Spatial and temporal patterns of long-term temperature change in Southern California from 1935 to 2014

by

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To my family, both by blood and choice, but especially my son,

Stephen Harold.

I hope to make you all proud.

Thank you for your love and support

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List of Abbreviations

ACC	Anthropogenic climate change
CDIAC	Carbon Dioxide Information analysis center
DEM	Digital Elevation Model
GCM	Global Climate Model
GIS	Geographic information system
masl	meters above sea level
NCDC	National Climate Data Center
NCEI	National Centers for Environmental Information
NCEP	National Centers for Environmental Protection
NED	National Elevation Dataset
NHGIS	National Historic Geographic Information System
NLCD	National Land Cover Dataset
NOAA	National Oceanic and Atmospheric Administration
OEHHA	Office of Environmental Health Hazard Assessment
QA	Quality assurance
QD	Cumulative deviation
SST	Sea and surface temperatures
UHI	Urban heat island
WRCC	Western Regional Climate Center

Abstract

Climate change is a pressing issue, and regional studies play an important part in understanding the impact of global climate change. This project explored the spatial and temporal patterns apparent in temperature records from 1935 to 2014 using homogenized station data from 66 stations in Southern California. Using Hurst Exponent, an index used to explore the persistence of trends in longitudinal data, the strength of the increasing temperature trend observed at every station was evaluated. Hurst Exponent values were calculated for the high, mean, and low temperature series for both the summer and winter 3-month period. The spatial distribution of each of the six Hurst values was examined with respect to location, elevation, aspect, land use, and population density of each station using Microsoft Excel and ArcGIS. Results show that there is persistence in the increase of temperature at all stations beginning around 1980, though the strength of this persistence varies. Winter High temperature persistence is strongest in coastal areas and weaker in the inland mountains as shown by the hot spot analysis.

Chapter 1 Introduction

Climate change is already affecting many places and people in the world. In order to understand where the climate is going, and attempt to mitigate the consequences, it is important to understand how climate has changed thus far. Evaluating climate long term and short term, on both global and regional scales are all crucial. There are many measures of climate change, and temperature change is a significant indicator (Karl et al 1997). This study evaluates spatio-temporal temperature trends for 66 weather stations using homogenized data in the ten counties of Southern California. Using the Hurst exponent, the degree of persistence of change at different elevations, slopes, and aspects was evaluated to determine if there is an association between the direction, magnitude, and speed of trends and these three variables in regards to station location. This study helps understand the direction and degree of climate change in Southern California.

The term “climate” is a broad term that incorporates many facets of the environment. In order to gauge climate change, quantifiable measures must be defined. Climate change can be measured by changes in trends and extremes of temperature and precipitation, by the changing patterns of flora and fauna, and variations in wildfire patterns (Karl et al. 1997). One of the most frequently evaluated measures in climate change is temperature change, and that was the indicator selected in this study to be analyzed. Global temperature increases have been observed by many agencies and researchers, with an overwhelming majority of climate scientists believing that the human activity is the cause of the observed temperature increases (Oreskes 2004, Doran and Zimmerman 2009, and Anderegg et al. 2010).

Figure 1 illustrates the changing temperatures recorded on land and sea. Figure 1A shows the global annual mean temperature change from the 1951-1980 base period. Figure 1B shows the distribution of change of temperature averaged over 2001 to 2005 compared to the base period. As can be seen in the first graph, in 1890 the mean global temperature was two degrees below the base period and in 2010, the temperature was about 6 degrees above the base mean (Hansen et al. 2006). This helps to demonstrate the pace at which temperatures are increasing across the globe. The figure also shows that until about 1980, there were fluctuations in temperatures above and below the mean; however, since about 1980 temperatures have only ranged above the mean.

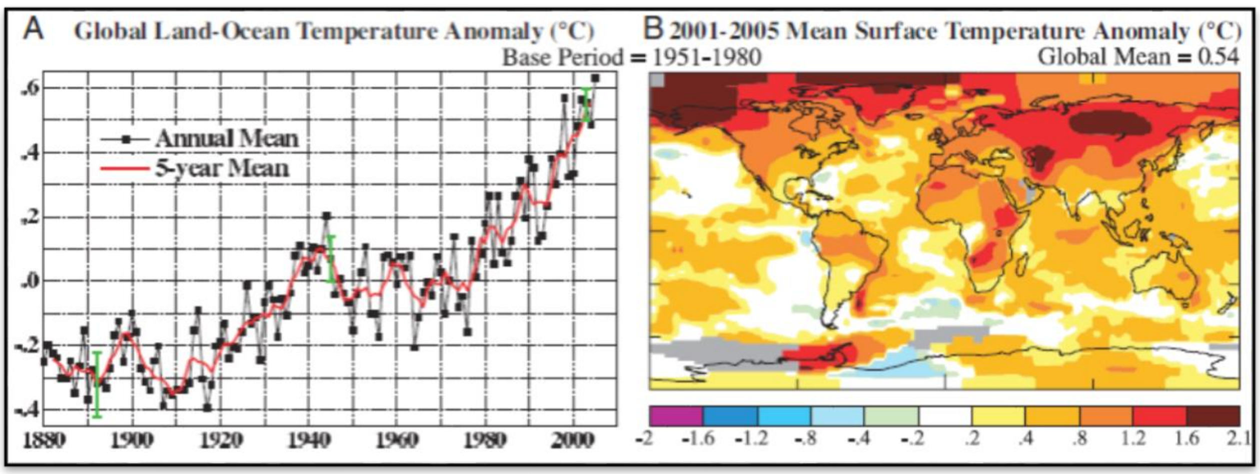


Figure 1: Surface temperature anomalies relative to 1951-1980 (A) Global annual mean anomalies. (B) Temperature anomaly for the first half decade of the 21st century.
Source: Hansen et al. 2006

Climate change is important because of how the changing climate impacts agriculture, economy, and environment on local and global scales. Where the effects of climate change can be observed globally, they are and will be felt locally. As evidenced by Figure 1B, the way the climate is changing can vary greatly by region. In order to understand what the impacts are going to be, it is important to understand how each region has been affected by climate change. Regional climate studies fill in this gap. Regional studies provide answers to the questions of how the climate has changed and indicate the direction of change for that region.

1.1 Study Area

California is an ecologically diverse state. According to the Western Regional Climate Center (WRCC 2015), biomes range from sub-tropic to sub-arctic depending on latitude, elevation and proximity to the coast, with nearly all biomes represented. This is because of the confluence of maritime air masses joining with continental currents, and the diverse topography. There are several mountain ranges in California, with the highest peaks reaching over 14 thousand feet. California also has many low elevation areas with Death Valley being the lowest point in the country with an elevation of 276 feet below sea level. Also, Southern California is home to two of the largest counties in the United States. San Bernardino County is the largest county by size, and Los Angeles County is the largest by population.

California has mostly dry summers and a comparatively wet winter. Northern California typically has more year round rain, and can provide the state with over 70 percent of the its water needs, when not experiencing severe drought as is the case as of 2015 (WRCC 2015). With irrigation, California's generally warm temperatures facilitate a lengthy growing season. The coldest temperature on record of -45 degrees Fahrenheit was reported in 1937 from a location at an elevation of 5,532 feet. To contrast the hottest temperature on record, as of December 2015 was 134 degrees Fahrenheit at -168 feet elevation (WRCC 2015). Figure 2 shows the 5-year average temperatures of California over a 100-year period. Consistent with other temperature data, temperatures have been entirely above the mean since 1980.

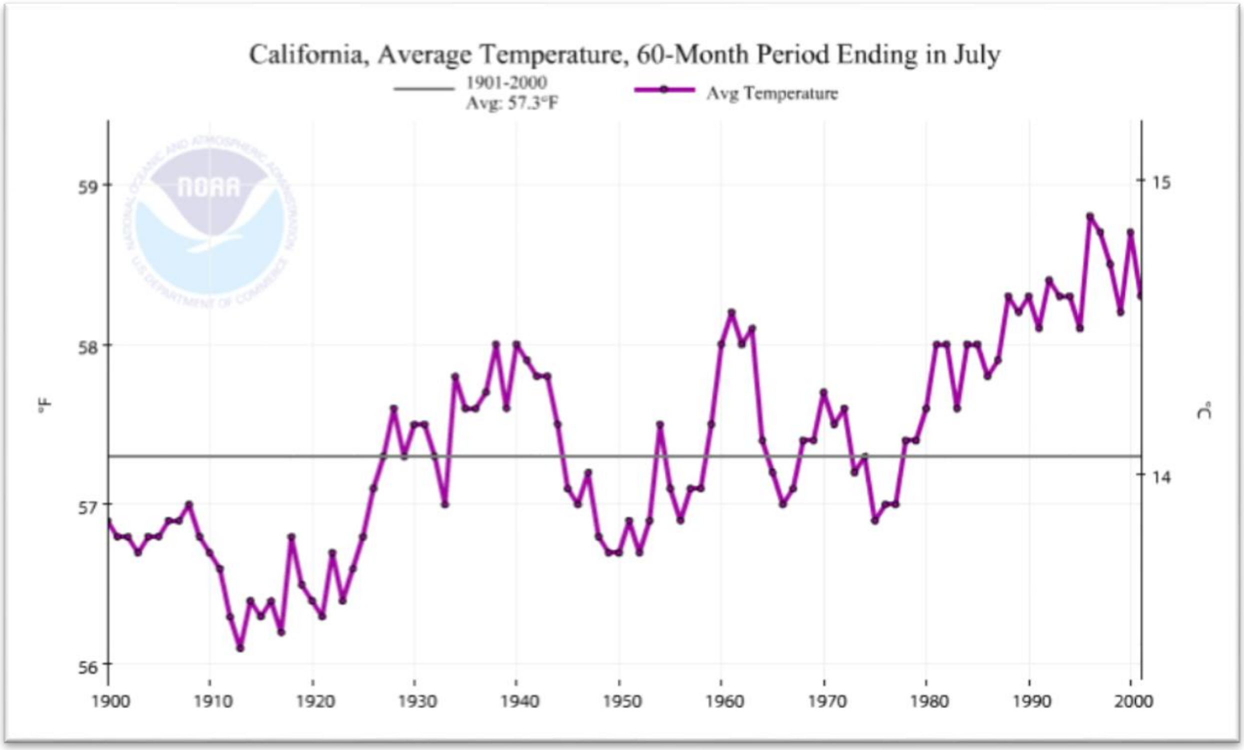


Figure 2: Temperature change in California from 1901 to 2000
Source: National Oceanic and Atmospheric Administration (NOAA)
http://ncdc.noaa.gov

Southern California has many definitions. Some definitions of Southern California are based on membership in the Southern California Association of Governments, an association of six counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. Where this is convenient because it has an official sound to it, it excludes counties that are conceptually ingrained in the concept of Southern California like San Diego. Other definitions based in economics include only eight counties: Santa Barbara, Ventura, Los Angeles, San Bernardino, Riverside, Orange, San Diego, and Imperial (US Census Bureau 1970). Because this project is so heavily spatial in nature, Southern California is defined by the Southern versus Northern division at 35° 47′ 28″ north latitude, as seen in Figure 3. This adds San Luis Obispo and Kern Counties to the list to make a total of ten counties that have a balanced shape to serve as the study area of this project.

Figure 3: Study Area: 10 counties of Southern California

Temperature change in Southern California was evaluated by the Office of Environmental Health Hazard Assessment (OEHHA). They found that the annual mean temperatures have increased 1.5 degrees Fahrenheit per century since 1895, while average minimum (low) temperatures are up 1.99 degrees (OEHHA 2013). According to the report, average maximum (high) temperatures were up only 1.01 degrees. These numbers serve as a foundation for understanding that temperatures are increasing in Southern California. The goal of this project is to contribute to the understanding of how persistent that change is.

1.2 Project Overview

This study evaluates persistence of temperature change using homogenized seasonal high, mean and low monthly temperature data from 66 stations across Southern California from December 1934 to August 2014. Persistence is measured using the Hurst Exponent. This study tests H-values in correlation to elevation, aspect, and land cover to provide insight to the spatial trend in temperature change. These are the Research Questions that were addressed:

1. Is there a spatial pattern of H-values by season as determined by optimized hot spot analysis; if present, how is the correlation best described?
2. Is there a correlation between H-values and elevation; if present, how is the correlation best described?
3. Is there a correlation between H-values and aspect; if present, how is the correlation best described?
4. Is there a correlation between H-values and the land covers “Urban” and “Rural”; if present, how is the correlation best described?

There are several different types of sciences involved in climate change research. In this case, the focus is on geographic information science (GISci). Mapping and spatial analysis, major components of GISci, have been important to understanding and displaying climate data (Thornthwaithe 1948, Daly et al. 2002). One of the best ways to interpret climate data is by understanding the space in which it occurs. As a result, much of the analysis in this project is illustrated with maps.

1.2.1. Homogenization

Homogenization is a process of treating climate data to remove the impact of urban heat islands (UHI), ensure that that recorded data is reliable, and maintain the consistency of the time series (Longobardi, and Mautone 2015). This editing, filtering and filling in of data creates a stronger, more consistently reliable set of data from which further analysis is strengthened. The NOAA Carbon Dioxide Information Analysis Center (CDIAC) published a report of homogenized stations (Menne et al. 2015) that produced a long-term series for the conterminous United States. The report details the homogenization and quality assurance processes that produce the end data. The quality assurance (QA) of the data is an integral step in data homogenization and includes (Durre et al 2010):

1. Basic Integrity Check - looks for data duplication;
2. Outlier tests (19 checks) - looks for values that are outside of the presumed value range.
3. Internal and temporal consistency - evaluates ranges in the data;
4. Spatial consistency - makes sure the values are consistent with surrounding sites;
5. Meta-consistency – observations not flagged by other checks are verified for integrity.

The specific methodology of homogenization is discussed in Chapter 2. In brief, Menne and Williams (2007) use a pairwise comparison algorithm to analyze consistency of the observations of adjacent stations, checking for outliers, missing data and possible errors. This is an important contribution to preparing data for climate change analysis because the alternative is to rely on station metadata that is not always consistent in availability and/or quality.

1.2.2. The Hurst Exponent

Harold Edwin Hurst created a method of rescaling time series data in 1951. The goal was to evaluate the discharge of the Nile before it was to be dammed. The resulting analysis process is seen as pioneering work in fractal geometry (Mandelbrot 1982, Outcalt 1997). The Hurst Formula, shown in (1), from Outcalt (1997), measures how the trends in a time series move towards or away from the mean of the entire series.

$$\left[\frac{R(n)}{S(n)}\right] \infty\ n^{H} \qquad (1)$$

Here, n is the number of data points in the time series, R(n) is the range of the n values, and S(n) is the standard deviation of the values. H is the slope of the line from log [R(n)/S(n)]. H is the vital portion of the equation, and is known as the Hurst Exponent. While Hurst used the method first, the equation was developed by Mandelbrot (1967) who named it after Hurst.

The power of the Hurst Exponent is its ability to qualify the time series. H-values range between 0 and 1. A value greater than 0 but less than 0.5, indicates that change within the series is cyclical. The further away from 0.5 the more pronounced the cyclic pattern. 0.5 indicates an entirely random series, so as values approach 0.5, the more random the series variation is. Values greater than 0.5 indicate persistence of change. As the value approaches 1, the stronger is the persistence of the apparent trend, and likewise the closer to 0.5 the value is, the weaker and more random the series variation is. The H-value does not report the direction of the persistence, only its strength. The direction of the persistence must be independently determined by reviewing the trends in the data itself. The Hurst Exponent is the theoretical construct where H-value is what can be calculated.

1.2.3. Spatial Properties

The H-value was used as a tool to evaluate the relationship between long-term temperature changes and various spatial variables associated with each station's location. The variables evaluated in this study were aspect, elevation and urbanization. The H-value of each station's series provided a means to evaluate the strength or persistence of the temperature increases at that station. To formally frame the analysis described here, a hypothesis for each spatial property is presented below.

1.2.3.1. Aspect

Aspect in this case is the cardinal direction of the slope of the plane valuing from 0 to 360 with 0/360 representing due north and 180 representing due south. The earth is far from a flat surface, and southern facing planes receive more sun in the northern hemisphere than northern facing planes. *The hypothesis is that stations on a southern facing plane will have higher H-values reflective of more persistent temperature changes over stations located on a northern facing plane.*

1.2.3.2. Elevation

There are myriad regional climate studies, and many of those studies are showing that high elevations are more sensitive to changing climate conditions and may act as early indicators of impending change at lower elevations (Giorgi, Hurrell and Marlnucci 1996; Diaz and Bradley 1997; Hansen et al. 1999; Van Beusekom, Gonzalez, and Rivera 2015). Because higher elevations are often more sensitive they can help show the direction that the regional climate trend is headed. *Therefore, the hypothesis is that stations located at higher elevations will produce higher H-values reflecting increased persistence of temperature change at higher elevations over stations at lower elevations*

1.2.3.3. Urbanization

The urban heat island (UHI) effect has been well studied (Easterling, Peterson, and Karl 1997; Tett et al. 1999; Kalnay and Cai 2003; Hayhoe et al. 2004, Ruddell 2013) and urbanization has been shown to have a significant impact on temperatures causing more pronounced temperature increases. Even though the data used in this study has been homogenized to minimize the UHI effect spatially, the expectation is that over the time series, stronger persistence of temperature increases should be observed at stations with an urban land cover. Because urbanization changes over time but land use data is difficult to find for the full range of dates included in this study, census population density was used as a proxy for urbanization. *The hypothesis is that there will be higher H-values showing higher degrees of persistence of temperature change at stations with higher population densities (i.e. more urbanized) than stations with lower population densities (i.e. more rural).*

1.3 Outline of this document

Chapter 2 discusses some of the myriad studies in climate change focusing on studies that are relevant to the study area or the study methodology. Works analyzing global temperature climate change show that around the world temperatures have been increasing over the last century with the most significant increases from 1980. Not only are temperatures increasing, but the driving forces linked to temperature increases are attributed to human activity. This is called anthropogenic climate change (ACC) (IPCC 2007), and is addressed in Section 2.1. Regional studies help scientists to understand which areas are being most affected by climate change. Section 2.2 discusses some of the methodology for regional analysis of temperature changes, and the results of regional studies for California and Southern California. Homogenization is discussed in Section 2.3. Section 2.4 talks about the Hurst-Exponent, and how it is used in a research setting. The rest of Chapter 2 discusses how the spatial variables used in the study are reflected in the research.

Chapter 3 addresses the methodology employed. The data that was used, how it was obtained and the important metadata are addressed in Section 3.1. The rest of the chapter is dedicated to explicating how the Hurst data was generated and employed in analysis. Section 3.2 focuses on the Hurst Exponent, and Section 3.3 looks at the Hot Spot Analysis. The spatial dimensions of the study are addressed in Section 3.4

All of the results of the study are displayed in Chapter 4. Section 4.1 reviews the temperature trends where Section 4.2 shows the results of the Hurst analyses.

The final chapter addresses the problems that arose during the study. Chapter 5 also covers a few afterthoughts and suggestions for future research based both on the methodology and the data set created. Lastly, the significance of this study is relayed. This very last section of Chapter 5 is arguably the most important because it not only covers what the study accomplished, but how it might help other studies in the future.

Chapter 2 Background Literature

Climate change is an incredibly widely studied field. There are journals, such as Climate Change, Climate, and Climate Dynamics, among others, exclusively dedicated to climate change. With an average of about 1,400 articles on climate published each year (Powell 2012), there is no shortage of studies to report. This chapter focuses on some major keystone articles, articles specifically about the study area, and some recent works relative to each section.

Climate is defined as the weather conditions prevailing in an area in general or over a long period. Weather conditions are generally thought of as temperature and precipitation, and maybe wind, but ways of measuring climate change extend far beyond that. Karl et al (1996) outline in detail many of the ways that climate change can be measured through its impacts on flora and fauna, oceanography, wildfire patterns, and of course atmospheric conditions like precipitation and temperature, the latter the focus of this research.

2.1 Global Temperature Change

Tracking temperature change is one of the primary means of evaluating climate change. As early climatic sensor technology proliferated, the ability to quantify climate became a reality (Thornthwaite 1948). The next challenge was to disambiguate climate study from meteorology, statistical rational analysis was one means of accomplishing this (Thornthwaite 1948). Chapter 1 already discussed how temperatures are rising around the globe, but many research studies cover the myriad aspects of the globally increasing temperatures. In 2006, Hansen et al. compared predictive temperature models from the 1980’s and compared their predictions to real instrument readings during the prediction years. This served to evaluate the accuracy of predictive models, and assess the current rate of temperature increase. Not only does their paper show the magnitude of global temperature increases, but it also looks at three scenarios for continuing trends based on carbon dioxide emissions estimates. Their conclusion is that the earth is as warm as the Holocene maximum. As temperatures approach the warmest in a million years, the effects of the temperature increases constitute significant levels of change.

Most scientists attribute the rise in temperatures to increases in greenhouse gasses such as carbon dioxide. Greenhouse gasses not only increase temperatures but also increase solar radiation levels as discussed by Schlesinger (2011). He reports that global air temperatures are expected to increase from 2 degrees to 4.5 degrees Celsius because of increased concentrations of greenhouse gasses.

These are just a couple articles that show that global surface temperatures are on the rise. Even though we know that temperatures are on the rise, regional studies help scientists understand how the global increases are impacting people, plants, and animals on a local level. This is part of the reason that there are so many regional studies on climate change, and temperature increases in particular. Temperature increases are happening globally, but change is observed on the regional scale.

2.1.1. Anthropogenic Climate Change

Anderegg et al. (2010) did a meta-study looking not at climate change or its causes, but instead looked at a database of 1,372 leading scientists and their research to address the apparent disagreement about anthropogenic climate change (ACC) perceived by the American public. According to that study, about 98 percent of researchers publishing in the field of ACC agree with the results of the Intergovernmental Panel on Climate Change. Not only this, but the roughly 2 percent of researchers who do not hold this belief are much less prominent professionally. This really translates to the vast majority of the scientific community as a whole agree that the patterns being observed as climate change have been caused by human action.

Studies regarding the changes seen in the climate and possible causes began decades ago. There was an IPCC on climate change in 1990 that attributed the increases in global temperature to human activities (Santer et al 1996). By 1999, scientist attributed increases in temperature to the increased levels of carbon dioxide in the atmosphere, and the increase use of sulphate aerosols (Tett et al 1999). In 2013, Ryerson et al. directly addressed atmospheric pollution and climate change. The goal was to record how much of what is going into the air, and how that might potentially be affecting the climate. The correlation here between population growth and urbanization with climate change is obvious. They were even able to record leaks in the natural gas infrastructure, which might have been overlooked as a contributing factor had it not been included in their research. They also looked at how air pollution in Los Angeles might be moving across the valleys and affecting air quality elsewhere.

One of the earliest papers identified that correlates climate change with population growth showed that even in the small towns of less than 10,000 people there was on average a 0.1 degree Celsius increase in temperature from nearby stations with more than 2,000 people (Karl et al. 1988). That study evaluated 1219 weather stations from 1901 to 1984.

One human activity other than carbon emissions that is known to increase temperatures is the amount of ground covered by pavement and buildings. Since soil is not very reflective, as the sun hits the soil it will absorb heat. Concrete on the other hand reflects the heat back to be bounced off nearby buildings. The reflectivity and absorption of heat by a surface is called albedo. Concrete and other man made structure have a high albedo and are very reflective, where trees, grass, and soil absorb heat more than reflect it, and have a low albedo (Taha 1997). As solar radiation as heat hits the earth, the radiation and heat are either absorbed by surface or reflected back functionally increasing temperatures (Raupach and Finnigan 1997). The effect is similar to the impact a mirror has on light. A single candle only produces so much light on its own, but if the candle is placed in front of a mirror the light of the candle is almost doubled.

2.2 Regional Climate Change Analysis

Regional climate studies are important in understanding how the changing climate has impacted and will impact specific areas on a smaller scale. Kuepper et al. (2005) discuss the significance and importance of regional studies in understanding global climate change. As of 2015, Global Climate Models (GCM) must be used and parred down to facilitate projections for a region (Pierce 2004, Cayan 2008). Quality data and analysis for a region helps to fill in the data gaps of the GCM to make the regional model more comprehensive, highlighting the importance of quality regional climate change studies.

Studies of historical climate and temperature change at the local level are dependent upon the availability of data. Ideally, the best data that has been collected or is available for that region will be used. The data must have been consistently and reliably collected to be utilized as an indicator in a study to evaluate temperature change, or any other aspect of climate change for that matter. Each collected temperature set is a separate indicator. Daily high data is one example of an indicator, and daily low temperatures is another. Indicators can also be the result of data set analysis. This study used seasonal measures derived from the monthly high, mean and low temperature reports.

Different climate stations report data differently; some stations report on daily temperature high, and low, sometimes including a daily mean, while some stations in Europe, report data according to Manheim hours (Rebetez and Reinhard 2007). Manheim hours take the temperature measurements at specific times of day (morning, afternoon and evening) to calculate monthly means instead of using the simply daily high and low temperatures. Other stations do not report the daily mean at all, only the high and low. If the data for a specific measure is sporadic or inconsistently collected, or has been shown to be in any other way unreliable, that indicator is likely to be eliminated entirely from the analysis.

Data quality is an issue addressed in many ways. Most projects are usually only able to use between three to five indicators to determine rate of change because of issues in data quality for the other indicators. Garzena's (2015) study of temperature change in the Italian Alps uses 6 indicators: Cold spell duration, Warm nights, Warm days, Cool nights, cool days, and Warm spell duration. They used some satellite data to fill in some blanks offered from intermittent ground station data. Some studies, such as Liu at al. (2004), have used interpolation to fill in short periods of missing data. They evaluated 305 stations high, mean and low readings. They likely interpolated missing values in order to maintain an even statistical weight between the figures.

