eight cities across five "dry" climate zones, 6B through 2B. The expected trend from 6B through 2B shifting from cooler to warmer holds true, but starting in April, the differences within climate zones become as pronounced as the differences between climate zones. From June through September, Las Vegas (3B, brown) has high temperatures more similar to Phoenix (2B, red) than its climate zone partner, Fresno (3B, brown). Similarly, in the summer months, Tucson (2B, red) tracks closer to Fresno (3B, brown) than its climate zone partner, Phoenix (2B, red).

Baechler et al. note that energy consumption increases by more than 0.56 percent per °F (1 percent per °C) increase in temperature.[53] The difference between high temperatures in July and August in Flagstaff (green squares) and Boulder (green triangles) is greater than 5 °F, indicating at least a 2.8 percent difference in energy consumption despite both cities being in climate zone 5B. Accounting for differences within climate zones that may be as great or greater than differences between climate zones demands a more precise measurement than climate zones.

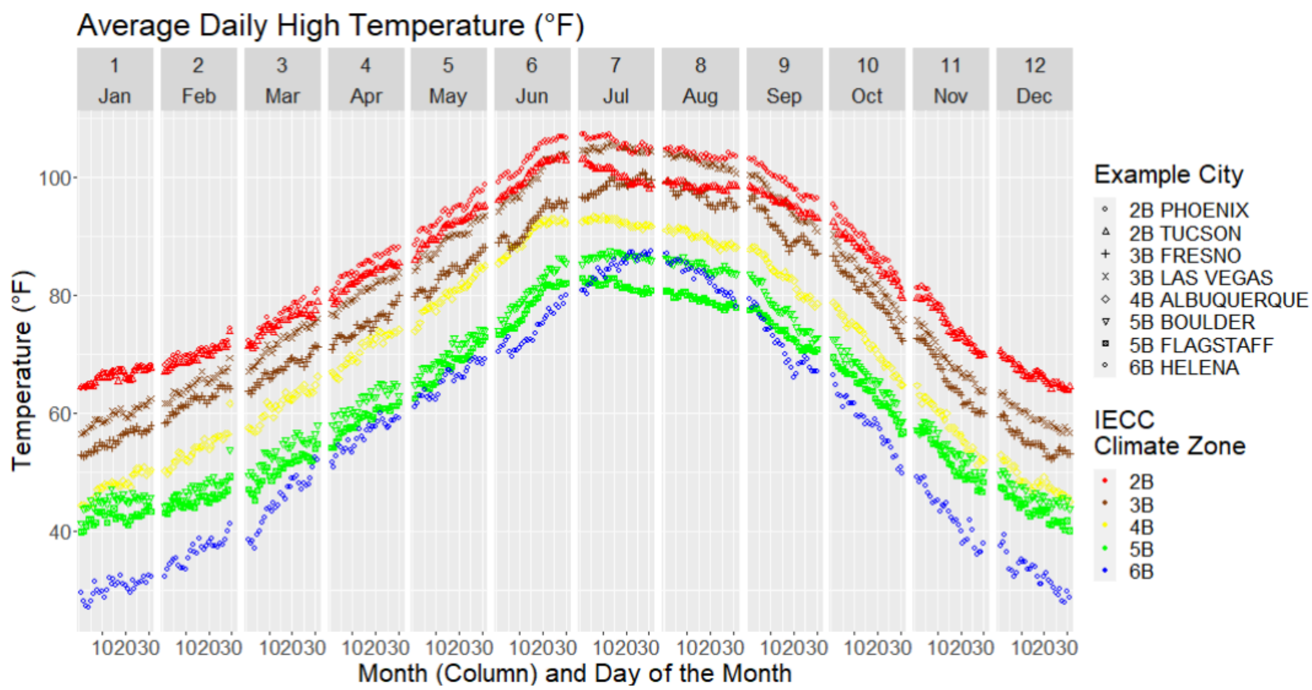

Figure 6.2. Daily Average High Temperatures (°F) for Example Cities. Data from the Global Historical Climatology Network - Daily (GHCN-Daily).[54]

The California Energy Commission (CEC) attempts to address California's microclimates and the inadequacies of IECC climate zones by establishing 16 climate zones across California with a set of standard climate data for each.[55] The CEC zones are not subdivisions of IECC, and so are not completely consistent with them. While the CEC zones provide more resolution in some areas—addressing microclimates in the Los Angeles, San Diego, and San Francisco metropolitan areas—they offer less resolution than the IECC in Northern California and the Sierra Mountains. In addition, CEC climate zones are not available outside of California. While we could merge IECC and CEC climate zones in California for more resolution than either one alone, analyses incorporating these would not extend nationally or internationally.

6.2 A Local Temperature-Driven Energy Load Profile

We used local weather data to determine the temperature and weather-dependent components of the example load profiles from REopt and EPRI and multiple years of empirical data from a community college in San Mateo County. We adjusted energy load profiles based on the differences in daily local weather data between each site and the example cities. Example cities for each building category and climate zone are shown in **Table 6.1**. By normalizing energy use profiles by local temperature, we easily adapt to gaps in the example data and differences in example cities across the data sources.

For community colleges, we have actual energy load data collected from San Bruno, California. While the lack of data for community colleges outside the temperate San Francisco region presents a limitation, we develop temperature- and occupancy-based predictions of energy use from other building category and extend the temperature-dependent energy use from secondary schools (the nearest proxy) to estimate community college energy and power estimates outside this temperate region.

Oktay et al. show that hourly outdoor temperature trends can be established using the daily maximum and minimum temperatures.[56] We compare a representative hourly temperature profile from Lake Tahoe California[57] with Oktay et al.'s[56] Z scores and find that data from California has a similar hourly profile to Oktay's data from Turkey. We, therefore, use the same technique to build hourly temperature profiles from the daily high and low temperatures from the Global Historical Climatology Network - Daily (GHCN-Daily).[58]

Example city daily average weather statistics for temperature and humidity were collected from GHCN-Daily by matching example cities to the nearest weather stations with at least 10 years of data and data at least as recent as 2020. To convert local temperature profiles to local energy profiles, we first determine the relationship between temperature and energy for the building categories in the example cities. Fan et al. (2018) show that building energy use can be modeled as a function of temperature, temperature squared, humidity, direct radiation, occupancy, and lighting and equipment power.[59] We follow the Fan et al., method and describe below our process to estimate each of the required dependent variables.

Table 6.1 Climate Zone Example Cities and Data Sources						
IECC Zone	**Climate Zone Description**	**City**	**State**	**Community Center and Place of Worship**	**Primary and Secondary School**	**Community College**
1A	Very Hot, Humid	Miami	FL	EPRI	REopt	
2A	Hot, Humid	Houston	TX	EPRI	REopt	
2B	**Hot, Dry**	**Phoenix**	**AZ**	**EPRI**	**REopt**	
3A	Warm, Humid	Atlanta	GA	EPRI	REopt	
3B	**Warm, Dry**	**Las Vegas**	**NV**	**EPRI**	**REopt**	
3C	**Warm, Marine**	**San Bruno**	**CA**			**Empirical**[2]
		San Francisco	**CA**	**EPRI**	**REopt**	
3X	**Warm, Dry, California Coast**	**Los Angeles**	**CA**	**EPRI**	**REopt**	
4A	Mixed, Humid	Baltimore	MD	EPRI	REopt	
4B	**Mixed, Dry**	**Albuquerque**	**NM**		**REopt**[3]	
4C	**Mixed, Marine**	**Medford**	**OR**	**EPRI**		
		Seattle	**WA**		**REopt**	
5A	Cool, Humid	Chicago	IL	EPRI	REopt	
5B	**Cool, Dry**	**Boulder**	**CO**		**REopt**	
		Flagstaff	**AZ**	**EPRI**		
6A	Cold, Humid	Concord	NH	EPRI		
		Minneapolis	MN		REopt	
6B	**Cold, Dry**	**Helena**	**MT**	**EPRI**	**REopt**	
7	Very Cold	Duluth	MN		REopt	
8	Subarctic	Fairbanks	AK		REopt	

Table 6.1. Climate Zone Example Cities and Data Sources. Climate Zones existing in California are shown in bold.

