A Method for Quantifying Sidewalk Shade to Assess Pedestrian Access to Relief From Direct Sun

A Method for Quantifying Sidewalk Shade to Assess Pedestrian Access to Relief from Direct Sun

Kimberly C. Perez

A Thesis in the Field of Sustainability

for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

March 2020

Abstract

Urban heat is a public health risk and is increasing due to climate change, with heat waves more intense and longer-lasting than before. Meanwhile, many cities are designing for walkability, encouraging people to drive less and walk more. The convergence of these trends leaves people vulnerable when temperatures are dangerously high and there's no escape from direct sun. Pedestrian access to shade offers relief from the heat. Quantifying shade can help citizens assess walkability and enable city planners to design shade-rich environments. My primary hypothesis was that shade can be accurately modeled and quantified using a Geographic Information System (GIS). My secondary hypotheses were that areas of higher heat-related risk will have less shade than areas of lower risk, and income will be the variable most closely associated with shade.

I used GIS, building footprints, LiDAR-derived elevation and height data, and tree mapping to map, measure and analyze shade on 16 sample walking routes of 540 meters each in the increasingly hot City of Pasadena, CA. I created 3D models of walking routes with Esri's ArcGIS Pro (v. 2.3.0), using LiDAR data to extract 3D trees and add height to building footprints. I manually moved, sized and shaped each building and tree, using Google Street View (GSV) as a source of information, and ground-truthed each model by comparing shade maps to field measurements. Modeled shade maps matched field tests with a mean match rate of 91.6% for total meters shaded and 70.4% for distribution of shade. I conclude that it is possible to quantify sidewalk shade using 3D modeling in ArcGIS Pro and GSV as a source of information, with some limitations.

To see if access to shade is correlated with risk factors related to income, age, or access to a car, I mapped shade for two different times of day and calculated minutes walking unshaded and gaps in shade for each route. Employing statistical analysis using linear mixed effects models (LMM), and additional analysis and data visualization in Excel, I found that neither of my secondary hypotheses was supported by the data.

Assessing access to shade is complex and site-specific. Having a method for quantifying shade can help policy-makers identify where people spend a dangerous amount of time in direct sun, and then use that insight to help people remain safe during heat waves, to consider shade when designing for walkability, and to plan for more equitable access to shade across a city.

Dedication

To my fellow urban wanderers, who roam the sidewalks to get somewhere or nowhere in particular. Those of us who have become expert shade-stalkers—chasing patches of sidewalk closest to buildings, favoring streets with thicker canopies, plotting meandering paths following the shadows of any possible obstruction to the punishing rays. We who wait for the walk sign by folding ourselves into the lone narrow band of shade from the light pole. Especially for those who don’t have a choice—who stand with arms full of groceries, waiting for the bus in the scorching sun, on day three of a heat wave. May we all find the sweet relief of shade.

Acknowledgments

I could not believe my luck five years ago when I discovered that Harvard University offered this master's degree in sustainability through such a flexible program, meaning I could pursue this new path from my home in Pasadena and while continuing my full-time work as a writer.

Jeff Blossom of Harvard's Center for Geographic Analysis, thank you for teaching me how to investigate maps and spatial data—it's as if I've gained unlimited new ways to explore the world. Thank you for all of your guidance along the way, as I embarked on a research project that would require skills and knowledge I didn't yet possess when I began. Dr. Mark Leighton of Harvard University, thank you for helping me learn how to think about research, how to pose a question and look for ways to explore the possibilities. Dr. Steven Worthington from Harvard's Institute for Quantitative Social Science, thank you for your help with the statistical analysis and your seemingly infinite patience with my "just a few more follow-up questions."

I owe everything to my dad and mom, Richard and Nancy Dixon, who have given me the gift of never doubting that I am infinitely cherished and fully supported. You filled my childhood with joyful outdoor meanderings in town and in the mountains, and you have shown me what it looks like to spend life in service to the people around you.

At a moment in my life when I felt I had no service to offer, my dearest friend Lilli Cloud consistently supplied inspiration, fun and support—and an introduction to Dr. Don Thomas who invited me to join one of his annual visits to Malawi. That was an experience that kicked off for me an appreciation of the complex systems that make up

our world and a desire to learn more about those systems, introducing me to sustainability as a field of study and a life mission—and introducing me to dear friends Ian Commissiong and Catherine Koverola, who told me about the Harvard program.

Lilli also spent many days and hours by my side in the sun, manning the measuring wheel for the field tests for this research. Andi Simpson, Aubin Wilson, Karen Klein Scauzillo and Paula Johnson also gave up the comforts of air conditioning to help me measure shade for several hours at a time, walking the routes when the sun was bright and the temperature high. That's true friendship.

My life is filled with family and friends who are quick with support when I'm stressed, with words of encouragement when I'm tired, with understanding when I go into hermit mode, and with celebration whenever and wherever. I am truly blessed.

Table of Contents

List of Tables

List of Figures

Definition of Terms

ArcGIS	Geographic Information Systems software from Esri
GIS	Geographic Information System: computer software that allows the user to create maps and analyze data according to geography or other spatial elements.
GSV	Google Street View
Multipatch	A GIS data type that lets the featured tree or building not just look 3D but also act 3D, so the software sees it as an obstruction for the sun's rays.

Chapter I

Introduction

Urban heat is a public health risk and is increasing due to climate change, with heat waves more intense and longer-lasting than before (U.S. EPA, 2014a). Cities experience the urban heat island effect—exacerbated heat due a city's built environment absorbing solar energy that is released as heat (especially impervious surfaces) (CalEPA, n.d.). Meanwhile, walkability has become a desirable feature of city living. Cities are cultivating walkable, transit-friendly neighborhoods as a way to reduce dependence on single-vehicle transportation and to promote public health (Florida, 2014; Brown, Carlson, Kumar, & Fulton, 2018). But access to shade is not considered in walkability scores (Walk Score, n.d.). The convergence of these two trends leaves people vulnerable on days when temperatures are dangerously high and there's no escape from direct sun. Seniors who live alone (and therefore have less access to help getting around or running errands) and people with low income may not have alternatives to walking in the heat.

Cities are employing strategies to ease temperatures, like cool roofs, cool pavements, and more green space (Mohegh et al., 2017; Bowler, Buyung-Ali, Knight, & Pullin, 2010). But for pedestrians walking the sidewalks, air temperature is just one factor affecting their thermal comfort—the other is shade. While air temperature is easy to measure, sidewalk-level pedestrian shade is harder to map with accuracy in a way that is useful for understanding the role of shade as a variable separate from air temperature, and for analyzing and comparing access to shade on sidewalks throughout a city. It's more common to assess or count the objects that create shade—total canopy, number of trees, and placement of buildings—without quantifying the shade itself. But we can't know the role lack of shade plays in pedestrian safety on hot days or during heat waves without a method for quantifying sidewalk shade.

Shadow analysis tools and 3D modeling offer the ability to map shade once buildings and trees have been added to a model. But while building footprints and heights are relatively easy to obtain, detailed tree inventories that include up-to-date tree height and crown width are not as accessible for cities without the resources to take manual inventory in the field. Also, to understand shade's role in pedestrian safety and its distribution across a city, a map is not enough: the shade needs to be quantified.

Research Significance and Objectives

To fill these research gaps, I created and tested a new model for quantifying sidewalk shade. It involved mapping, measuring and analyzing shade below the canopy at the sidewalk level. This research can help cities identify neighborhoods where people who are at high risk in heat waves have to spend a dangerous amount of time in direct sun. With this insight, a city could plan heat wave strategies, like temporarily boosting bus service along certain routes or providing temporary shade to protect those at risk. This model also might be useful as policy makers plan long-term mitigation strategies like increasing shade where it's needed most. The model also could enable pedestrian shade to be included as a consideration in neighborhood walkability scores.

My objectives were:

- To help cities safely plan for a future of more heat and more people walking in that heat, by introducing a way to map, measure and analyze sidewalk shade.

- To present a method for mapping sidewalk shade using GIS-enabled 3D modeling of the buildings and trees along designated walking routes, using height and elevation data from LiDAR and using Google Street View as a source for information about how to place, size and shape buildings and trees.
- To propose a way to measure shade by turning shade maps into quantifiable units of total shade and distribution of shade—to make it easier for policy makers or researchers to consider shade as a variable when assessing risk and when planning for walkability or heat-related health impacts.
- To analyze and compare the presence of sidewalk shade in census tracts of varying levels of risk, to give cities a way to assess and plan for the equitable distribution of sidewalk shade.

Background

Urban heat is a public health risk and is increasing due to climate change, and heat waves are more intense and longer-lasting than before (U.S. EPA, 2014a). There is no universally accepted definition of a heat wave, but it generally involves temperatures at the high end of regional norms for at least two days; temperature indicators can include maximum temperature, mean temperature, apparent temperatures or heat index (Xu, FitzGerald, Guo, Jalaludin, & Tong, 2016). Extended heat events are particularly dangerous: on the first day, average mortality increases 4.1% over the typical daily average; by day five the mortality rate can be 11.9% higher than average (Kalkstein, 2018). In the United States, more people die in heat waves than in all other extreme weather events combined (Klinenberg, 2015).

Many populations are considered at risk during heat waves: infants and children up to four years of age, people age 65 and older, and people with conditions such as heart disease, obesity, and more (CDC, 2017b). But people outside those populations are also at risk if they continue with outdoor activity in a heat wave. Comparing deaths during a 2006 large-scale heat wave in California with deaths on reference days, researchers found that total mortality risk was higher for those between ages 35 to 64 than for children and for adults 65 and older (Joe, et al., 2016). The authors suggest this pattern "may be due, in part, to these persons being unaware of the increased risk, thus continuing with normal activity patterns and not taking protective action" (p. 9).

People of any age whose lives depend on walking may not have a choice to curtail that particular outdoor activity on a hot day. If they continue to walk to the bus to get to work, or walk to run errands, they might not realize that those relatively short bursts of activity put them at risk during a heat wave. Heat stroke is a life threatening condition that occurs when the body becomes unable to regulate its own temperature—in those cases, someone's body temperature can rise to 106°F or higher within 10-15 minutes (CDC, 2017b).

Walkability Increasing in Cities

Walkability is measured by factors that include the accessibility on foot of amenities such as transit, grocery stores, parks, restaurants, and cultural and recreational destinations (Duncan, Aldstadt, Whalen, & Melly, 2013). Access to shade is not a consideration in a neighborhood's walkability score (Walk Score, n.d.).

In particular, walkability and transit use are often closely linked (Syrkett, 2016). Most transit trips involve getting to work (49%) or to the store (21%), and more riders use transit five days a week (50%) than any other usage pattern (Clark, 2017). These trends indicate the kind of habitual and essential travel activity that is not likely to be abandoned even in the case of extreme heat. A heat event can cause interruptions to public transport network services, leaving commuters waiting in extreme heat for transport services (Norton et al., 2015). Sixty-nine percent of transit users walk to the bus stop (Clark, 2017), increasing their exposure to the heat and sun even more.

Seniors want to be able to walk, use transit and enjoy public space (Grabar, 2014). The AARP advocates for safe senior walkability, lobbying cities to design streets for pedestrians (not just cars), to make it safer to be an older pedestrian who walks slower and might have vision or hearing impairments (AARP, n.d.).

People with age- and health-related risk factors walk slower than those who are younger and healthier. Typical walking speeds for healthy adults range from 0.90 to 1.30 meters per second (m/s), while people in poor health have speeds closer to 0.60 to 0.70 m/s (Graham, Fisher, Bergés, Kuo, & Ostir, 2010). There is also a relationship between walking speed and the trajectory of both age and wealth: researchers found that someone age 71 in the poorest wealth quintile had a mean walking speed of 0.75 m/s, while someone the same age in the richest wealth quintile had a mean walking speed of 0.91 m/s—and speeds for both declined as they aged (Zaninotto, Sacker, & Head, 2013).

Cooling Strategies: Effects of Shade

Cities are seeking ways to mitigate the impacts of extreme heat. Strategies that make the pavement solar-reflective (called "cool pavement" strategies) have been shown to increase albedo and reduce surface air temperatures (Mohegh et al., 2017). Greening strategies such as tree planting, the creation of parks and green roofs have also been shown to create sites that are cooler than non-green sites (Bowler, Buyung-Ali, Knight, & Pullin, 2010). Street trees and vegetated ground were shown to help reduce air temperatures on sidewalks at the pedestrian level (temperatures measured at the average heights of adults and children) in College Station, Texas (Kim, Lee, & Kim, 2018). However, vegetated ground (irrigated grass) had almost no impact on reducing the surface temperature in a study in Los Angeles—tree shade, by comparison, was found to be a significant source of cooling (Saatchi, n.d.).

Field surveys on Arizona State University's Tempe campus found that in hot, dry climates shade from a tree or photovoltaic solar canopy increased thermal comfort by approximately 1 point on a 9-point scale (Middel, Selover, Hagen, & Chhetri, 2016). Kántor, Chen, & Gál (2018) compared the cooling effects of shade provided by trees with shade from sun sails and found that at pedestrian level, even small shading with low-hanging sun sails or a single tree with sparse canopy reduced heat stress levels by at least one category on a sunny summer day. But they also noted that trees were more effective overall at pedestrian level—"even a tree with sparse canopy has more layers [than the artificial sun sail], which are able to reduce incoming short-wave radiation more effectively" (p. 252). The researchers also noted the importance of detailed small-scale field measurements for understanding effective shade strategies.

Tree shade has been found to have significant cooling impact in studies considering another hot, dry climate: Los Angeles County in Southern California. City blocks with more than 30 percent tree cover can be up to 5 degrees cooler than those with less than 1% tree cover (Saatchi, n.d.). “Percentage of shaded tree cover in city blocks explains more than 60 percent of land surface temperature (LST) variations. Other factors such as distance to the coast and topography explains the rest of variations … The ratio of impervious surfaces to trees was the main determinant of heat distribution over the city regardless of vicinity to the coast or across elevation” (Saatchi, n.d.).

Fan et al. (2017) researched the differences in temperature and humidity of various land cover classes in three Los Angeles County neighborhoods. They compared temperature and physical attributes of several points along three half-mile walking routes, during heat events and non-heat events for comparison. One of their findings: “The largest consecutive difference in temperature occurred between two land cover classes that were only 20 feet apart: from a residential home with tree shade to a bus stop without shade, there was a temperature increase of 10°F” (p. 12). The team also collected data to compare within shade and outside shade at the same bus stop, and found that on average it was 5.4°F cooler under the shade for the same stop. In one example, the temperature on an unshaded sidewalk was 102°F while the temperature under the shade was 95°F.

Heat Intensifying in Pasadena

The city of Pasadena is in Los Angeles County, located roughly 10 miles northeast of downtown Los Angeles (Figure 1). Pasadena has a population of 141,371 as of as of July 1, 2018 (U.S. Census Bureau, 2018a). The region experiences an increasing number of days with oppressive air masses in the fall—8% of days now, up from 6% in the 1940s and 1950s (Vanos, Kalkstein, Sailor, Shickman, & Sheridan, n.d.). The number of annual days hotter than 95°F in Pasadena is expected to more than double

Figure 1. Reference map of Pasadena within Los Angeles County.

Map created by author. County boundary data: California Open Data Portal (2019). City boundary data: City of Pasadena Open Data Site (2018).

(from 24 to 59) by 2060 and to quadruple (from 24 to 100) by 2100 (Hall, 2013). Pasadena experiences temperatures that are 7°F to 12°F higher than rural comparisons due to its urban heat island, calculated as a positive temperature differential over time between an urban census tract and nearby upwind rural reference points (CalEPA, 2015).

The city of Pasadena has assembled a Climate Action Plan and identified as one of the city's four potential climate-related impacts: "more extreme heat days and longer heat waves" (City of Pasadena, 2018, p. 98). Pasadena's climate plan includes two general actions related to reducing the urban heat island effect: studying the feasibility of implementing cool pavement strategies; and continuing to increase tree planting and urban green space "with emphasis on shading home, critical infrastructure, and bicycle and pedestrian routes" (p. 100). The city's goal is to plant 500 new trees by 2020.

Also a priority in Pasadena's climate plan is shifting travel from personal automobile to walking, biking, and public transit and supporting pedestrian and transit-oriented development (City of Pasadena, 2018). But many of Pasadena's transit lines have 20- to 30-minute wait times between scheduled stops (City of Pasadena, n.d.), meaning lots of time in the heat and sun for those riders.

Methods for Measuring Shade

It's easier to count trees than measure shade, which is probably why it is hard to find a method for accounting for sidewalk shade below the canopy at the pedestrian level. At minimum, an accurate measure of sidewalk shade should account for shade provided by both buildings and trees. Many studies focus on one or the other, and often studies of tree canopy use remote sensing to take a top-down view to assess total canopy cover, which inevitably obscures nuance at sidewalk level. Chen (2012) measured tree canopy for a study on walkability using the USGS National Land Cover Dataset Tree Canopy Layer, but she acknowledged that it didn't provide the best representation and resulted in inaccurate tree canopy score results. LiDAR remote sensing data is often used to map tree canopy, but has its own limitations around getting accurate data for tree height or distinguishing individual tree crowns (Crowley, 2011). Maco & McPherson (2002) addressed street trees in particular, testing a method for quantifying a city's total canopy cover over public pavement and sidewalks—but they were focused on zone totals rather than pedestrian-scaled measurements.

Researchers have tested the veracity of using Google Street View (GSV) to assess aspects of the built and natural environments. Richards & Edwards (2017) analyzed hemispherical photographs extracted from Google Street View (images of canopy from the ground looking up) to map street tree ecosystem services across a whole city. They were able to quantify the proportion of green canopy coverage at 50m intervals, and then estimate the proportion of annual radiation that would be blocked by that canopy. But their priority was not to collect ground-truth data with which to compare GSV photos to field measurements; instead, the accuracy they assessed was the comparison of a photo-analysis process done by machine compared with one done by human hand (all using the GSV photos).

Kelly, Wilson, Baker, Miller and Shootman (2013) found that using GSV imagery was a reliable way to audit the built environment when compared with observational field audits in both urban and suburban neighborhoods. To get a more nuanced sidewalk-level view of pedestrian-level safety infrastructure (not including shade), Nesoff et al. (2018) compared in-person observation with observations made of the same blocks using GSV. They found that the majority of items had good or excellent levels of reliability between the observational styles. Li, Ratti, & Seiferling (2018) presented a method for quantifying shade provision from street trees with a combination of GIS tools like the sky view factor (how much sky is obstructed) and GSV panoramas for capturing the images needed for analysis. However, the researchers acknowledge that the method, which uses panoramas taken from traffic lanes, doesn't necessarily offer a way to accurately capture shade accessible to pedestrians on the sidewalks.

Research Questions, Hypotheses and Specific Aims

The central research questions I addressed were: Can sidewalk shade be quantified to help assess pedestrian access to shade across a city, and to determine where vulnerable people spend a dangerous amount of time in direct sun? Is access to shade correlated with risk factors related to income, age, or access to a car?

Hypothesis 1: It is possible to accurately map sidewalk shade using GIS by combining building footprints and height with estimated tree height and crown width assessed from Google Street View (GSV) photos. I predicted the resulting shade maps to be at least 75% accurate, determined by ground-truthing the models by comparing them to actual measurements from the field.

Hypothesis 2: Mapped routes in areas of higher heat-related risk will have less total shade than in areas of lower risk, high-risk areas will have longer gaps in shade, and people in high-risk areas will have to spend at least 10 minutes without shade walking to the nearest bus stop.

Hypothesis 3: Statistical analysis of the data gathered from the quantified shade maps will reveal that income is the variable most closely correlated with total shade, distribution of shade, and time spent without shade. In other words, lower income will correlate positively with lower access to shade.

Specific Aims

To investigate these hypotheses, I (a) segmented the city into neighborhoods defined by census tracts, (b) defined risk and identified census tracts/study areas of varying risk, (c) chose sample walking routes within those study areas, (d) created shade maps for the sample routes, (e) measured and segmented the shade maps into quantifiable units, and (f) compared those units across areas of varying levels of risk.

