Novel Metrics for Analyzing Extreme Heat Patterns across US Cities

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NOVEL METRICS FOR ANALYZING EXTREME HEAT PATTERNS ACROSS US
CITIES

By

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Key Takeaways

- Established novel metrics for describing extreme summertime heat, and found that latitude is the strongest controller for describing the range of extreme temperature, while latitude and elevation have similar control over extreme heat index

- Southern cities experience extreme temperature and heat index values with smaller deviations from their respective averages, but these daytime heat values remain at dangerous levels for significantly longer periods while also having comparatively high nighttime heat values

- Extreme heat occurrences vary if using temperature or heat index for analysis; some cities have stronger differences than others

- We propose a definition for chronic humid heat as cities with daily maximum heat index greater than 90 degrees occurring for more than 90 days out of the year and 2 consecutive weeks of daily maximum heat index greater than 90 degrees

The characteristics of urban heat vary across cities. High humidity levels pose a threat to public health for those in close proximity to coastlines, particularly for cities with higher average temperature. With temperatures rising around the world due human activity, developing a more complete understanding of the main determinants of extreme heat is

important for predicting future heat levels. While average temperature for a city makes a good general descriptor for its climate, it alone can't give a complete picture, especially as it relates to human health. The variability around this average can better describe the climate and even serves as an indicator for the frequency of heat advisories needed. Using histograms of daily average and maximum readings for heat index and dry bulb temperature, different characteristics of each city's histograms were analyzed and compared against each other. We found that the upper range of a city's histogram is primarily dependent on latitude (R^2 of .713 for temperature, .408 for heat index), but is also influenced by average relative humidity, elevation, and distance from coast. This suggests that a city's most extreme heat values are closely tied to geographical constraints. By comparing our analysis with results from various heat-health studies, we also explored a potential definition of chronic heat as cities experiencing daily extreme heat values that lasted for more than 2 consecutive weeks and a total of 90 days out of the year.

TABLE OF CONTENTS

Page

List of Figures

List of Tables

Chapter 1: Introduction

This paper offers analysis of the climatologies of US cities and attempts to categorize different regions as experiencing humid or dry, acute or chronic heat in order to provide information for future heat-health studies to consider the acclimatization of their observed population, while also basing its analysis on frameworks put forth by similar research. Additionally, it presents a new framework for relating occurrences of extreme heat for a particular region based on the latitude and average temperature/heat index experienced, which can serve as a basis for predicting future maximum temperatures and heat index values, aiding the discussion of how warnings of extreme heat should be communicated to the public. It does not investigate the heat-health consequences of the different climatologies in the US, nor does it analyze the efficacy of the heat alert systems already in place.

Projections of extreme heat have become a focus of several recent studies. As the planet warms and is anticipated to continue warming, both researchers and policy makers are concerned about a growing frequency of heat-health consequences affecting global populations. Increased exposure to extreme heat has been correlated with higher mortality rates[1], shorter life spans[2], and decreased cardiovascular function [3]. This also presents a risk to productivity, as some areas may experience a growing number of days during which typical working hours become too hot for outdoor work to take place[4].

There have been recent occurrences of heatwaves across countries that reached unprecedented temperatures, calling the public's attention to the risk they pose. In the Zhang et al. 2020 paper, the researchers describe the problem: "The 2010 Russian Heat

wave, 2019 European heat wave, and 2021 pacific Northwest heatwave set temperature records more than three standard deviations beyond the mean hottest day of the year for their respective areas". This has emphasized a need for a better understanding of the underlying processes involved in extreme heat events[5]. Current knowledge of midlatitude heatwaves describes the importance of a variety of atmospheric anticyclones and associated atmospheric blocking[6], as well as soil moisture-atmospheric feedback[7-8]. However, understanding general trends that expand across multiple regions may be just as important as investigating individual processes restricted to a handful of regions.

Additionally, there are significant differences in the types of heat metrics that are appropriate for analyzing different cities. The typical discussion of humid versus dry heat introduces additional dimensions in understanding both heat-health consequences and the metrics used when deciding to issue heat alerts in response to heat waves[9]. However, not all regions experience periods of significant increases from average temperature, or heat waves, in an easily discernible way as is the case in midlatitude regions. New discussions of chronic heat, or prolonged periods where mean temperature/heat index remain at levels dangerous to human health are emerging amongst researchers focused on the heat in the tropics. This is in contrast to the acute heat typically described by a heat wave in midlatitude regions.

Further concern should be raised for the populations consistently exposed to prolonged periods of extreme heat, and therefore will be included in this analysis. Heat acclimatization occurs when a person's metabolic processes adjust to prolonged exposure of extreme heat, occurring between one to two weeks of consistent exposure[10]. This introduces new health risks when considering heat impacts on an interregional basis as

well as between subpopulations within the same region; indoor versus outdoor workers will have different types of exposure and thus have different metabolic responses to changes in outdoor temperature[11]. Furthermore, acclimatized workers still experience significant changes in skin temperature and cardiovascular activity when exposed to prolonged periods of extreme heat[12], suggesting that those with tolerance might be subject to risks begetting separate studies from unacclimatized subpopulations. There is also a capacity to heat tolerance, and the upper limit to survivable temperatures have already been observed in inhabited regions[13]. This information reinforces the need for classifying regions where almost none of the population is acclimatized (such as midlatitude regions that experience heat waves), some of the population is acclimatized (where outdoor workers regularly experience dangerous levels of heat), and virtually all of the population is acclimatized (like tropical regions where dangerous levels of heat last for two or more weeks).

Finally, recent research has drawn attention to the inconsistency of the heat alert systems across the country. Local National Weather Service offices are allowed to set their own guidelines for what temperatures or heat index levels trigger heat warnings, however the efficacy of this is questionable considering some cities (such as Miami) have disproportionately high heat mortalities considering the relatively limited number of heat alerts issued[9]. The complexity of this problem depends on both the wide variety of climatologies seen across the U.S. as well as the cultures inhabiting the different regions. By maintaining public faith in heat alerts by conservatively issuing them, these programs may fail to warn people who are unable to endure the extreme temperature for a given day; however, by overissuing alerts the public may decide to disregard them entirely.

In this paper, we seek to answer a series of questions:

- Do different cities observe differences in extreme heat frequency and duration?

- Are there significant differences in extreme heat occurrence if we observe heat index rather or temperature?

- Is there a way to correlate extreme heat occurrences or patterns with geographical constraints such as latitude?

  - Is this metric we used to examine extreme heat consistent with time?

Chapter 2: Data

All data were taken from the National Oceanic and Atmospheric Administration's Local Climatological Database (https://www.ncei.noaa.gov/cdo-web/datatools/lcd). This included observations of temperature, humidity, wet bulb temperature, and the date of recording. The meteorological python package was used to calculate heat index using this information. The data was then cleaned of alphabetical characters assumed to be erroneously entered.

Based on data availability, a 70-year period between 1950-2020 was examined for every city's analysis. Some weather stations were established more recently, so cities with at least 40 years of observations were permitted for analysis. The full map of cities selected can be seen below (see figure 1).
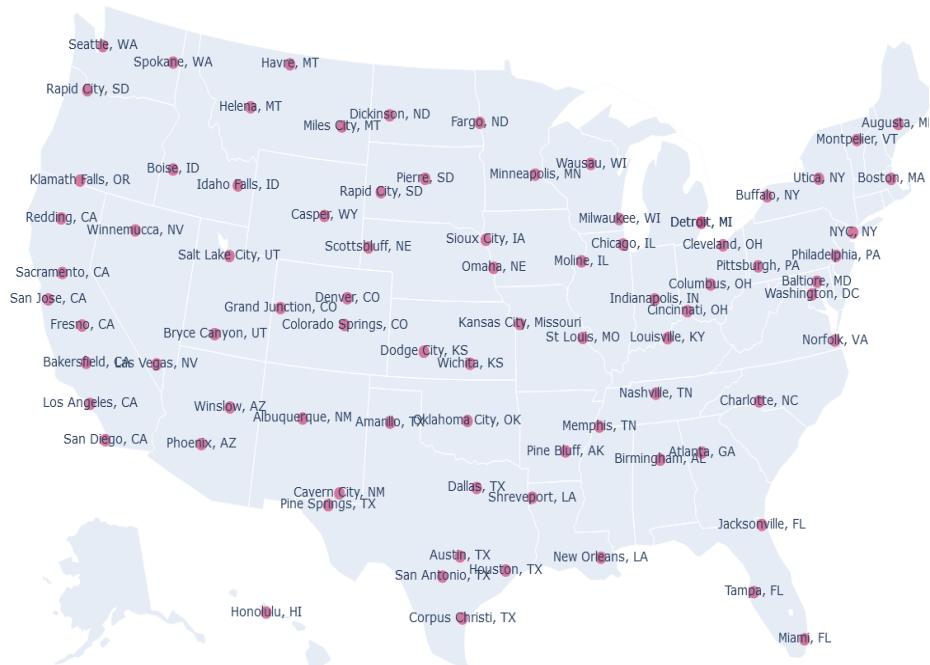

Figure 1. Map of all cities selected for analysis. Initial city selection was based on major population centers for each state (with the exception of Alaska). Subsequent cities were selected to fill in empty space on the map.

Chapter 3: Methodology

The hourly heat index and temperature (hereby referred to as heat values) were reorganized by day to locate daily maximums, averages, and minimums for each city. This information was then used to create separate histograms of daily values for the summer (June to August), as well as the full year (see figure 2).

