1. Introduction and motivation for thesis projects

This study works to provide information to scientists concerned with dangerous near surface air temperatures, specifically in three areas: large-scale temporal variability, small-scale spatial variability, and the validity of useful datasets. Extremely high temperatures contribute to death (Baccini 2008; Basu 2009) and between 2001-2010 the average United States fatalities for heat was behind hurricanes by only one fatality per year (NWS 2011). Globally the number of deaths will likely increase due solely to population growth (Kapitza 2006) and urbanization (United Nations 2012). However, a climate assessment (IPCC AR4) recently reported the minimum 21st century increase in global mean surface air temperatures to be 0.1 °C per decade. Furthermore, it is generally speculated that heat as a cause of death is underestimated (Donoghue et al. 1997). Understanding how extreme temperatures vary in time and space, and which datasets describe them properly is currently important and will remain important in the future.

Climate scientists generally undertake examining past trends in extreme surface air temperatures, but to save lives the public health sector must play major roles by establishing the relevant exposure variables (meteorological) and designing the systems that protect the public. Practical trend analyses of extreme heat events (EHEs) should consider the findings within the epidemiological literature. However, extreme temperature trend analyses rarely are designed to quantify those important aspects; for example annual counts of elevated temperatures lack summertime focus. A lack of trend analyses from the pubic health community is likely due to the difficulties in assessing climate trends (e.g. availability and limitations of datasets). Subsequently there is a lack of EHE trend studies that particularly contribute to both the public health and climate EHE discussions.

Similarly, urban climate studies quantifying alteration of exposure variables deemed relevant in the epidemiology literature would contribute to the heat-health discussion. While urban climate studies are extensive and numerous, they rarely are designed to cater to the public health users of such information. Conversely, the urban climatologists often overlook studies by scientists not familiar with urban meteorological observing practices because important steps are often absent (e.g. instrument siting consistency, data quality control, etc.). Urban climate studies regarded as legitimate by urban climatologists/meteorologists, that are significant contributions to the public health community's heat-health discussion, are not commonplace.

Additionally, there is a new generation of gridded climate datasets being used by climate information end users that have not been robustly validated. These datasets originate out of the need for high-resolution datasets by various modeling sectors outside of the atmospheric science sector. The datasets are of such high resolution that many scientists use them, but are unaware of the limitations regarding trends. In the literature, studies evaluating these datasets are scarce, and subsequently many of these datasets exist without robust validation being published. Thus this is a third gap between the end users and the climate community that could be bridged better.

In general, this work looks to bridge these gaps between the climate community and climate information end users. The next three sections will elaborate on the how this body of work accomplishes that.

2. EHE trends analysis

a) Literature review

The relationships between elevated temperatures and mortality statistics have been investigated in the epidemiological literature. The majority of studies use the daily maximum temperature to predict mortality (Hajat et al. 2002; Diaz et al. 2002; Grize et al. 2005; Hajat et al. 2006; Tan et al. 2007; Fouillet et al. 2007; Baccini et al. 2008; Fouillet et al. 2008; Anderson and Bell 2009). Many studies also show daily minimum temperatures to relate to mortality statistics (Kalkstein 1989; Hajat et al. 2002; Grize et al. 2005; Schwartz 2005; Hajat et al. 2006; Fouillet et al. 2007; Fouillet et al. 2008; Basu et al. 2008), and numerous studies also demonstrate the daily mean (usually derived from the daily minimum and maximum) temperature's ability (Hajat et al. 2002; Hajat et al. 2006; Basu et al. 2008; Anderson and Bell 2009; Ostro et al. 2009). Notably, biometeorological indices (e.g. heat index) are typically better correlated with mortality statistics than the traditional measure of temperature (Grize et al. 2005; Hajat et al. 2006). Many of the EHEs with infamously intense mortality impacts had both elevated daily minimum and maximum temperatures. Fouillet et al. (2006) showed in France during the 2003 EHE that mortality was associated with simultaneously elevated daily highs and lows. Similarly Karl and Knight (1997) in the 1995 Chicago EHE, Henschel et al. (1969) in the 1966 St. Louis EHE and Grumm (2011) in the 2010 Russian EHE, observed elevated daily highs and lows. EHEs with both daily extremes elevated are potentially interesting to the heat-health discussion but have a lack of representation in the literature.

In the epidemiological literature there exist extreme heat exposure variables that influence an EHE's impact on mortality. For example, duration of elevated temperatures is important (Kalkstein 1989; Díaz et al. 2002; Hajat et al. 2002; Anderson and Bell 2009; Ostro et al. 2009), as is the event's sum of "cumulative degree-days" over a heat stress-relevant threshold (Díaz et al. 2002; Díaz et al. 2006; Fouillet et al. 2007; Fouillet et al. 2008; Gershunov et al. 2009). Also timing within the heat season is significant; studies indicate that EHEs earlier in the season have a larger impact on mortality (Kalkstein 1989; Kalkstein and Smoyer 1993; Rooney et al. 1998; Hajat et al. 2002; Páldy et al. 2005; Baccini et al. 2008). Trend analyses of EHE characteristics linked with mortality are potentially valuable to the heat-health discussion.