To accomplish this, I pursued these specific aims:

1. Identified census tracts of varying risk using Pasadena, California as a case study. I mapped and ranked census tracts according to prevalence of indicators tied to heat-related risk. I chose census tracts to be my study areas based on those results, and identified two walking routes within each study area: one north/south (NS), one east/west (EW).
2. Gathered building and tree data and used ArcGIS Pro to create 3D models of the walking routes, manually placing and sizing buildings and trees along the walking routes using Google Street View as a guide.
3. Ground-truthed the 3D models by measuring and mapping the sidewalk shade on all walking routes in their entirety, in the field and also within the 3D models at the same day and time as the corresponding field tests.
4. Verified the accuracy of the 3D models by comparing the field measurements to the modeled shade and calculating match rates between the two.
5. Corrected all modeled walking routes to match their corresponding field tests.
6. Modeled the shade and created maps of the shade for each of the 16 walking routes at two times of day: August 31, 2018, at 12 p.m. and 2:30 p.m. PDT.

7. Calculated total shade for each route, time people spend without shade while walking each route, the longest gap for each route, and the number of gaps ≥21 meters—for both times of day—giving me 32 observations for each measurement.
8. Compared those results between the areas of varying levels of risk.

Chapter II

Methods

I used Esri ArcGIS Pro version 2.3.0 software (Esri, 2018a) to organize and analyze geographic data, to create the 3D models of the walking routes, and to model the shade used in my analysis. Statistical analysis was conducted using R version 3.6.0 (R Core Team, 2019) and RStudio version 1.2.1335 (RStudio Team, 2018). Additional analysis was conducted using Microsoft Excel version 16.26.

Identify Study Areas of Varying Degrees of Risk

To rank census tracts by risk, I chose variables that reflect a known risk—advanced age—plus variables that indicate pedestrian activity levels that are likely to continue regardless of heat: households with no access to a vehicle; per-capita income levels, with low income representing higher risk, since they would have less access to alternative transportation like ride-sharing; and people age 65+ living alone, and therefore less access to help getting around or help running errands. There were eight different combinations of variables that I needed to represent (Table 1).

I used Social Explorer (n.d.) to investigate the variables at the census tract level, using the Census Bureau dataset American Community Survey 2016 5-Year Estimates (U.S. Census Bureau, 2016). I chose census tracts rather than block groups because block groups were too small to give me two walking routes of at least 540 meters. I chose the 5-Year Estimates because they use the largest sample size and are the most reliable when examining at the tract or block level (U.S. Census Bureau, 2018b). I used these variables

Table 1. Combinations of variables needed to rank census tracts.

Study Area	Combination of Variables	Census Tract
1	High Income High 65+ Living Alone High No Car	3601
2	High Income Low 65+ Living Alone High No Car	1902
3	High Income High 65+ Living Alone Low No Car	3800
4	High Income Low 65+ Living Alone Low No Car	2600

Study Area	Combination of Variables	Census Tract
5	Low Income High 65+ Living Alone High No Car	2201
6	Low Income Low 65+ Living Alone High No Car	1901
7	Low Income High 65+ Living Alone Low No Car	3200
8	Low Income Low 65+ Living Alone Low No Car	0900

from the dataset:

- "Per Capita Income in the Past 12 Months (in 2016 inflation-adjusted dollars.)" I chose per-capita income as a way to compare income levels across census tracts without regard to the number of people living in a household, since I am analyzing households of various sizes (including one-person households).
- "Occupied Housing Units: No Vehicle Available."
- "Households with One or More People 65 Years and Over: 1-Person Household."

To identify which census tracts best matched each combination of variables, I classified the data using quantiles and ran "Select by Attributes" queries. I started with two quantiles, low and high (Table 2), to see if there were census tracts that would represent each of these eight combinations of variables. Each combination resulted in at least one match. In fact, all but one study area had multiple matches (Table 3), since the categories were the broadest possible categories at this point—upper half and lower half of the distributions. Next I narrowed the options by working my way through three quantiles and four quantiles, until I was left with one option for each combination.

Table 2. Query parameters for two quantiles.

Per-Capita Income Top Quantile:	≥ $44,815
Per-Capita Income Bottom Quantile:	≤ $44,814
Age 65+ Living Alone Top Quantile:	≥ 156
Age 65+ Living Alone Bottom Quantile:	≤ 155
No Access to Vehicle Top Quantile:	≥ 148
No Access to Vehicle Bottom Quantile:	≤ 147

Table 3. Query results for two quantiles.

Area	Combinations	Census Tracts
1	High Income High 65+ Living Alone High No Car	2500, 3400 3500, 3601 3602, 3900
2	High Income Low 65+ Living Alone High No Car	1902
3	High Income High 65+ Living Alone Low No Car	0000, 0100 3800 4000
4	High Income Low 65+ Living Alone Low No Car	0800, 1700 2600, 2900 3000, 3700

Area	Combinations	Census Tracts
5	Low Income High 65+ Living Alone High No Car	1400, 1502 2201 2301
6	Low Income Low 65+ Living Alone High No Car	1600, 1901 2001, 2002 2302, 2800
7	Low Income High 65+ Living Alone Low No Car	2400 2700 3200
8	Low Income Low 65+ Living Alone Low No Car	0401, 0900 1501, 2100 2202

For the Area 7 combination there were three possible census tracts identified in the two-quantile query, and no options given for three- and four-quantile queries. I examined the individual variables for the three options and there was no obvious stand-out, so I selected the area that was located in the south-eastern part of the city—an area not yet represented in the study. The full process gave me eight study areas throughout the city (Figure 2), one representing each combination of variables.

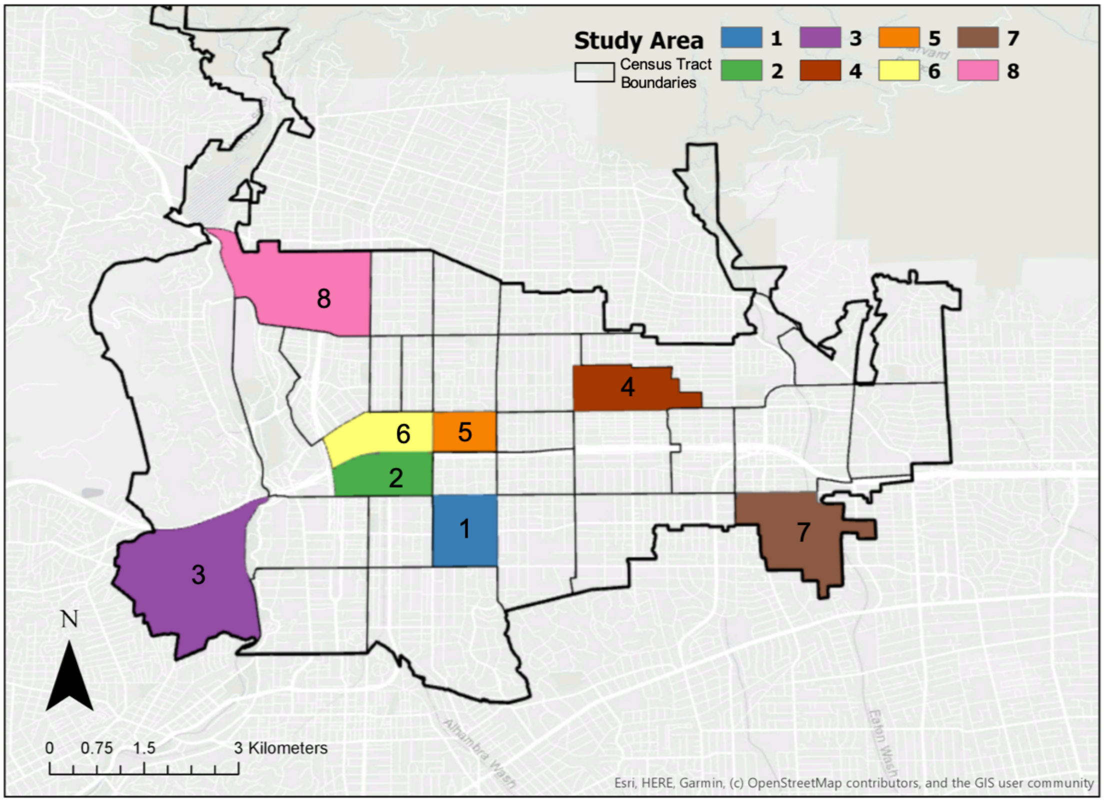


Figure 2. Study areas.

Census tract boundaries from Centers for Disease Control (CDC, 2017a).

Within each study area I identified two 540-meter walking routes (one running east-west and one running north-south) based on visual analysis of the ground conditions, trying to closely simulate a typical walk to or from a bus stop (Figure 3). In order to keep the routes realistically connected to bus stops, the NS route in Area 5 needed to take a turn, so 135 meters of that route actually run EW.

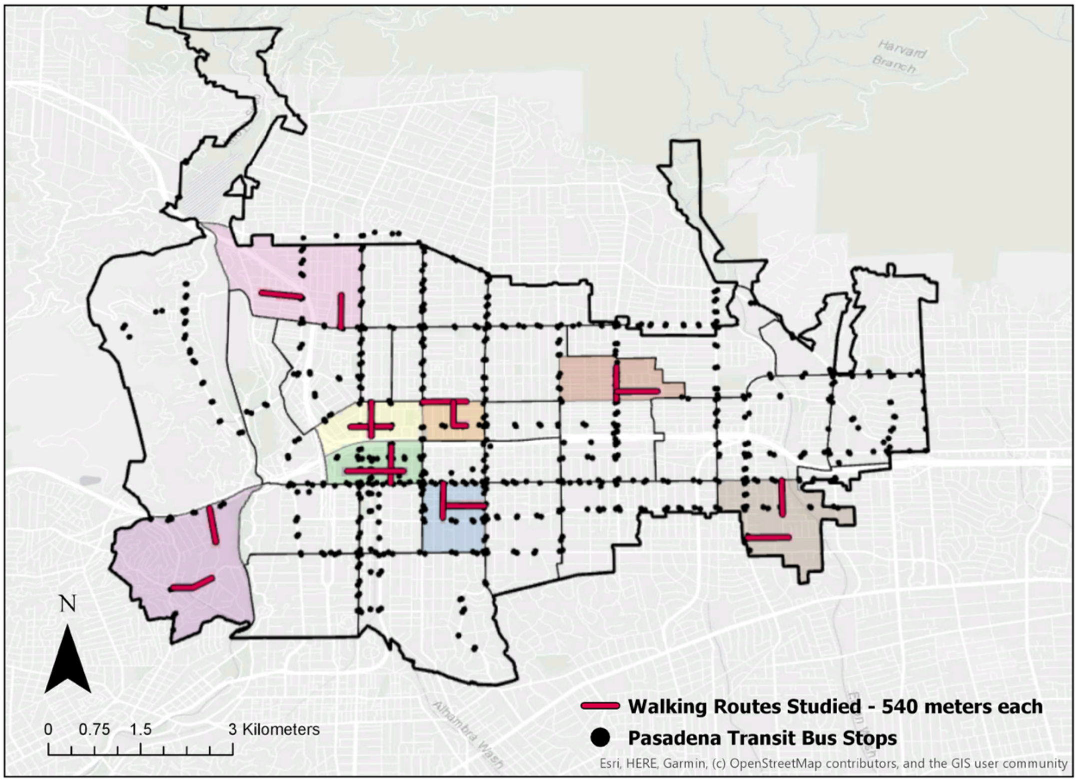


Figure 3. Walking routes within each study area.

Pasadena Transit data: City of Pasadena Open Data Site (n.d.).

Create 3D Models of Walking Routes

To map the shade along the designated walking routes, I created 3D models of each route that included multipatch features of all trees and buildings. Multipatch is a GIS data type that lets the featured tree or building not just look 3D but also act 3D, so the software sees it as an obstruction for the sun's rays. To act 3D, I had to add elevation and height data to a 2D layer of building footprints, and extract vegetation from the elevation and height data to generate a layer of trees. Two critical pieces were needed for these steps: the layer of building footprints and elevation and height data obtained through LiDAR.

Creating Multipatch Layers of Trees and Buildings

I obtained a GIS layer of building footprints for Los Angeles County (Los Angeles County GIS Data Portal, 2008), and clipped it to include only the buildings within the city of Pasadena. I obtained LiDAR data from the NOAA Office for Coastal Management (NOAA, 2015-2016) (Table 4).

Table 4. LiDAR spatial reference parameters.

2015-2016 LARIAC LiDAR:	Los Angeles Region, CA-1
Projection:	State Plane 1983 Zone 0405 California 5
Horizontal datum:	NAD83; horizontal units: US Feet
Vertical datum:	NAVD88; vertical units: Feet
Output product:	Point
Output format:	Points LAS
Data classes:	All

I deployed the “ArcGIS Solutions for Local Government: Local Government 3D Basemaps” (Esri, 2019a) to create multipatch feature layers of trees and buildings. The solution packages the tasks and tools necessary to create these 3D layers within an ArcGIS Pro scene. In ArcGIS, “maps” are mostly two-dimensional (2D) with some ability to visualize contours and other 3D elements. To achieve true 3D involving the vertical axis, ArcGIS Pro uses “scenes”—a Global Scene when the curvature of the Earth is important, and a Local Scene when it’s not (Esri, n.d.).

The first step was to use the LiDAR data (LAS point data) to create the elevation layers that would add that third dimension to the scene. I followed the tasks to use the “Create LAS Dataset” data management tool to add my LAS point data to the scene and then use that point data to create a LAS dataset. Then I used the “Extract Elevation from

LAS Dataset" task to extract three different elevation layers: Digital Terrain Model (DTM), which provides elevation of the ground; Digital Surface Model (DSM), which provides elevation of trees and buildings on top of the ground; and normalized Digital Surface Model (nDSM), which provides the height of features sitting above the ground (Esri, 2018b). For the parameters, I kept all of the defaults. Cell size: 1.58. Classify noise: true. Minimum height: -5 feet. Maximum height: 3000 feet. Processing extent: default. First time las: false.

Creating 3D trees. After extracting the elevation layers, I created the multipatch layer of trees by following the Local Government 3D Basemap tasks for "Publishing Schematic Local Government Scene," which walked me through the steps to use the "Vegetation Extraction" tool to create a layer of multipatch 3D schematic trees using the LAS dataset and building footprint layer. For the parameters, I kept all of the defaults. Point spacing: 2. Vegetation class codes: 1. Buffer distance: 3. Minimum canopy height: 12. Maximum canopy height: 90.

This process created a layer of multipatch trees throughout the city. The location, size and shape of the individual trees were not very accurate when compared to Google Street View photos of the area (Figure 4), but this layer of 3D trees suited my purposes—giving me an inventory of trees that I could then move and size as needed as I manually built the models for my 3D walking routes. To make this data-heavy layer easier to work with, for each walking route I selected all trees within a few blocks and created individual layer packages from those selections.

Figure 4. Sample GSV photo of route 1NS.

Source: Google Maps GSV.

Creating 3D buildings. The process for creating a layer of multipatch buildings city-wide was more involved. I followed the Local Government 3D Basemap solution "Publish Schematic Buildings" tasks, designed to create buildings with a Level of Detail 2 (LOD2) by adding elevation and height data to the building footprints. (The solution classifies LOD1 as basic shapes; LOD2 as schematic with more nuance; LOD3 as realistic). I used the "Segment Roof Parts" task to create LOD2 buildings. For the parameters, I kept all defaults. Spectral detail: 12. Spatial detail: 12. Minimum segment size (in pixels): 214. Regularization tolerance: 3 meters. Segment flat roofs only: false.

I then used the "Extract Roof Form" task to segment the building footprints into more detailed roof forms, to add nuance to the building shapes. For the parameters, I kept all defaults. Minimum flat roof area: 250. Minimum slope roof area: 75. Minimum roof height 8. Simplify buildings: true. Simplify tolerance: 0.1. First time: false.

Those tasks gave me a city-wide layer of buildings with more refined roof forms, but the buildings were still 2D polygon features. To turn them into 3D multipatch features, I selected only the buildings within a few blocks of each walking route to be modeled, created a layer from each selection, then ran the "Layer 3D to Feature Class" tool to convert the polygons into multipatch features that could be used in the Shadow Impact Analysis solution.

I ended up with two multipatch layers for each walking route: a layer of trees and a layer of buildings. I used Save as Layer Package to export the layers, along with all data, for each route.

Editing the 3D Models of Walking Routes

I deployed the "ArcGIS Pro Shadow Impact Analysis" solution (Esri, 2019b), which includes a Check Shadows tool within a global scene and an Evaluate Shadows tool within a local scene. I chose to use the Check Shadows tool because it most closely suited my needs for simply displaying the shadows at a particular day and time. I added the tree and building layer packages to the global Check Shadows scene within the solution, creating separate ArcGIS Pro project files for each study area (Figure 5). Since the Check Shadows tool uses a global scene, the layers were projected on the fly to the WGS 1984 coordinate system. (Figures of all study areas and walking routes are included in Appendix 1 and 2.)

Figure 5. Area 1 with both walking routes.

In this view, four GIS layers are activated: the separate building and tree layers for routes 1EW and 1NS.

This became my editing environment. Rather than rely on the accuracy of the tree and building placement and size from LiDAR, I considered those layers to be an inventory of multipatch features that I could manually move, size and shape as needed—following photos from Google Street View as a reference—to create 3D versions of the walking routes to be studied.

To start editing a walking route, I activated the building and tree layers for that route only, and used the OpenStreetMap basemap as an on-screen guide, moving the buildings and trees to align with the basemap's street line to serve as the curb—to give myself a straight line to follow. I manually edited every individual building and tree feature along the entirety of each walking route using the Move, Scale and Rotate editing tools within ArcGIS Pro. I only edited the buildings and trees on the sidewalks and properties along the south sides of the EW routes and the west sides of the NS routes (Figure 6). As a source for information about where to place and how to size the features, I used Google Street View photos of the walking routes.

Figure 6. Walking route 1 EW.

Blue indicates the area within which I edited the buildings and trees.

Verifying the Modeled Walking Routes

To ground-truth the models, I went to each route in the field and measured and mapped shade in 3-meter segments, with the help of research assistants using a measuring wheel, for the entire length of all 16 routes. I also took photos at points along each route, to use as a source to help me investigate discrepancies when comparing the field tests to the models. I designated each 3-meter segment as either Shade or No Shade (Figure 7). If a segment was at least half shaded I counted it as Shade. For every route I calculated total meters shaded and not shaded, length of the longest gap in shade, and number of gaps 21 meters or more. I repeated the shade-mapping and calculation process for each route within the 3D models (Figure 8), modeling shade at the same day and time as each corresponding field test.

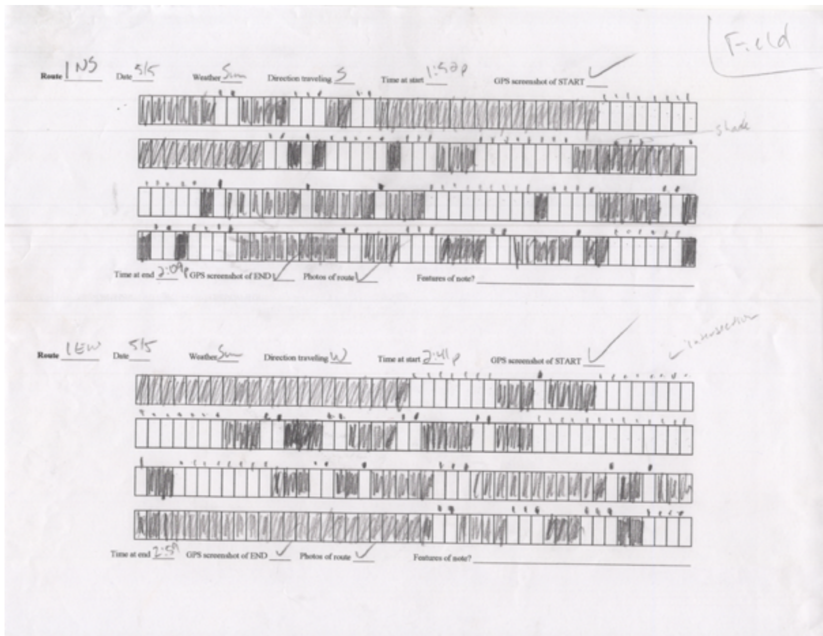


Figure 7. Shade map from field test for Area 1 routes.

