

University of Nevada, Reno

**Determining Heat Island Response to Varying Land Cover Changes Between 2004
and 2017 Within the City of Reno, Nevada**

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in
Geography

by

Brendan W. Lawrence

Dr. Jill S. Heaton/Thesis Advisor

August, 2018

Copyright by Brendan W. Lawrence 2018
All Rights Reserved



THE GRADUATE SCHOOL

We recommend that the thesis
prepared under our supervision by

BRENDAN W. LAWRENCE

Entitled

**Determining Heat Island Response To Varying Land Cover Changes Between 2004
And 2017 Within The City Of Reno, Nevada**

be accepted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE

Jill S. Heaton, Ph.D., Advisor

Scott Bassett, Ph.D., Committee Member

Wendy Calvin, Ph.D., Graduate School Representative

David W. Zeh, Ph.D., Dean, Graduate School

August, 2018

Abstract

The objective of this research was to investigate the role of land cover changes through time in influencing spatial variability of the surface urban heat island of the metropolitan area of Reno-Sparks, Nevada. Free and widely available thermal data from Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) sensor was gathered for a period between 2004 and 2017 and processed to at-satellite surface temperature. Using parcel data and the National Land Cover Database, the time series of Landsat data was sampled for areas which had undergone development during that time. This sample was cross-validated with ten iterations of equal sample size, with a mean correlation coefficient of 0.623 (standard deviation of 0.008) versus the model's value of 0.624. A set of generalized linear models was conducted on this sample to determine expected temperature change with land cover class. It was found that recently developed regions within Reno-Sparks are 0.6 °C warmer on average than the undeveloped desert grasses and sage. When wetlands/irrigated greenery were converted to impervious surfaces, it resulted in a positive surface temperature change of over 2 °C. Once developed, no significant difference was found in the surface temperature trends. This research, using remote sensing technologies, has shown that the Reno-Sparks surface urban heat island has undergone local, but measurable growth in the last fourteen years.

Table of Contents

List of Tables	iii
List of Figures	iv
Introduction	1
Methods	6
Results	11
Discussion	13
Conclusion	16
References	18
Appendices	32

List of Tables

Table 1: Akaike Information Criterion (AIC) Table	23
Table 2: Generalized Linear Model (GLM) output	23
Table 3: Tukey's Honest Significant Difference	25

List of Figures

Figure 1: Map of Reno/Urban AOI	26
Figure 2: Example of at-satellite surface temperature map: July 17, 2005	27
Figure 3: Dry and Green in the study area AOI	28
Figure 4: Parcels that had undergone development (2004 through 2017)	29
Figure 5: Bar chart of approximate acreage built per year	30
Figure 6: Boxplot of all data for all years, categorized by Land Cover Class	30
Figure 7: Boxplot of all samples for all years, categorized by Land Cover Class	31

Introduction

The Urban Heat Island (UHI) phenomena describes a situation in which urban cores and developed areas exhibit higher surface and air temperatures than surrounding non-developed regions. This gradient in temperatures is caused by several factors; first and foremost it is induced by the transition of latent heat flux into sensible heat via the transformation of vegetative and soil surfaces to the lower albedo materials that are commonly found amongst city centers (Imhoff et al., 2010). Secondly, man-made materials such as asphalt and concrete absorb high amounts of solar radiation and release a percentage of it later in the day as sensible heat (Bokaie et al., 2016). Finally, the introduction of high-rises and skyscrapers can inhibit prevailing wind patterns and prevent more even temperature gradients (Bokaie et al., 2016).

The intensity and impact of the UHI are of significant interest as the world's population is rapidly urbanizing with as many as 54% of the global population residing in cities as of 2014, with estimates around two-thirds of the world's population dwelling in cities by 2050 (United Nations, 2014). An extensive proportion of the human population will be subjected to artificially increased temperatures that may be as high or higher than 8 °C above the surrounding regions (Imhoff et al., 2010). High spatial resolution data from the Airborne Thermal and Land Applications Sensor (ATLAS) shows surface temperature in microclimate extremes within a city to be as high as 60 °C (Wang and Quattrochi, 2007). The negative effects of such conditions include increased air pollution (Estoque et al., 2017), increased power consumption which may strain power grids (Azevedo et al., 2016), and increased severity of summer time heat waves, which claim

thousands of lives in an average year (Mirzaei and Haghighat, 2010). More rarely, prolonged or severe heat waves in populated regions can push death tolls into the tens of thousands (Robine et al., 2007). All of these consequences will be aggravated by larger scale climate changes and continued migration into city centers (Jones et al., 2015).

Research shows the exact magnitude of UHI impacts to be more complex than a simple relationship to population growth as originally postulated by Oke (1973). While the general positive correlation of temperatures and population holds (Oke, 1973), the temperature does not retain a set value above the surrounding areas. The temperature gradient is more pronounced depending on season and time of day (Wang and Quattrochi, 2007). Atmospheric stability also plays a role in the day-to-day magnitude of the UHI phenomena (Wang and Quattrochi, 2007).

Space borne remote sensing systems are capable of analyzing UHI effects with a wide range of spatial and temporal scales when funding for a dedicated sensor and/or aerial missions is not available. These systems provide more complete coverage than station-based measurements. Data from many systems such as Landsat is free; with its' thermal band proving to be of great use for studying UHI signals (Imhoff et al., 2010; Bokaie et al., 2016; Estoque et al., 2017). There are drawbacks, including but not limited to systematic errors in gain (Aniello et al., 1994) and distortions due to atmospheric conditions, both of which can be accounted for with pre-processing (Bokaie et al., 2016). Urban Heat Island and Surface Urban Heat Island signals may be influenced by building height variability that exists within cities due to changes in shading throughout the day (Small and Zappa, 2017). Deep street canyons show the same surface temperature as

densely vegetated areas such as city parks during the afternoon hours (Small and Zappa, 2017).

UHI research centered on larger cities (i.e. Phoenix and Las Vegas) utilized remote sensing techniques, lacking are similar studies on small to mid-sized cities. (Cayan and Douglas, 1984; Xian and Crane, 2006; Ramaurthy and Sangobanwo, 2016). A case in point is the Reno-Sparks metropolitan area (Figure 1) with its estimated population of over 400,000 (Washoe County Consensus Forecast, 2016). From the 1960's onward, a growing discrepancy between the minimum temperature records at the Reno/Tahoe International airport and Tahoe, California exists (Ardnt and Redmond, 2004). Comparisons with other rural stations show further contrast in temperatures and continuing UHI-driven warming in the intensely developed regions of Reno-Sparks (Hatchett et al., 2016).

Washoe County has undergone a large population expansion in the last several decades (Forstall, 1996), that includes conversion of agricultural and wetlands in the south and east parts of the valley to developed lands. This may lead to an even hotter Reno-Sparks as healthy vegetation plays an important role in mitigating the effect of the UHI (Akbari et al., 2001; Rahman et al., 2017). The Reno-Sparks area, the largest developed area within Washoe County, is categorized as mid-latitude steppe on the Köppen Climate Classification System, with a wide-swinging temperature range between seasons (Houghton et al., 1975). Precipitation is variable every year as Reno-Sparks Metropolitan area lies in the Sierra Nevada's rain shadow whose average elevation is 1,338 meters (U.S. Geological Survey, 2006) with more rainfall/snowfall than lower basins to the east (Hatchett et al., 2016). Although the cities reside in a dry environment,

the Truckee River flows through the area creating an oasis for vegetation. Plants appropriate incoming shortwave solar insolation for food use and prevent the transformation into sensible heat (Rahman et al., 2017). Water uptake by vegetation also plays a role as a conduit for transpiration, which is a considerable heat sink (Gillner et al., 2015).

Current projections show the Reno-Sparks area gaining 100,000 additional inhabitants by the year 2036 (Washoe County Consensus Forecast, 2016), and many Planned Unit Developments (PUDs) to house these individuals are slated for prime greenspace (Northern Nevada Regional Growth Study, 2015); the summertime temperatures in the valley may start to negatively impact sensitive species in the urban environment (Mason et al., 2017).

This project analyzes alterations of land surface temperature in the urban environment of Reno-Sparks using imagery collected by the Landsat 7 Satellite's ETM+ (Enhanced Thematic Mapper Plus) sensor's thermal band. These data are the effective skin temperature or land surface temperature of all surfaces in the Landsat scene, which may be comprised of asphalt, vegetation, or building roof. This study did not make use of atmospheric corrections as only relative temperature differences are being compared; absolute surface temperature was not required (Small and Zappa, 2017).

Nighttime scenes are sometimes used in studies as the heat island's signal shows the sharpest contrast after the peak heating of the day as man-made materials continue to release sensible heat, whereas the surrounding desert environment has cooled (Xian and Crane, 2006). Hatchett (et al., 2016) further enforces this for the Reno-Sparks high desert

environment as the stronger growth trend in the UHI signal is seen historically in the minimum temperatures during the summer months.