The climatology literature has several studies concerning the trends in occurrences of daily maximum and minimum extreme (e.g. 90^{th} and 10^{th} percentiles) temperature. Studies exist on the global scale (Frich et al. 2002; Alexander et al. 2006), and regional studies have focused on regions such as the Northeastern U.S. (Griffiths and Bradley 2007; Brown et al. 2010), the CONUS (Gaffen and Ross 1998; DeGaetano and Allen 2002; Peterson et al. 2008; Portmann et al. 2009), Italy (Tomozeiu et al. 2006), Europe (Klein Tank and Können 2003; Moberg and Jones 2005; Della-Marta et al. 2007), South Africa (New et al. 2006), and south and central Asia (Klein Tank et al. 2006). The findings are that warm (cold) nighttime lows are becoming more (less) frequent; and hot (cool) daytime highs are becoming more (less) frequent. Nevertheless, these studies also show trends very considerably in space and time.

Occasionally extreme temperature trend analyses include a requirement of duration, which makes them extreme temperature *event* trend analyses (e.g. Gaffen and Ross 1998; Frich et al. 2002; DeGaetano and Allen 2002; New et al. 2006; Alexander et al. 2006; Tomozeiu et al. 2006; Della-Marta et al. 2007; Griffiths and Bradley 2007; Tamrazian et al. 2008; Gershunov et al. 2009; Kyselý et al. 2010; Brown et al. 2010; Kuglitsch et al. 2010; Wu et al. 2012). Unfortunately the majority of the studies that do require duration use oversimplified indices. For example the commonly used indices "Warm Spell Duration Indicator" (Frich et al. 2002; Alexander et al. 2006; New et al. 2006; Brown et al. 2010), Heat Wave Frequency index (Wu et al. 2012) and Heat Wave Duration Index (Griffiths and Bradley 2007) do not require anything of the daily minimum temperatures, quantify the number of separate EHEs nor consider EHE's with short durations (e.g. under five days).

Many studies that have duration requirements do not use definitions, or indices, that require both elevated daily high and daily low temperatures. Most studies with EHE definitions only impose requirements on the daily lows (Tamrazian et al. 2008) or daily highs (Tomozeiu et al. 2006; Kyseĺý et al. 2010; Huth et al. 2000; Meehl and Tebaldi 2004). The Kuglitsch et al. (2010) study was the only study found that required both extremes to be elevated. Furthermore it is important to have requirements on both daily extremes because it is not uncommon for the daily high (low) to be warm while the daily low (high) is cool.

Aside from those shortcomings, it is also unusual for studies to analyze the EHE trends in multiple aspects. Quantifying the trends in only one aspect (e.g. mean EHE duration) only partially describes the trends in EHEs. One study that did a robust job of EHE characterization was a study by Gershunov et al. (2009) that evaluated the California region's trends in EHE intensity, duration and spatial extent. In the Kuglitsch et al. (2010) study of the Mediterranean region; the EHE intensity was quantified as well as duration and number of EHEs per summer. Studies that characterize varied aspects of the EHE trends are scarce and none found focused on the CONUS.

A similar study to this endeavor (DeGaetano and Allen 2002) focused on the long-term (1900-1996) CONUS trends in both EHEs and single-day extreme temperature occurrences. The EHEs had either two or three days, at various percentiles, for either (not both) the daily maximums or minimums. This study has many differences from the DeGaetano and Allen (2002) study for example the quantification of the EHEs is from numerous aspects, the EHEs are specific to summertime and dynamic (with calendar date) percentiles were used instead of annual percentiles.

The Gaffen and Ross (1999) study quantified the trends across the CONUS in EHEs in regards to heat stress. Trends of high interest were presented to public health scientists as apparent temperatures (Steadman 1984) were used instead of conventional temperatures. Differences between that study and this project are also plentiful such as independence from the hydrological trends, quantifying more than one EHE characteristic and quantifying EHEs with respect to the daily extreme (instead of daily average) temperatures.

b) Project general hypothesis

In this study some specific questions about EHE trends are explored. First since 1930 do CONUS average trends exist in the characteristics of EHEs? Is there spatial variability in those trends over the CONUS? Do the trends differ from the earlier to later half of the 81 years? Do discrepancies exist between the trends of EHEs with different definitions? Lastly, how do the trends in EHEs relate to the trends in average summertime temperature trends?

c) Data and Methods

The United States Historical Climate Network (USHCN) climate dataset is a long-term climate dataset based on the COOP network observations. It has two versions, one is daily and not homogenized (Menne et al. 2012) and the other is monthly (Menne et al. 2009, 2011) and not homogenized (Menne and Williams 2005, 2009; Williams et al. 2012). Homogenization refers to a process of making all stations spatially and temporally consistent with themselves and their neighbors; primarily correcting non-climatic biases such as station moves, urbanization and instrument changes. In order to create a daily dataset that includes the bias corrections from the monthly dataset, this study combined the two datasets similarly to how past datasets have (Hamlet and Lettenmaier 2005, Di Luzio et al. 2008).

First the anomaly of each day's minimum (maximum) w.r.t. the current monthly mean of minimum (maximum) temperatures was calculated. That anomaly time series was superimposed onto the monthly timeseries to give the dataset this study utilized. Following the methodology of the Zhang et al. (2005) study, those temperatures are then converted into percentiles w.r.t. a 30-year base period of that stations temperatures. This study is separated into three periods, from 1930-1970, 1970-2010 and 1930-2010; which allowed two periods of equal length as well as focus on the general CONUS warming since 1970 and cooling from roughly 1930 until 1970.