6.2.1 Occupancy Dependence

To identify the occupancy and occupancy-driven components, we filtered the energy load data, considering only when the outdoor temperature was less than 65°F, focusing on periods when the load was generated by people rather than outdoor air temperature-driven cooling

[2] A community college in San Mateo County, empirical data.
[3] No EPRI data examples for CC and W in this climate zone.

needs. We took into account differences in building use cases for different days of the week and during holidays and school breaks. We determined that for different building categories, occupancy-driven energy use patterns emerge, as shown in **Figure 6.3**. Only community colleges demonstrated a difference in occupancy-driven power on Fridays. For all other building categories, weekday patterns are consistent Monday through Friday. Place of worship data came from churches, and as such, Sunday is the peak usage day; we differentiate between Saturday and Sunday for this building category. For other building categories, weekend occupancy is consistently low on both Saturday and Sunday. Other than places of worship, weekdays have the highest occupancy-driven load, with clear occupancy and energy intensity schedules indicated by the median power without cooling. Differences between occupancy-driven load emerge on weekdays for all categories, and for Fridays for community colleges and Sundays for places of worship. Of note, places of worships' highest loads are during the Christmas season, as indicated by Break being higher than Normal. We then take the 95th percentile value across all hours of the day, day of week types, and occupancy types (shown with the dashed line for each building category in **Figure 6.3**) and divide the occupancy-based load by this number. We use the 95th percentile rather than the maximum value to prevent outlier maximums from overly influencing the resulting fraction. Places of worship provide the key example—if occupancy from Christmas day is used—then typical occupancy becomes a tiny fraction of that particular holiday's occupancy. Instead, we allow Christmas Day (and other outliers) to have occupancy rates above 100 percent. We use the result as a proxy for occupancy percent. This proxy takes into account both occupancy and occupancy-driven load, as we have no way to separate out lighting or equipment loads.

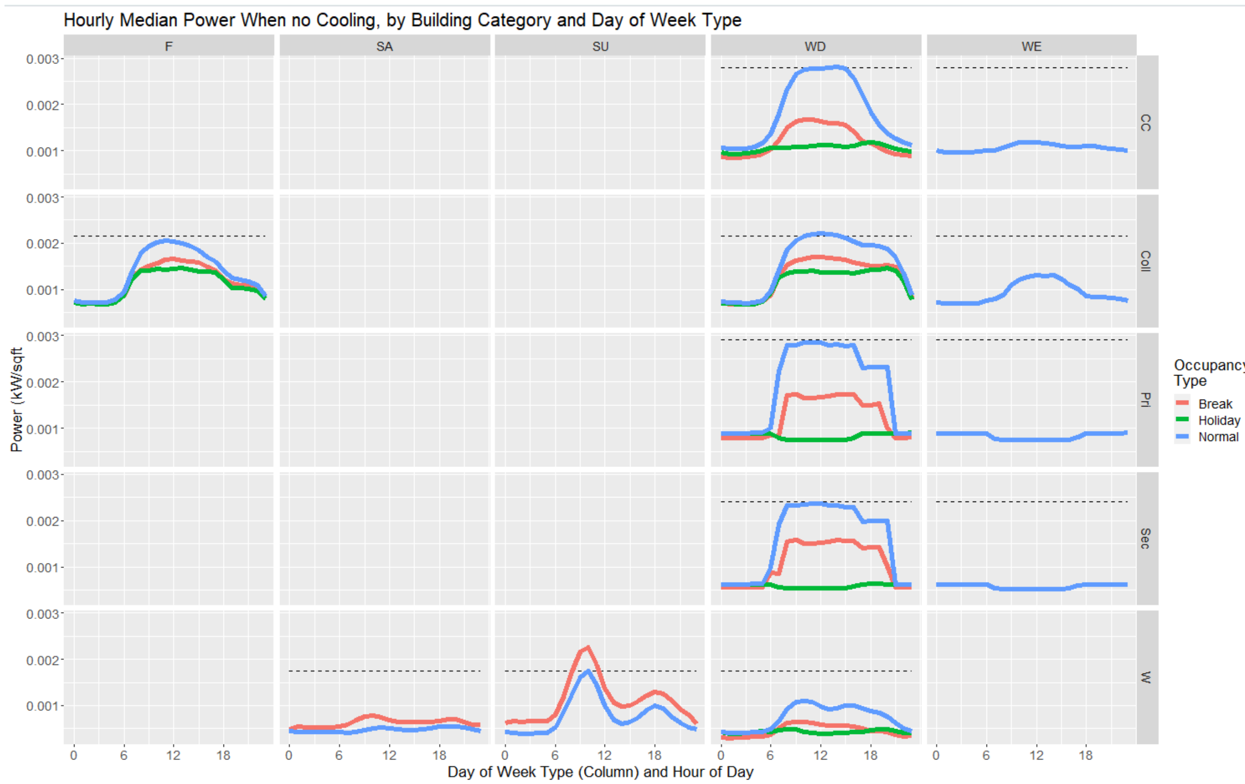

Figure 6.3. Trends in Demand. Hourly median demand (kW) when no cooling is required. The black dashed line shows the 95th percentile of power across all hours, weekday classifications, and occupancy types. Friday (F), Saturday (SA), Sunday (SU), weekday (WD), and weekend (WE).

6.2.2 Temperature, Humidity, and Radiation Dependence

Temperature, humidity, and radiation data are available from GHCN-Daily, and occupancy and occupancy-driven load available from this proxy, we can then build a regression model for building load across all temperature regimes. We use GHCN-Daily averages, as average radiation and humidity have very little hour-to-hour and day-to-day variation. Early regressions allowed us to reject them as explanatory variables of building energy.

6.2.3 Regression Against Occupancy and Temperature

In order to have regression variables consistent in scale, we convert temperature to a normalized scale between zero and one, with zero corresponding to the lowest temperature observed in the dataset and one corresponding to the highest. Occupancy is already scaled as a percentage. Our analysis showed that a parsimonious model, using the same variables across all building categories, gives power as a function of occupancy and temperature, with explanatory variables being occupancy, occupancy interacting with temperature, and temperature squared such that hourly power (P) can be estimated as:

$P = C_{K.B} + C_{O.B}*O + C_{OT.B}*O*T + C_{OTT.B}*O*T^2$ (Model 1)

where

P = Electric power

O = Occupancy percentage,

T = Temperature, as a percentage of the range between statewide observed minimum and maximum temperatures.

$C_{x.B}$ = regression fitted coefficients by term (X) and building category (B) with

X in {

K = constant term,

O = Occupancy,

OT = Occupancy*Temperature,

OTT = Occupancy*Temperature*Temperature}

Model parameters and statistics are shown in **Table 6.2**. P-values for all regression terms are less than 0.05. The highest P-value is for the constant term for colleges at 6E(-12). R-squared are above 0.90 for all building categories except places of worship, with these coming in at 0.717.

Table 6.2. Model Parameters for Regressions Against Occupancy and Temperature					
Building Category	**Adjusted R^2**	**Constant $C_{K.C}$**	**Occupancy $C_{O.C}$**	**Occupancy, Temperature $C_{OT.C}$**	**Occupancy, T^2 $C_{OTT.C}$**
Community Center (CC)	0.906	1.21E(-4)	9.14E(-3)	-2.39E(-2)	2.15E(-2)
Community College (Coll)	0.967	2.67E(-5)	7.81E(-3)	-1.92E(-2)	1.62E(-2)
Primary School (Pri)	0.942	-9.93E(-5)	6.94E(-3)	-1.63E(-2)	1.61E(-2)
Secondary School (Sec)	0.902	-6.61E(-5)	7.88E(-3)	-2.25E(-2)	2.23E(-2)
Places of Worship (W)	0.713	2.24E(-4)	8.37E(-3)	-2.50E(-2)	2.16E(-2)
All	0.858	-1.00E(-4)	7.66E(-3)	-1.95E(-2)	1.86E(-2)

Table 6.2. Model Parameters for Regressions Against Occupancy and Temperature.

6.3 Generating Energy Load Profiles for Each Site

Using regression Model 1, and the average hourly GHCN-Daily temperature profiles from the weather stations in California we generate an average hourly load profile for each building category. As this load profile is a function of average hourly temperature, it lacks the stochasticity that existed in the original source data and in real-world data. As optimal and feasible solar+storage sizes, especially storage size, will be in part driven by the need to meet peak rather than average load, we modify the load profile to include some realistic randomness. This is accomplished by comparing the regression-predicted load profiles ($\mathbf{P}_{\mathbf{pred}}$) to the original load profile ($\mathbf{P}$), and determining the hourly percent difference between modeled and measured data for each building category at each of the example sites as $\mathbf{P}_{\mathbf{deltapct}}$ = ($\mathbf{P}$-$\mathbf{P}_{\mathbf{pred}}$)/$\mathbf{P}_{\mathbf{pred}}$ in each hour of the year. We then use $\mathbf{P}_{\mathbf{deltapct}}$ as a multiplier to adjust P_{pred} for each site in the same IECC climate zone as the example site, such that $\mathbf{P}_{\mathbf{adj}}$ = (**1**+$\mathbf{P}_{\mathbf{pred}}$)*$\mathbf{P}_{\mathbf{deltapct}}$. This inserts the regression error back into the load profile for each weather station based on the regression error for each building category in each climate zone. These load profiles are then used to calculate the load at each site by converting them from a load per square foot of floor space to a total building energy load by multiplying by the site area in square feet.

