Differential Vulnerability to Extreme Heat Events Among the UC Campuses:
A quantitative analysis of social vulnerability to extreme heat in communities surrounding UC Campuses

By:

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List of Abbreviations

Environmental Protection Agency	EPA
Extreme Heat Event	EHE
Extreme Heat Event Vulnerability Index	EHEVI
Extreme Heat Event Vulnerability Score	EHEVS
Population Characteristic	Pop Char
Representative Concentration Pathway	RCP
Social Vulnerability Index	SVI
Urban Heat Island	UHI
University of California	UC
UC Berkeley	UCB
UC Davis	UCD
UC Irvine	UCI
UC Los Angeles	UCLA
UC Merced	UCM
UC Riverside	UCR
UC Santa Barbara	UCSC
UC Santa Cruz	UCR

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1. Abstract

Extreme heat events are becoming more frequent, intense, and longer as a result of global climate change. Individual characteristics and conditions amplify exposure and impact of extreme heat events. I seek to explore how each University of California (UC) campus community is socially vulnerable to extreme heat in comparison to each other. Using data from CalAdapt and CalEnviroScreen, I created three cumulative impact indices on the census tract and campus scale using historic (1961-1990), mid-century (2035-2064), and end of century (2070-2099) climate projections (RCP 4.5). I analyzed the scores to determine which UC campuses were most vulnerable and experienced the highest exposure to extreme heat days. I found that UC Merced and UC Riverside were the most vulnerable overall, and experienced high exposure to extreme heat and high social vulnerability. I also developed four categories of vulnerability which each index score adheres to. The results of this tool can be used by campus planners and stakeholders to inform decision-making on extreme heat adaptation and mitigation. The index methodology can be replicated for other universities and localities to analyze social vulnerability to extreme heat.

2. Introduction

Extreme heat will have an increasingly severe impact on the UC campus community due to global climate change. Despite this, no quantitative research exists to identify these impacts and determine which UC campus communities will be most affected. I seek to understand which UC campuses are particularly socially vulnerable to extreme heat and which factors contribute to this vulnerability. I will also explore how social vulnerability to extreme heat will change throughout the century as a result of global climate change.

To answer these research questions, I created an Extreme Heat Event (EHE) Vulnerability Index which measures social vulnerability to extreme heat. Social vulnerability to extreme heat is defined as the intersection of the physical environment and climate with individual socioeconomic and health characteristics and conditions. The use of a cumulative impact index is particularly useful because it provides a holistic and transparent approach to the quantitative basis for climate decision-making (Morello-Frosch et al., 2011).

This study finds four distinct types of campuses; 1) those with both high heat exposure and demographic vulnerability, 2) those with high heat exposure but low demographic vulnerability, 3) those with low heat exposure but high demographic vulnerability, and finally 4) those with both low heat exposure and demographic vulnerability. Several campuses fall into multiple categories depending on the time period of extreme heat projection.

This study advances an understanding of how UC campus communities are differentially impacted by extreme heat. The index findings can be used by policymakers and planners to inform resource allocation for heat mitigation and adaptation solutions. Campuses that are identified as high heat exposure and high demographic vulnerability should be prioritized for extreme heat planning. This study also provides a quantitative model for measuring extreme heat that can be replicated by other universities and localities.

The results of this analysis provide compelling evidence on the need for rapid decarbonization and climate adaptation solutions by UC leadership. Therefore, it simultaneously advances the goals of the UC Carbon Neutrality Initiative, which is a UC wide commitment to achieve carbon neutrality in scope-one emissions by 2025. Without successful climate mitigation, the UC campus community will increasingly endure health impacts from extreme heat events. These impacts will fall on the most socially vulnerable members of the UC community.

3. Literature Review

In the past 30 years, extreme heat has caused the most weather related deaths in the United States (NOAA, 2020). As a result of global climate change, extreme heat events are continuing to become more frequent and intense. EHEs are defined as “stagnant, warm air masses” that lead to consecutive nights with warm temperatures (Luber & McGeehin, 2008). EHEs are projected to continue increasing in intensity and duration as a result of human activities, particularly the addition of greenhouse gasses (Sarofim, 2016). These events have a wide range of impacts including; increased rate of heat related illness and death, increased water and power demand, impacts to agriculture, and damage to the natural environment (EPA, 2021; OEHHA & calEPA, 2018; Wuebbles et al., 2017). The impact of extreme heat varies across populations. Social vulnerability to extreme heat is determined by two main factors: the physical environment and climate, and individual socioeconomic and health characteristics and conditions (Wilhelmi & Hayden, 2010; Kovats & Hajat, 2008).

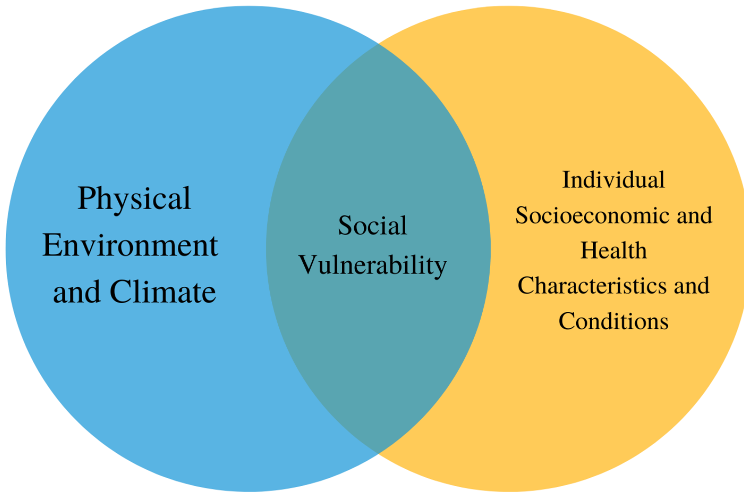

Figure 1: Contributing factors to social vulnerability to extreme heat

3.1: Physical Environment and Climate

The wide variety of California climate and geography results in a range of exposure to extreme heat. Despite this, the majority of California has already experienced an increase in extreme heat, although at different rates across the state. By 2050, heat waves in the Central Valley could last two weeks longer, and occur four to ten times as frequently in the Northern Sierra (State of California, 2022).