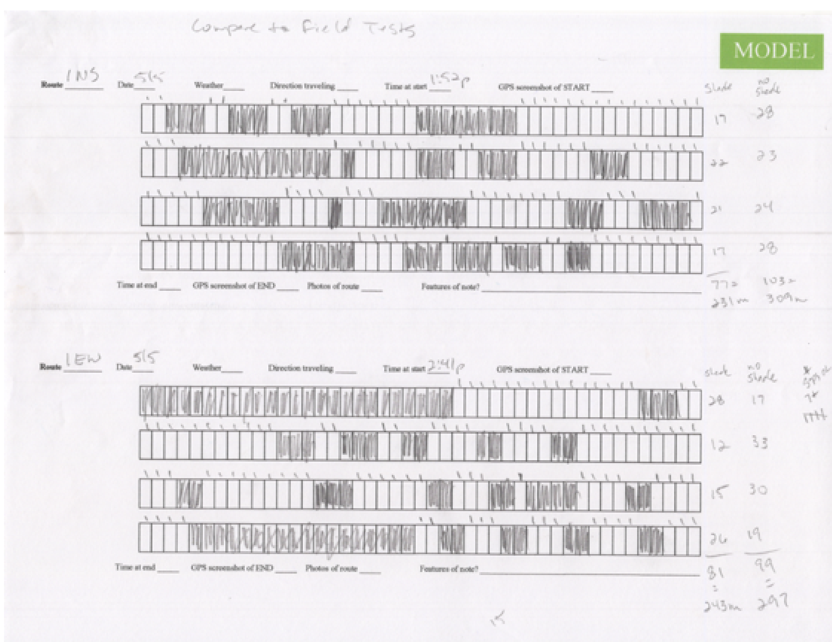


Figure 8. Shade map from model for Area 1.

To model shade in the Shadow Impact Analysis Solution, I used the Check Shadows tasks for creating a layer of sun positions for each day on which I conducted field tests. The parameters included selecting one of the building or tree layers as the input observer and setting the elevation, time zone, date and time. The tool automatically filled in parameters for the observer horizon distance, atmospheric pressure and temperature. I used the same process to create sun layers for each day I conducted field tests, on these dates in 2019: April 25, May 3, May 4, May 5, and May 14.

After creating the sun layer, the tasks walked me through setting the scene illumination by turning on Display Shadows in 3D, setting Light Contribution to 50, and setting the map to Map Time. Then I enabled time on the sun layer by setting Layer Time at "Each feature as a single time field," setting Time Field to Local Time; and setting the time zone at Pacific time with Daylight Saving Time enabled.

To measure and map the shade within the models, I activated the appropriate sun layer and set the time to match the time of the field test. This resulted in shadows cast in the model based on the sun position of that day and time. I used the ArcGIS Pro measuring tool, set to meters, and measured each stretch of sun and shade along each route. Again I created maps in 3-meter segments, and designated each segment as either Shade or No Shade. If a segment was at least half shaded I counted it as Shade.

I did the same calculations as the field tests—total meters shaded and not shaded, length of the longest gap in shade, and number of gaps 21 meters or more. I compared the field tests with the modeled routes to determine the accuracy of the models.

Comparison Process to Address Hypothesis 1

With calculations for both the field tests and the modeled shade in hand, I first compared the overall shade/no shade designations to determine how many meters differed between the field and the model. For example, route 1NS shown above (Figures 7 and 8): the field test showed 306 meters shaded, while the model showed 231 meters shaded—which means 75 meters differed out of 540 meters total, for an accuracy level (match rate) of 86%. For all routes, match rates for total shade ranged from a low of 85% (route 4NS) to a high of 100% (route 3NS), with a mean match rate of 91.6%. Results for all routes are included in the Appendix 4.

These results exceed Hypothesis 1 where I predicted at least 75% accuracy. However, upon further analysis, total percent accuracy is not all that revealing as a comparison tool. To use route 1NS as an example: it was 86% accurate for total shade, but the length of the longest gap measured in the model was double the length of the longest gap measured in the field (54 meters and 27 meters respectively). Likewise, the number of gaps ≥ 21 meters was double in the model when compared with the field test (the model had six gaps of ≥ 21 meters, while the field test had three). Many of the routes had similar results (even the route with a 100% match rate for total shade).

So I calculated an accuracy level/match rate for each measure of the distribution of shade— longest gap and number of gaps ≥21 meters—and combined all of those to determine a mean match rate for distribution as a whole. Unlike with total shade, these distribution measurements don’t combine to add up to a standard total. So I used the highest measurement of each as a proxy for the total, and then did the same calculation to determine a percent accuracy level (e.g., if the field test showed a longest gap of 30 meters but the model showed a gap of 60 meters, the match rate would be 50%). Match rates for the measurements of the gaps ranged from 0 to 100%, with a mean of 70.4%.

The lower levels of accuracy for the distribution measurements led me to conclude that the models would be most useful if I took the time to correct them to match their corresponding field tests. I investigated all discrepancies to determine whether the errors in the models were the result of old or bad GSV data or the result of imperfect modeling on my part. For example, for route 5EW, the field test showed shade where the model showed none (Figure 9). After investigating, I saw that the modeled trees on the inside of the sidewalk were either too far or too small. I went back to GSV to determine the best way to correct it. That 5EW photo also revealed another challenge when trying to model the real world: the curb tree in the background of the left photo (Figure 9 left side) is broader than the one in the model, and is leaning over the sidewalk. I changed the modeled tree to be broader, but it's difficult to capture the effects of a tree that leans. In those cases I moved the tree inside a bit, to bring more of its shadow to the inside.

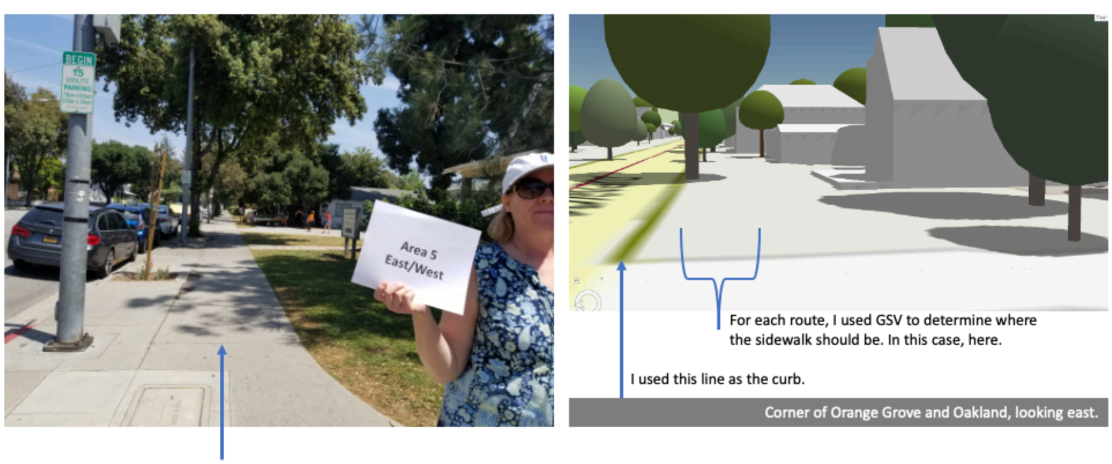


Figure 9. Example of verification process in action, using Route 5EW.

On left, a photo from the field test. On right, the same area as originally modeled.

Overall, there were only two instances of a GSV photo not matching reality—trees had been cut down since the GSV photos were taken (two photos involving three trees). All other discrepancies were the result of the difficulty in mirroring reality within a 3D model. I discuss the modeling challenges and the causes of the errors in more detail in the Discussion section.

I then re-modeled every walking route to make all routes match their field tests as much as possible, and created new shade maps for the revised models. While they do now match on paper, it's important to note that there are still many qualitative factors at play: I often had to make judgment calls regarding where shade was coming from; accuracy might vary depending on the time of day and year as the sun moves across the sky; and even my own measuring process in the field and in the model is subject to human error and variability.

Mapping and Measuring the Routes for Analysis

Once the models were as accurate as possible, I modeled, mapped and calculated shade for each route for two different times of day: August 31, 2018 at 12 p.m. and 2:30 p.m. PDT. I chose August 31 because, based on historical daily normal temperatures, it is the ninth and last day of the stretch of hottest days of the year for Pasadena (U.S. Climate Data, 2019). I chose 12 p.m. because it's the middle of the day and the sun is high, and 2:30 p.m. because the sun is still high but has moved across the sky—and it's still a time of day that seniors might be out and about. It's also a time of day where the objects casting shadows on the routes are within the perimeter of the areas modeled. To model times of day and times of year when the shadows are long, the perimeter of the total area modeled would have to be wider to capture all obstructions.

For each route and for both times of day, I calculated number of meters shaded and not shaded, total percent shaded and not shaded, length of the longest gap in shade, and the number of gaps ≥ 21 meters. To calculate minutes walking with no shade, I used a walking speed of 0.75 meters per second (45 meters/minute) and divided total meters without shade by 45 to get minutes of no shade. The speed of 0.75 meters per second (m/s) is the pace for someone elderly and low-income (Zaninotto, Sacker, & Head, 2013).

Chapter III

Results

I introduced the results for Hypothesis 1 in the previous section, in my summary of the accuracy of the models when compared to the field tests. I hypothesized that modeled maps would be at least 75% accurate when compared to measurements from the field. Accuracy levels for total shade ranged from 85% to 100%, with a mean of 91.6%. Accuracy levels for distribution of shade (longest gap and number of gaps ≥21 meters) ranged from 0 to 100% with a mean match rate of 70.4% (only one measurement scored 0% and just three total scored below 50%). The average of both means is 81%, leading me to conclude that Hypothesis 1 is supported, with the observation that total shade matched more closely than distribution of shade.

In this section I focus on Hypotheses 2 and 3, both of which are related to possible associations among the variables of risk and access to shade. I started with a general analysis using Excel to address Hypothesis 2, and then conducted statistical analysis using linear mixed effects models (LMM) to test Hypothesis 3.

General Analysis to Address Hypothesis 2

I hypothesized that routes in areas of higher heat-related risk would have less total shade than in areas of lower risk, high-risk areas would have longer gaps in shade, and people in high-risk areas would have to spend at least 10 minutes without shade walking to the nearest bus stop. Since total shade is used to calculate the time walking without shade (total meters with no shade divided by the walking speed mentioned earlier), "Minutes With No Shade" serves as a stand-in for both of those measures.

Right off the bat I can reject my hypothesis of spending at least 10 minutes without shade, as the highest number of minutes measured was 8.87 for 7NS. Total minutes in shade is partly dependent upon the total length of a walk—the routes studied were limited to 540 meters, which is a 12-minute walk based on the walking speed used here. That route distance was determined by the size of the smallest census tract in order to keep the walking routes fully contained within a tract. Still, within a walk that lasts 12 minutes, pedestrians along mid-income route 7NS spend nearly three-fourths (74%) of their time unshaded at noon on one of the hottest days of the year. Pedestrians on lower-income route 8EW spend almost the same time (8.6 and 8.7 minutes, nearly three-fourths) in direct sun at both times of day.

To examine the rest of the hypothesis, I defined high risk as study areas with lower per-capita income, a higher number of households with someone age 65 or over living alone, and a higher number of households with no access to a vehicle. I did a visual examination of the data using Excel, to see how lower-risk areas compared to higher-risk areas for each of the measurements, and to see if there were any obvious trends in how the three predictor variables relate to the various measurements of access to shade.

No clear trends emerge among the predictor variables. The highest number of minutes of no shade occur in study areas of both higher income and lower income (Figure 10); and in areas of both higher and lower numbers of households with no access to a vehicle (Figure 11).

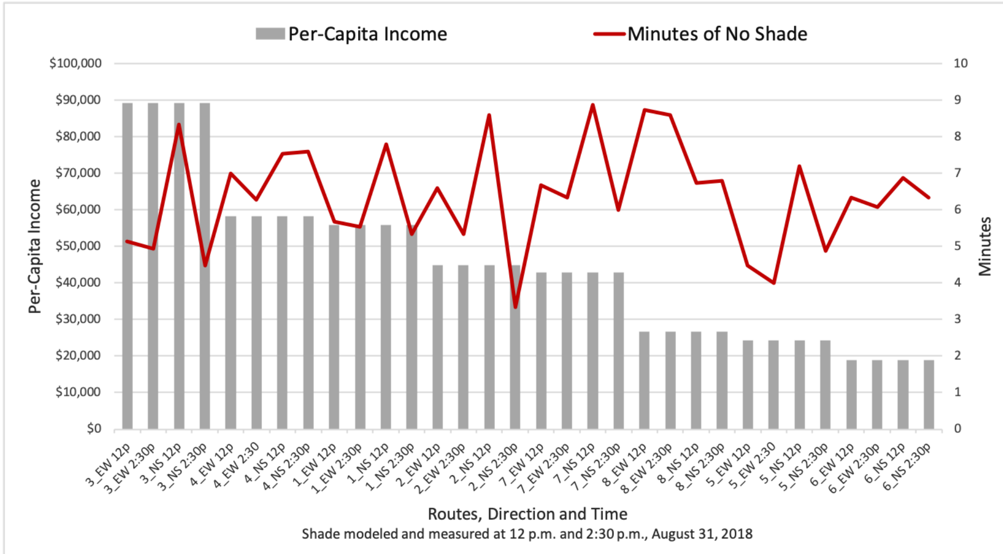


Figure 10. Minutes of no shade, per-capita income.

Shade data by author. Income data: U.S. Census Bureau ACS 2016 5-Year Estimates.

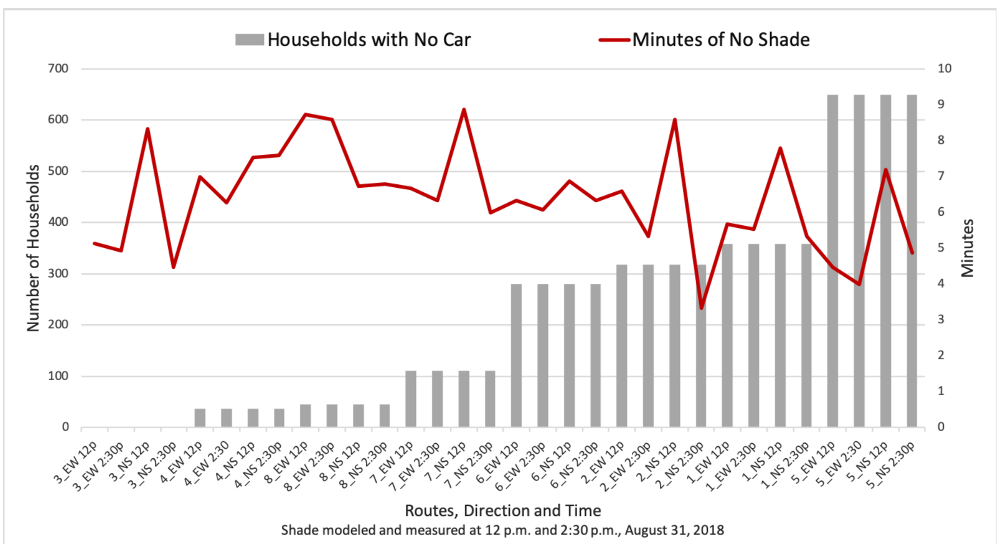


Figure 11. Minutes of no shade, households with no car.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

The same is true for areas of both lower and higher numbers of households with someone age 65 living alone. Although, in that case, the lower risk areas (with fewer older people living alone) don't have any scores toward the lowest end of the scale of minutes without shade (Figure 12).

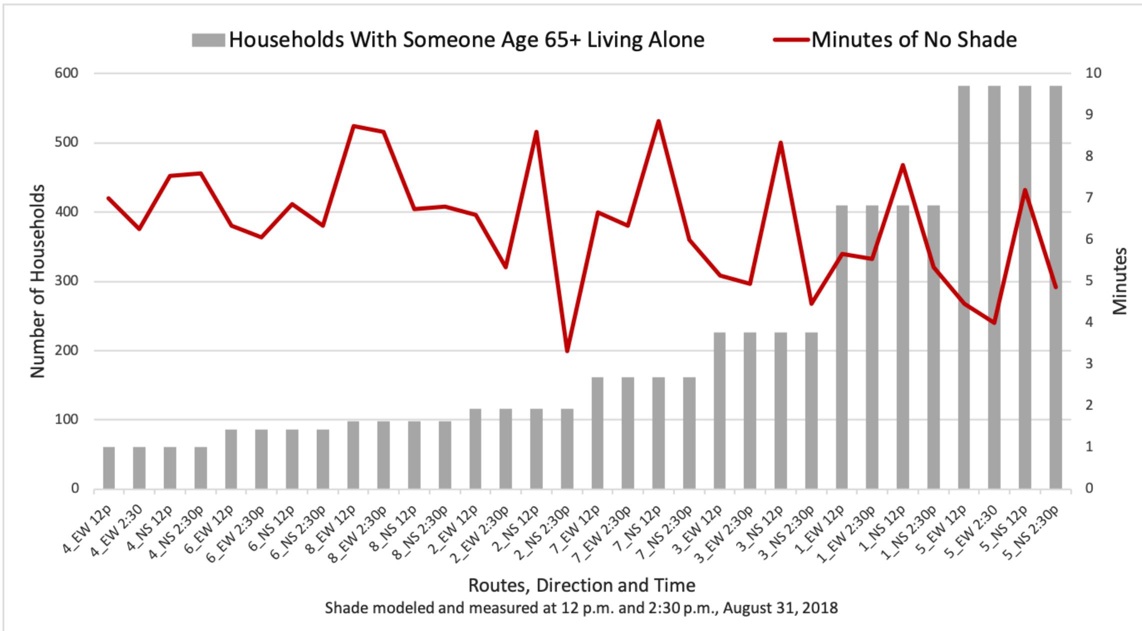


Figure 12. Minutes of no shade, households with 65+ living alone.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

For the longest gap in shade and the number of gaps, there are no strong trends but there are a few notable differences. The three lowest income levels have shorter longest gaps than those in the higher income areas, though they still have gaps that exceed 60 meters (Figure 13 and Appendix 5). The two routes with the lowest numbers of gaps ≥21 meters occur in the areas with lower incomes (Figure 14 and Appendix 5).

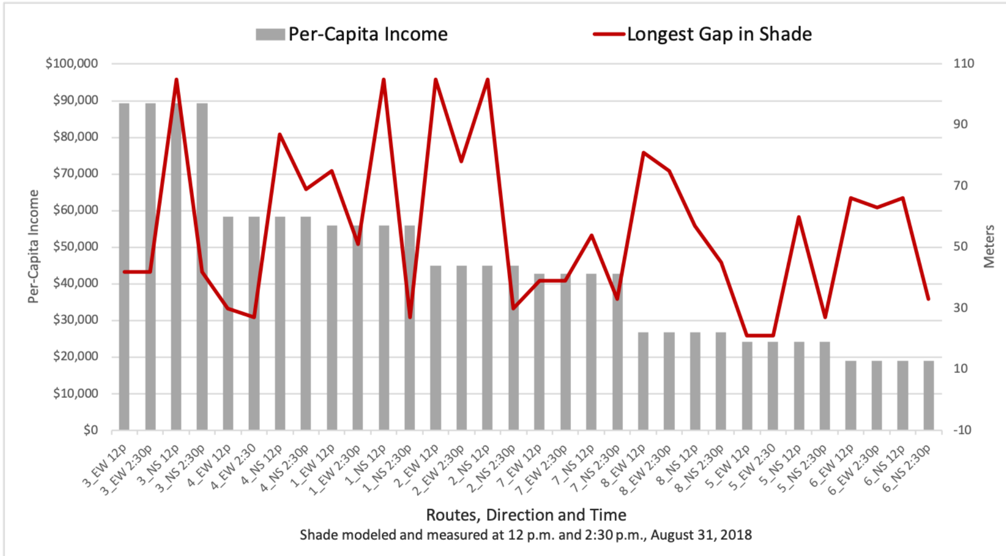


Figure 13. Longest gap in shade, per-capita income.