Using the temperature and occupancy relationships developed from example cities, we adjusted each building category's load profile to local climate by calculating the power intensity (kilowatts per square foot) for each building class based on weather data from the nearest of the 400 weather stations across California. Note Community Centers tend to have the highest energy use per square foot while Places of Worship have the lowest, except on Sunday mornings. Community Colleges tend to have the latest evening operations, except on Fridays, when they appear to have fewer afternoon and evening classes and events.

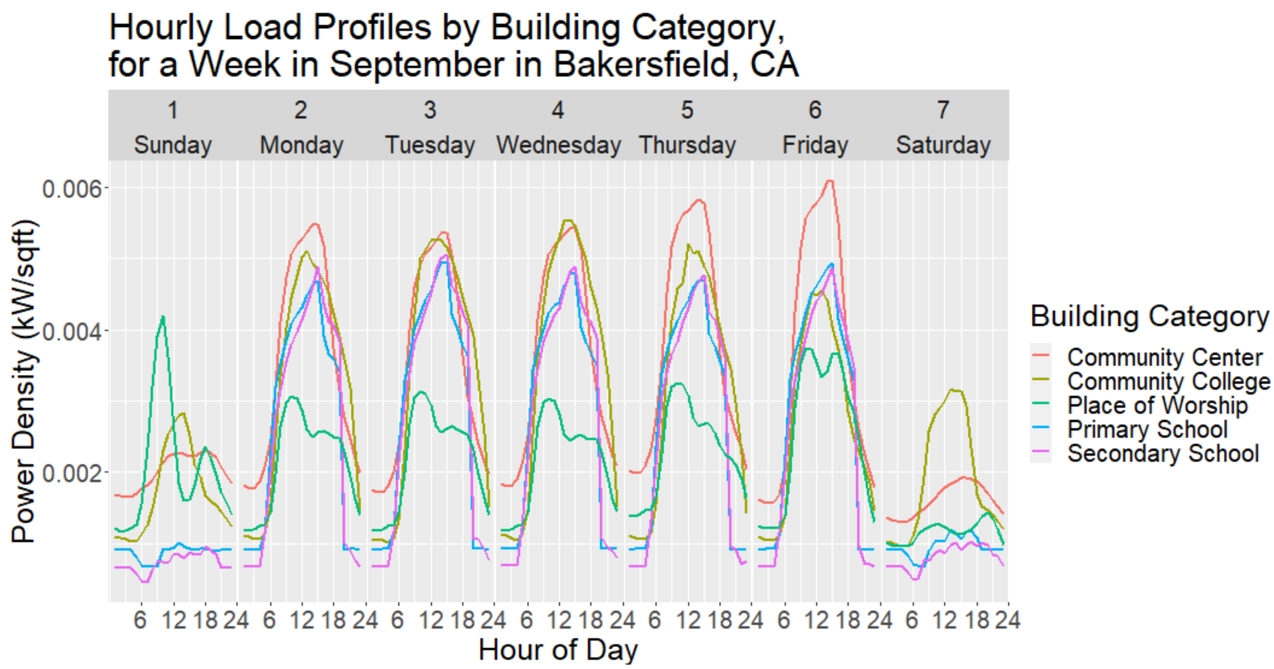

Figure 6.4 Example Load Profiles. Example load profiles for each building category, example week. Load profiles show the average power density (kW per square foot) used in each building category during each hour of the day for a representative week in September in Bakersfield, California. Buildings have different energy requirements during different times of year, so load profiles were created for each month, adjusted for the building's local climate at that time of year.

6.4 Power and Energy Per Person

To develop a per-person energy and power estimate consistent with location and season, we used the load profiles developed above combined with school enrollment data to determine the average energy per person in each month, consistent with the temperature profiles from each of the weather stations used above.

We used schools as the source data because the schools data set had occupancy information. We calculated the average square footage per student across the state, and then used the load profiles to obtain the average energy per day per student. We used this as a proxy for per person energy requirements for everyday operations at the school. While not a perfect proxy for resilience missions, this does at least provide an estimate for plug, lighting, and heating and cooling loads per person.

7.0 Solar+Storage Potential for Everyday and Resilience Operations

After estimating energy requirements and designs for solar+storage for the candidate resilience hubs, we model the economic costs, benefits, and the greenhouse gas emission reductions of outfitting candidate sites across California with solar+storage optimized for everyday operations. We then identify design modifications and additional costs required for resilient energy production and storage to support critical loads through a range of outage scenarios. Finally, we explore the impact of regional variation in solar irradiance, temperature profiles, and utility rates on design requirements; and how utility rate design–including Time-of-Use (TOU) rates, demand charges, and net-metering rates–impacts the financing requirements for the sites.

7.1. Resilient Energy Analysis with REopt

REopt has been demonstrated as a useful tool for evaluating off-grid and on-grid resilience for hospitals, clinics, offices, public buildings, and critical facilities.[60–64] We are not aware of peer-reviewed research on solar+storage systems designed for resilience hubs using REopt or another tool. The closest work we find is our own work toward energy design for resilience hubs.[65]

REopt does not have a built-in value of resilience, but does include a method to calculate the cost of a lack of resilience by calculating cost of unmet load. The dollar value to put on unmet load, or the value of resilience (VoR), is a field of ongoing research, with estimates that range over three orders of magnitude, from less than $1/kWh unserved to more than $60/kWh in residential applications and more than $400/kWh in industrial applications.[66,67] Resilience hub critical loads may have even higher value, given that some of these loads may be for storing expensive, life-saving medicines, powering medical devices, and providing clean, cool air for people who might otherwise die in heat waves or smoke events. Rather than put a dollar value on these benefits, this analysis calculates the additional capital costs required to meet certain resilience levels (duration of outage and percent of normal load served) and the economic value provided in normal operations from systems designed to meet those resilience constraints.

For each potential site identified, we determined the optimal solar+storage designs for everyday operation of these sites and calculated the additional solar+storage that might be necessary for various needs during outage scenarios. The economics of everyday operations and resilience operations were modeled using the U.S. National Renewable Energy REopt tool. REopt also provides greenhouse gas and pollution emission reduction estimates, as described in **Section 8** below. We detail the site inputs necessary in **Section 7.2**, and methods for modeling for economic operations in **Section 7.3**, for resilience operations in **Section 7.4**.

7.2 Site Identification and Characteristics

To model the economic and resilience potential for these sites, we used the input data shown in **Table 7.1**, some of which is directly available from the sources listed above (e.g., location by latitude and longitude). Methods of estimation for the remaining input data follow.

Table 7.1: Input Data Modeling Economics and Resilience of Candidate Site	
Data Element	**Supporting Data Element**
Location	Latitude, longitude
Load Profile	Building category
	Building size (footprint and number of floors)
	Local climate (daily and hourly temperature profiles)
Utility Costs	Utility (utility service area)
	Utility rate (building maximum load)
Outage Scenario	Outage duration
	Critical load profile

Table 7.1. Input Data Modeling Economics and Resilience of Candidate Site.

7.2.1 Load Profiles

Section 6 explained how power and energy density load profiles were developed consistent with building category and local climate. To convert the energy intensity per square foot into a building energy load profile, we needed building area. We calculated the roof area using OSM building footprints and estimated building floor area from roof area to account for multi-floor buildings. For this, we sampled 200 schools (124 primary and 76 secondary) and 50 community centers from the combined building data set, and estimated the number of floors for each sample building using Google Street View imagery. We then averaged by building class and locale based on the National Center for Education Statistics locale classification.[68] Significant differences were observed for community centers, primary schools, and secondary schools based on whether or not their location was in a city (i.e., suburban, town, or rural) (**Table 7.2**). Buildings that were not found in OSM were assigned the mean building area from that building category.