The local physical environment impacts how people experience extreme heat events. In general, urban populations experience these impacts more than rural populations (Reidmiller et al., 2018). This is in part due to the urban heat island effect in urban centers and areas with little vegetative land cover. The urban heat island effect refers to the phenomena where urban areas experience higher temperatures than rural areas. Structures like roads and buildings absorb and re-emit the sun's heat at higher rates than natural landscapes (EPA, n.d.).

3.2: Individual Socioeconomic and Health Characteristics and Conditions

A wide range of individual characteristics and conditions can amplify the impact of extreme heat events on health. Some physical characteristics amplify the health impacts of extreme heat, particularly among older adults, children, and pregnant people. These people are less physiologically capable of adjusting to extreme heat (Hayden et al., 2011). Furthermore, pre-existing medical conditions like asthma or cardiac diseases can be exacerbated during an extreme heat event (EPA, 2021). Additionally, unhoused people and those who work outside are less protected from the heat and thus experience increased heat related illness and death (Gubernot et al., 2015). Social factors like linguistic isolation, fear of crime, and cultural/linguistic isolation can inhibit people from coping with extreme heat (Gronlund, 2014).

Race and class also have a significant impact on vulnerability to extreme heat. Low income communities also have a reduced capacity to prepare for and cope with extreme heat events (Jay et al., 2018). This means that these groups have fewer social, financial, and physical resources to reduce their exposure to heat and systematically reduce potential harm (Hayden et al., 2011). Race and ethnicity is increasingly a determinate in vulnerability to extreme heat. Between 2005 and 2015, heat related emergency department visits for minority populations grew at a much faster rate for white populations in California. This is likely explained by occupational differences. For example, many more Hispanic and Latino Californians work in agriculture than white Californians, and are more exposed to extreme heat (Abualsaud, 2019).

3.3: Social Vulnerability to Extreme Heat

Together, these factors determine the social vulnerability of a community. Social vulnerability refers to "the propensity or predisposition to be adversely affected" to climate impacts as determined by exposure, susceptibility to harm, and ability to adapt (Oppenheimer et al., 2014). More socially vulnerable populations experience an elevated rate of heat related illness and death (State of California, 2022). These types of illness include heat cramps, heat exhaustion, heatstroke, and hyperthermia (Sarofim, 2016). Low income and minority populations in urban areas are the most vulnerable groups to heat related mortality (Hayden et al., 2011).

The unequal distribution of urban heat islands exemplifies the interaction between exposure and individual characteristics. The urban heat island effect disproportionately impacts disadvantaged communities. This is in part due to past planning decisions that have shaped the urban environment and housing inequality (Wilson, 2020). For example, areas that were targeted for disinvestment under redlining now have higher land surface temperatures than those that were not (Wilson, 2020). Additionally, low income and minority populations are more likely to live in these neighborhoods and thus experience greater exposure to heat (Harlan et al., 2006; Chakraborty et al., 2019).

In summary, the increasing frequency and intensity of extreme heat events disproportionately impacts disadvantaged urban communities, and people with conditions or characteristics that make them more susceptible to heat related illness. These patterns of inequality may be repeated within University of California campus communities.

3.4: University of California Context

Understanding who is affected by extreme heat and why they may have increased exposure is of central importance for policymakers and planners. The evaluation of vulnerability and exposure to extreme heat across populations is critical for the creation of effective and just policy responses (Benz & Burney, 2021). However, there is little academic consensus on how these evaluations of vulnerability should be conducted. Thus, it is important to develop “novel comprehensive and comparative” methods for evaluating vulnerability to extreme heat (Karanja & Kiage, 2021, p.3). Therefore, this study aims to understand how the community members around the University of California campuses are differentially affected by extreme heat events using a comparative and cumulative impact index.

A disproportionate amount of UC students are likely vulnerable to extreme heat events due to their income and race. A large portion of UC students come from low income families. In 2018, 48% of UC students experienced food insecurity and seven percent of UC students experienced housing insecurity (University of California, 2021). The UC student population is also very racially diverse. In 2020, less than 30% of domestic UC students identified as White, and over 60% of the domestic UC students identified as Asian or Hispanic/Latin0. Additionally, the demographic group least able to access air conditioning throughout the United States are people living in the West who are of two or more races (non-Hispanic), 25-34 years old, and making less than $30,000 per year (Wilhelmi et al., 2021). Many UC affiliates, specifically graduate and older undergraduate students, likely fall into this category. UC staff members may also be disproportionately impacted by extreme heat events; the majority of “professional and support staff” are people of color (University of California, 2021). These characteristics amplify the impacts of extreme heat events on the student population.

Thus far, there has been little research on how to measure social vulnerability to extreme heat and other climate related impacts among UC students, staff, and faculty. In particular, it is difficult to understand exactly how students, staff, and faculty are affected by extreme heat events using existing data. First, these groups travel to campus from many different localities due to high housing prices and limited on campus housing. This makes on campus census tracts an unviable unit of analysis. Furthermore, international students, students who use their parent's address, undocumented students, and students with limited English may not be accurately represented in the census (deBoer et al., 2017). Data on students who use their parent's address to complete the census is disconnected from the geographical sitting of each campus. International residents, undocumented residents, and those with limited English skills are often discouraged from taking the census due to political, cultural, and language barriers. It is my hope that this index will aid campus and city planners in identifying the most socially vulnerable communities and effectively conducting just extreme heat resiliency planning.