Shade data by author. Income data: U. S. Census Bureau ACS 2016 5-Year Estimates.

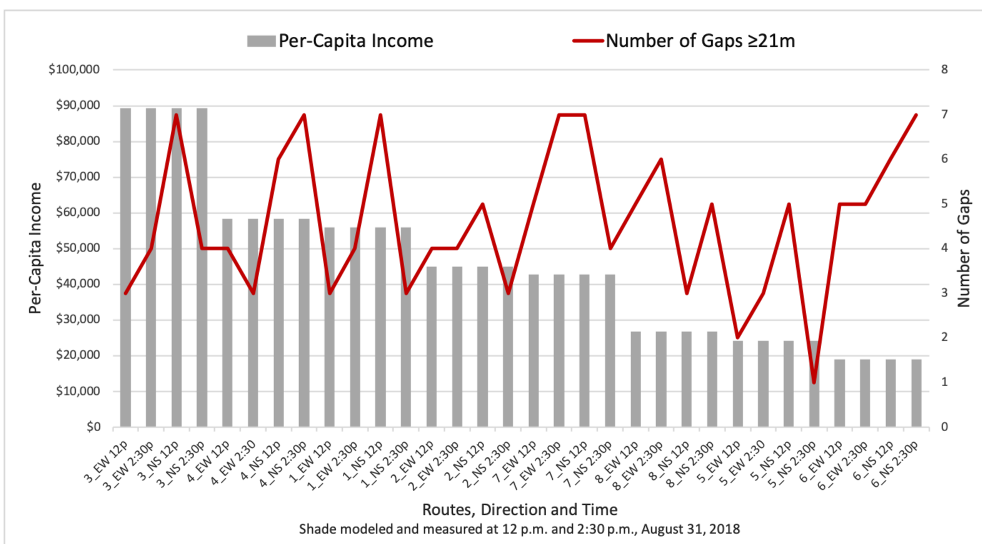


Figure 14. Number of gaps ≥ 21 meters, per-capita income.

Shade data by author. Income data: U. S. Census Bureau ACS 2016 5-Year Estimates.

Under the conditions of risk described earlier, study area 5 is the area of highest total risk when considering all three predictor variables combined, while study area 4 is the area of lowest total risk (Figure 15). I charted and examined those two areas against minutes with no shade and longest gap in shade. Again I failed to demonstrate my predicted association between the risk factors and access to shade. In fact, the area of highest risk had less time without shade and shorter gaps in shade than the area of lowest risk. This was true at both times of day and in both directions (Figures 16 and 17).

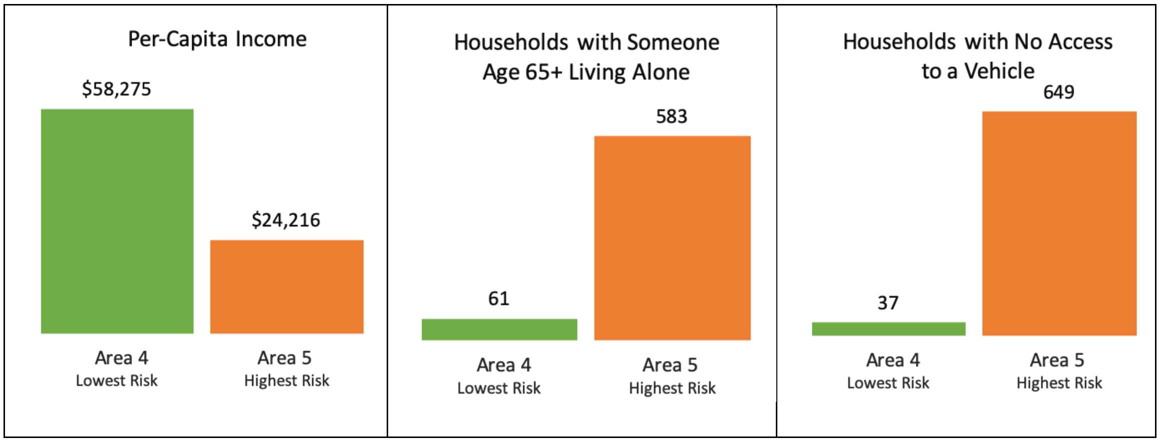


Figure 15. Variables that determined areas of lowest and highest risk.

Data: U. S. Census Bureau ACS 2016 5-Year Estimates.

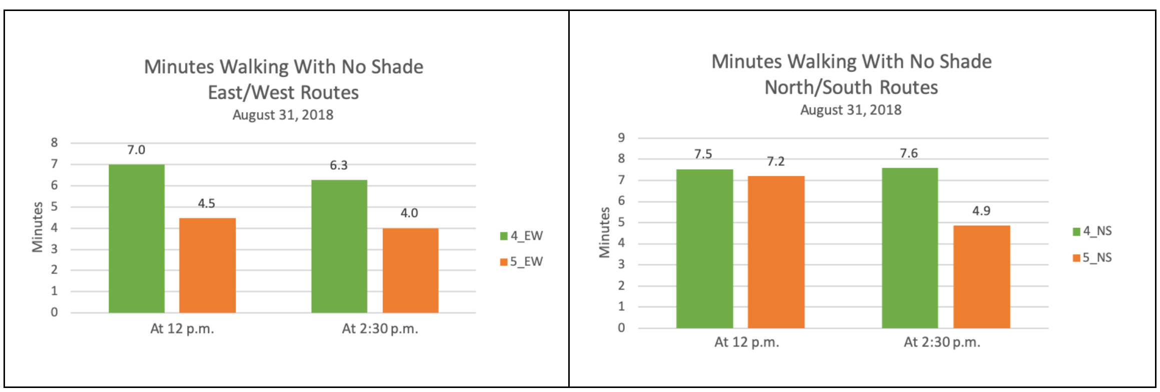


Figure 16. Minutes of no shade in areas of lowest and highest risk.

Shade data by author. Green represents lowest risk, orange is highest risk.

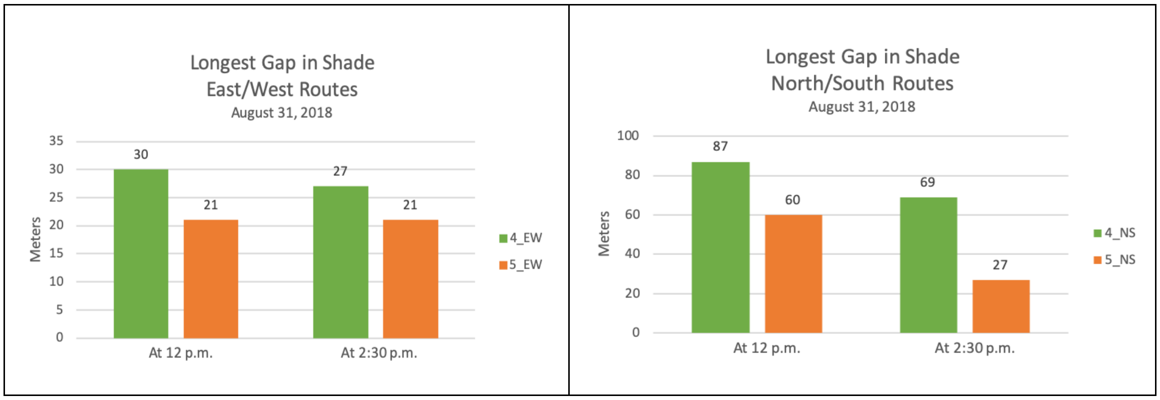


Figure 17. Longest gap in areas of lowest and highest risk.

Shade data by author. Green represents lowest risk, orange is highest risk.

Statistical Analysis to Address Hypothesis 3

I conducted statistical analysis to address Hypothesis 3, which states that the quantified shade maps will reveal that income is the variable most closely associated with total shade, distribution of shade, and time spent without shade. In other words, lower income will correlate positively with lower access to shade.

I have 16 total walking routes, each observed:

- at two different times of day (12 p.m. and 2:30 p.m.),
- with three time-variant outcomes as response variables (minutes of no shade, longest gap in shade, and number of gaps ≥21 meters), and
- three time-invariant predictors (per-capita income, households with someone ≥65 living alone, and households with no access to a vehicle).

The data are non-independent in a few ways: outcomes at the two time points are clustered within each route, and the response variables are correlated (e.g., a route with less overall shade might be more likely to have a longer gap or more gaps overall).

To control for the nesting by route, and for the direction of the route and time of the shade, I used linear mixed effects models (LMM). I used R version 3.6.0 (R Core Team, 2019) and RStudio version 1.2.1335 (RStudio Team, 2018). To estimate LMMs I used the R Package "lme4," version 1.1-21 (Bates, Maechler, Bolker, & Walker, 2015). To visualize quantities of interest from the LMMs I used the R Package "effects," version 4.1-1 (Fox & Weisberg, 2019). I received considerable help and guidance for this analysis from senior data scientist Steven Worthington, Ph.D., manager of data science services for the Institute for Quantitative Social Science at Harvard University.

The specification of the first LMM included Income (natural log), Age65Alone, NoCar, Time (noon and mid, for 12 p.m. and 2:30 p.m., respectively), and Direction (EW and NS) as fixed effects. Random effects included random intercepts grouped by route. I used that model for Minutes of No Shade (Figures 18 and 19).

```
MinutesLog = lmer(MinutesNoShade ~ log_Income + Age65Alone + NoCar +
        Time + Direction + (1|Route), data = shade)
```

```
> summary(MinutesLog)
Linear mixed model fit by REML ['lmerMod']
Formula: MinutesNoShade ~ log_Income + Age65Alone + NoCar + Time + Direction +      (1 | Route)
   Data: shade

REML criterion at convergence: 116.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0191 -0.4210 -0.0721  0.7822  1.8610

Random effects:
 Groups   Name        Variance Std.Dev.
 Route    (Intercept) 0.01126  0.1061
 Residual             1.28267  1.1325
Number of obs: 32, groups:  Route, 16

Fixed effects:
              Estimate Std. Error t value
(Intercept) 15.5121321  6.0778328   2.552
log_Income  -0.8699354  0.5664253  -1.536
Age65Alone  -0.0002452  0.0021696  -0.113
NoCar       -0.0034669  0.0020738  -1.672
Timenoon     1.2958337  0.4004165   3.236
DirectionNS  0.5625000  0.4039170   1.393

Correlation of Fixed Effects:
            (Intr) lg_Inc Ag65Al NoCar  Timenn
log_Income  -0.997
Age65Alone   0.529 -0.549
NoCar       -0.682  0.679 -0.843
Timenoon    -0.033  0.000  0.000  0.000
DirectionNS -0.033  0.000  0.000  0.000  0.000
>
```

Figure 18. Summary of LMM model for minutes no shade.

Screen shot from R version 3.6.0.

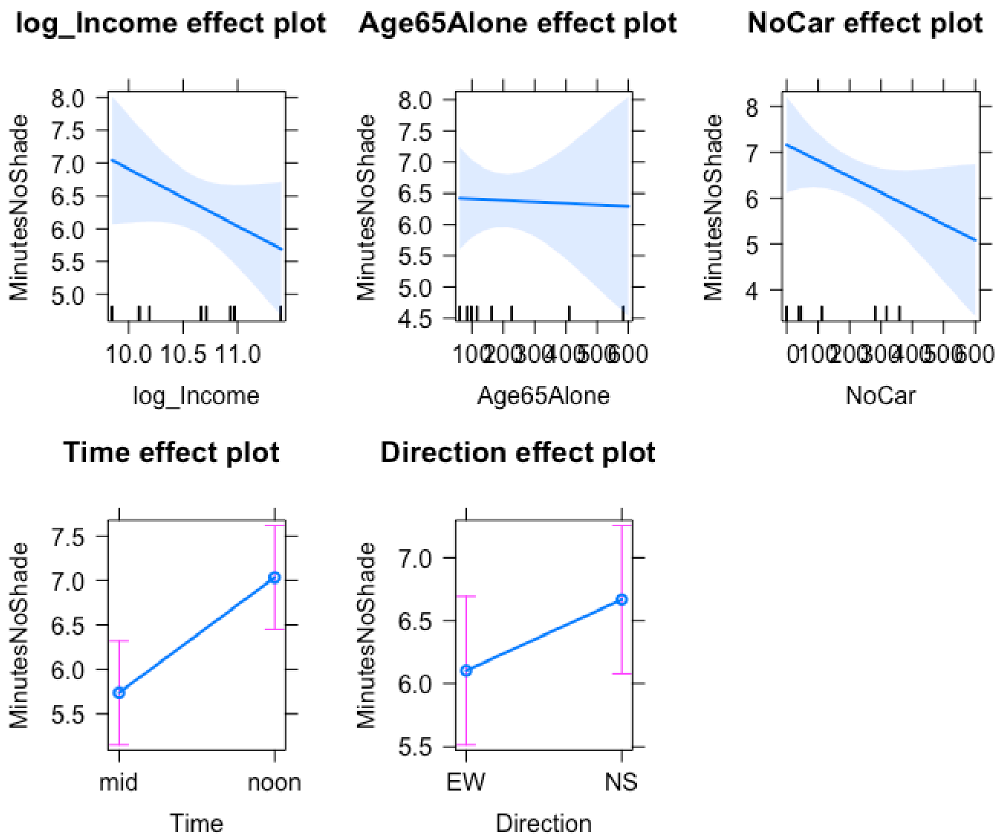


Figure 19. Plots of LMM for minutes of no shade.

Plots provided by R Package "effects" version 4.1-1.

I used the same LMM model to model Longest Gap and Number of Gaps ≥21m (summaries and plots are included in Appendix 6):

LongGap2 = lmer(LongestGap ~ log_Income + Age65Alone + NoCar + Time + Direction + (1|Route), data = shade)

Gap21 = lmer(GapCount21 ~ log_Income + Age65Alone + NoCar + Time + Direction + (1|Route), data = shade)

Among income, age and car, there were no statistically significant results for any of the three initial models. Next, I modeled 3-way interactions for MinutesNoShade, interacting Income with Time and Direction:

MinutesInteract = lmer(MinutesNoShade ~ log_Income * Time * Direction +

Age65Alone + NoCar + (1|Route), data = shade)

The 3-way interaction was not statistically significant (Figures 20 and 21).

```
> MinutesInteract = lmer(MinutesNoShade ~ log_Income * Time * Direction + Age65Alone + NoCar + (1|Route), d
ata = shade)
> summary(MinutesInteract)
Linear mixed model fit by REML ['lmerMod']
Formula: MinutesNoShade ~ log_Income * Time * Direction + Age65Alone +      NoCar + (1 | Route)
   Data: shade

REML criterion at convergence: 101.4

Scaled residuals: 
     Min       1Q   Median       3Q      Max 
-1.78869 -0.47918 -0.00586  0.48250  1.76292 

Random effects:
 Groups   Name        Variance Std.Dev.
 Route    (Intercept) 0.2134   0.4620  
 Residual             0.9086   0.9532  
Number of obs: 32, groups:  Route, 16

Fixed effects:
                                  Estimate Std. Error t value
(Intercept)                      2.020e+01  9.199e+00   2.196
log_Income                      -1.272e+00  8.630e-01  -1.474
Timenoon                        -3.609e-01  1.040e+01  -0.035
DirectionNS                      1.954e-01  1.156e+01   0.017
Age65Alone                      -2.452e-04  2.195e-03  -0.112
NoCar                           -3.467e-03  2.098e-03  -1.653
log_Income:Timenoon              7.570e-02  9.799e-01   0.077
log_Income:DirectionNS          -4.595e-02  1.089e+00  -0.042
Timenoon:DirectionNS            -1.470e+01  1.471e+01  -1.000
log_Income:Timenoon:DirectionNS  1.548e+00  1.386e+00   1.117

Correlation of Fixed Effects:
            (Intr) lg_Inc Timenn DrctNS Ag65Al NoCar  lg_I:T l_I:DN Tm:DNS
log_Income  -0.999                                                        
Timenoon    -0.565  0.567                                                 
DirectionNS -0.628  0.630  0.450                                          
Age65Alone   0.354 -0.364  0.000  0.000                                   
NoCar       -0.456  0.451  0.000  0.000 -0.843                            
lg_Incm:Tmn  0.565 -0.568 -0.999 -0.449  0.000  0.000                     
lg_Incm:DNS  0.627 -0.631 -0.449 -0.999  0.000  0.000  0.450              
Tmnn:DrctNS  0.400 -0.401 -0.707 -0.636  0.000  0.000  0.706  0.636       
lg_In:T:DNS -0.399  0.401  0.706  0.636  0.000  0.000 -0.707 -0.636 -0.999
> 
```

Figure 20. 3-way interaction: minutes with income, time, direction.

Screen shot from R version 3.6.0.

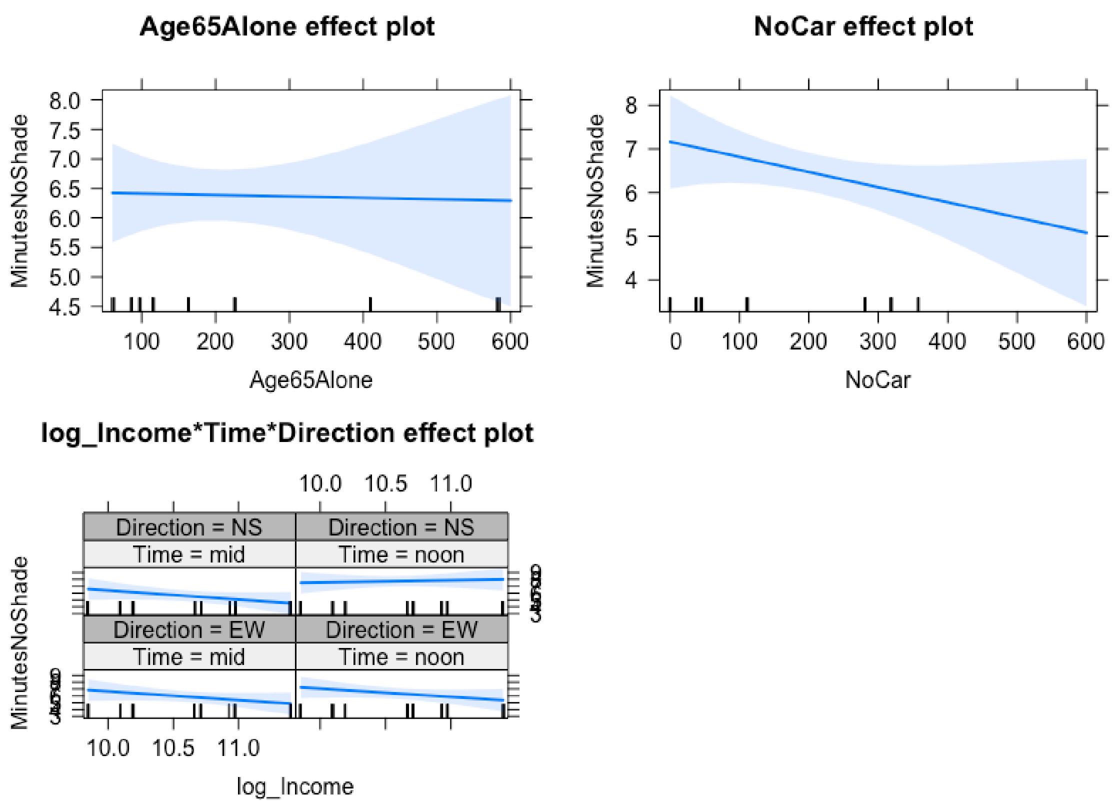


Figure 21. 3-way interaction: minutes with income, time, direction.

Plots provided by R Package "effects" version 4.1-1.

I tried a simplified model with a 2-way interaction for MinutesNoShade, interacting Income with Time (summary and plots are included in Appendix 6):

Minutes2way = lmer(MinutesNoShade ~ log_Income * Time + Direction + Age65Alone + NoCar + (1|Route), data = shade)

The 2-way interaction was not statistically significant. Based on this analysis, there does not appear to be an association between income and access to shade.

