**NASA DEVELOP National Program**



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Heat-Health & Spatial Variation in Maricopa County, Arizona

Enhancing Extreme Heat Intervention and Preparedness Activities Using Remote Sensing and Spatial Analysis of Heat-Related Risks and Mortality in Maricopa County, Arizona

 **Technical Report** 

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# I. Abstract

[Placeholder - do not put anything here until the final draft submission. The abstract in the project summary is where the working draft of the abstract should “live”]

**Keywords**

Remote Sensing, Heat, Urban Climate, Spatial, Public Health, Vulnerability, Socioeconomic

# II. Introduction

**Project Objectives**

Our project creates a climatology map of Maricopa County, Arizona for detection of extreme heat anomalies on various scales (i.e. daily, monthly, seasonal) and the understanding of consistency between such events (where, how, and why variations occur). In conjunction, we will determine the current use and frequent users of relief resources for establishing how this correlates with current socioeconomic vulnerability assumptions in literature. From this, we will analyze the variability within anomalies and survey results as a means of determining where, when, and how relief efforts should intervene

**Current Issue - Urbanization & Heat-Related Risks**

With compounding issues from a warming climate and the vastly increasing rates of land use change to include more impermeable surfaces and less vegetative cover, dense urban areas around the globe are experiencing amplified urban heat island effects resulting in an increase in heat related and heat caused deaths (Anderson & Bell, 2010, Greene et al., 2011, Hartz et al., 2012, and Zhang et al. 2013). Maricopa County, Arizona is currently experiencing such a phenomenon. According to the U.S. Census Bureau, Maricopa County’s population increased by 10,160,000 individuals in a period of four years (USCB, 2015 and Hondula, 2014). Maricopa County, Arizona is the leading megapolitan area in the U.S. for population growth and urbanization (Hondula, 2014). On top of this, the area is specifically recognized for its high heat index (Hondula, 2014). The region’s hot desert climate and extended periods of high temperatures cause human health consequences to continually escalate and with the county’s increased rate of urbanization, extreme heat rises as a human health concern. (Coutts et al., 2007, Greene et al., 2011 and Hondula, 2014).

From 2006 - 2013 about 1,050 deaths due to extreme heat and the body’s inability to regulate its internal temperature were reported (MCDPH, 2014 and Uejio, 2011). Other common physical health symptoms include heat cramps and heat exhaustion (Harlan, 2006 and Uejio, 2011). Of all 50 states, Arizona has the greatest reported death rates related to extreme heat for individuals older than 24 (LoVeccho et al., 2005). Those who were considered to be the most vulnerable (lack of resources to cope with the environmental threat) mirror other cities facing this issue and included males, elderly, poor, homeless, socially isolated, and minorities (MCDPH, 2014, Harlan, 2006, Johnson & Wilson, 2009). Most heat-related illnesses and deaths were found in major cities at home, sports and recreational areas, construction and industrial sites, and streets and highways (MCDPH, 2014 and Davis et al., 2003). While county wide relief efforts exist, there is currently no policy explicitly related to monitoring and/or preventing heat caused and heat related deaths.

Recent studies examine this phenomenon in Maricopa county in terms of satellite data on temperature and surface features of larger time scales and socioeconomic factors predicted and assumed from statistical regressions (Dousset et al, 2011, Golden et al., 2008, Grossman-Clark et al., 2010, Harlan et al., 2012, and Hondula et. al, 2015). However, these studies have yet to examine the nuances of extreme heat days and nights, such as potential differences within the hot days themselves as well as throughout an entire season. On top of that, recent surveys conducted by MCDPH provide novel content in the actual distribution and use of relief aid resources, such as warning system deployment and cooling center location use. With our data we may then establish how these resources are used and how the daily heat threats vary in order to establish where future cooling centers and warning message systems should be deployed.