Booth, Byrne and Johnson (2012) evaluated climate change in western North America using data from 485 stations. They were able to utilize consistent daily data from 1950 to 2005. Six stations had long-term records that were analyzed for a hundred year interval starting in 1906. There were able to analyze 4 temperature indicators and 4 precipitation indicators from the 27 core climate change indicators developed by the World Meteorological Organization (WMO). They evaluated the 22 westernmost states of the contiguous United States and 4 provinces from Canada. Results showed that because of the diversity within the region, result of increases varied, though warming trends were ubiquitous, and precipitation trends fluctuate between increasing and decreasing trends. In California and southern California specifically, they found a general warming trend with some coastal cooling.

An important paper that influenced this research is Rebetez and Reinhard (2007). Their study also sought to analyze long-term temperature trends using spatial attributes like aspect, and elevation. Using homogenized data, they evaluated temperature change in Switzerland at 13 stations. They compared temperatures to the global mean to assess degree of change. Using the Ward Method for hierarchical clustering based on a Euclidean distance matrix they analyzed the relationship between stations. They found that temperatures had increased 0.135 degrees Celsius per decade in the last century, but 0.57 degree increase can be attributed to the last 30 years alone. Seasonal warming trends fell into the 95 percent significance range. This key research is reviewed in detail later in this chapter as a means of setting the framework for the research reported in this document.

2.2.1. Impacts of Climate Change in California

Climate change is more than just temperature and precipitation changes. The impact that these changing patterns have affects multiple systems. In this section, some of the other ways that climate change has impacted California and Southern California are explored.

As temperatures increase and, especially in California, as precipitation decreases, some species of plants thrive, while others wither or migrate to more suitable areas. Evaluating where and how plant distribution is changing is one of the indicators of climate change (Karl et al. 1996). Kelly and Goulden (2008) cover over 30 years of floral distribution in Southern California. They found that as temperatures increased and precipitation decreased, the elevation of dominant species increased by approximately 65 m. Even some climate modeling scenarios include projections regarding flora. Projections predict an increase in deciduous forest cover as coniferous forests decline (Lenihan et al 2003, 2008). The viability and accuracy of modeled plant ranges with projected climate change suggest that predictions may not have the desired accuracy and how to possibly adjust the projections (Dobrowski et al. 2011).

Plant life migration patterns are only one of the impacts of climate change. Rising sea level is one of the primary concerns in a global climate change scenario. The Pacific Ocean is a significant contributor to the overall climate patterns in California. Cayan et al. (2008) examine what effects climate change will have on sea levels along California's coast. Because California has such a long coast line, this global trend is regionally relevant. Ocean currents affect El Nino patterns that contribute to precipitation patterns across the globe. Cayan et al. suggest that even with the changes in precipitation in California, the increased temperatures will continue to reduce snow pack. Further analysis of ocean cycles is seen in other articles.

Even though the primary focus of Hayward (1997) is on the Pacific Ocean as a whole, the paper looks at changing plant life within the Pacific. The expectation is that there will be a proliferation and abundance of some sea life, where other sea life will wither. The long ranging effects of these changes was not evaluated in the paper, but because California has such a long coast line, it may be assumed that climate changes affecting the abundance of ocean flora and fauna will significantly influence California's economy.

As temperatures increase and precipitation in California decreases, fire patterns are one of the big climate change indicators. Fried, Tom, and Mills (2004) show that changes in the fire patterns can demonstrate climate change in California. Their paper focuses on Northern California specifically, and they found that as CO_2 increases, fires are projected to burn more intensely and spread faster. Westerling and Bryant (2008) discuss the importance of climate change on fire seasons, and what possible impacts the regional climate change may have upon

California's fire season. The study reported that the reduction in air and land moisture with increased temperatures indicate there will be more large fires more often.

2.3 Homogenization of Climate Data

Ideally, data collected for any research objective is perfect with no instrument error or gaps in data recording, and no external factors influencing readings. With most data sets this is not the case, and climate data is no exemption. Changes in instruments, how data is recorded, station location, and increases in urbanization all have impacts on climate data that make solid meaningful statistical analysis difficult (Aguilar et al. 2003). This is where homogenization of weather data for climate change research steps in.

Different studies use various methodologies for selecting data collection sites to use for their studies, but many studies value homogeneity because it ensures consistency within the data. (Vincent and Guillett 1999; Rebetez and Reinhard 2007; Garzena, Fratianni and Acquaotta 2015; Longobardi and Mautone 2015). When sites have been moved, or have only sporadically collected data, it can significantly affect analysis of temporal trends (Christensen et al. 2008; Dibike et al. 2008). The results from statistical analysis can also be altered by sporadic and erratic data. Using homogenized data ensures that these errors and gaps are eliminated from the data as much as possible.

Much research has been dedicated to how to identify non-climatic contributions to climate data, so there are many techniques and means by which homogenization can be done. While some methods focus on analysis of the metadata to give clues to how data should be adjusted, others use analytic methods directly on the data itself (Easterling, Peterson, and Karl 1995). For the research reported here, homogenization was performed using Mene and Williams (2007) guidelines. They created an automated algorithm that performs pairwise comparisons of data from a network of stations. The process looks at each of the readings from a diverse set of stations to establish the most likely range of temperatures that exclude artificial discontinuities, or “inhomogeneities” (Menne and Willaims 2007). The goal is to be able to detect disparities in temperature that do not reflect the true variability. This is why the metadata is not as significant. Regardless of the completeness of the metadata, or any previous knowledge regarding the circumstances around the data collection, inhomogeneities should be snuffed out.

The pairwise comparison is combined with another algorithm that uses recursive testing to correct multiple inhomogeneities simultaneously. Recursion relies on testing and analyzing smaller versions of the same type of data. The series of data are also examined for improbable shifts in temperatures from one day or one station to another. This method has a lower rate of false alarm readings than the other methods for homogenization (Mene and Williams 2007). The result produces homogenized monthly data from which further analysis can be performed.

2.4 The Hurst Exponent in Climate Change Studies

The Hurst exponent has seen most use in the financial sector to calculate predictability of various markets. Carbone, Castelli, and Stanley (2004) calculated the H value for the minute to minute ticks of the German market to determine the predictability. They estimated H using the Detrending Moving Average technique. H-values calculated were all close to .5 in value, and it was determined that the market has a low predictability.

Cajueiro and Tabak (2004) provides another example of the Hurst Exponent being employed in finance. They sought to determine if emerging markets gain efficiency over time. They evaluated 4 years of global market trends of young markets, such as Brazil, Latin America, and Thailand. They found that higher H values reflected increasing efficiency expressed by most young markets but not all.

Despite its popularity in financial studies, the Hurst exponent was created for evaluating geophysical time series data (Hurst 1951, Mandelbrot 1968), but it has many applications. Outcalt (1997) outlines a number of other uses and applications. He suggests using H-values to assess distribution of trees and sunspot pattern analysis, and, with respect to climate studies, for temperature, precipitation and drought analysis.

A very interesting study was done in 2003 by Koutsoyiannis. He took 1000 years of temperature data inferred from various sources such as isotope readings, tree ring analysis, and ice core samples. Because of the nature of the inferred data, the study covered the northern hemisphere. The researcher’s interest was to determine hydrological cycles based on temperature persistence. He found that climate fluctuates at all time scales, and calculated an H value of 0.88 for the long-term memory of the proxy annual temperatures.

Another long range temperature study that used inferred data covered 125 years of ocean compared to land temperatures of the Northern Hemisphere (Alvarez-Ramirez et al. 2008). They found that temperatures, while rising, are also cyclical annually and inter-annually determined by 12 month and 2 month running means.

Rangarajan and Sant (2004) used meaned monthly data to calculate seasonal H-values of monsoon seasons in India to see if there was a correlation between temperatures and precipitation. Their study used GHCN data of 31 stations .H-values greater that 0.5 can also show predictability. Some stations high H-values reflected high predictability, but not all.

Ruddell et al. (2013) used the Hurst exponent to evaluate long-term temperature changes to quantify the UHI. Temperature data from urban Phoenix, AZ was compared to temperature data from the nearby Gila Bend, AZ, a much less urbanized community. They examined the extremes in temperatures: frost days, and misery days from 1900 to 2007 and calculated H-values for the time series data. The results showed fewer frost days and increases in misery days in Phoenix, while the conditions were relatively stable with only moderate increases in Gila Bend.

2.5 The Environmental Variables Affecting the Rate of Climate Change

2.5.1. The Effect of Aspect

Around the northern world, as in California, on north-facing slopes snow tends to last longer and temperatures tend to be cooler (WRCC 2015). This is due to differences in solar radiation and suggests that south-facing slopes (in the northern hemisphere) may feel the effect of climate change more strongly. Rebetez and Reinhard (2007) found that to be the case in their study of the Alps. They found that stations on the south-facing sides warmed an average of 0.13 degrees, and temperatures on the north-facing sides increased only 0.10 degrees. No other studies that included aspect as part of a temperature change study were found, even though slope and aspect are key to understanding species distribution and ecosystem processes (Bennie et al. 2008). Environmental Variables Affecting the Rate of Climate Change

2.5.2. The Effect of Elevation

It is common knowledge that the high elevations have different climatic attributes from the low lands of Southern California (WRCC 2015). Many “flatlanders” escape the summer heat by retreating to the cooler mountain temperatures, and visits to the snow in winter, when there is snow, is not uncommon either. The question is how the effect of difference in elevation has been expressed in the climate change research.

There are studies dedicated exclusively to climate change at high elevations. In many measures of climate change, higher elevations are more sensitive to the impacts of higher temperatures. Beniston, Diaz and Bradley (1997) looked at a centuries worth of data and the impacts for climate change in high elevations exclusively. They note the difficulty in performing a thorough analysis because of the lack of high elevation stations. Even still they were able to find that the magnitude of change in high elevations exceeds the global rate of change.

Mote (2006) looked at snow pack levels in western North America. Though Southern California was left out of the study, the results for the mountains of Northern California and the Cascades show that Pacific climate variability accounts for 10 to 60 percent of April snow water equivalent levels. In other words, the snow pack is melting. Pacific climate variability is the interannual and decal oscillating patterns and fluctuations of currents within the oceans and atmosphere that have effects upon the weather in the northern hemisphere. (Di Lorenzo et al. 2010)

The Tibetan plateau has been the focus of many of the high elevation research studies (Liu et al 2008, You el al. 2010). You et al. (2010) tested correlations in the temperature trend for annual mean temperature and seasonal temperatures with elevation using National Center for Environmental Protection (NCEP) data. 11 indicators at 71 stations all above 2000 m found no correlation between elevation and the magnitude of the rising temperature trend. Liu et al (2008) found elevation dependency in the Tibetan Plateau similar to the types of dependency found in the Alps, and the Rockies. They found increasing temperature trends from 116 stations using monthly low temperature data.

2.5.3. Land Use and Climate Change

Evaluating land use change in association with temperature change is one component of understanding anthropogenic climate change. Changes in albedo is one of the most direct effects of population growth upon the local ecology and thus suggests impacts on temperature change.

Early studies such as Taynac and Toros (1997) focused on individual cities and climate change. They looked at four developing cities in Turkey from 1951-1990, and found urban heat islands with marked increases in annual temperature during this time period, but there were no perceived changes in precipitation. A 2003 study by Kalnay and Cai attributed a 0.25 degree temperature increase over the past fifty years to surface temperature changes. In 2008, Grimm et al. performed a continental research program to evaluate small and large cities and the effects of land cover change. Satterthwaite (2009) looked at carbon emissions as a driving force for climate change and argued that it is not so much population increase, but the carbon footprint of the populations that are driving climate change. Thus, the role of urbanization on climate change is a diversely studied and intensely interesting research topic.

2.6 Methodological Inspiration

After reading many academic articles on regional climate change, Rebetez and Reinhard's (2007) study of temperature changes in the Swiss Alps was selected as a preliminary study template. Station elevation ranged from 316 m to 2490 m in their report, which is similar enough to the range of values of Southern California stations (- 36.9 m to 2091.7 m) to serve as a viable model. Also, the time frame is similar; Rebetez and Reinhard were able to obtain homogenized data from 1901-2000. This study ranged from 1935 to 2014, providing an 80 year analysis in place of the 100 year study. At the initial inception of the project there were data for only 13 homogenized stations in Southern California, and the Rebetez and Reinhard study used 12 stations. The objective, data and ranges were thus similar enough to justify considering employing their research methodology as a model.

The data set used by Rebetez and Reinhard had 12 homogenized stations with monthly Manheim temperatures. Manheim temperatures report three values each day: an early morning, a peak afternoon, and an evening temperature instead of the high, low, and mean temperatures seen in the majority of U.S. temperature station data. It was from the daily Manheim values that their study calculated a mean temperature for each month. The monthly data available from NOAA that reports temperatures in North America, including Southern California, employs the more typical daily high and low and mean temperatures. This use of a different type of temperature series was the first major divergence from the original template methodology. The second was a fortuitous acquisition of more homogenized Southern California temperature data that permitted this study to expand to a consideration of 66 stations.

Rebetez and Reinhard used the Ward method to perform a cluster analyses to analyze the relationships between the stations. The Ward method is an agglomerative hierarchical clustering using a Euclidean distance matrix to explore similarities and differences in stations and months. Unfortunately, most programs which perform this type of analysis, such as SPSS, are not spatially oriented. They use latitude and longitude values, which are degree measurements that change in distance measure as the distance from the poles changes, as Cartesian x,y values. As a result, Euclidean distances from such coordinates are not accurate measures of true distance.

The Ward method puts greater importance on closer stations with results similar to a nearest neighbor distance weighting. This is done by sequentially incorporating clusters by proximity starting with each point as its own "cluster" and building from there. ArcGIS has the ability the run a distance analysis from a projected coordinate system where distance measured is relatively accurate to reality, and is therefore inherently a better means to perform the same type of analysis. In this study, an optimized hotspot analysis was used in place of the Ward clustering. This became another point in which the methodology of this study deviated from the original template study.

Rebetez and Reinhard employed a Fisher test to determine the exact p-value of trends for individual stations. P-value is the likelihood that a randomization of the variable will match what is actually observed. It is used to determine how likely the reality is to be random or correlated. The Fisher test runs every iteration of the possible paired values for all variables to produce a p-value that reports the strength of the correlation in the data.

The Hurst Exponent also measures the strength of temporal autocorrelation of a time series. In this study it was chosen over the Fisher test because the Hurst Exponent was developed to analyze time series specifically, where the Fisher test is employed in all forms of statistics for all forms of data types. Also the Hurst Exponent not only measures autocorrelation and randomness, but also identifies cyclical patterns and is therefore offers a stronger analysis of the time series.

Rebetez and Reinhard compared their results to global data from the Climatic Research Unit as a baseline for comparison of changes. However, the Hurst Exponent offers a cumulative deviation time series that can be used to understand the trends for each station. A more regional comparison was deemed a more appropriate means to evaluate change in this study.

The template study compared the north- and south-facing aspects of the slopes in the Alps by comparing the mean temperature increase at stations on the northern versus southern side of the Swiss mountain ranges. That inspired the aspect analysis performed by this project, but again GIS facilitates a more concise evaluation of slope and aspect derived from a DEM. Webster used the derived aspect to assign numerical aspect values (0-360) for each station. The H-values for each station were then compared to the aspect values using scatter plots as a correlation analysis.

Finally, in a complete deviation from the template study, this study also evaluated land use and population change to see if there was a connection between stations demonstrating higher persistence of increasing temperature change and higher urbanization levels.

This chapter could have continued to discuss climate change in depth for many more pages. This background chapter served to provide a foundation and justification for the research and methodology presented.

Chapter 3 Methods

This project sought to understand the spatial and temporal trends in temperature change in Southern California that are evident in homogenized monthly temperature data from 1935 to 2014. The Hurst Exponent was used as the key metric in assessing the strength of trends. By comparing elevation, aspect, land cover, and historic population density with the H-values at each station, relationships between long-term temperature changes and these environmental variables were explored.

The hypothesis for elevation was that temperature increases would be more pronounced and accelerated as indicated by higher H-values at stations at elevations greater than 1,000 meters above sea level. The hypothesis for aspect was that south-facing stations would have experienced higher temperatures overall, and more pronounced and intense temperature increases indicated by higher H-values. The hypothesis for land cover was that there would be more persistence in increasing temperature trends, or higher H-values, at stations in urban areas than stations in rural areas. Lastly, the hypothesis for population would mirror that for land cover as higher density was used as a proxy for urbanization.

3.1 Data Sets Employed

This project was data intensive. Weather data for 66 stations giving monthly high, mean, and low temperatures were required. Stations location and temperature data came from NOAA’s climate data website, the National Climatic Data Center. Homogenized station data was obtained from Mathew Mene at NOAA's National Centers for Environmental Information (NCEI).

NOAA has a great climate data download site at the National Climatic Data Center. The site provides access to stations and the associated data in .csv format. That document can then be imported to Excel, and from Excel a feature class can be created using the latitude and longitude coordinates provided. The coordinates are provided in the ten-thousandths, which for Southern California equals about 11 meter accuracy. The coordinates provided were in WGS 84. All data imported was projected into California State Plane V for spatial analysis. This projection was selected because it was designed specifically for Southern California to balance area and shape.

Because Rebetez and Reinhard (2007) used homogenized stations, homogenized station data was sought out on the NOAA site. A preliminary search yielded the 13 homogenized stations for Southern California shown in **Error! Reference source not found.**A couple problems were immediately evident: not all counties were represented with at least 1 station, and there is not a good distribution of stations in general across the landscape. That indicated that in order to perform the desired spatial analysis, more stations would need to be homogenized.

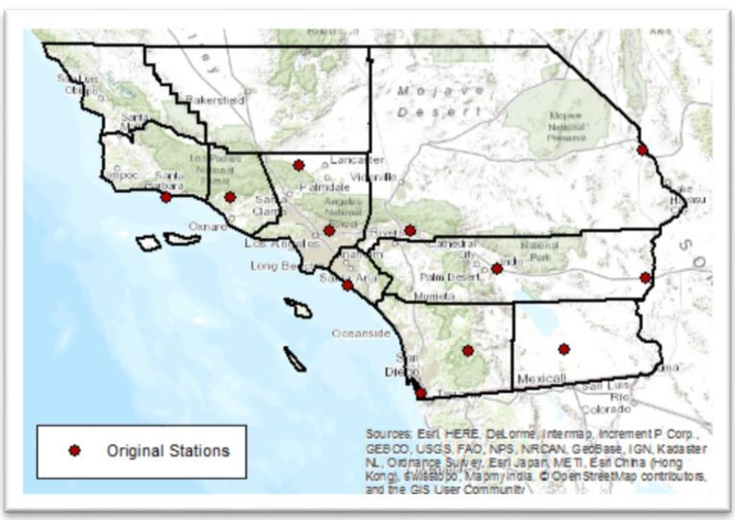


Figure 4: The Original 13 Homogenized Stations

Given that homogenized data for a larger set of stations was not immediately available, all of the stations in Southern California were evaluated for longevity and completeness of the time series. A map of all the stations evaluated is shown in **Error! Reference source not found.**This included 70 stations including the original 13 with available data dating from at least

1950 to the end of 2014 and with at least 70 percent complete data completeness. It was from these stations that the homogenized station data would be created.

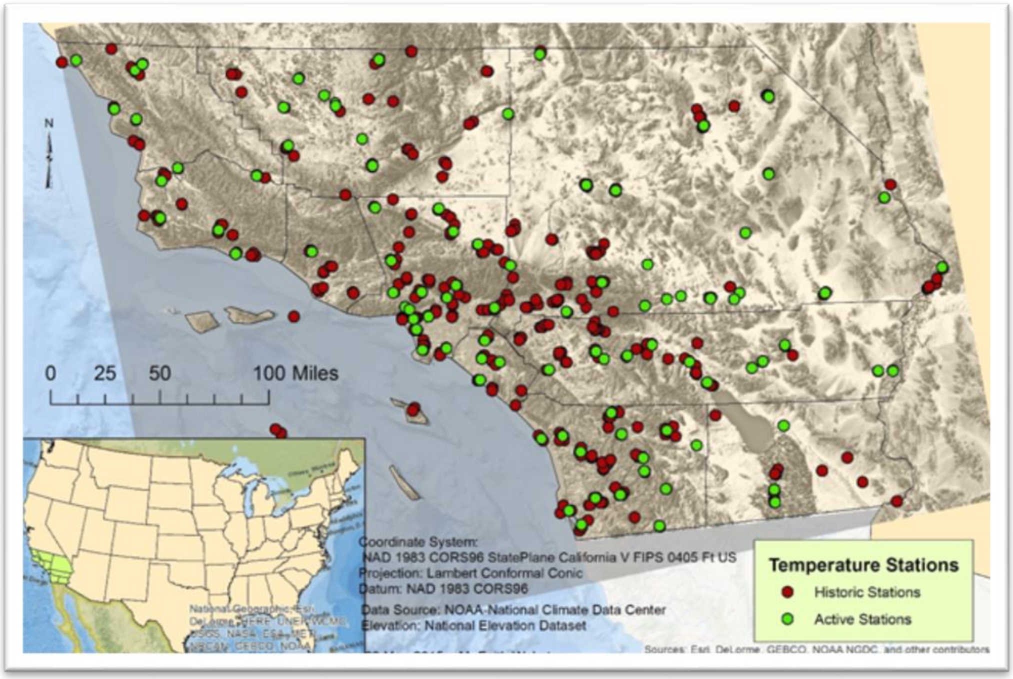


Figure 5: Active and Historic Temperature stations

Mene and Williams' homogenization methodology is provided in their 2007 report. This project attempted to obtain the program used to homogenize data. When Mathew Mene was contacted, he observed that it would be difficult to obtain the appropriate amount of data to homogenize stations out of context, and added that he was in the process of homogenizing many more stations nationwide. He offered to homogenize the Southern California stations that were already under consideration for homogenization. This meant that the stations would be homogenized using the same rigorous methodology employed by NOAA for all stations, ensuring the highest quality of authoritative data possible.

Within a couple of weeks, 66 stations were returned with 100 percent completeness from at least 1934 to 2014; a full list of station names and associated station number is shown in Table

1. A few stations of the 70 originally requested still had missing data and were eliminated from the analysis. The final station selection is shown in Figure 6. The final selection represents all counties more evenly. The only major area not well represented is the high desert of San Bernardino County. Unfortunately, the region did not have a complete enough data set meet the required completeness criteria.

Table 1: Homogenized station list with associated coop number

Station_ID	Station_Name	Station_ID	Station_Name	Station_ID	Station_Name
COOP:040439	BAKERSFIELD	COOP:044297	IRON MOUNTAIN	COOP:046730	PASO ROBLES
COOP:040442	BKFLD MEADOWS FIELD AP	COOP:044412	JULIAN CDF	COOP:047253	RANDSBURG
COOP:040519	BARSTOW	COOP:044647	LAGUNA BEACH	COOP:047306	REDLANDS
COOP:040521	BARSTOW	COOP:044735	LA MESA	COOP:047740	SAN DIEGO WSO
COOP:040609	BEAUMONT NUMBER 2	COOP:044747	LANCASTER	COOP:047785	SAN GABRIEL FIRE DPT
COOP:040741	BIG BEAR LAKE	COOP:044749	LANCASTER ATC	COOP:047810	SAN JACINTO
COOP:040742	BIG BEAR LAKE DAM	COOP:045064	LOMPOC	COOP:047888	SAN ANA FIRE STN
COOP:040924	BLYTHE	COOP:045107	LOS ALAMOS	COOP:047902	SANTA BARBARA
COOP:041048	BRAWLEY	COOP:045115	LOS ANGELES DWTN USC	COOP:047940	SANTA MARIA
COOP:041194	BURBANK VALLEY PUMP	COOP:045502	MECCA FIRE STN	COOP:047953	SANTA MONICA
COOP:041244	BUTTONWILLOW	COOP:045756	MOJAVE	COOP:047957	SANTA PAULA
COOP:041758	CHULA VISTA	COOP:046118	NEEDLES	COOP:048014	SAAUGUS PWR PLT
COOP:042214	CULVER CITY	COOP:046154	NEW CUYAMA	COOP:048826	TEHACHAPI
COOP:042239	CUYAMACA	COOP:046175	NEWPORT HARBOR BEACH	COOP:048829	TEHACHAPI 4 SE
COOP:042598	EAGLE MOUNTAIN	COOP:046377	OCEANSIDE MARINA	COOP:048839	TEJON RANCHO
COOP:042713	EL CENTRO 2 SSW	COOP:046399	OJAI	COOP:048973	TORRANCE AP
COOP:042805	ELSINORE	COOP:046569	OXNARD	COOP:049035	TRONA
COOP:042941	FAIRMONT	COOP:046624	PALMDALE	COOP:049099	TENTYNINE PALMS
COOP:043463	GLENNVILLE	COOP:046635	PALM SPRINGS	COOP:049152	UCLA
COOP:043468	GLENNVILLE MORROW RA	COOP:046657	PALOMAR MT OBSTRY	COOP:049325	VICTORVILLE PUMT PT
COOP:043855	HAYFIELD PUMP PLANT	COOP:046699	PARKER RESRV	COOP:049452	WASCO
COOP:044223	IMPERIAL	COOP:046719	PASADENA	COOP:049847	YORBA LINA

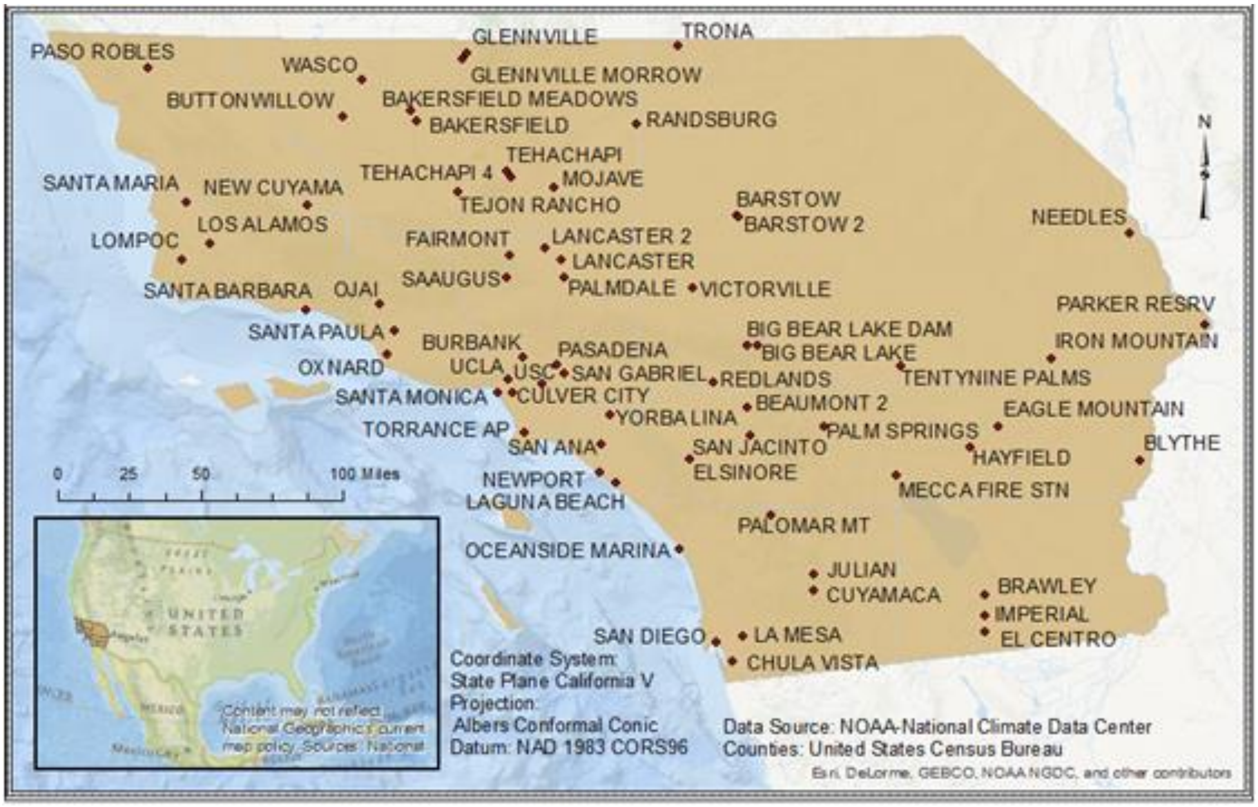


Figure 6: Homogenized stations by location

3.1.1. Station Elevation

The elevation for each station was provided by NCDC with the station data. Elevation is reported in meters to the nearest tenth. Figure 7 displays a histogram of the distributions of stations at given elevations. Ideally, a study of this kind would have an even distribution of stations across elevations. Reality very rarely meets the ideal, and this is no exception. There are a lot of stations at lower elevations and very few stations at the highest elevations. This uneven distribution of data may make it harder to show a dependency of persistence at higher elevations.

