USING DOWNSCALED CLIMATE MODEL OUTPUT TO EXAMINE CLIMATE CHANGE IN NORTH CAROLINA

by

Andrew Robinson

A thesis submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Master of Science in
Earth Science

Charlotte

2022

Approved by:

____
Dr. Brian Magi

____
Dr. Jacob Scheff

____
Dr. Deborah Thomas

ABSTRACT

ANDREW ROBINSON. Using Downscaled Climate Model Output to Examine Climate Change in North Carolina. (Under the direction of DR. BRIAN MAGI)

Climate change is a pressing issue people in North Carolina are already facing, and recent decades in North Carolina have exhibited a warming trend at the higher end of projected values. Due to North Carolina's diverse geography, climate is expected to change differently across the state. This geography can be broken down into three distinct regions: the Mountains, Piedmont, and Coastal Plain. We used downscaled climate model output to examine climate change in the largest population centers (Asheville, Charlotte, and Wilmington) in each of these regions to examine how climate change is projected to affect these places in the future for a representative month in the winter and summer. We examine how maximum temperature, minimum temperature, specific humidity, and precipitation change between the present and the end of the 21st Century using downscaled output from the 20 climate models in the Multivariate Adaptive Constructed Analogs (MACA) downscaling project. Climate is expected to warm and become more humid in North Carolina in Summer and Winter with wide variability in precipitation across the state, noting that the variability is only evident by considering output from multiple climate models. By examining North Carolina climate change at such a tangible level, this study intends to inform and equip decision makers as we prepare North Carolina and the distinct geographical regions for its future.

DEDICATION

This work is dedicated to my family as they have sacrificed so much to allow me to continue my education to this point and into the future in the Geography PhD program at UNC Charlotte.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Brian Magi, for his tireless support, encouragement, and motivation throughout this project. This would not have been possible without his help. I would not be the researcher I am today without his guidance over the past two years of working together.

I would also like to acknowledge my committee members, Dr. Deborah Thomas and Dr. Jacob Scheff for their insight and feedback into this project as it has developed.

I would also like to thank my research colleague, Roger Riggin, for his incredibly useful Python script that made many of the great figures contained in this work. This script is contained within Appendix B.

TABLE OF CONTENTS

LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF ABBREVIATIONS	xii
CHAPTER 1: INTRODUCTION	1
CHAPTER 2: METHODS	9
CHAPTER 3: RESULTS	16
3.1: SUMMER	16
3.1.1: MAXIMUM TEMPERATURE	16
3.1.2: MINIMUM TEMPERATURE	18
3.1.3: SPECIFIC HUMIDITY	21
3.1.4: PRECIPITATION	22
3.2: WINTER	26
3.2.1: MAXIMUM TEMPERATURE	26
3.2.2: MINIMUM TEMPERATURE	29
3.2.3 :SPECIFIC HUMIDITY	31
3.2.4: PRECIPITATION	34
CHAPTER 4: DISCUSSION	38
CHAPTER 5: CONCLUSIONS	55
REFERENCES	58
APPENDIX A: MODEL OUTPUT	63
APPENDIX B: FIGURE SCRIPT	70

LIST OF TABLES

TABLE 2.1: 9

Climate and Earth system models used by the MACA downscaling project.

LIST OF FIGURES

FIGURE 1.1: 2

Climate model projections of temperature from the year 2005 to 2100 using the different RCP scenarios (green, orange, purple, red), and observed temperatures (black) from the year 1980 to 2020 (Representative concentration pathways, 2015).

FIGURE 1.2: 4

How different emissions scenarios (RCP2.6, RCP4.5, RCP6.0, RCP8.5), the climate sensitivity, and feedback mechanisms all work together to give a range of temperature possibilities for a future world. Figure from Hausfather (2021).

FIGURE 1.3: 5

Displays how 72% of Americans believe in climate change (Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022).

FIGURE 1.4: 5

Displays how only 43% of Americans believe climate change will affect them (Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022).

FIGURE 1.5: 6

Figure 1.5 Displays how 45% of North Carolina residents believe climate change will affect them(Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022)

FIGURE 1.6: 7

Warming trend North Carolina has experienced since 1900. Figure from the NCCSR.

FIGURE 2.1: 11

An example of how the maps appeared when initially uploaded into ArcMap. The difference in July temperature maximums across the “Greater North Carolina Region” (example is from CCSM4 downscaled output from MACA). Color scale is associated with the figure 3.1 in the results chapter.

FIGURE 2.2: 12

An example of the same data set as Figure 2.1 (difference in average temperature maximums in July from “present” to “future” for CCSM4) but with the excess data trimmed to the political boundaries of North Carolina. Color scale is associated with the figure 3.1 in the results chapter.

FIGURE 2.3: 13

Displays how these different regions were divided out of the state as a whole. This is the same variable set as Figure 2.2, the difference in July max temperature using CCSM4. For Charlotte we used the area inside of I-485 since this area contains the city center and the majority of the population, development, and infrastructure. Color scale is associated with the figure 3.1 in the results chapter.

FIGURE 2.4: 14

Per Figure 2.3, but for the Asheville spatial domain

FIGURE 2.5: 14

Per Figure 2.3, but for the Wilmington spatial domain

FIGURE 3.1: 17

Change in July maximum temperatures for MACA-downscaled output from the 20 CMIP5 climate models and the composite mean average of the 20 models.

FIGURE 3.2: 18

Change in Minimum, maximum, median, and interquartile range for the change in July maximum temperatures across all climate models and as a function of spatial domain.

FIGURE 3.3: 19

Spatial differences & change in July minimum temperatures across all climate models.

FIGURE 3.4: 20

Change in Minimum, maximum, median, and interquartile range for the change in July minimum temperatures across all climate models and across spatial domains.

FIGURE 3.5: 21

This figure shows the spatial differences and change in July specific humidity between all climate models.

FIGURE 3.6: 22

This figure shows the change in minimum, maximum, median, and inter quartile range for July specific humidity between all climate models and across spatial domains.

FIGURE 3.7: 24

Spatial differences and change in July precipitation between all climate models.

FIGURE 3.8: 25

This figure shows the minimum, maximum, median, and inter quartile range for July precipitation changes between all climate models and across spatial domains.

FIGURE 3.9: 27

Spatial differences in the change in January maximum temperatures across climate models

FIGURE 3.10: 28

Minimum, maximum, median, and interquartile range for January maximum temperature changes between all climate models and across spatial domains.

FIGURE 3.11: 30

Spatial differences in the change in January minimum temperatures across all climate models.

FIGURE 3.12: 31

Minimum, maximum, median, and interquartile range for January minimum temperature changes between all climate models and across spatial domains.

FIGURE 3.13: 33

Spatial differences in the change in January specific humidity across all climate models.

FIGURE 3.14: 34

Minimum, maximum, median, and interquartile range for changes in January specific humidity across all climate models and across spatial domains.

FIGURE 3.15: 36

Spatial differences in changes in January precipitation across all climate models.

FIGURE 3.16: 36

Minimum, maximum, median, and interquartile range for changes in January specific humidity across all climate models and across spatial domains.

FIGURE 4.1.a: 39

Shows the R^2 value of 0.641 for the relationship between the change in minimum and maximum temperatures across the 20 models (blue points) in July

FIGURE 4.1.b: 40

Shows the R^2 value of 0.348 for the relationship between the change in Precipitation and Maximum Temperatures across the 20 models (blue points) in July

FIGURE 4.1.c: 40

Shows the R^2 value of 0.276 for the relationship between the change in Minimum Temperatures and Precipitation across the 20 models (blue points) in July.

FIGURE 4.1.d: 41

Shows the R^2 value of 0 for the relationship between the change in Specific Humidity and Maximum Temperatures across the 20 models (blue points) in July

FIGURE 4.1.e: 41

Shows the R^2 value of 0.170 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July

FIGURE 4.1.f: 42

Shows the R^2 value of 0.003 for the relationship between the change in Precipitation and Specific Humidity across the 20 models (blue points) in July

FIGURE 4.2.a: 43

Shows the R^2 value of 0.809 for the relationship between the change in Minimum Temperatures and Maximum Temperatures across the 20 models (blue points) in January

FIGURE 4.2.b: 44

Shows the R^2 value of 0.067 for the relationship between the change in Precipitation and Maximum Temperatures across the 20 models (blue points) in January

FIGURE 4.2.c: 44

Shows the R^2 value of 0.021 for the relationship between the change in Specific Humidity and Precipitation across the 20 models (blue points) in January

FIGURE 4.2.d: 45

Shows the R^2 value of 0.555 for the relationship between the change in Maximum Temperatures and Specific Humidity across the 20 models (blue points) in January.

FIGURE 4.2.e: 45

Shows the R^2 value of 0.025 for the relationship between the change in Minimum Temperatures and Precipitation across the 20 models (blue points) in January

FIGURE 4.2.f: 46

Shows the R^2 value of 0.533 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in January.

FIGURE 4.3.a: 47

Shows the R^2 value of 0.631 for for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Wilmington.

FIGURE 4.3.b: 48

Shows the R^2 value of 0.055 for for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Charlotte.

FIGURE 4.3.c: 48

Shows the R^2 value of 0.063 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Asheville.

FIGURE 4.4: 52

A large portion of North Carolina agriculture falls within the area of higher warming in the state. Compare to figure 3.1. Figure retrieved from

LIST OF ABBREVIATIONS

MACA: Multivariate Adaptive Constructed Analogs

RCPs: Representative Concentration Pathways

IPCC: Intergovernmental Panel on Climate Change

NCCSR: North Carolina Climate Science Report

LOCA: Localized Constructed Analogs

CMIP5: Fifth Iteration Coupled Model Intercomparison Project

CHAPTER 1: INTRODUCTION

Climate change is already well underway with nearly 2 degrees Fahrenheit of warming already (IPCC, 2021). The impacts of climate change are being felt globally (IPCC, 2022) and in the United States (Jay et al., 2018) The future will undoubtedly be warmer (IPCC, 2021), and the impacts will be magnified. There are many questions about how large-scale climate change will translate to local scales, and also how to decide what to plan for at local scales in terms of how much future warming there will be and what impacts it will have on localized environments.

Representative Concentration Pathways (RCPs) are scenarios created as input to Earth system models to simulate the climate of Earth into the future. There are four main RCP scenarios that are referred to as RCP2.6, RCP4.5, RCP6.0, and RCP8.5, and each scenario presents a future with different trajectories and levels of greenhouse gas emissions by the year 2100 (van Vuuren et al., 2011). The number (2.6, 4.5, 6.0, and 8.5) refers to the change in radiative forcing (in watts per square meter) of the climate in the year 2100 relative to the pre-Industrial period. The higher the radiative forcing, the more energy is trapped within the Earth system; this leads to higher overall atmospheric temperatures. Warmer atmospheric temperatures lead to changes in many other climate variables such as an increase in humidity and changes in precipitation (IPCC, 2021; IPCC, 2022), changing the way we live in our environment. For example, increases in heat and humidity lead to increased heat stress in climates similar to North Carolina (Barreca, 2012; Diem et al., 2017).

RCPs are determined by trends in population growth, resources consumed in developed and developing countries, and the growth of the world economy projected into the future (Moss et al., 2010; van Vuuren et al., 2011). By the end of the century, projections of climate change from the RCPs show broad-ranging impacts that, roughly, scale with the magnitude of greenhouse gas emissions (IPCC, 2022). The end-of-century temperatures projected by the RCPs are shown in Figure 1.1.

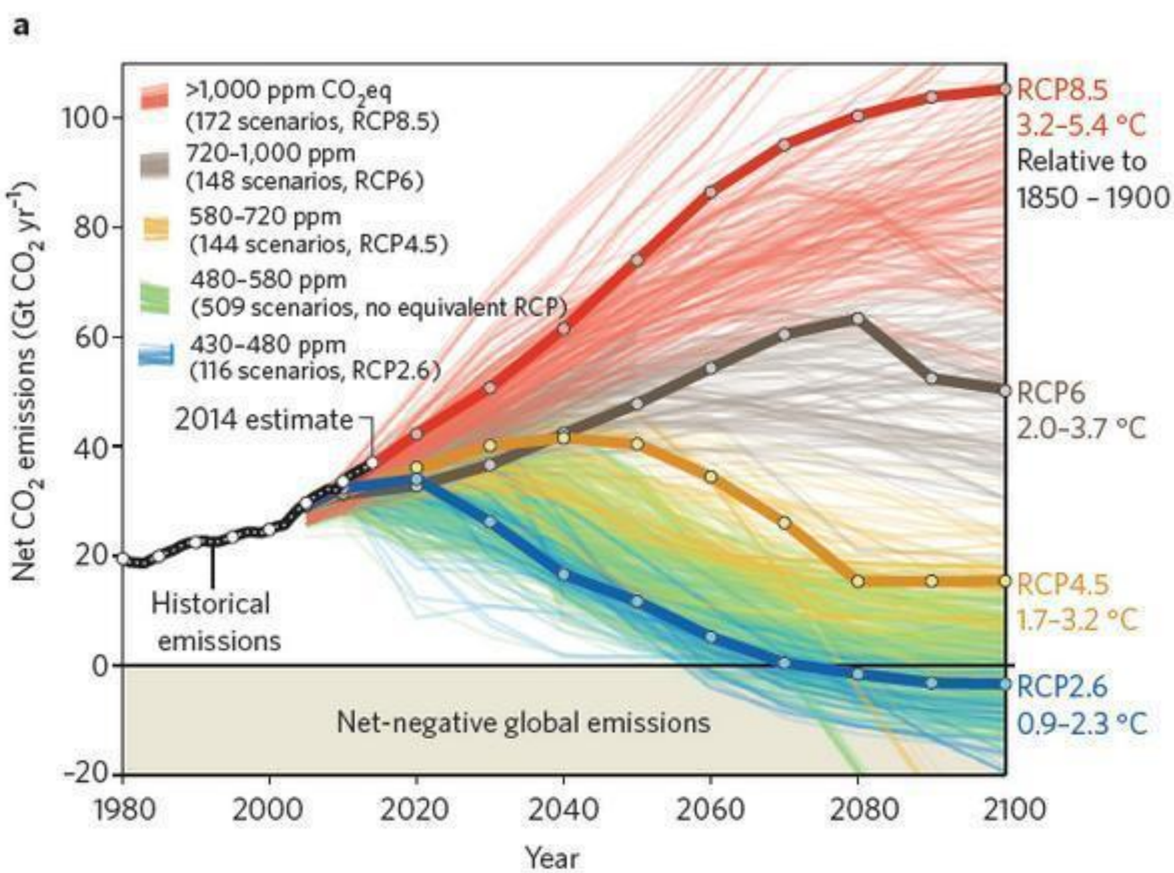


Figure 1.1. Climate model projections of temperature from the year 2005 to 2100 using the different RCP scenarios (green, orange, purple, red), and observed temperatures (black) from the year 1980 to 2020 (Representative concentration pathways, 2015).

RCP8.5 is a scenario that looks at how the Earth will change if we increase the radiative forcing in the year 2100 to 8.5 watts per square meter relative to the pre-Industrial Era (circa 1850) through continued extensive use of non-renewable sources of energy (Riahi et. al., 2011). RCP8.5 is a future world that continues heavy reliance on coal, methane gas, and oil for primary energy consumption through the end of the 21st Century.

There is considerable discussion of whether the RCP8.5 scenario is a realistic storyline for the future. Many argue that the "extreme" RCP8.5 is unlikely to happen given that it is a "business as usual" projection, meaning there are no further climate policies enforced to protect from global warming (Hausfather, 2019; Hausfather & Peters, 2020), but then there are also arguments that suggest that the median global temperature predicted by RCP8.5 is worth continued study since there are uncertainties in the severity of carbon cycle feedback loops and climate sensitivity. For example, even if the world does reduce emissions to a level more similar to RCP2.6 or RCP4.5, it is possible that we will see temperatures that are within the range projected by RCP8.5 (Figure 1.2). Uncertainty in projected temperature is due to uncertainty in emissions (RCP scenarios) (Webster et al., 2002), uncertainty in radiative forcing (Schwartz, 2004) and fast-timescale feedbacks such as cloud feedbacks (ie. climate sensitivity; Sherwood et al., 2020), and uncertainty in slow-timescale positive feedbacks that include carbon cycle feedbacks, ice sheet melt reducing global albedo (Golledge et al., 2019), and the release of greenhouse gasses by the thawing of permafrost making the land a net source of CO2 (Huntingford et al., 2009).

On a global scale, the current and future impacts of climate change (IPCC, 2021; IPCC, 2022) can feel like a distant issue because climate change is a process that unfolds over decades and centuries rather than days, weeks, or months. In a study about how people perceive climate change, 72% of Americans believe climate change is happening (Figure 1.3), 61% believe climate change will affect America, and 60% of Americans believe the President and Congress should do more to address global warming, but only 54% of Americans believe local officials should do more to address global warming and 43% think "global warming will harm them personally" (Howe et al., 2015), as shown in Figure 1.4. These polling-based results generally suggest that as the spatial scale decreases, Americans feel less endangered by climate change. Therefore, climate change seems like a global problem and not a local one even while localized climate impacts continue to mount (Jay et al., 2018). There is a clear need for studying and reporting on current and future impacts of climate change at a more local scale, noting that Figure 1.5 shows the results for counties in North Carolina.

