FUTURE PROJECTIONS OF HEAT WAVES AND COOLING DEGREE DAYS IN LARGE CITIES ACROSS THE SOUTH-CENTRAL UNITED STATES

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ABSTRACT

Urban environments are particularly vulnerable to extreme heat events, otherwise known as heatwaves. To help better prepare cities, regional future climate projections of heat waves are necessary. Previous studies have shown that heat waves will become more frequent, longer in duration and stronger in intensity. In this analysis, we focus on projections of heat waves and cooling degree days in six large cities across the south-central United States. An ensemble of statistically downscaled global climate model simulations were used to look at heat waves and cooling degree days for a historical period from 1981-2005 and a late century future time period from 2075-2099. Heat waves were found to more than triple for each city and cooling degree days were found to increase anywhere from 50 to 85% by late century. In conclusion, already vulnerable environments will experience even more heat stress with an increased need for cooling. This could lead to a higher energy demand, more frequent power outages, and increased mortality.

1. BACKGROUND

Heat is one of the leading causes of weather related mortality in America, accounting for 24% of all weather related deaths (Environmental Protection Agency and Center for Disease Control 2016). With the elevated mortality related to heat, it is important to prepare for extreme heat events (i.e. heat waves) in the future. Heat waves are intervals of time associated with relatively high temperatures when compared to the mean temperature for that region (Perkins and Alexander 2013). Prior research has indicated an increase in the frequency and duration of heat waves from anthropogenic climate change in the historical past (Easterling et al. 2000) as well as projected increases in intensity in the future with higher maximum and minimum temperatures (Meehl and Tebaldi 2004; Patz et al. 2005; Luber and Mcgeehin 2008; Stone et al. 2010; Thornton et al. 2014; Walsh et al. 2014; Kjellstrom et al. 2016). These increases could lead to multiple societal impacts with detrimental effects on mortality and the economy.

The most susceptible populations of the growth in mortality due to heat waves are the elderly, the young, people without proper air conditioning, or those living in urban environments (Environmental Protection Agency and Center for Disease Control 2016). Urban environments experience more intense temperatures during heat waves than surrounding rural environments due to the urban heat island effect (UHIE). This increase in temperatures within urban environments is due to low vegetation, low albedo, and an increase in thermal-storage capacity in large buildings (Stone et al. 2010; Luber and Mcgeehin 2008).

Commercial buildings account for 18% of all energy consumption in the United States with HVAC systems making up 32% of commercial buildings energy consumption (Pew Center on Global Climate Change 2009). During heat waves, it is not uncommon to have power outages that leave many people without proper air conditioning (US Department of Energy 2013). For example, in 1999 there was a heat wave that affected most of the midwestern United States, including Chicago. In northern Chicago, a power outage left more than 70,000 people without power due to overheating of underground transmission lines. Close to 20% of these residents had no power for more than three days (Palecki et al. 2001). This caused economic loss for many businesses and

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put many residents in dangerously hot conditions in their homes.

Those that live in the south-central United States rely heavily on HVAC systems to cool their homes and businesses. The urban heat island effect increases the need for cooling in commercial buildings in these large cities. Cooling primarily uses electricity, which tends to be more expensive than heating for commercial buildings (Rosenthal et al. 1995). In many areas of the United States, the increased need for cooling will outweigh the reduced need for heating as temperatures rise (US Department of Energy 2013). The U.S. department of energy has found that cooling degree days (CDDs) are an effective measure of energy consumption needed for cooling. A warmer region will have a higher average of annual cooling degree days. There have been studies showing an increase in CDDs across the U.S., but very little work has been done using downscaled models to look at specific regions (Rosenthal et al. 1995). By analyzing specific regions, energy suppliers will have a more useful tool to help plan for the future.