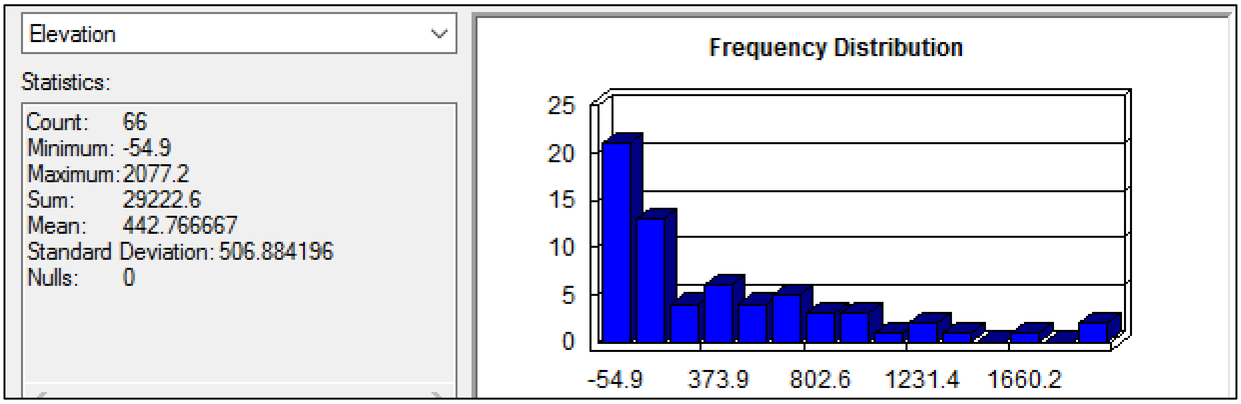


Figure 7: Histogram of Distribution of stations at elevation in meters.

3.1.2. Station Aspect

The digital elevation model (DEM) obtained from the National Elevation Dataset (NED) had 1 arc-second spacing, or 25.29 m at 35° latitude, and can be seen in Figure 8. The DEM shows all of the ranges of elevations seen in Southern California, where the station elevation data only addresses the elevations of climate stations. The most extreme elevations are not represented by stations. The aspect surface that was created from that 1 arc-second DEM can be seen in Figure 9.

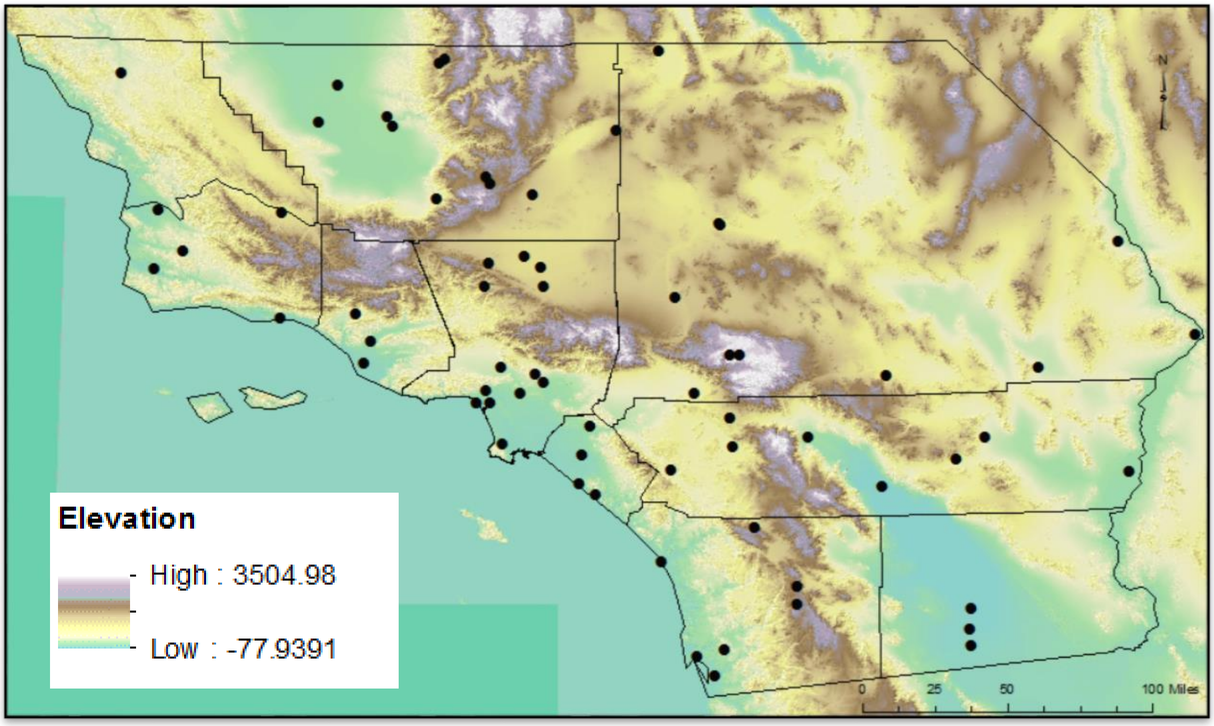


Figure 8: 1 arc-second DEM for Southern California

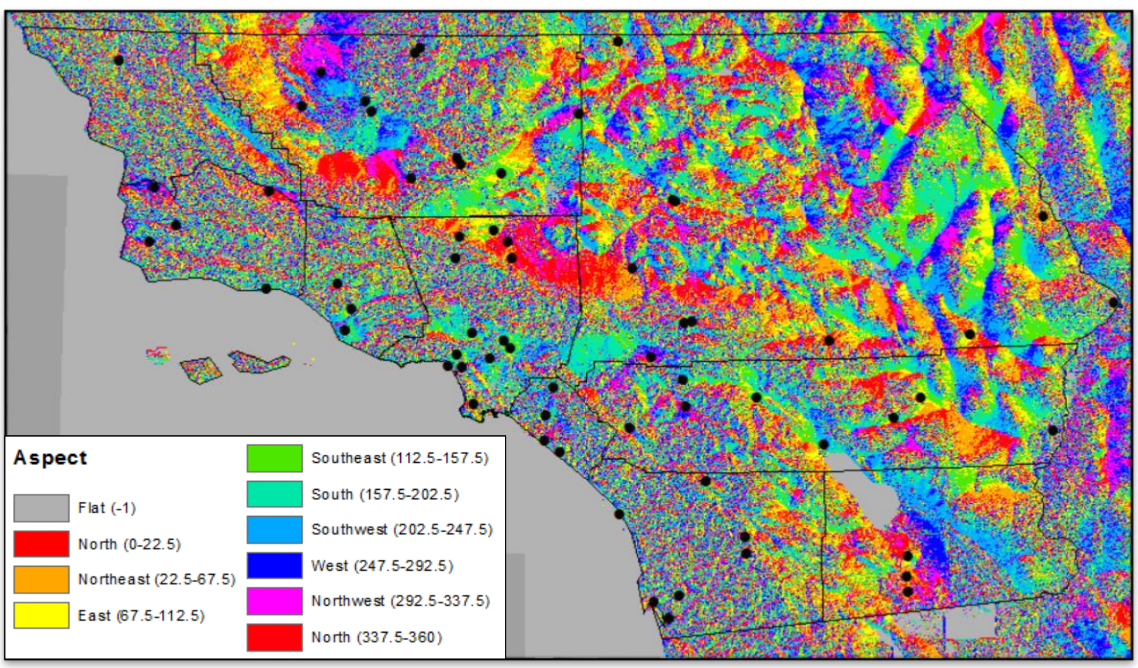


Figure 9: Aspect derived from the DEM for Southern California

Because of the well-known problems with error in DEM data (Fisher and Tate 2014), the aspect was smoothed by 3x3 pixel window. That smoothing created an overrepresentation of southern facing planes. This is because if a pixel with the value of 12 (N) is averaged with a pixel that has a value of 340 (also N), the new value will be 276 (S). If any interpolation or further surface analysis were being performed this would have been a much more difficult issue to tackle. However, because stations are points, it was possible to manually examine the smoothed aspect values for all stations that returned a value of Southwest, South or Southeast (112.5 to 247.5) in order to ensure that the station was truly in a predominately south-facing area.

Only about half of the stations needed to be manually evaluated. In this case the smoothed aspect values at station locations were compared to the unsmoothed aspect values. Stations that had a northern value (292.5 to 359.9 and 0 to 67.5) returned from the original unsmoothed aspect surface required further evaluation. This was the case for 15 stations. For those few stations, a new value was calculated manually. The values of the 9 pixels with the station at the center were averaged by adding 360 to values below 67.5. This way if a cell with the value of 12 is averaged with a cell of 340 ((12+360) +340)/2 is 356 which is a north-facing aspect.

3.1.3. Land Cover Data

Land use/land cover data at 100 m resolution was downloaded from The National Land Cover Database (NLCD). The 100 m dataset is a smoothed version of the original 30 m dataset, developed to aid in the visualization of regional land use/land cover conditions. The 100 m dataset was chosen for use in this project because it was determined that the 30 m resolution data would have been too detailed to appropriately estimate urbanization levels of the area surrounding the stations. This smoothed dataset was created in 2010 although it is based on 2001 Landsat satellite data. It is shown in Figure 10.

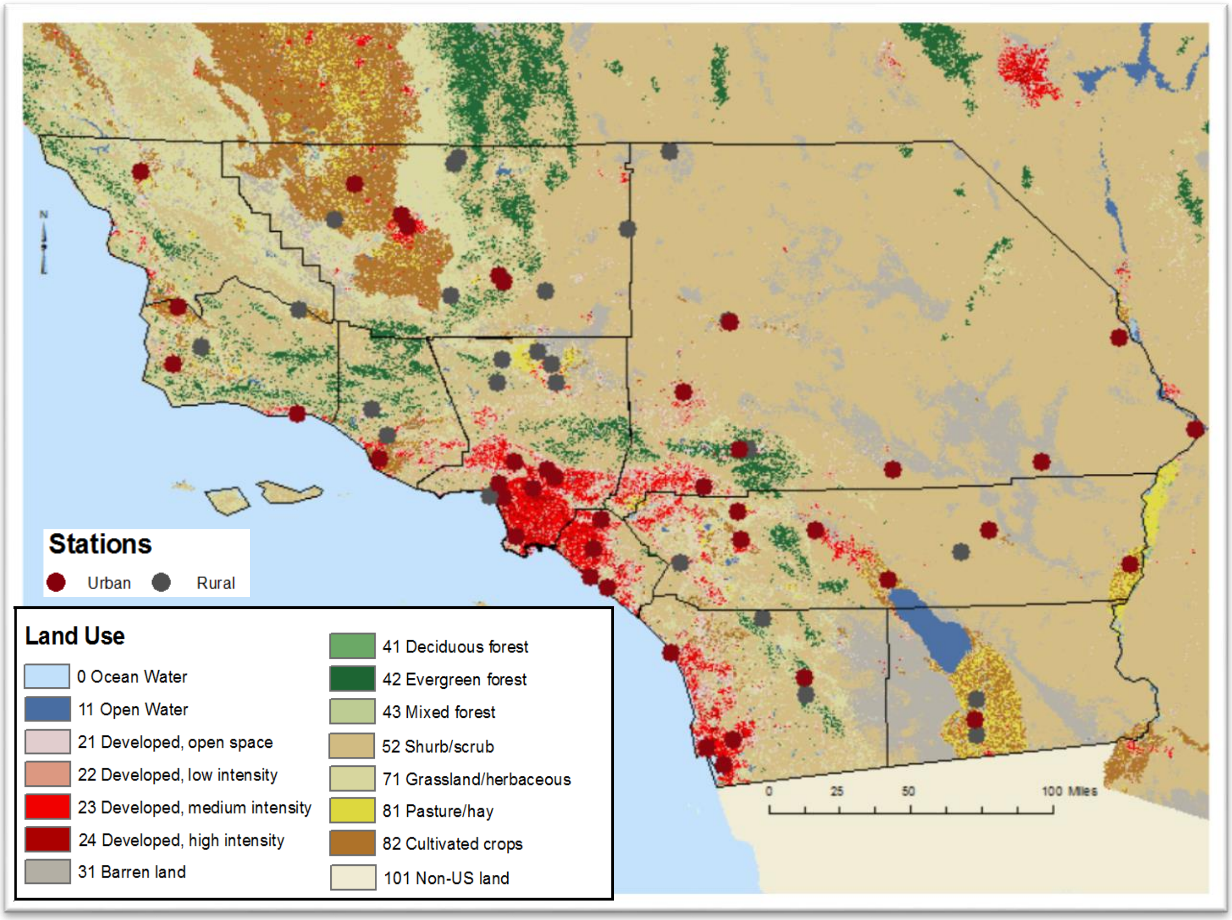


Figure 10: Land cover data with station urbanization

In order to extract land cover values for this analysis, the numeric class value was pulled for each station. Then the classes were divided into "urban" and "rural" values to facilitate comparison. "Urban" stations had a value of 22, 23 or 24. The value 21 (Developed open space) was not included in the "Urban" classification because it was decided that even though there is some development nearby, since weather stations should be at least 30 m from any large paved area (Campbell Scientific 2015), it is likely that the area around the station was still open, thus minimizing the impact from any Urban Heat Island effects. All other values were classed as

"Rural." There were 25 stations located in rural classifications, and 41 stations located in urban classifications.

3.1.4. Population Density

The extent of urbanization changes over time. The places that were urbanized in 2001 were likely either less urbanized or still rural in 1950. More often than not, high levels of urbanization are associated with higher population densities. Since historic land use data could not be obtained, population density was used as a proxy for urbanization because of the relationship between density and urbanization levels.

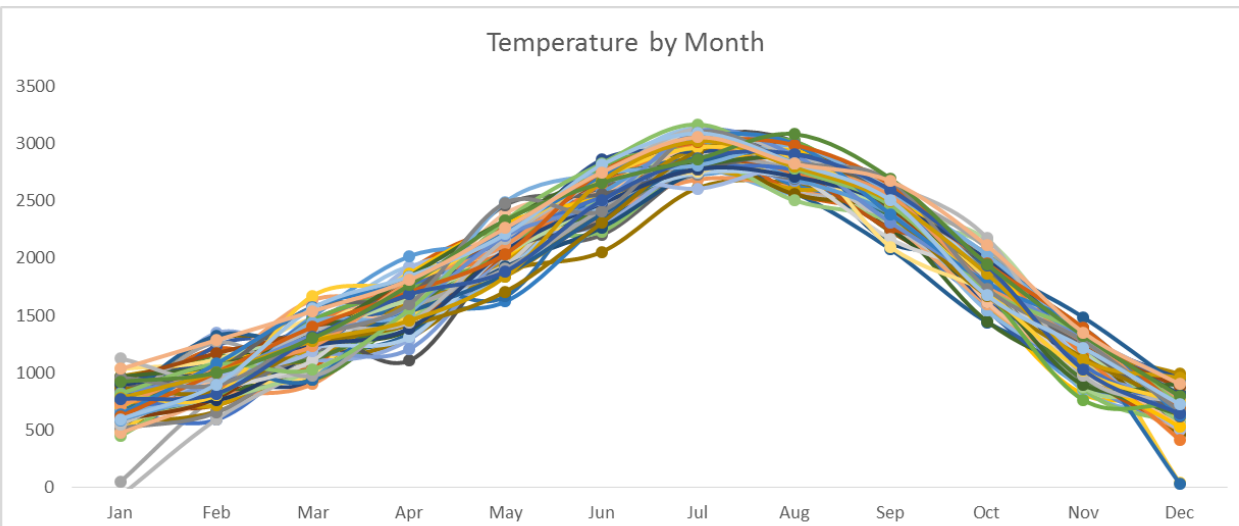
Decadal population data from 1940 to 2010 were obtained from the National Historic Geographic Information System (NHGIS). However this data contained population totals, not densities directly, and until 1970 most population was reported at the county level only. As of 1980, all counties had been divided into smaller tracts. For each decade, the population and the area of the coincident census zone were extracted for the location of each station using ArcGIS. The density values were calculated by dividing population by the area of the census zone. Densities for all decades were compiled into a single table, shown in Appendix A.

3.2 Calculation of the Hurst Exponent

The Hurst Exponent is a means to analyze a time series. A value of .01 to .049 indicates that the series is cyclical; the closer to zero the more consistent the cycle. A value of 0.5 indicates a random series. The closer the H-value is to .5 the more random the series is. A value greater than .5 and less than 1 indicates the persistence, or positive autocorrelation of the series (Outcalt 1997). The Hurst Exponent is the crux of this research project.

Calculation of H is approached by first calculating the mean of the series, then creating a mean-adjusted series, and then calculating the cumulative deviate (QD) series. Using the minimum value and the maximum value of the QD, the range is calculated. The standard deviation of the original series is then calculated. H is estimated by dividing the log of the range over the standard deviation by the log of the number of values in series.

Because seasons are inherently cyclical, only the hottest and coldest months were analyzed. The first step was to determine the pattern of temperatures for Southern California. Temperature data for several stations was graphed so that the hottest and coldest months could be determined. Figure 11 is one such graph. This is all 80 years of monthly data (x-axis) in degrees Celsius times 100 (y-axis). June, July and August form the peak, and are the hottest months; the coldest months were December, January and February.



MEAN	718	958	1252	1620	2082	2547	2895	2804	2431	1803	1132	694

Figure 11: 80 years of temperature data by month shown in *C x100

The mean for June, July, and August was calculated for each of the 80 years in the series to get Summer Means. December from the previous year was averaged with January and February to get the Winter Means. The analysis starts with December 1934, thus December 1934, January 1935, and February 1935 compose the 1935 winter season. Where this is more complicated than using the last month from the same year, it makes more logical sense in terms of seasons.

For each station's three temperature measures (high, mean and low), an H-value was calculated for each season (winter and summer). Each station had 6 H-values. To calculate the H-values, Outcalt's 1997 estimation of the Hurst Exponent was used (**Error! Reference source not found.**):

$$H = Log\ (Range/\ SD)/\ Log\ (n) \quad (2)$$

Thus, for each station, first the mean of each seasonal series was found. Then, for each year the distance from the mean of the series was determined. From that yearly difference, a running total of distance from the mean, or Cumulate Deviation (QD) was calculated. The QD shows the trend of the temperature change, and the winter and Summer High and Low QD graphed against the decadal temperature averages for all stations can be seen in Appendix B.

To actually calculate the Hurst exponent, the max and the min of the QD was found, and the *Range* (max- min) was established. The next step was to calculate the standard deviation (SD) of the seasonal series. H is calculated by using **Error! Reference source not found.** where n is the number of entries in the series. In the case n=80. All of the H-values for each station are shown in Appendix C calculated to the nearest ten-thousandths.

3.3 Hot Spot Analysis

As explained in Chapter 2, once the H-values were calculated, an optimized hot spot analysis was run using ArcGIS in place the Ward cluster analysis that Rebetez and Reinhard (2007) employed. This method was selected because it allowed analysis of not only the location of the stations, but also included the analysis of a single variable. In this instance, each H-series was selected. This would serve to identify spatial patterns of each of the 6 series of data.

3.4 Analysis of the Spatial Components

The primary means of evaluating the spatial components relied on correlation analysis. For the elevation analysis, each of the 6 H-value series were plotted against the elevation in a scatter plot as a correlation analysis with the trend line displayed. If the hypothesis is correct and there is more persistence in higher elevations, then the scatter plot would show an increasing slope along the H-values as the elevation increases. H-value is plotted on the Y axis, where the X axis is elevation in meters. R^2 shows how well the trend line fits the data, and was calculated automatically by Microsoft Excel. An R^2 value of 1 is a perfect match.

Aspect was analyzed using a scatter plot for correlation as well. Instead of a linear trend, a polynomial, or parabolic trend line was displayed. This is because both 0 and 360 represent a northern facing slope and 180 refers to a southern facing slope. If the hypothesis is correct, and there is a higher H value represented by southern facing stations, the trend line would be an inverted “U”. Also, an H-value was established for each station by averaging the 6 H-values from the indicators. Each station was assigned a cardinality based on the aspect value. A mean was created from H-values with the same cardinality to compare H-values by cardinality.

Urbanization was evaluated with comparison of Urban versus Rural H-values. For each indicator the mean rural value was compared to the mean urban value. The population density data was prepared to compare the QD data to the density data. If the hypothesis was correct, the QD would see an accent at significant rises in urbanization.

Chapter 4 Results

The following presents the results from the various analyses using the Hurst Exponent on historical homogenized monthly temperature station data from December 1934 to August 2014.

4.1 Southern California Temperature Trends

The QD trend lines for each station tell a unique story about the direction of temperature change. Recall that QD shows the cumulative deviation from the mean of the entire series. Each season, and each temperature measure has a unique pattern. Most lines have a decent, a plateau, and an incline, though not all do. Figure 12 shows an example of a graph of QD lines for the Summer and Winter High and Low temperatures at Bakersfield. A line showing the decadal average temperature is also included (grey line). The end of the decent is marked with red, and the start of the accent is marked in black. The individual stories for each station can be explored in Appendix B which contains the graphs for all stations.

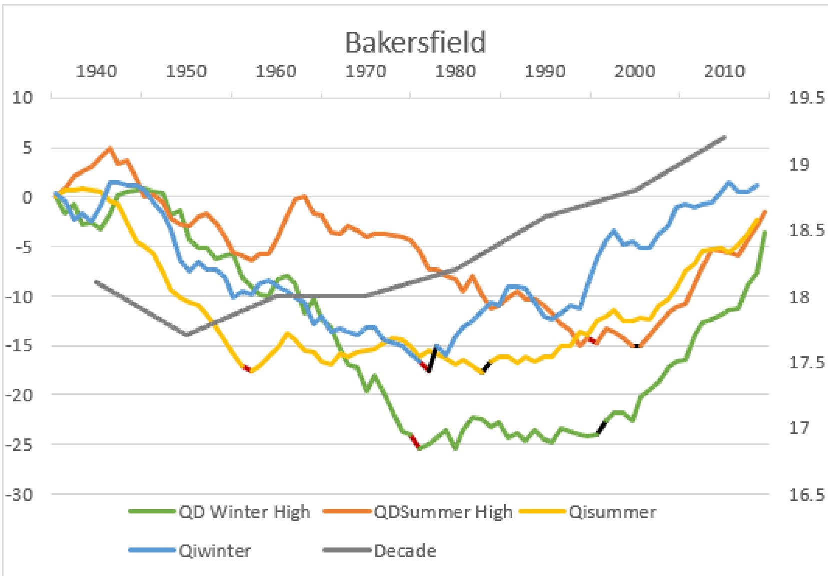


Figure 12: QD series graph for station 40439: Bakersfield

As Table 2 shows, the point of inflection upward, meaning the year at which the upward trend becomes strongly persistent, is generally between 1975 and 1995, tending around 1980, which is consistent with the global trend of temperature increases seen in **Error! Reference source not found.**. This table cannot be reliably expanded because of the difficulty measuring the inflection points precisely. The decadal temperature average lines plotted with the QD show that temperatures are increasing all along Southern California. The H-value and associated QD tell the story of the pattern of temperature changes, and the strength of the persistence of the seasonal trend.

