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Green Space as a Heat Wave Adaptation Strategy: A Health Impact Assessment for San Diego County

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GREEN SPACE AS A HEAT WAVE ADAPTATION STRATEGY

A Health Impact Assessment for San Diego County

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INTRODUCTION & BACKGROUND

Extreme heat and health

Extreme heat is a major public health issue, and is in fact the leading cause of weather-related mortality in the United States (NOAA, 2018). Exposure to extreme heat causes numerous health impacts, ranging from direct complications such as dehydration and heat stroke, to indirect impacts on other bodily systems including the cardiovascular, renal, and respiratory systems, especially for those with pre-existing conditions. The human body is healthy when internal temperatures range from 36.5–37°C (Hughes et al., 2016). When external temperatures become high, the body's ability to maintain this optimal temperature can be affected, and heat-related illness may occur (WHO, 2018). **Figure 1** summarizes some of the symptoms associated with heat-related illness. Moreover, not only is extreme heat associated with increased morbidity and hospitalizations (Vaidyanathan et al., 2019), but higher rates of all-cause mortality as well (Schaffer et al., 2012; Weinberger et al., 2020).

Figure 1: *How heat may affect the human body, and strategies for treatment. Image borrowed from the CDC's report "CLIMATE CHANGE and EXTREME HEAT What You Can Do to Prepare" (CDC, 2016).*

One of the highest-risk illnesses associated with extreme heat is heat stroke, which occurs when body temperatures reach 40°C, often due to overexertion in high temperatures (Bouchama and Knochel, 2002). Heat stroke is associated with other complications, such as potentially causing neurological dysfunction and failure of the body's temperature regulatory system, and making an individual more susceptible to bacterial infection (Hopp et al., 2018); and it also has high emergency department fatality rates (Hopp et al., 2018). However, direct impacts of heat such as heat stroke do not provide the full picture of heat-health impacts. Rather, there is a wide range of indirect health impacts of heat, and it is extremely common for heat-health impacts to result from underlying comorbidities. In fact, most heat wave mortality is *not* caused by the direct effects of heat (Kenney et al., 2014). In the 1995 Chicago heat wave, for instance, only 4.7% of the excess deaths attributable to the heat wave were caused primarily by the heat itself, with most deaths instead being caused by underlying conditions that were exacerbated by the high temperatures (Kenney et al., 2014).

One such comorbidity frequently associated with heat-related illness and death is cardiovascular disease. Heat waves have been demonstrated to result in elevated hospitalizations for cardiovascular disease compared to non-heat wave days (Schwartz et al., 2004). In the 1995 Chicago heat wave, a striking 93.7% of excess deaths were found to be due to underlying cardiovascular causes (Kenney et al., 2014). This is particularly important in older adults. Compared to younger adults, older adults have a more limited cardiovascular response to heat (for instance, cutaneous blood flow increases in response to heat to a lesser extent in older adults compared to younger adults), meaning their risk of mortality during heat waves is much greater (Kenney et al., 2014). Extreme heat also causes increased hospitalizations for respiratory issues (Michelozzi et al., 2009). Although the mechanisms for how heat affects respiratory illnesses are not yet fully understood (Michelozzi et al., 2009), hot temperatures appear to exacerbate existing respiratory conditions such as asthma and chronic obtrusive pulmonary disease (COPD) (Michelozzi et al., 2009, British Lung Foundation, 2018). It is also apparent that hot temperatures are associated with elevated amounts of ground-level ozone, which has its own respiratory effects (Kahle et al., 2015), such as reduced lung function and asthma complications (Bernstein and Rice, 2013). Extreme heat also causes an increase in hospitalizations associated with renal failure, urinary tract infection, fluid and electrolyte disorders, and septicemia, particularly in older adults, who are again more likely to experience underlying comorbidities in these areas (Bobb et al., 2014).

Heat and health in a changing climate

It is evident that the public health threat posed by extreme heat is already a major issue, but it is only expected to get worse as a result of anthropogenic climate change. Climate models project an increase in the frequency of heatwaves globally, as well as an increase in intensity and duration of these extreme heat events through the 21st century (IPCC AR5 3.3.1, 2014; Coumou and Robinson, 2013). Under the "business-as-usual" climate change scenario, we can expect to see what is now considered a 1-in-20-year annual extreme heat day become a 1-in-2 annual extreme in most regions globally by 2100 (IPCC, 2014). Projections show that in California, conditions which today would be considered heat waves may ultimately become the predominant summer-month conditions (Miller et al., 2008), making extreme heat one of the biggest challenges for the state in terms of climate change adaptation. General circulation models show that increases in extreme temperatures are expected to exceed the rate of increase in mean temperature in California (Miller et al., 2008), implying that acclimation to warmer climates will not be enough to avoid heat health impacts. Increases in extreme heat in California vary somewhat geographically, with projected increases in extreme heat of approximately twice the present number of days for inland regions, but up to four times the number of extreme heat days for many coastal cities, including San Diego (Miller et al., 2008), making mitigation efforts particularly important in this region. On top of this, San Diego is likely to see a larger portion of the year during which extreme heat events may take place, expanding from July and August to include June and September (Messner et al., 2011).

Previous studies have explored the impacts of extreme heat in the specific region of California. One recent study that looked at 19 heatwave events which took place over 11 years in California found that on peak heat-wave days hospital admissions increased by 7% on average, with a total of 11,000 excess hospitalizations due to heat over the period (Guirguis et al., 2014). They also found that the south coast (the region including San Diego) is among the regions in California that will face the strongest impacts, with a 5.6% increase in daily morbidity at heat-wave peak for the region (Guirguis et al., 2014). The differing temperature thresholds between regions at which health impacts occur indicates acclimation to local climatological conditions and the need for policies that account for this regional variation. Other research has attempted to understand future heat-related mortality in California using projections of climate change through the 21st century, finding that mortality due to heat could increase in the state by a factor of four under the worst-case IPCC climate change scenario (Sheridan et al., 2012). In the San Diego region, this estimate is much higher, with a more than seven-fold expected increase in heat-related mortality over the 21st century under the worst-case IPCC climate change scenario (Sheridan et al., 2012).

Heat vulnerability factors

Crucially, the public health impacts of extreme heat do not affect everyone equally. Rather, we see heterogeneity in the impacts of extreme heat based on demographic, geographic, and socioeconomic factors. One group that is particularly vulnerable to the effects of extreme heat is the elderly (WHO, 2018). Older adults, and similarly young children, are more vulnerable to the health impacts of heat due to being less able to efficiently thermoregulate; and older adults are also more likely to live alone or already be taking medications that impact fluid balance, further increasing their vulnerability (Bobb et al., 2014). Other populations may be more at risk of exposure as well, such as outdoor workers and the homeless (WHO, 2018). Individuals experiencing homelessness have limited access to services that provide heat relief, such as cooling stations, while simultaneously already living under stressful conditions, putting them at very high risk for heat impacts (Baker, 2019). Despite being one of the most vulnerable populations, people experiencing homelessness tend to be neglected in climate action plans. Another oft-overlooked sector of the population that is more vulnerable to heat is outdoor/manual workers, such as farm workers and construction workers, who in combination with spending a large amount of time in the sun, are also more likely to be performing intensive physical labor, exacerbating their risk for conditions such as heat stroke

(Xiang et al., 2014). In fact, US agricultural workers experience a heat-related mortality rate 20 times larger than for other civilian workers (Xiang et al., 2014).

Access to air conditioning (AC) is another social factor that impacts heat vulnerability. Access to AC can provide protection from the health impacts of extreme heat (Chestnut et al., 1998), but generally speaking, access is dependent on socioeconomic factors including race and level of income (Guirguis et al., 2018). For instance, in San Diego County, coastal residents in higher income brackets are more likely to have access to AC than coastal residents in lower income brackets, homeowners are more likely to have access to AC than renters, and Whites are more likely to have access to AC than Hispanics (Guirguis et al., 2018). Additionally, San Diego experiences a geographical effect, in which coastal residents are more vulnerable to extreme heat, and experience higher mortality rates during extreme heat events than those who live inland due to differences in acclimation (Guirguis et al., 2018).

The micro-urban heat island effect

There is also another important form of spatial heterogeneity in impacts associated with urban settings. Within a city, different neighborhoods may experience vastly different impacts due to heat. The urban heat island effect, in which cities experience much hotter temperatures than their more rural surroundings (with differences sometimes reaching up to 12°C (EPA, 2020)), is a well-established phenomenon in urban settings (Rizwan et al., 2008). But *within* a city, there is further geographic variability in temperature, and some areas, called **micro-urban heat islands**, can be much hotter than other parts of the same city (Aniello et al., 1995). Micro-urban heat islands (MUHIs) result from an energy imbalance in which artificial structures such as buildings and paved surfaces trap heat, and an absence of vegetation exacerbates the issue by depriving an area of the cooling effects associated with tree cover (Yow, 2007; Aniello et al., 1995). MUHIs, and microclimates in a broader sense, can be measured in a variety of ways, as demonstrated in the literature on the subject (Schinasi et al., 2018). Though they are defined as areas of an urban setting that are hotter than other areas, they can be measured using more than just air temperature or surface temperature (though these measures are used) (Schinasi et al., 2018). Because MUHIs are directly dependent on factors such as allocation of green space, vegetation cover, and impervious surface cover, these very factors can themselves be used as measures of MUHIs. Schinasi et al., 2018 reviews the literature on microclimate indicators, finding that MUHIs can be accurately captured and predicted by visualizing the spatial distribution of some of these factors such as percentage tree cover, level of greenness or NDVI (Normalized Difference Vegetation Index), settlement density, access to open space, proximity to a large body of water, and more (Schinasi et al., 2018). Results of this study are summarized in **Table 1**, adapted from the paper.

MUHIs are a crucial determinant of spatial vulnerability to heat. The risk of mortality on hot days has been found to be significantly higher for those who live in MUHIs (Smargiassi et al., 2009). And those living in hotter parts of a city and areas with less vegetation have a higher risk of morbidity and mortality related to high ambient temperatures than those who live in areas with lower surfaces temperatures or more vegetation (Schinasi et al., 2018). Not only is it true that people living in neighborhoods with high settlement density, sparse vegetation, and low access to open space experience significantly higher ambient temperatures when compared to other neighborhoods; but the people who are most likely to live in these most vulnerable neighborhoods are people of low socioeconomic status (SES) and people of color (Harlan et al., 2006). Additionally, people living in these warmer neighborhoods tend to have fewer resources available to them to help cope with extreme heat, making them even more vulnerable (Harlan et al., 2006). A summary of selected epidemiological studies highlighting the potential role of MUHIs in modulating heat-related health impacts is presented in **Table 1** below.

Paper	Outcome	Study Pop.	Study Period	Location	Microclimate Indicator
Smargiassi, 2009	Natural cause mortality	All residents	June-Aug 1990-2003	Montreal, Canada	Land surface temperature
Goggins, 2012	Natural cause mortality	All residents	June-Sept 2001-2009	Hong Kong	Urban heat island index
Goggins, 2013	Natural cause mortality	All residents	May-Oct 1999-2008	Kaohsiung City, Taiwan	Urban climate map
Madrigano, 2013	All cause mortality following acute MI, acute MI	Patients ages 25+ hospitalized with independently confirmed acute MI	April-Oct 1995, 1997, 1999, 2001, 2003	Worcester, MA	Recreation/conservation area, having a large (> 100,000 m^2) lake or reservoir within 400m of residence, elevation, greenness (mean NDVI), housing density, number of units in building; with all characteristics evaluated individually
Xu, 2013	All cause mortality	All residents	May-Oct 1999-2006	Barcelona, Spain	Percentage of residents perceiving little surrounding greenness, percentage of single dwellings (as opposed to apartment blocks) at census tract level, percent tree cover around residence
Burkart et al., 2016	All cause mortality	Ages 65+	June-Aug 1998-2008	Lisbon, Portugal	Spatial mean land surface temperature at parish level, greenness (NDVI) at parish level, mean distance to the Atlantic Ocean and Tagus Estuary Coast for the entire parish
Gronlund, 2015	Cardiovascular and respiratory disease mortality	Ages 65+	May-Sept 1990-2007	8 cities in Michigan, US	Percent vegetation
Gronlund, 2016	Emergency hospitalizations for heat, renal, or respiratory causes	Ages 65+	May-Sept 1992-2006	109 US cities, with effect estimates combined by meta-analysis	Percent vegetation
Ho, 2016	All cause mortality	All residents	1998-2014; restricted based on daily mean air T values	Vancouver, Canada	Heat exposure maps for land surface temperature, daily air temperature, maximum daily humidex
Milojevic, 2016	All cause mortality	All residents	June-Aug 1993-2006	London, England	Urban heat island
Son, 2016	All cause mortality except external causes	All residents	May-Sept 2000-2009	Seoul, Korea	Greenness (NDVI) at the administrative area converted to a percentage scale

Kondo et al., 2020	All cause mortality	Ages 18+	2014-2025 (projections)	Philadelphia, PA	Tree canopy cover

Table 1: *Selection of papers on the protective effects of green spaces, adapted from Tables 1 and 2 in Schinasi et al. (2018), with the addition of Kondo et al. This list is not exhaustive, but provides an overview of some of the previous studies in the field, and the microclimate indicators they used to measure MUHI.*

Techniques for mitigating and adapting to extreme heat

Given the vast and unequal health impacts associated with extreme heat and MUHIs, and the fact that climate change is projected to bring increased frequency, intensity, and duration of extreme heat events, it is imperative that action be taken to mitigate this public health issue. One strategy to reduce the health threat of extreme heat is the implementation of extreme heat early warning systems. The National Weather Service (NWS) issues extreme heat alerts based on temperature thresholds chosen by its various Weather Forecast Offices across the nation (Vaidyanathan et al., 2019). These heat early warning systems are meant to alert the public of upcoming extreme temperatures and reduce risk by providing information on how to avoid health impacts, but data on their efficacy has been mixed, with some studies claiming that they decrease mortality (Ebi et al., 2004), and others claiming that there is little evidence that they lead to reduced mortality in the general population (Heo et al., 2019). These warning systems are also not without complications. There is sometimes a mismatch between the temperatures at which health impacts become apparent and the temperatures at which a heat warning is sent out, due mainly to a lack of regionally specific health data to base these alerts on (Vaidyanathan et al., 2019; Guirguis et al., 2018). Furthermore, while heat early warning systems are an important component of protecting public health during a heat wave, they are reactive short-term strategies rather than proactive long term solutions. A more sustainable policy for protecting public health during extreme heat should involve long term strategies that can reduce the burden of extreme heat by preventing or mitigating extreme temperatures through urban landscape modification. A variety of mitigation strategies exist, including reducing energy consumption (Yow, 2007), installing cool/green roofs, planting trees and vegetation, and using “cool” paving materials that increase albedo (Zhou and Shepherd, 2009). One strategy that seems to not only be promising in terms of mitigating the health impacts of heat, but is also easily actionable and comes with a plethora of beneficial side effects, is increasing urban green space.

Urban greening (i.e. increasing the amount of trees and vegetation in a city) reduces ambient air temperatures through the production of shade, which blocks solar radiation from reaching surfaces and then transmitting that heat into the surrounding air, as well as through evapotranspiration from soils and plants, a process that uses surrounding heat to convert water into water vapor (Yow, 2007; Son et al., 2016). The cooling effects of green spaces can be quite strong – sometimes up to 7°C cooler than less vegetated surrounding areas – and their cooling impact can stretch as far as several hundred meters beyond their boundaries (Zhang et al., 2017). This can translate directly into avoided negative health impacts when temperatures become extreme. Illustrating this fact, one recent meta-analysis determined that the level of surrounding greenness is inversely associated with all-cause mortality, concluding that green space management should be considered as a public health intervention (Rojas-Rueda, 2019).

But health benefits actually go beyond avoiding heat-related mortality. Green spaces provide many health co-benefits, including removal of air pollutants. Trees and shrubs in urban settings can filter gaseous air pollutants by taking them up through their stomata, and these plants can also filter particulate matter by collecting it on their leaf surfaces (Nowak et al., 2006). Green space has also been demonstrated to have positive impacts on mental health (Nutsford et al., 2013, Wolch et al., 2014). Studies have found that anxiety and mood disorder treatment counts decrease with proximity to usable green space (Nutsford et al., 2013), and there appears to be a strong relationship between self-reported stress, cortisol secretion, and quantity of nearby green space, indicating that proximity to green space may be associated with improved mental health (Thompson et al., 2012). Green space may also decrease general stress, based on findings that individuals living near more green space were less affected by stressful life events than those with lower access to green space (Van den Berg et al., 2010). Access to green space also may provide physical health benefits, as those who live closer to green space are more likely to achieve daily exercise recommendations of 30 minutes or more, and are less likely to be overweight or obese (Coombes et al., 2010). **Figure 2** illustrates some of the positive health effects of trees, a form of green space.

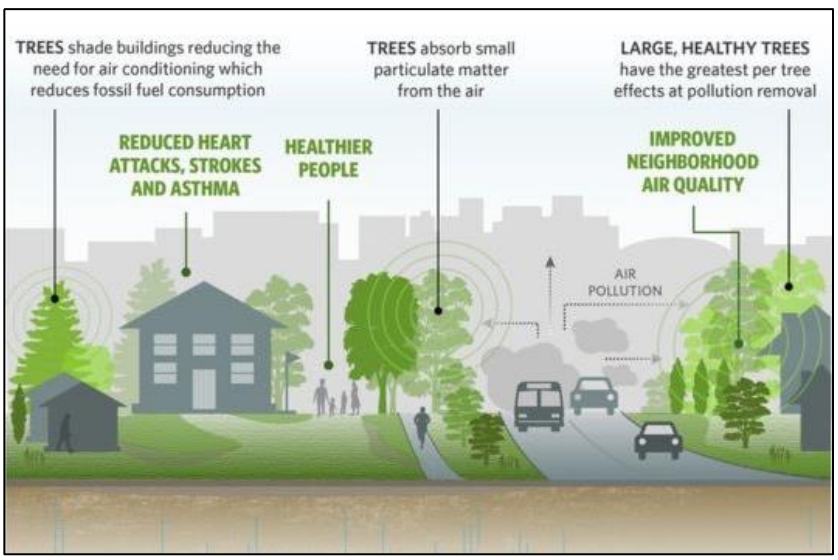


Figure 2: *Trees provide health benefits by reducing temperatures through shade and filtering harmful air pollutants. Image source: Erica Simek Sloniker, The Nature Conservancy.*

On top of serving as a way to mitigate the *effects* of climate change (particularly extreme heat), urban greening also provides an opportunity to mitigate climate change itself by reducing atmospheric carbon dioxide through carbon sequestration (Nowak and Crane, 2002), and urban greening could therefore be incorporated as part of a city's climate action and mitigation plans. Large green spaces with a thick soil layer, when placed strategically, also provide the ability to make a city more resilient to flooding (Kim et al., 2016) by acting like a sponge to absorb and store water following extreme precipitation events (Farrugia et al., 2013). Urban greening is also an appealing option for cities because it is a strategy that is easily and clearly actionable. Simply planting and maintaining more vegetation is fairly simple, and in addition to providing health co-benefits, it has an aesthetic value as well (Yow, 2007). Other strategies such as implementing "cool" streets that can either increase the reflectivity or permeability of paved roads (Zhou and Shepherd, 2009), or reducing energy consumption through improved building design (Yow, 2007), are good options for reducing urban heat, but may be more difficult to implement in an already developed urban center. Green space is just one part of reducing the effects of micro-urban heat islands, and as many of the above-mentioned strategies as possible should be used in combination to effectively tackle the problem; but increasing a city's green space is an actionable, effective, simple, and relatively inexpensive (Vieira et al., 2018) place to start.

Objectives of this project

This capstone project aims to understand the relationship between green spaces and the impacts of extreme heat on human health, and intends to quantify the health benefits associated with different greening scenarios, using San Diego as a case study. This approach, the first of its kind, is important because it goes beyond describing past heat-health impacts in the region and how they might have been modified by green space, and uses this data to directly quantify the benefits of potential future increases in green space. This Health Impact Assessment approach is intended to aid political decision-makers in considering appropriate measures for adapting to and increasing resiliency in San Diego in the face of extreme heat events.

San Diego County as case study

San Diego is a natural fit for this study because it already experiences extreme heat and the resulting health impacts. For instance, a recent study showed that the total number of hospitalizations attributable to heat from 1999–2013 in San Diego County was a staggering 11,708 (McElroy et al., 2018). Furthermore, in the San Diego region, it is expected that climate change will make this extreme heat issue worse – i.e. more frequent, intense, and prolonged heat waves should be expected. Evidence points to many coastal Californian cities, including San Diego, facing increases in extreme heat much higher than for inland Californian cities (Miller et al., 2008). In fact, the City's 2015 Climate Action Plan identifies increased temperature and heat waves as one of seven main impacts for the city of San Diego (City of San Diego, 2015).