EHEs in this study were required to have a two-day duration requirements of temperatures exceeding the 92.5th local percentile. This study separately quantified EHEs requiring a) only daily minimum compliance (*Tmin type*), b) only daily maximum compliance (*Tmax type*) and c) both minimum and maximum compliance (*Tmnx type*). In this study, *EHE type* refers to one of these three types of EHEs. The seven following characteristics of each EHE were quantified each summer: number of EHEs, mean EHE duration, number of days classified as EHEs, mean EHE intensity (Diaz et al. 2006), summer sum of EHE intensities, number of early season EHE days and mean EHE onset date. The magnitude and significance of trends in those EHE characteristics is then calculated.

First the continental average trends for each EHE characteristic, EHE type and time period were calculated. Then for all periods, EHE types and EHE characteristics, the ratio of the sample mean to standard deviation and percentage of significant (and insignificant) positive and negative trends were calculated. Next, the maps of the trend magnitudes and significance at each station created and used to spatially characterize the trends. For example the results were spatially structured or consist of entirely noise. Lastly regions of warming and cooling are called attention to.

To understand the relationships between the Tmin, Tmax and Tmin&Tmax type EHE trends the Pearson's correlation coefficients were calculated between the three trends for each EHE characteristic and time period. Furthermore, Student's t-tests were used to determine if the magnitude means were statistically different at the 0.10 significance level.

d) Current results/conclusions

For EHEs w.r.t. either the daily minimum or maximum temperatures (Tmin or Tmax type EHEs), the different non-timing EHE aspects (e.g. duration, intensity, frequency) were consistent in sign, leading to unambiguous results. This was predominantly seen in the CONUS average results where all periods and EHE types were consistent in sign throughout the EHE characteristics, and also the similar spatial patterns of EHE characteristics supported this conclusion. The Kuglitsch et al. (2010) study in Europe showed a similar consistency between intensity, duration and number of EHEs during the 1960-2010 period. The results of the Gershunov et al. (2009) study also showed (for both Tmin and Tmax type EHEs) in California the EHE intensity, spatial extent and frequency all increased.

During the 1930-190 period all EHE types grew weaker, shorter and less commonplace, but during the 1970-2010 period all EHE types grew stronger, longer and more frequent. The CONUS average EHE characteristics indicated that during the 1930-1970 period all non-timing EHE characteristics, regardless of EHE type, decreased and during the 1970-2010 period all non-timing EHE characteristics increased. Also the disparity in the percentages of stations with significant negative and positive trends, per time period, supported such conclusions. These conclusions agree with the findings of Peterson et al. (2008) that showed both Tmin and Tmax extreme percentiles decreased during the 1950-1970 period and increased in the 1970-2005 period. The DeGaetano and Allen 2002 study by showing the percentage of increasing trend stations since 1960 was much larger than the percentage of decreasing stations loosely supported these results as well. We do not believe our results disagree with the Gaffen and Ross (1998) paper that found a larger increase in the CONUS average number of EHEs from 1949 to 1995. We believe the hydrological trends, as well as the differences in EHE definitions and time period, caused the difference between the two studies results.

Over the 1930-2010 period the Tmin type EHEs grew stronger, longer and more commonplace, the Tmax type EHEs became weaker, shorter and less commonplace and the EHEs w.r.t. both daily extreme temperatures (Tmnx type) became negligibly stronger, longer and more commonplace. This was seen in the CONUS average EHE characteristic results that showed during the 1930-2010 period all non-timing EHE characteristics increased for the Tmin type, all non-timing characteristics decreased for the Tmax type EHE and the results of the Tmnx type EHE non-timing characteristics increased by an order of magnitude less than the other EHE types. The only study that is able to compare with our study, the DeGaetano and Allen (2002) study, suggested the Tmin and Tmax 90^{th} and 99^{th} percentiles decreased (weaker) between 1930-1996, and increased (stronger) between 1970-1996.

Spatial variability existed across the CONUS for all periods, EHE characteristics and EHE types. This was indicated in the mean-to-standard deviation ratios, but regional-scale spatial patterns were also clearly seen in the maps. For example the lack of warming in the central and north central CONUS during the 1970-2010 period or the cooling in the central and north central CONUS regions during the 1930-2010 period. Several other studies also showed regional-scale spatial variability (Gaffen and Ross 1998; Degaetano and Allen 2002; Peterson et al. 2008; Portmann et al. 2009; Wu et al. 2012). Additionally, small-scale variability was seen in the maps. This likely arises from the local level where landcover/landuse play larger roles; a study by Pielke Sr. et al. (2011) elaborates on the local land use/land cover impact on surface temperature trends. Maps in similar studies (Gaffen and Ross 1998; Degaetano and Allen 2002; Portmann et al. 2009) confirmed the existence of such small-scale variability.

The spatial pattern of the trends differed strongly with time period, differed some with EHE type and did not discernibly differ with EHE characteristic. During the 1930-1970 period the overall general pattern was negative trends in the north Central and East regions and mixed results in the West and south Central regions. No maps were found that could corroborate with these earlier period conclusions. During the 1970-2010 period the general spatial pattern of increase was that of a loose horseshoe with a lack of positive significance in the middle of the country. The map of 90th percentile trends during the 1960-1996 period in the DeGaetano and Allen (2002) paper was different from our results, but we believe the differences can be explained by study/figure differences. During the 1930-2010 period, the general spatial pattern was negative in the central/interior region and positive in the East and West. The DeGaetano and Allen (2002) manuscript has a map of daily maximum type EHE trends from 1930-1996 that supports those conclusions. The Peterson et al. (2008) study also presented a map in the number of daily minimum 90th percentile exceedence days during the 1950-2005 period similar to our 1930-2010 period map of the number of Tmin EHE days in all regions except the south East region; where that study showed insignificant decrease but our map showed significant increase.