Landsat 7's thermal band (Band 6) covers the window from 10.4 to 12.5 micrometers and has a native spatial resolution of 60 meters (U.S. Geological Survey -A, 2018). The U.S. Geological survey, however, resamples this band to 30 meters within its standard level-1 product to match the spatial resolution of the other sensor's bands using the Landsat Product Generation System (U.S. Geological Survey -B, 2018) With this spatial resolution, distinct city morphologies can easily be detected and major landmarks such as dense city cores and airport runways are apparent (Figure 2). An issue with resolving individual buildings is there are some examples of structures appearing to read between 10°C and -35 °C within the city boundaries. This variation is most likely due to the emissivity of the building's metal roofs (Morton, 2018). Some metals, especially highly reflective ones, have low emissivity coefficients at temperatures below one hundred degrees Celsius (Smithells, 1976). Landsat's sensor with its limited thermal window simply reads this as being cold without the input of additional information.

In particular, this research addresses whether or not recent development of the region's desert landscape has made any quantifiable impact on the local surface urban heat island. Secondly, the effect that irrigated and natural green space has, and how it acts upon, the local UHI signal is examined. Being able to detect fine scale nuances in UHI impacts using freely available data should also allow a wider variety of growing urban areas to do simple assessments and create zoning plans for better future outcomes where artificial microclimate alterations are minimized.

Methods

The area of interest (Figure 1), is approximately 68,500 acres; filling the majority of the Truckee Meadows valley and includes the urban centers of both Reno and Sparks. It also contains important features such as the Reno-Tahoe International Airport, as well as multiple large sections of crop land and natural wetlands.

Imagery used in the study spanned a duration of fourteen years (between 2004 and 2017) of Landsat 7 thermal images or scenes. These scenes (Row: 211/Path 139) have the Reno-Sparks Metropolitan area in the northern center of the scene. As heat island behavior shows the strongest signal in June, July, and August for Reno-Sparks region (Hatchett et al., 2016); only nighttime scenes in and immediately around this meteorological summertime (the hottest months in the annual temperature cycle in the Northern Hemisphere) were chosen. This set of scenes was then visually filtered for clouds, with any that contained clouds above the area of interest being rejected. This left a total list of 60 usable scenes (Appendix 1).

All scenes were georeferenced using major road intersections and prominent building edges as controls (Yuan and Bauer, 2007). Scenes were then projected to Universal Transverse Mercator Coordinate system, Zone 11 North, Datum of World Geodetic System of 1984 and then clipped to a smaller spatial area for statistical analysis using the bilinear interpolation approximation method. As the mountains around the valley were not of interest, the clipping footprint was the main body U.S. Census Bureau's 2016 urban boundary that lay within the valley (U. S. Census Bureau, 2017).

This polygon was additionally convenient as the majority of it fell within the small band in the center of the scenes that was not impacted by the scan line corrector fault.

Land surface temperatures were calculated by following the procedure in the Landsat 7 Science Data Users Handbook (Goddard Space Flight Center, 2018). The first step was converting the digital number product directly downloaded from Earth Explorer (U. S. Geological Survey-C, 2018) to Spectral Radiance, done via Equation 1.

(Equation 1: Digital Numbers to Spectral Radiance)

$$L_{\lambda} = \frac{(L_{max\lambda} - L_{min\lambda})}{(QCAL_{max} - QCAL_{min})} * (QCAL - QCAL_{min}) + L_{min\lambda}$$

Where:

L_{λ} =	Spectral Radiance at the sensor's aperture (watts/m ² *ster*μm)
QCAL =	The quantized calibrated pixel value in DN
QCAL _{min} =	The minimum quantized calibrated pixel value (corresponding to $L_{min\lambda}$) in DN
QCAL _{max} =	The maximum quantized calibrated pixel value (corresponding to $L_{max\lambda}$) in DN
$L_{min\lambda}$ =	The spectral radiance that is scaled to QCAL _{min} (watts/m ² *ster*μm)
$L_{max\lambda}$ =	The spectral radiance that is scaled to QCAL _{max} (watts/m ² *ster*μm)

The second step was to convert spectral radiance to at-satellite surface temperature in Kelvin using an estimation of Planck's Law of electromagnetic radiation emission via Equation 2 (Yuan and Bauer, 2007; Chander and Markham, 2003; Goddard Space Flight Center, 2018).

(Equation 2: Spectral Radiance to at-satellite Temperature)

$$T = \frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)}$$

Where:

- T = Surface Temperature in Kelvin
- K1 = Calibration Constant 1 (From scenes' MTL document)
- K2 = Calibration Constant 2 (From scenes' MTL document)
- L_λ = Spectral Radiance at the sensor's aperture (watts/m²*ster*μm)

To negate the potential of sampling a falsely cold value due to emittance metal roofs, histograms were calculated for all scenes and values beyond four standard deviations were removed. This value removed the unrealistically cold pixels around the buildings in question, but did not eliminate the lower values seen along waterways or in low lying fields.

Land cover classifications for this study are defined by the 2001 National Land Cover Database (2001 NLCD) (Homer et al., 2007). Once projected to the same coordinate system as all Landsat scenes and clipped to the area of interest, they were reclassified into two categories: dry and green (Figure 3). Dry consisted of classes 31 (barren land), 52 (shrub/scrub), and 71 (grassland/herbaceous); with scrublands comprising 72.9% of the undeveloped environment. These three classes represent the standard high desert environment in which the Reno and Sparks urban cores have grown. Green was a conglomeration of classes 21 (developed open space), 81 (pasture/hay), 82 (cultivated crops), and 95 (emergent herbaceous wetlands). These four classes represent

large grass areas around public facilities, city parks, and human irrigated fields in the region.

The land use dataset covering the entire study area included individual parcels with year built/modified, developed by the Truckee Meadow Regional Planning Agency (Truckee Meadows Regional Planning Agency, 2017) and was used to determine areas that had been developed during the study period (Figure 4). This map shows properties that were constructed between 2004 and 2017 and used to determine green built and dry built, totaling approximately 23.2 km² or 5,733 acres (Figure 5). Parcels that had been built in 2001 through 2004 were masked out of the 2001 NLCD as Landsat has few nighttime flyovers of the Reno Sparks Region during that time frame. Changes in land cover class between 2001 and 2004 were accounted for by referencing this dataset.

The processed Landsat scenes were grouped by year, and at-satellite temperature was averaged on a pixel by pixel basis as the parcel data was only described to the year level. This also helped to account for meteorological variations for each year. This yearly average temperature value was converted into a spatial data table with columns of whether the pixel was developed or unaltered and whether it was originally dry land cover or green. This created four classes with associated temperatures: dry built, green built, dry unbuilt, green unbuilt for each year.

All years were combined into a single spatial data table (Figure 6) and then a stratified random sample with a size of 300 per class, per year was conducted on the records in this dataset (Figure 7). This resulted in a total of 1,200 per year and a grand total of 15,600. As hundreds of thousands of records existed within the main spatial data table, it was deemed that 300 should be able to capture the variation of each of the four

classes at a high confidence level without increasing the chance of a convergence of probabilities (Cochran, 1977; Israel, 1992; Fischer, 2010). A Cross-Validation was completed to assess the effectiveness of the model. A total of ten random iterations was completed with the same parameters (300 per class, per year) was conducted on the population of the spatial points data frame.

A set of general linear models was fitted to the sampled data; a null model with “Temperature” being predicted only, another with the predictor variable of “Land Cover Class”, a third with the variation between “Year”, and fourth and finally a model with an intersection between the terms “Land Cover Class” and “Year”. Akaike’s Information Criterion (AIC) was chosen as the determinant of the relatively best fit model (Akaike, 1974). A pair wise comparison was completed to shore up the results of the Generalized Linear Model and summarize its interpretations. This contrast test is known as Tukey’s Honestly Significant Difference Test (Tukey, 1949).

Results

According to the AIC estimate, the model with “Year” intersecting “Land Cover Class” described the system best (Table 1). Essentially this means that “Land Cover Class” is a large driver of the system, but the model can be reasonably improved upon by considering year to year variability in temperature. The generalized linear model gave an expected surface temperature for the area of interest of 288.68 K or 15.53 °C (Table 2) with an R-squared of 0.40. The Cross-Validation had also shown the model was favorable with a mean correlation coefficient of 0.623 (standard deviation of 0.008) compared to the model’s 0.624.

The analysis of variance F-Test that was conducted on the main effects to test for differences between the land cover classes (F-Statistic of 1,390.8), with significance ($P < 0.001$). Areas that originated as green unbuilt that were constructed during the study period show a non-significant change between the expected pre-developed temperature with a difference of 0.087 °C. This lack of significance showed that while a slight discrepancy in temperatures existed, there was no real difference between developed land originating as either green unbuilt or dry unbuilt. The surrounding dry unbuilt class within the area of interest however shows a cooler temperature than the model’s expected value, with a change of -0.64 °C that was significant ($P < 0.001$). The largest discrepancy from the expected values fell to the green built landscape; which was approximately 2.24 degrees cooler than the intercept of the model ($P < 0.001$). Table 3 also shows a significant difference between many of the years, further compounding that one or two years of temperature data may not fully describe an area’s, region’s, or city’s thermal

regimes completely. Tukey's Test (Table 3) further suggests that there is indeed a significant difference between all land cover classes, save for green built versus dry built.

