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FINAL PROJECT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

California Energy Commission
Gavin Newsom, Governor

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PREFACE

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution, and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation, and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities – Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company – were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that benefit their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and, finally, with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures is the final report for the Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures project (Contract Number EPC-14-073) conducted by Lawrence Berkeley National Laboratory. The information from this project contributes to Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

To relate fine-scale spatial air-temperature variations in local urban heat islands and urban cool islands—increases and decreases in outside air temperature—within a large urban-climate archipelago to variations in land-use and land-cover properties in the Los Angeles Basin, the research team sought to (a) use fine-resolution meso-urban climate models to identify areas of urban heat and cool islands, select sites for fixed weather monitoring, and choose routes for mobile observations; (b) relate observed intraurban temperature variations to land use and land cover and surface physical properties; and (c) calibrate/validate the climate models. The research team assessed urban temperature variations via simulations and observations, including mobile transects, mesonet, dense networks of personal weather stations, and sparse but more accurate research-grade monitors. To identify the causative factors of the urban heat and cool islands at the neighborhood scale, the research team collected detailed urban morphometric and land use and land cover datasets, such as 1-meter (3.3 foot) resolution roof albedo (solar reflectance) and tree canopy cover. The research team used the observation-validated model to finalize the transect routes and site the stationary monitors.

This study provides the first observational evidence from analysis of high-spatial-density weather stations that increases in roof albedo at neighborhood scale are associated with reductions in near-surface air temperature. This finding was corroborated with the analysis from mobile transect measurements and correlation of observed air temperature with neighborhood-scale albedo and vegetation. This correlation revealed a cooling effect from area-wide increase in albedo or canopy cover or both.

The calibrated meteorological model accurately identified the localized urban heat and cool islands observed in this study. Interested stakeholders/researchers can use the same models and calibration/validation methodology to characterize within-city microclimate variations elsewhere in California, and can apply them to analyze the benefits from using urban heat island countermeasures.

This project report is an extended and more detailed version of a related report prepared for California's Fourth Climate Change Assessment.

Keywords: Urban heat islands, urban cool islands, land-use and land-cover, intra-urban temperature variability, mobile transects, personal weather stations, stationary weather monitor, fine-scale meteorological model

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EXECUTIVE SUMMARY

Introduction

The urban heat island effect is the increase of air temperature in cities from surrounding rural areas. Urban heat islands are either skin-surface urban heat islands or air-temperature urban heat islands. Air-temperature urban heat islands are relevant to building energy use, thermal comfort, public health, precursor air emissions, air pollutant formation, and climate and, as such, are the focus of this study. Urban heat islands result in part from the transformation of urban land cover from trees and vegetation to buildings and other heat-absorbing urban infrastructure.

Future climate change scenarios project that the annual number of extreme heat days in California's urban areas will increase. In the San Fernando Valley in the Los Angeles Basin, the number of extreme heat days—those with maximum air temperatures exceeding 39.7 °C (103.4 °F), based on the ninety-eighth percentile of daily maximum temperatures recorded April–October 1961–1990—are estimated to increase on average to 12 days per year from 4 by midcentury. Temperature increases induced by climate change would exacerbate existing heat islands, threatening human and nonhuman health and straining energy resources. While warming from climate change requires global action to mitigate, urban heat islands are city-specific phenomena with solutions a city can implement locally. Modeling studies have found that urban heat island countermeasures, such as “cool roofs” and tree canopies, reduce urban temperatures when implemented at scale in cities.

Project Purpose

Understanding the variations in local heat and cool islands and the related interaction with land use land-use and land-cover properties can help cities implement policies to address urban heat islands now and build resiliency to future urban warming from climate change. To design and implement appropriate countermeasures, cities need to characterize urban heat and related causes. This project sought to understand spatial variations in local heat and cool islands and the relationship to land-use and land-cover properties, providing guidance for future mitigation via control measures such as higher albedo (solar reflectance) and more vegetation. The objective was to establish the causative factors of the local heat and cool islands at the neighborhood scale in the study areas, based on site-specific and upwind micrometeorological dynamics (for example, local generation of heat and transport of heat from upwind sources); land-use and land-cover properties; and surface physical properties. The research team sought to use fine-resolution climate models to identify urban heat and cool island areas, relate observed intra-urban temperature variations (from mobile transects and fixed weather stations) to land-use and land-cover and surface physical properties, and (c) calibrate/validate the fine-resolution meso-urban climate models used in identifying the urban heat islands and urban cool islands.

Project Approach

To characterize the meteorological variables in the study areas, the research team collected data from existing weather networks; conducted detailed, fine resolution meteorological modeling; installed research-grade stationary weather monitors; and performed mobile transects (measurement of temperature along a path). The research team partnered with the City of Los Angeles, County of Los Angeles, and Los Angeles Unified School District to help identify and host stationary monitors in two study areas that the research team identified: “SFV5”, an area that is part of the San Fernando Valley; and “LA1”, a region that includes and extends to the southeast of downtown Los Angeles. The research team installed three research-grade stationary monitors in the SFV5 study area. The research team also installed a research-grade monitor at the University of Southern California campus west of downtown Los Angeles. To supplement the data collected from these stationary monitors, the research team designed and executed multiple mobile transects. To identify the causes of the local heat and cool islands at the neighborhood scale, the research team collected detailed land-use and land-cover datasets for the Los Angeles Basin, such as 1-meter (3.3 foot) resolution roof albedo and tree canopy cover, as inputs for the meteorological modeling and analysis. The fine-scale meteorological model was used to design mobile-transect routes and site the stationary weather monitors based on the definition of urban heat island/urban cool island areas.

Project Results

The research team found the first observational evidence from analysis of high-spatial-density weather stations that increases in roof albedo at neighborhood scale are associated with reductions in near-surface air temperature. The research team corroborated this finding with analysis from mobile transect measurements, which revealed a cooling effect from areawide increase in albedo or canopy cover or both. The albedo and canopy cover values in the analysis are existing conditions in Los Angeles neighborhoods where there has not been a concerted effort to address urban heat islands. This situation suggests there are opportunities for community cooling using existing technologies and practices to increase urban albedo and canopy cover. Knowing that these are effective cooling measures, cities can also accelerate implementation of these urban heat island countermeasures in heat-vulnerable neighborhoods.

In addition, the calibrated meteorological model accurately identified the localized urban heat islands and urban cool islands observed in this study. Therefore, it can be applied by stakeholders, including city and state government, to characterize the intraurban microclimate variations elsewhere in California. Stakeholders can also apply the model to analyze the benefits from using urban heat island countermeasures.

Knowledge Transfer

The research team installed four research-grade stationary monitors: a reference monitor at University of Southern California (Monitor 0) and three at carefully selected sites in Los Angeles (Monitors 1-3). The data from Monitors 1-3 can be accessed for free via Weather Underground. The monitors will remain in place after the project concludes, providing valuable new weather stations in the urban core of the Los Angeles region. These monitors will help urban and

environmental professionals, planners, and researchers conduct future analysis of urban heat island mitigation strategies, building energy modeling, urban planning, local weather forecasts, and other modeling activities (for example, air quality analysis).

Los Angeles Unified School District staff in the Magnet Schools Assistance Program will share the data in the Global Learning and Observations to Benefit the Environment program, a worldwide hands-on science and education program focusing on the environment. This project information and experiences will help enable students to carry out their own research projects about their urban environments.

Research Recommendations

To further validate the research team's findings and to build upon these findings to help cities implement effective local urban heat island countermeasures, the team recommends the following future research:

- Guide the implementation of cool-community measures by determining the minimum changes in albedo and vegetation cover (in heat-vulnerable communities) that are required to achieve cooling benefit.
- Identify a neighborhood in which UHI countermeasures can be adopted and their air cooling effects can be monitored.
- Repeat the personal weather station analysis over the next few years as land cover properties evolve (for example, increasing prevalence of cool roofs) and more personal weather stations are added to networks.
- Repeat the personal weather station analysis using WeatherBug network data and measurements from the newly installed stationary monitors of the project.
- Carry out additional transects, modeling, and analysis of personal weather stations in other parts of the Los Angeles Basin.
- Design a specialized air temperature sensor that piggybacks on ride-share vehicles to provide detailed time-and-space maps of urban air temperature.
- Repeat the study for other areas in California.
- Complete related modeling and analysis for future-climate scenarios.
- Enhance analysis (observations, modeling, and so forth) by including year-round conditions.

Benefits to California

The research team found the first observational evidence that increases in roof albedo and vegetation at neighborhood scale are associated with reductions in near-surface air temperature. This lends credibility to many cool-cities studies done to date and suggests that measurable and significant community-scale cooling can be attained by using existing technologies and practices to increase urban albedo and canopy cover. Cities can also accelerate implementation of these heat island countermeasures, especially in heat-vulnerable neighborhoods.

The ability to cool neighborhoods with these simple technologies means that cities and ratepayers can save energy; reduce emissions of greenhouse gases, particulate matter, and ozone precursors, thereby attaining better air quality; improve thermal environmental conditions inside buildings and at street-level; and locally offset some of the potential impacts of heat events or climate change.

The carefully sited research-grade weather stations installed by the team will help researchers track how implementation of these heat island countermeasures cools neighborhoods in Los Angeles and, thus, realizes the benefits listed above.

In addition, the calibrated meteorological model accurately identified the localized urban heat islands and urban cool islands observed in this study. Therefore, the methodologies developed in this project can be applied by stakeholders, including city and state government, to characterize the intraurban microclimate variations elsewhere in California, and stakeholders can apply the model to analyze the benefits from launching urban heat island countermeasures.

CHAPTER 1:

Introduction

1.1 About Urban Heat Islands

The urban heat island effect (UHIE) is the elevation of air temperature in urban areas above that in surrounding rural areas. Urban heat islands (UHI)—that is, regions of elevated urban temperature—are categorized as either skin-surface UHIs or air-temperature UHIs. Air-temperature UHIs are relevant to building energy use, thermal comfort, public health, precursor emissions, air-pollutant formation, and climate and, as such, are the focus of this study. UHIs result in part from the transformation of urban land cover from trees and vegetation to buildings and other heat-absorbing urban infrastructure.

Future climate change scenarios project that the annual number of extreme heat days in California's urban areas will increase. In the San Fernando Valley in the Los Angeles Basin, the number of extreme heat days—those with maximum air temperatures exceeding 39.7 °C (103.4 °F), based on the ninety-eighth percentile of daily maximum temperatures recorded April–October 1961–1990—are estimated to increase on average to 12 days per year from 4 by midcentury. Temperature increases induced by climate change would exacerbate existing heat islands, threatening human and nonhuman health and straining energy resources. While warming from climate change requires global action to address, UHIs are city-specific phenomena with solutions a city can implement locally. UHI countermeasures, such as cool roofs and tree canopy cover, have been found in modeling studies to reduce urban temperatures when implemented at scale in cities.

1.2 Objective and Scope

To design and implement appropriate countermeasures, cities need to characterize urban heat and related causes. This project seeks to understand spatial variations in local heat and cool islands and the relationship to land-use and land-cover (LULC) properties, providing guidance for future mitigation via control measures such as higher albedo (solar reflectance) and more vegetation. The objective was to establish the causative factors of the local heat and cool islands at the neighborhood scale in the study areas, based on site-specific and upwind micrometeorological dynamics (for example, local generation of heat and transport of heat from upwind sources), LULC properties, and surface physical properties. The research team sought to use fine-resolution climate models to identify UHI/urban cool island (UCI) areas, relate observed intra-urban temperature variations (from mobile transects and fixed weather stations) to LULC and surface physical properties, and calibrate/validate the fine-resolution meso-urban climate models that were used in identifying the UHI/UCI. By understanding the variations in local heat and cool islands and the associated interaction with LULC properties, cities can implement policies to address UHIs now and build resiliency to future urban warming from climate change.

To characterize the meteorological variables in the study areas, the research team collected data from existing weather networks; conducted detailed, fine resolution meteorological modeling; installed research-grade stationary weather monitors; and performed mobile transects. The research team partnered with the City of Los Angeles, County of Los Angeles, and Los Angeles Unified School District (LAUSD) to help identify and host stationary monitors in two study areas that the research team identified: “SFV5,” an area that is part of the San Fernando Valley; and “LA1,” a region that includes and extends to the southeast of downtown Los Angeles. The research team installed three research-grade stationary monitors in the SFV5 study area. The research team also installed a research-grade monitor at the University of Southern California campus west of downtown Los Angeles. To supplement the data collected from these stationary monitors, the research team designed and executed multiple mobile transects. To identify the causative factors of the local heat and cool islands at the neighborhood scale, the research team collected detailed LULC datasets for the Los Angeles Basin, such as 1-m. (3.3-ft.) resolution roof albedo and tree canopy cover, as inputs for the meteorological modeling and analysis. The fine-scale meteorological model was used to design mobile-transect routes and site the stationary weather monitors based on the definition of UHI/UCI areas.

1.3 Brief Overview of Project Technical Tasks

This project has three technical tasks, numbered 2 through 4:

- Task 2: Identify and characterize study regions in the Los Angeles Basin.
- Task 3: Develop a monitoring plan, design instrumentation, and deploy a sensor network to measure the UHIE in the selected study region.
- Task 4: Collect and analyze weather data from fixed and mobile monitors.

Task activities and outcomes are summarized in Chapters 2–4 and detailed in a series of task reports (Appendices A – F).

1.4 Relationship to Report Prepared for California’s Fourth Climate Change Assessment

A briefer report prepared for California’s Fourth Climate Change Assessment—*Modeling and Observations to Detect Neighborhood-Scale Heat Islands and Inform Effective Countermeasures in Los Angeles* (Taha et al. 2018a)—summarizes most of the work performed in this study but omits many details presented in the current report.

CHAPTER 2:

Identifying and Characterizing Study Regions in the Los Angeles Basin (Task 2)

Task 2 identified and characterized study regions in the Los Angeles Basin suitable for UHI assessment. Task elements included:

- Assessing and acquiring data from existing monitors by reviewing the locations, sensors, outputs, availabilities, and data-access costs of several existing networks of weather monitors in the study region.
- Evaluating the quantity, quality, and spatial density of air temperature, relative humidity (RH), wind speed, and wind direction measurements obtainable from existing monitors.
- Statistically analyzing and correlating observational data from all sources.
- Characterizing, compiling, and upscaling LULC data and supplementing these data with characterizations from remote sensing.
- Applying a fine-resolution meso-urban meteorological model to the LULC information to simulate annual or seasonal hourly values of air temperature, humidity, wind speed, and wind direction in the study region.
- Comparing simulation results to any relevant weather data from existing monitors nearby.
- Assessing wind patterns and the variations of air temperatures with LULC, as well as variations with respect to height above ground in various areas of the study.
- Identifying the likely areas where an urban heat island might be detected with the monitors, as well as an initial, first-order guess of expected UHI intensity in different regions.

2.1 Acquisition of External Weather Measurements

To inform placement of new stationary monitors and provide observations to compare to modeled temperatures, the research team created a database of accessible historical weather data from all sources that had at least 10 stations available for the Los Angeles Basin. These sources included the California Irrigation Management Information System (CIMIS), WeatherBug, and Weather Underground (Figure 1). However, for simplicity and to avoid temperature differences that might result from variations in measurement techniques between networks, the research team's analysis of PWS data included only monitors from the Weather Underground network and focused on a single season (summer 2015). Data downloaded from the existing weather station sources were postprocessed to remove outliers. Acquisition and refinement of external weather measurement data are detailed in the Task 4 Report, Part III: *Observational Evidence of Neighborhood Scale Reductions in Air Temperature Associated With Increases in Roof Albedo* (Appendix G; also published as Mohegh et al. 2018).

Figure 1: Locations of Existing Weather Stations Used in the Study

The cross-hatched black polygons outline the team's initial areas of interest for study of existing weather data. The red, blue, and black points identify Weather Underground, WeatherBug, and CIMIS weather stations, respectively.

Source: Research Team

2.2 Study Area Characterization

LULC analysis was the first step in identifying urban areas with delineations or transitions of interest—that is, changes in physical properties. The research team performed this analysis to derive surface inputs to the meteorological model and provide a basis for relating observed air temperature to LULC properties at stationary monitor sites or along mobile-transect routes. Figure 2 shows an example of LULC characterization in one study area selected in this project. LULC analysis is detailed in the Task 2 Report, Part I: *Land-Use/Land-Cover Analysis and Atmospheric Modeling to Support Site Identification and Selection for Fixed Meteorological Monitors and Mobile-Observation Routes* (Appendix A).

Figure 2: Sample Detail From Land-use and Land-cover Analysis

Image shows an area including downtown Los Angeles (area LA1). There are about 50 LULC classes represented in this figure; the USGS Level-IV system includes more than 100 classifications. The darker areas are residential land uses, and the areas color-coded blue, dark green, and red in the middle are industrial and commercial land functions. Bright green represents open or vegetated areas or both.

Source: Research Team

2.3 Study Area Selection

Figure 3 shows four study areas initially considered for meteorological modeling (LA1, LA2, LA3, and SFV5), along with the two areas used in analysis of personal weather station data (Central Los Angeles and SFV_R). The two most promising study areas identified—LA1, containing downtown Los Angeles in its northwestern tip, and SFV5, a portion of the San Fernando Valley—were modeled to assess the potential UHI or UCI signals or both that stationary monitors and mobile transects in this area would capture. This preparatory modeling is detailed in the Task 2 Report, Part I: *Land-Use/Land-Cover Analysis and Atmospheric Modeling to Support Site Identification and Selection for Fixed Meteorological Monitors and Mobile-Observation Routes* (Appendix A).

To quantitatively evaluate the model prediction of temperature tendency and spatial gradients in temperature in the modeled areas, the research team devised preliminary mobile-transect measurements of temperature for initial feedback and preparation for more rigorous model performance evaluation. The transect was conducted in Area LA1 during April 2016. Execution of the preliminary transect is detailed in the Task 2 Report, Part II: *Preliminary Mobile Measurements of Air Temperature via Transect* (Appendix B). Design of the mobile monitor is summarized in Chapter 3 and detailed in the Task 3 Report, Part I: *Monitoring Plan, Instrumentation Design, and Sensor Deployment* (Appendix C).

The transect observations confirmed the findings from the model, allowing the team to use the modeled results to select the study areas of interest. Therefore, the research team chose to install stationary monitors in areas SFV5 and LA1 to capture the interactions between LULC and microclimates in inland regions (the San Fernando Valley) and areas influenced by the sea breeze flow and climate archipelago¹ effects (the semi-coastal region that includes Area LA1). Monitoring two unlike areas helps the team understand the role of local surface properties and impacts on temperature in different climate regimes—here, inland valleys, and quasi-coastal areas.

Figure 3: Boundaries of Initial and Selected Study Areas

Boundaries of initial study areas LA1, LA2, LA3, and SFV5 (solid white lines) considered for meteorological modeling, installation of new stationary monitors, and mobile transects; LA1 and SFV5 were selected. Also shown are the boundaries of study areas Central Los Angeles and SFV_R (solid gold lines) used in analysis of personal weather station data, and the boundaries of the San Fernando Valley (SFV) and downtown Los Angeles (dotted white lines).

Source: Research Team

¹ An archipelago is group of islands or a body of water containing a group of islands. The research team uses the term “climate archipelago” to refer to the complex climate effects of a very large, continuous urban area in which upwind portions can affect downwind portions.

CHAPTER 3:

Developing a Monitoring Plan, Designing Instrumentation, and Deploying a Sensor Network to Measure the Urban Heat Island Effect in the Selected Study Regions (Task 3)

In Task 3 the research team developed a monitoring plan, designed instrumentation, and used a sensor network to measure the UHIE in the selected study regions. Task elements included:

- Designing a mobile monitor for transects.
- Designing stationary monitors to install on buildings.
- Deciding where to install new stationary monitors in the selected study regions.
- Acquiring suitable sites for installation of the stationary monitors.
- Calibrating, installing, and verifying operation of the new monitors.

All Task 3 activities are detailed in the Task 3 Report, Part I: *Monitoring Plan, Instrumentation Design, and Sensor Deployment* (Appendix B).

3.1 Mobile Monitor Design

Horizontal variations in air temperature near the ground—say, 2 meters above ground level—can be mapped by attaching a thermometer to roof of a vehicle, such as a car, then logging temperature, position, and time during a transect. To ensure that the thermometer accurately measures air temperature, the sensor should be aspirated by the motion of the vehicle, shielded from the sun, and radiatively isolated (decoupled) from the shield. The sensor should also respond quickly to air temperature changes to minimize spatial inaccuracies, or blurring, in the air temperature map induced by the motion of the vehicle.

The research team's mobile monitor contains five elements:

1. A shielded temperature sensor aspirated by vehicle motion (Figure 4).
2. A quick-install mount to attach the shielded sensor to the roof of a vehicle (Figure 5).
3. A portable data logger to record the temperature time series (Figure 6).
4. A global positioning system (GPS) to record the position time series.
5. A dash camera (dash cam) to record time-stamped video of the transect from the perspective of the driver.

Figure 4: Mobile Monitor Temperature Sensor

A clip secures a foil-wrapped bead thermistor in the center of the shield.

Source: Research Team

Figure 5: Mobile Monitor on Quick-Install Car-Roof Mount

System includes white PVC-pipe shield, gray PVC-pipe vertical risers, aluminum tube roof mounting on plastic and rubber feet, and white PVC-pipe crossbeams. Straps with hooks (not shown) secure the bars to the vehicle frame.

Source: Research Team

Figure 6: Mobile Monitor Temperature Logger

Logger shown with stock thermistor probe. The detachable probe was replaced by a 4 meter extension cable leading to the foil-wrapped bead thermistor shown in Figure 4.

Source: Lascar Electronics

3.2 Stationary Monitor Design

The research team sought the following performance characteristics for each stationary monitor:

- The monitor should accurately and continuously measure the primary signal, dry-bulb air temperature; secondary signals, including wind speed, wind direction, solar irradiance, and relative humidity, useful for interpreting variations in air temperature; and monitor diagnostics, such as radiation-shield fan speed, needed to verify that the sensors are operating as designed.
- To ease installation and subsequent maintenance, the monitor should be easy to assemble and program.
- The monitor should be readily installed on an elevated surface, such as that of a low-slope roof, to measure air temperature at some fixed height above ground.
- The monitor should communicate over the internet or by cellular modem for convenient data collection and (if necessary) reprogramming.
- The monitor should be durable, ideally with a service life approaching a decade.

The research team reviewed the specifications and prices of two loggers, six wind speed/direction sensor kits, two silicon pyranometers, two temperature sensors, one RH sensor, and four aspirated radiation shields. The research team also factored in positive and negative experiences with some of these instruments in past projects. After considering all these inputs, the research team specified and purchased a system from Onset Corporation that connects to a logger (RX3000) plug-and-play digital-output sensors that measure wind speed (S-

WSB-M003 three-cup anemometer), wind direction (S-WDA-M003 wind vane), solar irradiance (LIB-M003 silicon pyranometer), and temperature/RH (S-THB-M002 temperature/RH). The logger also has a four-channel analog module (RXMOD-A1) that can excite and measure analog signals, such as the output of a thermistor circuit (air temperature) and a pulse-counting circuit (fan speed). The logger can upload its measurements to a cloud data server via cellular modem. All components can be mounted on a tripod structure, which in turn can be installed on a roof. (They can also be connected to an existing pole if desired.)

The research team acquired evaluation units of two aspirated radiation shields. After extensive testing, the research team determined that both were suitable but selected the Apogee Instruments TS-100 shield with ST-110 precision thermistor because the fan drew less power than that of the other unit. (This is helpful for monitors powered by solar-charged batteries.)

3.3 Selecting Stationary Monitor Sites

Several points in the LA1 and SFV5 study areas were identified as localized UHI or UCI areas based on model and initial mobile-transect results. The research team shared these points and study areas with project partners—including the City of Los Angeles, County of Los Angeles, and LAUSD—and collectively developed a list of their facilities that could serve as potential sites for the stationary monitors. Upon further evaluation of these sites via examination of three-dimensional imagery (for example, Google Earth Pro) and location visits, certain sites were assigned a lower priority because of such factors as unavailability of flat roofs (sloped roofs can be an issue for installing weather stations), lack of secure sites in open areas (at ground level), and physical characteristics of the site. These factors resulted in a top tier of 10 potential sites, some of which are shown in Figure 7.

3.4 Acquiring Monitor Installation Sites

The research team struggled to get local approval and find suitable locations for monitor installation at each of the potential sites. While the research team had high-level support from our partners, many layers of approval were required. For example, the research team had support from City of Los Angeles Fire Department management to install monitors but ran into a barrier with the labor union representing the firefighters, which did not want a rooftop monitor on their fire station transmitting data via a cellular modem. Partners also expressed concerns about the ability of old roofs to support the (lightweight) monitors.²

² Each roof-mounted monitor (sensors on a tripod) weighs 43 lb. (19.5 kg) and is secured to three 5' by 5' by 0.75" (1.5 m by 1.5 m by 1.9 cm), 44 lb. (20 kg) plywood plates. Each plate is further ballasted with 44 lb. of bricks. Hence, a secured station weighs about 255 lb. (116 kg) and exerts 3.4 lb.-force/square ft (163 Pa) pressure on the roof. That's about 0.3% of the ground pressure exerted by a standing human male (1,150 lb-force/ft² [55 kPa]) (https://en.wikipedia.org/wiki/Ground_pressure).

Figure 7: Prospective Installation Sites for Stationary Monitors

(a) Potential sites in SFV5 (red markers circled in yellow) along a sample mobile-transect route.

Source: Research Team

(b) Potential sites in SFV5 (red markers circled in yellow) along a sample mobile-transect route.

Source: Research Team

3.5 Installing and Calibrating Monitors

After extensive negotiation, the research team received partner approvals to install four monitors (Figure 8). The first monitor (Monitor 0, the reference monitor) was installed October 26, 2016, on the campus of the University of Southern California (USC) inside a gated area in a parking lot, 2 m above ground level (AGL). Monitor 1 was installed July 25, 2017, at the City of Los Angeles' Bureau of Street Services Facility Yard in Topanga Canyon, 2 m above the roof of a structure that shades a parking lot. Monitor 2 was installed January 11, 2018, at LAUSD's Sunny Brae Elementary School, 2 m above the roof of a school building. Monitor 3 was installed April 13, 2018, at LAUSD's Melvin Elementary School, also 2 m above the roof surface of a school building.

The temperature sensors in all four monitors were cross-calibrated at the USC (Monitor 0) site before Monitors 1, 2, and 3 were deployed.

Figure 8: Locations of the Four Stationary Monitors Installed in Los Angeles

Monitor 0 was installed on the campus of the University of Southern California, while **Monitors 1 – 3** were installed in the **San Fernando Valley**.

Source: Research Team

CHAPTER 4:

Collecting and Analyzing Weather Data From Fixed and Mobile Monitors (Task 4)

Task 4 sought to observationally quantify the UHIE and the relationship to LULC, establish a baseline for future UHI mitigation, and calibrate/validate a fine-resolution mesoscale climate model. Task elements included:

- Collecting data from the new stationary monitors.
- Designing and conducting mobile measurements of near-ground air temperature.
- Using stationary and mobile measurements to update fine-resolution model simulations and parameterizations, such as those supported by the California Environmental Protection Agency for UHI Index development, and to calibrate/validate these models.
- Using hourly air temperature measurements and other meteorological variables from the existing weather stations to evaluate the UHIE, and to correlate spatial variations in air temperature and UHIE intensity with LULC and urban morphological characteristics.

For full details of mobile measurements and the related application to model calibration/validation, please see the Task 4 Report, Part I: *Model Validation and Development of Correlations Between Observed Air Temperature and Surface Physical Properties* (Appendix E), and Task 4 Report, Part II: *Air-Temperature Response to Neighborhood-Scale Variations in Albedo and Canopy Cover in the Real World: Fine-Resolution Meteorological Modeling and Mobile Temperature Observations in the Los Angeles Climate Archipelago* (Appendix F; also published as Taha et al. 2018b). For full details of using measurement from existing weather stations to relate urban air temperature to LULC, please see Task 4 Report, Part III: *Observational Evidence of Neighborhood-Scale Reductions in Air Temperature Associated With Increases in Roof Albedo* (Appendix G).

4.1 Stationary Monitor Measurements

The research team has continuously collected data from Monitors 0–3 since installation. However, because of logistical delays in the installations of Monitors 2 and 3, the analysis in the current study is based instead on the team’s mobile transect measurements. Data from the stationary monitors can be used in subsequent research. The research team also presents here analysis of data drawn from many personal weather stations.

4.2 Mobile Transect Measurements

Mobile-observation transects were carried out to measure microclimate variations along the routes. Of particular interest was air temperature variation as the LULC and surface properties change along each route segment. The goal was to develop correlations that quantify the responses in temperature to changes in albedo and vegetation canopy.

The research team identified points of interest (for example, UHI and UCI) in the SFV5 and LA1 domains based on the modeled temperature-field characteristics.

The selected mobile-observation routes were designed to cut across the LULC boundaries and transitions and capture the possible effects of changes in LULC from one neighborhood to another. The routes also were designed to yield small changes in elevation and keep the duration of each transect subsegment under 20 minutes (minimizing variations in air temperature that result from change in time of day).

In all, 15 transects were carried out in the summers of 2016 and 2017 in SFV5 and LA1. Figure 9 shows a composite of all transects that were carried out, as well as a random example detail of one transect subsegment. Some transect routes are duplicates (superimposed on each other) and, hence, appear as one. While the research team considered all transects shown in LA1 in the analysis, only the parts of the transects within the red box were considered in the analysis for SFV5.

Figure 9: Superimposed Routes of 15 Transects

While all transects shown in area “LA1” were considered in the analysis, only the parts of the transects within the red box were considered in the analysis for SFV5. Inset: example detail.

Source: Research Team

The first transects were conducted in personal vehicles, with two researchers in each vehicle—one to drive and the other to make measurements. The research team soon switched to ride-share services, hiring Uber drivers to install the apparatus on their cars and drive along the transect paths with a researcher in the car to manage the equipment. This proved to be a time- and cost-saving improvement because (1) it was cheaper to hire Uber than to reimburse researchers for personal vehicle use and (2) only one researcher was needed in the car.

The design of the apparatus also withstood the wear and tear from being installed, uninstalled, and stored over the project duration. Hurdles to carrying out the mobile transects included time wasted being stuck in traffic traveling to and from study areas, the need to modify initial transect routes on the fly because of unexpected road construction and closures, and crime safety concerns (that went unmerited) of driving through certain locations at night (20:00 - 22:00 local daylight time).³

4.3 Calibration of Climate Model to Mobile Observations

The research team evaluated the model performance against fine-scale observations from mobile transects. For transect-specific modeling (500-m resolution), modeled air temperature was compared to observations from transects at the coincident time (subhourly intervals). The goal was to ascertain that the model correctly captures the micrometeorological variations in the urban areas and to validate the modified WRF model against the mobile observations. The modeled and observed air temperatures from mobile transects were assessed at 2 m AGL.

While the transect-specific WRF model (TSM) runs were initiated a week ahead of the actual transect time and were continued for two days past that, the team evaluated the performance of TSM runs only and specifically at the transect time. The research team found good agreement between along-transect roadway observations and area-averaged model results. Mean absolute error (MAE) and root mean square error (RSME) in temperatures ranged 0.55–1.73 °C and 0.60–2.00 °C, respectively, and were often significantly better than the recommended performance benchmarks of $MAE \leq 2^{\circ}C$ (3.6 °F) and $RMSE \leq 2^{\circ}C$ (3.6 °F).

4.4 Relating Mobile Air Temperature Observations to LULC

Following model performance evaluation, the research team evaluated correlations between observed temperature and surface physical properties. In this case, two surface properties of interest were examined: neighborhood-scale albedo and vegetation canopy cover (500-m scale). The research team examined these two properties because they have been shown in many studies to influence significantly the urban air temperature and they are easy to control and use as mitigation measures. The relationships between observed air temperature (predictand) and either albedo or canopy cover (predictors) or both were examined in three manners: (1) simple linear regression, (2) multiple regression, and (3) CART analysis for further detail. Examples of each analysis are given in this discussion.

³ Los Angeles is in the Pacific time zone, where local daylight time (LDT) is UTC/GMT -7 hours.

4.4.1 Simple Linear Regression

In the downtown Los Angeles (LA1) domain, observed air temperature from mobile transects was correlated to grid-level albedo and canopy cover. For the San Fernando Valley study area, the observed temperature was correlated only with canopy cover (as predictor) since albedo has a smaller variability in this domain (Figure 10).

Figure 10: Detail From the San Fernando Valley Study Domain

Image shows 30-m tree cover (yellow: < 10%, light green: 10 – 20%, black: > 20% cover), building-specific roof albedo (red: 0.05 – 0.25, orange: 0.25 – 0.50, light orange: 0.50 – 0.90), and a sample mobile transect segment (white dots).

Source: Research Team

All but two transects yielded statistically significant correlations (probability value < 0.05) of air temperature to albedo or canopy cover fraction, and correlations for all but two transects were negative (when albedo or canopy cover or both increase, temperature decreases).

4.4.2 Multiple Regressions

Multiple regression was carried out for albedo and canopy cover as predictors to observed air temperature from the transects. This analysis applies only to the downtown area, LA1, since the SFV5 analysis involved only variations in one predictor (canopy cover) because the variability in albedo in SFV5 is small.

The correlations were overwhelmingly negative—as albedo and canopy cover increase, temperature decreases—and statistically significant except in one transect, where the role of canopy cover was insignificant, and in two other transects, in which the role of albedo was insignificant.

4.4.3 Classification and Regression Tree

A classification and regression tree (CART) analysis was undertaken to assess the multiple interactions among predictors of mobile-observed air temperature. This analysis is an extension to the multiple regression analysis above and provides additional information. In the CART analysis, the roughness length parameter was introduced as an additional predictor to evaluate the role, if any, relative to that of albedo and canopy cover.

A CART is interpreted in the following manner: the variable above each node (circle) is a “splitting” variable, that is, the criterion used in the correlation. The top splitting variable (that is, the most important) is given above the top node. The yellow nodes are “terminal” nodes that show the results (regression or classification) in which the research team is interested. At each node, there is a logical criterion: for values smaller than the criterion, follow the path to the left of the node. For values larger than the criterion, follow the path to the right. Each node is numbered inside the circle. The number in italics below each node is the number of observational samples, and the number below that is the predicted value (in this case, air temperature) at the end of each path leading to a terminal node.

The example discussed here is for a daytime (13:00 LDT) transect in the downtown area (LA1) carried out on April 22, 2016. This transect segment consists of 798 temperature observations. The following can be deduced from this CART analysis (Figure 11):

- In this transect segment, the most influential variable (top splitting node) is albedo. The analysis shows that the contribution of higher albedo just in this transect is to lower air temperature by 0.81 °C (1.45 °F), which is significant.
- Temperature is lower where albedo is larger. For grid-level albedo greater than 0.125, the temperatures are lowest—for example, compare terminal Nodes 6 and 7 with Nodes 5, 9, 16, 34, and 35.
- In this transect, where albedo is lower than 0.125, canopy cover also has a significant effect. Comparing Node 5 (where canopy cover is greater than 0.195) and Nodes 9, 16, 34, and 35 (where cover is lower than 0.195), the contribution of canopy cover is to cool the air by 0.12 °C (0.22 °F). This effect is smaller than the effects of albedo in this specific transect.
- The effects of roughness length are secondary and vary from one subtree to another.

Figure 11: CART for Daytime Transect in Downtown Los Angeles

This CART example is for 13:00 LDT in the downtown area (LA1) on April 22, 2016. It represents 798 temperature observations from mobile transects. Temperature is the dependent variable; albedo, vegetation cover, and roughness length are the independent variables (predictors).

Source: Research Team

4.5 Detection of Intraurban Heat and Cool Islands

Because the Los Angeles region is one large urban climate archipelago (a built-up area stretching from the ocean to the mountains), there is no rural reference against which the urban temperature is compared as in a “conventional” urban heat island definition. As such, the task was to identify intraurban variations in heat or cool islands or both as a function of LULC (as an embedded signal) and correlate the temperature variations to changes in LULC and surface physical properties. As discussed above, the research team’s LULC analysis coupled with the fine-scale meteorological modeling result allowed the team to identify such signals in the study areas, as depicted in Figure 12.

The model performance evaluation in this study demonstrated that the WRF model and the modifications to the associated urban modules performed in this project can reproduce reasonably well the observations in the temperature, including the locations of UHI and UCI spots. As such, the model can be reliably applied to other urban areas and regions in California, as well as for other applications such as in designing community- or neighborhood-scale UHI mitigation strategies.

Figure 12: Modeled Heat and Cool Islands in the San Fernando Valley

Total degree-hours (DH) for interval May 30 – June 16 (2013) in the San Fernando Valley 500-m domain. (SFV5 is in the western part of this domain.) The derived average temperature (computed as DH/hour), blue to red, is 17.7–22.9 °C (63.9 – 73.2 °F) for this period. Color bar is total DH, range: 7,228 – 9,364.

Source: Research Team

4.6 Neighborhood-Scale Interactions Between Air Temperature and Land Cover

The research team chose two study areas (“regions”) of interest within the Los Angeles Basin that met two requirements: (1) the study area should be sufficiently small such that distance from the coast does not dominate temperature variations, and (2) there should be sufficient variation in land-cover properties of interest (for example, roof albedo) to enable discerning effects of land cover on measured air temperatures. The first region encompasses an area of roughly 500 square kilometers (km²) and includes downtown Los Angeles; the research team refers to this region as Central Los Angeles (Central Los Angeles contains all of LA1). The second region encompasses roughly 160 km² and is within the San Fernando Valley; the research team refers to this region as SFV_R.

The research team investigated the effects of LULC properties on observed air temperatures for different neighborhoods in each region, using Weather Underground near-ground air temperatures measurements recorded in July 2015. Here a “neighborhood” is an area of 500 m radius, centered on a weather station (Figure 13).

Figure 13: Neighborhood Surrounding a Personal Weather Station

Image shows the aggregation area, or “neighborhood” (green circle of radius 500 m), around an example weather station (red dot) in SFV. The underlying imagery shows the building footprint dataset.

Source: Research Team

The research team focused on roof albedo (and solar power reflected from roofs) and tree cover, although further LULC parameters were analyzed. The research team found that the sensitivity of air temperatures to these LULC properties varied by region, likely due to the related different baseline land cover and meteorology. Increases in roof albedo were associated with observed air temperature reductions. Average daily sensitivities were 1.84 °C and 0.25 °C

per 0.1 increase in roof albedo in neighborhoods in Central Los Angeles and SFV, respectively. Observed sensitivities in air temperature to albedo were substantially higher than reported by previous modeling studies.

In Central Los Angeles, variations in solar power reflected from roofs (and thus roof albedo) appear to dominate variations in observed air temperature relative to the effects of tree fractions. This observation is based on current neighborhood-to-neighborhood variability in tree fraction in this region and may not predict how adding more trees would affect temperatures. For SFV_R, observations suggest an overnight (00:00 – 07:00 LT) temperature reduction of up to about 1.5 °C per 0.1 increase in tree fraction at night. To the team's knowledge, this study is the first to report observational evidence that roof albedo increases are associated with neighborhood-scale temperature reductions.

CHAPTER 5:

Lessons Learned and Policy Implications

5.1 Lessons Learned

The research team envisioned installing more than 10 stationary research-grade monitors in select locations to detect differences in air temperature from variations in LULC. However, installing stationary monitors proved more challenging than planned, while the mobile transects were easier than expected. Therefore, the research team installed fewer stationary monitors (four installed) than originally planned but completed 15 mobile transects to provide the observational data necessary for this analysis.

The research team had strong institutional partners for this project in the Los Angeles Basin. The team's plan was to use their facilities across the basin to site the stationary monitors. Since they were governmental organizations, the research team expected they would be able to make a long-term (5+ years) commitment to hosting the monitors and ensuring the security of the monitors over time. However, the research team struggled to secure the many layers of approval needed to place monitors at buildings. The research team spent 18 months negotiating agreements, sites, and installation with partners. For future work, the research team would suggest allowing more time to negotiate all the approvals or include some financial agreement to ensure participation from specific facilities or both.

There were some beneficial changes the research team made from the project plan that aided implementation. For the mobile transects, the research team completed the first few transects using personal vehicles as planned. However, switching to the Uber ride-share service saved time and money by reducing both vehicle and staff costs. For future work, using ride-share services to help conduct mobile transects and measurements could be a good collaboration to take advantage of their large network of drivers and broad service area. Some of the ride-share fleet could be equipped with specialized sensors that track location and air temperatures across the city while the vehicles are in service.

5.2 Policy Implications

The research team found empirical evidence that there is intraurban temperature variability correlated to LULC properties. The albedo and vegetation coverage values in the analysis are existing conditions in Los Angeles neighborhoods where there has not been a concerted effort to address UHIs. This finding suggests that there are opportunities for community cooling using existing technologies and practices to increase urban albedo and canopy cover. Knowing that these are effective cooling measures, cities can also accelerate the implementation of these UHI countermeasures in heat-vulnerable neighborhoods. Addressing UHIs helps locally offset future warming in cities from climate change. This action helps the city build resiliency to future extreme heat events.

Local and state government policy makers can conduct similar modeling to identify local UHI areas to target policies to increase roof albedo and canopy cover. They can also review their city/community LULC datasets to identify areas where there is potential to increase roof albedo and vegetation cover. This review will help them develop targeted strategies to implement UHI countermeasures. In turn, these strategies can conserve city resources, program budgets, and staff while improving climate resiliency in the most heat-vulnerable communities. For example, the City of Los Angeles' Department of Water and Power runs a residential cool roof rebate program. Department officials can direct communication efforts to residential areas identified as local UHIs following the method of modeling used for this study. The installation of cool roofs in these UHI areas provide the neighborhood cooling benefits and building energy savings, while conserving program funds from citywide outreach and implementation.

The California Natural Resources Agency also offers urban greening grants to cities, counties, and nonprofits. Local or state agencies can review LULC datasets to target areas of low canopy coverage within disadvantaged communities for project implementation. If planted appropriately, trees could achieve the program objectives as well as providing the cooling benefit in heat-vulnerable communities.

CHAPTER 6:

Conclusions

California's urban heat islands are exacerbated by climate change in a manner that can compromise electricity sector resilience and public health. It is important to understand the factors that contribute to UHI, as well as how UHI can be mitigated. In this study, the research team carried out a multidimensional assessment of urban temperature variations based on state-of-the-science numerical modeling and several types of observations, including mobile transects and personal weather stations. The research team sought to understand spatial air-temperature variations in local heat and cool islands and the relationship to land-use and land-cover properties in the Los Angeles Basin.

The research team collected detailed LULC datasets for the Los Angeles Basin that were used as inputs for the meteorological modeling and analysis. The research team also developed a database of historical micrometeorological information from existing weather station networks.

The research team collaborated with the City of Los Angeles, County of Los Angeles, and Los Angeles Unified School District to find sites and hosts for stationary monitors in two study areas that the research team identified, San Fernando Valley (SFV5) and downtown Los Angeles (LA1). The research team used fine-resolution climate models to assess the potential local UHI or UCI signals or both in these two areas. The results of the modeling informed the design of mobile-transect routes and siting of the stationary monitors. The research team designed a highly accurate and affordable stationary monitor that was installed in three locations in the SFV5 study area and at the University of Southern California campus west of downtown Los Angeles. To supplement the data collected from the stationary monitors, the research team completed 15 mobile transects. The research team designed and constructed an apparatus that is easily mounted on the roof of a car to measure air temperature along the transect routes.

The research team assessed data from personal weather stations in the Weather Underground network to relate observed intraurban temperature variations to LULC and surface physical properties. The research team also analyzed observational micrometeorological data from mobile transects and correlated them with neighborhood-scale albedo and vegetation canopy cover.

The research team found the first observational evidence from analysis of high-spatial-density weather stations that increases in roof albedo at neighborhood scale are associated with reductions in near-surface air temperature. This evidence was corroborated with the analysis from mobile transect measurements, which revealed a cooling effect from areawide increase in albedo or canopy cover or both. The albedo and canopy cover values in this analysis are existing conditions in Los Angeles neighborhoods where there has not been a concerted effort to address UHIs. This finding suggests that there are opportunities for community cooling using existing technologies and practices to increase urban albedo and canopy cover. Knowing

that these are effective cooling measures, cities can also accelerate implementation of these UHI countermeasures in heat-vulnerable neighborhoods.

In addition, the calibrated meteorological model accurately identified the localized urban heat islands and urban cool islands observed in this study. Therefore, the model can be applied by stakeholders, including city and state government, to characterize the intraurban microclimate variations elsewhere in California, and stakeholders can use the model to analyze the benefits from launching UHI countermeasures.

GLOSSARY AND ACRONYMS

Term	Definition
AGL	Above ground level
Albedo	Solar reflectance
Anemometer	Wind speed meter
Aspirated radiation shield	Shield through which air is drawn to improve accuracy of air temperature measurement by an enclosed thermometer
CART	Classification and regression tree: a multiple-regression statistical analysis often represented graphically with a tree-like structure
Central Los Angeles	A study region in Central Los Angeles used in the research team's analysis of personal weather station measurements
Climate archipelago	The complex climate effects of a large, continuous urban area in which upwind portions can affect downwind portions
Cool roof	Roof whose surface stays cool in the sun by exhibiting high solar reflectance (ability to reflect sunlight) and high thermal emittance (ability to emit thermal radiation)
Dry-bulb air temperature	Air temperature measured by a dry thermometer
EPIC (Electric Program Investment Charge)	The Electric Program Investment Charge, created by the California Public Utilities Commission in December 2011, supports investments in clean energy technologies that benefit electricity ratepayers of Pacific Gas and Electric Company, Southern California Edison Company, and San Diego Gas & Electric Company.
GPS	Global positioning system
LA1	Study region near downtown Los Angeles used in the team's climate-modeling analysis
LAUSD	Los Angeles Unified School District
LDT	Local daylight time
LULC	Land use/land cover
MAE	Mean absolute error. This is a measure of the average deviation of a model prediction of a property, such as temperature, from the observed value of the property at the same location, time, and overall conditions.

Mesonet	A regional network of weather stations
Meso-urban	Scales that range from the regional to the sub-urban
Mobile transect	Measurement of temperature along a path
Monitor	A device that measures and records weather parameters
PWS	Personal weather station (a privately owned, consumer-grade stationary monitor)
Pyranometer	Sunlight meter
Roughness length parameter	An indicator of the ability of a surface to exchange heat and momentum with the atmosphere
RSME	Root mean square error: the root of the mean of the squares of the errors (see definition of MAE above). RMSE is more sensitive to outliers than MAE.
SFV	San Fernando Valley
SFV_R	A study region in the San Fernando Valley used in the team's analysis of personal weather station measurements
SFV5	Selected study region within the San Fernando Valley used in the team's climate-modeling analysis
TSM	Transect-specific (WRF) modeling: Weather simulations of the exact routes and at the exact times of the mobile transects
Thermistor	Semiconductor thermometer
UCI	Urban cool island
UHI	Urban heat island
UHIE	Urban heat island effect
Urban climate archipelago	The climate of an expansive continuous urban area or chains of urban areas that is large enough to produce its own characteristics and influences on the climate system
USC	University of Southern California
WRF	Weather Research and Forecasting (a numerical weather prediction system)

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APPENDICES

Appendix A-1: *Land-Use/Land-Cover Analysis and Atmospheric Modeling to Support Site Identification and Selection for Fixed Meteorological Monitors and Mobile-Observation Routes* (Task 2 Report, Part I). Publication number CEC-500-2019-020-APA1.

Appendix A-2: *Land-Use/Land-Cover Analysis and Atmospheric Modeling to Support Site Identification and Selection for Fixed Meteorological Monitors and Mobile-Observation Routes* (Task Report Appendix A). Publication number CEC-500-2019-020-APA2.

Appendix B: *Preliminary Mobile Measurements of Air Temperature via Transect* (Task 2 Report, Part II). Publication number CEC-500-2019-020-APB.

Appendix C: *Monitoring Plan, Instrumentation Design, and Sensor Deployment* (Task 3 Report, Part I). Publication number CEC-500-2019-020-APC.

Appendix D: *Atmospheric Modeling to Support Site Identification and Selection for Fixed Weather Stations: Siting of Weather Stations* (Task 3 Report, Part II) . Publication number CEC-500-2019-020-APD.

Appendix E: *Model Validation and Development of Correlations Between Observed Air Temperature and Surface Physical Properties* (Task 4 Report, Part I) . Publication number CEC-500-2019-020-APE.

Appendix F: *Air-Temperature Response to Neighborhood-Scale Variations in Albedo and Canopy Cover in the Real World: Fine-Resolution Meteorological Modeling and Mobile Temperature Observations in the Los Angeles Climate Archipelago* (Task 4 Report, Part II) . Publication number CEC-500-2019-020-APF.

Appendix G: *Observational Evidence of Neighborhood-Scale Reductions in Air Temperature Associated With Increases in Roof Albedo* (Task 4 Report, Part III) . Publication number CEC-500-2019-020-APG.

California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix A-1

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APA-1

Appendix A: Land-use/land-cover analysis and atmospheric modeling to support site identification and selection for fixed meteorological monitors and mobile-observation routes (Task 2 Report, Part I)

Haider Taha

Altostratus, Inc.

7 July 2016

Land-use/Land-cover Analysis and Atmospheric Modeling to Support Site Identification and Selection for Fixed Meteorological Monitors and Mobile Observation Routes

Technical report submitted as summary for Tasks 2b, 2c, and 3a of
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LIST OF ACRONYMS

AGL	Above Ground Level
AMSL	Above Mean Sea Level
ARB	Air Resources Board
Archipelago	Urban archipelago is a continuous, very large expanse of urban land use
ARW	Advanced Research WRF
Cal/EPA	California Environmental Protection Agency
Crosswalk	A statistical correlation among different land-use/land-cover categories
DH	Degree-Hours
FDDA	Four Dimensional Data Assimilation
IBL	Internal Boundary Layer
IQR	Inter-Quartile Range
JJA	June, July, and August
LBNL	Lawrence Berkeley National Laboratory
LCP	Lambert Conformal Projection
LSM	Land Surface Model
LULC	Land Use / Land Cover
mb	millibar
MPE	Model Performance Evaluation
NCAR	National Center for Atmospheric Research
NCDC	National Climatic Data Center
NLCD	National Land Cover Data
NOAA	National Oceanic and Atmospheric Administration
NUDAPT	National Urban Database and Access Portal Tool
NWS	National Weather Service
UCI	Urban Cool Island
UCM	Urban Canopy Model
UHI	Urban Heat Island
USGS	United States Geological survey
UTC	Coordinated Universal Time
uWRF	Urbanized WRF model
WRF	Weather Research and Forecasting model

A. Characterization of land use and land cover

A.1. Objectives

The objectives of this task are to characterize the land-use, functions, and cover in areas of interest in the Los Angeles region. Based on this characterization, an initial assessment of potential sites is then determined. The focus, as will be shown below, is on areas in Los Angeles's west basin and in the San Fernando Valley. The characterizations encompass both the City of Los Angeles and the Los Angeles County territories.

A.2. Data sources

Nine land-use/land-cover (LULC) data sources were identified and datasets were acquired (Table A.1). These include: 1) 30-m National Land Cover Data (NLCD) for year 2011 -- most recent year (MRLC 2014), 2) 30-m USGS Level-II classification LULC (Anderson et al. 2001), 3) Area-specific LULC from the City of Los Angeles (City of LA 2015), 4) Area-specific LULC and building outlines from the County of Los Angeles (LAR-IAC 2008), 5) Google Earth morphological and land-cover data, 6) 1-m area-specific satellite-derived roof albedo from a Berkeley Lab's ARB study (Ban-Weiss et al. 2014), 7) 1-m Area-specific urban morphological and geometrical data from the National Urban Datasets and Portal Tool (NUDAPT; Burian et al. 2003), 8) SCAG USGS Level-IV LULC (SCAG 2012), and 9) CALFIRE urban tree canopy cover (Bjorkman et al. 2015).

All data were acquired, processed, recast, and prepared for input to the meteorological model (WRF) as discussed in the following sections. The data, in different native formats, were converted for manipulation and preparation of input to meteorological models. The data domains were superimposed in GIS to evaluate their spatial coverages, domain overlaps, and to identify areas that lack coverage for further analysis and data cross-walking.

LULC was further analyzed in more detail in subdomains of interest, i.e., near areas where observational data analysis would be required (in the vicinities of monitors to be installed in this project). The monitor locations were defined initially based on modeling results (discussed in Section C below).

Figure A.1 depicts the data domains, i.e., geographical areas covered by each dataset listed in Table A.1. The NLCD, USGS Level-II, and Google Earth data are nation-wide in extent and cover all sub-domains of interest in this study (thus they cover the entire region shown in Figure A.1). The SCAG LULC and LA County buildings datasets cover the entire LA County domain including the City of Los Angeles. The CALFIRE dataset covers many urban areas in California and thus most of the domain seen in the figure; however, it characterizes tree cover only in urbanized areas. The Los Angeles City LULC dataset covers only the areas within the city boundaries (area shown in light gray in the figure) and so does the remotely-sensed LBNL-ARB roof-albedo dataset. Finally, the NUDAPT dataset covers only smaller subdomains in the area (demarcated with four darker grey rectangles in Figure A.1). Figure A.2 shows the relationship between LULC coverage and locations of existing weather monitors in the region as well as areas selected for initial analysis.

In situations where data does not exist for a domain or area of interest, the characterization is derived in this study based on correlations (and cross walk) with other datasets. For example, and

as discussed further below, some parts of the west basin modeling domain are not covered by the LBNL roof albedo dataset. In this case, roof albedo is statistically correlated with LULC classes and the latter used as a basis for extrapolating roof albedo to areas with no direct data.

Table A.1: Model parameters (for surface characterization) and available sources.

(α : albedo, η : soil moisture, Z_0 : roughness length, C_d : drag coefficient, ε : emissivity, $\lambda_{(p,t)}$ plan-, top-, and frontal-area densities, $f2p$: floor-to-plan ratio, $h2w$: height-to-width ratio, Q_f : anthropogenic heat flux, shd : shade factor, svf : sky-view factor, and LAI: leaf-area index.

In the table, the following acronyms are used: NUDAPT: National Urban Data and Access Portal Tool; NLCD: National Land Cover Data (2011); USGS L-II: United States Geological Survey Level-II LULC classification; ARB: Air Resources Board; SCAG: Southern California Association of Governments Level-IV LULC classification; and CALFIRE: California Department of Forestry and Fire Protection, tree-canopy cover.

	NLCD 2011 ■	USGS L-II ■	LA City LULC	LA County LULC	Google Earth ≡	ARB / LBNL albedo	NUDAPT	SCAG LULC	CALFIRE
Status:	acquired	acquired	acquired	acquired	acquired	acquired	acquired	acquired	acquired
α	i	i			i, PC	d, PS §			i
η	i	i							i
Z_0, C_d	i	i	i, PS	i, PC	i		d, PS	i	i
ε	i	i				i, PS §			
$\lambda_p, \lambda_t, \lambda_f$			i, PS	i, PC	d		d, PS	i	d
$f2p, h2w$	i	i	i, PS	i, PC	d		d, PS	i	
Q_f	i	i							
shd	i	i		i, PC	d		d, PS	i	d
svf					d		d, PS	i	
LAI	i	i		i, PC	i, PC				d

■ Cross-walked

§ Roof albedo only

≡ Intensive effort, use only in limited areas if necessary

- d: direct characterization (where spatial coverage is available)
- i: indirect characterization
- PS: partial spatial coverage (e.g., relative to Area 1); cross-walking required
- PC: partial categorical coverage

Table A.1 indicates how the data are used in characterizing each grid cell individually in both the west basin and San Fernando Valley domains. Some data can be used to derive model-input parameters directly (d) others indirectly (i). The shaded areas in Table A.1 indicate that the dataset is not suitable for computing the given variable.

As seen in the table, each dataset is suitable (alone or in combination with other data) for the derivation of certain input variables to the model. The goal is to improve the characterization of the surface in the model, in addition to vast amounts of other data types such as meteorological initial and boundary conditions, terrain elevation, soil conditions, and upper air data.

Figure A.1: Graphical representations of the LULC datasets coverage.

Figure A.2: LULC data coverage in relation to existing weather monitors in the region. Areas LA1, LA2, LA3 and parts of San Fernando Valley (SFV) were identified for possible analysis and modeling.

A.3 Initial selection of potential monitoring areas (subdomains)

Based on initial LULC analysis from NLCD 2011, USGS Level-II, USGS Level-IV, and Google Earth data, focusing on changes and demarcations in LULC, four initial areas were identified for modeling, data analysis, and further detailed evaluation of LULC properties for possible siting of fixed monitors.

The areas are in 1) the west basin and 2) San Fernando Valley. In the west basin, areas labeled 1, 2, and 3 (in Figure A.3) were identified because of their distinct LULC boundaries and different physical characteristics relative to surrounding areas. Area LA1 was selected as initial focus since it includes downtown Los Angeles and the high-density developments with commercial / industrial land functions to the south and southeast of downtown. In San Fernando Valley, several areas were also selected based on LULC demarcations, as seen in Figure A.3. These will be discussed later in this report.

Within each of LA1 and San Fernando Valley, further identification of potential monitoring sites are based on meteorological modeling results discussed further below in Sections B and C.

Figure A.3: First-guess sub-regions (areas LA1, LA2, LA3, and San Fernando Valley, SFV) for meteorological modeling and observational data analysis.

A.4 LULC analysis

The datasets were converted from their native formats into a form suitable for use in 1) characterizing the surface near selected monitors and areas of interest, 2) developing input to meteorological models, 3) correlating with observed micro-meteorology, and 4) characterizing the technical potential for mitigation of heat islands in the future.

Furthermore, all datasets (Table A.1) were converted to the Lambert Conformal projection system (LCC) for consistent cross-referencing and use in the meteorological model (which is configured based on the LCC projection in this study). Analysis of the datasets was conducted with characterization of gridded values for several parameters including within two 500-m resolution meteorological modeling domains in west basin and in San Fernando Valley.

The LULC characterization was carried out with a goal to derive surface inputs to the meteorological model and to provide a baseline for relating observational weather data to LULC at each monitor station in the future. Among the different datasets, crosswalks were developed, where necessary, such that each grid cell of the modeling domain was characterized simultaneously based on several sources of information (Figure A.4).

Figure A.4: Convergence of various data sources in characterizing the modeling domains on a grid-cell by grid-cell basis (500 m).

With this customized approach, parameters were calculated for each grid cell and used to override the generic/default WRF model input. The calculated parameters include 1) albedo, 2) roughness length, 3) soil moisture, 4) vegetation cover, 5) shade factor, 6) sky view factor, 7) mean building and vegetation heights, and 8) vertical profiles (distributions) of building plan-area densities. The derivation of these parameters is discussed further below.

Figures A.5 through A.11 provide examples from the LULC analysis based on different datasets. Figures A.5 and A.6 depict the characterization of LA1 and various parts of San Fernando Valley based on the USGS Level-IV scheme as used by SCAG to characterize the entire Los Angeles County territory.

Figure A.5: Sample detail from the Level-IV SCAG LULC classification system showing area LA1 selected for modeling and observational data analysis. There are about 50 LULC classes represented in this figure (and the Level-IV system includes more than 100 classifications). The darker areas are residential land uses and the colored ones in the middle are industrial and commercial land functions. Bright green represents open and/or vegetated areas.

Figure A.6: Sample detail from the Level-IV SCAG LULC classification system showing the San Fernando Valley areas selected for modeling and observational data analysis. The darker areas are residential land uses and the colored ones are industrial, commercial, and academic land functions. Bright green are open and/or vegetated areas. Purple is transportation (in this case, Van Nuys airport).

Figure A.7: Sample detail from the Los Angeles County buildings dataset showing area LA1. The darker areas are residential land uses and the colored ones are industrial and commercial land functions. Light brown color is medium height whereas dark brown and red are tall buildings (~100 m). White areas are open spaces, highways/roadways, and/or vegetated areas.

Figure A.8: Sample detail from the Los Angeles County buildings dataset showing a part of the San Fernando Valley. The darker areas are residential land uses and the colored are industrial and commercial land functions. Light brown color is medium height whereas dark brown and red are tall buildings. White areas are open spaces, highways/roadways, and/or vegetated areas.

Figure A.9: Sample tree-cover characterization in area LA1 based on data from EarthDefine / CALFIRE. Black pixels indicate tree-cover presence.

Figure A.10: Sample tree-cover characterization in the San Fernando Valley domain based on data from EarthDefine / CALFIRE. Black pixels indicate tree-cover presence.

Figures A.7 and A.8 depict the characterization of these areas in terms of building heights and is based on building outlines datasets from the Los Angeles County. Figures A.9 and A.10 depict a characterization of vegetation cover in these two areas, based on the dataset from EarthDefine / CALFIRE. Finally, Figure A.11 is a sample analysis based on NLCD 2011 data for area LA1, as an example. The goal of the NLCD LULC analysis was to identify (e.g., see dashed white lines) the demarcations in LULC properties in the area which is expected to affect the local micrometeorological fields across those boundaries.

In all of the analysis depicted in Figures A.5 through A.11, LULC demarcations are evident. This was the basis for initial selection of area LA1 and several areas in San Fernando Valley for modeling and monitoring. Based on these and other datasets listed in Table A.1, several areas within each of LA1 and San Fernando Valley were characterized.

Figure A.11: Sample LULC characterization in and around area LA1 based on 30-m National Land Cover Data (NLCD 2011). The purple color represents commercial and industrial land use, the red represents mostly residential land functions, and the light grey represents open spaces and/or vegetated areas. Green is vegetation cover.

A.5 Crosswalk among datasets

Correlations were established across different LULC datasets in situations where a modeling domain (e.g., around area LA1 and the San Fernando Valley domain) is larger than a dataset's geographical domain. Two cases are discussed below.

A.5.1 LULC and local climate zones (LCZ) correlations

Initially, and to perform the first sets of simulations, a correlation between USGS Level-IV LULC classes and Local Climate Zones (LCZ) were developed – the LCZ scheme is discussed in Stewart and Oke (2012). This was done so that certain thermo-physical surface characterizations, including 1) view factors, 2) building plan areas, 3) roughness lengths, 4) pervious and impervious surface areas, 5) anthropogenic heating profiles, 6) building (or roughness elements) heights, 7) albedo, 8) vegetation cover, and 9) soil moisture, could be defined on a cell-specific basis according to the USGS Level-IV characterization at 100-m resolution. This is then physically up-scaled to 500-m (model resolution) before running the meteorological model. The resulting gridded properties from various approaches were compared and tested in meteorological simulations.

The Level-IV classes on the left side of Figure A.12 were mapped into the LCZ categories shown in the right side (these Level_IV categories, among ~100 classes, are the ones found in the Los Angeles region's LA1 and San Fernando Valley domains). The physical and thermal properties of these LCZs are applied to the corresponding Level-IV categories in each cell of the modeling domains. In Table A.2, the resulting mapping performed in this study is shown and the mapped properties are those values listed in columns 2 through 6 of the table.

This approach was used in deriving some model-input parameters during the early stages of the modeling. In later stages (discussed below), the LCZ approach was no longer use and, instead, cell-level characterizations were carried out using actual input data, e.g., based on the EarthDefine / CALFIRE vegetation data and the Los Angeles County buildings datasets.

Level-4 (Anderson et al 2001)
(e.g., present in D09)

1110 Single-family residential
1111 High-density single family residential
1120 Multi-family residential
1130 Mobile homes and trailer parks
1140 Mixed residential
1210 Commercial and services
1240 Public facilities
1241 Government offices
1242 Police and sheriff stations
1244 Major medical health care facilities
1246 Other public facilities
1247 Public parking facilities
1260 Educational institutions
1265 Colleges and universities
1311 Manufacturing and industrial services
1320 Heavy industrial
1323 Open storage
1340 Wholesaling and warehousing
1411 Transportation/Airports
1437 Improved flood waterways and structures
1800 Open space and recreation
1820 Local parks and recreation
1840 Cemeteries
4000 Water

Local Climate Zones
(Stewart and Oke 2012)

Built types	Definition	Land cover types	Definition
1. Compact high-rise	Dense mix of tall buildings to tens of stories. Few or no trees. Land cover mostly paved. Concrete, steel, stone, and glass construction materials.	A. Dense trees	Heavily wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
2. Compact mid-rise	Dense mix of mid-rise buildings (3-9 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	B. Scattered trees	Lightly wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
3. Compact low-rise	Dense mix of low-rise buildings (1-3 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	C. Bush, scrub	Open arrangement of bushes, shrubs, and short, woody trees. Land cover mostly pervious (bare soil or sand). Zone function is natural scrubland or agriculture.
4. Open high-rise	Open arrangement of tall buildings to tens of stories. Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	D. Low plants	Featureless landscape of grass or herbaceous plants/crops. Few or no trees. Zone function is natural grassland, agriculture, or urban park.
5. Open mid-rise	Open arrangement of mid-rise buildings (3-9 stories). Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	E. Bare rock or paved	Featureless landscape of rock or paved cover. Few or no trees or plants. Zone function is natural desert (rock) or urban transportation.
6. Open low-rise	Open arrangement of low-rise buildings (1-3 stories). Abundance of pervious land cover (low plants, scattered trees). Wood, brick, stone, tile, and concrete construction materials.	F. Bare soil or sand	Featureless landscape of soil or sand cover. Few or no trees or plants. Zone function is natural desert or agriculture.
7. Lightweight low-rise	Dense mix of single-story buildings. Few or no trees. Land cover mostly hard-packed. Lightweight construction materials (e.g., wood, sheath, corrugated metal).	G. Water	Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons.
8. Large low-rise	Open arrangement of large low-rise buildings (1-3 stories). Few or no trees. Land cover mostly paved. Steel, concrete, metal, and stone construction materials.	VARIABLE LAND COVER PROPERTIES Variable or ephemeral land cover properties that change significantly with synoptic weather patterns, agricultural practices, and/or seasonal cycles.	
9. Sparsely built	Sparse arrangement of small or medium-sized buildings in a natural setting. Abundance of pervious land cover (low plants, scattered trees).	h. bare trees	Leafless deciduous trees (e.g., winter). Increased sky view factor. Reduced albedo.
10. Heavy industry	Low-rise and mid-rise industrial structures (towers, tanks, stacks). Few or no trees. Land cover mostly paved or hard-packed. Metal, steel, and concrete construction materials.	i. snow cover	Snow cover >10 cm in depth. Low albedo. High albedo.
		j. dry ground	Parched soil. Low albedo. Large Bowen ratio. Increased albedo.
		k. wet ground	Waterlogged soil. High albedo. Small Bowen ratio. Reduced albedo.