In addition, urban settings such as San Diego frequently experience spatial inequalities, including in green space allocation. Accessibility of green space often decreases as the level of neighborhood social deprivation increases, and green spaces in more socially deprived neighborhoods tend to be of lower quality (Hoffimann et al., 2017). These kinds of spatial inequalities in green space distribution are affected by factors such as income and race (Heynen et al., 2006). San Diego, like a majority of urban centers, experiences spatial inequality based on socioeconomic factors, implying a possible overlap between more socially deprived neighborhoods and the areas which are most in need of green space.

There are other spatial and demographic inequalities that make the issue of differential vulnerability to heat particularly notable in San Diego. San Diego has the fourth largest homeless population in the United States as of 2018 (Warth, 2018), and, as previously described, people experiencing homelessness are particularly vulnerable to the effects of extreme heat (Baker, 2019). San Diego's population is also aging, and it is estimated that by 2050 up to one quarter of San Diego's residents will be above the age of 65 (Messner et al., 2011), resulting in a very large sector of the population that will be at high risk of health complications due to heat. Additionally, as previously noted, the health impacts of extreme heat tend to occur on a gradient ranging from inland to coast due to the residents of these inland regions being more acclimated to high temperatures (Guirguis et al., 2018). All of these factors make San Diego of particular interest when analyzing disparities in heat-related health outcomes and how green spaces might act to modify them.

Currently, the City of San Diego does have some programs in place to implement urban greening strategies. The 2015 Climate Action Plan identifies green spaces as offering recreational value while simultaneously serving "as a climate change adaptation resource where they can alleviate the heat island effect and potentially reduce the impact of flooding" (City of San Diego, 2015). One of the actions outlined in the City's Climate Action Plan is the Urban Tree Planting Program, which aims to achieve 15% urban tree canopy coverage by 2020 and 35% urban tree canopy coverage by 2035, which the city estimated would bring reductions of 43,839 MT/CO_2e and 102,290 MT/CO_2e for each year respectively (City of San Diego, 2015). The City also adopted an Urban Forestry Program five year plan in 2017 (City of San Diego, 2017). It is evident that the City of San Diego cares about increasing green spaces in its city boundaries. It is my hope that my research can help provide decision makers at the City of San Diego with guidance on where and how to implement urban greening strategies in order to effectively reduce inequalities in vulnerability, as well as to provide reasoning and guidance for other cities and incorporated areas in San Diego County to implement equitable greening strategies as well.

METHODS

Study Design

This study uses a health impact assessment approach in order to explore and quantify the potential health benefits of multiple types of green space interventions and their ability to minimize the micro-urban heat island effect in San Diego County. **Figure 3**, below, depicts the three-step approach utilized in this study.

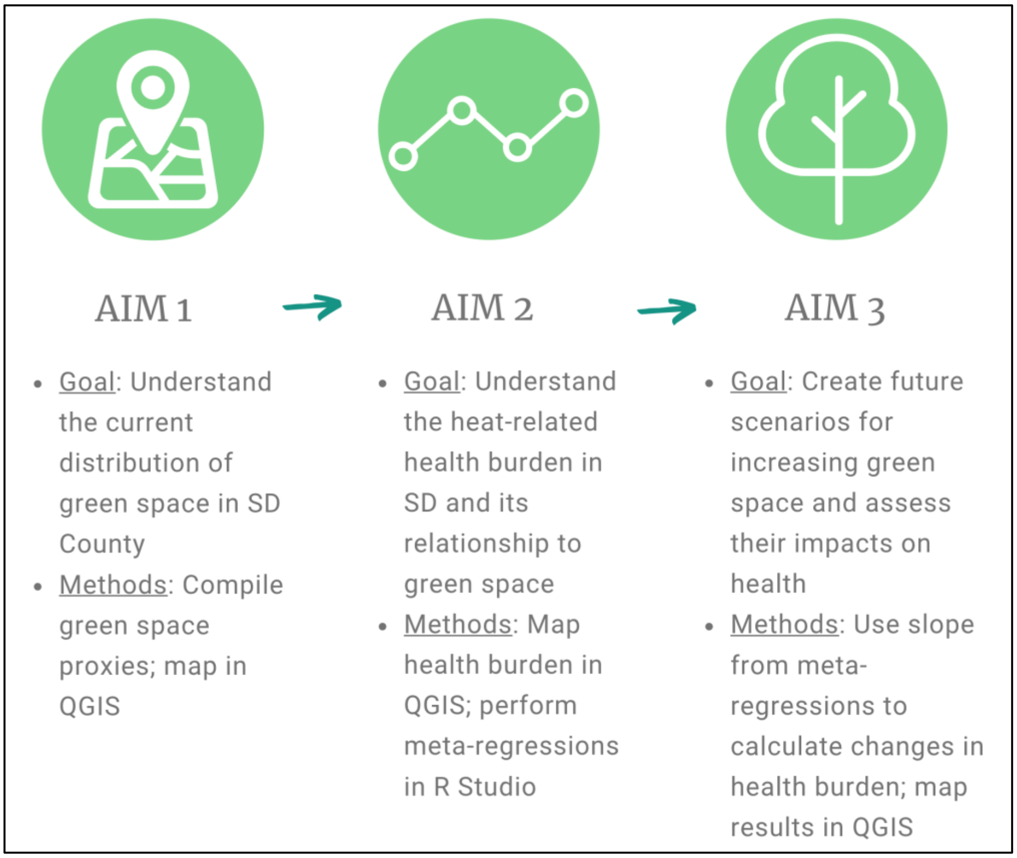


Figure 3: *Flowchart depicting the general layout and methodology of this study.*

Data sources for green space proxies

This project looked at five main proxies for green space, eventually choosing three as the main focus. These five indexes, interpolated at the zip code level, are described below and include NDVI, Tree Canopy, Park Access, Tree Cover, and Impervious Surface Cover. For this study, I will focus on Tree Canopy and Impervious Surface Cover as I found that they are the most important predictors of heat-related health impacts in San Diego. Furthermore, with the help of my capstone chair, Tarik Benmarhnia, we created a composite index incorporating all five indexes (see details below).

NDVI (or Normalized Difference Vegetation Index) is a measure of the "greenness" of a given area of land, and is obtained by satellite imagery. It was ascertained per the NOAA Climate Data Record (CDR) NDVI remote sensing product. NDVI is calculated by taking (NIR – VIS)/(NIR + VIS) where NIR is the near-infrared radiation reflected by vegetation and VIS is the visible radiation reflected by vegetation (NASA, 2000). Values range from -1 to 1, with 1 representing completely green, lush vegetation, values around 0 indicating dead vegetation or barren areas, and values near -1 usually representing surfaces such as water. The NDVI CDR measures and summarizes surface vegetation activity across the globe and has been used in several epidemiological studies (see Table 1). NDVI is calculated using the spectral bands in the visible and near infrared wavelengths, which are derived from the Advanced Very High

Resolution Radiometer (AVHRR) on NOAA polar orbiting satellites. This NDVI CDR product generates daily measurements of NDVI on a 0.05°x0.05° grid from 1981 to 10 days before the present date with data obtained from eight orbiting satellites. The NDVI data was obtained from Hansen et al. (in review), in which Google Earth Engine was utilized to create an average annual NDVI measure for each census tract in San Diego County. This was done by filtering the NDVI daily images to the desired year and selecting the "NDVI" band. The *reduceRegion* command, which applies a "reducer" to all pixels in a specific region, was employed to calculate the mean of all pixels within a census tract, resulting in one annual mean NDVI measure per tract. In order for the proxy data to be consistent with the hospitalization data, I converted these census tract-level results to zip code level by using the results from CalEnviroScreen 3.0 (OEHHA, 2018), which provided a corresponding census tract for each zip code in California.

Tree Canopy is, a measure of the amount of tree canopy present in an area, specifically the "Population-weighted percentage of the census tract area with tree canopy" (HPI Documentation (Delaney et al., 2018)). This data was obtained from the California Healthy Places Index, which in turn obtained the data from the California Department of Public Health. This data was originally presented by census tract and was therefore converted to zip code level for this study.

Park Access similarly measures "Percentage of the population living within a half-mile of a park, beach, or open space greater than 1 acre" (HPI Documentation (Delaney et al., 2018)). Data for this measure also came from the California Healthy Places Index and was converted from census tract to zip code level.

Impervious Surface Cover measures the imperviousness of land surfaces – i.e. to what degree they are covered in impervious materials such as pavement. These data were obtained from Hansen et al. (in review), but the National Landcover Database (NLCD) is available in Google Earth Engine from USGS. This is a 30m resolution dataset that exists in 8 iterations from 1992 to 2016. Hansen et al. used the 2006 image to get the imperviousness estimate, which is the only image in the collection containing the pertinent bands within the 2004-2013 study period for which hospitalization data is available. They then calculated the proportion of a given zip code with imperviousness land surfaces to obtain this measure.

Finally, Tree Cover represents a percentage of land surface area covered by trees based on satellite imagery, and was also obtained from Hansen et al. (in review), using Google Earth Engine and the approach described above, but using the 2011 image to obtain Tree Cover.

Creating a composite index for greenness in San Diego County

In order to incorporate all proxies of greenspace (or lack thereof for impervious surfaces), capstone chair Tarik Benmarhnia created an aggregate greenness index. We used a principal component analysis as typically applied to such composite indexes (Joint Research Centre, 2008; Benmarhnia et al., 2013; Rice et al., 2014). We used the 5 different variables described above at the zip code level. We calculated principal components and used scores from the first component (Overall Eigenvalue=2.78; 46% of total variance explained) for all zip codes. Variable-specific eigenvalues (from the first component) ranged from -0.46 for impervious surfaces to 0.45 for tree canopy. We then calculated a linear combination of variable-specific eigenvalues and each zip code specific value for the 5 variables of interest. We obtained a greenness index with a mean of 0 and a standard deviation of 1.60 (minimum and maximum index values were -2.82 and 4.63 respectively).

Heat-attributable hospitalization data

As the health outcome of interest, I relied on zip code estimates of heat-attributable hospitalization for the years 2004-2013 as estimated in Hansen et al. [in review]. Below is a brief description of the time-series approach adopted in that paper to estimate such heat-attributable hospitalization at the zip code level.

First, the authors defined for each zip code a heat wave day as any day where the maximum temperature was greater than or equal to the 95th percentile of the distribution of maximum temperatures across the warm season (May-September). Daily maximum temperature (°C) was derived from 1/16° (~6 km) gridded observed data from this dataset for all of California and interpolated for each zip code (Livneh et al. 2013). This method resulted in heat wave definitions that accounted for spatial variability by being specific to each zip code.

They then collected data for hospitalizations in San Diego County for the years 2004 – 2013 from the Office of Statewide Health Planning and Development (OSHPD). The following primary diagnoses were evaluated, as listed in the International Classification of Disease codes, 9th Revision, Clinical Modification (ICD-9): acute myocardial infarction (MI) (410), acute renal failure (584), cardiac dysrhythmias (427), cardiovascular disease (CVD) (390–459), dehydration/volume depletion (276.5), essential hypertension (401), heat illness (992), ischemic heart disease (410–414), ischemic stroke (433–436), and all respiratory diseases (460–519). These particular diseases were chosen because they have previously been linked to extreme temperature (Bunker et al, 2016; Li et al., 2015; Sherbakov et al., 2018). For this analysis, the authors grouped all causes of hospitalizations together. Only unscheduled hospitalizations were included. Data were aggregated into daily counts for each zip code.

Then, they estimated daily number of hospitalizations attributable to heat waves (using the definition above) for each zip code. For each heat wave (HW) day and for each zip code in the study period, they randomly selected 3 non-HW days that matched the HW day on month, weekday/weekend (binary variable), and zip code. These matched days were only included if they were above the 75th percentile of the warm season (May-September) distribution of daily-maximum temperature for the zip code where the HW day is observed. Some of the heat wave days had only 3 matched days and thus 3 were chosen to avoid resampling of any days. This aimed at removing long term and seasonal trends and making HW and non-HW days as similar as possible regarding potential confounding variables including population size, age, race/ethnic composition and any other time-fixed variable at the zip code level. They then calculated the difference in number of hospitalizations between the HW day and the median of the non-HW matches. Finally, they calculated the average of the contrast between all HW days and matched non-HW days for each zip code to obtain the count of hospital admission attributable to heat for each zip code. They used a bootstrap-T procedure, also known as the studentized bootstrap (Efron & Tibshirani, 1993; Wilcox, 2017) to obtain standard errors for each zip code.

This quantity represents the average number of hospitalizations (for relevant ICD causes) for each HW day in each zip code. This quantity has been multiplied by 100 to represent the average number of hospitalizations for 100 heat waves (as defined above).

Approach for Aim 1*: *Understanding the current distribution of green space in San Diego County

In order to understand how green space is spatially distributed across San Diego County, I used QGIS (version 3.10 'A Coruña') for Mac to map each index at the zip code level. Tree cover, impervious surface cover, tree canopy, and park access were mapped as is, and NDVI was mapped not only for each individual year spanning from 2000-2019, but also as a 20-year average over this time period, and as NDVI change over time (calculated as (NDVI 2019–NDVI 2000)/NDVI 2000). The aggregate index was also mapped. Some zip codes were excluded from the analysis due to incomplete data, which is why there are some empty zip codes in the resulting figures. Selected green space proxy maps are presented in **Figure 5**, with the rest presented in the Appendix. I also mapped three scenarios from CalEnviroScreen: Education, Unemployment, and Housing Burden (see **Figure 6** and Appendix), which I use in Aim 3 as the basis for some equity-focused green space intervention scenarios.

Approach for Aim 2: Understanding the heat-related health burden and its relationship to green space

For the next part of the project, I aimed to quantify the relationship between hospital admissions attributable to heat and each selected greenness index of interest including Tree Canopy, Impervious Surface Cover and the Aggregate Index.

To do this, I implemented random-effect meta-regressions in which the dependent variable was the zip code-specific average number of hospital admissions attributable to heat and the independent variables were Tree Canopy, Impervious Surface Cover and the Aggregate Index. The random effect meta-regression aims at quantifying the change in hospitalizations attributable to heat in relation to different green spaces indexes while accounting for the zip code statistical precision in hospitalizations. I used a separate model for each of these 3 greenness indicators and estimated from these meta-regressions the regression coefficients (slope and 95% confidence interval [CI]). The slopes represent the change in hospital admissions attributable to heat for one unit increase in each greenness indicator. As the slope for Impervious Surface Cover was in the opposite direction as compared to Tree Canopy and the Aggregate Index, I multiplied it by -1 to represent a decrease in impervious surfaces and facilitate calculations and interpretations in the Aim 3 simulations. I then applied these slopes to the set of scenarios in Aim 3 to simulate the expected change in hospital admissions attributable to heat for potential green space interventions. I conducted similar analyses for the other greenness indicators, the results of which are presented in the Appendix.

Additionally, I created a map of the zip code-level heat-attributable hospitalization data in QGIS, which is presented in **Figure 7**.

Approach for Aim 3: Future scenarios for increasing green space & health impact assessment

To understand the effects of increasing green space I created a number of different scenarios that involved manipulation of the index data. 33 scenarios were considered, which were separated into three categories: population-based approaches, targeted approaches, and proportionate universalism approaches (see **Table 2** and **Figure 4** for a summary). These three categories are loosely adapted from Benach et al. (2012) and are meant to illustrate various types of possible policy interventions. Given that extreme heat affects different populations to different extents, it's especially important that policies aimed at tackling the health impacts of extreme heat tackle these health inequalities as well. These three different approaches are intended by Benach et al. to serve as a tool that can be used to see the different impacts that different types of intervention can have, and to help in creating policies that aim to reduce health inequalities. The three approaches are described in more detail as followed:

A population-based approach delivers the same intervention to the whole population regardless of existing health or social inequalities. This approach was represented in my green space scenarios as a change in value of the three indexes (Tree Canopy Cover, Impervious Surface Cover, and the Aggregate Index) of 15% or 35% across all zip codes. These scenarios were chosen specifically to align with the goals that have already been outlined by the City of San Diego's own Climate Action Plan to achieve 15% urban tree canopy coverage by 2020 and 35% urban tree canopy coverage by 2035 (City of San Diego, 2015).

The targeted approach delivers interventions only to the worst-off among the population. Here this approach was represented in three ways. The first of the targeted approach sub-categories involved increasing green space only in zip codes that fell below (or above, in the case of imperviousness) the mean value for that index (scenarios **2a**–**2f**). The next targeted approach involved increasing green space only in zip codes that fell above the county-wide mean for heat-attributable hospitalizations for the baseline period of 2004–2013 (scenarios **2g**–**2i**). The last of the targeted approach scenarios involved incorporating data from CalEnviroScreen 3.0 (OEHHA, 2018), a project of the California Office of Environmental Health Hazard Assessment (OEHHA). For these scenarios (**2j**–**2r**), green space was increased only in zip codes that fell in the upper quintiles of the Housing Burden, Unemployment, and Education variables (see **Table 2** caption for definitions of these variables).

Finally, the proportionate universalism approach involved increasing green space for the entire population, but by different amounts for different zip codes based on the distribution of social inequality. Values of the three CalEnviroScreen variables were analyzed for San Diego

County zip codes and then divided into quintiles. For each variable, zip codes in the upper quintile (i.e. the most disadvantaged zip codes) received the largest increases in green space (30%). Zip codes in the lowest quintile received a lesser increase in green space of only 10%. The three quintiles between these two ends of the spectrum received green space increases of 25%, 20%, and 15% based on their relative social inequalities.

Approach	Scenario Name	Scenario Description
Population-based approach	**1a:** Tree Canopy: 15% Increase	Increase tree canopy cover by 15% for all zip codes
	1b: Tree Canopy: 35% Increase	Increase tree canopy cover by 35% for all zip codes
	1c: Imperviousness: 15% Decrease	Decrease impervious surface cover by 15% for all zip codes
	1d: Imperviousness: 35% Decrease	Decrease impervious surface cover by 35% for all zip codes
	1e: Aggregate Index: 15% Increase	Increase aggregate index by 15% for all zip codes
	1f: Aggregate Index: 35% Increase	Increase aggregate index by 35% for all zip codes
Targeted approach	**2a:** Tree Canopy: Below Mean Raise to Mean	In zip codes where tree canopy cover is below the mean, increase tree canopy cover to be equal to the mean. In zip codes where tree canopy cover is above the mean, leave as is.
	2b: Tree Canopy: Below Mean Increase 30%	In zip codes where tree canopy cover is below the mean, increase tree canopy cover by 30%. In zip codes where tree canopy cover is above the mean, leave as is.
	2c: Imperviousness: Above Mean Drop to Mean	In zip codes where impervious surface cover is above the mean, decrease impervious surface cover to be equal to the mean. In zip codes where impervious surface cover is below the mean, leave as is.
	2d: Imperviousness: Above Mean Decrease 30%	In zip codes where impervious surface cover is above the mean, decrease impervious surface cover by 30%. In zip codes where impervious surface cover is below the mean, leave as is.
	2e: Aggregate Index: Below Mean Raise to Mean	In zip codes where the aggregate index is below the mean, increase the aggregate index to be equal to the mean. In zip codes where the aggregate index is above the mean, leave as is.
	2f: Aggregate Index: Below Mean Increase 30%	In zip codes where the aggregate index is below the mean, increase the aggregate index by 30%. In zip codes where the aggregate index is above the mean, leave as is.
	2g: Tree Canopy: Above Mean Burden Increase 30%	In zip codes where the burden of heat-attributable hospitalizations is above the mean, increase tree canopy cover by 30%. In zip codes where the burden is below the mean, leave as is.
	2h: Imperviousness: Above Mean Burden Decrease 30%	In zip codes where the burden of heat-attributable hospitalizations is above the mean, decrease impervious surface cover by 30%. In zip codes where the burden is below the mean, leave as is.
	2i: Aggregate Index: Above Mean Burden Increase 30%	In zip codes where the burden of heat-attributable hospitalizations is above the mean, increase the aggregate index by 30%. In zip codes where the burden is below the mean, leave as is.
	2j: Tree Canopy: Lowest Education Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, increase tree canopy cover by 30%. Otherwise, leave as is.
	2k: Tree Canopy: Highest Unemployment Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, increase tree canopy cover by 30%. Otherwise, leave as is.
	2l: Tree Canopy: Highest Housing Burden Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, increase tree canopy cover by 30%. Otherwise, leave as is.