Discussion

The nighttime surface thermal environment is altered by development, and to a much greater degree if the land developed was originally green built (Table 3). Of an original 91.0 km² of dry unbuilt within the area of interest, a total of approximately 18.2 km² was developed; and of an original 29.5 km² of green unbuilt, approximately 4.6 km² was developed. I use approximate because a parcel may have been carved out of a larger section and declared by the county as developed in a certain year, but construction of the entire footprint of said parcel may or may not have happened within that exact year.

Some parcels were also slated for development as lower density suburban housing. Areas featuring mixed pixels as yards and other personal greenspace are still an ongoing trend in the southwestern U.S. (Yabiku et al., 2008). As many parcels were not entirely built upon, i.e. a suburban home with a front and or back yard, and thus not being a true 100% change of class from green unbuilt or dry unbuilt. This research's model undervalued, in areas, the true temperature change that would happen in an idealized world. These value changes of one and two degrees Celsius when developed are not unexpected for the South West United States (Cayan and Douglas, 1984)

Some assumptions had to be made when choosing to use the National Land Cover Database for this project. While it is a freely available and an incredibly versatile product, it does have some inaccuracies as expected with any remotely sensed product. The great basin region was shown to have an 84.1% user's accuracy (probability that the product's stated class represents the actual class) and an approximate 75.95% producer's accuracy (classification quality of the training data used to create the dataset) across all classes

(Wickham et al., 2010). Additional inaccuracy may have been introduced by the temporality of water as it is influenced by human consumption and even more so by precipitation trends. This causes wetland classified vegetative areas to fluctuate in remotely sensed imagery over time (Pavri and Aber, 2004). Both of these previous factors would have impacted how well the original NLCD, and therefore how well this research's four classes (dry unbuilt, dry built, green unbuilt, green built) would have performed in representing the actual land cover.

Development during the study period does not seem to override the influences of the local climate or topography to any observable degree, as direct comparisons of the total area of interest's surface thermal signal over the study period did not return any significant trends. This means that while developed regions in the area of interest show a significant increase in surface temperature from once undeveloped, the climatology for Reno-Sparks as a whole does not seem to have been impacted for the duration of 2004 through 2017.

Some years are warmer or colder/wetter or dryer than others and Landsat only passes over once every 16 days, severely limiting the sample size of each year and the ability to correct for abnormal years and conditions. This is especially important in a steppe environment where small differences in available moisture can be a large driver of vegetative health and density (Moore et al., 2015). The yearly variations in temperature and precipitation trends made a quantifiable city-wide change in the surface urban heat island's signal difficult to detect due to the city's relatively small size and location nestled between multiple mountain ranges. It is possible to infer and quantify a real change in thermal regime using remotely sensed products. A positive shift in temperature

of just over 0.6 °C to the total native landscape converted between 2004 and 2017, or 8.2% of the entire area of interest's footprint, was clearly seen. The building over of green space is certainly the more noteworthy driver of change with a 2.2 °C temperature increase; however, only 4.6 km² of green space were built during the last 14 years. This is less than 1.7% of the total area of interest or 15.6% of green space present in the area of interest. Reno-Spark's growth was, however, encumbered during multiple years of the research's imagery period (Truckee Meadows Regional Planning Agency, 2017).

While expansion into green space in Reno-sparks was negligible for the years between 2004 and 2017, subdivisions are currently being constructed into the area's wetlands. Current plans also show numerous additional units slated for the next few years expanding into the valley's southeast wetlands and agricultural lands, as well as into alluvial catch basins along the mountain fronts (Truckee Meadows Regional Planning Agency, 2017). If development follows current plans, it can be expected that the Reno-Sparks UHI will continue to expand and possibly show even stronger signals through the next decades as development covers a higher fraction of greenspace than it did since 2004.

Conclusion

In this research, a series of 60 Landsat 7 thermal scenes covering 14 years of development in the Reno-Sparks metropolitan area were analyzed. Spaces that had been developed from natural desert grasses and sage (dry unbuilt) showed a surface temperature increase of 0.6 °C. Portions that had been developed from green unbuilt, be it natural or human-made green space, showed a 2.2 °C increase in surface temperature. Since these areas of change account for 18.2 and 4.6 km² respectively, Reno-Sparks UHI signal has measurably increased since the turn of the millennia.

Not all development is equal, and future work could be done to account for varying degrees of impervious surfaces throughout Reno-Sparks. Suburban versus more intensely developed areas such as industrial or highly urbanized zones could be individually categorized and planners/policy makers will be able to better allot for the potential change in surface heat retention to result in less contribution to the UHI.

Due to income disparities, the development of green spaces in urban landscapes is inequitable. This disproportion is seen in the percentage of green space within a given neighborhood, with a significant positive gradient in green space following economic classes in southwestern U.S. metropolitan areas (Jenerette et al., 2013). This owes to the wealthier classes generally living in lower density areas, thus dwelling upon larger lots and are more likely to have access to the resources to landscape/manage them as well (Clarke et al., 2013). Socioeconomic data for Reno-Sparks could determine to what extent income divergence exposes its citizens to UHI impacts, and whether or not future planned regions of the valley perpetuate this.

The UHI phenomena will continue to be a feature of the global landscape; exacerbated by the world's growing population, by the trend of urbanization of this population, and by meteorological extremes/climate change (IPCC, 2014). In order to mitigate this human-created issue, we must first understand it, and its unique fingerprint within every city. This type of data was a premium before the 1970's and therefore was unavailable to many. With the advancements of remote sensing, it is now available at no cost. Landsat thermal data is available for the majority of the Earth's surface, and looks to be so in the future with the recent Landsat 8 and upcoming Landsat 9 (to be launched in the end of 2020); it is hoped that this research can provide a template for future studies. With remote sensing and ever-advancing technologies, UHIs can be studied in a greater temporal and spatial resolution in many small and growing cities throughout the world.

References

Akaike, H., 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control* 19 (6): 716-723

Akbari, H., Pomerantz, M., &Taha, H. 2001. Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. *Solar Energy* 70 (3): 295–310

Aniello, C., Morgan, K., Busbey, A., Newland, L. 1994. Mapping micro-urban heat islands using Landsat TM and a GIS. *Computers & Geosciences* 21 (8): 965-969

Arndt, D.S., Redmond, K.T., 2004. Toward an automated tool for detecting relationship changes within a series of observations. American Meteorological Society Annual Metting, Applied Climatology Conference, January 11-15, 2004, Seattle, Washington

Azevedo, J.A., Chapman, L., Muller, C.I. 2016. Urban heat and residential electricity consumption: A preliminary study. *Applied Geography* 70: 59-67

Bokaie, M., Zarkesh, M.K., Arasteh, P.D., Hosseini, A. 2016. Assessment of urban heat island based on the relationship between land surface temperature and land use/land cover in Tehran. *Sustainable Cities and Society* 23: 94-104

Cayan, D.R., Douglas, A.V. 1984. Urban Influences on Surface Temperatures in the Southwestern United States during Recent Decades. *Journal of Climate and Applied Meteorology* 23: 1520-1530

Chander, G., Markham, B. 2003. Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges. *IEEE Transactions on Geoscience and Remote Sensing* 41 (11): 2674-2677

Clarke, L.W., Jenerette, G.D., Davila, A. 2013. The luxury of vegetation and the legacy of tree biodiversity in Los Angeles, CA. *Landscape and Urban Planning* 116: 48-59

Cochran, W.G. 1977. *Sampling Techniques (3rd Edition)*. John Wiley & Sons, Inc.

Estoque, R.C., Murayama, Y., Myint, S.W. 2017. Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the Megacities of Southeast Asia. *Science of the Total Environment* 577: 349-359

Fischer, H. 2010. *A History of the Central Limit Theorem*. Springer. New York, New York.

Forstall, R.L., 1996. Population of States and Counties of the United States: 1790-1990. U.S. Department of Commerce, National Technical Information Service, Springfield, VA

Gillner, S., Vogt, J., Tharang, A., Dettmann, S., Roloff, A. 2015. Role of street trees in mitigating effects of heat and drought at highly sealed urban sites. *Landscape and Urban Planning* 143: 33-42

Goddard Space Flight Center, National Aeronautics and Space Administration. 2018. *Landsat 7 Science Data Users Handbook*; Greenbelt, Maryland
https://landsat.gsfc.nasa.gov/wp-content/uploads/2016/08/Landsat7_Handbook.pdf

Hatchett, B.J., Koračin, D., Mejía, J.F., Boyle, D.P. 2016. Assimilating urban heat island effects into climate projections. *Journal of Arid Environments* 128: 59-64

Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J.N., and Wickham, J. 2007. Completion of the 2001 National Land Cover Database for the Conterminous United States. *Photogrammetric Engineering and Remote Sensing* 73 (4): 337-341.

Houghton, J.G., Sakamoto, C.M., Gifford, R.O. 1975. *Nevada's Weather and Climate*. Special Publication 2. Nevada Bureau and Mines and Geology, Mackay School of Mines, University of Nevada, Reno.