The heat index values were calculated using python's Metpy package, which utilizes the Rothfusz equation in its calculation. The python function was altered to return heat index values for temperature and RH values outside of the ranges deemed appropriate for the equation. Because the conclusions drawn in this paper are based on extreme heat values, this served as a way to include the full dataset in analysis, even if the full dataset is not utilized in the more novel calculations.
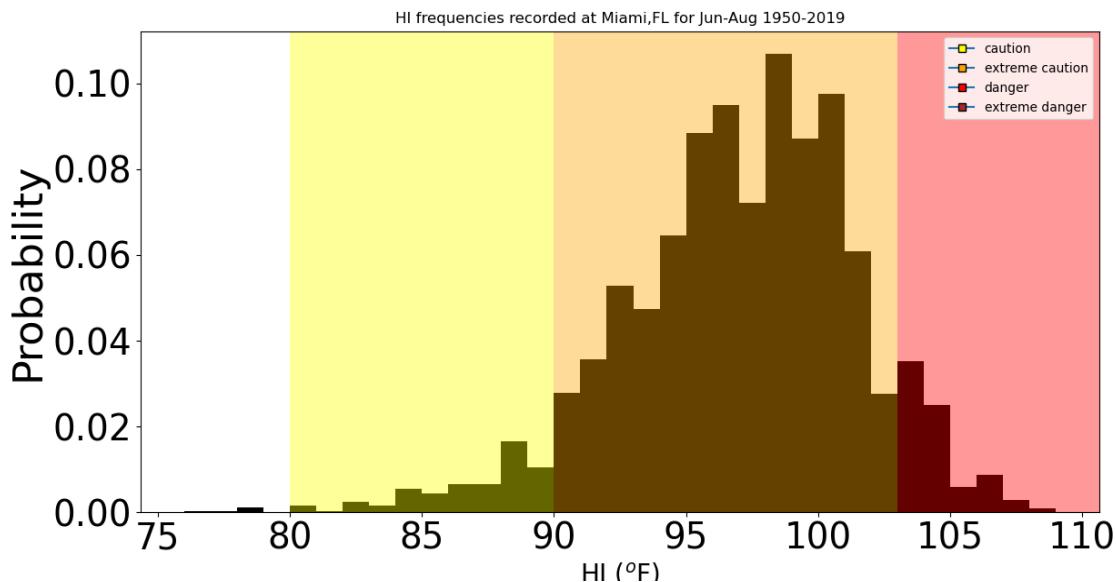

Figure 2. Example histogram for HImax for summertime days in the city of Miami, FL. Data was accumulated over the full period from 1950-2022. The National Weather Service's (NWS) heat index categories are overlayed onto the graph (see figure 3)

Classification	Heat Index	Effect on the body
Caution	80°F - 90°F	Fatigue possible with prolonged exposure and/or physical activity
Extreme Caution	90°F - 103°F	Heat stroke, heat cramps, or heat exhaustion possible with prolonged exposure and/or physical activity
Danger	103°F - 124°F	Heat cramps or heat exhaustion likely, and heat stroke possible with prolonged exposure and/or physical activity
Extreme Danger	125°F or higher	Heat stroke highly likely

Figure 3. The NWS heat index categories[19]. The 90º cutoff indicating heat stroke and related effects was used for several thresholds in this study

Several characteristics of each city's histogram (such as average, standard deviation, skewness, etc.) were then recorded for analysis (see figure 4). These were compared against city-specific geographical constants (like latitude, distance from coast, elevation, Koeppen climate zone type) and average relative humidity in joint hypothesis tests to determine the effects they had on PDF variables(see figure 5). A primary variable was chosen based on which univariable model had the highest R^2 value (typically latitude), and additional terms were included in subsequent fitting models. The p-value derived from the f-statistic was used to determine each model's significance.

Thresholds based on the minimum values of NWS heat index categories (see figure 3) were used to calculate the percentage of days that lie within the different categories or were equal or greater than the minimum value threshold (see figure 6). The analysis of these values were not included in this paper, however the values are available in the appendix.

The average of the daily values within the 99th-100th percentiles were recorded to sample each region for their hottest temperature/heat index value for a given year (max99 variable). This calculation gave representation for the hottest values a city typically experiences without giving too much consideration to the maximum recorded

temperature or heat index, thereby correcting for outliers. We subtracted this extreme heat value from the city's average heat value to depict the upper range of a region's temperature or heat index (which we called the Delta variable). This delta value can be used to characterize how strongly high heat periods in a city differ from their typical temperature or heat index. This quantity describes the range of heat-relevant exposure to which a city's population is exposed.

$$[1]\ \Delta = T^{99} - T^{avg}$$

Where T^{99} is the average heat value of the 99th-100th percentile for a given city. A similar formula is used for heat index

The full database was then subdivided and separate histograms were created for each year. The same average and delta values were recorded for timeseries analysis. This was used to determine how consistent a city's delta value is with time.

The length of each period of consecutive days over 90 degrees were also recorded as a metric for the length of periods of extreme heat in the area (the ACDO90, average consecutive days over 90). 90 degrees was chosen as it is the cutoff for the category where heat stroke and related effects begin to become a risk. Similarly, the annual number of days over 90 degrees (AAO90) was also recorded to demonstrate the occurrences of extreme heat in a city. Daily minimum temperatures were also analyzed in a similar manner, though the cutoff was lower to 70 degrees. This cutoff was lowered from its original value of 90 until the results displayed similar trends to daily maximum AAO90 were replicated (see Chronic versus Acute heat values section in results and discussion).

Relative Humidity (RH) data was also utilized in this analysis. To derive a representation of the typical RH for each city, we averaged the daily average RH values (RHavg,avg). Daily averages were chosen over daily maximums because their calculation includes more hourly values.

Variable	Name	Explanation	Variable	Name	Explanation
Avg	Average	Average value of all daily max or daily average values (uses summer months)	Mode		Mode of daily maximum or daily average values (summer)
Std	Standard Deviation	Standard deviation of daily maximum or daily average values (summer)	AAO90	Annual Average Number of days over 90	Average of annual number of days over 90º F (uses all months)
Skew	Skewness	Skewness of histograms (summer)	95Q	95th percentile	Value of the 95th percentile of all daily maximum (summer)
Min	Minimum	Smallest observed daily maximum or daily average (summer)	ACDO90	Annual Consecutive number of days over 90	Average of each year's average length of high heat period (consecutive days over 90º F) (summer)
Max99		Average of values between the 99th-100th percentile (summer)	Delta		Upper range of histogram values using Max99 (i.e. Max99 value - Average) (summer)
Max	Maximum	Largest observed daily maximum or daily average (summer)			
Median		Median of daily maximum or daily average values (summer)			

Table 1. Characteristics of histograms recorded for analysis. Values were gathered for every city using the full number of years available based on daily maximums or daily averages. Most values were gathered only using days within summer months, except for the AAO90. Values were gathered separately for temperature, heat index, and wet bulb temperature.

Geographical constant	Latitude	Distance from coast	Elevation	Koeppen climate zone type
Method information was gathered	Station coordinates	Geodesic distance between station coordinates and closest coastal point	Given with station information	Peel MC, Finlayson BL & McMahon TA (2007), Updated world map of the Köppen-Geiger climate classification, Hydrol. Earth Syst. Sci., 11, 1633-1644.

Table 2. Geographical constraints used in multivariate linear regression fittings

Variable	Pcau	POcau	Pexcau	POexcau
Heat index range	80-90	>=80	90-103	>=90
Variable	Pdan	POdan	Pexdan	
Heat index range	103-124	>=103	>=125	

Table 3. Heat index characteristics for each city's analysis. Describes the percentage of days that fit within a certain threshold. Results available in appendix.

All elements of this analysis were repeated using wet bulb temperature data, however the data was not used to make conclusions in this paper. The information for wet bulb temperature can be seen in the appendix.

Chapter 4: Results and Discussion

Average, Standard Deviation, and Skewness

The original analysis only included comparisons of each cities' daily maximum average, skewness, and standard deviation with latitude. Trends were compared using each city's $RH_{avg,avg}$. The following graphs only include days from summer months (June-August), so RH values were also only derived from summer months.
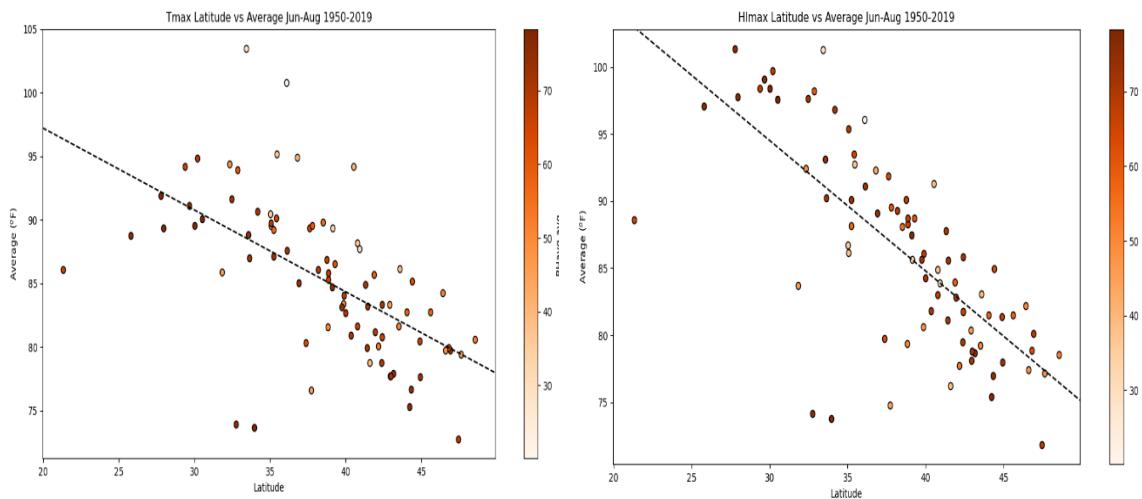

Figure 4. Latitude relationship with PDF average for daily maximum temperature (left, R^2 of .35) and daily maximum heat index (right, R^2 of .53) values. This graph depicts results for every city's summer months (June to August). The cities are color coded based on the $RH_{avg,avg}$ for each city. A line of best fit has been included in both graphs.