The relationships Tmin and Tmax type EHE trends had with the Tmnx type EHE trends were modest but no relationship was seen between the Tmin and Tmax trends. These conclusions stem from both the correlation coefficient and Student's t-test results between the EHE types. Theoretically, weather patterns conducive to each type of EHE are dissimilar; for example cloudy overcast weather lends itself to Tmin type EHEs, but not Tmax type EHEs. Our conclusion of a lack of relationship between the Tmin and Tmax type EHE trends was loosely supported by the Portmann et al. (2009) study that showed substantially different spatial patterns and continental averages in the 90th percentile exceedence occurrences for minimum and maximum temperatures. Also the Gaffen and Ross (1998) study supported these conclusions; it showed substantial differences in the average (both continental and regional) trends in the daily minimum and maximum apparent temperature percentile exceedences.

3. Investigation into Detroit's urban climate

a) Urban climate literature review

Air temperatures 2-meters above ground level vary spatially because the land cover land use (LCLU) types vary. Specifically, LCLU types affect the way energy interacts with the environment at the ground level. LCLU types can affect heating/cooling rates and storage; latent and sensible heat flux partitioning; effectiveness of radiative energy exchanges and turbulent heat transport (Oke 1982, Grimmond 2010). Metropolitan areas are essentially congregations of LCLU types that cause the overnight temperatures to be warmer than the rural surroundings; this effect is termed the Urban Heat Island effect (UHI effect) (Oke 1982). On a smaller scale than the UHI effect, within a city the temperature also varies (Oke 1984). In urban climate science the delineation of scales was a major theoretical advancement with a microscale (related to the immediate vicinity, commonly 0.1 – 100 m), local scale (related to neighborhoods with similar types of urban development, often 1-5 km) and the mesoscale (related to the size of the entire metropolitan region, 10s of km) (Oke 1984).

Observational studies have not substantially changed since the 1980's, although numerical modeling studies have emerged. Typical methods of the observational studies include time trends at singular locations (i.e. the site is becoming more urban) (e.g. Tarleton and Katz 1995; Tereshchenko and Filonov 2001), comparative time trends at one or more urban stations and one of more rural stations (e.g. Ackerman 1985; Magee et al. 1999; Philandras et al. 1999; Morris and Simmonds 2000; Zhou and Shepherd 2009), networks of fixed stations within and around a city (e.g. Basara et al. 2008, 2010; Camilloni, I., and M. Barrucand, 2010) and transects across an urban area (e.g. Saitoh et al. 1996; Goh and Chang 1999; Bottyán and Unger 2003; Wong and Yu 2005; Yokobori and Ohta 2009). Nor is it uncommon for studies to use more than one method in concert (Kuttler et al. 1996; Montávez et al. 2000; Longxun et al. 2003).

Most urban climate studies focus on the UHI effect on a large scale, or the temperature differences between an urban station and its rural counterparts (Zhou and Shepherd 2009; Basara et al. 2008; Camilloni and Barucand 2011; Chow and Roth 2006; Morris et al. 2001; Mohsin and Gough 2011; Velazquez-Lozada et al. 2006). The metric is often termed the *magnitude of the UHI, UHI magnitude*, *Intensity of the UHI* or *UHI Intensity*. Its effectiveness of this metric is dependent to the studies ability to site the stations as rural and urban, and a limitation is the ability to convince the reader the temperature gradient is radial.

Some studies investigated the smaller scale variability of temperatures throughout a city. Some of those studies confirm the existence/amount/sign of variability over urban and/or suburban areas (Saaroni et al. 2000, Basara et al. 2008, Gaffin et al. 2008); others mapped the spatial structure (Montávez et al. 2000; Longxun et al. 2003; Bottyán and Unger 2003; Kim and Baik 2005, Hart and Sailor 2009). More involved studies linked the variability to local scale spatial attributes (Kuttler et al. 1996; Goh and Chang 1999; Bottyán and Unger 2003; Hart and Sailor 2009; Buttstädt et al. 2010) and land cover types (Wong and Yu 2005; Yokobori and Ohta 2009). Spatial variables found to be good predictors were building height, building area, building height-to-street width ratios, building use type, canopy cover, sky view factor, water surface ratio, percentage of impervious surface and ground elevation.

Studies have shown the largest UHI magnitude resides after sunset but before the daily low (Oke 1982, Morris and Simmonds 2000) and this is the time of day nearly all UHI studies focus, because they focus on the physical impacts of the urban landscape. However epidemiology literature shows the summertime daily high to be associated with both heat-related medical dispatches (Dolney and Sheridan 2006; Golden et al. 2008) and mortality rates (Basu 2009, Gosling et al. 2009). Also summertime daily minimums are associated with mortality rates, as well as daily mean (often derived from the daily maximum and minimum) temperatures (Basu 2009, Gosling et al. 2009); is not clear which of the three variables is more important. Therefore this study focuses on the spatial variability only during summertime daily maximum and minimum temperatures; exchanging the most robust signal from the urban landscape with practicality to the public health scientists.

b) Project hypotheses

Do summertime average daily extreme temperatures vary spatially across the urban/suburban domain? Is the magnitude of that variability diagnosable by the large-scale weather? Is the spatial pattern predictable by the land attributes? Lastly, does the spatial variability exist during hot/oppressive weather?

c) Data and Methods

To improve spatial density, this study integrated multiple observation networks into a single network. The standard observations managed by the NWS were used as this network's baseline. To this baseline, observations were added from both an existing network run by the Michigan Department of Environmental Quality (MDEQ) and a temporary network that was established for this study. The temporary network ran for the length of this study, and consisted of only the 110 days from 13 June – 30 September 2009.