Figure A.12: USGS Level-IV classes in the Los Angeles region and LCZ.

Table A.2: Mapping (crosswalk) of USGS Level-IV classes onto local climate zone (LCZ) classes and associated surface physical properties.

LCZ	svf	bldg cov	impervious	pervious	Qf	Level-4 mapped onto LCZ																	
1	0.3	0.5	0.55	0.05	50	1212																	
2	0.45	0.55	0.4	0.15	70	1122	1123	1124	1211	1231	1233	1241	1247	1310	1311	1500							
3	0.4	0.55	0.35	0.25	60	1242	1243	1340															
4	0.6	0.3	0.35	0.35	40	1125																	
5	0.65	0.3	0.4	0.3	20	1120	1121	1245	1246	1265	1600												
6	0.75	0.3	0.35	0.45	20	1110	1112	1132	1140	1151	1261												
7	0.35	0.75	0.15	0.25	30	1111	1130	1131	1271														
8	0.7	0.4	0.45	0.15	40	1220	1221	1222	1223	1224	1232	1234	1251	1252	1263	1264	1266	1274	1312	1314	1411	1415	1440
9	0.8	0.15	0.15	0.7	10	1150	1152	1262															
10	0.75	0.25	0.3	0.45	300	1313	1321	1322	1325	1320	1431												
A	0.3	0.05	0.05	0.95	0	1850	1860	2200	2300														
B	0.65	0.05	0.05	0.95	0	1438	1820	1830	3200														
C	0.8	0.05	0.05	0.95	0	1272	1275	1870	1880	2400	2700												
D	0.95	0.05	0.05	0.95	0	1273	1276	1412	1810	1840	2110	2121	2500	2600	3100	3300							
E	0.95	0.05	0.9	0.05	0	1323	1324	1330	1331	1332	1410	1413	1414	1415	1416	1417	1418	1420	1435	1450	1460	1900	
F	0.95	0.05	0.05	0.95	0	1432	1433	3400															
G	0.95	0.05	0.05	0.95	0	1434	1436	1437	4100	4200	4300	4400	4500										

A.5.2 LULC and roof-albedo correlations

Whereas the entire SVF domain is characterized in terms of roof albedo in the LBNL-ARB dataset (Ban-Weiss et al. 2014), only about 1/3 of the Area-1 domain is so characterized (Figure A.13). Thus the remaining 2/3 of the LA1 modeling domain required a crosswalk to characterize the roof albedo in each grid cell of the remaining areas.

Figure A.13: LA1 modeling domain (black dots) compared to the area covered by roof-albedo dataset (black-filled area).

The crosswalk was developed in this study by correlating the USGS Level-IV classes with LBNL-ARB roof albedo throughout the data domain, i.e., where roof albedo data is available in LA1 and San Fernando Valley. To do so, a centroid was assigned to each roof in the dataset (see Figure A.14 as an example) so that each roof could be tracked in terms of its area, albedo, and location and subsequently aggregated at the 500-m level for correlation with the Level-IV classes.

Figure A.15 shows the resulting correlations between roof albedo and LULC for those LULC categories that exist in the dataset domain overlapping with the LA1 modeling domain. These categories include: 1) single-family residential, 2) multi-family residential, 3) high-density single-family residential, 4) mixed residential, 5) mobile homes, 6) commercial and services, 7) educational institutions, 8) manufacturing / industrial, 9) transportation / airports, 10) heavy industrial, and 11) open space / recreation. Based on these results, a representative (statistical mode) albedo value was assigned to each of the Level-IV LULC listed in the table. These values are then used throughout the 2/3 remainder of the LA1 domain.

Figure A.14: Example detail showing assignment of centroids to roofs in the LBNL dataset to facilitate computation of gridded albedo as input to meteorological model (shown here is a detail of an area near the University of Southern California campus).

Mixed residential, n = 10
Representative roof albedo = 0.17

Mobile homes / trailer parks, n = 277
Representative roof albedo = 0.16

Commercial and Services, n = 16
Representative roof albedo = 0.20

Educational institutions, n = 11
Representative roof albedo = 0.20

Manufacturing and industrial, n = 66
Representative roof albedo = 0.20

Transportation / airports, n = 23
Representative roof albedo = 0.20

Heavy industrial, n = 6
Representative roof albedo = 0.19

Open space and recreation, n = 39
Representative roof albedo = 0.17

Figure A.15: Frequency distribution of roof albedo for eleven Level-IV LULC type in the LA1 modeling domain.

B. Meteorological modeling

B.1 Objectives

The goal of performing detailed meteorological modeling in this study is to assist in selecting areas and sites for deploying fixed weather monitors as well as devising mobile-transect routes. The modeling results provide a basis for correlating micrometeorology at each site with the surrounding LULC and surface physical characteristics among other factors affecting the local temperature fields, i.e., local heat or cool islands (UHI or UCI).

In addition to horizontal siting of monitors, per meteorological modeling results, vertical positioning of the weather instruments also considers some guidelines, e.g., based on flow theory, as discussed in Section C.

B.2 Modeling configurations, data preparation, and customizations

The WRF-ARW meteorological modeling system (Skamarock et al. 2008) was selected for use in this study. Several urban parameterizations were applied and inter-compared. These include 1) an approach used by Altostratus Inc. (AREAMOD) which involves modified modules and overriding urban input to the model (Taha 2007, 2008a-c), 2) a study-modified Urban Canopy Model (Kusaka et al. 2001) that adds a single-layer urban parameterization (urban canyon) to the WRF NOAA land-surface model (Pleim et al. 2001), and 3) a study-modified Building Environment Parameterization (Martilli et al. 2002) which adds a multi-layered urban parameterization to WRF.

Meteorological input for summers of 2013 and 2006 were prepared as used in a prior modeling effort for a Cal/EPA project (Taha and Freed 2015). These periods represent typical summer and heat-wave conditions in California and are used again in this project for the sake of compatibility with the Cal/EPA Urban Heat Island Index (UHII) modeling work.

Three first-guess sub-regions in the Los Angeles west basin and one in San Fernando Valley, shown earlier in Figure A.3, were identified for further evaluation and for possible initial meteorological modeling to assess the potential UHI and/or UCI signals that monitors in this area would capture. The meteorological modeling domain (discussed in the following section) is configured such that the finest grids (500-m resolution) encompass these areas of interest.

Four periods were first simulated to evaluate whether the near-surface temperature field and UHI and/or UCI patterns are significantly affected by different summer conditions. These periods are 1) May 30 through June 16, 2013 representing relatively typical summer conditions in California, 2) June 29 through July 16, 2013 representing warmer conditions, 3) June 30 through July 16 2006, representing windier conditions, and 4) July 14 through August 1 2006, representing the California heat wave of 2006 (Gershunov et al. 2009). This is discussed in Section B.4.1.

The simulations were further continued using the typical conditions of May 30 – June 16, 2013 with model customizations and parameterizations beginning with overriding model input with domain-specific characterizations that are defined for each grid cell (AREAMOD approach). This approach improves area-specificity of surface input to the meteorological model. The initial modeling incorporated study-specific updates and customizations to input of surface albedo,

vegetation cover, roughness length, soil moisture, and shade factor. This was then followed by simulations using study-modified Urban Canopy Model (mod-UCM) and study-modified Building Environment Parameterization (mod-BEP) modules. All of these are discussed in more detail below.

The initial modeling also included performing sensitivity simulations to perturbations in roof albedo for a few selected buildings in central part of the domain (near Downtown Los Angeles) to identify the threshold of albedo change (at small scales) necessary to produce a significant and clear model response (i.e., detect a temperature-change signal). Similar sensitivity simulations were also carried out for perturbations in soil moisture and vegetation fraction. The results indicate that the model modifications were implemented correctly and that the model's response to perturbations in surface properties occurs at the correct locations and with expected magnitudes.

B.2.1 Modeling domains

The top part of Figure B.1 depicts the modeling configuration used in this study. The grids have consecutive resolutions of 27 km (western U.S. and Pacific Ocean), 9 km (state of California), and 3 km (from Lake Tahoe to Mexico). Two 500-m resolution domains (bottom part of Figure B.1 as well as Figure B.2) are centered over area LA1 in the west basin and over the western part of San Fernando Valley. In Figures B.1 and B.2, the 500-m domains are depicted with grid center points (mass points) overlaid on USGS Level-IV LULC classifications in each domain (colored background). These LULC classes were discussed earlier in Section A and Figure A.12.

In the vertical direction, 55 computational (eta) levels were used for the mesoscale grids. In the two configurations where urban parameterizations were used in the 500-m grids (mod-UCM and mod-BEP modules), as discussed below, an additional 23 urban vertical levels were meshed with the 55 mesoscale levels, for a total of 78 vertical computational levels. The resolution of the urban levels is 5 m throughout the UCL, up to a height of 120 m above ground level (AGL) whereas the mesoscale domain extends to about 15 km AGL.

Figure B.1: Structure of the modeling domains as configured in this study (top). Bottom figure depicts the 500-m resolution modeling sub-domain encompassing “Area 1” in the west Basin. The black dots represent the cell centers of the 500-m domain and the colored background represents the USGS Level-IV LULC classification (also seen in Figure A.5).

Figure B.2: 500-m resolution modeling sub-domain encompassing San Fernando Valley areas of interest. The black dots represent the cell centers of the 500-m domain and the colored background represents the USGS Level-IV LULC classification (also seen in Figure A.6).

The locations of these two 500-m domains relative to utilities service territories in the Los Angeles region are depicted in Figure B.3. As can be seen, there is overlap with utility service territories, i.e., IOU (Southern California Edison) and that of the LADWP. Whereas the San Fernando Valley domain is almost entirely within the LADWP territory, the LA1 domain straddles LADWP, SCE, and City of Vernon territories.

Modeling of both domains was carried out with equal emphasis in order to identify and diversify potential locations for monitoring. It is of interest to model both LA1 and San Fernando Valley domains so as to study the effects of the sea breeze in the former and the internal valleys in the latter.

Figure B.3: Model analysis sub-domains “LA1” and San Fernando Valley (rectangular domains), relative to utilities service territories in the Los Angeles region.

B.2.2 Development of surface-characterization input

In this study, several aspects of the input were developed based on site-specific (i.e., cell-specific) data to override the typical / default input to WRF. The 500-m cell-specific input was developed for both area LA1 and the San Fernando Valley domains as discussed earlier in Section A. Overriding the WRF input significantly increases the specificity of the simulations, which is important in this type of application, i.e., UHI characterization.

As discussed in Section A, the cell-specific input is based on a convergence of various datasets to derive the parameters needed (Table A.1 and Figure A.4). For each grid cell (500-m resolution) the value of a property P is the weighted values of its components, That is:

$$P_{i,j} = \sum_{n=1}^N p_{i,j,n} a_{i,j,n} \quad (B.1)$$

where P is the cell-level value of a property, N is the number of different land covers in the grid cell, p is the value of the property in a certain land-cover of a grid cell, and a is the fractional area of the given land cover in the grid cell. The averaging in equation B.1 is applied to physical properties and is thus more accurate in characterizing a grid cell (especially at fine resolutions) than determining LULC majority in a grid cell and then assigning to it a set of physical properties, which is the conventional approach, e.g., in WRF.

B.2.2.1 Characterization of albedo

The grid-cell-level albedo is computed per equation B.1, where the urban LULC components (n) include: 1) roofs, 2) pavements, 3) vegetation, 4) water surfaces, and 5) other cell-specific land functions or covers.

Roof albedo is computed based on remote-sensed values from the LBNL-ARB dataset (Ban-Weiss et al. 2014) and is thus highly building- and cell-specific. Pavements albedo is computed from past research of California (Akbari et al., 1999; Rose et al. 2003) which is based on USGS Level-II classifications within each grid cell (Taha 2007). Vegetation and water were assigned constant values based on field measurements and literature review (Taha et al. 2015).

Figures B.4, B.5, and B.6 depict the cell-specific albedo (computed with equation B.1) for the LA1 and the San Fernando Valley modeling domains. Figures B.4 and B.5 are provided for comparison of two methods. In Figure B.4, the LA albedo is computed based on LBNL roof-albedo data in areas where the modeling and data domains overlap, while using the first approach (Section A.5.1) to characterize albedo in areas where the domains do not overlap, i.e., based on mapping the Level-IV categories onto LCZs. On the other hand, Figure B.5 shows albedo computed using domain-specific values for vegetation cover (from EarthDefine / CALFIRE data), building cover (from LA County buildings data), and roof albedo (from LBNL data). The small graph to the right of Figure B.4) depicts the default albedo in WRF (for LA1 domain), that is, the albedo that would have been used if the modeler followed the standard WRF processing.

While the general spatial pattern of albedo is relatively similar between the two derivation methods (Figure B.4. vs. B.5), the albedo range is slightly higher for the LCZ-based approach (Figure B.4) than the second approach (Figure B.5). In the initial simulations, the LCZ-based approach was tested. However, in doing the full simulations and analysis of results, the more cell-specific second approach was used to characterize albedo input to WRF. Figure B.6 depicts the albedo of the San Fernando Valley modeling domain computed based on the second approach (Section A.5.2) and the CALFIRE tree cover data.

Finally, it is to be noted that for grid cells in the modeling domains where no LBNL-ARB roof albedo is available, and where no other cell-specific data are available from this LULC analysis, then the albedo of the grid cells is reverted to WRF default input. These are typically non-urban regions, mountains, ocean, etc.

Figure B.4: Model input development for LA1 domain 500-m gridded albedo. This derivation is based on LBNL-ARB dataset albedo (where domains overlap) and based on Level-IV-to-LCZ mapping (Section A.5.1) where domains do not overlap. Points of interest for further analysis and modeling are identified on the figure.

Figure B.5: Model input development for LA1 domain 500-m gridded albedo. This derivation improves upon the one shown in Figure B.4 by including cell-specific vegetation cover from EarthDefine / CALFIRE, and cell-specific roof albedo from LBNL-ARB study (Section A.5.2). Points of interest for further analysis and modeling are identified on the figures.

Figure B.6: Model input development for San Fernando Valley domain 500-m gridded albedo. This derivation includes cell-specific vegetation cover from EarthDefine / CALFIRE data and cell-specific roof albedo from LBNL-ARB study (Section A.5.2).

B.2.2.2 Characterization of vegetation cover, shade factor, and non-vegetated fraction

As discussed in Section A, the tree-cover characterization was based on data from EarthDefine / CALFIRE (Bjorkman et al. 2015). The raster data was vectorized in this study and a scaling factor (0-1) was computed based on the vegetation cover in each polygon that falls within defined grid cells (500-m resolution). The scaling factor was then applied to tree-cover ranges based on canopy characterization studies (e.g., Simpson and McPherson 2007) and/or typical ranges such as those in WRF lookup. That is, tree cover ranging from 0.02-0.35 is scaled by the values derived from the EarthDefine / CALFIRE dataset via polygons, i.e., a scaling value of 1 corresponds to a tree cover of 0.35.

In WRF, the tree cover translates directly into the shade-factor parameter. Similarly, soil moisture values for vegetation types (ranging from about 0.05 to 0.35) are scaled by the tree-cover characterization based in the EarthDefine / CALFIRE dataset. The remaining part of a cell is considered non-vegetated. The non-vegetated portion of each cell is then further broken down into roofs areas (based on LBNL and LA_County datasets), pavements, and other surfaces depending on the NLCD 2011 LULC classification of each cell.

The EarthDefine / CALFIRE data is a raster layer at a 1×1 meter cell (pixel) size that is binary – a value of 1 is assigned to a pixel where a tree canopy is present, all other areas are no data. In this study, a centroid was generated for each tree (each 1-m pixel with tree cover), then vectorized and up-scaled to 500 m. While the Earth Define / CALFIRE data is categorized into low, medium, and high cover, as in Table B.1, this study calculates the cover with a range from 0 – 100% based on the up-scaling of the pixel values.

Table B.1 Canopy cover rank, per EarthDefine / CALFIRE

Canopy Cover Rank	% Canopy Cover
L (1)	<10%
M (2)	10-20%
H (3)	>20%

Of note, grid cells in the modeling domain where no EarthDefine / CALFIRE tree-cover data is available are reverted to WRF default vegetation-fraction characterization. These are typically non-urban regions and occur only in very small areas. Figures B.7 and B.8 depict the resulting tree cover computed following the approach discussed above.

Figure B.7: Tree-cover, soil moisture, and shade-factor characterizations of sub-domain for meteorological modeling of “Area 1”: vegetation cover (left) and scaling factor for soil moisture content (right) compared with default WRF model input (top right). UHI-reference points for vegetation effects are highlighted with black circles. These are points of potential interest for further modeling and siting the fixed weather monitors.

Figure B.8: Tree-cover, soil moisture, and shade-factor characterizations of sub-domain for meteorological modeling of the San Fernando Valley domain: vegetation cover (left) and scaling factor for soil moisture content (right). UHI-reference points for vegetation effects are highlighted with black circles.

B.2.2.3 Characterization of building heights, plan-, top-, and frontal-area densities

The characterization of cell-specific building geometrical / morphological parameters (PAD, TAD, FAD, mean height, and sky-view factor; SVF) in this study relies mainly on calculations performed using the Los Angeles County buildings information, and also indirectly based on NUDAPT as well as prior Google Earth Pro analysis of Californian urban areas (Taha 2008a-c).

Every building in each grid cell was accounted for in computing several parameters, including the mean building height in each cell and the cumulative (vertical distribution of) plan-area density (PAD) at a moving reference height to derive other morphometric parameters. These are defined below in equations B.2 through B.7 (Taha 2008a,b).

To compute the building-specific site area (building footprint), the calculations subtract vegetation cover and buildings plan area from the total cell area and then divide by the number of buildings to determine an average open-space area that is then used in computing the building footprint. In the vertical direction, to derive the profiles of PAD and FAD over 23 urban vertical levels for use in urbanized WRF modules (e.g., mod-BEP), the calculations were integrated sequentially at 5-m intervals to compute probability of buildings plan-area densities within vertical intervals and above them.

In equations B.2 – B.7, A_i is the footprint area of building i , h_i is the height of the building, A_w is the total surface area of walls, A_T is the area of the grid cell, H_1 and H_2 are the heights of two buildings along the wind path, D is the average horizontal distance between them, $A_p(z)$ is the plan area of roughness elements at height z , A_T is area of the grid cell, and Δz is the height increment used in the calculation, e.g., 5 m in this case, and θ is wind direction.

Mean building height weighted by building plan area: $\bar{h}_{AW} = \frac{\sum_{i=1}^N A_i h_i}{\sum_{i=1}^N A_i}$ (B.2)

Wall-to-plan area ratio (W2P): $\lambda_w = \frac{A_w}{A_T}$ (B.3)

Building height-to-width ratio (H2W): $\lambda_h(\theta) = 0.5 \frac{[H_1(\theta) + H_2(\theta)]}{D(\theta)}$ (B.4)

Plan area density (PAD) within a height increment Δz :

$$A_p(z) = \frac{\frac{1}{\Delta z} \int_{z - \frac{1}{2}\Delta z}^{z + \frac{1}{2}\Delta z} A_p(z) dz}{A_T \Delta z} \quad (B.5)$$

Top area density (TAD) within a height increment Δz :

$$A_t(z) = \frac{A_p\left(z - \frac{\Delta z}{2}\right) - A_p\left(z + \frac{\Delta z}{2}\right)}{A_T \Delta z} \quad (B.6)$$

Frontal area density (FAD): $A_f(z, \theta) = \frac{A(\theta)}{A_T \Delta z}$ (B.7)

where $A(\theta)$ is the area of roughness elements projected into the plane normal to the wind approach direction (θ) within a height increment (Δz). In this study, wind approach direction was not accounted for, that is, the calculations assume frontal area density to be similar for all wind directions.

B.2.2.4 Characterization of roughness length

Roughness length for vegetation and buildings was characterized for each grid cell based on the approach by MacDonald et al. (1998). To calculate roughness length in this manner, several morphological variables were derived first for every grid cell as discussed above. These include 1) frontal area densities of roughness elements (buildings and vegetation), 2) plan-area densities

of roughness elements, and 3) heights of the roughness elements. Thus based on the calculations in Section B.2.2.3, these parameters are further derived as follows:

Plan-area density is computed as:
$$\lambda_p = \int_0^{h_e} A_t(z) dz \quad (\text{B.8})$$

The frontal-area index is defined as the total area (A) projected into the wind approach direction (θ) (of all roughness elements) divided by the cell area (in this case, $500 \text{ m} \times 500 \text{ m}$):

$$\lambda_f(\theta) = \frac{A}{A_T} \quad (\text{B.9})$$

Using these two parameters in conjunction with building (or roughness element) height, the calculation of roughness length proceeds as follows:

$$\frac{z_d}{z_H} = 1 + \alpha^{-\lambda_p} (\lambda_p - 1) \quad (\text{B.10})$$

$$\frac{z_o}{z_H} = \left(1 - \frac{z_d}{z_H} \right) \exp \left\{ - \left(0.5 \beta \frac{C_D}{k^2} \left(1 - \frac{z_d}{z_H} \right) \lambda_f(\theta) \right)^{-0.5} \right\} \quad (\text{B.11})$$

Here, z_H is the building (or roughness element) height, α is an empirical coefficient, C_D is a drag coefficient, k is the von Kármán constant, and β is a correction factor for the drag coefficient. Macdonald et al. (1998) recommended for staggered arrays of cubes that $\alpha \approx 4.43$ and $\beta \approx 1.0$. These values were also used by Grimmond and Oke (1999). In equation (B.11), the drag coefficient C_D is set to 1.2 and λ_f and λ_p are as computed in equations (B.8) and (B.9) respectively. Figures B.9 and B.10 depict the resulting gridded roughness length parameter (m) for the LA1 and San Fernando Valley modeling domains, respectively. Plan-, frontal-, and top-area densities were calculated based on NUDAPT, LA County building outlines, and EarthDefine / CALFIRE tree-cover datasets, as discussed above.

Figure B.9: Roughness length (m) in the LA1 500-m modeling domain which includes Downtown Los Angeles, computed based on equations B.8 – B.11 and weighting by land-cover (equation B.1) in each grid cell.

Figure B.10: Same as Figure B.9, but for the 500-m San Fernando Valley modeling domain.

B.2.3 Modeling approaches

In this study, three modeling approaches were applied which, along with two different temperature diagnostics, provide an ensemble of simulations to evaluate the consistency of the UHI and/or UCI signals in the domains of interest. If consistent, the signals are then used as a basis for siting the fixed weather monitors as well as for designing mobile temperature transects.

B.2.3.1 AREAMOD approach

This approach involves overriding all (or as much as possible) of the look-up type of WRF surface-characterization input so that the thermo-physical properties of urban areas (e.g., within the UCL) are better characterized on site-specific basis, in more detail, and at finer resolutions. The goal of this approach is to increase the site- and cell-specificity of the simulations. Taha (2007) has successfully applied this approach in several studies and found that model performance was consistently acceptable.

While simple in concept, the approach requires 1) generation of cell-specific input for all cells in a domain of interest, which can become exhaustive and time-consuming, and 2) modification of the mesoscale model (WRF) code to accept different input and perform internal calculations and conversions to merge these “externally-computed” parameters with model internal parameterizations and characterizations of both urban and non-urban parts of every grid cell. In cases where urban cells have less than 100% urban cover, this approach seamlessly meshes and weighs the physical properties of the urban and non-urban parts of each cell (Taha and Freed 2015), which circumvents some of the problems associated with urbanized parameterizations in WRF (e.g., UCM and BEP) – problems related to abrupt changes in morphological and physical properties between urban and non-urban parts of the domain.

This approach is suited for any resolution, e.g., 500 m – 5 km, whereas UCM and BEP, at least in theory, should be applied only when resolution approaches 500-m or finer. Otherwise there is no real benefit from using these additional urbanized modules. The AREAMOD approach is also CPU-cost efficient especially if modeling a large number of urban areas simultaneously and over a long period of time, e.g., statewide at relatively fine resolutions (~1 km).

In this study, the AREAMOD approach was applied first and compared to results from other two approaches as discussed below.

B.2.3.2 Modified UCM approach

This approach uses the urban canopy model (UCM) of Kusaka et al. (2001). In this study, two modifications were carried out on this module: 1) revising the trigger to the UCM parameterization and 2) overriding the default lookup surface input to the UCM. As such, this approach is referred to as “mod-UCM”.

The trigger to the model, i.e., flagging grid cells in which the UCM parameterization is called, has been changed in this study to be more specific to the region. Rather than base the trigger on only 3 urban categories, which is the standard approach in WRF, the trigger in this study is based on a more resolved LULC classification system, e.g., USGS Level-IV. This, coupled with the finer resolution of the simulations (500 m), causes the model to be applied more accurately.

The other modification is that the typical application of UCM reads in default (lookup) values of thermo-physical parameters that are assigned to 3 generic urban LULC classes. In this study, the approach was modified so that mod-UCM ingests thermo-physical input for each grid cell independently and based on cell-specific characterizations of relevant input parameters, as discussed earlier.

B.2.3.3 Modified BEP approach

The Building Environment Parameterization (Martilli et al. 2002) is another urban module available in the WRF modeling system. It includes multi-level urban canopy calculations (instead of a single layer in the UCM).

As with UCM (Section B.2.3.2), two modifications on BEP were carried out in this study and is thus referred to as “mod-BEP”. One is to modify the trigger and the other is the use of cell-specific 3-dimensional input to replace the default / lookup parameters in WRF. Thus the restriction on number of urban categories (3) in BEP has also been eliminated in this study and all input is ingested on a cell-specific basis directly from the calculations discussed above.

B.3 Meteorological initial and boundary conditions

Four-dimensional NCEP-NCAR Reanalysis (Kistler et al. 2001) was used to provide boundary conditions and for data assimilation (FDDA). Additional data (NWS/NOAA) was obtained to complement the reanalysis, including surface temperature, sea-surface temperature, soil moisture, and upper-air meteorology. Observational data were used in carrying out quantitative model performance evaluation. Furthermore, data from surface-monitor networks, such as regional mesonets, were also used in qualitative comparison with model results (Taha and Freed 2015).

B.4 Modeling results

Simulations of the LA1 and San Fernando Valley domains were carried out using the modeling approaches discussed in Section B.2.3 above. In all approaches, the temperature field was characterized for each grid point in the modeling domain using two diagnostics. The first is 2-m air temperature calculated from interpolation between surface and first atmospheric level; this will be referred to as “Tair” in the rest of this report. The second diagnostic is 2-m air temperature based on surface temperature and heat transfer calculations; this is referred to as “T2” in the rest of this report.

Thus Tair is more representative of the prognostic temperature field and above-UCL temperature, whereas T2 is more of a diagnostic air temperature and more representative of in-canyon or in-UCL air temperature. T2 is more sensitive to surface properties and less sensitive to advection of heat (which is captured by Tair).

Based on results from this analysis, some points in the LA1 and San Fernando Valley domains were identified as localized UHI and others as localized UCI – these will be discussed in detail later in this report.

The model produces a large array of output fields and variables. The focus in this task is on air temperature. While, there are several ways to examine the model's output fields, e.g., temperature, including horizontal and vertical cross sections (e.g., Figures B.11 and B.12), time series, maxima, minima, departures and averages, tendencies, and so on, this analysis relies on cumulative temperature indicators, e.g., degree-hours (DH) because they are more useful in capturing the UHI and/or UCI signals over certain periods of time and different weather conditions, and thus are more suitable in selection of monitoring sites.

Figures B.11 and B.12 show a random snapshot horizontal cross-section example of meteorological output (in this case air temperature at 2 m AGL and skin surface temperature) for June 1st, 2013. However, this type of output is not very useful for the application at hand, i.e., identifying UHI / UCI locations for monitoring. Thus the model output is further converted into DH equivalents as discussed next.

Figure B.11: 2-m air temperature (T_{air}) in the LA1 500-m resolution domain, simulated for 1700 PDT, June 1, 2013 with the AREAMOD approach (axis units: km).

Figure B.12: skin surface temperature in the LA1 500-m resolution domain, simulated for 1700 PDT, June 1, 2013 with the AREAMOD approach (axis units: km).

B.4.1 Comparison of different summer episodes

The modeled temperature field was converted into DH metrics for evaluation and analysis. The DH metrics were examined as totals, e.g., DH per 17 days (since the model was run in overlapping 17-days periods), or averages, e.g., DH per day, DH per daytime hours, DH per nighttime hours, as well as temperature. The examination of the DH patterns can be used to identify areas with localized UHI and/or UCI signals.

As a first step, and before using model output to suggest siting of monitors, DH fields (T2) from four different periods were examined. The goal was to evaluate whether the general temperature pattern was consistent across different summer conditions.

Figures B.13 and B.14 depict a summary of DH/17 days for LA1 and San Fernando Valley domains, respectively. In each case, four summer episodes are presented: a) May 30 - June 16, 2013 representing typical summer conditions in California, b) June 29 - July 16, 2013 representing warmer conditions than typical, c) May 30 - June 16, 2006 representing windier and warm conditions (warmer than “a” but cooler than “b”), and d) July 14 - August 1, 2006 which is the California heat wave of 2006.

Figure B.13a: LA1 DH/17 days, May 30 - June 16, 2013 (typical summer)

Figure B.13b: LA1 DH/17 days, June 29 - July 16, 2013 (warmer conditions)

Figure B.13c: LA1 DH/17 days, May 30 - June 16, 2006 (windier)

Figure B.13d: LA1 DH/17 days, July 14 - August 1, 2006 (CA heat wave)

Figure B.14a: San Fernando Valley DH/17 days, May 30 - June 16, 2013 (typical summer)

Figure B.14b: San Fernando Valley DH/17 days, June 29 - July 16, 2013 (warmer conditions)

Figure B.14c: San Fernando Valley DH/17 days, May 30 - June 16, 2006 (windier)

Figure B.14d: San Fernando Valley DH/17 days, July 14 - August 1, 2006 (CA heat wave)

In these figures, it can be observed that the absolute ranges of DH are shifted to larger values during hotter weather, as seen in columns 2 and 5 in Table B.2.

Table B.2: Degree-hours ranges in San Fernando Valley and LA1

1	2	3	4	5	6
LA1	Range DH/day	Δ DH/day	San Fernando Valley	Range DH/day	Δ DH/day
a	412-493	81	a	425-550	125
b	511-606	95	b	527-658	131
c	471-568	97	c	504-616	112
d	571-670	99	d	600-718	118

Columns 1 and 4 are the intervals (per definition above), columns 2 and 5 are the absolute DH/day ranges in the respective domains, and columns 3 and 6 are the DH/day range (differences) across the domain for each interval. It can be seen that the range in San Fernando Valley (inland valley) is larger than in LA1 which is affected by the sea breeze (compare columns 2 and 5). Furthermore, the range of DH/day within each scenario is also larger in San Fernando Valley (112-131) than in LA1 (81-99) (compare columns 3 and 6) because of the moderating effect of the ocean in LA1. The windier conditions impart smaller ranges of air temperature (compare row “c” in column 6 with other rows in column 6) because of increased venting and mixing, but not in LA1 (compare row “c” in column 3 with other rows in column 3). This is again likely caused by the moderating influence of the sea breeze.

Since the different periods (Figures B.13 and B.14) appear to have similar spatial patterns of temperature field near the points of interest (discussed in the following sections), one of these four periods was selected for further analysis, modeling, and as a basis for development of siting criteria. The period selected for this purpose is representative of typical summer conditions in JJA of 2013 and 2006 (May 30 through June 16, 2013). Thus in the remaining discussions in this report, results from different model parameterizations are evaluated and compared using this modeling period.

B.4.2 Results from different parameterizations

As discussed earlier, three modeling approaches (parameterizations) were used in this study (AREAMOD, modified-UCM, and modified-BEP) along with two diagnosis variables, Tair and T2, as defined above. Thus results from 3 approaches and two temperature metrics are evaluated in this and following sections, using a cumulative metric (DH) for the reasons explained earlier.

B.4.2.1 San Fernando Valley

Figure B.15(a-g) depicts the modeled DH from various parameterizations and diagnosis metrics for the San Fernando Valley domain. It is important to note that the figures show an analysis subdomain which is smaller than the actual 500-m modeling domain; namely, 8 grid points on each of the four sides were removed (to avoid contamination with boundary effects) leaving the analysis subdomain shown in Figure B.15.

In this figure, several points (locations) of interest are identified (UHI and/or UCI) for siting considerations, further modeling analysis, and initial mobile-transects characterizations of temperature. It can be seen that in all figures, a general SE-to-W warming tendency exists, such that that highest urban air temperatures are found in the western and southwestern parts of the San Fernando Valley domain. The exact locations of peak temperatures depend on the approach being applied and also on the diagnosis variable (Tair or T2). Whereas the peak T2 is typically localized, the Tair peak is generally advected downwind, e.g., compare Figure B.15a with B.15c, although the patterns of the temperature field are similar in both cases.

In general, areas SFV1, SFV2, SFV3, SFV5, and SFV7 (within the San Fernando Valley domain) are identified as localized UHIs (Figure B.15a) whereas points SFV4 and SFV6 are identified a localized UCIs. This pattern is consistent in all Figures B.15a through B.15g, except for point SFV4 which is diagnosed as a UCI in some approaches but a UHI in others (e.g., Figures B.15e and B.15f). Similarly, point SFV3 is defined as a UHI in some cases, but not well defined in others. Thus, initially, these two points should not be considered for siting purposes or monitoring since the signal does not seem to be consistent in those locations.

The results indicate that the three approaches (AREAMOD, modified-UCM, and modified-BEP), if examined using the same diagnosis metric (T2), appear to produce similar urban effects on temperature. While the ranges of DH in these three approaches differ somewhat, they still are within same magnitudes (e.g., ~ 7200 – 9300 DH/17-days) and the intra-urban variations are generally similar (UHI and UCI points) as seen in Figures B.15 a, d, and f. On the other hand, diagnosing with Tair, while still showing relatively similar spatial patterns in temperature, produces higher DH values (~ 8100 – 10880 DH/17-days) – compare Figures B.15a and B.15b. This is a result of the fact that Tair captures the advected effects of heat over the region (horizontally and from above) and thus the range is shifted upward by some 1000 DH/17-days, which is roughly equivalent to an average of 2°C increase in temperature area-wide.

Evaluation of these figures shows relatively consistent signals at points SFV1, SVF2, SFV5, SFV6, and SFV7. As will be discussed later, these points will be considered for possible siting of fixed monitors and for conducting mobile transects, in particular area SFV5.

Figures B.15b and B.15e depict the DH totals of all 1400 PDT hours (to asses daytime UHI/UCI and compare with daytime mobile transects to be discussed later). Figure B.15b is for the AREAMOD approach whereas Figure B.15e is for the modified-UCM approach. Comparing Figures B.15a and B.15b suggests that the overall spatial patterns are similar for 1400 PDT averages versus all hour averages but that the larger UHIs are more concentrated in the western and southwestern parts of the domain in the 1400 PDT plot suggesting that that area is where daytime UHIs are largest. This will be discussed later in this report.

On the other hand, comparing Figures B.15e to B.15d (both for the modified-UCM approach) shows different spatial patterns – whereas the all-hours DH is clearly associated with LULC pattern, the 1400 PDT average shows a uniform large UHI without LULC-related demarcations. However, it still indicates that the largest UHI is in the western and southwestern part of the San Fernando Valley domain. Thus taken together, these results indicate the location of the largest and more consistent UHI signals in this domain, as listed above.

Figure B.15a: Modeled temperature gradients, DH/17-days in San Fernando Valley domain for interval “a” for all episode hours, T2-based, AREAMOD approach, contours interval = 0.33°C (x- and y- axis are in km).

Figure B.15b: Modeled temperature gradients, DH/17-hours in San Fernando Valley domain for interval “a” for all 1400 PDT hours in the episode, T2-based, AREAMOD approach, contours interval = 0.41°C (x- and y- axis are in km).

Figure B.15c: Modeled temperature gradients, DH/17-days in San Fernando Valley domain for interval “a” for all episode hours, Tair-based, AREAMOD approach, contours interval = 0.45°C (x- and y- axis are in km).

Figure B.15d: Modeled temperature gradients, DH/17-days in San Fernando Valley domain for interval “a” for all episode hours, T2-based, modified-UCM approach, contours interval = 0.3°C (x- and y- axis are in km).

Figure B.15e: Modeled temperature gradients, DH/17-hours in San Fernando Valley domain for interval “a” for all 1400 PDT hours in the episode, T2-based, modified-UCM approach, contours interval = 0.30°C (x- and y- axis are in km).

Figure B.15f: Modeled temperature gradients, DH/17-days in San Fernando Valley domain for interval “a” for all episode hours, T2-based, modified-BEP approach, contours interval = 0.22°C (x- and y- axis are in km).

Figure B.15g: Modeled temperature gradients superimposed over San Fernando Valley domain (white rectangle) for interval “a” to highlight the locations of points of interest SFV1 through SFV7. The yellow markers show the locations of weather monitors currently in the area (from all data sources).

B.4.2.2 West basin (area LA1)

Figure B.16(a-h) shows the same type of information but for the LA1 subdomain. Again, we note that the figures show an analysis subdomain that is smaller than the actual LA1 500-m meteorological modeling domain (8 grid points on each of the four sides were removed to avoid contamination of results with boundary effects).

Several points of interest are identified (UHI and/or UCI) for potential siting of monitors, further modeling, and initial mobile-transects characterizations of temperature (points are labeled “A” through “L” in the figures). A strong SW-to-NE warming tendency is seen in all figures, which results from the sea-breeze and archipelago warming effects. The highest urban air temperatures are consistently found in the northeastern parts of this domain. The exact locations of peak temperatures vary depending on approach being applied and on diagnosis variable (Tair or T2).

In general, points A, B, C, E, F, G, H, and K are identified as localized UCIs (Figure B.16a) whereas points D, I, J, and L (L1/L2) are identified as localized UHIs (Figures B.16a and B.16d). However, some of these points are not consistent (in terms of UHI or UCI signals) across all modeling approaches and/or diagnosis variables. Thus some of these points will have a lower priority for potential monitors siting, as will be further evaluated in this and following sections.

Unlike in the SFV domain, the results indicate that the three approaches (AREAMOD, modified-UCM, and modified-BEP), if examined using the same diagnosis metric (T2), appear to produce urban effects on temperature that vary from one approach to another (i.e., greater variability than in the SFV domain). Comparing Figures B.16a, B.16d, and B.16g, it can be seen that the UHI and/or UCI points A, E, G, and K are not consistent (i.e., they occur in two approaches but not the third). Other points appear to be more consistent and, thus, will be assigned a relatively higher priority (as discussed later).

The ranges of DH in these three approaches differ somewhat; in terms of T2, the AREAMOD approach produces larger temperatures (DH range from 7007 to 8404) whereas the mod-UCM approach produces relatively similar but lower ranges (DH ~7200 – 8100). Evaluation of these figures shows some relatively consistent signals at points **B, C, F, H, I, J, and L**. As will be discussed later, these points will be considered for possible siting of fixed monitors and for conducting mobile transects. These points are also depicted in Figure App_A1 (in Task Report Appendix A).

Figures B.16c and B.16e depict the DH totals of all 1400 PDT hours (to assess daytime UHI and/or UCI and compare with daytime mobile transects to be discussed later). Figure B.16c is for the AREAMOD approach whereas Figure B.16e is for the modified-UCM approach. Comparing Figures B.16b and B.16c suggests that the overall spatial patterns are similar for 1400 PDT averages versus all hour averages, suggesting a daytime-dominant UHI and/or UCI effect.

On the other hand, comparing Figures B.16e to B.15d (both for the modified-UCM approach) shows different spatial patterns – i.e., that points A, B, and C are well-defined in the all-hours average but not so in the 1400 PDT averages. This suggests that points A, B, and C UCI/UHI patterns are nighttime effects, whereas the other points in the domain are relatively more daytime effects. Finally, Figure B.16h presents the DH contours as an overlay in Google Earth so that a general picture can be formed with regard to the locations of these points of interest. These points can be seen in more detail in Figure App_A1 (in Task Report Appendix A).

Figure B.16a: Modeled temperature gradients, DH/17-days in LA1 domain for interval “a” for all episode hours, T2-based, AREAMOD approach, contours interval = 0.15°C (x- and y- axis are in km).

Figure B.16b: Modeled temperature gradients, DH/17-days in LA1 domain for interval “a” for all episode hours, Tair-based, AREAMOD approach, contours interval = 0.15°C (x- and y- axis are in km).

Figure B.16c: Modeled temperature gradients, DH/17-hours in LA1 domain for interval “a” for all 1400 PDT hours in the episode, Tair-based, AREAMOD approach, contours interval = 0.25°C (x- and y- axis are in km).

Figure B.16d: Modeled temperature gradients, DH/17-days in LA1 domain for interval “a” for all episode hours, T2-based, modified-UCM approach, contours interval = 0.16°C (x- and y- axis are in km).

Figure B.16e: Modeled temperature gradients, DH/17-hours in LA1 domain for interval “a” for all 1400 PDT hours in the episode, T2-based, modified-UCM approach, contours interval = 0.14°C (x- and y- axis are in km).

Figure B.16f: Modeled temperature gradients, DH/17-days in LA1 domain for interval “a” for all episode hours, Tair-based, modified-UCM approach, contours interval = 0.15°C (x- and y- axis are in km).

Figure B.16g: Modeled temperature gradients, DH/17-days in LA1 domain for interval “a” for all episode hours, T2-based, modified-BEP approach, contours interval = 0.10°C (x- and y- axis are in km).

Figure B.16h: Modeled temperature gradients superimposed over LA1 domain (white rectangle) for interval “a” to highlight the locations of points of interest “A” through “L”. The yellow markers show the locations of weather monitors currently in the area (from all sources). Red lines are service-territory boundaries.

B.4.2.3 Initial suggestions for monitoring sites

Based on the initial results discussed in Sections B.4.2.1 and B.4.2.2, it is suggested that fixed monitors be installed in *both* the San Fernando Valley and LA1 domains in order to capture various effects, i.e., the interactions between LULC and microclimates in 1) inland regions (Valley) and 2) areas impacted by the sea breeze flow and climate archipelago effects (LA1). Monitoring two different areas can provide further information as a basis for better understanding the role of local surface-properties and impacts on temperature in different climate regimes i.e., inland valleys and relatively more coastal areas.

For points A through L in area LA1 and points SFV1 through SFV7 in San Fernando Valley (Figure App_A1), analysis of UHI and/or UCI was done by diagnosing two variables, T2 and Tair, as discussed earlier. The goal was to identify those points where UCI and/or UHI signals are relatively consistent across various modeling approaches and diagnostic metrics. Table B.3 lists the combinations of modeling approaches and diagnostic metrics that were evaluated. Results from this matrix are discussed later in this report.

Table B.3: Modeling approaches and temperature metrics combinations evaluated at each of points A-L in LA1 and SFV1-SFV7 in San Fernando Valley.

LA1	AREAMOD	T2
		Tair
	mod-UCM	T2
		Tair
	mod-BEP	T2
		Tair
San Fernando Valley	AREAMOD	T2
		Tair
	mod-UCM	T2
		Tair
	mod-BEP	T2
		Tair

Furthermore, the meteorological-model output was examined to 1) analyze the UCI and/or UHI patterns (e.g., based on DH totals), 2) analyze the number of UHI and/or UCI hours at each point of interest, 3) quantify the absolute temperature differences of UHI or UCI at each point, 4) identify the times of UHI and UCI occurrences at each point, and 5) compute the relative DH ratios (ratio of target DH to the DH of the opposite signal at that location). A sample of this analysis is shown in Table B.4, corresponding to the shaded cell in Table B.3, and the detailed analysis can be found in Task Report Appendix A and Task Report Appendix B.

Another way to examine the results was to generate statistics, time-series, scatter plots, and distributions. In Figure B.17 (corresponding to the shaded box in Table B.3), a small sample is

provided to show the type of information that can be gleaned, in this case, from scatter plots. The detailed distributions can be found in Appendix A and will be discussed further below.

Thus in Figure B.17 (for approach AREAMOD, domain LA1, and diagnostic variable T2), it can be seen that point “A” is a UCI relative to its reference point (S_of_A). The scatter plot shows that there are a few hours (1100 – 1600 PDT) when point A is actually a UHI relative to its reference point. However, the dominant effect in that location (see green bars) is a UCI (-0.2 to -0.8 °C). It can also be seen that most of the cooling effect occurs at night suggesting that the area is cooler than its surroundings at those hours because it is relatively more open (whereas the surrounds have a smaller view factor and thus higher canyon-related nighttime temperatures).

The same flow of discussion applies to all other points, periods, approaches, and diagnostic variables and are listed in Task Report Appendix A and B. They will not be discussed here, but the details can be found in Figure App_A2 (in the Appendix). Table B.4 (corresponding to shaded cell in Table B.3) shows information for each listed location (second column), whether it is predominantly a UHI or UCI relative to its surroundings (third column), percentage of hours as a UHI or a UCI (fourth and fifth columns), dominant UCI and/or UHI temperatures (top three most frequent bins in the scatter plot figures (sixth and seventh columns), times of UCI or UHI (eighth and ninth columns) and, finally, the degree-hour (DH) totals for UHI and/or UCI at each point (columns ten and eleven).

Table B.4: UHI and UCI analysis at selected points in LA1 domain for approach AREAMOD and diagnostic variable T2. This corresponds to shaded cell in Table B.3.

							Average UHI or UCI (°C) (largest 3 bins)						
							%hrs UHI	%hrs UCI	UHI (°C)	UCI (°C)	Time of UHI	time of UCI	
Area_1													
		A_minus_S_of_A	UCI				18.0%	82.0%		0.2-0.8	mostly daytime	all hours	13
AREAMOD		B_minus_SW_of_B	UCI				0.5%	99.5%		0.4-1.0	negligible	all hours	0
		C_minus_N_of_C	UCI				1.6%	98.4%		0.4-1.0	negligible	all hours	1
		L_minus_H	UHI				98.1%	1.9%	0.2-0.8		all hours	negligible	256
		L_minus_G	UHI				98.9%	1.1%	0.4-1.0		all hours	negligible	309
		K_minus_J	UCI				3.2%	96.8%		0.4-1.0	negligible	all hours	2
		J_minus_F	UHI				98.1%	1.9%		0.4-1.0	all hours	negligible	313
		F_minus_I	UCI				0.5%	99.5%		0.6-1.2	negligible	all hours	0
		I_minus_G	UHI				99.5%	0.5%	0.4-1.0		all hours	negligible	323

Figure B.17: Examples from analysis of UHI and/or UCI at points of interest (shown here for a few points in LA1 domain, as an example). Period shown in this example is May 30 – June 16, 2013. Left vertical axis is temperature difference between control point (UHI and/or UCI) and its respective reference point. Right vertical axis is frequency of UHI and/or UCI temperature differences and the horizontal axis is time of day.

The figures corresponding to all approaches and diagnostic can be found in Task Report Appendix A (Figure App_A2). Here, the examples show results for approach AREAMOD and diagnostic variable T2 in area LA1.

Another type of analysis (full details are found in Task Report Appendix A) is shown in Figure B.18. This figure is discussed as a sample (an example) here to explain the information contained in the appendix. All points, periods, approaches (AREAMOD and modified-UCM) analyzed in this manner are listed in detail in Task Report Appendix A (Figure App_A3).

The goal of this analysis is to add further information per hourly bin (distribution) as well as an indication to percentiles, maxima, minima, and outliers relative to the inter-quartile ranges (IQR). Here, near outliers are defined as 1.5 IQR, and far outliers as 3 IQR. This analysis is useful in understanding and inter-comparing the hour-to-hour variations in localized UCI and/or UHI as well as in identifying the hourly ranges of the temperature effects. It is also useful in comparing model results with mobile-transect measurements. The latter occur during a certain hour of the day and thus it is possible to compare with modeled results corresponding to that hour using information from Figure B.18.

In this example, it can be seen that point A is generally cooler (UCI) than its reference point, i.e., the medians are smaller than zero, and that the largest cooling effect occurs between 0800 and 1200 PDT. However, there is a large spread in the UHI/UCI, especially during hours before 1400 PDT. Even considering the full range of IQR, point A still appears to be a UCI, except for a few UHI instances at night, between 0000 and 0700 PDT.

Other information that can be gleaned from this analysis is how the UHI and/or UCI compare at certain relevant times, e.g., night, morning, mid-day, and evening. Thus in this example, it can be seen that there is relatively small variability between hours 0000 and 0500 as well as between 1400 and 2300 PDT, but larger variability between 0700 and 1300 PDT.

In addition to the box-and-whiskers plot, Figure B.18 (and similar figures in Task Report Appendix A) also includes tabulations of the results by hour, including the mean, variance, standard deviation, quartiles, maxima, minima, and IQR.

Based on this analysis and, taking into consideration the ratios of UHI/UCI temperatures (sixth and seventh columns in Table B.4) as well as the ratios of UHI to UCI degree-hours (last two columns in Table B.4), an initial ranking (prioritization) was developed for locations of potential interest for siting the fixed monitors as well as for carrying out the mobile temperature transects.

In Figure B.19, this initial ranking is summarized. The figure has two main parts, the left column represents the LA1 domain and the right column represents the San Fernando Valley domain. Within each, there are two sub-columns, one for the T2 diagnostic, and another for the Tair diagnostic. Then for each geographical point of interest (vertically), there are three modeling approaches (AREAMOD, modified-UCM, and modified-BEP). Thus this table is a reflection of the matrix discussed earlier in Table B.3, and shows the ratio of the target DH (i.e., the target UCI or UHI) to the DH of the opposite effect (UHI or UCI). Thus for example, the value “6” under Tair of point “A” in LA1 domain, i.e., the very top row, second sub-column from left (which is identified as a UCI) means that the UCI effect (DH) at that location is 6 times greater

than the UHI effect (DH) at that same location. Ratios greater than 2 are denoted with yellow, greater than 5 with orange, and greater than 10 with red.

N 377					
<u>A_minus_S_of_A by hh</u>	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.0565308	0.05930387	0.0426668	0.2065595
1	16	-0.1149583	0.05742072	0.1062101	0.3258990
2	16	-0.0244273	0.05742072	0.0623641	0.2497280
3	16	-0.1486732	0.05742072	0.0526105	0.2293698
4	16	-0.0320221	0.05742072	0.0903459	0.3005759
5	16	-0.0437033	0.05742072	0.1175156	0.3428056
6	16	-0.1257633	0.05742072	0.0569290	0.2385979
7	16	-0.1566474	0.05742072	0.1268390	0.3561446
8	16	-0.2760610	0.05742072	0.0826017	0.2874051
9	16	-0.4172306	0.05742072	0.0415256	0.2037783
10	16	-0.5368726	0.05742072	0.0500441	0.2237053
11	16	-0.2971685	0.05742072	0.0622183	0.2494360
12	16	-0.1872361	0.05742072	0.1461871	0.3823442
13	16	-0.2665436	0.05742072	0.0340429	0.1845073
14	16	-0.0538827	0.05742072	0.0170815	0.1306962
15	16	-0.1191289	0.05742072	0.0336075	0.1833235
16	16	-0.0952443	0.05742072	0.0181081	0.1345664
17	16	-0.0999441	0.05742072	0.0212476	0.1457654
18	15	-0.1093243	0.05930387	0.0085905	0.0926848
19	15	-0.1449132	0.05930387	0.0105458	0.1026929
20	15	-0.1834651	0.05930387	0.0085802	0.0926293
21	15	-0.1181157	0.05930387	0.0135141	0.1162503
22	15	-0.2125149	0.05930387	0.0231340	0.1520987
23	15	-0.0983501	0.05930387	0.0236874	0.1539071
Pooled	377			0.0527542	0.2296829

A_minus_S_of_A by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.441284	-0.1937257	-0.0900080	0.0987582	0.371548	0.2924838
1	-1.020555	-0.2317492	-0.1040580	0.0404776	0.432342	0.2722268
2	-0.426340	-0.1943352	-0.0702925	0.1266118	0.424183	0.3209470
3	-0.612208	-0.2950421	-0.1529065	-0.0007408	0.247292	0.2943013
4	-0.470888	-0.2210171	-0.1295755	0.0833252	0.594777	0.3043422
5	-0.538731	-0.2118426	-0.1786335	0.1457302	0.637708	0.3575727
6	-0.436465	-0.2511065	-0.1760560	-0.0331305	0.478460	0.2179760
7	-1.010586	-0.3747381	-0.2004960	0.1520304	0.293826	0.5267685
8	-0.633108	-0.5050956	-0.3334400	-0.1595077	0.343046	0.3455879
9	-0.954546	-0.5179803	-0.4335195	-0.2604247	-0.078697	0.2575557
10	-0.827528	-0.6993485	-0.6011675	-0.4205901	-0.122086	0.2787584
11	-0.803428	-0.4386998	-0.2969695	-0.1319590	0.113726	0.3067407
12	-0.974834	-0.3774448	-0.2317485	0.0234956	0.546964	0.4009403
13	-0.740591	-0.3165462	-0.2754475	-0.1668100	0.110523	0.1497362
14	-0.286430	-0.1401482	-0.0438680	0.0465255	0.177838	0.1866737
15	-0.587317	-0.2062366	-0.1043230	-0.0010838	0.171179	0.2051527
16	-0.339161	-0.1939964	-0.0955785	0.0120029	0.133287	0.2059993
17	-0.468702	-0.1871841	-0.0942555	-0.0026425	0.125706	0.1845416
18	-0.309059	-0.1458012	-0.0930650	-0.0455470	-0.003172	0.1002542
19	-0.406082	-0.1918880	-0.1539840	-0.0551855	-0.018221	0.1367025
20	-0.347582	-0.2405037	-0.2047110	-0.1203158	0.028840	0.1201878
21	-0.332953	-0.2208333	-0.1374150	-0.0267452	0.069128	0.1940882
22	-0.524195	-0.3309117	-0.1606050	-0.1024297	0.056733	0.2284820
23	-0.450979	-0.1953505	-0.1061270	0.0129782	0.147602	0.2083287

Figure B.18: Hourly distributions and ranges of UCI and/or UHI (the example below is for point A (relative to south_of_A reference point) in the LA1 domain, for the AREAMOD approach, and the Tair diagnostic.

Figure B.19: Initial ranking of points for monitoring and mobile transects for temperature.

Thus based on these ratios and combinations of approaches and metrics, an initial ranking is proposed for each point, as indicated with P1, P2, P3, and P4 (meaning priorities 1 to 4, respectively), with P1 being the highest priority and P4 the lowest. From Figure B.19, it is also clear that the points of interest in San Fernando Valley have a stronger UHI and/or UCI signal than the west basin (LA1).

B.4.3 Correlations with albedo and vegetation cover

As discussed in Section B.4.2.3, and listed in Figure B.19, several points (locations) within each domain were identified for evaluation, further modeling, and possible initial mobile transects to validate the model's predictions of temperature gradients. Some of these points are also investigated in terms of their local albedo and vegetation cover.

Thus in Figure B.20 (based on the AREAMOD approach), the average temperature deviation (vertical axis) at each point was correlated with departures of local albedo and vegetation cover (horizontal axis) from those of the background (domain modes of albedo and vegetation cover). This helps focus the initial auto transects and modeling analysis on some points of potentially stronger correlations between localized temperature departures and surface properties, e.g., albedo and vegetation cover (since they are some of the most commonly suggested UHI mitigation measures).

The localized albedo and vegetation cover departures are computed relative to their respective domain modes. In the LA1 domain, the albedo mode is 0.115 (covering 54% of the domain) and vegetation-cover mode is 0.05 (covering 50% of domain). In SFV, the albedo mode is 0.125 (covering 46% of the domain) and vegetation-cover mode is 0.05 (covering 51% of the domain).

Thus, as seen in Figure B.20, in area LA1, points I, J, and L are UHIs and correlate well with localized low albedo (albedo that is lower than the domain mode) and with localized low vegetation cover (lower than the domain vegetation-cover mode). On the other hand, points C and F are UCIs that correlate with higher localized albedo and vegetation cover, respectively (relative to domain mode values). Point E is also a UCI that correlates with both higher albedo and vegetation cover, but more so with vegetation cover.

In the San Fernando Valley domain, areas SFV1, VN (SFV7) and SFV5 are localized UHIs. SFV1 correlates with low albedo and VN (SFV7) correlates with low vegetation cover. While SFV5 has a high albedo (commercial and industrial area), it correlates more with low vegetation cover. On the other hand, point SFV4 is a UCI that correlates with higher vegetation cover and SFV6, also a UCI, correlates with higher albedo and vegetation cover (but more so with higher vegetation cover).

LA1

LA1

- I (UHI) : low alb + low veg
- J (UHI) : low alb
- L (UHI) : low veg
- C (UCI) : high alb
- E (UCI) : high veg + mod-high alb
- F (UCI) : high veg

Note: deltaA and deltaV are departures from respective modes in domain.
 Albedo mode: 0.1150 (54% of domain)
 Veg cover mode: 0.05 (50% of domain)

San Fernando Valley

San Fernando Valley

- SFV1 (UHI) : low alb
- SFV5 (UHI) : low veg (but high alb)
- VN (UHI) : low veg
- SFV4 (UCI) : high veg
- SFV6 (UCI) : high veg + mod-high alb

Note: deltaA and deltaV are departures from respective modes in domain.
 Albedo mode: 0.1250 (46% of domain)
 Veg cover mode: 0.05 (51% of domain)

Figure B.20: Local temperature deviations vs. local albedo and vegetation-cover departures from domain-mode values.

C. Site identification for fixed monitoring

C.1 Goal

The goal of this task is to identify areas within the Los Angeles Basin for more detailed modeling and characterization based on synthesizing information from Sections A and B, as discussed earlier. The selection of potential monitoring sites relies on information from different LULC characteristics and results from various modeling approaches. Furthermore, the goal also is to identify initial routes for mobile-transect measurements of air temperature.

C.2 Technical siting considerations

Figure C.1 lists some of the criteria to consider when selecting monitoring sites. These include technical considerations as well as non-technical issues. Oftentimes, the non-technical considerations are the overriding factors in site selections and, thus, they must be weighted very carefully.

In terms of technical considerations, the horizontal (geographical) siting of monitors depends on LULC analysis and meteorological-modeling results (Sections A and B). In the vertical direction, the positioning of sensors relies on understanding some aspects of flow theory, as discussed further below. In terms of non-technical factors, the most critical considerations are i, ii, and iii (in Figure C.1). Thus the initial selection of monitor sites (discussed in Section B), based on technical considerations, will be revised after regional partners provide information on the non-technical aspects.

Figure C.1: Technical and non-technical considerations in siting of fixed weather monitors in urban areas.

Reiterating, the main goal of this project is to understand the spatial variations in UHI and its interaction with land-use and land-cover properties in order to monitor and provide guidance for future mitigation via control measures such as increased albedo and vegetation cover. This is important, since it dictates the scale of interest in this case to about 500 m – 1500 m. UHI mitigation, as a community-scale strategy, does not apply to a single roof or a single tree – it is more of a measure affecting a city block or an urban development project, hence the scale defined above.

Considering this scale, the question then becomes: how high should a monitor be placed above the ground surface or above roof level (Figure C.2) in order to capture land-cover effects within an upwind fetch of 0.5 – 1.5 km? Hypothetically, the sensors should not be placed too close to the surface (ground, wall, or roof) that its temperature reading is influenced mostly by those surfaces (grey bar in Figure C.2), nor too high above the surface such that the temperature reading becomes regional in nature and unrelated to the 0.5 – 1.5 km fetch of interest. Thus it is desirable to place the sensors vertically within the range indicated with the blue bar in Figure C.2. Flow theory can provide some general guidance in this respect.

As depicted in Figure C.3, a transition in roughness or surface properties, in this case a change in LULC physical properties, induces an internal boundary layer (IBL) that grows downwind of the transition area. The IBL consists of a transition layer (TL) where the flow is still adjusting to the change in LULC and an internal equilibrium layer (IEL) where the flow has adjusted to changes in surface properties.

Thus in this project, it is desirable to place the sensors within the IBL that corresponds to the land-cover being characterized, that is, below the red line in Figure C.3. The goal is to capture the effects of the surrounding LULC, between 0.5 and 1.5 km upwind. If the sensors are placed above the red line, then the temperature readings will be those of the background flow, unrelated to the fetch (LULC) of interest.

Figure C.2: Parameter definitions in relation to vertical placement of weather monitors (temperature, wind direction and speed, and solar radiation).

Figure C.3: Boundary-layer and flow characterizations as a guide for siting new monitors in the vertical. The empirical relations provide estimates to sensor height above ground that is required to capture the desired signal downwind of a step change in roughness.

Several studies, e.g., Cheng and Castro (2002), Arya (1988), and Panofsky and Dutton (1984), attempted to devise an analytical expression for the growth of the IBL over distance away from the transition boundary, i.e., the step change in roughness. These expressions were based on empirical results from wind tunnel experiments as well as real-world measurements. Two such characterizations are shown in Figure C.3. The assumptions made in developing these relations are that the IBL growth is similar to a diffusion analogue and that vertical (w) and/or friction (u^*) velocities determine the growth of the IBL.

Thus in this study, it is desirable to place the sensors below the IBL height, $H_i(x)$ (in Figure C.3), but at or higher than the blending height (Z_r) in Figure C.2 (in this example, Z_r in Figure C.2 is used to approximate the height of IEL in Figure C.3). Using the above relations, $H_i(x)$ was computed as a function of x for several configurations and step changes in roughness length. The goal of this demonstration exercise was to establish a range of $H_i(x)$ as a function of distance and an average was derived. This average is listed in Table C.1. However, these calculations will be performed again on a building-by-building basis once the sites have been identified (with feedback from project partners) and the height above roof or above ground will be computed accordingly. This example here is simply provided to show a magnitude of scales. In this exercise, it is assumed that building height (Z_H) is 8 m (e.g., 1-story school / classrooms building). Thus in this case, Z_r is 12 m (AGL) or 2-4 m above roof level.

Per Table C.1 in this example, the monitors would be placed at least 75 m downwind from the step change in roughness (again, each case will be different and computed based on final

selection of sites and building-specific calculations). But as we will see in the following calculation, the 75-m distance is a minimum and to capture a fetch of 0.5-1.5 km, the sensors need to be further away (downwind) from the step change.

Table C.1: Growth of the internal boundary layer as a function of distance (an example).

X (m)	$H_i(x)$ (m)	Z_r (m) homogeneous
0	0	12 (or 2-4 m ARL)
25	5	12 (or 2-4 m ARL)
50	10	12 (or 2-4 m ARL)
75	15	12 (or 2-4 m ARL)
100	20	12 (or 2-4 m ARL)

*ARL: Above Roof Level

To obtain an estimate of the downwind displacement of monitors (from a step change in roughness) needed to capture a fetch of 0.5-1.5 km, Figure C.4 depicts some approximations based on WMO (2006). Per these approximations, the blending height (Z_r) is estimated as 1.5 the building height in dense and/or homogeneous urban areas but 4 times the building height in low density and/or sparse built up areas. WMO (2006) also estimates the fetch (F) to be between 1:10 and 1:500, thus a very wide range. In the exercise in Figure C.4, a ratio of 1:100 is assumed and thus F is 100 times the difference between Z_r and Z_d (the latter being the displacement height).

This example calculation yields a fetch of 800 m (if buildings are homogeneous) and 3.3 km (if low-density or sparse). This illustrates the very wide range of possible downwind displacements needed but gives a general indication of magnitude. Thus while 75 m is a minimum (from above example), 800 m is needed to capture the fetch effect.

For footprint capture: position in the inertial sublayer, that is at or higher than Z_r

$$Z_r = \begin{cases} 1.5 Z_H & (\text{dense or homogeneous}) \\ 4.0 Z_H & (\text{low density or variable}) \end{cases}$$

Assume / approximate:

$$1.5 Z_H \leq Z_r < 4.0 Z_H$$

So, the fetch is:

$$F = 100 [Z_r - Z_d]$$

Highly variable

If $Z_d = 7\text{m}$, $Z_H = 10\text{m}$, so $Z_r = 15\text{m}$ (at $1.5 Z_H$), and therefore $F = 800\text{m}$
 If $Z_d = 7\text{m}$, $Z_H = 10\text{m}$, so $Z_r = 40\text{m}$ (at $4.0 Z_H$), and therefore $F = 3300\text{m}$

Figure C.4: Approximate fetch vs. height of roughness elements.