Predictably, both average daily maximum temperature and heat index demonstrate correlation with latitude (see figure 4), though average daily maximum heat index has a stronger relationship with latitude as suggested by the graph's accompanying R^2 value and line of best fit. Compared to daily maximum heat index, several cities in the average daily maximum temperature graph have stronger deviations from the line of best fit that is not completely explained by relative humidity (a multivariable fitting model of latitude and RH only revealed an R^2 of .54). This suggests a dependence on another variable not included in this analysis. Relative humidity was was not found to explain a significant

amount of the variance found in the daily maximum heat index graph. In summation, these graphs suggest that higher average temperatures are observable in lower latitudes and dryer cities, while higher average heat index is primarily observable in lower latitudes.
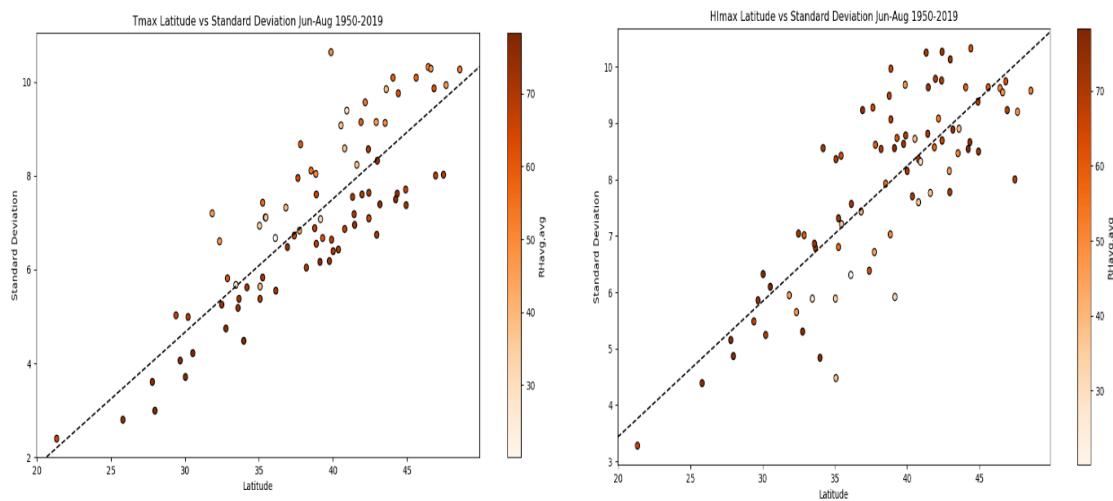
Figure 5. Latitude relationship with PDF standard deviation for daily maximum temperature (left, R^2 of .72) and daily maximum heat index (right, R^2 of .67) values. This graph depicts results for every city's summer months (June to August). The cities are color coded based on the RHavg,avg for each city.

Standard deviation demonstrates a surprisingly strong linear relationship for both daily maximum temperature and heat index when compared to latitude (see figure 5), revealing that heat value variation from the typical maximum temperature increases in northern cities compared to southern ones. It was this discovery that served as a basis for creating the delta variable (i.e. a descriptor of the variance above the average of the pdf). Interestingly, relative humidity does play a role in both these graphs (adding RH to the fitting model increases R^2 to .83 for daily maximum temperature and .70 for daily

maximum heat index), however higher relative humidity has a mitigating effect on daily
maximum temperature variance while it increases the variance of daily maximum heat
index.
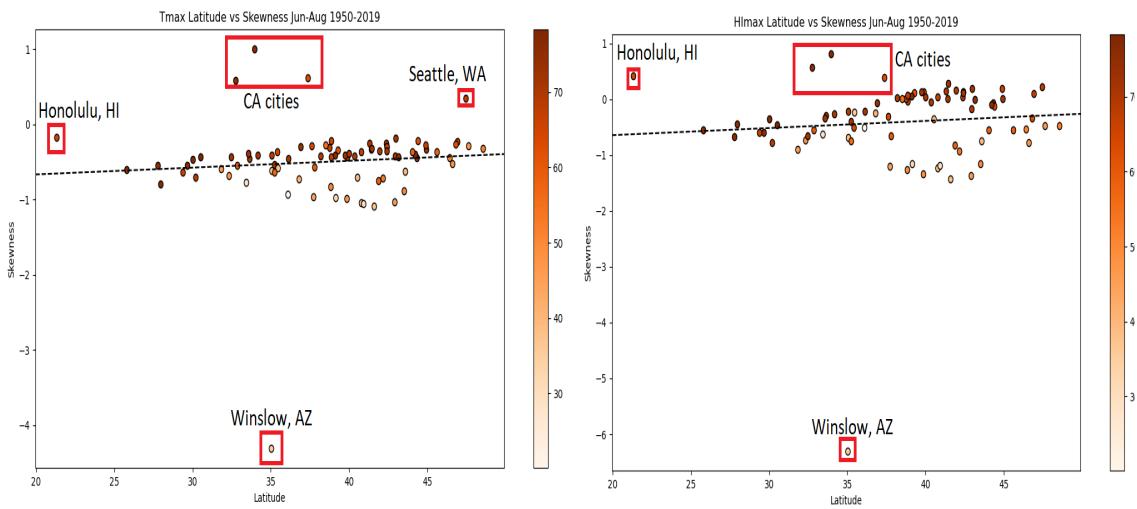
Figure 6. Latitude relationship with PDF skewness for daily maximum temperature values. This
graph depicts results for every city's summer months (June to August). The cities are color coded
based on the RHavg,avg for each city. Outlier cities have been labelled to aid discussion.

Skewness for both daily maximum heat values is seen to be consistent for the
majority of cities, independent of latitude. This demonstrates a very slight inclination to
heat values lower than the average daily maximum heat value. Honolulu, HI also
demonstrates this slightly negative skew, though it is less extreme than other cities that
more faithfully follow the skew line. As this was the only US city observed at this
latitude level, it becomes difficult to say if this is a result of the lower latitude or the
station being located on an island compared to other mainland cities. Several Californian
cities (San Jose, San Diego, Los Angeles) and Seattle Washington have distinctly positive

skew values for daily maximum temperature (though Seattle is not observed to replicate

this in the heat index graph). Winslow, AZ is observed to have the only distinctly

negative skewness of the cities observed. Because the weather data of this city expands

the same 70 year period as many of the other cities in this analysis, it is unlikely that this

outlier is due to a lack of data.

Upper range of heat values in relation to geographical constraints

The delta values for daily maximum temperature were found to be highly

correlated with the latitude of the respective city (see figure 7).
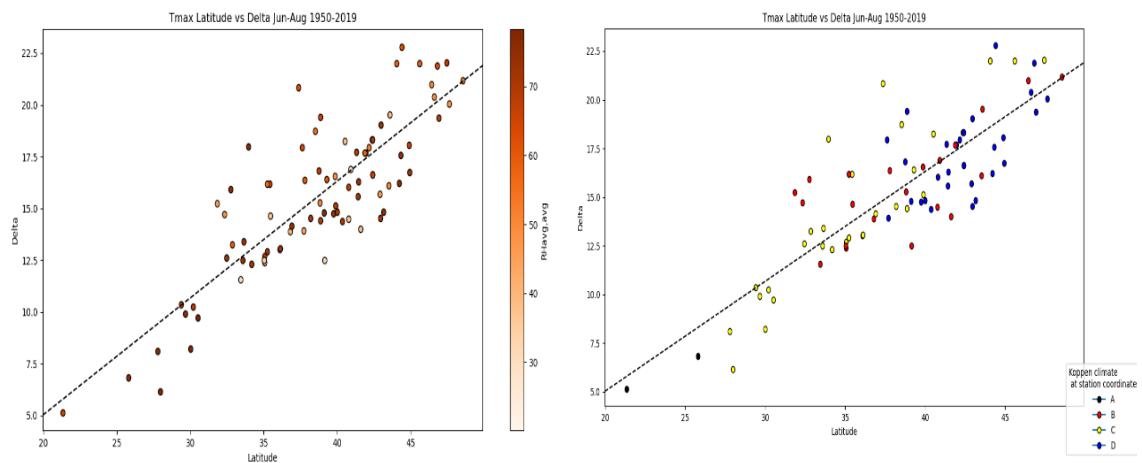
Figure 7. Latitude relationship with delta variable for daily maximum temperature values (R^2 of
.71). This graph depicts results for every city's summer months (June to August). The cities are
color coded based on the RHavg,avg (left) and the Koeppen climate zone at the station
coordinates (right).

The delta values very closely follow a trend line when compared to latitude. No

particular trend can be observed based on RHavg,avg, as the graph displays cities of all

RH levels on either side of the trend line and the addition of RH to the fitting model does

not result in a change of the R^2 value. Coupling this with the results from figure 8 would suggest that it is the variance below the PDF average that is most sensitive to relative humidity, or (less likely) that the most extreme temperatures excluded in our max99 calculation are both incredibly sensitive to relative humidity and were strong enough to influence the standard deviation plots seen in figure 5. The Koeppen climate zones did not display significant influence over the delta function, however the graph does manage to display the array of cities analyzed and how their climate zone type changes with latitude.

A similar relationship can be seen when considering each daily maximum heat index values (see figure 8), though a number of cities deviate more strongly from the trend line than in figure 7. This is observed to be influenced by the variation of humidity between cities.
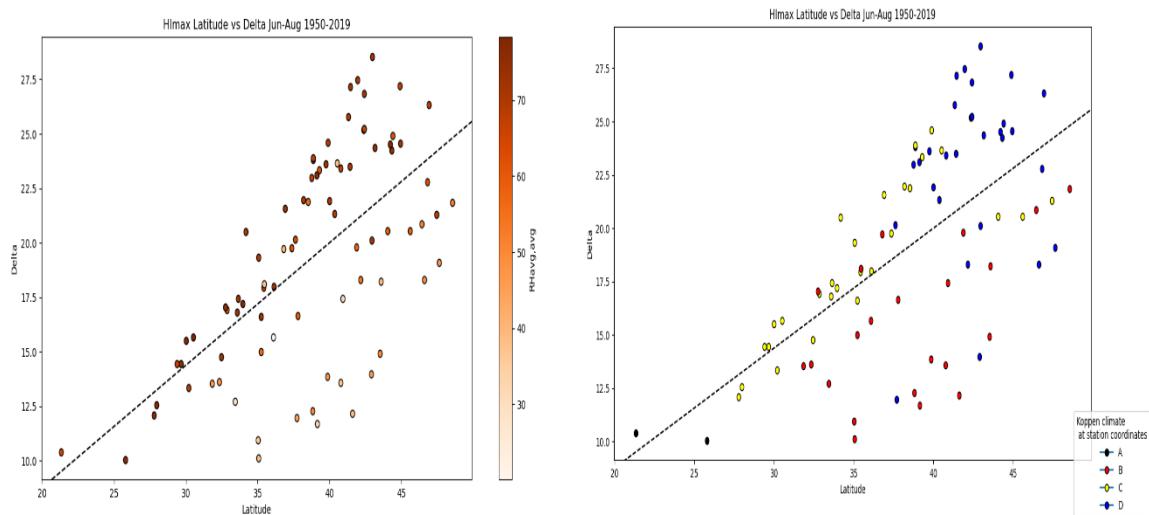

Figure 8. Similar to figure 10, but for the daily maximum heat index values of every city analyzed (R^2 of .41). The same month range (June to August) is used. The cities are color coded based on the RHavg,avg (left) and the Koeppen climate zone at the station coordinates (right).