This unique observational network, in part, led to unique methods. First the observations are reported as *spatial anomalies* instead of *temperatures*; anomalies with respect to the network-wide average at that particular time (e.g. daily low on June 21st) but beyond the specific monitoring uncertainty inherent to each network (i.e. uncertainty subtracted from the anomaly magnitude). For example, if a downtown airport monitor showed a daily high of 30°C, that date's daily high network mean value was 26°C and there is a 0.5°C uncertainty associated with the airport network's daily highs, then there was a +3.5°C spatial anomaly at the downtown airport location on this date.

Furthermore, the network used in this study lacked true representation of the rural surroundings; therefore this study could only assess the spatial variability throughout the urban and suburban regions of Detroit. This variability is herein referred to as the intra-urban/suburban spatial variability in temperature (IUSSVT). The IUSSVT was quantified by calculating the range of the simultaneously (e.g. same date and daily extreme) observed spatial anomalies (herein referred to as the *range of simultaneously observed spatial anomalies (SOSAs)*). The range of SOSAs quantifies the range in temperature across the urban and suburban landscapes whereas the common metrics *UHI magnitude* and *UHI intensity* quantify the temperature difference between sufficiently urban and rural locations. At night the range of SOSAs is similar to the UHI magnitude metric but likely underestimates it. During the daytime the range of SOSAs allows a positive value even if the downtown area is cooler than the suburban areas (commonly known as an urban cool island or oasis effect). Knowledge of the typical spatial pattern of temperature is essential when using the range of SOSAs metric.

First the amount of IUSSVT was examined by examining the range of SOSAs. The histograms, means and maximums of the range of SOSAs were calculated for both daily extremes. Then the range in SOSAs' relationship with the lager scale weather was investigated. The spatially averaged airport weather observations of overnight wind speed, overnight cloud cover and the previous afternoon's cloud cover were correlated with the daily low ranges of SOSAs; the variables correlated with the daily high were afternoon cloud cover and afternoon wind speed. Then for both predictands, stepwise multiple regression was performed using the variables deemed appropriate. Bootstrapping techniques were used to evaluate confidence in the regression coefficients. The regression coefficients determined from scaled inputs was done in order to determine each predictor's relative contributions to the models. Then the goodness of those regression models was determined from model diagnostics such as RMSE and R^2. Models that passed initial scrutiny were further tested for their functionality by evaluating their ability in a cross-validation test (Draper and Smith 1981). Once the relationships with the airport weather observations were investigated the investigation was repeated with corresponding reanalysis data in order to assess the ability to forecast Detroit's UHI magnitude from model data. The North American Regional Reanalysis data was similarly averaged and correlated with the range of SOSAs.

Confirmation of the existence of IUSSVT during hot weather was undertaken because of its implications on heat stress during heat events. Initially this subject was to be evaluated by isolating times classified as heat events or oppressive via three independent methods but the summer of 2009 in Detroit lacked heat events and NWS heat advisories. Instead it was explored via ordinary least squares regression fitting between apparent temperature percentiles and the amount of spatial variability; to test the statistical significance the confidence intervals were calculated in the slopes and intercepts of those regressions.

Then the relationships were investigated between the spatial anomalies means and three land-cover and location variables. First, the variables distance to sizeable water body, distance from city center, and local percent impervious surface were theoretically justified and then created with ArcGIS software. Then each station was assigned values for each variable and those three values were correlated with both each other and the observed mean spatial anomalies across all stations. Then the backwards elimination method was employed with these variables, to determine the appropriate multiple regression model for both daily temperature extremes. Again bootstrapping methods were employed to explore the confidence in the regression coefficients. Regression coefficients calculated with normalized input indicated which variables were most influential. Then the goodness of those regression models was determined from model diagnostics such as RMSE and R^2. Models that passed initial scrutiny were subjected to the leave-one-out cross validation testing method (Hoek et al. 2008, Draper and Smith 1981).

d) Main conclusions

The IUSSVT is typically larger during the daily low, which was indicated by examining the simple statistics (mean, maximum, histogram) of the range of SOSAs. The observed day-to-day variability in the daily low range of SOSAs was also large however. A multiple regression method indicated that all three large-scale weather variables should be used (cloud cover, previous day cloud cover and wind speed; from strongest to weakest predictor) to predict the amount of daily low variability. Cross validation efforts confirmed its utility as a predicative model. A similar model using analogous NARR derived large-scale weather variables was also found to be successful. These findings are consistent with other recent studies that indicated both the nighttime intra-urban spatial variability (Eliasson 1996, Wilby 2003, Kim and Baik 2005, Erell and Williamson 2007) and UHI magnitude (Runnalls and Oke 2000, Morris et al. 2001, Gedzelman et al. 2003, Wilby 2003, Camilloni and Barrucand 2010) to be largest during low wind speed and clear sky weather conditions. However, our results elaborate on these findings by suggesting an explicit relationship between daily low IUSSVT and the previous afternoon's average cloud cover, which was not found in the literature. Conversely, the daily high range of SOSAs could not be effectively modeled using the large-scale weather variables.