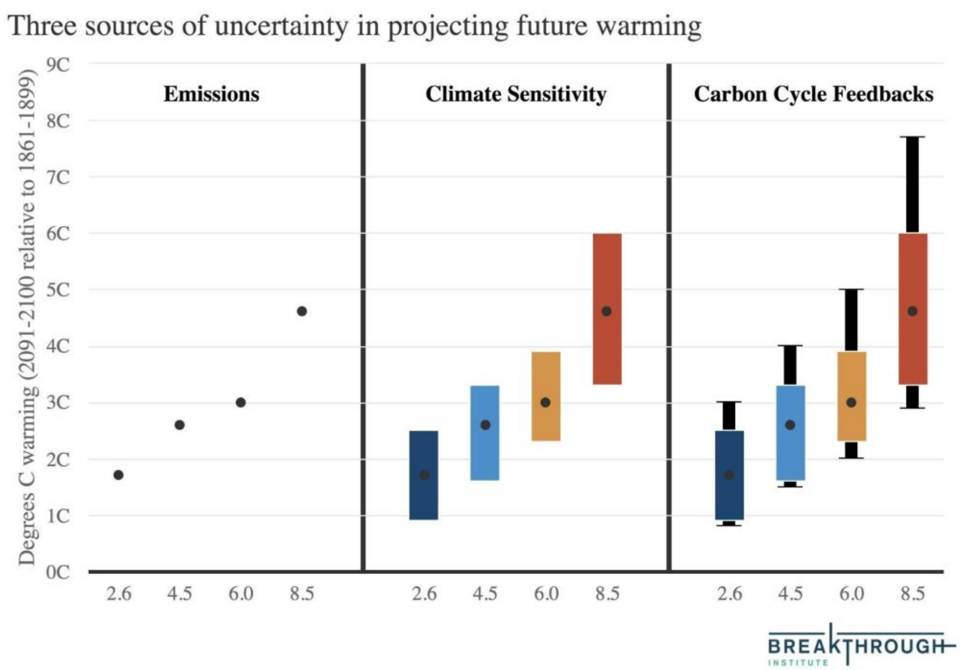


Figure 1.2 How different emissions scenarios (RCP2.6, RCP4.5, RCP6.0, RCP8.5), the climate sensitivity, and feedback mechanisms all work together to give a range of temperature possibilities for a future world. Figure from Hausfather (2021).

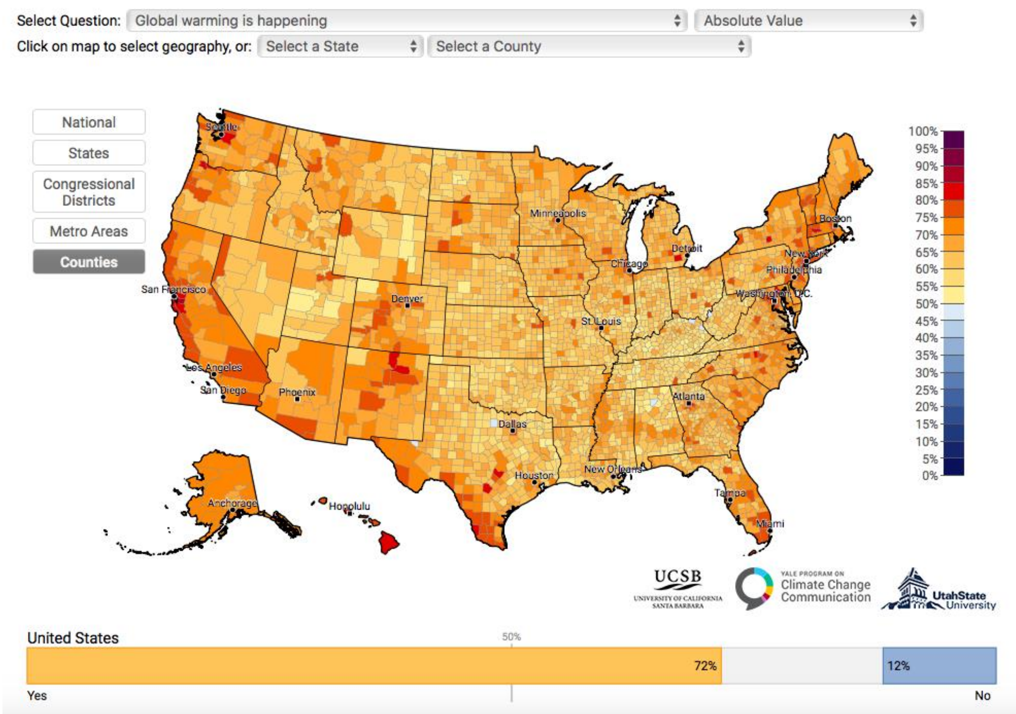


Figure 1.3. Displays how 72% of Americans believe in climate change (Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022).

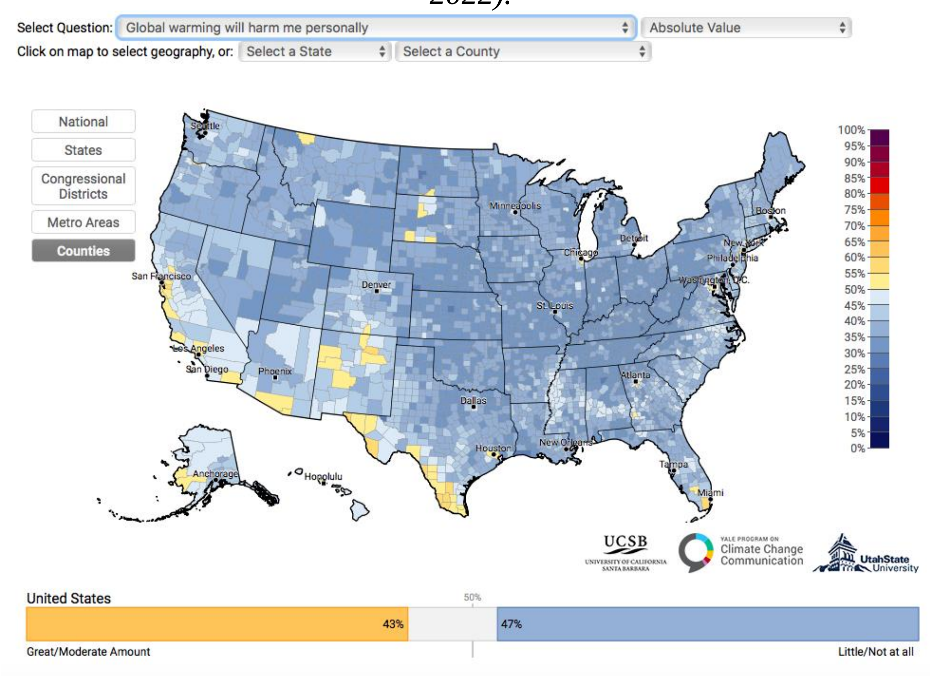


Figure 1.4. Displays how only 43% of Americans believe climate change will affect them (Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022).

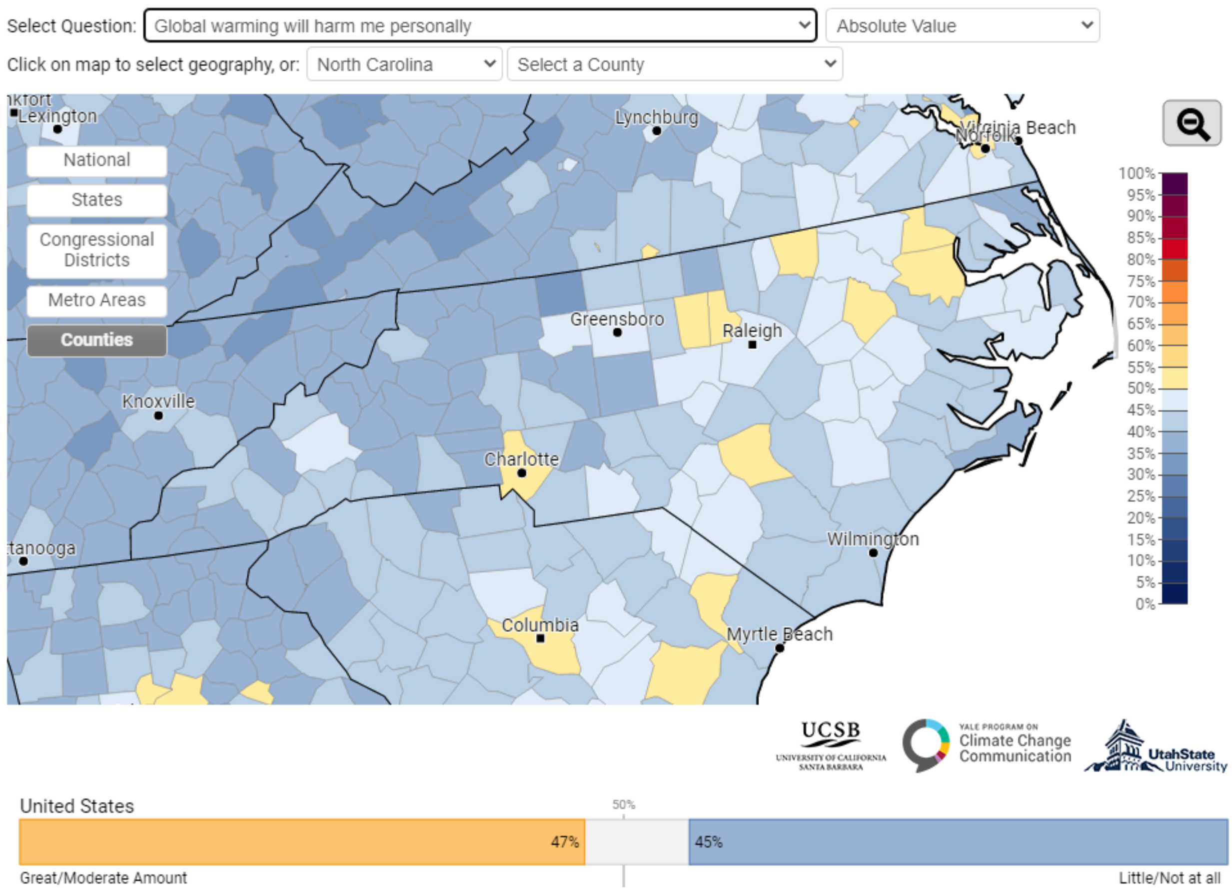


Figure 1.5 Displays how 45% of North Carolina residents believe climate change will affect them(Howe et al., 2015; figure from https://climatecommunication.yale.edu/visualizations-data/ycom-us/ accessed Spring 2022)

Thinking of local scale impacts of climate change, the North Carolina Climate Science Report (NCCSR) examines how the climate in North Carolina could change from present to 2040-2060 using output from the Localized Constructed Analogs (LOCA) statistical downscaling project (Pierce et al., 2014) which downscaled output from 32 climate models. LOCA used climate model output from the fifth Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012), which is roughly one generation older than the climate model output discussed in the IPCC AR6 report (IPCC, 2021). NCCSR discussed projections of future climate (such as temperature and precipitation changes) in North Carolina to allow time for stakeholders, planners, and politicians to plan for a future with more extreme climate outcomes.

NCCSR (Kunkel et al., 2020) showed that the lack of obvious warming trend that the Southeast experienced from 1930-1960 is being replaced in the last 50 years by a warming trend (Figure 1.6) more similar to the higher end of projected values (i.e. RCP8.5). Therefore, the NCCSR conclusions suggest that we should not discount the possibility of higher warming projections related to RCP8.5 (Kunkel et al., 2020), which is similar to findings at a global scale driven by the uncertainties highlighted in Figure 1.2.

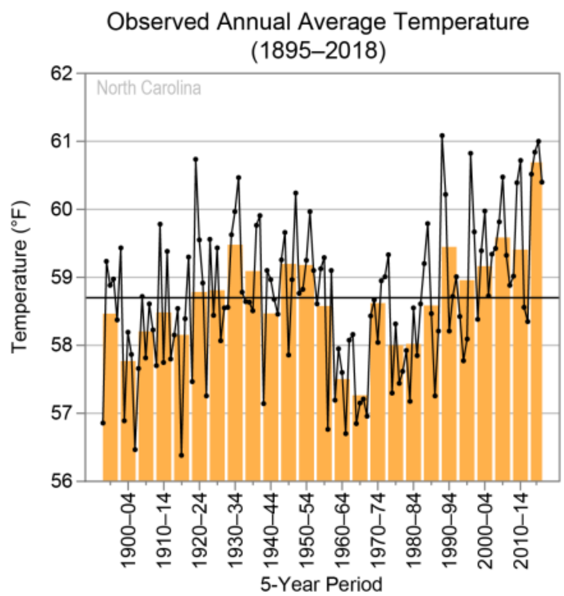


Figure 1.6. Warming trend North Carolina has experienced since 1900. Figure from the NCCSR.

My objective is to use downscaled climate model output from the RCP8.5 scenario to study changes in the wintertime and summertime climate in North Carolina between the present and the year 2100. In contrast to the NCCSR (Kunkel et al., 2020), my work explores North Carolina climate at a finer spatial scale and at a seasonal timescale, and focuses on changes expected by the year 2100 in CMIP5 RCP8.5. Also, my work uses downscaled climate model output from the Multivariate Adaptive Constructed Analogs (MACA) data portal (Abatzoglou and Brown, 2012;

Abatzoglou, 2011), which is a different source than what NCCSR (Kunkel et al., 2020) used, although the downscaling techniques (Pierce et al., 2014; Abatzoglou and Brown, 2012) are related.

In my thesis, we summarize changes evident in the MACA downscaled climate model output numerically and visually for North Carolinians to be prepared for local environmental changes from future global warming. A cost-benefit analysis of climate change impacts and societal resilience is clear: It is more effective and economical to prepare for climate change impacts through planning and development than to react to them when they are already here (Williams et al., 2020). By providing North Carolina decision makers with climate data specific to our state and that encompasses output from multiple climate models, it arms everyone with pertinent information to prepare for climate change in North Carolina. In order to plan for the future, we start with what the climate of North Carolina is projected to be by the end of the century under the RCP8.5 climate scenario. RCP8.5 is a key projection for planners as it sets the upper boundary for a warmer North Carolina climate and allows decision makers to prepare for what we hope to be the high end of warming scenarios, remembering the upper range of temperatures predicted by the more realistic emissions scenarios (e.g. RCP4.5) is the same as the middle of the range RCP8.5 (Figure 1.2).

CHAPTER 2: METHODS

I use downscaled fifth phase Coupled Model Intercomparison Project (CMIP5) climate model output (Taylor et al., 2012) from the Multivariate Adaptive Constructed Analogs (MACA) data portal (Abatzoglou and Brown, 2012; Abatzoglou, 2013). MACA was compiled for the contiguous USA, and originally intended to provide gridded downscaled climate model data that would be suitable for national wildfire projection as well as ecological and modeling applications, but the dataset can also be used to study smaller spatial scales of climate change in the USA and practical applications that are relevant to policy-makers, stakeholder groups, and local leaders.

The MACA downscaled temperature, humidity, and precipitation compare well with independently-compiled reanalysis data (Abatzoglou and Brown, 2012). The MACA downscaling procedure pays special attention to dew point temperature and uses analog patterns rather than relying solely on mathematical interpolation (Abatzoglou and Brown, 2012). This work has already been used to examine climate change in the United States in other work (Dahl et al., 2019, Heidari et al., 2021).

CCSM4	NorESM1-M	bcc-csm1-1	MRI-CGCM3
Miroc5	inmcm4	MIROC-ESM	BNU-ESM
GFDL-ESM2G	GFDL-ESM2M	CanESM2	IPSL-CM5A-LR
IPSL-CM5A-MR	bcc-csm1-1-m	MIROC-ESM-CHEM	IPSL-CM5B-LR
HadGEM2-ES365	HadGEM2-CC365	CSIRO-Mk3-6-0	CNRM-CM5

Table 2.1. Climate and Earth system models used by the MACA downscaling project.

MACA compiles ecological and meteorological model output from 20 CMIP5 climate and Earth system models (Taylor et al., 2012) and data from existing US weather stations onto a 4 km raster grid (Abatzoglou, 2011). MACA downscaled output uses daily timescales and includes downscaled 2-m maximum/minimum temperature, 2-m maximum/minimum relative humidity, 10-m zonal and meridional wind, downward shortwave radiation at the surface, 2-m specific humidity, and precipitation (Abatzoglou and Brown, 2012; Abatzoglou, 2011). We used the downscaled 2-m maximum/minimum temperature, 2-m specific humidity, and precipitation accumulation averaged on a monthly timescale to study future climate at the spatial scale of North Carolina.

I used MACA output version 2 with the METDATA option (Abatzoglou, Maca statistical downscaling method) for monthly maximum temperatures, minimum temperatures, specific humidity, and precipitation totals from the 20 CMIP5 models in Table 2.1. We used the months of January and July to study changes for a representative wintertime and summertime month. The data from January and July were averaged across two 20-year periods: 2006-2025, which we call the “Present”, and 2080-2099, which we call the “Future”. We subtracted the Present from the Future such that positive differences meant the Future was warmer, more humid, or experienced more precipitation compared to the Present, and vice versa for negative values. We studied the MACAv2-METDATA downscaled output for the CMIP5 simulations of RCP8.5, and will refer to MACAv2-METDATA downscaled output as simply “MACA” for the remainder of this discussion.

These NetCDF difference files of MACA output were named and organized in Google Drive and uploaded to ArcMap using the “make netcdf raster layer” tool. This resulted in maps of climate differences for the “greater North Carolina region” which we trimmed down to just North Carolina (Figure 2.1-2.2).

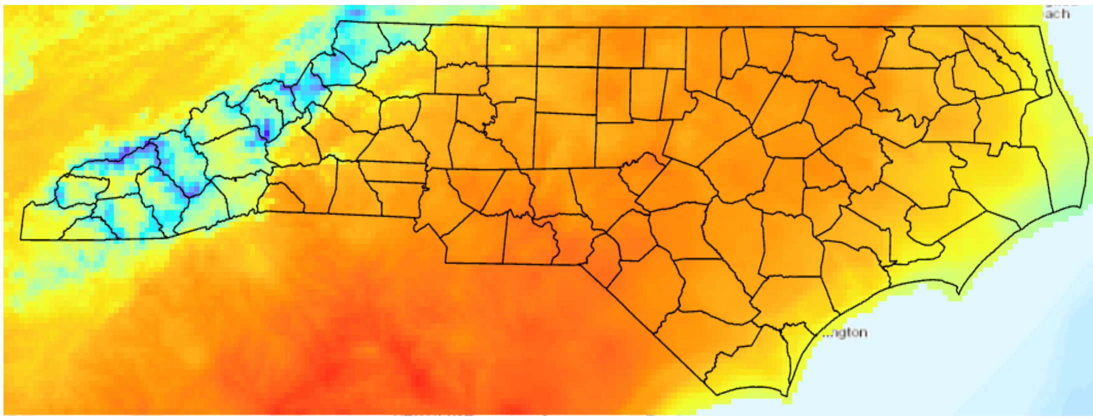


Figure 2.1. An example of how the maps appeared when initially uploaded into ArcMap. The difference in July temperature maximums across the “Greater North Carolina Region” (example is from CCSM4 downscaled output from MACA). Color scale is associated with the figure 3.1 in the results chapter.