Exploring Minutes Without Shade

All routes experienced minutes of no shade ranging from a low of 3.33 minutes for mid-income route 2NS at 2:30 p.m., to a high of 8.87 minutes for mid-income route 7NS at 12 p.m. (Figure 22). Five routes experienced eight minutes or more without shade: highest-income 3NS at 12 p.m., lower-income 8EW at 2:30 p.m., mid-income 2NS at 12 p.m., lower-income 8EW at 12 p.m., and mid-income 7NS at 12 p.m. That group includes both directions and both times of day, though only one instance at 2:30 p.m.

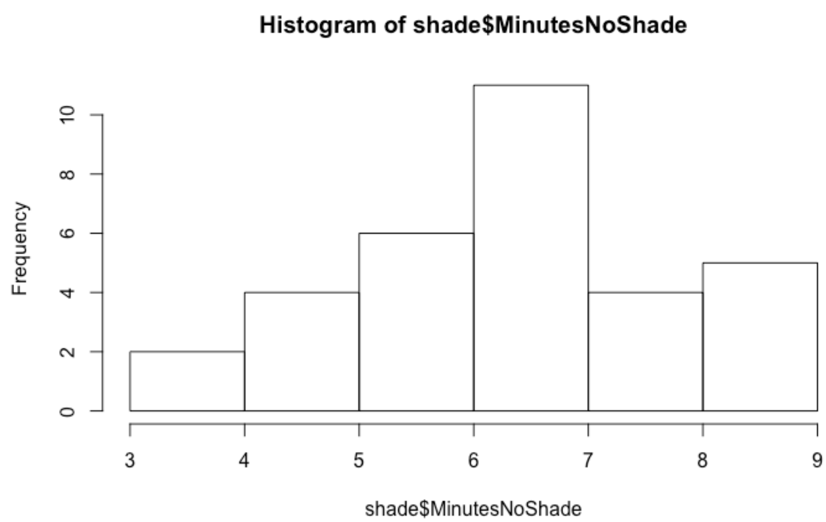


Figure 22. Histogram for minutes with no shade.

Screen shot from R version 3.6.0.

Both NS and EW routes are represented at both ends of the chart: lowest minutes and highest minutes. Two different NS routes (2NS and 3NS) have big differences in minutes from 12 p.m. to 2:30 p.m. For 2NS, minutes of no shade is 8.6 at noon (third highest overall) and then drops to 3.33 mid-afternoon (lowest overall). Route 3NS makes a similar drop though not as wide, going from 8.33 to 4.46 minutes from noon to mid-afternoon. The same is true for both routes for longest gap: both have the longest gap overall at 105 meters at noon, but gaps of just 30 meters and 42 meters (for 2NS and 3NS, respectively) when measured at mid-afternoon. Based on field observations, both of those routes have taller obstructions on the west side of their streets: 2NS has buildings in a dense part of downtown, while route 3NS has taller trees in a hilly part of town.

Exploring Gaps in Shade

The distribution of the longest gap measurements ranged from 21 meters to 105 meters. There were four routes with longest gaps of 105 meters (all in areas of mid- to highest levels of income): routes 1NS, 2NS, 3NS and 2EW, all at 12 p.m. The distribution of number of gaps ≥21m ranged from 1 to 7. There were six routes with the highest number of gaps, three at 12 p.m. and three at 2:30 p.m.: 1NS at 12 p.m., 3NS at 12 p.m., 7NS at 12 p.m., 6NS at 2:30 p.m., 7EW at 2:30 p.m., and 4NS at 2:30 p.m. (half of those are in areas of higher income and half are in areas of lower income).

A route that is 50% unshaded will be experienced differently if the sun is felt in one long gap or if it is distributed in smaller gaps throughout the entire route. I plotted minutes against longest gap and number of gaps (Figures 23 and 24). Obvious trends emerged for the routes with highest unshaded minutes: as the length of gap lowers toward that end of the chart, the number of gaps rises.

One trend looks surprising at first glance: 1NS at 12 p.m. and 3NS at 12 p.m. both have highest length of gap (105 meters) and highest number of gaps (7), yet don’t have the highest number of minutes without shade. So I pulled out the shade maps to see why. On the route with the most minutes unshaded (7NS at 12 p.m.), the patches of shade breaking up the sun are much smaller: its longest patch of shade is only 18 meters, and there are only two that are that length. In comparison, the other two routes have patches of shade that are 24 meters, 30 meters, 36 meters and 45 meters—providing more relief between those long stretches of sun.

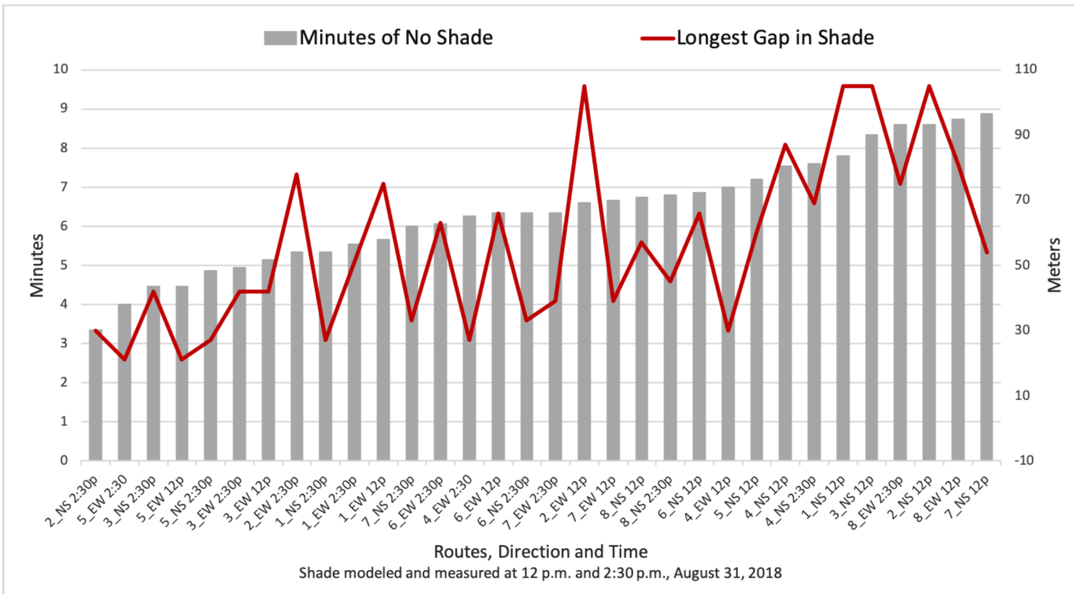


Figure 23. Minutes of no shade, longest gap in shade.

Shade data by author.

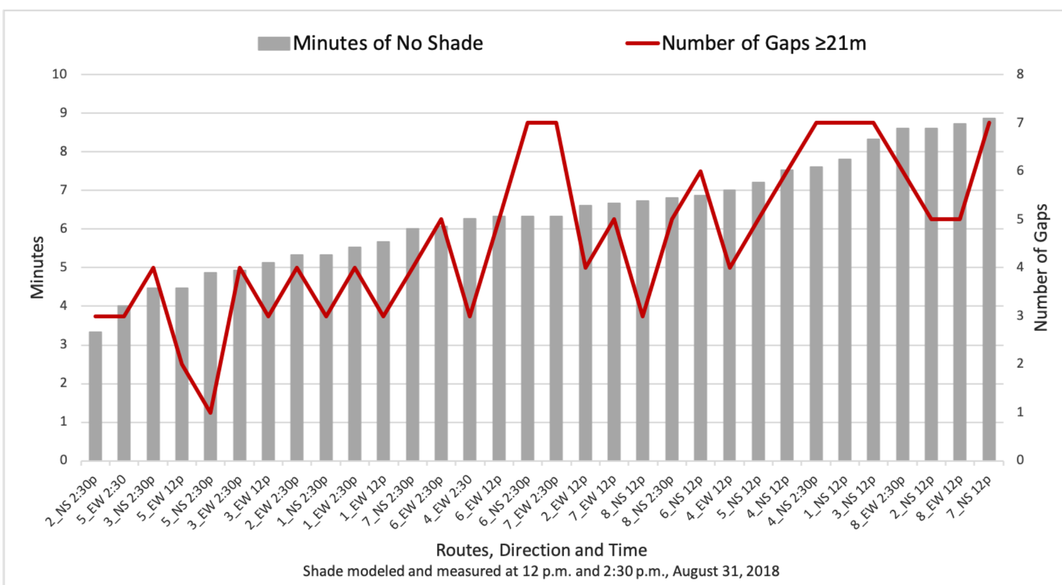


Figure 24. Minutes of no shade, number of gaps ≥21m or more.

Shade data by author.

Chapter IV

Discussion

I will begin this section with a discussion of the analysis and results, and of the selection of response variables used in the study. Then, since a main goal of this research was to propose a new method for quantifying shade, I will also discuss some of the challenges of the techniques I have presented to help others who are interested in quantifying sidewalk shade.

Identifying Risk and Dangerous Time in Sun

Both Hypothesis 2 and Hypothesis 3 attempted to predict which areas of the city would have the least access to shade—asserting that areas of higher heat-related risk would have less shade than areas of lower risk, and that income would be most closely associated with access to shade. Neither was supported by the research.

The comparison of the study areas of highest risk (area 5) and lowest risk (area 4) offers some clues as to why those predictions didn't play out across the city. Observations from the field revealed that low-risk study area 4 is in a residential neighborhood with wide streets and houses set far back from the sidewalk, meaning the only possible sources of sidewalk shade are the trees along the sidewalk. High-risk study area 5 is likewise mostly residential but also has some two-story commercial buildings and is generally more dense with all houses and buildings closer to the sidewalk and closer to each other. In fact, population density in area 5 is more than three times higher than it is in area 4 (U.S. Census Bureau, 2016). Area 5 routes benefited from the access to occasional building shade and from the density of trees closer together.

I chose variables that would help me assess time without shade and distribution of shade along walking routes, as both contribute to a pedestrian's thermal discomfort. After studying the results, I can see that time without shade would be difficult to interpret on its own—without the accompanying measures of distribution. A total of eight minutes without shade would be felt much differently all at once versus 30 seconds at a time. In fact, of the variables studied, longest gap seems to be the one most directly and reliably associated with potential pedestrian discomfort.

With that in mind, I examined the data to see which routes had more long gaps. Route 8EW had three gaps of 60 meters or more at noon and two gaps of 60 meters or more at 2:30 p.m. As the only route with multiple ≥60m gaps at both times of day, 8EW might arguably be considered the least-comfortable route studied. But here's why that designation is interesting and why the assessment of access to shade must be approached with careful thought: 8EW does not subject pedestrians to the single longest gap (8EW longest gaps are 81 meters at noon and 75 meters at 2:30 p.m., while other routes recorded a gap of 105 meters). All of the longest gaps (105 meters) occurred in the areas with higher incomes, while the EW route in Area 5— the area of highest combined risk and second-lowest income level—registered longest gaps of just 21 meters at both noon and mid-afternoon. That's likely why the routes in area 5 also register three of the five lowest number of minutes without shade, ranging from 4 minutes to 4.9 minutes.

So, one of the challenges of quantifying shade will be in the identification of variables to be studied. For any future studies, that will likely depend on the purpose of the study and the design of the research. For example, for walking routes, long gaps in shade are significant; for someone studying access to shade at bus stops or other locations where people stand in one place, minutes of no shade would be more meaningful.

The Challenges of Quantifying Shade

The comparison and correction process gave me insights that might be helpful for others who want to use GIS and/or GSV to help model and map sidewalk shade.

The process of creating the 3D models of the walking routes was labor-intensive and time consuming. With 16 routes of 540 meters each, I manually placed, sized and shaped trees and buildings along a total of 8.64 kilometers (5.4 miles) of sidewalk and the areas surrounding the properties along the sidewalks. Once I discovered that the distribution of shade would only be a useful comparison if I fixed all the routes to match the field tests, that meant that I then had to go back and revise every model accordingly. I did not begin this project with any experience in 3D modeling, so it’s possible that those with more experience would have an easier time working with the 3D data and creating the models.

One of the factors making the modeling process challenging was the need to estimate tree height and crown width. That process could be made easier if cities included those measurements in their tree inventories, for those that are able to maintain such inventories. The city of Pasadena maintains a GIS dataset, but the only size-related variable it includes is trunk diameter (City of Pasadena, 2019).

The Reliability of GSV as a Source of Data

There were only two instances when a GSV photo showed incorrect information: a tree that appeared in the GSV photo did not appear in the field, presumably because it had been cut down. The majority of the corrections I had to make involved inaccurate modeling on my part: incorrect placement, sizing or shaping of the trees; or trees from the background that I had missed the first time around. That said, there were a handful of challenges in working with GSV, related to the perspective of the GSV camera and from my decision to use the basemap line as a guide for the curb. I will give an overview of the challenges faced and lessons learned.

Building placement. Route 1NS introduced me to the challenge inherent in my decision to use the basemap line as stand-in for the curb. The basemaps are not necessarily accurate in terms of street width and curb placement. As I edited Route 1NS I saw that I had modeled the buildings too far from the curb (Figure 25). I corrected this for every route, moving buildings closer to the curb and placing them according to GSV.

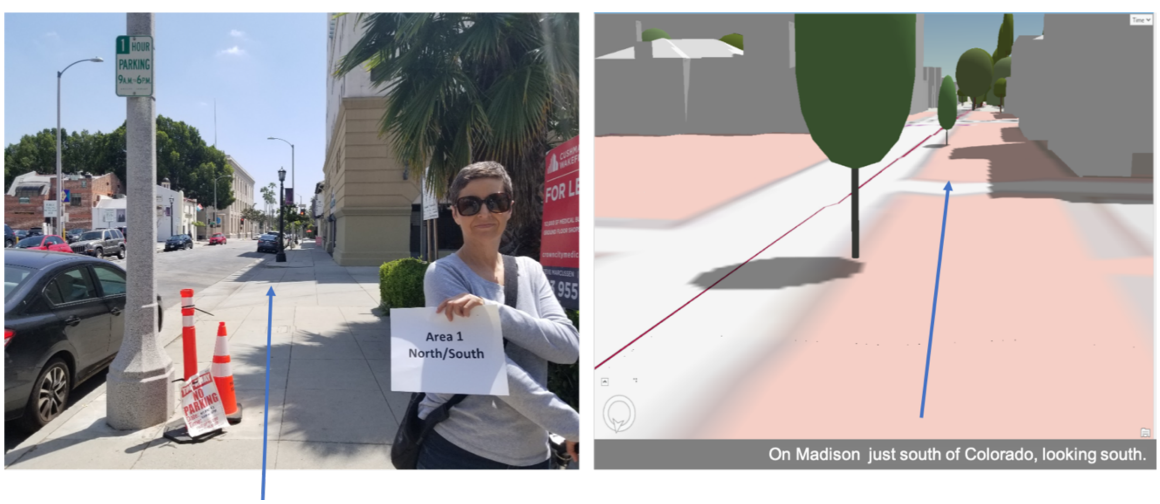


Figure 25. Example of building placement discrepancy.

The only discrepancy I couldn't correct. For Route 2NS, the model showed an extra three meters of building shade from the church on the southwest corner of Holly and Marengo (Figure 26). There was no way to correct it without changing the building shape. So I left a 3-meter discrepancy in this modeled route, which affected the longest gap at the day and time of the field test but is not a factor on the day and times mapped for analysis—since the disputed segment falls within a stretch of sun on August 31 at 12 p.m. and within a stretch of shade at 2:30 p.m. (rather than defining the edge of either stretch).

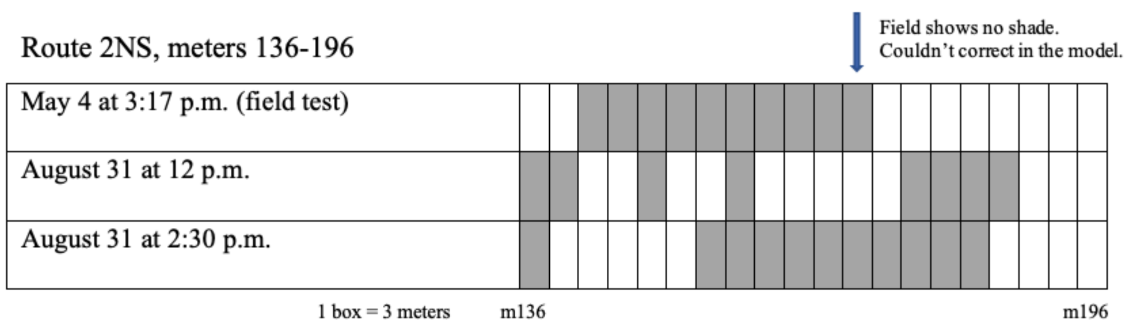


Figure 26. The only discrepancy I couldn't correct.

These boxes represent meters 136-196 of route 2NS (all rows represent the same stretch of sidewalk). Shade data by author.

Scale and perspective. Route 4NS illustrates the challenge of perspective when using GSV as a visual source. From the GSV photo it appeared that a few small trees sat back away from the sidewalk (Figure 27), so that is how I modeled them (Figure 28). As I corrected all routes, I noticed several instances of similar modeling mistakes due to the challenge of relying on GSV photos that have fixed angles and distances out of the user's control.

Figure 27. GSV of 4NS, to demonstrate perspective.

Source: Google Maps GSV.

Figure 28. Model of 4NS, to demonstrate perspective.

Once I compared the 4NS field test to the model, I could see that the field test showed shadows where the model had none. Upon investigation of the photos I took in the field (Figure 29) and another examination of the GSV photos, I could see that my interpretation of the GSV photo was wrong. I corrected the model accordingly.

Figure 29. Field photo of 4NS, to demonstrate perspective.

Schematic shapes of trees. Pasadena has many tall palm trees that were difficult to model correctly because the schematic tree shapes don't allow it (Figure 30). The ArcGIS Pro scaling abilities did not allow me to stretch the height of the tree without also stretching the width of the crown. So it was hard to model those tall palms accurately.

Figure 30. Route 7NS example of palm trees.

Source of photo on the left: Google Maps GSV.

The geometric shapes of the trees also made it impossible to capture dappled shade in the model—it was either solid shade or no shade. In the field tests, I usually counted dappled shade as solid shade, though in one instance on Route 6EW the shade was so dappled (Figure 31) I didn't count it, and it showed up as a discrepancy when comparing the field test to the modeled shade. I went back and created a gap of shade in the model, since GSV shows a gap in the otherwise relatively connected canopy.

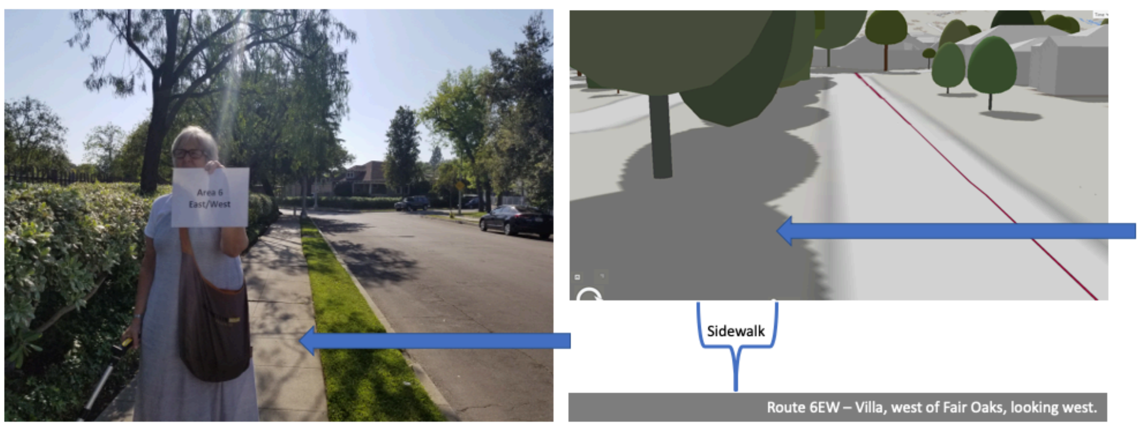


Figure 31. Route 6EW field test and model, dappled shade discrepancy.