Table 7.2: Average Number of Floors for Each Building Class

Building Category	Supporting Data Element	Average Number of Floors (Not in a City)
Community Center	1.2	1.0
Community College	1.0	1.0
Primary School	1.3	1.0
Secondary School	1.4	1.2
Place of Worship	1.0	1.0

Table 7.2: Average Number of Floors for Each Building Class

7.2.2 Utility Costs

Utility rates impact solar+storage adoption. Higher grid electricity prices and higher payback prices from net metering rules (the price paid by the utility for distributed solar sent back to the grid instead of used on-site) shorten the payback period for solar installations. Battery adoption increases with higher charges for peak power use, sometimes called capacity or demand charges, especially when those charges are greater than $15/kW at 2017 battery storage costs. Decreased storage costs have also increased adoption of batteries for peak power shaving.[69] In addition to high peak power charges, high energy costs (especially greater than $0.40/kWh) combined with low solar sell-back prices during daylight hours (especially below $0.10/kWh) can incentivize battery adoption.[70] We also expect that highly differentiated TOU rates, with evening prices higher than daytime prices and daytime sell-back rates, will incentivize battery adoption. To evaluate the economic value of solar+storage, electric utility rates must, therefore, be included in the analysis.

There are more than 40 electric utilities in California with different rates, rate structures, and net metering rules. These range from large investor-owned utilities, such as Pacific Gas & Electric Company (PG&E) with more than half a million commercial customers, to public utilities such as the City of Shasta Lake that serve fewer than five thousand commercial customers. The five largest utilities serve 90 percent of the customers in California, while no other single utility provider accounts for more than one percent of utility customers.[71] We include the five largest utilities and five additional utilities in our analysis to ensure statewide representation, coverage of urban and rural communities, and coverage of disadvantaged communities. **Table 7.3** lists the utilities selected for modeling. Each of the five small utilities selected was chosen because it serves customers in census tracts ranking in the 90th-100th percentile of disadvantaged communities, as noted by California's environmental justice screening tool, CalEnviroScreen 4.0.[7]

Table 7.3: California Utilities Selected for Modeling		
Utility Name	**Utility Abbreviation**	**Percentage of California Customers**
Pacific Gas & Electric Co.	PG&E	33
Southern California Edison Co.	SCE	31
San Diego Gas & Electric Co.	SDG&E	9
Sacramento Municipal Utility District	SMUD	9
Los Angeles Department of Water & Power	LADWP	9
Imperial Irrigation District	IID	<1
Modesto Irrigation District	MID	<1
City of Anaheim, California (Utility Company)	COAPUD	<1
City of Riverside, California (Utility Company)	COR	<1
Turlock Irrigation District	TID	<1
Total		**~95**

Table 7.3. California Utilities Selected for Modeling.

We identified specific rates in each utilities' service area from the International Utility Rate Database.[72] In each region, we selected active or most recently available commercial rates covering a range of power service levels. Where TOU rates were available, we used these. In regions where TOUs were not available, rates with demand charges were selected. Appendix B summarizes the selected utility rates in each utility service area.

7.3 Economics for Everyday Operations

To explore the economically optimal solar+storage designs for everyday operations and various outage scenarios, we modeled the candidate buildings in REopt. In addition to the site characteristics (load profiles, roof space available, utility rates) outlined above, some additional key inputs for economic analysis include solar and battery costs, rebates and tax incentives, and net metering rules.

We constrained this study to roof-top solar installations. Future work will add on-parcel off-roof potential (e.g., parking lots) and off-parcel (e.g., community microgrid) potential, and we discuss where such expansion might be most valuable in the discussion section.

7.3.1 Installation and Maintenance Costs and Incentives

While solar and battery installation costs vary (generally decreasing over time and with installation size), we use constant installed costs with REopt defaults: solar PV costs $1,592/kW with annual maintenance costs of $17/kW; batteries cost $775/kW and $388/kWh for initial installation, with replacement costs of $440/kW and 220/kWh every ten years. In addition, Inflation Reduction Act tax credits for solar and battery are 30 percent (0.3). As they are now applicable to nonprofits, we used this fraction for all sites.

7.3.2 Net Metering Rules

We conduct our baseline site analysis under the California Public Utility Commission's (CPUC) 2023 net billing regime (NEM 3.0) but compare outcomes to the previous regime (NEM 2.0).[73] NEM 2.0 featured full retail price net metering, where the price of energy supplied to the grid was equal to the price of purchasing energy from the grid. NEM 3.0 reduces the price paid to distributed generators to a rate that reflects the value of that energy to the grid at the time of export. The value will usually be lower than the retail rate. The change was made to reduce cost shifting from those with solar to those without solar.[73] The sell-back price for electricity exports under the new net billing tariff will vary based on the utility value of energy at the time of export, with seasonal, daily, and even hourly fluctuation. To put a lower bound on the possible value of exports, we set the price to zero. The as-yet-undefined and likely volatile sell-back prices pose a significant challenge for solar designers; this analytical method provides a conservative estimate of the impacts on solar and storage sizing under this new net billing regime.

7.3.3 Discount Rate

We used a discount rate of 8.1 percent. REopt uses this to calculate net present value (NPV) from the initial cost and utility savings cash flows over the 20-year analysis period.

7.4 Economics and Resilience for Outage Operations

In addition to economic operations, we model resilience scenarios as a combination of outage duration and resilient energy needs during the outage. We study a range of outage scenarios across the economic-resilience spectrum, considering everyday operation economic optimization with no outages, and also design changes and costs incurred to provide energy for outages lasting two, four, and eight days (48, 96, and 192 hours) at various levels of critical load.

7.4.1 Outage Durations

Long-duration outage causes include hurricanes, seasonal storms, wildfires, and recently in California, Public Safety Power Shutoffs (PSPS). According to utility reliability reports, the average outage duration for customers served by PG&E was two hours and forty five minutes in 2021, but some can last much longer.[74] For example, PSPS events in California, which have impacted 3.2 million customers over the last 10 years, lasted an average of approximately two days—but ten percent of PSPS customer outages have been longer than four days, and the longest PSPS customer outages reported so far were six days.[75] Gorman et al. study the resilience potential of economically optimized solar+storage using a sample of ten historical events, including hurricanes, wildfires, and winter storms.[76] Their base scenario assumes a three-day outage.

While most outages are less than three hours, and most long-duration outages caused by extreme weather last less than four days, climate change is likely to increase the frequency, duration, and geographic range of severe weather and associated outages. As such, resilience hub design should reflect the uncertainty in this risk, and be designed for extreme events.

7.4.2 Critical Loads

Resilience hub planning must consider the services to be provided during outages and their power and energy requirements. Roode and Martinac describe a resilient power spectrum covering the most resilient systems that provide little or no benefit during everyday operations but offer long-duration backup to critical loads during power outages to the most economic systems that provide environmental and economic benefits with less resilience.[36] This study explores this spectrum by investigating trade-offs between economically optimal solutions for everyday operations and various resilience-focused solutions.

A challenge for a resilient solar+storage power system occurs when, over the course of an outage, solar energy input is lower than energy needs. For each potential resilience hub location, we combined data from the National Solar Radiation Data Base (NSRDB)[77] with load profile data for each site and generated a daily average ratio of solar energy versus energy needs for each month of the year. We assumed a solar conversion efficiency of 20 percent, consistent with current commercially available technology.[78] We also assumed that half of the roof space is available for solar panel installation, as commercial estimates for roof space available prior to detailed site-studies assume 50 percent obstruction and shading.[79] However, actual available roof space will vary by building as a function of shading, roof pitch, equipment obstruction, and other factors with regional estimated averages ranging from 22 percent to 95 percent.[80]

For any given site, prioritizing energy needs to identify critical loads would be the role of site operators and stakeholders, which is beyond the scope of this work. Here, we estimate critical loads as percentages of normal load. For each site and outage duration, we selected critical load percentages (CLPs) to test how different ratios of solar production affect the site's ability to meet critical loads. If S_m is the daily average solar energy generated in a given month, and Ln is the normal-load daily average energy used in that month, the ratio of load-to-solar is $R_n = L_n/S_m$. To study a range of contingencies, we simulated a broad set of CLPs, with CLP being a scalar constant used to modify the normal load profile such that critical load $L_c = (CLP)*(L_n)$. We select CLPs for each site in order to test a range of critical load to solar ratios (Rc) such that the daily ratio of critical load over solar energy in ($R_c = L_c/S_m$) extends from solar energy providing half of the critical daily energy needs ($R_c = 2$) to solar providing four times the critical daily energy needs ($R_c = 0.25$), with a range of intermediate values also tested. CLPs selected range from seven percent (low sunlight, high load) to 800 percent (high sunlight, low load) of everyday loads. We expected battery size and cost would increase with increasing R_c, and this range allowed us to study the implications on the cost of resilience for each site.