Imhoff, M.L., Zhang, P., Wolfe, R.E., Bounoua, L. 2010. Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sensing of Environment* 114 (3): 504-513

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

Israel, G.D. 1992. Determining Sample Size. University of Florida. Florida Cooperative Extension Office, Fact Sheet PEOD-6

- Jenerette, G.D., Miller, G., Buyantuev, A., Pataki, D.E., Gillspie, T.W., Pincetl, S. 2013. Urban vegetation and income segregation in drylands: a synthesis of seven metropolitan regions in the southwestern United States. *Environmental Research Letters* 8
- Jones, B., O'Neill, B.C., McDaniel, L., McGinnis, S., Mearns, L.O., Tebaldi, C. 2015. Future population exposure to US heat extremes. *Nature Climate Change* 5: 652-655
- Mirzaei, P., Haghighat, F., 2010. Approaches to study Urban Heat Island – Abilities and limitations. *Building and Environment* 45: 2192-2201
- Mason, T., Brivio, F., Stephens, P., Apollonio, M., Grignolio, S. 2017. The behavioral trade-off between thermoregulation and foraging in a heat-sensitive species. *Behavioral Ecology* 28 (3): 909-918
- Mirzaei, P., Haghighat, F., 2010. Approaches to study Urban Heat Island – Abilities and limitations. *Building and Environment* 45: 2192-2201
- Moore, L.M., Lauenroth, W.K., Bell, D.M., Schlaepfer, D.R., 2015. Soil Water and Temperature Explain Canopy Phenology and Onset of Spring in a Semiarid Steppe. *Great Plains Research, University of Nebraska Press* 25 (2): 121-138
- Morton, C., Personal interview conducted at Desert Research Institute, Reno, NV; November 29, 2018
- Northern Nevada Regional Growth Study 2015-2019, Volume I: A Forecast of Northern Nevada's Employment, Population, Households & Associated Tax Revenues. Economic Planning Indicators Committee, Economic Development Authority of Western Nevada. 2015. http://edawn.org/wp-content/uploads/2015/09/2015-8-31-Vol-1-No-NV-Regional-Growth-Study-Final_Compressed.pdf
- Oke, T.R., 1973. City size and the urban heat island. *Atmospheric Environment* 7 (8): 769-779
- Pavri, F., Aber, J.S. 2004. Characterizing Wetland Landscapes: A Spatiotemporal Analysis of Remotely Sensed Data at Cheyenne Bottoms, Kansas. *Physical Geography* 25 (1): 86-104
- Rahman, R.A., Moser, A., Rotzer, T., Pauleit, S., 2017. Within canopy temperature differences and cooling ability of *Tiliacordata* trees grown in urban conditions. *Building and Environment* 114: 118-128

Ramamurthy, P., Sangobanwo, M. 2016. Inter-annual variability in urban heat island intensity over 10 major cities in the United States. *Sustainable Cities and Society* 26: 65-75

Robine, J.M., Cheung, S.L., Le Roy, S., Van Oyen, H., Griffiths, C., Michel, J.P., Herrmann, F.R. 2007. Death toll exceeded 70,000 in Europe during the summer of 2003. *La Revue Du Praticien* 54 (12): 1289-1297

Small, C., Zappa, C., 2017. Mapping the diurnal thermal response of the urban heat island with Landsat TIRS. *IEEE Joint Urban Remote Sensing Event (JURSE)*, 2017: 1-4

Smithells, C.J. 1976. *Metals Reference Book*, 5th edition, Butterworth & Co. Industrial Estate Chichester

Truckee Meadows Regional Planning Agency. 2017. Land Use Fabric Dataset.

Tukey, J. 1949. Comparing Individual Means in the Analysis of Variance. *Biometrics* 5 (2): 99-114

United Nations. 2014. *World Urbanization Prospects 2014 Revision*. UN DESA's Population Division, New York, New York

U.S. Census Bureau, U.S. Department of Commerce. 2017. 2016 Cartographic Boundary File, 2010 Urban Areas for United States. 4600 Silver Hill Road, Washington, D.C.

U.S. Geological Survey. 2006. Shuttle Radar Topography Mission. 1 Arc Second Scene, Global Land Cover Facility, University of Maryland, College Park, 2000

U.S. Geological Survey-A, U.S. Department of the Interior. 2018. *What are the band designations for the Landsat satellites?* Web. Updated: April 25, 2018
<https://landsat.usgs.gov/what-are-band-designations-landsat-satellites>

U.S. Geological Survey-B, U.S. Department of the Interior. 2018. Landsat 7 Data Users Handbook – Section 5.
<https://landsat.usgs.gov/landsat-7-data-users-handbook-section-5>

U.S. Geological Survey-C, U.S. Department of the Interior. 2018. Earth Explorer-Home
<https://earthexplorer.usgs.gov/>

Wang, Y., Akbari, H. 2016. Analysis of urban heat island phenomena and mitigation solutions evaluation for Montreal. *Sustainable Cities and Society* 26: 438-446

Washoe County Consensus Forecast 2016-2036. Truckee Meadows Regional Planning. 2016.

[http://www.tmrpa.org/files/reports/16-09-](http://www.tmrpa.org/files/reports/16-09-28%20WC%20Consensus%20Forecast%202016%20Final%20with%20Appendices.pdf)

[28%20WC%20Consensus%20Forecast%202016%20Final%20with%20Appendices.pdf](http://www.tmrpa.org/files/reports/16-09-28%20WC%20Consensus%20Forecast%202016%20Final%20with%20Appendices.pdf)

Wang, Q., Quattrochi, D. A. 2007. *Urban Remote Sensing*. CRC Press, Taylor and Francis Group

Wickham, J.D. Stehman, S.V., Fry, J.A., Smith, J.H., Homer, C.G. 2010. Thematic accuracy of the NLCD 2001 land cover for the conterminous United States. *Remote Sensing of Environment* 114 (6): 1286-1296

Xian, G., Crane, M., 2006. An analysis of urban thermal characteristics and associated land cover in Tampa Bay and Las Vegas using Landsat satellite data. *Remote Sensing of Environment* 104 (2): 147-156

Yabiku, S.T., Casagrande, D.G., Farley-Metzger, E. 2008. Preferences for Landscape Choice in a Southwestern Desert City. *Environment and Behavior* 40 (3): 382-400

Yuan, F., Bauer, M.E. 2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment* 106: 375-386

(Table 1: AIC Table)

	Intercept	degrees freedom	AIC	delta	weight
Land Cover Class * Year	288.7	53	62,437.0	0.0	1
Year	288	14	65,610.6	3,173.6	0
Land Cover Class	288.8	5	66,682.1	4,375.1	0
Null (Temperature)	288.1	2	69,392.4	6,955.4	0

(Table 2: Generalized Linear Model output)

Coefficients	Estimate	Std. Error	t value	Pr(> t)	signif. code
Intercept	288.675	0.102	2834.658	< 2e -16	***
Dry Unbuilt	-0.635	0.144	-4.412	1.03e - 05	***
Green Built	0.087	0.144	0.604	0.5458	
Green Unbuilt	-2.237	0.144	-15.53	< 2e -16	***
year 2005	0.262	0.144	1.816	0.0694	.
year 2006	1.722	0.144	11.956	< 2e -16	***
year 2007	-0.379	0.144	-2.632	0.0085	**
year 2008	-0.670	0.144	-4.832	1.37e - 06	***
year 2009	0.893	0.144	6.201	5.77e -10	***
year 2010	-2.037	0.144	-14.146	< 2e -16	***
year 2011	0.060	0.144	0.419	0.6751	
year 2012	1.190	0.144	8.263	< 2e -16	***
year 2013	-0.902	0.144	-6.263	3.88e -10	***
year 2014	-0.564	0.144	-3.918	8.98e - 05	***
year 2016	0.200	0.144	1.390	0.1645	
year 2017	1.612	0.144	11.192	< 2e -16	***
Dry Unbuilt : Year 2005	-0.326	0.204	-1.602	0.1092	
Green Built : Year 2005	0.060	0.204	0.296	0.7675	
Green Unbuilt : Year 2005	-0.105	0.204	-0.516	0.6062	