2. DATA AND METHODS

2.1 *Methodology*

Global climate models (GCMs) are too coarse (> 100km resolution) and therefore cannot capture local effects relevant to regional impacts (Wootten et al. 2014). To help prepare cities in the south-central United States for future change, downscaled climate projections are needed. Downscaling is a group of techniques used to create high resolution products from translating GCM output to look at regional climates. For this analysis downscaled climate projections are used to examine the potential change in six cities of interest. These cities are Oklahoma City, OK, Dallas/Fort Worth, TX, Houston, TX, Albuquerque, NM, Little Rock, AR, and Baton Rouge, LA (Table 1). These cities are chosen based on their location and their size. Figure 1 shows the spread of the cities in our region. The locations of the different cities reflect different climates across the south-central United States. Four metrics are used to examine characteristics of extreme heat: maximum annual temperature, minimum annual temperature, heat waves for specific time periods, and mean annual cooling degree days for specific time periods. Observations are compared to modeled historical simulations for a 25-year period from 1981 to 2005 for annual mean maximum temperatures, annual mean minimum temperatures and temperature trends. A 25-year period was chosen due to a limitation in the historic observation dataset that started at 1981. To examine the projected change easily, another 25-year period from 2075 to 2099 is used for future projections.

City	Abbr.	Sq. mi
Albuquerque, NM	Alb	~190
Oklahoma City, OK	OKC	~620
Little Rock, AR	LR	~120
Dallas/Ft Worth, TX	DFW	~700
Houston, TX	Hou	~625
Baton Rouge, LA	BR	~100

Table 1: Abbreviations of cities assessed.

Figure 1: Cities assessed.

2.2 *Data*

There are two types of downscaling methods that can be used to downscale GCM outputs – dynamical and statistical. Dynamical downscaling is a process where the GCM output is used as input for a regional climate model. This can be quite computationally expensive and is not always efficient. Statistical downscaling methods use statistical relationships between the GCMs and observational training data to produce higher resolution regional products. The downscaled products used in this study were created with a statistical downscaling method. The data used for this analysis was created through a joint project between the South-Central Climate Science Center

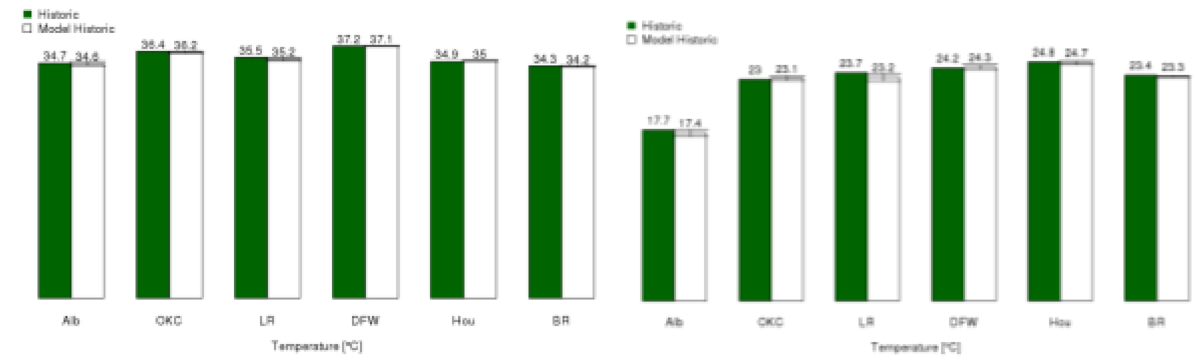

Figure 2: Comparing Observations and Model Historic (left: 95th percentile daily maximum temperature, right: 95th percentile daily minimum temperature)

and the NOAA Geophysical Fluid Dynamics Laboratory. It includes three GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5,Taylor et al. 2012): CCSM4, MIROC5, and MPI-ESM-LR. These three GCMs were downscaled using equi-distant quantile mapping (Pierce et al. 2015). Three different training data sets, Livneh (Livneh et al. 2015), Daymet (Thornton et al. 2017), and PRISM (Daly et al. 2008), were used in the downscaling. This resulted in a total of nine different simulations. For this analysis, daily maximum and minimum temperatures from two representative concentration pathways (RCP 8.5 - high emissions scenario and RCP 4.5 - mid-range emissions scenario; Vuuren et al. 2011) are examined. Observational data used to assess the historical performance came from the Livneh dataset.