On average there was a statistically significant amount of IUSSVT, and during days flagged as hot, or oppressive, the range of SOSAs was comparable to the overall mean value. Our results agreed with the findings of a previous study (Basara et al. 2010) that demonstrated the existence of intra-urban and intra-suburban temperature variability in general and during a heat event. Specifically, our results showed during the daily high the range of SOSAs was indifferent of apparent temperature percentile but the daily low decreased with increasing apparent temperature percentile. Neither daily minimum nor maximum trend decreased to zero at the 100th percentile.

Results suggested that the land cover-location variables could predict the mean intra urban/suburban spatial pattern in temperatures. The daily low spatial pattern could be predicted well, as oppose to the daily highs, which were not predicted meaningfully. For the daily low the most influential predictor was the percent impervious surface, with distance to city center and distance to water being secondary. Cross validation efforts again confirmed the utility of this model as a predictor. Similar studies using statistical models to statistically explain the nighttime intra-urban/suburban spatial pattern of temperature (Kuttler et al. 1996, Bottyán and Unger 2003, Buttstädt et al. 2010) confirmed it could be done well (R^2 between 0.50-0.85) and with only a small number of variables (e.g. between two and four).

4. A trend evaluation of three modern high-resolution climate datasets

a) Climate community datasets

In general, observational datasets developed within the climate community are the appropriate choice for determining trends, oscillations and behavior of temperature at multiple spatial scales. Decades have been invested to creating the optimal systematic processes of homogenization (i.e. a spatially and temporally consistent network), and subsequent updating, that each dataset has in current operation. Common datasets are the National Climatic Data Center's (NCDC) Global Historical Climatology Network (GHCN)/United States Historical Climatology Network (USHCN), (Lawrimore et al. 2011, Menne et al. 2009), the NCDC's United States Climate Reference Network (USCRN) (Heim Jr. 2001), the Hadley Centre and University of East Angila's CRU datasets (Mitchell and Jones 2005), the National Aeronautics and Space Administration's

(NASA) GISS dataset (Hansen et al. 2010) and the University of Delaware's (UDel) datasets (Matsuura and Willmott 2009). Most datasets operate at the monthly resolution although some have daily data available. The GHCN, USHCN and USCRN are ungridded datasets and the CRU, GISS and UDel datasets are all gridded datasets with resolutions of 0.5°, 2.0° and 0.5°, respectively.

The USHCN and GHCN datasets use roughly 1,200 and 7,300 stations, respectively. The USHCN is a subset, generally based on quality and longevity of the data, of the COOP network (Newkirk 2007). The GHCN also includes similarly trusted data from countries around the globe, not including ocean temperature measures. The gridded (0.5°) version of the GHCN has serious limitations to it's utility. The newest quality control (QC) algorithms used for the monthly USHCN and GHCN datasets are considered to be the best at what they do (compare a station to it's neighbors to detect abrupt and gradual discontinuities) (Menne and Williams 2009). The daily versions of the both datasets do not have any homogenization or infilling applied to them.

The CRU dataset is a global dataset with many more stations than the GHCN dataset. The GHCN is one of the data sources and another is the World Weather Records (WWR) dataset (NCDC 2011a), numerous sources are included (Mitchell and Jones 2005, New et al. 2000, Jones and Moberg 2003). The homogenization process is similar to the newest versions of the USHCN and GHCN, but with requirements relaxed to maximize the number of stations accepted into the dataset. The large number of stations in turn allow for confident high-resolution grids to be created. The interpolation method to grid is simple angular distance weighting (New et al. 2000).

The GISS dataset is a global dataset that uses only a subset of the GHCN dataset's stations. Additionally, Antarctic data (Turner et al. 2004) and an oceanic gridded dataset (Rayner et al. 2003) are used to fill those areas the GHCN did not include. The method used to correct for the urbanization effect, was through a satellite derived nightlight (radiance) dataset. The interpolation methods are unclear in the publications but there is indication that the gridding is simple.

The UDel dataset is a global dataset that uses a significantly larger number of stations from a variety of networks (NCDC's Global Summary of the Day is a large portion (NCDC 2011b)). The QC and homogenization efforts were very little to none for this dataset. However the interpolation techniques employed are robust; elevation changes are explicitly accounted for (Willmott and Matsuura 1995) and a technique called "climatology aided interpolation" (Willmott and Robeson 1995) allowed for smart interpolation.

The United States Climate Reference Network (USCRN) (Heim Jr. 2001) is a new network with a focus on measurement accuracy and quality. The monitoring sites are robust in the variables they observe, specifically sited away from any biases and operated by the USCRN network. A network of 114 stations has been operating since 2008 and covers the CONUS well.

b) Hydrological community datasets

Recently climate datasets have emerged from the hydrological community with very high resolution. Hydrological models require as inputs, serially complete gridded surface observational datasets of such resolution (Ghosh and Misra 2010). However climate information end users, including atmospheric scientists, use these datasets with confidence. Here is a review of datasets spanning the complete CONUS domain with temporal resolution of a day and spatial resolution higher than a third of a degree latitude.