C.3 Other considerations

In addition to the technical factors discussed in Section C.2, other siting considerations include accessibility, ease of maintenance, and potential for surface modifications in the area (Figure C.1). These aspects were discussed with project partners in the Los Angeles region and as of this report's date, several suggestions were made in connection with potential future urban enhancements sites and/or roadway maintenance areas.

Suggestions were received from the Los Angeles Department of Water and Power (LADWP) in relation to the Mayor's Great Streets Initiatives. Streets targeted for potential urban amelioration are identified in Figure C.5 (red circles). Other sites exist throughout the Los Angeles region, but the ones shown in the figure are closest to the LA1 and San Fernando Valley domains of interest discussed earlier. Other suggestions were received from Caltrans, namely, maintenance facilities in these two domains that could be used for siting the weather monitors. These are shown in Figure C.6 for San Fernando Valley (top) and the LA1 domain (bottom).

While these additional suggestions for sites do not coincide with the UHI and/or UCI points identified in the technical tasks, they will nevertheless be considered as potential alternatives.

Figure C.5: A sub-part of the LA Mayor Great Streets Initiatives that identifies streets where landscape and environmental improvement measures may be implemented (source: City of Los Angeles / Craig Tranby, LADWP). The circled streets in San Fernando Valley and near Downtown Los Angeles occur within potential areas considered for siting in this study.

Figure C.6: A sub-part of the Caltrans maintenance facilities in Southern California (source: Tom Pyle, Caltrans). Circled facilities occur near areas considered for possible siting in the study and could potentially host the new monitors to be deployed.

C.4 Design of preliminary mobile transects

As discussed earlier, a number of points of interest were identified in both the San Fernando Valley and LA1 domains based on their modeled UHI and/or UCI characteristics. In order to semi-quantitatively evaluate the model prediction of temperature tendency and gradients in these areas, preliminary mobile-transect measurements of temperature were devised. Several transect routes were designed in each domain around points identified earlier (points A through L in LA1 and points SFV1 through SFV7 in the San Fernando Valley domain). A temperature-measurement apparatus was constructed at the Lawrence Berkeley National Laboratory explicitly for this task.

The preliminary routes were designed such that they cut across the LULC transitions, e.g., to capture the possible effects of changes in LULC from one neighborhood to another. The routes were also developed keeping in mind the scale of interest 0.5 – 1.5 km. Furthermore, the routes were designed such that the change in elevation was relatively small, i.e., under 15 m and minimize the transect sub-routes to under 10 minutes (to avoid the effects of changing background temperatures between the start and end of each sub-transect). Figure C.7(a-i) shows examples from the selected transect routes (white lines).

Figure C.7a: Mobile transect route in-between points I, J, F, and G in area LA1. Red letters indicate UHI points and blue letters indicate UCI points.

Figure C.7b: Mobile transect route in-between points L1, L2, and H in area LA1. Red letters indicate UHI points and blue letters indicate UCI points.

Figure C.7c: Mobile transect route for point A (in area LA1) relative to reference area to the south. Point A is a UCI.

Figure C.7d: Mobile transect route in-between points E, J, and F in area LA1. Red letters indicate UHI points and blue letters indicate UCI points.

Figure C.7e: Mobile transect route for point B (in area LA1) relative to reference area to southwest. Point B is a UCI.

Figure C.7f: Mobile transect route for point SFV1 (in San Fernando Valley) relative to reference areas to the east and west. Point SFV1 is a UHI.

Figure C.7g: Mobile transect route for point SFV4 (in San Fernando Valley) relative to reference areas to the west. Point SFV4 is identified as a UCI.

Figure C.7h: Mobile transect route for point SFV5 (in San Fernando Valley) relative to reference areas to the north and south. Point SFV5 is identified as a UHI.

Figure C.7i: Mobile transect route for point SFV6 (in San Fernando Valley) relative to reference areas to the west. Point SFV6 is identified as a UCI.

C.5 Comparison of modeled and transect temperature gradients

As discussed in Section C.4, several points were selected for preliminary mobile-transect routes. To get a crude assessment of how the modeled gradients in temperature compare with observed gradients at these locations, mobile transects were carried out on two summer days in area LA1 (April 25) and San Fernando Valley (June 2, 2016). The goal was simply to compare directionality and gradients in temperature across several points, but not absolute temperature (this neutralizes potential errors in apparatus operation, calibration, and/or model errors).

Model results from the year 2013 were used for this purpose. More specifically, averaged temperature for all 1400 PDT hours between May 30 and June 16, 2013, were compared to the observational transect data from the two dates mentioned above. This discussion refers to Figure App_A4 (in Task Report Appendix A) which contains detailed information on transect and modeled temperatures.

Table C.2 provides a very brief summary of some of the comparisons between simulations and observations. The top part of the table is for the T2 diagnostic and the bottom part is for the Tair diagnostic. The AREAMOD and modified-UCM approaches are presented in this table (the modified-BEP approach is not discussed).

Table C.2 is examined in the context of comparing the sign (positive or negative) of the temperature gradient of model vs. observations as well as to qualitatively compare the IQR with the observed (instantaneous) temperature readings from the transects. The orange-colored cells in

Table C.2 indicate slight deviations in the opposite sign, whereas the red color indicates significant deviation.

It can be seen, in general, that the results from the modified-UCM approach have larger deviations than the AREAMOD approach. UCM is known to exhibit a cold bias in modeled air temperature (Taha and Freed 2015) – whether that applies to temperature differences (gradients) in this case is to be further investigated in the next stages of this project. It is also evident that in both approaches (AREAMOD and modified-UCM) and metrics (T2 and Tair), that points SFV4 and L2-H deviate significantly from the observations.

Thus, based on results in Table C.2, it is suggested that points SFV4 in the San Fernando Valley and point L2-H in the LA1 domain be dropped from first-round considerations in site selection. In fact, this agrees well with the priorities (rankings) established in Table B.19, where both SFV4 and L2-H were assigned the lowest rankings.

The recommendations are that the priorities established in Table B.19 be considered for site selection pending feedback and approval by project partners in the Los Angeles region at which point these priorities may be revised.

Table C.2: Model temperature gradients vs. observed gradients (mobile transects)

	Points	Transect ΔT (°C)	Model 1400 PDT average (over 17 days)*					
			AREAMOD T2 ΔT (°C)			mod-UCM T2 ΔT (°C)		
			mean	Q1	Q3	mean	Q1	Q3
LA1	L2 - G	+0.67	+0.58	+0.40	+0.70	+0.10	-0.19	+0.16
	E - S_of_E	-0.40						
	L2 - H	+0.60	+0.51	+0.35	+0.89	+0.03	-0.09	+0.16
	J - F	+1.10	+0.80	+0.52	+1.17	+0.10	-0.02	+0.14
San Fernando Valley	SFV1 – NW_of_SFV1 (SE)	+0.54	+1.40	+1.01	+1.54	+0.52	+0.32	+0.62
	SFV6 – S_of_SFV6 (W)	-1.66	-0.75	-0.97	-0.56	-0.24	-0.46	0.00
	N1 – N2	-1.06						
	M2 – M1	+1.68						
	SFV2 – E_of_SFV2 (SE)	+1.98	+1.23	+1.05	+1.40	+0.31	+0.17	+0.53
	SFV4 – S_of_SFV4 (W)	+0.19	-2.55	-2.94	-2.21	-0.28	-0.42	-0.14
	S1 – S2 (SFV5)	+0.53						
	T1 – T2 (SFV5)	+0.79	+1.16	+1.01	+1.30	+0.05	-0.23	+0.40

*See Figure App_A3 in Task Report Appendix A

Table C.2: Continued

	Points	Transect ΔT (°C)	Model 1400 PDT average (over 17 days)*						
			AREAMOD Tair ΔT (°C)			mod-UCM Tair ΔT (°C)			Contours ΔT (°C)
			mean	Q1	Q3	mean	Q1	Q3	AREAMOD
LA I	L2 - G	+0.67	+0.14	0.00	+0.30	-0.13	-0.40	-0.07	+0.16
	E - S_of_E	-0.40							-0.98
	L2 - H	+0.60	+0.20	-0.02	+0.46	-0.08	-0.19	+0.08	-0.17
	J - F	+1.10	+0.61	+0.32	+0.97	+0.17	+0.06	+0.20	+0.25
San Fernando Valley	SFV1 – NW_of_SFV1 (SE)	+0.54	+1.39	+0.95	+1.53	+0.71	+0.49	+0.84	+0.80
	SFV6 – S_of_SFV6 (W)	-1.66	-0.63	-0.88	-0.46	-0.38	-0.56	-0.12	-1.20
	N1 – N2	-1.06							-0.80
	M2 – M1	+1.68							+2.00
	SFV2 – E_of_SFV2 (SE)	+1.98	+1.17	+0.90	+1.36	+0.45	+0.33	+0.67	+1.20
	SFV4 – S_of_SFV4 (W)	+0.19	-1.60	-1.90	-1.33	-0.25	-0.38	-0.13	-0.80
	S1 – S2 (SFV5)	+0.53	+1.03	+0.77	+1.19	+0.23	-0.06	+0.60	+1.20
	T1 – T2 (SFV5)	+0.79							+1.20

*See Figure App_A3 in Task Report Appendix A

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California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix A-2

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APA-2

TASK REPORT APPENDIX A

Figure App_A1

Points of interest (potential siting of monitors) in area LA1 and San Fernando Valley domains

Area A, LA1: UCI

Area B, LA1: UCI

Area C, LA1: UCI

Area D, LA1: UHI

Area E, LA1: UCI

Area F, LA1: UCI

Area G, LA1: UCI

Area H, LA1: UCI

Area I, LA1: UHI

Area J, LA1: UHI

Area K, LA1: UCI

Area SFV_1, San Fernando Valley: UHI

Area SFV_2, San Fernando Valley: UHI

Area SFV_3, San Fernando Valley: UHI

Area SFV_4, San Fernando Valley: UCI

Area SFV_5, San Fernando Valley: UHI

Area SFV_6 (UCI) and SFV_7 (UHI), San Fernando Valley

Figure App_A2

Time-series scatter plots and frequency distributions of UHI and/or UCI ($^{\circ}\text{C}$) at areas A through L in LA1 and areas SFV_1 through SFV_7 in San Fernando Valley. Each set of plots is defined in terms of area (LA1 or San Fernando Valley), approach (AREAMOD, modified-UCM, or modified-BEP), and diagnostic variable (T2 or Tair), as indicated below the figures. The vertical axis is temperature (UHI and/or UCI) and the horizontal axis is time of day.

LA1, AREAMOD, T2

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, AREAMOD, T2

I_minus_G: UHI

LA1, AREAMOD, T2

A_minus_S_of_A: UCI

B_minus_SW_of_B: UCI

C_minus_N_of_C: UCI

L_minus_H: UHI

LA1, AREAMOD, Tair

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, AREAMOD, Tair

LA1, AREAMOD, Tair

LA1, mod-UCM, T2

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, mod-UCM, T2

I_minus_G: UHI

LA1, mod-UCM, T2

A_minus_S_of_A: UCI

B_minus_SW_of_B: UCI

C_minus_N_of_C: UCI

L_minus_H: UHI

LA1, mod-UCM, Tair

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, mod-UCM, Tair

L_minus_G: UHI

LA1, mod-UCM, Tair

A_minus_S_of_A: UCI

B_minus_SW_of_B: UCI

C_minus_N_of_C: UCI

L_minus_H: UHI

LA1, mod-BEP, T2

A-A17

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, mod-BEP, T2

I_minus_G: UHI

LA1, mod-BEP, T2

A_minus_S_of_A: UCI

B_minus_SW_of_B: UCI

C_minus_N_of_C: UCI

L_minus_H: UHI

LA1, mod-BEP, Tair

L_minus_G: UHI

K_minus_J: UCI

J_minus_F: UHI

F_minus_I: UCI

LA1, mod-BEP, Tair

I_minus_G : UHI

LA1, mod-BEP, Tair

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, AREAMOD, T2

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, AREAMOD, T2

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, AREAMOD, Tair

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, AREAMOD, Tair

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, mod-UCM, T2

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, mod-UCM, T2

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, mod-UCM, Tair

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, mod-UCM, Tair

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, mod-BEP, T2

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, mod-BEP, T2

SFV1 minus SE_of_SFV1: UHI

SFV2 minus SE_of_SFV2: UHI

SFV4 minus W_of_SFV4: UCI

SFV5 minus SE_of_SFV5: UHI

San Fernando Valley, mod-BEP, Tair

SFV6 minus W_of_SFV6: UCI

SFV7 minus SE_of_SFV7: UHI

San Fernando Valley, mod-BEP, Tair

Figure App_A3

Time-series box-and-whiskers plots (hourly frequency distributions) of UHI and/or UCI (°C) at points A through L in LA1 and points SFV_1 through SFV_7 in San Fernando Valley. Each figure is followed by two tables listing corresponding statistics. Each set of plots is defined in terms of area (LA1 or San Fernando Valley), approach (AREAMOD or modified-UCM), and diagnostic variable (T2 or Tair), as indicate at the top of the set. The vertical axis is temperature (UHI and/or UCI) and the horizontal axis is time of day.

FOLLOWING: LA1, AREAMOD, Tair

A_minus_S_of_A by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.0565308	0.05930387	0.0426668	0.2065595
1	16	-0.1149583	0.05742072	0.1062101	0.3258990
2	16	-0.0244273	0.05742072	0.0623641	0.2497280
3	16	-0.1486732	0.05742072	0.0526105	0.2293698
4	16	-0.0320221	0.05742072	0.0903459	0.3005759
5	16	-0.0437033	0.05742072	0.1175156	0.3428056
6	16	-0.1257633	0.05742072	0.0569290	0.2385979
7	16	-0.1566474	0.05742072	0.1268390	0.3561446
8	16	-0.2760610	0.05742072	0.0826017	0.2874051
9	16	-0.4172306	0.05742072	0.0415256	0.2037783
10	16	-0.5368726	0.05742072	0.0500441	0.2237053
11	16	-0.2971685	0.05742072	0.0622183	0.2494360
12	16	-0.1872361	0.05742072	0.1461871	0.3823442
13	16	-0.2665436	0.05742072	0.0340429	0.1845073
14	16	-0.0538827	0.05742072	0.0170815	0.1306962
15	16	-0.1191289	0.05742072	0.0336075	0.1833235
16	16	-0.0952443	0.05742072	0.0181081	0.1345664
17	16	-0.0999441	0.05742072	0.0212476	0.1457654
18	15	-0.1093243	0.05930387	0.0085905	0.0926848
19	15	-0.1449132	0.05930387	0.0105458	0.1026929
20	15	-0.1834651	0.05930387	0.0085802	0.0926293
21	15	-0.1181157	0.05930387	0.0135141	0.1162503
22	15	-0.2125149	0.05930387	0.0231340	0.1520987
23	15	-0.0983501	0.05930387	0.0236874	0.1539071
Pooled	377			0.0527542	0.2296829

A_minus_S_of_A by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.441284	-0.1937257	-0.0900080	0.0987582	0.371548	0.2924838
1	-1.020555	-0.2317492	-0.1040580	0.0404776	0.432342	0.2722268
2	-0.426340	-0.1943352	-0.0702925	0.1266118	0.424183	0.3209470
3	-0.612208	-0.2950421	-0.1529065	-0.0007408	0.247292	0.2943013
4	-0.470888	-0.2210171	-0.1295755	0.0833252	0.594777	0.3043422
5	-0.538731	-0.2118426	-0.1786335	0.1457302	0.637708	0.3575727
6	-0.436465	-0.2511065	-0.1760560	-0.0331305	0.478460	0.2179760
7	-1.010586	-0.3747381	-0.2004960	0.1520304	0.293826	0.5267685
8	-0.633108	-0.5050956	-0.3334400	-0.1595077	0.343046	0.3455879
9	-0.954546	-0.5179803	-0.4335195	-0.2604247	-0.078697	0.2575557
10	-0.827528	-0.6993485	-0.6011675	-0.4205901	-0.122086	0.2787584
11	-0.803428	-0.4386998	-0.2969695	-0.1319590	0.113726	0.3067407
12	-0.974834	-0.3774448	-0.2317485	0.0234956	0.546964	0.4009403
13	-0.740591	-0.3165462	-0.2754475	-0.1668100	0.110523	0.1497362
14	-0.286430	-0.1401482	-0.0438680	0.0465255	0.177838	0.1866737
15	-0.587317	-0.2062366	-0.1043230	-0.0010838	0.171179	0.2051527
16	-0.339161	-0.1939964	-0.0955785	0.0120029	0.133287	0.2059993
17	-0.468702	-0.1871841	-0.0942555	-0.0026425	0.125706	0.1845416
18	-0.309059	-0.1458012	-0.0930650	-0.0455470	-0.003172	0.1002542
19	-0.406082	-0.1918880	-0.1539840	-0.0551855	-0.018221	0.1367025
20	-0.347582	-0.2405037	-0.2047110	-0.1203158	0.028840	0.1201878
21	-0.332953	-0.2208333	-0.1374150	-0.0267452	0.069128	0.1940882
22	-0.524195	-0.3309117	-0.1606050	-0.1024297	0.056733	0.2284820
23	-0.450979	-0.1953505	-0.1061270	0.0129782	0.147602	0.2083287

N | 377

B_minus_SW_of_B by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.3383670	0.07627655	0.0678974	0.2605712
1	16	-0.4641680	0.07385445	0.1042587	0.3228911
2	16	-0.4048969	0.07385445	0.1045510	0.3233434
3	16	-0.3369186	0.07385445	0.1134750	0.3368606
4	16	-0.2933756	0.07385445	0.1193319	0.3454445
5	16	-0.2704213	0.07385445	0.0826424	0.2874760
6	16	-0.3978091	0.07385445	0.0894280	0.2990451
7	16	-0.6242512	0.07385445	0.2313117	0.4809488
8	16	-0.6380015	0.07385445	0.1951410	0.4417477
9	16	-0.7247396	0.07385445	0.1705353	0.4129592
10	16	-0.8796153	0.07385445	0.0925204	0.3041717
11	16	-0.5465314	0.07385445	0.0417635	0.2043613
12	16	-0.4299795	0.07385445	0.0776770	0.2787060
13	16	-0.2747174	0.07385445	0.1197224	0.3460092
14	16	-0.3130396	0.07385445	0.2005739	0.4478547
15	16	-0.2926708	0.07385445	0.0513140	0.2265259
16	16	-0.1650394	0.07385445	0.0346434	0.1861275
17	16	-0.2278911	0.07385445	0.0343852	0.1854326
18	15	-0.1389533	0.07627655	0.0082546	0.0908546
19	15	-0.1235059	0.07627655	0.0087615	0.0936028
20	15	-0.1941880	0.07627655	0.0156141	0.1249562
21	15	-0.2200107	0.07627655	0.0329284	0.1814617
22	15	-0.2379708	0.07627655	0.0213575	0.1461421
23	15	-0.3022820	0.07627655	0.0493135	0.2220665
Pooled	377			0.0872717	0.2954178

B_minus_SW_of_B by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.865616	-0.4750762	-0.3004150	-0.1471287	0.049538	0.3279475
1	-1.205403	-0.5794632	-0.4245690	-0.2502309	0.053985	0.3292322
2	-0.917933	-0.5960321	-0.4033300	-0.2507748	0.227303	0.3452573
3	-0.794691	-0.5826525	-0.3998090	-0.1537164	0.309531	0.4289361
4	-1.126923	-0.4723187	-0.2799815	-0.0950803	0.224175	0.3772383
5	-0.629075	-0.5737665	-0.2785940	-0.0632780	0.273848	0.5104885
6	-0.826595	-0.6704119	-0.4031195	-0.2087179	0.127839	0.4616940
7	-1.477584	-1.0806558	-0.6001435	-0.2267987	0.082902	0.8538571
8	-1.408406	-0.9741100	-0.5451930	-0.3757985	0.393751	0.5983115
9	-2.013851	-0.8491916	-0.6464185	-0.4597611	-0.298542	0.3894305
10	-1.285242	-1.1669790	-0.8721235	-0.6165342	-0.427654	0.5504448
11	-0.991281	-0.6365703	-0.5207555	-0.4193138	-0.132665	0.2172565
12	-0.968603	-0.6765371	-0.3443295	-0.2189478	-0.040426	0.4575893
13	-0.985685	-0.5684229	-0.2265785	-0.0072606	0.275404	0.5611623
14	-1.330338	-0.5976743	-0.3172265	-0.0904146	0.544178	0.5072597
15	-0.775272	-0.4184292	-0.3044685	-0.1505491	0.139927	0.2678801
16	-0.522572	-0.2603271	-0.1653250	-0.1104507	0.383057	0.1498764
17	-0.850915	-0.2804894	-0.1549225	-0.1221382	-0.096001	0.1583513
18	-0.326817	-0.1819493	-0.1186730	-0.0649065	-0.023707	0.1170428
19	-0.291042	-0.1844525	-0.1230850	-0.0897990	0.104397	0.0946535
20	-0.562857	-0.2138315	-0.1711370	-0.1149458	-0.057327	0.0988857
21	-0.659092	-0.3015143	-0.1726210	-0.1243395	0.055833	0.1771748
22	-0.537033	-0.3056580	-0.2337980	-0.1864830	0.011851	0.1191750
23	-0.911886	-0.3681903	-0.2999720	-0.1544705	0.003283	0.2137198

C_minus_N_of_C by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.3388749	0.06249700	0.0569550	0.2386524
1	16	-0.4202596	0.06051246	0.0717152	0.2677969
2	16	-0.4220730	0.06051246	0.0418456	0.2045619
3	16	-0.3480971	0.06051246	0.0515962	0.2271480
4	16	-0.3605989	0.06051246	0.0489408	0.2212256
5	16	-0.3126094	0.06051246	0.0681294	0.2610160
6	16	-0.2821516	0.06051246	0.0369336	0.1921811
7	16	-0.4736331	0.06051246	0.2172342	0.4660839
8	16	-0.5606939	0.06051246	0.0929209	0.3048293
9	16	-0.6270055	0.06051246	0.0816520	0.2857481
10	16	-0.7755241	0.06051246	0.0382487	0.1955728
11	16	-0.6877563	0.06051246	0.0752117	0.2742475
12	16	-0.6013936	0.06051246	0.0216843	0.1472558
13	16	-0.5729606	0.06051246	0.1315850	0.3627465
14	16	-0.6080946	0.06051246	0.0517488	0.2274837
15	16	-0.5647491	0.06051246	0.0526240	0.2293991
16	16	-0.5048499	0.06051246	0.0190534	0.1380340
17	16	-0.4210738	0.06051246	0.1062118	0.3259015
18	15	-0.4553029	0.06249700	0.0141226	0.1188386
19	15	-0.4211268	0.06249700	0.0289946	0.1702780
20	15	-0.4695039	0.06249700	0.0272201	0.1649851
21	15	-0.4317845	0.06249700	0.0277494	0.1665817
22	15	-0.4058048	0.06249700	0.0149856	0.1224158
23	15	-0.4075551	0.06249700	0.0136566	0.1168615
Pooled	377			0.0585881	0.2420498

C_minus_N_of_C by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.614994	-0.5269038	-0.4422900	-0.1444792	0.148289	0.3824247
1	-0.784781	-0.6506845	-0.4648210	-0.2227870	0.078857	0.4278975
2	-0.765375	-0.5749138	-0.4049905	-0.2793709	-0.075702	0.2955429
3	-0.626508	-0.5747185	-0.3294060	-0.1689390	0.098810	0.4057795
4	-0.637516	-0.5599545	-0.3269325	-0.2332908	0.145270	0.3266638
5	-0.681982	-0.4981572	-0.3645440	-0.1065679	0.180309	0.3915893
6	-0.490763	-0.4409610	-0.2866925	-0.1952280	0.278264	0.2457330
7	-1.333946	-0.8319551	-0.4014460	-0.1178860	0.236039	0.7140691
8	-1.255713	-0.6947921	-0.5752420	-0.3669145	0.144112	0.3278776
9	-1.098907	-0.8444352	-0.6079295	-0.5455872	0.064522	0.2988480
10	-1.059662	-0.9239633	-0.8116770	-0.6585482	-0.459358	0.2654150
11	-1.119839	-0.8566767	-0.7343295	-0.5799128	0.070629	0.2767639
12	-0.802311	-0.6952154	-0.6073250	-0.5226708	-0.203144	0.1725447
13	-1.412634	-0.7114583	-0.5874685	-0.4220098	0.182893	0.2894484
14	-0.970461	-0.7860126	-0.5672750	-0.4551762	-0.236940	0.3308364
15	-1.238119	-0.6221491	-0.5122705	-0.4117052	-0.308127	0.2104439
16	-0.704963	-0.5836588	-0.5184995	-0.4428262	-0.203073	0.1408326
17	-0.824360	-0.6177341	-0.4941660	-0.3148847	0.515301	0.3028494
18	-0.605577	-0.5372918	-0.4662530	-0.3850718	-0.216904	0.1522200
19	-0.818124	-0.5162868	-0.4287630	-0.3121933	-0.136794	0.2040935
20	-0.830332	-0.5132225	-0.4839840	-0.3565073	-0.099552	0.1567152
21	-0.747328	-0.4966347	-0.4559570	-0.3275597	-0.076931	0.1690750
22	-0.560440	-0.5209867	-0.4527440	-0.3018195	-0.207760	0.2191672
23	-0.609045	-0.4965587	-0.4215850	-0.2908482	-0.235770	0.2057105

N | 377

$L_{\text{minus_H}}$ by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	0.1996727	0.06727130	0.0153755	0.1239979
1	16	0.1899983	0.06513516	0.0362484	0.1903902
2	16	0.1932044	0.06513516	0.0485462	0.2203320
3	16	0.2056336	0.06513516	0.0223159	0.1493851
4	16	0.1838732	0.06513516	0.0428016	0.2068854
5	16	0.2517023	0.06513516	0.0244510	0.1563683
6	16	0.2358256	0.06513516	0.0668265	0.2585082
7	16	0.3272913	0.06513516	0.0753553	0.2745091
8	16	0.3884333	0.06513516	0.0720653	0.2684499
9	16	0.4472605	0.06513516	0.0180306	0.1342779
10	16	0.5676853	0.06513516	0.0551160	0.2347680
11	16	0.3746026	0.06513516	0.1473692	0.3838869
12	16	0.2508498	0.06513516	0.1982216	0.4452208
13	16	0.3281186	0.06513516	0.1763966	0.4199960
14	16	0.1981933	0.06513516	0.0974760	0.3122115
15	16	0.1779676	0.06513516	0.1317900	0.3630289
16	16	0.2994384	0.06513516	0.0597566	0.2444516
17	16	0.0921444	0.06513516	0.0819239	0.2862236
18	15	0.0804032	0.06727130	0.0567736	0.2382721
19	15	0.0384019	0.06727130	0.0405689	0.2014171
20	15	0.1210551	0.06727130	0.0287563	0.1695768
21	15	0.0457944	0.06727130	0.0633687	0.2517314
22	15	0.1883045	0.06727130	0.0279167	0.1670829
23	15	0.2112607	0.06727130	0.0273674	0.1654310
Pooled	377			0.0678814	0.2605406

L_minus_H by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.056277	0.1150290	0.2031790	0.2625215	0.470529	0.1474925
1	-0.134812	0.0019766	0.2118750	0.3462578	0.509984	0.3442812
2	-0.126614	0.0225567	0.1897315	0.3231861	0.587579	0.3006294
3	-0.068590	0.1192180	0.2377375	0.2488299	0.576387	0.1296119
4	-0.145155	0.0392499	0.1875540	0.2884084	0.615298	0.2491585
5	-0.155306	0.1583346	0.2607675	0.3612880	0.469849	0.2029534
6	-0.336624	0.0384569	0.3328865	0.4353123	0.504885	0.3968554
7	-0.399602	0.2390973	0.3672630	0.4206778	0.754135	0.1815806
8	-0.266899	0.3040663	0.3583280	0.5621154	0.838779	0.2580491
9	0.254963	0.3449343	0.4064440	0.5703281	0.707806	0.2253938
10	0.145605	0.4127361	0.5226365	0.7966920	0.940260	0.3839559
11	-0.150961	0.0968110	0.3586290	0.4627703	1.173378	0.3659593
12	-0.565510	-0.0070327	0.1522545	0.5770482	0.930015	0.5840809
13	-0.499781	0.1068075	0.2859535	0.6750363	1.045979	0.5682288
14	-0.462736	-0.0293365	0.2238230	0.4648678	0.686037	0.4942043
15	-0.499702	0.0028548	0.1140125	0.5481793	0.682047	0.5453245
16	-0.171869	0.1306199	0.2740305	0.5082019	0.727782	0.3775820
17	-0.417780	-0.0792236	0.0749270	0.2232345	0.713098	0.3024581
18	-0.205949	-0.0668242	0.0249120	0.1272340	0.668036	0.1940582
19	-0.300430	-0.0468140	-0.0002510	0.1195285	0.629551	0.1663425
20	-0.038612	0.0383148	0.0707420	0.1713677	0.653291	0.1330528
21	-0.576181	-0.0423583	0.0904920	0.1715517	0.514475	0.2139100
22	-0.005882	0.0840125	0.1367210	0.2325253	0.556421	0.1485128
23	-0.097725	0.1398992	0.1871750	0.2741823	0.581735	0.1342832

L_minus_G by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	0.1343871	0.07136819	0.0376528	0.1940433
1	16	0.2595888	0.06910195	0.0242896	0.1558511
2	16	0.2408981	0.06910195	0.0377293	0.1942404
3	16	0.2582396	0.06910195	0.0682406	0.2612291
4	16	0.1386461	0.06910195	0.1197473	0.3460452
5	16	0.2470454	0.06910195	0.0593917	0.2437041
6	16	0.1801202	0.06910195	0.0863696	0.2938871
7	16	0.3716489	0.06910195	0.1140884	0.3377698
8	16	0.5570451	0.06910195	0.1102601	0.3320543
9	16	0.5112841	0.06910195	0.0574985	0.2397884
10	16	0.6446359	0.06910195	0.0771185	0.2777022
11	16	0.4484833	0.06910195	0.1617372	0.4021657
12	16	0.2396773	0.06910195	0.1730776	0.4160260
13	16	0.2840967	0.06910195	0.1328384	0.3644700
14	16	0.1421855	0.06910195	0.0364733	0.1909799
15	16	0.2452114	0.06910195	0.1532260	0.3914410
16	16	0.2885063	0.06910195	0.0795248	0.2820014
17	16	0.0923165	0.06910195	0.0699537	0.2644877
18	15	0.0488978	0.07136819	0.0264208	0.1625448
19	15	-0.0085997	0.07136819	0.0511511	0.2261661
20	15	0.0068713	0.07136819	0.0334550	0.1829072
21	15	0.0872370	0.07136819	0.0341551	0.1848111
22	15	0.1604406	0.07136819	0.0413036	0.2032329
23	15	0.1502117	0.07136819	0.0291600	0.1707629
Pooled	377			0.0764013	0.2764078

L_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.147802	-0.0093392	0.0998350	0.2768407	0.494461	0.2861798
1	-0.018674	0.1449567	0.2347340	0.3957040	0.534731	0.2507473
2	-0.068480	0.1396261	0.2252475	0.3266731	0.605612	0.1870470
3	-0.302163	0.0958602	0.2447700	0.4203856	0.843181	0.3245254
4	-0.563874	-0.0907525	0.2447715	0.3652763	0.659434	0.4560288
5	-0.368624	0.0975871	0.2863260	0.4329063	0.624871	0.3353192
6	-0.425261	0.0297027	0.2088790	0.3616678	0.664832	0.3319651
7	-0.199650	0.1116199	0.2875985	0.6010468	1.149885	0.4894268
8	-0.160435	0.3408819	0.5364965	0.7952493	1.220371	0.4543673
9	0.236663	0.3040258	0.5213780	0.6504497	1.165162	0.3464238
10	-0.052038	0.5028510	0.6541785	0.8554580	1.015034	0.3526070
11	-0.280933	0.2456072	0.4233435	0.5788993	1.328140	0.3332921
12	-0.543455	-0.0637124	0.3343280	0.5712714	0.932791	0.6349838
13	-0.636963	0.1079491	0.2549285	0.5357948	0.919384	0.4278458
14	-0.183090	-0.0075313	0.1289890	0.2938713	0.455826	0.3014027
15	-0.660419	0.0769879	0.2891025	0.4631017	1.130430	0.3861138
16	-0.190500	0.0385036	0.3811700	0.4911677	0.751841	0.4526641
17	-0.408596	-0.0464293	0.0961690	0.1717580	0.668493	0.2181873
18	-0.190611	-0.0707020	0.0323030	0.1361018	0.414391	0.2068038
19	-0.261906	-0.1750438	-0.0720610	0.0380463	0.444452	0.2130902
20	-0.232160	-0.0823908	-0.0334000	0.0598722	0.449759	0.1422630
21	-0.091057	-0.0175082	0.0138240	0.0734898	0.462919	0.0909980
22	-0.017669	0.0328615	0.0951900	0.1809365	0.737036	0.1480750
23	-0.092159	0.0390813	0.0970290	0.3565983	0.400383	0.3175170

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K_minus_J by hh		N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	15	-0.3543263	0.07463674	0.0166041	0.1288570
1	16	16	-0.3084773	0.07226672	0.0653372	0.2556114
2	16	16	-0.2295292	0.07226672	0.0349854	0.1870438
3	16	16	-0.2758096	0.07226672	0.0547561	0.2340003
4	16	16	-0.1395703	0.07226672	0.1149101	0.3389840
5	16	16	-0.2455153	0.07226672	0.0194363	0.1394143
6	16	16	-0.2296456	0.07226672	0.0474734	0.2178840
7	16	16	-0.4036705	0.07226672	0.1539996	0.3924278
8	16	16	-0.3868889	0.07226672	0.0701793	0.2649137
9	16	16	-0.5227123	0.07226672	0.0241683	0.1554615
10	16	16	-0.6889969	0.07226672	0.0402654	0.2006625
11	16	16	-0.5415134	0.07226672	0.1130082	0.3361670
12	16	16	-0.5019014	0.07226672	0.2215192	0.4706582
13	16	16	-0.7522680	0.07226672	0.0710932	0.2666331
14	16	16	-0.4594770	0.07226672	0.2910794	0.5395178
15	16	16	-0.4704711	0.07226672	0.3282351	0.5729181
16	16	16	-0.5099169	0.07226672	0.1042505	0.3228784
17	16	16	-0.5416178	0.07226672	0.0768572	0.2772313
18	15	15	-0.5760001	0.07463674	0.0431952	0.2078345
19	15	15	-0.4970044	0.07463674	0.0209302	0.1446727
20	15	15	-0.4521981	0.07463674	0.0213667	0.1461735
21	15	15	-0.3832623	0.07463674	0.0165246	0.1285479
22	15	15	-0.3539156	0.07463674	0.0148315	0.1217846
23	15	15	-0.3413301	0.07463674	0.0110654	0.1051923
Pooled		377			0.0835597	0.2890669

K_minus_J by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.709169	-0.3807375	-0.3380300	-0.2771348	-0.216072	0.1036027
1	-0.747084	-0.5002955	-0.3268230	-0.1697539	0.184846	0.3305416
2	-0.503219	-0.3976238	-0.1932940	-0.0785647	0.106431	0.3190591
3	-0.821369	-0.3919685	-0.2743795	-0.1170756	0.048288	0.2748929
4	-0.538014	-0.3778823	-0.2547840	0.0320863	0.528847	0.4099687
5	-0.461870	-0.3454323	-0.2795460	-0.0942983	-0.059137	0.2511339
6	-0.661896	-0.3552713	-0.2582695	-0.1056072	0.302708	0.2496641
7	-1.083861	-0.6354909	-0.4543595	-0.1727739	0.417769	0.4627170
8	-1.158169	-0.5049984	-0.3728415	-0.2171203	-0.028540	0.2878782
9	-0.848301	-0.5589240	-0.5208105	-0.4545683	-0.175284	0.1043557
10	-1.003670	-0.8209277	-0.7281150	-0.5058578	-0.335318	0.3150699
11	-0.973620	-0.8498828	-0.6493275	-0.1707443	-0.048044	0.6791385
12	-1.321167	-0.8139453	-0.5745275	-0.1949869	0.264828	0.6189584
13	-1.206680	-0.9472937	-0.7721535	-0.5373330	-0.243239	0.4099607
14	-1.449398	-0.7594253	-0.5613110	-0.1035020	0.444635	0.6559233
15	-1.521746	-0.9110360	-0.5093290	0.0134101	0.542997	0.9244461
16	-1.034208	-0.8182263	-0.4862450	-0.3270432	0.047167	0.4911830
17	-0.845440	-0.6581166	-0.6197540	-0.4422313	0.337550	0.2158853
18	-0.835646	-0.7269328	-0.6022140	-0.4914037	-0.021468	0.2355292
19	-0.780596	-0.5975062	-0.4827620	-0.3634287	-0.263959	0.2340775
20	-0.796844	-0.5456200	-0.4376220	-0.3287345	-0.231769	0.2168855
21	-0.732854	-0.4110748	-0.3750390	-0.3074545	-0.231410	0.1036203
22	-0.581018	-0.4328425	-0.3473550	-0.2788703	-0.078459	0.1539722
23	-0.526680	-0.4410150	-0.3157930	-0.2637663	-0.157561	0.1772487

K_minus_J by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.3543263	0.07463674	0.0166041	0.1288570
1	16	-0.3084773	0.07226672	0.0653372	0.2556114
2	16	-0.2295292	0.07226672	0.0349854	0.1870438
3	16	-0.2758096	0.07226672	0.0547561	0.2340003
4	16	-0.1395703	0.07226672	0.1149101	0.3389840
5	16	-0.2455153	0.07226672	0.0194363	0.1394143
6	16	-0.2296456	0.07226672	0.0474734	0.2178840
7	16	-0.4036705	0.07226672	0.1539996	0.3924278
8	16	-0.3868889	0.07226672	0.0701793	0.2649137
9	16	-0.5227123	0.07226672	0.0241683	0.1554615
10	16	-0.6889969	0.07226672	0.0402654	0.2006625
11	16	-0.5415134	0.07226672	0.1130082	0.3361670
12	16	-0.5019014	0.07226672	0.2215192	0.4706582
13	16	-0.7522680	0.07226672	0.0710932	0.2666331
14	16	-0.4594770	0.07226672	0.2910794	0.5395178
15	16	-0.4704711	0.07226672	0.3282351	0.5729181
16	16	-0.5099169	0.07226672	0.1042505	0.3228784
17	16	-0.5416178	0.07226672	0.0768572	0.2772313
18	15	-0.5760001	0.07463674	0.0431952	0.2078345
19	15	-0.4970044	0.07463674	0.0209302	0.1446727
20	15	-0.4521981	0.07463674	0.0213667	0.1461735
21	15	-0.3832623	0.07463674	0.0165246	0.1285479
22	15	-0.3539156	0.07463674	0.0148315	0.1217846
23	15	-0.3413301	0.07463674	0.0110654	0.1051923
Pooled	377			0.0835597	0.2890669

K_minus_J by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.709169	-0.3807375	-0.3380300	-0.2771348	-0.216072	0.1036027
1	-0.747084	-0.5002955	-0.3268230	-0.1697539	0.184846	0.3305416
2	-0.503219	-0.3976238	-0.1932940	-0.0785647	0.106431	0.3190591
3	-0.821369	-0.3919685	-0.2743795	-0.1170756	0.048288	0.2748929
4	-0.538014	-0.3778823	-0.2547840	0.0320863	0.528847	0.4099687
5	-0.461870	-0.3454323	-0.2795460	-0.0942983	-0.059137	0.2511339
6	-0.661896	-0.3552713	-0.2582695	-0.1056072	0.302708	0.2496641
7	-1.083861	-0.6354909	-0.4543595	-0.1727739	0.417769	0.4627170
8	-1.158169	-0.5049984	-0.3728415	-0.2171203	-0.028540	0.2878782
9	-0.848301	-0.5589240	-0.5208105	-0.4545683	-0.175284	0.1043557
10	-1.003670	-0.8209277	-0.7281150	-0.5058578	-0.335318	0.3150699
11	-0.973620	-0.8498828	-0.6493275	-0.1707443	-0.048044	0.6791385
12	-1.321167	-0.8139453	-0.5745275	-0.1949869	0.264828	0.6189584
13	-1.206680	-0.9472937	-0.7721535	-0.5373330	-0.243239	0.4099607
14	-1.449398	-0.7594253	-0.5613110	-0.1035020	0.444635	0.6559233
15	-1.521746	-0.9110360	-0.5093290	0.0134101	0.542997	0.9244461
16	-1.034208	-0.8182263	-0.4862450	-0.3270432	0.047167	0.4911830
17	-0.845440	-0.6581166	-0.6197540	-0.4422313	0.337550	0.2158853
18	-0.835646	-0.7269328	-0.6022140	-0.4914037	-0.021468	0.2355292
19	-0.780596	-0.5975062	-0.4827620	-0.3634287	-0.263959	0.2340775
20	-0.796844	-0.5456200	-0.4376220	-0.3287345	-0.231769	0.2168855
21	-0.732854	-0.4110748	-0.3750390	-0.3074545	-0.231410	0.1036203
22	-0.581018	-0.4328425	-0.3473550	-0.2788703	-0.078459	0.1539722
23	-0.526680	-0.4410150	-0.3157930	-0.2637663	-0.157561	0.1772487

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J_minus_F by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	0.5196327	0.08327234	0.0384825	0.1961696
1	16	0.4963099	0.08062810	0.0431041	0.2076152
2	16	0.4171060	0.08062810	0.0782300	0.2796962
3	16	0.4877474	0.08062810	0.0631276	0.2512521
4	16	0.4240017	0.08062810	0.0937341	0.3061603
5	16	0.3969619	0.08062810	0.0445033	0.2109580
6	16	0.3241059	0.08062810	0.0474737	0.2178846
7	16	0.5356511	0.08062810	0.1121498	0.3348878
8	16	0.5740315	0.08062810	0.1283343	0.3582378
9	16	0.7781933	0.08062810	0.0904961	0.3008257
10	16	0.9038109	0.08062810	0.1748324	0.4181297
11	16	0.6606829	0.08062810	0.1983926	0.4454128
12	16	0.6287443	0.08062810	0.3425327	0.5852630
13	16	0.8962924	0.08062810	0.1089155	0.3300234
14	16	0.6129591	0.08062810	0.1458677	0.3819264
15	16	0.5448857	0.08062810	0.2299889	0.4795716
16	16	0.4761166	0.08062810	0.2279016	0.4773904
17	16	0.4912381	0.08062810	0.0779673	0.2792263
18	15	0.3592509	0.08327234	0.0928753	0.3047545
19	15	0.3415377	0.08327234	0.0698533	0.2642978
20	15	0.4404405	0.08327234	0.0071669	0.0846574
21	15	0.4296163	0.08327234	0.0100684	0.1003416
22	15	0.4633681	0.08327234	0.0183212	0.1353560
23	15	0.4519515	0.08327234	0.0206430	0.1436766
Pooled	377			0.1040142	0.3225124

J_minus_F by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.249593	0.3217770	0.5560110	0.6857235	0.827711	0.3639465
1	0.097989	0.3887831	0.4856920	0.6625868	0.830218	0.2738038
2	-0.274061	0.2081775	0.5200855	0.6269536	0.723505	0.4187761
3	0.043584	0.2570223	0.5526185	0.6487173	0.958099	0.3916950
4	-0.322300	0.2292739	0.4685650	0.5887275	0.986149	0.3594536
5	-0.109170	0.2347724	0.4738235	0.5702387	0.619173	0.3354663
6	-0.100750	0.1909219	0.2778845	0.5368131	0.619721	0.3458912
7	-0.063963	0.2118528	0.6089570	0.7521028	1.160836	0.5402501
8	0.063419	0.3081189	0.4674690	0.9005348	1.310327	0.5924159
9	0.335358	0.6366857	0.7309335	0.8605602	1.578596	0.2238745
10	-0.050490	0.5881531	1.0618010	1.2154027	1.432433	0.6272496
11	-0.152653	0.1974565	0.8133230	1.0433650	1.199011	0.8459085
12	-0.282429	0.0341013	0.8585815	1.1873780	1.234110	1.1532768
13	0.281950	0.6920455	1.0082870	1.1184618	1.338301	0.4264162
14	-0.003074	0.3236787	0.5252860	0.9672233	1.336256	0.6435447
15	-0.207126	0.1592577	0.5560215	0.9597021	1.258364	0.8004444
16	-0.339990	0.0142353	0.5206980	0.9381058	1.032486	0.9238704
17	-0.006706	0.3255200	0.4418725	0.6091093	1.060229	0.2835893
18	-0.492001	0.2742975	0.3716910	0.4965177	0.936708	0.2222202
19	-0.472302	0.2841108	0.3942980	0.4800478	0.701572	0.1959370
20	0.281351	0.3777377	0.4534280	0.4929975	0.614567	0.1152598
21	0.275816	0.3278000	0.4413070	0.4828060	0.620272	0.1550060
22	0.285847	0.3336817	0.4461230	0.5868205	0.708158	0.2531388
23	0.193833	0.3862363	0.4535430	0.5213320	0.715124	0.1350957

F_minus_I by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	15	-0.4711501	0.08411851	0.0495766	0.2226581
1	16	-0.4402874	0.08144739	0.0454951	0.2132958
2	16	-0.4314406	0.08144739	0.0851557	0.2918145
3	16	-0.4354184	0.08144739	0.0423676	0.2058339
4	16	-0.4233701	0.08144739	0.0865555	0.2942031
5	16	-0.3865632	0.08144739	0.0899438	0.2999064
6	16	-0.3430436	0.08144739	0.0170221	0.1304687
7	16	-0.5129112	0.08144739	0.1391625	0.3730449
8	16	-0.6768897	0.08144739	0.1062549	0.3259676
9	16	-0.8184502	0.08144739	0.1011367	0.3180200
10	16	-1.0167529	0.08144739	0.1356605	0.3683212
11	16	-0.6851706	0.08144739	0.2450389	0.4950140
12	16	-0.4815751	0.08144739	0.2549324	0.5049083
13	16	-0.7274788	0.08144739	0.2062414	0.4541381
14	16	-0.7764211	0.08144739	0.2394553	0.4893417
15	16	-0.4450445	0.08144739	0.1720751	0.4148194
16	16	-0.5962756	0.08144739	0.1966947	0.4435027
17	16	-0.5423193	0.08144739	0.1054207	0.3246855
18	15	-0.4306356	0.08411851	0.0370517	0.1924882
19	15	-0.4583079	0.08411851	0.0340908	0.1846369
20	15	-0.4739903	0.08411851	0.0621461	0.2492912
21	15	-0.4064171	0.08411851	0.0272073	0.1649462
22	15	-0.3750369	0.08411851	0.0166163	0.1289044
23	15	-0.4327957	0.08411851	0.0188699	0.1373676
Pooled	377			0.1061388	0.3257896

F_minus_I by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.977011	-0.5430937	-0.4857530	-0.2717543	-0.202552	0.2713393
1	-0.733782	-0.6319202	-0.4303950	-0.2930830	-0.077442	0.3388372
2	-0.791152	-0.6066507	-0.5157425	-0.2326816	0.306895	0.3739691
3	-0.680725	-0.6211469	-0.4802285	-0.2614361	-0.025526	0.3597108
4	-0.865291	-0.5790077	-0.4832515	-0.2835303	0.330676	0.2954773
5	-0.970808	-0.5842668	-0.3997785	-0.1882930	0.232504	0.3959738
6	-0.577055	-0.4465190	-0.3429815	-0.2269854	-0.153004	0.2195336
7	-1.314621	-0.7875037	-0.4364140	-0.2812570	0.036008	0.5062467
8	-1.310791	-0.9834552	-0.5893175	-0.4180275	-0.280581	0.5654277
9	-1.658903	-0.9266235	-0.7762090	-0.6461068	-0.337799	0.2805168
10	-1.566552	-1.2624685	-1.0788390	-0.9173822	-0.122595	0.3450863
11	-1.433458	-1.1696792	-0.6792390	-0.1820414	0.019100	0.9876378
12	-1.244155	-0.7844588	-0.6130035	-0.1922469	0.522350	0.5922118
13	-1.377834	-1.0871314	-0.8251595	-0.3525013	0.083601	0.7346301
14	-1.521521	-1.2343885	-0.6836890	-0.4112212	0.055086	0.8231673
15	-1.188128	-0.7367108	-0.3283660	-0.0639622	0.046261	0.6727487
16	-1.521378	-0.9187669	-0.5106880	-0.3674530	0.104267	0.5513139
17	-1.324405	-0.8066695	-0.4904305	-0.2832312	-0.117441	0.5234383
18	-0.727232	-0.6283983	-0.3941840	-0.2566688	-0.163765	0.3717295
19	-0.893283	-0.5691240	-0.4059600	-0.3153877	-0.254387	0.2537363
20	-1.017981	-0.6401627	-0.3687380	-0.2914397	-0.199760	0.3487230
21	-0.849987	-0.4752860	-0.3665470	-0.2820272	-0.250245	0.1932588
22	-0.624207	-0.4404545	-0.3532150	-0.3152142	-0.077081	0.1252403
23	-0.631584	-0.5598867	-0.4208160	-0.3220912	-0.171603	0.2377955

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l_minus_G by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	15		0.4523798	0.07200074	0.0400306	0.2000765
1	16		0.4714775	0.06971442	0.0248626	0.1576787
2	16		0.3991823	0.06971442	0.0376865	0.1941300
3	16		0.4151455	0.06971442	0.0305089	0.1746680
4	16		0.3294669	0.06971442	0.0745803	0.2730940
5	16		0.4020600	0.06971442	0.0566898	0.2380961
6	16		0.3108187	0.06971442	0.0442081	0.2102572
7	16		0.4201248	0.06971442	0.0776319	0.2786250
8	16		0.6245385	0.06971442	0.1339302	0.3659647
9	16		0.7313604	0.06971442	0.0820779	0.2864924
10	16		1.0067147	0.06971442	0.0935904	0.3059255
11	16		0.8111600	0.06971442	0.1159062	0.3404500
12	16		0.5920126	0.06971442	0.1633355	0.4041478
13	16		0.7921983	0.06971442	0.1984602	0.4454888
14	16		0.9525214	0.06971442	0.1855316	0.4307338
15	16		0.6345703	0.06971442	0.1119439	0.3345802
16	16		0.7819557	0.06971442	0.1159900	0.3405730
17	16		0.5649759	0.06971442	0.0650120	0.2549746
18	15		0.4986571	0.07200074	0.0254440	0.1595118
19	15		0.4068699	0.07200074	0.0376156	0.1939474
20	15		0.3419347	0.07200074	0.0772366	0.2779148
21	15		0.4094609	0.07200074	0.0169216	0.1300830
22	15		0.3844832	0.07200074	0.0127167	0.1127686
23	15		0.4361855	0.07200074	0.0236529	0.1537950
Pooled	377				0.0777616	0.2788577

I_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.147098	0.2917952	0.4179640	0.5953248	0.867534	0.3035297
1	0.137846	0.4018958	0.4505540	0.5622917	0.760306	0.1603958
2	0.080122	0.2451656	0.4227450	0.5537739	0.693425	0.3086083
3	-0.008363	0.3265311	0.4458860	0.5137610	0.670806	0.1872299
4	-0.340955	0.1420184	0.4311685	0.5079708	0.697399	0.3659524
5	0.111638	0.2089262	0.3760585	0.5654490	1.034274	0.3565228
6	-0.314574	0.2224526	0.3691635	0.4365730	0.565134	0.2141204
7	-0.013375	0.1595906	0.5376935	0.6026864	0.921074	0.4430958
8	0.140205	0.3750018	0.5080155	0.8251838	1.646656	0.4501820
9	0.437488	0.5122907	0.6662210	0.9057777	1.517376	0.3934870
10	0.469583	0.7951032	0.9942140	1.2208943	1.584923	0.4257912
11	0.124848	0.5737078	0.9128960	1.0033123	1.307146	0.4296044
12	-0.095958	0.2349861	0.6314640	0.9843474	1.171487	0.7493613
13	0.079783	0.4331565	0.7910475	1.1418643	1.649773	0.7087078
14	0.159149	0.6263247	1.0235355	1.2833390	1.506931	0.6570143
15	-0.160685	0.4587109	0.7311900	0.9404070	0.994064	0.4816961
16	0.137797	0.5406862	0.7927145	1.0507553	1.352408	0.5100690
17	0.258514	0.3637171	0.5239615	0.7438818	1.188022	0.3801648
18	0.262293	0.3253792	0.4892270	0.6501838	0.742988	0.3248047
19	-0.077198	0.2876890	0.4509210	0.5321660	0.762788	0.2444770
20	-0.489354	0.2658705	0.4015010	0.4968183	0.672460	0.2309478
21	0.243411	0.3063008	0.3805520	0.5287883	0.651872	0.2224875
22	0.193922	0.2831417	0.3744240	0.4927745	0.569067	0.2096328
23	0.232478	0.2988947	0.4040160	0.5484817	0.748516	0.2495870

FOLLOWING: LA1, mod-UCM, Tair

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A_minus_S_of_A by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	0.0042924	0.05962270	0.0959889	0.3098207
1	16	-0.0606472	0.05962270	0.1480053	0.3847146
2	16	-0.1917623	0.05962270	0.1453025	0.3811856
3	16	-0.1887342	0.05962270	0.1386806	0.3723984
4	16	-0.2077514	0.05962270	0.1934461	0.4398251
5	16	-0.2939474	0.05962270	0.1857466	0.4309832
6	16	-0.3330466	0.05962270	0.1408569	0.3753091
7	16	-0.0921878	0.05962270	0.0376732	0.1940958
8	16	0.0729182	0.05962270	0.0136994	0.1170445
9	16	0.0394974	0.05962270	0.0169852	0.1303274
10	16	0.0892425	0.05962270	0.0130501	0.1142368
11	16	0.1011787	0.05962270	0.0154679	0.1243700
12	16	0.1113316	0.05962270	0.0049903	0.0706422
13	16	0.0767275	0.05962270	0.0138931	0.1178691
14	16	0.1074425	0.05962270	0.0097612	0.0987987
15	16	0.1302468	0.05962270	0.0103282	0.1016280
16	16	0.1186289	0.05962270	0.0049344	0.0702453
17	16	0.1534685	0.05962270	0.0062850	0.0792782
18	15	0.0792019	0.06157806	0.0151551	0.1231060
19	15	0.0786467	0.06157806	0.0050970	0.0713932
20	15	0.0150330	0.06157806	0.0027116	0.0520730
21	15	0.0279500	0.06157806	0.0044920	0.0670227
22	15	-0.0556629	0.06157806	0.0593173	0.2435515
23	15	-0.0377977	0.06157806	0.0709655	0.2663935
Pooled	378			0.0568779	0.2384908

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A_minus_S_of_A by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.664271	-0.0884809	0.0214515	0.1890122	0.593230	0.2774932
1	-1.043568	-0.1132082	-0.0504565	0.1618015	0.553582	0.2750098
2	-1.143158	-0.3992638	-0.0445810	0.0276193	0.309733	0.4268831
3	-1.134150	-0.3638548	-0.0612035	0.0859163	0.264622	0.4497712
4	-1.333713	-0.4316535	-0.1717910	0.1429950	0.379386	0.5746485
5	-1.318466	-0.5768577	-0.1893715	0.0125682	0.387612	0.5894259
6	-1.285836	-0.5719561	-0.2908440	-0.0485361	0.197080	0.5234200
7	-0.480994	-0.2276680	-0.0283475	0.0327346	0.194760	0.2604026
8	-0.141887	-0.0105617	0.0629170	0.1675740	0.276650	0.1781357
9	-0.302950	-0.0171501	0.0655780	0.1530879	0.175781	0.1702380
10	-0.191537	0.0657548	0.1070985	0.1421915	0.300123	0.0764367
11	-0.173965	0.0116082	0.1170675	0.2106014	0.242664	0.1989932
12	-0.038159	0.0638213	0.1141880	0.1704334	0.207976	0.1066122
13	-0.299313	0.0373639	0.1083075	0.1489498	0.188278	0.1115858
14	-0.097071	0.0821229	0.0983175	0.1811647	0.300825	0.0990418
15	-0.064844	0.0628383	0.1526475	0.1809283	0.310749	0.1180899
16	-0.050097	0.0783017	0.1348360	0.1742634	0.203499	0.0959617
17	0.054836	0.1075688	0.1382095	0.1734267	0.398389	0.0658578
18	-0.252034	0.0439040	0.1204930	0.1715700	0.213631	0.1276660
19	-0.084495	0.0331572	0.1036360	0.1283263	0.165386	0.0951692
20	-0.072086	-0.0352513	0.0373890	0.0570045	0.088333	0.0922558
21	-0.125198	-0.0092545	0.0278400	0.0632128	0.180193	0.0724673
22	-0.773153	-0.0579905	0.0324770	0.0825353	0.136874	0.1405258
23	-0.937563	-0.0692773	0.0233280	0.0879267	0.177352	0.1572040

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B_minus_SW_of_B by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD	
0	16	-0.0922667	0.08231183	0.1156467	0.3400687	
1	16	-0.2573699	0.08231183	0.1700320	0.4123494	
2	16	-0.4166952	0.08231183	0.2708484	0.5204310	
3	16	-0.4927328	0.08231183	0.2616018	0.5114702	
4	16	-0.5341919	0.08231183	0.3610406	0.6008665	
5	16	-0.4843952	0.08231183	0.4060725	0.6372382	
6	16	-0.4861139	0.08231183	0.3954527	0.6288503	
7	16	-0.1753291	0.08231183	0.1137060	0.3372032	
8	16	-0.0068157	0.08231183	0.1197399	0.3460345	
9	16	-0.0494079	0.08231183	0.0066242	0.0813893	
10	16	-0.0324463	0.08231183	0.0300796	0.1734347	
11	16	0.0184759	0.08231183	0.0306972	0.1752061	
12	16	0.1334326	0.08231183	0.0666356	0.2581387	
13	16	0.1695559	0.08231183	0.0186691	0.1366349	
14	16	0.1987306	0.08231183	0.0260799	0.1614928	
15	16	0.2028025	0.08231183	0.0119579	0.1093522	
16	16	0.1903095	0.08231183	0.0239134	0.1546397	
17	16	0.1649887	0.08231183	0.0088187	0.0939079	
18	15	0.1448105	0.08501130	0.0162116	0.1273247	
19	15	0.1139569	0.08501130	0.0053267	0.0729841	
20	15	0.0790463	0.08501130	0.0169642	0.1302466	
21	15	0.0235516	0.08501130	0.0105231	0.1025819	
22	15	-0.0091201	0.08501130	0.0307552	0.1753716	
23	15	-0.0580381	0.08501130	0.0495553	0.2226103	
Pooled	378			0.1084038	0.3292473	

B_minus_SW_of_B by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.920732	-0.2255523	-0.0764940	0.1051972	0.510478	0.3307494
1	-1.324938	-0.4652128	-0.1695650	-0.0193619	0.342031	0.4458509
2	-1.472435	-0.8115505	-0.2262555	0.0516874	0.136567	0.8632379
3	-1.406765	-0.8764447	-0.5834630	-0.0642050	0.338916	0.8122397
4	-1.666614	-0.9941691	-0.4184055	-0.0598224	0.294017	0.9343467
5	-1.579306	-1.0365198	-0.4490845	0.1404093	0.383532	1.1769291
6	-1.501866	-1.0617485	-0.4497430	0.1168621	0.275066	1.1786106
7	-0.894608	-0.3056225	-0.0737175	0.0195461	0.422324	0.3251686
8	-0.744436	-0.1970353	-0.0910300	0.1656062	0.894263	0.3626415
9	-0.254458	-0.0841305	-0.0332770	0.0153173	0.052621	0.0994478
10	-0.540172	-0.1163278	0.0274740	0.0609078	0.137306	0.1772356
11	-0.432989	-0.0271527	0.0453245	0.1374348	0.218836	0.1645875
12	-0.215481	-0.0045401	0.0797720	0.1583838	0.897278	0.1629239
13	-0.020967	0.0688232	0.1530165	0.2243482	0.551491	0.1555250
14	-0.043403	0.0836740	0.1936425	0.2705803	0.658760	0.1869063
15	-0.069788	0.1343335	0.2243565	0.2681396	0.411924	0.1338061
16	-0.131134	0.1376370	0.1668275	0.1941938	0.628809	0.0565568
17	0.078884	0.0966198	0.1329380	0.1935999	0.402950	0.0969801
18	-0.114128	0.0830023	0.1352410	0.1996958	0.476850	0.1166935
19	-0.032869	0.0785613	0.0986730	0.1724532	0.242850	0.0938918
20	-0.191128	0.0028952	0.0775740	0.1680998	0.345805	0.1652047
21	-0.163700	-0.0474433	0.0085430	0.1206008	0.181810	0.1680442
22	-0.386898	-0.1057308	0.0008870	0.1468818	0.210058	0.2526127
23	-0.555439	-0.1852055	0.0002750	0.1098528	0.264801	0.2950583

C_minus_N_of_C by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.2492089	0.05803985	0.0532907	0.2308477
1	16	-0.2652192	0.05803985	0.0747424	0.2733905
2	16	-0.3515370	0.05803985	0.1160308	0.3406329
3	16	-0.3239712	0.05803985	0.1899429	0.4358244
4	16	-0.2385089	0.05803985	0.1883381	0.4339794
5	16	-0.2733988	0.05803985	0.1169343	0.3419566
6	16	-0.4028237	0.05803985	0.1316844	0.3628834
7	16	-0.1076743	0.05803985	0.0629510	0.2509004
8	16	-0.0709644	0.05803985	0.0379261	0.1947461
9	16	-0.0851022	0.05803985	0.0103855	0.1019095
10	16	-0.1398631	0.05803985	0.0130130	0.1140746
11	16	-0.1408269	0.05803985	0.0114461	0.1069865
12	16	-0.1762192	0.05803985	0.0146546	0.1210563
13	16	-0.1731553	0.05803985	0.0369586	0.1922461
14	16	-0.1942566	0.05803985	0.0057825	0.0760430
15	16	-0.2523608	0.05803985	0.0102675	0.1013288
16	16	-0.2852459	0.05803985	0.0110955	0.1053351
17	16	-0.2700716	0.05803985	0.0321646	0.1793450
18	15	-0.3333182	0.05994330	0.0255795	0.1599360
19	15	-0.2321745	0.05994330	0.0655305	0.2559892
20	15	-0.2567193	0.05994330	0.0327793	0.1810505
21	15	-0.2038537	0.05994330	0.0210844	0.1452047
22	15	-0.2191750	0.05994330	0.0061950	0.0787083
23	15	-0.2166315	0.05994330	0.0142426	0.1193425
Pooled	378			0.0538980	0.2321594

C_minus_N_of_C by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.707284	-0.3871672	-0.2129655	-0.0723578	0.075224	0.3148095
1	-0.786808	-0.4568293	-0.2043485	-0.0662367	0.108120	0.3905927
2	-1.069385	-0.5675920	-0.3040025	-0.0999179	0.110440	0.4676741
3	-1.142813	-0.6991676	-0.2670535	0.0597468	0.305936	0.7589143
4	-0.976183	-0.5938993	-0.2122320	0.0880222	0.417595	0.6819214
5	-1.148834	-0.4810128	-0.2286100	-0.0162748	0.117683	0.4647381
6	-1.370585	-0.5031155	-0.3351395	-0.1780007	0.050134	0.3251148
7	-0.609129	-0.3064859	-0.0847685	0.0982071	0.293465	0.4046930
8	-0.364947	-0.2872726	-0.0462515	0.0863602	0.232400	0.3736328
9	-0.335308	-0.1242146	-0.0727700	-0.0408742	0.080045	0.0833404
10	-0.431049	-0.1789866	-0.1440015	-0.0803827	0.120034	0.0986039
11	-0.270306	-0.2186638	-0.1487665	-0.0968193	0.118377	0.1218446
12	-0.497152	-0.2458453	-0.1634370	-0.1100052	0.025207	0.1358401
13	-0.508033	-0.2618853	-0.1874535	-0.1090057	0.398653	0.1528796
14	-0.304973	-0.2574672	-0.1916245	-0.1541126	0.001244	0.1033546
15	-0.398790	-0.3045957	-0.2561450	-0.2182773	0.001467	0.0863183
16	-0.503620	-0.3361304	-0.2918360	-0.2440737	-0.006541	0.0920567
17	-0.508506	-0.3697819	-0.2944050	-0.2042079	0.277603	0.1655740
18	-0.811422	-0.4157520	-0.3053340	-0.2283413	-0.143921	0.1874107
19	-0.705763	-0.3356357	-0.2737660	-0.2314765	0.402279	0.1041592
20	-0.550546	-0.3531478	-0.2408040	-0.1753398	0.054837	0.1778080
21	-0.534174	-0.2501652	-0.2165520	-0.1097205	0.047157	0.1404447
22	-0.361454	-0.2961497	-0.2033750	-0.1525810	-0.095632	0.1435687
23	-0.460737	-0.2931413	-0.1940060	-0.1652815	0.066126	0.1278598