**Study Area and Study Period**

Maricopa County is a 9,203 square mile range located in the southwestern portion of Arizona and lies within the Basin and Range Province (Rasmussen, 2012 and Golden, et al., 2008). This landscape includes steep, linear mountain ranges that alternate with lengthy deserts created from sand filling in the basins (Rasmussen, 2012). Due to Arizona’s diverse landscape, arid climate, and sparse cloud cover, the temperature varies dramatically from season to season and from daytime to nighttime. Located in an arid subtropical climate, Maricopa County has an average annual temperature of 71.25 °F, an annual high temperature of 88.5 °F, and the highest average high during the month of July at 108 °F (U.S. Climate Data, 2015 and USA, 2015). The county also has an annual average humidity of 80.59%, a UV index of 6.4, a heat index of 72 °F (giving how hot it feels by comparing temperature and humidity where exposure to full sunshine can increase this value by 15 °F), and a comfort index of 46/100, with higher numbers being more comfortable than lower (Sperlings Best Places, 2014, USA, 2015, and National Weather Service, 2014). The hottest temperature was 122 °F on July 27 and 28 in 1995 and the average number of days per year where the high temperature was 100 °F or more was 116 days (Mesa.AZweather, 2014). 104-128 °F is NOAA’s Heat Index “danger” zone and serves as an appropriate threshold for severe heat stress as anything higher will likely result in sunstroke and heatstroke (Harlan, 2003). Maricopa County has an average of 296 sunny days a year and receives an annual average precipitation of 8.92 inches with the greatest amount received in the months of March, July, and December (USA, 2015, U.S. Climate Data, 2015, and Sperlings Best Places, 2014). In most cases, the majority of heat distress calls occur during the hot and moist North American Monsoon period later in the summer when the ground gets excessively heated and that moisture-filled air rises along the mountain ranges to produce thunderstorms (Golden et al., 2008 and Sperlings Best Places, 2014).

This research focuses on the extreme heat during the hottest months of the year from May through October during the period between 2006 and 2014. Our climatology goes back to 2002 to include more reference data.

**National Applications Addressed**

Our project primarily addresses Health & Air Quality as well as Climate. The results of this project primarily contribute to the public health facet, as it will help Maricopa County ensure its residents are safe during the periods of extreme heat.

**Project Partners**

Partnering with this project are the Arizona Department of Health Services (ADHS), the Environmental Remote Sensing and Informatics Lab (ERSL) at Arizona State University (ASU), and the Center for Policy Informatics (CPI) at ASU. ADHS coordinates the statewide heat safety task force, for which the Maricopa County Department of Public Health and ASU are active participants, and leads the state’s participation in Centers for Disease Control and Prevention’s (CDC) Building Resilience against Climate Effects initiative. Decision support tools and project findings will be shared through statewide heat safety meetings.

# III. Methodology

DATA ACQUISITION

Ground truthing data to cross reference remotely sensed air temperature is available through the University of Utah’s MesoWest database. Utilizing the MesoWest API and python scripting, the data for 285 weather observation stations throughout Maricopa County was obtained from 2006-Present for the months of May through October. The data was then georeferenced in ArcMap and organized in a custom built geodatabase.

**Table 1:** **NASA Earth Observations utilized**. Most data came from the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor on the Aqua satellite, as these pass over times, 1:30 AM and 1:30 PM, more closely proximate the true minimum and maximum daily temperature values as compared to the MODIS sensor on the Terra satellite. Data downloaded with ‘dnppy’ module. *Source*: Land Processes Distributed Active Archive Center (LP DAAC) FTP collection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Name** | **Source** | **Dates of Acquisition** | **Product Details** | **Bands** |
| *Aqua/MODIS* | LP DAAC FTP | May - Sept (2005 - 2015) | MYD11A1 Grid: h08v05Level 3 (1km) | land surface temperature/emissivity |
| *Terra/MODIS* | LP DAAC FTP | May 21 - 24 2005 | MOD11A1 Grid: h08v05Level 3 (1 km) | land surface temperature/emissivity |
| *Landsat 8* | LP DAAC FTP | TBD | Path 41 Row 33 | all |

Shapefiles of Maricopa County (including county borders and census blocks) were collected from the ASU Repository of GIS data.

As a means of comparison and to put the above data in further context for analysis, we gathered information on the percent of impermeable surfaces as well the percent of tree cover from the National Land Cover Database, hosted by United States Geological Survey (USGS). National Centers for Environmental Prediction (NCEP) Reanalysis data will also be utilized to determine the synoptic atmospheric conditions in the desert southwest during extreme heat events in Maricopa County. The reanalysis will be generated using Matlab.