7.4.3 Outage Start Times

All simulated outages start at 9 a.m. on the first Tuesday of the month, even though real outages are typically not scheduled. This consistent morning start time allows for comparisons of difficult design cases, as batteries will be at their lowest state of charge after serving nighttime load. We use monthly average load and average solar production to select scenarios and we model sites in REopt using realistic hourly load profiles developed using the methods in **Section 6** and solar data from the PVWatts database.[81] We deterministically choose the first Tuesday of challenging outage months, which could miss the most challenging days in the most challenging month. In future iterations of this work, we will look at different weather events and resulting outages to better characterize design needs consistent with extreme weather events like heat waves and winter storms that coincide with long periods of poor sunlight. This type of reliability analysis is beyond our current scope, as the goal is to identify where there will be challenges in funding resilience, not to calculate exact design parameters for every site or contingency.

We choose the most challenging months for each site to stress resilience designs. When net daily energy—the difference between total daily energy consumed and daily solar production—is positive, the site is using more energy than can be produced by rooftop solar.

Table 7.4, defines some of the key variables for this analysis. We modeled outages in both the most challenging month at each site, where R_{nm}, the ratio of normal load to solar input, is highest (typically in winter), and the least challenging month at each site, where R_{nm} is lowest (typically in spring or early summer).

Table 7.4: Key Variables Included in the Statewide Analysis	
Variable	**Description**
NPV	Net present value, the discounted worth of all costs (up-front, operations, maintenance, disposal) and benefits (bill reductions) over the 20 year lifecycle
$NPV_{everyday}$	NPV for the economically optimal design
$NPV_{scenario}$	NPV for the outage scenario design
$\Delta NPV_{resilience}$	Difference in NPV, or the NPV cost of resilience, given by $NPV_{everyday}$-$NPV_{scenario}$
CLP	Critical load percentage, or fraction of everyday energy deemed necessary for critical missions during an outage
S_m	Daily average solar energy generated for month m
L_{nm}	Daily average energy load for normal everyday operations for month m
L_{cm}	Daily energy load for critical operations for month m (CLP*L_{nm})
R_{nm}	Ratio of daily average energy to solar energy generated for month m (L_{nm}/S_m)
R_{cm}	Ratio of daily critical energy to solar energy generated for month m (L_{cm}/S_m); coincident with R_{nm}
P_{n_annual}	Average annual power, everyday operations
P_{nm}	Average power during the outage month, everyday operations
P_{cm}	Average critical power (P_{nm}*CLP)

Table 7.4. Key Variables Included in the Statewide Analysis.

7.4.4 Interpolating from Modeled Sites

We modeled a sample of 1,097 sites out of the 18,000 potential sites identified. To minimize computation time, we used the modeled results to estimate key outputs for all sites by running a series of regressions on the modeled results and interpolating the results of these regressions back to the full set of potential sites.

We ran a series of linear regressions to characterize the influence of local building load and utility rate on everyday and resilience designs and costs. The key output variables included solar+storage system designs, financial metrics, and emissions reduction metrics. Financial metrics include initial capital costs after incentives (in dollars) and the NPV in dollars. Emissions reductions were calculated for CO_2, nitrogen oxides (NO_x), and primary fine particulate matter ($PM_{2.5}$).

For the economic base case analysis, we performed regressions against annual average power (P_{n_annual}). Where there were enough sites in each category, utility, and utility rate to develop statistically significant regressions, we did so. For outage durations of 48, 96, and 192 hours, we performed regressions against critical average power during the outage (P_{cm}) for battery and financial variables. For solar installation size and the emissions reductions we continue to use P_{n_annual} as the regression variable. In addition to category, utility, and utility rate, we also grouped models by the critical-load-to-solar ratio (R_{cm}).

Each regression was performed considering a non-zero intercept and a zero intercept, and mean values for each output variable were also calculated. In many cases, we could assume that the regression constant must be zero because the dependent variable in each regression could be assumed to be zero if average power or average critical power were zero. That is, if power equals zero, then no solar nor battery would be needed, no pollution would be emitted, and no costs would be incurred. In these cases, regression through the origin (constant equals zero) would be appropriate. Assuming a zero constant would introduce errors if, for example, solar installation size were limited by regulation under an upper bound (as is true in California). Below this upper boundary, a linear regression through the origin fits best; above this boundary, a constant term (the regulated maximum) with zero slope fits best. Textbooks caution against dropping the constant term from a regression, but in some cases, as discussed here, regression through the origin is necessary.[82]

From the candidate regressions and mean value models for each sample building set, we selected the model(s) that met significance thresholds of $p \leqq 0.05$ for the regression parameter and the constant, as appropriate. If more than one was significant, we selected the model with the lowest standard deviation in the residuals. If multiple candidates still existed, we selected the model with the highest adjusted R-squared value. We then used the selected model to estimate the design, financial, and environmental outputs for all 18,000 sites.

We estimate the financial costs of resilience, using the difference between the cost for the solar+storage design to survive an outage (e.g., a resilience scenario) and the solar+storage design for everyday operations. If the economically optimal design in either type of scenario has a positive NPV, it likely can be financed and would not require grant funding or other state support beyond loan guarantees. The designs to meet resilience scenarios, especially those of long duration and high critical loads, will have higher initial costs and lower (possibly negative) NPVs. For each site, the difference in cost between the resilience scenario and everyday operations is thus the marginal cost for that level of resilience for the site. While resilience has value, there is no commonly agreed upon approach to assigning it an economic value. There are fewer funding mechanisms for resilience-only operations.

7.4.5 Resilience Hub Capacity or "Seats"

It is important to quantify how many people can be served by a hub simultaneously throughout an outage. We estimate resilience hub capacity, or simultaneous "seats," in two ways: first with an available building space constraint and second with building space and available energy constraints.

If grid power is available and critical services like clean, conditioned air for an emergency shelter are needed, we estimate this capacity by dividing the total square footage by the 70 square feet per person required for a bed and storage space for emergency housing according to the California Building Code.[83] We consider this an upper bound on hub capacity from these buildings, as not every event will require beds and storage space. However, we note that this rough estimate assumes that every room, space, and hallway in the resilience hub is available for emergency use.

We also considered an energy-per-person constraint. We do not have occupancy numbers for places of worship, community centers, or community colleges to determine energy use per occupant. However, we do have enrollment numbers for primary and secondary schools, and have used those to estimate energy needs for everyday operations at each school per person. We then used that energy intensity to constrain capacity at nearby locations.

8.0 Greenhouse Gas and Co-Pollutant Estimates

REopt provides emission reduction estimates for CO_2 and other air pollutants based on hourly local marginal emissions intensity data from EPA's AVERT model based on the 2020 National

Emissions Inventory (NEI) and projections of emissions from NREL's Cambium model.[81] For this work, we used REopt to calculate emissions reductions for CO_2, NO_x, and $PM_{2.5}$.

9.0 Hub Deployment Optimization Models

The complexity of the trade-offs between population vulnerability, climate risk, hub design, existing social infrastructure, and transportation makes it challenging to understand how these variables interact in the deployment of resilience hubs. It is also difficult to quantify the number of hubs that would be needed, or the amount of distributed solar and storage required to meet a given resilience target. Methods similar to those used for disaster preparation or logistical deployment of resources (often referred to as locational allocation models) can help frame how these variables interact with each other in hypothetical hub deployment scenarios, as well as estimate the total resources needed to meet certain resilience targets. However, we stress that the utility of these models is limited to specific questions and is not intended to determine which specific sites are turned into hubs, for multiple reasons. One leading reason is that these models are not aware of some of the most important aspects of resilience hubs, including whether they are actively in use and if they are considered safe places to go for help.

9.1 Location Allocation Modeling Overview

In location-allocation models, the locations of certain resources are chosen in such a way as to meet certain goals while minimizing a quantity, such as the cost to build those resources. The structure of these models is demonstrated in **Figure 9.1**. Specifically, these models choose which sites from the inventory to turn into hubs (red X's) and the number of people to travel from each block group (purple stars) to each site within a three-mile range (blue lines show for one example site). We build sites that consider all sites simultaneously across California.