Table 2: Approximate QD inflection points of representative stations

	WINTER HIGH		**SUMMER HIGH**		**SUMMER LOW**		**WINTER LOW**	
Station ID	Decent End	Accent Begins	Decent End	Accent Begins	Decent End	Accent Begins	Decent End	Accent Begins
COOP:040439	1976	1996	1996	2001	1957	1983	1977	1977
COOP:040519	1951	1980	1983	1993	1957	1966	1977	1977
COOP:040521	1949	1975	1993	1993	1960	1983	1976	1976
COOP:040741			1984	1993		1983		1979
COOP:040742	1952	1979	1966	1993	1956	1969		1979
COOP:040924		1977	1955	1985	1957	1984		
COOP:041048				2000			1976	1976
COOP:041194		1993				1976		1994
COOP:041244	1974	1990		2000		1980		1976
COOP:041758		1977		1980		1980		1976

4.2 Analysis of the Hurst Exponent Results

Each series of H-values has its own distribution patterns. Those patterns can be seen in the histograms in Figure 13. Only 2 H-values were less than 0.5 for any indicator: Palm Springs Summer High H= 0.47, and Big Bear Lake Winter High H=0.42. All other values are above .51 with the highest value being 0.795 at Newport for the Winter High. Summer Low H-values show the highest level of persistence, meaning that there is stronger upward trend in the low temperatures experienced during the summer months, while the Winter High H-values are on average lower as indicated in the mean value.

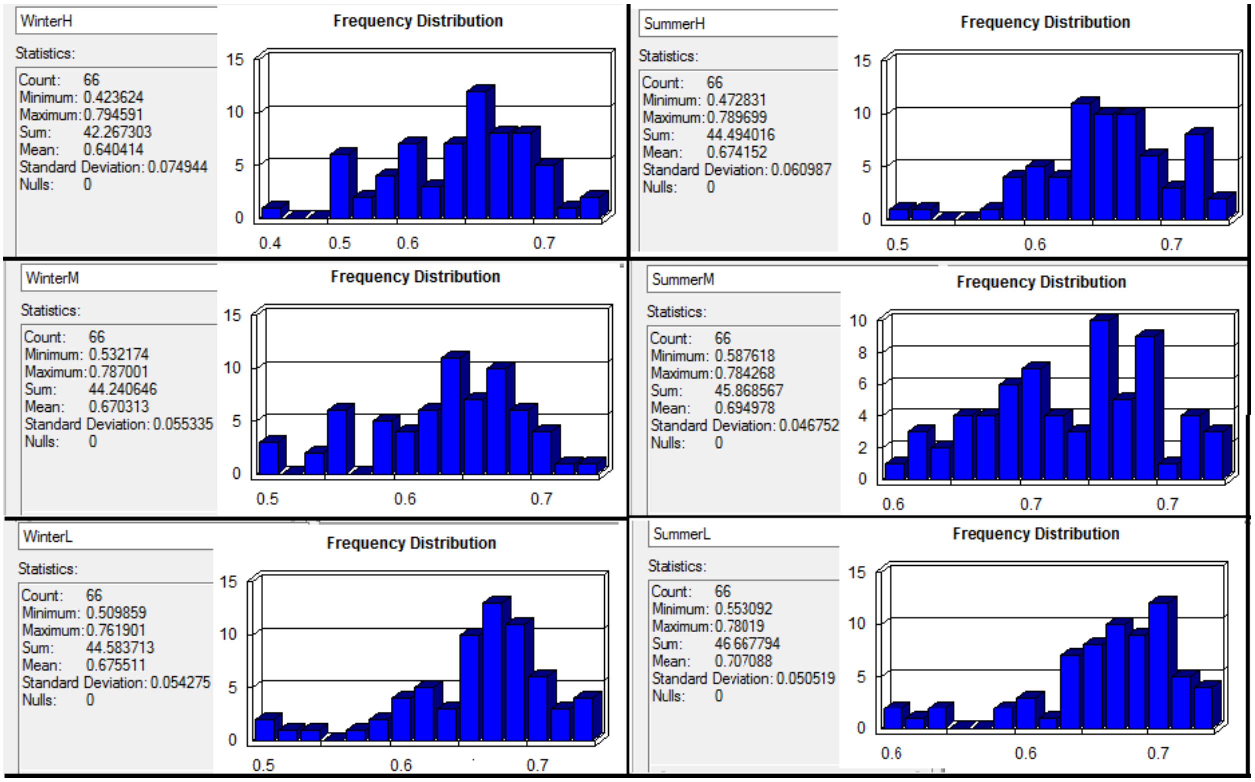


Figure 13: Distribution of H-value data as a histogram

In order to classify the stations, the mean and range of H-values was calculated for each station. The results of this are shown in Table 3 and the average H-value for stations ranged from 0.6 to 0.76, while the lowest value in the range was 0.60, and the highest range from 0.71 to 0.76. Given that 0.5 is random, and anything above that shows persistence. Therefore, the Hurst values were classified as 0.4 to 0.5 showing no persistence; 0.51 to 0.6 as showing weak persistence; 0.61 to 0.7 as persistence and 0.71 to 0.8 as strong persistence. This means in general terms that most stations are showing persistence, 16 stations are showing strong persistence and only 2 stations are showing weak persistence.

Table 3: Stations by mean H-value, highlighting the persistence categories

Station_Name	Range	Mean	Station_Name2	Range3	Mean4	Station_Name5	Range6	Mean7
TEHACHAPI 4 SE	0.144	0.6031	TRONA	0.073	0.6635	SAN JACINTO	0.111	0.6903
PALM SPRINGS	0.269	0.6051	OCEANSIDE MARINA	0.138	0.6644	SANTA BARBARA	0.103	0.6905
BEAUMONT NUMBER 2	0.144	0.6087	UCLA	0.052	0.6664	GLENNVILLE	0.144	0.6912
RANDSBURG	0.221	0.6093	LOS ANGELES DWTN USC	0.120	0.6676	SAN ANA FIRE STN	0.132	0.6942
FAIRMONT	0.115	0.6111	BAKERSFIELD	0.056	0.6688	LAGUNA BEACH	0.164	0.6962
TENTYNINE PALMS	0.208	0.6180	BARSTOW	0.204	0.6693	TEJON RANCHO	0.135	0.7001
PASO ROBLES	0.169	0.6220	PALOMAR MT OBSTRY	0.246	0.6703	LOS ALAMOS	0.069	0.7075
HAYFIELD PUMP PLANT	0.140	0.6234	BARSTOW	0.191	0.6711	YORBA LINA	0.045	0.7109
MOJAVE	0.182	0.6248	GLENNVILLE MORROW RA	0.055	0.6718	BAKERSFIELD MEADOWS	0.031	0.7110
PALMDALE	0.153	0.6321	TORRANCE AP	0.064	0.6736	SANTA MONICA	0.138	0.7118
VICTORVILLE PUMT PT	0.132	0.6430	PARKER RESRV	0.159	0.6779	SAN GABRIEL FIRE DPT	0.099	0.7144
NEW CUYAMA	0.141	0.6508	BUTTONWILLOW	0.114	0.6805	OJAI	0.063	0.7171
CUYAMACA	0.201	0.6514	WASCO	0.080	0.6807	SANTA MARIA	0.091	0.7183
JULIAN CDF	0.226	0.6514	BRAWLEY	0.142	0.6830	SANTA PAULA	0.130	0.7189
LANCASTER ATC	0.097	0.6520	IRON MOUNTAIN	0.137	0.6833	OXNARD	0.039	0.7192
BIG BEAR LAKE DAM	0.188	0.6561	TEHACHAPI	0.163	0.6841	ELSINORE	0.111	0.7193
EL CENTRO 2 SSW	0.209	0.6572	SAN DIEGO WSO	0.073	0.6856	MECCA FIRE STN	0.140	0.7241
EAGLE MOUNTAIN	0.118	0.6604	BURBANK VALLEY PUMP	0.143	0.6869	CULVER CITY	0.122	0.7313
LANCASTER	0.111	0.6618	IMPERIAL	0.049	0.6875	CHULA VISTA	0.058	0.7390
SAAUGUS PWR PLT	0.144	0.6622	LA MESA	0.123	0.6890	LOMPOC	0.112	0.7400
BIG BEAR LAKE	0.357	0.6627	BLYTHE	0.251	0.6891	PASADENA	0.093	0.7497
NEEDLES	0.096	0.6628	REDLANDS	0.059	0.6901	NEWPORT HARBOR BEACH	0.079	0.7579

A complete visual representation of all the H-values by station is shown in Figure 14. The H-values reflect degree of persistence quantified. Winter displays trends in the mean of observations for the period December-February, and Summer displays trends in observations for June-August. The H-values have also been qualified so there is a description of the strength of the persistence attached. Anything below 0.5 is random and shows no persistence. Those stations are represented in yellow, and there are very few stations in any season with that symbology. Most stations show between weak to strong persistence.

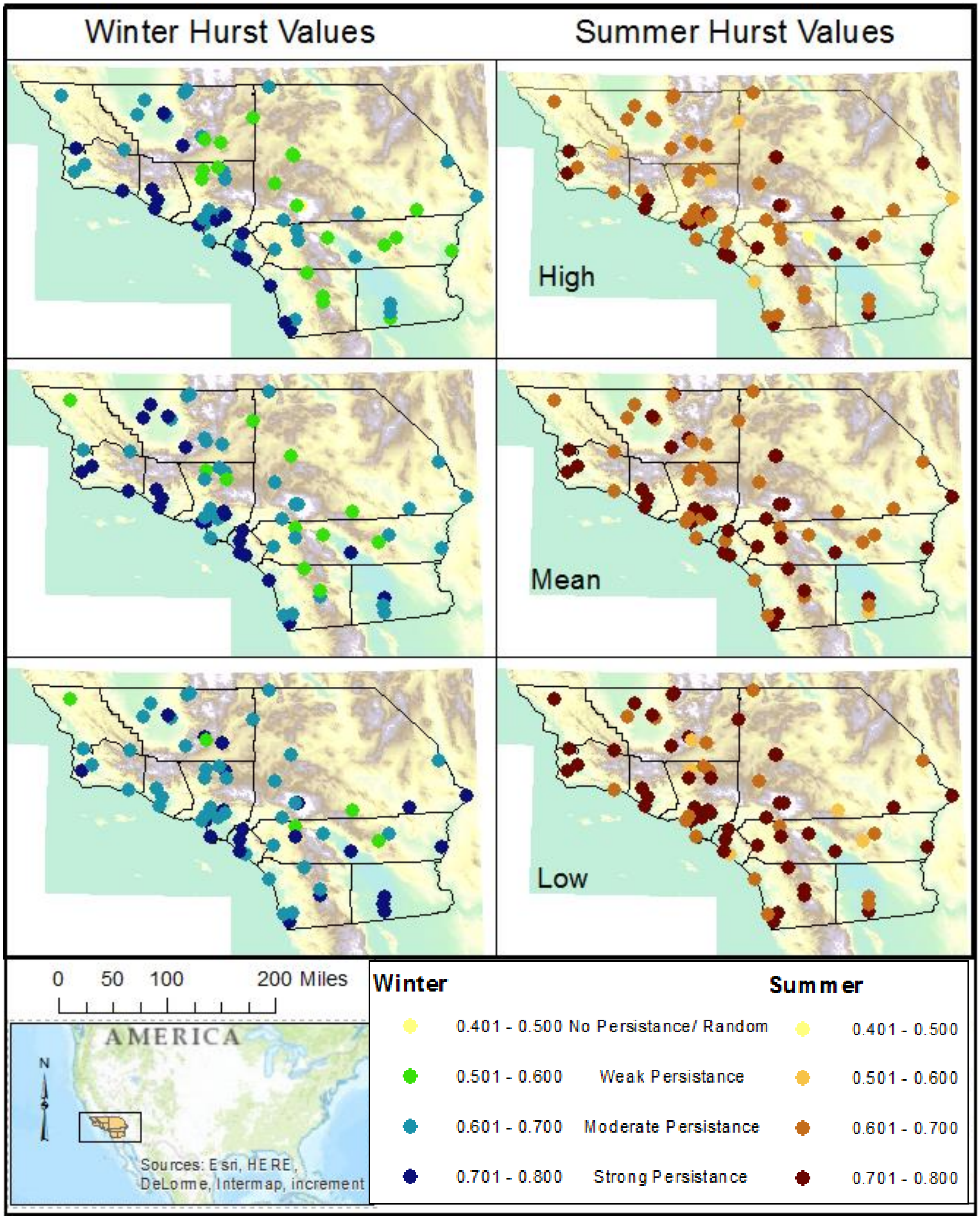


Figure 14: Persistence of Temperature change in H-values

4.3 Relationship between Elevation and Temperature Trends

Figure 15 shows the scatter plot and trend line for the H-values for each indicator measured against elevation. Winter High H-values offer a clear trend even if the R^2 of a fitted trend line isn't very strong. The slope is very small because the graph is in tenths. The most interesting aspect of Winter High trend is that it shows a negative correlation between elevation and the H-values. As the elevation increases, the H-values decrease. The expectation was to see the inverse. The hypothesis was that there would be more persistent temperature increases at higher elevations; that is not the pattern the data is demonstrating.

Summer High H-values show a very weak negative correlation. The slope is shallow, and the R^2 is close to zero. The trend is so weak, it makes more sense to say there is no correlation between persistence expressed as H-values and elevation. This supports the null hypothesis that there is no difference in persistence of temperature increases at different elevations. Winter Mean H-values also show a slight negative correlation. It is weak, with a low R^2 value, but is not so weak as to claim it is nonexistent. The negative correlation works against the hypothesis.

Summer Mean H-values have no correlation to elevation. This supports the null hypothesis. The Winter Low trend has a very weak R^2 combined with a very weak slope. This shows support for the null hypothesis that there is no correlation between higher H-values and higher elevations. Summer Low correlation also supports the null hypothesis that there is no relationship between H-values and elevation. There is no visible slope and the R^2 is very low. Both of those things suggest that the pattern of dispersion is random.

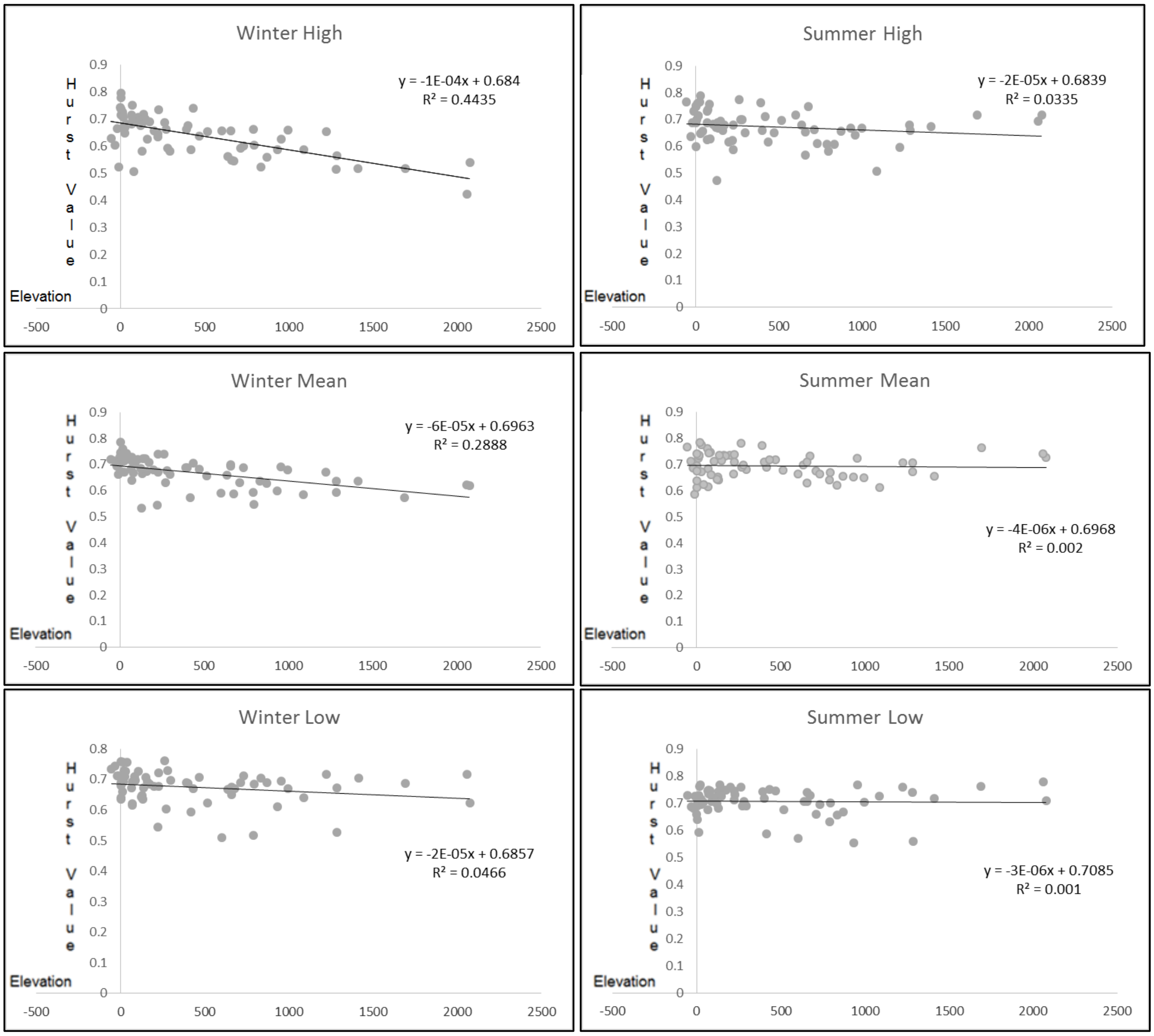


Figure 15 Hurst exponent values against the elevation of the station

4.4 Relationship between Aspect and Temperature Trends

Each of the 6 H-value series was plotted against the Aspect values using a scatter plot as correlation analysis. If the hypothesis is correct there would be an inverted U shape in the graph showing that as the H-values are increasing as to points approach a the southern values. In order to accomplish that, a polynomial (parabolic) trend line was used. Where some of the trend lines did display a weak arch, none of the R^2 values were high enough to really demonstrate any correlation between persistence, expressed via the H-value, and station aspect. Figure 16 shows the aspect correlation analysis charts by seasonal series. The highest R^2 value was for Winter Mean values at 0.14; all other R^2 values were less than 0.1. They all support the null hypothesis that there is no increase in persistence at temperature stations with a south-facing aspect.

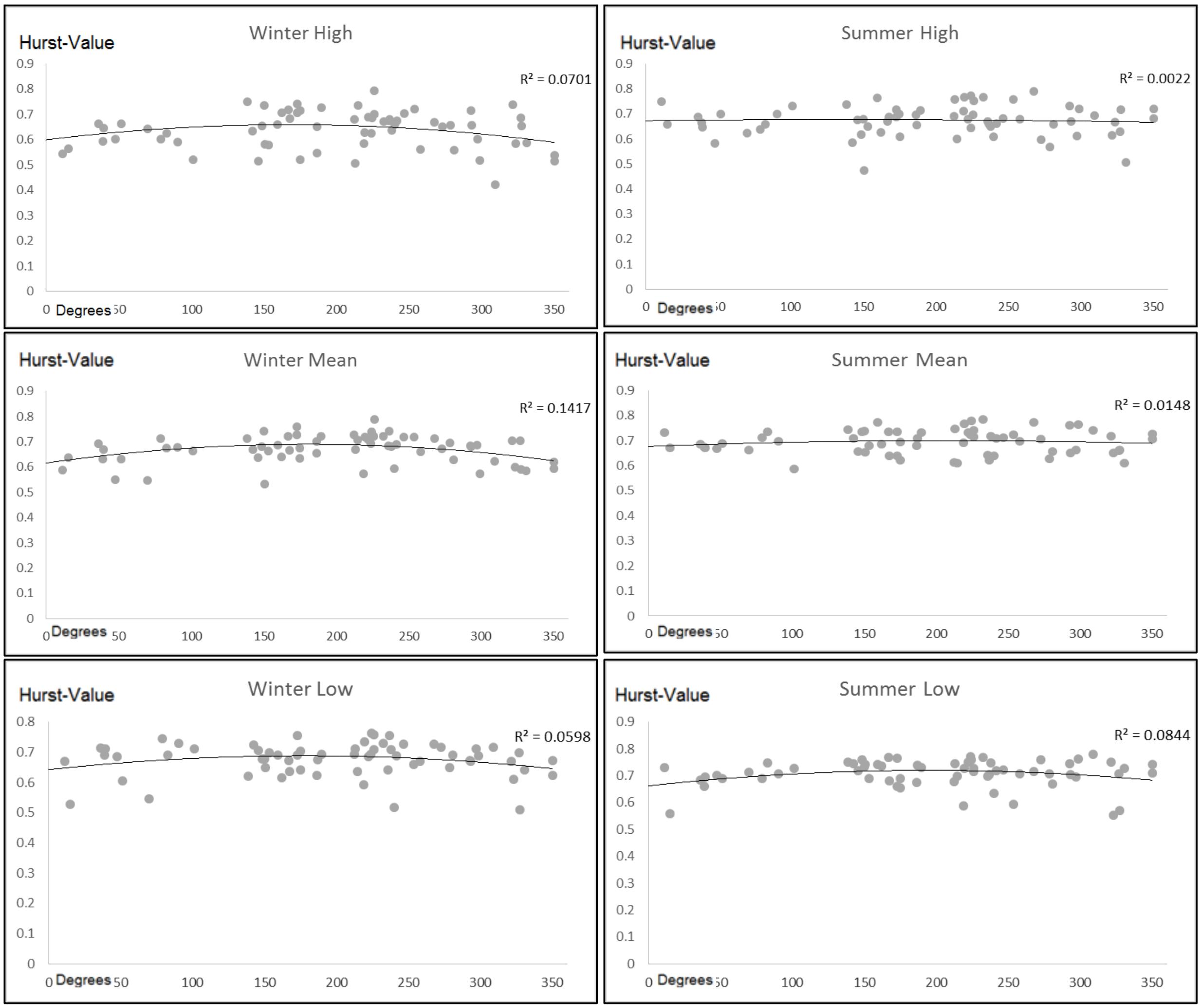


Figure 16: Seasonal H-values plotted against numerical aspect

Because a weak relationship seemed to be evident, the station mean of the H-values was used to average the H-values of stations with the same cardinality. A summary table, Table 4 shows the there is a slight difference in the mean H-values. The full data is included in Appendix C. Stations with a northern cardinality have a mean H-value of .645, where stations with a southern cardinality have a mean of .687. Where the difference is slight, it does show what the slight parabolic inflections were indicating.

Table 4: Mean H-value of stations based on cardinality

Cardinality	Mean H-value
North	0.6450
North East	0.6550
East	0.6849
South East	0.6642
South	0.6874
South West	0.6942
West	0.6837
North West	0.6540

4.5 Land Use, Population Density and Temperature Trends

Each of the 6 H-value series (winter and Summer High, mean and low) were averaged for each set of stations (Urban and Rural) producing 2 mean values for each H-value series. These are summarized in Table 5. The idea for this came from Rebetez and Reinhard. They averaged the mean temperatures for north side and south side stations to compare change on one side versus the other. Because the Urban and Rural classes provided a similar dichotomist classification, that approach was applied to examining the Urbanization factor's effect on temperatures.

Table 5: Mean H-values for urban and rural stations

	Winter High	**Summer High**	**Winter Mean**	**Summer Mean**	**Winter Low**	**Summer Low**	Land-Class Mean
Mean Rural:	0.5919	0.6467	0.6239	0.6628	0.6408	0.6796	0.6410
Mean Urban:	0.6700	0.6909	0.6986	0.7146	0.6967	0.7238	0.6991
Indicator Mean	0.6380	0.6730	0.6685	0.6943	0.6742	0.7070	

Consistently, the urban H-values are higher than the rural. Summer Mean and Summer Low mean urban H-values range in the strong persistence category. Only Winter High rural mean H-value is in the weak persistence range. The evidence fails to disprove that there is not stronger persistence shown at stations with an urban land cover over stations with a rural land cover; however, it also should be noted that the difference of 0.058 in the H-value puts both classification in the “persistent” category. Urban stations’ H-values are only marginally higher.