3.5: Index Construction

Existing literature stresses the importance of cumulative impact analysis on the neighborhood scale for analyzing differential vulnerabilities to environmental and climate stressors. It is important to assess vulnerability to extreme heat events using a cumulative index as minority and low income groups are exposed to multiple social stressors (Morello-Frosch, 2011). Johnson et al. (2012) present a justification for using cumulative social and environmental indices for measuring differential vulnerability to extreme heat. It proposes an Extreme Heat Vulnerability Index (EHVI) which predicts local vulnerability to extreme heat events in various census tracts in Chicago, Illinois. The study argues that vulnerability indices can be effectively applied on scales smaller than the county level (Johnson et al., 2012). This is an important basis for the creation of the EHEVI in this study, which is conducted on the census tract scale. They also write that most climate vulnerability models exclusively analyze either sociodemographic variables or the built environment. Despite this, community vulnerability to heat is most accurately gauged when an index combines physical and social variables (Johnson et al., 2012). My study applies principles outlined in Johnson et al.'s EHVI by including sociodemographic and physical/environmental characteristics. It is limited, however, because it does not include racial and age related variables.

My study also employs demographic data and the index calculation methodology from CalEnviroScreen 4.0. CalEnviroScreen 4.0 is a geographic cumulative environmental risk assessment created by the California Office of Environmental Health Hazard Assessment (OEHHA). The tool creates a "CalEnviroScreen score" which combines a *Population Characteristic* score*,* which measures individual conditions and characteristics, with a *Pollution Burden* score, which measures the presence and severity of a variety of environmental hazards. I used the Population Characteristic data as a tool for measuring individual socioeconomic and health characteristics and conditions. I used the CalEnviroScreen score algorithm methodology as a basis for this study's score development. This method and data source was selected because CalEnviroScreen 4.0 provides an effective and widely accepted mechanism for developing a simple census tract cumulative vulnerability index.

The "Population Characteristic" presented in CalEnviroScreen employs variables for evaluating the cumulative effect of multiple non-environmental stressors on extreme heat health outcomes. The Population Characteristic is calculated by assessing the cumulative impact of seven health and socioeconomic indicators. While the CalEnviroScreen Population Characteristic does not include race as an indicator, the results of the tool reflect racial disparities as communities of color most often live in the most impacted areas (August et al., 2021). Furthermore, the health indicators included in the score are disproportionately experienced by people of color, particularly African-American people (Morello-Frosch, 2011).

While the variables included in the Pollution Burden score are not relevant for the creation of the UC Extreme Heat Vulnerability Index, the methodology for creating the overall CalEnviroScreen score provides a methodological basis for the index creation in this study. The CalEnviroScreen score is created by multiplying the population characteristic score and pollution characteristic score. According to the OEHHA, the multiplicative aspect of the score is useful for several reasons. First, it reflects how the indicators included in Population Characteristics often modify and multiply how people experience environmental risks. Next the multiplication of the two characteristics reflects that some people may be more sensitive to risk than others. Finally, the multiplicative model is widely accepted as a method for assessing risk.

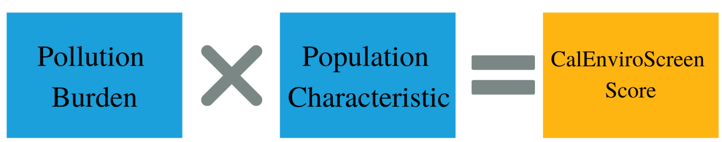

Figure 2: CalEnviroScreen Score calculation methodology. *Adapted from CalEnviroScreen*

4: Methods

Area of study

Considering the limitations with using existing datasets for student populations discussed above, I have chosen to focus my analysis on census tracts directly adjacent to main UC campuses. While it is impossible to tell exactly how many students, staff, and faculty live in these areas, it is likely that many of these census tracts have high populations of UC affiliates. I expect that the chosen area of study will also reveal vulnerability inequalities across the neighborhoods surrounding each UC campus.

The nine UC Campuses included for analysis are: UC Berkeley (UCB), UC Davis (UCD), UC Irvine (UCI), UC Los Angeles (UCLA), UC Merced (UCM), UC Riverside (UCR), UC San Diego (UCSD), UC Santa Barbara (UCSB), and UC Santa Cruz (UCSC). I excluded UC San Francisco from my analysis because it does not have a central campus location, large undergraduate population, or a significant population of campus affiliates in direct proximity to campus facilities.

In total, 60 census tracts were included for analysis. However, the quantity of census tracts per campus varied. The average number of census tracts per campus was 6.67. The minimum number was five (UCSC, UCSB), and the maximum was nine (UCI, UCLA). The census tract which included the main campus was excluded at UCB and UCLA because there was insufficient data available in CalEnviroScreen.

Data Acquisition

I retrieved census tract level quantitative data from each census tract bordering a UC campus using data provided by the CalAdapt and CalEnviroScreen 4.0 (Appendix 5). I combined one indicator from each source to allow for cumulative analysis of environmental (CalAdapt) and sociodemographic (CalEnviroScreen) data.

I sourced environmental indicators from CalAdapt. CalAdapt is a tool developed by the Geospatial Innovation Facility at UC Berkeley. I used data on the number of "extreme heat days" in lieu of the number of extreme heat events, which was not available. CalAdapt defines "extreme heat day" as a day where the "daily maximum/minimum temperature exceeds the 98th historical percentile of daily maximum/minimum temperatures" using historical data (1961-1990) from April to October. I utilized the baseline, mid-century, and end of century "extreme heat day" measurement and projections to create three distinct vulnerability indices. The mid-century and end of century models were created using a medium emission (RCP 4.5) scenario. RCPs measure different plausible scenarios of future greenhouse gas emissions. I chose this scenario because it is the most realistic given current emissions and commitments from government agencies and private industries.