	2m: Imperviousness: Lowest Education Decrease 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, decrease impervious surface cover by 30%. Otherwise, leave as is.
	2n: Imperviousness: Highest Unemployment Decrease 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, decrease impervious surface cover by 30%. Otherwise, leave as is.
	2o: Imperviousness: Highest Housing Burden Decrease 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, decrease impervious surface cover by 30%. Otherwise, leave as is.
	2p: Aggregate Index: Lowest Education Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, increase the aggregate index by 30%. Otherwise, leave as is.
	2q: Aggregate Index: Highest Unemployment Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, increase the aggregate index by 30%. Otherwise, leave as is.
	2r: Aggregate Index: Highest Housing Burden Increase 30%	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, increase the aggregate index by 30%. Otherwise, leave as is.
Proportionate Universalism approach	**3a:** Tree Canopy: Education-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, increase tree canopy cover by 30%. Lower the amount by which tree canopy cover is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in tree canopy cover of only 10%.
	3b: Tree Canopy: Unemployment-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, increase tree canopy cover by 30%. Lower the amount by which tree canopy cover is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in tree canopy cover of only 10%.
	3c: Tree Canopy: Housing Burden-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, increase tree canopy cover by 30%. Lower the amount by which tree canopy cover is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in tree canopy cover of only 10%.
	3d: Imperviousness: Education-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, decrease impervious surface cover by 30%. Lower the amount by which impervious surface cover is decreased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving a decrease in impervious surface cover of only 10%.
	3e: Imperviousness: Unemployment-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, decrease impervious surface cover by 30%. Lower the amount by which impervious surface cover is decreased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving a decrease in impervious surface cover of only 10%.
	3f: Imperviousness: Housing Burden-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, decrease impervious surface cover by 30%. Lower the amount by which impervious surface cover is decreased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving a decrease in impervious surface cover of only 10%.
	3g: Aggregate Index: Education-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Education" variable*, increase the aggregate index by 30%. Lower the amount by which the aggregate index is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in the aggregate index of only 10%.

	3h: Aggregate Index: Unemployment-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Unemployment" variable**, increase the aggregate index by 30%. Lower the amount by which the aggregate index is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in the aggregate index of only 10%.
	3i: Aggregate Index: Housing Burden-based	In zip codes that fall in the upper quintile for San Diego Co. of CalEnviroScreen's "Housing Burden" variable***, increase the aggregate index by 30%. Lower the amount by which the aggregate index is increased by intervals of 5% for each of the remaining four quintiles, ending with the lower quintile receiving an increase in the aggregate index of only 10%.

***Table 2**: Definitions for green space intervention scenarios. Each scenario is categorized into one of three main approach types, loosely based on Benach et al. (2012).*
**CalEnviroScreen 3.0 defines the "Education" variable as "Percent of population over 25 with less than a high school education" (OEHHA, 2018).*
***CalEnviroScreen 3.0 defines the "Unemployment" variable as "Percent of the population over the age of 16 that is unemployed and eligible for the labor force"(OEHHA, 2018).*
****CalEnviroScreen 3.0 defines the "Housing Burden" variable as "Percent housing burdened low income households," where housing burdened refers to being "highly burdened by housings costs" (OEHHA, 2018; OEHHA, n.d.).*

***Figure 4:** Outline of the three types of intervention approaches adapted from Benach et al. (2012).*

Calculations for each scenario were performed in Microsoft Excel (version 15.30), with the proportionate universalism scenarios being calculated in Google Sheets. The strategy involved calculating for each zip code a value that represented the amount by which the given green space index would be increased by. For instance, if tree canopy cover in a given zip code had a value of 10 and the scenario being tested was an increase in green space of 15%, I multiplied 10 by 0.15 to get 1.5. This value represented the amount by which that index would be increased, and was then multiplied by the slopes obtained in Aim 2 between the selected index and the hospitalizations attributable to heat. This gave the value of heat-attributable hospitalizations that would be avoided when the given green space index is increased by a given amount for each scenario (in this example by 15%). A "new burden" was then calculated by subtracting this value from the original burden of heat-attributable hospitalizations associated with the zip code.

Finally, a relative change in burden was calculated as a percent by subtracting this new burden from the original burden and diving by the original burden. It must be noted that when performing calculations on the Aggregate Index, a transformation needed to be performed, as some zip codes had negative values. For this reason, in scenarios that involved the Aggregate Index, a value of 3 was added to each zip code's value to bring everything above 0 before performing the calculations described above.

I then used QGIS to create maps of each of these 33 greening scenarios in order to visualize how their effects differed. For each scenario, I created a map representing the differential burden (i.e. the number of avoided heat-attributable hospitalizations) associated with the greening scenario. I also created maps for each scenario that represented the relative change in burden (compared to the baseline no-intervention hospitalization data) associated with that scenario, for a total of 66 maps (presented in **Figure 8** and the Appendix).

RESULTS

Aim 1: Understanding the current distribution of green space in San Diego County

Figure 5 depicts the existing allocation of three proxies for green space: Tree Canopy Cover, Impervious Surface Cover, and the Aggregate Index. Maps of the remaining indexes (NDVI, Park Access and Tree Cover (non-HPI)) are presented in the Appendix. If each of the various indexes used here are thought of as proxies representing green space allocation, then these maps demonstrate a fairly consistent and expected trend of low levels green space in the most densely urbanized areas of San Diego County. We can also see a general trend of green space increasing as one moves inland and northward.

Of course, all of these indexes are variable in their distribution, and no index perfectly matches another. This is to be expected, as each index is only a proxy of green space – something that represents green space more-or-less but is not an exact measure of it. This is part of the motivation behind including an Aggregate Index, which incorporates data from all of the various proxies. For instance, Impervious Surface Cover does not perfectly map to tree canopy cover (or other proxies). Unlike the other indexes, Impervious Surface Cover is distributed in a much smoother gradient, with high levels of imperviousness near the coast and successively lower levels as you move inland. However, Tree Canopy is much more scattered relative to Impervious Surface Cover. How could two proxy measures of green space look so different? The reason is likely that some of the more inland zip codes with very low levels of imperviousness almost exclusively contain natural landscapes such as desert and chaparral, which could be considered green space, but do not actually contain trees, yet they will show up more intensely than city parks that are located in otherwise urbanized zip codes.

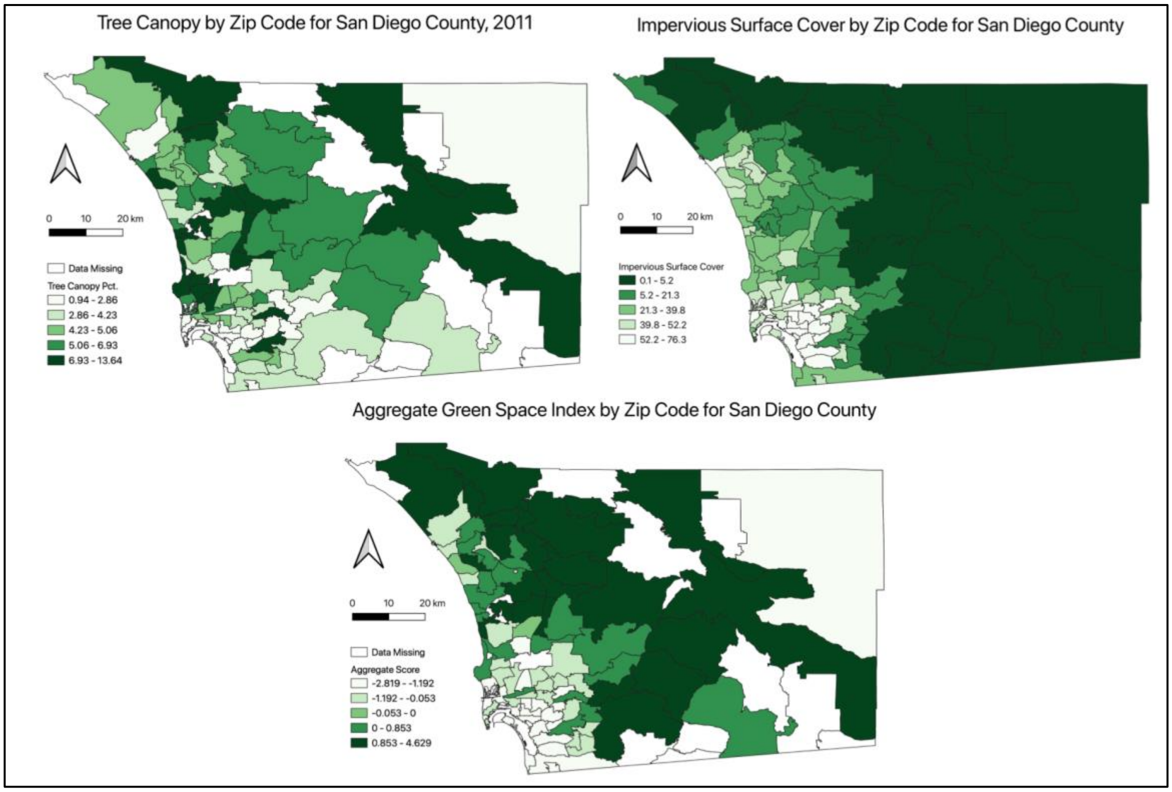


Figure 5: *Maps of three selected green space proxy indexes. Clockwise from upper left: Tree Canopy Cover, Impervious Surface Cover, and the Aggregate Index. Dark green represents the zip codes with higher levels of Tree Canopy Cover and Aggregate Index values, but colors are inverted in the map of Impervious Surface Cover, with dark green representing areas with the least impervious surfaces. Some zip codes are missing as a result of incomplete data.*

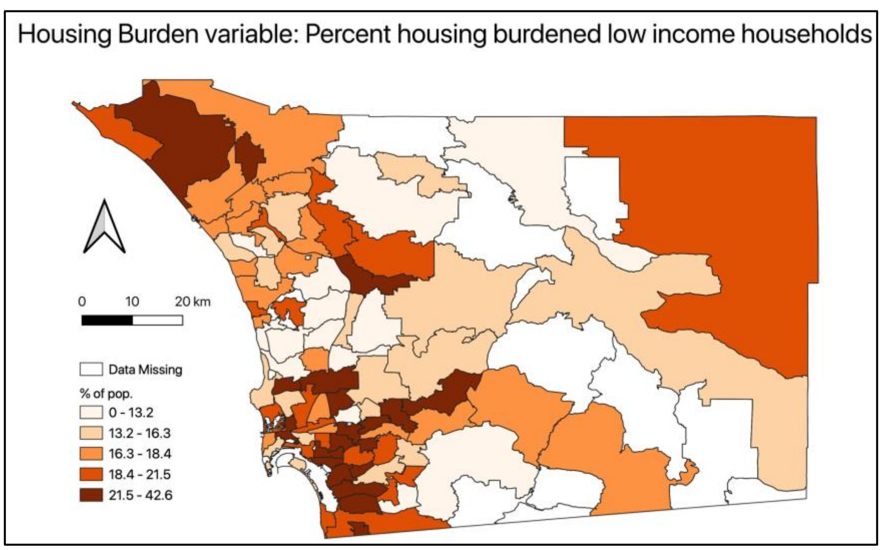


Figure 6: *Distribution of housing burden in San Diego County. Dark red indicates the highest housing burdened zip codes.*

Figure 6 depicts the distribution of housing burdened households across San Diego County, and represents one of the three equity-related variables that I used later (in Aim 3) as a basis for some of my green space intervention scenarios (maps of the Education and Unemployment variables can be found in the Appendix.). The distribution of housing burden (and similarly the two other CalEnviroScreen variables) is somewhat similar to the distribution of green space. That is, areas that have lower amounts of green space (AKA the proxies shown in **Figures 5 and 6**) tend to also have higher levels of unemployment, or tend to be more socially disadvantaged.

Aim 2: Understanding the heat-related health burden and its relationship to green space

Data for heat-attributable hospitalizations were mapped (**Figure 7**) in order to understand the current distribution of the heat-health burden and so this distribution could then be compared to the distributions of green space. There is a general trend of higher levels of hospitalization towards the coast, and lower levels more inland, which is likely due in part to the population being mainly located towards the coast, and partially as a result of the trend described in Guirguis et al. (2018), in which coastal residents are more vulnerable to heat than those who live inland. There are also notable hot spots of high levels of hospitalization, especially in and around downtown San Diego, in areas such as Chula Vista and El Cajon, and in some parts of northern San Diego County. These hotspots roughly match with the areas that have the least green space as well as the more socially deprived parts of the county (see maps in Aim 1).

Meta-regressions between each of the various green space indexes and heat-attributable hospitalizations were performed in order to gain an understanding not just of how green space and heat-health impacts are related, but which indexes represent this relationship well in San Diego specifically. All of these factors were chosen because it is already known that they have the potential to reduce MUHIs. Those indexes that represented this already-established feature of urban landscapes well were the indexes that were chosen for the next part of the project. Relevant statistics are presented in **Table 3** and the Appendix. The crucial value here is the slope, which represents this relationship, and provides a value by which heat-attributable hospitalizations would change if the given green space index were to be adjusted by one unit.

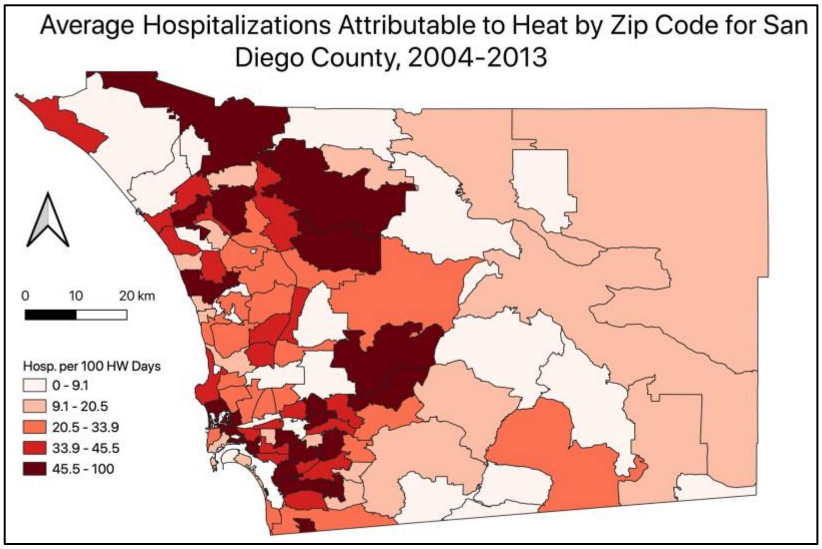


Figure 7: *Heat-attributable hospitalizations by zip code from the period 2004-2013 (data from Hansen et al. (in review.). Values are presented as hospitalizations per 100 heat wave days. Areas of dark red experience the highest burden of hospitalizations.*

Regression	Intercept	Slope	Std. Error	Lower 95%	Upper 95%
Hospitalizations vs. Imperv.	0.1941	0.003415	0.0009606	0.001509	0.005321
Hospitalizations vs Tree Canopy (HPI)	0.4969	-0.0317	0.01184	-0.05523	-0.008163

Table 3: *Results of the linear regressions between heat-attributable hospitalization and two green space proxies: Impervious Surface Cover and Tree Canopy. This table only includes results for the indexes used in Aim 3; the remaining regressions involving the other indexes (Tree Cover, NDVI, and Park Access) can be found in the Appendix.*

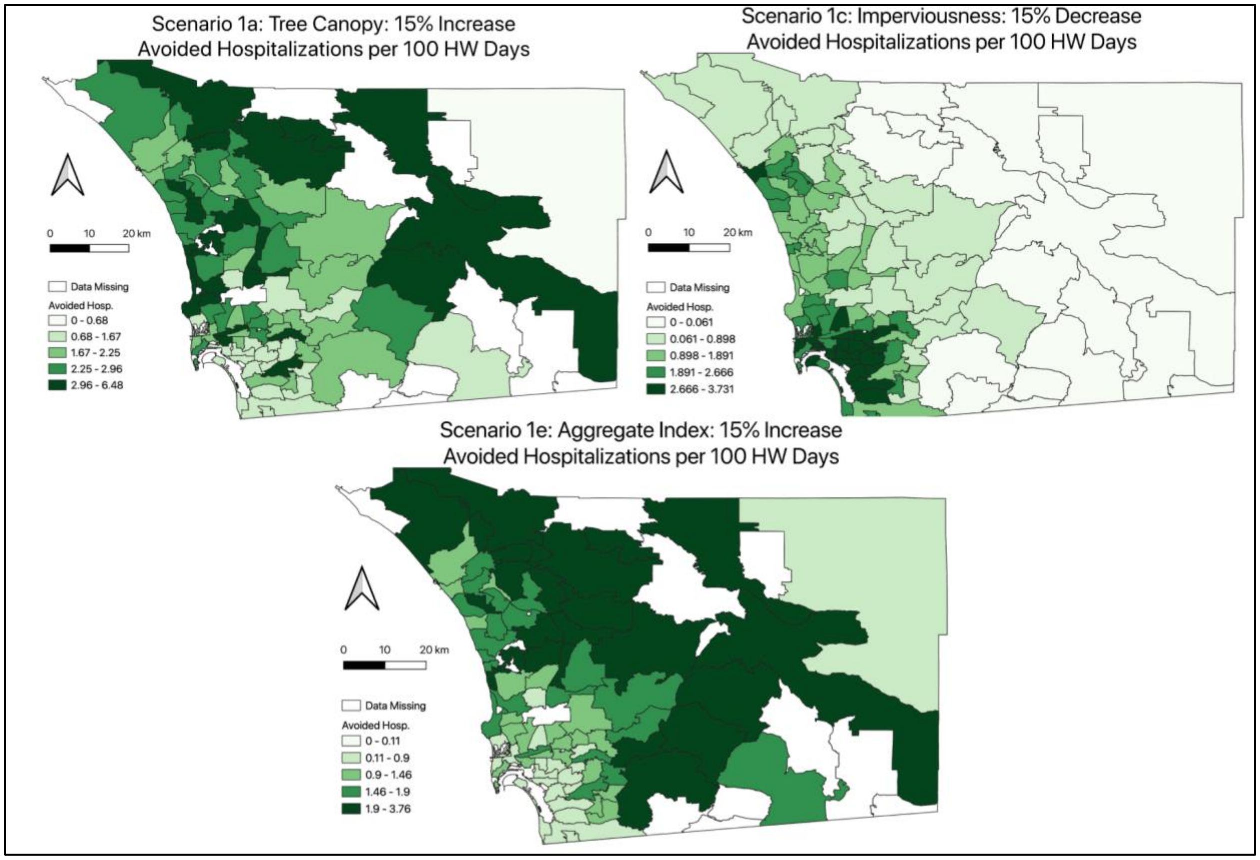
Aim 3: Future scenarios for increasing green space & health impact assessment

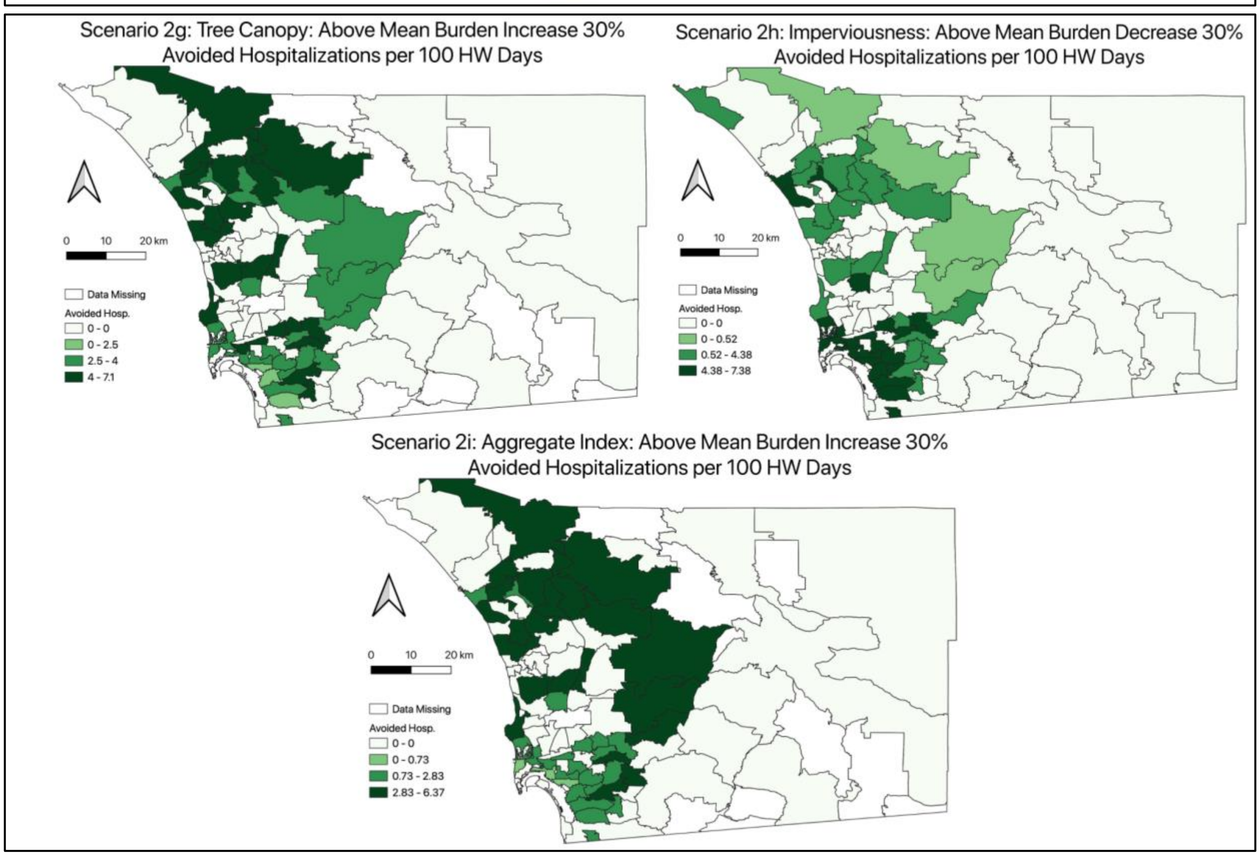
Results for all 33 scenarios can be found in **Table 4** and their distribution is depicted in **Figure 9**. The scenarios produced a wide range of results in terms of "Total Benefits," which is defined as the total avoided heat-hospitalizations for a given scenario. Total benefits ranged from a minimum of 39.14 avoided hospitalizations (scenario 2q) to a maximum of 472.9 avoided hospitalizations (scenario 1b) per 100 heat wave days, with an average of 176.4 across all scenarios. These avoided hospitalizations when compared to the original hospitalization data for a zip code provide a percentage change in hospitalization ("Average Relative Change"). The minimum relative change was 1.31% (scenario 2q) and the maximum was 28.4% (scenario 1b), with an average relative change of 9.54%. Maps of some selected scenarios are included in **Figure 8** (maps for all remaining scenarios can be found in the Appendix).