2.3 *Heat Waves and Cooling Degree Day Calculations*

Given the climatic differences across regions, there is no standard definition of a heat wave. For this analysis, heat waves are defined as periods three days or longer when:

1. Maximum daily temperature is above the model historic 95th percentile of maximum temperature (T_{95ma})
2. Minimum daily temperatures is above the model historic 95th percentile of minimum temperature (T_{95mi})

The criteria used in this analysis were adapted from Perkins and Alexander (2013). Since minimum nighttime temperature plays a large role in relieving the stress of high temperatures during the day (Perkins and Alexander 2013), it is important to include T_{95mi} to consider the overall severity of a heat wave.

In Figure 2, observational 95th percentile is compared to modeled historic 95th percentile. Observations and modeled historic were found to be similar in magnitude, with slight variations between model runs (denoted by error bars). Therefore, it is appropriate to use modeled historic as the T_{95ma} and T_{95mi} threshold to directly compare each model historic run to the corresponding model future run.

Daily cooling degree days were found using the standard formula (equation 1) with a threshold of 65°F for observations, model historic and model future.

$$CDD = \frac{Max\ Daily\ Temp + Min\ Daily\ Temp}{2} - 65°\mathrm{F} \qquad [1]$$

This assumes that the degree at which cooling is required to stay comfortable indoors will remain at an outdoor temperature of 65°F. If the value of CDD is below zero, the number cooling degree days for that day is zero. CDDs are then added up by year to look at annual cooling degree days per year for each 25-year time period. This was then averaged for the 25 years to find a mean annual CDD for observations, model historic and model future.

3. RESULTS

First, model simulations are compared to observations. Then the results of the different model runs for the historic time period (1981-2005) and future time period (2075-2099) are analyzed. These results include annual maximum and minimum temperature, total number of heat waves, and mean annual cooling degree days.

	Cities	Observations	Multi-model mean (sd of models)		
			Model Historical	RCP 4.5	RCP 8.5
T_{max}	Alb	37.59	37.18 (0.517)	40.58 (0.290)	43.12 (0.479)
	OKC	39.64	39.12 (0.405)	42.93 (1.263)	44.66 (0.882)
	LR	38.62	37.92 (0.366)	42.03 (0.874)	44.16 (1.333)
	DFW	39.59	39.53 (0.253)	43.13 (1.176)	44.66 (0.797)
	Hou	37.12	37.20 (0.136)	39.71 (0.929)	41.43 (0.919)
	BR	35.84	35.91 (0.142)	38.68 (0.744)	40.42 (0.832)
T_{min}	Alb	-13.52	-14.33 (0.583)	-12.05 (0.748)	-9.28 (1.023)
	OKC	-15.28	-14.90 (0.218)	-12.56 (0.439)	-9.08 (0.421)
	LR	-12.06	-12.42 (0.320)	-9.65 (0.840)	-6.70 (0.807)
	DFW	-9.80	-10.06 (0.785)	-7.97 (0.751)	-5.08 (0.264)
	Hou	-4.18	-4.71 (0.586)	-2.78 (0.914)	-0.21 (0.562)
	BR	-6.50	-6.85 (0.256)	-4.81 (0.660)	-2.08 (0.993)

***Table 2**: Maximum and Minimum Temperatures for Observations, Model Historic and Model Future – RCP 4.5 and RCP 8.5 (using a multi-model mean with the standard deviation for the nine models)*

	Cities	Observations	Multi-model mean (sd of models)
T_{max} trend line Slope	Alb	0.00438	0.0630 (0.0475)
	OKC	-0.0472	0.0357 (0.0620)
	LR	-0.0188	0.0546 (0.0521)
	DFW	0.0185	0.0431 (0.0369)
	Hou	0.0601	0.0686 (0.0191)
	BR	0.0205	0.0445 (0.0115)
T_{min} trend line Slope	Alb	0.111	0.0442 (0.0894)
	OKC	0.271	0.0519 (0.0793)
	LR	0.237	0.0819 (0.0792)
	DFW	0.194	-0.0136 (0.0413)
	Hou	0.266	0.0211 (0.0453)
	BR	0.186	0.0943 (0.0160)

***Table 3**: Slope of Trend Lines for Maximum and Minimum Temperatures for Observations and Model Historic (using a multi-model mean with the standard deviation for the nine models)*

3.1 *Comparing Observations to Model Historic*

In this section, observations from Livneh are compared to the nine model historical runs to evaluate the performance of the model simulations. Four metrics are examined to compare observations to model output: magnitude of the mean maximum and minimum temperatures and trends of the annual maximum and minimum temperatures. In Table 2 annual maximum (T_{max}) and annual minimum (T_{min}) temperatures averaged over the 25-year time period are listed in degrees Celsius for each of the cities. The magnitude of T_{max} and T_{min} are very similar across observations and model historic for all cities. In contrast, the multi-model mean tends to overestimate the slope for T_{max} and underestimate the slope for T_{min} (Table 3).