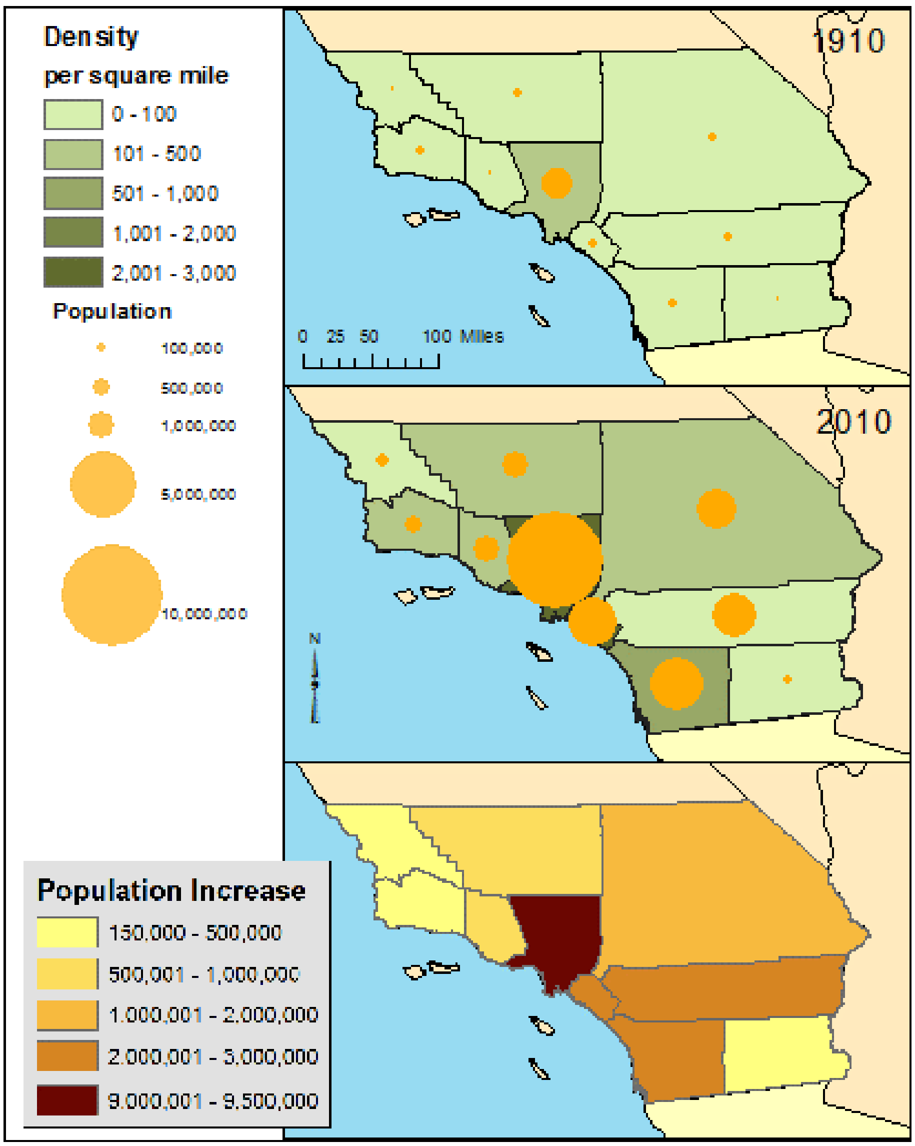


Figure 17: Proportional Symbol Population and Population Density change in Southern California from 1910 to 2010

The hope was that the census data would provide valuable information about the changing population density of Southern California. Since all Southern California county populations, and thus their densities, have increased significantly from 1910 to 2010, as shown in Figure 17, there was an expectation to see increasing population densities that could then be compared to the QD lines to determine if the inflection points coincided with significant increases in population density. This trend is simply not reflected in the census tract data by station location.

Unfortunately, since census tracts change each decade and in the early years population was reported only at the county level for most of this region, the modifiable area unit problem (MAUP) is exaggerated. As shown by the selection of data in Table 6, in the tracts that contain stations, the population density does not appear to increase over time. In most cases the population density remains fairly consistent, or fluctuates wildly. The density data is simply too variable to provide any consistent information about the urbanization levels of the area around each station. The full data set of population densities is shown in Appendix A. Maps of the population density by station, included in Appendix D, do little to add further insight.

Table 6: Selection of population density data

Station	1940	1950	1960	1970	1980	1990	2000	2010
Bakersfield	16.6	28.0	2,695.9	1,420.0	1,471.0	1,506.5	1,136.4	999.5
Beaumont 2	14.4	23.3	1,230.5	1,647.1	1,708.1	2,098.4	2,171.4	2,303.0
Burbank	1,705.6	7,264.5	8,494.8	7,165.7	7,163.7	7,085.2	7,265.8	7,354.2
Eagle Mountain	14.4	23.3	0.7	1.1	1.2	1.2	2.9	0.5
Redlands	8.0	14.0	4,906.7	5,560.5	5,103.3	5,451.9	5,418.3	5,642.1

4.6 Hot Spot Analysis

In place of the Ward cluster analysis performed by Rebetez and Reinhard, an optimized hot spot analysis was run to test the spatial relationship between the stations’ H-values to visualize any spatial patterns present. Figure 18 shows the results for the 6 analyses run, one for each H-series. The only series that has any real spatial pattern is the Winter High temperatures. The pattern of hot spots and cold spots do not correlate very well with any of the other variables explored. The hotspots seem to have a loose relationship with coastal regions which generally have a low elevation, and the cold spots are generally in a mountain region, not all the hotspots are coastal, and not all the cold spots are in higher elevations. This seems to be reflective of the weak negative correlation between elevation and H-value seen in Figure 15 of the elevation correlation results.

In the hotspot maps of H-values of monthly mean temperature, both summer and winter show weak cold spots in the northern part of Los Angeles County but it is difficult to suggest a cause for these within the context of this analysis. In summary, the hot spot analysis indicates that the distribution of H-values is mostly random across the landscape. This supports all of the null hypotheses that there are no increases in persistence corresponding to any spatially dependent attribute evaluated by this study.

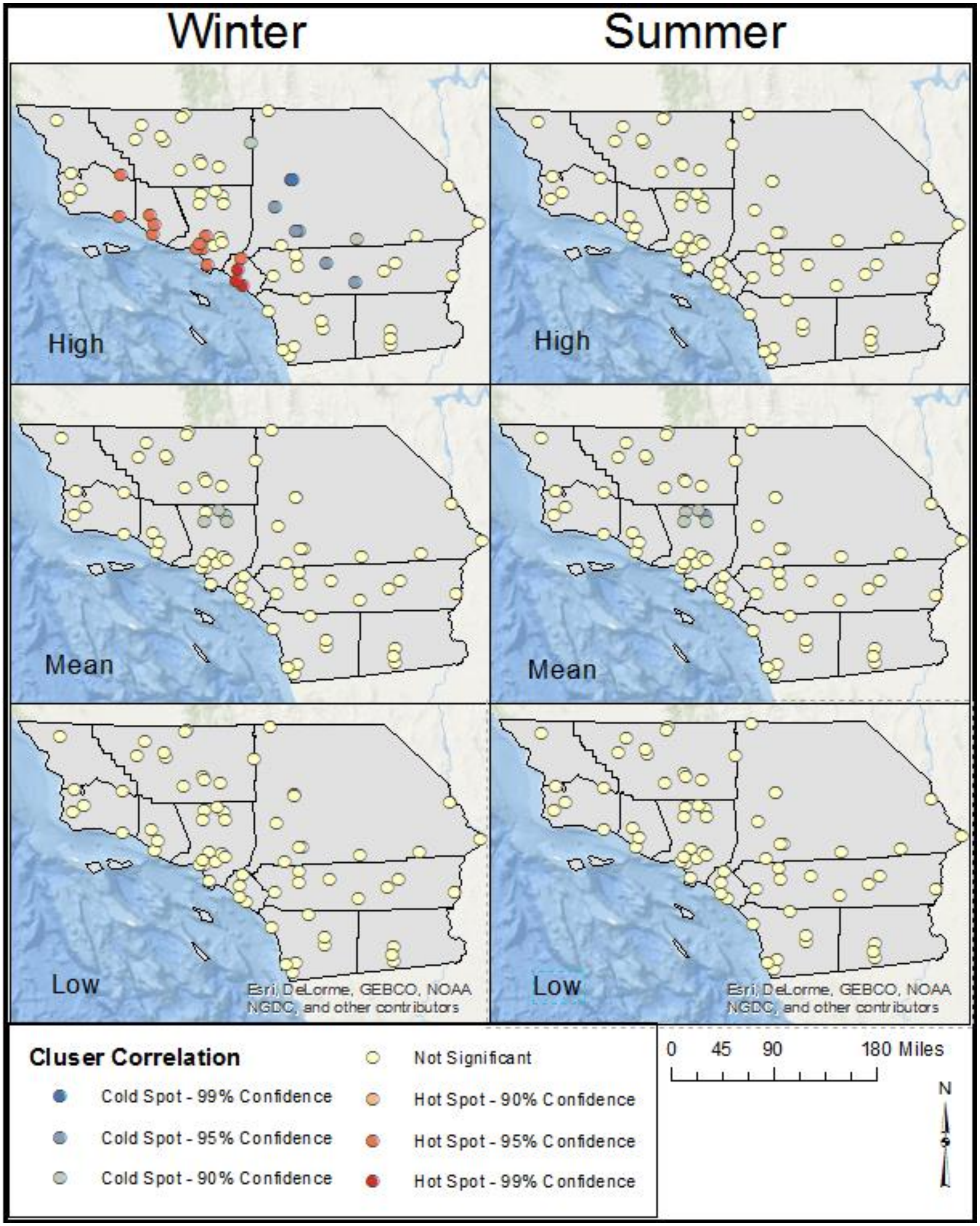


Figure 18: Optimized hot spot analysis of seasonal H-values by station.

4.7 Chapter 4 Summary

H-values of the summer and winter seasons were used to analyze spatial attributes of 66 temperature stations. H-value when analyzed against station elevation data displayed a negative correlation supporting the elevation null hypothesis. Mean H-values of stations with a southwest facing cardinality were the highest compared to all other cardinalities, though southern facing stations did mean a higher H-value than northern facing stations. This provides weak support for the aspect hypothesis. Urban stations have a mean H-value that is marginally higher than Rural stations. This provides weak support for the land cover hypothesis. The hypothesis for population density changes was not able to be tested.

Chapter 5 Discussion

This project sought to understand what trends in temperature change are evident based on homogenized monthly data in Southern California from approximately 1935 to 2014 using the Hurst Exponent evaluating seasonal data. The study examined elevation, aspect, and land cover for each station using the H-values and optimized hotspot analysis to evaluate trends. This final chapter reviews the results discussed in Chapter 4 and draws the final conclusions. The research questions are re-examined to determine if they were addressed, and what conclusions can be drawn. This chapter also discusses some areas of future research.

5.1 Evaluation of the Research Questions

The research questions are the backbone of a research project. This section looks at each research question and addresses how well it was answered and the implications.

5.1.1. What is the spatial pattern of H-values by season as determined by optimized hot spot analysis?

The only indicator that displayed a significant spatial trend was Winter High. All other indicators displayed no significant trend. The expectation was that the hot spot analysis would show trends that could be connected to the spatial variables. Without any trends, the analysis of the trends to determine the nature of the spatial relationships could not be done. This is one of the areas where much more is possible. There are a plethora of spatial analysis tools that could be employed to evaluate if there are any spatial trends in the distribution of the H-values. Just because the optimized hot spot analysis did not yield results does not necessitate that there is no spatial trend in the spatial distribution of the H-values. Good avenues to explore are the other hot spot analysis tools, as well as the regression analysis tools.

5.1.2. What is the correlation between H-values and elevation?

The null hypothesis was that there will be no persistence in temperature increases. The hypothesis for elevation was persistence would be more pronounced expressed by higher H-values as elevation increases. The results from the elevation analysis were surprising. The correlation analysis showed that there is a negative correlation between elevation and persistence, even though so many mountain ranges even those relatively local to Southern California showed that the mountains were more sensitive to temperature increase exact opposite. The hypothesis was rejected in favor of the null hypothesis.

5.1.3. What is the correlation between H-values and aspect?

The hypothesis for aspect was that stations on a southern face would have experienced higher more persistent temperature increases than northern facing stations indicated by higher H-values. Where the differences in H-values according to aspect were minor, they trends were there. The mean H-value for stations on a north facing plane were the lowest, and southern facing stations were markedly higher, with the highest being stations on a south-western face. Averaging data does marginalize the figures, but also allowed the trend to present itself. The correlation analysis alone yielded nothing but very weak results. The evidence marginally supports the hypothesis. The null hypothesis can be rejected. There are more pronounced increases in southern facing stations.

There is possibility for further study here also. One of the ways that aspect has been evaluated by other climate studies has been to not necessarily look at the orientation of the exact face that upon which that station rests, but rather to divide the mountain ranges into predominate faces. There are norther, southern, eastern and western faces of the ranges that could be evaluated for correlations in persistence. It could be that a stronger pattern would present itself if the side of the mountain were evaluated over the face of the slope.

5.1.4. What is the correlation between H-values and the land covers "Urban" and "Rural"?

The hypothesis for land cover is that station located in more urban areas will experience higher persistence expressed as higher H values than stations located in more rural areas. This was another area where there was little to no precedent set on how to approach analyzing H-values in correlation to urbanization levels. Because most comparisons were based on urban versus rural readings, again averaging the stations with urban versus rural land covers seemed to be the most quantifiable approach. The results were not as pronounced as expected. There is speculations that this is due to the normalizing of the temperature data during homogenization. One of the goals of homogenization is to mitigate the impact of urbanization on temperature readings. However even using homogenized data, a marginal difference was detected between persistence in urban stations versus rural stations supporting the hypothesis and rejecting the null hypothesis that there is no relationship.

5.1.5. Can census data be used to track changes in population density to evaluate changes in urbanization?

This area was an overall loss for the project. No analysis was possible because of the inconsistency within census tracts. Where generally, urbanized areas are more densely populated, census data is too malleable between census years to be able to provide viable comparisons. It would have been exciting to evaluate the QD trends in association with periods of pounced increases in population density. This is one area where future research is possible. The relationship between urbanization and temperature increases are well documented. The issue here is simply in the availability of the data. Perhaps individual counties have the data necessary to perform this type of analysis. If viable data could be obtained, it would be interesting to see if the QD lines reflected increases in population density.

5.2 Issues Addressed in the Study

Every project faces challenges. This section reviews the significant hiccups, how they were addressed, and if there were any consequences upon the research.

5.2.1. Issues from Data Quantity and Quality

The final data set used for the analysis was both extensive and multi-dimensional. Three temperature measurements for each of the 66 stations for 80 years created a large, bulky dataset to manipulate in Excel. After analysis, the master table had station attribute data, H-values, decadal temperature means, and decadal census tract densities. The master table was then divided into more manageable tables for each of the station attributes evaluated. Database management was essential to maintaining data integrity. The advantage of creating and managing such a dataset in Excel, however, is the multiple ways the set can be manipulated and analyzed using the available tools. Given the richness of the final data collection, many additional questions arouse that remain to be addressed in future projects. Many of those opportunities for further analysis are discussed below.

5.2.2. Using H-values in spatial analysis

Since there has been little previous research using H-values in spatial analysis, it was difficult to determine the best means of employing the H-values to evaluate the persistence in relation to the various spatial attributes of stations. Much additional research to mine the data developed in this research remains to be done.

5.2.3. Exploration of the QD series

A lot of the research done with the Hurst Equation focuses on the trend of the series viewed through the QD series (Oatcalt 1997, Ruddell 2013). That is not the direction this project took. Where the QD is a significant part of the story that each station has to tell, it did not become a major focus of this project. Evaluation of the spatial patterns was better served by the Hurst Exponent. Also, when analyzing the trends in the QD series there was a degree of subjectivity that made the researcher uncomfortable. The lowest point in the series was often after a brief incline. It seemed arbitrary to place the end of decline inflection point at one place versus the other. The graphs themselves are too individually unique to facilitate generalized conclusions. Quantification of the data presented in the QD series is certainly one avenue for future work on this data set.

5.3 Conclusion

The Hurst exponent is a powerful analysis tool. The persistence found in temperature increases at Southern California stations were not surprising. Temperatures are increasing worldwide, and regional studies show that temperatures are increasing in Southern California as well. The interesting aspect of the work done lies in the ability to quantify the strength of the trend using a different analysis than the Fisher test with p-value. While p-value is a useful statistical tool, it overlooks the fractal nature of climatological processes. The H-value recognizes that temporal patterns are assessed not only by the strength of their randomness, but also their persistence or cyclical nature. This study makes a small step forward in showing how the Hurst Exponent can be used to examine spatial attributes.

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Appendix A: Population Density

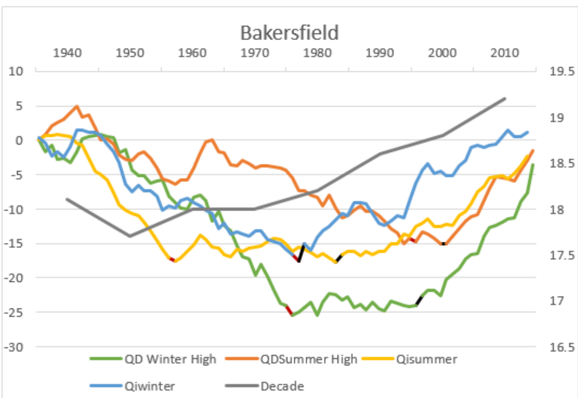
Population Density for stations by station and decade

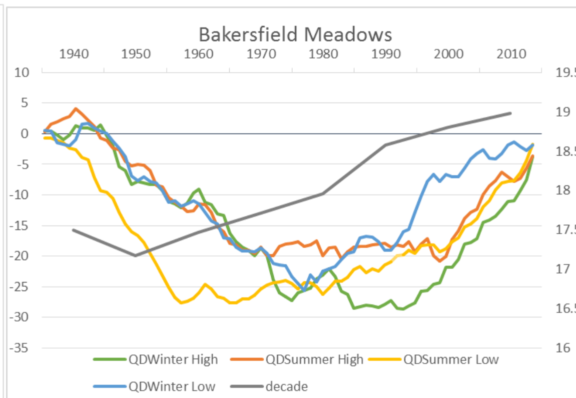
Station ID	1940	1950	1960	1970	1980	1990	2000	2010
40439	16.6	28.0	2,695.9	1,420.0	1,471.0	1,506.5	1,136.4	999.5
40442	16.6	28.0	734.0	511.3	604.1	795.4	986.2	1,547.4
40519	8.0	14.0	1,988.6	1,547.5	1,213.8	908.2	698.4	813.8
40521	8.0	14.0	3,506.2	3,485.1	3,049.5	3,430.1	3,333.3	3,440.9
40609	14.4	23.3	1,230.5	1,647.1	1,708.1	2,098.4	2,171.4	2,303.0
40741	8.0	14.0	7.6	23.3	41.4	823.8	1,034.6	1,111.7
40742	8.0	14.0	7.6	23.3	41.4	5.2	6.4	7.3
40924	14.4	23.3	2,156.1	1,078.2	1,365.2	1,804.0	2,925.0	2,680.1
41048	13.3	14.0	16.1	16.1	1,263.8	1,286.1	1,840.5	2,093.5
41194	1,705.6	7,264.5	8,494.8	7,165.7	7,163.7	7,085.2	7,265.8	7,354.2
41244	16.6	28.0	17.2	12.5	13.3	15.1	16.3	21.2
41758	68.2	4,734.2	4,576.9	10,422.4	11,267.8	14,056.0	15,636.3	15,705.4
42214	2,611.3	7,072.3	9,995.4	14,821.0	9,264.6	10,350.3	10,214.6	9,779.5
42239	68.2	131.3	4.0	6.8	12.1	12.6	14.1	12.8
42598	14.4	23.3	0.7	1.1	1.2	1.2	2.9	0.5
42713	13.3	14.0	16.1	16.1	1,001.8	123.2	257.9	1,230.2
42805	14.4	23.3	516.0	98.9	182.9	507.8	1,431.3	1,665.9
42941	4.4	7.0	7.6	6.3	5.4	10.1	5.6	7.1
43463	16.6	28.0	1.2	0.7	1.3	5.9	5.9	5.6
43468	16.6	28.0	1.2	0.7	1.3	5.9	5.9	5.6
43855	14.4	23.3	0.7	1.1	1.2	1.2	2.9	0.5
44223	13.3	14.0	16.1	16.1	71.6	79.9	112.3	173.1
44297	8.0	14.0	4.6	5.7	7.1	2.0	2.1	2.2
44412	68.2	131.3	4.0	4.7	7.6	9.4	54.8	53.2
44647	163.8	270.8	152.1	265.0	439.3	686.0	720.0	721.4
44735	68.2	2,279.7	3,304.7	4,070.9	4,308.1	4,611.3	7,669.7	8,529.4
44747	23.7	56.6	323.2	351.1	578.9	1,591.3	5,169.8	5,620.2
44749	23.7	56.6	8.5	7.3	15.8	31.4	28.5	46.3
45064	25.7	35.7	8.7	992.0	1,113.0	2,870.6	3,349.1	3,203.1
45107	25.7	35.7	16.0	27.6	23.3	32.1	38.4	48.0
45115	4,561.1	5,078.8	2,194.1	5,448.5	9,038.0	3,659.8	2,771.0	1,618.3
45502	14.4	23.3	23.5	26.2	20.6	35.9	61.4	83.8
45756	16.6	28.0	190.8	201.1	212.9	204.0	171.9	189.2
46118	8.0	14.0	0.5	0.6	0.7	0.8	0.3	0.6
46154	37.5	61.7	1.2	1.0	1.0	1.0	1.2	1.1
46175	163.8	270.8	6,266.1	6,531.5	6,489.3	6,195.6	6,028.7	6,046.6
46377	68.2	131.3	123.6	5,127.1	6,721.5	6,942.6	6,362.7	4,579.1
46399	37.5	61.7	107.2	104.2	137.8	142.9	106.4	101.0
46569	37.5	61.7	107.2	333.9	766.1	12,621.2	8,248.1	3,656.2
46624	11.2	20.7	25.6	39.2	23.6	36.8	32.7	71.1
46635	14.4	23.3	817.8	852.2	1,535.7	1,896.5	144.4	438.7
46657	68.2	131.3	4.0	4.7	7.6	9.4	5.9	6.4
46699	8.0	14.0	0.5	0.6	0.7	0.8	0.3	0.6

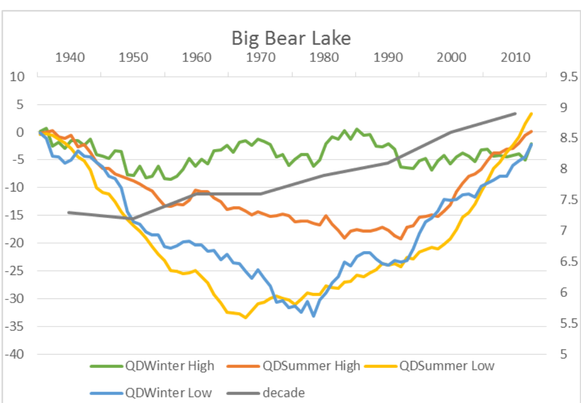
Station ID	1940	1950	1960	1970	1980	1990	2000	2010
46719	8,780.4	10,641.3	10,390.7	8,937.5	7,939.3	9,045.4	9,981.3	5,130.3
46730	10.0	15.5	24.4	31.8	491.9	675.9	751.1	2,886.1
47253	16.6	28.0	2.9	5.2	7.3	5.5	4.3	6.6
47306	8.0	14.0	4,906.7	5,560.5	5,103.3	5,451.9	5,418.3	5,642.1
47740	68.2	661.4	99.6	33.0	183.9	179.8	207.8	113.7
47785	3,572.6	5,419.7	5,608.7	5,604.5	5,159.0	4,947.7	4,100.9	4,325.5
47810	14.4	23.3	2,581.2	4,354.1	4,613.2	6,150.7	6,544.2	5,367.5
47888	163.8	270.8	6,830.7	6,924.5	7,428.9	11,921.6	16,050.2	14,688.7
47902	25.7	35.7	5,086.0	5,027.5	5,643.8	5,577.9	6,198.5	6,417.9
47940	25.7	35.7	913.2	793.2	765.9	3,777.4	7,220.7	7,248.6
47953	7,507.8	9,123.8	6,452.6	4,489.9	3,971.7	3,745.9	3,892.9	5,807.7
47957	37.5	61.7	107.2	131.2	157.4	181.2	199.9	209.6
48014	10.7	19.6	8.6	9.5	37.8	52.9	14.3	23.4
48826	16.6	28.0	571.6	727.6	754.5	1,023.9	1,051.3	1,392.6
48829	16.6	28.0	2.5	1.9	5.5	10.8	14.4	8.0
48839	16.6	28.0	2.5	1.9	5.5	10.8	14.4	8.0
48973	172.6	686.5	1,070.5	3,983.1	2,590.3	2,334.5	2,373.0	2,369.8
49035	8.0	14.0	1.8	3.0	3.1	2.6	1.7	1.6
49099	8.0	14.0	4.6	5.7	7.1	53.4	404.1	1,161.3
49152	3,021.5	4,893.5	8,075.6	6,951.3	6,255.9	8,147.2	10,263.8	15,165.3
49325	8.0	14.0	3,045.8	3,298.9	3,296.5	3,825.5	3,448.9	3,877.6
49452	16.6	28.0	3,907.2	4,257.3	4,319.7	5,551.8	5,492.5	6,145.3
49847	163.8	270.8	89.3	2,516.8	3,793.8	3,967.6	4,000.6	4,264.5

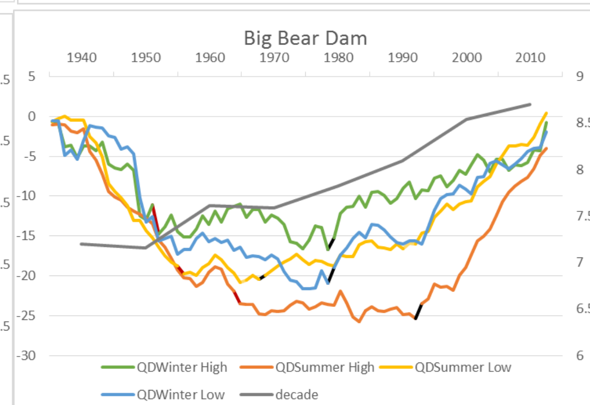
Appendix B: Station Cumulative Deviation Series

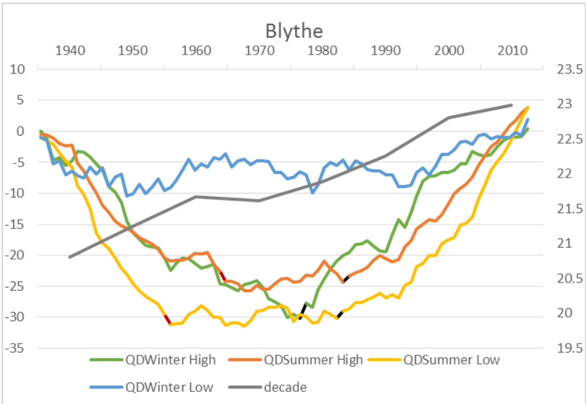
The following are the high and low QD trend lines for both the summer and winter seasons for each station as indicated. The four colored lines are the QD trend lines. The grey line indicates the decal mean temperatures. Each chart has a unique temperature scale to reflect each stations unique temperature ranges. The QD scales are not all exactly the same, but the range of the scales are within proximity of each other. Some stations have inflection points indicated. Red shows the end of the decent in the series, and black shows the incline of series.