Shade from beyond the perimeter. On Route 6NS, the field test revealed shade in the intersection of Esther and Raymond that didn't show up in my original map of the modeled shade. Field photos confirmed that the intersection is shaded from something coming from beyond the property on the northwest corner (Figure 32). Another look at the GSV photos confirmed that there is a big tree on Esther just west of the intersection that is large enough to cast shadow across the intersection (Figure 33). I hadn't paid attention to that tree in my first pass at creating the model. I added the tree to account for the shade in my corrected model.

Figure 32. Field photo of 6NS, beyond the perimeter.

Figure 33. GSV photo of 6NS, beyond the perimeter.

Source of photo: Google Maps GSV.

The advantage of field photos. Having photos from the field tests helped when trying to determine where shade is coming from when it shows up in the field test but not in the model. On route 7EW the field test showed patches of small shade (Figure 34). GSV showed an oddly shaped tree, next to the curb, which I thought provided the shade (Figure 35). But after consulting the field test photo, I could see that the tree in fact was not giving shade to the sidewalk, but the small patches of shade were coming from bushes on the inside of the sidewalk. I corrected the model accordingly (Figure 36).

Figure 34. Field photo 7EW, advantage of field photos.

Figure 35. GSV photo 7EW, advantage of field photos.

Blue arrow points to oddly shaped tree. Orange arrow points to actual source of shade: small trees on the inside of the sidewalk. Source of photo: Google Maps GSV.

Figure 36. Model screen shot 7EW, advantage of field photos.

Trees removed. GSV keeps historical photos, and sometimes changes the photo the user sees, even along the same stretch of road. That's how I noticed that I built the model for this patch of route 8EW using a January 2018 photo, then as I was correcting the model the photo switched to an April 2019 photo from further back (Figure 37). Two trees had been taken down between the time of the two photos. I removed the trees based on the field test and the more recent GSV photo.

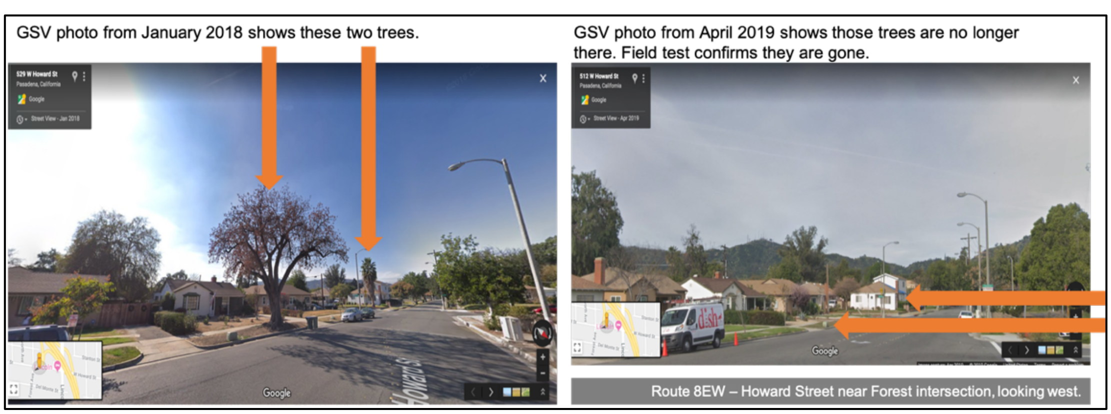


Figure 37. Route 8EW, example of trees removed.

Source of both photos: Google Maps GSV.

Conclusions

It is possible to quantify sidewalk shade using GIS as a tool for 3D modeling and using Google Street View (GSV) as a source of information about the environment. That said, I would be skeptical of any 3D models that weren't ground-truthed in some way, since the process of placing, sizing and shaping the individual trees is qualitative and dependent upon the perspective of the person doing the modeling. In determining pedestrian access to shade on walking routes across a city, the analysis should include measurements that capture both total shade and distribution of shade—as neither fully captures the pedestrian experience alone.

The question of determining where vulnerable people spend a dangerous amount of time in direct sun will depend on how vulnerability is defined. In this study, the area of highest risk had more access to shade than the area of lowest risk, and there did not appear to be an association between income and access to shade.

Research Limitations

The results presented in this study are subject to several limitations.

The accuracy of the 3D models cannot be guaranteed 100% and will vary for others depending on the area studied and the skills of the individual creating the models. As discussed earlier, the 3D modeling process depended on a number of qualitative factors and decisions made about the placement, size and shape of the trees in the models. While I took the time to make all 16 models match their field tests, that doesn't necessarily mean they are 100% accurate. First, in making the modeled shade maps match the field shade maps, I had to make decisions along the way to determine what was casting shadows in the field. I may or may not have always been right. Second, since shade changes based on date and time, it's possible there were elements beyond the perimeter of where I modeled that didn't affect shade during the time of the field test (which is what I used to ground-truth the model) but would in fact cast a shadow at a different time of day or time of year. This limitation could be addressed by conducting multiple field tests for each route, at various times of day and times of year—to provide more data for ground-truthing by increasing the likelihood of capturing field measurements for all angles of shade at various sun positions.

GSV turned out to be a mostly accurate source of information about buildings and trees (with only two instances of the photos not matching reality). But this finding is specific to Pasadena, CA, and doesn't necessarily reflect the accuracy of GSV as a source for other cities. Accuracy depends on how recent the photos are, and how often the area changes. The accuracy related to tree crown width might also depend on the time of year when the GSV photos are taken, if deciduous trees are common in the area.

The study only covered 16 walking routes in one U.S. city. The method of quantifying shade can be applied elsewhere, with the caveats mentioned above. But because shade and urban design are site-specific, the comparisons of the areas of higher risk and lower risk, along with the analysis of whether or not income is associated with access to shade, are specific to the areas studied. Finally, the small sample size limited the statistical power in the analysis.

Questions for Further Research

With a method for mapping, measuring and analyzing shade in hand, a logical next step would be to see if absence of shade is associated with pedestrian safety and/or pedestrian activity. It would be interesting to quantify shade to use it in studies of public health—for example, using data about the time and location of emergency response calls during heat waves to see if there are correlations with absence of sidewalk shade. For cities trying to persuade residents to use transit, it would be useful to study whether or not absence of shade at bus stops is correlated with ridership. Shade could be factored into walkability scores using measurements of minutes without shade and longest gap in shade, for neighborhoods in hot climates—comparing walking routes of standardized lengths across neighborhoods.

In order to keep the scope of the study realistic, I limited my study of access to shade to three predictor variables related to income, age and access to a car. Future studies could benefit from including some of the known health risks in heat waves, like heart disease and obesity.

Appendix 1

Study Areas

Following are the areas modeled and studied. Each study contains two walking routes: east/west and north/south. All figures by author.

Figure 38. Study area 1.

Figure 39. Study area 2.

Figure 40. Study area 3.

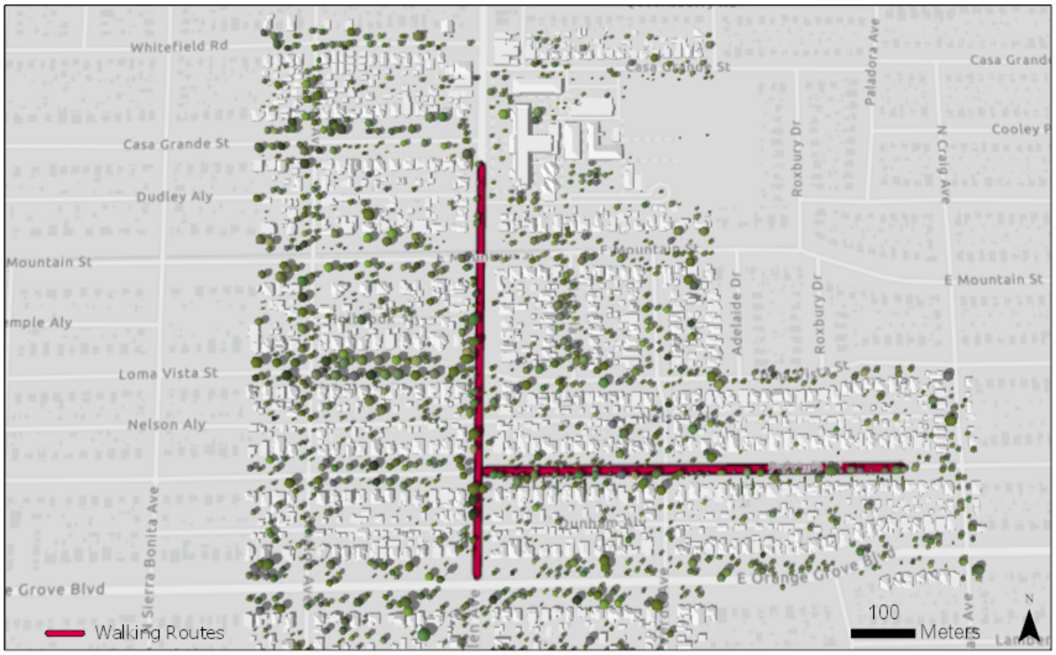


Figure 41. Study area 4.

Figure 42. Study area 5.

Figure 43. Study area 6.

Figure 44. Study area 7.

Figure 45. Study area 8.

Appendix 2

Walking Routes

Following are the individual walking routes modeled and studied. The blue indicates the perimeter within which I edited buildings and trees. All figures by author.

Figure 46. Route 1 EW.

Figure 47. Route 1 NS.

Figure 48. Route 2 EW.

Figure 49. Route 2 NS.

Figure 50. Route 3 EW.

Figure 51. Route 3 NS.

Figure 52. Route 4 EW.

Figure 53. Route 4 NS.

Figure 54. Route 5 EW.

Figure 55. Route 5 NS.

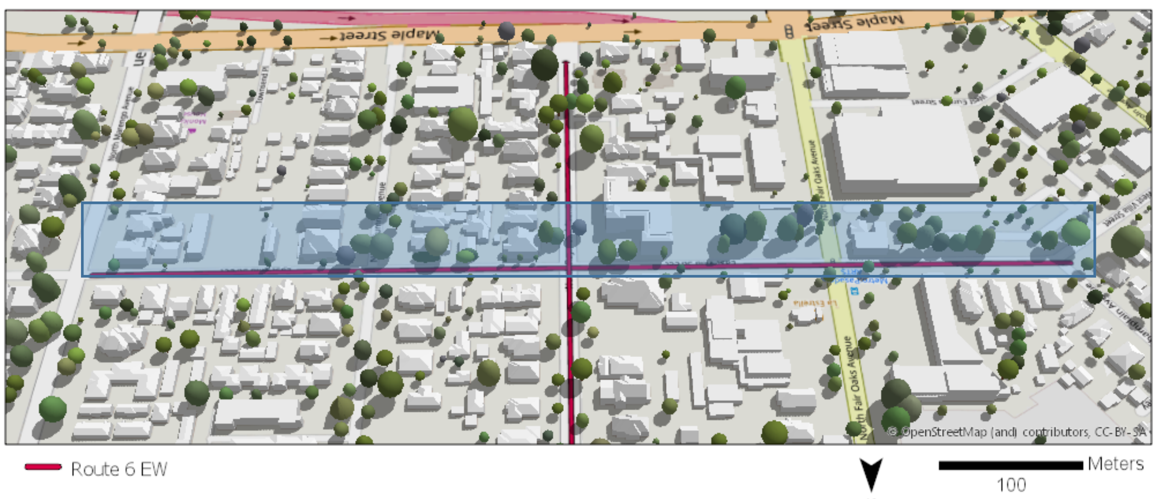


Figure 56. Route 6 EW.

Figure 57. Route 6 NS.

Figure 58. Route 7 EW.

Figure 59. Route 7 NS.

Figure 60. Route 8 EW.

Figure 61. Route 8 NS.

Appendix 3

ArcGIS Command Screenshots

Create LAS Dataset (Data Management Tools)

Completed Tuesday, February 26, 2019 at 8:45:15 AM

Parameters

Input Files	'C:\Users\kim\OneDrive\Desktop\Thesis Shapefiles\LIDAR Pasadena - from NOAA 2 - all classes'
Output LAS Dataset	C:\Users\kim\OneDrive\Documents\ArcGIS\Packages\LocalGovernment3DBasemaps (11)_87909B47-E3FA-4FAF-964D-3F506656F237\p20\LIDAR_Pas_ALL_CLASSES.lasd
Include Subfolders	NO_RECURSION
Surface Constraints	
Coordinate System	PROJCS['NAD83(NSRS2007) / California zone 5 (ftUS)',GEOGCS['NAD83(NSRS2007)',DATUM['NAD83_National_Spatial_Reference_System_2007',SPHEROID['GRS 1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic_2SP'],PARAMETER['false_easting',6561666.667],PARAMETER['false_northing',1640416.667],PARAMETER['central_meridian',-118.0],PARAMETER['standard_parallel_1',34.03333333333333],PARAMETER['standard_parallel_2',35.46666666666667],PARAMETER['latitude_of_origin',33.5],UNIT['Foot_US',0.3048006096012192]],VERTCS['NAVD88 height (ftUS)',VDATUM['North American Vertical Datum 1988'],UNIT['Foot_US',0.3048006096012192]]
Compute Statistics	COMPUTE_STATS
Store Relative Paths	RELATIVE_PATHS
Create PRJ For LAS Files	NO_FILES

Figure 62. Parameters used to create a LAS Dataset.

Screenshot from ArcGIS Pro.

Extract Elevation From LAS Dataset (LocalGovernmentScenes)

Completed Tuesday, February 26, 2019 at 9:05:35 AM

Parameters

Input LAS Dataset	LIDAR_Pas_ALL_CLASSES.lasd
Cellsize	1.58284456545358
Output raster	C:\Users\kim\OneDrive\Documents\ArcGIS\Packages\LocalGovernment3DBasemaps (11)_87909B47-E3FA-4FAF-964D-3F506656F237\p20\localgovernmentscenes.gdb\Lidar_Pas_ALL_CLASSES
Classify Noise	true
Minimum Height	-5 Feet
Maximum Height	3000 Feet
Processing Extent	DEFAULT
first_time_las	false
previous_las	LIDAR_Pas_ALL_CLASSES
dem_layer	Lidar_Pas_ALL_CLASSES_dtm_surface
dsm_layer	Lidar_Pas_ALL_CLASSES_dsm_surface
ndsm_layer	Lidar_Pas_ALL_CLASSES_ndsm_surface

Figure 63. Parameters used to extract elevation from LAS Dataset.

Screenshot from ArcGIS Pro.

VegetationExtraction (Vegetation)

Completed Tuesday, February 26, 2019 at 1:51:33 PM

Parameters

Input LAS dataset	LIDAR_Pas_ALL_CLASSES.lasd
Point spacing	2
Vegetation class codes	1
Building footprints	pasadena_buildings_Clip_inPro_Exported
Buffer distance	3
Minimum canopy height	12
Maximum canopy height	90
Ground Elevation Surface (DTM)	Lidar_Pas_ALL_CLASSES_dtm_surface
out_layer	C:\Users\kim\OneDrive\Documents\ArcGIS\Packages\LocalGovernment3DBasemaps (11)_87909B47-E3FA-4FAF-964D-3F506656F237\p20\localgovernmentscenes.gdb\Tree3D

Figure 64. Parameters used to create layer of multipatch trees.

Screenshot from ArcGIS Pro.

Segment Roof Parts (LOD2buildings)

Completed Tuesday, February 26, 2019 at 7:59:22 PM

Parameters

Building Footprints	pasadena_buildings_Clip_inPro_Exported
Elevation Surface (DSM)	Lidar_Pas_ALL_CLASSES_dsm_surface
Spectral Detail	12
Spatial Detail	12
Minimum Segment Size (In Pixels)	214
Regularization Tolerance	3 Meters
Segment Flat Roofs Only	false
Output Segmented Buildings	C:\Users\kim\OneDrive\Documents\ArcGIS\Packages\LocalGovernment3DBasemaps (11)_87909B47-E3FA-4FAF-964D-3F506656F237\p20\localgovernmentscenes.gdb\pasadena_buildings_Clip_inPro_SEGMENTED
layer	pasadena_buildings_Clip_inPro_SEGMENTED_segmented

Figure 65. Parameters used to create buildings, segment roof parts.

Screenshot from ArcGIS Pro.

ExtractRoofForm (LOD2buildings)

Completed Wednesday, February 27, 2019 at 11:19:26 AM

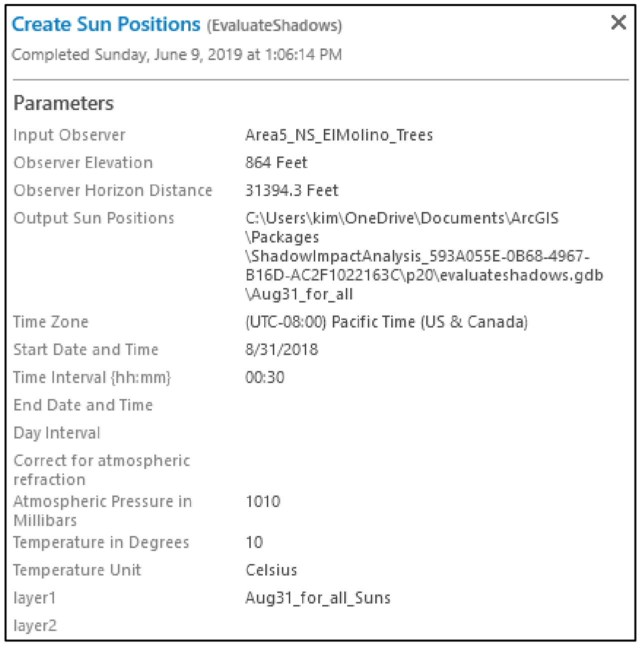
Parameters

Buildings	pasadena_buildings_Clip_inPro_SEGMENTED_segmented
Elevation Surface (DSM)	Lidar_Pas_ALL_CLASSES_dsm_surface
Ground Elevation Surface (DTM)	Lidar_Pas_ALL_CLASSES_dtm_surface
Normalized Elevation Surface (nDSM)	Lidar_Pas_ALL_CLASSES_ndsm_surface
Minimum Flat Roof Area	250
Minimum Slope Roof Area	75
Minimum Roof Height	8
Output Building Polygons	C:\Users\kim\OneDrive\Documents\ArcGIS\Packages\LocalGovernment3DBasemaps (11)_87909B47-E3FA-4FAF-964D-3F506656F237\p20\localgovernmentscenes.gdb\Pas_Buildings_LOD2
Simplify Buildings	true
Simplify Tolerance	0.1
layer1	Pas_Buildings_LOD2_roofform
first_time	false
previous_layer	pasadena_buildings_Clip_inPro_SEGMENTED_segmented

Figure 66. Parameters used to create more detailed roof forms.

Screenshot from ArcGIS Pro.

This screenshot for creating sun positions is just to serve as an example. These are the parameters used to create the sun layer for final analysis using August 31, 2018. I also created sun layers for all days on which I conducted field tests.



Create Sun Positions (EvaluateShadows)

Completed Sunday, June 9, 2019 at 1:06:14 PM

Parameters

Input Observer	Area5_NS_ElMolino_Trees
Observer Elevation	864 Feet
Observer Horizon Distance	31394.3 Feet
Output Sun Positions	C:\Users\kim\OneDrive\Documents\ArcGIS \Packages \ShadowImpactAnalysis_593A055E-0B68-4967-B16D-AC2F1022163C\p20\evaluateshadows.gdb \Aug31_for_all
Time Zone	(UTC-08:00) Pacific Time (US & Canada)
Start Date and Time	8/31/2018
Time Interval {hh:mm}	00:30
End Date and Time	
Day Interval	
Correct for atmospheric refraction	
Atmospheric Pressure in Millibars	1010
Temperature in Degrees	10
Temperature Unit	Celsius
layer1	Aug31_for_all_Suns
layer2	

Figure 67. Parameters used to create sun positions for August 31, 2018.

Screenshot from ArcGIS Pro.

Appendix 4

Comparisons of Field Tests to Modeled Shade

Each route was modeled on the day and time of its corresponding field test, then maps of field shade and modeled shade were compared to determine how accurately the models matched total shade, longest gap, and number of gaps ≥21 meters (Table 5).