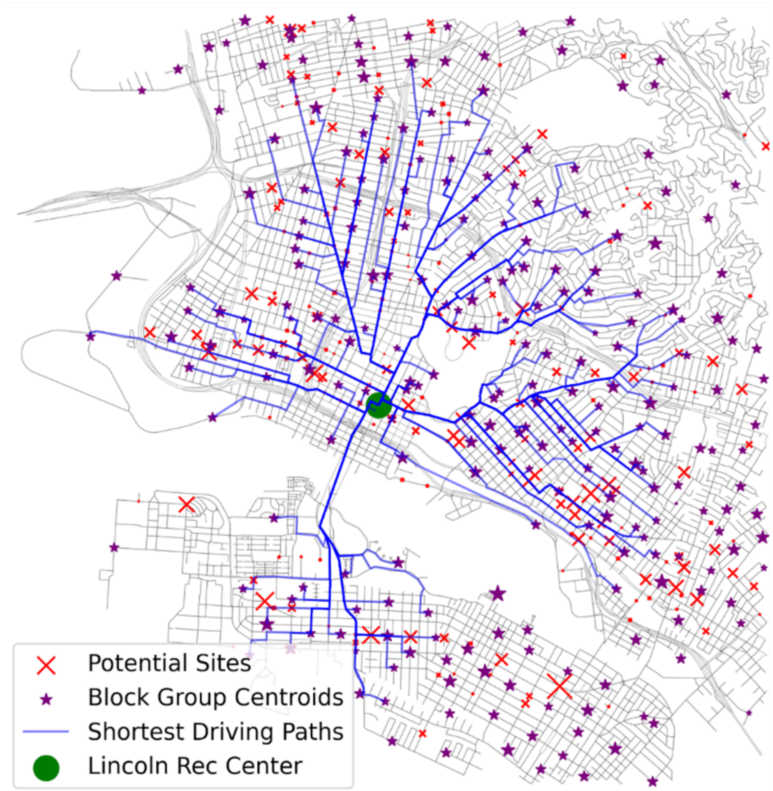

Figure 9.1. Schematic of Location Allocation Modeling Data. Map of Oakland road network downloaded from OpenStreetMaps centered on the Lincoln Recreation Center. Purple stars are located at the node nearest to the centroid of a block group and its size is proportional to the population of that block group. Each site's nearest node is marked with an "X" and its size is proportional to the number of people that can be served through a 96-hour outage once retrofitted with solar+storage. The blue lines are the shortest driving paths from each block group to the Lincoln Recreation Center. Block groups greater than three miles away are not mapped as their population is deemed too far from the chosen site in models used here.

We build three different types of models depending on the question of interest. The first is a **Number of Hubs Minimization** model. This model chooses the fewest sites from the inventory such that a minimum predetermined number of people lives within range of them. These models assume all sites have unlimited capacity. Since this dataset does not capture the cost or capacity for serving populations during everyday operations when there is no outage, this class of model is useful for modeling year-round resilience services. The second is a **Capital Cost Minimization** model. This model minimizes the total cost for retrofitting the existing building with backup solar and storage through a 96-hour outage. As such, this model accounts for the number of people that can be simultaneously served through an outage. The third model is a **Demand Maximization** model. Demand refers to the number of people that can be served. This model can take two forms. The first form is for everyday operations when we assume there is a maximum number of hubs and that hubs can serve everyone living within driving range of the hub. The second form is for considering backup power during an outage. In this form, we assume that there is a maximum budget for backup energy and the model tries to serve the most people possible given the limited capacity of hubs. In each model, we additionally incorporate ways to target priority populations typically based on their vulnerability.

Each model can be represented with mathematical equations. Optimization models are composed of an objective function and a set of constraints. The objective function is the calculation the model is trying to minimize (e.g., cost). It minimizes this function by choosing values from a set of two types of decision variables. The first decision variable is K_s, which is a one for each site s (red X's in **Figure 9.1**) that is chosen to build into a hub and a zero for the rest. The second decision variable is $N_{\{s,b\}}$, which counts the number of people that are assigned to a site s from a block group b from the list of all pairs of sites and block groups within driving distance of each other, $\{s, b\}$ represented by the blue paths in **Figure 9.1**. Using these decision variables, the objective functions for each model take the form shown in **Table 9.1**.

Table 9.1: Objective Functions for Each Optimization Model	
Objective Function Description	**Mathematical formulation**
Number of Hubs Minimization. Choose the fewest number of sites.	$min_{K_s} \sum_{s}^{S} K_s$
Capital Cost Minimization. Choose the sites that have the lowest total capital cost.	$min_{K_s} \sum_{s}^{S} K_s C_s$
Demand Maximization. Assign the most number of people within range to hubs.	$max_{N_{\{s,b\}}, K_s} \sum_{\{s,b\}} K_s N_{\{s,b\}}$

Table 9.1. Objective functions for each optimization model.

Multiple additional constraints are used to design models. Some constraints are more obvious. These include that people cannot travel greater than the maximum driving distance and that the number of people assigned to hubs from a block group cannot exceed the total population of that block group.

One constraint worth more attention is that a certain minimum number of people must be served by a hub. Mathematically, this constraint takes the general form of:

$$\sum_{\{s,b\}} N_{\{s,b\}} > D_{min}$$

where $\{s, b\}$ represent all pairs of sites and block groups that are within a maximum driving distance of each other, $N_{s,b}$ is the number of people traveling from block group b to site s, and D_{min} is the minimum population or "demand" that the user specifies must be assigned to a site. Importantly, this constraint may exist multiple times in a model for multiple population groups. For example, a constraint may state that "at least 1,000 persons in block groups in the most vulnerable quartile in Los Angeles must be served." In mathematical form, this would be written as:

$$\sum_{\{s,b\}} N_{\{s,b\}} I_V(b) I_{LA}(b) > D_{min},$$

where $I_V(b) = 1\ if\ V_b > 75\ else\ 0$ where V_b is the vulnerability percentile for block group b and $I_{LA}(b) = 1\ if\ b\ in\ Los\ Angeles\ else\ 0$. As such, many such constraints may exist for a given model and can be specific for populations from only specific block groups, such as those identified as vulnerable, or for those from a given subregion.

Models will return optimal values for each of these variables depending on the set of input variables the user specifies. In the case of California resilience hubs, these user specified variables include the following:

- The cost to deploy a resilience hub at a given site. In practice, we choose the scenario of a 96-hour outage and the total capital cost of solar+storage whose parameters are discussed in **Section 7**.
- The maximum number of people that can simultaneously be served by a hub, also referred to as the number of "seats" for a given scenario. These are also estimated above in the section Resilience Hub Capacity or "Seats."
- The population or "demand" minimum that must be served. Through repeated use of the minimum demand constraint, this can be specified for multiple population subsets. For example, the constraint may consider only block groups that are above a certain minimum vulnerability threshold.

Each of these models can be run as a whole across the entirety of California and for specific areas such as counties or municipal areas. For example, we explore how the cost increases as we increase the minimum population that must have access to a hub. We use the Pyomo[84] package in Python to build these optimization models and solve them with open-source solvers, including GLPK.

9.2 Geographies for Geospatial Modeling

There are multiple choices possible for the geography of the sub-region to conduct a location allocation model. Each has its own set of advantages and disadvantages and as such, we use different geographies for different purposes.

- Entire state of California. Performing a model at the scale of all of California has the disadvantage of concentrating all of the sites in spatially very dense areas while entirely neglecting large areas of California. In **Figure 9.2**, we demonstrate how we use state Senate districts, areas that roughly match one million individuals each, to encourage a more realistic geographic dispersion.
- Counties are useful as they can be a decision-making geography. However, their population sizes vary drastically with Los Angeles covering nearly 10 million people, while Alpine County only has around one thousand people. As such, county geographies make it challenging to perform comparisons. Dividing Los Angeles into county subdivisions can help produce geographies of smaller populations.
- Senate and assembly districts address the weaknesses of modeling the entire California and county geographies. They have roughly uniform populations of one million and half a million people respectively. As such, they are useful for making comparisons such as identifying areas where more sites may be needed per capita due to a spread-out population. Their disadvantage is that decision making is less common at the district level than other geographies.
- Metropolitan statistical areas are useful for looking at trends in urban areas.
- Utility service areas may be useful for decision making for utility programs; however, utility service areas overlap so it is not clear whether sites would be customers of any given utility.