Figure 2.1 is an example of the maps initially generated in Arcmap from the MACA output. To focus on North Carolina, we trimmed the difference data to the state of North Carolina (Figure 2.2) using the Google Earth Pro polygon tool and uploaded this shapefile into Arcmap, as a .KML layer file, to overlay the existing data. Using the “trim raster layer with mask” tool the data points outside the shape of North Carolina were eliminated from the dataset.

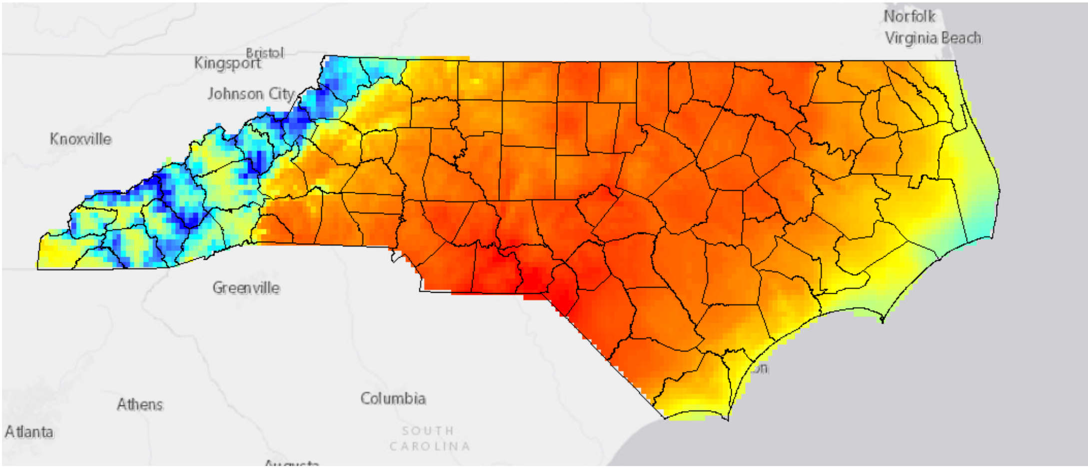


Figure 2.2. An example of the same data set as Figure 2.1 (difference in average temperature maximums in July from "present" to "future" for CCSM4) but with the excess data trimmed to the political boundaries of North Carolina. Color scale is associated with the figure 3.1 in the results chapter.

Because North Carolina is a geographically diverse state with multiple climate zones, the state was further broken down into smaller subsection areas so that the differences between them can be calculated. For this study, we worked with three locations in the state that represent different climate types within North Carolina: Asheville, Charlotte, and Wilmington. The Asheville sub-domain represents the climate of the western North Carolina mountain region, and is the most populous city in that part of North Carolina. The Charlotte sub-domain represents the Central Piedmont and includes the largest and most populous city in the state. The Wilmington sub-domain represents the Coastal region of North Carolina, but is also the largest city directly on the Atlantic Ocean in North Carolina. So the sub-domains we used are a combination of representative climate and population centers.

To partition the sub-domains from the data set that represent the entire state, polygons were formed in Google Earth pro to approximately capture each city. When the polygons were uploaded in ArcMap, the project once again used the "Trim raster layer with mask" tool to further divide the data set so layers that represent each variable for each individual location were formed.

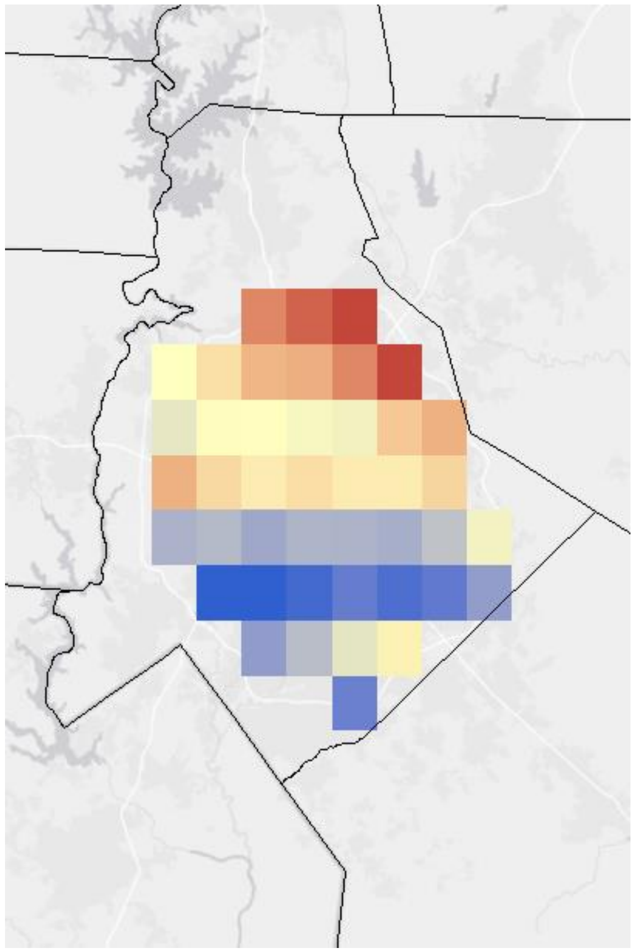


Figure 2.3. Displays how these different regions were divided out of the state as a whole. This is the same variable set as Figure 2.2, the difference in July max temperature using CCSM4. For Charlotte we used the area inside of I-485 since this area contains the city center and the majority of the population, development, and infrastructure. Color scale is associated with the figure 3.1 in the results chapter.

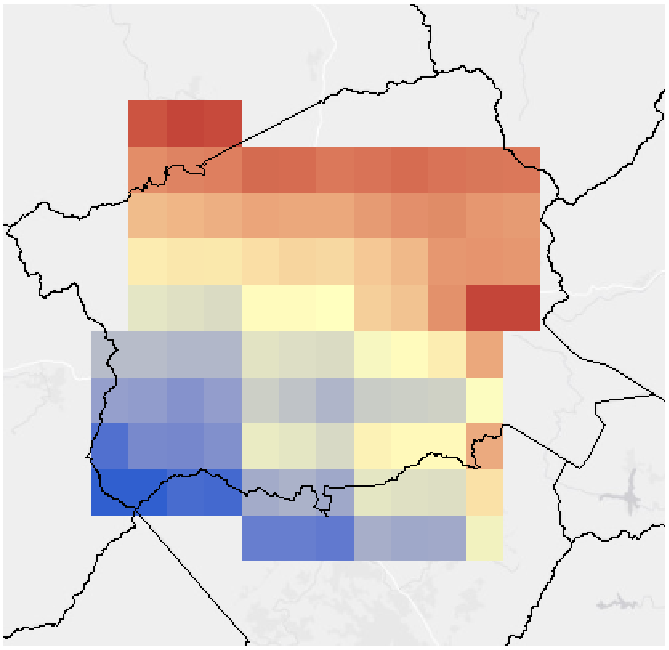


Figure 2.4. Per Figure 2.3, but for the Asheville spatial domain.

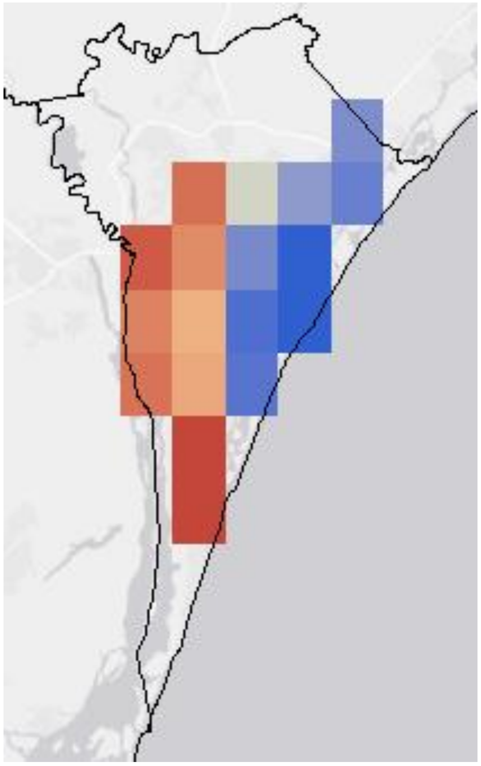


Figure 2.5. Per Figure 2.3, but for the Wilmington spatial domain

I used the statistical analysis tools in Arcmap to compile the numerical values of the differences in minimum temperature, maximum temperature, specific humidity, and precipitation for the state and the three sub-domains. This process was applied to MACA downscaled output from the 20 CMIP5 climate models (Table 2.1). We compiled, organized, entered, and saved the results in a Google Sheets document where further statistics were compiled. Part of my analysis included comparisons of the metrics in a 20-model composite average as well, and we called this output the “composite mean model”.

CHAPTER 3: RESULTS

MACA downscaled results from the ensemble of 20 CMIP5 climate models using RCP8.5 (MACAv2-METDATA) are presented for each of the four physical variables (monthly maximum temperature, minimum temperature, specific humidity, and precipitation), the two representative months (January and July), and the four spatial domains (North Carolina, Asheville, Charlotte, and Wilmington).

3.1 Summer

3.1.1. Maximum Temperature

Summertime maximum temperatures are an important metric in North Carolina climate as that is generally the warmest temperature metric. Maximum temperature is often considered when defining extreme heat outbreaks (Tan et al., 2009)

According to the composite mean of the 20 models, the statewide average maximum temperature in July will rise by 7.63 °F (Figure 3.1). The range across models was quite wide, with one model (INMCM4) predicting 4.10 °F of warming while another (HadGEM2-ES365) projected 12.02 °F. The middle 50% of the data (10 models) fell between 6.70 °F and 8.49 °F of warming.

Asheville is projected to warm 7.70 °F according to the composite mean model (Figure 3.2), slightly more than the state overall. The smallest increase in maximum temperature for Asheville is 4.09 °F (INMCM4), and the largest increase in maximum temperature is 12.60 °F (HadGEM2-ES365). The middle 50% of models fell between 6.58 °F and 8.43 °F of warming.

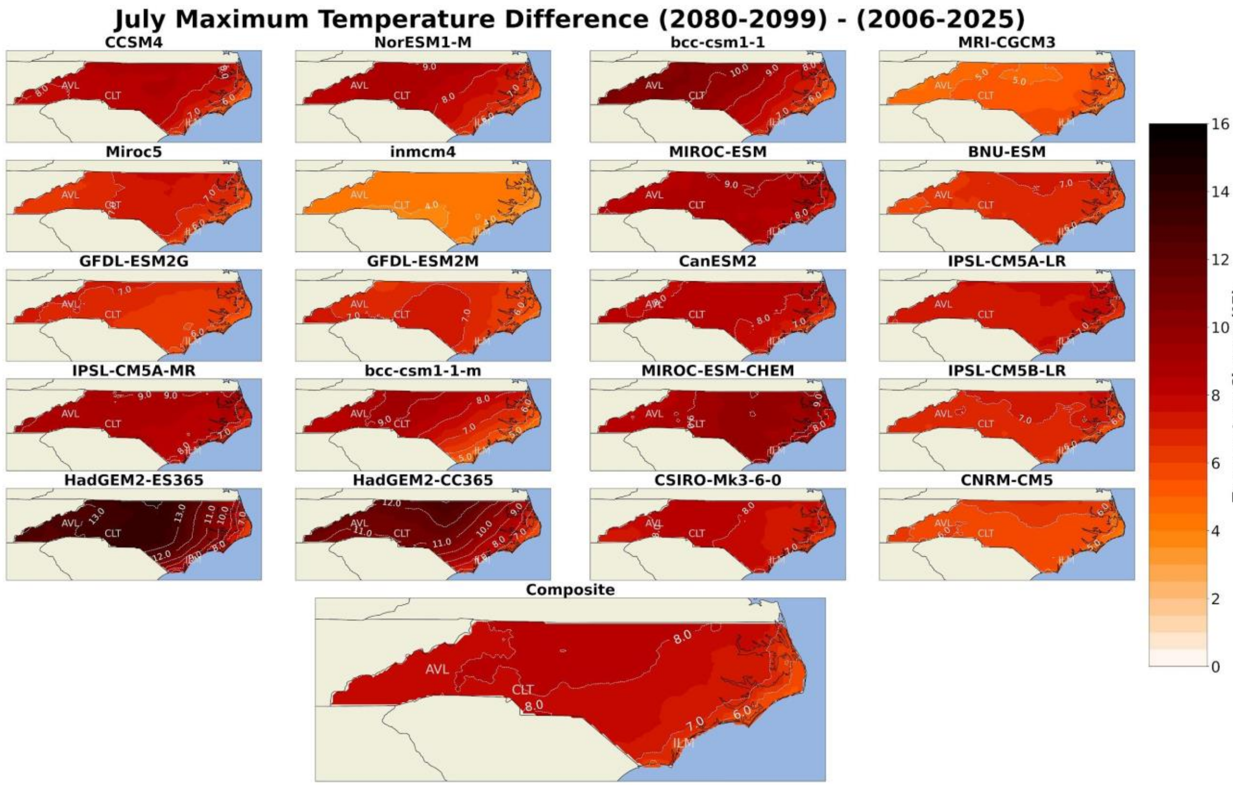


Figure 3.1 Change in July maximum temperatures for MACA-downscaled output from the 20 CMIP5 climate models and the composite mean average of the 20 models.

Charlotte is projected to warm 7.96 °F according to the composite mean model (Figure 3.2), slightly more than the state overall and more than Asheville. The minimum warming for Charlotte is 4.00 °F (INMCM4) and the maximum is 13.39 °F (HadGEM2-ES365). The middle 50% of models fell between 6.61 °F and 8.65 °F of warming.

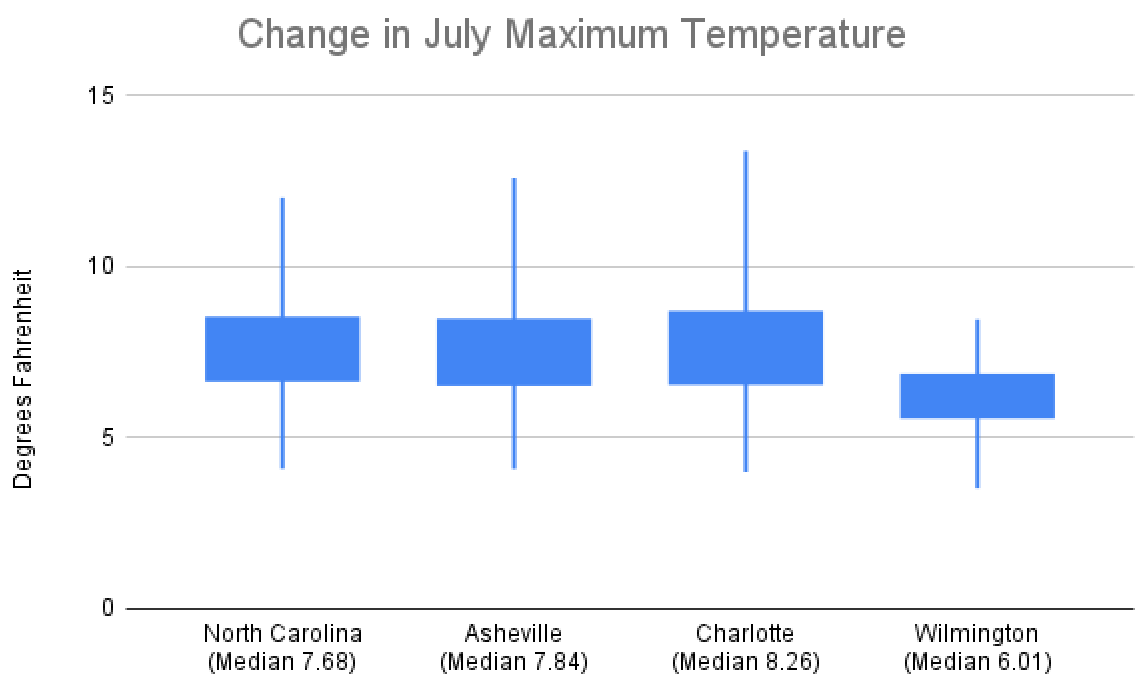


Figure 3.2. Change in Minimum, maximum, median, and interquartile range for the change in July maximum temperatures across all climate models and as a function of spatial domain

Wilmington is projected to warm the least of any spatial domain across models (Figure 3.2). The composite mean suggests 6.19 °F of warming, with a minimum of 3.53 °F (INMCM4) and maximum of 8.46 °F (MIROC-ESM-CHEM). The middle 50% of data fell between 5.63 and 6.82 °F, so Wilmington also has the smallest interquartile range.

3.1.2. Minimum Temperature

Increases in minimum temperature relates to increased risk of heat related illness due to the lack of relief experienced in the nighttime hours (Wilhelmi et al., 2021). According to our composite mean model, there will be a mean increase of 7.24 °F across the state for minimum temperatures in the month of July (Figure 3.3). The largest increase in minimum temperature is 10.04 °F

(HadGEM2-ES365), while the smallest temperature increase is 5.29 °F (GFDL-ESM2M). The middle 50% of models fell between 5.92 °F and 8.43 °F of warming.