Table 1: CalAdapt Scenarios

Scenario Title	Time Period	Emission Scenario
Baseline Extreme Heat Days	1961-1990	None (historical data)
Mid-Century Extreme Heat Days	2035-2064	RCP 4.5 (medium emissions)
End of Century Extreme Heat Days	2070-2099	RCP 4.5 (medium emissions)

Source: CalAdapt

I sourced my population indicator from CalEnviroScreen. CalEnviroScreen 4.0 is a cumulative impact model that uses data from multiple sources to create a nationwide assessment using environmental quality and sociodemographic data. I utilized the "Population Characteristic", which includes seven sub-indicators. These indicators are asthma rates, cardiovascular health, percent low birth weight infants, housing burden, low income population, linguistic isolation, poverty rates, and unemployment (CalEnviroScreen, 2021). A low population characteristic signifies a lower level of social vulnerability.

Table 2: Indicator Information

	Population Characteristic	Extreme Heat Days (Baseline, Mid-century, End of Century)
Year Published	2021	2018
Source	https://oehha.ca.gov/calenviroscreen	https://cal-adapt.org/tools/extreme-heat/
Primary or Secondary	Secondary, sourced from multiple datasets. Full inventory available at https://oehha.ca.gov/media/downloads/calenviroscreen/report/calenviroscreen40reportf2021.pdf	Secondary, sourced from multiple datasets. Full inventory available at https://cal-adapt.org/tools/extreme-heat/

Data Processing

I used the three Extreme Heat Day projections to create an Extreme Heat Day Score for each model. This score assesses the number of extreme heat days per census tract in comparison to the other census tracts included in my analysis. It was created by dividing the amount of recorded/projected extreme heat days per year by census tract by the overall average number of extreme heat days, and then multiplying by 100 to place the score on the same scale as the population characteristic. The resulting number is referred to as an Extreme Heat Score. A low Extreme Heat Day Score signifies a lower amount of experienced/projected heat days.

$$\text{Extreme Heat Score} = (\text{number of projected/recorded extreme heat days} \div \text{average number of extreme heat days projected/recorded}^{1}) \times 100$$

Index Creation

I created the EHE vulnerability scores by multiplying the population characteristic with the Extreme Heat Day Score for each census tract and projection model. I then divided each result by 100 to find the final EHE Vulnerability Score. Across all models, the EHE Vulnerability Scores ranged from 7.2 (least vulnerable) and 143.7 (most vulnerable).

$$\text{EHE Vulnerability Score} = (\text{Extreme Heat Score} \times \text{Population Characteristic}) \div 100$$

Assumptions and Limitation

This index is most useful to examine the vulnerability scores in relation to the other campuses in each model. It is important to note that this index should not be used to compare scores between one campus method to evaluate change in vulnerability over time. Instead, this tool develops a score for each campus based on its vulnerability compared to other campuses within each model. Therefore, the scores do not reflect the change in vulnerability over time. Additionally, because the population characteristic is a constant throughout the models, variation between the models represents an increase of extreme heat days on each campus.

This index also assumes that the characteristics of the built environment are constant across census tracts. It does not include a variable on the built environment, and thus does not reflect extreme heat variation as a result of the urban heat island effect.

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[1] Baseline average- 3.4 days, Mid-century average- 12.49 days, End of Century average- 17.61

5: Findings

The findings portion of my research categorizes each UC Campus into one or two categories based on their population and climate data in comparison to other campuses. It will discuss the findings of each UC Campus in the baseline, mid-century, and end of century models.

Table 3: Extreme Heat Event Vulnerability Scores (EHEVS) By Campus

Campus	Baseline EHEVS	Mid-Century EHEVS	End-Century EHEVS
ALL CAMPUS AVERAGE	**43.83**	**47.52**	**47.67**
UC LOS ANGELES	21.54	18.21	19.34
UC SANTA CRUZ	26.68	15.41	15.85
UC IRVINE	27.42	22.34	22.45
UC SAN DIEGO	31.81	30.20	30.51
UC BERKELEY	39.00	19.08	18.07
UC DAVIS	49.74	72.35	70.50
UC SANTA BARBARA	54.96	35.72	30.64
UC RIVERSIDE	78.86	118.07	114.20
UC MERCED	80.11	117.56	128.27

Source: CalEnviroScreen, CalAdapt

There were a vast range of EHE Vulnerability Scores between campuses. Across each model, UCLA has the lowest EHE vulnerability score and UC Merced has the highest EHE vulnerability score. Detailed information on the composition of each score is included in the appendix (Appendix 1). Each campus fell into one of four categories; 1) high extreme heat days, high population characteristic, 2) high extreme heat days, low population characteristic, 3) low extreme heat days, high population characteristic, and 4) low extreme heat days, low population characteristic. These categories are determined based on whether the population characteristic and extreme heat score for each campus was above or below the UC wide average (Appendix 4).