Dry Unbuilt : Year 2006	0.107	0.204	0.525	0.5997	
Green Built : Year 2006	-0.295	0.204	-1.449	0.1474	
Green Unbuilt : Year 2006	-0.051	0.204	-0.253	0.8002	
Dry Unbuilt : Year 2007	-0.086	0.204	-0.420	0.6746	
Green Built : Year 2007	-0.076	0.204	-0.374	0.7085	
Green Unbuilt : Year 2007	0.081	0.204	0.399	0.6902	
Dry Unbuilt : Year 2008	-0.198	0.204	-0.974	0.3300	
Green Built : Year 2008	-0.460	0.204	-2.260	0.0238	*
Green Unbuilt : Year 2008	-0.029	0.204	-0.142	0.8870	
Dry Unbuilt : Year 2009	-0.235	0.204	-1.152	0.2492	
Green Built : Year 2009	-0.105	0.204	-0.517	0.6050	
Green Unbuilt : Year 2009	0.301	0.204	1.475	0.1401	
Dry Unbuilt : Year 2010	-0.225	0.204	-1.104	0.2695	
Green Built : Year 2010	-0.021	0.204	-0.101	0.9198	
Green Unbuilt : Year 2010	0.195	0.204	0.960	0.3372	
Dry Unbuilt : Year 2011	0.398	0.204	1.953	0.0509	.
Green Built : Year 2011	0.065	0.204	0.321	0.7483	
Green Unbuilt : Year 2011	-0.102	0.204	-0.505	0.6132	
Dry Unbuilt : Year 2012	-0.110	0.204	-0.539	0.5898	
Green Built : Year 2012	0.242	0.204	1.193	0.2329	
Green Unbuilt : Year 2012	0.226	0.204	1.109	0.2673	
Dry Unbuilt : Year 2013	-0.171	0.204	-0.842	0.3998	
Green Built : Year 2013	0.144	0.204	0.710	0.4778	
Green Unbuilt : Year 2013	0.380	0.204	1.868	0.0617	.
Dry Unbuilt : Year 2014	-0.451	0.204	-2.218	0.0265	*
Green Built : Year 2014	0.130	0.204	0.642	0.5209	
Green Unbuilt : Year 2014	0.281	0.204	1.381	0.1674	
Dry Unbuilt : Year 2016	0.381	0.204	1.869	0.0616	.
Green Built : Year 2016	0.156	0.204	0.768	0.4426	
Green Unbuilt : Year 2016	0.155	0.204	0.761	0.4467	
Dry Unbuilt : Year 2017	0.220	0.204	1.081	0.2799	
Green Built : Year 2017	0.031	0.204	0.149	0.8814	
Green Unbuilt : Year 2017	0.321	0.204	1.576	0.1150	

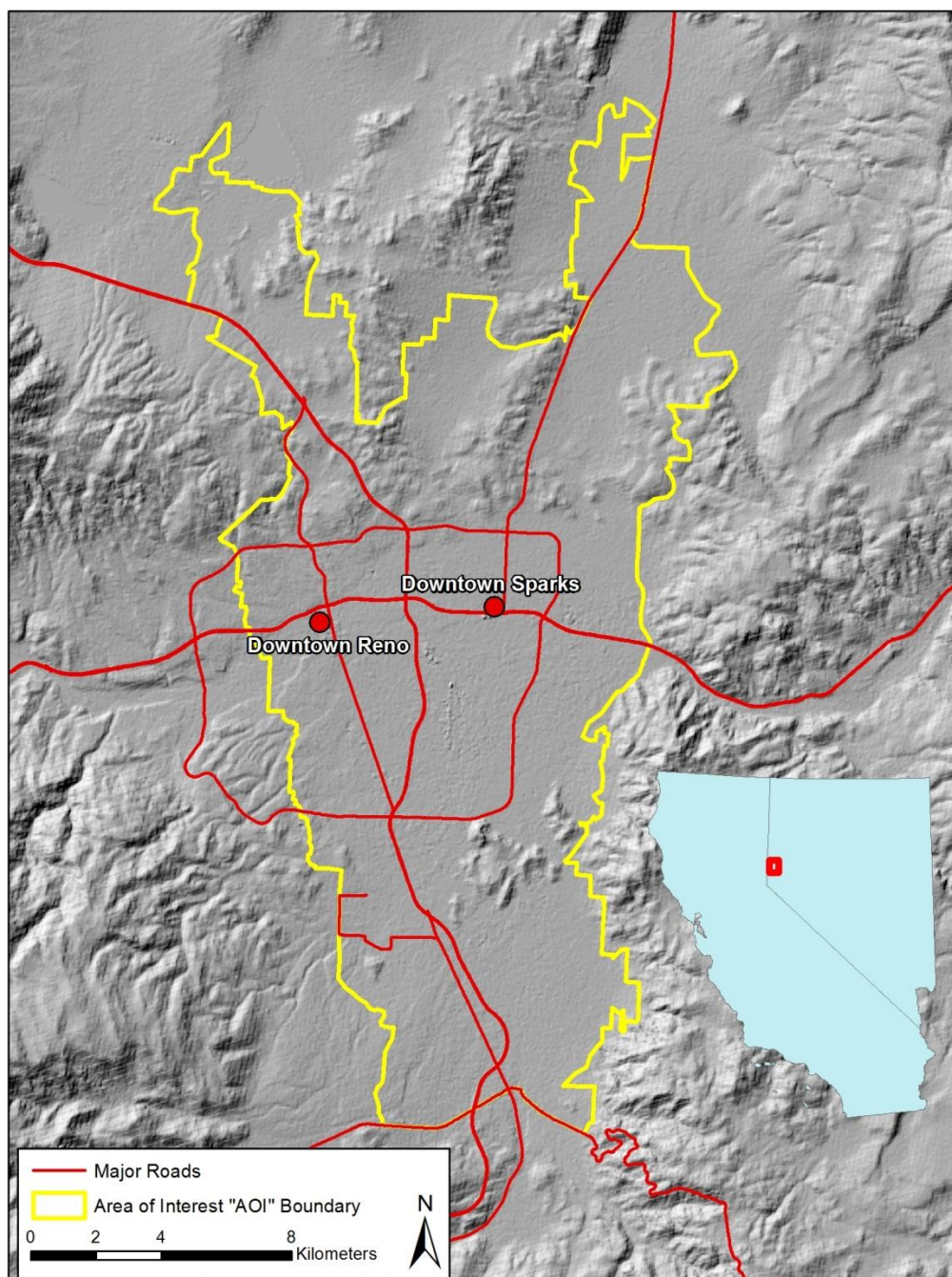
*Note: Estimate is in Kelvin. Signif Codes are as follows: 0 '***', 0.001 '**', 0.5 '*', 0.1 '.

(Table 3: Tukey's Honest Significant Difference)

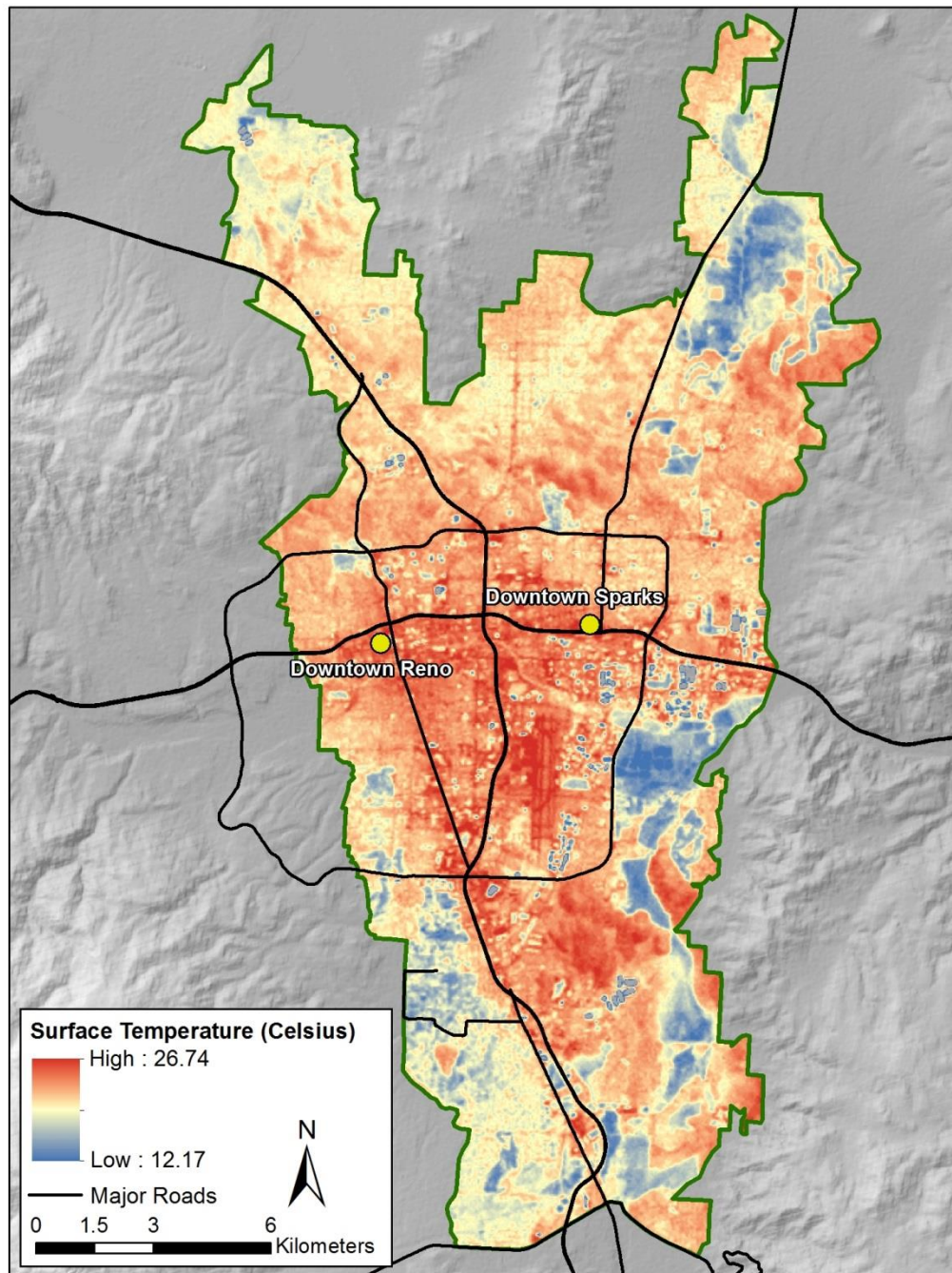
Class Contrast	Estimate	Std. Error	z value	Pr (> z)	Signif. code
Dry Unbuilt - Dry Built	-0.635	0.14402	-4.412	< 1e - 04	***
Green Built - Dry Built	0.087	0.14402	0.604	0.931	
Green Unbuilt - Dry Built	-2.237	0.14402	-15.530	< 1e - 04	***
Green Built - Dry UnBuilt	0.722	0.14402	5.016	< 1e - 04	***
Green Unbuilt - Dry UnBuilt	-1.601	0.14402	-11.118	< 1e - 04	***
Green Unbuilt - Green Built	-2.324	0.14402	-16.134	< 1e - 04	***