3.2 *Annual Maximum and Minimum Temperatures*

Next, the average annual maximum and minimum temperature are considered for each city for the historical (1981-2005) and future (2075-2099) periods (Table 2). The observed maximum ranged from 35 to 40°C. This increases by around 2 to 4°C for RCP 4.5 and 4.5 to 6°C for RCP 8.5 for each of the cities (Figure 3a). The observed minimum had a much wider range from -15 to -4°C. This increases by around 2 to 3°C for RCP 4.5 and 4 to 6°C for RCP 8.5 (Figure 3b). Therefore, it is evident that maximum and minimum temperatures are projected to increase in all six cities.

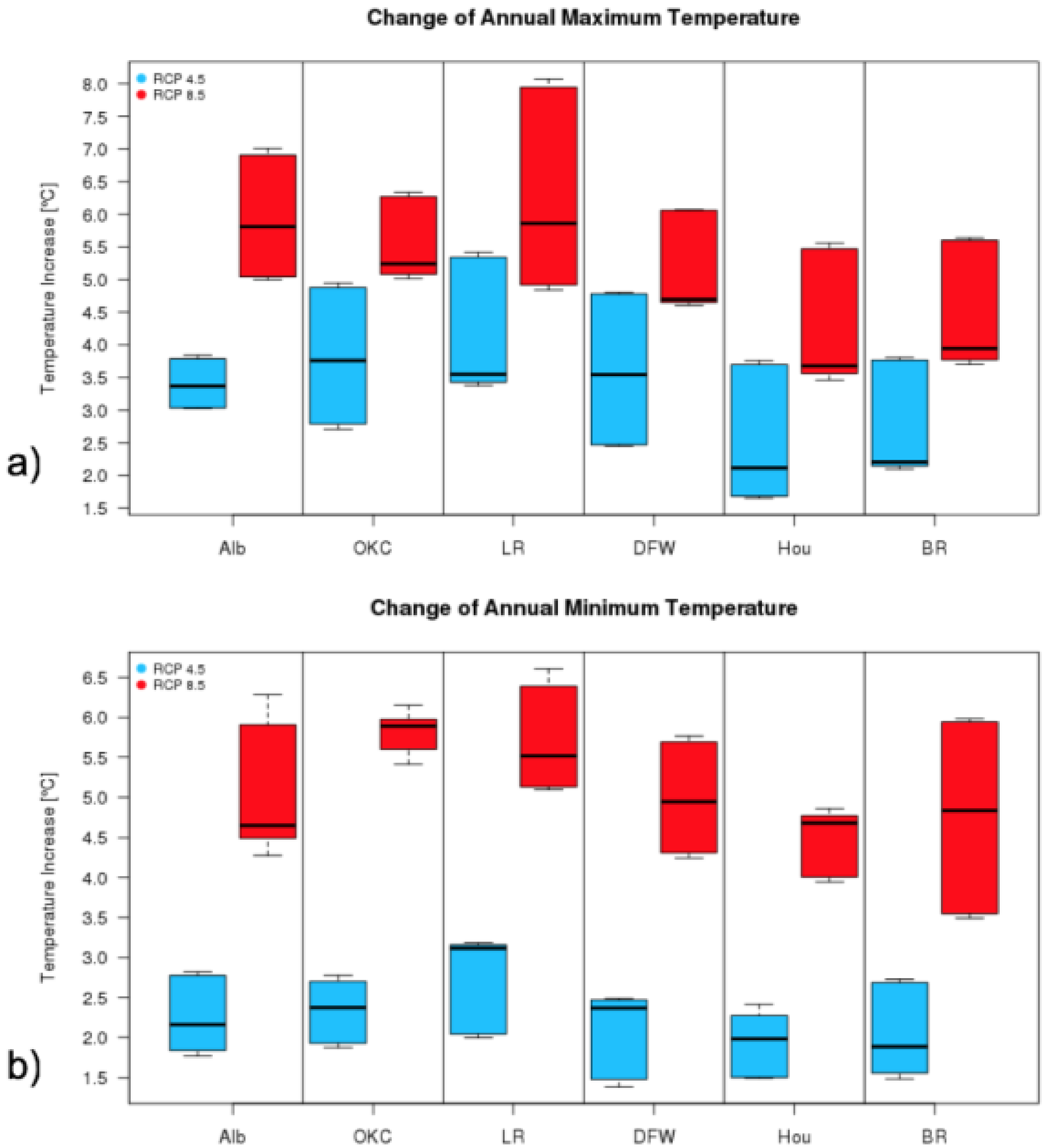

***Figure 3**: Box and Whisker Plots of Change of Temperature (Model Future - Model Historical) (a) Change of Annual Maximum Temperature (b) Change in Annual Minimum Temperature*

3.3 *Heat Waves*

The observed and projected change in heatwaves is examined in this section. There were anywhere from 21 to 33 heatwaves found in observational data from 1981-2005, or around 1 heat wave per year (Figure 4a). The model simulations are similar to the observed number of heatwaves from 1981-2005, with a multi-model mean range of heatwaves from 25 to 35. For the future time period of 2075-2099 the number of heat waves increases (Figure 4b). RCP 4.5 has a multi-model mean range of 112 to 145 heat waves per 25 years, or 4 to 5 heat waves per year. Under RCP 8.5 there is multi-model mean range of 130-150 heat waves per 25 years, or 5 to 6 heat waves per