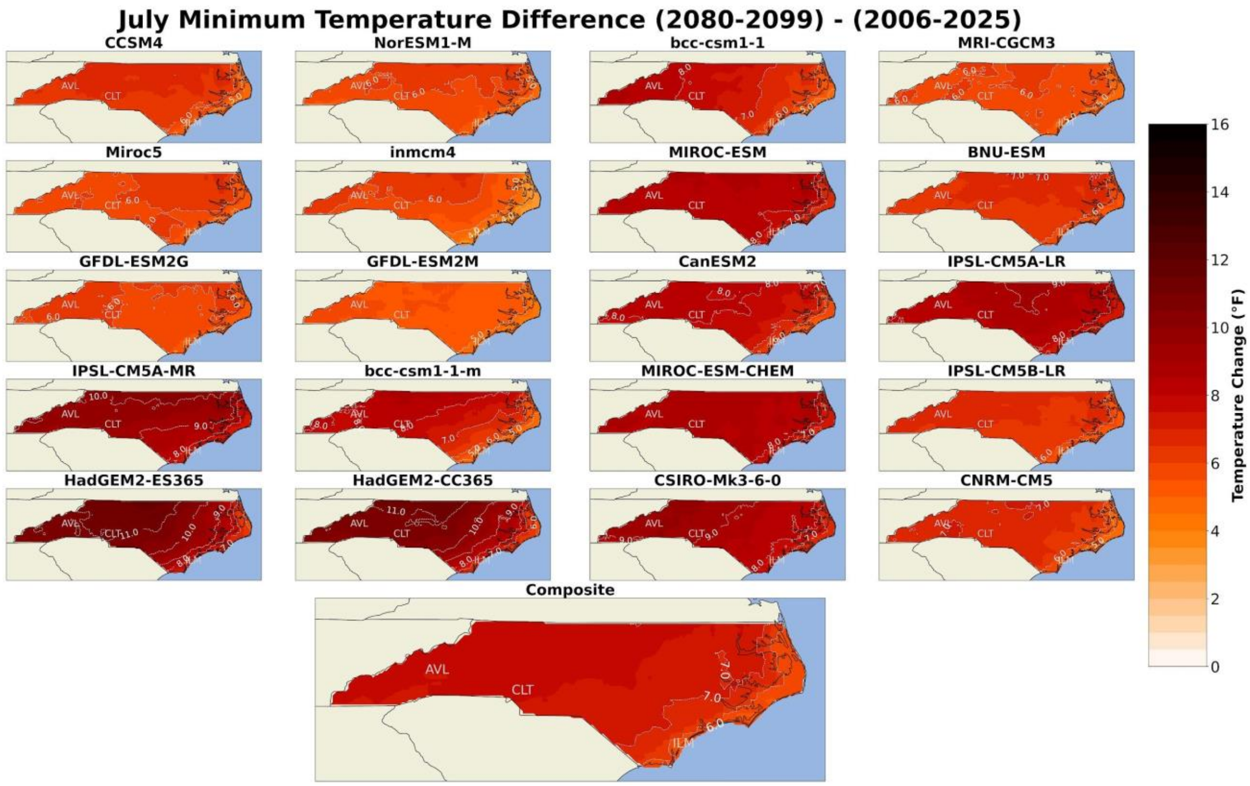


Figure 3.3. Spatial differences & change in July minimum temperatures across all climate models.

In Asheville, our composite mean model indicates a change of 7.54 °F, slightly more than the state as a whole (Figure 3.4). The largest increase in minimum temperature is 10.78 °F (HadGEMES365), while the smallest increase in minimum temperature is 5.60 °F (GFDL-ESM2M). The middle 50% of models predicted an increase in minimum temperature of 6.09 °F to 8.38 °F.

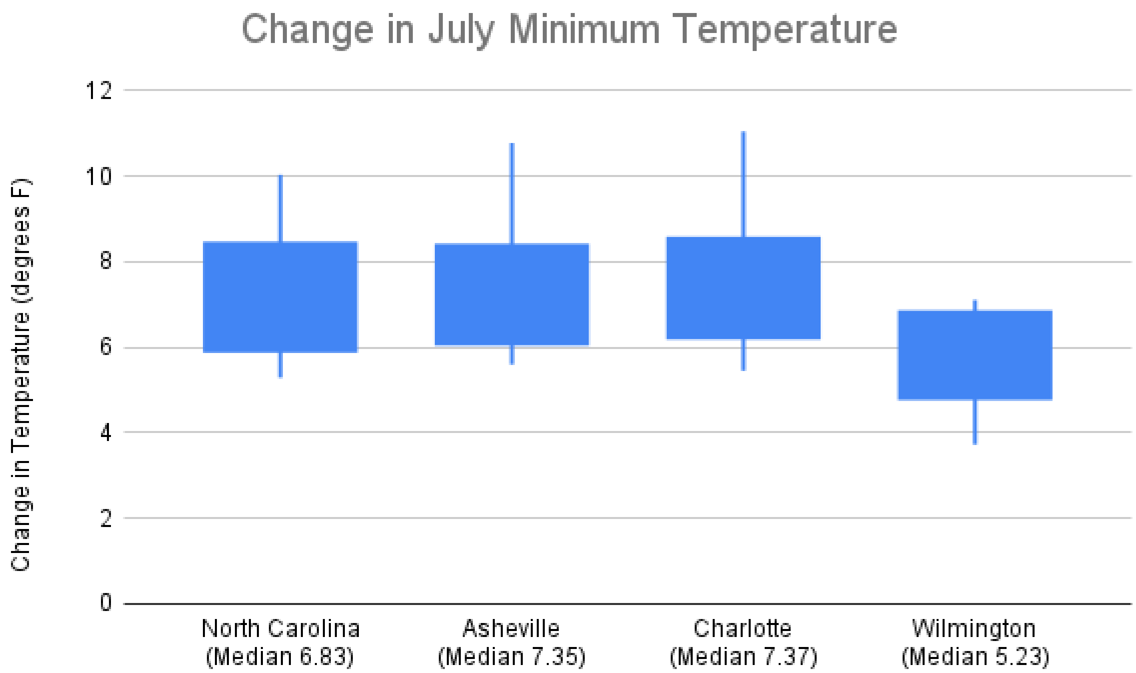


Figure 3.4 Change in Minimum, maximum, median, and interquartile range for the change in July minimum temperatures across all climate models and across spatial domains.

Of the three sub-domains, it is projected that July minimum temperatures will increase the most in the Charlotte study area (Figure 3.4). The composite mean indicates an increase in minimum temperature of 6.89 °F. The largest increase in minimum temperature is 11.05 °F (HadGEM2-ES365), while the smallest increase is 5.45 °F (GFDL-ESM2M). The interquartile range across models falls between 6.23 °F and 8.54 °F of warming.

Wilmington is expected to see the smallest increase of July minimum temperatures of any of our spatial domains (Figure 3.4). The composite mean projects 5.58 °F of warming, averaged over the state. The smallest increase is projected at 3.73 °F of warming (inmcm4). The largest increase is projected at 7.11 °F of warming (MIROC-ESM-CHEM). The interquartile range falls between 4.81 °F and 6.82 °F of temperature increase.

3.1.3. Specific Humidity

Specific humidity (measured in grams of water per kilogram of air or g/kg) is projected to increase across the state under the RCP8.5 scenario (Figure 3.5), as expected given the temperature increase. This is an important metric as it measures the amount of water vapor that is actually in the atmosphere and affects how the atmosphere feels. An increase in specific humidity along with an increase in summertime temperatures will lead to increased heat stress and morbidity rates (Barreca, 2012; Diem et al., 2017).

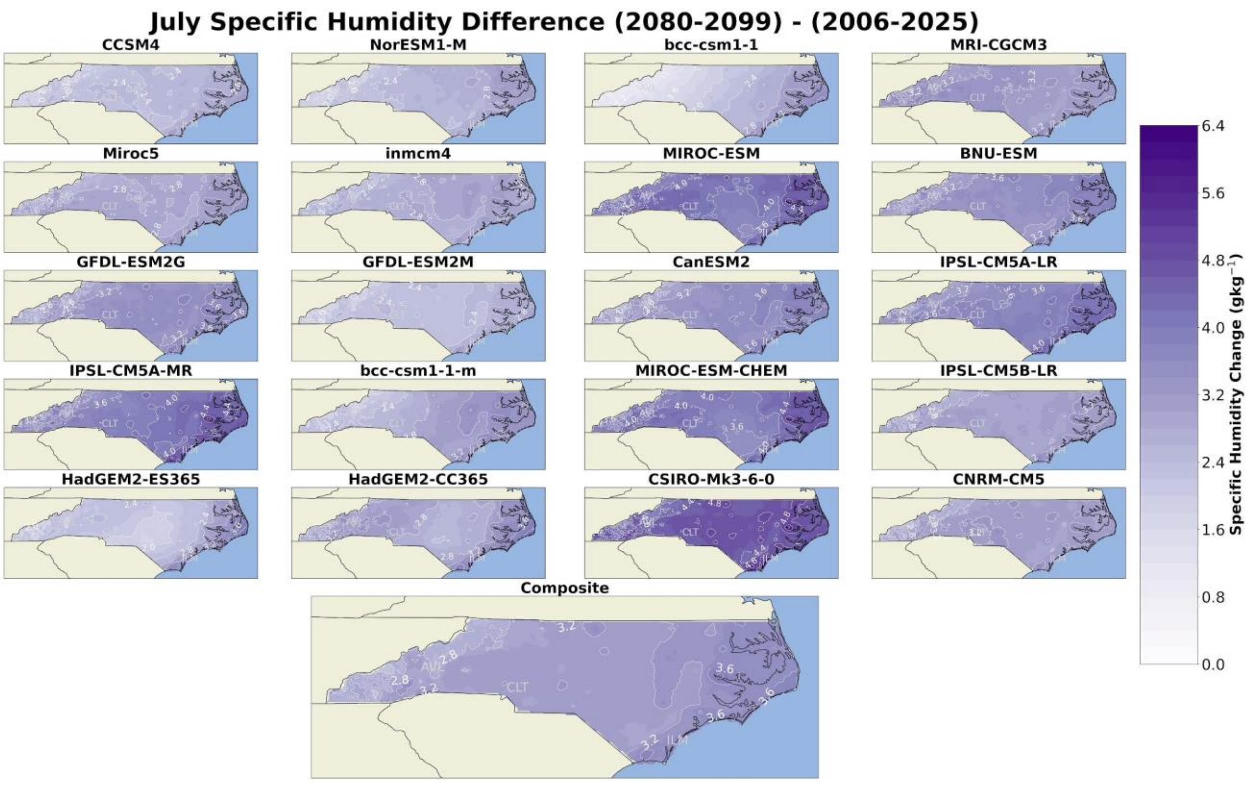


Figure 3.5. This figure shows the spatial differences and change in July specific humidity between all climate models.

North Carolina is projected to experience an increase of 3.15 g/kg of specific humidity according to our composite mean model. The minimum expected increase is projected at 2.26 g/kg (bcc-csm1-1). The maximum expected increase is projected at 4.59 g/kg (CSIRO-Mk3-6-0). The interquartile range falls between 2.73 g/kg and 3.53 g/kg.

The composite mean model projects 2.93 g/kg of specific humidity increase for the Asheville spatial domain (Figure 3.6). The maximum projected increase is 4.36 g/kg (CSIRO-Mk3-6-0). The projected minimum expected increase is 1.21 g/kg (bcc-csm1-1). The middle 50% of models fall between 2.31 g/kg and 3.37 g/kg.

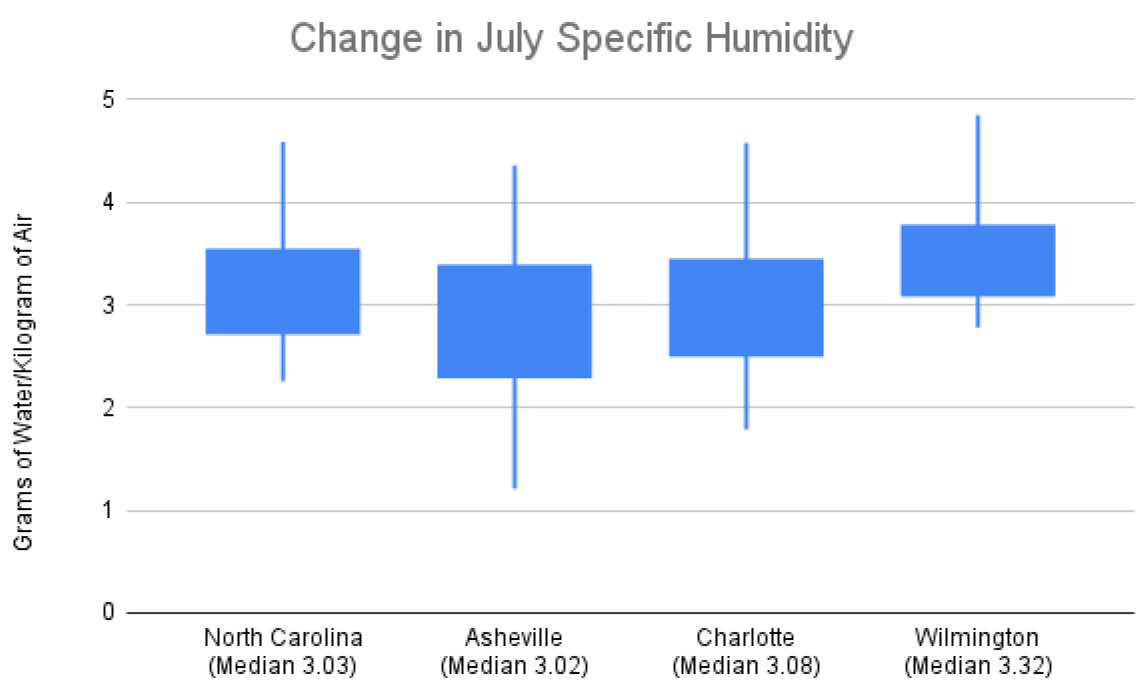


Figure 3.6. This figure shows the change in minimum, maximum, median, and inter quartile range for July specific humidity between all climate models and across spatial domains.

The composite mean model projects Charlotte's specific humidity will increase 3.06 g/kg (Figure 3.6). The maximum projected increase across models is 4.58 g/kg (CSIRO-Mk3-6-0)l. The minimum projected increase is 1.79 g/kg (bcc-csm1-1) of specific humidity increase. The middle 50% of models fall between 2.52 g/kg and 3.43 g/kg.

Wilmington is expected to see the highest increase of summertime specific humidity across all of the spatial domains (Figure 3.6). The composite mean model projects a 3.45 g/kg increase. The minimum projected increase in specific humidity is 2.78 g/kg (NorESM1-M). The maximum increase is projected at 4.85 g/kg (CSIRO-Mk3-6-0). The interquartile range falls between 3.10 g/kg and 3.76 g/kg.

3.1.4. Precipitation

Change in precipitation across the state in July is variable across models and across locations, but generally the state will expect to see slightly more precipitation in the month of July in the future than we currently see in the present. Precipitation is an important metric to study since it has so many societal scale impacts ranging from water resources to agricultural growing seasons.

For this report precipitation will be reported in inches of monthly precipitation. For the state of North Carolina, the composite mean model projects an increase of 0.06 inches of increased precipitation. However, there is a lot of variability across models (Figure 3.7). The range of precipitation change averaged across the state and across models lies between -2.47 inches and +1.53 inches of precipitation. The interquartile range falls within -0.47 and +0.65 inches.

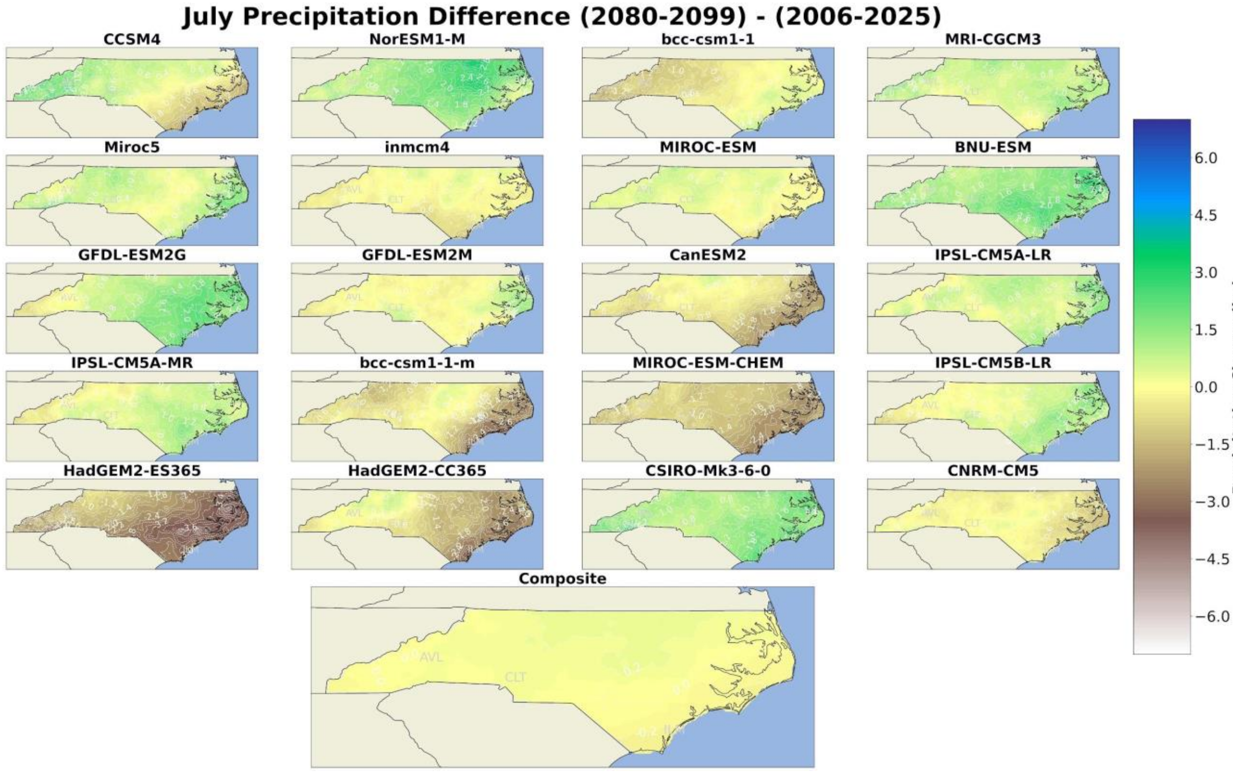


Figure 3.7. Spatial differences and change in July precipitation between all climate models.

Figure 3.7 visually represents how diverse the climate models are for summertime precipitation across the state. Where some models show increases in precipitation in the east and decreases in the west, some models show the opposite. Overall, the median change in precipitation is +0.22 inches, with median increases in all spatial domains except Asheville (Figure 3.8).