Note: Estimate is in Kelvin/degrees Celsius. Signif Codes are as follows: 0 '*', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '.*

(Figure 1: map of Reno/Urban AOI)

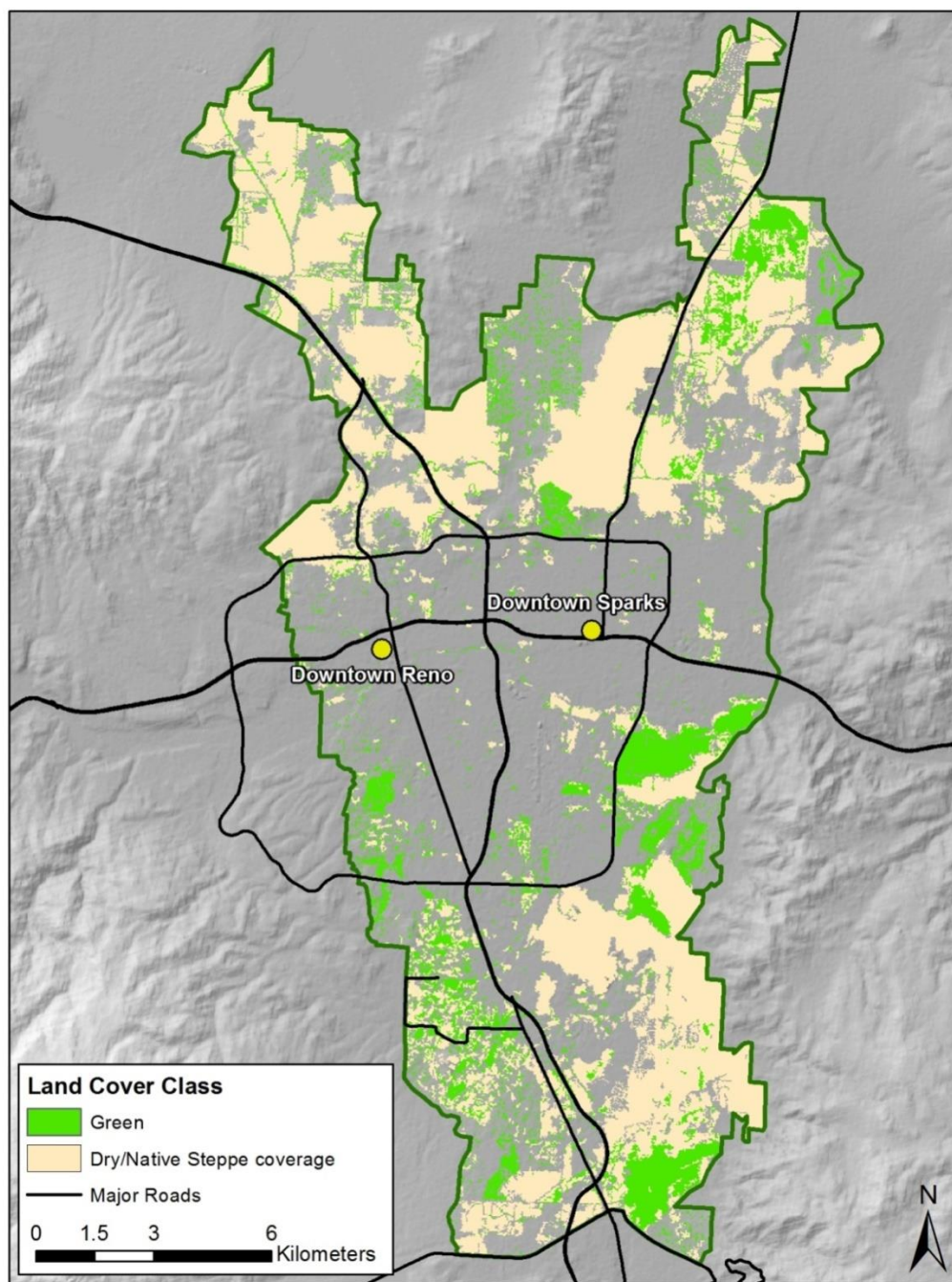


(Figure 2: Example of at-satellite surface temperature map: July 17, 2005)

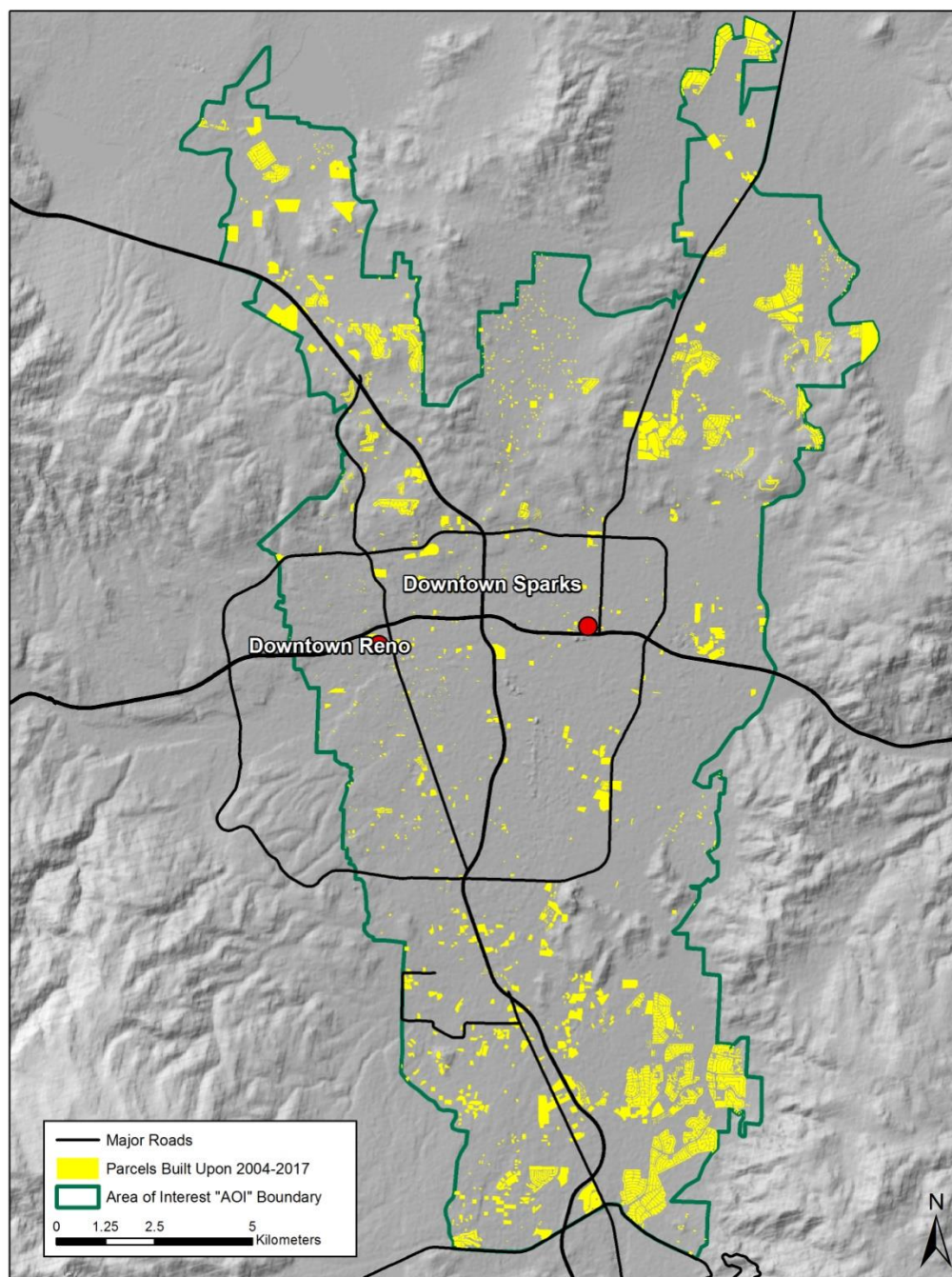


A direct comparison between an automated surface observing station located at Reno-Tahoe International Airport (towards the center of the area of interest polygon) and the underlying pixel show approximate temperatures of 27.8 °C (air temperature for closest measurement to Landsat 7 flyover) and 24.0 °C, respectively.