Approach	Scenario	Total Benefits per 100 HW Days (SE)	Average Relative Change (SE)
Population-based approach	**1a:** Tree Canopy: 15% Increase	202.7 (0.09752)	12.2% (1.72%)
	1b: Tree Canopy: 35% Increase	472.9 (0.2276)	28.4% (4.00%)
	1c: Imperviousness: 15% Decrease	159.4 (0.1126)	8.70% (2.28%)
	1d: Imperviousness: 35% Decrease	371.9 (0.2628)	20.3% (5.33%)
	1e: Aggregate Index: 15% Increase	128.8 (0.08458)	8.43% (1.56%)

	1f: Aggregate Index: 35% Increase	300.5 (0.1973)	19.7% (3.65%)
Targeted approach	**2a:** Tree Canopy: Below Mean Raise to Mean	218.0 (0.3168)	9.62% (1.96%)
	2b: Tree Canopy: Below Mean Increase 30%	177.1 (0.1960)	8.61% (2.28%)
	2c: Imperviousness: Above Mean Drop to Mean	335.4 (0.4084)	16.4% (6.12%)
	2d: Imperviousness: Above Mean Decrease 30%	259.4 (0.2665)	13.0% (4.50%)
	2e: Aggregate Index: Below Mean Raise to Mean	174.7 (0.2940)	6.91% (1.34%)
	2f: Aggregate Index: Below Mean Increase 30%	80.68 (0.1148)	3.63% (0.77%)
	2g: Tree Canopy: Above Mean Burden Increase 30%	193.3 (0.2468)	5.09% (0.60%)
	2h: Imperviousness: Above Mean Burden Decrease 30%	181.7 (0.2335)	4.11% (0.51%)
	2i: Aggregate Index: Above Mean Burden Increase 30%	119.8 (0.1782)	3.16% (0.42%)
	2j: Tree Canopy: Lowest Education Increase 30%	59.06 (0.1467)	1.76% (0.41%)
	2k: Tree Canopy: Highest Unemployment Increase 30%	58.95 (0.1592)	5.30% (2.45%)
	2l: Tree Canopy: Highest Housing Burden Increase 30%	68.16 (0.1760)	4.97% (2.36%)
	2m: Imperviousness: Lowest Education Decrease 30%	81.41 (0.2051)	6.43% (4.73%)
	2n: Imperviousness: Highest Unemployment Decrease 30%	83.04 (0.2146)	7.75% (4.85%)
	2o: Imperviousness: Highest Housing Burden Decrease 30%	100.8 (0.2341)	8.25% (4.85%)
	2p: Aggregate Index: Lowest Education Increase 30%	40.87 (0.1194)	1.31% (0.36%)
	2q: Aggregate Index: Highest Unemployment Increase 30%	39.14 (0.1244)	4.86% (2.80%)
	2r: Aggregate Index: Highest Housing Burden Increase 30%	39.54 (0.1220)	4.37% (2.75%)
Proportionate Universalism approach	**3a:** Tree Canopy: Education-based	258.0 (0.1248)	14.3% (1.80%)
	3b: Tree Canopy: Unemployment-based	245.4 (0.1190)	14.9% (2.68%)
	3c: Tree Canopy: Housing Burden-based	248.6 (0.1462)	14.7% (2.48%)
	3d: Imperviousness: Education-based	202.2 (0.1916)	7.97% (0.94%)
	3e: Imperviousness: Unemployment-based	208.9 (0.2068)	8.80% (1.35%)
	3f: Imperviousness: Housing Burden-based	225.7 (0.2213)	9.61% (1.45%)
	3g: Aggregate Index: Education-based	170.6 (0.1359)	10.0% (1.48%)
	3h: Aggregate Index: Unemployment-based	159.9 (0.1305)	11.0% (2.86%)
	3i: Aggregate Index: Housing Burden-based	153.6 (0.1155)	10.4% (2.74%)

Table 4: *Summary of results for each green space intervention scenario, broken down into the three approaches adapted from Benach et al. (2012). Total Benefits are defined as the avoided hospitalizations across all zip codes associated with each scenario and are represented here as the number of avoided hospitalizations per 100 heat wave days. The column Average Relative Change represents the average change in hospitalizations across all zip codes for each scenario when compared to the baseline pre-intervention hospitalization data. Standard errors are included in parentheses. The highlighted rows indicate the scenarios represented in **Figure 8**, which include three scenarios from each approach, covering each of the three chosen indexes per approach. This choice attempts to capture a range of different results while keeping the number of maps presented in the main text at a minimum – the remaining rows are presented as maps in the Appendix.*


Scenario 1a: Tree Canopy: 15% Increase
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.68
0.68 - 1.67
1.67 - 2.25
2.25 - 2.96
2.96 - 6.48
Scenario 1c: Imperviousness: 15% Decrease
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.061
0.061 - 0.898
0.898 - 1.891
1.891 - 2.666
2.666 - 3.731
Scenario 1e: Aggregate Index: 15% Increase
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.11
0.11 - 0.9
0.9 - 1.46
1.46 - 1.9
1.9 - 3.76


Scenario 2g: Tree Canopy: Above Mean Burden Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 2.5
2.5 - 4
4 - 7.1
Scenario 2h: Imperviousness: Above Mean Burden Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.52
0.52 - 4.38
4.38 - 7.38
Scenario 2i: Aggregate Index: Above Mean Burden Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.73
0.73 - 2.83
2.83 - 6.37

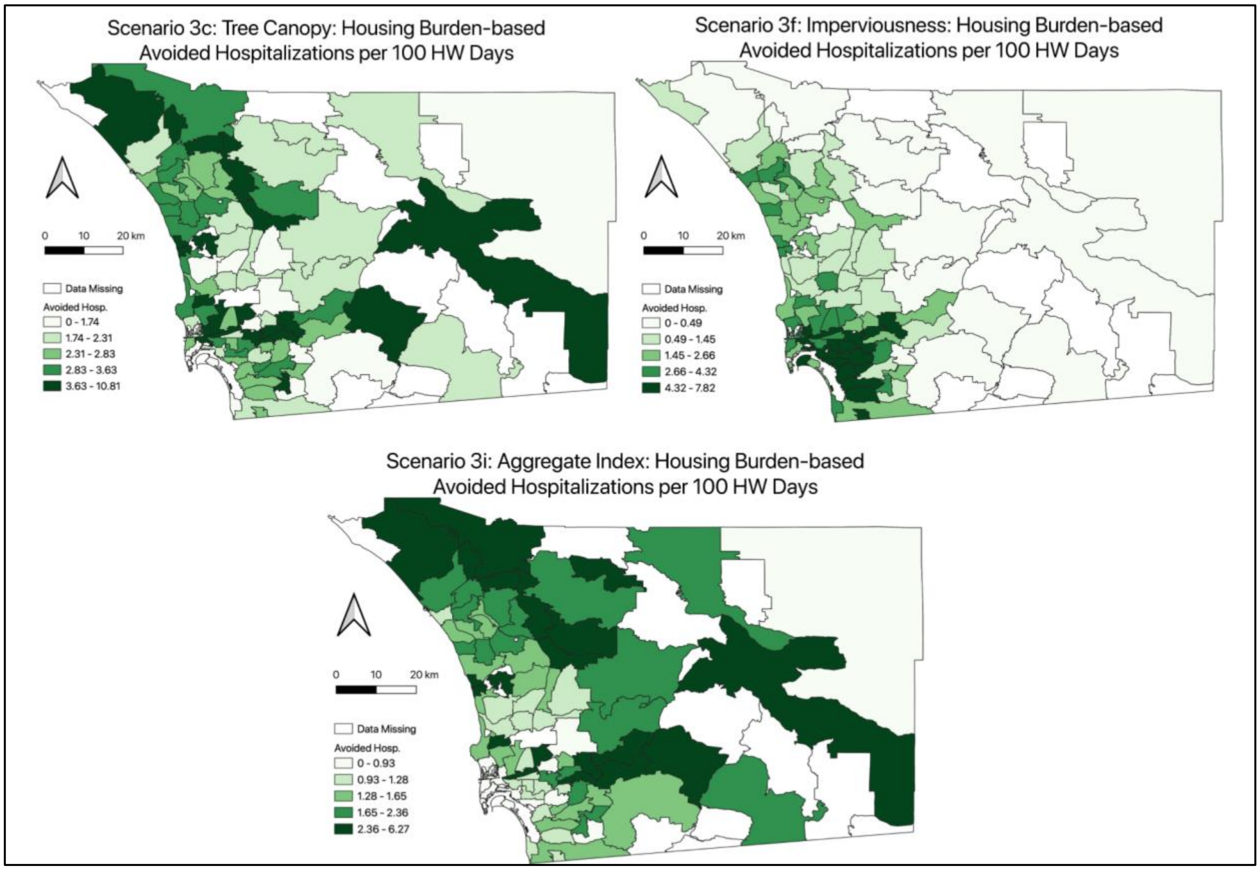


Figure 8: *Selection of 9 maps representing the total benefits associated with various scenarios of green space intervention strategies. I included three maps for each intervention approach (population-based, targeted, and proportionate universalism), with a representative from each index for each of these approaches in order to cover a range of different results. The remaining figures for all other scenarios can be found in the Appendix.*

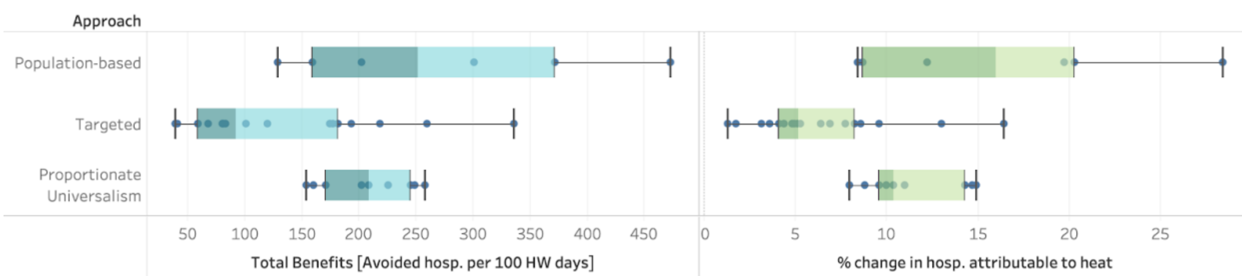


Figure 9: *This figure illustrates the distribution of the results for each of the 33 scenarios broken down by approach type.*

DISCUSSION

Summary of main findings

This project aimed to understand the relationship between heat, health, and green space allocation in San Diego County, and to quantify the potential benefits of various greening strategies. I found that both green space and the health burden associated with extreme heat are unevenly distributed across San Diego County, and that these two factors are associated such that areas with less green space will have higher levels of heat-related hospitalizations – as has already been established in other studies from around the world (see **Table 1**). My novel finding is that a wide range of intervention strategies focused on greening demonstrate quantitatively that greening does reduce the health burden associated with heat, and that this impact varies depending on the type of intervention strategy used.

Significance of this study

This research is set apart from previous studies in the field in that it is the first effort to actually quantify the total benefits associated with multiple greening strategies and indexes at such a fine scale in relation to heat-related health impacts specifically. This study goes beyond previous research, which has established this link between green space and health and even provided estimates of total benefits, by incorporating zip code level data and a wide variety of scenarios. Because the dose-response function derived in Aim 2 was specific to the zip code level in San Diego, it results in data that is more sound for the purposes of informing policy in San Diego. Furthermore, this study incorporated a variety of indexes/proxies for green space that go beyond the usual index of choice in similar studies, NDVI (see **Table 1**). One of these indexes was a unique aggregate index created specifically for this project that incorporated all five of the included proxies for green space. Finally, this research goes beyond simply understanding the protective role of green space indexes to actually creating 33 different evidence-based greening scenarios that allow us to compare and contrast the benefits associated with these different strategies.

Detailed discussion of results

In general terms, I found that the population-based and proportionate universalism approaches resulted in higher benefits on both absolute (total burden) and relative (change in burden) scales when compared to targeted approaches (see **Figure 9**). As hypothesized, targeted approaches by definition only include a subsection of the population, though this subsection generally includes those who are most disadvantaged and therefore most in need of the intervention. The average total benefits across scenarios broken down by approach are: 272.7 avoided hospitalizations per 100 HW days on average for the population based approaches, 128.4 for the targeted approaches, and 208.1 for the proportionate universalism approaches. However, there are some exceptions, and many of the scenarios included in the targeted approach category do result in total benefits that are on par with the population-based and proportionate universalism approaches.

Taking a closer look within the targeted approach category, we can see that the scenarios that result in the highest total benefits are those that either involve i) increasing green space in the zip codes that have the lowest levels of green space (roughly scenarios **2a**–**2f**), or ii) increasing green space in the zip codes that have the highest pre-existing health burden (i.e. those that have the largest numbers of hospitalizations attributable to heat before intervention; scenarios **2g**–**2i**). The scenarios that involve increasing green space in zip codes that score highly in the 3 CalEnviroScreen measures (Education, Unemployment, and Housing Burden) (scenarios **2j**–**2r**) result in fewer total benefits; however, it should be noted that scenarios **2j**–**2r** are fundamentally different from scenarios **2a**–**2i** in that they involve changing green space levels in a much smaller amount of zip codes. Scenarios **2j**–**2r** increase green space only in the zip codes that score in the upper *quintile* for the various CalEnviroScreen measures, whereas scenarios **2a**–**2i** involve adjusting green space in zip codes that are either above or below the *mean* of some measure.

Comparing scenarios based on the index used (Tree Canopy, Imperviousness, or the Aggregate Index) is also insightful. When narrowing in on the proportionate universalism approach, it is apparent that results tend to vary not based on the CalEnviroScreen measure used, but rather most variability in total benefits depends on the green space index used. Apparently, within the proportionate universalism approach, scenarios that involve increasing Tree Cover (scenarios **3a**–**3c**) resulted in the highest total benefits on average, followed by scenarios that involve decreasing Imperviousness (scenarios **3d**–**3f**), then by scenarios that involve increasing the Aggregate Index (scenarios **3g**–**3i**). This trend seems to be consistent over for the population-based approaches as well, in which scenarios that focus on Tree Canopy again result in the highest levels of total benefits, with those that focus on the Aggregate Index resulting in the lowest levels of total benefits. However, the trend does not seem to persist within the targeted approach strategies.

It is worth noting that these results likely represent an underestimate of total health benefits. This study exclusively considered hospitalization data, which represents only the tip of the iceberg. There are likely to be many people who experience negative health impacts related to heat but who do not seek medical care. These people would not have been considered in the original data pertaining to hospitalizations attributable to heat, off of which this entire study was based. Therefore, they are not included in this study's results even though green space interventions would help them as well. It is also safe to assume that if green space intervention can lead to decreased hospitalizations for heat-related morbidity, it would also lead to decreased heat mortality, another facet that this study did not consider.

Project limitations

Though this project provides compelling quantitative evidence to support the use of green space to mitigate the micro-urban heat island effect, it is not without its limitations. To start, because of the nature of the hospitalization data, my analysis essentially assumes that all hospitalizations occur in the same zip codes where the heat exposure occurred, which is almost definitely not the case. In reality, it's likely that at least some people must travel across zip codes to reach a hospital, and there is therefore some level of error in these calculations as I cannot account for this fact.

Another limitation to this study is that some of the values of total benefit and average relative change for the different green space scenarios represent extremes that may not be feasible in reality. For instance, while my results show that scenario **1b** could prevent 472.9

heat-attributable hospitalizations per 100 heatwave days, it's likely impossible to actually increase green space by 35% in all zip codes across the county, especially because this study does not account for the wide variety of climates and ecosystems that exist across the county. It is also likely unreasonable, for instance, to increase tree cover in some of the more arid or desert-like parts of the county. Similarly, impervious surface cover was used as a proxy of green space in this analysis with the intention of understanding how having less of it could be beneficial in terms of health, but it is probably not feasible to actually remove surfaces such as pavement and cement on a large scale. Policymakers should therefore interpret these imperviousness results to simply mean that keeping some parts of an urban environment reserved for natural landscapes can be immensely beneficial.

It must also be noted that while I worked with the data that was most readily available to me, some of it is not as recent as would have been ideal. For instance, the Impervious Surface Cover measure obtained from Google Earth Engine dates back to 2006. I therefore am relying on data that could be outdated, as impervious surface cover has almost certainly changed to some extent in San Diego County in the past 14 years.

My research also used only one definition for a heat wave day – this definition being "any day above the 95th maximum temperature zip code specific distribution during the warm season," adapted from Hansen et al. (in review). However, a plethora of heat wave definitions exist and will likely provide differing results from what I found. Future research may therefore want to consider different definitions of heat waves, as well as other climatological factors such as humidity and wind, which were left out of this study.

Finally, this study looked at green space (and imperviousness) specifically, but these are only one facet of the micro-urban heat island effect, and many other mitigation strategies exist. Though green space expansion is effective, it should be incorporated as one part of a broader strategy to reduce the health effects of MUHIs. On top of this, it may not be feasible to increase green space as much as desired in parts of a city that are already highly developed. City planners should also keep in mind that trees can take up to 10-30 years to mature to the point that their positive effects are realized (Health Canada, 2020). Other measures that can be used to help minimize the effects of MUHIs aside from expanding green space and vegetation include: "climate-sensitive" urban design strategies, such as increasing the surface albedo or reflectivity of roads and buildings; integrating water features (natural or man-made) into urban designs; implementing natural ventilation features in new developments; and reducing energy usage via energy retrofits, implementation of energy-efficient design, and more (Health Canada, 2020).

A note on the potential negative impacts of increasing green space

Though increasing green space seems like a win-win strategy, municipal officials must take extra care in how they implement green space interventions across neighborhoods, as increasing green space can also come with unintended negative side effects. Efforts to implement green space improvements in low-income or socially deprived neighborhoods, while well-intentioned, can sometimes hasten gentrification (Cole et al., 2017). This is particularly important to keep in mind when creating a greening strategy that emphasizes social equity, as uncareful planning may result in an outcome that is antithetical to the desired goals.

To avoid these unintended effects, local governments should work in tandem with residents to understand their needs and desires and to create strategies that are "just green enough" so that they can improve health outcomes while avoiding skyrocketing property values (Wolch et al., 2014). Increasing green space while simultaneously avoiding the threat of gentrification may involve implementing smaller scale green spaces, and green spaces that are more scattered, as opposed to large parks (Wolch et al., 2014). Governments can also place an emphasis on planting street trees in at-risk neighborhoods. Though planting street trees may be relatively expensive and labor-intensive (compared to planting trees in existing parks) (Garrison, 2017), the investment may be necessary if a city's goal involves decreasing health inequality. Additionally, the city could explore options such as providing financial assistance to individuals/families in more socially deprived communities who plant trees on their private property.