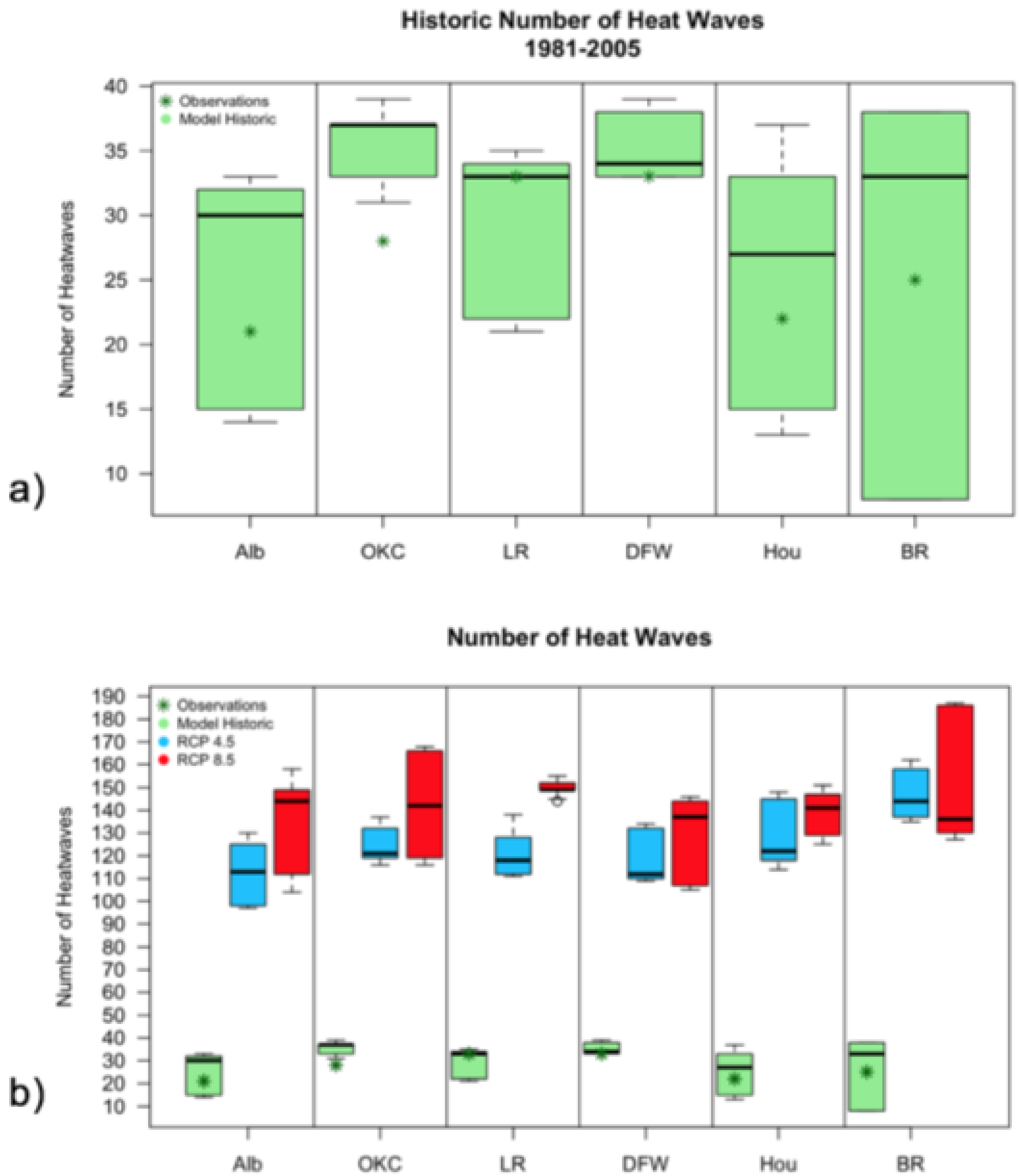

Figure 4:*Number of Heat Waves per 25 year time period (a) Heatwaves for the Historical time period of 1981-2005 (Observations and Model Historic) (b) Heatwaves for the Historical time period of 1981-2005 (Observations and Model Historic) and for future time period of 2075-2099 (RCP 4.5 to RCP 8.5)*

year. The most heat waves occur in Baton Rouge, with a multi-model mean of 147 heatwaves per 25 years for RCP 4.5 and 150 heat waves per 25 years for RCP 8.5. It is interesting to note that although Baton Rouge's multi-model mean increases from RCP 4.5 to RCP 8.5, the median actually decreases. We speculate that this is the result of most models having values smaller than the median, while there are a few outlier models project an increase in heat waves larger than the median. Overall, all cities are projected to experience more than triple the number of heat waves per year.