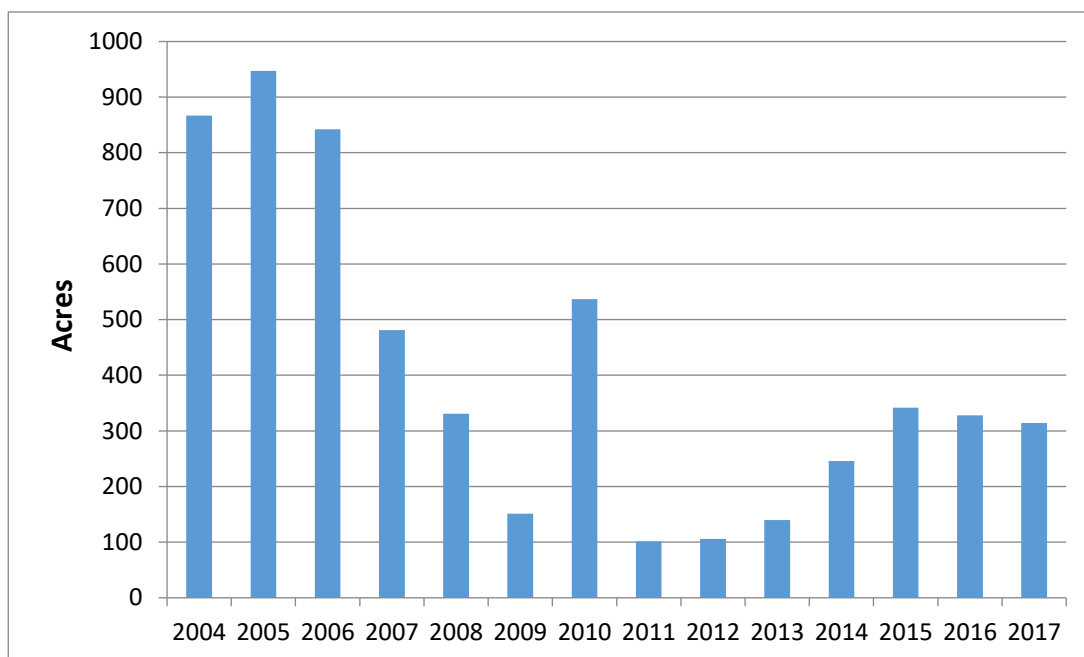
(Figure 3: Dry and Green in the study area AOI)



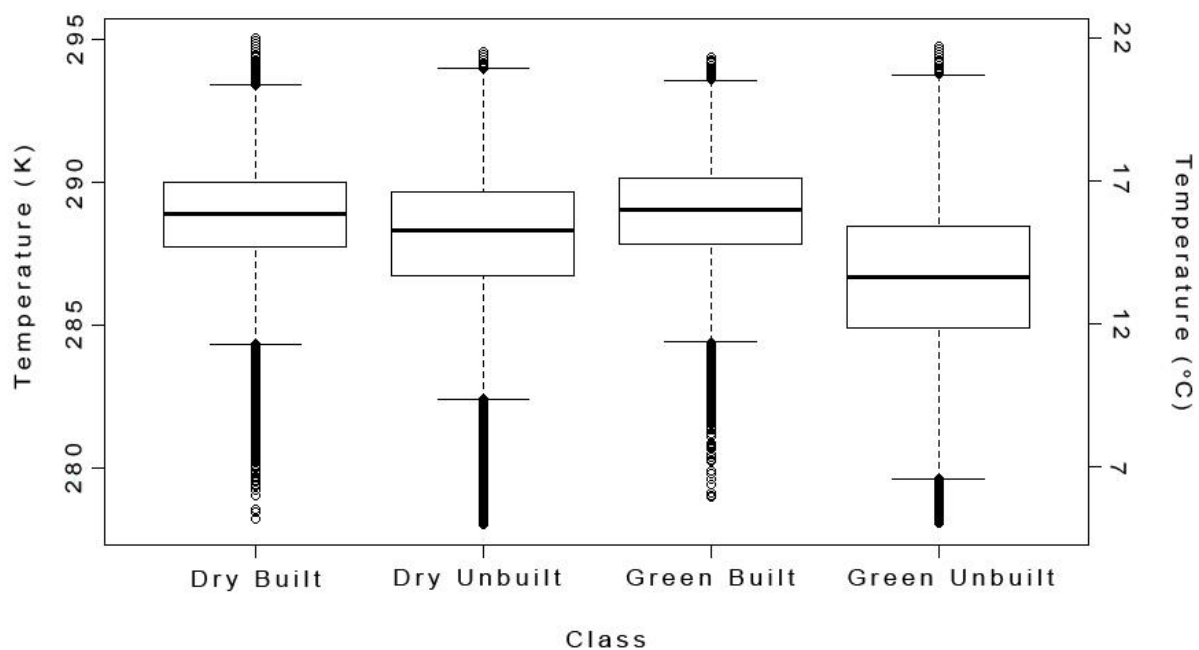
(Figure 4: Parcels that had undergone development between the years of 2004 and 2017)



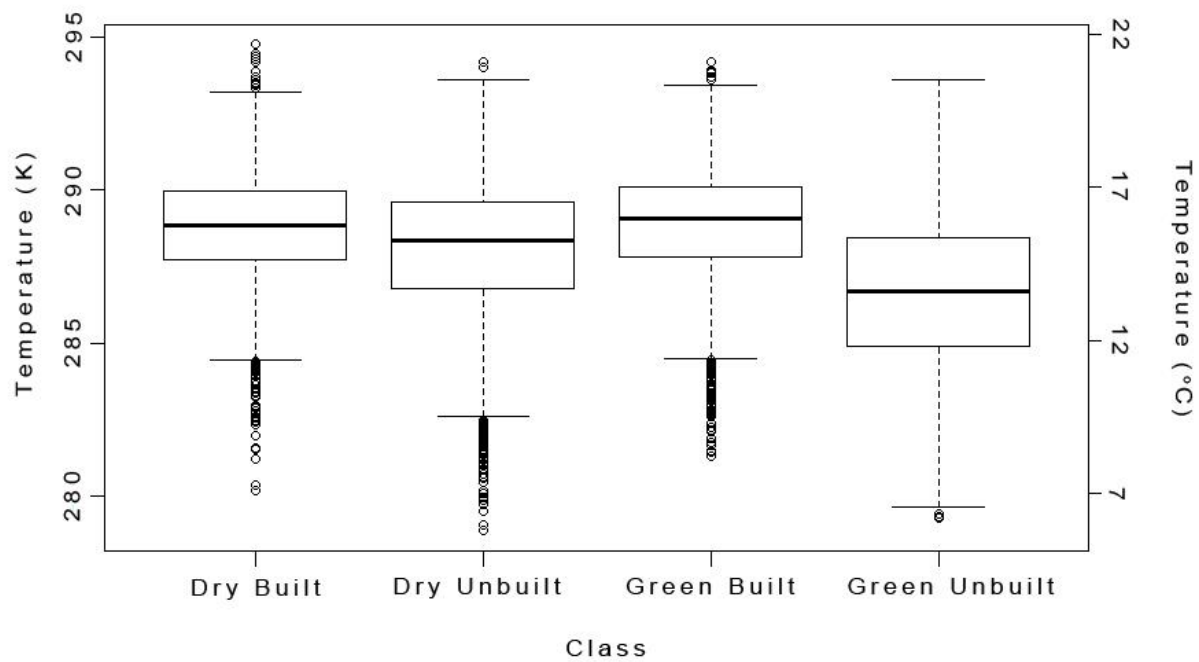
(Figure 5: Bar chart of approximate acreage built per year)



(Figure 6: Boxplot of all data for all years, categorized by Land Cover Class)



(Figure 7: Boxplot of all samples for all years, categorized by Land Cover Class)



Appendices

(Appendix 1: List of Landsat 7 scenes)