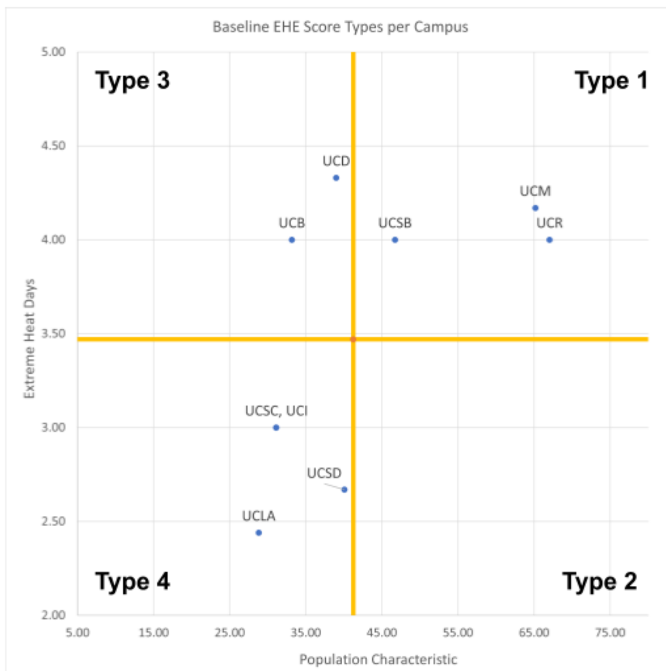

Figure 3: Baseline EHE Vulnerability Score Type Categorization

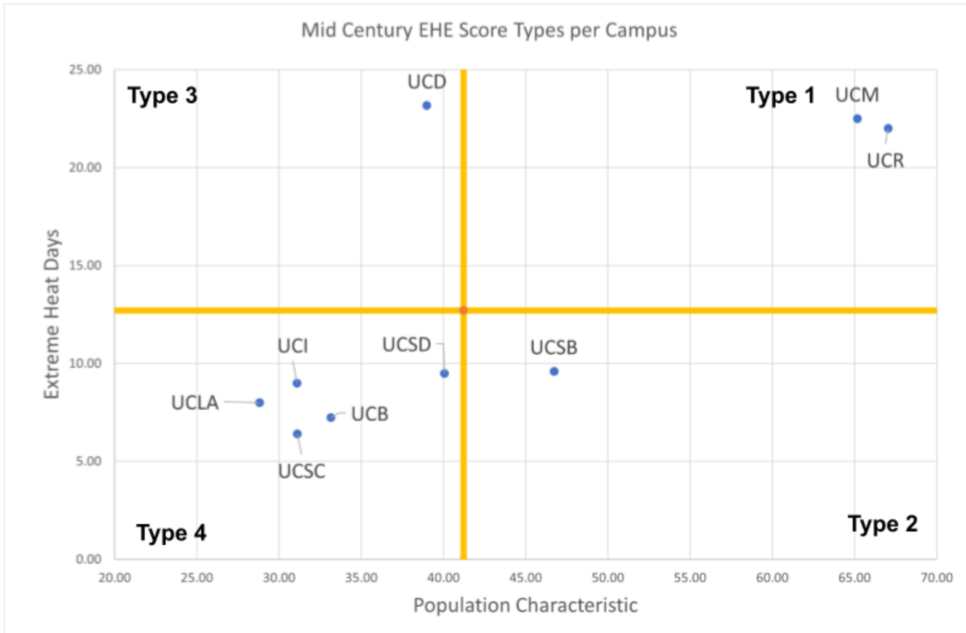

Figure 4: Mid-Century EHE Vulnerability Score Type Categorization

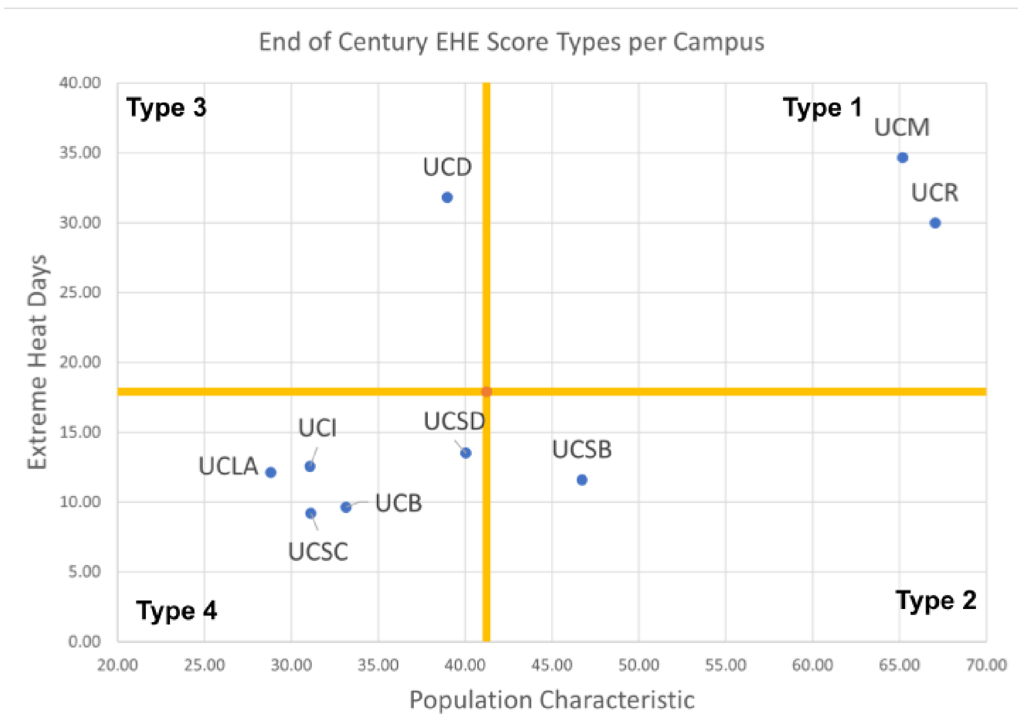

Figure 5: End of Century EHE Vulnerability Score Type Categorization

Type 1) High Extreme Heat Days, High Population Characteristic

UC Riverside and UC Merced are classified as Type 1 among all three models. As viewed in Figures 6 through 8, the EHE Vulnerability scores for these campuses are much higher than the rest of the campuses. This signifies a large increase in extreme heat days compared to other campuses. In the baseline model, the majority of census tracts at UCR and UCM are above the 75th percentile of the total UC EHE Vulnerability Scores. In the mid-century and end of century models, all census tracts are above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3).