The heat index graphs demonstrate the importance of average relative humidity levels in relation to a city's delta value. When adding RH to our fitting model, we see a new R^2 value of .65. Cities with higher average relative humidity more closely follow their own trend line, similar to the pattern seen in figure 7. Cities with lower relative humidity have a lower delta value compared to cities of similar latitudes, although this trend is only observable sometime above 30° in latitude. This suggests that cities with lower relative humidity have extreme temperatures closer to their average. This drop in delta values appears to occur after 30° latitude, where B type (arid) climate zones start appearing on the map. D type (continental) climate zones also experience this drop in delta value, with cities of similar latitude having high delta values based on average RH. Most C type (temperate) climate zones very closely follow the trend shared by other high RH cities; a few exceptions can be seen in the Northernmost cities.

For both daily maximum temperature and heat index, the smaller delta values observed at lower latitudes and several desert cities suggest a difference in behavior for what may be considered extreme heat for a given city. While strong deviations from average heat values are easily discernable in the majority of northern cities (approximately 20 degrees for temperature or 30 degrees for heat index), southern and desert cities observe more subtle changes (5-10 degrees for temperature and 10-15 for heat index). Coupling these results with the ones found in our average daily maximum temperature graph, we see that southern cities experience hotter days with extreme days closer to their average, while northern cities experience comparatively milder heat and extreme heat days that strongly deviate from their average.

Using multivariable linear regression, the relationship between delta with latitude, distance from coast, and elevation were calculated, with. The R^2 values for different models can be seen below (see Table 4).

Variable	Latitude	Latitude + Elevation	Latitude + DFC + Elevation
Delta (Temperature)	.713 (<.001)	.714 (<.001)	.719 (<.001)
Delta (Heat Index)	.408 (<.001)	.804 (<.001)	.808 (<.001)

Table 4. R^2 values from linear fits of delta with several different fitting models. The numbers in parenthesis describe the significance probabilities derived from the F-statistics

The upper range of both heat values is primarily dependent on latitude, though with heat index elevation appears to be just as important. Distance from coast and elevation have a more significant role when considering heat index, and is thought to be a result of humidity's contribution to the heat value (temperature or heat index). Distance from coast and elevation have significantly less important in affecting temperature delta values and it is questionable if they are relevant factors. As relative humidity was thought to be a function of both elevation and distance from coast, this is in agreement with the assessments drawn from figure 7.

<u>Delta variation with time</u>

Delta was tested to see if it is a stable heat descriptor of a city, as its validity as a climate predicting variable is contingent on consistency with time. To test this, each city's delta value was recalculated for each year (see figure 9). A wide variety of slopes and probability values were observed, as well variance between yearly values (see appendix B).
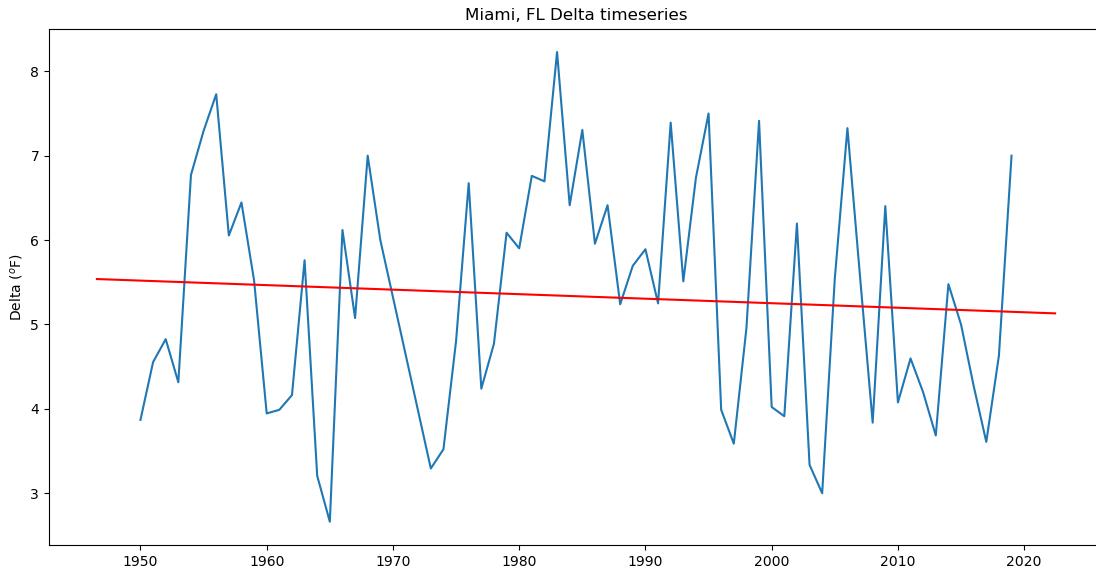
Figure 9. Example of summer time (June-August) delta timeseries (blue) linear regression for Miami, FL from 1950 to 2020. The graph is based on daily maximum temperature values. A line of best fit (red) has been overlayed.

Despite the variation of linear regression results as well as the values between years, the delta values display a degree of consistency when examined over extended periods of time (see Table 5).

Heat Value	Median Upper range from average (ºF)	Median range variance from average (ºF)	Strongest average change over analysis period (ºF)
Daily Max Temperature	5.69	4.43	3.93
Daily Max Heat index	9.91	5.56	4.68

Table 5. Table sampling the results of time dependence on delta values. The upper/lower range from averages are the differences between the maximum/minimum delta values and the average delta values of the timeseries, with the median being computed from the results of all cities. The strongest average change over analysis is the average absolute value of the difference between each year's delta value and the average delta values of the time series; the largest value has been selected to be shown here. The full version of this table can be seen in appendix B.

Based on the average change of delta over the analysis period, delta can be expected to deviate from its average by 4-5 degrees. The upper and lower ranges agree

with the average change results, with the exception of the upper range for daily maximum

heat index. This large variation could be explained by outliers observed for specific years

in particular cities (see figures 10 and 11).
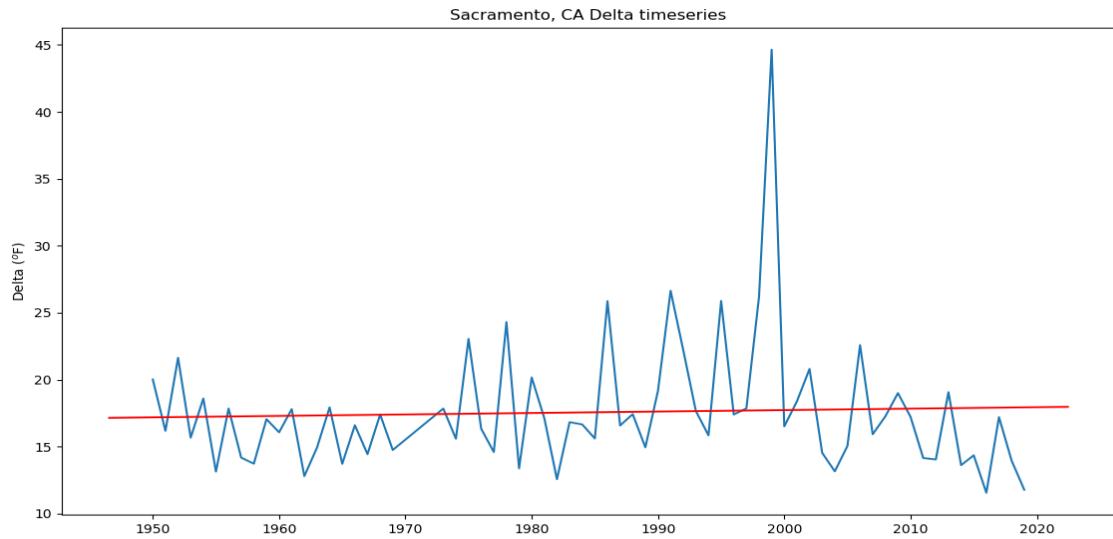
Figure 10. Timeseries analysis of delta using daily maximum heat index for the city of
Sacramento, CA for the summer months (June-August). The delta values display consistent
behavior for the majority of years with the exception of 1999 when a singular 128 °F day was
recorded.