Date	Scene Center Time (GMT)	Scene ID
6/12/2004	5:32:52	LE71392112004164EDC01
7/14/2004	5:32:48	LE71392112004196EDC02
7/30/2004	5:32:41	LE71392112004212EDC02
8/31/2004	5:32:34	LE71392112004244EDC02
9/16/2004	5:32:27	LE71392112004260EDC02
7/1/2005	5:33:14	LE71392112005182EDC00
7/17/2005	5:33:15	LE71392112005198EDC00
8/2/2005	5:33:13	LE71392112005214EDC00
9/3/2005	5:33:00	LE71392112005246EDC00
9/19/2005	5:32:53	LE71392112005262EDC00
6/18/2006	5:33:48	LE71392112006169EDC00
7/4/2006	5:33:42	LE71392112006185EDC00
9/6/2006	5:33:25	LE71392112006249EDC00
6/21/2007	5:34:05	LE71392112007172EDC00
7/7/2007	5:34:03	LE71392112007188EDC00
7/23/2007	5:33:59	LE71392112007204EDC00
8/8/2007	5:33:54	LE71392112007220EDC00
8/24/2007	5:33:48	LE71392112007236EDC00
9/9/2007	5:33:40	LE71392112007252EDC00
9/25/2007	5:33:35	LE71392112007268EDC00
6/7/2008	5:33:38	LE71392112008159EDC00
6/23/2008	5:33:29	LE71392112008175EDC00
7/9/2008	5:33:18	LE71392112008191EDC00
7/25/2008	5:33:07	LE71392112008207EDC00
8/10/2008	5:33:01	LE71392112008223EDC00
8/26/2008	5:32:54	LE71392112008239EDC00
9/11/2008	5:32:46	LE71392112008255EDC00
5/25/2009	5:34:16	LE71392112009145EDC00
6/26/2009	5:34:13	LE71392112009177EDC00
7/28/2009	5:34:05	LE71392112009209EDC00
6/13/2010	5:35:57	LE71392112010164EDC00
7/31/2010	5:36:03	LE71392112010212EDC00
8/16/2010	5:36:03	LE71392112010228EDC00
9/1/2010	5:36:06	LE71392112010244EDC00

9/17/2010	5:36:06	LE71392112010260EDC00
7/2/2011	5:37:21	LE71392112011183EDC00
7/18/2011	5:37:20	LE71392112011199EDC00
8/3/2011	5:37:16	LE71392112011215EDC02
8/19/2011	5:37:13	LE71392112011231EDC00
9/4/2011	5:37:10	LE71392112011247EDC00
9/20/2011	5:37:05	LE71392112011263EDC00
7/4/2012	5:38:27	LE71392112012186EDC00
7/20/2012	5:38:40	LE71392112012202EDC00
8/21/2012	5:39:01	LE71392112012234EDC00
6/21/2013	5:39:27	LE71392112013172EDC00
7/7/2013	5:39:16	LE71392112013188EDC00
9/9/2013	5:39:24	LE71392112013252EDC00
6/8/2014	5:41:14	LE71392112014159EDC00
6/24/2014	5:41:16	LE71392112014175EDC00
8/27/2014	5:41:26	LE71392112014239EDC00
9/12/2014	5:41:27	LE71392112014255EDC00
6/13/2016	5:46:22	LE71392112016165EDC00
7/15/2016	5:46:23	LE71392112016197EDC00
7/31/2016	5:46:26	LE71392112016213EDC00
8/16/2016	5:46:27	LE71392112016229EDC01
9/1/2016	5:46:31	LE71392112016245EDC00
9/17/2016	5:46:32	LE71392112016261EDC01
6/16/2017	5:46:26	LE71392112017167EDC00
7/2/2017	5:46:29	LE71392112017183EDC00
7/18/2017	5:46:29	LE71392112017199EDC00

(Appendix 2: 24 hour meteorology for day of and day preceding Landsat 7 flyover
(Temperatures in Degrees Celsius) (T in comments denotes "Trace" or ~0.01 inches
precipitation recorded)

Day of Flyover

Date of Flyover	High Temp	Low Temp	Comment
6/12/2004	26.1	7.8	clear
7/14/2004	34.4	15.6	clear
7/30/2004	34.4	16.1	clear
8/31/2004	36.7	14.4	clear
9/16/2004	28.9	7.2	clear
7/1/2005	33.3	16.1	clear
7/17/2005	38.9	21.1	clear
8/2/2005	32.2	17.2	clear
9/3/2005	32.8	12.2	haze 7am (brief)
9/19/2005	22.2	6.7	clear
6/18/2006	33.3	15.6	clear
7/4/2006	35.0	14.4	clear
9/6/2006	35.6	14.4	clear
6/21/2007	33.3	17.2	clear
7/7/2007	37.2	21.7	brief squall 1 pm precip: T
7/23/2007	36.7	16.1	clear
8/8/2007	30.0	10.6	clear
8/24/2007	33.3	16.7	clear
9/9/2007	32.2	12.8	clear
9/25/2007	17.2	2.2	clear
6/7/2008	23.9	10.6	clear
6/23/2008	31.7	15.6	clear
7/9/2008	36.7	17.2	clear
7/25/2008	35.6	15.6	clear
8/10/2008	31.7	15.0	clear
8/26/2008	33.3	14.4	clear
9/11/2008	28.9	9.4	clear
5/25/2009	27.8	8.9	clear
6/26/2009	32.2	16.1	clear
7/28/2009	37.2	18.9	clear

6/13/2010	25.0	11.1	clear
7/31/2010	35.0	17.2	clear
8/16/2010	33.3	17.2	light shower 3:45-4 pm precip 0.03in
9/1/2010	26.1	8.3	clear
9/17/2010	30.6	8.3	clear
7/2/2011	32.8	13.3	clear
7/18/2011	30.6	12.2	clear
8/3/2011	33.9	16.7	clear
8/19/2011	34.4	13.3	clear
9/4/2011	32.2	10.0	clear
9/20/2011	31.7	10.0	clear
7/4/2012	34.4	16.1	clear
7/20/2012	27.8	18.3	light rain 11:55 am precip: T
8/21/2012	36.7	16.1	clear
6/21/2013	25.0	8.3	clear
7/7/2013	35.6	15.6	clear
9/9/2013	33.3	12.2	clear
6/8/2014	33.3	16.1	t-storm 5:30-6pm precip: T
6/24/2014	33.3	12.2	clear
8/27/2014	28.3	12.2	clear
9/12/2014	32.2	10.6	clear
6/13/2016	26.1	11.1	clear
7/15/2016	36.7	16.1	clear
7/31/2016	37.2	19.4	clear
8/16/2016	34.4	15.6	clear
9/1/2016	32.8	17.8	clear
9/17/2016	27.8	7.8	clear
6/16/2017	31.1	11.7	clear
7/2/2017	35.6	18.3	clear
7/18/2017	34.4	16.7	clear

Day Preceding Flyover

Date of Flyover	High Temp	Low Temp	Comment
6/12/2004	23.9	5.6	t-storm 2am-3am, Precip: T
7/14/2004	34.4	15.0	clear
7/30/2004	36.7	17.8	clear
8/31/2004	33.3	11.7	clear
9/16/2004	24.4	9.4	clear
7/1/2005	30.0	13.9	clear
7/17/2005	38.9	21.7	clear
8/2/2005	33.3	18.9	clear
9/3/2005	32.8	10.6	clear
9/19/2005	22.2	8.9	clear
6/18/2006	31.1	10.0	clear
7/4/2006	35.0	16.7	clear
9/6/2006	33.9	15.0	clear
6/21/2007	36.1	15.0	clear
7/7/2007	42.2	19.4	clear
7/23/2007	33.9	13.9	clear
8/8/2007	30.0	11.7	clear
8/24/2007	35.6	16.1	clear
9/9/2007	33.3	12.2	clear
9/25/2007	11.7	5.6	rain showers precip: 0.18
6/7/2008	26.7	5.6	clear
6/23/2008	34.4	16.1	clear
7/9/2008	36.1	16.1	haze through 5 am
7/25/2008	35.0	15.0	smokey around 6 pm
8/10/2008	33.3	17.2	clear
8/26/2008	36.1	16.7	clear
9/11/2008	30.6	12.8	clear
5/25/2009	30.0	13.3	clear
6/26/2009	35.0	14.4	clear
7/28/2009	38.3	17.8	clear
6/13/2010	20.6	8.3	clear
7/31/2010	36.1	16.7	clear
8/16/2010	35.6	16.1	clear

9/1/2010	22.8	8.9	clear
9/17/2010	29.4	9.4	clear
7/2/2011	30.0	11.1	clear
7/18/2011	28.9	13.3	clear
8/3/2011	33.9	17.8	clear
8/19/2011	34.4	11.7	clear
9/4/2011	30.0	10.6	clear
9/20/2011	29.4	9.4	clear
7/4/2012	34.4	16.1	clear
7/20/2012	31.7	12.8	clear
8/21/2012	35.0	20.0	clear
6/21/2013	22.2	9.4	clear
7/7/2013	36.1	19.4	clear
9/9/2013	32.2	11.7	clear
6/8/2014	33.3	15.0	clear
6/24/2014	32.2	10.6	clear
8/27/2014	26.7	14.4	lgt rain 1-1:45pm precip: T
9/12/2014	30.6	11.7	clear
6/13/2016	25.0	11.1	rain 5:05-5:30pm precip: T
7/15/2016	34.4	13.9	clear
7/31/2016	39.4	21.1	t-storm 3:15-3:40 pm precip: 0.00
8/16/2016	36.1	16.1	clear
9/1/2016	33.9	16.1	clear
9/17/2016	26.1	8.3	clear
6/16/2017	30.0	10.0	clear
7/2/2017	35.0	17.2	clear
7/18/2017	37.8	20.0	haze/smoke 10-11:55 am