Accuracy of meters shaded was calculated by taking the total meters of each route (540 meters) and subtracting the number of meters that differed (shown as Difference in the table), then dividing by the total meters to get percent accurate. For longest gap and # of gaps, accuracy was determined by using the same calculation, but since the Field and Model measurements don't combine to add up to a standard total, I used the largest measurement of each as a proxy for the total.

Table 5. Accuracy levels comparing field to models.

Route	Field	Model	Difference	Accuracy
1 EW				
Meters shaded	321m	243m	78m (out of 540)	86%
Longest gap in shade	45m	45m	0m	100%
# of gaps ≥ 21m	4	5	1 gap	80%
1 NS				
Meters shaded	306m	231m	75m	86%
Longest gap in shade	27m	54m	27m	50%
# of gaps ≥ 21m	3	6	3 gaps	50%

Route	Field	Model	Difference	Accuracy
2 EW				
Meters shaded	261m	306m	45m	92%
Longest gap in shade	114m	96m	18m	84%
# of gaps ≥ 21m	5	3	2 gaps	60%
2 NS				
Meters shaded	417m	438m	21m	96%
Longest gap in shade	36m	30m	6m	83%
# of gaps ≥ 21m	3	1	2 gaps	33%
3 EW				
Meters shaded	276m	258m	18m	97%
Longest gap in shade	42m	72m	30m	58%
# of gaps ≥ 21m	4	3	1 gap	75%
3 NS				
Meters shaded	321m	321m	0m	100%
Longest gap in shade	39m	51m	12m	76%
# of gaps ≥ 21m	5	3	2 gaps	60%
4 EW				
Meters shaded	255m	237m	18m	97%
Longest gap in shade	27m	18m	9m	67%
# of gaps ≥ 21m	5	0	5 gaps	0%
4 NS				
Meters shaded	231m	150m	81m	85%
Longest gap in shade	69m	81m	12m	85%
# of gaps ≥ 21m	5	4	1 gap	80%
5 EW				
Meters shaded	330m	264m	66m	88%
Longest gap in shade	24m	33m	9m	73%
# of gaps ≥ 21m	3	2	1 gap	67%
5 NS				
Meters shaded	339m	270m	69m	87%
Longest gap in shade	27m	21m	6m	78%
# of gaps ≥ 21m	2	2	0 gaps	100%

Route	Field	Model	Difference	Accuracy
6 EW				
Meters shaded	237m	270m	33m	94%
Longest gap in shade	111m	81m	30m	73%
# of gaps ≥ 21m	3	4	1 gap	75%
6 NS				
Meters shaded	234m	183m	51m	91%
Longest gap in shade	84m	60m	24m	71%
# of gaps ≥ 21m	6	6	0 gaps	100%
7 EW				
Meters shaded	243m	180m	63m	88%
Longest gap in shade	39m	63m	24m	62%
# of gaps ≥ 21m	7	7	0 gaps	100%
7 NS				
Meters shaded	267m	210m	57m	89%
Longest gap in shade	54m	60m	6m	90%
# of gaps ≥ 21m	5	7	2 gaps	71%
8 EW				
Meters shaded	135m	141m	6m	99%
Longest gap in shade	114m	54m	60m	47%
# of gaps ≥ 21m	5	8	3 gaps	63%
8 NS				
Meters shaded	240m	192m	48m	91%
Longest gap in shade	60m	51m	9m	85%
# of gaps ≥ 21m	4	7	3 gaps	57%

Data by author.

Appendix 5

Additional Data Charts

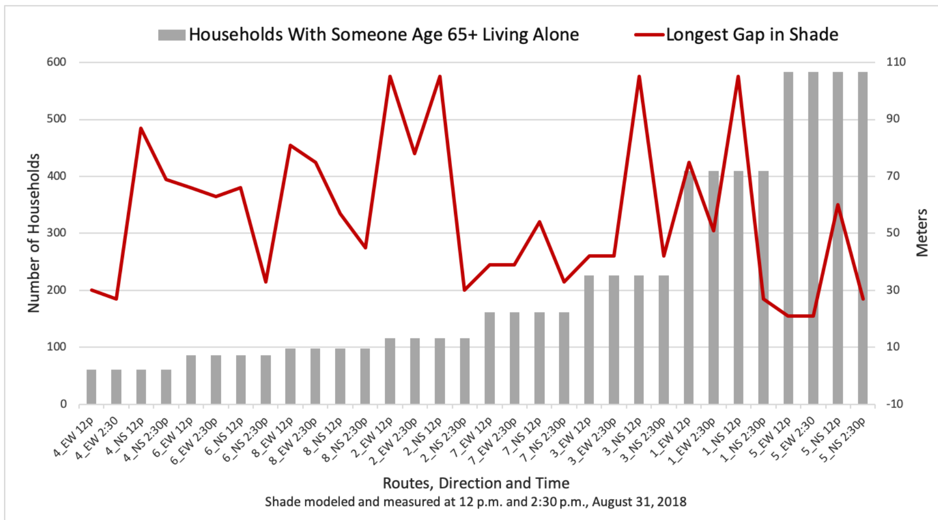


Figure 68. Longest gap, age 65+ living alone.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

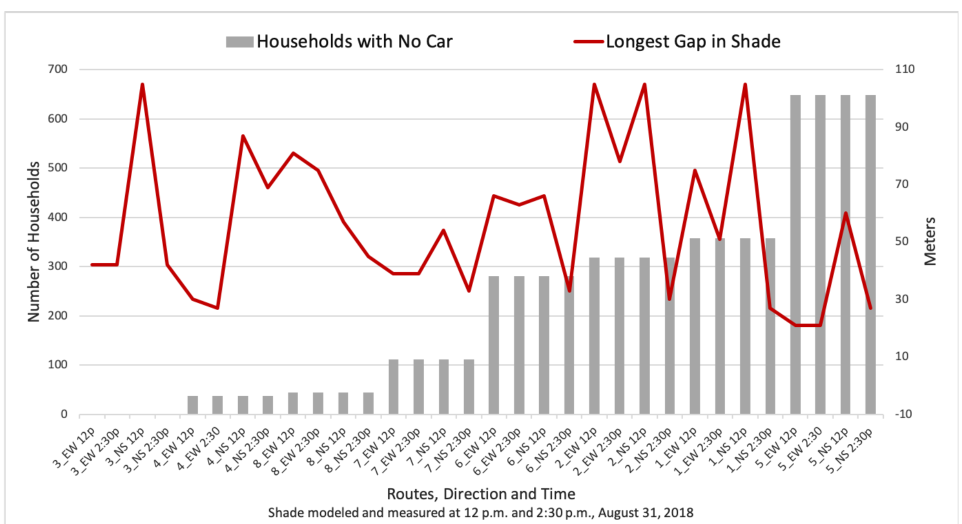


Figure 69. Longest gap, households with no car.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

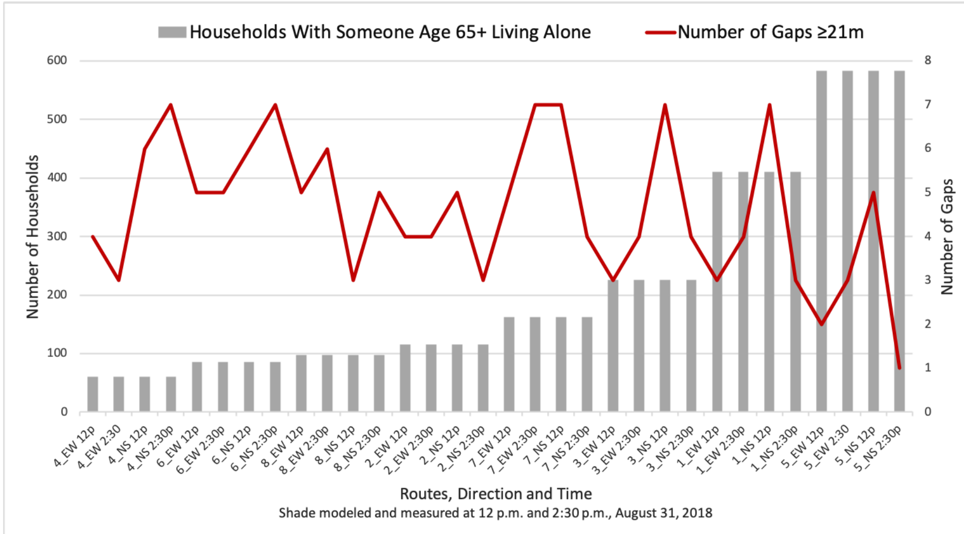


Figure 70. Number of gaps ≥21m, age 65+ living alone.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

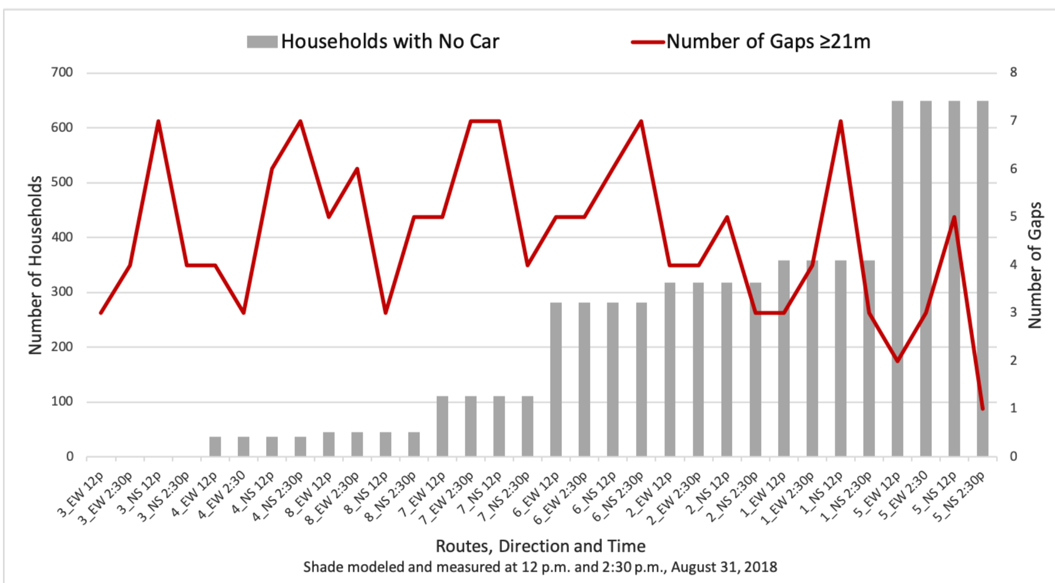


Figure 71. Number of gaps ≥21m, households with no car.

Shade data by author. Household data: U. S. Census Bureau ACS 2016 5-Year Estimates.

Appendix 6

Additional Statistical Analysis Summaries and Plots

For linear mixed effects models using R version 3.6.0 (R Core Team, 2019), RStudio version 1.2.1335 (RStudio Team, 2018), R Package "lme4," version 1.1-21 (Bates, Maechler, Bolker, & Walker, 2015), and R Package "effects," version 4.1-1 (Fox & Weisberg, 2019).

```
> LongGap2 = lmer(LongestGap ~ log_Income + Age65Alone + NoCar + Time + Direction + (1|Route), data = shad
e)
> summary(LongGap2)
Linear mixed model fit by REML ['lmerMod']
Formula: LongestGap ~ log_Income + Age65Alone + NoCar + Time + Direction +      (1 | Route)
   Data: shade

REML criterion at convergence: 270.7

Scaled residuals:
    Min      1Q  Median      3Q     Max 
-1.5233 -0.4711  0.1354  0.4041  1.6942 

Random effects:
 Groups   Name        Variance Std.Dev.
 Route    (Intercept) 219.2    14.80   
 Residual             344.1    18.55   
Number of obs: 32, groups:  Route, 16

Fixed effects:
              Estimate Std. Error t value
(Intercept) -121.94731  148.76507  -0.820
log_Income    15.98335   13.86836   1.153
Age65Alone    -0.08583    0.05312  -1.616
NoCar          0.05447    0.05078   1.073
Timenoon      24.75000    6.55839   3.774
DirectionNS    5.62500    9.88950   0.569

Correlation of Fixed Effects:
            (Intr) lg_Inc Ag65Al NoCar  Timenn
log_Income  -0.998                            
Age65Alone   0.529 -0.549                     
NoCar       -0.682  0.679 -0.843              
Timenoon    -0.022  0.000  0.000  0.000       
DirectionNS -0.033  0.000  0.000  0.000  0.000
>
```

Figure 72. Summary of LMM for longest gap.

Screen shot from R version 3.6.0.

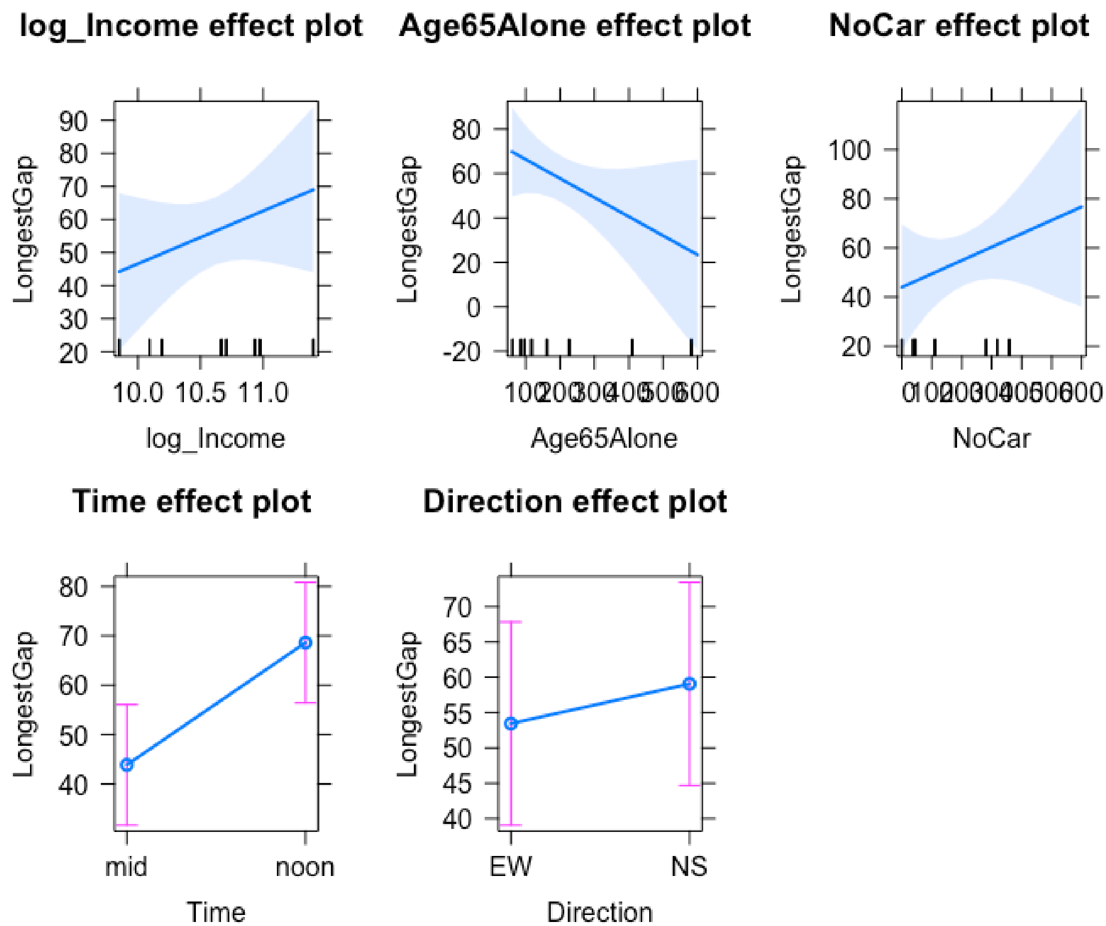


Figure 73. Plots of LMM for longest gap.

Plots provided by R Package "effects" version 4.1-1.

```
> Gap21 = lmer(GapCount21 ~ log_Income + Age65Alone + NoCar + Time + Direction + (1|Route), data = shade)
> summary(Gap21)
Linear mixed model fit by REML ['lmerMod']
Formula: GapCount21 ~ log_Income + Age65Alone + NoCar + Time + Direction +      (1 | Route)
   Data: shade

REML criterion at convergence: 130.3

Scaled residuals:
     Min       1Q   Median       3Q      Max
-2.08561 -0.61769  0.00195  0.65345  1.80845

Random effects:
 Groups   Name        Variance Std.Dev.
 Route    (Intercept) 0.003999 0.06324
 Residual             2.197937 1.48254
Number of obs: 32, groups:  Route, 16

Fixed effects:
             Estimate Std. Error t value
(Intercept) 10.574181   7.901533   1.338
log_Income  -0.531791   0.736380  -0.722
Age65Alone  -0.002051   0.002821  -0.727
NoCar       -0.002316   0.002696  -0.859
Timenoon     0.437500   0.524158   0.835
DirectionNS  0.812500   0.525111   1.547

Correlation of Fixed Effects:
            (Intr) lg_Inc Ag65Al NoCar  Timenn
log_Income  -0.997
Age65Alone   0.529 -0.549
NoCar       -0.682  0.679 -0.843
Timenoon    -0.033  0.000  0.000  0.000
DirectionNS -0.033  0.000  0.000  0.000  0.000
>
```

Figure 74. Summary of LMM for gaps ≥21 meters.

Screen shot from R version 3.6.0.

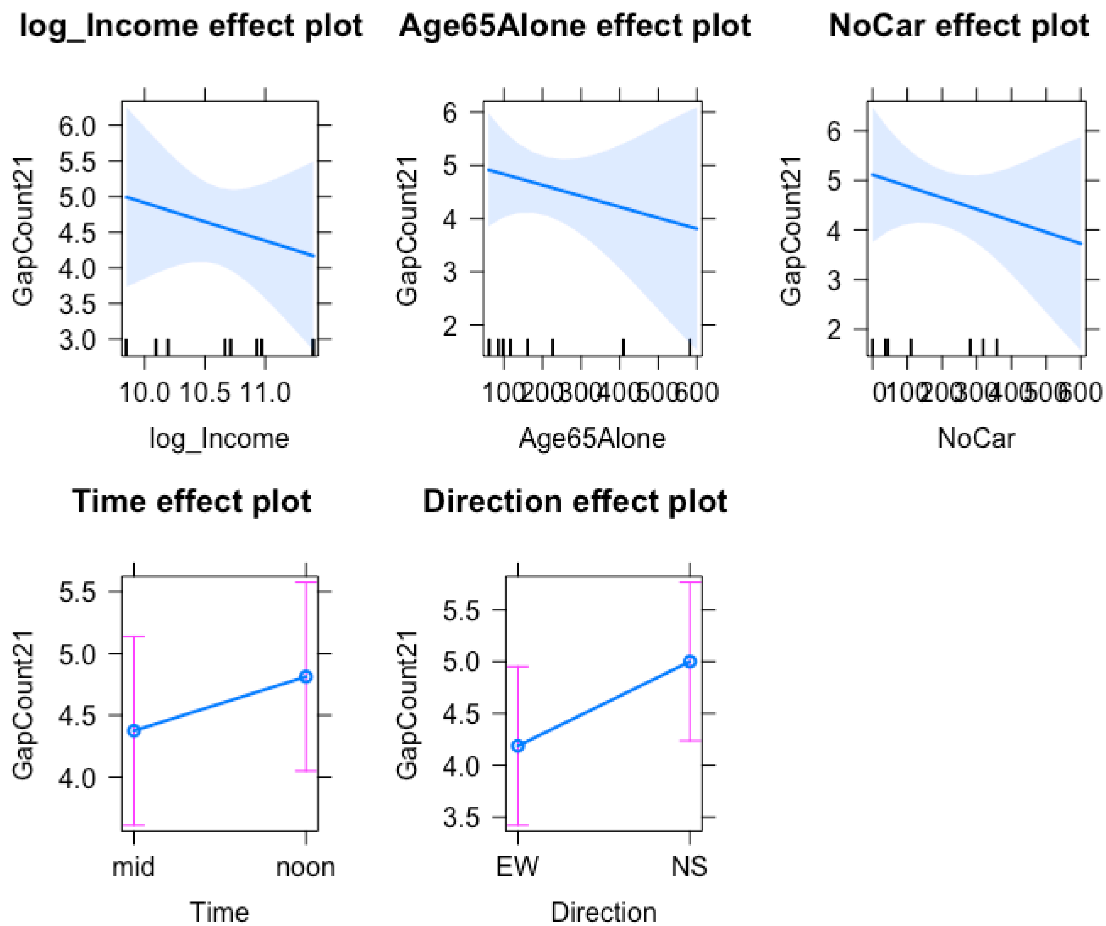


Figure 75. Plots of LMM for gaps ≥21 meters.