The DAYMET (Thornton et al. 1997) dataset (1 km resolution) is an example of such a dataset; its spatial domain is global but its temporal domain is short (1980-1997). The Maurer et al. (2002) dataset (12 km resolution) is another example of one of these datasets, and has made its way into in the climate community literature. The dataset described by Hamlet and Lettenmaier (2005) corrects important issues in the Maurer et al. (2002) dataset but it is only available west of the continental divide. This methodology by Hamlet and Lettenmaier (2005) has been used to create other sub-continental-scale datasets for regional assessments (Sinha et al. 2010). ~~The dataset described by DeGaetano and Belcher (2007) covers only the northeastern U.S. and is not focused on here. The serially complete dataset described by Eischeid et al. (2000) is not focused on here because it is not gridded.~~ The PRISM (Daly et al. 2008) dataset (4 km) is not an example because it is monthly, however the Di Luzio et al. (2008) dataset (4 km) is essentially a daily version of the monthly PRISM dataset. ~~The global dataset described by Hijmans et al. (2005) dataset (1 km) is also not focused on because it is monthly.~~

These datasets vary by more than just resolution. The interpolation methods used are more sophisticated than the climate community datasets, and manuscripts explaining these datasets spend a significant portion describing both the interpolation methods and the variables used in the interpolation process. The density of source stations used in the interpolations is much larger due to relaxed requirements. Besides the Hamlet and Lettenmaier (2005) manuscript, there is surprisingly little quality control discussion and no discussion regarding the detection and correction of temporal discontinuities due to non-climatic biases (e.g. equipment change, small station move, etc.). Typical validation efforts are accomplished often only through cross-validation (Thornton et al. 1997; Daly et al. 2008), by comparison to one another (Daly et al. 2008), through the ability for hydrological models to recreate historical stream flows (Maurer et al. 2002) or not explicitly validated within the literature (Di Luzio et al. 2008).

Some studies (Hamlet et al. 2005; Bonfils et al. 2008, Lobell et al. 2008) have mentioned the Maurer et al. (2002) dataset is less optimal for use and opted for either using other datasets or correcting it using the Hamlet and Lettenmaier (2005) method. Conversely, another study (Das et al. 2009) did not see significant differences between the Maurer et al. (2002) and Hamlet and Lettenmaier (2005) datasets. Scully (2010) evaluated the PRISM and DAYMET datasets and concluded the PRISM dataset should be preferred unless daily data is required, and Guentchev et al. (2010) tested the Maurer et al. (2002) and PRISM datasets for inhomogeneities and found both to contain them but the Maurer et al. (2002) dataset had more.

Hydrological models require these datasets, not only because of the high resolutions but because they require more than just temperature and precipitation (e.g. humidity, precipitation, wind speed, short and long wave radiation). A large literature body exists of hydrological modeling studies that employed temperature data from these datasets. Here a few examples involving the Maurer et al. (2002) dataset (Haddeland et al. 2006;

Haddeland et al. 2007; Mao et al. 2009; Acharya et al. 2011), the DAYMET (Schaefer and Alber 2007; Schaefer et al. 2009; Potter et al. 2010) dataset and the Di Luzio et al. (2008) dataset (Marshall 2011; Kannan et al. 2008; Santhi et al. 2008; Srinivasan et al. 2010) are listed.

Many non-hydrological modeling studies use these datasets as well. For example the Maurer et al. (2002) dataset has been used to assess summer nighttime temperature trends in the California's Central Valley (Bonfils et al. 2007), assess trends in annual maximum temperatures in Florida (Waylen et al. 2012) and quantify the U.S. spatio-temporal patterns in surface temperature caused by the El-Niño/Southern Oscillation (Zhang et al. 2012). The DAYMET dataset has been widely used by several non-climate groups such as those modeling past fire hazard and risk (Keane et al. 2010), modeling past productivity of forest (Turner et al. 2011; Littell et al. 2010), modeling past biogeochemical cycling rates (Hartman et al. 2011; Pan et al. 2009), mapping past and future corn pest risk (Diffenbaugh et al. 2008) and modeling the transmission risk of human diseases (Konrad et al. 2011; Wimberly et al. 2008). Similar examples for the Di Luzio et al. (2008) dataset were not found, however one paper (Williams et al. 2010) did cite the findings Di Luzio et al. (2008) of a 0.65°C increase in average annual temperatures over the continental U.S.

c) Project hypothesis

First do the Maurer et al. (2002), Di Luzio et al. (2008) and DAYMET (Thornton et al. 1997) datasets reproduce the CONUS average trends of the reference climate dataset? Do they reproduce the spatial structure of the reference dataset? Lastly, do the biases or uncertainties act as random spatial variables or are they a function of physical characteristics of the stations themselves (e.g. elevation)?

d) Project Methods

This study tests the ability of these datasets to reproduce the trends of the reference dataset by quantifying the bias or uncertainty. This requires a reference dataset, and the USHCN dataset will be used because it is a) considered to be a top tier climate reference dataset for trends, b) it is not gridded and c) it has a version (Menne et al. 2012) which describes the daily scale variability. For this project the grids points are interpolated to the reference dataset locations, and then compared over the temporal duration of each dataset being evaluated. This was done because evaluation of the interpolation methods was not desired, rather we wanted to evaluate at the locations where no interpolations are needed. There is no reason to believe these three datasets would not use these stations in the reference dataset in creating their respective grids.

This study compared the trends of four variables between the datasets at each location. The first two are the number of summertime occurrences of summertime daily minimum and maximum 90^{th} percentile exceedences. These variables are straightforward, physical and at a temporal scale of interest to most users of these datasets (daily scale). The third and fourth variables are the number and average duration of summertime EHEs, respectively. These variables are less straightforward/physical but at a temporal scale of interest to many users of these datasets (event or synoptic timescale). These EHEs require two days of both elevated daily highs and lows.