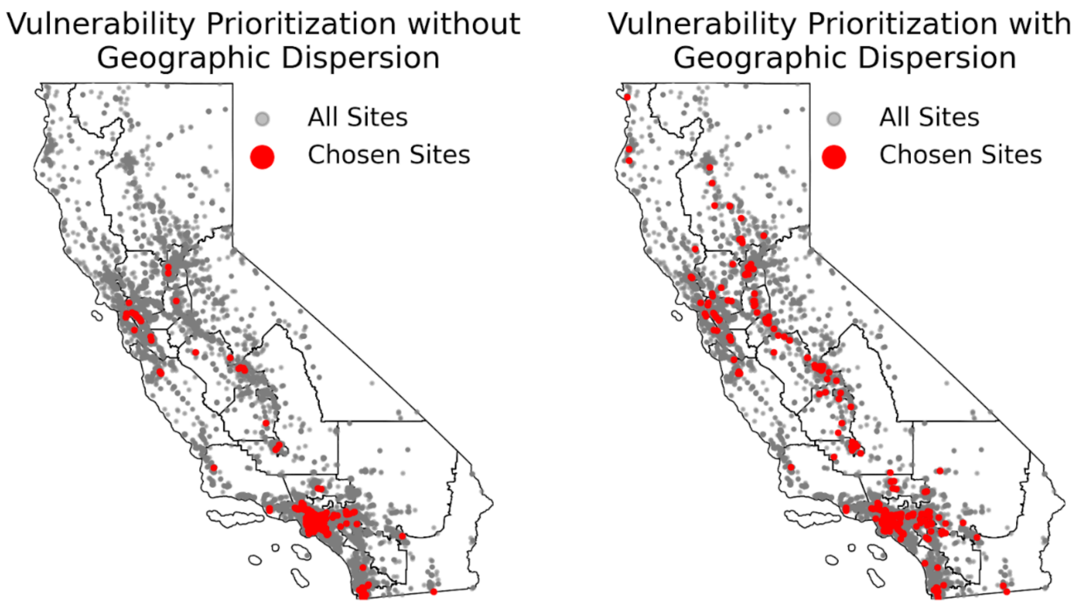

Figure 9.2 Modeling results from two site minimization models. The left requires at least 20 percent of all population to reside within a three-mile range of a hub. Moreover, 25 and 50 percent of the third quartile and fourth quartile population must also be served with a resilience hub respectively. The majority of hubs are concentrated in LA and 199 hubs were required. On the right, a further constraint requires that at least half of the vulnerable populations served must be proportionally distributed in each senate district, outlined in black. For example, if ten percent of all the California population in vulnerable tracts lives in a given district, then at least five percent of the population within range of a hub must also live in that district. In this map, hubs are more distributed across California while still meeting the same overall and vulnerable population constraints. This model required 236 hubs.

APPENDIX A: CBE Resilience Hub Survey

Resilience Hub Survey

COMMUNITIES FOR A BETTER ENVIRONMENT established 1978

Communities for a Better Environment wants to work with the community to identify and build out a resilience hub. A resilience hub is a safe and welcoming space that offers services and resources all-year long, especially prepared to handle emergency situations and climate disasters, and is equipped with solar and back-up energy.We are collecting research to identify a location and what resources should be prioritized. As you know, there are several refineries, oil wells, and industrial sites that harm our health, air quality, and increase industrial risks. As climate disasters increase in frequency and strength it is important that community centers are equipped to handle emergencies and community members have a strong emergency plan to react and adapt to a changing climate. The following questions will ask you first what location would be most optimal for the folks of Wilmington to conveniently and quickly access the hub; secondly, what resources this hub should be home to so that it is safe and suited to the needs of the people.

1. Full name (*Required)

2. Phone number and/ or email *

3. Age?(Pick one)
    - 12- 17
    - 18- 30
    - 31- 40
    - 41- 50
    - 51- 65
    - 66 and up
4. What is your preferred language?

5. What is your address? Or what are your cross streets?

6. Ethnicity/ race? **(check all that apply)**
    - Hispanic OR Latinx
    - Black or African American
    - Asian
    - Indigenous or Native American
    - Native Hawaiian or other Pacific Islander
    - White

7. Gender?
    - Man
    - Woman
    - Non-binary
    - Prefer not to say

8. Do you have dependents? Children, seniors, etc?

- Yes
- No

9. How many people live in your household?

Since Wilmington and surrounding Harbor/South Bay Communities have a large industry presence, the following questions will ask your levels of concern regarding climate disasters and how industrialized communities are at greater risk of being harmed in such an event.

10. **Select top 5:** What types of natural disasters, industrial impacts or climate impacts are you most concerned about? (mark all that apply)

- Earthquakes
- Extreme heat
- Wildfires/Wildfire Smoke
- Refinery Flaring
- Air Pollution
- Oil Drilling
- Water and food insecurity
- Droughts
- Power Outages
- Vector Borne Diseases
- Flooding
- Tsunami

11. Approximately how close do you live near to an industrial site (refineries, oil drilling, other industry)?

- Neighboring me
- Less than a mile
- 5 miles

12. **All that apply:** Who or where do you go to in times of disaster or need?
- Yes there is a places i trust
- I reach out to family
- I reach out to public services
- I reach out to community

- No there is not a place or person to go to
- I seek public resources

13. **Choose one:** How often have you felt a need for emergency shelter?
    - Not at all - never
    - Sometimes - once every year
    - Often - a couple of times a year
    - Very Often - monthly

We know that climate and natural disasters can disproportionately impact communities near industry; these events can also greatly impact those with unique medical needs and those who are immunocompromised.

14. Do you have unique medical needs or are immunocompromised?
    - Yes
    - No
    - Prefer not to answer

15. Do you use health equipment?
    - Yes
    - No
    - Prefer not to answer

16. If answered yes, does the health equipment need electricity to power?

17. In case the energy goes out, what would your energy priority be?

18. **Choose five:** What information or materials do you need for an emergency kit during a disaster?
    - Disaster Training
    - Self Defense Training
    - Air Mask
    - Food and Water
    - Solar Charging Battery Pack
    - Flashlight and batteries
    - Tools
    - Clothes
    - Whistle

19. What do you have at home to prepare for an emergency?

20. How would you feel if there were a community Resilience Hub Center where there were resources and safety in times of climate crisis?

- Not Excited
- Somewhat Excited
- Very Excited

21.How far do you feel comfortable walking to a Resilience Hub center? (check all that apply)

- A couple of blocks down
- 1 mile
- 3 miles
- 5 miles

22. What times of the day would you utilize this center? (check all that apply)

- 12am- 12pm
- 1pm- 5pm
- 6pm- 9pm
- 10pm- 12am

23. **Choose five:** What services or training would you like to see offered at the resilience hub?

- Wifi
- Water/ food
- Phone charging stations
- Gender neutral restrooms
- Personal Protection Equipment (masks, hand sanitizer, etc)
- Supportive Staff
- Sexual health resources (sex ed, birth control, STI testing)
- Transportation
- Outdoor and indoor activities (art rooms, sports, library)
- Counseling
- Self- defense classes
- Tutoring for youth
- Funding resources for families
- Opportunities for engaging in social justice issues
- Emergency Response Trainings
- De-escalation/ Non-violence trainings
- Know Your Rights training
- Computer and Technology training

- Renewable Energy training

24. **Choose five:** What materials and resources would you like to see at the center in the case of an emergency (earthquake, power outage, refinery flare or explosion, wildfire, etc.)?

- Wi-Fi
- Phone charging
- Refrigeration
- Air filtration
- N95 masks
- Power generators
- Evacuation plans
- Lists of emergency phone numbers
- Earthquake kits
- Flash lights and lamps
- First aid kits

25. When power outages occur, how long do you feel comfortable at home before you begin to look for a place to go to?

26. Any comments or input?

Thank you for taking the time to fill out this survey!

APPENDIX B: Utility Rate Database Descriptions

Differing utility rates across California offer natural experiments in rate designs. The City of Anaheim Public Utilities District (COAPUD), City of Riverside (COR), Imperial Irrigation District (IID), and Modesto Irrigation District (MID) did not have TOU rates in the URDB, and so only have constant prices for purchase and sell-back for solar and solar+storage; prices range from $0.093/kWh (IID) to $0.206/kWh (COR). Non-TOU rates will likely disincentivize battery adoption, given that there is no economic incentive for time-shifting consumption to cheaper rate periods. Higher prices should correlate with higher solar adoption, given similar insolation.