Considering the accuracy of the delta value is compromised by outliers, the

reduced numbers of days in a yearly analysis will make recording errors have drastic

effects on timeseries analysis. This is why the original calculation for delta spanned as

many years as possible while only sampling results from the 99th-100th percentile.
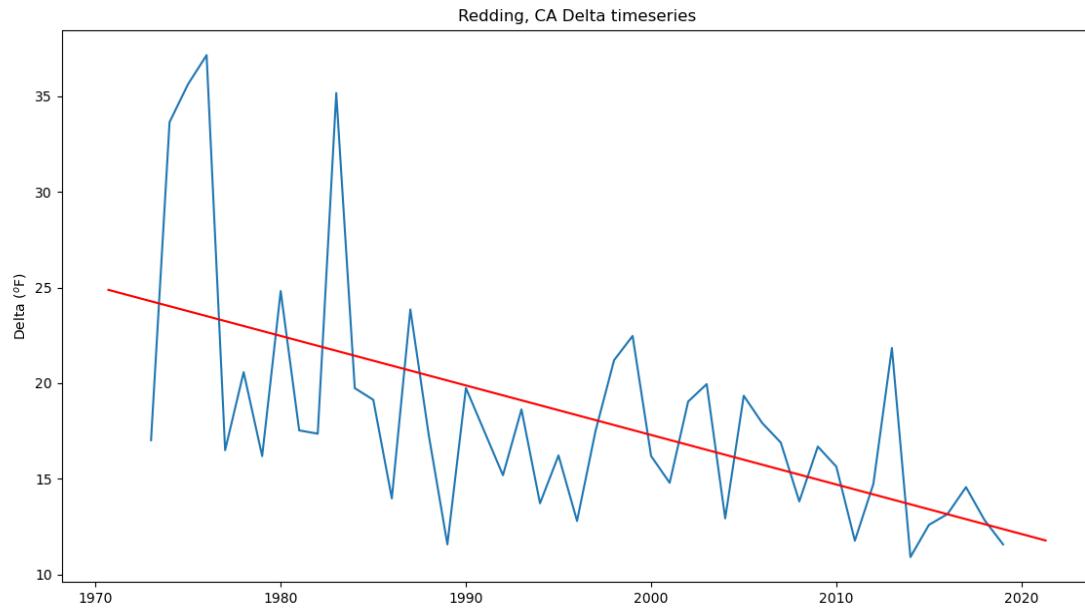
Figure 11. Timeseries analysis of delta using daily maximum heat index for the city of Redding, CA for the summer months (June-August). The delta values in later years display more consistency than the later years, however due to the relatively limited number of observations the earlier years were still included in analysis.

  With the current results it becomes difficult to conclude whether or not this climate predicting variable is precise enough to have useful applications, therefore further research is required. Based on the current results, it would appear consistent for some cities, others have a trend, and a few have occasional spikes. Careful consideration for which cities are chosen in the timeseries analysis is a necessity, as a single entry recorded for Sacramento, CA (figure 10) drew into question its usefulness in this analysis. Despite the ambiguity of the consistency of the delta values, the latitudinal dependence observed in the previous section is unmistakable. This continues to aid the argument that northern and southern cities experience very different patterns in their extreme heat.

Chronic versus Acute heat values

The final analysis of this study compares the types of extreme heat between different cities in the U.S. The efficacy of the criteria concerning the NWS heat alerts has become a prevalent topic in recent studies, however no simple solution has been found. To demonstrate the complexity of the problem, the annual average over 90 (AAO90) for each city was compiled in a single graph, with both temperature and heat index values displayed side by side (see figure 12).
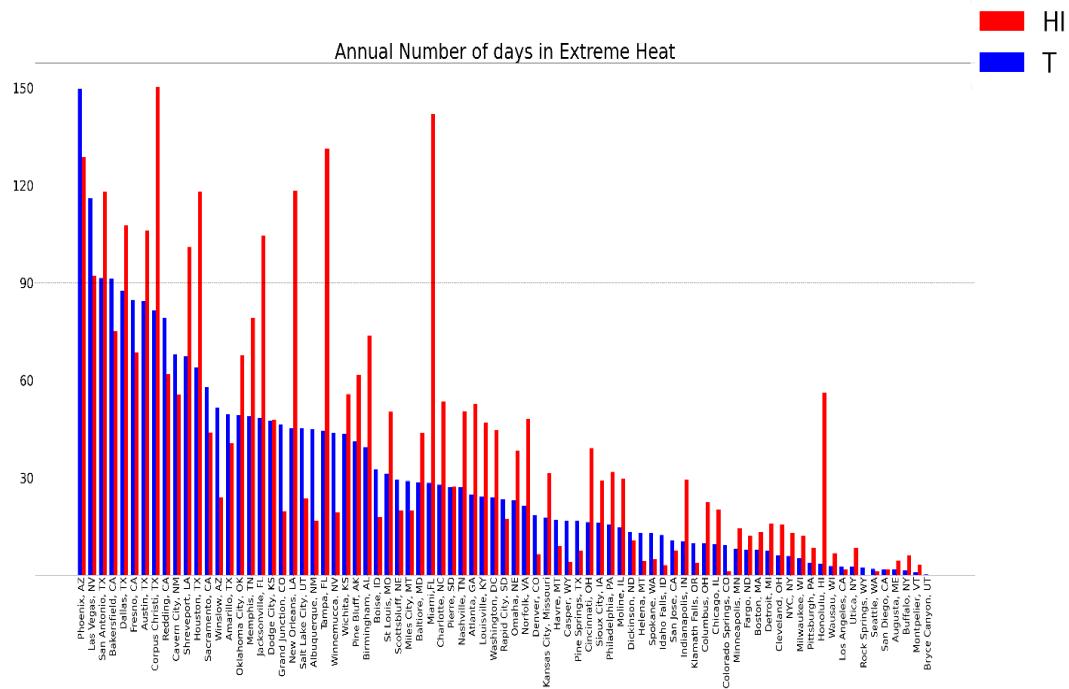
Figure 12. The annual number of days over 90 degrees for both temperature and heat index values. The data is based on daily maximums for both heat values. This graph uses data from the full year.
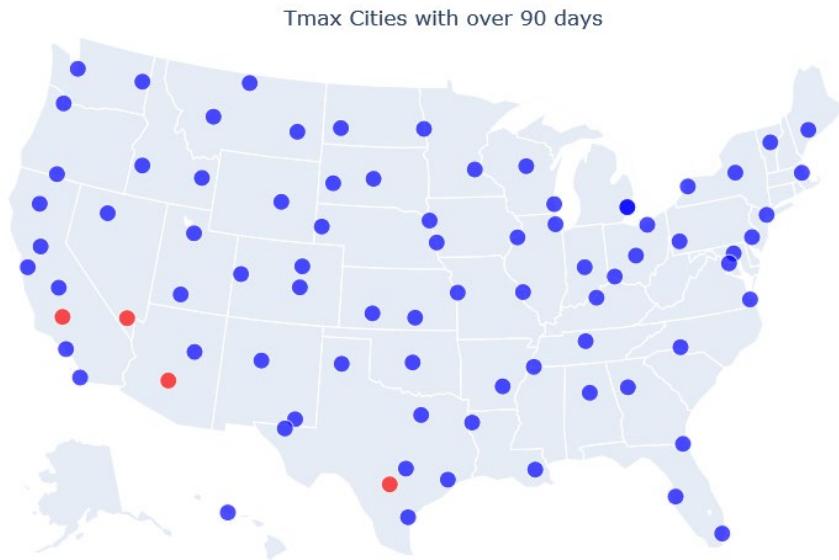
Figure 12a. Map of cities whose annual number of days over 90 degrees cross over the 90-day cut-off, based on daily maximum temperature observations
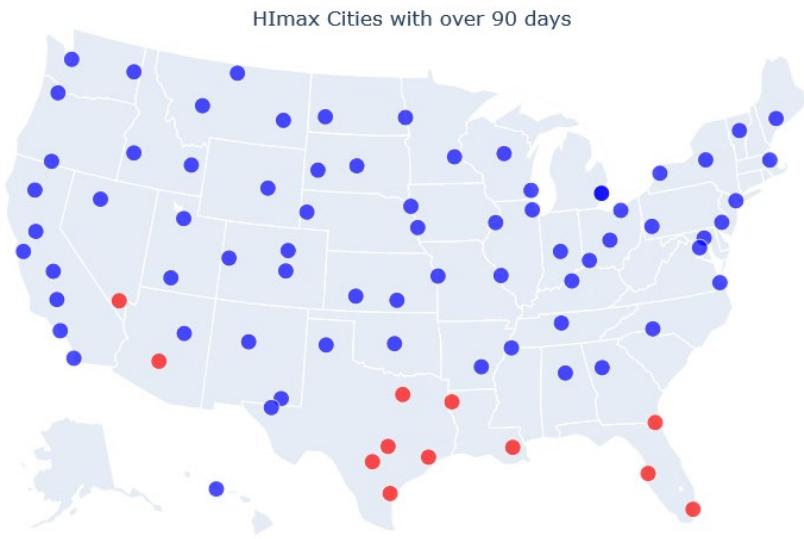
Figure 12b. Same as figure a, but uses daily maximum heat index observations

As can be seen in the graph above, choosing temperature or heat index as an appropriate heat value is highly based on the city in question. For example, some cities that rarely reach extreme temperature values demonstrate the highest frequency of extreme heat index values (e.g. Miami, Tampa, New Orleans). Some desert cities like

Phoenix and Las Vegas see slightly fewer days over 90 when Heat Index is considered

rather than temperature. A cut-off-line of 90 days was included in the graph to

demonstrate which cities regularly see 3 months worth (or a full summer) of days with

extreme heat values. Included with this graph are two geospatial plots depicting cities that

cross over this 90-day threshold (see figures 12a and b). By comparing the temperature to

heat index maps, one can see that the majority of the cities that are only highlighted on

the heat index map have close proximity to the Gulf of Mexico, but are also some of the

southern-most cities in the US.