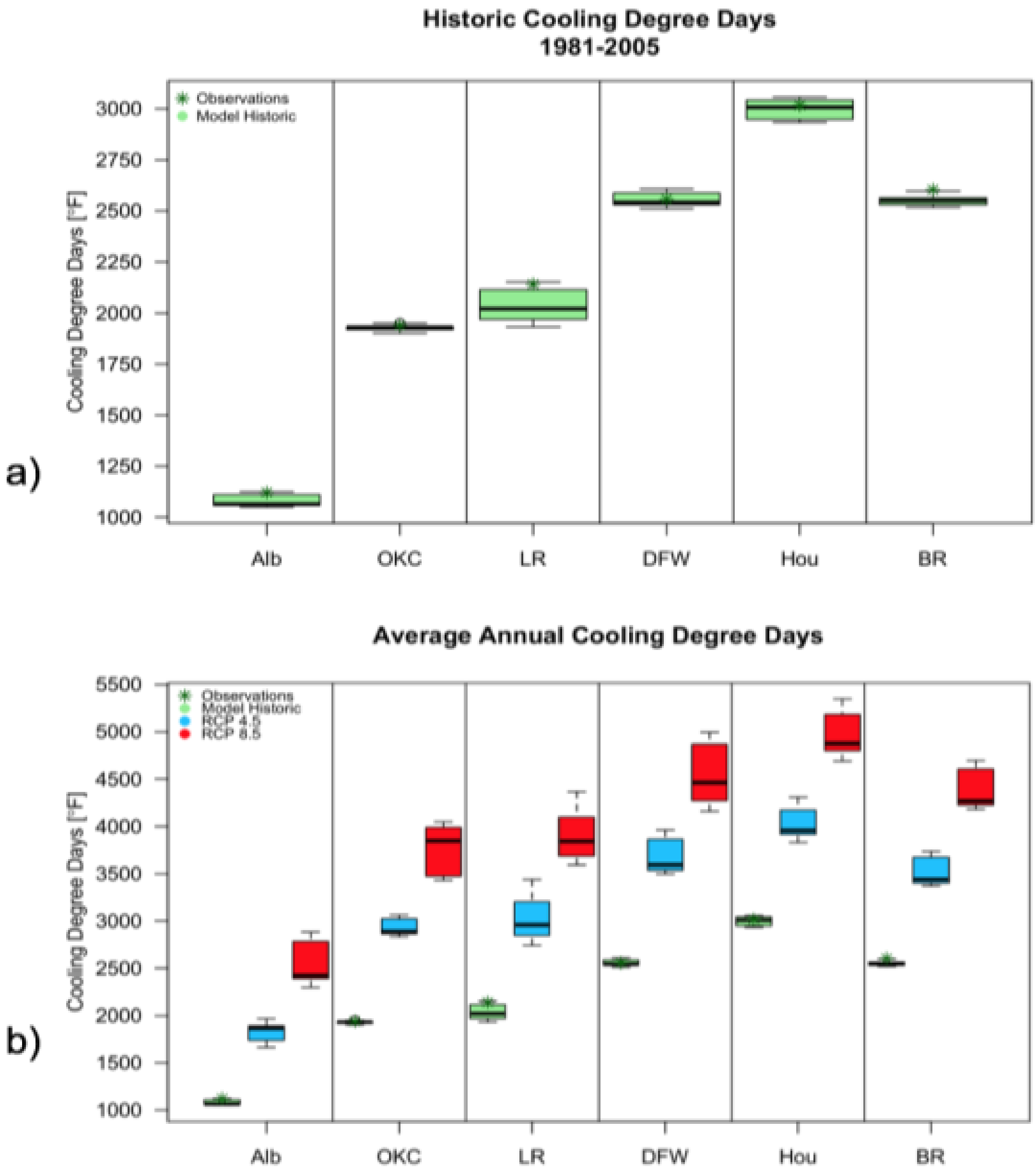

***Figure 5**: Annual Cooling Degree Days [Degrees Fahrenheit] (a) Annual Cooling Degree Days for the Historical time period of 1981-2005 (Observations and Model Historic) (b) Annual Cooling Degree Days for the Historical time period of 1981-2005 (Observations and Model Historic) and for future time period of 2075-2099 (RCP 4.5 to RCP 8.5)*

3.4 *Cooling Degree Days*

Finally, Cooling Degree Days (CDDs) are analyzed for each city. (CDDs are in units of degrees Fahrenheit.) All cities have vastly different number of CDDs with very little variation within models for each city, although modeled historic and observations tend to be similar for each city (Figure 5a). The large difference in CDDs between cities arises from different average daily temperatures for the climate zones. Albuquerque has lower minimum temperatures at night that can drive down the average temperatures, therefore it has only around 1000 CDDs. In contrast, Houston has very high maximum temperatures that drive the average temperature up, therefore it has around 3000 CDDs. There is a large projected change in CDDs regardless of RCP (Figure 5b). CDDs are projected to increase on average around 50% for RCP 4.5 and around 85% for RCP 8.5.