Differing utility rates across California offer natural experiments in rate designs. The City of Anaheim Public Utilities District (COAPUD), City of Riverside (COR), Imperial Irrigation District (IID), and Modesto Irrigation District (MID) did not have TOU rates in the URDB, and so only have constant prices for purchase and sell-back for solar and solar+storage; prices range from $0.093/kWh (IID) to $0.206/kWh (COR). Non-TOU rates will likely disincentivize battery adoption, given that there is no economic incentive for time-shifting consumption to cheaper rate periods. Higher prices should correlate with higher solar adoption, given similar insolation.

Maximum energy prices in summer afternoons range from $0.093 (IID) to $0.376/kWh (Southern California Edison (SCE)) while summer evening prices range from $0.083 (COR) to $0.361/kWh (San Diego Gas and Electric ((SDG&E)). TOU schedules and prices vary across the utilities that apply them, with different start-stop times both seasonally and daily. SDG&E offers a unique case among the rates modeled, having a TOU rate on weekday summer evenings ($0.36/kWh) that is $0.10 higher than its afternoon rate ($0.26/kWh). This should incentivize battery adoption to enable solar energy collected in the afternoon to be used in lieu of higher-priced grid energy in the evening. More utilities are providing rates with higher evening prices than daytime prices to address duck curve and ramp rate concerns, since solar production quickly drops off in summer evenings even as the system typically reaches its peak load.[85] This SDG&E rate was the only one of this type in California available in the URDB at the time of this analysis.

The remaining TOU rates have prices where weekday summer afternoon rates are higher than evening rates, ranging from $0.007/kWh in Los Angeles Department of Water and Power (LADWP) to $0.255/kWh in SCE. Higher rate differential may incentivize larger solar but smaller battery, given the limited value of time-shifting solar consumption to after sunset.

Demand charges also incentivize battery storage, especially if load profiles have short, intense demand peaks that can be mitigated with stored energy. Demand rates range from $0/kW (at multiple utilities) to $25/kW (Pacific Gas and Electric (PG&E)).

Table B1: Utility Rate Summary									
Utility	**Is TOU**	**TOU rate 3pm ($/kWh)**	**TOU rate 7pm ($/kWh)**	**TOU rate 11pm ($/kWh)**	**Maximum Demand Rate ($/kW)**	**Minimum Maximum Demand (kW)**	**Maximum Maximum Demand (kW)**	**Effective Date**	**Link to URDB**
PG&E	y	0.2899	0.2662	0.2389	0.00	0	75	2020-01-01	https://apps.openei.org/USURDB/rate/view/5e162d795457a3223473e3af
PG&E	y	0.2349	0.1798	0.1517	21.63	75	500	2020-01-01	https://apps.openei.org/USURDB/rate/view/5e1630285457a3d35f73e3af
PG&E	y	0.11325	0.11325	0.10727	24.93	500	1000	2021-03-01	https://apps.openei.org/USURDB/rate/view/608c4eec5457a357322165f8
PG&E	y	0.16299	0.1196	0.08981	21.30	1000	10000	2021-03-01	https://apps.openei.org/USURDB/rate/view/5ed987ec5457a3487edd15ae
SCE	y	0.22544	0.18244	0.15384	0.00	0	20	2018-10-01	https://apps.openei.org/USURDB/rate/view/5bc7b6c75457a3a2783b43ec
SCE	y	0.37561	0.12014	0.05575	15.89	20	200	2018-10-01	https://apps.openei.org/USURDB/rate/view/5bc7ba425457a3b5483b43ed

SCE	y	0.34712	0.11336	0.05616	18.29	200	10000	2018-10-01	https://apps.openei.org/USURDB/rate/view/5bc7bf095457a3b5483b43ef
LADWP	y	0.2417	0.1888	0.15812	8.34	0	30	2019-04-01	https://apps.openei.org/USURDB/rate/view/5cd304535457a30e7954e9d3
LADWP	y	0.13136	0.12409	0.10336	10.00	30	10000	2019-04-01	https://apps.openei.org/USURDB/rate/view/5a3821035457a32645d2dd80
SMUD	y	0.3037	0.1111	0.1111	0.00	0	20	2019-06-25	https://apps.openei.org/USURDB/rate/view/5dbc7e515457a3d81edc72bb
SMUD	y	0.2634	0.0914	0.0914	7.66	20	300	2019-06-25	https://apps.openei.org/USURDB/rate/view/5dbc85155457a38c20dc72bb
SMUD	y	0.2027	0.2027	0.1101	7.73	300	500	2019-06-25	https://apps.openei.org/USURDB/rate/view/5dbc9a5f5457a33c1fdc72bb
SMUD	y	0.1969	0.1969	0.1044	7.05	500	1000	2019-06-25	https://apps.openei.org/USURDB/rate/view/5dbc89695457a3d23fdc72bc
SMUD	y	0.1698	0.1698	0.1084	4.06	1000	10000	2019-06-25	https://apps.o

									penei.org/USURDB/rate/view/5dbc87985457a37e1cdc72bb
SDG&E	y	0.2566	0.36055	0.2566	0.00	0	5	2019-03-01	https://apps.openei.org/USURDB/rate/view/5cb73fe75457a35a0a9b6ec3
SDG&E	y	0.2566	0.36055	0.2566	0.00	5	20	2019-03-01	https://apps.openei.org/USURDB/rate/view/5c3930105457a3991c91e8cb
SDG&E	y	0.2566	0.36055	0.2566	0	20	50	2019-03-01	https://apps.openei.org/USURDB/rate/view/5c3930165457a3470c91e8cf
SDG&E	y	0.2566	0.36055	0.2566	0	50	10000	2019-03-01	https://apps.openei.org/USURDB/rate/view/5c39300a5457a3bd1091e8cd
COR	n	0.02064	0.02064	0.02064	0	0	20	2013-03-26	https://apps.openei.org/USURDB/rate/view/5b4e59355457a3d45fc6d674
COR	n	0.1217	0.1217	0.1217	10.48	20	150	2013-03-26	https://apps.openei.org/USURDB/rate/view/5b4e59875457a3bb64c6d676
COR	y	0.1033	0.0828	0.0727	6.88	150	10000	2013-03-26	https://apps.openei.org/US

									URDB/rate/view/5b4e5a895457a34913c6d675
IID	n	0.093	0.093	0.093	6.75	0[4]	10000	2015-01-01	https://apps.openei.org/USURDB/rate/view/54bff5315357a34f756bdba2
MID	n	0.1583	0.1583	0.1583	0	0	20	2012-01-01	https://apps.openei.org/USURDB/rate/view/5b2809e05457a3f778e5d862
MID	y	0.1294	0.1294	0.0696	16.37	20[5]	1000	2017-01-01	https://apps.openei.org/USURDB/rate/view/5b2815535457a3cc4ce5d862
MID	y	0.1148	0.1148	0.0621	17.8	1000	10000	2017-01-01	https://apps.openei.org/USURDB/rate/view/5b2822665457a30764e5d864
COAPUD	n	0.119	0.119	0.119	15.65	200	500	2017-05-01	https://apps.openei.org/USURDB/rate/view/5b1ffd8e5457a3317835b56a
COAPUD	n	0.1269	0.1269	0.1269	12.27	0	200	2018-05-01	https://apps.openei.org/USURDB/rate/vie

[4] URDB indicates that an IID rate to cover max demand levels of 0-100kW exists (https://apps.openei.org/USURDB/rate/view/54bfef0a5357a3db776bdba2), but that rate fails in REopt. Thus we used this rate as a proxy.

[5] URDB indicates that an MID rate to cover max demand levels of 20-500kW exists (https://apps.openei.org/USURDB/rate/view/5b280bc95457a3723de5d862) but that rate fails in REopt.Thus we used this rate as a proxy in that power range.

									w/5b1ed2aa5457a3ef4335b56b
COAPUD	y	0.1535	0.1226	0.0842	15.68	500	10000	2017-05-01	https://apps.openei.org/USURDB/rate/view/5b1ee9f55457a3cb4d35b56b
TID	y	0.1818	0.1818	0.1195	0	0	35	2015-01-01	https://apps.openei.org/USURDB/rate/view/5b4ccdff5457a3e50dc6d674
TID	y	0.1284	0.1284	0.0893	13.24	35	500	2015-01-01	https://apps.openei.org/USURDB/rate/view/5b4d09295457a3ca09c6d674
TID	y	0.1263	0.1263	0.0855	11.88	500	10000	2015-01-01	https://apps.openei.org/USURDB/rate/view/5b4d105a5457a3a85fc6d678

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