Green space implementation has incredible potential to provide positive outcomes, especially to socially deprived groups. As discussed in the introduction, green spaces not only provide health benefits in terms of mitigating extreme heat, but also provide a number of other societal and health benefits ranging from opportunities for recreation, physical health, mental health, enhancing social ties, and even aesthetic enjoyment (Zhou and Rana, 2012). For this reason, it's important that this possibility of gentrification is not used as an excuse to avoid the use of greening strategies, but is instead met head on and considered thoroughly in urban planning projects that emphasize equity.

Heat and health in the context of COVID-19

The upcoming summer season is anticipated to pose a unique threat when it comes to heat waves and health due to the ongoing outbreak of the 2019 Novel Coronavirus (COVID-19). Stay at home orders across the country are requiring people to stay indoors, limiting access to normally available cooling stations as well as access to public parks and other green space. Because many of the people who are most vulnerable to the health impacts of extreme heat are people who may lack access to AC, or elderly folks who may live alone, and these folks will be required to stay home as much as possible this summer, it's critical that municipalities plan to accommodate these people in the midst of the ongoing COVID-19 outbreak, especially as temperatures this summer are expected to break records (City of New York, 2020). Some cities, such as New York, are already acting to adapt to these new circumstances. New York City is planning to distribute over 74,000 air conditioning units to some of its most vulnerable residents, low-income seniors, in preparation for extreme summer temperatures (City of New York, 2020). The city is also planning to continue offering cooling centers this summer with new adjustments to uphold social distancing, and is petitioning the New York Public Service Commission for $72 million to help 450,000 low-income New Yorkers afford to keep their AC running over the hot summer months (City of New York, 2020).

New York is setting an example, but all municipalities need to create plans for protecting the vulnerable during this pandemic. And there are many other potential threats associated with extreme heat and COVID-19 transmission that must be taken into account. For instance, heat early warning system efficacy may be lessened due to the steady influx of COVID-19-related health warnings, and the threat of extreme heat may not be taken as seriously in the midst of a pandemic (Martinez et al., 2020). Additionally, the co-morbidities related to heat that were discussed at the beginning of this paper (cardiovascular, respiratory, and renal diseases) are largely the same co-morbidities associated with COVID-19 (Martinez et al., 2020). Now, more than ever, cities must plan to protect the vulnerable from the impacts of extreme heat.

CONCLUSIONS

The demonstrated ability of extreme heat to lead to adverse health outcomes and even death, coupled with the looming threat of rising temperatures brought on by climate change, together represent a dire need for cities and municipalities to adopt extreme heat adaptation strategies. In this study, I found that the use of green space as a heat-wave adaptation strategy shows promise in terms of reducing hospitalizations attributable to heat in 33 different greening scenarios in San Diego County, California.

My findings illustrate that out of a wide range of greening approaches, almost all had a strong impact in terms of reduced hospitalizations, with the strongest benefits in the population-based and proportionate universalism approaches. These results exemplify that there is no one-size-fits-all approach to greening strategies. Rather, there are numerous ways they can be implemented with positive results. Legislators should therefore consider the many different options that exist and find the approach that is best suited for the needs of their given city. It is my hope that this research can demonstrate to local governments – especially those in large urban centers where heat-health impacts are compounded by the micro-urban heat island effect – that not only do greening strategies work, but they are an actionable choice, and there are many options for how to implement them.

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REFERENCES

Aniello, C., Morgan, K., Busbey, A., & Newland, L. (1995). Mapping micro-urban heat islands using LANDSAT TM and a GIS. *Computers & Geosciences, 21*(8), 965-969. doi:10.1016/0098-3004(95)00033-5

Baker, M. (2019). Heat Waves and Homelessness: Analysis of San Diego and Recommendations. UC San Diego: Climate Science and Policy. Retrieved from https://escholarship.org/uc/item/3s49k58k

Benach, J., Malmusi, D., Yasui, Y., & Martínez, J. M. (2012). A new typology of policies to tackle health inequalities and scenarios of impact based on Rose's population approach. *Journal of Epidemiology and Community Health, 67*(3), 286-291. doi:10.1136/jech-2011-200363

Benmarhnia, T., Laurian, L., & Deguen, S. (2013). Measuring Spatial Environmental Deprivation: A New Index and its Application in France. *Environmental Justice, 6*(2), 48-55. doi:10.1089/env.2013.0001

Bernstein, A. S., & Rice, M. B. (2013). Lungs in a Warming World: Climate Change and Respiratory Health. *Chest, 143*(5), 1455-1459. doi:10.1378/chest.12-2384

Bobb, J. F., Obermeyer, Z., Wang, Y., & Dominici, F. (2014). Cause-Specific Risk of Hospital Admission Related to Extreme Heat in Older Adults. *Jama, 312*(24), 2659. doi:10.1001/jama.2014.15715

Bouchama, A., & Knochel, J. P. (2002). Heat Stroke. *New England Journal of Medicine, 346*(25), 1978-1988. doi:10.1056/nejmra011089

British Lung Foundation. (2018, May). Looking after your lungs in hot weather. Retrieved June 11, 2020, from https://www.blf.org.uk/support-for-you/hot-weather

Bunker, A., Wildenhain, J., Vandenbergh, A., Henschke, N., Rocklöv, J., Hajat, S., & Sauerborn, R. (2016). Effects of Air Temperature on Climate-Sensitive Mortality and Morbidity Outcomes in the Elderly; a Systematic Review and Meta-analysis of Epidemiological Evidence. *EBioMedicine, 6*, 258-268. doi:10.1016/j.ebiom.2016.02.034

CDC. (2016). *CLIMATE CHANGE and EXTREME HEAT What You Can Do to Prepare* (Publication). Centers for Disease Control and Prevention.

Chestnut, L. G., Breffle, W. S., Smith, J. B., & Kalkstein, L. S. (1998). Analysis of differences in hot-weather-related mortality across 44 U.S. metropolitan areas. *Environmental Science & Policy, 1*(1), 59-70. doi:10.1016/s1462-9011(98)00015-x

City of New York. (2020, May 15). Mayor de Blasio Announces COVID-19 Heat Wave Plan to Protect Vulnerable New Yorkers. Retrieved June 11, 2020, from https://www1.nyc.gov/office-of-the-mayor/news/350-20/mayor-de-blasio-covid-19-heat-wave-plan-protect-vulnerable-new-yorkers

City of San Diego. (2015). *City of San Diego Climate Action Plan* (Publication). San Diego, CA. Retrieved 2020, from https://www.sandiego.gov/sites/default/files/final_july_2016_cap.pdf

City of San Diego. (2017). *Urban Forestry Program Five Year Plan* (Publication). San Diego, CA: The City of San Diego. Retrieved June 11, 2020, from https://www.sandiego.gov/sites/default/files/final_adopted_urban_forestry_program_five_year_plan.pdf

Cole, H. V., Lamarca, M. G., Connolly, J. J., & Anguelovski, I. (2017). Are green cities healthy and equitable? Unpacking the relationship between health, green space and gentrification. *Journal of Epidemiology and Community Health*. doi:10.1136/jech-2017-209201

Coombes, E., Jones, A. P., & Hillsdon, M. (2010). The relationship of physical activity and overweight to objectively measured green space accessibility and use. *Social Science & Medicine, 70*(6), 816-822. doi:10.1016/j.socscimed.2009.11.020

Coumou, D., & Robinson, A. (2013). Historic and future increase in the global land area affected by monthly heat extremes. *Environmental Research Letters, 8*(3), 034018. doi:10.1088/1748-9326/8/3/034018

Delaney, T., Dominie, W., Dowling, H., Maizlish, N., Chapman, D., Hill, L., . . . Woolf, S. (2018). *Healthy Places Index* (Publication). Public Health Alliance of Southern California & Virginia Commonwealth University.

Efron, B., & Tibshirani, R. (1993). *An introduction to the bootstrap*. New York: Chapman and Hall.

EPA. (2020, May 18). Heat Island Effect. Retrieved June 11, 2020, from https://www.epa.gov/heat-islands

Farrugia, S., Hudson, M. D., & Mcculloch, L. (2013). An evaluation of flood control and urban cooling ecosystem services delivered by urban green infrastructure. *International Journal of Biodiversity Science, Ecosystem Services & Management, 9*(2), 136-145. doi:10.1080/21513732.2013.782342

Garrison, J. D. (2017). Seeing the park for the trees: New York's "Million Trees" campaign vs. the deep roots of environmental inequality. *Environment and Planning B: Urban Analytics and City Science, 46*(5), 914-930. doi:10.1177/2399808317737071

Guirguis, K., Basu, R., Al-Delaimy, W. K., Benmarhnia, T., Clemesha, R. E., Corcos, I., . . . Gershunov, A. (2018). Heat, Disparities, and Health Outcomes in San Diego County's Diverse Climate Zones. *GeoHealth, 2*(7), 212-223. doi:10.1029/2017gh000127

Guirguis, K., Gershunov, A., Tardy, A., & Basu, R. (2014). The Impact of Recent Heat Waves on Human Health in California. *Journal of Applied Meteorology and Climatology, 53*(1), 3-19. doi:10.1175/jamc-d-13-0130.1

Hansen, K., Schwartzman, A., Benmarhnia, T. A within-community matched design analysis of the spatial distribution of heat-related hospitalizations in California. American Journal of Epidemiology [in review].

Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. *Social Science & Medicine, 63*(11), 2847-2863. doi:10.1016/j.socscimed.2006.07.030

Health Canada. (2020). *Reducing Urban Heat Islands to Protect Health in Canada: An Introduction for Public Health Professionals* (Publication). Ottawa, ON: Health Canada.

Heynen, N., Perkins, H. A., & Roy, P. (2006). The Political Ecology of Uneven Urban Green Space. *Urban Affairs Review, 42*(1), 3-25. doi:10.1177/1078087406290729

Hoffimann, E., Barros, H., & Ribeiro, A. (2017). Socioeconomic Inequalities in Green Space Quality and Accessibility—Evidence from a Southern European City. *International Journal of Environmental Research and Public Health, 14*(8), 916. doi:10.3390/ijerph14080916

Hopp, S., Dominici, F., & Bobb, J. F. (2018). Medical diagnoses of heat wave-related hospital admissions in older adults. *Preventive Medicine, 110*, 81-85. doi:10.1016/j.ypmed.2018.02.001

Hughes, L., Hanna, E., & Fenwick, J. (2016). *The silent killer: Climate change and the health impacts of extreme heat* (Publication). The Climate Council of Australia.

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Joint Research Centre. (2008). *Handbook on Constructing Composite Indicators METHODOLOGY AND USER GUIDE* (Publication). OECD.

Kahle, J. J., Neas, L. M., Devlin, R. B., Case, M. W., Schmitt, M. T., Madden, M. C., & Diaz-Sanchez, D. (2015). Interaction Effects of Temperature and Ozone on Lung Function and Markers of Systemic Inflammation, Coagulation, and Fibrinolysis: A Crossover Study of Healthy Young Volunteers. *Environmental Health Perspectives, 123*(4), 310-316. doi:10.1289/ehp.1307986

Kenney, W. L., Craighead, D. H., & Alexander, L. M. (2014). Heat Waves, Aging, and Human Cardiovascular Health. *Medicine & Science in Sports & Exercise, 46*(10), 1891-1899. doi:10.1249/mss.0000000000000325

Kim, H., Lee, D., & Sung, S. (2016). Effect of Urban Green Spaces and Flooded Area Type on Flooding Probability. *Sustainability, 8*(2), 134. doi:10.3390/su8020134

Li, M., Gu, S., Bi, P., Yang, J., & Liu, Q. (2015). Heat Waves and Morbidity: Current Knowledge and Further Direction-A Comprehensive Literature Review. *International Journal of Environmental Research and Public Health, 12*(5), 5256-5283. doi:10.3390/ijerph120505256

Livneh, B., Rosenberg, E. A., Lin, C., Nijssen, B., Mishra, V., Andreadis, K. M., . . . Lettenmaier, D. P. (2013). A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States: Update and Extensions. Journal of Climate, 26(23), 9384-9392. doi:10.1175/jcli-d-12-00508.1

Martinez, G., Linares, C., De'Donato, F., & Diaz, J. (2020). Protect the vulnerable from extreme heat during the COVID-19 pandemic. *Environmental Research, 187*, 109684. doi:10.1016/j.envres.2020.109684

Messner, S., Miranda, S. C., Young, E., & Hedge, N. (2011). Climate change-related impacts in the San Diego region by 2050. *Climatic Change, 109*(S1), 505-531. doi:10.1007/s10584-011-0316-1

Michelozzi, P., Accetta, G., Sario, M. D., D'ippoliti, D., Marino, C., Baccini, M., . . . Perucci, C. A. (2009). High Temperature and Hospitalizations for Cardiovascular and Respiratory Causes in 12 European Cities. *American Journal of Respiratory and Critical Care Medicine, 179*(5), 383-389. doi:10.1164/rccm.200802-217oc

Miller, N. L., Hayhoe, K., Jin, J., & Auffhammer, M. (2008). Climate, Extreme Heat, and Electricity Demand in California. *Journal of Applied Meteorology and Climatology, 47*(6), 1834-1844. doi:10.1175/2007jamc1480.1

NASA. (2000, August 30). Measuring Vegetation (NDVI & EVI). Retrieved June 11, 2020, from https://earthobservatory.nasa.gov/features/MeasuringVegetation/measuring_vegetation_2.php

NOAA. (2018). Weather Related Fatality and Injury Statistics. Retrieved June 11, 2020, from https://www.weather.gov/hazstat/

Nowak, D. J., & Crane, D. E. (2002). Carbon storage and sequestration by urban trees in the USA. *Environmental Pollution, 116*(3), 381-389. doi:10.1016/s0269-7491(01)00214-7

Nowak, D. J., Crane, D. E., & Stevens, J. C. (2006). Air pollution removal by urban trees and shrubs in the United States. *Urban Forestry & Urban Greening, 4*(3-4), 115-123. doi:10.1016/j.ufug.2006.01.007

Nutsford, D., Pearson, A., & Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public Health, 127*(11), 1005-1011. doi:10.1016/j.puhe.2013.08.016

OEHHA. (2018, June 25). CalEnviroScreen 3.0. Retrieved June 11, 2020, from https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30

OEHHA. (n.d.). Housing Burden. Retrieved June 11, 2020, from https://oehha.ca.gov/calenviroscreen/indicator/housing-burden

Rice, L., Jiang, C., Wilson, S., Burwell-Naney, K., Samantapudi, A., & Zhang, H. (2014). Use of Segregation Indices, Townsend Index, and Air Toxics Data to Assess Lifetime Cancer Risk Disparities in Metropolitan Charleston, South Carolina, USA. *International Journal of Environmental Research and Public Health, 11*(5), 5510-5526. doi:10.3390/ijerph110505510

Rizwan, A. M., Dennis, L. Y., & Liu, C. (2008). A review on the generation, determination and mitigation of Urban Heat Island. *Journal of Environmental Sciences, 20*(1), 120-128. doi:10.1016/s1001-0742(08)60019-4

Rojas-Rueda, D., Nieuwenhuijsen, M. J., Gascon, M., Perez-Leon, D., & Mudu, P. (2019). Green spaces and mortality: A systematic review and meta-analysis of cohort studies. *The Lancet Planetary Health, 3*(11). doi:10.1016/s2542-5196(19)30215-3

Schaffer, A., Muscatello, D., Broome, R., Corbett, S., & Smith, W. (2012). Emergency department visits, ambulance calls, and mortality associated with an exceptional heat wave in Sydney, Australia, 2011: A time-series analysis. *Environmental Health, 11*(1). doi:10.1186/1476-069x-11-3

Schinasi, L. H., Benmarhnia, T., & Roos, A. J. (2018). Modification of the association between high ambient temperature and health by urban microclimate indicators: A systematic review and meta-analysis. *Environmental Research, 161*, 168-180. doi:10.1016/j.envres.2017.11.004

Schwartz, J., Samet, J. M., & Patz, J. A. (2004). Hospital Admissions for Heart Disease: The Effects of Temperature and Humidity. *Epidemiology, 15*(6), 755-761. doi:10.1097/01.ede.0000134875.15919.0f

Sherbakov, T., Malig, B., Guirguis, K., Gershunov, A., & Basu, R. (2018). Ambient temperature and added heat wave effects on hospitalizations in California from 1999 to 2009. *Environmental Research, 160*, 83-90. doi:10.1016/j.envres.2017.08.052

Sheridan, S. C., Allen, M. J., Lee, C. C., & Kalkstein, L. S. (2012). Future heat vulnerability in California, Part II: Projecting future heat-related mortality. *Climatic Change, 115*(2), 311-326. doi:10.1007/s10584-012-0437-1

Smargiassi, A., Goldberg, M. S., Plante, C., Fournier, M., Baudouin, Y., & Kosatsky, T. (2009). Variation of daily warm season mortality as a function of micro-urban heat islands. *Journal of Epidemiology & Community Health, 63*(8), 659-664. doi:10.1136/jech.2008.078147

Son, J., Lane, K. J., Lee, J., & Bell, M. L. (2016). Urban vegetation and heat-related mortality in Seoul, Korea. *Environmental Research, 151*, 728-733. doi:10.1016/j.envres.2016.09.001

Thompson, C. W., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning, 105*(3), 221-229. doi:10.1016/j.landurbplan.2011.12.015

Vaidyanathan, A., Saha, S., Vicedo-Cabrera, A. M., Gasparrini, A., Abdurehman, N., Jordan, R., . . . Elixhauser, A. (2019). Assessment of extreme heat and hospitalizations to inform early warning systems. *Proceedings of the National Academy of Sciences, 116*(12), 5420-5427. doi:10.1073/pnas.1806393116

Van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine, 70*(8), 1203-1210. doi:10.1016/j.socscimed.2010.01.002

Vieira, J., Matos, P., Mexia, T., Silva, P., Lopes, N., Freitas, C., . . . Pinho, P. (2018). Green spaces are not all the same for the provision of air purification and climate regulation services: The case of urban parks. *Environmental Research, 160*, 306-313. doi:10.1016/j.envres.2017.10.006

Warth, G. (2018, December 17). San Diego again has 4th-largest homeless population in nation. *The San Diego Union Tribune*. Retrieved June 11, 2020, from https://www.sandiegouniontribune.com/news/homelessness/sd-me-homeless-report-20181217-story.html

Weinberger, K. R., Harris, D., Spangler, K. R., Zanobetti, A., & Wellenius, G. A. (2020). Estimating the number of excess deaths attributable to heat in 297 United States counties. *Environmental Epidemiology, 4*(3). doi:10.1097/ee9.0000000000000096

WHO. (2018, July 31). Information and public health advice: Heat and health. Retrieved June 11, 2020, from https://www.who.int/globalchange/publications/heat-and-health/en/

Wilcox, R. R. (2017). *Modern statistics for the social and behavioral sciences: A practical introduction*. Boca Raton: Chapman & Hall/CRC.