    To demonstrate which cities experience durations of extreme heat reaching past

the acclimatization period, another graph was created to depict the annual consecutive

days over 90 (see figure 13).
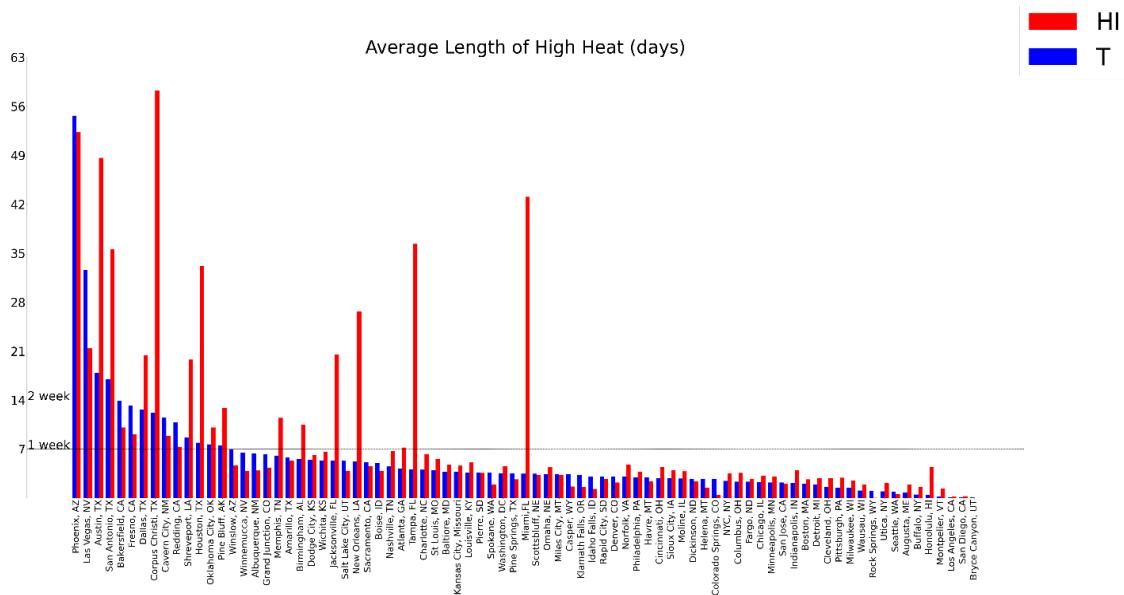
Figure 13. Average length of high heat periods (consecutive days over 90 degrees) for every city analyzed. This graph only uses data from the summer (Jun-Aug)
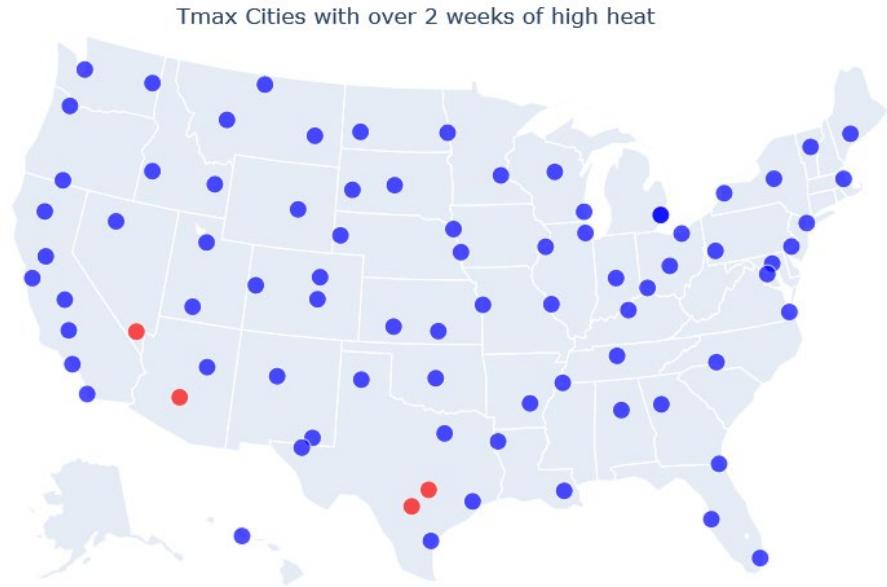
Figure 13a. Map of cities whose average length of high heat extends past the 2-week cut off, based on daily maximum temperature observations
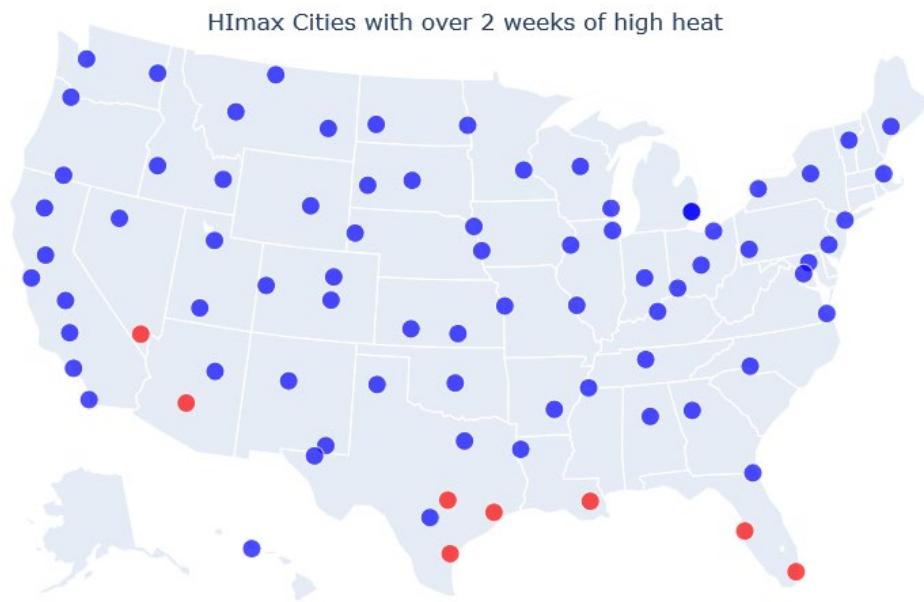
Figure 13b. Same as figure a, but uses daily maximum heat index observations

One can see again that heat index is only an appropriate metric for certain cities.

While the majority of cities do not experience periods of high heat crossing the 2 week

mark, a handful do and even extend far past the cutoff. Demonstrated by the geospatial plots (see figures 13a and b) included, the majority of the ones that are highlighted only on the heat index map have close proximity to the gulf of Mexico, but are also the southern most cities in the US.

These results suggest that extreme heat (and its associated effects) varies drastically for different cities depending on climate zone type and latitude. The prolonged exposure only seen in certain areas implies a lack of a typical "heat wave" as seen in northern cities but rather extended periods of high heat that have differing degrees of severity not included in this analysis.

This experiment was repeated using daily minimum temperatures, with the intention of analyzing each city's potential for "cool off periods" typically seen during nighttime. The threshold was gradually lowered from 90 degrees in order to display results similar to the graphs shown above, with the final threshold being 70 degrees. Because the Rothfusz equation for heat index is not appropriate for calculating values that low, only temperature was included in this analysis.
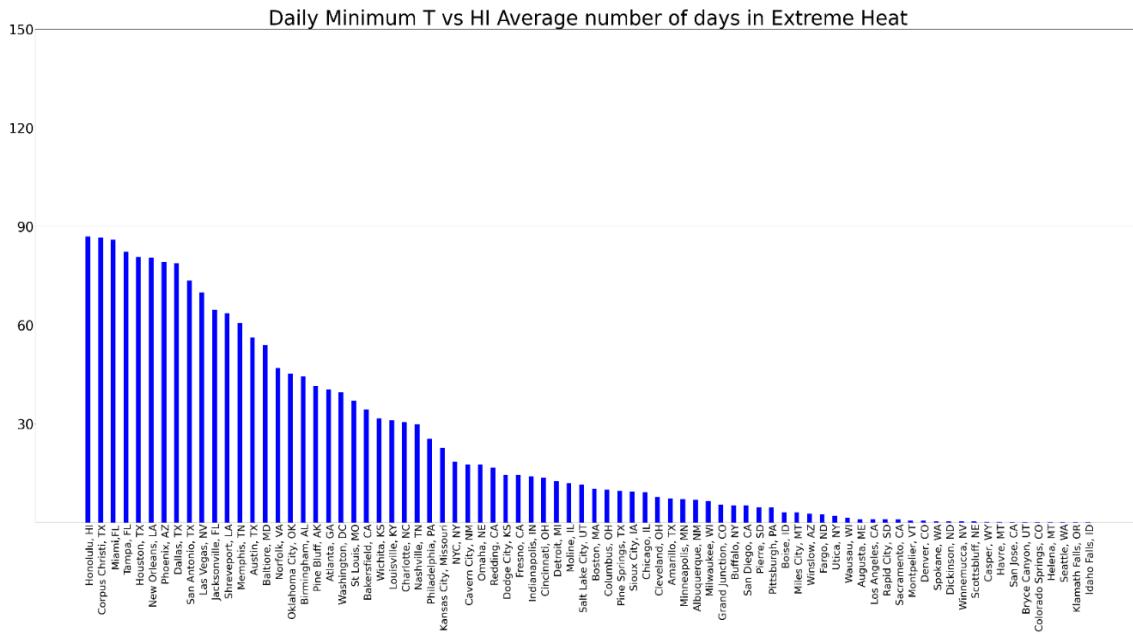
Figure 14. Annual average number of days over 70 degrees using daily minimum temperature.

As seen in figure 14, no cities cross over the 90 day threshold. Although a number of cities do come close; among them are Corpus Christi, Miami, Tampa, and others that were all determined to be cities of interest from graphs 12 and 13. This shows that cities that regularly experience extreme heat offer very few potential "cool off periods", which may exacerbate heat related effects for their respective populaces.

Daily Minimum T vs HI Average Length of High Heat (days)
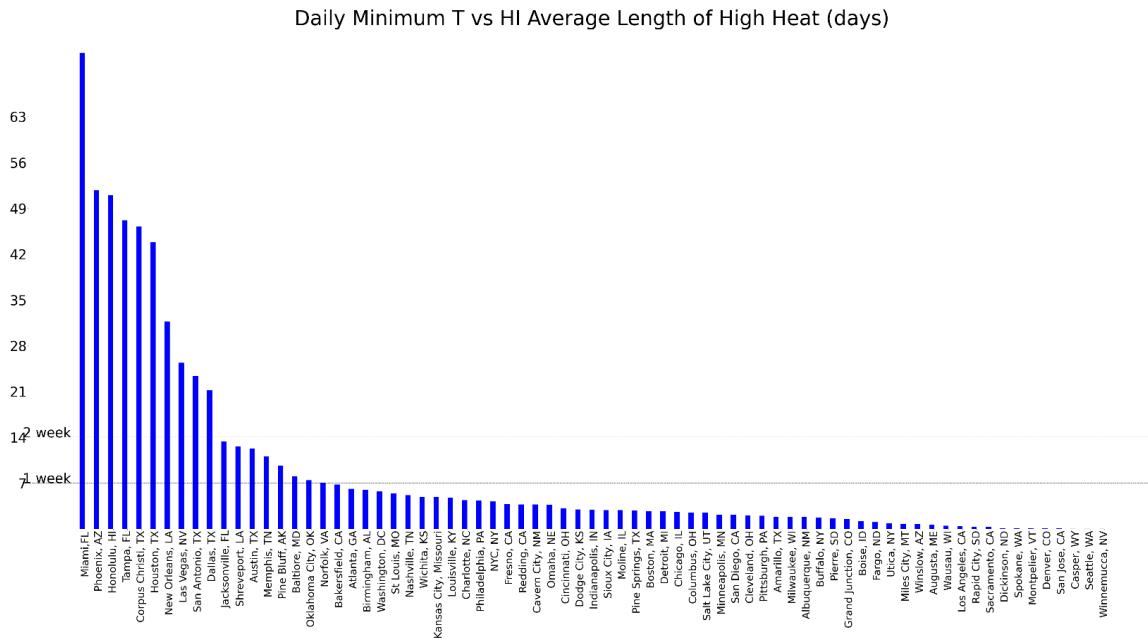
Figure 15. Average length of high heat periods (consecutive days over 70 degrees) using daily minimum temperature for every city analyzed.