The method of evaluation will be the same for all variables. Time series of raw and absolute difference between the reference dataset and each target dataset will be constructed for each location. To quantify the *trend bias* the raw difference time series was used, and the *trend uncertainty* used the absolute difference time series. For both variables, the magnitude and significance of any trend will be calculated using the ordinary least squares method because it is so commonly used.

First, maps of the station-specific results showing trend bias and uncertainty magnitudes and significance will be constructed. Then conclusions of the ability to reproduce the spatial structure will be based on these results. Also the maps may be insightful into whether the causation of bias and uncertainty is the same between the three datasets the maps may be helpful. If not helpful, the 2D spatial correlations between biases and uncertainties derived from different datasets can be calculated. Then the percent of locations with statistically significant/non-significant positive/negative trends will also be given. Also continental averages of the trend biases and uncertainties will be calculated.

Lastly the causes behind the bias and uncertainty are examined. Testing for spatial autocorrelation allowed investigation into whether the bias/uncertainty behaves as a random variable. Then regression analysis between physical land characteristics (e.g. elevation and distance to water) will be used to further investigate the cause.

e) Desired results and conclusions

In general the CONUS average uncertainty and bias of the gridded datasets will give end users an idea of the suitability of these datasets for trend analysis at the continental scale. Next, maps of uncertainty and bias will give climate information end user's the knowledge of whether these datasets can reproduce the spatial pattern and how the gridded datasets perform in a particular region.

The rest of the investigation will attempt to explain the cause of bias and uncertainty amongst the gridded datasets. Preliminary tests determining whether the biases and uncertainties are similar between gridded datasets and whether there is spatial autocorrelation give rise to the causation of errors. Then regression between the physical characteristics of the stations and the bias and uncertainty will give us insight into the causes behind the errors. Lastly, our results in the context of the results of a paper by Menne et al. (2009) that discusses the non-climatic biases detected in the USHCN datasets by an objective pairwise detection method will be discussed in the context of our findings.

5. How the conclusions of the three projects satisfies the thesis motivations

The obvious connection between the projects is presenting information for end users who are concerned with summertime near surface air temperatures. Trends in EHE characteristics and how they relate to average trends and EHE definition differences is useful information to public health scientists protecting the public from hazardous heat. How the intra-urban spatial variability of daily maximums and minimums relates to synoptic weather and the urban landscape might aid public health officials in metropolitan regions protect the community. Evaluation of two high-resolution climate datasets w.r.t. trends in hazardous heat could give climate information end user's confidence in using these datasets for trend analyses.

A less obvious commonality between projects was the attempt to act as an interface to transfer knowledge by employing vital meteorological and climatological practice standards to quantify specific variables relevant to end users. Approaching the first study like a climatologist, a dataset well suited to assess long-term trends was used, the stations used were carefully selected and percentiles calculated with pitfalls in mind. To transfer the knowledge directly to the public health discussion, this project a) studied trends in EHE characteristics important to that discussion, b) required elevated temperatures to have a duration, c) focused on summertime EHEs and d) evaluated the differences between different EHE definitions.

For the second project, approaching the problem from a meteorologist's perspective included explicitly considering uncertainties in urban meteorological monitoring and basing our network on the local NWS standard observing sites. Then to facilitate the translation of knowledge into the heat-health discussion this study a) focused on daily extreme temperatures, b) evaluated the spatial variability during hot weather and c) provided a methodology for temporally and spatially predicting the variability. The third venture was approached carefully as it used an appropriate reference dataset and the stations used were warily selected and percentiles calculated with pitfalls in mind. Evaluating datasets popular within end user assessments and evaluating a phenomenon important to the heat-health discussion aided the translation of knowledge to end-users.

The last theme these projects share was to advance the level of knowledge within the climate discussion. Our first project was an extension of the DeGaetano and Allen (2002) study that focused in the continental U.S.'s long-term trends (1900-1996) in EHE trends and the Gaffen and Ross (1998) study that quantified apparent temperature trends. Foremost it is an extension simply because it includes the more recent 1996/1997-2010 data. However, neither of those studies required both elevated daily highs and lows in their EHE definitions. Lastly, the DeGaetano and Allen (2002) study didn't focus on summertime EHEs and the Gaffen and Ross (1998) study didn't focus on trends in temperature only. Additionally, our study more robustly characterized the EHE trends, similar to how the Kuglitsch et al. (2010) Mediterranean region study did. Our study was also designed to look at the differences between the trends of EHEs w.r.t. the daily extreme temperature requirements (Kuglitsch et al. (2010) did not). Thus we felt this project added to the EHE discussion from the climatologist's perspective.

The second project studied Detroit, MI, USA for the first time in over thirty years, and in a much more spatially robust way. While there are previous studies that built statistical models between observed temperatures and land cover attributes, our study uses two variables not used in the previous studies (distance to city center, local imperviousness). Additionally, no previous studies were found that looked at the relationship between apparent temperature percentiles and the amount of spatial variability over a metropolitan region. Similar studies have used synoptic scale meteorological variables to predict the urban heat island magnitude, however this study used a variable unused previously (previous day cloud cover) in the statistical model. Lastly, our study's unique observing network can be an example for future urban climate studies (Grimmond et al. 2010). Subsequently, we felt from an urban climate science point of view this project added to the level of knowledge.

The third project also adds to the climate community discussion. Evaluation of datasets occasionally used in the climate community (e.g. to downscale GCM output (Hayhoe et al. 2010)) and sometimes used to calculate trends gives climate scientists confidence to use them more. Also the discussion of how lack of climate data homogenization affects index trends in gridded high-resolution datasets is beneficial as well.

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