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning, 125*, 234-244. doi:10.1016/j.landurbplan.2014.01.017

Xiang, J., Bi, P., Pisaniello, D., & Hansen, A. (2014). Health Impacts of Workplace Heat Exposure: An Epidemiological Review. *Industrial Health, 52*(2), 91-101. doi:10.2486/indhealth.2012-0145

Yow, D. M. (2007). Urban Heat Islands: Observations, Impacts, and Adaptation. *Geography Compass, 1*(6), 1227-1251. doi:10.1111/j.1749-8198.2007.00063.x

Zhang, Y., Murray, A. T., & Turner, B. (2017). Optimizing green space locations to reduce daytime and nighttime urban heat island effects in Phoenix, Arizona. *Landscape and Urban Planning, 165*, 162-171. doi:10.1016/j.landurbplan.2017.04.009

Zhou, X., & Rana, M. P. (2012). Social benefits of urban green space : A conceptual framework of valuation and accessibility measurements. *Management of Environmental Quality: An International Journal, 23*(2), 173-189. doi:10.1108/14777831211204921

Zhou, Y., & Shepherd, J. M. (2009). Atlanta's urban heat island under extreme heat conditions and potential mitigation strategies. *Natural Hazards, 52*(3), 639-668. doi:10.1007/s11069-009-9406-z

APPENDIX

I. Remaining Green Space Index Maps

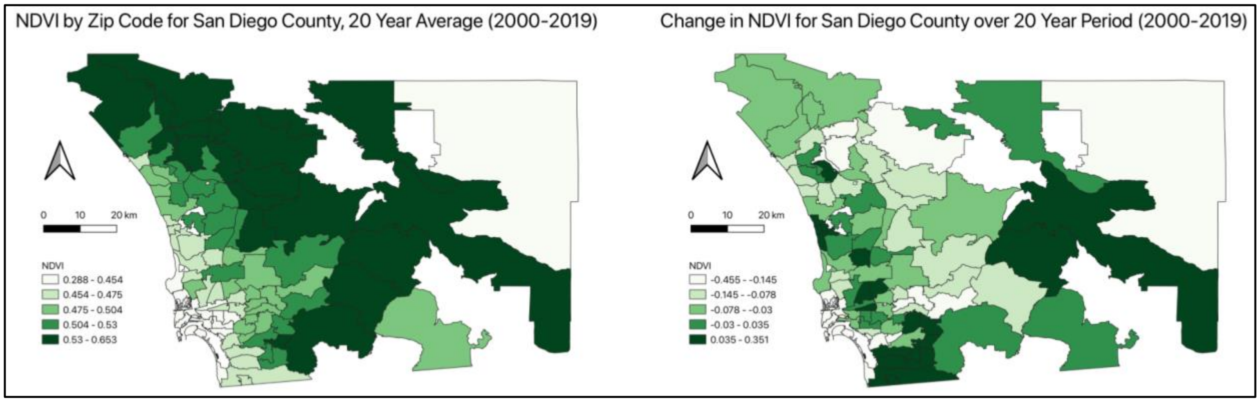


Figure A 1: *Maps of NDVI in San Diego County over the years 2000-2019. The map on the left depicts the average value for each zip code over this 20-year period. The map on the right depicts the change in NDVI over this time period, with negative values representing a decrease in NDVI and positive values representing an increase.*

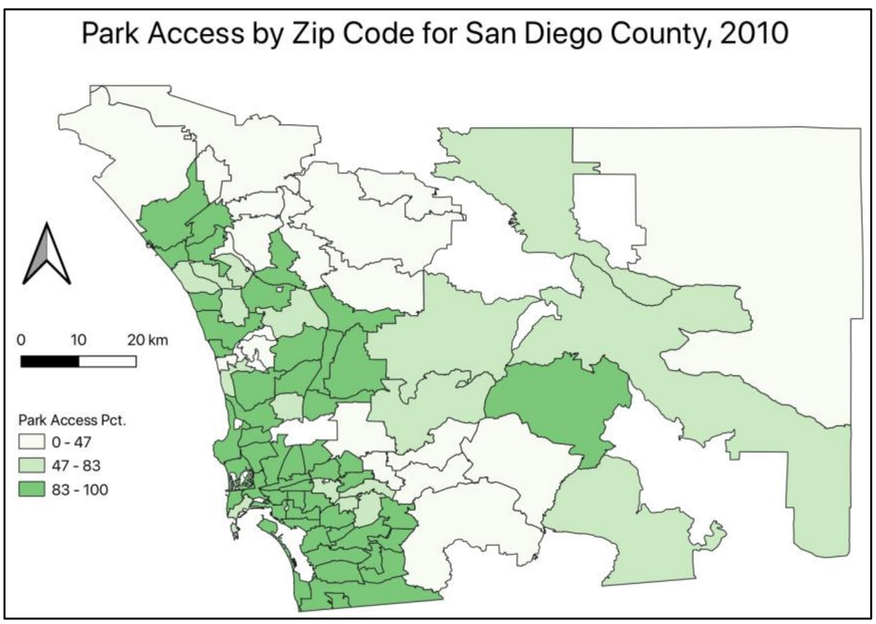


Figure A 2: *Map of Park Access in San Diego, where Park Access is defined as "Percentage of the population living within a half-mile of a park, beach, or open space greater than 1 acre" ([HPI Documentation]).*

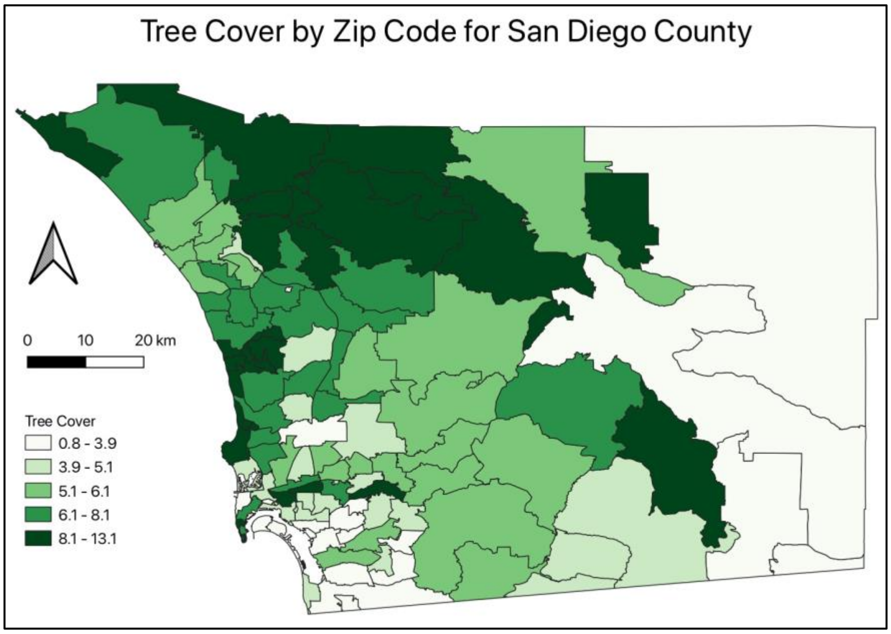


Figure A 3: *Map of Tree Cover, defined as percentage of land surface area covered by trees; based on satellite imagery from 2011. Data obtained from Hansen et al. (in review), originally from Google Earth Engine.*

II. Remaining CalEnviroScreen Variable Maps

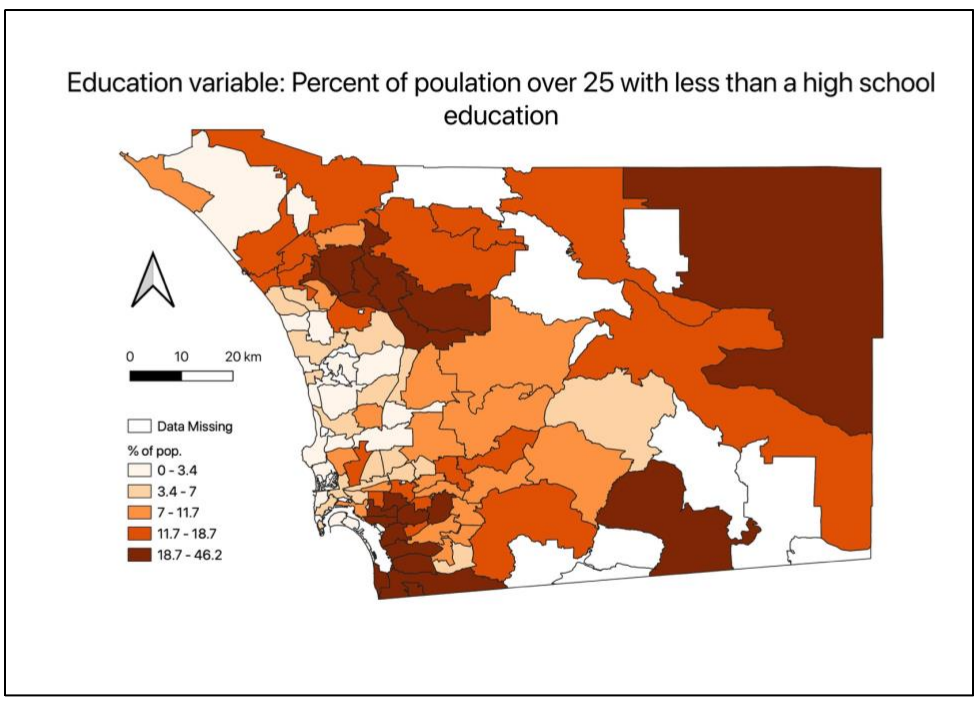


Figure A 4: *Map of the distribution of education level in San Diego County. Dark red indicates zip codes with the highest percentage of people over 25 with less than a high school education.*

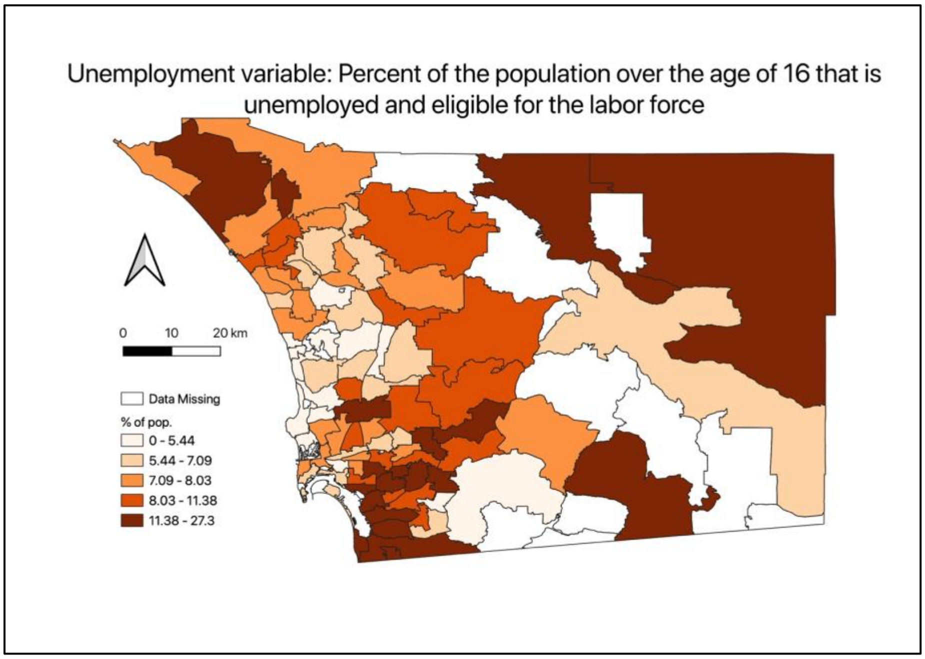


Figure A 5: *Map of the distribution of unemployment in San Diego County. Dark red indicates zip codes with the highest percent of unemployed people over the age of 16.*

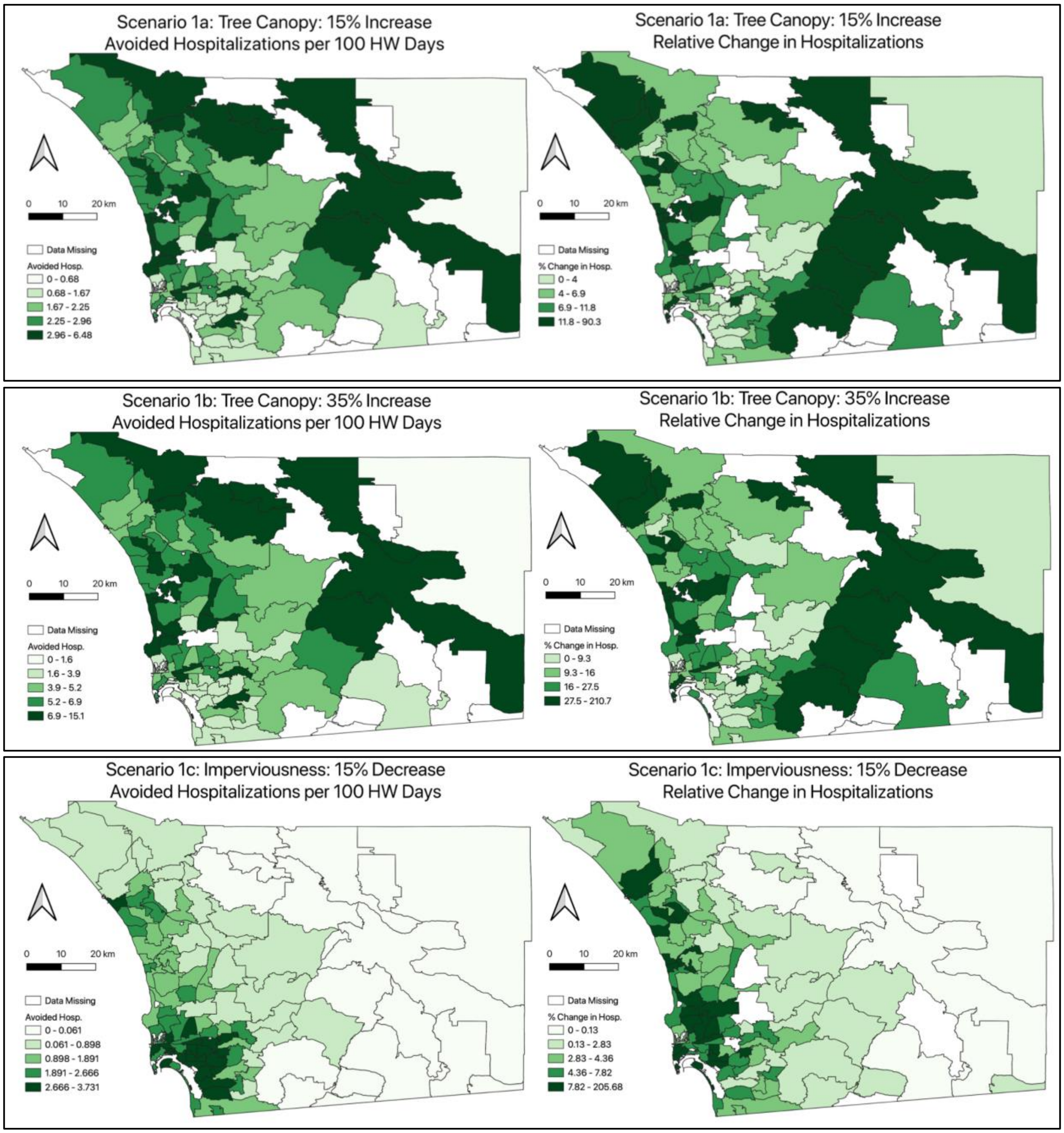
III. Full Regression Results

Regression	Intercept	Slope	Std Error	Lower 95%	Upper 95%
Hospitalizations vs. Tree Cover	0.331121	-0.005725	0.009557047	-0.024683449	0.013233772
Hospitalizations vs. Imperv	0.1941413	0.0034151	0.000960623	0.001509437	0.005320672
Hospitalizations vs. NDVI Avg	0.4812	-0.3124	0.40603265	-1.119200511	0.494355942
Hospitalizations vs. NDVI Change	0.32968	0.0482	0.177836298	-0.305155158	0.401558714
Hospitalizations vs. Tree Canopy (HPI)	0.49688	-0.0317	0.011836929	-0.05523336	-0.008163389
Hospitalizations vs. Park Access (HPI)	0.236883	0.0013436	0.000991564	-0.000627942	0.003315049

Table A 1: *Results of the linear regressions between heat-attributable hospitalization and each of the six green space indexes/proxies that were used in this study and in the calculation for the Aggregate Index.*

IV. All Greening Scenario Maps

a. Population-based Approach Maps



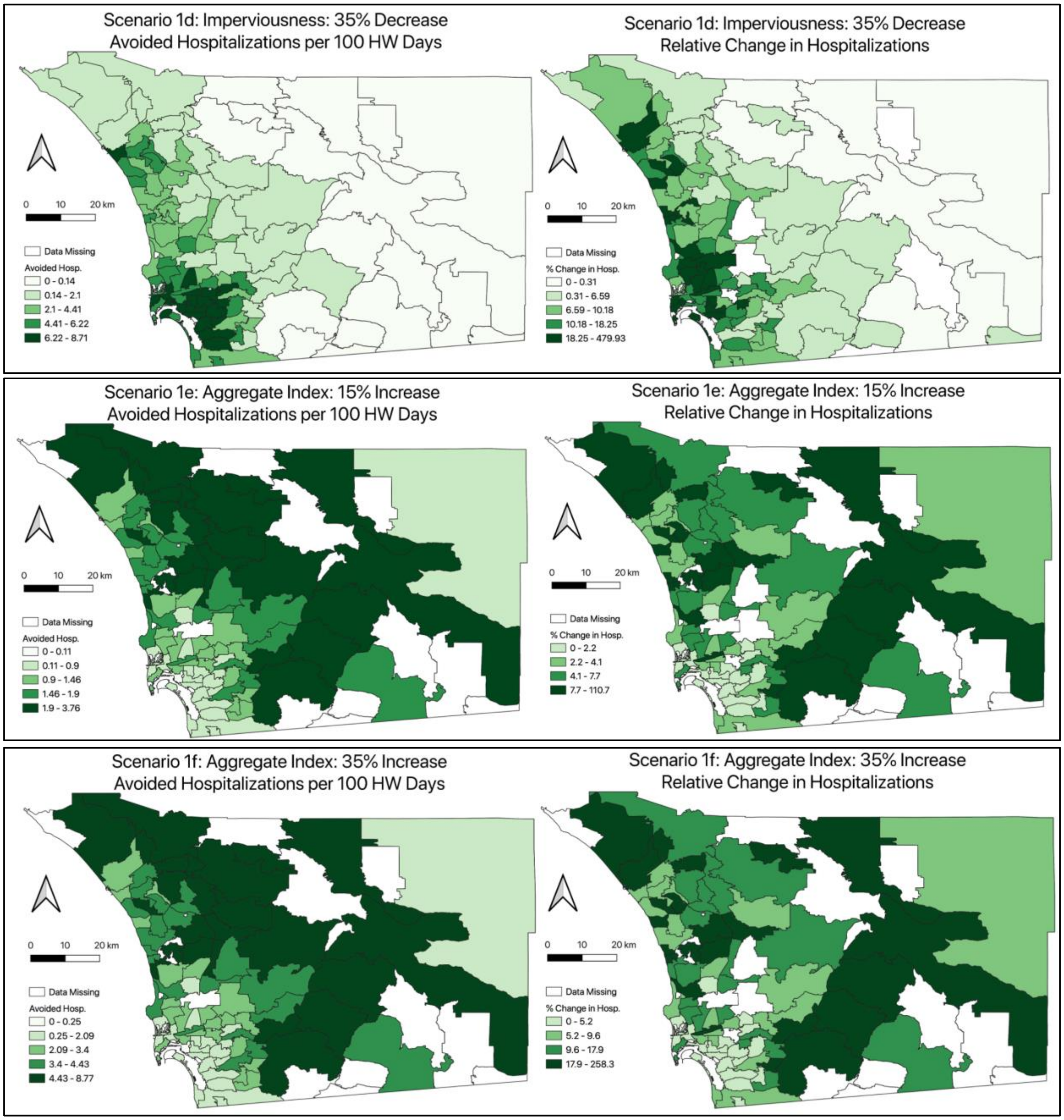
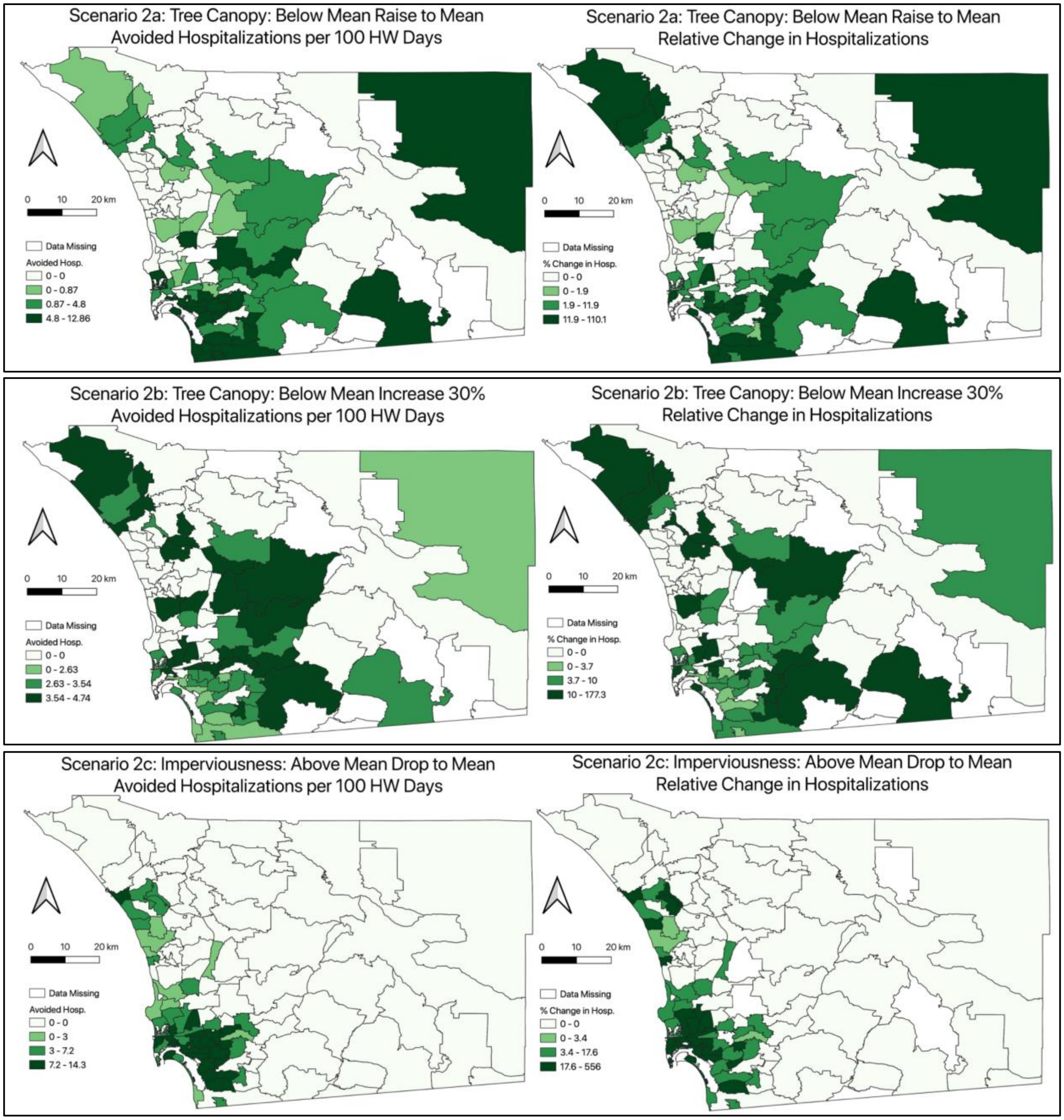
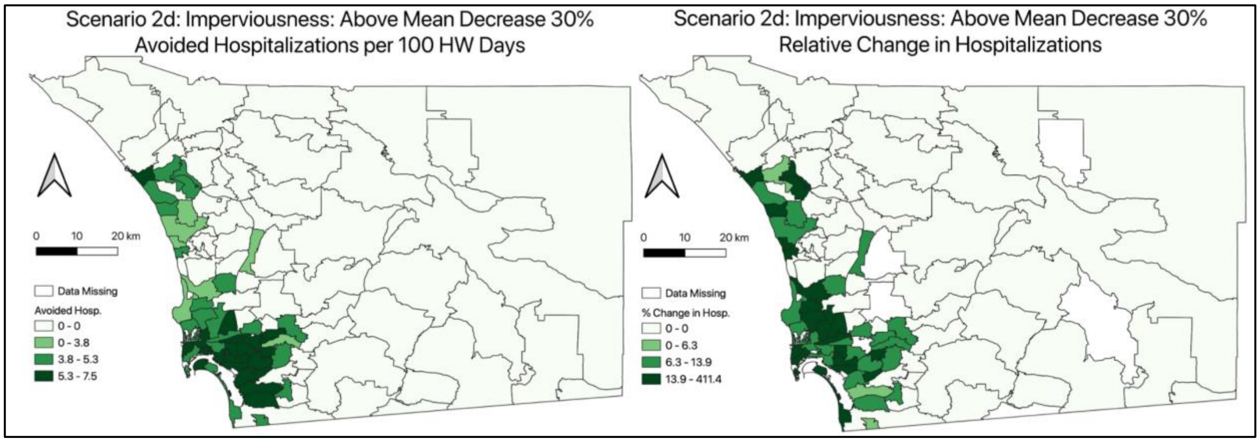
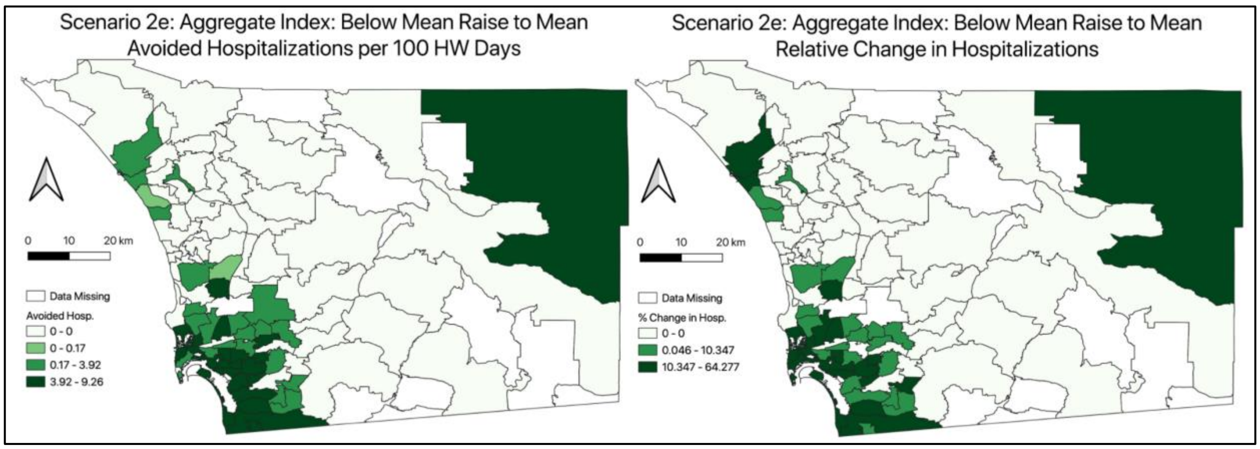