To gain an even better understanding of how precipitation will change across the state as we move forward it is important to look at smaller spatial scales given North Carolina's diverse topography and geography (Figure 3.8). According to the composite mean model Asheville is projected to receive an extra 0.06 inches of precipitation in the month of July. The minimum change in precipitation projected by a model is -1.34 inches of precipitation (HadGEM2-ES365).

The maximum increase of rain we could project to see is 1.74 inches (CCSM4). The interquartile range falls between -0.25 inches and +0.47 inches of precipitation.

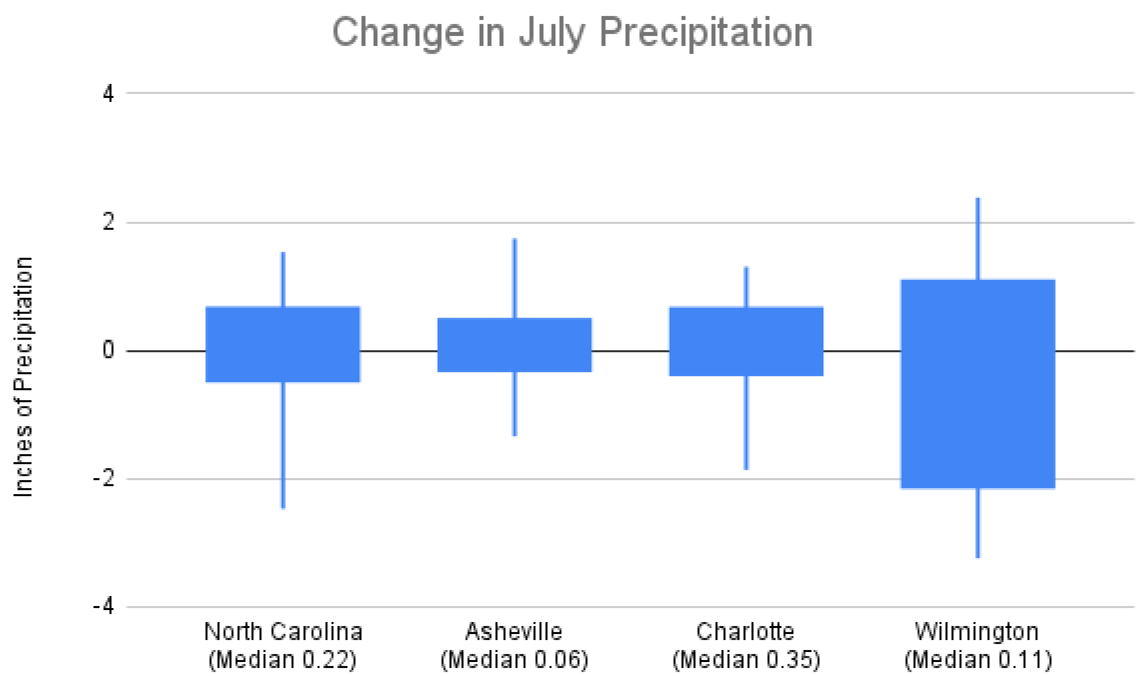


Figure 3.8. This figure shows the minimum, maximum, median, and inter quartile range for July precipitation changes between all climate models and across spatial domains.

In Charlotte, the variability is just as evident (Figure 3.8). The composite mean model projects a change of +0.16 inches of precipitation in July. The minimum projected change in precipitation is -1.86 inches (HadGEM2-ES365). The maximum projected change is +1.30 inches (NorESM1-M). The interquartile range falls between -0.37 and +0..64 inches of precipitation.

Wilmington also has a large spread of potential precipitation outcomes, the largest in this study, and is the only spatial domain in this study that the composite mean model projects a decrease in July precipitation (Figure 3.8). The composite mean model projects a change of -0.28 inches of precipitation. The range falls within -3.24 inches (HADGEM2-CC365) and 2.38 inches (GFDL-

ESM2G). The middle 50% of models fall between -2.125 inches and 1.07 inches of precipitation change.

Figure 3.8 statistically displays the wide range of potential precipitation changes across the state, specifically in Wilmington. This could be because in July much of the precipitation in North Carolina is driven by convection and thunderstorms (e.g. Sayemuzzaman and Jha, 2014; Boyles and Raman, 2003), which are processes that are not well-captured by climate model simulations (Maher et al., 2018; Becker et al., 2009). Given that large scale climate models are the input to the MACA downscaling, it may be a challenge for thunderstorm-driven rain to be consistently captured across 20 different climate models.

3.2. Winter

3.2.1. Maximum Temperature

Overall the composite mean model projetcs North Carolina maximum temperatures will warm 5.58 °F in January by the end of the century. The least change is 1.96 °F and the largest increase in maximum temperature is 7.88 °F. These increases are predicted by the inmcm4 model and BNU-ESM models, respectively. The interquartile range falls between 4.40 °F and 7.45 °F. Figure 3.9 visually shows the modeled range of warming outcomes for North Carolina. Generally, the further inland one moves the more pronounced the warming becomes. It also becomes evident that January is likely to warm less than July across the state when compared to Figure 3.1, noting they use the same scale.

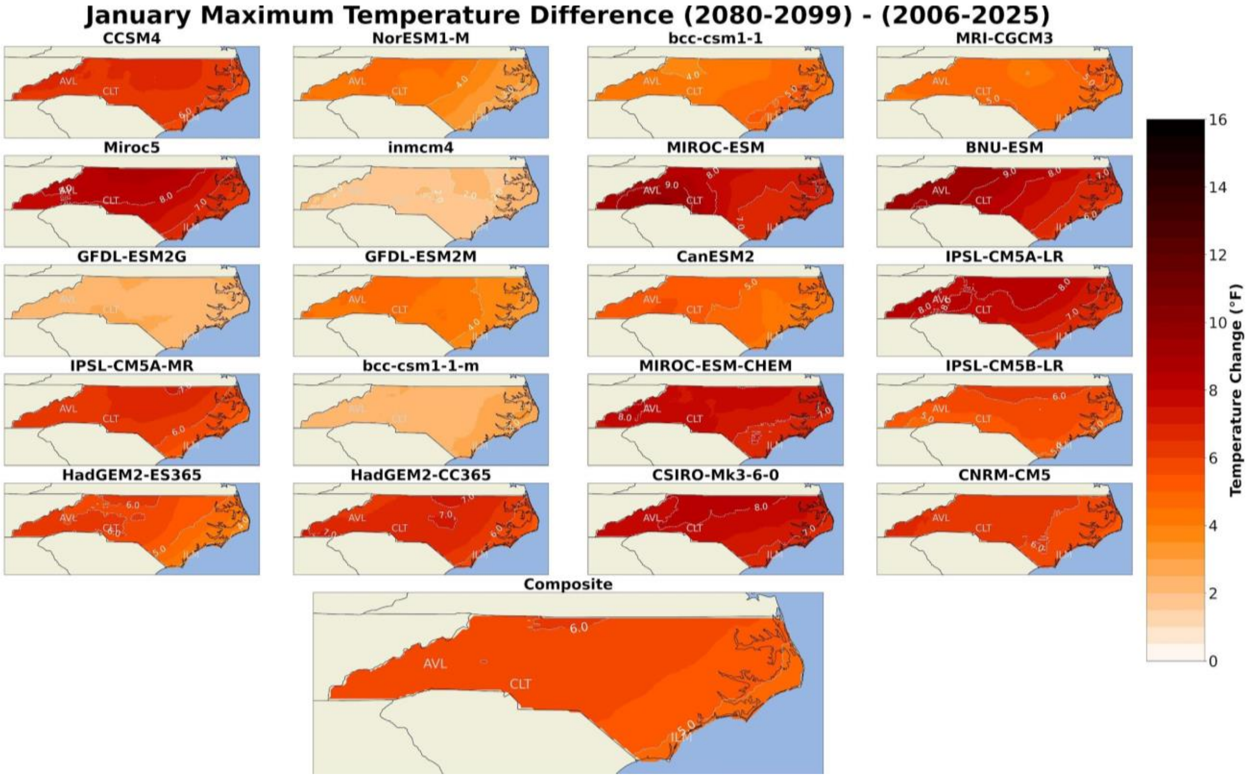


Figure 3.9. Spatial differences in the change in January maximum temperatures across climate models.

Asheville is typically on the cooler end of the state as it lies at a much higher elevation than our other two spatial domains. The composite mean model predicts a 5.87 °F increase for Asheville (Figure 3.10). The range of increases in maximum January temperature is 1.85 °F (inmcm4) and 9.14 °F (BNU-ESM). The interquartile range falls within 4.46 °F and 7.83 °F.

Charlotte will also warm in January (Figure 3.10). The composite mean model predicts a 5.83 °F increase in January maximum temperatures. The range of increase falls between 1.76 °F and 9.05 °F. These are predicted by the inmcm4 and the MIROC-ESM models,respectively. The middle 50% of models fall between 4.67 °F and 7.77 °F.

Wilmington is expected to warm as well although it is similar to July in terms of how it will likely warm less when compared to other areas of the state (Figure 3.10). The composite mean model predicts a warming of 4.88 °F. The smallest expected temperature increase in Wilmington is 1.91 °F (inmcm4) and the largest is 6.71 °F (MIROC-ESM-CHEM). The interquartile range of models falls between 3.97 °F and 6.28 °F of warming.

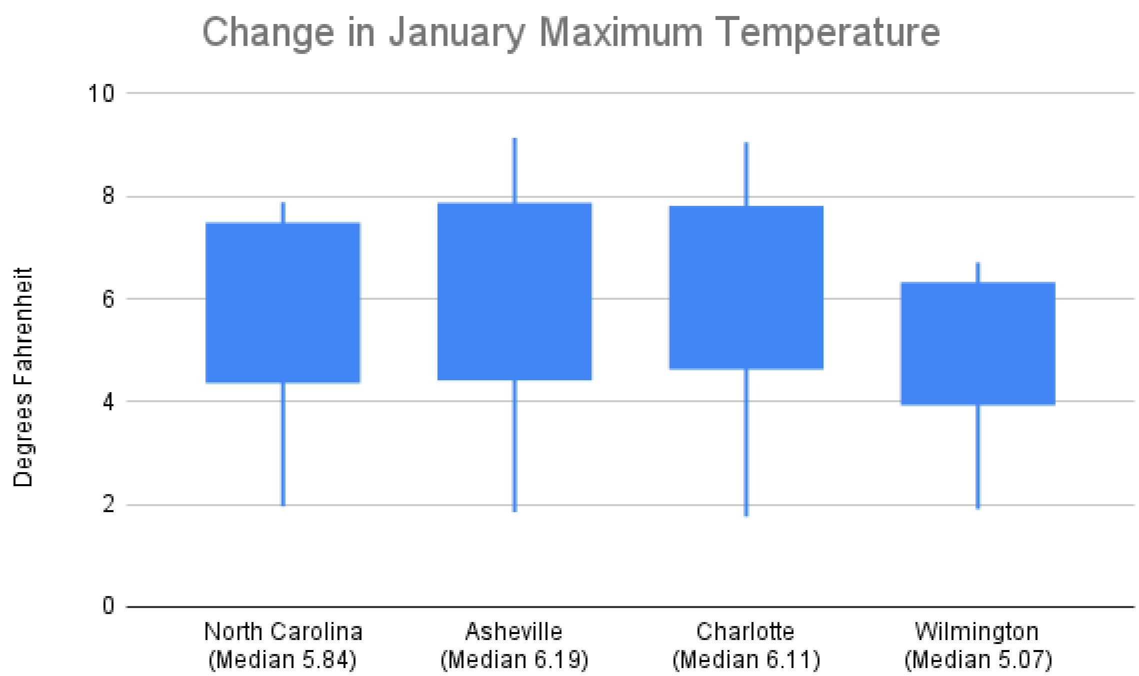


Figure 3.10. Minimum, maximum, median, and interquartile range for January maximum temperature changes between all climate models and across spatial domains.

It can be seen here, the change in the maximum temperature averaged across NC in January is fairly uniform, with proximity to the ocean dictating the most influence on the spatial pattern. It should also be noted the smallest increases in maximum temperature across all spatial domains are a result of the inmcm4 climate model, which is a consistently low outlier.

3.2.2. Minimum Temperature

Minimum temperatures in January follow the trend of our other temperature metrics with increases seen in all spatial domains. Tracking changes in minimum winter temperatures is important as it affects precipitation type, the freeze-thaw cycles, and growing seasons. According to the composite mean model, North Carolina will warm 5.71 °F as a whole. The range of models falls between 2.72 °F (GFDL-ESM2G) and 8.55 °F (BNU-ESM) of increase in the minimum temperature. The middle 50% of models fall between 4.39 °F and 6.91 °F.

The composite mean model predicts 5.80 °F of warming for Asheville while the spread around the composite mean model falls between 2.75 °F (GFDL-ESM2G) and 9.14 °F (BNU-ESM). The interquartile range falls between 3.82 °F and 7.42 °F.

The composite mean model predicts 5.65 °F of warming in the Charlotte spatial domain. The minimum increase seen across models is 2.92 °F (GFDL-ESM2G) and the maximum predicted temperature change is 8.87 °F (BNU-ESM). The middle 50% of models fall between 3.94 °F and 6.97 °F.

In Wilmington we once again see slightly less temperature change relative to the rest of the state. The composite mean model predicts 5.20 °F of warming across the state. The total range of predicted warming outcomes falls between 2.41 °F and 7.31 °F with the interquartile range falling between 4.19 °F and 6.46 °F.

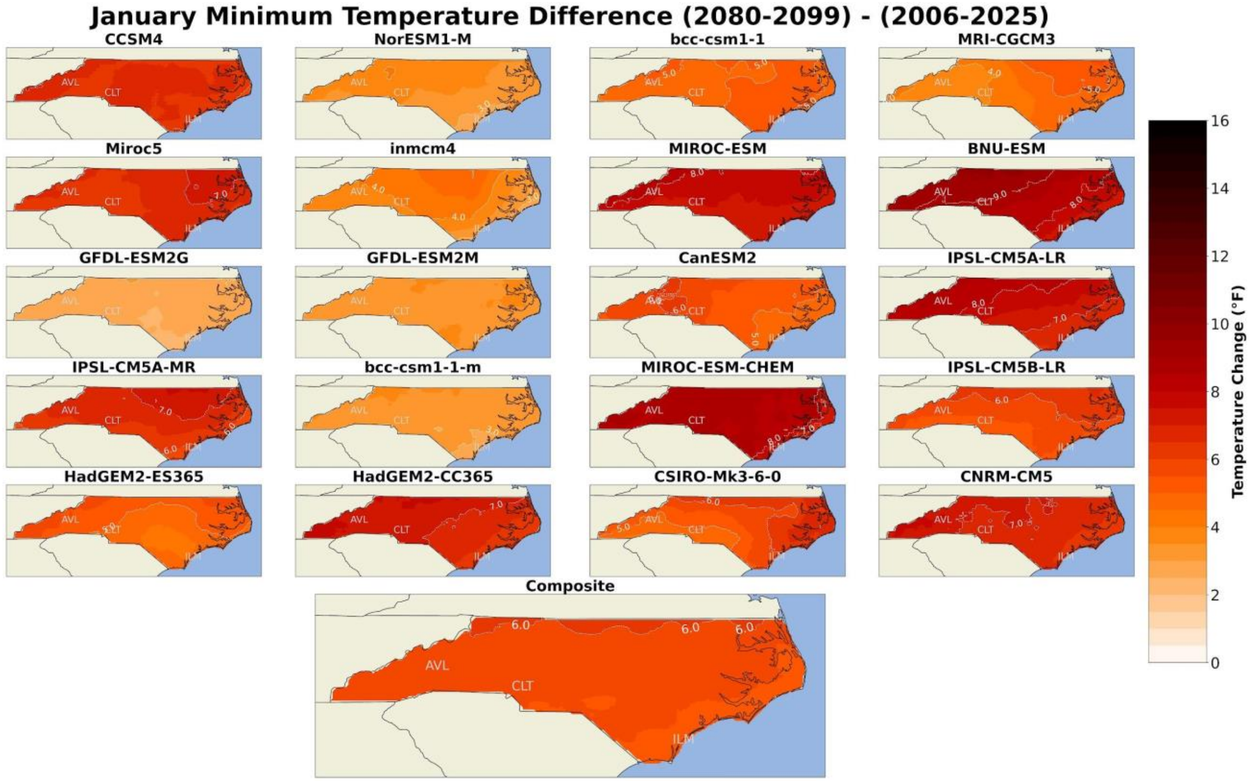


Figure 3.11. Spatial differences in the change in January minimum temperatures across all climate models.

Figure 3.11 shows the spatial differences between climate models. It can also be seen when comparing to Figures 3.1, 3.3, 3.9, and 3.11 that January minimum temperatures are expected to change the least when taking into account all 20 models.