Community Assessment for Public Health Emergency Response (CASPER) survey data from the Maricopa County Department of Health from 2006 - 2015.

DATA PROCESSING AND ANALYSIS

**Task 1: Remote Sensing Climatology of Maricopa County Surface Temperatures to Determine Extreme Heat Days and Nights**

*Processing*

The MODIS product downloaded already controls for quality via the quality control band. The Kelvin (K) values ranged from 7500 – 65535, requiring band math that applied the scale factor of 0.02 for true K values. Each ‘.hdf’ file was converted into ‘.tif’ format and projected into ‘Sinusoidal’ in order to ensure each consistent projection of each file. This conversion and projection definition was performed with the ‘extract\_from\_hdf’ function in the ‘dnppy’ module. As a final processing step, MODIS images were subset to the contour line of Maricopa County using the ‘clip\_to\_shape’ function in the ‘dnppy’ module.

*Analysis*

The MODIS data are stored as a daytime and a nighttime surface temperature for each pixel. Once we pre-processed the MODIS data, we had a loosely based climatology of surface temperatures in Maricopa County for the specified date range.

A later task utilizes Landsat 8 imagery to compare extreme heat clusters on a finer scale. Because of the difference in Passover times from Aqua to Landsat 8, we compared differences between Aqua and Terra satellite imagery. Due to the reliability and quality of the Aqua satellite’s MODIS thermal bands we chose to utilize the Aqua satellite despite diurnal effects creating differences in Aqua-to-Landsat 8 comparisons. However, we visually examined the differences between Terra and Aqua on five dates with a band subtraction (Aqua – Terra, due to the later time and presumably higher surface temperatures of Aqua).

**Task 2: Determine and Analyze Extreme How and When Heat Anomalies Occur**

*Processing*

MODIS data used in Task 1 (remote sensing climatology of Maricopa County) was utilized and therefore went through the same processing. On top of that, we calculated census tract surface temperature averages for each clipped MODIS image in RStudio using a census tract shapefile (Appendix 1). These surface temperatures were converted into celsius (C). Landsat 8 images were downloaded, converted into ‘.tif’ files and covered an area specified by a cluster analysis of our MODIS surface temperature data. If the cluster analysis went beyond the bounds of the Landsat 8 image, we mosaicked multiple images. Anomalous day temperature values from the weather station data were exported as a ‘.csv’ format and stacked appropriately for analysis in RStudio.

*Analysis*

Temperature anomaly dates were isolated with the weather station data by running a script in Matlab to separate all days with a maximum temperature above 104°F (313.15 K). We then ran a Python script to convert the dates into julian day and year format to then delete MODIS images not in this specified date file (Appendix 1). Before performing analyses on clusters and measures of central tendencies between days, we executed a chi-squared contingency table test for association where the variables tested for association were month (May – September) and year (2005 – 2014) and the count data compared was extreme heat days within each month for every year. Once this association was established, we performed a nearest neighbor analysis (by Ripley’s K function with L-transform) in RStudio for census tract average surface temperature on the hottest 30% of census tracts on all anomalous days. A threshold of 30% was chosen based on a t-test comparing the top census tracts to the overall average, where 30% yeilded a significant result (*p* = 0.03, α = 0.05). We then explored variations in measures of central tendency. A series of One-Way ANOVAs were performed in RStudio to compare how the average surface temperature values of the top 30% census tracts on each day compared on extreme heat days throughout the season and between years, where temperature is the independent variable and the months of extreme heat days are the levels. Of averages deemed significantly different, a post-hoc Tukey’s Honestly Significant Difference (HSD) test was performed to determine which hot days were statistically significant. These dates further provided options for analysis with finer resolution data of Landsat 8.

After the MODIS cluster analysis, we downscaled to examine Landsat images matching dates of interest (chosen based on clustering patterns and average comparisons). We performed the same cluster analysis but using census block averages to refine the spatial resolution and the same One-way ANOVA.

As a final test of the anomalies we looked at the duration of an extreme heat event in number of days. As a statistical test, we considered the duration as count data and we therefore used another chi-squared test for association.