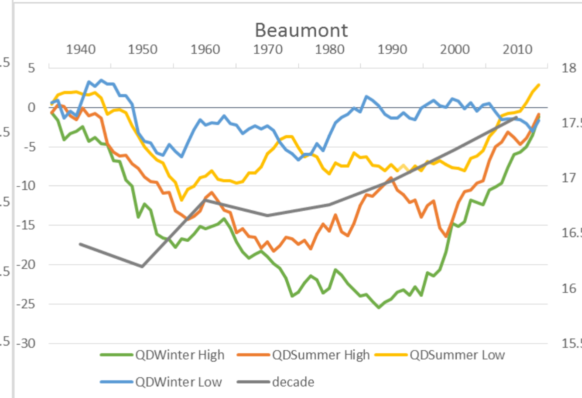


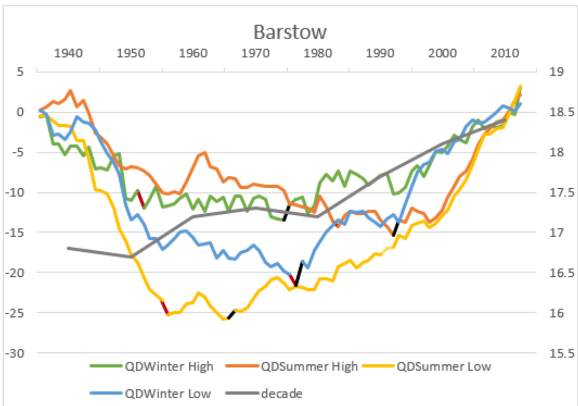


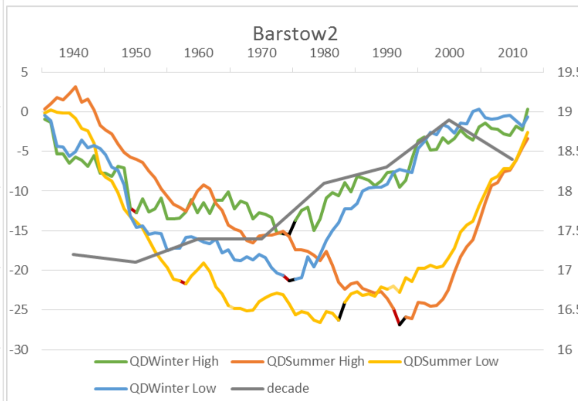


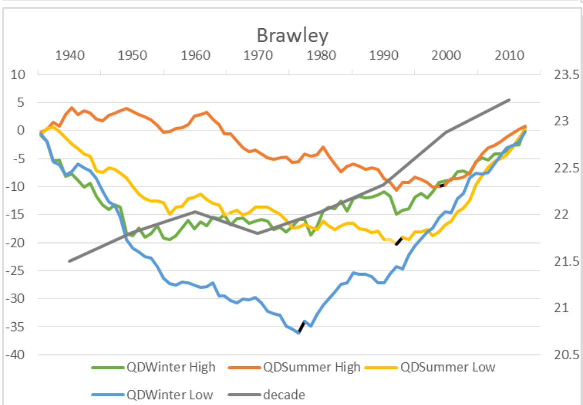



Blythe
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35
23.5 23 22.5 22 21.5 21 20.5 20 19.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Beaumont
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
18 17.5 17 16.5 16 15.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Barstow
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
19 18.5 18 17.5 17 16.5 16 15.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Barstow2
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
19.5 19 18.5 18 17.5 17 16.5 16
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Brawley
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35 -40
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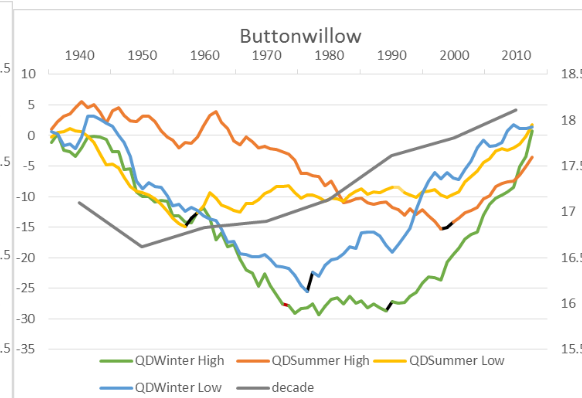
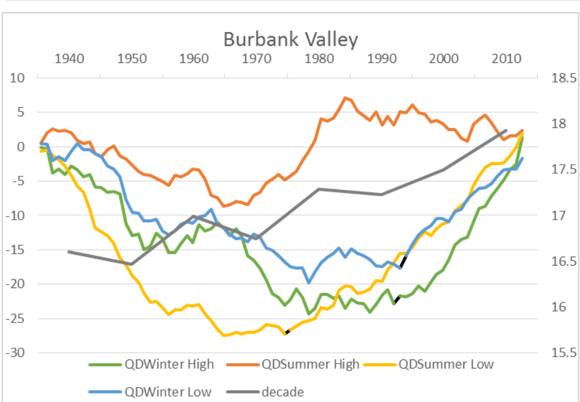
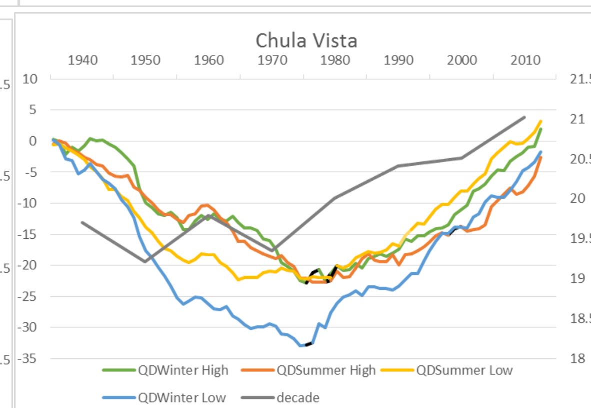
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Buttonwillow
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35
18.5 18 17.5 17 16.5 16 15.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Burbank Valley
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30
18.5 18 17.5 17 16.5 16 15.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Chula Vista
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35
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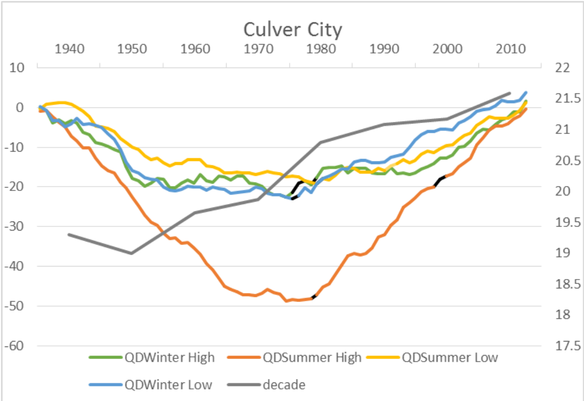
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Culver City
1940 1950 1960 1970 1980 1990 2000 2010
10 0 -10 -20 -30 -40 -50 -60
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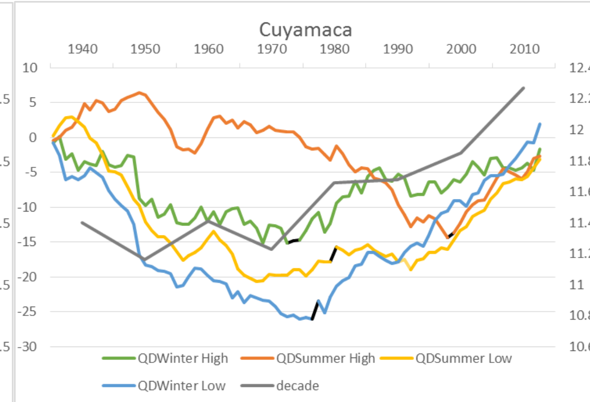
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Cuyamaca
1940 1950 1960 1970 1980 1990 2000 2010
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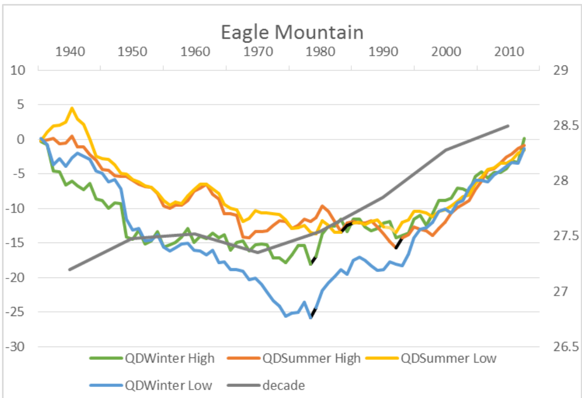
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Eagle Mountain
1940 1950 1960 1970 1980 1990 2000 2010
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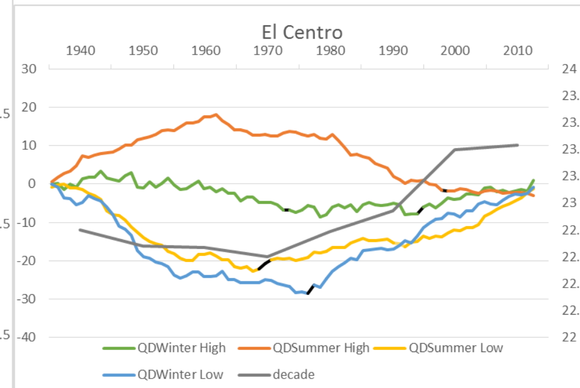
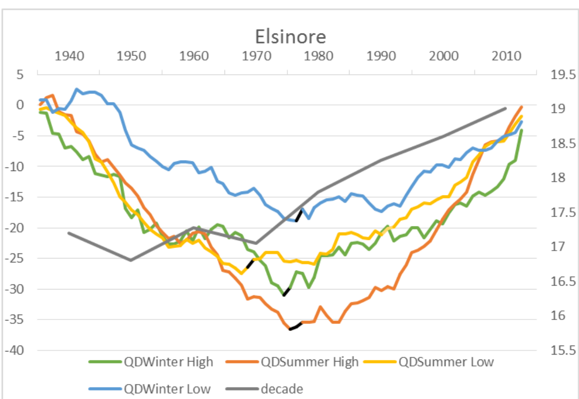
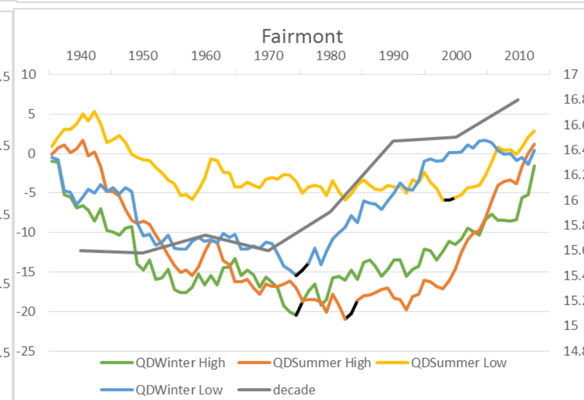
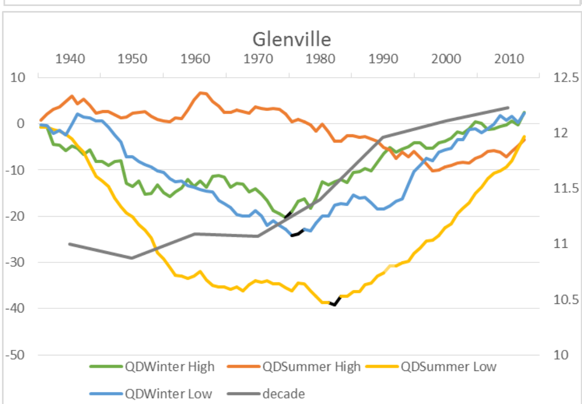
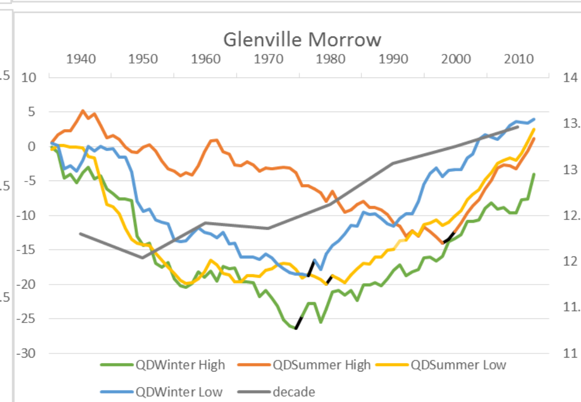
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


El Centro
1940 1950 1960 1970 1980 1990 2000 2010
30 20 10 0 -10 -20 -30 -40
24 23.8 23.6 23.4 23.2 23 22.8 22.6 22.4 22.2 22
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Elsinore
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30 -35 -40
19.5 19 18.5 18 17.5 17 16.5 16 15.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Fairmont
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25
17 16.8 16.6 16.4 16.2 16 15.8 15.6 15.4 15.2 15 14.8
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Glenville
1940 1950 1960 1970 1980 1990 2000 2010
10 0 -10 -20 -30 -40 -50
12.5 12 11.5 11 10.5 10
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Glenville Morrow
1940 1950 1960 1970 1980 1990 2000 2010
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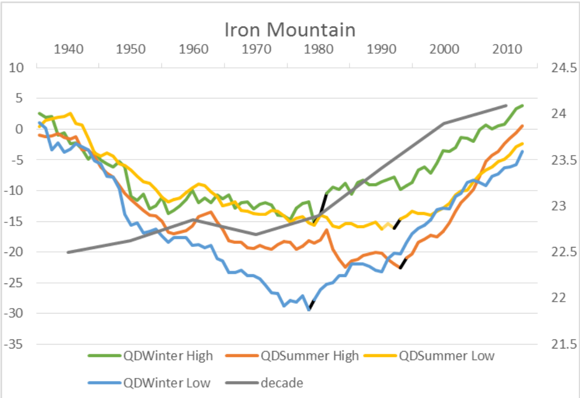
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Iron Mountain
1940 1950 1960 1970 1980 1990 2000 2010
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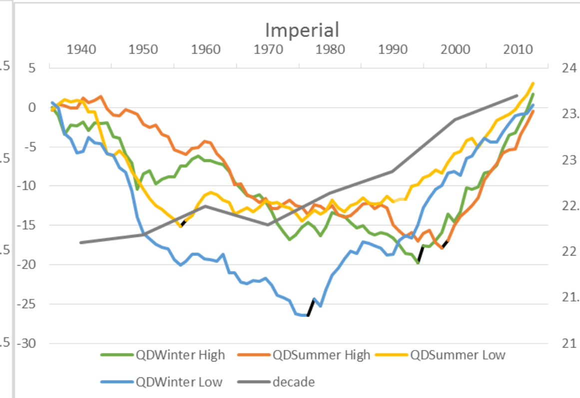
QDSummer High
QDSummer Low
QDWinter Low
decade


Imperial
1940 1950 1960 1970 1980 1990 2000 2010
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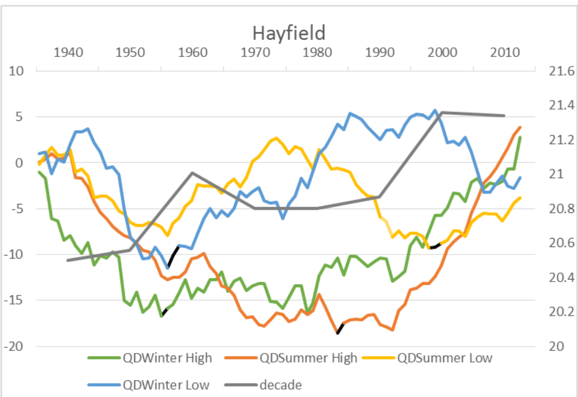
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Hayfield
1940 1950 1960 1970 1980 1990 2000 2010
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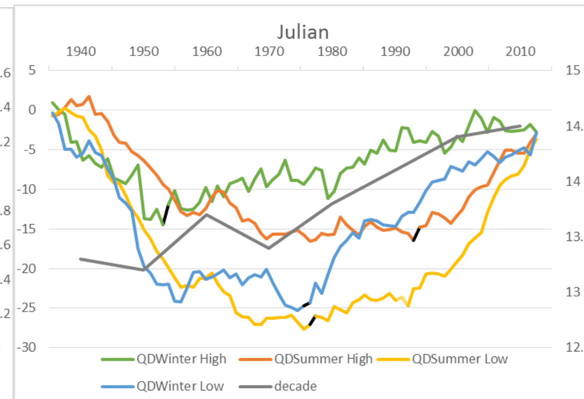
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Julian
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QDWinter High
QDSummer High
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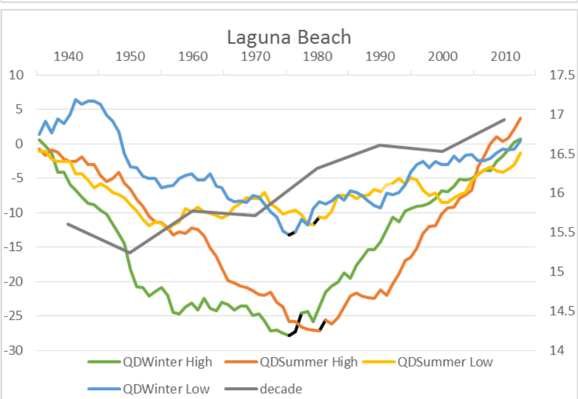
QDWinter Low
decade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10 5 0 -5 -10 -15 -20 -25 -30
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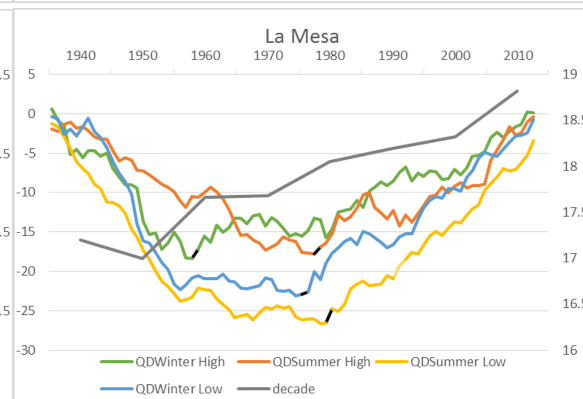
QDSummer High
QDSummer Low
QDWinter Low
decade


La Mesa
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
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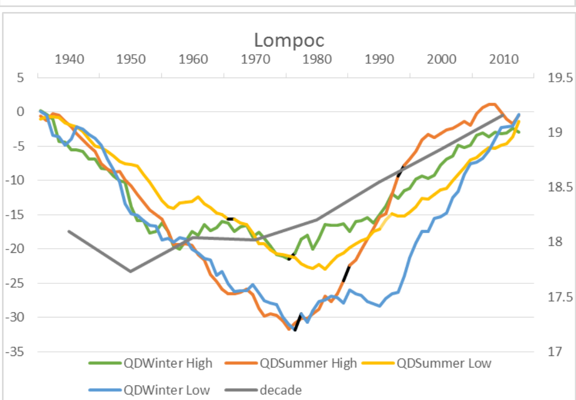
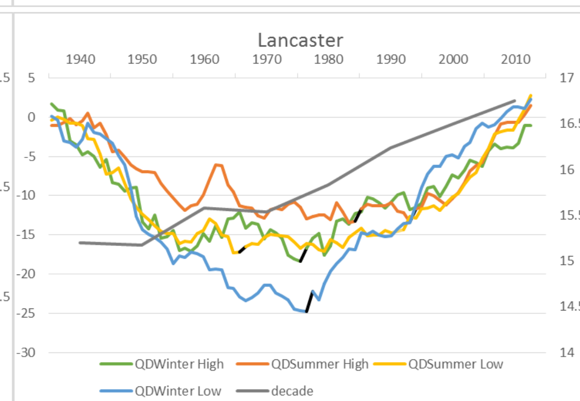
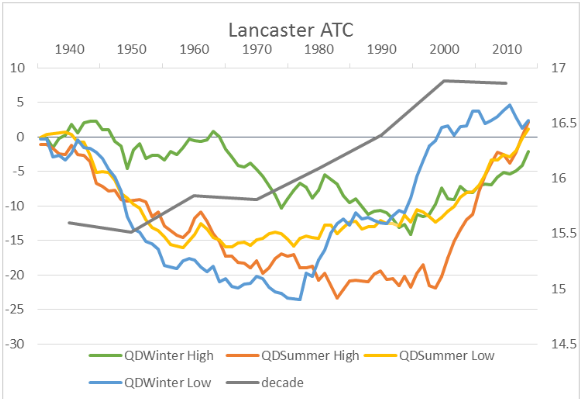
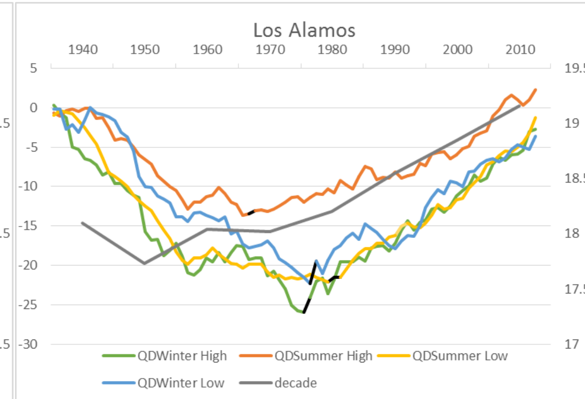
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Lompoc
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30 -35
19.5 19 18.5 18 17.5 17
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Lancaster
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
17 16.5 16 15.5 15 14.5 14
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Lancaster ATC
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30
17 16.5 16 15.5 15 14.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Los Alamos
1940 1950 1960 1970 1980 1990 2000 2010
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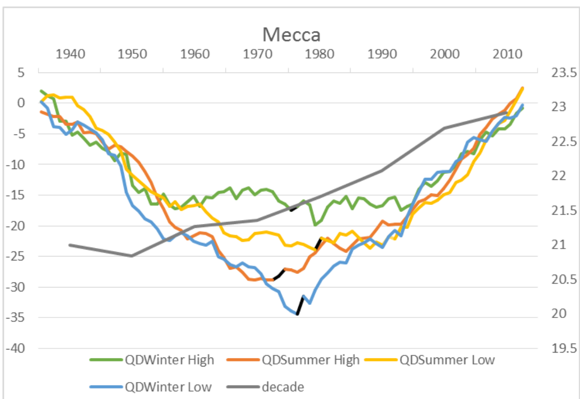
19.5 19 18.5 18 17.5 17
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Mecca
1940 1950 1960 1970 1980 1990 2000 2010
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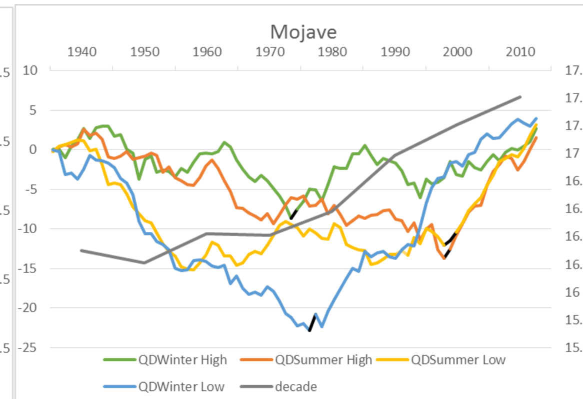
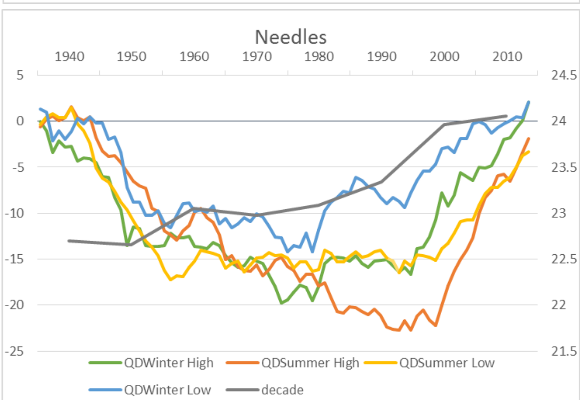
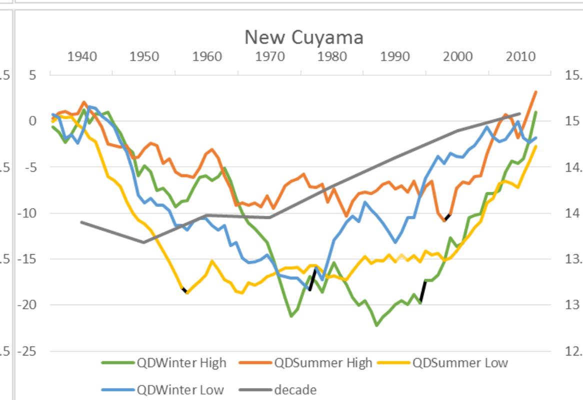
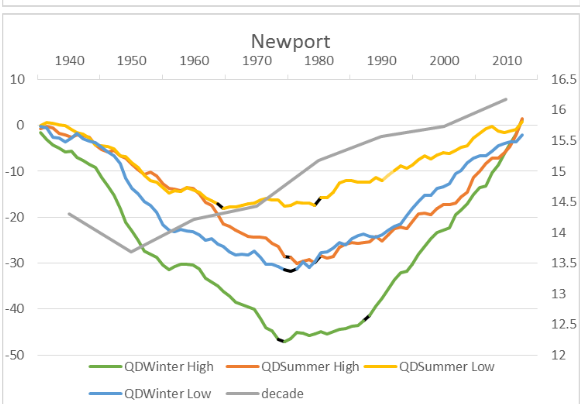
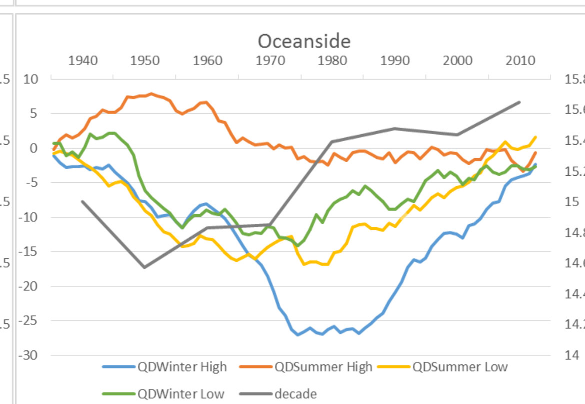
23.5 23 22.5 22 21.5 21 20.5 20 19.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