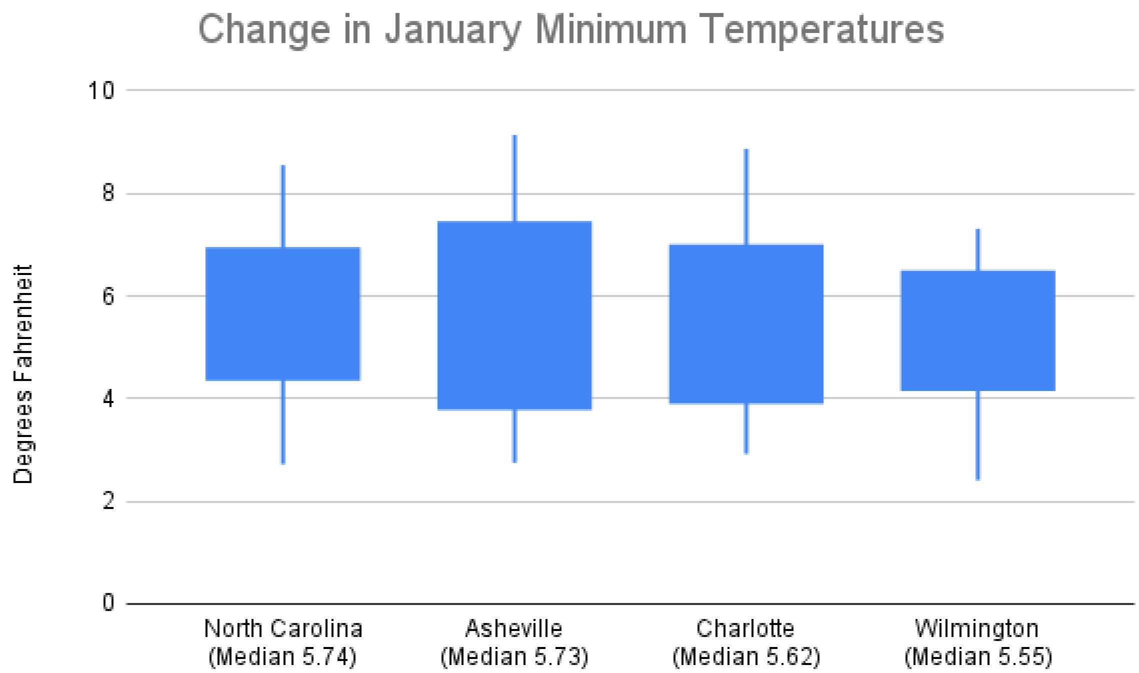


Figure 3.12. Minimum, maximum, median, and interquartile range for January minimum temperature changes between all climate models and across spatial domains.

It can be seen from Figure 3.12 how the different spatial domains have the potential to change, with Asheville having the most warming potential and Wilmington predicted to have more moderate warming outcomes.

3.2.3. Specific Humidity

Specific Humidity is an important wintertime metric as it helps determine how the air will feel as the temperature gets colder. As the temperature drops high humidity will cause the air to feel damp and cold.

Across the state we expect to see an increase in specific humidity (measured in grams of water/kilogram of air) in January. The composite mean model predicts an increase of 0.77 g/kg across the state. The spread falls between 0.39 g/kg (NorESM1-1) and 1.19 g/kg (BNU-ESM). The middle ten models fall between 0.52 g/kg and 1.00 g/kg.

In Asheville, the composite mean model predicts 0.76 g/kg of specific humidity increase (Figure 3.14). The spread across models ranges from 0.37 g/kg (NorESM1-1) and 1.29 g/kg (BNU-ESM). The interquartile range falls between 0.58 g/kg and 1.03 g/kg of specific humidity increase.

For Charlotte, the composite mean model predicts 0.78 g/kg of specific humidity increase (Figure 3.14). The smallest expected increase in specific humidity across models is predicted by NorESM1-1 at 0.39 g/kg. The largest expected increase is predicted to be 1.27 g/kg again by BNU-ESM. The interquartile range falls between 0.58 g/kg and 1.03 g/kg.

Wilmington is predicted to see 0.81 g/kg of specific humidity increase according to the composite mean model (Figure 3.14). The range across models falls between 0.43 g/kg (NorESM1-M) and 1.23 g/kg (CSIRO-Mk3-6-0). The interquartile range falls between 0.57 g/kg and 1.01 g/kg.

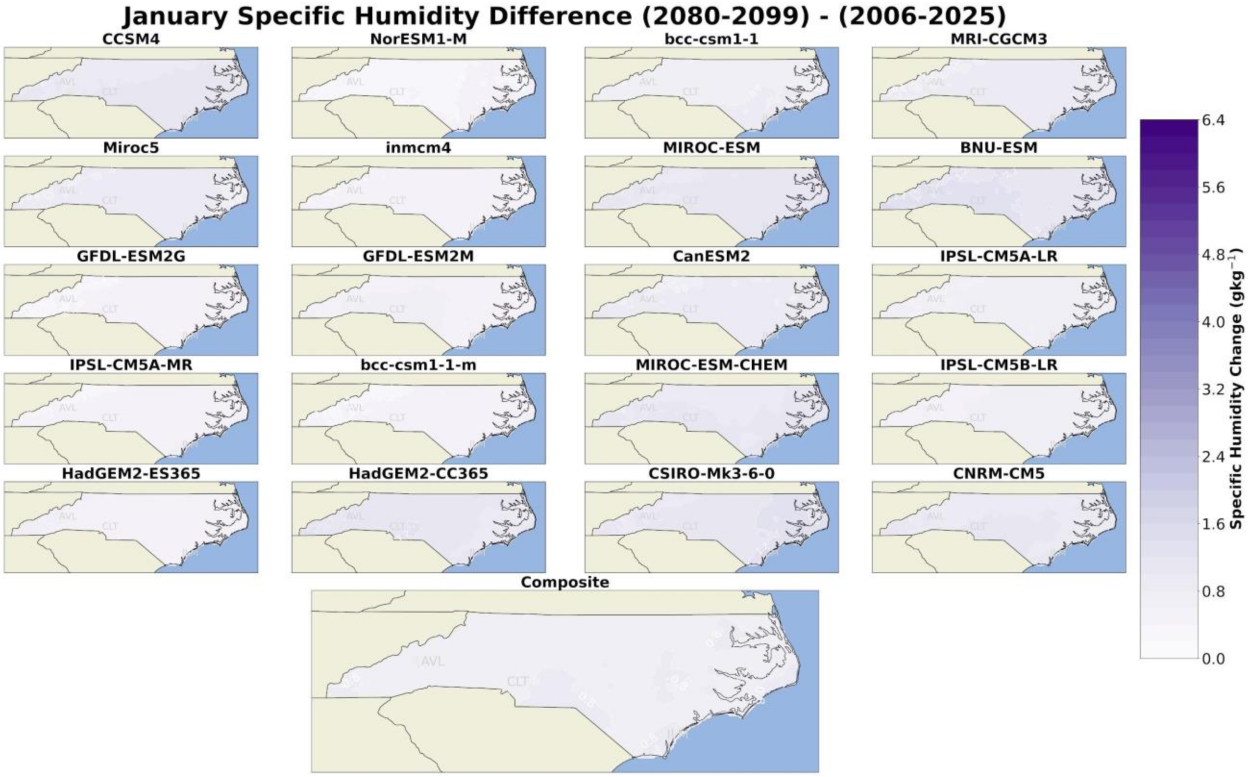


Figure 3.13. Spatial differences in the change in January specific humidity across all climate models.

Figure 3.13 demonstrates the relative consistency between models when projecting change in January specific humidity. It can also be seen when compared to Figure 3.5 that January increases in specific humidity will be less than July across the state. Figure 3.14 shows how there are relatively uniform specific humidity increases across the state.

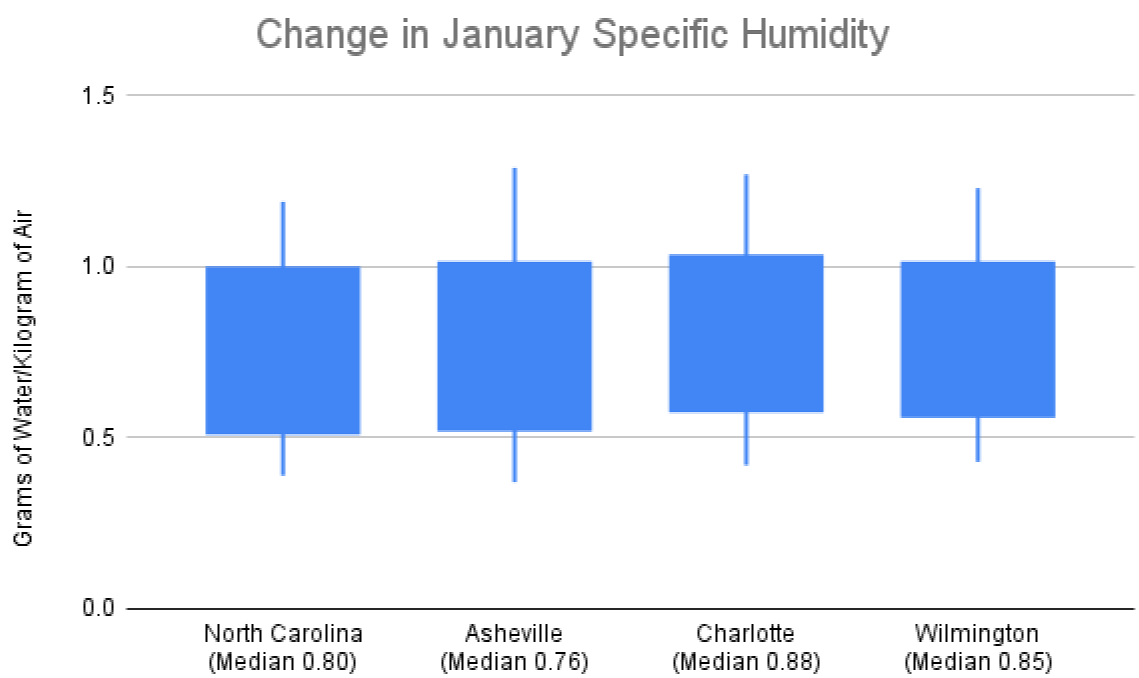


Figure 3.14. Minimum, maximum, median, and interquartile range for changes in January specific humidity across all climate models and across spatial domains.

3.2.4. Precipitation

Winter precipitation affects regional water supply, school participation, and workforce hours.

Across North Carolina, most of the 20 models predict an increase in winter precipitation. According to the composite mean model we are predicted to experience an additional 0.49 inches of precipitation across the state. The maximum predicted increase is projected to be 1.52 (HADGEM2-CC365) inches while the minimum expected increase is -0.75 inches (GFDL-ESM2M). The interquartile range falls within 0.05 and 1.05 inches of precipitation. The changes in precipitation in January are a bit more evenly distributed than the month of July, but due to the geographic diversity North Carolina has there is still a bit of variability across the state.

In Asheville, the composite mean model predicts an increase of 0.44 inches of precipitation. The minimum expected change in precipitation in Asheville is -0.93 inches (HadGEM2-ES365) and the maximum predicted increase is 1.78 inches (CCSM4). The interquartile range falls between -0.15 and 0.74 inches. Asheville has the most model to model variability of any of our spatial domains for changes in January precipitation.

The composite mean model predicts a precipitation increase of 0.48 inches for Charlotte in the month of January by the end of the century. The smallest expected change is -0.69 inches (HadGEM2-ES365) and the largest predicted increase is 1.94 inches (HADGEM2-CC365). The interquartile range falls between 0.08 inches and 0.90 inches.

In Wilmington, the composite mean model predicts an increase of 0.55 inches of precipitation in the month of January. The smallest expected change is -0.95 inches of precipitation (IPSL-CM5A-LR) while the largest change is predicted to be 1.79 inches (IPSL-CM5B-LR). The interquartile range falls between 0.27 and 1.07 inches.

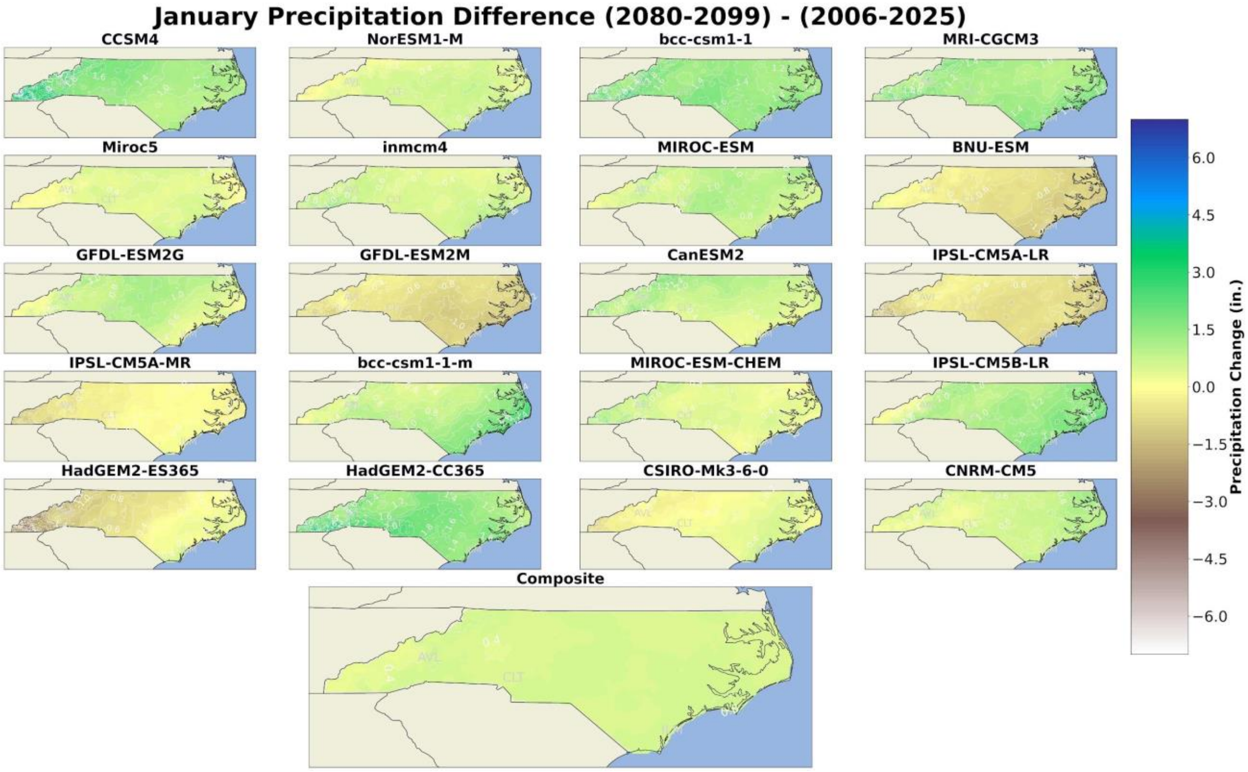


Figure 3.15. Spatial differences in changes in January precipitation across all climate models.

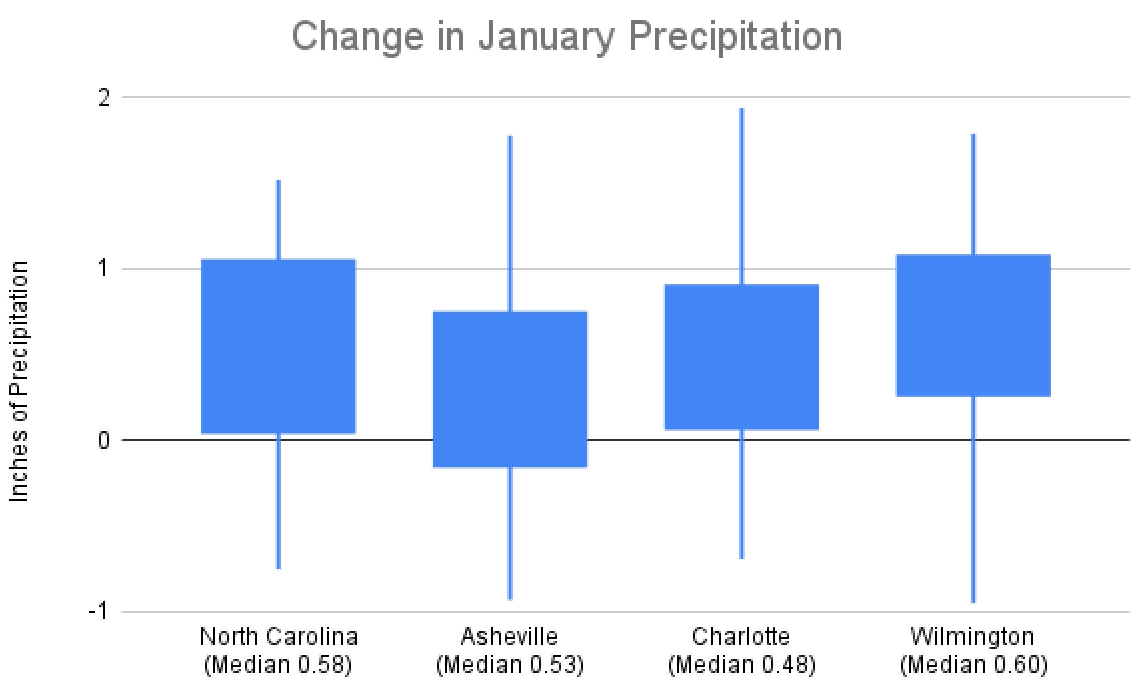


Figure 3.16. Minimum, maximum, median, and interquartile range for changes in January specific humidity across all climate models and across spatial domains.

Figures 3.15 and 3.16 demonstrate the spatial and statistical relationship across models for precipitation in the month of January across the different spatial domains.

CHAPTER 4: DISCUSSION

The future projected by RCP8.5 is warmer and more humid in North Carolina with uncertainties surrounding precipitation in both seasons, but there are important differences in the changes for all variables depending on what part of North Carolina is considered. For example, Charlotte summertime maximum temperatures could increase by up to 11 °F. When combined with increases in specific humidity, this could be a dangerous summertime outcome for the highly-populated Charlotte region (Raymond et al., 2020) because when the temperature of the air and moisture content rise, so will the heat index. Heat index is often considered a measurement of what the atmosphere actually feels like for the body and is a stronger predictor of how the body will respond to heat than simply temperature alone. Heat index factors in both air temperature and humidity (Anderson et al. 2013).

Minimum temperatures will also rise according to all 20 models. A rise in minimum temperature will rob people of the relief they typically experience from extreme temperatures once the sun goes down (Zhang et al., 2012), and research suggests that morbidity is not associated solely with anomalously high maximum temperatures (Petitti et al., 2016).

Figure 4.1 displays the statistical relationship between variables in July, testing how one variable relates to another variable for each model. For example, does a model that predicts an above-average increase in maximum temperature also predict an above-average increase in minimum temperature? Indeed, Figure 4.1.a shows that models that predict a larger increase in the maximum temperature are likely to predict a larger increase in the minimum temperature (R^2 = 0.641). However, the relationship between other variables is not as strong.

Humidity and precipitation are more complex than minimum and maximum temperatures. This can be seen in maximum temperature and precipitation (R^2 = 0.348), minimum temperature and precipitation (R^2 = 0.276), maximum temperature and specific humidity (R^2 = 0), minimum temperature and specific humidity (R^2 = 0.17), and specific humidity and precipitation (R^2 = 0.003).