N | 378

L_minus_H by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.0330408	0.07900344	0.0405656	0.2014089
1	16	16	0.0291858	0.07900344	0.0404401	0.2010973
2	16	16	0.0964375	0.07900344	0.1102503	0.3320396
3	16	16	0.1826781	0.07900344	0.1160891	0.3407185
4	16	16	0.2536088	0.07900344	0.1268350	0.3561390
5	16	16	0.3136608	0.07900344	0.1740905	0.4172415
6	16	16	0.2900800	0.07900344	0.1695295	0.4117396
7	16	16	0.0979510	0.07900344	0.0498514	0.2232743
8	16	16	-0.0347984	0.07900344	0.0746504	0.2732223
9	16	16	0.0007956	0.07900344	0.0560534	0.2367561
10	16	16	-0.0041891	0.07900344	0.1293295	0.3596241
11	16	16	0.0299635	0.07900344	0.1747596	0.4180426
12	16	16	0.0556241	0.07900344	0.2908911	0.5393432
13	16	16	0.0766996	0.07900344	0.2294785	0.4790392
14	16	16	-0.0824762	0.07900344	0.0321939	0.1794265
15	16	16	-0.1424439	0.07900344	0.0533891	0.2310608
16	16	16	-0.1265493	0.07900344	0.0401291	0.2003225
17	16	16	-0.1419584	0.07900344	0.0296370	0.1721539
18	15	15	-0.0638078	0.08159440	0.0562490	0.2371687
19	15	15	-0.1853011	0.08159440	0.0790894	0.2812284
20	15	15	-0.0342276	0.08159440	0.0382243	0.1955105
21	15	15	-0.1557147	0.08159440	0.0750065	0.2738732
22	15	15	-0.0600885	0.08159440	0.0953144	0.3087303
23	15	15	0.0080425	0.08159440	0.1046634	0.3235172
Pooled	378	378			0.0998647	0.3160138

L_minus_H by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.136046	-0.0974535	-0.0439540	0.1272339	0.598984	0.2246874
1	-0.201037	-0.0952775	-0.0019420	0.1083665	0.526466	0.2036440
2	-0.343097	-0.1477605	0.0370865	0.3422975	0.915233	0.4900580
3	-0.438545	-0.0649237	0.1150010	0.4670499	0.810469	0.5319736
4	-0.210110	0.0146937	0.1227320	0.5414102	0.950123	0.5267164
5	-0.387649	0.0690304	0.2884420	0.5749636	1.348154	0.5059332
6	-0.332634	0.0431608	0.2442200	0.4334089	1.240905	0.3902482
7	-0.360343	-0.0248770	0.0985260	0.2167694	0.538567	0.2416464
8	-0.410063	-0.2595907	-0.1160215	0.1928526	0.455702	0.4524433
9	-0.502802	-0.1445340	-0.0067135	0.1094457	0.436807	0.2539797
10	-0.347666	-0.1963373	-0.0954010	0.0170328	1.113893	0.2133702
11	-0.397417	-0.1657835	-0.0909845	0.0806220	1.472494	0.2464055
12	-0.379973	-0.1821179	-0.1083995	-0.0096622	1.868350	0.1724558
13	-0.270710	-0.1453623	-0.0658005	0.0166123	1.735254	0.1619747
14	-0.460391	-0.1968922	-0.0971270	0.0827604	0.180849	0.2796526
15	-0.625586	-0.2658998	-0.0853085	-0.0153625	0.206814	0.2505372
16	-0.464823	-0.2243502	-0.1694295	-0.0941897	0.391525	0.1301605
17	-0.351070	-0.2638580	-0.1880290	-0.0169508	0.182186	0.2469072
18	-0.325789	-0.2269835	-0.1222940	0.0783087	0.528633	0.3052922
19	-0.971535	-0.2571893	-0.1413090	-0.0467482	0.308682	0.2104412
20	-0.462461	-0.1182122	-0.0657850	0.0280455	0.344871	0.1462577
21	-0.955969	-0.2169152	-0.0666710	-0.0063723	0.170873	0.2105428
22	-0.921992	-0.1530433	0.0070490	0.0626768	0.508410	0.2157202
23	-0.461679	-0.1436205	-0.0384510	0.0384250	1.000019	0.1820455

N | 378

L_minus_G by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.0558998	0.10199929	0.0488889	0.2211083
1	16	0.1221933	0.10199929	0.0854337	0.2922904
2	16	0.2211738	0.10199929	0.2262860	0.4756953
3	16	0.3651912	0.10199929	0.2908376	0.5392936
4	16	0.4532864	0.10199929	0.5293093	0.7275365
5	16	0.5517719	0.10199929	0.5660792	0.7523823
6	16	0.5136313	0.10199929	0.5056778	0.7111102
7	16	0.2430546	0.10199929	0.2619791	0.5118389
8	16	0.1281319	0.10199929	0.2004035	0.4476645
9	16	-0.0254080	0.10199929	0.0527759	0.2297301
10	16	0.0125989	0.10199929	0.0707900	0.2660639
11	16	-0.0564347	0.10199929	0.1199044	0.3462722
12	16	-0.0784768	0.10199929	0.1186662	0.3444796
13	16	-0.0535101	0.10199929	0.1684144	0.4103832
14	16	-0.1344029	0.10199929	0.1990906	0.4461957
15	16	-0.1269856	0.10199929	0.0596057	0.2441429
16	16	-0.1369828	0.10199929	0.0597461	0.2444302
17	16	-0.1750131	0.10199929	0.0379072	0.1946977
18	15	-0.1304385	0.10534441	0.0926824	0.3044378
19	15	-0.1343035	0.10534441	0.0522419	0.2285649
20	15	-0.1491846	0.10534441	0.0543389	0.2331070
21	15	-0.1621968	0.10534441	0.0475629	0.2180893
22	15	-0.0784946	0.10534441	0.0445777	0.2111344
23	15	-0.1124633	0.10534441	0.0586321	0.2421407
Pooled	378			0.1664617	0.4079972

N | 378

L_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.330808	-0.1974593	-0.1541955	0.0807056	0.402808	0.2781649
1	-0.349037	-0.0472596	0.0000680	0.3005173	0.752912	0.3477769
2	-0.642985	-0.0401948	0.1549020	0.4448875	1.097742	0.4850823
3	-0.376848	-0.0147805	0.1958470	0.7078158	1.442024	0.7225963
4	-0.871741	-0.1958992	0.5779425	0.9605698	1.600819	1.1564690
5	-0.643083	-0.1055269	0.6008985	1.3111243	1.526228	1.4166512
6	-0.432883	-0.1917684	0.5742540	1.2682829	1.566373	1.4600513
7	-0.439380	-0.1179453	0.1296400	0.5022310	1.692050	0.6201763
8	-0.527587	-0.1957024	0.0204410	0.3818653	0.947832	0.5775678
9	-0.548574	-0.1320831	0.0164175	0.1442228	0.273159	0.2763059
10	-0.300394	-0.1527077	-0.1160115	0.1180299	0.535332	0.2707376
11	-0.462969	-0.2244111	-0.1165065	-0.0250974	1.033009	0.1993137
12	-0.413569	-0.2619388	-0.1534025	-0.0063391	1.073178	0.2555997
13	-0.461834	-0.3089637	-0.2335920	0.0723033	1.046774	0.3812670
14	-0.634058	-0.4283304	-0.2014695	-0.0708073	0.985393	0.3575231
15	-0.454163	-0.3028404	-0.1613335	-0.0196325	0.411438	0.2832079
16	-0.442522	-0.3290388	-0.2024350	0.0594545	0.353744	0.3884933
17	-0.467716	-0.3187585	-0.2004135	-0.0348528	0.189735	0.2839058
18	-0.492090	-0.2791548	-0.1721340	-0.0217010	0.814644	0.2574538
19	-0.401111	-0.3041547	-0.1588930	0.0533127	0.267574	0.3574673
20	-0.518263	-0.2787290	-0.1587080	-0.0606458	0.454878	0.2180832
21	-0.535605	-0.3114400	-0.0676110	-0.0032622	0.207226	0.3081778
22	-0.376550	-0.2422937	-0.0819500	0.0164942	0.323088	0.2587878
23	-0.459413	-0.2285513	-0.1112690	-0.0322145	0.554500	0.1963368

N | 378

K_minus_J by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.0283541	0.07017974	0.0909345	0.3015534
1	16	16	-0.0130383	0.07017974	0.0830762	0.2882295
2	16	16	0.0072584	0.07017974	0.0279794	0.1672705
3	16	16	-0.0971157	0.07017974	0.0683862	0.2615075
4	16	16	0.0101608	0.07017974	0.0626913	0.2503823
5	16	16	0.1243143	0.07017974	0.0587967	0.2424803
6	16	16	0.1246164	0.07017974	0.1110748	0.3332788
7	16	16	-0.0129511	0.07017974	0.0162224	0.1273671
8	16	16	-0.0971695	0.07017974	0.0142413	0.1193371
9	16	16	0.0173846	0.07017974	0.0253506	0.1592188
10	16	16	-0.0933508	0.07017974	0.0393171	0.1982854
11	16	16	0.0750872	0.07017974	0.2313552	0.4809940
12	16	16	-0.0324763	0.07017974	0.1640568	0.4050392
13	16	16	0.0182013	0.07017974	0.2268152	0.4762512
14	16	16	0.0493680	0.07017974	0.1118285	0.3344077
15	16	16	-0.1088661	0.07017974	0.0607514	0.2464780
16	16	16	-0.1902781	0.07017974	0.0621798	0.2493587
17	16	16	-0.3057513	0.07017974	0.1352006	0.3676964
18	15	15	-0.2206122	0.07248132	0.0493138	0.2220671
19	15	15	-0.2936101	0.07248132	0.1021364	0.3195879
20	15	15	-0.1722046	0.07248132	0.0409530	0.2023684
21	15	15	-0.1115237	0.07248132	0.0200743	0.1416837
22	15	15	-0.0978052	0.07248132	0.0307689	0.1754105
23	15	15	-0.0796556	0.07248132	0.0454994	0.2133058
Pooled	378	378			0.0788031	0.2807190

K_minus_J by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.402315	-0.1782620	-0.0555460	0.2018809	0.658537	0.3801429
1	-0.562893	-0.1793620	0.0239080	0.1388969	0.680742	0.3182589
2	-0.206323	-0.1458479	0.0114155	0.0948578	0.318766	0.2407057
3	-0.726945	-0.2073452	-0.0757900	0.0516682	0.384758	0.2590133
4	-0.252929	-0.1986662	-0.0492850	0.1257407	0.499225	0.3244068
5	-0.245674	-0.1028325	0.0894050	0.3415590	0.580157	0.4443915
6	-0.246828	-0.1547718	0.0024660	0.4664995	0.677220	0.6212713
7	-0.247246	-0.0412422	-0.0149680	0.0561394	0.201145	0.0973816
8	-0.286921	-0.1994061	-0.0776330	-0.0086037	0.122503	0.1908023
9	-0.405213	-0.0331674	-0.0015535	0.0830152	0.340402	0.1161826
10	-0.565909	-0.1769661	-0.0445815	0.0294273	0.144497	0.2063934
11	-0.526068	-0.1014386	-0.0466355	0.0277417	1.506859	0.1291803
12	-0.804222	-0.1485108	-0.0381965	0.0826683	1.100119	0.2311792
13	-0.516079	-0.1804567	-0.0775885	0.0664093	1.689141	0.2468660
14	-0.204985	-0.1690769	-0.0077245	0.1215654	1.173773	0.2906423
15	-0.451870	-0.2485486	-0.1521765	-0.0573823	0.662374	0.1911663
16	-0.596138	-0.2952791	-0.2306615	-0.0168707	0.404310	0.2784083
17	-1.431957	-0.3700070	-0.2869820	-0.1421041	0.326908	0.2279029
18	-0.501202	-0.3516338	-0.2646410	-0.1489080	0.424029	0.2027258
19	-1.385498	-0.3031883	-0.2756120	-0.1655645	0.009708	0.1376238
20	-0.560220	-0.2190137	-0.1619100	-0.0869697	0.314842	0.1320440
21	-0.460850	-0.1991752	-0.0854990	-0.0435715	0.138885	0.1556037
22	-0.233865	-0.2071810	-0.1451700	-0.0634863	0.451439	0.1436947
23	-0.316948	-0.2159072	-0.1384480	0.0152172	0.547873	0.2311243

N | 378

J_minus_F by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	0.2392750	0.06537994	0.0686661	0.2620421
1	16	0.2788828	0.06537994	0.1168579	0.3418449
2	16	0.4278781	0.06537994	0.1266150	0.3558300
3	16	0.4386905	0.06537994	0.1535465	0.3918501
4	16	0.4111651	0.06537994	0.2206869	0.4697733
5	16	0.4233467	0.06537994	0.2369436	0.4867685
6	16	0.4063139	0.06537994	0.2560122	0.5059765
7	16	0.0988160	0.06537994	0.0620341	0.2490664
8	16	-0.0136779	0.06537994	0.0123757	0.1112463
9	16	0.0074514	0.06537994	0.0330919	0.1819118
10	16	-0.0073654	0.06537994	0.0306131	0.1749659
11	16	-0.0167889	0.06537994	0.0517865	0.2275665
12	16	0.1615668	0.06537994	0.0155084	0.1245328
13	16	0.0891701	0.06537994	0.0272768	0.1651569
14	16	0.1753133	0.06537994	0.0385699	0.1963923
15	16	0.1546201	0.06537994	0.0105503	0.1027145
16	16	0.1681571	0.06537994	0.0056642	0.0752608
17	16	0.1366231	0.06537994	0.0209219	0.1446442
18	15	0.1287413	0.06752411	0.0117746	0.1085110
19	15	0.1215856	0.06752411	0.0137076	0.1170793
20	15	0.1386333	0.06752411	0.0113278	0.1064320
21	15	0.0836927	0.06752411	0.0246770	0.1570891
22	15	0.1944102	0.06752411	0.0222304	0.1490987
23	15	0.2046473	0.06752411	0.0516513	0.2272691
Pooled	378			0.0683926	0.2615198

N | 378

J_minus_F by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.096907	0.0794203	0.1452905	0.3821082	0.843197	0.3026878
1	-0.356333	0.1066781	0.1752025	0.5014095	0.926245	0.3947314
2	-0.226567	0.1927689	0.3615155	0.6120120	1.041468	0.4192431
3	-0.110267	0.0700339	0.3885595	0.7828278	1.119407	0.7127938
4	-0.442675	0.0875063	0.4203510	0.8371444	1.074363	0.7496382
5	-0.342692	0.0386246	0.3969855	0.7507912	1.384492	0.7121666
6	-0.298464	0.0310135	0.3189530	0.8195586	1.393535	0.7885451
7	-0.334887	-0.0708772	0.1018405	0.2298574	0.698920	0.3007346
8	-0.239763	-0.0685892	-0.0395105	0.0737454	0.215881	0.1423346
9	-0.581228	-0.0099247	0.0581125	0.0870642	0.213085	0.0969889
10	-0.489573	-0.0992321	0.0160295	0.1121089	0.237755	0.2113410
11	-0.778349	-0.0500123	0.0732030	0.0992618	0.160626	0.1492740
12	-0.048269	0.0568581	0.1722080	0.2338166	0.390297	0.1769585
13	-0.267385	0.0102942	0.1056655	0.1977396	0.393207	0.1874453
14	-0.024042	0.0597620	0.1403525	0.2036921	0.718410	0.1439301
15	-0.144665	0.1255364	0.1518945	0.1963784	0.322824	0.0708420
16	-0.027235	0.1205742	0.1832305	0.2154709	0.288628	0.0948967
17	-0.177766	0.0700809	0.1422260	0.2194962	0.473053	0.1494153
18	-0.075234	0.0719972	0.1137180	0.1759768	0.361095	0.1039797
19	-0.206776	0.0787048	0.1501840	0.2060928	0.272425	0.1273880
20	-0.059723	0.0647702	0.1399480	0.1938787	0.342171	0.1291085
21	-0.321306	-0.0125730	0.1496790	0.1875470	0.227102	0.2001200
22	-0.053959	0.1039198	0.2034910	0.2504160	0.595123	0.1464962
23	-0.022532	0.0744485	0.1380080	0.2826287	0.859047	0.2081802

N | 378

F_minus_I by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	-0.1583558	0.06439724	0.0608948	0.2467686
1	16	16	-0.1311124	0.06439724	0.0733476	0.2708276
2	16	16	-0.1535307	0.06439724	0.0357913	0.1891859
3	16	16	-0.1483148	0.06439724	0.0916398	0.3027207
4	16	16	-0.1199551	0.06439724	0.0910128	0.3016833
5	16	16	-0.0980029	0.06439724	0.0885239	0.2975296
6	16	16	-0.1849925	0.06439724	0.0930581	0.3050543
7	16	16	0.0512857	0.06439724	0.0210384	0.1450463
8	16	16	-0.0028403	0.06439724	0.0722201	0.2687381
9	16	16	-0.0326788	0.06439724	0.0276913	0.1664070
10	16	16	-0.0210969	0.06439724	0.0384396	0.1960602
11	16	16	-0.0447998	0.06439724	0.0634868	0.2519659
12	16	16	0.0152882	0.06439724	0.1088610	0.3299409
13	16	16	0.0431145	0.06439724	0.0658407	0.2565944
14	16	16	-0.0190977	0.06439724	0.0446479	0.2113005
15	16	16	0.0704219	0.06439724	0.0232478	0.1524721
16	16	16	-0.0169999	0.06439724	0.0228941	0.1513078
17	16	16	-0.0160803	0.06439724	0.0218624	0.1478595
18	15	15	-0.1349553	0.06650918	0.3003529	0.5480446
19	15	15	-0.0604055	0.06650918	0.0361636	0.1901672
20	15	15	-0.1486587	0.06650918	0.0817205	0.2858680
21	15	15	-0.0471663	0.06650918	0.0132624	0.1151625
22	15	15	-0.1364987	0.06650918	0.0842306	0.2902251
23	15	15	-0.1722435	0.06650918	0.0429242	0.2071816
Pooled	378	378			0.0663521	0.2575890

N | 378

I_minus_G by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	0.1823383	0.04287590	0.0133467	0.1155278
1	16	0.1861504	0.04287590	0.0195957	0.1399846
2	16	0.1037185	0.04287590	0.0249613	0.1579915
3	16	0.1379238	0.04287590	0.0144629	0.1202616
4	16	0.0468966	0.04287590	0.0386389	0.1965677
5	16	0.0354105	0.04287590	0.0333844	0.1827141
6	16	0.0968416	0.04287590	0.0389442	0.1973429
7	16	0.0364138	0.04287590	0.0243705	0.1561105
8	16	-0.0302523	0.04287590	0.1149733	0.3390771
9	16	-0.0316354	0.04287590	0.0121414	0.1101880
10	16	0.0792141	0.04287590	0.0157215	0.1253853
11	16	0.1350151	0.04287590	0.0605199	0.2460079
12	16	0.1060945	0.04287590	0.0115822	0.1076208
13	16	0.0586160	0.04287590	0.0606184	0.2462081
14	16	0.0243550	0.04287590	0.0546682	0.2338123
15	16	0.0816327	0.04287590	0.0115626	0.1075296
16	16	0.1381007	0.04287590	0.0478261	0.2186918
17	16	0.0914951	0.04287590	0.0217993	0.1476460
18	15	0.0662715	0.04428204	0.0125672	0.1121035
19	15	0.1439843	0.04428204	0.0071477	0.0845442
20	15	0.0989441	0.04428204	0.0172941	0.1315069
21	15	0.1157318	0.04428204	0.0142180	0.1192391
22	15	0.1576321	0.04428204	0.0189730	0.1377424
23	15	0.1992261	0.04428204	0.0102010	0.1010001
Pooled	378			0.0294135	0.1715036

N | 378

I_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.040289	0.1111168	0.1874120	0.2361457	0.436252	0.1250289
1	-0.087495	0.1115050	0.1599760	0.2943963	0.422082	0.1828913
2	-0.164055	0.0123608	0.1018495	0.2315717	0.365928	0.2192108
3	-0.031525	0.0540685	0.1278640	0.2090679	0.420182	0.1549994
4	-0.456861	-0.0354897	0.0910030	0.1420812	0.311716	0.1775708
5	-0.236722	-0.1196572	-0.0024700	0.1798407	0.339826	0.2994978
6	-0.248619	-0.0604787	0.1043835	0.2089565	0.450563	0.2694352
7	-0.227957	-0.0572694	0.0165440	0.1299184	0.349019	0.1871878
8	-1.240008	-0.0611317	0.0340055	0.1049398	0.248905	0.1660715
9	-0.268928	-0.0878351	-0.0338025	0.0113962	0.180860	0.0992312
10	-0.118111	0.0018338	0.0553995	0.1500712	0.376606	0.1482374
11	-0.420400	0.0607881	0.1005475	0.1756020	0.826901	0.1148139
12	-0.175964	0.0631410	0.1270410	0.1509749	0.267218	0.0878339
13	-0.667509	0.0234164	0.1423935	0.1669542	0.428346	0.1435378
14	-0.753257	-0.0311678	0.0864315	0.1482066	0.251796	0.1793744
15	-0.149529	0.0304494	0.0999460	0.1416262	0.291044	0.1111768
16	-0.162554	0.0398688	0.1200005	0.1565096	0.874403	0.1166407
17	-0.175484	0.0111858	0.0895645	0.1481785	0.499010	0.1369927
18	-0.140858	0.0224168	0.0491830	0.1435373	0.275221	0.1211205
19	-0.000314	0.0904212	0.1470320	0.1918860	0.328461	0.1014648
20	-0.225344	0.0452068	0.0948940	0.1815732	0.296129	0.1363663
21	-0.159017	0.0287673	0.1454780	0.2087793	0.296516	0.1800120
22	-0.075658	0.0911853	0.1181960	0.2556070	0.500508	0.1644217
23	0.013014	0.1386922	0.1962370	0.2899598	0.348352	0.1512677

FOLLOWING: LA1, AREAMOD, T2

N | 378

A_minus_S_of_A by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.589850	0.0859995	0.117995	0.343504
1	16	-0.635947	0.0859995	0.198627	0.445676
2	16	-0.561126	0.0859995	0.189703	0.435549
3	16	-0.660547	0.0859995	0.153004	0.391157
4	16	-0.532968	0.0859995	0.224174	0.473470
5	16	-0.499647	0.0859995	0.189419	0.435223
6	16	-0.577048	0.0859995	0.132584	0.364120
7	16	-0.613703	0.0859995	0.254547	0.504527
8	16	-0.741965	0.0859995	0.242195	0.492133
9	16	-0.851825	0.0859995	0.173554	0.416598
10	16	-0.862376	0.0859995	0.123103	0.350860
11	16	-0.402038	0.0859995	0.121764	0.348947
12	16	-0.092713	0.0859995	0.203773	0.451412
13	16	-0.044668	0.0859995	0.059917	0.244780
14	16	0.206705	0.0859995	0.040856	0.202129
15	16	0.093742	0.0859995	0.040381	0.200951
16	16	0.005019	0.0859995	0.029313	0.171212
17	16	-0.132631	0.0859995	0.037624	0.193970
18	15	-0.256181	0.0888199	0.019833	0.140828
19	15	-0.405448	0.0888199	0.025803	0.160633
20	15	-0.597770	0.0888199	0.039422	0.198551
21	15	-0.586429	0.0888199	0.037867	0.194594
22	15	-0.691766	0.0888199	0.084830	0.291256
23	15	-0.622351	0.0888199	0.070993	0.266446
Pooled	378			0.118335	0.343998

A_minus_S_of_A by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.17221	-0.804334	-0.618500	-0.275646	0.09448	0.528688
1	-1.71091	-0.842372	-0.653395	-0.424258	0.13559	0.418114
2	-1.22100	-0.902276	-0.570390	-0.166263	0.09180	0.736013
3	-1.29212	-0.979195	-0.592455	-0.295799	-0.10590	0.683396
4	-1.34299	-0.842646	-0.645400	-0.280699	0.34061	0.561947
5	-1.05011	-0.765250	-0.608445	-0.473884	0.39429	0.291366
6	-1.15930	-0.848633	-0.580860	-0.405697	0.25781	0.442936
7	-1.83661	-0.958258	-0.611845	-0.212873	0.07748	0.745386
8	-1.51300	-1.209478	-0.675310	-0.435700	0.07208	0.773777
9	-1.77961	-1.097549	-0.804625	-0.473893	-0.39349	0.623657
10	-1.66882	-1.034108	-0.940855	-0.669583	-0.23840	0.364525
11	-1.02487	-0.631315	-0.317310	-0.156133	0.17001	0.475182
12	-0.94378	-0.285368	-0.102785	0.256946	0.59179	0.542313
13	-0.57999	-0.132168	-0.045285	0.061401	0.44321	0.193568
14	-0.16651	0.113862	0.237945	0.350202	0.57458	0.236340
15	-0.35889	-0.037748	0.099530	0.208216	0.44357	0.245963
16	-0.26712	-0.144396	0.008055	0.174039	0.27520	0.318435
17	-0.60572	-0.261813	-0.141930	0.029322	0.13159	0.291136
18	-0.53070	-0.353392	-0.232700	-0.125568	-0.07178	0.227823
19	-0.77671	-0.506645	-0.441010	-0.252923	-0.20297	0.253722
20	-0.99491	-0.750767	-0.590400	-0.416010	-0.37750	0.334757
21	-1.00519	-0.693532	-0.611300	-0.410667	-0.32001	0.282865
22	-1.20038	-0.932675	-0.642820	-0.471545	-0.28589	0.461130
23	-1.05069	-0.808008	-0.620600	-0.438550	-0.18671	0.369458

B_minus_SW_of_B by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.876178	0.0988916	0.129428	0.359760
1	16	-1.002719	0.0988916	0.217374	0.466234
2	16	-0.923461	0.0988916	0.218402	0.467335
3	16	-0.875129	0.0988916	0.265179	0.514955
4	16	-0.768880	0.0988916	0.210695	0.459015
5	16	-0.790613	0.0988916	0.215069	0.463755
6	16	-0.877736	0.0988916	0.166271	0.407764
7	16	-1.113491	0.0988916	0.416724	0.645541
8	16	-1.180054	0.0988916	0.313810	0.560187
9	16	-1.370678	0.0988916	0.343492	0.586082
10	16	-1.526634	0.0988916	0.207996	0.456066
11	16	-1.102515	0.0988916	0.074454	0.272862
12	16	-0.883446	0.0988916	0.110347	0.332185
13	16	-0.674806	0.0988916	0.135590	0.368226
14	16	-0.688516	0.0988916	0.206795	0.454747
15	16	-0.682821	0.0988916	0.050580	0.224900
16	16	-0.582713	0.0988916	0.040818	0.202034
17	16	-0.655853	0.0988916	0.042924	0.207181
18	15	-0.551815	0.1021348	0.014346	0.119775
19	15	-0.523779	0.1021348	0.015720	0.125381
20	15	-0.642803	0.1021348	0.039132	0.197819
21	15	-0.697894	0.1021348	0.073927	0.271896
22	15	-0.763895	0.1021348	0.081404	0.285315
23	15	-0.856865	0.1021348	0.125626	0.354437
Pooled	378			0.156473	0.395566

B_minus_SW_of_B by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.52939	-1.090599	-0.843815	-0.629821	-0.24860	0.460778
1	-1.93530	-1.268343	-0.859035	-0.712274	-0.32541	0.556069
2	-1.68951	-1.322717	-0.894915	-0.566932	-0.13382	0.755785
3	-1.66132	-1.393338	-0.899765	-0.481180	-0.03430	0.912158
4	-1.61502	-1.059948	-0.737640	-0.419903	-0.09293	0.640044
5	-1.40000	-1.253604	-0.801450	-0.351521	-0.02939	0.902083
6	-1.54159	-1.229306	-0.861435	-0.525197	-0.19422	0.704109
7	-2.25619	-1.585596	-1.040205	-0.498183	-0.24380	1.087413
8	-2.04559	-1.710338	-1.239900	-0.759027	-0.08478	0.951311
9	-2.82202	-1.643357	-1.261440	-0.930813	-0.69519	0.712544
10	-2.50082	-1.868056	-1.536435	-1.107388	-0.89868	0.760668
11	-1.64200	-1.254590	-1.070560	-0.923113	-0.58670	0.331478
12	-1.67108	-1.098129	-0.799410	-0.642506	-0.44271	0.455623
13	-1.38650	-0.933504	-0.625445	-0.407006	-0.15430	0.526498
14	-1.71038	-0.947661	-0.725050	-0.413979	0.14682	0.533682
15	-1.17011	-0.839517	-0.723005	-0.547902	-0.32937	0.291615
16	-0.91519	-0.736303	-0.567655	-0.485254	-0.02509	0.251049
17	-1.32861	-0.714314	-0.564785	-0.534800	-0.49903	0.179514
18	-0.79077	-0.644923	-0.519380	-0.462937	-0.40250	0.181987
19	-0.76090	-0.605833	-0.544620	-0.426945	-0.32679	0.178888
20	-1.11582	-0.768245	-0.616300	-0.466977	-0.43280	0.301268
21	-1.18732	-0.869682	-0.668430	-0.494877	-0.31640	0.374805
22	-1.19357	-1.037185	-0.746300	-0.530475	-0.29828	0.506710
23	-1.50391	-1.148988	-0.962580	-0.528512	-0.30262	0.620477

N 378						
C_minus_N_of_C by hh		N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	-0.713083	0.0788995	0.122205	0.349578
1	16	16	-0.712474	0.0788995	0.123335	0.351191
2	16	16	-0.722411	0.0788995	0.085846	0.292995
3	16	16	-0.667459	0.0788995	0.093934	0.306487
4	16	16	-0.687963	0.0788995	0.088265	0.297094
5	16	16	-0.632032	0.0788995	0.126944	0.356292
6	16	16	-0.590956	0.0788995	0.101679	0.318872
7	16	16	-0.759071	0.0788995	0.307866	0.554856
8	16	16	-0.894271	0.0788995	0.183892	0.428827
9	16	16	-1.041043	0.0788995	0.214982	0.463662
10	16	16	-1.172496	0.0788995	0.102570	0.320265
11	16	16	-0.955183	0.0788995	0.102538	0.320215
12	16	16	-0.766170	0.0788995	0.037863	0.194585
13	16	16	-0.669576	0.0788995	0.171506	0.414132
14	16	16	-0.693626	0.0788995	0.051076	0.225999
15	16	16	-0.666945	0.0788995	0.051591	0.227136
16	16	16	-0.651345	0.0788995	0.022017	0.148383
17	16	16	-0.607101	0.0788995	0.104155	0.322731
18	15	15	-0.646425	0.0814870	0.016145	0.127064
19	15	15	-0.623779	0.0814870	0.033229	0.182287
20	15	15	-0.722455	0.0814870	0.050763	0.225306
21	15	15	-0.725087	0.0814870	0.070860	0.266196
22	15	15	-0.713060	0.0814870	0.033857	0.184002
23	15	15	-0.770806	0.0814870	0.071942	0.268220
Pooled		378			0.099602	0.315598

C_minus_N_of_C by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.16290	-1.033763	-0.794510	-0.427755	-0.00488	0.606008
1	-1.23010	-0.992573	-0.758620	-0.440088	-0.08539	0.552485
2	-1.17270	-0.977165	-0.697540	-0.420273	-0.29748	0.556893
3	-0.99982	-0.963389	-0.709010	-0.371358	-0.22998	0.592031
4	-1.11780	-0.918085	-0.755750	-0.355235	-0.25729	0.562850
5	-1.10162	-0.910493	-0.677090	-0.416572	0.05090	0.493921
6	-1.15991	-0.833068	-0.611460	-0.368415	0.15741	0.464652
7	-1.65332	-1.274293	-0.766360	-0.263594	0.10840	1.010698
8	-1.70502	-1.090033	-0.974195	-0.526776	-0.00558	0.563258
9	-1.84201	-1.414263	-0.977340	-0.791511	-0.07278	0.622752
10	-2.01661	-1.358803	-1.170490	-0.972014	-0.67059	0.386788
11	-1.46881	-1.138493	-1.025145	-0.803477	-0.13199	0.335017
12	-1.10330	-0.887167	-0.775495	-0.611099	-0.32779	0.276068
13	-1.66720	-0.864603	-0.644440	-0.509086	0.14423	0.355518
14	-1.07107	-0.860577	-0.685945	-0.515825	-0.37650	0.344752
15	-1.29550	-0.774808	-0.600720	-0.508392	-0.44101	0.266417
16	-0.86609	-0.754282	-0.655595	-0.560297	-0.36120	0.193985
17	-0.98493	-0.803767	-0.686755	-0.527636	0.33103	0.276131
18	-0.88110	-0.735112	-0.636810	-0.545785	-0.43683	0.189327
19	-0.98721	-0.737337	-0.602780	-0.492190	-0.33329	0.245147
20	-1.20810	-0.837538	-0.748200	-0.548853	-0.25531	0.288685
21	-1.13809	-0.980505	-0.736120	-0.484265	-0.32928	0.496240
22	-0.93531	-0.887183	-0.800510	-0.497515	-0.45791	0.389668
23	-1.28637	-1.005607	-0.807220	-0.490490	-0.44650	0.515117

L_minus_H by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	0.683931	0.0850492	0.078546	0.280260
1	16	0.648043	0.0850492	0.093184	0.305260
2	16	0.662856	0.0850492	0.146845	0.383204
3	16	0.666848	0.0850492	0.102640	0.320375
4	16	0.603436	0.0850492	0.115422	0.339738
5	16	0.698980	0.0850492	0.126747	0.356016
6	16	0.726956	0.0850492	0.175108	0.418459
7	16	0.789973	0.0850492	0.202066	0.449517
8	16	0.887645	0.0850492	0.188536	0.434207
9	16	1.041594	0.0850492	0.101660	0.318841
10	16	1.138564	0.0850492	0.090124	0.300207
11	16	0.840468	0.0850492	0.179278	0.423413
12	16	0.631896	0.0850492	0.214490	0.463131
13	16	0.659019	0.0850492	0.155812	0.394730
14	16	0.512072	0.0850492	0.094127	0.306802
15	16	0.515604	0.0850492	0.133974	0.366024
16	16	0.675763	0.0850492	0.071899	0.268140
17	16	0.502111	0.0850492	0.085449	0.292317
18	15	0.483585	0.0878384	0.064994	0.254939
19	15	0.436555	0.0878384	0.043704	0.209054
20	15	0.541500	0.0878384	0.045883	0.214203
21	15	0.500659	0.0878384	0.058766	0.242416
22	15	0.636493	0.0878384	0.089671	0.299451
23	15	0.669711	0.0878384	0.099207	0.314972
Pooled	378			0.115734	0.340197

L_minus_H by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.22742	0.459783	0.677885	0.864842	1.39309	0.405059
1	0.25061	0.357416	0.685745	0.893048	1.23560	0.535632
2	0.18143	0.321887	0.652345	0.881813	1.58990	0.559927
3	0.28549	0.425507	0.587845	0.856187	1.41360	0.430680
4	0.20770	0.313243	0.529680	0.806261	1.45782	0.493018
5	0.11697	0.479013	0.680190	0.814961	1.59119	0.335948
6	0.01068	0.345763	0.752015	1.105161	1.28391	0.759398
7	-0.05450	0.479738	0.774105	1.108101	1.77377	0.628363
8	0.12570	0.589252	0.842940	1.133799	1.63471	0.544548
9	0.65140	0.764528	0.958940	1.294578	1.72171	0.530051
10	0.72549	0.901408	1.083910	1.297976	1.84799	0.396568
11	0.26257	0.558937	0.821610	0.914008	1.81677	0.355071
12	-0.22193	0.397336	0.591815	0.920578	1.45489	0.523242
13	-0.10059	0.404082	0.702655	0.964178	1.30622	0.560097
14	-0.08859	0.281093	0.528685	0.772718	0.94568	0.491624
15	-0.18908	0.351904	0.526395	0.896367	0.96262	0.544463
16	0.19278	0.507461	0.658680	0.926127	1.14920	0.418666
17	0.06391	0.311817	0.504060	0.600004	1.16071	0.288188
18	0.16452	0.330417	0.416800	0.532063	1.12918	0.201647
19	0.18350	0.310650	0.430300	0.486257	1.07010	0.175607
20	0.34249	0.402430	0.449680	0.586767	1.11871	0.184337
21	0.06693	0.388798	0.451500	0.589882	1.00360	0.201083
22	0.27750	0.445312	0.509800	0.720218	1.40491	0.274907
23	0.26867	0.480225	0.579930	0.825293	1.51397	0.345068

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L_minus_G by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.781036	0.0893318	0.104336	0.323011
1	16	16	0.887450	0.0893318	0.059081	0.243065
2	16	16	0.870227	0.0893318	0.086547	0.294189
3	16	16	0.861748	0.0893318	0.135999	0.368780
4	16	16	0.748038	0.0893318	0.236083	0.485884
5	16	16	0.795623	0.0893318	0.112736	0.335762
6	16	16	0.733183	0.0893318	0.158781	0.398474
7	16	16	0.961934	0.0893318	0.188420	0.434074
8	16	16	1.200582	0.0893318	0.256391	0.506350
9	16	16	1.228135	0.0893318	0.183495	0.428363
10	16	16	1.352971	0.0893318	0.155027	0.393735
11	16	16	1.038747	0.0893318	0.201825	0.449249
12	16	16	0.747456	0.0893318	0.190360	0.436303
13	16	16	0.740696	0.0893318	0.132145	0.363518
14	16	16	0.581194	0.0893318	0.039680	0.199200
15	16	16	0.702115	0.0893318	0.143863	0.379293
16	16	16	0.786361	0.0893318	0.082533	0.287285
17	16	16	0.624949	0.0893318	0.083748	0.289393
18	15	15	0.576448	0.0922615	0.044010	0.209785
19	15	15	0.516739	0.0922615	0.064653	0.254269
20	15	15	0.584359	0.0922615	0.074987	0.273837
21	15	15	0.666839	0.0922615	0.086873	0.294742
22	15	15	0.768301	0.0922615	0.131746	0.362968
23	15	15	0.785251	0.0922615	0.093011	0.304977
Pooled	378				0.127683	0.357327

L_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.29910	0.532157	0.785095	0.978483	1.58432	0.446326
1	0.39243	0.740755	0.871690	1.048288	1.34421	0.307533
2	0.38992	0.678351	0.833645	1.048491	1.42322	0.370140
3	0.13550	0.662993	0.904060	1.059627	1.72259	0.396633
4	-0.10571	0.397149	0.792845	1.101012	1.63382	0.703863
5	0.05451	0.544949	0.838350	1.002607	1.39679	0.457657
6	0.00541	0.454939	0.771150	1.037843	1.35883	0.582903
7	0.20151	0.562773	0.933760	1.326858	1.72869	0.764085
8	0.24310	0.833490	1.091245	1.583924	2.18192	0.750434
9	0.68821	0.808949	1.239365	1.464408	2.15631	0.655459
10	0.65609	1.089723	1.382705	1.586357	2.24390	0.496634
11	0.25360	0.771402	1.059900	1.207403	1.90268	0.436001
12	-0.08770	0.424702	0.855590	1.080833	1.42639	0.656130
13	-0.20181	0.516681	0.732905	1.019198	1.37598	0.502518
14	0.27728	0.404432	0.599440	0.699756	0.89740	0.295324
15	-0.23718	0.540638	0.770095	0.895328	1.52582	0.354690
16	0.35150	0.499203	0.903460	1.004065	1.19062	0.504862
17	0.05362	0.455083	0.610260	0.699256	1.25602	0.244172
18	0.31610	0.406418	0.556880	0.727578	1.02600	0.321160
19	0.18201	0.367037	0.409090	0.621833	1.03159	0.254797
20	0.22443	0.418460	0.442720	0.772705	1.19439	0.354245
21	0.40820	0.440430	0.511600	0.960917	1.30573	0.520487
22	0.45261	0.478513	0.705720	1.001133	1.72030	0.522620
23	0.38440	0.541093	0.728730	0.973208	1.53369	0.432115

K_minus_J by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.664188	0.0894556	0.063153	0.251302
1	16	-0.652585	0.0894556	0.176925	0.420625
2	16	-0.568469	0.0894556	0.079188	0.281404
3	16	-0.571155	0.0894556	0.086323	0.293808
4	16	-0.403687	0.0894556	0.180869	0.425287
5	16	-0.523432	0.0894556	0.071331	0.267078
6	16	-0.522236	0.0894556	0.129059	0.359248
7	16	-0.672731	0.0894556	0.229429	0.478988
8	16	-0.768216	0.0894556	0.210025	0.458285
9	16	-0.961956	0.0894556	0.133705	0.365657
10	16	-1.147468	0.0894556	0.118124	0.343691
11	16	-0.885105	0.0894556	0.145772	0.381801
12	16	-0.762148	0.0894556	0.265570	0.515335
13	16	-0.961791	0.0894556	0.066796	0.258449
14	16	-0.649246	0.0894556	0.288935	0.537527
15	16	-0.681218	0.0894556	0.304650	0.551951
16	16	-0.741557	0.0894556	0.103339	0.321464
17	16	-0.784155	0.0894556	0.079268	0.281547
18	15	-0.797518	0.0923894	0.037762	0.194324
19	15	-0.698694	0.0923894	0.027514	0.165873
20	15	-0.693189	0.0923894	0.053225	0.230705
21	15	-0.656350	0.0923894	0.068844	0.262382
22	15	-0.659418	0.0923894	0.049057	0.221487
23	15	-0.669145	0.0923894	0.073465	0.271045
Pooled	378			0.128037	0.357822

K_minus_J by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.12952	-0.855205	-0.642105	-0.449216	-0.34720	0.405989
1	-1.25049	-0.974877	-0.697645	-0.317624	0.01981	0.657253
2	-0.97702	-0.772657	-0.625415	-0.365164	-0.00159	0.407493
3	-1.16910	-0.687033	-0.482190	-0.412252	-0.08139	0.274782
4	-1.04840	-0.630557	-0.499375	-0.261208	0.37650	0.369348
5	-1.13489	-0.721721	-0.520295	-0.271573	-0.14390	0.450147
6	-1.27298	-0.712533	-0.471050	-0.342171	0.20840	0.370363
7	-1.34800	-1.024717	-0.756365	-0.352409	0.27072	0.672308
8	-1.67551	-1.151922	-0.712800	-0.391508	-0.17230	0.760413
9	-1.70560	-1.177954	-0.904740	-0.669887	-0.36871	0.508067
10	-1.97421	-1.340903	-1.143705	-0.794025	-0.74390	0.546877
11	-1.46591	-1.190357	-1.041705	-0.474571	-0.30600	0.715786
12	-1.55758	-1.159421	-0.827175	-0.384630	0.06808	0.774791
13	-1.33371	-1.112781	-1.018750	-0.748929	-0.48892	0.363852
14	-1.56848	-0.961644	-0.764645	-0.253884	0.27469	0.707760
15	-1.71301	-1.087789	-0.749970	-0.198325	0.32672	0.889464
16	-1.20783	-1.055690	-0.752445	-0.523860	-0.19132	0.531830
17	-1.12872	-0.945359	-0.850755	-0.655823	0.05090	0.289536
18	-1.05499	-0.931398	-0.793180	-0.694898	-0.32053	0.236500
19	-1.01059	-0.800953	-0.687320	-0.551040	-0.46417	0.249913
20	-1.15451	-0.813542	-0.667210	-0.550867	-0.36212	0.262675
21	-1.22769	-0.849878	-0.579890	-0.456167	-0.36490	0.393712
22	-1.25202	-0.775843	-0.635620	-0.475577	-0.39309	0.300267
23	-1.36933	-0.765538	-0.642580	-0.451635	-0.32422	0.313903

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J_minus_F by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.839964	0.1008157	0.114318	0.338110
1	16	16	0.842645	0.1008157	0.131111	0.362093
2	16	16	0.756380	0.1008157	0.184902	0.430002
3	16	16	0.845679	0.1008157	0.157841	0.397292
4	16	16	0.791554	0.1008157	0.207161	0.455149
5	16	16	0.709694	0.1008157	0.112441	0.335322
6	16	16	0.629494	0.1008157	0.114977	0.339082
7	16	16	0.830671	0.1008157	0.246533	0.496521
8	16	16	0.909864	0.1008157	0.295243	0.543363
9	16	16	1.207106	0.1008157	0.273347	0.522826
10	16	16	1.332654	0.1008157	0.266896	0.516620
11	16	16	0.992436	0.1008157	0.232461	0.482142
12	16	16	0.882955	0.1008157	0.380352	0.616727
13	16	16	1.098587	0.1008157	0.096222	0.310197
14	16	16	0.800610	0.1008157	0.141319	0.375924
15	16	16	0.756112	0.1008157	0.208632	0.456762
16	16	16	0.715083	0.1008157	0.223120	0.472356
17	16	16	0.745450	0.1008157	0.078292	0.279806
18	15	15	0.604782	0.1041220	0.085370	0.292181
19	15	15	0.560920	0.1041220	0.065627	0.256177
20	15	15	0.683011	0.1041220	0.032243	0.179564
21	15	15	0.694412	0.1041220	0.056338	0.237357
22	15	15	0.765452	0.1041220	0.070301	0.265143
23	15	15	0.788601	0.1041220	0.089428	0.299045
Pooled	378	378			0.162621	0.403263

J_minus_F by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.43033	0.506215	0.804015	1.026123	1.58209	0.519908
1	0.22913	0.549563	0.845390	1.137873	1.41931	0.588310
2	-0.09549	0.406988	0.800105	1.053427	1.47742	0.646439
3	0.20318	0.547670	0.851745	1.178278	1.35581	0.630608
4	-0.18811	0.433897	0.930420	1.109293	1.42533	0.675395
5	0.00858	0.544022	0.760590	0.984431	1.19580	0.440409
6	0.04142	0.315687	0.678995	0.901060	1.14969	0.585373
7	0.03912	0.338561	0.927370	1.254353	1.60788	0.915793
8	0.14661	0.504904	0.802415	1.401310	1.87851	0.896406
9	0.53803	0.827062	1.137390	1.442661	2.63101	0.615599
10	0.40329	0.918894	1.430695	1.667863	2.31439	0.748969
11	0.12200	0.482402	1.196760	1.347267	1.69949	0.864864
12	-0.08380	0.263933	1.127795	1.447272	1.53711	1.183339
13	0.51519	0.926610	1.173755	1.335842	1.48077	0.409232
14	0.18271	0.523653	0.743650	1.168998	1.45929	0.645344
15	0.09052	0.373981	0.747015	1.181251	1.44861	0.807270
16	-0.08310	0.300358	0.757185	1.164808	1.30191	0.864451
17	0.23291	0.609077	0.738950	0.927393	1.27832	0.318316
18	-0.15628	0.512462	0.621190	0.730665	1.14170	0.218203
19	-0.14761	0.451393	0.609370	0.682818	0.97848	0.231425
20	0.43540	0.541567	0.659120	0.767457	1.11508	0.225890
21	0.43530	0.466220	0.650120	0.853225	1.14890	0.387005
22	0.42533	0.515710	0.748590	1.002142	1.26459	0.486432
23	0.31860	0.549025	0.755100	1.009902	1.30762	0.460877

F_minus_I by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.940866	0.1028966	0.136692	0.369719
1	16	-0.942661	0.1028966	0.140722	0.375129
2	16	-0.917264	0.1028966	0.212498	0.460975
3	16	-0.949963	0.1028966	0.132132	0.363499
4	16	-0.948160	0.1028966	0.188821	0.434535
5	16	-0.855521	0.1028966	0.176580	0.420214
6	16	-0.793369	0.1028966	0.065028	0.255006
7	16	-0.955090	0.1028966	0.264305	0.514106
8	16	-1.157680	0.1028966	0.254263	0.504245
9	16	-1.391280	0.1028966	0.289757	0.538291
10	16	-1.584245	0.1028966	0.222231	0.471414
11	16	-1.153750	0.1028966	0.285378	0.534208
12	16	-0.864999	0.1028966	0.292440	0.540777
13	16	-1.056606	0.1028966	0.199158	0.446271
14	16	-1.084559	0.1028966	0.226123	0.475524
15	16	-0.782399	0.1028966	0.154988	0.393685
16	16	-0.964474	0.1028966	0.200710	0.448006
17	16	-0.932407	0.1028966	0.108414	0.329262
18	15	-0.812661	0.1062712	0.049241	0.221904
19	15	-0.821871	0.1062712	0.047604	0.218184
20	15	-0.870980	0.1062712	0.099931	0.316119
21	15	-0.829144	0.1062712	0.085187	0.291868
22	15	-0.835455	0.1062712	0.091474	0.302446
23	15	-0.923866	0.1062712	0.106223	0.325918
Pooled	378			0.169403	0.411587

F_minus_I by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.87958	-1.091785	-0.889515	-0.611099	-0.46557	0.480686
1	-1.72351	-1.165882	-0.919450	-0.678099	-0.40750	0.487782
2	-1.82382	-1.246773	-0.967940	-0.530136	-0.00873	0.716638
3	-1.66962	-1.222687	-0.965960	-0.722365	-0.39328	0.500322
4	-1.49851	-1.379369	-1.026965	-0.743928	0.04352	0.635442
5	-1.51532	-1.157981	-0.921695	-0.588768	-0.03998	0.569213
6	-1.31439	-0.908960	-0.735960	-0.623924	-0.40412	0.285036
7	-1.94378	-1.413248	-0.924955	-0.564569	-0.21679	0.848678
8	-2.05802	-1.635603	-0.998720	-0.793302	-0.48980	0.842300
9	-2.84899	-1.644813	-1.356100	-0.997767	-0.76440	0.647047
10	-2.64389	-1.839558	-1.645090	-1.334157	-0.55732	0.505402
11	-1.96258	-1.656252	-1.136595	-0.613712	-0.39321	1.042539
12	-1.67240	-1.231522	-0.967790	-0.554643	0.19699	0.676878
13	-1.73520	-1.357659	-1.110610	-0.683909	-0.27569	0.673750
14	-1.88001	-1.474163	-1.038190	-0.730613	-0.31088	0.743550
15	-1.46692	-1.087079	-0.611955	-0.427502	-0.36432	0.659578
16	-1.92739	-1.263178	-0.844785	-0.736286	-0.20801	0.526892
17	-1.67939	-1.170643	-0.900495	-0.668773	-0.48871	0.501871
18	-1.16931	-1.021720	-0.784700	-0.637873	-0.53171	0.383847
19	-1.29791	-1.020600	-0.748990	-0.631905	-0.57452	0.388695
20	-1.52688	-1.063677	-0.790800	-0.612335	-0.48551	0.451342
21	-1.55771	-0.955882	-0.774420	-0.598307	-0.53601	0.357575
22	-1.45538	-0.963033	-0.735800	-0.625365	-0.35111	0.337668
23	-1.59210	-1.112377	-0.876400	-0.638073	-0.44199	0.474303

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I_minus_G by hh		N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.804699	0.0892358	0.122007	0.349295
1	16	16	0.822204	0.0892358	0.072390	0.269053
2	16	16	0.745890	0.0892358	0.106376	0.326153
3	16	16	0.742544	0.0892358	0.072682	0.269596
4	16	16	0.663684	0.0892358	0.160648	0.400809
5	16	16	0.677745	0.0892358	0.120632	0.347321
6	16	16	0.589430	0.0892358	0.088064	0.296756
7	16	16	0.742319	0.0892358	0.195157	0.441766
8	16	16	0.998008	0.0892358	0.285645	0.534458
9	16	16	1.176870	0.0892358	0.210892	0.459230
10	16	16	1.446111	0.0892358	0.177436	0.421231
11	16	16	1.140364	0.0892358	0.150762	0.388281
12	16	16	0.840206	0.0892358	0.179611	0.423805
13	16	16	0.990986	0.0892358	0.201178	0.448529
14	16	16	1.129654	0.0892358	0.178185	0.422119
15	16	16	0.835719	0.0892358	0.105655	0.325046
16	16	16	1.013809	0.0892358	0.116809	0.341773
17	16	16	0.825602	0.0892358	0.067470	0.259750
18	15	15	0.748773	0.0921623	0.034428	0.185548
19	15	15	0.648869	0.0921623	0.044555	0.211080
20	15	15	0.639549	0.0921623	0.092460	0.304073
21	15	15	0.707139	0.0921623	0.076197	0.276038
22	15	15	0.715519	0.0921623	0.068015	0.260796
23	15	15	0.789343	0.0921623	0.107817	0.328355
Pooled		378			0.127408	0.356943

I_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.29318	0.484516	0.724635	0.974770	1.46891	0.490254
1	0.27169	0.667033	0.846800	1.011673	1.20990	0.344640
2	0.21329	0.394825	0.824295	1.019080	1.17981	0.624255
3	0.12811	0.684212	0.782590	0.903227	1.23920	0.219015
4	-0.17639	0.344921	0.719435	0.996278	1.19308	0.651357
5	0.22141	0.371468	0.637540	0.911538	1.42331	0.540069
6	-0.16259	0.466331	0.633805	0.766228	1.10062	0.299897
7	0.09609	0.317197	0.897290	1.161292	1.34738	0.844095
8	0.27600	0.569681	0.821500	1.425006	2.12198	0.855325
9	0.64569	0.781623	1.089420	1.457220	2.23449	0.675598
10	0.75541	1.136829	1.499295	1.648913	2.55631	0.512084
11	0.39801	0.862104	1.249650	1.358550	1.86880	0.496446
12	0.09769	0.487739	0.818295	1.252563	1.46781	0.764823
13	0.34869	0.644522	0.985110	1.327181	1.98678	0.682659
14	0.35479	0.761221	1.249800	1.457028	1.69602	0.695808
15	0.10492	0.631758	0.912065	1.107446	1.21179	0.475688
16	0.38889	0.726139	0.990585	1.252429	1.62469	0.526290
17	0.46482	0.631131	0.775345	1.001998	1.41239	0.370867
18	0.47949	0.585082	0.723480	0.954375	1.02103	0.369293
19	0.18048	0.532157	0.623630	0.762495	1.05380	0.230338
20	0.02801	0.446047	0.666290	0.882805	1.23190	0.436758
21	0.39480	0.486205	0.622710	0.955573	1.24082	0.469368
22	0.43930	0.456452	0.676080	0.897035	1.24029	0.440583
23	0.39881	0.482348	0.698700	0.994352	1.44242	0.512003

FOLLOWING: LA1, mod-UCM, T2

A_minus_S_of_A by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-1.0668325	0.22986261	2.2816432	1.5105109
1	16	-1.2058613	0.22986261	2.2919408	1.5139157
2	16	-1.5413681	0.22986261	2.3260406	1.5251363
3	16	-1.5641244	0.22986261	2.2643795	1.5047855
4	16	-1.7115281	0.22986261	2.2639039	1.5046275
5	16	-1.9731698	0.22986261	2.4020527	1.5498557
6	16	-1.8453312	0.22986261	2.3077250	1.5191198
7	16	-0.2318519	0.22986261	0.1004564	0.3169485
8	16	0.0396075	0.22986261	0.0177818	0.1333484
9	16	0.0280100	0.22986261	0.0144316	0.1201315
10	16	0.0661850	0.22986261	0.0142082	0.1191983
11	16	0.0734812	0.22986261	0.0164471	0.1282461
12	16	0.0445081	0.22986261	0.0160453	0.1266700
13	16	0.0225144	0.22986261	0.0161609	0.1271254
14	16	0.0413794	0.22986261	0.0123993	0.1113521
15	16	0.0463625	0.22986261	0.0130574	0.1142690
16	16	0.0301112	0.22986261	0.0042043	0.0648403
17	16	0.0344837	0.22986261	0.0083933	0.0916152
18	15	-0.0645633	0.23740108	0.0146869	0.1211896
19	15	-0.1043573	0.23740108	0.0089961	0.0948475
20	15	-0.2304320	0.23740108	0.0048206	0.0694308
21	15	-0.4728947	0.23740108	0.5850332	0.7648746
22	15	-0.7774753	0.23740108	1.3118936	1.1453792
23	15	-0.8949833	0.23740108	1.9101888	1.3820958
Pooled	378			0.8453891	0.9194504

A_minus_S_of_A by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-4.032890	-2.3930717	-0.2329000	0.0445925	0.420990	2.4376642
1	-4.260100	-2.2467225	-0.5127100	0.0259333	0.440710	2.2726558
2	-4.095090	-2.8518542	-1.1067350	-0.1565692	0.214330	2.6952850
3	-4.215570	-2.8257567	-1.2845000	-0.0535292	0.173310	2.7722275
4	-4.324890	-2.9058008	-1.7568550	-0.0018017	0.292910	2.9039992
5	-4.424590	-3.1224892	-2.1781180	-0.1639092	0.312630	2.9585800
6	-4.267210	-3.0753250	-2.0474395	-0.1131667	0.099120	2.9621583
7	-1.178220	-0.3972992	-0.1080950	-0.0250558	0.115300	0.3722433
8	-0.199590	-0.0445808	0.0309050	0.1507475	0.258700	0.1953283
9	-0.268890	-0.0241775	0.0637950	0.0936842	0.170990	0.1178617
10	-0.185700	-0.0170000	0.0841700	0.1381367	0.297210	0.1551367
11	-0.189090	-0.0358033	0.1063100	0.1886833	0.223480	0.2244867
12	-0.267580	-0.0073017	0.0784000	0.1427608	0.189390	0.1500625
13	-0.325600	-0.0125100	0.0647600	0.1028392	0.163610	0.1153492
14	-0.251500	0.0058108	0.0465400	0.1290783	0.195500	0.1232675
15	-0.129790	-0.0695667	0.0827000	0.1203808	0.245790	0.1899475
16	-0.100010	-0.0274125	0.0361000	0.0831283	0.122310	0.1105408
17	-0.091180	-0.0258075	0.0173950	0.0808975	0.300210	0.1067050
18	-0.309690	-0.1682183	-0.0444900	0.0344750	0.079410	0.2026933
19	-0.290710	-0.1715633	-0.0521800	-0.0299100	-0.005700	0.1416533
20	-0.360500	-0.2897450	-0.2160000	-0.1784017	-0.131690	0.1113433
21	-2.981300	-0.3371800	-0.1922000	-0.1577633	-0.102200	0.1794167
22	-3.484280	-0.8603983	-0.2002900	-0.1229300	-0.052920	0.7374683
23	-4.092010	-1.3533600	-0.1660200	-0.1139000	0.000210	1.2394600

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B_minus_SW_of_B by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD	
0	16	-1.4931931	0.25168964	1.7517820	1.3235490	
1	16	-1.7575331	0.25168964	2.3546125	1.5344747	
2	16	-2.0050406	0.25168964	2.8434337	1.6862484	
3	16	-2.1940381	0.25168964	2.9748337	1.7247706	
4	16	-2.2965981	0.25168964	3.1901192	1.7860905	
5	16	-2.2177863	0.25168964	3.0698464	1.7520977	
6	16	-1.8867956	0.25168964	3.4158353	1.8481978	
7	16	-0.4516656	0.25168964	0.1904137	0.4363642	
8	16	-0.1232181	0.25168964	0.1245008	0.3528468	
9	16	-0.1294563	0.25168964	0.0124966	0.1117880	
10	16	-0.0928406	0.25168964	0.0213181	0.1460072	
11	16	-0.0582525	0.25168964	0.0314723	0.1774043	
12	16	0.0725219	0.25168964	0.1230883	0.3508394	
13	16	0.0696894	0.25168964	0.0278984	0.1670282	
14	16	0.0939812	0.25168964	0.0341749	0.1848646	
15	16	0.0774581	0.25168964	0.0112033	0.1058457	
16	16	0.0429219	0.25168964	0.0285671	0.1690180	
17	16	-0.0228206	0.25168964	0.0070367	0.0838852	
18	15	-0.0866460	0.25994394	0.0132543	0.1151275	
19	15	-0.1663153	0.25994394	0.0047275	0.0687565	
20	15	-0.2986107	0.25994394	0.0148701	0.1219430	
21	15	-0.6918080	0.25994394	0.8985298	0.9479081	
22	15	-0.9490040	0.25994394	1.3262518	1.1516300	
23	15	-1.2956487	0.25994394	1.7146328	1.3094399	
Pooled	378			1.0135628	1.0067585	

B_minus_SW_of_B by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-4.062500	-2.5635942	-1.2170100	-0.3282833	-0.027280	2.2353108
1	-4.390290	-2.9247400	-1.9655550	-0.2765717	0.052010	2.6481683
2	-4.678190	-3.2815867	-2.3477050	-0.1897350	-0.059390	3.0918517
3	-4.925110	-3.3409233	-2.8953700	-0.2551333	0.155090	3.0857900
4	-5.299010	-3.5214117	-2.8608550	-0.3032258	0.118280	3.2181858
5	-4.898500	-3.5288525	-2.6373600	-0.0344225	0.196200	3.4944300
6	-4.635680	-3.6657742	-1.3196550	-0.0683525	0.085080	3.5974217
7	-1.298610	-0.7903567	-0.3183450	-0.1571542	0.258080	0.6332025
8	-0.865420	-0.2932017	-0.1893000	0.0461450	0.793880	0.3393467
9	-0.406190	-0.1876000	-0.0934450	-0.0511050	-0.012900	0.1364950
10	-0.400790	-0.1540017	-0.0369550	0.0013858	0.061800	0.1553875
11	-0.442290	-0.1493292	-0.0095800	0.0844158	0.146090	0.2337450
12	-0.293090	-0.1035817	0.0095350	0.0793500	1.242520	0.1829317
13	-0.124600	-0.0343375	0.0467800	0.1255508	0.581110	0.1598883
14	-0.138790	-0.0317233	0.0562100	0.1606517	0.658290	0.1923750
15	-0.145320	0.0029875	0.0831400	0.1574642	0.235690	0.1544767
16	-0.254820	-0.0330133	0.0070050	0.0587383	0.536100	0.0917517
17	-0.117670	-0.0779842	-0.0499000	0.0099250	0.187720	0.0879092
18	-0.356820	-0.1302733	-0.0916200	-0.0418017	0.188200	0.0884717
19	-0.315190	-0.1800450	-0.1691000	-0.1468383	-0.000700	0.0332067
20	-0.522980	-0.3553900	-0.2857100	-0.2176300	-0.027710	0.1377600
21	-3.337310	-0.5144800	-0.3806200	-0.2396917	-0.157590	0.2747883
22	-3.420200	-0.8136333	-0.4105300	-0.3308417	-0.145290	0.4827917
23	-3.551910	-2.3994600	-0.4892900	-0.3370033	-0.071810	2.0624567

C_minus_N_of_C by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-1.175886	0.2002832	1.223364	1.106058
1	16	-1.369846	0.2002832	1.841544	1.357035
2	16	-1.507200	0.2002832	2.047083	1.430763
3	16	-1.578237	0.2002832	2.106741	1.451462
4	16	-1.266016	0.2002832	2.086524	1.444480
5	16	-1.263289	0.2002832	1.626187	1.275220
6	16	-1.586462	0.2002832	1.893021	1.375871
7	16	-0.196825	0.2002832	0.148840	0.385797
8	16	-0.008155	0.2002832	0.044471	0.210882
9	16	0.031361	0.2002832	0.015916	0.126159
10	16	-0.044618	0.2002832	0.012904	0.113594
11	16	-0.031618	0.2002832	0.020087	0.141727
12	16	-0.081646	0.2002832	0.018809	0.137145
13	16	-0.089427	0.2002832	0.040543	0.201353
14	16	-0.120231	0.2002832	0.008597	0.092719
15	16	-0.197124	0.2002832	0.010762	0.103740
16	16	-0.253798	0.2002832	0.010119	0.100592
17	16	-0.269356	0.2002832	0.034114	0.184701
18	15	-0.376671	0.2068516	0.019270	0.138815
19	15	-0.344447	0.2068516	0.059363	0.243645
20	15	-0.469069	0.2068516	0.031350	0.177059
21	15	-0.560014	0.2068516	0.197773	0.444716
22	15	-0.849810	0.2068516	0.797054	0.892779
23	15	-1.068390	0.2068516	0.992171	0.996078
Pooled	378			0.641814	0.801133

C_minus_N_of_C by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-3.16282	-2.109325	-0.685450	-0.234269	-0.09799	1.875056
1	-4.36429	-2.423761	-0.920945	-0.182489	0.02459	2.241272
2	-4.40329	-2.592958	-1.061690	-0.274758	-0.02271	2.318199
3	-4.30600	-2.708809	-1.429745	-0.104494	0.06760	2.604315
4	-3.62522	-2.451385	-0.790890	0.027665	0.36521	2.479050
5	-4.08230	-2.166352	-1.147610	-0.052440	0.07300	2.113912
6	-4.36600	-2.448982	-1.913255	-0.244934	0.00921	2.204048
7	-1.10678	-0.386633	-0.077945	0.090965	0.27231	0.477598
8	-0.35208	-0.247976	0.037335	0.137995	0.30130	0.385971
9	-0.28778	-0.020910	0.034460	0.079211	0.33658	0.100121
10	-0.30271	-0.098141	-0.030050	-0.007105	0.19251	0.091036
11	-0.22979	-0.120506	-0.047545	0.023546	0.34672	0.144052
12	-0.36423	-0.171788	-0.081360	0.021557	0.14318	0.193346
13	-0.42392	-0.186262	-0.103245	0.002753	0.46569	0.189014
14	-0.28039	-0.180754	-0.109100	-0.068997	0.08648	0.111757
15	-0.33970	-0.265118	-0.211685	-0.144048	0.04401	0.121071
16	-0.46729	-0.307681	-0.244795	-0.228648	0.03080	0.079033
17	-0.53339	-0.362261	-0.272790	-0.218028	0.32450	0.144233
18	-0.76748	-0.428025	-0.345400	-0.309597	-0.15921	0.118428
19	-0.73749	-0.478055	-0.381500	-0.316067	0.27671	0.161988
20	-0.79019	-0.588762	-0.444310	-0.393393	-0.14371	0.195368
21	-1.92599	-0.586938	-0.407900	-0.373617	-0.14740	0.213322
22	-2.81329	-0.574963	-0.430690	-0.368900	-0.27472	0.206063
23	-2.87628	-2.002497	-0.518500	-0.384695	-0.12530	1.617802