Plots provided by R Package "effects" version 4.1-1.

```
> Minutes2way = lmer(MinutesNoShade ~ log_Income * Time + Direction + Age65Alone + NoCar + (1|Route), data =
 shade)
> summary(Minutes2way)
Linear mixed model fit by REML ['lmerMod']
Formula: MinutesNoShade ~ log_Income * Time + Direction + Age65Alone +      NoCar + (1 | Route)
   Data: shade

REML criterion at convergence: 114

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.9813 -0.4422 -0.2219  0.6235  1.7050

Random effects:
 Groups   Name        Variance Std.Dev.
 Route    (Intercept) 0.01427  0.1195
 Residual             1.27668  1.1299
Number of obs: 32, groups:  Route, 16

Fixed effects:
                      Estimate Std. Error t value
(Intercept)         20.0158622  7.4763313   2.677
log_Income          -1.2947441  0.6996324  -1.851
Timenoon            -7.7116264  8.7165896  -0.885
DirectionNS          0.5625000  0.4039215   1.393
Age65Alone          -0.0002452  0.0021696  -0.113
NoCar               -0.0034669  0.0020739  -1.672
log_Income:Timenoon  0.8496175  0.8213176   1.034

Correlation of Fixed Effects:
            (Intr) lg_Inc Timenn DrctNS Ag65Al NoCar
log_Income  -0.998
Timenoon    -0.583  0.586
DirectionNS -0.027  0.000  0.000
Age65Alone   0.430 -0.444  0.000  0.000
NoCar       -0.554  0.550  0.000  0.000 -0.843
lg_Incm:Tmn  0.582 -0.587 -0.999  0.000  0.000  0.000
>
```

Figure 76. 2-way interaction of minutes with log of income and time.

Screen shot from R version 3.6.0.

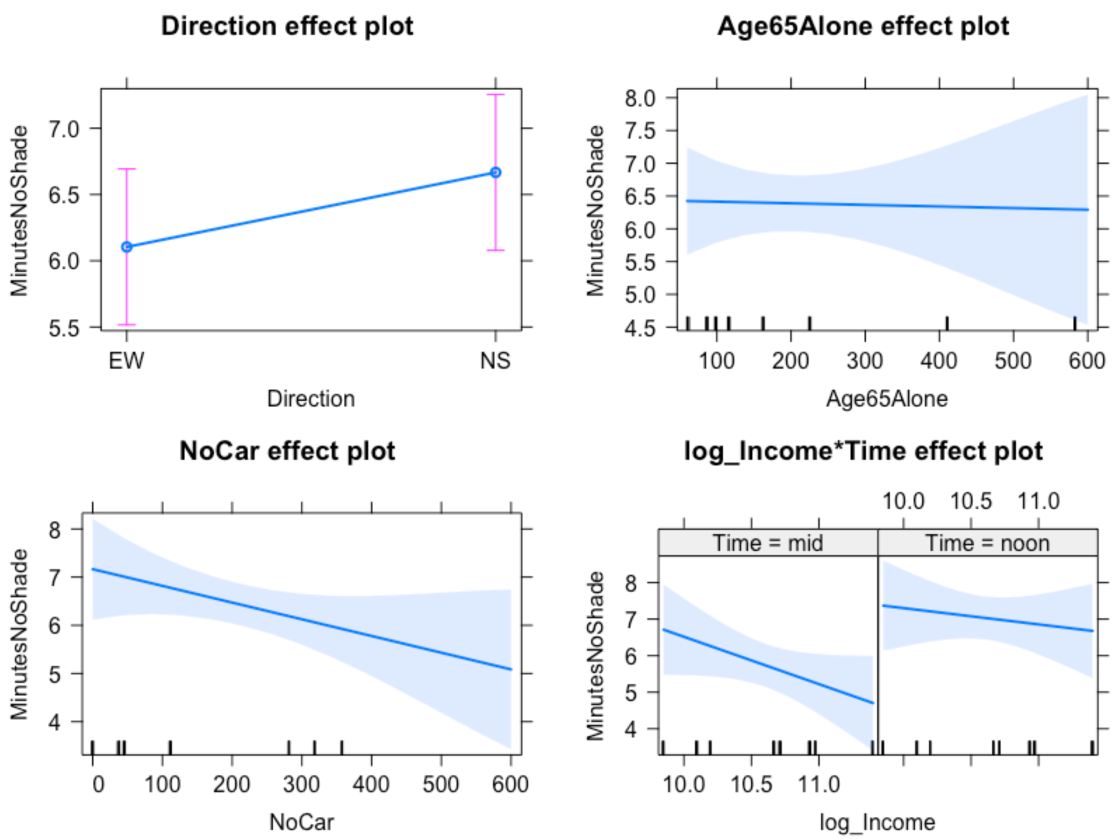


Figure 77. 2-way interaction of minutes with log of income and time.

Plots provided by R Package "effects" version 4.1-1.

References

AARP (n.d.). *Livable communities*. Retrieved from https://www.aarp.org/livable-communities/archives/info-2014/complete-streets.html

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1-48. doi:10.18637/jss.v067.i01.

Bowler, D.E., Buyung-Ali, L., Knight, T.M., & Pullin, A.S. (2010, September 15). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning*, *97*, 147-155. DOI: 10.1016/j.landurbplan.2010.05.006. Retrieved from http://www.sciencedirect.com/science/article/pii/S0169204610001234

Brown, D.R., Carlson, S.A., Kumar, G.S., & Fulton, J.E. (2018). Research highlights from the status report for Step it up! The surgeon general's call to action to promote walking and walkable communities, *Journal of Sport and Health Science, 7*, 5-6. DOI: 10.1016/j.jshs.2017.10.003.

California EPA (CalEPA) (n.d.). *Urban heat island index for California.* Retrieved from https://calepa.ca.gov/climate/urban-heat-island-index-for-california/

California EPA (CalEPA) (2015). *Urban heat island interactive maps.* [Dataset]. Retrieved from https://calepa.ca.gov/climate/urban-heat-island-index-for-california/urban-heat-island-interactive-maps/

California Open Data Portal (2019, September 10). *CA county boundaries* [GIS shapefile]. Retrieved from https://data.ca.gov/dataset/ca-geographic-boundaries/resource/b0007416-a325-4777-9295-368ea6b710e6

Centers for Disease Control and Prevention (CDC) (2017a). *500 Cities Project* [GIS shapefile, used for census tract boundaries]. Retrieved from https://chronicdata.cdc.gov/500-Cities/500-Cities-Census-Tract-Boundaries/x7zy-2xmx

Centers for Disease Control and Prevention (CDC). (2017b, September 15). *Natural disasters and severe weather: Frequently asked questions about extreme heat.* Retrieved from https://www.cdc.gov/disasters/extremeheat/faq.html

Chen, S. (2012), December. *Investigating bus route walkability: Comparative case study in Orange County, California* (Unpublished thesis). University of Southern California, Los Angeles. Retrieved from https://pqdtopen.proquest.com/doc/1288414798.html?FMT=AI

City of Pasadena, CA (n.d.). *Pasadena transit schedules and maps*. Retrieved from https://ww5.cityofpasadena.net/pasadena-transit/

City of Pasadena, CA. (2018, March 5). *Climate action plan.* Retrieved from http://ww2.cityofpasadena.net/councilagendas/2018%20Agendas/Mar_05_18/AR%2010%20ATTACHMENT%20A.pdf

City of Pasadena, CA (2019, February 22). *City of Pasadena open data site: Street ROW trees*. [Web page]. Retrieved from http://data.cityofpasadena.net/datasets/593b88391b614123890f54a1db8fbf55_2

City of Pasadena Open Data Site (n.d.). *Pasadena Transit bus stop*. [GIS shapefile]. Retrieved from: http://data.cityofpasadena.net/datasets/f093c609fcf043139b4f37551bd7289b_0

City of Pasadena Open Data Site (2018, December 12). *City boundary.* [GIS shapefile]. Retrieved from http://data.cityofpasadena.net/datasets/99c8a90563014264baa54167e38568fb_0

Clark, H.M. (2017, January). *Who rides public transportation*. American Public Transportation Association [Report]. Retrieved from https://www.apta.com/resources/reportsandpublications/Documents/APTA-Who-Rides-Public-Transportation-2017.pdf

Crowley, J.W. (2011, December). *City of Redlands safe routes to schools shadow mapping*. [Master's thesis, University of Redlands]. Retrieved from https://inspire.redlands.edu/gis_gradproj/46/

Duncan, D.T., Aldstadt, J., Whalen, J., & Melly, S. J. (2013). Validation of Walk Scores and Transit Scores for estimating neighborhood walkability and transit availability: A small-area analysis. *GeoJournal*, *78*, 407-416. DOI: 10.1007/s10708-011-9444-4. Retrieved from https://search-proquest-com.ezp-prod1.hul.harvard.edu/docview/1324276889?OpenUrlRefId=info:xri/sid:primo&accountid=11311

Esri (n.d.). *Help: Maps and scenes/author maps and scenes/scenes.* [Web page]. Retrieved from https://pro.arcgis.com/en/pro-app/help/mapping/map-authoring/scenes.htm

Esri (2018a). ArcGIS Pro (version 2.3.0) [Computer software]. Redlands, CA: Esri.

Esri (2018b). *Learn ArcGIS: Extract roof forms for municipal development: Create 3D buildings*. [Web page]. Retrieved from https://learn.arcgis.com/en/projects/extract-roof-forms-for-municipal-development/

Esri (2019a). *ArcGIS Solutions for Local Government: Local government 3D basemaps* [Computer software]. Redlands, CA: Esri. Retrieved from https://solutions.arcgis.com/local-government/help/local-government-scenes/

Esri (2019b). *ArcGIS Solutions for Local Government: Shadow impact analysis: Publish shadow impact results* [Computer software]. Redlands, CA: Esri. Retrieved from https://solutions.arcgis.com/local-government/help/shadow-assessment/get-started/publish-shadowimpact/

Fan, N., Li, S., Maradiaga, I., Perera, A., Tedjakusnadi, J., & Wang, J. (2017). *Improving microclimates in Los Angeles' heat-vulnerable communities.* UCLA Environmental Science Practicum 2016-2017 [Unpublished Report]. UCLA Institute of the Environment and Sustainability.

Florida, R. (2014, December 11). Walkability is good for you. *CityLab*. Retrieved from https://www.citylab.com/design/2014/12/growing-evidence-shows-walkability-is-good-for-you-and-for-cities/383612/

Fox, J. & Weisberg, S. (2019). An R companion to applied regression, 3rd Edition. Thousand Oaks, CA. Retrieved from http://tinyurl.com/carbook.

Grabar, H. (2014, November 3). As boomers age, walkable cities become more important. *CityLab*. Retrieved from https://www.citylab.com/transportation/2014/11/as-boomers-age-walkable-cities-become-more-important/382190/

Graham, J.E., Fisher, S.R., Bergés, I.M., Kuo, Y.F., & Ostir, G. V. (2010, November). Walking speed threshold for classifying walking independence in hospitalized older adults. *Physical Therapy*, *90*(11), 1591-1597. DOI: 10.2522/ptj.20100018. Retrieved from https://academic-oup-com.ezp-prod1.hul.harvard.edu/ptj/article/90/11/1591/2737720

Hall, A. (2013, December). *Climate change in the Los Angeles region: Temperature results.* UCLA Dept. of Atmospheric and Oceanic Sciences [Research Study Fact Sheet]. Retrieved from http://research.atmos.ucla.edu/csrl/docs/Hall-LA_temp_study_fact_sheet-Dec2013.pdf

Joe, L., Hoshiko, S., Dobraca, D., Jackson, R., Smorodinsky, S., Smith, D. & Harnly, M. (2016). Mortality during a large-scale heat wave by place, demographic group, internal and external causes of death, and building climate zone. *International Journal of Environmental Research and Public Health*, *13*(299), 1-16. DOI: 10.3390/ijerph13030299. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4808962/

Kalkstein, L. (2018, March 28). Reducing heat-related death in Los Angeles County. *Los Angeles Urban Cooling Collaborative* [Webinar]. Retrieved from https://www.treepeople.org/urbancooling

Kántor, N., Chen, L., & Gál, C. V. (2018). Human-biometeorological significance of shading in urban public spaces—summertime measurements in Pécs, Hungary. *Landscape and Urban Planning, 170,* 241-255. DOI: 10.1016/j.landurbplan.2017.09.030. Retrieved from https://www-sciencedirect-com.ezp-prod1.hul.harvard.edu/science/article/pii/S016920461730261X

Kelly, C. M., Wilson, J.S., Baker, E.A., Miller, D.K., & Shootman, M. (2013). Using Google Street View to audit the built environment: Inter-rater reliability results. *Annals of Behavioral Medicine, 45* (Suppl 1), S108-S112. DOI: 10.1007/s12160-012-9419-9. Retrieved from https://academic.oup.com/abm/article-abstract/45/suppl_1/S108/4563959

Kim, Y.J., Lee, C., & Kim, J.H. (2018, January). Sidewalk landscape structure and thermal conditions for child and adult pedestrians. *International Journal of Environmental Research and Public Health*, *15*(148). DOI: 10.3390/ijerph15010148. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/29346312

Klinenberg, E. (2015). *Heat wave: A social autopsy of disaster in Chicago, second edition*. Chicago: The University of Chicago Press.

Li, X., Ratti, C., & Seiferling, I (2018). Quantifying the shade provision of street trees in urban landscape: A case study in Boston, USA, using Google Street View. *Landscape and Urban Planning*, *169*, 81-91. DOI: 10.1016/j.landurbplan.2017.08.011. Retrieved from https://www.sciencedirect.com/science/article/pii/S0169204617301950

Los Angeles County GIS Data Portal (2008). *Countywide building outlines*. Retrieved from https://egis3.lacounty.gov/dataportal/2016/11/03/countywide-building-outlines-2014-update-public-domain-release/

Maco, S. E., & McPherson, E.G. (2002, November). Assessing canopy cover over streets and sidewalks in street tree populations. *Journal of Arboriculture*, *28*(6), 270-276. Retrieved from https://www.fs.fed.us/psw/publications/mcpherson/psw_2002_mcpherson001_maco.pdf

Middel, A., Selover, N., Hagen, B., & Chhetri, N. (2016, December). Impact of shade on outdoor thermal comfort—a seasonal field study in Tempe, Arizona. *International Journal of Biometeorology, 60*(12), 1849-1861. DOI: 10.1007/s00484-016-1172-5. Retrieved from https://link.springer.com/article/10.1007/s00484-016-1172-5

Mohegh, A., Rosado, P., Jin, L., Millstein, D., Levinson, R. & Ban-Weiss, G. (2017). Modeling the climate impacts of deploying solar reflective cool pavements in California cities. *Journal of Geophysical Research: Atmospheres, 122*, 6798-6817. DOI: 10.1002/2017JD026845. Retrieved from https://agupubs-onlinelibrary-wiley-com.ezp-prod1.hul.harvard.edu/doi/abs/10.1002/2017JD026845

National Oceanic and Atmospheric Administration (NOAA) (2015-2016). *Digital Coast Data Access Viewer. Custom processing of "2015 - 2016 LARIAC Lidar: Los Angeles Region, CA".* Charleston, SC: NOAA Office for Coastal Management. Retrieved from https://coast.noaa.gov/dataviewer

Nesoff, E.D., Milam, A.J., Pollack, K.M., Curriero, F.C., Bowie, J.V., Gielen, A.C., & Furr-Holden, D.M. (2018, February). Novel methods for environmental assessment of pedestrian injury: Creation and validation of the Inventory for Pedestrian Safety Infrastructure. *Journal of Urban Health*, *95*, 208-221. DOI: 10.1007/s11524-017-0226-2. Retrieved from https://link-springer-com.ezp-prod1.hul.harvard.edu/content/pdf/10.1007%2Fs11524-017-0226-2.pdf

Norton, B.A., Coutts, A.M., Livesley, S. J., Harris, R.J., Hunter, A.M. & Williams, N.S.G. (2015). Planning for cooler cities: A framework to prioritize green infrastructure to mitigate high temperatures in urban landscapes. *Landscape and Urban Planning, 134,* 127-138. DOI: 10.1016/j.landurbplan.2014.10.018. Retrieved from https://www.sciencedirect.com/science/article/pii/S0169204614002503

R Core Team (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/

Richards, D. R., & Edwards, P.J. (2017). Quantifying street tree regulating ecosystem services using Google Street View. *Ecological Indicators, 77*, 31-40. DOI:10.1016/j.ecolind.2017.01.028. Retrieved from https://www-sciencedirect-com.ezp-prod1.hul.harvard.edu/science/article/pii/S1470160X17300341

RStudio Team (2018). *RStudio: Integrated Development for R. RStudio, Inc*. Boston, MA. Retrieved from http://www.rstudio.com/.

Saatchi, S. (n.d.). *Urban heat island & cooling effect of trees*. Million Trees LA Research & Results, UCLA. [Web site]. Retrieved from http://www.sscnet.ucla.edu/geog/latree/saatchi.html

Social Explorer (n.d.). *Explore maps* [Online software]. Retrieved from https://www.socialexplorer.com/explore-maps

Syrkett, A. (2016, July 13). Walkability is key for transit use, says new study. *Curbed*. Retrieved from https://www.curbed.com/2016/7/13/12166562/transportation-design-urban-planning-transitcenter-study

U.S. Census Bureau (2016). *American Community Survey 2016 (5-year estimates)* [Data set]. Retrieved and explored using Social Explorer www.socialexplorer.com

U. S. Census Bureau (2018a, July 1). *QuickFacts: Population estimates for Pasadena, California*. Retrieved from https://www.census.gov/quickfacts/pasadenacitycalifornia

U.S. Census Bureau (2018b, September 6). *American Community Survey: When to use 1-year, 3-year, or 5-year estimates*. Retrieved from https://www.census.gov/programs-surveys/acs/guidance/estimates.html

U.S. Climate Data (2019). *Climate Pasadena, California.* Retrieved from https://www.usclimatedata.com/climate/pasadena/california/united-states/usca0840

U.S. EPA (2014a, June 17). *Climate change and heat islands.* Retrieved from https://www.epa.gov/heat-islands/climate-change-and-heat-islands

U.S. EPA (2014b, June 17). *Heat islands: Heat island impacts*. Retrieved from https://www.epa.gov/heat-islands/heat-island-impacts

Vanos, J., Kalkstein, L. S., Sailor, D., Shickman, K., & Sheridan, S. (n.d.). *Assessing the health impacts of urban heat island reduction strategies in the cities of Baltimore, Los Angeles, and New York*. [Report]. Retrieved from https://www.coolrooftoolkit.org/wp-content/uploads/2014/07/Three-City-Heat-Health-Report-FINAL-adj.pdf

Walk Score (n.d.). *Walk score methodology*. Retrieved from https://www.walkscore.com/methodology.shtml

Xu, Z., FitzGerald, G., Guo, Y., Jalaludin, B., & Tong, S. (2016, April-May). Impact of heatwave on mortality under different heatwave definitions: A systematic review and meta-analysis. *Environment International*, *89-90*, 193-203. DOI: 10.1016/j.envint.2016.02.007. Retrieved from https://www-sciencedirect-com.ezp-prod1.hul.harvard.edu/science/article/pii/S0160412016300411

Zaninotto, P., Sacker, A., & Head, J. (2013, December). Relationship between wealth and age trajectories of walking speed among older adults: Evidence from the English Longitudinal Study of Aging, *Journals of Gerontology: J Gerontol A Biol Sci Med Sci.*, *68*(12), 1525–1531. DOI: 10.1093/gerona/glt058. Retrieved from https://academic.oup.com/biomedgerontology/article/68/12/1525/533901