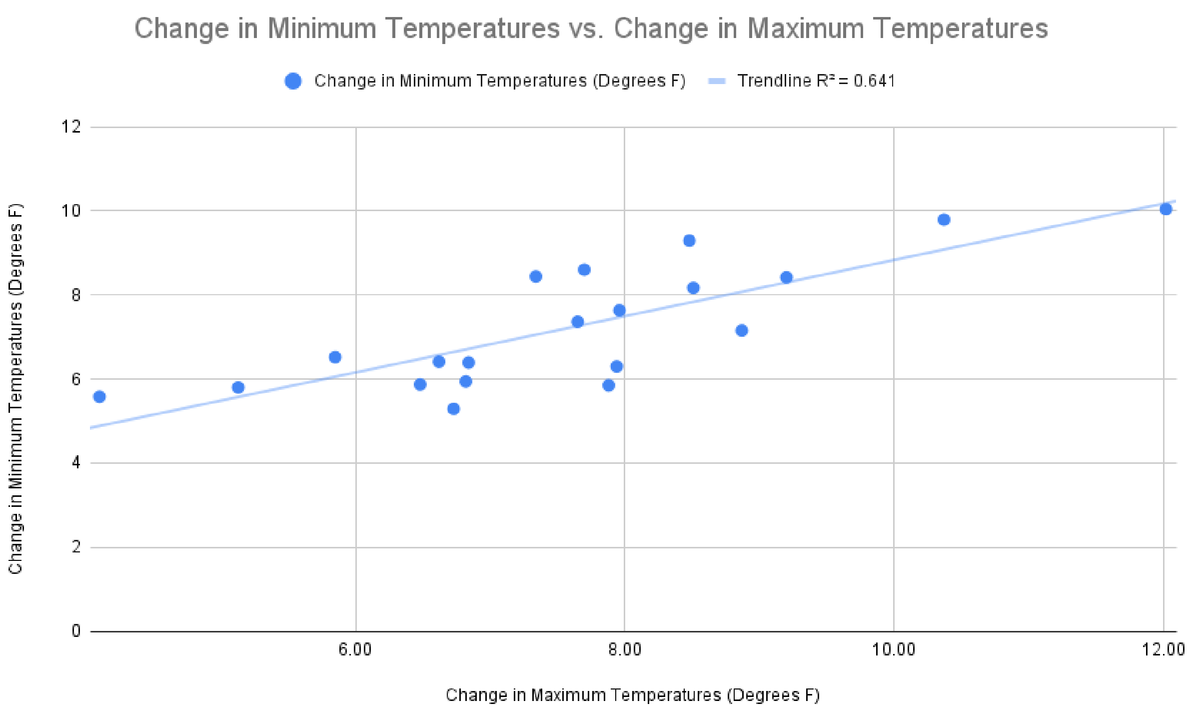


Figure 4.1.a. Shows the R^2 value of 0.641 for the relationship between the change in minimum and maximum temperatures across the 20 models (blue points) in July

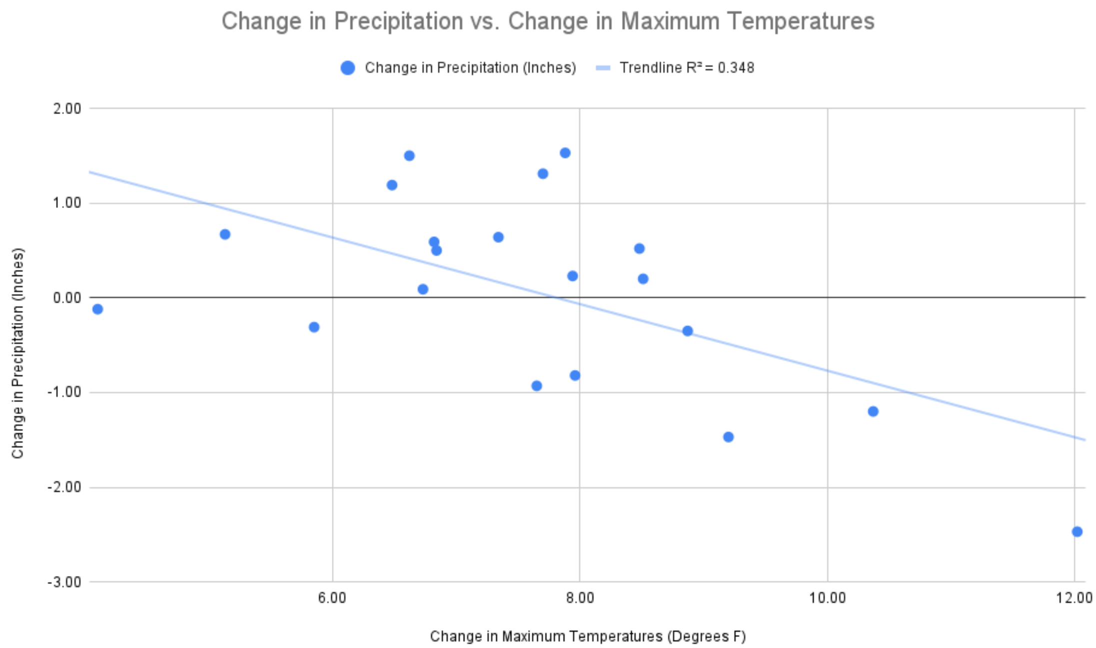


Figure 4.1.b. Shows the R^2 value of 0.348 for the relationship between the change in Precipitation and Maximum Temperatures across the 20 models (blue points) in July

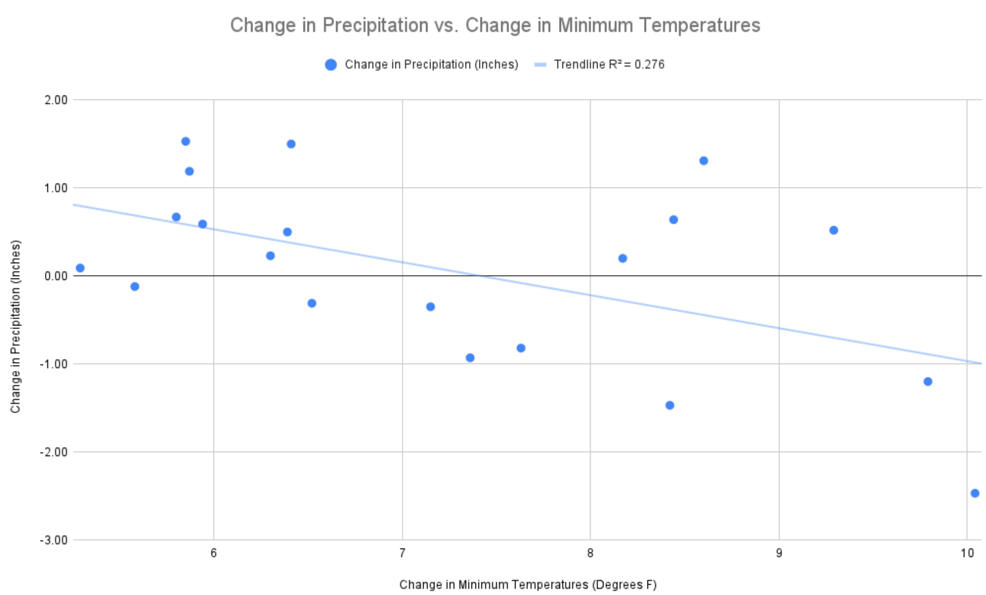


Figure 4.1.c. Shows the R^2 value of 0.276 for the relationship between the change in Minimum Temperatures and Precipitation across the 20 models (blue points) in July.

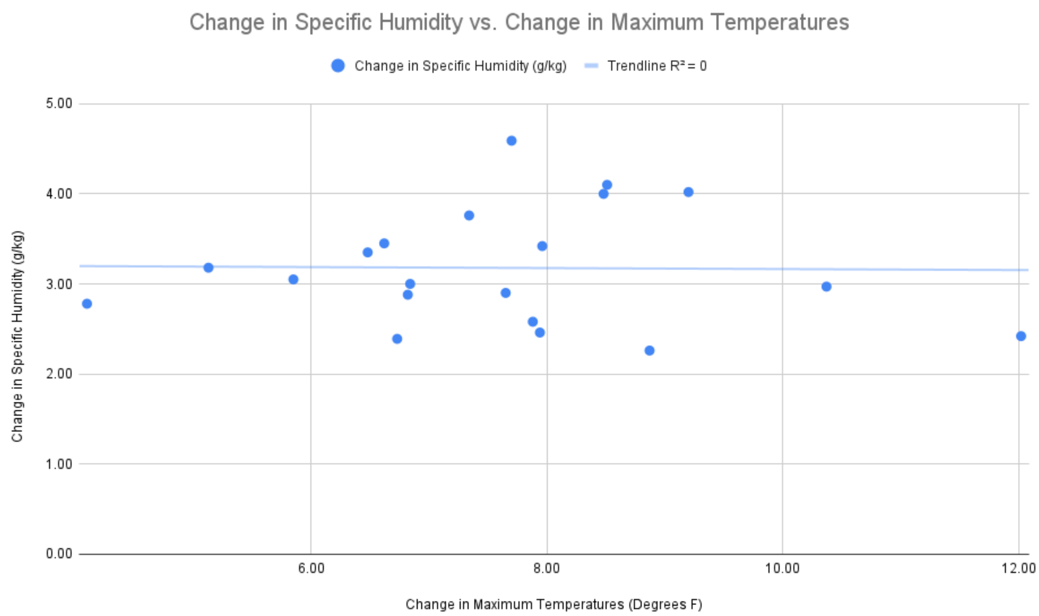


Figure 4.1.d. Shows the R^2 value of 0 for the relationship between the change in Specific Humidity and Maximum Temperatures across the 20 models (blue points) in July

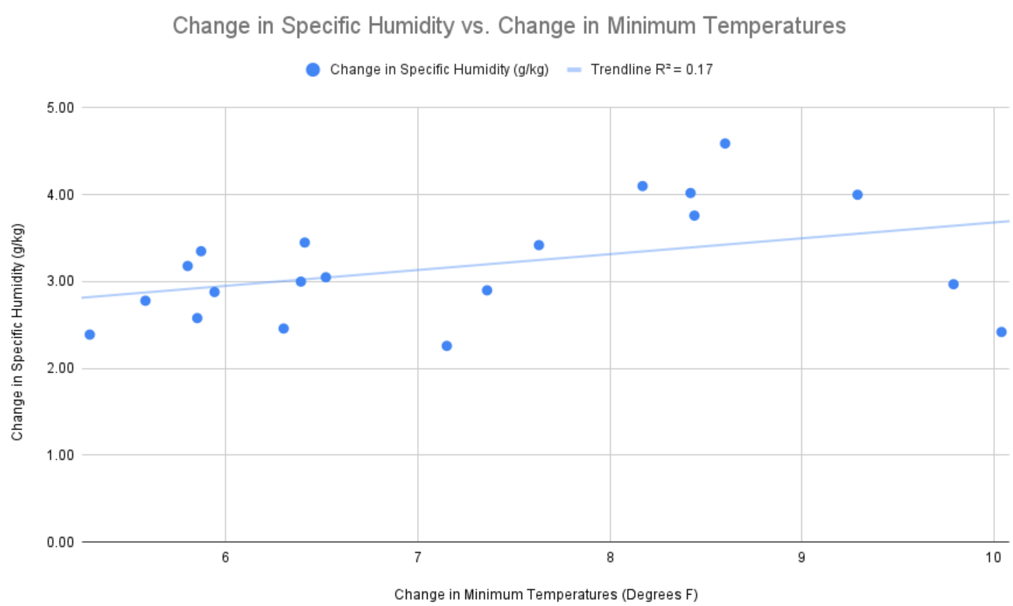


Figure 4.1.e. Shows the R^2 value of 0.170 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July

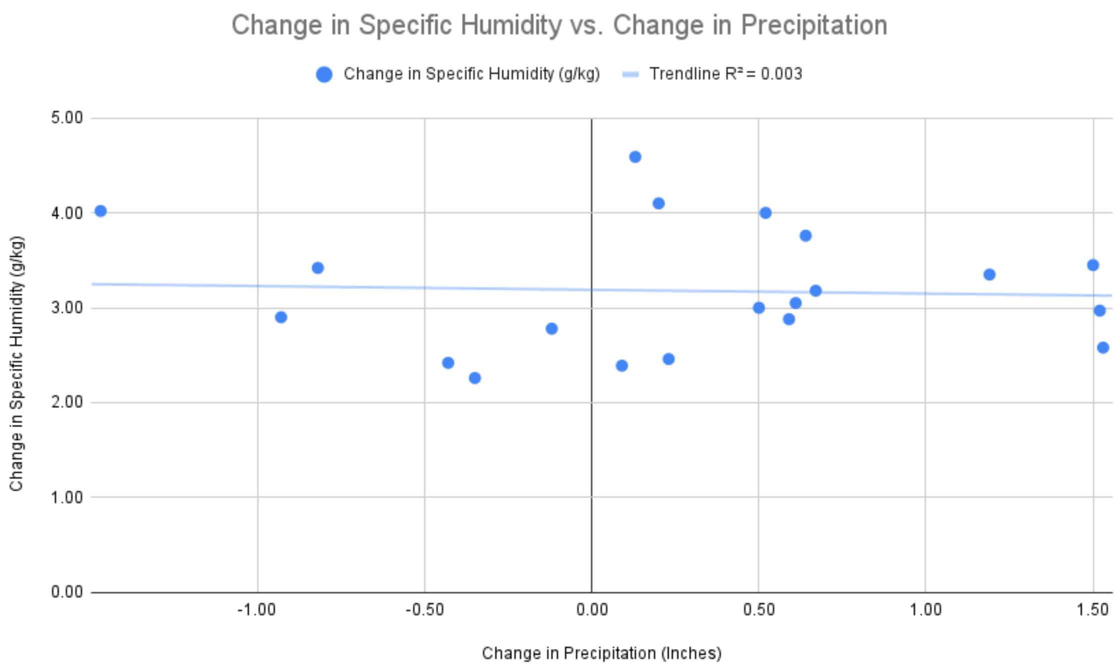


Figure 4.1.f. Shows the R^2 value of 0.003 for the relationship between the change in Precipitation and Specific Humidity across the 20 models (blue points) in July

Summertime rainfall is the variable with the widest possible outcome. While our composite mean model suggests there will only be slight increases in summertime precipitation across the state and even a decrease along the coast, the predicted changes in precipitation across the downscaled model output from the 20 CMIP5 model varies from -2.47 inches to +1.53 inches. The 2000-2019 average July precipitation is 5.2 inches (NOAA NCEI, 2022), so the percentage change in precipitation ranges from 48% lower to 29% higher than the most recent 20 years. Most of the precipitation in North Carolina in July is driven through convection (Sayemuzzaman and Jha, 2014; Boyles and Raman, 2003). The statistical methods used to downscale CMIP5 climate depend on modeled data that itself does not necessarily capture convective precipitation consistently (Maher et al., 2018; Becker et al., 2009).

Figure 4.2 displays the same information as Figure 4.1 but for our winter season. There was more statistical correlation in winter than summer. Changes in minimum and maximum temperature were again strongly linked ($R^2 = 0.809$). Changes in precipitation still almost had no correlation to changes in minimum ($R^2 = 0.025$) or maximum temperature ($R^2 = 0.067$). Changes in specific humidity are correlated with changes in minimum ($R^2 = 0.533$) and maximum ($R^2 = 0.555$) temperature, which is a stronger correlation than summer. Specific humidity and precipitation changes do not correlate well ($R^2 = 0.021$).