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L_minus_H by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.088338	0.2007481	1.111251	1.054159
1	16	1.234193	0.2007481	1.216951	1.103155
2	16	1.387754	0.2007481	1.483990	1.218191
3	16	1.546630	0.2007481	1.694166	1.301601
4	16	1.713609	0.2007481	1.888333	1.374166
5	16	1.833094	0.2007481	2.222387	1.490767
6	16	1.726666	0.2007481	2.066459	1.437518
7	16	0.307283	0.2007481	0.098286	0.313505
8	16	0.060669	0.2007481	0.070259	0.265064
9	16	0.080777	0.2007481	0.066345	0.257575
10	16	0.080662	0.2007481	0.163771	0.404687
11	16	0.117710	0.2007481	0.207830	0.455883
12	16	0.145838	0.2007481	0.279007	0.528211
13	16	0.169401	0.2007481	0.185760	0.430999
14	16	0.027193	0.2007481	0.036485	0.191010
15	16	-0.013085	0.2007481	0.055433	0.235443
16	16	0.024101	0.2007481	0.032809	0.181132
17	16	0.042004	0.2007481	0.024515	0.156573
18	15	0.160774	0.2073318	0.051410	0.226738
19	15	0.111695	0.2073318	0.076644	0.276846
20	15	0.345840	0.2073318	0.032925	0.181454
21	15	0.473273	0.2073318	0.436395	0.660602
22	15	0.876912	0.2073318	0.780720	0.883583
23	15	1.117120	0.2073318	1.100305	1.048954
Pooled	378			0.644797	0.802992

L_minus_G by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.328118	0.2449759	1.562331	1.249932
1	16	1.673758	0.2449759	1.866369	1.366151
2	16	1.858792	0.2449759	2.329052	1.526123
3	16	2.109467	0.2449759	2.612145	1.616213
4	16	2.116531	0.2449759	3.452766	1.858162
5	16	2.243444	0.2449759	3.474078	1.863888
6	16	2.040838	0.2449759	3.068466	1.751704
7	16	0.594274	0.2449759	0.301024	0.548656
8	16	0.330818	0.2449759	0.197876	0.444832
9	16	0.174609	0.2449759	0.064674	0.254310
10	16	0.204931	0.2449759	0.061421	0.247832
11	16	0.134976	0.2449759	0.119969	0.346366
12	16	0.111991	0.2449759	0.100100	0.316386
13	16	0.147567	0.2449759	0.148223	0.384997
14	16	0.096972	0.2449759	0.206011	0.453884
15	16	0.116749	0.2449759	0.058894	0.242681
16	16	0.129104	0.2449759	0.058935	0.242766
17	16	0.126829	0.2449759	0.032896	0.181371
18	15	0.214290	0.2530100	0.080784	0.284225
19	15	0.277871	0.2530100	0.044741	0.211521
20	15	0.358763	0.2530100	0.047991	0.219067
21	15	0.463192	0.2530100	0.208207	0.456297
22	15	1.043220	0.2530100	1.331756	1.154017
23	15	1.297293	0.2530100	1.442679	1.201116
Pooled	378			0.960211	0.979904

L_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.11661	0.336751	0.696445	2.454024	3.57791	2.117273
1	0.30841	0.444383	1.064255	2.889738	4.14309	2.445354
2	0.20431	0.477400	1.383650	3.373010	4.44202	2.895610
3	0.18128	0.459068	1.975890	3.622475	4.66079	3.163407
4	-0.50509	0.414058	1.965680	3.810164	5.36920	3.396106
5	-0.14990	0.260704	2.906750	3.949071	4.68219	3.688367
6	-0.12378	0.186670	1.985500	3.774496	4.37192	3.587826
7	-0.11889	0.190741	0.399550	0.943542	1.91330	0.752801
8	-0.35641	0.001463	0.195665	0.603300	1.15610	0.601837
9	-0.44321	0.032212	0.173310	0.340943	0.53140	0.308730
10	-0.12198	0.021078	0.144045	0.341861	0.73068	0.320783
11	-0.27478	-0.043521	0.080000	0.162921	1.23642	0.206442
12	-0.15192	-0.042028	0.043940	0.136975	1.18592	0.179003
13	-0.27917	-0.085868	0.039200	0.234989	1.18091	0.320857
14	-0.44590	-0.198075	0.041460	0.155358	1.14301	0.353433
15	-0.22787	-0.067499	0.085800	0.232883	0.65180	0.300382
16	-0.19150	-0.075630	0.066405	0.348083	0.55011	0.423713
17	-0.18991	-0.013323	0.104205	0.265836	0.43549	0.279159
18	-0.12701	0.054132	0.161190	0.302447	1.08279	0.248315
19	0.01279	0.110288	0.211310	0.460262	0.64822	0.349973
20	-0.01081	0.234622	0.325290	0.515567	0.88369	0.280945
21	-0.04321	0.190570	0.410090	0.616282	1.87421	0.425712
22	0.15338	0.289507	0.404790	1.758892	3.51102	1.469385
23	0.15012	0.312645	0.800780	2.110428	3.67779	1.797783

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K_minus_J by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.827034	0.1877110	0.689653	0.830454
1	16	-0.997353	0.1877110	0.961108	0.980361
2	16	-1.216424	0.1877110	1.422017	1.192484
3	16	-1.358053	0.1877110	1.185901	1.088991
4	16	-1.316015	0.1877110	1.418019	1.190806
5	16	-1.220921	0.1877110	1.473617	1.213926
6	16	-1.145111	0.1877110	2.104045	1.450533
7	16	-0.060559	0.1877110	0.087527	0.295850
8	16	-0.020606	0.1877110	0.014474	0.120308
9	16	0.112476	0.1877110	0.030910	0.175813
10	16	0.015158	0.1877110	0.024497	0.156514
11	16	0.172023	0.1877110	0.273500	0.522972
12	16	0.051054	0.1877110	0.162552	0.403177
13	16	0.080901	0.1877110	0.240953	0.490870
14	16	0.102066	0.1877110	0.116243	0.340944
15	16	-0.071760	0.1877110	0.073903	0.271852
16	16	-0.176324	0.1877110	0.069734	0.264071
17	16	-0.319784	0.1877110	0.143269	0.378509
18	15	-0.270359	0.1938671	0.060395	0.245755
19	15	-0.382339	0.1938671	0.090640	0.301065
20	15	-0.332852	0.1938671	0.041542	0.203818
21	15	-0.390766	0.1938671	0.209372	0.457572
22	15	-0.831720	0.1938671	1.202756	1.096702
23	15	-0.978285	0.1938671	1.409196	1.187095
Pooled	378			0.563767	0.750844

Box plot showing the distribution of $J_{\text{minus_F}}$ for different values of hh (0 to 23). The y-axis represents $J_{\text{minus_F}}$ and ranges from -1 to 5. The x-axis represents hh and ranges from 0 to 23. The plot displays the median, quartiles, and range (whiskers) for each hh value. Outliers are marked with '+' for near outliers and 'x' for far outliers.

hh	Median	Q1	Q3	Lower Whisker	Upper Whisker	Near Outliers	Far Outliers
0	0.6	0.2	2.1	0.1	3.6		
1	0.8	0.2	2.7	-0.3	3.5		
2	2.0	0.3	3.1	-0.3	4.1		
3	2.2	0.1	3.3	-0.2	4.1		
4	2.2	0.1	3.3	-0.4	4.4		
5	2.1	0.0	3.2	-0.4	4.8		
6	1.9	-0.1	3.2	-0.4	4.5		
7	0.1	-0.1	0.3	-0.3	0.7		1.466980
8	-0.1	-0.2	-0.1	-0.3	0.1		
9	-0.1	-0.2	-0.1	-0.3	0.1	0.197600	-0.361000
10	-0.1	-0.2	-0.1	-0.3	0.1	-0.658600	-0.897310
11	0.0	-0.1	0.1	-0.3	0.3	-0.4020	
12	0.0	-0.1	0.1	-0.3	0.3		
13	0.0	-0.1	0.1	-0.3	0.3		
14	0.0	-0.1	0.1	-0.3	0.3	0.596990	0.419220
15	0.0	-0.1	0.1	-0.3	0.3	-0.209780	
16	0.1	0.0	0.2	-0.2	0.4	0.174530	
17	0.1	0.0	0.2	-0.2	0.4	0.118410	
18	0.2	0.1	0.3	-0.1	0.5		
19	0.2	0.1	0.3	-0.1	0.5		
20	0.3	0.2	0.4	0.0	0.6		
21	0.3	0.2	0.4	0.0	0.6	0.122880	-0.175510
22	0.4	0.3	0.5	0.1	0.8	0.875520	1.890810
23	0.4	0.3	0.5	0.1	0.8	3.830990	

J_minus_F by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.1774706	0.23120114	1.4286283	1.1952524
1	16	1.3850150	0.23120114	1.9034499	1.3796557
2	16	1.7575550	0.23120114	2.2573775	1.5024572
3	16	1.8535556	0.23120114	2.5726353	1.6039437
4	16	1.8812506	0.23120114	2.7450290	1.6568129
5	16	1.8408117	0.23120114	2.9410552	1.7149505
6	16	1.7459944	0.23120114	3.1234213	1.7673204
7	16	0.1757819	0.23120114	0.1826023	0.4273198
8	16	-0.0963150	0.23120114	0.0139795	0.1182349
9	16	-0.0976225	0.23120114	0.0356361	0.1887753
10	16	-0.1166138	0.23120114	0.0370720	0.1925409
11	16	-0.1225338	0.23120114	0.0551770	0.2348978
12	16	0.0549594	0.23120114	0.0198903	0.1410330
13	16	0.0011938	0.23120114	0.0287835	0.1696571
14	16	0.0996481	0.23120114	0.0336642	0.1834780
15	16	0.0980769	0.23120114	0.0151973	0.1232774
16	16	0.1418044	0.23120114	0.0077015	0.0877583
17	16	0.1484950	0.23120114	0.0166492	0.1290318
18	15	0.1824787	0.23878351	0.0117710	0.1084943
19	15	0.2338427	0.23878351	0.0149618	0.1223186
20	15	0.3400333	0.23878351	0.0099792	0.0998959
21	15	0.4231460	0.23878351	0.2094812	0.4576912
22	15	1.0118013	0.23878351	1.2854245	1.1337656
23	15	1.0168720	0.23878351	1.4322410	1.1967627
Pooled	378			0.8552635	0.9248046

J_minus_F by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.057800	0.2655758	0.6099550	2.0575317	3.609800	1.7919558
1	-0.223080	0.2309467	0.7834450	2.7456250	3.540710	2.5146783
2	-0.206300	0.3352850	2.0207350	3.1262783	4.108490	2.7909933
3	-0.094490	0.1744100	2.2367550	3.2972083	4.164000	3.1227983
4	-0.398620	0.1372083	2.1923950	3.2957208	4.362210	3.1585125
5	-0.323610	0.0562783	2.1363035	3.2478058	4.852690	3.1915275
6	-0.282590	0.0219100	1.8569050	3.2623492	4.498200	3.2404392
7	-0.337100	-0.1080100	0.1150500	0.2573400	1.466980	0.3653500
8	-0.275300	-0.1721608	-0.1118650	-0.0166633	0.203490	0.1554975
9	-0.658600	-0.1499217	-0.0463150	-0.0135525	0.197600	0.1363692
10	-0.654020	-0.2187167	-0.0667600	0.0001883	0.187110	0.2189050
11	-0.897310	-0.1627292	-0.0491500	-0.0039417	0.118980	0.1587875
12	-0.154600	-0.0552692	0.0677700	0.1386908	0.375000	0.1939600
13	-0.330990	-0.0979708	0.0062550	0.1134567	0.263970	0.2114275
14	-0.114810	-0.0205117	0.0751500	0.1385558	0.596990	0.1590675
15	-0.209780	0.0272833	0.0909600	0.1550408	0.322600	0.1277575
16	-0.076210	0.0803000	0.1641400	0.2023325	0.283380	0.1220325
17	-0.174380	0.0974317	0.1499300	0.2351642	0.414000	0.1377325
18	-0.031620	0.1052267	0.1618900	0.2487533	0.370690	0.1435267
19	-0.118410	0.1731050	0.2393200	0.3238900	0.368720	0.1507850
20	0.214330	0.2558067	0.3273900	0.3918800	0.572200	0.1360733
21	-0.175510	0.2929333	0.3172000	0.3971200	1.890810	0.1041867
22	0.100400	0.2752583	0.4095800	1.7221533	3.535670	1.4468950
23	0.128110	0.2970833	0.4057000	1.5768033	3.830990	1.2797200

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F_minus_I by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-1.1838956	0.20339489	1.3949010	1.1810593
1	16	-1.3272975	0.20339489	1.7375049	1.3181445
2	16	-1.5669019	0.20339489	1.7063475	1.3062724
3	16	-1.6438819	0.20339489	1.8820399	1.3718746
4	16	-1.6660175	0.20339489	1.6872518	1.2989426
5	16	-1.6054192	0.20339489	1.8188006	1.3486291
6	16	-1.6132381	0.20339489	1.7056363	1.3060001
7	16	-0.1322688	0.20339489	0.0322573	0.1796033
8	16	-0.0670250	0.20339489	0.0710138	0.2664841
9	16	-0.0918731	0.20339489	0.0305319	0.1747337
10	16	-0.1062313	0.20339489	0.0645000	0.2539686
11	16	-0.1521987	0.20339489	0.0557870	0.2361927
12	16	-0.0978650	0.20339489	0.1087976	0.3298447
13	16	-0.0813881	0.20339489	0.0639004	0.2527852
14	16	-0.1587056	0.20339489	0.0595214	0.2439701
15	16	-0.0840362	0.20339489	0.0300952	0.1734797
16	16	-0.1922144	0.20339489	0.0288029	0.1697142
17	16	-0.2158463	0.20339489	0.0247069	0.1571843
18	15	-0.3554580	0.21006534	0.2846868	0.5335605
19	15	-0.3102267	0.21006534	0.0432370	0.2079350
20	15	-0.4532220	0.21006534	0.0767177	0.2769796
21	15	-0.4834373	0.21006534	0.2227299	0.4719427
22	15	-1.0426067	0.21006534	1.3898652	1.1789254
23	15	-1.0674820	0.21006534	1.3242493	1.1507603
Pooled	378			0.6619117	0.8135796

F_minus_I by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-3.274020	-2.2284433	-0.5878450	-0.2427467	0.062930	1.9856967
1	-3.277800	-2.6327183	-0.9653000	-0.1429792	0.123470	2.4897392
2	-3.326690	-2.7361375	-1.8642850	-0.2428733	0.086580	2.4932642
3	-3.462410	-2.7018392	-2.0651550	-0.3784483	0.372930	2.3233908
4	-3.261200	-2.8462533	-2.0027750	-0.2656517	0.554900	2.5806017
5	-3.705290	-2.7072017	-1.8984535	-0.3265533	0.402410	2.3806483
6	-3.752690	-2.7555867	-1.8120100	-0.3136192	-0.088110	2.4419675
7	-0.594880	-0.2194150	-0.1020050	-0.0339808	0.182800	0.1854342
8	-0.802310	-0.2107375	-0.0293400	0.1146533	0.305120	0.3253908
9	-0.474390	-0.1378408	-0.0842450	-0.0190092	0.264090	0.1188317
10	-0.771970	-0.2134092	-0.1040650	0.0201350	0.292510	0.2335442
11	-0.732420	-0.2955500	-0.0851600	-0.0037708	0.139580	0.2917792
12	-1.049290	-0.1447417	-0.0577400	0.0273950	0.522180	0.1721367
13	-0.767030	-0.1494292	-0.0684950	-0.0025008	0.514800	0.1469283
14	-0.670110	-0.3067875	-0.1593950	-0.0509183	0.426600	0.2558692
15	-0.393920	-0.2055050	-0.1387500	0.0973583	0.175780	0.3028633
16	-0.549380	-0.3141367	-0.1873500	-0.0865292	0.115510	0.2276075
17	-0.585730	-0.3087117	-0.1691450	-0.1456342	0.034390	0.1630775
18	-2.146000	-0.3595683	-0.2303200	-0.1387000	0.170780	0.2208683
19	-0.767310	-0.4988100	-0.2209200	-0.1783600	0.065880	0.3204500
20	-1.234980	-0.5396283	-0.3497000	-0.2635083	-0.225670	0.2761200
21	-2.004520	-0.4817167	-0.3444200	-0.2458733	-0.050290	0.2358433
22	-3.488800	-1.6774350	-0.3044100	-0.2174500	-0.141330	1.4599850
23	-3.636780	-1.7020150	-0.4177300	-0.3217500	-0.160610	1.3802650

I_minus_G by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.213295	0.1956338	1.399832	1.183145
1	16	1.389220	0.1956338	1.647290	1.283468
2	16	1.379797	0.1956338	1.748127	1.322167
3	16	1.526893	0.1956338	1.566552	1.251620
4	16	1.368349	0.1956338	1.848538	1.359609
5	16	1.395809	0.1956338	1.634481	1.278468
6	16	1.297214	0.1956338	1.490756	1.220965
7	16	0.077553	0.1956338	0.055471	0.235523
8	16	-0.092701	0.1956338	0.145117	0.380942
9	16	-0.095212	0.1956338	0.015716	0.125365
10	16	0.026514	0.1956338	0.013291	0.115286
11	16	0.101423	0.1956338	0.054559	0.233580
12	16	0.091495	0.1956338	0.011652	0.107946
13	16	0.055593	0.1956338	0.065061	0.255071
14	16	0.047973	0.1956338	0.047416	0.217752
15	16	0.108293	0.1956338	0.010483	0.102385
16	16	0.181102	0.1956338	0.047435	0.217797
17	16	0.159277	0.1956338	0.021483	0.146571
18	15	0.158389	0.2020497	0.013839	0.117639
19	15	0.262656	0.2020497	0.008779	0.093697
20	15	0.281130	0.2020497	0.019200	0.138565
21	15	0.405331	0.2020497	0.189952	0.435835
22	15	0.929627	0.2020497	1.254523	1.120055
23	15	1.255869	0.2020497	1.329923	1.153223
Pooled	378			0.612361	0.782535

I_minus_G by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.05661	0.204516	0.580965	2.257601	3.34961	2.053085
1	-0.09292	0.195498	1.082700	2.538659	3.54379	2.343161
2	-0.20361	0.074873	1.349855	2.788792	3.30829	2.713919
3	-0.04181	0.080370	1.765180	2.583425	3.55600	2.503055
4	-0.45151	0.017670	1.430680	2.532777	3.62583	2.515107
5	-0.19782	-0.090304	1.557910	2.525058	3.10052	2.615362
6	-0.22541	-0.010079	1.622995	2.324386	3.05161	2.334465
7	-0.25562	-0.089294	0.032195	0.198108	0.71680	0.287403
8	-1.46109	-0.106353	-0.021610	0.058134	0.18921	0.164488
9	-0.36740	-0.132557	-0.115605	-0.051151	0.17621	0.081406
10	-0.14288	-0.048810	0.012985	0.074400	0.30691	0.123210
11	-0.40610	0.021702	0.074805	0.113909	0.73831	0.092207
12	-0.15820	0.041326	0.125200	0.156658	0.24680	0.115332
13	-0.67032	0.009276	0.128845	0.168817	0.42862	0.159541
14	-0.65329	-0.015338	0.069045	0.195478	0.27310	0.210816
15	-0.04089	0.034636	0.101565	0.159492	0.31021	0.124856
16	-0.13181	0.065357	0.151900	0.226661	0.85397	0.161304
17	-0.11801	0.066372	0.178010	0.246920	0.49609	0.180548
18	-0.09738	0.088472	0.189610	0.236725	0.34061	0.148253
19	0.13092	0.182962	0.260400	0.322833	0.44831	0.139872
20	-0.06891	0.226967	0.250490	0.390282	0.45950	0.163315
21	0.00900	0.201643	0.304600	0.454897	1.88782	0.253253
22	0.04022	0.212950	0.293880	2.013887	3.21622	1.800937
23	0.14652	0.242368	0.786590	2.191967	3.12249	1.949598

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SFV1_minus_SE_of_SFV1 1 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.0080279	0.18268696	0.2586001	0.5085274
1	16	0.9567462	0.18268696	0.2215009	0.4706388
2	16	1.4650837	0.18268696	1.2271198	1.1077544
3	16	1.4598575	0.18268696	0.9602004	0.9798982
4	16	1.2868081	0.18268696	1.2176728	1.1034821
5	16	1.1521172	0.18268696	1.0938342	1.0458653
6	16	0.9765309	0.18268696	0.3947663	0.6283043
7	16	1.1534076	0.18268696	0.4740502	0.6885131
8	16	1.2338451	0.18268696	1.8273753	1.3518045
9	16	1.2985413	0.18268696	1.2433934	1.1150755
10	16	1.0823709	0.18268696	0.4191089	0.6473862
11	16	1.1714201	0.18268696	0.1768264	0.4205073
12	16	1.1394667	0.18268696	0.1691114	0.4112315
13	16	1.1980807	0.18268696	0.2938792	0.5421062
14	16	1.3917019	0.18268696	0.8338703	0.9131650
15	16	1.3658101	0.18268696	0.3562270	0.5968475
16	16	1.1250848	0.18268696	0.1215221	0.3486002
17	16	1.0061503	0.18268696	0.1342550	0.3664083
18	15	0.9574107	0.18867828	0.1369561	0.3700758
19	15	1.0961901	0.18867828	0.3910985	0.6253787
20	15	1.1247365	0.18867828	0.2035943	0.4512143
21	15	1.0848855	0.18867828	0.1442574	0.3798123
22	15	1.0624365	0.18867828	0.1461243	0.3822621
23	15	0.9938961	0.18867828	0.2410846	0.4910036
Pooled	378			0.5339924	0.7307479

SFV1_minus_SE_of_SFV 1 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.106874	0.6426558	0.9697135	1.4026149	1.819853	0.7599591
1	-0.388761	0.8870639	0.9940715	1.1919344	1.810817	0.3048705
2	0.034218	0.9634942	1.1785990	1.5637479	4.444216	0.6002538
3	0.452685	0.8784725	1.1124495	1.5564771	3.548284	0.6780046
4	0.502061	0.7221069	0.9966735	1.3053856	4.787079	0.5832787
5	0.042122	0.6065678	0.8078210	1.3060948	4.488220	0.6995270
6	-0.726992	0.7319844	0.8928010	1.3531929	2.160919	0.6212085
7	0.422441	0.6895024	0.8831010	1.5069488	3.148911	0.8174464
8	0.202091	0.4058477	0.7287430	1.7409808	5.363606	1.3351332
9	0.351176	0.8210878	0.9153460	1.2573088	5.205772	0.4362209
10	0.253367	0.8098131	1.0004245	1.2229725	3.192663	0.4131594
11	0.645466	0.8248814	1.1035175	1.4551225	1.991533	0.6302411
12	0.672901	0.8377607	0.9984925	1.3863673	1.924612	0.5486067
13	0.450525	0.8229274	1.0388665	1.6902131	2.145870	0.8672857
14	0.499775	0.9548159	1.1369030	1.5318461	4.439488	0.5770302
15	0.576393	0.9483312	1.1979985	1.7235116	3.008591	0.7751804
16	0.690735	0.8587698	0.9973390	1.3734991	1.831665	0.5147293
17	0.614323	0.6800292	0.9419725	1.2637372	1.776663	0.5837080
18	0.290791	0.7215827	0.8012750	1.2801140	1.567465	0.5585313
19	-0.188249	0.7216137	1.1487960	1.3506168	2.484795	0.6290032
20	0.289414	0.8698067	1.1572130	1.4805665	1.778423	0.6107598
21	0.425308	0.7941432	1.0604190	1.3279560	1.809391	0.5338128
22	0.433166	0.7723212	1.0008980	1.3442803	1.768202	0.5719592
23	0.356533	0.5329805	0.9089470	1.5101047	1.675386	0.9771242

SFV2_minus_SE_of_SFV 2 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.1823404	0.17511338	0.3671731	0.6059481
1	16	1.3254027	0.17511338	0.6650995	0.8155363
2	16	1.2727320	0.17511338	1.3565629	1.1647158
3	16	1.3765841	0.17511338	1.0038854	1.0019408
4	16	1.3566840	0.17511338	0.3488185	0.5906086
5	16	1.2820929	0.17511338	0.3113474	0.5579851
6	16	1.1921044	0.17511338	0.4421010	0.6649068
7	16	1.2521893	0.17511338	0.2778866	0.5271495
8	16	1.3017799	0.17511338	0.5299693	0.7279899
9	16	1.6668087	0.17511338	2.7020908	1.6438038
10	16	1.4139404	0.17511338	0.8694051	0.9324190
11	16	1.1775583	0.17511338	0.2870106	0.5357337
12	16	1.0157794	0.17511338	0.1263263	0.3554242
13	16	1.1846564	0.17511338	0.1848625	0.4299564
14	16	1.1768695	0.17511338	0.2761544	0.5255040
15	16	1.0394670	0.17511338	0.1428021	0.3778917
16	16	1.0331447	0.17511338	0.1856869	0.4309140
17	16	0.9336844	0.17511338	0.1431467	0.3783473
18	15	0.6544749	0.18085632	0.3395317	0.5826935
19	15	0.7535553	0.18085632	0.4630315	0.6804642
20	15	1.0678917	0.18085632	0.2139175	0.4625122
21	15	1.0215215	0.18085632	0.1221655	0.3495219
22	15	1.0880764	0.18085632	0.1487194	0.3856415
23	15	1.1214723	0.18085632	0.1683409	0.4102936
Pooled	378			0.4906351	0.7004535

SFV2_minus_SE_of_SFV 2 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.124039	0.6475270	1.3275920	1.5745618	2.183937	0.9270348
1	0.276262	0.8192579	1.2881590	1.5997762	3.900879	0.7805182
2	-1.542040	1.0077226	1.1589520	1.5395365	4.605043	0.5318139
3	-1.274830	0.9994995	1.3854315	1.6620941	3.691224	0.6625946
4	-0.107176	1.0215793	1.3725965	1.7313812	2.524912	0.7098019
5	0.142391	0.8323450	1.3903370	1.7284810	2.296044	0.8961360
6	0.361017	0.7059097	1.0856200	1.5631498	2.856458	0.8572400
7	0.725450	0.8612942	1.1427990	1.4690338	2.791649	0.6077396
8	0.082956	0.7000247	1.2207930	1.9087113	2.771599	1.2086866
9	0.505818	0.8015248	1.2889890	1.8269606	7.554220	1.0254358
10	0.704045	0.8446193	1.2503240	1.5184767	4.630848	0.6738574
11	0.285559	0.8809318	1.0955920	1.4772532	2.354183	0.5963213
12	0.477373	0.7811452	0.9396595	1.1895853	1.903798	0.4084402
13	0.492945	0.8206609	1.2048145	1.5421029	2.111677	0.7214420
14	0.088715	0.9058976	1.1827840	1.3685979	2.572766	0.4627003
15	0.351341	0.8025355	0.9792975	1.3491063	1.647520	0.5465708
16	0.288342	0.7663524	1.0719650	1.4257258	1.742592	0.6593733
17	0.317421	0.6480997	0.8699605	1.2950097	1.515012	0.6469100
18	-0.532240	0.1750872	0.7113570	1.0695047	1.474564	0.8944175
19	-0.452482	0.1548363	0.8073140	1.3813138	1.579891	1.2264775
20	0.099367	0.8920370	1.1913190	1.3803958	1.738539	0.4883588
21	0.073752	0.8377678	1.0499620	1.2096975	1.487668	0.3719297
22	0.176441	0.9560893	1.0823190	1.3822860	1.597716	0.4261967
23	0.155603	0.9801522	1.2357160	1.4454630	1.490400	0.4653108

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SFV4_minus_W_of_SFV4 4 by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	-1.5740641	0.12006057	0.1054915	0.3247945
1	16	16	-1.5188160	0.12006057	0.2024581	0.4499534
2	16	16	-1.5761706	0.12006057	0.1696060	0.4118325
3	16	16	-1.5950637	0.12006057	0.1985831	0.4456267
4	16	16	-1.4002202	0.12006057	0.2271566	0.4766095
5	16	16	-1.3646713	0.12006057	0.5392926	0.7343654
6	16	16	-1.6591472	0.12006057	0.9085498	0.9531788
7	16	16	-0.9530398	0.12006057	0.0956800	0.3093218
8	16	16	-1.1039293	0.12006057	0.2718954	0.5214359
9	16	16	-1.2494278	0.12006057	0.3204037	0.5660421
10	16	16	-1.1197237	0.12006057	0.1200714	0.3465132
11	16	16	-1.1908461	0.12006057	0.2902147	0.5387158
12	16	16	-1.5986319	0.12006057	0.1115721	0.3340240
13	16	16	-1.6652870	0.12006057	0.3320739	0.5762585
14	16	16	-1.6150706	0.12006057	0.2031489	0.4507205
15	16	16	-1.5520171	0.12006057	0.1516831	0.3894652
16	16	16	-1.7107197	0.12006057	0.1901581	0.4360712
17	16	16	-1.6778253	0.12006057	0.1018953	0.3192104
18	15	15	-1.7574563	0.12399802	0.1182218	0.3438340
19	15	15	-1.7328953	0.12399802	0.1455056	0.3814519
20	15	15	-1.5305307	0.12399802	0.1219420	0.3492020
21	15	15	-1.4903999	0.12399802	0.4023351	0.6342989
22	15	15	-1.4769053	0.12399802	0.0632760	0.2515471
23	15	15	-1.5490681	0.12399802	0.1162155	0.3409039
Pooled	378	378			0.2306326	0.4802423

SFV4_minus_W_of_SFV 4 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-2.148401	-1.8348428	-1.6065980	-1.3188443	-0.980328	0.5159986
1	-2.128403	-1.8646589	-1.5828180	-1.1113454	-0.679960	0.7533135
2	-2.271851	-1.8992294	-1.5247040	-1.2463953	-0.886135	0.6528341
3	-2.412474	-1.9826554	-1.5901030	-1.2501415	-0.889641	0.7325139
4	-2.339453	-1.7423167	-1.2383420	-1.0143565	-0.824556	0.7279602
5	-3.048488	-1.6839567	-1.2652120	-1.1297493	0.343057	0.5542074
6	-3.976091	-1.9086976	-1.4036675	-1.1575779	-0.124010	0.7511197
7	-1.573955	-1.1510621	-0.9630545	-0.7728173	-0.197014	0.3782448
8	-2.381365	-1.2346176	-1.1097115	-0.8255530	-0.218649	0.4090646
9	-3.110823	-1.3907476	-1.0891970	-0.9624190	-0.662450	0.4283286
10	-1.830215	-1.3848893	-1.0691625	-0.8500417	-0.631222	0.5348476
11	-1.892823	-1.5590172	-1.3748550	-0.9090143	0.218838	0.6500028
12	-2.194825	-1.7565401	-1.6176035	-1.3955282	-0.782227	0.3610119
13	-2.949667	-2.0772324	-1.6448735	-1.2550756	-0.514736	0.8221568
14	-2.399426	-1.9051460	-1.7487830	-1.3356251	-0.546211	0.5695209
15	-2.129551	-1.8526300	-1.5868550	-1.3402142	-0.697751	0.5124158
16	-2.248680	-2.1251042	-1.7445565	-1.3532665	-0.789604	0.7718377
17	-2.200259	-1.8929629	-1.7289135	-1.4767949	-0.930709	0.4161680
18	-2.588696	-1.8704872	-1.7616270	-1.5689893	-1.008370	0.3014978
19	-2.433372	-1.9719603	-1.7617110	-1.4318500	-1.179079	0.5401103
20	-2.400793	-1.5727790	-1.4471040	-1.4214410	-0.941227	0.1513380
21	-2.305100	-1.7673913	-1.6369780	-1.4173100	0.578075	0.3500813
22	-1.854466	-1.5923087	-1.4716840	-1.4161508	-0.759862	0.1761578
23	-2.472346	-1.6463575	-1.4944090	-1.3469000	-1.141912	0.2994575

SFV5_minus_SE_of_SFV 5 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.2457879	0.15739598	0.2781487	0.5273981
1	16	1.4640424	0.15739598	0.2946044	0.5427747
2	16	1.6402418	0.15739598	1.0053525	1.0026727
3	16	1.3438949	0.15739598	0.3878169	0.6227494
4	16	1.4652770	0.15739598	0.4903731	0.7002665
5	16	1.3119369	0.15739598	0.2411632	0.4910837
6	16	1.2264182	0.15739598	0.4059195	0.6371181
7	16	1.5496701	0.15739598	0.6365310	0.7978289
8	16	1.5273724	0.15739598	0.7268445	0.8525518
9	16	1.6384471	0.15739598	0.5760588	0.7589854
10	16	1.5307348	0.15739598	0.6649338	0.8154348
11	16	1.3251422	0.15739598	0.1199262	0.3463036
12	16	1.1472907	0.15739598	0.1909104	0.4369330
13	16	1.0768165	0.15739598	0.3692387	0.6076501
14	16	1.0321871	0.15739598	0.0998770	0.3160332
15	16	0.8009938	0.15739598	0.0904579	0.3007621
16	16	0.8301533	0.15739598	0.2109943	0.4593412
17	16	0.7259054	0.15739598	0.2358331	0.4856265
18	15	0.6727472	0.16255787	0.2410339	0.4909521
19	15	0.5887174	0.16255787	0.2440695	0.4940339
20	15	0.4096983	0.16255787	0.3635940	0.6029876
21	15	0.4275070	0.16255787	0.8078627	0.8988118
22	15	0.7512723	0.16255787	0.5605986	0.7487313
23	15	0.9410687	0.16255787	0.2787214	0.5279407
Pooled	378			0.3963759	0.6295839

SFV5_minus_SE_of_SFV 5 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.015454	0.9779223	1.3042040	1.5118124	2.294674	0.5338901
1	0.965180	1.0383868	1.3136510	1.6474740	3.042259	0.6090872
2	0.890743	1.1009908	1.3219860	1.5861627	4.315279	0.4851718
3	-0.103989	1.0728339	1.2488520	1.5519273	2.836293	0.4790934
4	0.151232	1.0605902	1.3898010	1.6190778	3.320112	0.5584876
5	-0.008255	1.0163742	1.4118085	1.5592360	2.267613	0.5428618
6	-0.092868	0.8351883	1.3085400	1.4965721	2.383408	0.6613837
7	0.582736	0.9640036	1.2261570	1.9776775	3.509468	1.0136739
8	0.359276	0.7854997	1.2994570	2.3152444	2.925418	1.5297448
9	0.634526	1.0296683	1.4554025	2.1440472	3.089651	1.1143788
10	0.402394	1.0709532	1.3971200	1.9007431	3.962587	0.8297899
11	0.920872	1.0587579	1.2830445	1.4377448	2.184135	0.3789869
12	0.611314	0.7408305	1.0096890	1.4976485	1.939358	0.7568180
13	0.523754	0.7381787	0.8941805	1.2066098	3.006935	0.4684311
14	0.613728	0.7702290	1.0358990	1.1963111	1.762175	0.4260821
15	0.411385	0.5483203	0.7957695	1.0133841	1.475947	0.4650638
16	-0.210083	0.5156847	0.8403775	1.2308001	1.477744	0.7151154
17	-0.077020	0.4356421	0.7011890	0.9549714	1.697485	0.5193293
18	-0.016174	0.3542095	0.5736710	0.9170203	1.661844	0.5628108
19	-0.280672	0.2839373	0.6475920	1.0265282	1.265310	0.7425908
20	-0.549684	-0.1571873	0.4355770	0.7835648	1.361608	0.9407522
21	-1.532621	0.0996987	0.5325380	1.1529023	1.695780	1.0532037
22	-0.685404	0.0409293	1.0672590	1.2702258	1.567019	1.2292965
23	-0.210211	0.4823730	1.1316690	1.3644660	1.493516	0.8820930

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SFV6_minus_W_of_SFV6 6 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.9441247	0.17091211	0.1649533	0.4061444
1	16	-0.8019927	0.17091211	0.1698458	0.4121236
2	16	-0.7527564	0.17091211	1.5328344	1.2380769
3	16	-0.8187228	0.17091211	0.1026795	0.3204365
4	16	-1.1960933	0.17091211	1.2190184	1.1040917
5	16	-1.3202301	0.17091211	2.2676974	1.5058876
6	16	-1.0950049	0.17091211	1.3005263	1.1404062
7	16	-1.2007253	0.17091211	1.7935519	1.3392356
8	16	-0.9327995	0.17091211	0.5689387	0.7542803
9	16	-0.8243418	0.17091211	0.2247172	0.4740435
10	16	-0.6725826	0.17091211	0.2724563	0.5219734
11	16	-0.6724521	0.17091211	0.0794059	0.2817905
12	16	-0.7205300	0.17091211	0.0874018	0.2956379
13	16	-0.6912654	0.17091211	0.1521404	0.3900518
14	16	-0.6337188	0.17091211	0.1308633	0.3617503
15	16	-0.7563047	0.17091211	0.1129147	0.3360279
16	16	-0.6650311	0.17091211	0.0391556	0.1978776
17	16	-0.6122442	0.17091211	0.0588203	0.2425290
18	15	-0.4462863	0.17651727	0.1023988	0.3199981
19	15	-0.4989415	0.17651727	0.0651740	0.2552921
20	15	-0.5887347	0.17651727	0.1676853	0.4094939
21	15	-0.7389376	0.17651727	0.2187957	0.4677560
22	15	-0.8065211	0.17651727	0.0973213	0.3119636
23	15	-0.8247721	0.17651727	0.1544818	0.3930417
Pooled	378			0.4673752	0.6836484

SFV6_minus_W_of_SFV 6 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-1.793375	-1.2600451	-0.9382755	-0.5818489	-0.361072	0.6781962
1	-1.691077	-1.0348848	-0.7720030	-0.4912159	-0.019558	0.5436688
2	-4.389780	-0.9783672	-0.7030505	-0.4469802	2.183767	0.5313870
3	-1.492468	-1.0136261	-0.8006550	-0.5701617	-0.348554	0.4434644
4	-4.732943	-1.1652235	-0.8674915	-0.7400249	-0.273978	0.4251986
5	-5.886631	-1.1774738	-0.7954220	-0.6033040	-0.319389	0.5741698
6	-5.102638	-1.1645767	-0.8121875	-0.5292507	-0.072115	0.6353260
7	-5.952486	-1.2540845	-1.0021340	-0.6104478	0.181175	0.6436368
8	-2.012638	-1.7011181	-0.8060385	-0.3156792	0.306626	1.3854388
9	-1.639591	-1.2688091	-0.7132995	-0.5037302	0.081955	0.7650789
10	-2.374424	-0.7780590	-0.5962095	-0.3722121	-0.029890	0.4058469
11	-1.562908	-0.7248512	-0.6099390	-0.4894932	-0.385692	0.2353580
12	-1.200438	-0.9916267	-0.7004325	-0.5068212	-0.232607	0.4848056
13	-1.157124	-1.0197459	-0.6890900	-0.4001240	0.181439	0.6196219
14	-1.167546	-0.8796217	-0.6949275	-0.4594722	0.381101	0.4201494
15	-1.569367	-0.8909428	-0.6933845	-0.5069155	-0.362110	0.3840273
16	-0.984779	-0.8522333	-0.6026930	-0.5243441	-0.333683	0.3278892
17	-1.026959	-0.8140593	-0.6375230	-0.4707807	-0.170173	0.3432786
18	-0.863146	-0.6825843	-0.5139900	-0.3325813	0.229629	0.3500030
19	-0.886990	-0.6455538	-0.5738010	-0.3196408	0.006428	0.3259130
20	-1.243986	-0.9311490	-0.6207140	-0.3193823	0.283955	0.6117667
21	-1.911249	-1.0118780	-0.5718830	-0.4879712	0.021980	0.5239068
22	-1.511847	-0.9460222	-0.8229780	-0.6010858	-0.212808	0.3449363
23	-1.385706	-1.1633815	-0.7789140	-0.4782848	-0.041467	0.6850967

SFV7_minus_SE_of_SFV 7 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.2081263	0.16101375	0.1733438	0.4163457
1	16	1.5233084	0.16101375	1.0062743	1.0031322
2	16	1.4694863	0.16101375	0.6887298	0.8298975
3	16	1.3926260	0.16101375	0.4706430	0.6860342
4	16	1.3571067	0.16101375	0.2795487	0.5287236
5	16	1.3334678	0.16101375	0.4873824	0.6981278
6	16	1.3059926	0.16101375	0.5459745	0.7389009
7	16	1.1902597	0.16101375	0.3638676	0.6032144
8	16	1.1621369	0.16101375	0.5936658	0.7704971
9	16	1.3213694	0.16101375	0.2285750	0.4780951
10	16	1.2124249	0.16101375	0.4777099	0.6911656
11	16	1.2336243	0.16101375	0.1542284	0.3927192
12	16	1.1301511	0.16101375	0.0650762	0.2551003
13	16	1.2440366	0.16101375	0.1402508	0.3745007
14	16	1.0777548	0.16101375	0.0837697	0.2894299
15	16	1.2497489	0.16101375	0.1275160	0.3570939
16	16	1.3340808	0.16101375	0.3585639	0.5988021
17	16	1.1305018	0.16101375	0.1370824	0.3702464
18	15	1.0940105	0.16629428	0.1540930	0.3925468
19	15	1.4421662	0.16629428	0.4150921	0.6442765
20	15	1.4503281	0.16629428	0.7637353	0.8739195
21	15	1.4070665	0.16629428	0.8702799	0.9328880
22	15	1.4121075	0.16629428	0.7226078	0.8500634
23	15	1.3723695	0.16629428	0.7248052	0.8513549
Pooled	378			0.4148068	0.6440550

SFV7_minus_SE_of_SFV 7 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.415777	0.9508897	1.2029535	1.6297628	1.714262	0.6788731
1	0.834940	1.0385844	1.2290920	1.6482185	5.073784	0.6096341
2	0.596613	0.9966104	1.3114540	1.6978689	4.045622	0.7012585
3	0.485846	0.9613805	1.2526565	1.5938944	3.176845	0.6325139
4	0.712885	0.8678185	1.2892605	1.6468742	2.754177	0.7790557
5	0.252588	0.9684545	1.2229310	1.5670978	3.385608	0.5986433
6	0.477914	0.9487771	1.1274000	1.5181084	3.729769	0.5693313
7	0.006869	0.7809341	1.2090985	1.6657923	2.261107	0.8848582
8	0.120202	0.5471908	1.0623475	1.8506385	2.487095	1.3034478
9	0.472961	0.9371513	1.3997930	1.6620676	2.192091	0.7249162
10	-0.276976	0.9961033	1.1321475	1.3604490	3.335104	0.3643457
11	0.488005	1.0615105	1.2333225	1.4325063	2.078693	0.3709958
12	0.501606	0.9866788	1.1373065	1.3275368	1.556248	0.3408580
13	0.507766	0.9631837	1.2908525	1.4126202	2.029449	0.4494365
14	0.577764	0.8031036	1.1413575	1.2742313	1.545441	0.4711277
15	0.481245	1.1107359	1.2395780	1.5222683	1.812921	0.4115323
16	0.679503	0.9104010	1.2937965	1.5212480	3.205845	0.6108470
17	0.488420	0.8555883	1.1764680	1.3796807	1.844978	0.5240923
18	0.383659	0.7821967	0.9966020	1.5126337	1.624745	0.7304370
19	0.652799	1.0953303	1.2447740	1.5358520	3.129708	0.4405217
20	0.145540	0.9811508	1.2643450	1.8283807	3.725922	0.8472298
21	-0.015768	0.9087140	1.3940360	1.6935072	4.161045	0.7847932
22	0.629369	0.8777958	1.3751640	1.5383395	4.210878	0.6605437
23	0.337146	0.8315170	1.1923030	1.6634325	4.034530	0.8319155

FOLLOWING: San Fernando Valley, mod-UCM, Tair

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SFV1_minus_SE_of_SFV1 1 by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	0.7597256	0.25028681	0.5747592	0.7581287
1	16	16	1.0671905	0.25028681	3.7653143	1.9404418
2	16	16	1.1332834	0.25028681	3.5209243	1.8764126
3	16	16	1.4144564	0.25028681	4.3005546	2.0737779
4	16	16	0.9190929	0.25028681	2.5398507	1.5936909
5	16	16	0.8386099	0.25028681	2.8313159	1.6826514
6	16	16	0.7818769	0.25028681	0.4825380	0.6946496
7	16	16	0.4821230	0.25028681	0.3939663	0.6276673
8	16	16	0.9300952	0.25028681	1.5256287	1.2351634
9	16	16	0.7115678	0.25028681	1.1594870	1.0767948
10	16	16	0.4132681	0.25028681	0.2230367	0.4722676
11	16	16	0.3915550	0.25028681	0.1318870	0.3631625
12	16	16	0.6062733	0.25028681	0.0700505	0.2646706
13	16	16	0.7831536	0.25028681	0.4313554	0.6567765
14	16	16	0.7176383	0.25028681	0.0700735	0.2647139
15	16	16	0.5885293	0.25028681	0.1258770	0.3547915
16	16	16	0.5599178	0.25028681	0.1040819	0.3226172
17	16	16	0.5502460	0.25028681	0.1008625	0.3175885
18	15	15	0.3868955	0.25849510	0.2099852	0.4582414
19	15	15	0.7973450	0.25849510	0.4664319	0.6829582
20	15	15	0.5927361	0.25849510	0.1917128	0.4378502
21	15	15	0.5698359	0.25849510	0.0973782	0.3120547
22	15	15	0.5611313	0.25849510	0.2420494	0.4919852
23	15	15	0.5513521	0.25849510	0.1881038	0.4337094
Pooled	378	378			1.0022958	1.0011472

SFV1_minus_SE_of_SFV 1 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.122822	0.2876953	0.5728900	0.8870388	3.293396	0.5993435
1	-0.507814	0.4066829	0.5716315	0.8881333	8.060900	0.4814503
2	-0.729582	0.3429593	0.6152015	0.9859197	7.409460	0.6429603
3	-0.813964	0.2478485	0.6768955	1.6546813	6.425798	1.4068328
4	-1.073157	0.1924917	0.7826575	1.2211180	6.279993	1.0286263
5	-1.109232	0.1944519	0.5779480	1.0096235	6.497444	0.8151716
6	-0.839838	0.4605016	0.7742410	1.3663070	1.881169	0.9058054
7	-0.710938	0.0761920	0.4442275	1.1017926	1.494112	1.0256006
8	-0.564178	0.2512235	0.4994770	1.1737309	3.932553	0.9225074
9	-0.452692	-0.0396592	0.3497830	1.5685460	3.310911	1.6082052
10	-0.972515	0.3262211	0.4238460	0.6928343	1.027232	0.3666133
11	-0.680123	0.2757725	0.4520875	0.5684984	0.999253	0.2927259
12	0.186766	0.4274921	0.5368335	0.7880973	1.115970	0.3606052
13	0.369336	0.4206841	0.5326015	0.9981117	3.010830	0.5774276
14	0.327149	0.4919389	0.6939490	0.8461515	1.209992	0.3542126
15	-0.058903	0.2935684	0.6087540	0.8378823	1.154329	0.5443138
16	0.066730	0.2957594	0.5421755	0.8148103	1.053267	0.5190508
17	-0.055080	0.3288093	0.5483875	0.8320597	1.024395	0.5032504
18	-0.426046	-0.0198388	0.5596330	0.7259325	1.097927	0.7457713
19	-0.259108	0.4520713	0.7583270	0.9305107	2.699383	0.4784393
20	-0.394420	0.4504353	0.6995710	0.8299330	1.332400	0.3794977
21	-0.228403	0.3459232	0.6293060	0.8055268	0.994827	0.4596037
22	-0.369125	0.3117258	0.5368390	0.9785920	1.339119	0.6668662
23	-0.194847	0.2913605	0.4188690	0.7656513	1.386095	0.4742908

SFV2_minus_SE_of_SFV 2 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.0951379	0.17889770	2.5227292	1.5883102
1	16	1.2153326	0.17889770	2.2831227	1.5110005
2	16	0.9825366	0.17889770	0.7490431	0.8654728
3	16	0.9935846	0.17889770	1.1412605	1.0682979
4	16	1.1598929	0.17889770	1.2385866	1.1129180
5	16	1.1710376	0.17889770	0.9205964	0.9594771
6	16	0.8521595	0.17889770	0.6733653	0.8205884
7	16	0.7607682	0.17889770	0.1017038	0.3189104
8	16	0.3409981	0.17889770	0.1237686	0.3518077
9	16	0.3960843	0.17889770	0.2141777	0.4627934
10	16	0.2907425	0.17889770	0.1332151	0.3649864
11	16	0.4913390	0.17889770	0.2968571	0.5448459
12	16	0.4603846	0.17889770	0.1303707	0.3610688
13	16	0.5157753	0.17889770	0.0758853	0.2754729
14	16	0.4537780	0.17889770	0.1320480	0.3633841
15	16	0.4088208	0.17889770	0.1256760	0.3545081
16	16	0.4199479	0.17889770	0.0889179	0.2981910
17	16	0.3752320	0.17889770	0.0561094	0.2368742
18	15	0.1890161	0.18476475	0.1400911	0.3742874
19	15	0.1970599	0.18476475	0.2243627	0.4736694
20	15	0.4500854	0.18476475	0.1864242	0.4317687
21	15	0.6202100	0.18476475	0.2157503	0.4644892
22	15	0.7684589	0.18476475	0.1920487	0.4382336
23	15	0.9340208	0.18476475	0.1957050	0.4423855
Pooled	378			0.5120702	0.7155908

SFV2_minus_SE_of_SFV 2 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.115619	0.3669399	0.7943255	1.1762355	6.729363	0.8092956
1	-0.475286	0.5221087	1.1000730	1.3662933	6.419260	0.8441846
2	-0.899378	0.4434300	1.1767810	1.5123608	2.654606	1.0689308
3	-0.903404	0.4169077	0.9327640	1.5363938	3.878471	1.1194861
4	-1.080204	0.6270931	1.0466620	1.6027495	4.236870	0.9756564
5	-0.816589	0.7289403	1.1336000	1.6432434	3.126646	0.9143032
6	-1.647539	0.5423678	0.8822665	1.4399747	1.715277	0.8976068
7	0.056667	0.5906486	0.7395955	1.0088138	1.285619	0.4181653
8	-0.044797	0.0556935	0.1865700	0.6756937	1.131163	0.6200002
9	-0.324948	0.0688699	0.3429145	0.6494923	1.436051	0.5806224
10	-0.282942	0.0041053	0.2697760	0.5667232	0.912025	0.5626179
11	0.063961	0.2158504	0.2964630	0.5610823	2.247717	0.3452318
12	-0.122602	0.3070892	0.4315450	0.4825561	1.571611	0.1754669
13	-0.225405	0.4113408	0.4589480	0.6582655	0.948467	0.2469248
14	-0.663402	0.3281821	0.4604940	0.6769567	0.926639	0.3487746
15	-0.532318	0.2096815	0.4799430	0.5897720	0.927517	0.3800905
16	-0.026237	0.1954579	0.3863335	0.6655031	0.955433	0.4700452
17	0.047684	0.1725456	0.3608065	0.5156066	0.877918	0.3430610
18	-0.377689	-0.0953352	0.1722900	0.4282302	0.789854	0.5235653
19	-0.588009	-0.2263368	0.2875980	0.5224683	0.863594	0.7488052
20	-0.300798	0.2280395	0.4498730	0.6792505	1.154731	0.4512110
21	-0.317665	0.4338397	0.6135200	0.8132255	1.681379	0.3793858
22	0.046427	0.5982978	0.7206910	0.9322903	1.913594	0.3339925
23	0.139154	0.6052542	0.8967570	1.2931267	1.678808	0.6878725

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SFV4_minus_W_of_SFV4 4 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-0.2091109	0.10887655	0.1196839	0.3459536
1	16	-0.1978769	0.10887655	0.1360562	0.3688580
2	16	-0.2700711	0.10887655	0.0611759	0.2473377
3	16	-0.2629825	0.10887655	0.1088923	0.3299883
4	16	-0.4413061	0.10887655	0.6376594	0.7985358
5	16	-0.3839085	0.10887655	1.1598727	1.0769739
6	16	-0.3533914	0.10887655	0.6754359	0.8218491
7	16	-0.1138450	0.10887655	0.1219220	0.3491733
8	16	0.0297518	0.10887655	0.1375082	0.3708210
9	16	-0.0835169	0.10887655	0.1147972	0.3388173
10	16	-0.0474847	0.10887655	0.0726313	0.2695019
11	16	-0.0407425	0.10887655	0.0431953	0.2078349
12	16	-0.1419841	0.10887655	0.0512138	0.2263047
13	16	-0.2430346	0.10887655	0.3311295	0.5754385
14	16	-0.2532810	0.10887655	0.0311602	0.1765225
15	16	-0.1931844	0.10887655	0.0393589	0.1983907
16	16	-0.2624169	0.10887655	0.0533090	0.2308873
17	16	-0.2585721	0.10887655	0.0696676	0.2639462
18	15	-0.1564933	0.11244721	0.0773118	0.2780501
19	15	-0.3893854	0.11244721	0.2065446	0.4544718
20	15	-0.2716890	0.11244721	0.0913355	0.3022176
21	15	-0.2879473	0.11244721	0.0153643	0.1239527
22	15	-0.2687593	0.11244721	0.0881930	0.2969731
23	15	-0.4129151	0.11244721	0.0692219	0.2631006
Pooled	378			0.1896656	0.4355062

SFV4_minus_W_of_SFV 4 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.660357	-0.4574951	-0.2170555	-0.0512165	0.497862	0.4062786
1	-0.962282	-0.4283551	-0.1643145	-0.0157507	0.539852	0.4126044
2	-0.901129	-0.3734201	-0.1978195	-0.0915117	0.045547	0.2819083
3	-0.980734	-0.3785391	-0.1717930	-0.1282503	0.250532	0.2502888
4	-3.061764	-0.4320728	-0.2090880	0.0072861	0.207449	0.4393589
5	-4.332863	-0.3205450	-0.1865460	0.0489082	0.348007	0.3694532
6	-3.096464	-0.2849247	-0.1448235	-0.0068124	0.390516	0.2781123
7	-0.707177	-0.2824389	-0.1475275	-0.0096903	0.993649	0.2727487
8	-0.535725	-0.1461235	0.0296610	0.1725878	0.971766	0.3187113
9	-0.981625	-0.1924408	-0.0699425	0.0807632	0.401408	0.2732040
10	-0.860008	-0.0574164	0.0554980	0.0895224	0.239889	0.1469388
11	-0.356373	-0.1716144	-0.0534640	0.0601064	0.527840	0.2317208
12	-0.503025	-0.3172640	-0.1565820	0.0440726	0.206998	0.3613366
13	-2.091587	-0.3553257	-0.2260010	0.0609403	0.585034	0.4162659
14	-0.514925	-0.3842187	-0.2678440	-0.1370587	0.128586	0.2471601
15	-0.494312	-0.3609028	-0.2246385	-0.0684329	0.203167	0.2924698
16	-0.529038	-0.4453943	-0.3055295	-0.1437088	0.216354	0.3016854
17	-0.717971	-0.3598928	-0.3220460	-0.1142109	0.315801	0.2456818
18	-0.486664	-0.3690390	-0.2467020	0.0654170	0.363104	0.4344560
19	-1.656891	-0.4213608	-0.3577470	-0.2442722	0.397622	0.1770887
20	-0.679224	-0.3962720	-0.3344160	-0.2067265	0.532610	0.1895455
21	-0.454722	-0.3925637	-0.2932070	-0.2093943	-0.052155	0.1831693
22	-0.551319	-0.4259162	-0.3584380	-0.1912358	0.692875	0.2346803
23	-0.688908	-0.6220695	-0.4516600	-0.3062035	0.308826	0.3158660

SFV5_minus_SE_of_SFV 5 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.6411464	0.20867754	1.5675620	1.2520231
1	16	1.8983384	0.20867754	1.6271448	1.2755959
2	16	2.2494918	0.20867754	2.2566207	1.5022053
3	16	2.2807568	0.20867754	1.6840100	1.2976941
4	16	2.0225453	0.20867754	1.9012194	1.3788471
5	16	1.9851994	0.20867754	1.1129236	1.0549520
6	16	2.1725520	0.20867754	0.8856699	0.9411004
7	16	1.2355706	0.20867754	1.0151160	1.0075296
8	16	0.4022970	0.20867754	0.1955798	0.4422440
9	16	0.2713953	0.20867754	0.2521591	0.5021545
10	16	0.3467484	0.20867754	0.2742555	0.5236941
11	16	0.1943298	0.20867754	0.1481509	0.3849038
12	16	0.1161008	0.20867754	0.1055042	0.3248141
13	16	0.2330059	0.20867754	0.1058202	0.3253001
14	16	0.2323057	0.20867754	0.1802632	0.4245742
15	16	0.2553683	0.20867754	0.2509029	0.5009021
16	16	0.1030811	0.20867754	0.2865409	0.5352951
17	16	0.1428725	0.20867754	0.1366494	0.3696613
18	15	0.1898491	0.21552124	0.0871306	0.2951789
19	15	0.2856316	0.21552124	0.1239529	0.3520695
20	15	0.3670475	0.21552124	0.1662712	0.4077636
21	15	0.8666395	0.21552124	0.5420551	0.7362439
22	15	1.2316859	0.21552124	0.7994336	0.8941105
23	15	1.3989221	0.21552124	0.9136531	0.9558521
Pooled	378			0.6967411	0.8347102

SFV5_minus_SE_of_SFV 5 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.688162	0.8960596	1.6972165	2.1702814	4.913803	1.2742218
1	0.306183	0.8083816	1.9109220	2.6031588	5.378498	1.7947772
2	0.163853	0.9450937	2.3566595	2.9485756	6.162401	2.0034818
3	0.278856	1.2773176	2.2104755	3.1022470	5.656627	1.8249294
4	0.342035	1.1106951	1.9143425	2.4748636	5.921843	1.3641685
5	-0.054325	1.3413183	2.2722710	2.7800203	3.542172	1.4387020
6	0.512139	1.4359667	2.3127520	2.7221883	3.683696	1.2862216
7	-0.587574	0.4450347	1.0194335	2.2914907	2.749470	1.8464560
8	-0.262190	0.1768491	0.3527830	0.4500394	1.537723	0.2731903
9	-1.105380	0.0053063	0.2408240	0.6804547	1.046201	0.6751483
10	-0.646757	-0.0395166	0.3573260	0.7062592	1.382637	0.7457758
11	-0.697391	0.0027003	0.2511925	0.4581280	0.875449	0.4554277
12	-0.456368	-0.1086539	0.1572165	0.4355114	0.524269	0.5441653
13	-0.336073	0.0531893	0.2344730	0.4631465	0.772215	0.4099572
14	-0.716474	-0.0650288	0.3552320	0.5786322	0.768052	0.6436611
15	-0.854742	-0.0918805	0.4102665	0.6190488	0.811100	0.7109293
16	-0.977457	-0.3424407	0.2142840	0.5442033	0.842718	0.8866439
17	-0.624906	-0.1347988	0.0798005	0.4519274	0.781769	0.5867262
18	-0.268286	-0.0558918	0.1924720	0.3779527	0.827917	0.4338445
19	-0.249098	-0.0034675	0.2775610	0.5436377	0.899401	0.5471052
20	-0.360872	0.1216545	0.3793310	0.6903892	1.049694	0.5687347
21	-0.594347	0.4689375	0.6707960	1.2001507	2.721064	0.7312132
22	0.324526	0.5150727	0.8086510	2.0783653	2.912171	1.5632927
23	0.228415	0.5765377	1.3098600	2.0472320	3.638078	1.4706943

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SFV6_minus_W_of_SFV6 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-1.0008260	0.21037748	0.5297439	0.7278351
1	16	-0.8463939	0.21037748	0.5110591	0.7148840
2	16	-1.3125554	0.21037748	0.6707652	0.8190026
3	16	-1.5642886	0.21037748	1.0602352	1.0296772
4	16	-1.9287433	0.21037748	2.6730879	1.6349581
5	16	-2.1575313	0.21037748	4.9810462	2.2318258
6	16	-1.4679250	0.21037748	1.1705071	1.0818998
7	16	-1.0258558	0.21037748	1.2510720	1.1185133
8	16	-0.5440234	0.21037748	1.1181252	1.0574144
9	16	-0.3790439	0.21037748	0.2406198	0.4905301
10	16	0.0003739	0.21037748	0.3162540	0.5623646
11	16	-0.0521595	0.21037748	0.2683349	0.5180105
12	16	-0.2885213	0.21037748	0.0535400	0.2313872
13	16	-0.3661747	0.21037748	0.1107048	0.3327232
14	16	-0.3777410	0.21037748	0.0734795	0.2710710
15	16	-0.1997076	0.21037748	0.1185987	0.3443816
16	16	-0.2364342	0.21037748	0.1203953	0.3469802
17	16	-0.0981371	0.21037748	0.1506850	0.3881816
18	15	-0.1948670	0.21727693	0.0833960	0.2887836
19	15	-0.1192612	0.21727693	0.1711801	0.4137392
20	15	-0.4078282	0.21727693	0.2546249	0.5046037
21	15	-0.5167185	0.21727693	0.2424809	0.4924235
22	15	-0.5877843	0.21727693	0.1795929	0.4237840
23	15	-0.8841162	0.21727693	0.4549670	0.6745124
Pooled	378			0.7081390	0.8415099

SFV6_minus_W_of_SFV 6 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-2.564992	-1.5844298	-0.8997890	-0.4496365	0.008654	1.1347933
1	-2.208753	-1.5588695	-0.7804200	-0.2455788	0.203087	1.3132907
2	-2.798527	-1.8349952	-1.2779085	-0.9516502	0.118706	0.8833450
3	-3.617662	-1.9368862	-1.5259335	-0.9753513	0.317719	0.9615348
4	-5.766604	-2.4662078	-1.5010575	-0.8513402	0.153011	1.6148677
5	-9.041926	-2.1947670	-1.2876310	-1.0806756	-0.357174	1.1140914
6	-4.495775	-1.6463165	-1.1784025	-0.7636797	-0.490167	0.8826368
7	-4.321522	-1.2396514	-0.9558475	-0.6064223	0.836522	0.6332291
8	-3.355768	-0.9472383	-0.5766970	-0.2460829	1.390623	0.7011554
9	-1.437488	-0.6986568	-0.1237375	-0.0254208	0.077583	0.6732360
10	-0.601832	-0.3948017	-0.0805910	0.0827089	1.440593	0.4775106
11	-0.536673	-0.4063958	-0.0688790	0.0386088	1.699605	0.4450047
12	-0.555832	-0.4833075	-0.3148440	-0.1174560	0.150681	0.3658515
13	-0.808632	-0.5680344	-0.4055500	-0.1215061	0.443426	0.4465283
14	-0.866643	-0.5568487	-0.3863535	-0.1205703	-0.027226	0.4362784
15	-0.883066	-0.4060506	-0.1971785	0.0300575	0.432106	0.4361081
16	-0.670604	-0.4899635	-0.3876670	0.0907294	0.373638	0.5806929
17	-0.833734	-0.3370971	-0.1025325	0.0057070	0.815672	0.3428041
18	-0.555910	-0.3791607	-0.3392350	0.0880887	0.323016	0.4672493
19	-0.875463	-0.5200242	0.0031430	0.2498255	0.531368	0.7698497
20	-1.319617	-0.6705030	-0.3462880	0.0119802	0.466297	0.6824832
21	-1.298705	-0.8157555	-0.3501830	-0.2161250	0.548878	0.5996305
22	-1.262699	-1.0210330	-0.5617030	-0.2029013	0.011743	0.8181317
23	-2.478437	-1.1633197	-0.6258260	-0.3937875	-0.069918	0.7695322

SFV7_minus_SE_of_SFV 7 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.4977478	0.22945268	0.4180123	0.6465387
1	16	1.8549561	0.22945268	1.0611161	1.0301049
2	16	2.0936418	0.22945268	2.7131793	1.6471731
3	16	2.1118300	0.22945268	1.7738331	1.3318533
4	16	2.0804274	0.22945268	1.7360451	1.3175907
5	16	2.1704397	0.22945268	2.1627123	1.4706163
6	16	1.5763767	0.22945268	2.4587737	1.5680477
7	16	1.1254778	0.22945268	1.6970150	1.3026953
8	16	0.5659197	0.22945268	0.6045680	0.7775397
9	16	0.2787922	0.22945268	0.7293334	0.8540102
10	16	-0.1323023	0.22945268	0.7420745	0.8614375
11	16	0.4832533	0.22945268	0.0842051	0.2901811
12	16	0.5444757	0.22945268	0.0795857	0.2821093
13	16	0.6274132	0.22945268	0.0762395	0.2761150
14	16	0.7929148	0.22945268	0.2798002	0.5289614
15	16	0.7216463	0.22945268	0.1904854	0.4364463
16	16	0.6460970	0.22945268	0.1070967	0.3272563
17	16	0.6358599	0.22945268	0.1489732	0.3859704
18	15	0.5981573	0.23697771	0.2133694	0.4619192
19	15	0.8343442	0.23697771	0.7459063	0.8636587
20	15	1.1682279	0.23697771	0.2696357	0.5192646
21	15	1.3788539	0.23697771	0.7038326	0.8389473
22	15	1.5567788	0.23697771	0.7472946	0.8644621
23	15	1.4849771	0.23697771	0.3382158	0.5815632
Pooled	378			0.8423765	0.9178107