Tmin Cities with over 2 weeks of high heat
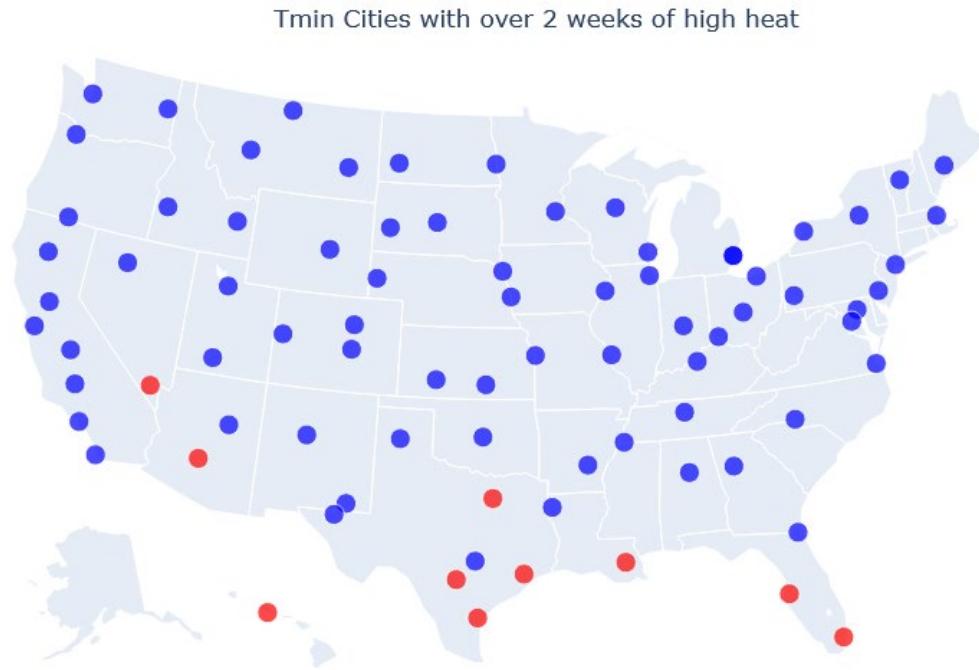
Figure 15a. Map of cities whose average length of high heat extends past the 2-week cut off, based on daily maximum temperature observations

Figure 15 and its accompanying figure shows the length of extreme heat periods

for daily minimum temperature. When compared to figures 12 and 13, one can again

see that cities demonstrating extended extreme heat periods do not offer "cool down periods", similar to figure 14. While this analysis does not cross-compare daily maximum extreme heat periods seen in each city with their respective daily minimums, it does offer some depiction of the nighttime periods.

The data of this section shows that extreme heat periods vary strongly across cities, and that the cities with the most extreme daytime heat similarly have comparatively high nighttime heat. We argue that the extreme differences in heat exposure suggest a need for different categorizations of cities into those that experience acute (shorter term, more rare periods of extreme heat) versus chronic heat (long lasting, more common periods of extreme heat).

Chapter 5: Conclusions

In this paper, we explored novel metrics for describing different patterns of extreme heat across multiple US cities. We sought to correlate extreme heat metrics with geographical constraints, and by using the delta variable we've described the relationship for the upper range of extreme heat for a given city. A strong latitudinal dependence was observed in both temperature and heat index, suggesting that at a certain latitude the behavior of extreme heat values changes drastically. While it was not possible to prove that delta remained constant with time, future research into this variable could result in it becoming a practical and valuable method of classifying different types of heat as well as predicting the degree of extreme heat a population will be exposed to.

The researchers also displayed variation in types of extreme heat based on the number of days that reached heat values hazardous to human health and the length of these periods. This served to suggest that extreme heat takes on drastically different behavior based on the city observed, as acclimatized populations would most likely be present in cities that are regularly exposed to dangerous levels for extended periods of time. Some cities were barely observing periods that extended past the acclimatizion cutoff, whereas others have periods of high heat that can last upwards of a month. Additionally, those same cities experiencing longer-lasting extreme heat periods maintain comparatively high heat during nighttime hours as well. These results correspond with the results seen in the delta section of this paper, and would suggest a need for different classes of heat health consequences for the populations of the respective cities. While southern cities experience prolonged periods of dangerous heat levels that extend well

past the acclimatization period, what is classifiable as relatively extreme heat for those cities strongly differs from the more dramatic heat spikes observed in northern cities.

Finally, we also explored the differences in extreme heat occurrence using both temperature and heat index. Our analysis revealed that, depending on the city in question, extreme heat index occurrences can be starkly different from that of extreme temperature. This supports a need not only for classifications of acute (shorter term, more rare periods of extreme heat) versus chronic heat (long lasting, more common periods of extreme heat), but also for chronic humid versus chronic dry heat.

There is a comparative lack of literature exploring the effects that prolonged exposure to dangerous levels has on acclimatized populations than what heat waves do to affect unacclimatized groups. While acclimatization offers resilience to extreme heat, studies suggest there is a limit to what can be endured and there are still serious heat-health consequences involved. It is the hope of the researchers that this study will provide motivation and basis for future studies to consider the effects of extreme heat across different classifications of cities separately in the future. There is a need for conclusions derived from studies that make appropriate considerations for the cities involved. This would greatly benefit at-risk populations by guiding future heat alert systems.

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Appendix A: City Information

City	Region	Koppen (by station coordinates)	Latitude	Longitude
MIA second try	Miami	A	25.78805	-80.3169
Albuquerque, NM	SW	B	35.04189	-106.615
Atlanta, GA	SE	C	33.62972	-84.4422
Austin, TX	SW	C	30.18311	-97.6799
Baltiore, MD	NE	C	39.2814	-76.6111
Birmingham, AL	SE	C	33.56545	-86.7449
Charlotte, NC	SE	C	35.22254	-80.9543
Colorado Springs, CO	W	B	38.80949	-104.689
Corpus Christi, TX	SW	C	27.77335	-97.513
Dallas, TX	SW	C	32.83839	-96.8358
Fresno, CA	WC	B	36.77999	-119.72
Houston, TX	SW	C	29.64586	-95.2821
Jacksonville, FL	SE	C	30.49529	-81.6937
Las Vegas, NV	W	B	36.0719	-115.163
Los Angeles, CA	WC	C	33.93816	-118.387
Memphis, TN	SE	C	35.05639	-89.9864
Nashville, TN	SE	C	36.11054	-86.6882
New Orleans, LA	SE	C	29.99755	-90.2777
NYC, NY	NE	D	40.77898	-73.9693
Oklahoma City, OK	SW	C	35.41667	-97.3833
Philadelphia, PA	NE	C	39.87326	-75.2268
Phoenix, AZ	SW	B	33.4278	-112.004
Salt Lake City, UT	W	B	40.77069	-111.965
San Antonio, TX	SW	C	29.38333	-98.5833
San Diego, CA	WC	B	32.7336	-117.183
San Jose, CA	WC	C	37.35938	-121.924
Tampa, FL	SE	C	27.96331	-82.54
Denver, CO	W	B	39.84657	-104.656
Wichita, KS	MW	D	37.61667	-97.2667
Kansas City, Missouri	MW	D	38.84389	-94.5603
St Louis, MO	MW	D	38.75246	-90.3734
Indianapolis, IN	MW	D	39.72515	-86.2816
Louisville, KY	SE	C	38.17738	-85.7308
City	Region	Koppen (by station coordinates)	Latitude	Longitude

City	Region	Koppen (by station coordinates)	Latitude	Longitude
Columbus, OH	MW	D	39.99068	-82.877
Cincinnati, OH	MW	D	39.106	-84.4161
Washington, DC	NE	C	38.84721	-77.0345
Pittsburgh, PA	NE	D	40.3551	-79.9215
Buffalo, NY	NE	D	42.93998	-78.7361
Norfolk, VA	SE	C	36.90371	-76.1927
Utica, NY	NE	D	43.145	-75.3839
Boston, MA	NE	D	42.36057	-71.0098
Augusta, ME	NE	D	44.3161	-69.797
Cleveland, OH	MW	D	41.40568	-81.8519
Detroit, MI	MW	D	42.40725	-83.009
Chicago, IL	MW	D	41.96017	-87.9316
Milwaukee, WI	MW	D	42.95489	-87.9045
Wausau, WI	MW	D	44.9275	-89.6253
Minneapolis, MN	MW	D	44.88523	-93.2313
Fargo, ND	MW	D	46.92424	-96.8119
Pierre, SD	MW	D	44.38191	-100.286
Dickinson, ND	MW	D	46.79968	-102.797
Omaha, NE	MW	D	41.31186	-95.9019
Miles City, MT	W	B	46.42647	-105.883
Scottsbluff, NE	MW	B	41.87466	-103.601
Casper, WY	W	D	42.89778	-106.474
Helena, MT	W	D	46.60444	-111.989
Boise, ID	W	B	43.56705	-116.241
Seattle, WA	WC	C	47.44467	-122.314
Rapid City, SD	WC	C	45.59578	-122.609
Honolulu, HI	H	A	21.32402	-157.939
Montpelier, VT	NE	D	44.20503	-72.5655
Detroit, MI	MW	D	42.40725	-83.009
Rapid City, SD	MW	B	44.04582	-103.054
Redding, CA	WC	C	40.51462	-122.298
Rock Springs, WY	W	B	41.59465	109.0529
Klamath Falls, OR	WC	D	42.14702	-121.726
Bakersfield, CA	WC	B	35.43424	-119.055
Sacramento, CA	WC	C	38.50659	-121.496
Spokane, WA	WC	D	47.62168	-117.528
Idaho Falls, ID	W	B	43.52044	-112.068
Winnemucca, NV	W	B	40.90178	-117.808
Havre, MT	W	B	48.54254	-109.764
City	Region	Koppen (by station coordinates)	Latitude	Longitude