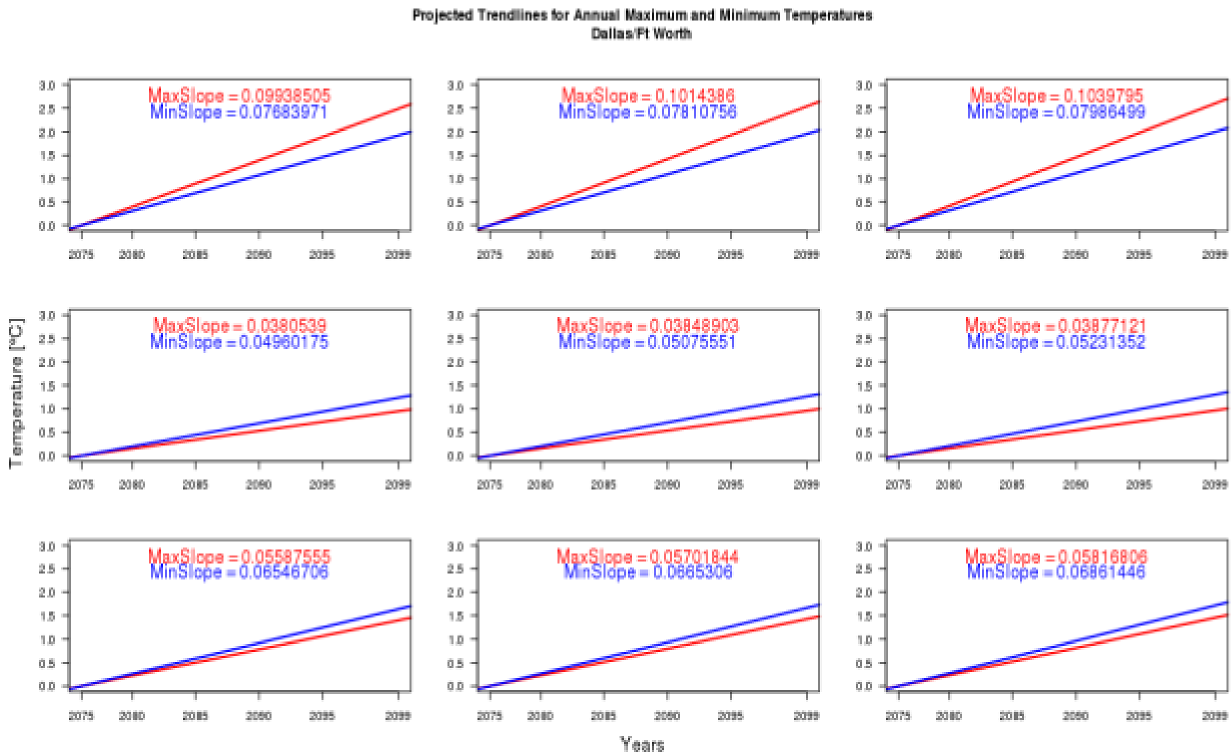

***Figure 6**: slope of trend lines of Maximum (red line) and Minimum (blue line) Temperatures for the nine model historical runs in Dallas/Fort Worth (rows: the first row is associated with CCSM4, middle row is MIROC5 and the last row is MPI-ESM-LR)(columns: the first column is associated with Livneh, middle column is Daymet, and the last column is associated with PRISM)*

To examine what is causing CDDs to increase, trends of the maximum and minimum temperatures were examined separately. Maximum and minimum trends were examined across model historic, RCP 4.5, and RCP 8.5. Trends were found to be the similar across all models. We chose RCP 4.5 for Dallas/Fort Worth to illustrate the results since it is in the middle of the regional spread of our cities (Figure 6). The first row, associated with CCSM4, shows maximum temperatures increasing more than minimum temperatures while the remaining GCMs show that the minimum temperature increasing faster than the maximum temperature. So, there is no one variable driving the CDDs upward. Therefore, the difference between GCMs used in this study affects which variable (maximum or minimum temperatures) is driving the projected increase in CDDs.

4. DISCUSSION AND CONCLUSIONS

Our projections show an increasing number of heat waves and CDDs for the six cites examined across the south-central United States. Heat waves per year are projected to at least triple in all cities. This could lead to increases in the number of power outages from overheating. Increases in mortality in these cities and economic loss for local businesses could also occur. Energy suppliers use CDDs to measure energy demand used for cooling. This analysis found that CDDs are projected to increase by 50% to 85% depending on future emissions scenarios. Therefore, increased cooling will be required in order to combat the heat.

The Energy Information Administration has developed climatic zones for CDD (US Energy Information Administration 2013). The six cites we looked at were split into two climatic zones. Albuquerque and Little Rock lie within Zone 4 with less than 2,000 CDDs per year. The other four cities lie within Zone 5 with more than 2,000 CDDs per year. This analysis showed that under a high emissions scenario both cities in Zone 4 increase past 2,000 CDDs therefore pushing them into Zone 5. In the future, rezoning of these climates might be required to more accurately show the future of CDDs.

This work can be extended to include evaluating changes in the frequency, duration, and length of heat waves as well as assessing other cities in the region or the entire United St

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