SFV7_minus_SE_of_SFV 7 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.360836	1.0151399	1.5766885	1.8619548	2.785872	0.8468148
1	0.324854	1.1620747	1.6637290	2.5726780	4.138563	1.4106033
2	0.370774	1.2684324	1.6387555	2.5417374	7.312094	1.2733050
3	-0.048733	1.2690760	1.7822610	2.9184533	5.660818	1.6493773
4	-0.513953	1.2569518	2.0685045	2.4990796	5.284876	1.2421278
5	-0.573779	1.3410493	2.1102960	2.5786810	5.910916	1.2376318
6	-2.633848	1.0531920	1.4668470	2.3521793	4.657759	1.2989873
7	-2.665674	0.7136446	1.2581760	1.7614187	3.646587	1.0477741
8	-1.591419	0.1483707	0.6641550	1.1933073	1.348796	1.0449366
9	-1.220228	-0.2971688	0.2433860	0.6160582	2.091387	0.9132270
10	-2.814066	-0.3305592	-0.0334720	0.4074330	0.893297	0.7379922
11	-0.338905	0.3270527	0.4749495	0.7004096	0.810716	0.3733569
12	-0.140068	0.3848293	0.6052650	0.7404831	0.932584	0.3556538
13	0.069592	0.4542781	0.6404490	0.8623750	1.003311	0.4080969
14	0.156288	0.4052523	0.8264890	0.9642971	2.398732	0.5590448
15	0.125698	0.4181128	0.6855935	0.9352118	1.967010	0.5170990
16	-0.095307	0.4665391	0.6064255	0.8515388	1.347907	0.3849997
17	-0.153439	0.3930305	0.6672785	0.8707093	1.441378	0.4776788
18	-0.228157	0.2332533	0.5883990	0.9969737	1.264288	0.7637203
19	-0.206260	0.3405592	0.5631770	0.8964255	3.157688	0.5558663
20	0.262485	0.8277087	1.1080420	1.4357493	2.373663	0.6080407
21	0.338375	0.8424300	1.2715380	1.7621753	3.822018	0.9197453
22	0.614284	0.8373042	1.5540220	1.8863518	3.973158	1.0490477
23	0.567936	0.9774025	1.3830280	1.9149915	2.460915	0.9375890

FOLLOWING: San Fernando Valley, AREAMOD, T2

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SFV1_minus_SE_of_SFV1 1 by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	1.304343	0.1850049	0.257887	0.507825
1	16	16	1.258834	0.1850049	0.294045	0.542259
2	16	16	1.722187	0.1850049	0.963835	0.981751
3	16	16	1.714896	0.1850049	0.857373	0.925944
4	16	16	1.600066	0.1850049	1.195745	1.093501
5	16	16	1.453966	0.1850049	1.037832	1.018741
6	16	16	1.241523	0.1850049	0.421791	0.649455
7	16	16	1.347318	0.1850049	0.697231	0.835004
8	16	16	1.441876	0.1850049	1.959150	1.399696
9	16	16	1.552008	0.1850049	1.396604	1.181780
10	16	16	1.361228	0.1850049	0.506241	0.711506
11	16	16	1.340313	0.1850049	0.209526	0.457740
12	16	16	1.217229	0.1850049	0.177700	0.421545
13	16	16	1.221389	0.1850049	0.304077	0.551432
14	16	16	1.400558	0.1850049	0.837629	0.915221
15	16	16	1.402560	0.1850049	0.365807	0.604820
16	16	16	1.221303	0.1850049	0.107828	0.328372
17	16	16	1.154675	0.1850049	0.115113	0.339283
18	15	15	1.138976	0.1910722	0.099344	0.315189
19	15	15	1.257798	0.1910722	0.402435	0.634377
20	15	15	1.337805	0.1910722	0.245478	0.495457
21	15	15	1.326139	0.1910722	0.168729	0.410766
22	15	15	1.279230	0.1910722	0.168822	0.410880
23	15	15	1.244348	0.1910722	0.220870	0.469968
Pooled	378	378			0.547629	0.740020

SFV1_minus_SE_of_SFV 1 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.06109	0.860093	1.459255	1.663483	1.88848	0.803390
1	-0.22568	1.126845	1.340990	1.494568	2.21210	0.367723
2	0.18179	1.225744	1.578355	1.855646	4.28022	0.629902
3	0.59970	1.175164	1.453640	1.897120	3.52903	0.721956
4	0.70151	1.020028	1.261050	1.667909	4.72281	0.647882
5	0.21390	0.917268	1.153155	1.534428	4.52933	0.617160
6	-0.57571	1.034593	1.251595	1.444773	2.55780	0.410181
7	0.52982	0.729542	1.140195	1.652455	3.88651	0.922913
8	0.37609	0.591854	0.801480	1.939783	5.78427	1.347929
9	0.63483	1.032427	1.229950	1.399532	5.71201	0.367105
10	0.56110	1.106630	1.215135	1.467828	3.77808	0.361197
11	0.81808	0.953553	1.229905	1.579693	2.18280	0.626139
12	0.72031	0.889240	1.072420	1.596203	2.02509	0.706963
13	0.45648	0.798264	1.051240	1.773466	2.17581	0.975202
14	0.45361	1.016952	1.193495	1.542452	4.44940	0.525500
15	0.59210	0.954015	1.312910	1.742620	3.09491	0.788605
16	0.74289	0.990993	1.116650	1.503271	1.88079	0.512278
17	0.76278	0.900317	1.053805	1.416479	1.86429	0.516162
18	0.68799	0.866705	1.051030	1.357092	1.66229	0.490387
19	0.11661	0.915875	1.215120	1.441638	2.87057	0.525763
20	0.56460	0.947007	1.351500	1.686803	2.52188	0.739797
21	0.66470	1.068733	1.384400	1.624353	2.15729	0.555620
22	0.63079	0.924430	1.174070	1.667685	1.80890	0.743255
23	0.50229	0.903842	1.186620	1.683043	1.82889	0.779202

SFV2_minus_SE_of_SFV 2 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.407473	0.1792790	0.396660	0.629810
1	16	1.577233	0.1792790	0.636637	0.797895
2	16	1.543284	0.1792790	1.273119	1.128326
3	16	1.679851	0.1792790	0.956108	0.977808
4	16	1.635981	0.1792790	0.429394	0.655281
5	16	1.552455	0.1792790	0.307122	0.554186
6	16	1.479378	0.1792790	0.439801	0.663175
7	16	1.461581	0.1792790	0.416324	0.645232
8	16	1.502099	0.1792790	0.692806	0.832350
9	16	1.893431	0.1792790	2.824643	1.680667
10	16	1.680228	0.1792790	0.926038	0.962309
11	16	1.362071	0.1792790	0.359589	0.599658
12	16	1.125666	0.1792790	0.146480	0.382727
13	16	1.248003	0.1792790	0.191603	0.437725
14	16	1.232174	0.1792790	0.282759	0.531751
15	16	1.122355	0.1792790	0.119749	0.346048
16	16	1.162422	0.1792790	0.146999	0.383404
17	16	1.108358	0.1792790	0.108755	0.329780
18	15	0.856851	0.1851586	0.286719	0.535461
19	15	0.945130	0.1851586	0.423150	0.650500
20	15	1.312966	0.1851586	0.308234	0.555188
21	15	1.268257	0.1851586	0.160878	0.401096
22	15	1.327187	0.1851586	0.173645	0.416707
23	15	1.330119	0.1851586	0.235065	0.484835
Pooled	378			0.514256	0.717116

SFV2_minus_SE_of_SFV 2 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.31417	0.926594	1.539195	1.873768	2.27179	0.947173
1	0.57241	1.034257	1.524045	1.810615	4.01221	0.776358
2	-1.41049	1.297830	1.538435	1.678766	4.63562	0.380936
3	-0.93891	1.348518	1.604945	1.892816	3.69427	0.544298
4	-0.12842	1.417500	1.614150	1.977123	3.03918	0.559623
5	0.30200	1.292612	1.550340	1.813113	2.79291	0.520501
6	0.65641	1.045679	1.365450	1.681759	3.38299	0.636080
7	0.79357	0.975697	1.471540	1.541003	3.36279	0.565306
8	0.23919	0.899232	1.304905	2.010146	3.52789	1.110914
9	0.68741	1.089591	1.478090	1.972674	7.89383	0.883083
10	0.97492	1.055440	1.549555	1.771758	4.99210	0.716318
11	0.42608	1.037003	1.260955	1.680496	2.83002	0.643493
12	0.62881	0.858223	1.008150	1.269752	2.05152	0.411529
13	0.53989	0.863349	1.275540	1.581821	2.23050	0.718472
14	0.12747	1.050713	1.186605	1.403758	2.69070	0.353046
15	0.54022	0.933479	1.035415	1.398719	1.70239	0.465240
16	0.55011	0.859956	1.224245	1.491478	1.81830	0.631522
17	0.63111	0.817788	1.007615	1.417591	1.63770	0.599803
18	-0.26217	0.464133	0.960510	1.274510	1.60950	0.810377
19	-0.20432	0.350968	1.058900	1.554123	1.74591	1.203155
20	0.27240	1.027167	1.282990	1.508830	2.46838	0.481663
21	0.20178	1.051410	1.290500	1.635283	1.77463	0.583873
22	0.27728	1.058977	1.416290	1.657693	1.78720	0.598717
23	0.23719	1.101983	1.417480	1.638670	1.89920	0.536687

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SFV4_minus_W_of_SFV4 4 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD	
0	16	-2.923868	0.1591778	0.466420	0.682949	
1	16	-2.815512	0.1591778	0.328467	0.573121	
2	16	-2.719759	0.1591778	0.274292	0.523729	
3	16	-2.708999	0.1591778	0.385999	0.621288	
4	16	-2.517239	0.1591778	0.256392	0.506352	
5	16	-2.393307	0.1591778	0.602478	0.776195	
6	16	-2.866391	0.1591778	1.072907	1.035812	
7	16	-1.758929	0.1591778	0.232471	0.482152	
8	16	-1.642161	0.1591778	0.288322	0.536956	
9	16	-1.806539	0.1591778	0.535214	0.731583	
10	16	-1.725217	0.1591778	0.202122	0.449579	
11	16	-1.872259	0.1591778	0.376832	0.613867	
12	16	-2.333408	0.1591778	0.176279	0.419856	
13	16	-2.468979	0.1591778	0.467377	0.683649	
14	16	-2.552222	0.1591778	0.222965	0.472192	
15	16	-2.601476	0.1591778	0.258373	0.508304	
16	16	-2.886093	0.1591778	0.342190	0.584970	
17	16	-3.050826	0.1591778	0.262955	0.512791	
18	15	-3.448839	0.1643981	0.376773	0.613818	
19	15	-4.019445	0.1643981	0.651035	0.806867	
20	15	-3.649415	0.1643981	0.501304	0.708028	
21	15	-3.270891	0.1643981	0.785980	0.886555	
22	15	-3.104651	0.1643981	0.263930	0.513741	
23	15	-3.111448	0.1643981	0.437489	0.661430	
Pooled	378			0.405401	0.636711	

SFV4_minus_W_of_SFV 4 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-4.34079	-3.412083	-2.959760	-2.333618	-1.93131	1.078465
1	-4.09390	-3.163046	-2.711305	-2.370638	-1.98569	0.792408
2	-3.94730	-3.027253	-2.696835	-2.338433	-1.93079	0.688819
3	-3.79208	-3.058973	-2.748150	-2.060052	-1.95959	0.998922
4	-3.31281	-2.956269	-2.386260	-2.094136	-1.83881	0.862133
5	-4.59040	-2.654694	-2.359225	-1.975583	-1.24777	0.679111
6	-5.71961	-3.520869	-2.564210	-2.166389	-1.61121	1.354480
7	-3.00430	-1.876905	-1.652460	-1.444737	-1.08710	0.432168
8	-2.91879	-1.893840	-1.532410	-1.295952	-0.80033	0.597888
9	-4.29621	-1.860733	-1.591345	-1.398178	-1.34363	0.462555
10	-2.74768	-1.993511	-1.650250	-1.368663	-1.11410	0.624848
11	-2.68012	-2.262299	-1.977910	-1.622438	-0.32792	0.639862
12	-3.02942	-2.686106	-2.307540	-2.035133	-1.42938	0.650973
13	-3.81519	-2.922825	-2.484750	-1.949573	-1.06698	0.973253
14	-3.41269	-2.947275	-2.567840	-2.219375	-1.78070	0.727900
15	-3.56750	-3.021695	-2.470000	-2.284753	-1.87860	0.736942
16	-3.90997	-3.343497	-2.739245	-2.477383	-2.00391	0.866114
17	-4.11661	-3.330947	-2.899685	-2.749125	-2.24768	0.581822
18	-4.78329	-3.818995	-3.257780	-2.906172	-2.73581	0.912823
19	-5.27902	-4.840192	-3.935180	-3.408397	-2.89468	1.431795
20	-5.72303	-3.860672	-3.471620	-3.287647	-2.89160	0.573025
21	-5.09430	-3.710017	-3.358710	-2.676015	-1.46289	1.034002
22	-4.18579	-3.353038	-3.036070	-2.791872	-2.19870	0.561167
23	-4.60580	-3.505142	-2.890810	-2.674715	-2.12970	0.830427

SFV5_minus_SE_of_SFV 5 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.573718	0.1590851	0.217747	0.466633
1	16	1.737343	0.1590851	0.296324	0.544356
2	16	1.985546	0.1590851	0.954530	0.977000
3	16	1.623723	0.1590851	0.356209	0.596833
4	16	1.740584	0.1590851	0.435711	0.660084
5	16	1.646426	0.1590851	0.295265	0.543383
6	16	1.593336	0.1590851	0.415127	0.644304
7	16	1.782067	0.1590851	0.702662	0.838249
8	16	1.763115	0.1590851	0.910289	0.954091
9	16	1.960866	0.1590851	0.915573	0.956856
10	16	1.863269	0.1590851	0.765938	0.875179
11	16	1.572616	0.1590851	0.147379	0.383899
12	16	1.330318	0.1590851	0.205475	0.453293
13	16	1.220481	0.1590851	0.388570	0.623354
14	16	1.167246	0.1590851	0.080425	0.283593
15	16	0.952139	0.1590851	0.080416	0.283577
16	16	1.016296	0.1590851	0.212272	0.460730
17	16	0.950048	0.1590851	0.211485	0.459875
18	15	0.904114	0.1643024	0.212354	0.460819
19	15	0.814068	0.1643024	0.207918	0.455980
20	15	0.805177	0.1643024	0.290994	0.539439
21	15	0.807631	0.1643024	0.610013	0.781033
22	15	1.089257	0.1643024	0.491296	0.700925
23	15	1.281961	0.1643024	0.292704	0.541021
Pooled	378			0.404929	0.636340

SFV5_minus_SE_of_SFV 5 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.54577	1.413185	1.642660	1.909063	2.33920	0.495878
1	1.07239	1.325578	1.666640	1.915143	3.19019	0.589564
2	1.13440	1.366147	1.756545	2.010652	4.46570	0.644505
3	0.50140	1.278115	1.467740	1.859958	2.98139	0.581843
4	0.61401	1.255672	1.620785	1.969183	3.16572	0.713512
5	0.55939	1.212193	1.672605	1.910755	2.95300	0.698562
6	0.48389	1.183616	1.465985	1.868058	3.13681	0.684442
7	0.86718	1.176052	1.511160	2.142773	3.52802	0.966721
8	0.57330	0.950277	1.419140	2.469478	3.63691	1.519201
9	0.81452	1.250891	1.679335	2.488199	4.34113	1.237308
10	0.80410	1.317583	1.671430	2.307725	4.48059	0.990142
11	1.11261	1.316599	1.481755	1.687999	2.67550	0.371400
12	0.71698	0.974859	1.211810	1.653529	2.31171	0.678670
13	0.60690	0.839968	1.046505	1.406994	3.18702	0.567026
14	0.68311	1.012481	1.150240	1.303785	1.81192	0.291304
15	0.61771	0.672761	0.976455	1.161336	1.59382	0.488575
16	-0.05450	0.703117	1.077605	1.375938	1.62649	0.672822
17	0.12201	0.682125	0.958355	1.144257	1.86648	0.462132
18	0.17920	0.629858	0.816810	1.056925	1.83771	0.427067
19	-0.13189	0.498880	0.790100	1.152863	1.43429	0.653983
20	-0.28949	0.420173	0.919400	1.298042	1.53790	0.877868
21	-0.71591	0.311282	0.990200	1.353393	2.13281	1.042112
22	-0.36820	0.435248	1.373320	1.606680	2.09729	1.171432
23	-0.07098	1.035352	1.433780	1.624963	2.04608	0.589612

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SFV6_minus_W_of_SFV6 6 by hh	N		Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	16	-1.192422	0.1777634	0.254880	0.504857
1	16	16	-1.055523	0.1777634	0.095620	0.309225
2	16	16	-0.994954	0.1777634	1.471480	1.213046
3	16	16	-1.088158	0.1777634	0.091329	0.302208
4	16	16	-1.481811	0.1777634	1.251715	1.118801
5	16	16	-1.609793	0.1777634	2.319349	1.522941
6	16	16	-1.352217	0.1777634	1.425517	1.193950
7	16	16	-1.374319	0.1777634	1.987100	1.409645
8	16	16	-1.143606	0.1777634	0.731020	0.854997
9	16	16	-1.075351	0.1777634	0.309504	0.556331
10	16	16	-0.980047	0.1777634	0.328694	0.573318
11	16	16	-0.899715	0.1777634	0.147554	0.384127
12	16	16	-0.877583	0.1777634	0.096581	0.310775
13	16	16	-0.810566	0.1777634	0.165005	0.406208
14	16	16	-0.749746	0.1777634	0.136519	0.369485
15	16	16	-0.874476	0.1777634	0.114670	0.338630
16	16	16	-0.821744	0.1777634	0.037407	0.193410
17	16	16	-0.803296	0.1777634	0.056689	0.238095
18	15	15	-0.655247	0.1835932	0.102975	0.320897
19	15	15	-0.706348	0.1835932	0.091306	0.302169
20	15	15	-0.859592	0.1835932	0.211008	0.459356
21	15	15	-1.027445	0.1835932	0.268513	0.518183
22	15	15	-1.066729	0.1835932	0.106251	0.325962
23	15	15	-1.061061	0.1835932	0.196510	0.443294
Pooled	378				0.505597	0.711054

SFV6_minus_W_of_SFV 6 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-2.54962	-1.415320	-1.150085	-0.900235	-0.53979	0.515085
1	-1.65122	-1.167038	-1.068715	-0.896228	-0.50247	0.270809
2	-4.49032	-1.188729	-0.974545	-0.668347	1.96802	0.520383
3	-1.88339	-1.225098	-1.026350	-0.899907	-0.73050	0.325191
4	-4.95019	-1.417780	-1.180845	-1.007025	-0.58609	0.410755
5	-5.96289	-1.304936	-1.145665	-0.860142	-0.71402	0.444794
6	-5.67020	-1.436829	-1.075145	-0.746813	-0.65729	0.690017
7	-6.38958	-1.468202	-1.188770	-0.687758	-0.15200	0.780443
8	-2.93210	-1.883783	-0.934460	-0.443158	0.00098	1.440625
9	-2.22839	-1.585835	-0.856000	-0.724947	-0.19980	0.860888
10	-2.92350	-1.085463	-0.842500	-0.709783	-0.45371	0.375680
11	-2.18860	-0.960076	-0.809845	-0.682733	-0.56180	0.277343
12	-1.49322	-1.133363	-0.811860	-0.617529	-0.37729	0.515833
13	-1.40490	-1.117251	-0.794585	-0.503573	0.10580	0.613678
14	-1.32840	-0.971564	-0.851150	-0.563380	0.30829	0.408184
15	-1.71750	-0.974903	-0.851200	-0.617884	-0.45291	0.357019
16	-1.16590	-0.992321	-0.778440	-0.675028	-0.51990	0.317293
17	-1.29221	-0.921158	-0.820980	-0.616139	-0.43583	0.305018
18	-1.07779	-0.917043	-0.764400	-0.486790	-0.05289	0.430253
19	-1.39032	-0.843387	-0.777100	-0.487318	-0.18048	0.356068
20	-1.68790	-1.149852	-0.896300	-0.525515	-0.06461	0.624337
21	-2.22052	-1.393558	-0.840880	-0.707985	-0.29260	0.685573
22	-1.89011	-1.222058	-0.978820	-0.872265	-0.58332	0.349793
23	-1.82632	-1.479950	-0.976630	-0.633970	-0.49390	0.845980

SFV7_minus_SE_of_SFV 7 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.453452	0.1712376	0.183417	0.428272
1	16	1.729198	0.1712376	1.147387	1.071162
2	16	1.662111	0.1712376	0.619272	0.786938
3	16	1.618483	0.1712376	0.538064	0.733528
4	16	1.599013	0.1712376	0.263393	0.513219
5	16	1.563856	0.1712376	0.615283	0.784400
6	16	1.554214	0.1712376	0.777179	0.881578
7	16	1.442469	0.1712376	0.569594	0.754715
8	16	1.418484	0.1712376	0.674221	0.821109
9	16	1.593447	0.1712376	0.319870	0.565570
10	16	1.522041	0.1712376	0.572660	0.756743
11	16	1.454150	0.1712376	0.252002	0.501998
12	16	1.260545	0.1712376	0.103220	0.321279
13	16	1.325168	0.1712376	0.185553	0.430759
14	16	1.151761	0.1712376	0.091430	0.302374
15	16	1.336503	0.1712376	0.136059	0.368861
16	16	1.459828	0.1712376	0.364864	0.604039
17	16	1.312882	0.1712376	0.130227	0.360870
18	15	1.291886	0.1768534	0.144768	0.380484
19	15	1.594812	0.1768534	0.465142	0.682013
20	15	1.659729	0.1768534	0.732059	0.855605
21	15	1.592339	0.1768534	0.889462	0.943113
22	15	1.643535	0.1768534	0.818999	0.904985
23	15	1.559203	0.1768534	0.730005	0.854403
Pooled	378			0.469157	0.684950

SFV7_minus_SE_of_SFV 7 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.66770	1.187593	1.538635	1.677073	2.11199	0.489480
1	0.94488	1.167142	1.375460	1.834003	5.44610	0.666861
2	0.77072	1.172814	1.473020	1.843822	3.83991	0.671008
3	0.50677	1.205406	1.429550	1.805894	3.14508	0.600488
4	0.90680	1.210212	1.506255	1.860838	2.65741	0.650627
5	0.44049	1.110171	1.431095	1.802717	4.03113	0.692546
6	0.41281	1.090733	1.290300	1.722983	4.32699	0.632250
7	0.01349	0.865196	1.258650	2.002058	2.72809	1.136862
8	0.14807	0.705476	1.246095	2.268768	2.70968	1.563292
9	0.67779	1.055862	1.569355	2.063975	2.55551	1.008113
10	0.01617	1.302802	1.426235	1.613465	3.93543	0.310663
11	0.66531	1.247721	1.395110	1.663093	2.88309	0.415373
12	0.59171	1.115895	1.221115	1.447393	2.04950	0.331498
13	0.54849	1.025149	1.371005	1.474629	2.37390	0.449480
14	0.60659	0.932636	1.208495	1.359929	1.67279	0.427293
15	0.53460	1.148185	1.334945	1.624319	1.84189	0.476134
16	0.78100	1.026771	1.457050	1.657886	3.32743	0.631115
17	0.62772	1.028139	1.367660	1.529521	1.98187	0.501382
18	0.73489	1.089575	1.207880	1.645958	1.92340	0.556383
19	0.87500	1.168983	1.409790	1.671708	3.41647	0.502725
20	0.72888	1.145165	1.319830	2.010622	3.87399	0.865457
21	0.32239	1.044877	1.474880	1.882983	4.29093	0.838107
22	0.74539	1.115090	1.467410	1.800463	4.56439	0.685373
23	0.62070	1.124437	1.319400	1.857318	4.26068	0.732882

FOLLOWING: San Fernando Valley, mod-UCM, T2

SFV1_minus_SE_of_SFV1 1 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	2.1770450	0.32181051	2.6428598	1.6256875
1	16	2.5147031	0.32181051	5.8220010	2.4128823
2	16	2.6666931	0.32181051	4.9331911	2.2210788
3	16	2.8539088	0.32181051	6.2238773	2.4947700
4	16	2.3213175	0.32181051	3.6225586	1.9033020
5	16	2.3345744	0.32181051	3.6840082	1.9193770
6	16	2.2149064	0.32181051	2.1013038	1.4495875
7	16	0.4238269	0.32181051	0.4714816	0.6866452
8	16	0.7142713	0.32181051	1.6150423	1.2708432
9	16	0.4825694	0.32181051	1.2474706	1.1169022
10	16	0.1598900	0.32181051	0.2624760	0.5123241
11	16	0.1276456	0.32181051	0.1567657	0.3959365
12	16	0.3680725	0.32181051	0.0565436	0.2377889
13	16	0.5677325	0.32181051	0.4358123	0.6601608
14	16	0.5235825	0.32181051	0.0765327	0.2766454
15	16	0.3956638	0.32181051	0.1199770	0.3463770
16	16	0.3901219	0.32181051	0.1049824	0.3240099
17	16	0.4167669	0.32181051	0.1003270	0.3167443
18	15	0.3254493	0.33236447	0.1944475	0.4409621
19	15	0.7713307	0.33236447	0.4509151	0.6715021
20	15	0.9708060	0.33236447	0.6180638	0.7861704
21	15	1.1928620	0.33236447	1.0959631	1.0468826
22	15	1.7663953	0.33236447	1.8311858	1.3532131
23	15	1.7327860	0.33236447	1.6249274	1.2747264
Pooled	378			1.6569921	1.2872421

SFV1_minus_SE_of_SFV 1 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.121490	0.7121875	2.0603000	3.3962225	6.048490	2.6840350
1	-0.062890	1.0253992	2.1373900	2.9409025	10.421500	1.9155033
2	-0.633510	1.4334925	2.6788050	3.0356583	9.731630	1.6021658
3	-0.743410	0.9862392	2.4119600	3.9110767	8.983000	2.9248375
4	-0.977600	1.2980300	2.0922550	3.2199150	7.782410	1.9218850
5	-1.032890	1.1733458	2.2207000	3.0697942	7.828220	1.8964483
6	-0.876800	1.3607242	2.6372700	3.2269500	4.119110	1.8662258
7	-0.850590	-0.0640567	0.3039550	1.0580567	1.439390	1.1221133
8	-0.845880	0.0327650	0.1832600	0.9597042	3.760810	0.9269392
9	-0.824400	-0.2880967	0.1355600	1.2938008	3.220180	1.5818975
10	-1.340700	0.0687633	0.1953600	0.4197667	0.820280	0.3510033
11	-1.123810	0.0324200	0.1981900	0.3350833	0.648680	0.3026633
12	-0.058810	0.2173183	0.3296350	0.5263425	0.817630	0.3090242
13	0.164280	0.2161308	0.3166950	0.7314933	2.833590	0.5153625
14	0.159700	0.3190000	0.5000000	0.6224042	1.144110	0.3034042
15	-0.221590	0.0748900	0.4314550	0.6275075	0.936670	0.5526175
16	-0.071070	0.1124708	0.3995950	0.6911692	0.889100	0.5786983
17	-0.148410	0.1583125	0.3774100	0.7115700	0.913170	0.5532575
18	-0.500180	-0.0670750	0.4765100	0.6521750	0.997100	0.7192500
19	-0.204100	0.3943550	0.7205800	0.9033217	2.634520	0.5089667
20	-0.138090	0.5885250	0.7923000	1.0648783	3.246220	0.4763533
21	-0.182100	0.7075467	0.8204100	1.8222200	3.741820	1.1146733
22	-0.199190	0.9041933	1.6084000	3.2755000	3.739500	2.3713067
23	-0.173610	0.6520650	1.6393700	2.8027550	3.798490	2.1506900

SFV2_minus_SE_of_SFV 2 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	1.8702663	0.27875437	4.8165371	2.1946610
1	16	2.2590688	0.27875437	4.5916744	2.1428193
2	16	1.8865900	0.27875437	3.0503762	1.7465326
3	16	1.4987125	0.27875437	3.2601816	1.8055973
4	16	1.5478419	0.27875437	1.8947112	1.3764851
5	16	1.8639363	0.27875437	2.3231200	1.5241785
6	16	1.6145156	0.27875437	1.6826021	1.2971515
7	16	0.6456238	0.27875437	0.1152316	0.3394578
8	16	0.1839775	0.27875437	0.1222148	0.3495924
9	16	0.2477525	0.27875437	0.2136347	0.4622063
10	16	0.1193000	0.27875437	0.1504243	0.3878457
11	16	0.3345238	0.27875437	0.2965396	0.5445545
12	16	0.3017081	0.27875437	0.1296145	0.3600202
13	16	0.3570675	0.27875437	0.0694455	0.2635251
14	16	0.3059762	0.27875437	0.1156766	0.3401126
15	16	0.2727887	0.27875437	0.1266710	0.3559087
16	16	0.2940519	0.27875437	0.0892517	0.2987502
17	16	0.2744300	0.27875437	0.0504916	0.2247033
18	15	0.1245307	0.28789628	0.1115300	0.3339611
19	15	0.1594667	0.28789628	0.1989718	0.4460625
20	15	0.8511013	0.28789628	1.3720538	1.1713470
21	15	1.2090027	0.28789628	1.6896287	1.2998572
22	15	1.0985820	0.28789628	1.6916400	1.3006306
23	15	1.7580720	0.28789628	1.6247104	1.2746413
Pooled	378			1.2432640	1.1150175

SFV2_minus_SE_of_SFV 2 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.175200	0.3501367	1.7489800	2.4223133	8.974610	2.0721767
1	-0.528470	0.5123917	2.5301950	2.9646225	8.637300	2.4522308
2	-1.378020	0.5679817	2.4387400	2.7761817	5.723480	2.2082000
3	-1.113620	0.4968408	1.3614650	2.3758617	6.535700	1.8790208
4	-1.179680	0.6493317	1.6591350	2.5237525	4.265810	1.8744208
5	-0.931190	1.0161233	2.0182900	2.9294517	4.628480	1.9133283
6	-2.199220	1.0217467	1.9796900	2.5229450	2.855105	1.5011983
7	-0.148890	0.4873825	0.6411400	0.8623775	1.258400	0.3749950
8	-0.381500	-0.0830283	0.0636550	0.5350708	0.927980	0.6180992
9	-0.440400	-0.0261108	0.2073950	0.4708683	1.365110	0.4969792
10	-0.425590	-0.2145125	0.0966500	0.4587525	0.864010	0.6732650
11	-0.142610	0.0203642	0.1542050	0.3791375	2.057400	0.3587733
12	-0.372620	0.1462142	0.2721550	0.3825808	1.332520	0.2363667
13	-0.409700	0.2863475	0.3663500	0.4967717	0.729400	0.2104242
14	-0.742920	0.1788667	0.3187400	0.5288283	0.722290	0.3499617
15	-0.660000	0.1354450	0.3046850	0.4859192	0.735600	0.3504742
16	-0.145780	0.0740100	0.2690900	0.5481875	0.827820	0.4741775
17	-0.071900	0.0974292	0.2428150	0.4191683	0.716400	0.3217392
18	-0.328000	-0.1305233	0.0854200	0.3815217	0.674490	0.5120450
19	-0.611210	-0.2331550	0.2146000	0.4485233	0.808100	0.6816783
20	-0.335210	0.3127317	0.5225800	0.8712950	3.740300	0.5585633
21	-0.306000	0.3757183	0.7550100	2.4681000	3.937900	2.0923817
22	-0.895990	0.3411683	0.6682200	1.9975617	4.068790	1.6563933
23	0.073910	0.6203933	1.5426000	2.8522317	4.110200	2.2318383

SFV4_minus_W_of_SFV4 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-1.9070944	0.19411760	1.2020144	1.0963642
1	16	-2.1899425	0.19411760	1.0473735	1.0234127
2	16	-2.3030781	0.19411760	0.8436520	0.9185053
3	16	-2.2612506	0.19411760	0.8048474	0.8971329
4	16	-2.3601638	0.19411760	1.1232628	1.0598409
5	16	-2.3456299	0.19411760	1.4078224	1.1865169
6	16	-2.2877164	0.19411760	1.4853103	1.2187331
7	16	-0.3566050	0.19411760	0.0795392	0.2820270
8	16	0.0485956	0.19411760	0.1540158	0.3924485
9	16	-0.0368575	0.19411760	0.1449732	0.3807535
10	16	-0.0207137	0.19411760	0.1037111	0.3220420
11	16	-0.0293712	0.19411760	0.0669323	0.2587127
12	16	-0.1590775	0.19411760	0.0656809	0.2562829
13	16	-0.2845675	0.19411760	0.4112160	0.6412613
14	16	-0.2887631	0.19411760	0.0401097	0.2002740
15	16	-0.2501025	0.19411760	0.0465746	0.2158114
16	16	-0.3294544	0.19411760	0.0611378	0.2472606
17	16	-0.3573650	0.19411760	0.0773371	0.2780954
18	15	-0.2977880	0.20048379	0.0760166	0.2757110
19	15	-0.5575213	0.20048379	0.2095391	0.4577545
20	15	-0.7095600	0.20048379	0.9560517	0.9777790
21	15	-1.1521080	0.20048379	1.5696613	1.2528612
22	15	-2.1813000	0.20048379	1.2996135	1.1400059
23	15	-2.2716193	0.20048379	1.3138435	1.1462301
Pooled	378			0.6029063	0.7764704

SFV4_minus_W_of_SFV 4 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-3.858400	-2.6593108	-2.1360200	-0.6624283	-0.333190	1.9968825
1	-3.368500	-2.9774817	-2.4351800	-1.2791758	-0.515190	1.6983058
2	-3.681800	-2.9744117	-2.4668550	-1.5889808	-0.600400	1.3854308
3	-3.576600	-2.6828642	-2.5871600	-1.6473775	-0.596100	1.0354867
4	-3.805780	-2.9865233	-2.7784900	-1.6536750	-0.486690	1.3328483
5	-5.543090	-2.7639850	-2.4595450	-1.8994400	-0.549380	0.8645450
6	-5.350310	-2.6437004	-2.3923050	-1.8271542	0.453520	0.8165463
7	-1.005130	-0.5067850	-0.3072950	-0.1653117	0.107820	0.3414733
8	-0.730500	-0.1846233	0.0766000	0.2128175	0.976200	0.3974408
9	-1.151000	-0.1801708	-0.0175450	0.1550842	0.477300	0.3352550
10	-1.001310	-0.0760792	0.0451650	0.1246858	0.386510	0.2007650
11	-0.506500	-0.1732525	-0.0337050	0.0712808	0.696110	0.2445333
12	-0.636690	-0.3382183	-0.1608450	0.0702892	0.223690	0.4085075
13	-2.391110	-0.4291942	-0.2286550	0.0257442	0.568210	0.4549383
14	-0.678280	-0.4256667	-0.2816500	-0.1432858	0.071590	0.2823808
15	-0.622810	-0.4139992	-0.2724500	-0.0964892	0.123290	0.3175100
16	-0.671690	-0.5153908	-0.3885200	-0.1865317	0.180030	0.3288592
17	-0.812010	-0.5142075	-0.3981050	-0.1905683	0.238800	0.3236392
18	-0.691100	-0.5352083	-0.3551100	-0.1696750	0.258510	0.3655333
19	-1.849000	-0.5747983	-0.5380300	-0.4019867	0.188330	0.1728117
20	-4.091980	-0.6892000	-0.5416800	-0.3772483	0.216190	0.3119517
21	-3.739990	-1.7828933	-0.5499900	-0.3823367	-0.239320	1.4005567
22	-3.771300	-2.9236817	-2.5455900	-1.0148800	-0.275700	1.9088017
23	-3.586480	-3.0757483	-2.7854000	-0.9912233	-0.375820	2.0845250

SFV5_minus_SE_of_SFV 5 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	3.5462063	0.34804366	4.9525229	2.2254265
1	16	3.8725575	0.34804366	4.2649697	2.0651803
2	16	4.2922456	0.34804366	4.7784576	2.1859684
3	16	4.4219194	0.34804366	3.1389794	1.7717165
4	16	3.9670251	0.34804366	4.2172313	2.0535899
5	16	3.9397567	0.34804366	3.3197996	1.8220317
6	16	4.2434218	0.34804366	2.6004131	1.6125796
7	16	1.1876181	0.34804366	1.0194767	1.0096914
8	16	0.2846731	0.34804366	0.2042880	0.4519823
9	16	0.0979100	0.34804366	0.2660048	0.5157565
10	16	0.1383113	0.34804366	0.3164005	0.5624949
11	16	-0.0068231	0.34804366	0.1449272	0.3806930
12	16	-0.0861669	0.34804366	0.1031032	0.3210968
13	16	0.0419688	0.34804366	0.1079928	0.3286225
14	16	0.0559888	0.34804366	0.1816631	0.4262196
15	16	0.0933638	0.34804366	0.2458531	0.4958358
16	16	-0.0089544	0.34804366	0.2770532	0.5263584
17	16	0.0691362	0.34804366	0.1182416	0.3438628
18	15	0.1786927	0.35945795	0.0785613	0.2802879
19	15	0.3466560	0.35945795	0.1000043	0.3162346
20	15	1.1183040	0.35945795	1.9106905	1.3822773
21	15	2.5275540	0.35945795	4.9647937	2.2281817
22	15	2.8634880	0.35945795	5.1074482	2.2599664
23	15	3.2145667	0.35945795	4.4273956	2.1041377
Pooled	378			1.9381502	1.3921746

SFV5_minus_SE_of_SFV 5 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-0.473910	1.6701600	3.7664200	5.0756267	7.678370	3.4054667
1	0.529290	2.5139900	4.0258500	5.3426433	7.886110	2.8286533
2	0.350100	2.3947458	4.1097450	5.7305775	8.629300	3.3358317
3	0.560000	3.2391425	4.5812050	5.7588850	7.726990	2.5197425
4	0.636290	2.6003508	3.7707100	5.3680950	8.403080	2.7677442
5	0.083800	3.0268017	4.4107550	5.2519683	6.922180	2.2251667
6	0.708920	3.2325071	4.5692620	5.3734900	7.049720	2.1409829
7	-0.671600	0.4516367	0.9229000	2.1866867	2.915800	1.7350500
8	-0.442590	0.0240275	0.2231000	0.4569608	1.389100	0.4329333
9	-1.257110	-0.1791700	0.1187950	0.4451258	1.081430	0.6242958
10	-0.869870	-0.2880550	0.1734500	0.4955617	1.408020	0.7836167
11	-0.885500	-0.2186875	0.0284600	0.2718567	0.594520	0.4905442
12	-0.733400	-0.3057583	-0.0309450	0.1751758	0.306000	0.4809342
13	-0.520600	-0.1251600	0.0428450	0.3070683	0.531000	0.4322283
14	-0.847200	-0.2334850	0.1146550	0.4076808	0.637210	0.6411658
15	-1.124780	-0.1613525	0.2209000	0.4462308	0.655670	0.6075833
16	-1.110900	-0.3895075	0.1219000	0.3912267	0.771180	0.7807342
17	-0.634490	-0.1582325	0.1067700	0.3304200	0.639890	0.4886525
18	-0.225710	-0.0719100	0.2106000	0.3826683	0.790490	0.4545783
19	-0.178710	0.1503633	0.2986200	0.5424433	0.921110	0.3920800
20	-0.084420	0.3677867	0.5943000	1.0155817	4.240120	0.6477950
21	-0.096620	0.6719983	0.8704800	4.6547450	6.256720	3.9827467
22	0.426300	0.6862217	2.7225100	5.1870933	6.256620	4.5008717
23	0.472590	0.7475150	3.6314100	4.7856167	6.688020	4.0381017

SFV6_minus_W_of_SFV6 6 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	-2.7944269	0.30178235	3.3288342	1.8245093
1	16	-2.5303500	0.30178235	1.9393438	1.3926032
2	16	-3.0547470	0.30178235	1.6824984	1.2971116
3	16	-3.3421716	0.30178235	1.9522144	1.3972167
4	16	-3.7877624	0.30178235	3.5577059	1.8861882
5	16	-3.9725949	0.30178235	4.9786664	2.2312925
6	16	-2.8879618	0.30178235	3.2687300	1.8079630
7	16	-0.9420150	0.30178235	1.3860158	1.1772917
8	16	-0.4017231	0.30178235	1.1552684	1.0748341
9	16	-0.2658900	0.30178235	0.3276868	0.5724393
10	16	0.1565825	0.30178235	0.3565480	0.5971164
11	16	0.1446094	0.30178235	0.2626752	0.5125185
12	16	-0.0987487	0.30178235	0.0530752	0.2303806
13	16	-0.1873838	0.30178235	0.0979184	0.3129192
14	16	-0.2372756	0.30178235	0.0755418	0.2748486
15	16	-0.0559394	0.30178235	0.1104216	0.3322974
16	16	-0.1139250	0.30178235	0.1185407	0.3442974
17	16	-0.0228469	0.30178235	0.1272980	0.3567884
18	15	-0.1497213	0.31167947	0.0724020	0.2690762
19	15	-0.1284093	0.31167947	0.1634218	0.4042546
20	15	-0.7553260	0.31167947	0.5957454	0.7718454
21	15	-1.7663600	0.31167947	2.6485415	1.6274340
22	15	-2.1451920	0.31167947	3.4755287	1.8642770
23	15	-2.3696293	0.31167947	3.3408176	1.8277904
Pooled	378			1.4571614	1.2071294

SFV6_minus_W_of_SFV 6 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	-5.492400	-4.4041808	-3.1854000	-0.9210617	-0.026430	3.4831192
1	-5.083200	-3.5442617	-2.9002100	-1.3905100	-0.138920	2.1537517
2	-5.579110	-3.8936250	-2.7814200	-2.2644392	-1.073210	1.6291858
3	-6.111116	-3.9553542	-3.5178550	-2.7137125	-0.725620	1.2416417
4	-7.397890	-5.2680975	-3.3688355	-2.7325533	-0.798090	2.5355442
5	-9.931970	-4.6930542	-3.3034355	-2.6755423	-1.321900	2.0175118
6	-6.827090	-3.6513500	-3.0522435	-1.3759967	-0.260800	2.2753533
7	-4.568420	-1.1411633	-0.8362400	-0.4725292	0.811400	0.6686342
8	-3.194880	-0.8507733	-0.4457550	-0.0989442	1.616310	0.7518292
9	-1.530300	-0.5570050	0.0148950	0.1183583	0.299280	0.6753633
10	-0.571680	-0.2352000	0.1032850	0.3087667	1.687680	0.5439667
11	-0.321280	-0.2020133	0.1006000	0.2734883	1.868680	0.4755017
12	-0.413700	-0.2525592	-0.1620300	0.0271592	0.390110	0.2797183
13	-0.599580	-0.3942333	-0.2543600	0.0198317	0.655000	0.4140650
14	-0.733610	-0.4633917	-0.2108050	0.0129542	0.125220	0.4763458
15	-0.665890	-0.2505583	-0.0480500	0.1204442	0.523320	0.3710025
16	-0.630190	-0.3728808	-0.2243650	0.1853875	0.487000	0.5582683
17	-0.678500	-0.2384417	-0.0459150	0.1019083	0.790990	0.3403500
18	-0.468010	-0.3377850	-0.2513100	0.0895167	0.382330	0.4273017
19	-0.836000	-0.4731183	-0.1018900	0.2715250	0.505620	0.7446433
20	-2.456690	-1.1987550	-0.5406800	-0.3408883	0.368590	0.8578667
21	-5.146000	-2.7995183	-0.8756200	-0.4169417	-0.180780	2.3825767
22	-5.127500	-3.9458133	-1.2440200	-0.4511533	-0.035980	3.4946600
23	-5.517390	-3.8675217	-2.9086000	-0.5342367	-0.094480	3.3332850

SFV7_minus_SE_of_SFV 7 by hh	N	Mean	Mean SE (based on pooled SD)	Variance	SD
0	16	2.7925813	0.34487158	3.0901966	1.7578955
1	16	3.4362950	0.34487158	4.1897355	2.0468843
2	16	3.7746419	0.34487158	6.3959477	2.5290211
3	16	3.6938081	0.34487158	3.6761036	1.9173168
4	16	3.6773293	0.34487158	4.1215189	2.0301524
5	16	3.8447711	0.34487158	3.8513341	1.9624816
6	16	2.8994271	0.34487158	5.3581800	2.3147743
7	16	1.0578194	0.34487158	1.9241619	1.3871416
8	16	0.4346944	0.34487158	0.5740050	0.7576312
9	16	0.0960813	0.34487158	0.8575733	0.9260526
10	16	-0.3944825	0.34487158	0.8561328	0.9252745
11	16	0.2232319	0.34487158	0.0923475	0.3038872
12	16	0.3021681	0.34487158	0.0854951	0.2923955
13	16	0.4079463	0.34487158	0.0744209	0.2728019
14	16	0.5751875	0.34487158	0.2548602	0.5048368
15	16	0.5419094	0.34487158	0.1976507	0.4445792
16	16	0.4939644	0.34487158	0.1065114	0.3263609
17	16	0.5251913	0.34487158	0.1315026	0.3626329
18	15	0.5476740	0.35618184	0.1715568	0.4141942
19	15	0.8443573	0.35618184	0.7220902	0.8497589
20	15	1.4700813	0.35618184	0.7096611	0.8424138
21	15	1.8069953	0.35618184	1.5793615	1.2567265
22	15	2.5988407	0.35618184	3.5634676	1.8877149
23	15	2.5641387	0.35618184	2.9746232	1.7247096
Pooled	378			1.9029825	1.3794863

SFV7_minus_SE_of_SFV 7 by hh	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Inter-quartile range
0	0.423190	1.3519475	2.4121750	4.5576042	5.938690	3.2056567
1	0.500490	1.3685733	3.9289050	4.8803875	7.016700	3.5118142
2	0.562680	1.5455217	3.8440550	5.3306225	10.359190	3.7851008
3	0.569880	2.3680333	3.4921400	5.2350817	7.444490	2.8670483
4	-0.291500	2.0635567	4.0472000	4.8326708	7.294410	2.7691142
5	-0.338100	2.9915779	3.8021085	4.7557225	7.830720	1.7641446
6	-2.200810	1.0704908	3.2529645	4.7902083	6.180290	3.7197174
7	-2.717800	0.6028883	1.1042500	1.6510725	4.203520	1.0481842
8	-1.446500	-0.0309075	0.5546400	1.1179483	1.203700	1.1488558
9	-1.597420	-0.4976642	0.0698400	0.4851725	2.041110	0.9828367
10	-3.381320	-0.5562333	-0.2676400	0.2100525	0.466090	0.7662858
11	-0.622310	0.0651842	0.2410500	0.4322825	0.671600	0.3670983
12	-0.410710	0.1310958	0.3232000	0.5116283	0.696190	0.3805325
13	-0.195400	0.2012183	0.4379400	0.6548767	0.761110	0.4536583
14	-0.067380	0.1802983	0.6299600	0.7742058	2.015190	0.5939075
15	0.002110	0.2202208	0.5081950	0.7520975	1.811890	0.5318767
16	-0.234710	0.3107558	0.4338500	0.7074875	1.133480	0.3967317
17	-0.203800	0.2612392	0.5549000	0.7572725	1.336700	0.4960333
18	-0.207490	0.3199017	0.4675900	0.9113083	1.147090	0.5914067
19	-0.084900	0.3393417	0.5651000	0.9554450	3.144100	0.6161033
20	0.367890	1.0356667	1.3091100	1.5993867	3.923800	0.5637200
21	0.436280	0.9096100	1.6014100	1.9962050	4.299410	1.0865950
22	0.683810	1.1278917	1.6304100	4.3264000	6.219120	3.1985083
23	0.625820	1.4096917	1.6090100	4.4521667	5.645410	3.0424750

Figure App_A4

Comparisons between modeled and observed (mobile-transect) temperature gradients near points of interest in LA1 and San Fernando Valley domains.

LA1: area L2 UHI (segment S1) relative to area G (segment S2)

$\Delta t = 10$ minutes, $\Delta z_{\max} = 11$ m

ΔT transect = $s1 - s2 = 0.67$ °C

ΔT model (daytime avg) = 0.25 °C (areamod/UBL); 0.54 °C (mod-UCM/UCL); 0.30 °C (mod-BEP/UCL)

ΔT model (1400 PDT avg) = 0.16 °C (areamod/UBL)

LA1: area E UCI (segment S2) relative to south reference area (segment S1)

$\Delta t = 10$ minutes, $\Delta z_{\max} = 65$ m

ΔT transect = $s1 - s2 = 0.40$ °C

ΔT model (daytime avg) = 0.67 °C (areamod/UBL); 0.32 °C (mod-UCM/UCL); -0.40 °C (mod-BEP/UCL)

ΔT model (1400 PDT avg) = 0.98 °C (areamod/UBL)

LA1: area L2 UHI (segment S1) relative to area H (segment S2)

$\Delta t = 17$ minutes, $\Delta z_{\max} = 9$ m
 $\Delta T_{\text{transect}} = s1 - s2 = 0.60$ °C
 $\Delta T_{\text{model}} (\text{daytime avg}) = 0.22$ °C (areamod/UBL); 0.54 °C (mod-UCM/UCL); 0.20 °C (mod-BEP/UCL)
 $\Delta T_{\text{model}} (1400 \text{ PDT avg}) = 0.17$ °C (areamod/UBL)

LA1: area J UHI (segment S1) relative to area F (segment S2)

$\Delta t = 13$ minutes, $\Delta z_{\max} = 10$ m
 $\Delta T_{\text{transect}} = s1 - s2 = 1.10$ °C
 $\Delta T_{\text{model}} (\text{daytime avg}) = 0.22$ °C (areamod/UBL); 0.54 °C (mod-UCM/UCL); 0.30 °C (mod-BEP/UCL)
 $\Delta T_{\text{model}} (1400 \text{ PDT avg}) = 0.25$ °C (areamod/UBL)

Locations of mobile transects in the San Fernando Valley domain.
Points are identified for referencing in the following figures.

San Fernando Valley: area SFV1 UHI relative to area NW of SFV1

speed > 10 km hr⁻¹

ΔT transect = SFV1 – NW_of_SFV1 = +0.54 °C

ΔT model (all hours avg) = +0.66 °C (areamod/T2)

ΔT model (1400 PDT avg) = +0.80 °C (areamod/T2)

San Fernando Valley: area SFV6 UCI relative to area S of SFV6

speed > 10 km hr⁻¹

ΔT transect = SFV6 – S_of_SFV6 = -1.66 °C

ΔT model (all hours avg) = -1.0 °C (areamod/T2)

ΔT model (1400 PDT avg) = -1.2 °C (areamod/T2)

San Fernando Valley: area N1 UCI relative to area N2

speed > 10 km hr⁻¹

ΔT transect = N1 – N2 = -1.06 °C

ΔT model (all hours avg) = -1.0 °C (areamod/T2)

ΔT model (1400 PDT avg) = -0.8 °C (areamod/T2)

San Fernando Valley: area M2 UHI relative to area M1

speed > 10 km hr⁻¹

ΔT transect = M2 – M1 = +1.68 °C

ΔT model (all hours avg) = +1.8 °C (areamod/T2)

ΔT model (1400 PDT avg) = +2.0 °C (areamod/T2)

San Fernando Valley: area SFV2 UHI relative to area E of SFV2

speed > 10 km hr⁻¹

ΔT transect = SFV2 – E_of_SFV2 = +1.98 °C

ΔT model (all hours avg) = +1.2 °C (areamod/T2)

ΔT model (1400 PDT avg) = +1.2 °C (areamod/T2)

San Fernando Valley: area SFV4 UCI relative to area S of SFV4

speed > 10 km hr⁻¹

ΔT transect = SFV4 – S_of_SFV4 = +0.19 °C

ΔT model (all hours avg) = -1.6 °C (areamod/T2)

ΔT model (1400 PDT avg) = -0.8 °C (areamod/T2)

San Fernando Valley: area S1 UHI relative to area S2

speed > 10 km hr⁻¹

ΔT transect = S1 – S2 = +0.53 °C

ΔT model (all hours avg) = +1.0 °C (areamod/T2)

ΔT model (1400 PDT avg) = +1.2 °C (areamod/T2)

San Fernando Valley: area T1 UHI relative to area T2

speed > 10 km hr⁻¹

ΔT transect = T1 – T2 = +0.79 °C

ΔT model (all hours avg) = +1.0 °C (areamod/T2)

ΔT model (1400 PDT avg) = +1.2 °C (areamod/T2)

California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix B

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APB

Appendix B: Preliminary mobile measurements of air temperature via transect (Task 2 Report, Part II)

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8 July 2016

From the analysis of the modeling results, several mobile transect routes were developed in Area_1 and SFV. We performed the first of the mobile transects in May and June 2016. Again, the mobile transect apparatus is installed on a compact vehicle and measures air temperature 2 m above the ground (Figure 1). The vehicle moves on a route (i.e. transect) developed to capture variations in temperature caused by land cover change. A camera is also installed in the vehicle with GPS to give the research team a better understanding of the surrounding environment and location during the mobile measurements. In addition, a cell phone application is utilized to record GPS location.

A thermistor installed inside the apparatus measures temperature and records the information via a data logger. The location of the vehicle is recorded using the GPS module of the camera and the GPS of a cell phone application. The temporal frequency of the temperature measurement is one second, and the cell phone application records the location every 10s or every 10m, whichever occurs first.

Figure 1. Left: The apparatus uninstalled. Right: Apparatus installed on a vehicle.

Two transects have been completed in April/June 2016 during this preliminary phase. These transects are located in (1) Area_1 near downtown Los Angeles and (2) the San Fernando Valley (Figure 2).

The Area_1 transect was performed on 22 April 2016. It was a total length of 31 km and took approximately 2 hours to complete. The air temperatures along selected streets from Commerce to Monterey Park were measured and an example of temperatures is shown in Figure 3.

The San Fernando Valley transect was done on 2 June 2016 (Figure 4). It was a total length of 90 km and took approximately 4 hours to complete. The air temperatures along selected streets in Reseda, Canoga Park and Chatsworth were measured and an example of temperatures is shown in Figure 4.

Once we identified specific locations in Area_1 and SFV to set-up our monitoring network, we reached out to our project partners (official) and collaborators (new stakeholders interested in project) to help start identifying specific sites. We hosted one-on-one calls with each organization and shared with them (a) a KMZ layer of the specific locations of interest, and (b) guidance on siting the fixed stations (e.g., secure location, stable ownership).

Figure 2. Locations of the completed transects. The Area_1 transect (red) and SFV transect (blue) are both shown.

Figure 3. Area_1 transect. Top right: The transect location. Top left: The location of the transect with the values along the route. Bottom: A closer look at the frequency of the measurements in the part of transect shown with black circle above.

Figure 4. SFV transect. Top: Location of the transect. Bottom: Frequency of the measurement in the route.

California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix C

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APC

Appendix C: Monitoring plan, instrumentation design, and sensor deployment (Task 3 Report, Part I)

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13 April 2018

1 Introduction

The urban heat island effect (UHIE) is the elevation of the air temperature near the ground within a city over that outside the city. The UHIE is driven in part by differences in local land use/land cover, or “urban fabric”. For example, the UHIE may be positive if a built-up city is darker and drier than the countryside, or negative if an irrigated suburban area is greener than surrounding desert.

The current project seeks to assess the variation of air temperature with the urban fabric in Los Angeles by establishing a network of fixed monitors, or “monitors”, that accurately and continuously measure local air temperature. These monitors will also record other environmental parameters that help to interpret spatial and temporal variations in air temperature, including wind speed, wind direction, solar irradiance, and relative humidity.

This task report describes the monitoring plan, the instrumentation design, and the deployment of the monitors. It also details the design of a mobile monitor used in transect measurement of near-ground air temperature.

2 Monitoring plan

Here we address selection of monitoring sites and plans for operation of the stationary monitors.

2.1 Site selection

2.1.1 Sites identification and selection: Step A

The atmospheric modeling, configurations, and analysis of results were discussed in our Task 2 report submitted July 2016. Therefore, we only discuss the additional siting considerations that followed the modeling results.

Several study areas were identified in the Area_1 and San Fernando Valley (SFV) study domains based on model and initial mobile-transect results (Figure 1). In Figure 1, the study areas are presented for both the Area_1 (a) and SFV (b) study domains. Each area of interest is marked with two polygons: a yellow polygon indicating the target zone [urban heat island (UHI) or urban cooling island (UCI)] and a white polygon outlining the reference area. We shared these study areas with partners and collectively developed a list of their facilities that could serve as potential sites for monitors (see Section 6.2.2). From that list, we evaluated the potential sites based on technical criteria and location relative to model-predicted UHI / UCI points. A summary evaluation of the potential sites is presented in Table 1.

It should be noted that the final selection of monitor sites will be based on the approval from and agreements with partners in Los Angeles. This finalized set of sites will be submitted to the Energy Commission's Agreement Manager for approval.

We will install at least one monitor in the target zone and the reference area. However, it is important to consider that, in some cases, it may be more effective to select two or more target points (in any yellow polygon) and two or more reference points (in corresponding white polygons) in each area to better capture area-wide flow and temperature patterns, as well as time-varying upwind reference points.

(a)

(b)

Figure 1. UHI / UCI areas for potential monitor siting (yellow balloons/polygons are target areas; white balloons/polygons are reference areas) based on meteorological model results. Area_1 is shown in the upper panel (a) and San Fernando Valley in shown in the lower panel (b).

Table 1. Potential monitor sites identified as of this task report's date. In this table, "Suitability" indicates whether the point is suitable to the UHI or UCI target or reference point as defined (conforms to anticipated UHI or UCI), "~500m uniformity" indicates if the point is surrounded by uniform urban land use and geometry up to 500 m upwind, and 'Status' indicates if both target and reference points have been identified to date.

Point ID	Address	Description	Suitability	Use	~500m uniformity	Status
San Fernando Valley						
SFV1	10241 N. Balboa	City facility (building)	Yes	Target (UHI)	Yes	OK
	Havenhurst at Devonshire	LADWP distributing station	No (local heat generation)	Ref point	Yes	
	16701 Mayall Street School	School (LAUSD)	Yes	Ref point	Yes	
	16111 Plummer Street	Health Center (LA City)	Yes (open / green)	Ref point	?	
	10640 Petit Avenue	Library (LA City)	Possible	Ref point	?	
	17221 Tuba Street	Home (via TreePeople)	Yes	Ref point	Mostly	
	16111 Plummer Street	Health Center (County facility) and open space	Yes	Ref point	Mostly	
SFV2	18250 Devonshire	Police station	No: too close to target (CSUN) ?	Ref point	?	No target point yet (in CSUN) UHI; near north parking lot
	18300 Lemarsh	Recreation center / open space	Yes	Ref point	Yes	
	10058 Reseda	Child care facility	Yes	Ref point	?	
	10210 Etiwanda	Industrial	No (opposite effect)	-	-	
		Dearborn Park	Yes	Ref point	Yes	
SFV3	10400 N. Mason	Mason Park recreation building	Yes	Ref point	Yes	No target point yet (UHI)
	10500 Tunney Avenue	County facility –shelter house / guard station	Yes	Ref point	Yes	
SFV5	9324 Topanga Cyn	City yard	somewhat-Yes	Target point (UHI)	?	OK
	20655 Plummer	Animal shelter	somewhat-Yes	Target point (UHI)	Yes	

	21800 Marilla	Fire station	Yes	Target point (UHI)	Yes	
	21615 Plummer Street	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	21415 Plummer Street	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	9035 Canoga Avenues	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	8401 Winnetka	Recreation center	Yes	Ref point	Yes (at park tip)	
	19940 Plummer	LADWP distributing station	No (local heat generation)	Ref point	No	
	7911 Winnetka Avenue	James Jordan Middle School (LAUSD)	Yes	Ref point	Yes	
	8530 Limerick Avenue	Limerick Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	20620 Arminta Street	Sunny Brae Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	7700 Melvin Avenue	Melvin Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	8552 Melvin Avenue	Home (via TreePeople)	Yes	Ref point (one of several)	Yes	
SFV6	Vanowen at White Oak	LADWP distributing station	No (local heat generation)	Ref point	?	OK
	7419 Reseda	Fire station	Yes	Ref point	?	
	Sherman Way at Reseda	City parking lots (non-fenced)	Yes	Ref point	Yes	
	Victory at Reseda	Reseda Park building	No (opposite effect)	Ref point	No	
		Jesse Owens Minipark	Yes	Target point (UCI)	Mostly	
		Louise Park	Yes	Target point (UCI)	Yes	
SFV7		Dearborn Park	Yes	Ref point	Yes	OK

	6461 Gaviota Avenue	Home (via TreePeople)	Yes	Ref point	Yes	
	6632 Lemona Avenue	Home (via TreePeople)	Yes	Ref point	?	
	16700 Roscoe Blvd. (Van Nuys Airport)	Dispatch center (County facility)		Target (UHI)	Yes	
Area_1						
A	1274 W 2 nd	Services	Yes – but not in model points	Ref point	No	No target point yet (UCI)
	203 S. Los Angeles Street	Little Tokyo library	Yes, could be used to represent medium-rise conditions	Ref point	Yes	
	630 W. 5 th Street	LA Public Library	Yes, could be used to represent high-rise conditions	Ref point	Yes	
	525 S. Hewitt Street	Industrial	Yes (close to model point)	Ref point	Yes	
B	525 S. Hewitt Street	Industrial	Yes (close to model point)	Ref point	Yes	OK (but preferable if more centralized site is found)
	1617 E. 7 th Street	Para Los Ninos charter (LAUSD)	Yes	Ref point	Yes	
	727 S. Wilson Street	Metropolitan High School (LAUSD)	Yes	Ref point	Yes	
	1314 Dacotah Street	Dena Elementary (LAUSD)	Yes	Target (UCI)	?	
	2750 E. Hostetter Street	Garza PC (LAUSD)	Yes	Target (UCI)	?	
	1016 S. Fresno Street	MSGR Ramon Garcia recreation center	Yes	Target (UCI)	?	
	3141 E. Olympic Blvd.	Lou Costello Jr. recreation center	Yes	Target (UCI)	?	
	933 S. Mott Street	Boyle Heights Sports Center (Parks&Rec)	Yes	Target (UCI)	? (but in tandem with above UCI points)	

	1601 S. Santa Fe Avenue	Fire station No. 17	Yes	Ref point	Yes	
	1055 N. Alameda Street	Parking garage (County facility)	Yes	Ref point	Yes	
	2765 E. Olympic Blvd.	Parking lot (County facility)	Yes	Ref point	No (and too close to target)	
K	4914 E. Cesar Chavez Avenue	Park	Yes	Target (UCI)	Mostly	OK
	5119 E. Beverly Blvd.	Office building (County facility)	Yes	Ref. point	Yes	
	420 S. Amalia Avenue	4 th Street Elementary	Yes	Ref. point	Yes	
G-L	6250 Northside Drive	Park	Yes	Target (UCI) instead of or with point G	Mostly	OK
	Southside Drive	Montebello Parkway (land) County facility	Yes	Target (UCI)	Mostly	
	6400 Northside Drive	Montebello Parkway (storage box) County facility	Yes	Target (UCI)	Yes	
	2327 S. Saybrook Avenue	Fire station (County facility)	Yes	Ref point	Yes	
	2700 Garfield Avenue	Supplies storage (DSS)	Yes	Ref point	Yes	
	1050 S Maple Avenue	Supplies storage (County facility)	Yes	Ref. point	Yes	

2.1.2 Sites identification and selection: Step B

We prioritized the deployment of monitors in area SFV5 in San Fernando Valley because of technical and implementation considerations described more in Section 6.2.3. We completed further analysis of the initial SFV5 sites from Table 1 to narrow down the possible locations. Table 2 provides a summary of sites and proposed weather-monitor positions in SFV5 that resulted from this additional screening.

Table 2. Potential weather sites identified in SFV5. In this table, “Suitability” indicates whether the point is suitable to the UHI or UCI target or reference point as defined (conforms to anticipated UHI or UCI), “Rank” lists the sites priority based on technical review, and “Use” indicates if the site is a target or reference point, “~500 m” indicates if the point is surrounded by uniform urban land use and geometry up to 500 m upwind, and “Details” provides information on where the monitors could be installed on the site .