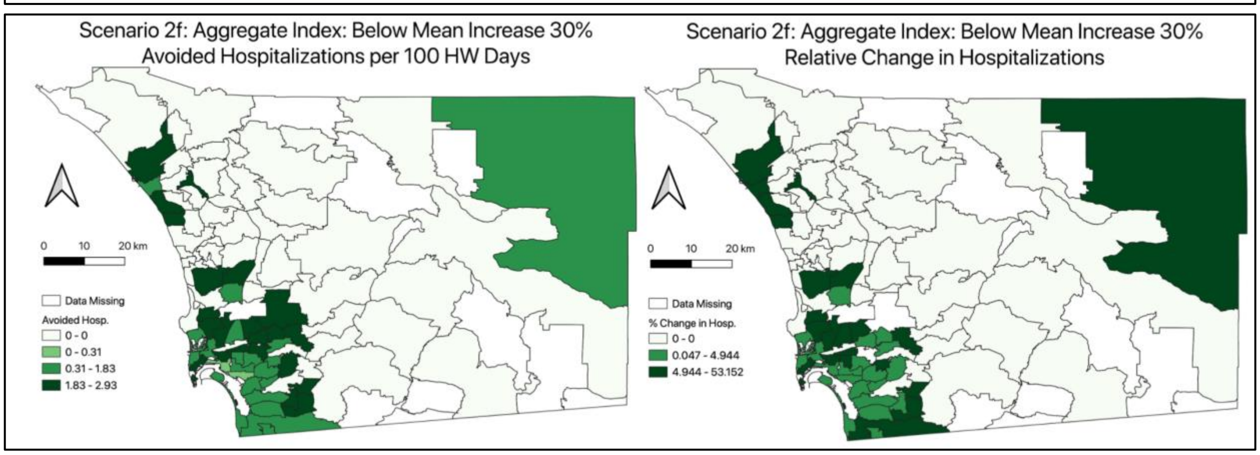
Figure A 6 – Figure A 11: *Maps representing the total benefits (avoided hospitalizations) and relative change in hospitalizations associated with scenarios 1a –1f.*

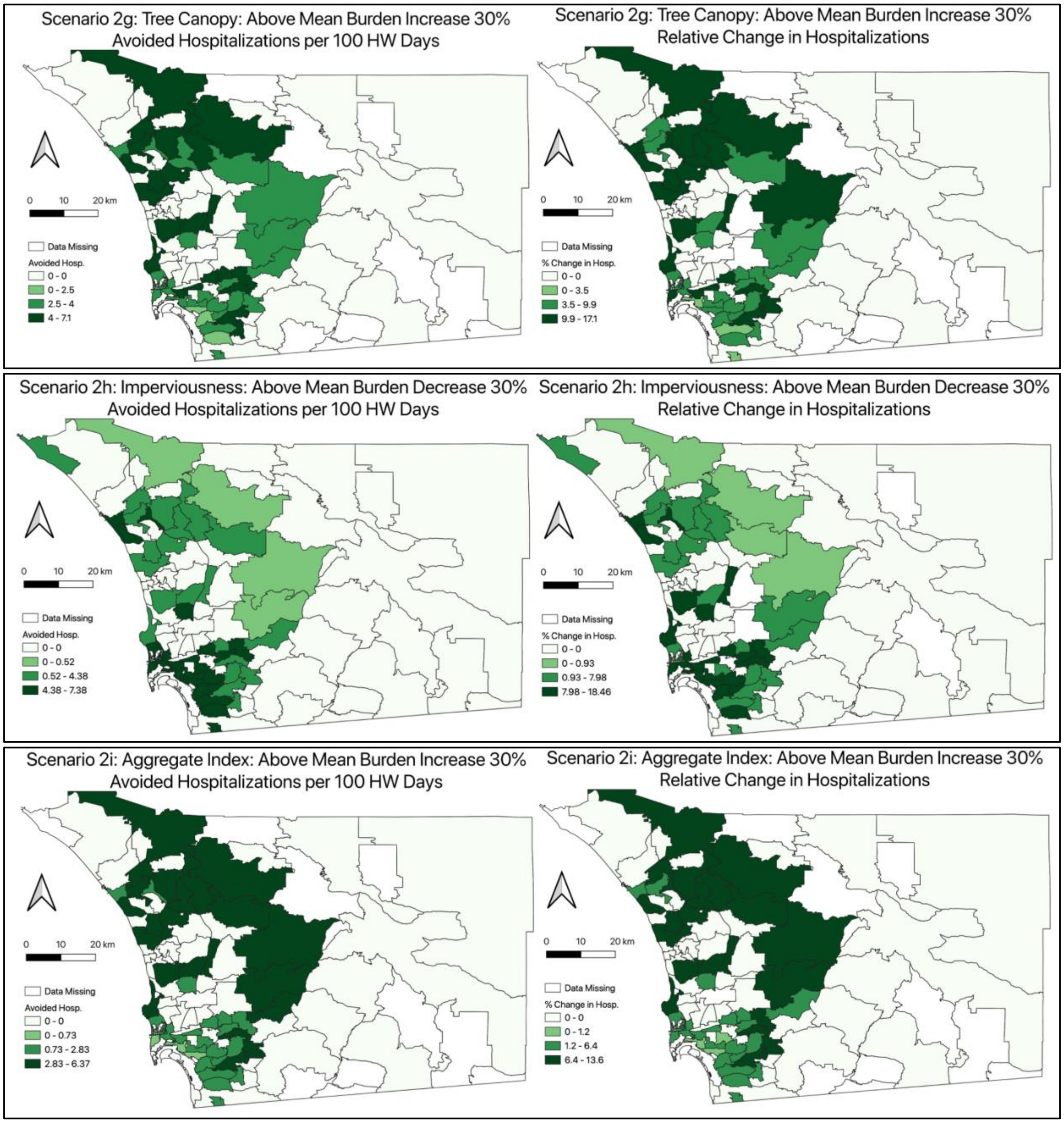
b. Targeted Approach Maps

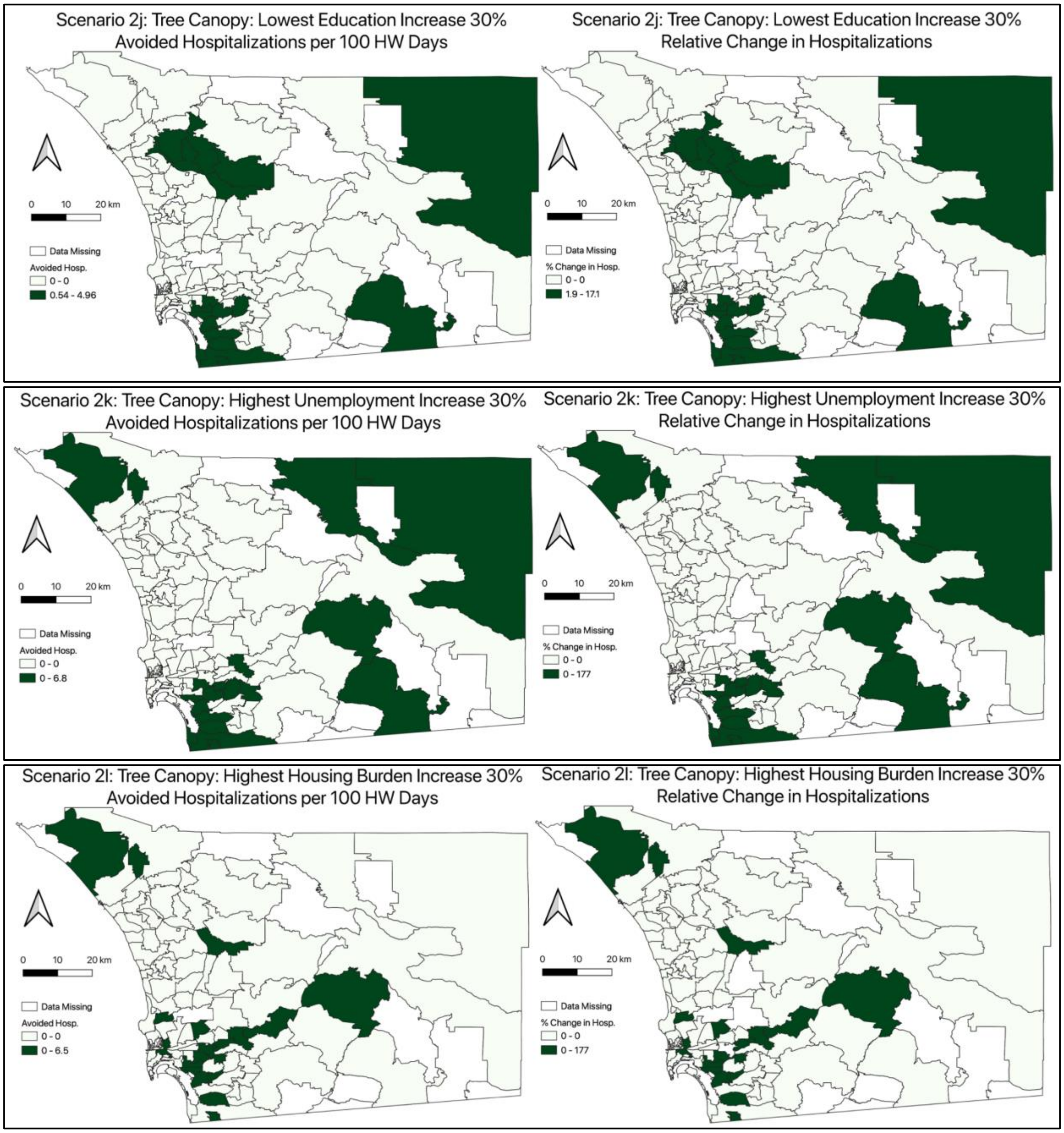



Scenario 2d: Imperviousness: Above Mean Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 3.8
3.8 - 5.3
5.3 - 7.5
Scenario 2d: Imperviousness: Above Mean Decrease 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 6.3
6.3 - 13.9
13.9 - 411.4

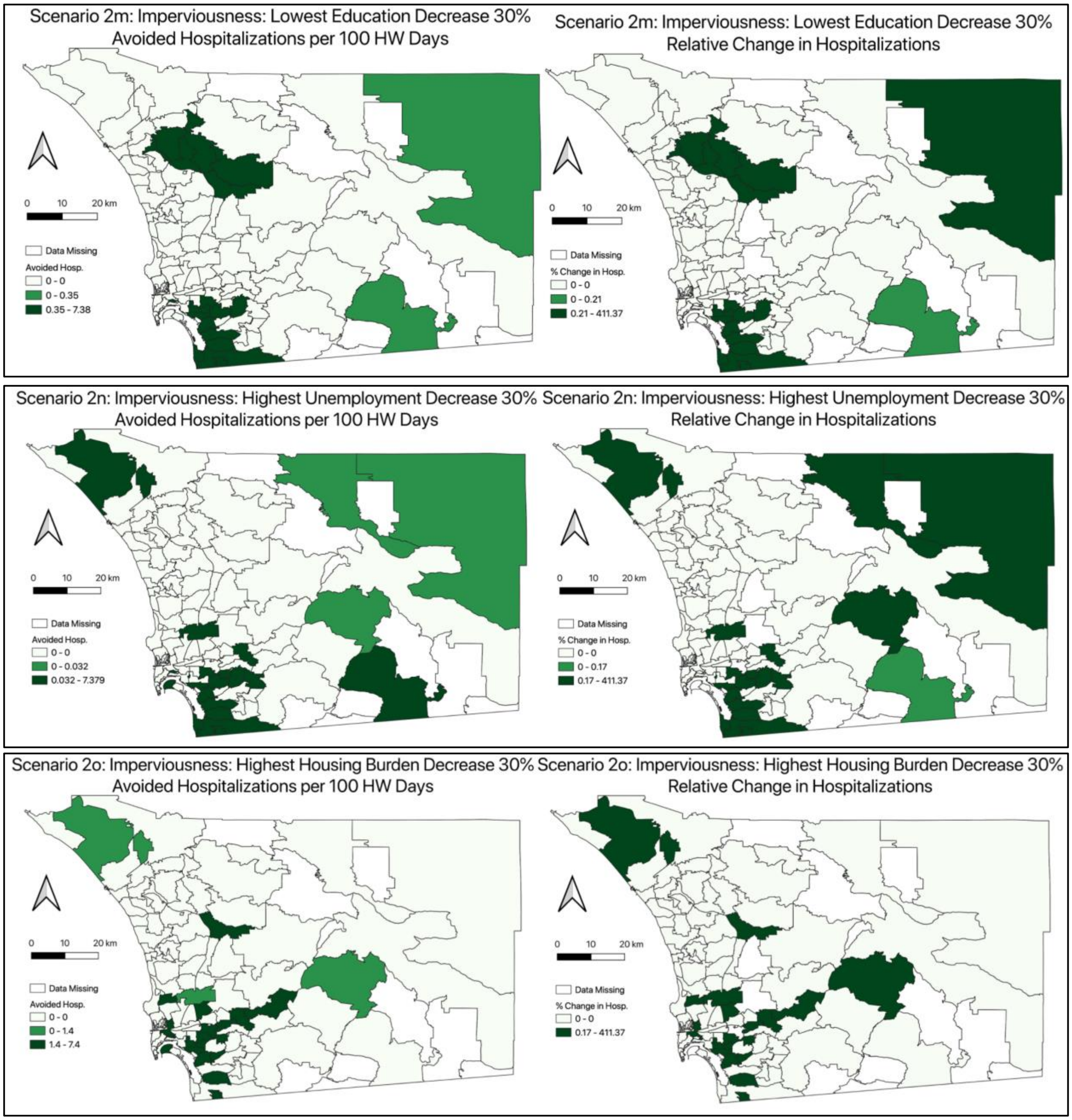

Scenario 2e: Aggregate Index: Below Mean Raise to Mean
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.17
0.17 - 3.92
3.92 - 9.26
Scenario 2e: Aggregate Index: Below Mean Raise to Mean
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0.046 - 10.347
10.347 - 64.277


Scenario 2f: Aggregate Index: Below Mean Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.31
0.31 - 1.83
1.83 - 2.93
Scenario 2f: Aggregate Index: Below Mean Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0.047 - 4.944
4.944 - 53.152


Scenario 2g: Tree Canopy: Above Mean Burden Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 2.5
2.5 - 4
4 - 7.1
Scenario 2g: Tree Canopy: Above Mean Burden Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 3.5
3.5 - 9.9
9.9 - 17.1
Scenario 2h: Imperviousness: Above Mean Burden Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.52
0.52 - 4.38
4.38 - 7.38
Scenario 2h: Imperviousness: Above Mean Burden Decrease 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 0.93
0.93 - 7.98
7.98 - 18.46
Scenario 2i: Aggregate Index: Above Mean Burden Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.73
0.73 - 2.83
2.83 - 6.37
Scenario 2i: Aggregate Index: Above Mean Burden Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 1.2
1.2 - 6.4
6.4 - 13.6



Scenario 2j: Tree Canopy: Lowest Education Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0.54 - 4.96
Scenario 2j: Tree Canopy: Lowest Education Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
1.9 - 17.1
Scenario 2k: Tree Canopy: Highest Unemployment Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 6.8
Scenario 2k: Tree Canopy: Highest Unemployment Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 177
Scenario 2l: Tree Canopy: Highest Housing Burden Increase 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 6.5
Scenario 2l: Tree Canopy: Highest Housing Burden Increase 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 177