UC Santa Barbara is classified as Type 1 in the baseline model. This signifies that the area has historically experienced a higher proportion of extreme heat days than many other UC campuses. 60% of census tracts within the baseline model are above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3). However, in the mid and end of century models UC Santa Barbara is predicted to have a lower proportion of extreme heat days.

Type 2) High Extreme Heat Days, Low Population Characteristic

UC Davis is classified as a Type 2 campus across all three models. This means that, while the campus experiences a high level of extreme heat days compared to other campuses, it has a lower than average population characteristic. Despite the lower population characteristic, it has a relatively high EHE vulnerability score due to the high level of extreme heat days. In the mid-century and end of century models, UC Davis has the third highest EHE Vulnerability score of the campuses. Each model also has at least one census tract that is above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3).

UC Berkeley is classified as a Type 2 campus in the baseline model. This signifies that the area has a lower than average population characteristic, but has historically experienced a higher proportion of extreme heat days than many other UC campuses. Despite this, none of the tracts in the UC Berkeley baseline model are above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3).

Type 3) Low Extreme Heat Days, High Population Characteristic

The mid-century and end of century models at UC Santa Barbara are the only EHE Vulnerability scores that meet the Type 3 criteria. This campus is projected to experience relatively few extreme heat days compared to the UC, despite having a high population characteristic score. The decline in EHE Vulnerability Scores from the Baseline Model to the other two models signifies a slower rate of projected extreme heat days than the UC average. Despite the high population characteristic, none of the Type 3 campus models contain a census tract with a EHE Vulnerability Score above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3).

Type 4) Low Extreme Heat Days, Low Population Characteristic

UC Los Angeles, UC Santa Cruz, UC Irvine, and UC San Diego are classified as Type 4 throughout all models. This means that the campuses experience relatively few extreme heat days, and have a low population characteristic. UC Berkeley is classified as a Type 4 campus in the mid-century and end of century models. This signifies that UC Berkeley is predicted to have a lower proportion of extreme heat days than other UC Campuses.None of the Type 4 campus models contain a census tract with a EHE Vulnerability Score above the 75th percentile of the total UC EHE Vulnerability Scores (Appendix 3).

Throughout the models, type 1 and 2 campuses become increasingly stratified from the Type 3 and 4 campuses. In the baseline model, EHE Vulnerability scores across campuses are more similar across campuses. Additionally, the Type 3 campus (UCSB) has a higher EHE Vulnerability score than a type 3 campus (UCD). Conversely, in the mid-century and end of century models, the type 1 and 2 campuses have much higher EHE Vulnerability Scores than the Type 3 and 4 campuses. This is reflective of the high rate of predicted extreme heat day frequency in inland campuses (UCM, UCR, UCD) compared to the coastal campuses.

6. Discussion

The results outlined above provide a quantitative measure of vulnerability to extreme heat across UC campuses. In the mid-century and end of century models, the three most inland campuses, UC Merced, UC Riverside, and UC Davis, are predicted to be the most vulnerable to extreme heat. They also are projected to experience more rapid increases in extreme heat days relative to the other campuses. This reflects statewide trends; inland California is increasingly prone to extreme heat and is home to a disproportionate amount of disadvantaged communities. UC Davis is unique, however, because it has a below average population characteristic. This may be a result of historical and contemporary planning decisions that limit the ability of disadvantaged people to live in Davis such as the frequent usage of restrictive covenants (Keller, 2018). The EHE Vulnerability score of UC Santa Barbara is reflective of the slow rate of extreme heat frequency in coastal campuses. Historically, UCSB was identified as the third most vulnerable campus. This was largely due to its high population characteristics. This could be a result of the high density of student housing on campus and in the Isla Vista area (census tracts 29.28, 29.26, and 29.24). In the mid-century and end of century models, however, the campus has a much lower vulnerability score than the inland campuses. This is reflective of the slower rate of predicted extreme heat frequency. UCSB is projected to experience a 150% increase in extreme heat days from the baseline to mid-century model, and an additional 20% increase from the mid-century model to the end of century model. This rate of increase is much slower than UC Merced, for example, which is projected to experience a 380% increase in extreme heat days from the baseline to mid-century model, and a further 50% increase from the mid-century model to end of century model.

Despite the utility of these results in identifying particularly vulnerable campuses, comparing campus to campus averages can overlook the uneven vulnerability within each campus. This exemplifies the Modifiable Areal Unit Problem, which occurs when geographical data is altered depending on the spatial scale used (Buzelli, 2020). While some campuses have relatively homogenous scores, other campuses have much larger differences in EHE Vulnerability Scores between tracts (Appendix 2).

For example, while UCLA is considered the least vulnerable campus, there remains vulnerable tracts that should be the subject of extreme heat planning. Notably, census tract 2653.03, the most vulnerable tract, has an EHE Vulnerability Score over six times that of tract 2621. Census tract 2653.03 is occupied predominantly by students, and has a higher percentage of people of color and people in poverty[2]. Conversely, census tract 2621 encompasses Bel Air, which is a wealthy housing development. Very few students live in the tract, are in poverty, or are people of color[3]. Considering this, the extremely low campus average obscures the vulnerable populations within the campus.

To prevent overlooking these differences, it is necessary to analyze each campus on a census tract scale. While a detailed analysis of each campus is beyond the scope of this study, the accompanying mapping figures provide information on the distribution of vulnerability across census tracts (Appendix 5).