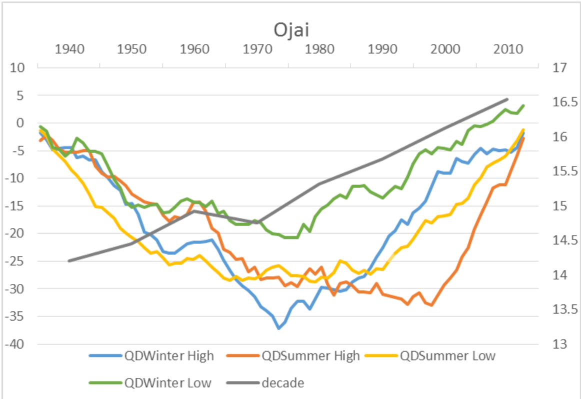

Mojave
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25
17.6 17.4 17.2 17 16.8 16.6 16.4 16.2 16 15.8 15.6
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

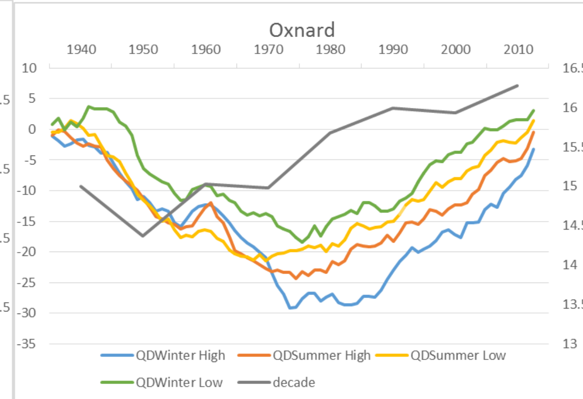

Needles
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25
24.5 24 23.5 23 22.5 22 21.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

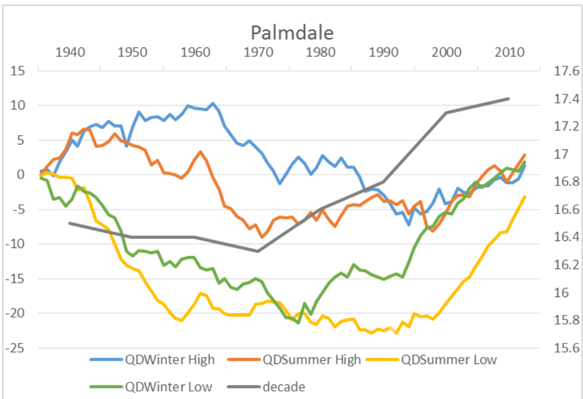

New Cuyama
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25
15.5 15 14.5 14 13.5 13 12.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

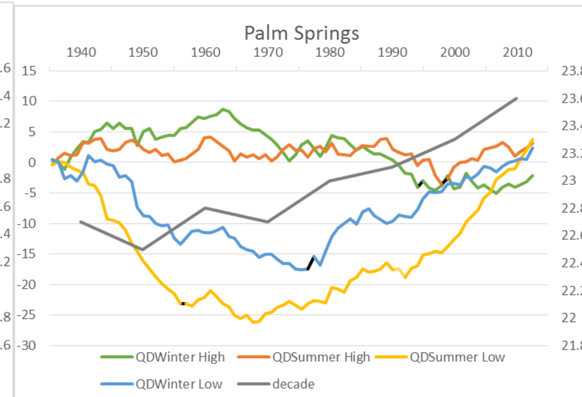

Newport
1940 1950 1960 1970 1980 1990 2000 2010
10 0 -10 -20 -30 -40 -50
16.5 16 15.5 15 14.5 14 13.5 13 12.5 12
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

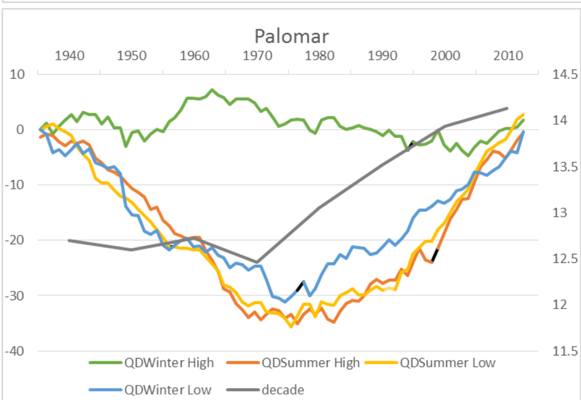

Oceanside
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30
15.8 15.6 15.4 15.2 15 14.8 14.6 14.4 14.2 14
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

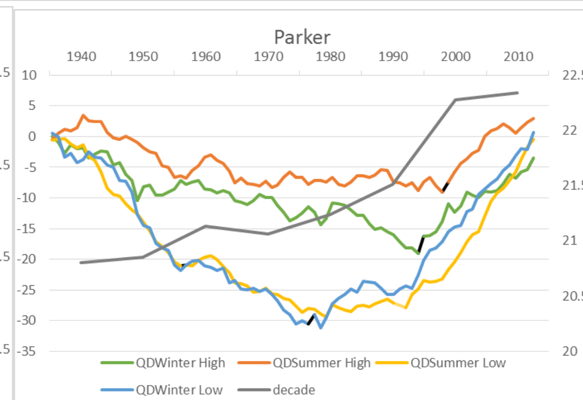

Ojai
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35 -40
17 16.5 16 15.5 15 14.5 14 13.5 13
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

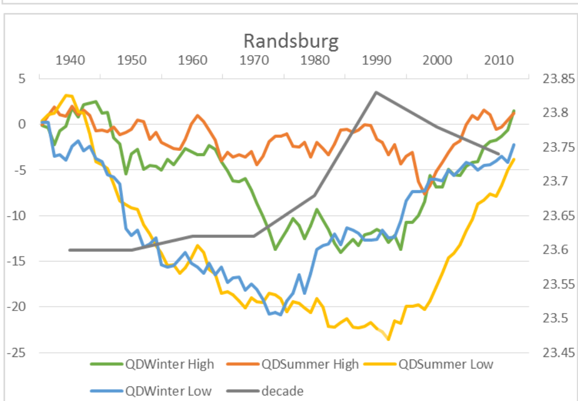

Oxnard
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35
16.5 16 15.5 15 14.5 14 13.5 13
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

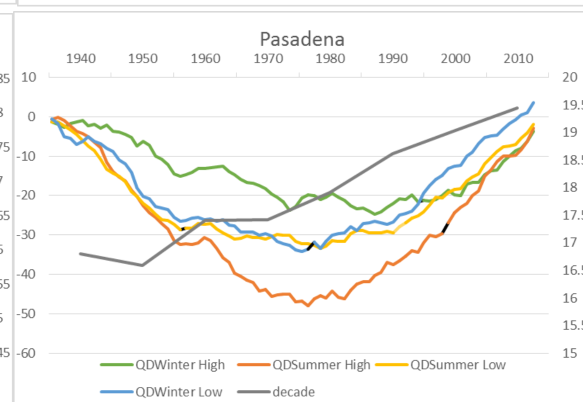

Palmdale
1940 1950 1960 1970 1980 1990 2000 2010
15 10 5 0 -5 -10 -15 -20 -25
17.6 17.4 17.2 17 16.8 16.6 16.4 16.2 16 15.8 15.6
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

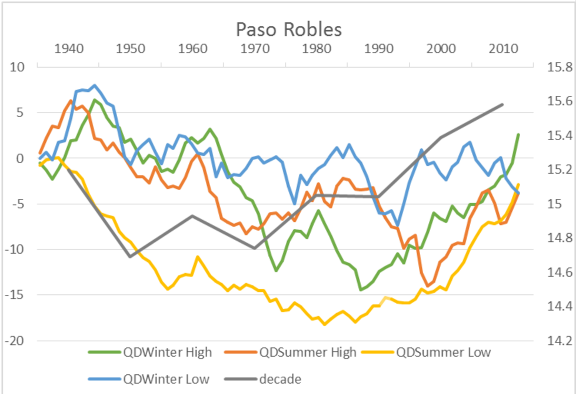

Palm Springs
1940 1950 1960 1970 1980 1990 2000 2010
15 10 5 0 -5 -10 -15 -20 -25 -30
23.8 23.6 23.4 23.2 23 22.8 22.6 22.4 22.2 22 21.8
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

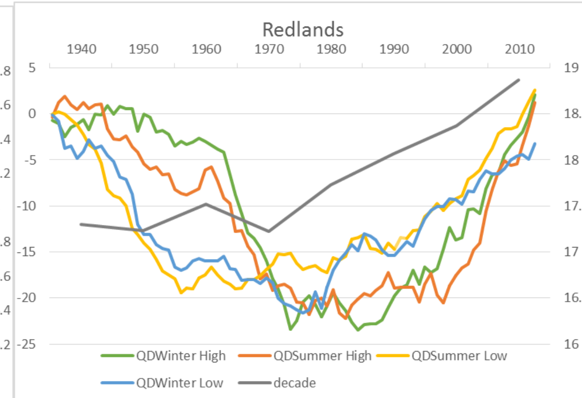

Palomar
1940 1950 1960 1970 1980 1990 2000 2010
10 0 -10 -20 -30 -40
14.5 14 13.5 13 12.5 12 11.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

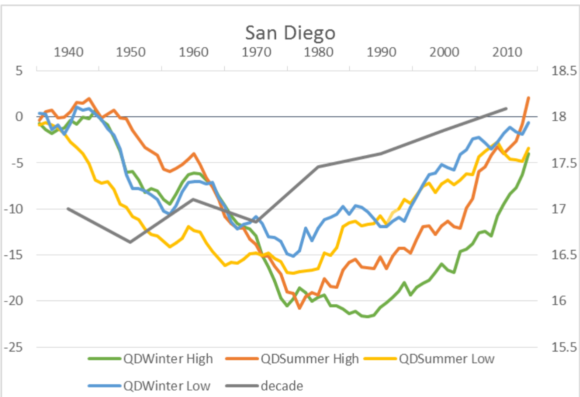

Parker
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35
22.5 22 21.5 21 20.5 20
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

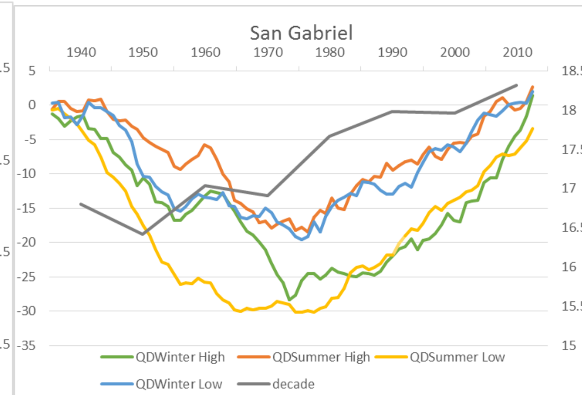

Randsburg
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25
23.85 23.8 23.75 23.7 23.65 23.6 23.55 23.5 23.45
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

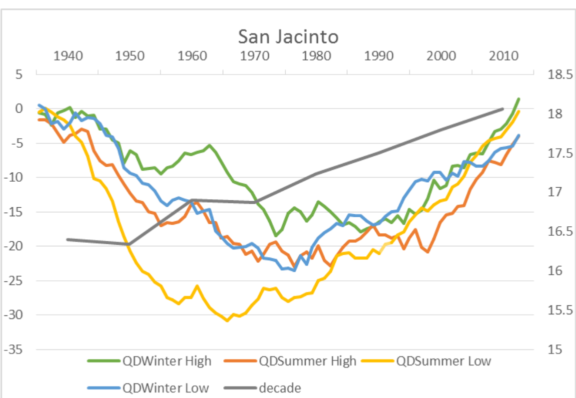

Pasadena
1940 1950 1960 1970 1980 1990 2000 2010
10 0 -10 -20 -30 -40 -50 -60
20 19.5 19 18.5 18 17.5 17 16.5 16 15.5 15
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

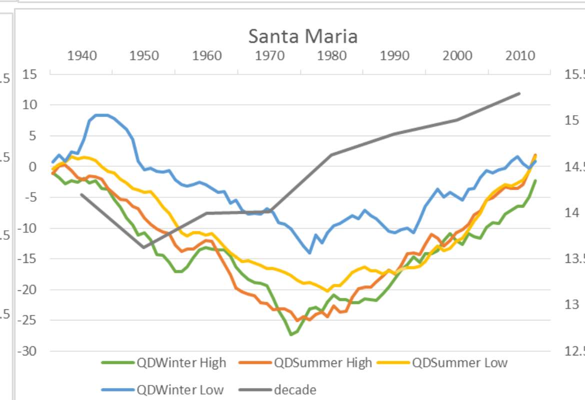

Paso Robles
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

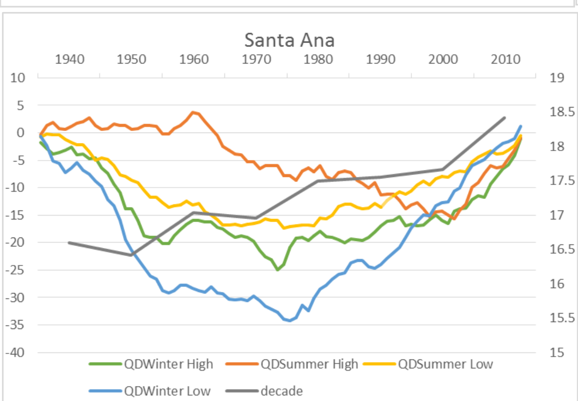

Redlands
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

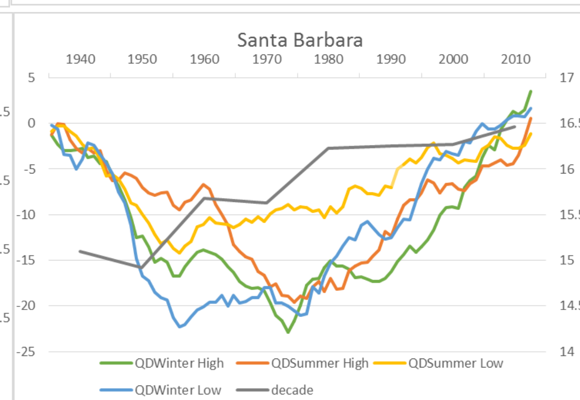

San Diego
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

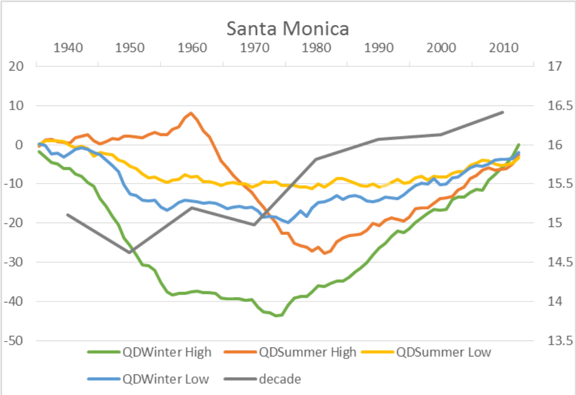

San Gabriel
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

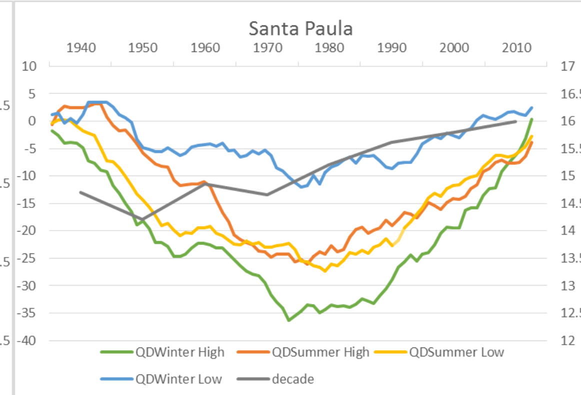

San Jacinto
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

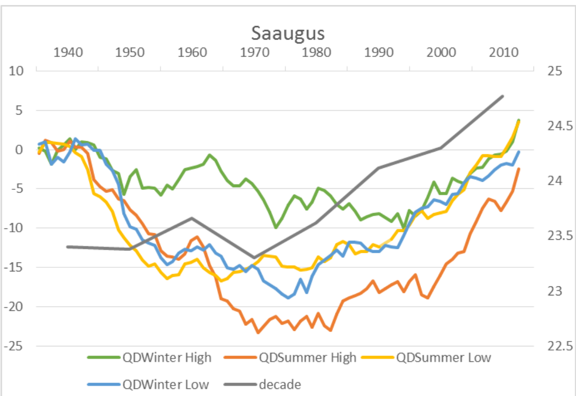

Santa Maria
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

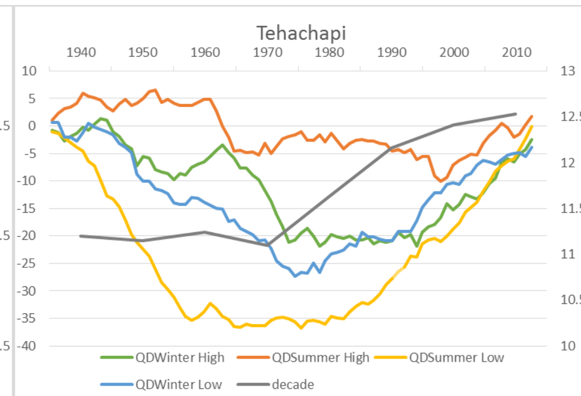

Santa Ana
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

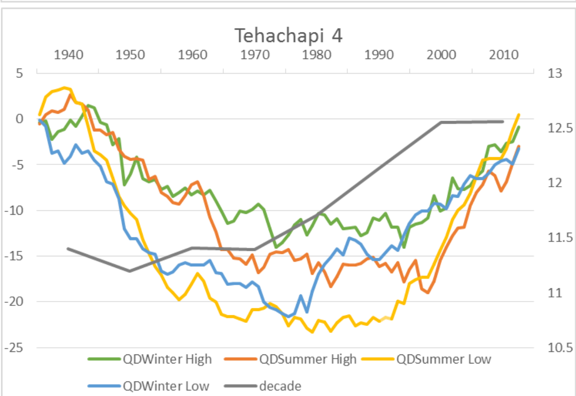

Santa Barbara
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

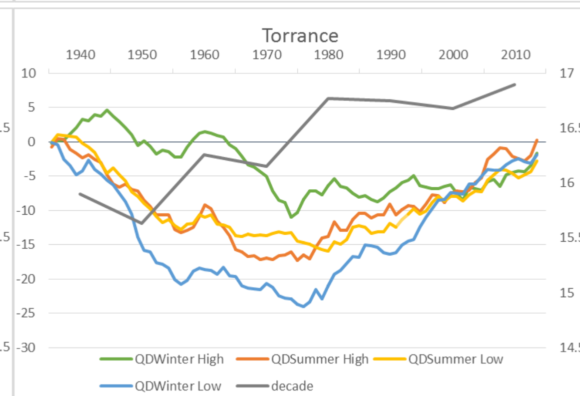

Santa Monica
1940 1950 1960 1970 1980 1990 2000 2010
20 10 0 -10 -20 -30 -40 -50
17 16.5 16 15.5 15 14.5 14 13.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

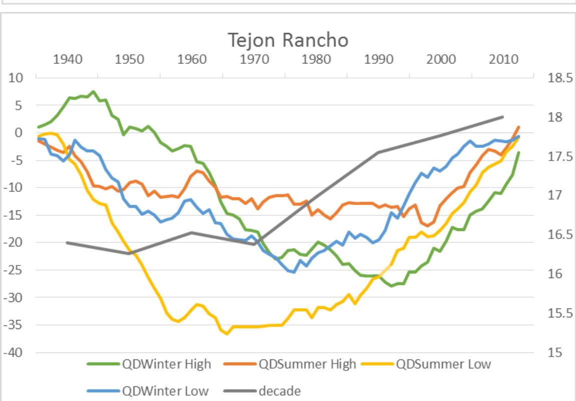

Santa Paula
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35 -40
17 16.5 16 15.5 15 14.5 14 13.5 13 12.5 12
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

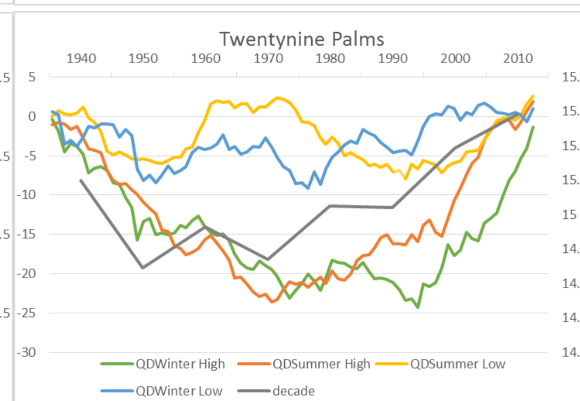

Saaugus
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25
25 24.5 24 23.5 23 22.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

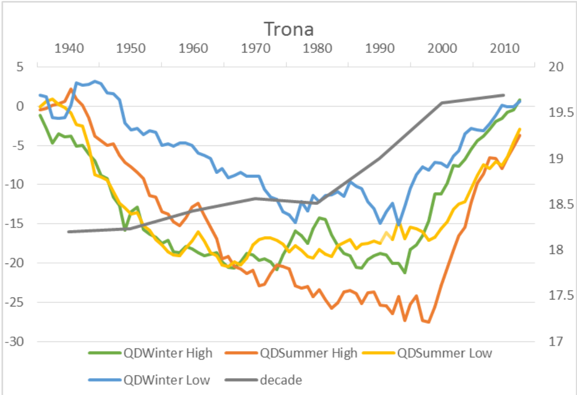

Tehachapi
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35 -40
13 12.5 12 11.5 11 10.5 10
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

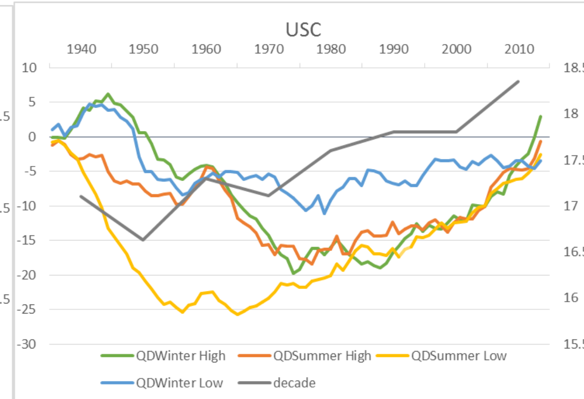

Tehachapi 4
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25
13 12.5 12 11.5 11 10.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

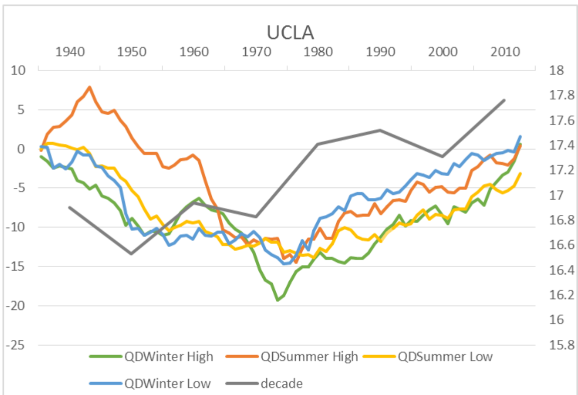

Torrance
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30
17 16.5 16 15.5 15 14.5
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

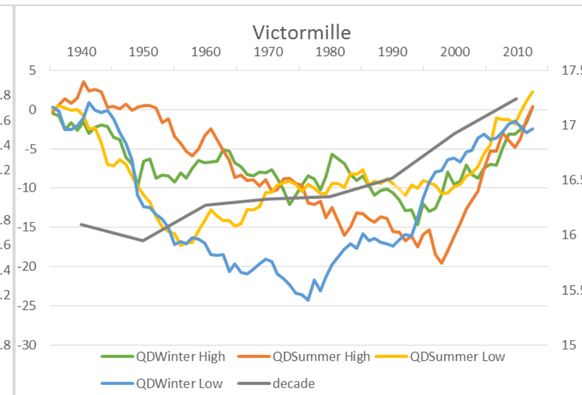

Tejon Rancho
1940 1950 1960 1970 1980 1990 2000 2010
10 5 0 -5 -10 -15 -20 -25 -30 -35 -40
18.5 18 17.5 17 16.5 16 15.5 15
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

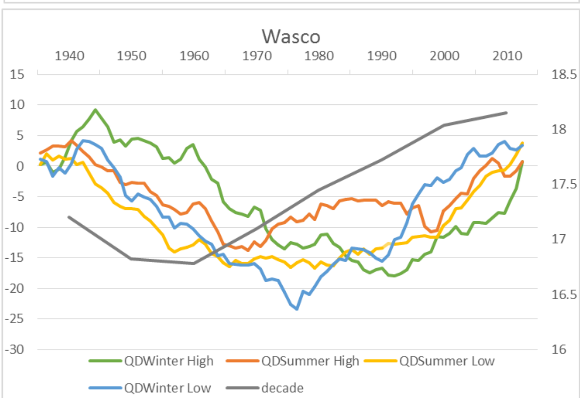

Twentynine Palms
1940 1950 1960 1970 1980 1990 2000 2010
5 0 -5 -10 -15 -20 -25 -30
15.8 15.6 15.4 15.2 15 14.8 14.6 14.4 14.2
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