Scenario 2m: Imperviousness: Lowest Education Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.35
0.35 - 7.38
Scenario 2m: Imperviousness: Lowest Education Decrease 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 0.21
0.21 - 411.37
Scenario 2n: Imperviousness: Highest Unemployment Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 0.032
0.032 - 7.379
Scenario 2n: Imperviousness: Highest Unemployment Decrease 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0 - 0.17
0.17 - 411.37
Scenario 2o: Imperviousness: Highest Housing Burden Decrease 30%
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0
0 - 1.4
1.4 - 7.4
Scenario 2o: Imperviousness: Highest Housing Burden Decrease 30%
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0
0.17 - 411.37

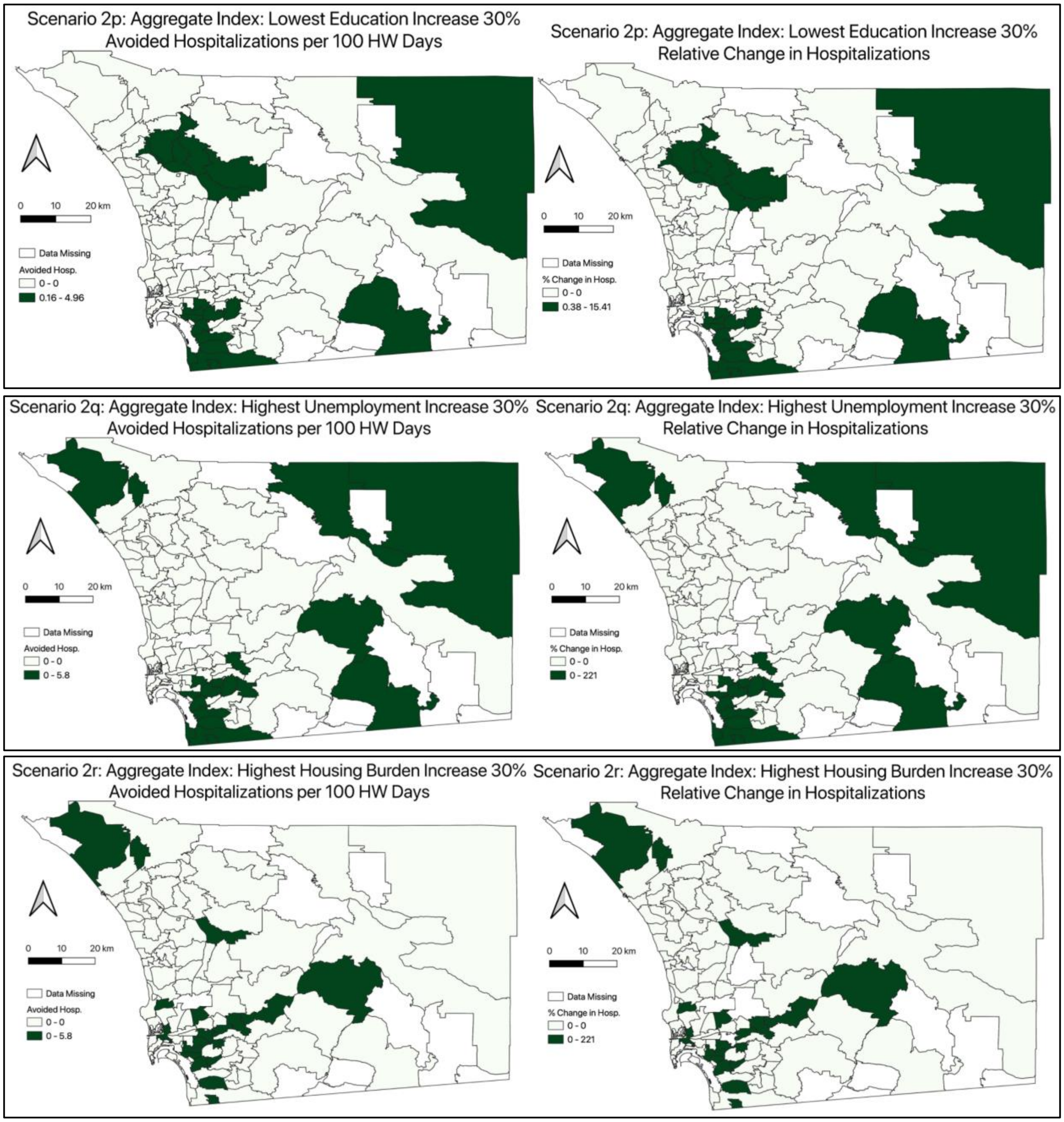
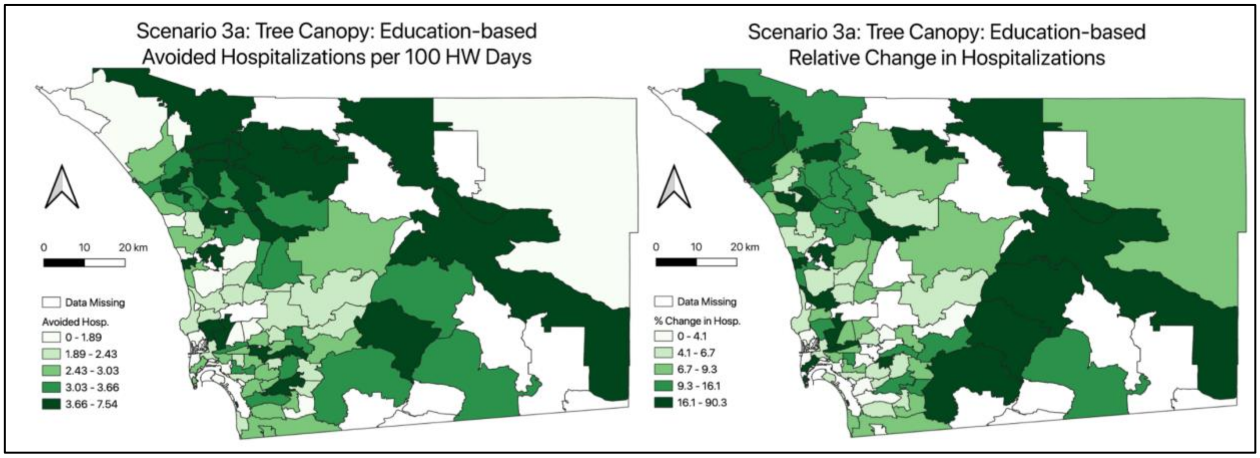
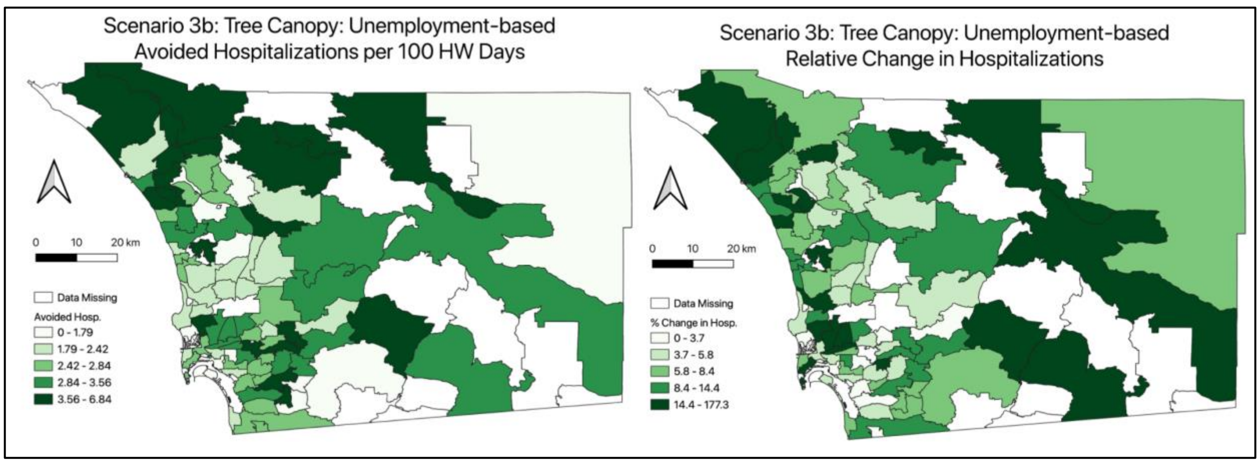
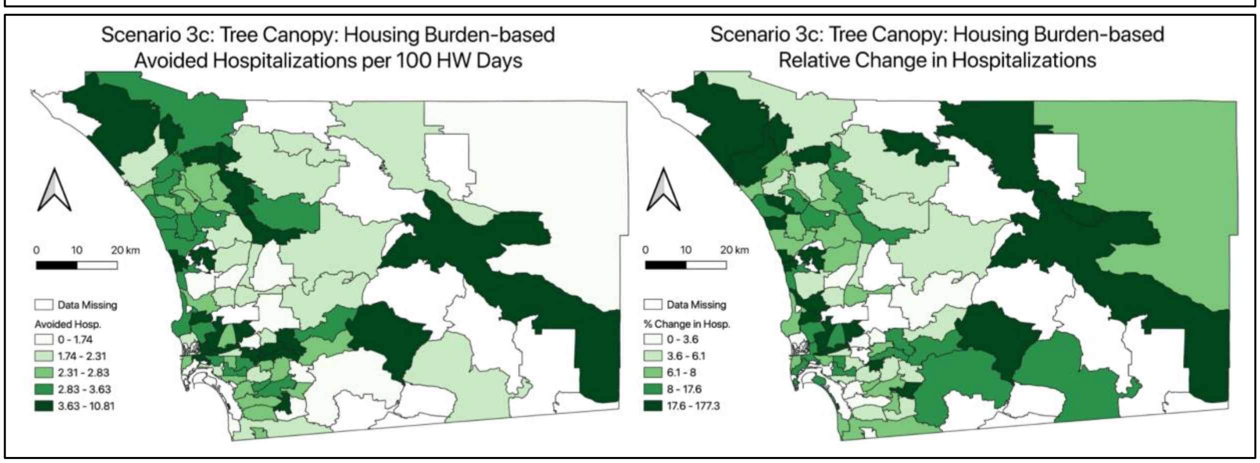


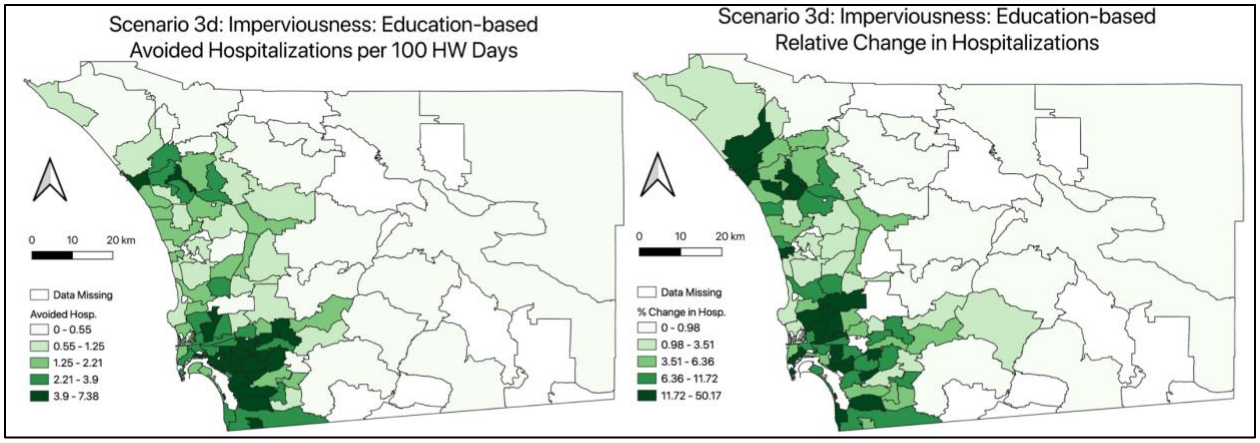
Figure A 12 – 29: *Maps representing the total benefits (avoided hospitalizations) and relative change in hospitalizations associated with scenarios 2a –2r.*

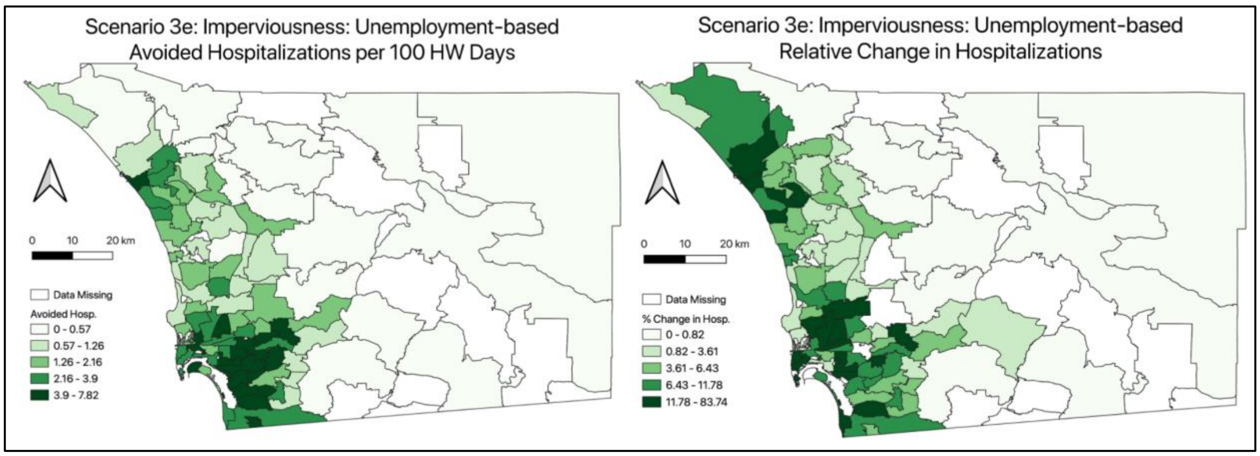
c. Proportionate Universalism Approach Maps

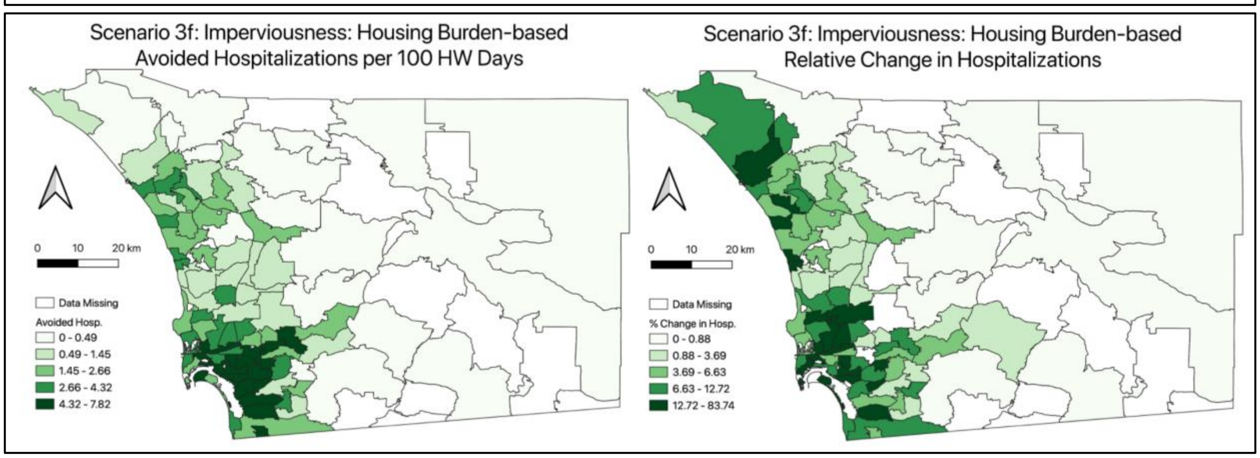







Scenario 3d: Imperviousness: Education-based
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.55
0.55 - 1.25
1.25 - 2.21
2.21 - 3.9
3.9 - 7.38
Scenario 3d: Imperviousness: Education-based
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0.98
0.98 - 3.51
3.51 - 6.36
6.36 - 11.72
11.72 - 50.17


Scenario 3e: Imperviousness: Unemployment-based
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.57
0.57 - 1.26
1.26 - 2.16
2.16 - 3.9
3.9 - 7.82
Scenario 3e: Imperviousness: Unemployment-based
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0.82
0.82 - 3.61
3.61 - 6.43
6.43 - 11.78
11.78 - 83.74


Scenario 3f: Imperviousness: Housing Burden-based
Avoided Hospitalizations per 100 HW Days
0 10 20 km
Data Missing
Avoided Hosp.
0 - 0.49
0.49 - 1.45
1.45 - 2.66
2.66 - 4.32
4.32 - 7.82
Scenario 3f: Imperviousness: Housing Burden-based
Relative Change in Hospitalizations
0 10 20 km
Data Missing
% Change in Hosp.
0 - 0.88
0.88 - 3.69
3.69 - 6.63
6.63 - 12.72
12.72 - 83.74

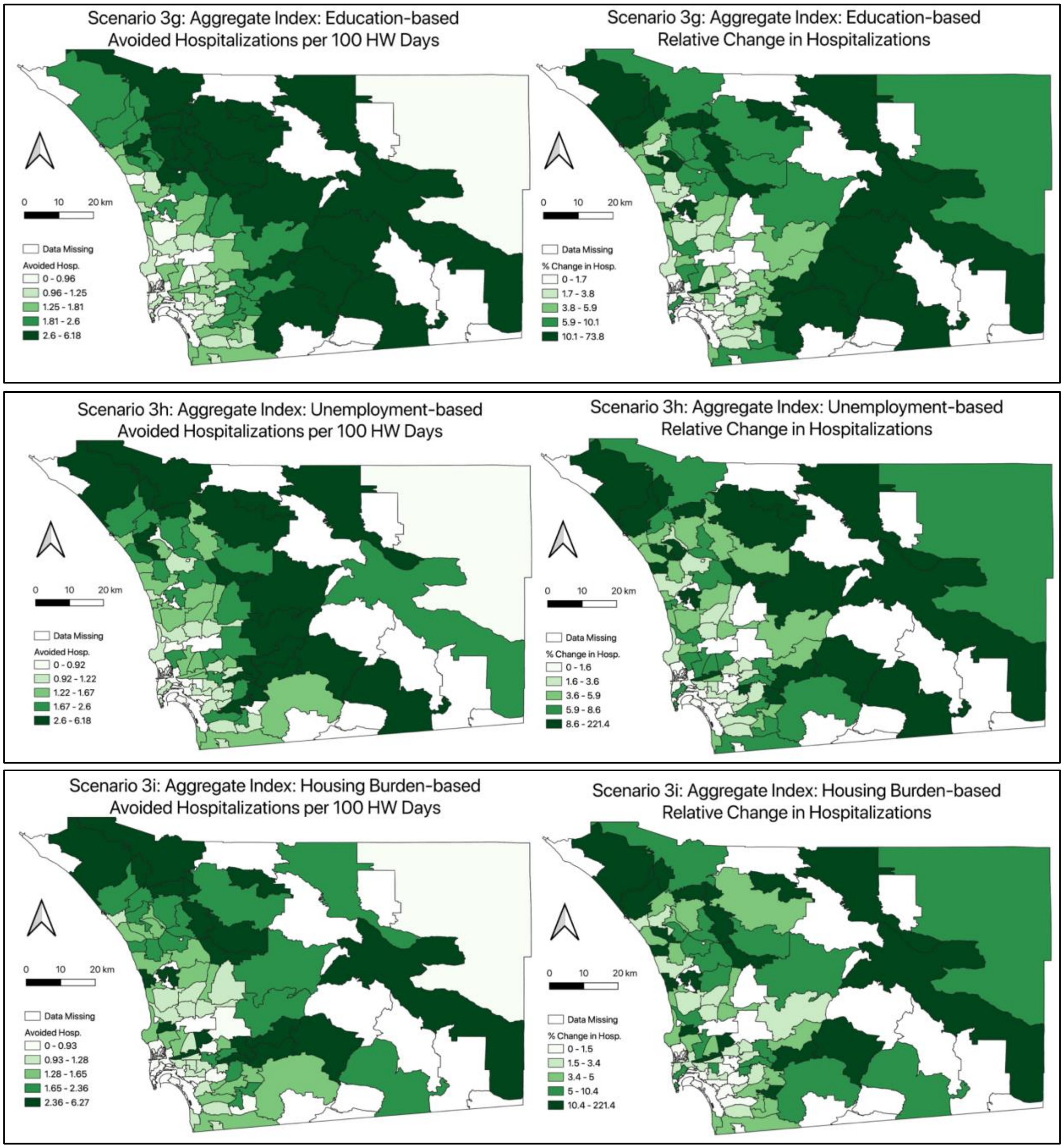


Figure A 30 – 38: *Maps representing the total benefits (avoided hospitalizations) and relative change in hospitalizations associated with scenarios 3a – 3i.*