Campus planners and stakeholders should use these tools to prioritize campuses and census tracts for heat mitigation and adaptation measures. This index and accompanying mapping tools allows planners to prioritize resources and develop solutions based on the cumulative impact of the sociodemographic characteristics and local climate of a place. Adaptation measures should be prioritized in vulnerable communities as identified by this index. Potential heat adaptation solutions could include the expansion of tree canopies, increased access to cooling centers, and installation of green roofs and cool streets (US EPA, 2018). Additionally, heat adaptation measures must be coupled with greenhouse gas emission reductions in order to see a significant decrease in extreme heat (Krayenhoff et al., 2018).

Conclusion

This study proposes an index which identifies the UC campuses most and least socially vulnerable to extreme heat over the next century. The inland campuses, UC Merced, UC

[2] Tract 2653.03 Characteristics- 68.39% of residents are people of color, and 62.67% of residents are in poverty (ACS 2015-2019).
[3] Tract 2621 Characteristics- 24.53% of residents are people of color, and 5.58% of residents are in poverty (ACS 2015-2019)

Riverside, and UC Davis, were found to be the most socially vulnerable across each model. UC Los Angeles, UC Santa Cruz, and UC Irvine were found to be the least vulnerable across each model. Variation across models occurred as a result of the differential pace in increase of extreme heat days. This tool can be used by campus planners and stakeholders to better understand which campuses are most in need of extreme heat mitigation, adaptation, and resiliency planning and resources.

This study has significant limitations which impact the ability of the EHE Vulnerability Index to effectively measure the impacts of extreme heat among campus populations. First, the index does not include an indicator to account for the built environment. Unlike other studies, which include variables such as vegetative land cover, this index only measures population and climate trends. However, the consideration of built environment, sociodemographic, and climate trends must all be considered in successful heat mitigation and adaptation strategies (Wilson, 2022). Decision makers using this index should also consider the impact of the urban heat island effect in vulnerability of communities to extreme heat. Secondly, as discussed previously, is it unclear how many students are included in this study due to the lack of accurate census data on student populations. Finally, this study does not address how the COVID-19 pandemic may have altered campus vulnerability to climate change. All data used in this study was collected before the onset of the pandemic to prevent abnormalities. Despite this, previous research concludes that the intersection of COVID-19 and extreme heat made more people vulnerable to extreme heat and amplified existing systematic vulnerabilities (Wilhelmi et al., 2021).

Future research should focus on analyzing the historical causes of unequal vulnerability within each UC Campus, expand the EHE Vulnerability Index to include a built environment indicator, and explore how the COVID-19 pandemic affected UC students' vulnerability to extreme heat. Additionally, comprehensive data collection should be conducted to achieve an accurate understanding of how UC students are impacted by extreme heat events.

6. Appendices

Appendix 1: Campus Overview Scores

Campus	Baseline EHEVS	Mid-Century EHEVS	End-Century EHEVS	Pop Char	Baseline Average Days	Mid-Century Average Days	End-Century Average Days
ALL CAMPUS AVERAGE	43.83	47.52	47.67	41.22	3.47	12.71	17.90
UC LOS ANGELES	21.54	18.21	19.34	28.81	2.44	8.00	12.11
UC SANTA CRUZ	26.68	15.41	15.85	31.12	3.00	6.40	9.20
UC IRVINE	27.42	22.34	22.45	31.08	3.00	9.00	12.56
UC SAN DIEGO	31.81	30.20	30.51	40.05	2.67	9.50	13.50
UC BERKELEY	39.00	19.08	18.07	33.15	4.00	7.25	9.63
UC DAVIS	49.74	72.35	70.50	38.98	4.33	23.17	31.83
UC SANTA BARBARA	54.96	35.72	30.64	46.72	4.00	9.60	11.60
UC RIVERSIDE	78.86	118.07	114.20	67.03	4.00	22.00	30.00
UC MERCED	80.11	117.56	128.27	65.16	4.17	22.50	34.67

This score was created by combining population characteristic (Pop Char) data sourced from CalEnviroScreen with average annual number of extreme heat days across three climate models (Baseline Average Days, Mid-Century Average Days, End of Century Average Days) data sourced from CalAdapt.

Appendix 2: Range in Campus EHE Vulnerability Scores

Campus	Baseline EHEVS Range	Mid-Century EHEVS Range	End-Century EHEVS Range	Average Range Across Models
ALL CAMPUS AVERAGE	36.99	32.29	31.91	33.73
UC BERKELEY	54.07	26.27	25.89	35.41
UC Davis	36.16	47.25	46.08	43.16
UC IRVINE	28.00	22.86	24.35	25.07
UC LOS ANGELES	38.78	26.24	27.92	30.98
UC MERCED	43.40	45.28	42.38	43.68
UC RIVERSIDE	36.54	54.71	52.92	48.06
UC SAN DIEGO	45.29	30.97	31.73	36.00
UC SANTA CRUZ	13.68	4.71	4.04	7.48

This score was created by combining population characteristic (Pop Char) data sourced from CalEnviroScreen with average annual number of extreme heat days across three climate models (Baseline Average Days, Mid-Century Average Days, End of Century Average Days) data sourced from CalAdapt.

Appendix 3: Percent of Census Tracts with EHE Vulnerability Scores Above 75th Percentile

	Baseline EHE Vulnerability Score	Mid Century EHE Vulnerability Score	End Century EHE Vulnerability Score
UC Berkeley	0%	0%	0%
UC Davis	**16.67%**	**33.34%**	**33.34%**
UC Irvine	0%	0%	0%
UC Los Angeles	0%	0%	0%
UC Merced	**83.33%**	**100%**	**100%**
UC Riverside	**83.33%**	**100%**	**100%**
UC San Diego	0%	0%	0%
UC Santa Barbara	**60%**	**0%**	**0%**
UC Santa Cruz	0%	0%	0%

Appendix 4: Campus Population and Heat Score Greater or Less than UC Average

Campus	Population Characteristic (average= 41.22)	Baseline Extreme Heat Days (average= 3.47)	Mid-Century Extreme Heat Days (average= 12.71)	End Century Extreme Heat Days (average= 17.90)
UC LOS ANGELES	low	low	low	low
UC SANTA CRUZ	low	low	low	low
UC IRVINE	low	low	low	low
UC SAN DIEGO	low	low	low	low
UC BERKELEY	low	high	low	low
UC DAVIS	low	high	high	high
UC SANTA BARBARA	high	high	low	low
UC RIVERSIDE	high	high	high	high
UC MERCED	high	high	high	high

This score was created by combining population characteristic (Pop Char) data sourced from CalEnviroScreen with average annual number of extreme heat days across three climate models (Baseline Average Days, Mid-Century Average Days, End of Century Average Days) data sourced from CalAdapt.