Grand Junction, CO	W	B	39.13437	-108.541
Bryce Canyon, UT	W	D	37.70127	-112.149
Winslow, AZ	SW	B	35.02795	-110.722
Dodge City, KS	MW	B	37.77105	-99.9692
Amarillo, TX	SW	B	35.22027	-101.717
Cavern City, NM	SW	B	32.33355	-104.258
Pine Springs, TX	SW	B	31.83274	-104.809
Sioux City, IA	MW	D	42.39169	-96.3795
Pine Bluff, AK	SW	C	34.17981	-91.9344
Shreveport, LA	SW	C	32.4473	-93.8244
Moline, IL	MW	D	41.44816	-90.5237

Appendix B: Delta Timeseries Results

city	U Range -Heat Index	L Range – Heat Index	Avg change – Heat Index	U Range -Temp	L Range – Temp	Avg change - Temp
Albuquerque, NM	4.446223	4.584044	1.291303	4.590953	3.496004	1.609984
Amarillo, TX	5.372846	3.769487	1.629512	4.519745	4.578081	1.915555
Atlanta, GA	10.03694	5.142222	2.005305	7.121512	4.258923	1.649375
Augusta, ME	16.17885	7.867255	3.457435	5.748328	4.360368	1.94488
Austin, TX	15.03241	5.61948	3.630752	5.239333	3.010667	1.558716
Bakersfield, CA	16.41507	5.657566	2.888389	5.009223	4.42556	1.666008
Baltiore, MD	10.93549	5.019323	2.788592	3.729106	3.337333	1.551487
Birmingham, AL	9.176822	4.217871	1.951783	5.459442	4.670993	1.679211
Boise, ID	6.836678	5.856013	1.956299	5.92854	5.888654	2.192511
Boston, MA	8.180584	7.070909	2.82203	5.371016	4.47681	1.928144
Bryce Canyon, UT	38.16726	4.469048	2.347707	20.2482	4.346253	2.059889
Buffalo, NY	12.27594	5.42147	2.577286	4.69644	4.542691	1.55877
Casper, WY	7.747012	3.870649	1.817808	5.594257	3.97096	1.761891
Cavern City, NM	7.27265	5.438464	1.817091	4.769147	4.483658	1.968087
Charlotte, NC	7.387044	4.223129	1.863463	4.647956	3.504218	1.592211
Chicago, IL	10.29179	10.48144	3.321052	5.68463	5.293631	1.921275
Cincinnati, OH	14.16118	6.684253	2.773961	5.31087	3.504348	1.602283
Cleveland, OH	9.674838	6.173098	3.196226	6.627515	4.698572	1.362059
Colorado Springs, CO	4.587255	4.279356	1.482001	4.403752	4.520161	1.581273
Columbus, OH	10.58018	6.586276	2.927656	6.471014	3.681159	1.543823
Corpus Christi, TX	6.209162	3.731801	1.747583	4.032453	3.000155	1.372218
Dallas, TX	18.44107	4.367163	2.34276	4.206832	3.086646	1.3152
Denver, CO	7.295271	11.02601	2.326874	3.720023	13.09519	2.225526
Detroit, MI	13.3945	6.969257	3.689872	5.132932	3.84243	1.772116
Dickinson, ND	9.84724	7.698134	2.844314	7.997763	6.17615	2.537934
Dodge City, KS	8.182649	4.925043	1.982153	5.202747	3.742905	1.813104
Fargo, ND	11.09437	8.111612	3.007382	7.613967	6.581685	2.336968
Fresno, CA	10.5589	6.680465	2.703573	5.882511	4.574011	1.688088
Grand Junction, CO	6.158329	3.710792	1.539871	4.951168	3.733615	1.598715
Havre, MT	15.51922	5.540977	2.912421	6.975437	4.785433	2.394129
Helena, MT	6.126637	4.662046	1.844407	6.669796	4.047596	2.011738
Honolulu, HI	8.286978	3.608242	1.799388	2.116304	1.655435	0.632228
Houston, TX	15.28497	4.166759	2.058045	5.204768	2.458275	1.395246
Idaho Falls, ID	4.608596	4.181241	1.640738	3.997684	4.274056	1.573987
Indianapolis, IN	11.17996	8.884369	3.118963	5.726963	3.45782	1.639292

city	U Range -Heat Index	L Range – Heat Index	Avg change – Heat Index	U Range -Temp	L Range – Temp	Avg change - Temp
Jacksonville, FL	9.835578	5.279286	2.503111	4.767426	2.906487	1.282225
Kansas City, Missouri	12.1283	19.16885	2.914656	5.613224	4.76315	2.305753
Klamath Falls, OR	9.907376	5.006777	2.768675	10.24027	5.571321	2.383104
Las Vegas, NV	11.96708	3.691163	1.762724	4.303195	3.696805	1.352083
Los Angeles, CA	9.367324	6.568736	2.997021	12.9197	6.634653	3.933349
Louisville, KY	8.352865	6.161006	2.807298	6.014925	3.724205	1.567552
Memphis, TN	5.814926	5.299114	1.866231	4.648605	3.829656	1.417964
MIA second try	3.776158	3.506016	1.353481	2.896658	2.668559	1.179347
Miles City, MT	9.157372	5.971625	2.743238	5.670949	4.774704	2.132022
Milwaukee, WI	14.57962	10.28157	3.683686	5.150245	7.023668	2.004196
Minneapolis, MN	10.9168	6.418003	3.129868	8.203277	4.37281	1.852286
Moline, IL	10.23481	7.195835	3.561039	5.924075	4.43462	1.713013
Montpelier, VT	25.3973	8.702365	4.684052	15.91539	5.497649	2.124272
Nashville, TN	7.527287	5.036243	2.161784	7.44003	3.766492	1.662501
New Orleans, LA	6.365655	3.925297	1.925913	3.494724	2.277015	1.143466
Norfolk, VA	7.717843	5.558431	2.583621	5.045587	3.617456	1.418303
NYC, NY	9.589905	7.295822	3.086505	6.64034	4.84879	1.833468
Oklahoma City, OK	10.51091	5.67637	2.109277	5.686508	3.704796	1.857061
Omaha, NE	8.287079	8.66482	2.916105	6.581862	4.483356	1.976285
Philadelphia, PA	26.36973	8.600249	3.932929	4.146009	5.310513	1.686238
Phoenix, AZ	6.187781	3.744438	1.474485	7.535853	4.496755	1.384897
Pierre, SD	8.547271	7.184422	2.788134	6.099448	5.987508	2.143341
Pine Bluff, AK	13.18856	5.62314	2.949693	6.441123	4.341486	1.586353
Pine Springs, TX	9.56629	4.156481	1.724814	3.471151	5.071969	1.836056
Pittsburgh, PA	16.02365	6.039704	3.257821	5.628072	2.458885	1.470843
Portland, OR	16.36264	9.174253	3.280607	8.823265	9.100648	2.810823
Rapid City, SD	7.509836	5.880779	2.252008	6.226449	6.893116	2.409914
Redding, CA	18.83477	7.382618	4.380753	5.650357	5.251817	2.589896
Rock Springs, WY	4.296007	3.691595	1.441535	5.144649	3.659699	1.629509
Sacramento, CA	27.07926	6.012842	3.091408	5.759896	4.229234	1.861822
Salt Lake City, UT	6.308544	3.325483	1.549891	7.001863	3.682919	1.484525
San Antonio, TX	9.066408	4.248337	2.439738	5.421671	3.197894	1.466169
San Diego, CA	10.54733	5.128627	2.305159	10.57008	6.190785	2.921722
San Jose, CA	12.66144	7.378776	3.042326	9.030715	6.143198	2.471612
Scottsbluff, NE	23.32845	5.105869	2.526995	6.751828	4.443824	1.839617
Seattle, WA	13.09418	6.23834	2.89121	8.626703	7.188514	2.961616

city	U Range -Heat Index	L Range – Heat Index	Avg change – Heat Index	U Range -Temp	L Range – Temp	Avg change - Temp
Shreveport, LA	5.233792	4.683239	1.362874	5.800941	3.851233	1.532761
Sioux City, IA	10.02302	6.334798	3.1208	6.881522	5.498913	2.268106
Spokane, WA	7.485013	5.121825	2.014613	6.217885	4.575593	1.904255
St Louis, MO	6.01619	5.291714	2.36979	8.426671	5.80159	2.024369
Tampa, FL	9.126071	4.288955	2.215576	2.488806	2.35902	0.910138
Utica, NY	14.91845	9.628009	3.98406	3.674623	3.629725	1.785138
Washington, DC	18.22382	7.104562	3.41759	6.622285	5.040758	1.665136
Wausau, WI	12.27574	10.32441	3.987327	6.444425	5.131662	2.051876
Wichita, KS	18.91708	6.705442	2.619762	5.105065	5.210152	2.026941
Winnemucca, NV	30.86295	4.523266	2.773232	28.83281	4.62371	2.166332
Winslow, AZ	10.41596	3.165007	1.68079	14.48526	4.40604	1.681601

Appendix C: GitHub Repository

Due to the large volume of data associated with this project the analysis results, cleaned source data, and code can be accessed from the GitHub repository: (https://github.com/AustinBozgoz/Novel-Metrics-for-Analyzing-Extreme-Heat-Patterns-Across-US-Cities-/).