	Address	Description	Suitability	Rank	Use	~500m	Details
SFV5_01	9324 Topanga Cyn	City yard / BSS (LA City)	somewhat-Yes	B (bl)	Target point (UHI)	?	Roof or ground
	20655 Plummer St.	Animal shelter (LA City)	somewhat-Yes	B (wr)	Target point (UHI)	Yes	Roof
SFV5_03	21800 Marilla Street	Fire station (LA City)	Yes	A	Target point (UHI)	Yes	Roof
SFV5_04	21615 Plummer St.	Office Building (LA County)	Yes	A (n)	Target point (UHI)	Yes	Roof (ground possible)
SFV5_05	21415 Plummer St.	Office Building (LA County)	Yes	A (n)	Target point (UHI)	Yes	Roof (ground possible)
SFV5_06	9035 Canoga Avenue	Office Building (LA County)	Yes	B (wr)	Target point (UHI)	Yes	Roof
SFV5_07	7911 Winnetka Avenue	James Jordan Middle School (LAUSD)	Yes	A	Ref point	Yes	Roof or ground
SFV5_08	8530 Limerick Avenue	Limerick Ave EL (LAUSD)	Yes	A	Ref point	Yes	Roof 18397, 18400 18399, 18393 (S / SE classrooms)
SFV5_09	20620 Arminta Street	Sunny Brae Avenue EL (LAUSD)	Yes	A	Ref point	Yes	Roof (roofs to N and NW)
SFV5_10	7700 Melvin Avenue	Melvin Avenue EL (LAUSD)	Yes	A	Ref point	Yes	Roof or playground 18706, 17904 14826 2 stories
	21050 Plummer Street	CDS Aggeler (LAUSD)		B (wr) (sh)	Target	?	Roof 24466
SFV5_12	9756 Oso Avenue	Superior EL (LAUSD)	Somewhat Yes	A	Ref point	Yes	Roof 18604 2 stories 14761 / 14532
	8140 Vanalden Avenue	Cleveland SH (LAUSD)	Yes	A	Ref point	Yes	Roof 23392 (slight slope)
	8552 Melvin Avenue	Residence (Tree People)	Yes	B	Ref point	Yes	Ground (backyard)
	8401 Winnetka	Recreation center	Yes	A	Ref point	Yes	Ground (Roof possible)

		Parthenia Park (LA City)	Yes	B (bl)	Ref point	?	Ground
SFV5_17		Vanalden Park (LA City)	Somewhat	A	Ref point	?	Roof or ground
		Dearborn Park (LA City)	Somewhat	A	Ref point	?	ground

wr: white roof

bl: boundary location

n: neighboring buildings

sh: shade

We evaluated the initial sites listed in Table 1 with three-dimensional imagery tools (e.g., Google Earth). From this exercise, certain sites were assigned a lower priority based on (1) unavailability of flat roofs (sloped roofs can be an issue for installing monitors), (2) lack of secure sites in open areas (at ground level), and/or (3) physical characteristics. The resulting set of potential sites is shown in Table 2.

While the final selection will depend on site visits by team members and the final agreements with project partners, Table 2 provides a quasi-final recommendation for siting of monitors in SFV5. Specifically, those sites with an entry in the first column of Table 2 should be given priority.

In Appendix A, we present Google Earth images of the SFV5 sites. The top image shows the relative location of each site within the broader neighborhood area and the bottom image depicts the suggested position for siting the monitors on the buildings. The tip of the red arrow in the bottom image locates the proposed position of the monitor at each site. These specific positions will be discussed with partners in Los Angeles and finalized according to partner feedback and model-based siting criteria.

2.2 Operation

For purposes of the current project, each monitor will operate continuously for at least 12 months, to capture spatial differences in air temperature in every hour of the year. This will evaluate the variation of air temperature with the urban fabric in today's Los Angeles.

To assess how these spatial differences evolve in response to the implementation of heat island countermeasures, such as cool roofs and urban vegetation, we will seek to establish a longer program to extend the operation of these monitors to about a decade. We will discuss this extension with our partners and the Energy Commission once the utility of the monitors has been demonstrated.

3 Stationary monitor design

3.1 Overview

We desire the following characteristics for each monitor.

1. The monitor should accurately and continuously measure the primary signal, dry-bulb air temperature; secondary signals, including wind speed, wind direction, solar irradiance, and relative humidity, useful for interpreting variations in air temperature; and monitor diagnostics, such as radiation-shield fan speed, needed to verify that the sensors are operating as designed.
2. To facilitate initial installation and subsequent maintenance, the monitor should be easy to assemble and program.
3. The monitor should be readily installed on an elevated surface, such as that of a low-slope roof, to measure air temperature at some fixed height above ground.
4. The monitor should communicate over the internet for convenient data collection and (if necessary) reprogramming.
5. The monitor should be durable, ideally with a service life approaching a decade.
6. The monitor should cost less than \$5K, in accordance with our proposed budget.

3.2 Fundamentals

A monitor typically comprises multiple weather sensors, a logger, and a support structure. The monitor will run off a battery charged by local AC power or a photovoltaic (PV) panel. If the monitor is to be accessed remotely, it will also have an internet connection, landline modem, or cellular modem.

3.2.1 Weather sensors

The following discussion of environmental measurement focuses on sensors suitable for use in an automated monitor. It omits instruments that are operated manually or only in a laboratory.

Dry-bulb air temperature can be measured with several types of sensor, including but not limited to thermistor (ceramic resistance thermometer), resistance temperature detector (RTD; metal resistance thermometer), or thermocouple.¹ Sensor choice depends on measurement range,

¹ https://en.wikipedia.org/wiki/Temperature_measurement#Technologies

speed, and accuracy, as well as instrument cost and durability. While each technology has merit, a precision thermistor is a low-cost, high accuracy option with sufficient range.²

When air temperature is measured outdoors, the sensor should be shielded and aspirated (ventilated) to reduce errors induced by short-wave (solar) and long-wave (thermal infrared) radiation. This can be accomplished by installing the sensor in a commercial or custom aspirated radiation shield. A commercial unit will typically output a signal indicating its fan speed, which can be monitored to verify that the sensor is being aspirated.

Wind speed can be measured with several types of sensor, including but not limited to three-cup anemometer, vane anemometer, hot-wire anemometer, ultrasonic anemometer, or pressure anemometer.³ Wind direction is usually measured with a wind vane. Weather stations will usually employ a three-cup anemometer to measure speed and a wind vane to measure direction, or a vane anemometer that determines both speed and direction.

Downwelling solar irradiance can be measured with a thermopile pyranometer or a semiconductor pyranometer. If solar irradiance is a secondary parameter, a less expensive semiconductor pyranometer will suffice. Note that if one needs to measure upwelling sunlight—say, to determine solar reflectance of a ground or roof surface—downwelling and upwelling solar radiation should each be measured with a thermopile pyranometer.

Relative humidity (RH) can be measured with several types of sensor, including but not limited to resistive hygrometer or capacitive hygrometer.⁴ A resistive hygrometer bases its RH determination on both the resistance and temperature of a sensing element, and therefore is integrated into a device that reports both RH and temperature.

3.2.2 Logger

A logger (also known as a data logger) typically integrates a programmable microprocessor, analog/digital inputs, analog/digital outputs, non-volatile memory, telecommunication hardware, and battery into a standalone unit that operates the sensors, locally stores their output, and may intermittently transmit recorded measurements to a remote computer or cloud data server. It is also possible to assemble a logger from discrete components, such as a laptop computer and a data acquisition device, or a single-board computer and an analog input module. If the logger is to be installed outdoors for a long time, a standalone unit that can tolerate a wide temperature range and be enclosed in a weather resistant box is the more practical choice.

² <https://www.nist.gov/pml/mercury-thermometer-alternatives-thermistor>

³ <https://en.wikipedia.org/wiki/Anemometer>

⁴ <https://en.wikipedia.org/wiki/Hygrometer>

3.2.3 Power

The logger (and any powered hardware connected to the logger) are usually run off a battery. The battery may be charged with line AC or a PV panel. If the power source is photovoltaic, the panel and battery must be each be large enough to ensure uninterrupted operation. Limited solar availability can present a challenge in winter and in rainy seasons.

While a typically logger and its sensor draw very little power (less than that required by a sleeping laptop computer), the fan in an aspirated radiation shield may consume as much power as the logger and its sensors combined. Some aspirated radiation shields draw much less power than others, and may be particularly suitable to use in a PV-powered system.

3.2.4 Communications

It is possible to manually download data from a local logger over a simple serial cable. However, distant loggers are usually equipped with a telecommunication device, such as a wired or wireless Ethernet adapter, a landline modem, or a cellular modem. If the distant logger is installed outdoors, wireless Ethernet and cellular modem are the most practical options.

A logger can be programmed to upload at regular intervals its recorded measurements and its status to a remote computer or a cloud data server. Frequent (at least daily) transmission and review of data lets the researchers verify that the monitor is healthy.

3.2.5 Research grade monitors vs. hobbyist monitors

All-in-one monitors for hobbyists that measure, record, and transmit air temperature, RH, solar irradiance, wind speed, wind direction, and rainfall are available for about \$1.5K. However, for about \$3K per monitor one can specify a monitor composed up of higher-grade, plug-and-play components that offer greater accuracy and potentially longer service. Since the project effort required to negotiate site access and to analyze measurements costs substantially more than \$1.5K per monitor, and because we would like the monitors to last about a decade, we elect to invest in better equipment.

3.3 Initial design and testing

3.3.1 Selection and purchase of components

We reviewed the specifications and prices of two loggers, six wind speed/direction sensor kits, two silicon pyranometers, two temperature sensors, one RH sensor, and four aspirated radiation shields. We also factored in our positive and negative experiences with some of these instruments in past projects.

After considering all these factors, we specified and purchased a system from Onset that connects to a logger plug-and-play digital-output sensors that measure wind speed, wind

direction, solar irradiance, and temperature/RH). The logger also has a four-channel analog module that can excite and measure analog signals, such as the output of a thermistor circuit (air temperature) and a pulse-counting circuit (fan speed). The logger can upload its measurements to a cloud data server via cellular modem. All components can be mounted on a tripod structure, which in turn can be installed on a roof.

Relevant specifications of the Onset sensors and logger are summarized in Table 4 and Table 5, respectively.

We acquired evaluation units of two aspirated radiation shields—the RM Young 43502, and the Apogee Instruments TS-100 (Table 6)—and an Onset U23 Pro v2 external temperature/relative humidity (T/RH) data logger (U23-002), which is a standalone version of the T/RH smart sensor (THB-M002) used in the monitor. We also purchased two models of precision thermistors: the US Sensor KS103G2, and the Apogee Instruments ST-110.

Table 3. Monitor system from Onset Corporation, including all components except for aspirated radiation shield and thermistor.

Item	Code	Price (\$)
RX3000 3G Remote Monitoring Station	RX3003-00-0	899
RX3000 4-channel Analog Module	RXMOD-A1	120
AC Battery Charger for U30 - 120V, 60Hz	AC-U30	39
Silicon Pyranometer Sensor w/3m Cable	LIB-M003	210
Temp/RH Sensor (12bit) w/2m Cable	THB-M002	189
Light Sensor Bracket	LBB	32
Light Sensor Level	LAA	39
Wind Speed and Detection Sensor Set (Wind Smart)	S-WSET-B (S-WSB-003 + S-WDA-M003)	560
Full Cross Arm Kit	ONM-CAA	72
Complete 2M Tripod Kit	ONM-TPB-Kit	200
Government Discount		-126
Freight		35
Delivered Total		2,420

Table 4. Specifications of Onset sensors, collected from <http://www.onsetcomp.com> . All sensors have a 1 y warranty.

Measurement	Sensor	Range	Accuracy	Resolution	Notes
Solar irradiance	LIB-M003 silicon pyranometer smart sensor	0 to 1280 W/m ²	±10 W/m ² or ±5%, whichever is greater in sunlight. Additional temperature induced error is ±0.38 W/m ² per °C from 25°C	1.25 W/m ²	Drift: < ±2%/y Spectrum: 300 to 1100 nm Cosine response error: ±5%, 0° to 70°; ±10%, 70° to 80° from vertical Azimuth error: ±2% at 45° from vertical, 360° rotation
Wind speed	S-WSB-M003 three-cup anemometer smart sensor	0 to 76 m/s	± 1.1 m/s or ± 4% of reading whichever is greater	0.5 m/s	Starting threshold: 1.0 m/s Operating range -40 to 75 °C Typical service life > 5 y
Wind direction	S-WDA-M003 wind vane smart sensor	0 to 355° with 5° dead band	± 5°	1.4°	Starting threshold: 1.0 m/s Operating range -40 to 75 °C Typical service life: 4 to 6 y
Temperature (used only to determine relative humidity)	S-THB-M002 temperature/RH smart sensor	-40°C to 75°C	± 0.21°C from 0° to 50°C	0.02°C at 25°C	Drift: < 0.1°C/y Response time: 5 min in air moving 1 m/s
Relative humidity	S-THB-M002 temperature/RH smart sensor	0 to 100% RH at -40° to 75°C	± 2.5% from 10% to 90% RH (typical), to a maximum of ± 3.5%	0.1% RH at 25°C	Typical drift: < 1%/y Hysteresis: 1% Response time: 5 min in air moving 1 m/s w/protective cap Exposure to < -20 °C or > 95% RH may temporarily increase maximum error by 1%

Voltage or current	RXMOD-A1 four channel analog module	Various (see next column)	0–25.6 mA DC, $\pm 5 \mu\text{A} \pm 0.15\%$ of reading 0–2.5 V DC, $\pm 0.25 \text{ mV} \pm 0.2\%$ of reading 0–5 V DC, $\pm 0.25 \text{ mV} \pm 0.2\%$ of reading 0–10 V DC, $\pm 0.3 \text{ mV} \pm 0.2\%$ of reading 0–20 V DC, $\pm 0.6 \text{ mV} \pm 0.2\%$ of reading 0–33 V DC, $\pm 1.20 \text{ mV} \pm 0.2\%$ of reading	15 bits	Input voltage 0 to 33 V Input current 0 to 25.6 mA 12 V DC $\pm 5\%$ at 200 mA maximum per module
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Table 5. Specifications of Onset RX3000 logger, taken from <http://www.onsetcomp.com/products/data-loggers/rx3000> .

Operating temperature range	-40 to 60 °C
Logging interval	1 min to 18 hours
Battery	4 V, 10 Ah rechargeable sealed lead-acid; service life 3 to 5 y when operated at -20 to 40 °C
Memory	32 MB (2 million measurements, continuous logging)
Smart sensor connectors	10 (with up to 15 data channels; some smart sensors use more than one channel)
Analog inputs	4 (via RDMOD-A1 analog input module)
Environmental rating	Weatherproof enclosure, NEMA 4X (requires proper installation of cable channel system)
Warranty	1 y

Table 6. Specifications of two aspirated radiation shields evaluated at LBNL.

	Apogee TS-100^a	RM Young 43502^b
Operating temperature range	-40 to 70 °C	-50 to 60 °C
Aspiration rate	6 m/s at full speed 3 m/s at half speed	5 to 11 m/s depending on sensor size
Fan voltage	10.8 to 13.2 VDC	12 to 14 VDC
Fan current	80 mA at full speed 25 mA at half speed	420 to 480 mA
Fan power demand (estimated as mean voltage × mean current)	0.96 W at full speed 0.3 W at half speed	5.9 W
Fan service life	50,000 hours (5.7 y) of continuous operation at full speed	> 80,000 hours (9.1 y) of continuous operation
Radiation error in measured air temperature	< 0.1 °C difference from Met One fan aspirated shield when measured over snow < 0.1 °C difference among replicate shields	< 0.2 °C RMS at 1 kW/m ² solar irradiance < 0.05 °C RMS with like shields equally exposed
Tachometer (fan speed) output	1 pulse/2 revolutions	2 pulses/revolution
Warranty	4 y	1 y
Price	\$445	\$454

^a <http://www.apogeeinstruments.com/content/TS-100-spec-sheet.pdf>

^b [http://www.youngusa.com/Brochures/43502\(1106\).pdf](http://www.youngusa.com/Brochures/43502(1106).pdf)

Table 7. Specifications of two precision thermistors.

	US Sensor KS103G2 ^a	Apogee ST-110 ^b
Description	10 kΩ at 25 °C negative temperature coefficient thermistor	same
Operating temperature range	-55 to 135 °C	-35 to 70 °C (?)
Uncertainty (interchangeability)	0.9 °C from -40 to <-20 °C 0.4 °C from -20 to <0 °C 0.1 °C from 0 to 70 °C 1.0 °C from >70 to 100 °C 1.8 °C from >100 to 125 °C 2.15 °C from >125 to 135 °C	0.15 °C from -35 to <0°C 0.1 °C from 0 to 70 °C
Repeatability	not reported	< 0.01 °C
Drift		< 0.02 °C/y in non-condensing environment with annual average temperature < 30 °C
Self-heating	1 °C/mW	< 0.01 °C typical with 2.5 V excitation
Response time	time constant 10 sec max in still air, 1 sec max in well-stirred oil	4 s equilibration time
Cabling	none	5 m shielded, twisted pair constantan wire (thermal conductivity 20X smaller than that of copper wire)
Voltage divider included	No	Yes
Price	\$5.6	\$50 when bundled with shield \$65 otherwise

^a <http://www.ussensor.com/standard-precision-interchangeable-thermistors-01%C2%B0c-and-02%C2%B0c-accuracy>

^b <http://www.apogeeinstruments.com/content/ST-100-110-200-300-spec-sheet.pdf>

3.3.2 Shield and temperature sensor tests

Extensive testing at LBNL in September 2016 of the Apogee Instruments (AI) and RM Young (RMY) shields with a pair of KS103G2 thermistors and the U23 T/RH sensor (Figure 2) indicated the following.

Figure 2. The two aspirated radiation shields mounted side-by-side during outdoor testing. On the left is the AI shield; on the right is the RMY shield. A pyranometer (foreground) monitors sunlight, while two data loggers (background) record sensor outputs at 10-sec intervals.

1. It is possible to install both the T/RH sensor and at least one thermistor in either shield.
2. It is more convenient to secure a thermistor in the horizontal center of the vertical inlet tube of the AI shield than in that of the RMY shield, because sensors are mounted nearly horizontally in the former, and vertically in the latter (Figure 3).
3. When inserted in the AI shield, the temperature sensing element of the T/RH probe (itself a thermistor) lies very close to the wall of the inlet tube near the probe's cable, and therefore

is not in the center of the air stream (Figure 3a). This may reduce the accuracy of the temperature and relative humidity reported by the T/RH sensor, although we were not able to quantify this potential error.

4. Either type of sensor can be installed in the RMY shield inlet tube, but spacers are needed to keep the sensors away from the tube's inner wall (Figure 3b).

Figure 3. Bottom view through the vertical inlet tube inside each shield. The AI shield (panel a; with T/RH probe and thermistor installed) mounts sensor probes at a near-horizontal angle, while in the RMY shield (panel b; with thermistor installed), sensor probes hang vertically downwards. Thermistor bead in AI shield is about 5 mm below T/RH probe. In the RMY shield, a circular metal wire spacer is used to prevent the thermistor bead from contacting the inner walls of the tube.

5. When placed in a single shield, or distributed across two shields, indoor air temperatures measured by the three sensors agreed to within < 0.1 °C (Figure 4). The response time of the T/RH sensor was clearly longer than that of the thermistor, but this is not likely to be important, given that air temperatures will be averaged over minutes, rather than seconds.

Figure 4. Indoor air temperatures, measured at 10 sec intervals by the T/RH sensor and thermistor(s) when mounted inside: (a) the RMY shield and (b) the AI shield. In both configurations, the sensors agreed to within 0.1 °C.

6. Wrapping a sensor in aluminum foil (Figure 5) is a simple and effective way to minimize its absorption of both short-wave and long-wave radiation.

Figure 5. The T/RH probe (panel a) and a thermistor bead (panel b) wrapped in foil. The red circle marks the approximate location of the temperature sensing element inside the T/RH probe.

7. When placed in a single shield, or distributed across two shields, outdoor air temperatures measured by the three sensors on a sunny afternoon in September can vary substantially, even if the sensors are wrapped in foil. Each shield demonstrated a similar ability (or inability) to mitigate radiation-induced errors in daytime outdoor air temperature measurement (Figure 6).

Figure 6. Outdoor air temperatures recorded at 10 sec intervals by each of the three sensors when arranged in the following configurations: (a) bare T/RH sensor and thermistor inside the RMY shield, and bare thermistor inside the AI shield; (b) foil-wrapped T/RH sensor and thermistor inside the RMY shield, and foil-wrapped thermistor inside the AI shield; (c) bare T/RH sensor and thermistor inside the AI shield, and bare thermistor inside the RMY shield; (d) foil-wrapped T/RH

sensor and thermistor inside the AI shield, and foil-wrapped thermistor inside the RMY shield. The agreement between the sensors improves when the probes are wrapped in foil.

8. The radiation-induced errors likely result from the absorption at the inner surface of the inlet tube of upwelling radiation, including ground-reflected short-wave radiation and ground-emitted long-wave radiation.
9. It may be possible to mitigate these errors by placing below the shield's inlet a shiny metal baffle (e.g., a piece of aluminum) that strongly reflects both short- and long-wave upwelling radiation. The challenge is to avoid impeding the intake of air. We are continuing to explore this matter.

Based on the above testing, we determined that the AI and RMY shields were each suitable for our purpose. We selected the AI shield because (a) it draws much less power, which may prove helpful if a monitor's battery must be charged with a PV panel; and (b) it is easier to mount a thermistor (though not a T/RH sensor) in the center of the air flow. We purchased the AI shield and returned the RMY shield.

We also decided that while it may be possible to use the T/RH probe to measure air temperature, the location of its temperature sensor is uncomfortably close to the inner wall of the AI shield's inlet tube. Therefore, we prefer to rely on a thermistor to measure air temperature in the AI shield, and will use the monitor's T/RH smart sensor primarily to measure RH. We returned the handheld U23 T/RH sensor.

Finally, while we were impressed with the high accuracy and low cost of the KS103G2 thermistor, it does not include the cabling or the voltage divider circuit needed to use it as a temperature sensor. Our experience is that is more economical to buy a complete product than to purchase and assemble components. Therefore, we are inclined to use instead the AI ST-110 thermistor, which is more expensive (\$50 vs. \$6) but is ready to connect to the logger's analog input module.

3.3.3 Initial test monitor (Monitor0)

The Onset logger, Onset sensors, AI shield, and AI thermistor were sent to University of Southern California (USC) for assembly and configuration of "Monitor0," our initial test monitor. Monitor0 is being used to learn how best to build, configure, and operate the monitor prior to deploying monitors at sites around Los Angeles. We will also cross calibrate the other monitors against Monitor0 before they are deployed to ensure differences measured between sites is due to outdoor temperature differences, and not inconsistencies in sensors.

Monitor0 was initially assembled in a lab at USC to learn the assembly process, and was later installed outdoors at a secure site just off campus (Figure 7). While being assembled in the lab, each sensor was tested by ensuring that logged values were as expected. Note that all sensors were factory calibrated.

The team found that assembling the monitor takes about three to four hours after mastering the technique. The monitor's "body" consists of a tripod, mast, and a cross arm that is installed on the top of mast. The assembled monitor is shown in Figure 8.

The weight of the body is about 13.5 kilograms. Once all sensors, wiring, and ballasts are connected to the body, the monitor weighs ~27 kilograms. To secure the monitor to the ground on site at USC, we connected a wooden board to each tripod foot, and placed heavy concrete bricks on each board (Figure 9). When monitors are installed on roofs, we may use more bricks for extra stability.

The team also extensively tested sensor connections to the data logger, transmission of data via the logger's cellular connection, and the HOBO website used for remotely accessing data.

The monitor's data logger provides various options for sampling frequency and data averaging. These options can be set on the logger website. Data from the logger are sent via cellular modem every four hours and are available for viewing and download from the HOBO website. Figure 10 shows the configuration options on the website. The logging time represents the time between measurements being recorded by the logger. The sampling time sets the number of measurements that are sampled and averaged per data record on the logger. This setting is only supported for the temperature and radiation sensors; the wind speed and wind direction sensors can only report instantaneous measurements and cannot be averaged as recorded by the logger. Currently we are using a six second sampling interval and 1 min logging interval. In this case, data are logged once per minute, and each data point is the average of 10 samples (per minute).

After receiving the data, the HOBO website presents a preview of the data received from the logger for each sensor. The logger using a cellular modem connects every four hours to the HOBO server to automatically upload data. The data can be downloaded from the server using direct download, ftp download, or scheduled for delivery over email. These options can be used in case any partners are interested in viewing the data. Figure 11 shows a preview of the recorded data over the past week and the HOBO website's user interface.

Figure 7. The location of Monitor0, marked on the map with a red star.

Figure 8. Monitor0 installed at the USC outdoor site. The light sensor, wind speed and direction sensors, and data logger are shown. The temperature/RH sensor is inside the shield, hanging from the cross arm.

(a)

(b)

Figure 9. A close-up of the monitor's tripod feet connected to the wooden boards (a), and concrete bricks on the plates used to secure the monitor (b).

(a)

General
Readout
Smart Sensors
Logging
Temperature
RH
Dew Point
Wind Speed
Gust Speed
Wind Direction
Solar Radiation
Module 2: Analog Sensors
Logging
Channel 1: Select Analog Sens
Channel 2: Select Analog Sens
Channel 3: Select Analog Sens
Channel 4: Select Analog Sens
Battery
Start/Stop
Alarms

Module Configuration

Back Save Next

*Logging Interval:
0 hours 1 minutes 0 seconds

Sampling Interval:
☒ Enable 0 minutes 6 seconds

Actual usage to date
2% of plan
This Month

Estimated usage with this configuration
18% of plan
This Month

*Data usage estimation assumes no tripped alarms or logger launches.

(b)

General
Readout
Smart Sensors
Logging
Temperature
RH
Dew Point
Wind Speed
Gust Speed
Wind Direction
Solar Radiation
Module 2: Analog Sensors
Logging
Channel 1: Select Analog Sens
Channel 2: Select Analog Sens
Channel 3: Select Analog Sens
Channel 4: Select Analog Sens
Battery
Start/Stop
Alarms

Sensor Configuration

Back Save Next

Latest Value: 30.12 °C

Label:

☒ Enable Graph

☐ Enable Scaling

KWh KW

*Scaled Units = *Multiplier x Value + *Offset

*Scaled Measurement Type:

Serial Number: 10993592-1

Product Code: S-THB

Figure 10. A preview of the settings available for the logging, sampling and scaling of the sensors. The two screens shown are logging and sampling interval options (a), and temperature scaling (b).

Figure 11. A preview of the graphical user interface on the HOBO website. Values show five days of measured temperature, humidity, dew point, and wind speed and direction sensors. The former three variables show one minute averages, while the latter two are instantaneous values for each minute.

4 Cross Calibration of Monitors

4.1 Deployment

Three monitors (Monitor1, Monitor2, and Monitor3) were placed near Monitor0 in the USC parking structure for cross calibration. Cross-calibration procedure was done in three stages starting from 20:30 local time (LT) on 2017-07-20 to 20:30 LT on 2017-07-23. In stage 1, the monitors were located near each other and the radiation shields were placed on two adjacent tripods (Figure 12). Each shield included a RH/T probe and a thermistor. In stage 2, all four thermistors were placed in one shield; we could not place all four RH/T sensors in one shield because they were too large to fit. Stage 3 was similar to stage 1, except that the locations of Monitors 1, 2, and 3 were swapped (Figure 13).

Figure 12. The location of four shields, installed on two tripods in stage one. The orange markers show the shield associated with each monitor.

Figure 13. The location of four shields in stage 3 (similar to stage 1, but swapping locations of Monitors 1, 2, and 3).

4.2 Results

The measurements from thermistors and RH/T probes were collected and compared to each other. The results of the cross calibration are presented in four sections: (1) comparison of all RH/T sensors with reference RH/T sensor; (2) comparison of thermistors in separate shields (in stages 1 and 3) with each other; (3) comparison of all thermistors with the reference thermistor (in stage 2, where we located them all together); and (4) comparison of measurements from thermistors to measurements from RH/T probes that were placed in the same shields.

In each stage, the data was collected from monitors in intervals of one minute for duration of 24 hours (60*24 points per day per sensor). Note that the sensors collect data every 6 s, and report average of collected data in span of each minute.

4.2.1 Comparison of RH/T sensors

The comparison of RH/T probes are available for stages 1 and 3, in which each shield contained an RH/T probe and a thermistor. Figures Figure 14 and Figure 15 show the results of the comparisons. The results of these comparisons show negligible difference between the measurements from RH/T sensors in both stages.

Figure 14. The comparison of RH/T probes in stage 1. The black lines represent $y=x$.

Figure 15. RH/T comparison in stage 3. Black lines represent $y=x$.

The bias for each thermistor has been calculated using two different methods. In Method 1, Monitor0 has been selected as reference and all other monitors were compared to it. In Method 2, we accepted that the mean of all the monitors as the ground truth and compared all other monitors.

Table 8 shows the root mean square deviation (RMSDs) for both methods. Overall the errors are negligible, as they are smaller than to RH/T probe accuracy of 0.2 °C. The errors from all monitors are within the same order of magnitude and as expected, the errors are smaller for method 1 because the measurements from all monitors are compared to the average of the four monitor.

Table 8. RMSD for RH/T probes comparison for Stage 1 and 3

	Stage 1		Stage 3	
	Method 1	Method 2	Method 1	Method 2
Monitor0	0.114	-	0.0465	-
Monitor1	0.0887	0.183	0.0901	0.118
Monitor2	0.0476	0.128	0.0444	0.0457
Monitor3	0.0931	0.183	0.0765	0.103

4.2.2 Comparison of thermistors in separate shields

The results for comparison of thermistors probes are available for stages 1 and 3. Figures Figure 16. The comparison of thermistors in stage 1. The black lines represent $y=x$.and Figure 17 show the results of the comparisons. The results of these comparisons show negligible difference between the measurements from RH/T sensors in both stages.

Table 9 shows the root mean squared errors for both methods. Overall the errors are negligible and rather consistent for all sensors. As expected, and as seen earlier, the errors are smaller for method 1 because its reference is the average of the four monitors.

Table 9. RMSD for thermistors in stages 1 and 3.

	Stage 1		Stage 3	
	Method 1	Method 2	Method 1	Method 2
Monitor0	0.132	-	0.102	-

Monitor1	0.193	0.317	0.0747	0.171
Monitor2	0.0997	0.177	0.0919	0.0880
Monitor3	0.130	0.137	0.110	0.202

Figure 16. The comparison of thermistors in stage 1. The black lines represent $y=x$.

Figure 17. Comparison of thermistors in stage 3. Black lines represent $y=x$.

4.2.3 Comparison of thermistors in same shield in stage 2

The measurements from all four thermistors that were located in the same shield in stage 2 are compared with each other. Figure 18 shows the results of the comparison. As all four sensors were located near each other and sensors were collecting data from the same environment, the data from all thermistors correlate with each other with negligible differences. The slopes of Monitors 1, 2, and 3 vs. Monitor 0 are close to unity.

4.2.4 Comparison of RH/T probes and thermistors

The measurements from RH/T probes and thermistors that were located in the same solar radiation shield are compared to each other for stages 1 and 3. Figures Figure 19 and Figure 20 show the results of the comparison. The slopes of the correlations are varying between 0.84 and 0.92. The only significant difference can be observed in Monitor1 results from Stage 1. This difference can be tracked to the measurements from the RH/T probe, seen in Figure 15. RH/T comparison in stage 3. Black lines represent $y=x$. Since the monitor does not report similar differences results in stage 1, thus we can assume that the differences were due to the differences in locations of the shields.

4.3 Conclusions

The results of cross calibration shows negligible biases. RMSD values are mostly lower than the accuracy of the RH/T sensors (± 0.2 °C). The results of comparing the thermistors and RH/T probes show correlation factors of 0.84-0.92 between the RH/T and thermistor measurements, based on monitor and time of measurements. The only inconsistency between thermistors and RH/T sensors is Monitor1 at stage 3, which shows a slightly higher slope than the rest of the sensors. As this difference in slopes only occurs in stage 3, and the comparison between the thermistor of Monitor1 and Monitor0, and the RH/T probe of Monitor1 and Monitor0 show negligible differences, we can assume that the differences are results of random biases.

Figure 18. Comparison of thermistors in stage 2. Black lines represent $y = x$.

Figure 19. Comparison of thermistors and RH/T probes that were placed in same shield in stage 1. Black lines represent $y=x$.

Figure 20. Comparison of thermistors and RH/T probes that were placed in same shield in stage 3. Black lines represent $y=x$.

5 Mobile apparatus for mapping near-ground air temperature

Air temperature near the ground (say, 2 m above ground level) can be mapped by attaching a thermometer to roof of a vehicle, such as a car, then logging temperature, position, and time during a transect. To ensure that the thermometer accurately measures air temperature, its sensor should be aspirated by the motion of the vehicle, shielded from the sun, and radiatively isolated from its shield. The sensor should also respond quickly to air temperature changes to minimize spatial inaccuracies, or blurring, in the air temperature map induced by the motion of the vehicle.

Our mobile transect apparatus (hereafter, the apparatus) contains five elements: (1) a shielded temperature sensor aspirated by vehicle motion; (2) a quick-install mount to attach the shielded sensor to the roof of a vehicle; (3) a portable data logger to record the temperature time series; (4) a global positioning system (GPS) to record the position time series; and (5) a dash camera (dash-cam) to record time-stamped video of the transect from the perspective of the driver.

5.1 Shielded temperature sensor

To minimize sensor response time and blurring of the temperature map, we selected the small negative temperature coefficient thermistor (US Sensor model KS103G2, diameter 2.5 mm, electrical resistance 10 k Ω @ 25 °C; US\$5) shown in Figure 21 as the temperature sensor. The manufacturer-reported time constant of this bead thermistor is not more than 10 s in still air, and should be substantially less in moving air. Note that a 5 s delay in response will yield a 50 m error in temperature measurement location if the apparatus is traveling at 10 m/s (22 mph).

The nominal accuracy of this thermistor is ± 0.1 °C from 0 to 70 °C, with an operating range of -80 to 135 °C.

To minimize the sensor's solar heat gain, we installed it at the center of a 25" length of size 6, schedule 40 white PVC pipe (length 63.5 cm, outer diameter 16.8 cm, inner diameter 15.4 cm, wall thickness 0.71 cm), as shown in Figure 22. If the pipe is horizontal and faces the sun, it shields the sensor from all beam sunlight when the solar elevation angle is 14° or greater.

We selected a wide pipe to facilitate air flow through the pipe and around the sensor when the length of the shield is parallel to the motion of the vehicle. This enhances convective heat transfer between air and sensor. We estimate that the convective heat transfer coefficient of the sensor is about 80 W/m²·K at an air speed of 1 m/s (2.2 mph), rising to 170 W/m²·K at 5 m/s (11 mph), 240 W/m²·K at 10 m/s (22 mph), and 340 W/m²·K at 20 m/s (45 mph).

To minimize radiative heat transfer between the sensor and the inner surface of the shield, we wrapped in the sensor in aluminum foil as shown in Figure 23 and Figure 24. (Since the sensor is

essentially enclosed by the much larger shield, there is little benefit to foil-lining the inner surface of the shield, which will act as a black body cavity regardless of its thermal emittance.) The foil has an initial (clean) thermal emittance of about 0.03. If soiling by dust in the air increases the foil's thermal emittance to 0.10, the radiative heat transfer coefficient between the foil-wrapped sensor and the shield will be about $0.6 \text{ W/m}^2\cdot\text{K}$. This is about 400 times smaller than the convective heat transfer coefficient when the sensor is in a 10 m/s air stream. Note that even if the foil were to vanish, the radiative heat transfer coefficient from the bare sensor (thermal emittance about 0.90) to the shield would be about $5.5 \text{ W/m}^2\cdot\text{K}$. This remains about 40 times smaller than the sensor's convective heat transfer coefficient in a 10 m/s air stream.

5.2 Quick-install mount

We built a quick-install mount for the shielded sensor that places the bead about 48 cm above the roof of the vehicle, or about 2 m above ground level when installed on 1.5 m tall passenger car. Vertical risers support the shield over pair of removable aluminum mounting bars (Proline Racks model CB-602 universal roof rack; US\$40) with straps that hook to the vehicle's frame, while crossbeams horizontally stabilize the mounting bars. The risers, crossbeams, and assorted fittings are all made of PVC. Each mounting bar rests on wide plastic feet with rubber soles that protect the roof (Figure 25).

The shield is permanently affixed to the mount, but the mount itself can be attached to a vehicle roof (Figure 26) in about 10 minutes.

5.3 Portable data logger

A handheld, battery-powered data logger with LCD screen (Lascar Electronics model EL-USB-TP-LCD; US\$100) records temperatures measured with the thermistor. The logger can store a time-stamped series of up to 32,000 values with a resolution of $0.1 \text{ }^\circ\text{C}$ and a frequency of up to 1 measurement per second. We detached the thermistor probe supplied with the data logger because the probe encapsulates its thermistor in a 75 mm long, stainless steel tube expected to respond slowly to changes in air temperature (Figure 27). We substituted the US Sensor bead thermistor described above, which was chosen to match exactly the resistance versus temperature curve of the thermistor in the original probe. The bead thermistor was soldered to the end of a 4 m cable that plugs into the logger, which in turn is placed inside the car. The cable is snaked through a slightly open window.

Temperature measurements are recorded at 1 Hz, at which frequency the logger can store nearly 9 hours of data. The logger must communicate with a computer to start logging and to download results, but can record data by itself, and does not require external power. The logger's clock is set to network time when connected to the computer.

5.4 Global positioning system

A smartphone app (MapMyTracks, iOS/Android; free) uses GPS and/or cellular tower data to record a time-stamped series of locations (latitude, longitude) at a frequency of one measurement every two to three seconds. The location time series is stored in the cloud, and later downloaded. The phone must be externally powered while recording position to avoid draining its battery.

Note that while both the smartphone clock and the temperature logger clock are synced to network time, the logger records temperatures more frequently than the location app records positions. Therefore, the combination of logger and app yields spatially located temperature measurements at the frequency of the location app (~ 0.3 to 0.5 Hz).

5.5 Dashboard camera

A dashboard camera (KDLINKS model X1; US\$170) records high-definition, time-stamped video through the vehicle's windshield (Figure 28), storing up to 88 min of 1920 by 1280 pixel, 30 frame/sec imagery on a 32 GB memory card (generic; US\$15). The camera must be externally powered while recording video to avoid draining its battery.

The camera is manually synced to network time to ensure that the times and dates displayed on the video match those recorded by the temperature logger and location app. While the use of a camera is optional, it provides a visual record of the transect for later reference.

Figure 21. Schematic of bead thermistor used in transect apparatus. Graphic from <http://USSensor.com> .

Figure 22. Clip used to secure bead thermistor in center of shield.

Figure 23. Bead thermistor wrapped in aluminum foil, then secured with clip in center of shield.

Figure 24. Close-up of bead thermistor wrapped in aluminum foil.

Figure 25. Sensor shield on quick-install mount, including white PVC-pipe shield, gray PVC-pipe vertical risers, aluminum tube roof mounting bars (left to right) on plastic and rubber feet, and white PVC-pipe crossbeams (front to back). Straps with hooks (not shown) secure the bars to the vehicle frame.

Figure 26. Shield on quick-install mount, strapped to the roof of a car.

Figure 27. Temperature logger shown with stock thermistor probe. The detachable probe was replaced by a 4 m extension cable leading to the foil-wrapped bead thermistor shown in Figure 24.

Figure 28. Dash-cam recording video through car windshield.

6 Stationary monitor deployment

6.1 Deployment plan

We decided to stage the deployment of the monitors and will initially focus on one study area. This decision is based on both technical and implementation considerations. This is technically a good decision because it allows us to learn from the initial installation of monitors. Once the first monitors have been installed, initial results will be examined and checked against anticipated UHI or UCI signal as well as against other potential indicators, such as such as wind speed and direction to determine upwind fetch. If the signal or other aspects of installation indicate potential issues, the monitors may be moved to other locations within the study area. In addition, based on the temperature observations in the first study area, we can select additional study areas that will provide complementary data.

By focusing on one study area, we have a shorter priority list of potential partner sites to focus on, which will simplify the installation approval process. This list was also much easier for

partners to share with their other departments and management, and reduces the number of department districts and regions that need to approve the installation.

Our first study area will be SFV5 (Figure 29). This study area was selected because there were many potential partner sites (Table 2), and it was identified as a high priority area from our modeling results noted in the Task 2 report. We have not yet finalized the number of monitors that we will install in SFV5. It will depend on the number and location of partner sites. However, we will need to install one or more monitors in the UCI or UHI target zone and reference area. We anticipate installing between three and seven monitors in SFV5.

Figure 29. SFV5 in the San Fernando Valley will be our first study area to deploy monitors.

We are planning to install the SFV5 monitors in early 2017. Once installed, we will monitor the data for a few weeks to check that the monitors are sited correctly. If the initial monitoring in SFV5 indicates potential issues or does not capture a significant climate signal, it may be necessary to relocate the monitors to other positions within each site or to alternate sites within SFV5 area. A similar approach will be adopted in other areas selected for monitoring.

After successful deployment of monitors in the first study area, we will begin installation of the remaining monitors. Planning for the second study area will be run in parallel with the deployment of monitors in SFV5. Since we have targeted a study area in San Fernando Valley for the first installations, we will aim to find a complementary study area in Area_1. However, since we have not finalized the number of monitors that will be installed in SFV5, we have not yet determined if we will install monitors in more than two study areas. That will depend on our observations from SFV5.

6.2 Acquisition of monitor sites

We have been in contact with our original project partners and new project partners to help us find suitable sites to install the monitors. Our original project partners were the Los Angeles Unified School District, City of Los Angeles, Los Angeles Department of Water and Power, and Los Angeles Regional Collaborative. New project partners include the County of Los Angeles and [TreePeople](#) (non-profit working on urban forestry in Los Angeles).

6.2.1 Monitor site parameters

Ideally, the sites we install monitors will be (have)

- Secure (not easily accessible to public)
- Easily accessible to project staff
- Stable ownership
- Minimum 2-year commitment
- Access to wireless or wired internet
- Access to electricity
- Long-term commitment to hosting (5 to 10 years)

We are communicating this list to our partners. We will also develop an agreement between LBNL and the site organizations to ensure the minimum participation of two years with the various location features.

6.2.2 Locating potential partner facilities in study areas

After the team identified the study areas described in Section 2.1.1, Taha and Gilbert reached out to all of the original partners with phone calls to present the study areas, discuss the process of selecting these areas, and describe the parameters needed for a monitor host site. Taha and Gilbert also traveled to Los Angeles to present the project at a UHI Convening hosted by Climate Resolve and the City of Los Angeles. At this meeting, we were able to enlist the participation of the County of Los Angeles and TreePeople to join the project partners.

The initial step in finding suitable locations for the monitors was to identify all partner facilities in the study areas. This was easy with some partners, such as the County of Los Angeles, and more difficult with others, such as the City of Los Angeles. While the County of Los Angeles had developed a map of all of their facilities, the City was still trying to develop this type of resource. Therefore, we manually found and located facilities from Bureau of Street Services (fleet yards), Fire Department (fire stations) and Los Angeles Public Library (library branches) that overlapped with our study areas.

Another challenge with finding potential sites was finding the best contacts within the partner organization. We had the support of the Los Angeles Unified School District but our initial contact was not within the Facilities Division. However, after back-and-forth communications and some meetings with our initial contact, we found someone in Facilities that was immediately able to

connect us with maps of their facilities and serve as the primary contact to install the monitors. This was a similar challenge with the City of Los Angeles as well. We had been in contact with several staff members that kept directing and redirecting us to other Departments. When we asked for specific Department contacts the request was not prioritized so was never answered. Recently, Gilbert visited Los Angeles and met with City staff and identified the staff that will be responsible for coordinating efforts across the City Departments.

After working for many weeks, we developed a good list of potential sites. The second step was to convey this list to the partners to see if these sites were feasible.

6.2.3 Targeting initial deployment in SFV5

Since we had many study areas, therefore many potential sites, communications with our partners became complicated. To simplify the selection of sites from the implementation and technical perspective, we decided to first focus on one study area SFV5 (more details in Section 6.1). This proved to be extremely helpful in guiding our partners to which locations were first priority. Table 2 lists the potential sites from our partners in SFV5. Gilbert visited Los Angeles in early November to meet with the three key partners with facilities in SFV5—County of Los Angeles, City of Los Angeles, and Los Angeles Unified School District. She hosted the school district staff at the USC location to check out Monitor0 in person, visited City Hall to meet with various staff from the Office of the Mayor and Departments, and had a meeting with the County of Los Angeles contacts. At each meeting, she shared the priority list of potential sites, reviewed the monitor site parameters and photos of the installed monitor at USC, presented a snapshot of the data that would be available to the partners, and discussed the monitor host agreement.

These in-person meetings appeared to be helpful. All partners agreed to most of the parameters for installing a monitor. However, there is still some negotiations and approvals that are needed to get final go-ahead to begin installations. Currently, we are working with LBNL and partner legal teams to find an agreement that will meet both institutions' requirements.

6.3 Deployment to date

For this project, we installed four weather stations in multiple locations across the regions of interest. Figure 30 shows the location of four monitors on the map. The first weather station (Monitor0) was deployed on Oct 2016, and has been used as the test monitor and the reference for calibration of other monitors. All monitors were installed temporary together in July 2017 in PSX structure and calibrated. Monitor0 is located in parking structure X (PSX) near USC campus for ease of access and the safety of that location (Figure 31). The date of installation and the location of the monitors are presented in Table 10. Figure 31 - Figure 34 show the location of the monitors in local neighborhoods.

Table 10. Location and installation date of installed monitors

Station	Date of installation	Location
Monitor0	10/26/2016	PSX structure of USC campus near downtown
Monitor1	7/25/2017	Bureau of Street Service parking in SFV
Monitor2	1/11/2018	Sunny Brae Ave elementary school in SFV
Monitor3	4/13/2018	Melvin Ave elementary school in SFV

Figure 30. Location of four installed monitors on map of Los Angeles county.

Figure 31. Location of Monitor0 near USC campus. The exact location is marked with a red mark.

Figure 32. Location of Monitor1 in SFV at parking structure of Bureau of Street Services. The exact location is marked with a red mark

Figure 33. Location of Monitor2 in SFV at Sunny Brae Ave elementary school. The exact location is marked with a red mark

Figure 34. Location of Monitor3 in SFV at Melvin Ave elementary school. The exact location is marked with a red mark.

All four monitors are installed at 2 m elevation from the surface (whether it is ground or roof) and Monitor0 is the only monitor that is placed on the ground. Figure 35 - Figure 38 show the details of installation of each monitor. Monitor0 and Monitor1 were secured on the surface using ballasts. Monitor1 also is secured to the surface using anchors that are connected to the parking structure, as it is installed on the roof and extra cautious is necessary.

Monitor2 and Monitor3 are installed on the roof of two elementary schools. Thus, we did not use ballasts (for safety purposes). Instead we installed the monitors on existing poles that were already at place on the roof of the buildings. LAUSD provided us with technical experts to install the monitors on the roof, which made the process of installation on the roof easier.

Figure 35. Monitor0 after installation. The ballasts used for securing the monitor are visible in this picture.

Figure 36. Monitor1 after installation on roof of BSS parking structure. The ballasts and the anchors used in securing the monitor are visible in this picture.

Figure 37. Monitor2 installed and connected to an existing pole in Sunny Brae Ave school. The sensors are connected to the south of the pole in order to be out of shadow of the pole.

Figure 38. Monitor3 installed and connected to an existing pole on the roof of a building in Melvin Ave elementary school.

Appendix A. Potential sites in SFV5

Potential sites in SFV5 (top image) with proposed monitor location identified with tip of red arrow (bottom image)

SFV5_03

SFV5_04

SFV5_05

SFV5_06

SFV5_07

SFV5_08

SFV5_09

SFV5_10

SFV5_12

SFV5_17

California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix D

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APD

Appendix D: Atmospheric modeling to support site identification and selection for fixed weather stations: Siting of weather stations (Task 3 Report, Part II)

Haider Taha

Altostratus, Inc.

31 Oct 2016

Atmospheric Modeling to Support Site Identification and Selection for Fixed Weather Stations: Siting of weather stations

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LIST OF ACRONYMS

AGL	Above Ground Level
ARB	Air Resources Board
ARW	Advanced Research WRF
GFS	Global Forecast Model
JJA	June, July, and August
LBNL	Lawrence Berkeley National Laboratory
LULC	Land Use / Land Cover
MADIS	Meteorological Data Assimilation Ingest System
MPE	Model Performance Evaluation
NCAR	National Center for Atmospheric Research
NCDC	National Climatic Data Center
NLCD	National Land Cover Data
NOAA	National Oceanic and Atmospheric Administration
NCEP	National Centers for Environmental Prediction
NUDAPT	National Urban Database and Access Portal Tool
NWS	National Weather Service
UCI	Urban Cool Island
UHI	Urban Heat Island
uWRF	Urbanized WRF model
WRF	Weather Research and Forecasting model

A. SITE SELECTION FOR FIXED MONITORING

A.1 Goal

The goal of this task is to identify sites for fixed weather monitoring (installation of weather stations) based on 1) results from meteorological modeling and 2) suggestions and availability as provided by project partners in the Los Angeles region. A related goal is to rank the sites in terms of anticipated signal (localized heat or cool islands – UHI / UCI), land-use and land-cover properties, and physical properties of the sites.

A.2 Sites identification and selection: Step A

The atmospheric modeling, configurations, and analysis of results were discussed in a prior technical report submitted July 7th, 2016. Here, we discuss only the additional siting considerations that followed the modeling results.

Several sites were identified in LA1 and San Fernando Valley study domains based on model and initial mobile-transect results (technical criteria). Those areas were further narrowed down based on suggestions from project partners in Los Angeles. The suggested sites were evaluated based on technical criteria and location relative to model-predicted UHI / UCI points. A summary listing and evaluation as of this report's date are shown in Table 1 and the areas of suggested sites are also indicated in Figure 1. In this figure, several areas of interest are shown both in LA1 (top figure) and San Fernando Valley (bottom figure) study domains. Each area of interest is marked with two polygons: a yellow polygon indicating the target zone (UHI or UCI) and a white polygon outlining the reference area (where reference monitors will be placed).

It should be noted, however, that the final selection of monitoring sites will be pending approval from and agreements with partners in Los Angeles with regard to site availability, accessibility, security, and other logistics. This finalized set of sites will then be submitted to the Energy Commission's Agreement Manager for full approval.

In Table 1, modeling points for which no sites have been suggested to date are not shown. It is important to consider that, in some cases, it may be more effective to select two or more target points (in any yellow polygon) and two or more reference points (in corresponding white polygons) in each area to better capture area-wide flow and temperature patterns, as well as time-varying upwind reference points. Table 1 also summarizes the attributes of sites initially recommended based on modeling results.

As of this report's date, area SFV5 in San Fernando Valley (see Figure 1, left side of bottom figure) appears to be the most suitable to begin monitoring at (installing the first fixed weather stations) based on model results. Once the stations have been installed in SFV5, initial results will be examined and checked against anticipated UHI / UCI signal as well as against other potential indicators. If the signal or other aspects of installation indicate potential issues, the weather stations may be moved to other locations within the SFV5 area.

A.3 Sites identification and selection: Step B

To prioritize deployment of weather stations in area SFV5 (in San Fernando Valley) as discussed above, further analysis of initial SFV5 sites (from Table 1) was undertaken to narrow down the possible selections. Table 2 provides a summary of sites and proposed weather-station positions in area SFV5 that resulted from this additional screening.

Upon further evaluation of sites listed in Table 1, via examination of 3-dimensional imagery (e.g., Google Earth), certain sites were assigned a lower priority because of such factors as 1) unavailability of flat roofs (sloped roofs can be an issue for installing weather stations), 2) lack of secure sites in open areas (at ground level), and 3) sites' physical characteristics. The resulting set of sites is shown in Table 2.

While the final selection will depend on 1) site visits by team members and 2) the final agreements with project partners, Table 2 provides a quasi-final recommendation for siting of fixed monitors in SFV5. Specifically, those sites with an entry in the first column of Table 2 should be given priority. Based on lessons learned from first deployment in SFV5, other sites and areas in each of San Fernando Valley and LA1 study domains will be evaluated accordingly.

In Figure 2 (figure pairs SFV5_01 through SFV5_17), the top part shows the relative location of each site within the broader neighborhood area and the bottom part depicts the suggested position for siting the monitors on the buildings (the tip of the red arrow is the proposed position of the weather station at each site). These specific positions of weather stations will be discussed with partners in Los Angeles and finalized according to their feedback and model-based siting criteria.

As discussed above, if the initial monitoring at certain points in SFV5 indicates potential issues or does not capture a significant climate signal, it may be necessary to move and relocate the stations to other positions within each site or to alternate sites within SFV5 area. A similar approach will be adopted in other areas selected for monitoring.

B. DESIGN OF MOBILE TRANSECTS

B.1 Goal

The goal of this task is to use results from meteorological modeling of transect routes, as well as initial mobile-transect results, to perform analysis and identify routes of potential interest for monitoring. A related objective is to dynamically downscale real-time and days-out forecasts for the region, down to the San Fernando Valley and LA1 500-m domains to provide guidance to mobile transects design and to compare with observations to assess model performance.

Thus the goal of real-time forecasting in this case is twofold: 1) to predict the temperature and wind-flow patterns in real time at specific locations so as to guide the simultaneous performance of mobile transects at those times and 2) to compare the model's forecasts with the observed temperatures from mobile transects and fixed monitors, as they become available, to evaluate performance.

B.2 Real-time forecasting

It is to be reiterated that mobile transects are a critical component of this monitoring project and may assume even greater significance if fixed weather stations fail to capture a significant UHI and/or UCI signal or that the results point to other potential issues.

To this end, real-time forecasting capabilities (transect-specific modeling) were updated and implemented to assist in design of mobile transects. A system for dynamical downscaling of a climate model output using the WRF model was put in place to develop the needed driving conditions and simulate areas of interest in the Los Angeles region.

The models were set up and configured with focus on areas selected for fixed monitoring and mobile transects (e.g., Table 1, Table 2). The modified WRF/uWRF model (customized in this study) was linked to NOAA-NCEP Global Forecast Model (GFS) so that real-time and days-out boundary conditions could be applied to drive the local, fine-scale simulations. The model linkages were successfully tested and extensive data input to WRF (output from GFS) were tested as well. A streamlined process for ingesting GFS fields and setting up initial and boundary conditions for the various nests and domains of the WRF model were implemented. Furthermore, when downscaling the GFS output, the WRF model also uses the land-use/land-cover data and urban surface characterizations developed earlier in this project.

To demonstrate functionality and provide an example in this report, the forecast system was run for all modeling domains in this study (e.g., Figure 3) for an arbitrary period starting September 13th, 2016 at 0600Z. A real-time, 24-hour forecast was performed and compared to observations from the Meteorological Assimilation Data Ingest System (MADIS). Sample comparison results are shown in Figure 4 for an arbitrary time slice. The figure shows both model and observed air temperature and the data indicates good model performance.

Table 1: Potential monitor sites identified as of this report's date.

In this table, "Suitability" indicates whether the point is suitable to the UHI or UCI target or reference point as defined (conforms to anticipated UHI or UCI), "~500m uniformity" indicates if the point is surrounded by uniform urban land use and geometry up to 500 m upwind, and 'Status' indicates if both target and reference points have been identified to date.

Point ID	Address	Description	Suitability	Use	~500m uniformity	Status
San Fernando Valley						
SFV1	10241 N. Balboa	City facility (building)	Yes	Target (UHI)	Yes	OK
	Havenhurst at Devonshire	LADWP distributing station	No (local heat generation)	Ref point	Yes	
	16701 Mayall Street School	School (LAUSD)	Yes	Ref point	Yes	
	16111 Plummer Street	Health Center (LA City)	Yes (open / green)	Ref point	?	
	10640 Petit Avenue	Library (LA City)	Possible	Ref point	?	
	17221 Tuba Street	Home (via TreePeople)	Yes	Ref point	Mostly	
	16111 Plummer Street	Health Center (County facility) and open space	Yes	Ref point	Mostly	
SFV2	18250 Devonshire	Police station	No: too close to target (CSUN) ?	Ref point	?	No target point yet (in CSUN) UHI; near north parking lot
	18300 Lemarsh	Recreation center / open space	Yes	Ref point	Yes	
	10058 Reseda	Child care facility	Yes	Ref point	?	
	10210 Etiwanda	Industrial	No (opposite effect)	-	-	
		Dearborn Park	Yes	Ref point	Yes	
SFV3	10400 N. Mason	Mason Park recreation building	Yes	Ref point	Yes	No target point yet (UHI)
	10500 Tunney Avenue	County facility –shelter house / guard station	Yes	Ref point	Yes	
SFV5	9324 Topanga Cyn	City yard	somewhat-Yes	Target point (UHI)	?	OK
	20655 Plummer	Animal shelter	somewhat-Yes	Target point (UHI)	Yes	
	21800 Marilla	Fire station	Yes	Target point (UHI)	Yes	
	21615 Plummer Street	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	21415 Plummer Street	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	9035 Canoga Avenues	Office Building (County facility)	Yes	Target point (UHI)	Yes	
	8401 Winnetka	Recreation center	Yes	Ref point	Yes (at park tip)	
	19940 Plummer	LADWP distributing station	No (local heat generation)	Ref point	No	
	7911 Winnetka Avenue	James Jordan Middle School (LAUSD)	Yes	Ref point	Yes	

	8530 Limerick Avenue	Limerick Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	20620 Arminta Street	Sunny Brae Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	7700 Melvin Avenue	Melvin Avenue Elementary (LAUSD)	Yes	Ref point	Yes	
	8552 Melvin Avenue	Home (via TreePeople)	Yes	Ref point (one of several)	Yes	
SFV6	Vanowen at White Oak	LADWP distributing station	No (local heat generation)	Ref point	?	OK
	7419 Reseda	Fire station	Yes	Ref point	?	
	Sherman Way at Reseda	City parking lots (non-fenced)	Yes	Ref point	Yes	
	Victory at Reseda	Reseda Park building	No (opposite effect)	Ref point	No	
		Jesse Owens Minipark	Yes	Target point (UCI)	Mostly	
		Louise Park	Yes	Target point (UCI)	Yes	
SFV7		Dearborn Park	Yes	Ref point	Yes	OK
	6461 Gaviota Avenue	Home (via TreePeople)	Yes	Ref point	Yes	
	6632 Lemona Avenue	Home (via TreePeople)	Yes	Ref point	?	
	16700 Roscoe Blvd. (Van Nuys Airport)	Dispatch center (County facility)		Target (UHI)	Yes	
Area LA1						
A	1274 W 2 nd	Services	Yes – but not in model points	Ref point	No	No target point yet (UCI)
	203 S. Los Angeles Street	Little Tokyo library	Yes, could be used to represent medium-rise conditions	Ref point	Yes	
	630 W. 5 th Street	LA Public Library	Yes, could be used to represent high-rise conditions	Ref point	Yes	
	525 S. Hewitt Street	Industrial	Yes (close to model point)	Ref point	Yes	
B	525 S. Hewitt Street	Industrial	Yes (close to model point)	Ref point	Yes	OK (but preferable if more centralized site is found)
	1617 E. 7 th Street	Para Los Ninos charter (LAUSD)	Yes	Ref point	Yes	
	727 S. Wilson Street	Metropolitan High School (LAUSD)	Yes	Ref point	Yes	
	1314 Dacotah Street	Dena Elementary (LAUSD)	Yes	Target (UCI)	?	
	2750 E. Hostetter Street	Garza PC (LAUSD)	Yes	Target (UCI)	?	
	1016 S. Fresno Street	MSGH Ramon Garcia recreation center	Yes	Target (UCI)	?	
	3141 E. Olympic Blvd.	Lou Costello Jr. recreation center	Yes	Target (UCI)	?	

	933 S. Mott Street	Boyle Heights Sports Center (Parks&Rec)	Yes	Target (UCI)	? (but in tandem with above UCI points)	
	1601 S. Santa Fe Avenue	Fire station No. 17	Yes	Ref point	Yes	
	1055 N. Alameda Street	Parking garage (County facility)	Yes	Ref point	Yes	
	2765 E. Olympic Blvd.	Parking lot (County facility)	Yes	Ref point	No (and too close to target)	
K	4914 E. Cesar Chavez Avenue	Park	Yes	Target (UCI)	Mostly	OK
	5119 E. Beverly Blvd.	Office building (County facility)	Yes	Ref. point	Yes	
	420 S. Amalia Avenue	4 th Street Elementary	Yes	Ref. point	Yes	
G-L	6250 Northside Drive	Park	Yes	Target (UCI) instead of or with point G	Mostly	OK
	Southside Drive	Montebello Parkway (land) County facility	Yes	Target (UCI)	Mostly	
	6400 Northside Drive	Montebello Parkway (storage box) County facility	Yes	Target (UCI)	Yes	
	2327 S. Saybrook Avenue	Firestation (County facility)	Yes	Ref point	Yes	
	2700 Garfield Avenue	Supplies storage (DSS)	Yes	Ref point	Yes	
	1050 S Maple Avenue	Supplies storage (County facility)	Yes	Ref. point	Yes	

Figure 1: UHI / UCI areas for potential monitor siting (yellow balloons/polygons are target areas; white balloons/polygons are reference areas) based on meteorological model results. Area LA1 is shown in top figure and San Fernando Valley in bottom.

Table 2: SFV5 sites assessment

	Address	Description	Suitability	Rank	Use	~500m	Details
SFV5_01	9324 Topanga Cyn	City yard / BSS (LA City)	somewhat-Yes	B (bl)	Target point (UHI)	?	Roof or ground
	20655 Plummer St.	Animal shelter LA City	somewhat-Yes	B (wr)	Target point (UHI)	Yes	Roof
SFV5_03	21800 Marilla Street	Fire station (LA City)	Yes	A	Target point (UHI)	Yes	Roof
SFV5_04	21615 Plummer St.	Office Building (County facility) (LA County)	Yes	A (n)	Target point (UHI)	Yes	Roof (ground possible)
SFV5_05	21415 Plummer St.	Office Building (County facility) (LA County)	Yes	A (n)	Target point (UHI)	Yes	Roof (ground possible)
SFV5_06	9035 Canoga Avenue	Office Building (County facility) (LA County)	Yes	B (wr)	Target point (UHI)	Yes	Roof
SFV5_07	7911 Winnetka Avenue	James Jordan Middle School (LAUSD ?)	Yes	A	Ref point	Yes	Roof or ground
SFV5_08	8530 Limerick Avenue	Limerick Avenue EL (LAUSD)	Yes	A	Ref point	Yes	Roof 18397, 18400 18399, 18393 (S / SE classrooms)
SFV5_09	20620 Arminta Street	Sunny Brae Avenue EL (LAUSD ?)	Yes	A	Ref point	Yes	Roof (roofs to N and NW)
SFV5_10	7700 Melvin Avenue	Melvin Avenue EL (LAUSD)	Yes	A	Ref point	Yes	Roof or playground 18706, 17904 14826 2 stories
	21050 Plummer Street	CDS Aggeler (LAUSD)		B (wr) (sh)	Target	?	Roof 24466
SFV5_12	9756 Oso Avenue	Superior EL (LAUSD)	Somewhat Yes	A	Ref point	Yes	Roof 18604 2 stories 14761 / 14532
	8140 Vanalden Avenue	Cleveland SH (LAUSD)	Yes	A	Ref point	Yes	Roof 23392 (slight slope)
	8552 Melvin Avenue	Residence (Tree People)	Yes	B	Ref point	Yes	Ground (backyard)
	8401 Winnetka	Recreation center	Yes	A	Ref point	Yes	Ground (Roof possible)
		Parthenia Park (LA City)	Yes	B (bl)	Ref point	?	Ground
SFV5_17		Vanalden Park (LA City)	Somewhat	A	Ref point	?	Roof or ground
		Dearborn Park (LA City)	Somewhat	A	Ref point	?	ground

wr: white roof

bl: boundary location

n: neighboring buildings

sh: shade

Figure 2: (SFV5_01 through SFV5_17): Site locations and suggested positions of fixed weather stations in SFV5 area of the San Fernando Valley study domain. In each pair, the top figure shows the location of the site within the surrounding area and the bottom figure shows the proposed position of the weather station (at tip of red arrow).

SFV5_01

SFV5_03

SFV5_04

SFV5_05

SFV5_06

SFV5_07

SFV5_08

SFV5_09

SFV5_10

SFV5_12

SFV5_17

Figure 3: GFS-WRF forecast example for 1400 PDT, September 13, 2016. This is for one of several domains, in this case, the 3-km domain of Southern California, showing 2-m AGL air temperature and wind vector fields.

Figure 4: Los Angeles basin model (circles) and observed (triangles) air temperature at 2 m AGL for forecast example at 1400 PDT, September 13, 2016.

California Energy Commission
CONSULTANT REPORT

Monitoring the Urban Heat Island Effect and the Efficacy of Future Countermeasures

Appendix E

California Energy Commission

Gavin Newsom, Governor

March 2019 | CEC-500-2019-020-APE

Appendix E: Model validation and development of correlations between observed air temperature and surface physical properties (Task 4 Report, Part I)

Haider Taha

Altostratus, Inc.

22 June 2018

Model validation and development of correlations between observed air temperature and surface physical properties

Technical report submitted as part of
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LIST OF ACRONYMS

AGL	Above Ground Level
ARB	Air Resources Board
ARW	Advanced Research WRF
GFS	Global Forecast Model
JJA	June, July, and August
LBNL	Lawrence Berkeley National Laboratory
LULC	Land Use / Land Cover
MADIS	Meteorological Data Assimilation Ingest System
MPE	Model Performance Evaluation
NCAR	National Center for Atmospheric Research
NCDC	National Climatic Data Center
NLCD	National Land Cover Data
NOAA	National Oceanic and Atmospheric Administration
NCEP	National Centers for Environmental Prediction
NUDAPT	National Urban Database and Access Portal Tool
NWS	National Weather Service
UCI	Urban Cool Island
UHI	Urban Heat Island
uWRF	Urbanized WRF model
WRF	Weather Research and Forecasting model

ABSTRACT

Activities in Task 4 were undertaken to (1) evaluate the performance of the meteorological model in order to establish its suitability for use in siting fixed weather stations and designing mobile-transect routes in the study areas selected in this project, and (2) develop correlations between neighborhood-scale albedo and observed temperatures and between neighborhood-scale vegetation canopy cover and observed temperatures.