Appendix 5: All Census Tract Extreme Heat Vulnerability Scores

Campus + Tract	Baseline EHEVS	Mid-Century EHEVS	End-Century EHEVS	Pop. Char	Daily Maximum Temperature
ALL CAMPUS AVERAGE	29.31	24.11	22.76	40.87	93.97
UC BERKELEY					
campus average	39.00	19.08	18.07	33.15	87.84
6001421600	5.43	2.96	2.62	4.62	89.6
6001423700	23.74	11.31	11.46	20.18	87.3
6001422400	37.17	17.71	16.15	31.60	87.7
6001422500	38.23	18.21	16.61	32.49	87.7
6001422800	43.24	20.60	18.78	36.75	88.3
6001422700	50.97	24.28	24.60	43.32	87.3
6001400100	53.69	29.23	28.51	45.64	86.5
6001422900	59.50	28.35	25.85	50.58	88.3
UC DAVIS					
campus average	49.74	72.35	70.50	38.98	103.32
6113010704	40.11	52.41	51.11	27.27	103.1
6113010602	40.99	64.15	61.33	34.84	103.4
6095253300	42.62	63.82	63.78	36.23	103.6
6113010701	47.31	74.05	73.07	40.21	103.2

6113010501	51.14	80.04	76.52	43.47	103.5
6113010703	76.27	99.65	97.18	51.86	103.1
UC IRVINE					
campus average	27.42	22.34	22.45	31.08	88.79
6059062629	14.35	11.72	11.08	16.26	91.5
6059062604	14.41	11.77	11.13	16.33	87.7
6059062644	15.66	12.79	12.09	17.74	86.5
6059062610	23.13	18.89	19.35	26.21	89.5
6059063007	24.20	19.76	18.69	27.42	86.9
6059062614	31.39	25.63	26.26	35.57	87.9
6059062627	40.48	33.06	33.87	45.88	89.7
6059062611	40.84	33.35	34.17	46.29	89.7
6059062626	42.34	34.58	35.42	47.99	89.7
UC LOS ANGELES					
campus average	21.54	18.21	19.34	28.81	90.70
6037262200	7.20	8.82	10.42	12.23	89.7
6037262100	7.65	8.33	9.60	13.00	90.9
6037265420	9.83	7.14	7.60	11.15	92.9
6037265100	10.34	11.25	10.98	17.57	90.5
6037265201	21.52	17.57	20.77	36.58	93.9
6037265305	23.16	25.21	24.59	39.37	88.4
6037265202	29.59	24.17	24.76	33.54	90

6037265304	38.63	28.04	29.83	43.78	90
6037265303	45.98	33.38	35.51	52.11	90
UC MERCED					
campus average	80.11	117.56	128.27	65.16	103.73
6047001801	59.97	89.79	101.32	50.98	103.9
6047002600	69.90	104.65	114.71	59.41	104
6047002500	79.90	125.06	134.98	67.91	103
6047001101	83.59	125.15	137.18	71.05	104.1
6047001002	83.92	125.64	137.72	71.33	104.1
6047001901	103.37	135.07	143.70	70.29	103.3
UC RIVERSIDE					
campus average	78.86	118.07	114.20	67.03	103.25
6065042206	60.19	90.11	87.15	51.16	102.3
6065046500	75.09	112.43	108.74	63.83	103.6
6065042213	75.67	113.30	109.58	64.32	102.3
6065030501	78.39	117.36	113.51	66.63	103.6
6065042210	87.10	130.41	126.13	74.04	103.6
6065042209	96.73	144.83	140.07	82.22	104.1
UC SAN DIEGO					
campus average	31.81	30.20	30.51	40.05	92.17
6073008312	14.72	18.03	18.48	25.03	92.2

6073008305	23.65	21.46	21.31	26.80	92.4
6073008339	27.54	33.74	34.56	46.82	92.5
6073008340	29.08	26.39	26.20	32.96	92.4
6073008341	35.89	32.56	32.33	40.67	92.4
6073008361	60.01	49.01	50.21	68.01	91.1
UC SANTA BARBARA					
campus average	54.96	35.72	30.64	46.72	89.08
6083002915	36.30	24.70	21.03	30.86	89.4
6083002922	36.57	24.89	21.18	31.09	88.4
6083002924	61.38	37.60	32.59	52.18	89.1
6083002926	62.08	38.02	32.96	52.76	89.1
6083002928	78.48	53.41	45.46	66.71	89.4
UC SANTA CRUZ					
campus average	26.68	15.41	15.85	31.12	92.6
6087100500	20.11	13.69	15.53	34.19	92.9
6087120200	24.71	15.13	14.31	21.00	91
6087120700	24.93	13.57	14.44	28.25	93
6087100300	29.86	16.26	15.37	33.84	93.1
6087100400	33.79	18.40	19.57	38.30	93

This score was created by combining population characteristic (Pop Char) data sourced from CalEnviroScreen with average annual number of extreme heat days across three climate models (Baseline Average Days, Mid-Century Average Days, End of Century Average Days) data sourced from CalAdapt.

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