**Task 3: Model Predictions for Current State of Resource Use**

*Processing*

Survey results will need to be converted from ArcMap ‘.xlsx’ format into a ‘.csv’ format for analysis in RStudio. Once in RStudio data columns will be stacked appropriately for the particular analysis and subsets will be created to facilitate a more organized data analysis approach.

*Analysis*

In RStudio we will perform ordinal least squares regressions, such as binary logistic regression or ordered logistic regression, in order to determine what demographic factors relate to certain uses of relief aid. A binary logistic regression will look at the likelihood of AC use (with the outcome variable as ‘yes’ or ‘no’) versus various predictor variables (age, income, class, residence, etc.). We are also interested in examining income (along with other potential predictor variables) versus the likelihood of visiting a cooling center by using an ordered logistic regression, where the likelihood of visiting a cooling center is the outcome variable and categories of responses are ordered (such as “Very Likely”, “Somewhat Likely”, etc.). Another set of binary logistic regressions will examine who is hearing the warning messages and who is acting on these messages.

**Task 4: Maps of Heat Duration and Recurrence with Surface Feature Classification**

*Processing*

For the purposes of classification and normalized differences, Landsat 8 images will first be converted to reflectance by using the conversion information in the metadata files in order to ensure normalized results over the time periods using the following equations:

*ρλ'* = *MρQcal* + *Aρ*

and

$ρλ = \frac{ρλ'}{sin(θSE)}$,

**Equation 1**: Converting digital number of pixel to a reflectance value, where *Mρ* represents the multiplicative value, *Qcal* represents the band being converted, and *Aρ* represents the additive value. Note: sun elevation angle (SE) is converted from degrees to radians *Source*: Using the USGS Landsat 8 Product. *USGS* < <http://landsat.usgs.gov/Landsat8_Using_Product.php>>, Accessed 17 June 2015.

Additionally, the Landsat data was interpreted both in terms of brightness temperature and surface temperature, so the ‘atsat\_bright\_temp\_8’ and ‘surface\_temp\_8’ was used.

*Analysis*

On anomalous heat days in which Landsat 8 images are available, we used these images to create maps of heat duration and recurrence on a finer scale with either brightness temperature or surface temperature. Using the Thermal Infrared Bands 10 (10.60 - 11.19 μm) and 11(11.50 - 12.51 μm) in Landsat 8 we first mapped surface temperature by applying color ramps to these bands in Exelis Visual Information Solutions (ENVI). We compared these maps to already generated maps by Sharon Harlan et al. in the publication “Neighborhood Effects on Heat Deaths: Social and Environmental Predictions of Vulnerabilities in Maricopa County, Arizona.” We visually analyzed how daily anomalies compare with current maps (i.e. where are shifts occurring).

To further this analysis, we completed supervised classification of the Landsat 8 images that have been pre-processed and converted into reflectance to determine what surface features are under these hot spots. Over various timescales of extreme heat anomalies we did a normalized difference of images in the same band (determined based on the classification under a hotspot) to see what features are different within these heat events in this image over time in a specified wavelength with the following equation:

$Normalized Difference = \frac{Day 1 Bx - Day 2 Bx}{Day 1 Bx + Day 2 Bx}$,

**Equation 2**: Normalized difference equation for a single band over two days, where Day 1 and Day 2 were determined by which day held the higher pixel value of interest and where x represents the band number.

As an added measure, we looked at the National Land Cover Database’s information on percent of impermeable surfaces and percent of tree cover in the study area to see if there is a temporal shift in surfaces that corresponds to a shift in hotspot locations. With this we were specifically interested in types of differences between extreme heat days rather than between extreme heat days versus status quo.

**Task 5: Revised Heat Vulnerability Maps**

*Processing*

Data for this task will be generated from the previous tasks, there will be no additional processing information before analysis.

*Analysis*

Using the spatial data from the surveys and the surface/air temperature data for extreme heat anomaly days (specific satellite data determined after we see what the results looks like), we will overlay both of these in ArcGIS with census block boundaries to visually explore how heat fluctuations vary with respect to socioeconomic concerns and what this means for vulnerability areas.

If analysis allows, we will conduct a series of regressions in RStudio including a combination of socioeconomic factors and percent land cover values to try and determine what causes the variations between heat events. This will allow suggestions on the future effective adaptive capacity of current relief efforts, primarily cooling center locations and warning message deployment.