To evaluate model performance, several sub-tasks were carried out. These included (1) improving the land-use/land-cover input to the atmospheric model, (2) carrying out meteorological modeling of summer conditions (2006 – 2013) and transect-specific simulations (at the times of the mobile transects in 2016 and 2017), (3) carrying out the mobile observations, (4) using model results to predict localized heat and cool islands, (5) evaluating model results against observations from mesonet monitors (fixed stations), and (6) evaluating model performance against mobile observations.

The correlations between observed temperature and neighborhood-scale albedo and between observed temperatures and neighborhood-scale vegetation canopy cover were examined via (1) simple linear regression, (2) multiple regression, and (3) classification and regression tree (CART) analysis.

In Section A, the model validation effort is discussed. In Section B the correlations between observations and neighborhood-scale surface physical properties are examined.

A. MODEL VALIDATION AND PERFORMANCE EVALUATION

A.1 Goal

The goal of this task is to evaluate the performance of the meteorological model in order to establish its suitability for use in siting fixed weather stations and designing mobile-transect routes in the study areas selected in this project.

In order to carry out the goal, i.e., model performance evaluation (MPE), several sub-tasks were carried out including model preparations and testing, development of model inputs, land-use and land-cover analysis and input to model, carrying out the simulations, and post-processing the output for specific use in MPE.

In addition, to provide the observational data for the MPE task, information from existing mesonet and metar stations in the study domains were obtained, checked, and formatted as suitable for use in this analysis.

All of these sub-tasks are discussed in the following sections.

A.2 Improved land-use/land-cover input to atmospheric model

The goal of improving the land-use/land-cover (LULC) characterization in this task is to develop a more area-specific (site-specific) input to the model (WRF) so as to improve its performance. The LULC analysis is applied in a bottom-up approach as discussed in Taha (2017) and in this report. This subtask of improving LULC and use as input to WRF builds upon the extensive LULC analysis in Task 2.

LULC analysis was carried out following a bottom-up approach to develop surface input in the urbanized meteorological model. In this subtask, LULC and surface physical properties were used to (1) develop urban-parameter inputs to the modified urban WRF model for the selected domains, and (2) use these computed parameters to correlate surface properties with observed air temperature from mobile transects, which will be discussed in Section B.

In the bottom-up approach to developing input to WRF (Taha 2017; Taha and Freed 2015), each model grid cell is characterized based on as much information as available from any and all sources. This is to directly characterize or scale each cell's properties in terms of parameters required by the meteorological and land-surface models and use them instead of the standard model's lookup parameters. These include, among others, surface albedo, urban morphology parameters, vegetation canopy cover, shade factor, view factor, roughness length or drag coefficient, and soil moisture. The following data sources were used:

- Fine-resolution (30 m) LULC classification of the Los Angeles region's six counties (134 classes total; 97 urban classes) generally following the Anderson Level-4 classification system (Anderson et al. 2001). The dataset was developed by the Southern California Association of Governments (SCAG) and the City of Los Angeles.
- Fine-resolution individual buildings footprint and height information throughout the Los Angeles County. This dataset was developed by SCAG and the County of Los Angeles.
- Building-specific roof albedo derived based on aerial imagery from the National Agriculture Imagery Program (NAIP). Albedo was developed for each roof within the boundaries of the City of Los Angeles. The dataset was generated by the Lawrence Berkeley National Laboratory (<http://albedomap.lbl.gov>) (Ban-Weiss et al. 2015).
- Fine-resolution tree-canopy cover for urban areas in California characterizing each 1-m pixel as either canopy or non-canopy. The data were developed by EarthDefine and CAL FIRE / Fire Resource Assessment Program (<http://frap.fire.ca.gov>).
- National Land Cover Datasets (NLCD) and United States Geological Survey (MRLC 2011) providing additional information in areas where other fine-resolution datasets are lacking or where such data are sparse.
- Fine-resolution, detailed Light Detection and Ranging (LiDAR)-derived urban morphology parameters for areas within the Los Angeles region (in Los Angeles and Orange counties). Data were based on the National Urban Data and Portal Tool (WUDAPT) effort of Ching et al. (2009).

- Google Earth PRO 3-D building attributes information for site-specific building and urban canyon geometrical characterizations.

In the bottom-up approach, the above datasets were merged at the grid-cell level and used to derive model parameters as needed. This cell-specific approach does away with the typical look-up that the model uses and significantly improves the site-specificity of surface characterization. The parameters discussed above were computed at 500-m resolution including roof and non-roof albedo; vegetation cover; ground cover; shade factor; soil moisture; roughness length; view factor; building and vegetation-canopy plan-area, frontal-area, and top-area densities; anthropogenic heat flux profiles; street orientations; street widths; and building heights.

Figure 1 shows the two study areas where this detailed ULC analysis was undertaken. One area is near downtown Los Angeles (quasi coastal) while the other is in an inland basin (San Fernando Valley). For these two domains, the meteorological model was run at 500-m horizontal resolution.

Figure 1: Urban WRF 500-m modeling domains for San Fernando Valley (left rectangle) and downtown area (right rectangle). Red diamonds locate the mesoscale network (mesonet) monitors closest to either domain. Downtown Los Angeles is near the northwest corner of the right rectangle.

A.3 Meteorological modeling

The WRF-urban model was modified at Altostratus Inc. and applied to study the domains identified above. The parameterizations, land-surface model, and input were modified and tailored specifically for this type of application. The approach in this study overrides the typical LULC lookup in urban WRF and characterizes every grid cell independently using a bottom-up approach discussed above that is significantly more resolved than the standard approach in the WRF model.

Modifications in this study were carried out within the Noah land-surface model of Pleim et al. (2001) and the urban canopy model of Kusaka et al. (2001). These modifications, discussed in Taha and Freed (2015) and Taha (2008, 2017), were carried out to (1) enable ingestion of new parameters computed in the bottom-up approach discussed above; (2) trigger the modified urban canopy model based on a different set of physical criteria rather than simply as a function of land use, which is how the standard model operates; (3) account for wind direction in the calculations of roughness- and drag-related parameters; and (4) mesh the urban and non-urban parts of each grid cell using cell-specific surface properties rather than a single default value for the non-urban part as in the standard model. In addition, the urban canopy model was also modified to directly use cell-specific building height, street width, orientation, building footprint, roof albedo, ground albedo, shade factor, vegetation cover, and anthropogenic heat flux, instead of the generic lookup values assigned to LULC types in the standard model.

The modified urban WRF was run to (1) characterize microclimate variations within the domains defined above to select the study areas; (2) help site fixed weather monitors in the study region and design mobile-observation routes to characterize urban heat; and (3) provide a full 4-dimensional picture of the state of the urban atmosphere before, during, and after the specific time of each mobile-transect segment. For objectives 1 and 2, the model was run June through September, 2013 – 2015 (long-term simulations). For objective 3, transect-specific (short-term) simulations were started one week prior to (leading up to) the time of the actual mobile transect and continued for two days past that time. Model validation and performance evaluation—i.e., comparison of model output with observations—for both long-term and transect-specific simulations, are discussed in the following sections.

The long-term simulations and results were discussed in Task 2 report, Here, we present results from the transect-specific simulations.

Figure 2 (a-k) provides samples from the WRF transect-specific modeling (TSM); simulated 2-m air temperature. Each figure corresponds to the hour (and date) of the actual transect performed. In the caption of each figure, the following information is provided: 1) the interval (T1 through T6 corresponding to the transect dates, i.e., six sets of transects), 2) the date range for the WRF simulations concatenating the date and time of the transect, 3) the target date and time, which is the actual time of the transect, and 4) the study domain (Area 1 or San Fernando Valley).

The modeled temperature field follows certain features, such as major roadways in the areas, downtown Los Angeles area, industrial / commercial areas in San Fernando and the downtown area, and locations of hot/cool spots.

TSM IntT1 (4/18/2016 – 4/24/2016: target: 4/22/2016 @ 1400 PDT) Area_1

TSM IntT2 (5/19/2017 – 5/25/2017: target: 5/23/2017 @ 1400 PDT) San Fernando

TSM IntT3 (6/10/2017 – 6/16/2017: target: 6/14/2017 @ 1400 PDT) Area_1

TSM IntT4 (6/17/2017 – 6/23/2017: target: 6/21/2017 @ 1500 PDT) San Fernando

(e)

TSM IntT5_1 (7/23/2017 – 7/29/2017: target: 7/27/2017 @ 1300 PDT) San
Fernando

(f)

TSM IntT5_2 (7/23/2017 – 7/29/2017: target: 7/27/2017 @ 1400 PDT) San
Fernando

(g)

TSM IntT5_3 (7/23/2017 – 7/29/2017: target: 7/27/2017 @ 2200 PDT) San Fernando

(h)

TSM IntT5_4 (7/23/2017 – 7/29/2017: target: 7/27/2017 @ 2300 PDT) San Fernando

TSM IntT6_1 (8/24/2017 – 8/30/2017: target: 8/28/2017 @ 1200 PDT) Area_1

TSM IntT6_2 (8/24/2017 – 8/30/2017: target: 8/28/2017 @ 1300 PDT) Area_1

TSM IntT6_3 (8/24/2017 – 8/30/2017: target: 8/28/2017 @ 2200 PDT) Area_1

Figure 2 (a-k): WRF transect-specific modeling (TSM); simulated 2-m air temperature. Each figure corresponds to the hour (and date) of the actual transect performed.

A.4 Mobile observations

Fifteen transects (Figure 3) were carried out for this analysis during the summers of 2016 and 2017, some on duplicate routes (but different times and dates) and others on different routes as well as different dates. To ensure a uniform basis for analyzing the mobile observations, changes in elevation (within each transect segment) were constrained to under 15 m. To minimize time-of-day effects (solar radiation and background temperature) the analysis was done for segments of well under one hour at a time. To minimize the effects of anthropogenic heating changes on the observations and to ensure that measurements represent air temperature, observations readings at travel speeds of under 10 km/h (~ 3 m/s) were discarded. Finally, transects were carried out only during clear-sky conditions to avoid effects of coastal stratus or other cloud cover.

Mobile temperature observations, subject to the above criteria, were compared to model temperature at nearest grid points (based on specification of radii of influence, as will be discussed in the following sections). In addition to the mobile observations, microclimate readings from existing nearby fixed mesonet monitors (NOAA/MADIS) were used to determine background temperature, cloud cover, wind speed, and wind direction during each transect segment.. As discussed in Task 2 report, the transects were designed to go through areas with

varying temperature, albedo, and canopy cover. As an example, Figure 4 shows a segment from one of the transects in the San Fernando Valley study domain.

Figure 3. Superimposed routes of 15 transects. Inset: a randomly-selected transect detail.

Figure 4: Detail from the San Fernando Valley domain in Figure 1, showing 30-m tree cover (yellow: < 10%, light green: 10 – 20%, black: > 20% cover), building-specific roof albedo (red: 0.05 – 0.25, orange: 0.25 – 0.50, light orange: 0.50 – 0.90), and a sample mobile transect segment (white dots).

A.5 Predicted urban heat and cool islands

In this section, modeling results for the two 500-m resolution domains (Figure 1) are discussed. Four time intervals from 2006-2013 simulations are presented, where interval 4 is the California heat wave of 2006:

Interval 1: 2013-05-30_00:00 through 2013-06-16_00:00 UTC
Interval 2: 2013-06-29_00:00 through 2013-07-16_00:00 UTC
Interval 3: 2006-05-30_00:00 through 2006-06-16_00:00 UTC
Interval 4: 2006-07-14_00:00 through 2006-08-01_00:00 UTC

Across the different summer periods in May-August (MJJA) 2006-2013, the model produces generally similar spatial patterns of air temperature in each region and relatively consistent geographical locations of UHI and UCI, as will be discussed next in this section. Since one goal of the modeling was to assist in siting fixed weather monitors and designing mobile-observations routes, the repeatability of these spatial patterns, i.e., areas with consistent hot or cool islands, could facilitate this task.

Figures 5 and 6 depict the modeled 2-m air temperature field (shown as degree-hours, °C·hr, to capture the cumulative rather than instantaneous signal) for interval 1 in the two 500-m domains. The purpose of these two figures is not to present the quantitative data per se but, rather, to give an idea where certain temperature patterns occur relative to the urban and geographical features in the area and also to show how the model captures the cooling and heating effects of certain land covers such as parks, large roof areas, and roadways. In subsequent graphs in Figures 7 and 8 the corresponding domains are shown again but without the background for easier visualization and assessment of the temperature-field characteristics. The contours are color-coded ranging from low to high degree-hours (blue to red).

In general, the spatial patterns of the temperature field are similar to those we obtain from the transect-specific simulations discussed in Section A.3. In the downtown area (Figure 7), the modeled air-temperature field captures the on-shore warming tendency (in the southwest-to-northeast direction) and also the consistently warmer commercial and industrial areas southeast of the Arts District, including the cities of Vernon, Maywood, and Commerce. In the northeastern parts of this domain, the model shows warmer urban areas in the region between the cities of Monterey Park and Alhambra and between Lincoln Heights and South Glendale. The temperature field also captures many areas of localized cool islands, mostly associated with open and/or green spaces and areas with higher urban albedo. Figure 7 also shows that the effects of on-shore warming are dominant and that the localized UHI / UCI effects are superimposed on this signal (Taha 2017).

In the San Fernando Valley domain (Figure 8), sea-breeze effects are practically non-existent and temperature is influenced mainly by topography and variations in land use and surface

properties. The graphs in Figure 8 show that the model predicts higher temperatures in the industrial and commercial areas from near Chatsworth in the north, to Canoga Park, and Woodland Hills in the south. Higher model temperatures are also seen along the major roadways, including, for example Sherman Way and Parthenia Street (running west to east) and Reseda Blvd. (running north to south). Cool islands in this domain are associated with areas of higher vegetation cover.

In Figures 7 and 8, the graphs show the 2-m model air-temperature field expressed as degree-hour totals (DH), in units of $^{\circ}\text{C}\cdot\text{hr}$, over each of the four intervals identified at the beginning of this section. A temperature equivalent is also provided as DH/hour, that is, the interval-average temperature. Since one goal of the modeling was to assist in siting the fixed weather stations and in designing the mobile-observation routes, the model DH in these figures were plotted with the same number of levels (across the data range) for all periods. This serves to show that the model consistently defines certain areas as heat or cool islands (at fine scales) and that this information can be useful in selecting the monitoring sites and the transect routes. Plotting at a different number of levels will make it difficult to visually identify these consistent features.

It is of interest to evaluate how the gradients (spacing) in DH (or average temperature) vary across the four periods and the two domains. In the downtown area (Figure 7), the gradients are 77 DH in interval 1, 90 DH in interval 2, 92 DH in interval 3, and 94 DH in interval 4. In the San Fernando Valley area (Figure 8), the DH gradients are 119, 124, 106, and 110 DH in intervals 1, 2, 3 and 4, respectively. Converting these DH values into temperature (calculated as DH/hour), we obtain the following averaged temperature gradients (spacing) per contour level; in the downtown area: 0.189 $^{\circ}\text{C}$, 0.220 $^{\circ}\text{C}$, 0.225 $^{\circ}\text{C}$, and 0.230 $^{\circ}\text{C}$ in intervals 1-4, respectively; in the San Fernando Valley: 0.291 $^{\circ}\text{C}$, 0.303 $^{\circ}\text{C}$, 0.259 $^{\circ}\text{C}$, and 0.269 $^{\circ}\text{C}$ in intervals 1-4, respectively.

Based on model results, several transect routes were designed to pass through areas of varying temperature (UHI / UCI spots) and land use properties (albedo and/or canopy cover).

Figure 5: Total DH for interval 1 in the downtown-area 500-m domain. The unlabeled contours are only meant to show the spatial pattern of the temperature field.

Figure 6: Total DH for interval 1 in the San Fernando Valley 500-m domain. The unlabeled contours are only meant to show the spatial pattern of the temperature field.

Figure 7: Modeled total degree-hours (DH) for intervals 1-4 in the downtown area. The derived interval-average temperature (computed as DH/hour), blue to red, is as follows: 17.2–20.6 °C for interval 1; 21.3–25.3 °C for interval 2; 19.6–23.7 °C for interval 3; and 22.5–27.9 °C for interval 4.

Figure 8: Modeled total degree-hours (DH) for intervals 1-4 in the San Fernando Valley domain. The derived interval-average temperature (computed as DH/hour), blue to red, is as follows: 17.7–22.9 °C for interval 1; 22.0–27.5 °C for interval 2; 21.0–25.7 °C for interval 3; and 23.6–30.0 °C for interval 4.

A.6 Model performance evaluation (MPE)

Model performance evaluation (MPE) was carried out against (1) observations from fixed weather stations (mesonet and metar monitor network in the area) as discussed in Section A.6.1 and (2) against observations from mobile transects, as discussed in Section A.6.2.

In comparing against observations from fixed monitors, MPE was carried out for (1) the coarse 3-km grid, covering Southern California, and (2) for the Area_1 and SFV 500-m domains shown in Figure 1. Because there are very few observational stations in each of these two 500-m domains, MPE relied on stations near the boundaries and, as expected, this is where poorest model performance is found (and this area is typically discarded in any analysis).

Figures 9 and 10, for example, show the locations of monitors CQ194 (in Area_1) and AR307 (in SFV) and how stations can be influenced by characteristics of their immediate surrounds.

Figure 11: Example monitor location in Area_1 (station CQ194): open area with extensive asphalt and soil cover. Very little roughness elements.

Figure 12: Example monitor location in SFV (station AR307): crowded / built-up area with significant roughness elements.

A.6.1 MPE against mesonet monitors (fixed stations)

3-km grid

As a first step, the model performance over the 3-km resolution domain encompassing the Southern California region was examined. For these coarse-scale WRF simulations, performance indicators are summarized in Table 1, as averaged over the seasonal (summer) model runs.

Table 1: Model performance indicators for seasonal simulations: bias, error, RMSE (root mean square error), and IOA (index of agreement). Model results were compared to observations from monitor networks.

Performance indicator	Units	Computed value
Wind speed bias	m/s	0.08
Wind speed RMSE	m/s	0.71
Wind speed IOA	-	0.80
Wind direction bias	°	0.92
Wind direction error	°	37.3
Temperature bias	°C	0.60
Temperature error	°C	2.10
Temperature IOA	-	0.95
Humidity bias	g/kg	-0.80
Humidity error	g/kg	1.41
Humidity IOA	-	0.71

500-m grid

Model results were compared to observations from three existing mesonet monitors in SFV5. For this purpose, the fine-resolution model results were recast into time series at the exact locations of the monitors to enable direct comparisons. The model results were also translated into metrics and time series at the locations of the proposed project monitors in the SFV5 area. Model preparations were initiated for further evaluation once the observations (from project monitors) become available near the end of April.

Since only the SFV domain has mesonet stations near the areas of interest to the east of Chatsworth (the domain near downtown LA has none), this discussion presents analysis of the model performance in the SFV domain. There are two existing mesonet stations near this area and an additional monitor further to the north. Figure 13 shows the locations of reference points (schools), target point (commercial/industrial area), three existing mesonet locations (yellow circles), and a mobile-transect route designed for this area. The existing mesonet stations are: “D0345” in the middle of the commercial/industrial area, “C7387” in mixed residential / commercial land use in the south, and E1734, which is residential land use in the north.

Figure 13. SFV sub-domain of WRF 500 m grid: White circles are existing mesonet monitors, blue circles are proposed sites for project monitors. Red route: final mobile transect proposed for this area; White dashed line: shortcut transect proposed for the area. White contours: DH/day from WRF model results.

Although located within the area of interest, none of these three mesonet stations is near the monitor locations proposed in this study (project monitors) as defined in Task 2. Nevertheless, it may be useful to analyze readings from these locations to supplement and compare with the observations from the new monitors to be installed.

In Figure 14, example random observations from two monitors (D0345 and C7387) are presented (except for top-left graph). Examination of these data suggests a nighttime UHI at station D0345 which becomes warmer than C7387 after sunset, exhibiting a well-defined nighttime UHI that continues through hours 1000 to 1200 PDT (see vertical dashed black lines). After ~1200 PDT, the order is reversed and station D0345 becomes somewhat cooler than C7387. There are several caveats to consider, including monitor accuracy (which is difficult to ascertain) and the data period (month of March) where the signal likely differs during hotter months. The reversal after ~1200 PDT may be caused by local physical properties (e.g., albedo and vegetative cover relative to surrounding areas) of the target vs. reference stations and, possibly, because of changes in the local wind flow pattern at that time of day. While there is data crudely suggesting this effect, it won't be possible to corroborate this until the project monitor's high quality sensors are installed and observational data from these monitors become available.

Model results were evaluated to assess these possible effects. Figure 15 represents back trajectories on the 2-km resolution modeling domain for a period of 12 hours leading up to a 1700-PDT arrival at the SFV study area. Typically, the parcel originates at the ocean, crosses the coastline near LAX, flows over the Santa Monica Mountains and then veers west to the SFV area. While the flow after ~1100 PDT is uniform in the 500-m SFV modeling domain (Figure 16) and the arrival at SFV5 is similar on most days (e.g., the example back trajectories), the local flow in SFV (indicated by the oval) can be different from one period to another and can be random as well. As the wind changes direction around ~1100 PDT, it is possible that this is causing the reversal in temperature at the two mesonet stations.

Figure 17 shows time series for two 2-week periods in 2013 as an example of observed temperature from the three mesonet stations in SFV5. There are some difficulties encountered when attempting to use observational data from these monitors including 1) missing hourly data, 2) long interruptions in data logging, 3) data quality issues, and 4) unknown elevation of stations above ground level (AGL). Still, the signal obtained from these three monitors generally shows a daytime UHI at C7387 as well as D0345 during some days. These stations are relatively similar and reverse positions on some days. At night both stations are relatively similar, in terms of temperature, but D0345 is slightly warmer at times.

Figure 18 represents WRF-model simulated air temperature at the locations of the three mesonet stations identified above. In this figure, the T2 metric is shown, which is temperature computed within the model at 2 m AGL as a function of the vertical heat transfer coefficient (diffusivity). Thus T2 is more closely associated with (and sometimes equal to) skin surface temperature. T2 is evaluated with three approaches discussed previously in the project (Task 2 report): Altostratus' AREAMOD, modified BEP (mod-BEP), and modified (mod-UCM) approaches.

In the AREAMOD approach (Figure 18, top graph), the model results indicate that C7387 and D0345 are similar in general, during the daytime, but that D0345 is slightly warmer at night. In the mod-BEP approach during the daytime, C7387 and D0345 can be generally similar and either one of the two could be warmer at times. At night, D0345 is a UHI (warmer than C7387). In the mod-UCM approach, again, both stations are roughly similar during the day and one or the other can become a UHI at certain times. At night, D0345 is a UHI. Thus all three approaches with T2 diagnostics suggest that D0345 is warmer at night, which is what the mesonet monitor observations (Figure 14) also indicate. Station D0345 can also be warmer in daytime during certain days.

Figure 19 represents WRF model simulated air temperature at the same three mesonet stations. In this figure, the Tair_2m metric is shown, which is a temperature computed by interpolating between skin surface temperature and the temperature at the first atmospheric level to 2 m AGL. Thus Tair_2m is more representative of and accounts for advective effects in addition to surface heat flux. Again, three approaches are shown, i.e., Altostratus' AREAMOD, mod-BEP, and mod-UCM.

With the Tair_2m diagnostics, the model results suggest smaller differences among the three stations than with the T2 metrics because Tair_2m is a more “mixed” air temperature variable. The results in Figure 19 for AREAMOD show, again, that C7387 and D0345 are similar in general during the daytime, but that D0345 can be slightly warmer during certain days. At night, the model suggests that the two stations are similar but that D0345 can be warmer. In the mod-BEP and mod-UCM approaches during the daytime, stations C7387 and D0345 are generally similar but D0345 can be warmer at time. At night, station D0345 is in a UHI (warmer than C7387), as was the case with the T2 diagnostics. Thus, overall, the Tair_2m analysis also indicates that D0345 is a nighttime UHI, but that the temperature differences relative to C7387 are now smaller than with the T2 diagnostics, as expected.

The purpose of the above discussion is to present how the model replicates the observations from the mesonet stations in SFV study area. Next, in the following discussion, we evaluate how the model simulates temperature at the proposed project sites.

Figure 20 shows WRF-simulated air temperature at the locations of three project sites (two reference and one target stations). The target (UHI) point is at Topanga Canyon service yard (BSS) whereas the reference points are at Arminta and Melvin schools (LAUSD). In this figure, the T2 metric is shown and suggests that the target (Topanga) station is warmer during the day, and also at night, relative to the two reference school sites. In Figure 21, the same information is presented (as in Figure 20), but now with the Tair_2m metrics instead of T2. Again, the results show that the target point (Topanga) is warmer than the reference sites at night, and also during the day.

Thus based on model results, it can be expected that installing project monitors at these three sites (Topanga, Arminta, and Melvin), will show a UHI at Topanga Canyon at night and a UCI during the day, but also a UHI during certain hours of the day.

Figure 14: Examples of observed temperatures at mesonet stations D0345 and C7387.

Figure 15: WRF back-trajectories for area SFV5 (D0345 monitor)

Figure 16: WRF simulated flow in the 500-m San Fernando modeling domain. The oval represents the general area of SFV5.

Figure 17: Example observed temperature at three mesonet stations in area SFV5

Figure 18: WRF model simulated air temperature at the locations of the three mesonet stations for diagnostic T2 in three different approaches

Figure 19: WRF model simulated air temperature at the locations of the three mesonet stations for diagnostic Tair_2m in three different approaches

Figure 20: WRF model simulated air temperature at the locations of three project sites (two reference and one target stations) with T2 diagnostics and three approaches

Figure 21: WRF model simulated air temperature at the locations of three project sites (two reference and one target stations) with Tair_2m diagnostic and three approaches

A.6.2 MPE against mobile observations

This component of MPE is based on comparing transect-specific simulation results to observations from the mobile transects at the coincident times. In this section, examples for the SFV area are discussed.

Some of the goals of the project are to (1) relate measured to simulated temperatures in order to evaluate model performance, and (2) relate modeled and observed temperatures to surface physical properties. Of the surface properties that can be modified and controlled (e.g., for UHI mitigation), the most important are (1) albedo, (2) vegetation canopy cover (and implications on soil moisture content), and (3) roughness length, to a lesser extent. Thus these three parameters were compared to observed temperatures from (1) mesonets in the area and (2) mobile transects. Examples are shown, qualitatively, in Figures 22-24, where the mobile-transect readings are color-coded to show four intervals of air temperature (as indicated in each figure's legend).

Figure 22, 23, and 24 show, respectively the model-input albedo, vegetation canopy cover, and roughness length, overlaid on measured air temperature from the transects (in this example, the transect is from May 23, 2017). In general, it can be seen that during the daytime (~ 1400 PDT), the areas with higher albedo or canopy cover have generally lower air temperatures, as expected. The exception is the large industrial area in SFV, where the effects of high albedo (on air temperature) override those of low canopy cover.

Theory suggests that at night, the effects of roughness can become relatively more important in heat transport than during the day. The initial analysis (e.g., in Figure 24) suggests that the observations support the model results (and input). In an area where mesonet monitor C7387 is located (a vegetated area), roughness length is larger than at a monitor (D0345) in the central industrial/commercial zone. Hence, it is expected that nighttime temperature at C7387 be lower than at D0345. Both model results and observations (from the monitors) indicate such effect (Figures 25 and 26). However, as we will see in the analysis of all mobile transects performed in this project, the effects of roughness can be secondary (smaller than those of albedo or canopy cover) and that the effects could go either way: cooling or heating.

The model also captures reasonably well the daytime effects of variations in albedo on air temperature. Figure 27 shows the average of measured temperature along three stretches of the mobile transect on 5/27/2017. The white dashed lines depict an area the meteorological model predicts as being slightly cooler than its surroundings (see Figure 28, near "Topanga Cyn BSS site"). Thus there is an agreement, at least qualitatively, between model and observed temperature variations in this area.

500-m albedo for AREAMOD approach
(reverse color-coding)

Transect air temperature (°C)
Yellow: 28-29
Orange: 29-30
Red: 30-31
Black: 31-33

Figure 22: Model-input albedo and measured air temperature (mobile transects)

500-m soil moisture for AREAMOD approach
(reverse color-coding)

Transect air temperature (°C)
Yellow: 28-29
Orange: 29-30
Red: 30-31
Black: 31-33

Figure 23: Model-input canopy cover and measured air temperature (mobile transects)

500-m z_0 (m) for AREAMOD approach
(reverse color-coding)

Transect air temperature (°C)
Yellow: 28-29
Orange: 29-30
Red: 30-31
Black: 31-33

Figure 24: Model-input roughness length (m) and measured air temperature (mobile transects)

Figure 25: Observed air temperature at mesonet stations C7387 and D0345 on May 22-23, 2017. Source: NOAA / MADIS.

Figure 26: Observed air temperature at mesonet stations C7387 and D0345 on various days.

Figure 27: Measured air temperature from mobile transects on 5/23/2017 in SFV.

Figure 28: Model DH/day results for area SFV.

Additional examples from this analysis are provided in Figure 29 (a-i) showing routes of selected mobile transects. Some of these figures also give a qualitative characterization of the temperature readings (e.g., color-coded in 5 quantile intervals). The caption on each figure identifies the date and the area where the transects were performed.

Tables 2 and 3 provide a summary discussion of two examples from the analysis of mobile transects (one segment at a time in the drive direction). This examines different segments from each transect and from different dates. In general, this encompasses ~10-minutes segments or distances of less than 1 km at a time. Figures 30, 31, and 32 show random samples of segments (a subset from those currently being analyzed).

(a) Transect date: 06/14/2017; Area: Downtown Los Angeles (Area 1)

(b) Transect date: 06/21/2017; Area: SFV

(c) Transect date: 06/21/2017; Area: San Fernando Valley SFV (detail)

(d) Transect date: 05/23/2017: Area: SFV

(e) Transect date: 05/23/2017; Area: San Fernando Valley SFV

(f) Transect date: 2016; Area: SFV

(g) Transect date: 2016; Area: SFV

(h) Transect date: 04/22/2016; Area: Downtown (Area 1)

(i) Transect date: 04/22/2016; Area: Area 1

Figure 29 (a-i): Sample mobile transects analyzed in this task.

Table 2: “Area 1” transect; Date: 6/14/2017

Intercomparable segments are grouped together and separated from others by shaded rows.

Segment	Mean Tair (°C)	Air temperature readings in this segment (°C)	Notes
s_20170614_A	28.0	27.9,28.0,27.9,28.2,27.9,28.1	residential with higher vegetation cover than surrounds, slightly lower PAD
s_20170614_B	28.7	29.2,29.2,28.4,28.4,28.1	residential with lower vegetation cover than *_A, slightly higher PAD
s_20170614_C	28.2	28.7,27.8,27.6,28.2,28.4,28.4	residential with similar PAD as *_B but adjacent to grassy park
s_20170614_D	28.8	28.0,28.7,29.2,29.7,28.8,27.8,29.0,29.1	mixed commercial and residential with similar PAD as *_C and lower vegetation cover (similar veg. cover to *_B)

s_20170614_E	28.6	28.1,28.4,29.1,28.7,28.6 (see Note 1)	residential with lower vegetation cover, slightly higher PAD, similar to *_B
s_20170614_F	28.6	28.6,28.8,28.8,28.8,28.7,28.2,28.6,28.6 (see Note 1)	residential with higher vegetation cover than surrounds, slightly lower PAD, similar to *_A
s_20170614_G	28.2	27.8,28.8,28.2,28.3,27.6,28.2,28.6,28.3	residential with higher vegetation cover than surrounds, slightly lower PAD (this is part of segment *_A)
s_20170614_H	28.8	28.3,28.4,29.3,27.8,28.8,29.5,29.2,29.3,28.2	commercial/industrial, with low vegetation cover, moderately low albedo
s_20170614_I	28.1	27.9,28.6,28.1,28.2,28.3,28.6,28.1,27.8,27.7,27.9,28.1	residential with higher vegetation cover than surrounds, slightly lower PAD (this is segment *_A)
s_20170614_J	28.7	28.4,28.2,28.1,29.2,27.7,28.5,28.9,29.8,28.9,28.7,28.9,29.3,29.3,28.1	commercial/industrial, with low vegetation cover, moderately low albedo
s_20170614_I	28.1	See note 3 27.9,28.6,28.1,28.2,28.3,28.6,28.1,27.8,27.7,27.9,28.1	residential with higher vegetation cover than surrounds, slightly lower PAD
s_20170614_K	28.7	27.8,28.6,28.6,29.1,29.4	residential with lower vegetation cover than *_A, slightly higher PAD
s_20170614_L	28.3	28.3,28.1,28.1,28.6,28.5	residential with similar PAD as *_B but adjacent to grassy park
s_20170614_M	28.8	29.1,29.6,28.7,27.8,28.2,29.0,28.8,29.1,29.0	mixed commercial and residential with similar PAD as *_C and lower vegetation cover (similar veg. cover to *_B)

s_20170614_N	29.4	28.4,29.6,29.4,29.2,29.9,29.9	residential with lower vegetation cover, slightly higher PAD (this is segment *_E)
s_20170614_O	28.4	28.0,28.4,27.4,27.8,28.3,28.2,28.0,28.4,29.1,29.6,29.2,28.4,27.4,28.3,28.8,29.2	residential with higher vegetation cover than surrounds, slightly lower PAD (this is segment *_F)
s_20170614_P	29.0	29.2,29.5,28.7,29.0,29.2,29.1,29.0,29.2,29.6,29.9,29.7,29.9,28.9,29.7,28.9,28.2,28.2,28.8,28.9,29.2,28.2,28.2,28.7,28.5,29.0,29.2,28.8,28.6,29.3,29.4	This segment is through uniform land use (commercial and industrial) as well as physical properties (albedo, veg cover, PAD, etc). The purpose here is to show the on-shore tendency.
s_20170614_Q	29.3	30.1,30.2,30.3,28.8,28.1,27.9,28.5,28.2,28.2,28.8,29.4,27.3,29.1,29.8,30.1,29.6,29.7,29.5,29.1,29.5,29.6,30.1,30.4,30.1,29.8,29.4	

Table 3: SFV transect; Date: 6/21/2017

Intercomparable segments are grouped together and separated from others by shaded rows.

Segment	Mean Tair (°C)	Air temperature readings in this segment (°C)	Notes
s_20170621_A	37.0	36.6,36.4,36.8,36.1,36.4,36.8,37.3,37.6,36.1,36.4,36.9,36.7,35.6,36.3,36.6,36.6,36.6,36.9,38.6,38.3,38.6,38.9,38.1,37.8,38.3	residential land use on both sides of the transect (N and S of 101) with similar albedo and vegetation cover (these residential areas have a high vegetation cover, especially to the south of the 101 Ventura Freeway).
s_20170621_B	37.7	38.6,37.9,37.1,36.5,37.3,37.9,37.7,37.3,37.1,37.1,37.2,37.4,37.3,36.8,36.6,36.2,36.2,37.4,37.8,38.6,39.6,39.1,38.4,39.4,39.2,39.4	one side (north of 101) is residential (mostly single homes / detached) and one side (south of 101) is mixed residential / commercial (residential is apartment buildings). The residential area north of 101 is relatively more vegetated and with lower albedo than the area to the south of 101, which is covered with large, homogeneous buildings with relatively higher roof albedo but lower vegetation cover.

s_20170621_C	40.0	39.7,39.0,38.8,38.6,39.2,40.6,39.7,40.1,41.1,40.1,40.6,39.7,39.7,40.4,41.5,40.9,40.6,40.6	on both sides of the transect, there are mixed residential / commercial land uses. The residential area is mostly apartments and the commercial consists of 3-4 story buildings. Both areas have relatively low vegetation cover and relatively low albedo (similar).
s_20170621_D	37.4	38.9,38.4,39.3,38.8,38.7,37.9,37.2,37.3,37.0,37.1,36.4,36.1,36.4,37.4,36.8,36.9,37.2,37.8,36.9,37.1,37.3,37.2,36.6,37.0,37.3,36.8	Residential area (single homes / detached), with moderately low albedo and relatively good vegetation cover (hence lower temperature). Interesting because this is counter gradient.

Figure 30: Sample segments (s-20170614A-D)

Figure 31: Sample segments (s-20170614E,F)

Figure 32: Sample segments (s-20170621A-D)

For the transect-specific simulations (500-m resolution) MPE, modeled air temperature was compared to observations from mobile transects at the coincident times (sub-hourly intervals). The goal was to ascertain successful model capture of the micrometeorological variations in the urban areas and to validate the modified WRF model against the mobile observations.

While the transect-specific model runs were initiated a week ahead of the actual transect time and were continued for 2 days past that, model performance evaluation for these runs was carried out only and specifically at the actual transect time. The statistics reported in Table 4 compare along-transect model temperature to along-transect observations and demonstrate a satisfactory performance for the approach adopted in this study. In Table 4, MAE is mean absolute error (°C) and RMSE is root mean square error (°C). Both MAE and RMSE are significantly better than the modeling-community-recommended performance benchmarks of $MAE \leq 2$ °C and $RMSE \leq 2$ °C (Tesche et al. 2001).

Table 4: Model performance metrics against observational mobile-transect temperature.

TRANSECT	MAE (°C)	RMSE (°C)
2016 04 22 (west basin)	1.15	1.33
2017 06 14 Part 1 (west basin)	0.88	1.00
2017 06 14 Part 2 (west basin)	0.61	0.76
2017 06 14 Part 3 (west basin)	0.80	0.94
2017 06 14 Part 4 (west basin)	0.70	0.86
2017 06 21 (San Fernando)	1.73	2.00
2017 07 27 day Part 1 (San Fernando)	0.97	1.20
2017 07 27 day Part 2 (San Fernando)	0.92	1.10
2017 07 27 night Part 1 (San Fernando)	0.55	0.68
2017 07 27 night Part 2 (San Fernando)	0.85	1.00
2017 08 28 day Part 1 (west basin)	0.48	0.60
2017 08 28 day Part 2 (west basin)	0.71	0.94
2017 08 28 night Part 1 (west basin)	1.00	1.10
2017 08 28 night Part 2 (west basin)	0.82	0.92

A.7 Summary

Model validation was carried out against (1) observations from weather monitoring networks (mesonet and metars) and (2) observations from mobile transects that were performed in this study. In evaluating model performance for the long term, the simulated meteorological variables (including temperature, humidity, wind speed, and wind direction) were all compared to corresponding observations from the networks. For the transect-specific simulations, air temperature from the model was compared to observations along the corresponding transects and at the corresponding times. Results show good model performance at both scales and that the

model captures reasonably well the effects of variations in albedo and/or canopy cover on air temperature.

Evaluation of coarse-scale regional simulations and fine-scale, transect-specific simulations against observations shows a meteorological-model performance that meets or is better than community-recommended benchmarks. For example, the temperature mean absolute error for transect-specific simulations is 0.86 °C (compare to a recommended threshold of ≤ 2 °C). The performance evaluation also demonstrates that the model can be used in siting fixed weather stations and designing mobile-observation routes to characterize urban heat and cool islands.

B. CORRELATING AIR TEMPERATURE TO SURFACE PHYSICAL PROPERTIES

B.1 Goal

The goal of this task is to develop correlations between neighborhood-scale albedo and observed temperatures from transects and between neighborhood-scale vegetation canopy cover and observed temperatures.

B.2 Correlations of observed temperature with albedo and canopy cover

Following model performance evaluation, correlations between observed temperature and surface physical properties were evaluated. In this case, two surface properties of interest were examined: neighborhood-scale albedo and vegetation canopy cover. The relationships between observed air temperature (predictand) and either albedo and/or canopy cover (predictors) were examined in three manners: (1) simple linear regression, (2) multiple regression, and (3) CART analysis.

To develop these correlations, weighted albedo and canopy cover corresponding to each mobile-transect observation point were calculated based on Cressman-type analysis, where

$$W_{p,i} = \frac{R^2 - d_{p,i}^2}{R^2 + d_{p,i}^2} \quad (1)$$

for $d_{p,i} \leq R$, and $W_{p,i} = 0$ for $d_{p,i} > R$.

In Eq. (1), $W_{p,i}$ is the weighting factor for the quantity of interest (e.g., albedo or canopy cover) at a model grid point, i , relative to a transect observation point, p ; R is a pre-determined radius of influence; and $d_{p,i}$ is the distance from the transect observation point p to the grid point i . The weighted property, P_{wv} (i.e., weighted albedo or canopy cover) per each transect observation point is simply:

$$P_{wv,p} = \frac{\sum_i W_{p,i} V_i}{\sum_i W_{p,i}} \quad (2)$$

where V is the property in question (albedo or canopy cover) at the grid point i .

B.2.1 Simple linear regression

In Figure 33 (a-i), observed air temperature (°C) from mobile transects is plotted on the vertical axis against grid-level (neighborhood-scale) albedo (ALB) or canopy cover (VEG), where ALB and VEG are each computed via Eqs. (1) and (2). This analysis is for the downtown area defined by the rectangle at right in Figure 1. For the San Fernando Valley (domain defined by white rectangle at left in Figure 1), the observed temperature in Figure 34 (a-e) is plotted against canopy cover only (as predictor) because albedo has a smaller variability in this domain.

The analysis in Figures 33 and 34 provides information for each transect segment including dates, slopes computed as temperature change per 0.1 increase in albedo or canopy cover (to normalize and facilitate inter-comparisons of effects across various transects), corresponding p-values (probability values), wind speed (WSP), and solar radiation (SOLRAD) at the time of the transect. The latter two were obtained from the NOAA/MADIS mesonet monitors closest to each mobile transect at the time it was conducted. In this analysis, a significance level of 0.05 was selected and, as such, a p-value < 0.05 represents a statistically significant correlation between observed temperature (from the transect) and surface properties (albedo and canopy cover).

The analysis in Figures 33 and 34 was based on the Cressman-weighting scheme discussed above and a radius of influence of 1 km. The fifteen transects are identified as TR01 through TR15 and if a transect is made up of parts carried out at different times, these will be indicated as P1, P2, etc. One transect (TR14) is not shown in this analysis because of missing data.

(a) TR01: 2017-06-14 day P1; WSP: 3.3 m/s; SOLAR: 875 W/m²
ALB: -3.65°C/0.1, p-value: <0.0001; VEG: -0.10°C /0.1, p-value: 0.5200

(b) TR02: 2017-06-14 day P2; WSP: 3.3 m/s; SOLAR: 872 W/m²
ALB: -1.04°C/0.1, p-value: 0.0817; VEG: +0.65°C /0.1, p-value: 0.0057

(c) TR03: 2017-06-14 day P3; WSP: 3.4 m/s; SOLAR: 865 W/m²
ALB: +1.00°C/0.1, p-value: 0.0001; VEG: -0.40°C /0.1, p-value: 0.0074

(d) TR04: 2017-06-14 day P4; WSP: 2.7 m/s; SOLAR: 860 W/m²
ALB: -14.7°C/0.1, p-value: <0.0001; VEG: -0.89°C /0.1, p-value: 0.0061

(e) TR05: 2017-08-28 day P1; WSP: 1.34 m/s; SOLAR: 853 W/m²
ALB: -9.25°C/0.1, p-value: <0.0001; VEG: -2.19°C /0.1, p-value: <0.0001

(f) TR06: 2017-08-28 day P2; WSP: 2.20 m/s; SOLAR: 830 W/m²
ALB: -1.01°C/0.1, p-value: <0.0001; VEG: -0.40°C /0.1, p-value: <0.0001

(g) TR07: 2017-08-28 night P1; WSP: 1.10 m/s; SOLAR: 0 W/m²
ALB: -4.00°C/0.1, p-value: <0.0001; VEG: -1.61°C /0.1, p-value: <0.0001

(h) TR08: 2017-08-28 night P2; WSP: 1.00 m/s; SOLAR: 0 W/m²
ALB: -3.40°C/0.1, p-value: <0.0001; VEG: -1.81°C /0.1, p-value: <0.0001

(i) TR13: 2016-04-22 day; WSP: 2.70 m/s; SOLAR: 828 W/m²
ALB: -4.90°C/0.1, p-value: <0.0001; VEG: -0.23°C /0.1, p-value: <0.0001

Figure 33 (a-i): Observed air temperature (from mobile transects) versus neighborhood-scale albedo and canopy cover in the downtown area. Vertical axis (T_{air}) is air temperature (°C); horizontal axis is albedo (ALB) or canopy cover (VEG), unitless.

(a) TR09: 2017-07-27 day P1; WSP: 1.70 m/s; SOLAR: 912 W/m²
VEG: -0.40°C /0.1, p-value: <0.0001

(b) TR10: 2017-07-27 day P2 (NW 1.5 fetch); WSP: 4.00 m/s; SOLAR: 803 W/m²
VEG: -0.11°C /0.1, p-value: 0.0105

(c) TR11: 2017-07-27 night P1; WSP: 1.30 m/s; SOLAR: 0 W/m²
VEG: -0.20°C /0.1, p-value: <0.0001

(d) TR12: 2017-07-27 night P2; WSP: 0 m/s; SOLAR: 0 W/m²
VEG: -1.06°C /0.1, p-value: <0.0001

(e) TR15: 2017-06-21 day; WSP: 3.3 m/s; SOLAR: 721 W/m²
 VEG: -0.53°C /0.1, p-value: <0.0001

Figure 34 (a-e): Observed air temperature (from mobile transects) versus neighborhood-scale canopy cover in the San Fernando Valley domain. Vertical axis (T_{air}) is air temperature (°C); horizontal axis is canopy cover (VEG), unitless.

Table 5 summarizes the main takeaways from the analysis in Figures 33 and 34. It shows the response of observed air temperature (°C) to a 0.1 increase in neighborhood-scale albedo, symbolically written as $\Delta T / (0.1 \Delta a)$, or in canopy cover, written as $\Delta T / (0.1 \Delta \eta)$, in columns 2 and 6, along with the corresponding p-value for each transect (in columns 3 and 7, respectively). Again, the reason for selecting a denominator of 0.1 is simply to normalize the temperature sensitivity and facilitate inter-comparisons of the effects across various transects. Also, an increase of 0.1 in neighborhood-scale albedo and/or canopy cover is one assumption often made as a mitigation scenario in UHI studies. Hence, it is used here as an indicator to what the real-world impact might be on air temperature.

Except for two entries (contribution of canopy cover to air temperature in transect TR01 and contribution of albedo to air temperature in transect TR02, as seen in columns 7 and 3, respectively), all other entries are statistically significant. For these two transects, the p-values suggest that in TR01, albedo is the main driver of air temperature and in TR02, canopy cover is the main driver.

In addition, all correlations are negative (i.e., when albedo and/or canopy cover increase, temperature decreases) except for transects TR02 (for canopy cover, column 6) and TR03 (for albedo, column 2). As will be discussed next, these two transects were among those carried out during periods of higher wind speeds, which can weaken the correlations. In transects TR04 and TR05, the large temperature response (sensitivity) to albedo change is likely caused by the extensive freeway and roof cover in these areas (> 95%).

Table 5: Summary of observed transect temperature response to changes in neighborhood-scale (500 m) albedo and/or canopy cover.

1	2	3	4	5	6	7	8	9
	Albedo effects				Canopy-cover effects			
Transect	$\Delta T / (0.1\Delta a)$	p-value	Actual range (a)	ΔT bounded	$\Delta T / (0.1\Delta \eta)$	p-value	Actual range (η)	ΔT bounded
TR01	-3.65	< 0.0001	0.023	-0.84	-0.10	0.5300	0.100	-0.10
TR02	-1.04	0.0817	0.021	-0.22	0.65	0.0057	0.054	0.35
TR03	1.00	0.0001	0.017	0.17	-0.40	0.0074	0.070	-0.28
TR04	-14.70	< 0.0001	0.012	-1.76	-0.89	0.0061	0.100	-0.89
TR05	-9.24	< 0.0001	0.030	-2.77	-2.20	< 0.0001	0.105	-2.29
TR06	-1.10	< 0.0001	0.038	-0.38	-0.40	< 0.0001	0.183	-0.73
TR07	-4.00	< 0.0001	0.030	-1.20	-1.61	< 0.0001	0.105	-1.69
TR08	-3.40	< 0.0001	0.030	-1.02	-1.81	< 0.0001	0.100	-1.81
TR13	-4.89	< 0.0001	0.037	-1.81	-0.22	< 0.0001	0.260	-0.60
TR09					-0.40	< 0.0001	0.330	-1.32
TR10					-0.11	0.0105	0.304	-0.33
TR11					-0.20	< 0.0001	0.330	-0.66
TR12					-1.06	< 0.0001	0.313	-3.31
TR15					-0.53	< 0.0001	0.310	-1.76

Columns 4 and 8 show the actual range of albedo and canopy cover, respectively, associated with each specific transects instead of a hypothetical range of 0.1 as used in columns 2 and 6. In other words, the ranges of albedo and canopy cover in columns 4 and 8 are “bounded” by the values encountered in the real world at each of these transects.

Columns 5 and 9 are temperature changes ($^{\circ}\text{C}$) computed by multiplying the corresponding actual range (from columns 4 or 8, respectively) by the slope given in columns 2 or 6 and dividing by 0.1. Thus the bounded temperature variations in columns 5 and 9 represent the maximum changes that can be expected in each specific transect (per its actual albedo or canopy-cover range) rather than the unbounded values in columns 2 and 6. By doing so, some of the unreasonably-large slopes (unbounded) in column 2, e.g., for TR04 and TR05, become much more reasonable, when bounded, as in column 5.

Thus, columns 5 and 9 represent the changes in temperature that one can expect as a result of increasing albedo and/or canopy cover by the amounts already encountered in the real world and that are achievable via current practices in building and planning. On the other hand, columns 2 and 6 represent the potential cooling effects that would result from implementations of high-albedo measures (cool roofs and cool pavements) and/or urban forestation, where each would be increased by 0.1.

Next, the correlations between mobile-observed temperature and albedo and/or canopy cover are re-examined but with smaller radii of influence (< 500 m). The goal is to evaluate whether a length-scale effect exists in these correlations. This analysis is done by comparing observations

directly to surface properties at grid points, that is, without the Cressman analysis discussed above.

This analysis shows that the correlations between observed temperature and neighborhood-scale albedo and/or canopy cover are negative and statically significant at $R < 500$ m when wind speed is under 3 m/s locally – compare the p-values of rows 1, 3, 5, 7, and 9 in the right half of Table 6 with all the rows in the left half, suggesting weaker correlation between temperature and surface properties within 500 m at wind speeds exceeding 3 m/s. That is, when wind speed exceeds 3 m/s, the correlations either become weaker (for one of the predictors or the other) or statistically insignificant (see TR01, TR02, TR03, TR10, and TR15). For these cases, the analysis was repeated once more by (1) increasing the radius of influence from 500 m to 1 km and (2) restricting the correlations to upwind model points.

In this repeated analysis, the correlations improved further, i.e., some positive or weak correlations converted into negative or stronger ones as seen in Table 6 (compare TR01-SE to TR01, TR02-NW to TR02, TR03-NE to TR03, TR10-NW to TR10, and TR15-NE to TR10). In these cases, the p-values and slopes improved after increasing the upwind fetch (from 500 m to 1 km) and including only grid points within the wind approach direction. This also explains why these adjusted correlations are better than the corresponding ones in Table 5 (in some cases) for one or the other predictors, since the correlations in Table 4 were not limited to upwind points.

The results from this analysis suggest that when wind speed is less than 3 m/s, the observed temperature is influenced by the physical properties of the immediate surroundings (less than 500 m radius). At wind speeds exceeding 3 m/s, temperature is influenced by surface properties in a longer fetch (~1 km) in the upwind direction. Physically, this is because advective effects are smaller than the localized convective effects when wind speed is lower. At higher wind speed, in this case > 3 m/s, temperature is influenced more by advective than localized effects. To provide context, the monthly average wind speeds in the study areas (from climatology) are as follows for January – December: 3.7, 3.5, 3.3, 3.1, 3.1, 2.6, 2.3, 2.2, 2.6, 2.6, 3.1, and 4.0 m/s. Thus the 3.3-4.0 m/s winds that were observed during some of the transects are relatively uncommon in this area and time of year, i.e., July and August, where 2.2 – 2.6 m/s is a more typical range.

Table 6: Correlations between air temperature (°C) (observed from transects) and neighborhood-scale (500 m) albedo and/or canopy cover. Transects with wind direction represent effects from a 1-km upwind fetch.

Transect	$\Delta T / (0.1\Delta a)$	p-value	$\Delta T / (0.1\Delta \eta)$	p-value	wind m/s	Transect	$\Delta T / (0.1\Delta a)$	p-value	$\Delta T / (0.1\Delta \eta)$	p-value	wind m/s
Wind speed < 3 m/s						Wind speed > 3 m/s					
TR04	-2.14	0.0120	-0.53	0.0017	2.7	TR01	-0.83	0.0500	0.12	0.0370	3.3
TR05	-5.03	< 0.0001	-0.49	< 0.0001	1.3	TR01-SE	-0.95	0.0003	-0.18	0.0087	
TR06	-1.08	< 0.0001	-0.22	< 0.0001	2.2	TR02	1.08	0.0007	-0.22	0.1000	3.3
TR07	-2.66	< 0.0001	-0.41	< 0.0001	1.1	TR02-NW	-0.44	0.0414	-0.11	0.6000	
TR08	-1.96	< 0.0001	-0.50	< 0.0001	1.0	TR03	1.41	0.0020	-0.19	0.0003	3.4
TR13	-2.35	< 0.0001	-0.22	< 0.0001	2.7	TR03-NE	1.15	0.0010	-0.30	0.0005	
TR09			-0.18	< 0.0001	1.7	TR10			0.08	0.0030	4.0
TR11			-0.13	< 0.0001	1.3	TR10-NW			-0.07	0.0800	
TR12			-0.39	< 0.0001	0.0	TR15			0.04	0.0330	3.3
					TR15-NE	-0.18			< 0.0001		

B.2.2 Multiple regression

Multiple regression was carried out for albedo and canopy cover as predictors to observed air temperature from the transects. This analysis applies only to the downtown area since the San Fernando Valley analysis involved only variations in one predictor, canopy cover.

Here, the form of the correlation is given by Eq. (3) where a is albedo and η is canopy cover. The coefficients ($C1$, $C2$, $C3$) and corresponding p-values ($p1$, $p2$, $p3$) are given in Tables 7 and 8. Coefficients $C1$, $C2$, and $C3$ are in °C, and the “0.1” denominator simply indicates that the changes in temperature ($C2$ and $C3$) correspond to a 0.1 increase in surface albedo or a 0.1 increase in canopy cover. This was done for reasons explained above.

$$T_{\text{air}} = C1 + \frac{C2}{0.1} a + \frac{C3}{0.1} \eta \quad (3)$$

Following the structure of the discussion above, results from the multiple-regression analysis are presented in two parts; Table 7 summarizes the analysis at 1-km radius of influence using the Cressman-type weighting discussed earlier, while Table 8 summarizes the 500-m analysis without weighting. The results in Table 7 show that the correlations are overwhelmingly negative (as albedo and canopy cover increase, temperature decreases) and statistically significant except for three situations. These are in transect TR01, where the role of canopy cover is insignificant, and in transects TR02 and TR03, where the role of albedo is insignificant. This was already discussed above, as were the large slopes in TR04 and TR05.

In Table 8, the sign of some correlations changes to negative or significance improves (smaller p-values) when the radius of influence is increased and wind from a specific direction is accounted for rather than an average from several directions (e.g., TR01-SE and TR02-NW). In other words, at wind speeds exceeding 3 m/s, extending the upwind fetch from 500 m to 1 km and accounting for LULC properties only in the wind-approach direction improves the p-values and/or the coefficients for albedo and/or canopy cover changes. This is similar to what was discussed above.

Table 7: Eqn. (3) applied to 1-km Cressman-type analysis of air temperature correlation to albedo and canopy cover. Coefficients $C2$ and $C3$ are, respectively, the responses of observed air temperature to a 0.1 increase in neighborhood-scale albedo and canopy cover.

Transect	$C1$ (°C)	$p1$	$C2$ (°C)	$p2$	$C3$ (°C)	$p3$
TR01	33.25	< 0.0001	-3.70	< 0.0001	-0.15	0.3350
TR02	31.65	< 0.0001	-1.81	0.1204	-1.08	0.0154
TR03	29.42	< 0.0001	-0.15	0.935	-0.75	0.0086
TR04	47.18	< 0.0001	-13.95	< 0.0001	-0.71	0.0052
TR05	43.17	< 0.0001	-8.17	< 0.0001	-1.97	< 0.0001
TR06	33.25	< 0.0001	-0.78	< 0.0001	-0.36	< 0.0001
TR07	27.83	< 0.0001	-2.42	< 0.0001	-1.47	< 0.0001
TR08	30.04	< 0.0001	-3.71	< 0.0001	-1.85	< 0.0001
TR13	28.52	< 0.0001	-4.63	< 0.0001	-0.10	0.0500

Table 8: Eqn. (3) applied to 500-m analysis of air temperature correlation to albedo and canopy cover without weighting (without and with correction for wind speed and direction). Coefficients $C2$ and $C3$ are, respectively, the responses of observed air temperature to a 0.1 increase in neighborhood-scale albedo and canopy cover.

Transect	$C1$ (°C)	$p1$	$C2$ (°C)	$p2$	$C3$ (°C)	$p3$
TR01	29.28	< 0.0001	-0.765	0.050	+0.119	0.0266
TR01-SE	29.59	< 0.0001	-0.881	0.010	-0.030	0.7000
TR02	27.37	< 0.0001	+1.087	0.008	-0.148	0.2660
TR02-NW	29.56	< 0.0001	-0.459	0.036	-0.161	0.5000
TR03	29.94	< 0.0001	-0.702	0.100	-0.207	0.0005
TR04	28.66	< 0.0001	-0.450	0.055	-0.417	0.1600
TR05	37.41	< 0.0001	-4.575	< 0.0001	-0.238	< 0.0001
TR06	33.98	< 0.0001	-1.211	< 0.0001	-0.353	< 0.0001
TR07	25.93	< 0.0001	-1.488	< 0.0001	-0.334	< 0.0001
TR08	27.21	< 0.0001	-1.910	< 0.0001	-0.491	< 0.0001
TR13	25.49	< 0.0001	-2.088	< 0.0001	-0.120	< 0.0001

The values listed in tables 7 and 8 are relative to a changes of 0.1 in albedo or vegetation cover and, thus, are unbounded. These can be converted into transect-specific bounded values as was

done in Table 5. Two examples are demonstrated here that will be referred to in the following discussion of example CART for transects TR04 and TR13 in Section B.2.3. The first example is the coefficient $C3$ (for canopy cover) in Table 8, corresponding to transect TR04 with a value of $-0.417\text{ }^{\circ}\text{C}$. If this is multiplied by the actual canopy-cover range of 0.1 (from Table 5, TR04 under column 8) and divided by 0.1, we obtain a bounded value of $-0.41\text{ }^{\circ}\text{C}$. The second example is the coefficient $C2$ (for albedo) in Table 8, corresponding to transect TR13 (value of $-2.088\text{ }^{\circ}\text{C}$). If this is multiplied by the actual albedo range of 0.037 (Table 5, transect TR13, under column 4), and divided by 0.1, we obtain a bounded value of $-0.77\text{ }^{\circ}\text{C}$.

B.2.3 Classification and regression tree (CART)

A classification and regression tree (CART) analysis was also undertaken to assess the interactions among predictors of observed air temperature (from the mobile transects). The purpose of the CART analysis was to identify the main driver (albedo or canopy cover) of air temperature in each case, i.e., in various transect segments, because of variations in land use and surface physical properties. In addition, the roughness length parameter, computed following the approach of MacDonald et al. (1998), was included in the following CART examples as an additional predictor to evaluate its role relative to that of albedo and canopy cover.

While the CART analysis was carried out for each of the 15 transects, two examples are presented here. Transect TR04 is a daytime transect at 14:00 Pacific Daylight saving Time (PDT) carried out on 14 June 2017 in the downtown area; TR13 also a daytime (13:00 PDT) transect in the downtown area, was carried out on 22 April 2016.

From the CART analysis of TR04 (Figure 35a), the following can be deduced:

- In this transect segment, canopy cover (top node) is the main splitting variable, i.e., the main driver of air temperature. The lowest temperatures are associated with the highest canopy cover (node 3).
- To estimate the influence of canopy cover on temperature in this sub-segment, we compare terminal nodes 3, 4, and 5. The difference between temperature at node 3 and the weighted temperatures at nodes 4 and 5 is $-0.35\text{ }^{\circ}\text{C}$, which is the contribution of canopy-cover change to air temperature in this sub-segment. This is comparable to the value $-0.41\text{ }^{\circ}\text{C}$ computed, above, in the last paragraph of Section B.2.2 (based on the multiple regression in Table 8). The reduction in air temperature is significant, considering that this is a short segment (57 temperature observations).
- Roughness length has minor, secondary effects. Within the range of lower canopy cover (<0.055), roughness length (Z_0) can play a role. In this case, the larger Z_0 (node 5) produces slightly higher air temperatures ($0.23\text{ }^{\circ}\text{C}$ warmer on average) during daytime.

Transect TR13 is a longer segment with 798 temperature observations. The following can be deduced from this CART analysis (Figure 35b):

- In this transect segment, the most influential variable on air temperature (top splitting node) is albedo.
- Observed temperature is lower where albedo is larger. For neighborhood-scale albedo greater than 0.125, the temperatures are lowest, e.g., compare terminal nodes 6 and 7 (temperatures of 22.34 and 21.97 °C) with nodes 5, 9, 16, 34, and 35 (with higher temperatures of 22.90, 23.05, 23.17, 22.20, and 23.17 °C, respectively).
- Calculating the weighted temperature differences for nodes with albedo higher then 0.125 (6 and 7) versus lower than 0.125 (nodes 5, 9, 16, 34, and 35) shows that the contribution of higher albedo in this transect is to lower air temperature by 0.81 °C, which is significant. This is comparable to the value of -0.77 °C computed in the last paragraph of Section B.2.2, which was based on multiple regression.
- Furthermore, within each subtree, the effects of increased albedo are evident. For example, comparing terminal nodes 6 and 7 shows that observed temperatures are 0.37 °C lower where albedo is larger than 0.145 relative to where albedo is lower than that.
- In this transect, where albedo is lower than 0.125, canopy cover also has a significant effect. Comparing node 5 (where canopy cover is greater than 0.195) and nodes 9, 16, 34, and 35 (where cover is lower than 0.195), the contribution of canopy cover is to cool the air by 0.12 °C. This effect is smaller than the effects of albedo in this transect.
- The effects of roughness length are secondary and different from one subtree to another. For instance, whereas increased roughness length in node 35 relative to node 34 does show increased temperature, comparing the increased roughness in nodes 34 and 35 relative to node 16, shows the opposite effect.

Figure 35: CART for transects (a) TR04 and (b) TR13

B.3 Summary

Observed air temperature from mobile-transects were correlated to 500-m (neighborhood-scale) albedo and/or vegetation canopy cover. A total of fifteen observational transects were carried out in summers of 2016 and 2017. The mobile-observation temperatures were compared to model fields and also correlated to surface physical properties focusing on neighborhood-scale albedo and vegetation canopy cover.

The model results and observational data analysis (measurements from mobile transects) show that as albedo increases, air temperature decreases during the day, but also at night in smaller extents likely because of lag effects or masking by other variables (co-variance). The increase in canopy cover lowers air temperature during both day and night via combined effects of canopy shading, soil moisture, roughness, and evapotranspiration. While both albedo and canopy cover have significant impacts on air temperature, CART analysis done in this study also shows that, depending on land-use, surface physical properties, and geographical location, that one or the other becomes the main driver of air temperature.

At the 500-m scale, the analysis of observed temperature from mobile transects indicates that the negative correlations between air temperature and surface albedo and/or canopy cover become weaker or statistically insignificant at wind speeds exceeding about 3 m/s. For observations when wind speeds exceeded this threshold, the analysis was repeated to increase the radius of influence (from 500 m to 1 km) and to consider land use and surface physical properties in the upwind fetch only (wind approach direction). This resulted in the correlations becoming stronger (lower p-values and statistically more significant) and, where they were positive, the correlations became negative. Based on bounded correlations between observed temperature and actual, transect-specific ranges of albedo and canopy cover, the analysis shows that cooling of up to 2.8 °C during the daytime can be achieved by increasing neighborhood-scale (500-m) albedo. Cooling of up to 2.3 °C during the day and up to 3.3 °C at night can be achieved by increasing canopy cover.

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Appendix F

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Appendix F: Air-temperature response to neighborhood-scale variations in albedo and canopy cover in the real world: Fine-resolution meteorological modeling and mobile temperature observations in the Los Angeles climate archipelago (Task 4 Report, Part II)

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Appendix G

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Appendix G: Observational evidence of neighborhood scale reductions in air temperature associated with increases in roof albedo (Task 4 Report, Part III)

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