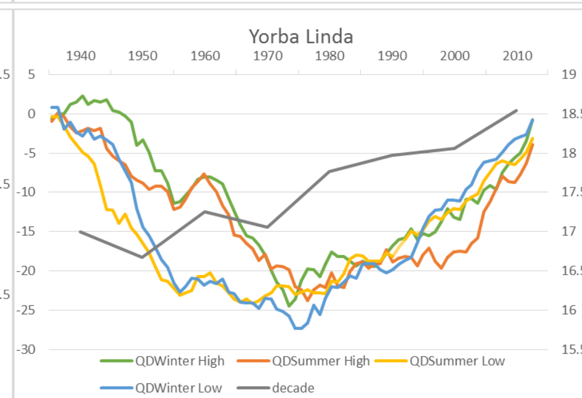

Trona
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


USC
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


UCLA
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Victormille
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Wasco
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade


Yorba Linda
1940 1950 1960 1970 1980 1990 2000 2010
QDWinter High
QDSummer High
QDSummer Low
QDWinter Low
decade

Appendix C: H-Values by Station

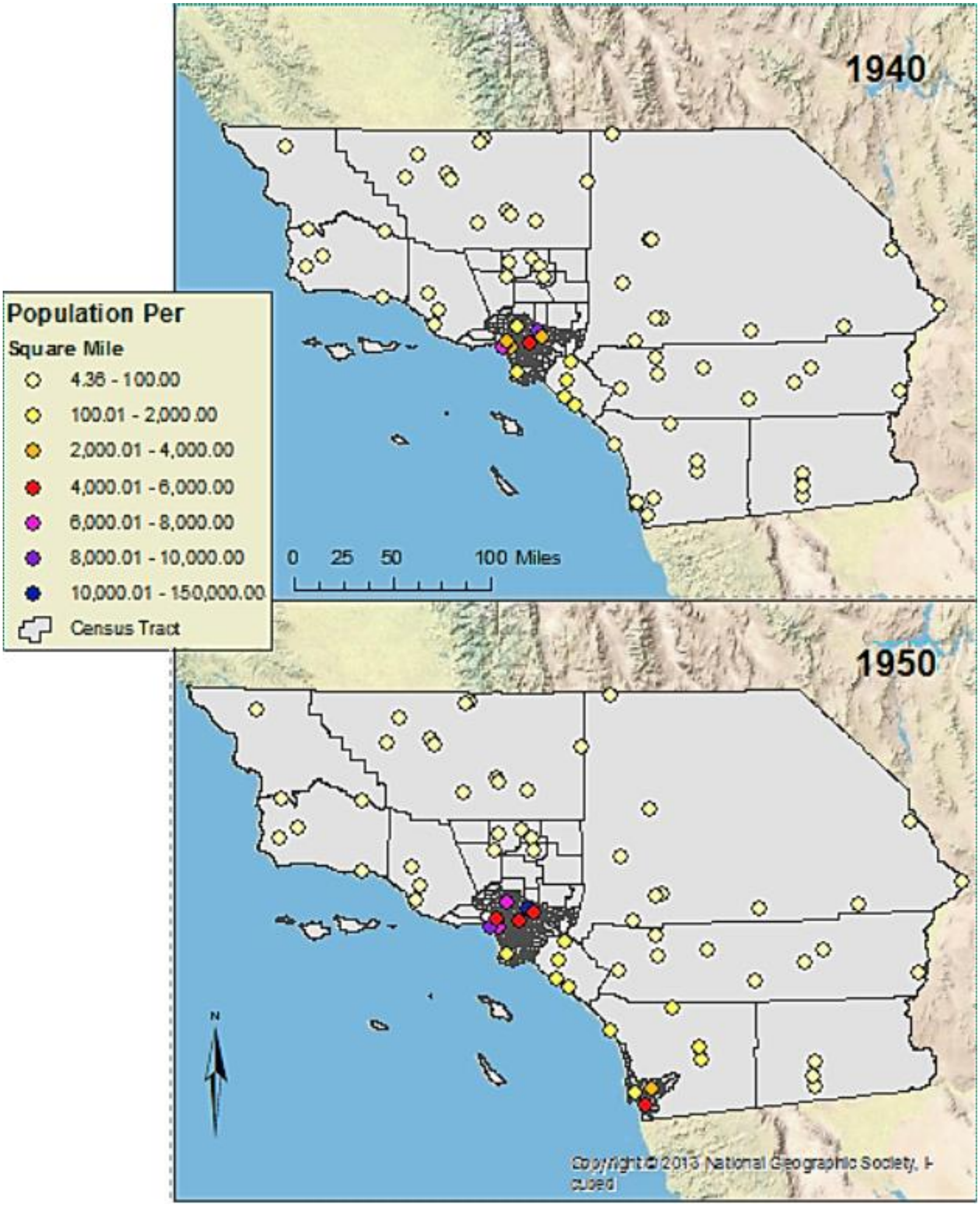
Station_ID	WinterH	SummerH	WinterM	SummerM	WinterL	SummerL
40439	0.6742	0.6703	0.6847	0.6432	0.6421	0.6983
40442	0.7014	0.6954	0.7216	0.7142	0.7073	0.7260
40519	0.5482	0.6544	0.7006	0.7086	0.6754	0.7396
40521	0.5458	0.7496	0.5879	0.7331	0.6699	0.7292
40609	0.6614	0.6083	0.5926	0.6399	0.5172	0.6330
40741	0.4236	0.6935	0.6226	0.7396	0.7169	0.7802
40742	0.5395	0.7183	0.6194	0.7277	0.6223	0.7097
40924	0.5068	0.7583	0.6680	0.7465	0.7098	0.7453
41048	0.6025	0.6366	0.7126	0.7129	0.7450	0.6887
41194	0.6551	0.6161	0.6802	0.7339	0.6773	0.7590
41244	0.6813	0.6892	0.7275	0.6139	0.6935	0.6776
41758	0.7056	0.7153	0.7593	0.7343	0.7556	0.7638
42214	0.6679	0.7897	0.7136	0.7740	0.7276	0.7150
42239	0.5165	0.6749	0.6377	0.6561	0.7055	0.7177
42598	0.5805	0.6506	0.6628	0.6795	0.6982	0.6905
42713	0.5226	0.7313	0.6629	0.5876	0.7119	0.7268
42805	0.6605	0.7633	0.6870	0.7720	0.6910	0.7420
42941	0.5854	0.6677	0.5987	0.6514	0.6105	0.5531
43463	0.6256	0.6434	0.6919	0.7226	0.6940	0.7695
43468	0.6582	0.6686	0.6802	0.6501	0.6690	0.7049
43855	0.5855	0.7121	0.5720	0.6904	0.5933	0.5870
44223	0.6636	0.6870	0.6925	0.6861	0.7126	0.6833
44297	0.5916	0.6984	0.6772	0.6985	0.7282	0.7058
44412	0.5145	0.6807	0.5931	0.7066	0.6731	0.7404
44647	0.7208	0.7587	0.7188	0.7247	0.6600	0.5944
44735	0.6257	0.6597	0.6741	0.7347	0.6913	0.7485
44747	0.6017	0.6114	0.6875	0.6622	0.7122	0.6959
44749	0.5933	0.6636	0.6310	0.6750	0.6899	0.6592
45064	0.6720	0.7666	0.7201	0.7843	0.7299	0.7673
45107	0.6904	0.6800	0.7090	0.7310	0.6852	0.7494
45115	0.7061	0.6255	0.6387	0.6847	0.6152	0.7352
45502	0.6278	0.7662	0.7195	0.7678	0.7349	0.7283
45756	0.5225	0.6085	0.6356	0.6218	0.7045	0.6557
46118	0.6621	0.7006	0.6314	0.6886	0.6041	0.6898
46154	0.6573	0.5663	0.6946	0.6289	0.6498	0.7077
46175	0.7946	0.7520	0.7870	0.7405	0.7579	0.7153
46377	0.7365	0.5989	0.7073	0.6108	0.6358	0.6973
46399	0.7350	0.6799	0.7406	0.7369	0.6775	0.7328
46569	0.7267	0.7129	0.7222	0.7317	0.6929	0.7290

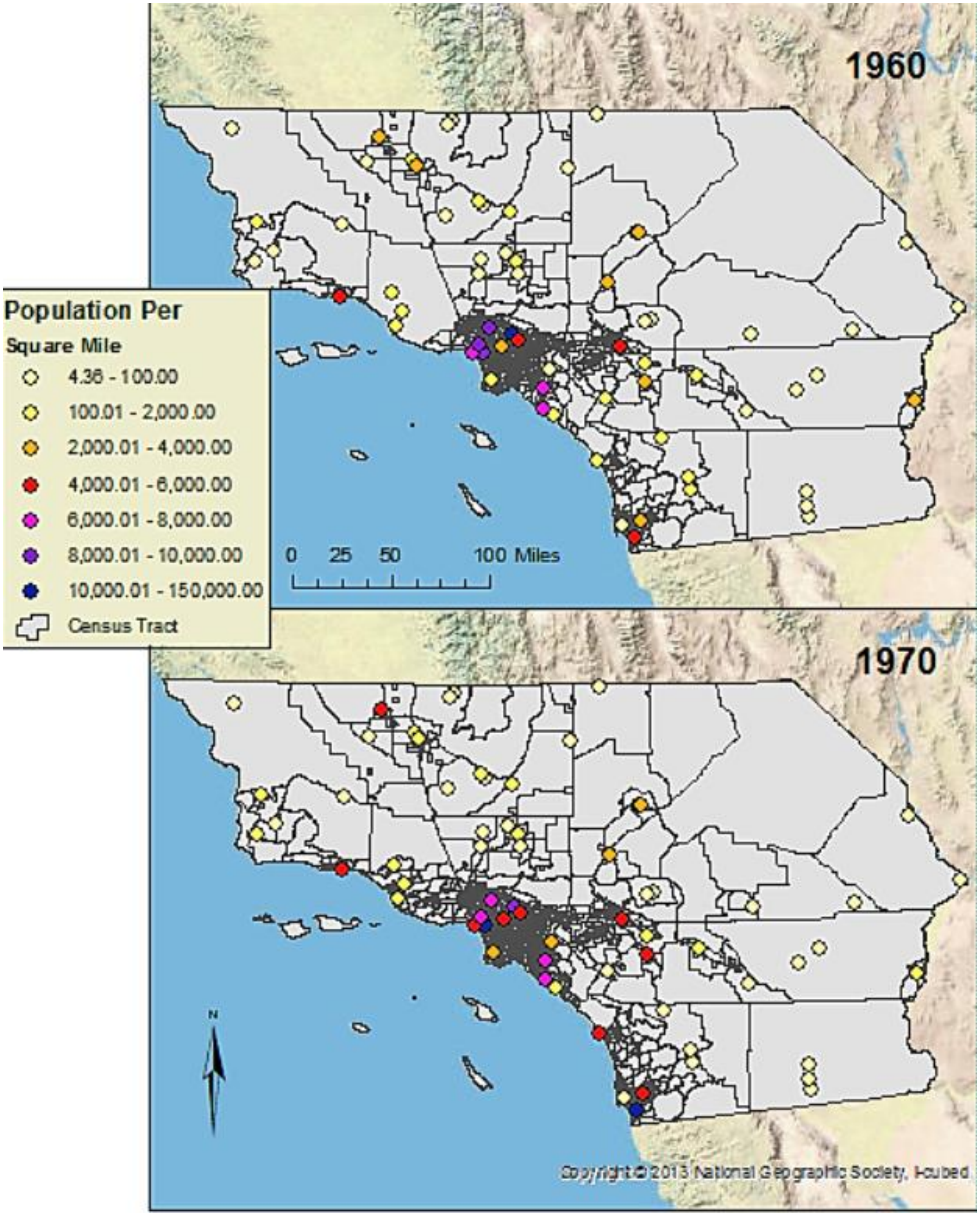
Station_ID	WinterH	SummerH	WinterM	SummerM	WinterL	SummerL
46624	0.6035	0.5834	0.5488	0.6698	0.6850	0.7022
46635	0.5821	0.4728	0.5322	0.6533	0.6480	0.7421
46657	0.5181	0.7184	0.5722	0.7638	0.6865	0.7628
46699	0.6341	0.5865	0.6701	0.7087	0.7232	0.7451
46719	0.6864	0.7732	0.7384	0.7798	0.7619	0.7588
46730	0.6436	0.6221	0.5460	0.6623	0.5447	0.7133
47253	0.5870	0.5060	0.5839	0.6110	0.6408	0.7272
47306	0.6752	0.6603	0.6882	0.7098	0.6882	0.7188
47740	0.7146	0.6999	0.6743	0.6938	0.6412	0.6896
47785	0.7183	0.6690	0.7223	0.7351	0.6735	0.7680
47810	0.6363	0.6497	0.6809	0.7192	0.7082	0.7473
47888	0.6813	0.6578	0.7427	0.6233	0.7553	0.7052
47902	0.7409	0.6868	0.7284	0.6382	0.6894	0.6592
47940	0.7155	0.7320	0.6826	0.7623	0.6717	0.7460
47953	0.7782	0.7499	0.7461	0.6751	0.6808	0.6406
47957	0.7506	0.7360	0.7131	0.7435	0.6204	0.7501
48014	0.5623	0.6782	0.6602	0.6972	0.6687	0.7064
48826	0.6526	0.5973	0.6711	0.7069	0.7168	0.7599
48829	0.5650	0.6597	0.6370	0.6711	0.5273	0.5587
48839	0.7403	0.6156	0.7046	0.7184	0.6705	0.7509
48973	0.6465	0.6469	0.6703	0.6712	0.7106	0.6962
49035	0.6533	0.6955	0.6559	0.6789	0.6224	0.6754
49099	0.6554	0.7181	0.5902	0.6635	0.5099	0.5708
49152	0.6851	0.6889	0.6664	0.6399	0.6364	0.6817
49325	0.5581	0.6570	0.6281	0.6560	0.6903	0.6687
49452	0.6881	0.6280	0.7030	0.6593	0.6972	0.7084
49847	0.7050	0.6813	0.7197	0.7109	0.7266	0.7221

H-values averaged by cardinality

Station_Name	Mean	Aspect	Directional Mean	Station_Name	Mean	Aspect	Directional Mean
EL CENTRO 2 SSW	0.6572	E		MOJAVE	0.6248	S	
PARKER RESRV	0.6779	E		TRONA	0.6635	S	
BRAWLEY	0.6830	E		UCLA	0.6664	S	
IRON MOUNTAIN	0.6833	E		LOS ANGELES DWTN USC	0.6676	S	
LA MESA	0.6890	E		BARSTOW	0.6711	S	
SANTA PAULA	0.7189	E		SAN DIEGO WSO	0.6856	S	
SANTA MONICA	0.7118	F		SANTA BARBARA	0.6905	S	
TEHACHAPI 4 SE	0.6031	N		SAN GABRIEL FIRE DPT	0.7144	S	
JULIAN CDF	0.6514	N		OXNARD	0.7192	S	
BIG BEAR LAKE DAM	0.6561	N		ELSINORE	0.7193	S	
BARSTOW	0.6693	N	0.64498	CHULA VISTA	0.7390	S	0.68740
PASO ROBLES	0.6220	NE		PALM SPRINGS	0.6051	SE	
PALMDALE	0.6321	NE		CUYAMACA	0.6514	SE	
LANCASTER ATC	0.6520	NE		EAGLE MOUNTAIN	0.6604	SE	
NEEDLES	0.6628	NE		BURBANK VALLEY PUMP	0.6869	SE	
TORRANCE AP	0.6736	NE		OJAI	0.7171	SE	0.66418
IMPERIAL	0.6875	NE	0.65501	BEAUMONT NUMBER 2	0.6087	SW	
RANDSBURG	0.6093	NW		HAYFIELD PUMP PLANT	0.6234	SW	
FAIRMONT	0.6111	NW		OCEANSIDE MARINA	0.6644	SW	
TENTYNINE PALMS	0.6180	NW		BAKERSFIELD	0.6688	SW	
LANCASTER	0.6618	NW		BUTTONWILLOW	0.6805	SW	
BIG BEAR LAKE	0.6627	NW		BLYTHE	0.6891	SW	
PALOMAR MT OBSTRY	0.6703	NW		REDLANDS	0.6901	SW	
GLENNVILLE MORROW RA	0.6718	NW		SAN JACINTO	0.6903	SW	
WASCO	0.6807	NW		GLENNVILLE	0.6912	SW	
TEJON RANCHO	0.7001	NW	0.65398	SAN ANA FIRE STN	0.6942	SW	
VICTORVILLE PUMT PT	0.6430	W		LOS ALAMOS	0.7075	SW	
NEW CUYAMA	0.6508	W		YORBA LINA	0.7109	SW	
SAAUGUS PWR PLT	0.6622	W		BAKERSFIELD MEADOWS	0.7110	SW	
TEHACHAPI	0.6841	W		MECCA FIRE STN	0.7241	SW	
LAGUNA BEACH	0.6962	W		LOMPOC	0.7400	SW	
SANTA MARIA	0.7183	W		PASADENA	0.7497	SW	
CULVER CITY	0.7313	W		NEWPORT HARBOR BEACH	0.7579	SW	0.69422

Appendix D: Population Density for Census Tract by Station




1960
Population Per
Square Mile
4.36 - 100.00
100.01 - 2,000.00
2,000.01 - 4,000.00
4,000.01 - 6,000.00
6,000.01 - 8,000.00
8,000.01 - 10,000.00
10,000.01 - 150,000.00
Census Tract
0 25 50 100 Miles
1970
N
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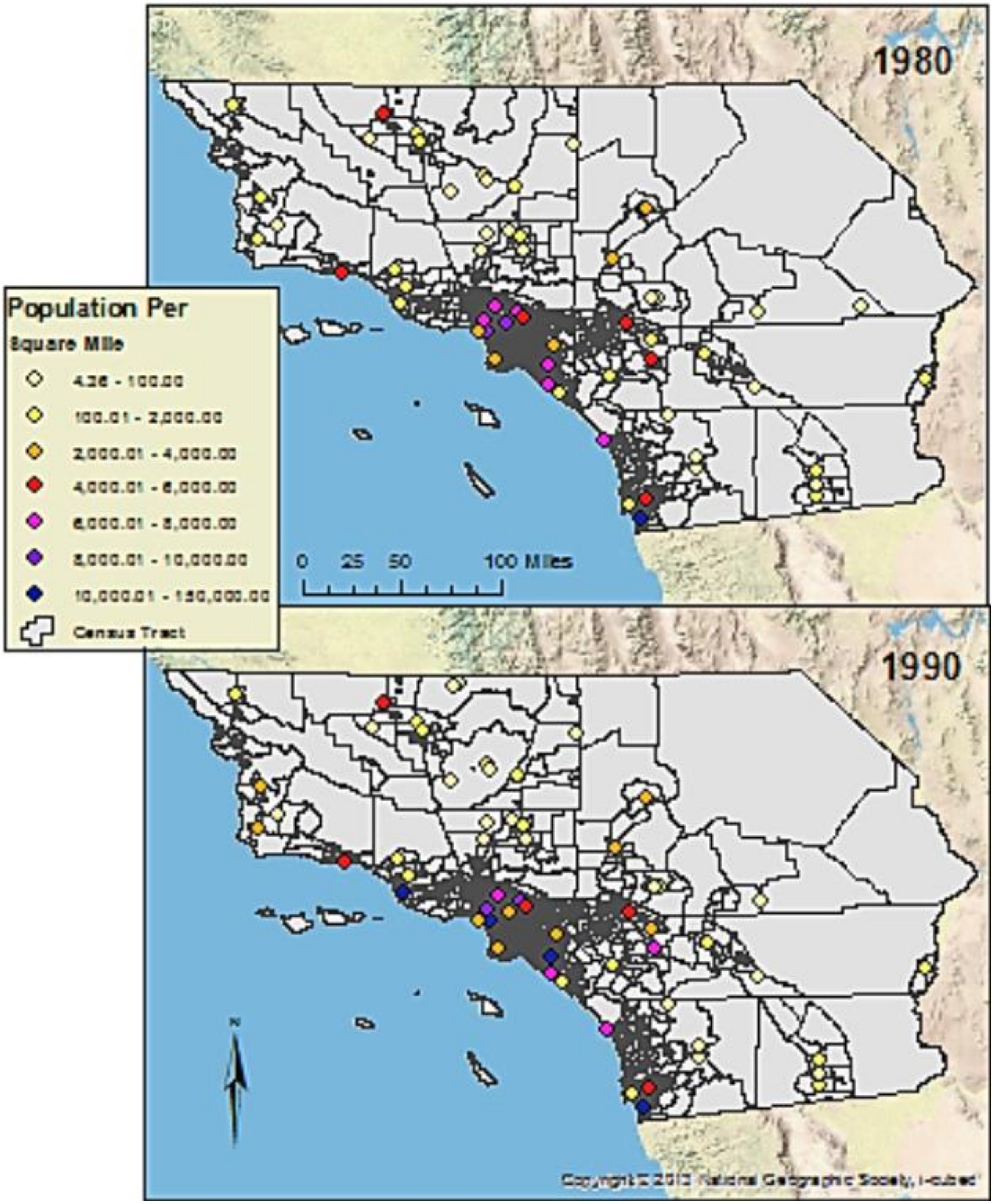
1980
1990
Population Per
Square Mile
4.26 - 100.00
100.01 - 2,000.00
2,000.01 - 4,000.00
4,000.01 - 6,000.00
6,000.01 - 8,000.00
8,000.01 - 10,000.00
10,000.01 - 150,000.00
Census Tract
0 25 50 100 Miles
N
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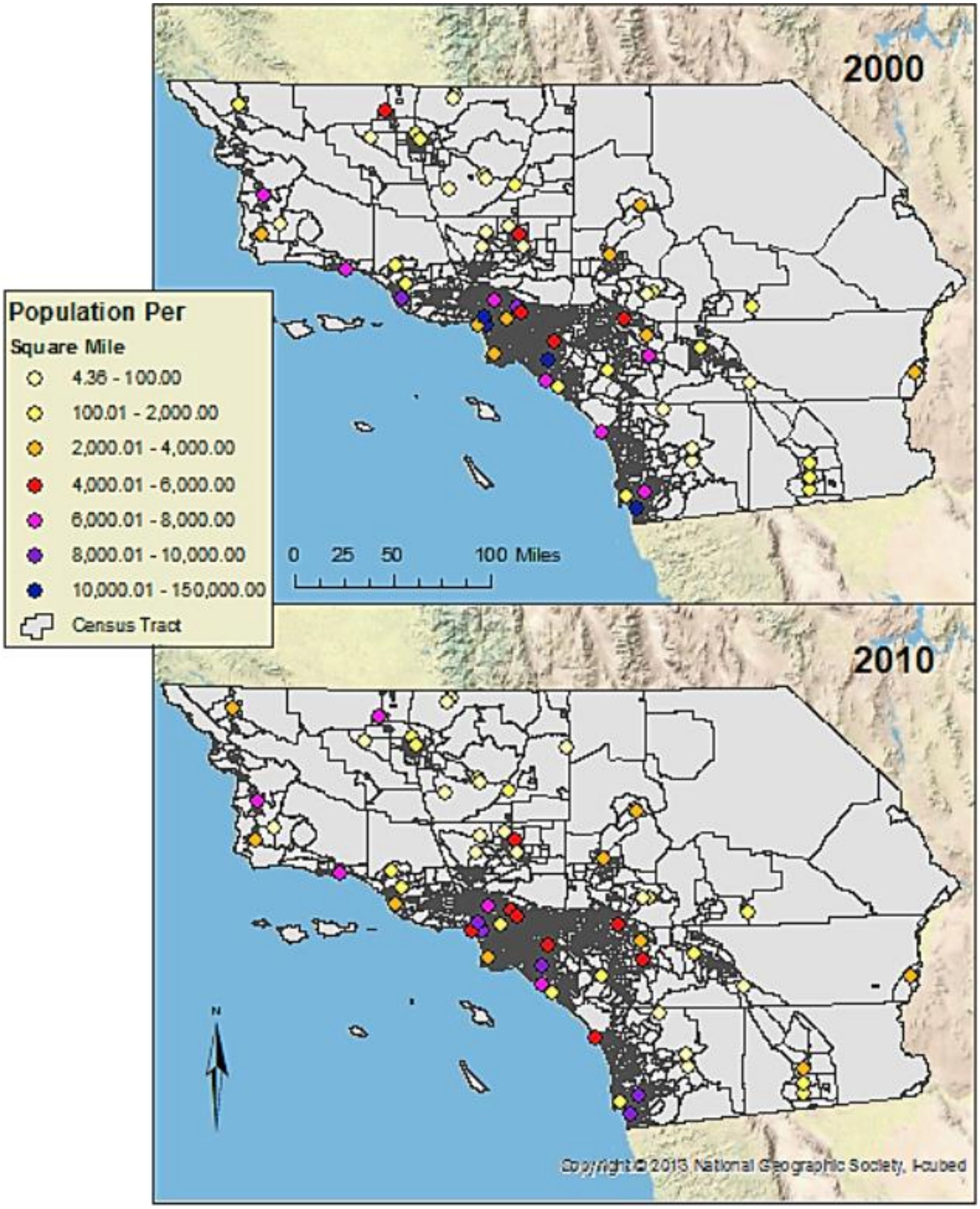
2000
Population Per
Square Mile
4.36 - 100.00
100.01 - 2,000.00
2,000.01 - 4,000.00
4,000.01 - 6,000.00
6,000.01 - 8,000.00
8,000.01 - 10,000.00
10,000.01 - 150,000.00
Census Tract
0 25 50 100 Miles
2010
N
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