# IV. Results & Discussion

A chi-squared contingency table test for association was performed to determine if there is a significant association between month (May – September) and year (2005 – 2014) for counts of extreme heat (°F) days. The analysis yielded a significant association (χ2(36) = 66.83, *p* = 0.001, α = 0.05) between month and year (Table 2).

**Table 2**: Temperature heat anomaly days (n = 768) for month (May – September) and year (2005–2014). Note: Bold values indicate entries where the standard residual indicated a value very different from the expected value. *Source*: University of Utah’s MesoWest database.

|  |  |
| --- | --- |
|  | ***Study Years*** |
| ***Month*** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** |
| **May** | 5 | 7 | 2 | 3 | 4 | 0 | 0 | 6 | 0 | 6 |
| **June** | 12 | 27 | 20 | 19 | 8 | 19 | 15 | 22 | 29 | 25 |
| **July** | 28 | 22 | 21 | 25 | 26 | 27 | 24 | 22 | 22 | 25 |
| **August** | 13 | 13 | 20 | 20 | 24 | 21 | 27 | 20 | 21 | 15 |
| **September** | 8 | 2 | 12 | 5 | 10 | 18 | 14 | 7 | 11 | 10 |
| ***Total*** | 66 | 71 | 75 | 72 | 72 | 85 | 80 | 77 | 83 | 81 |

Of note, July and August did not yield values very different from the expected count value, while May revealed the most variation. Given that May is in the beginning of the summer season and July and August are in the middle, the results concur that the beginning of the season is more vulnerable to variability in number of heat events between years while mid-season heat day count is fairly consistent over time. Similarly, the beginning of the season is more vulnerable than the end of the season (September). This will aid the focus of adaptive capacity for decision makers choosing when to focus on deploying additional relief resources.

To narrow in on what is going on in these extreme heat days, one-way ANOVAs were performed to compare average surface temperature (C) between months for the year 2005 and 2006. The test revealed that there is a significant difference between months for both 2005 and 2006 (F(4,40) = 2.62, *p* = 0.048, α = 0.05; F(,) = *p* < 0.001, α = 0.05,repectively). Post-hoc testing using Tukey’s HSD revealed July and August to have the only significantly different averages (Figure 1).



**Figure 1**: Average surface temperature (C) for each month in the year 2005 (left) and 2006 (right) in Maricopa County, AZ. Averages represent the hottest 30% of census tracts for each day that were then averaged monthly. Like letters above error bars indicate values that are not significantly different. *Source*: Aqua/MODIS MYD11A1 LST L3 product.

Based on this analysis, the year 2005 yielded fairly consistent surface temperature conditions except for a decrease in August. While August is consistent between years, its warmest census tracts are generally lower than the other months.

# V. Conclusions

N/A at this point, cluster analysis and the rest of the ANOVAs are still underway

# VI. Acknowledgments

Special thanks to David Hondula for his heavy involvement as the science advisor, helping to guide the project through completion and Dr. Kenton Ross as our NASA science advisor, providing logical and step-wise methods to complete certain aspects of the project and stay on task. Additional thanks go out to Emily Adams and Dan Wozniak, our Center Lead and Assistant Center Lead, for keeping our project progressing, as well as to Jeff Ely, whose geoinformatic expertise of the dnppy module made our data processing of large data sets possible. A special thanks to fellow participant Grant Mercer, whose Python expertise has been invaluable to our team.

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# VIII. Content Innovation

Data profile: All of our finalized data will be located in a database with a thorough explanation of where it came from, what processing it underwent, and what purpose it was utilized for. We have finished accumulating our data and are just beginning the explanations included with each dataset.

Inline Supplementary Material (figures, tables, computer code): We will include a database with our thoroughly commented code. See currently utilized code to be included in the appendices.

Interactive Map Viewer with Matlab: will demonstrate an animation of our cluster analysis to visualize the shift of clusters.

# IV. Appendices

Appendix 1:

*Python Code*

Example 1: Extract MODIS files based on csv of specific dates.



*Matlab Code*:

*R Code*

Example 1: Average surface temperature pixels over census block for entire county and write to individual csv for each day.