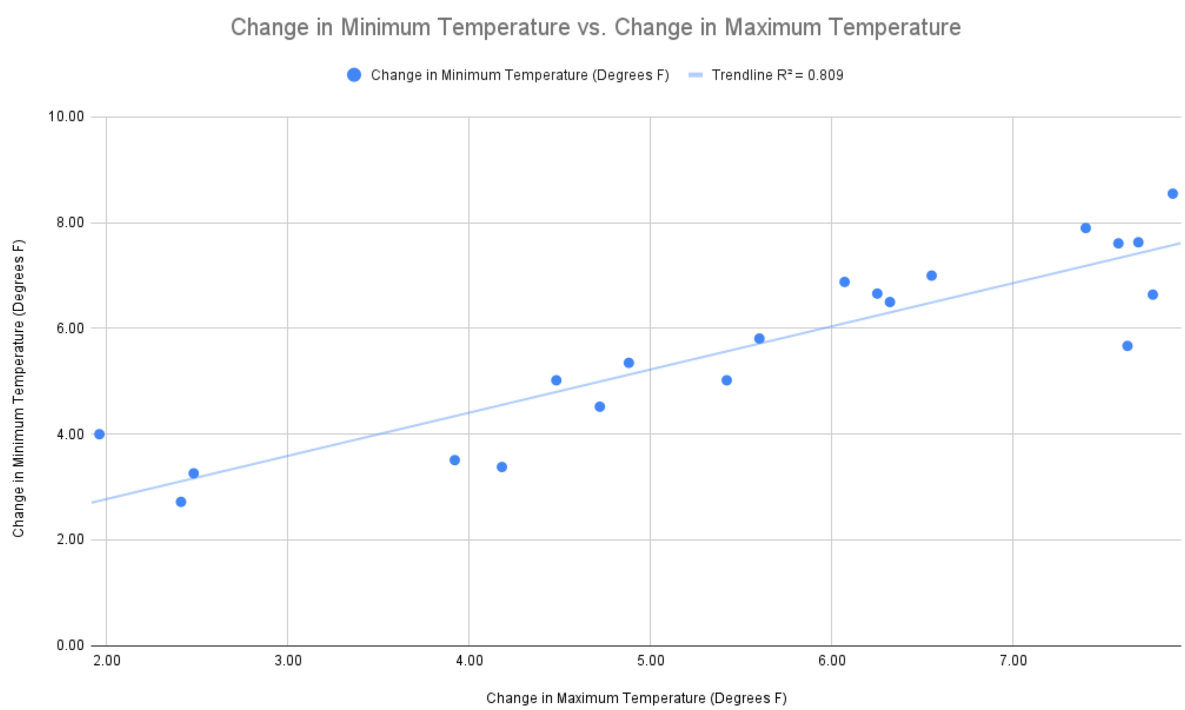


Figure 4.2.a. Shows the R^2 value of 0.809 for the relationship between the change in Minimum Temperatures and Maximum Temperatures across the 20 models (blue points) in January

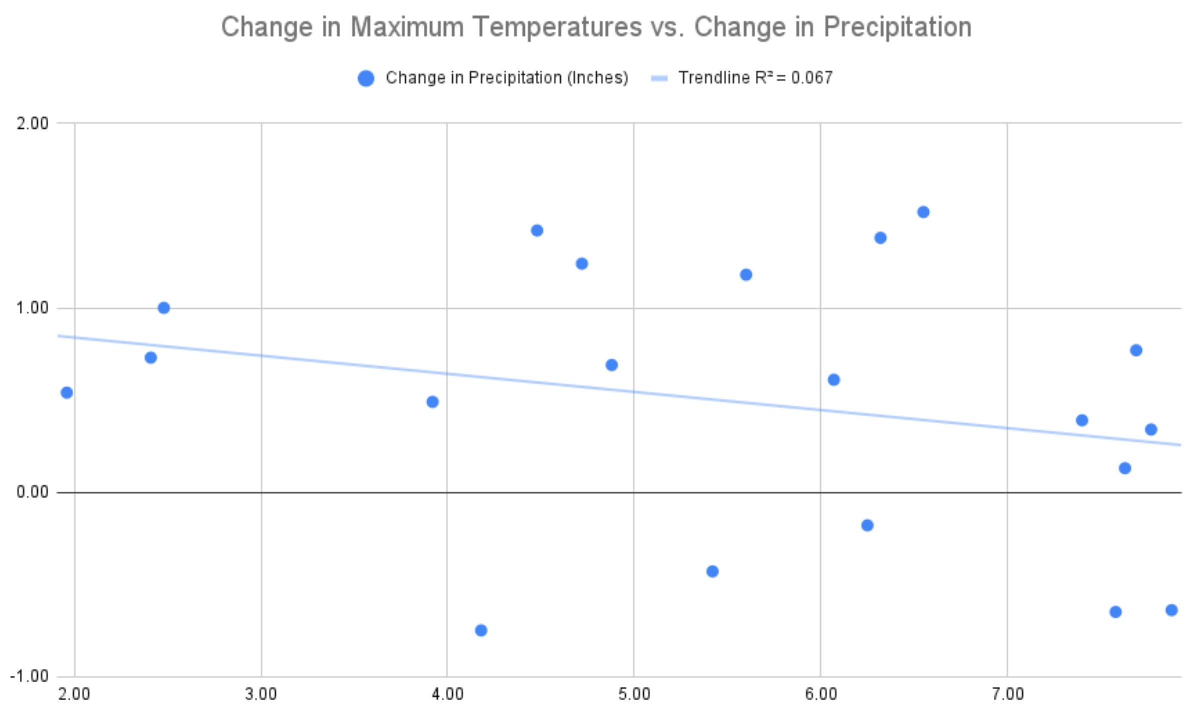


Figure 4.2.b. Shows the R^2 value of 0.067 for the relationship between the change in Precipitation and Maximum Temperatures across the 20 models (blue points) in January

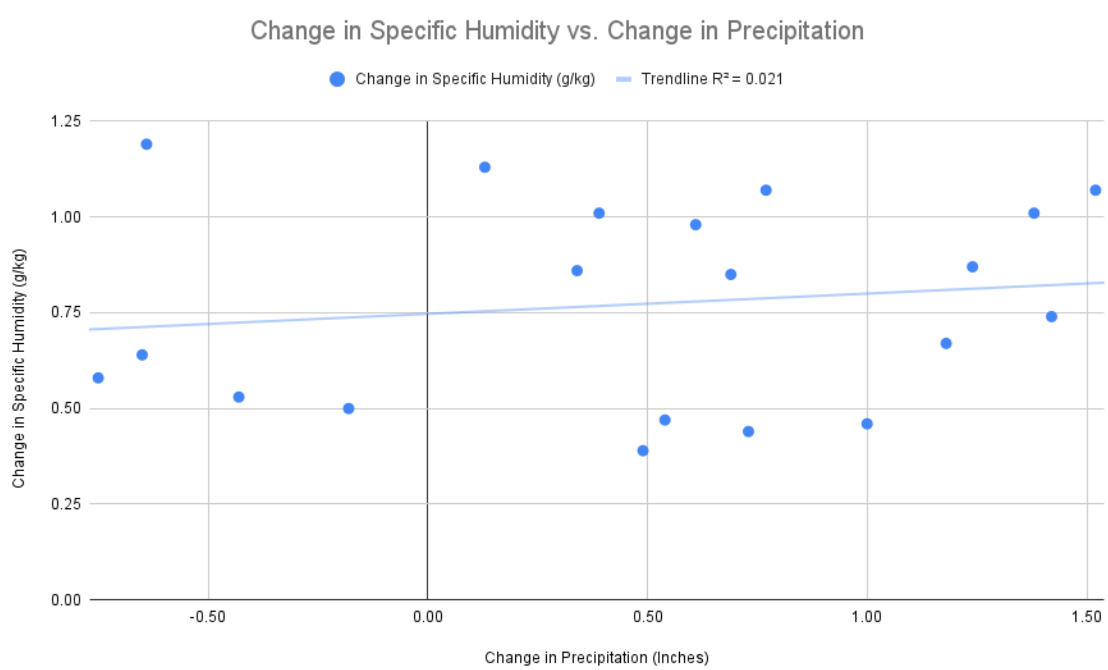
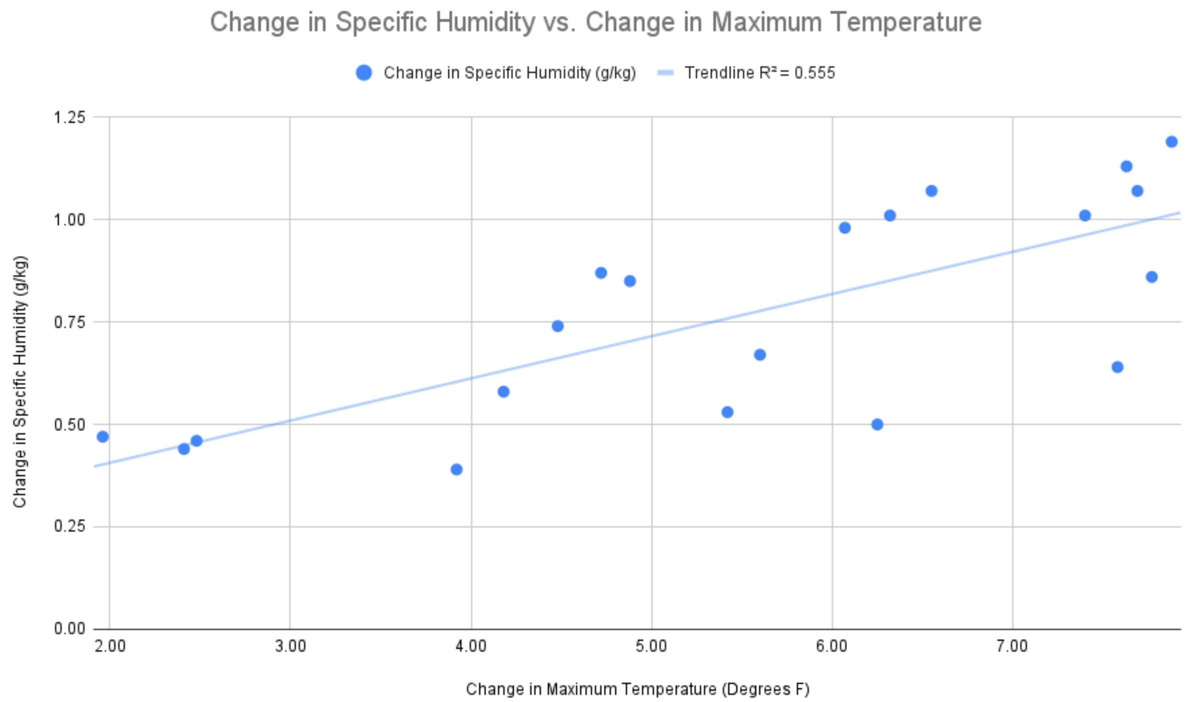


Figure 4.2.c. Shows the R^2 value of 0.021 for the relationship between the change in Specific Humidity and Precipitation across the 20 models (blue points) in January



.*Figure 4.2.d. Shows the* R^2 *value of 0.555 for the relationship between the change in Maximum Temperatures and Specific Humidity across the 20 models (blue points) in January.*

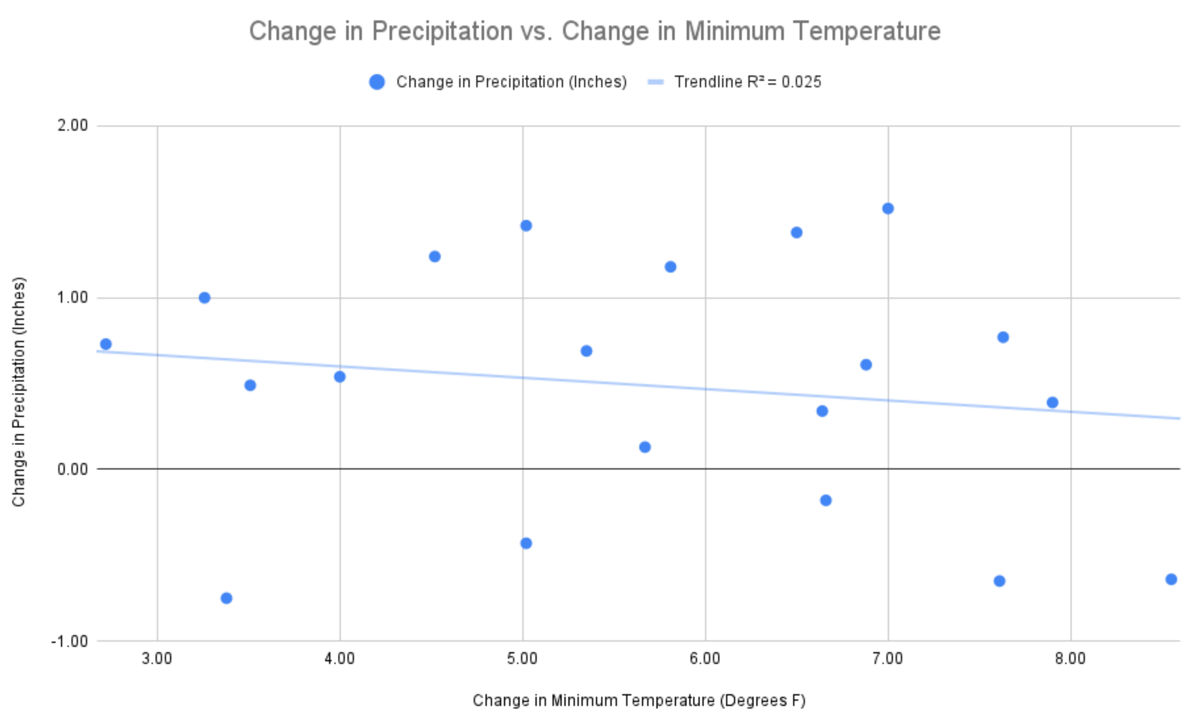


Figure 4.2.e. Shows the R^2 *value of 0.025 for the relationship between the change in Minimum Temperatures and Precipitation across the 20 models (blue points) in January*

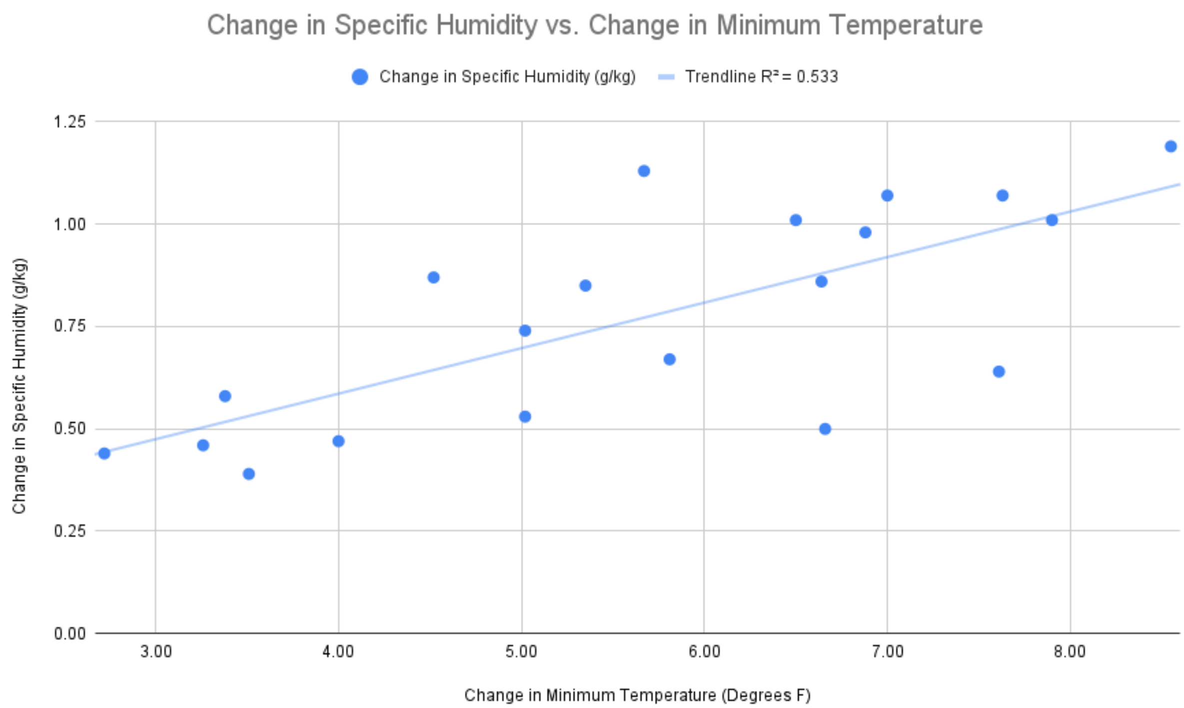


Figure 4.2.f. Shows the R^2 value of 0.533 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in January.

Figures 4.1 and 4.2 show how well each model performs across different variables in each season. A model that predicts a large increase in maximum temperature generally it will also predict a large increase in minimum temperature in both January and July. However, not all variables are so closely linked, which suggests why studying downscaled output from 20 climate models is important.

As air warms, physics tells us that the amount of moisture that can be held in vapor form increases. We expected to find that a model that predicted a larger increase in minimum and maximum temperatures would have a correspondingly larger increase in specific humidity.

While in general this held true in winter (specific humidity vs. maximum temperature R^2=0.555, specific humidity vs. minimum temperature R^2=0.533), summer is a different story (specific humidity vs. maximum temperature R^2=0.0, specific humidity vs. minimum temperature R^2=0.17). There was some correlation between a higher minimum temperature and higher specific humidity across the state in summer, but statistically no correlation between a higher maximum temperature and higher specific humidity (Figure 4.1.d.). The reason for this could be that the atmosphere is getting less cloudy and damp, relative to the temperature, and it is able to warm more. This could be because of the increase in sunlight and because having less water on the surface allows the surface to heat up more.

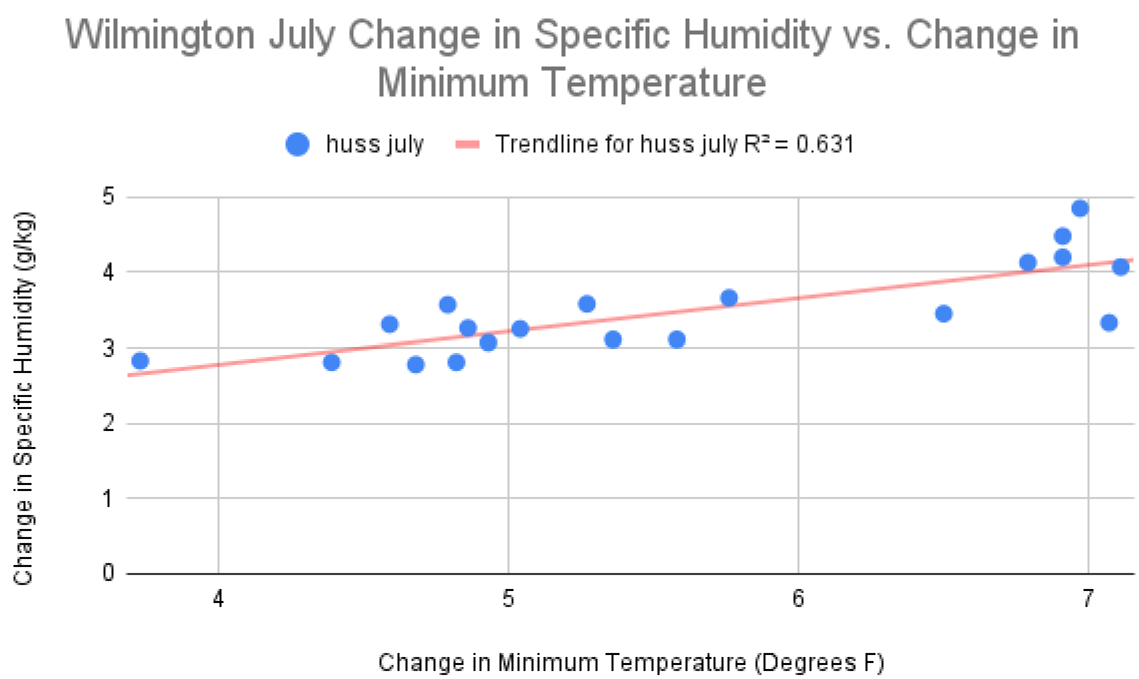


Figure 4.3.a. Shows the R^2 value of 0.631 for for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Wilmington.

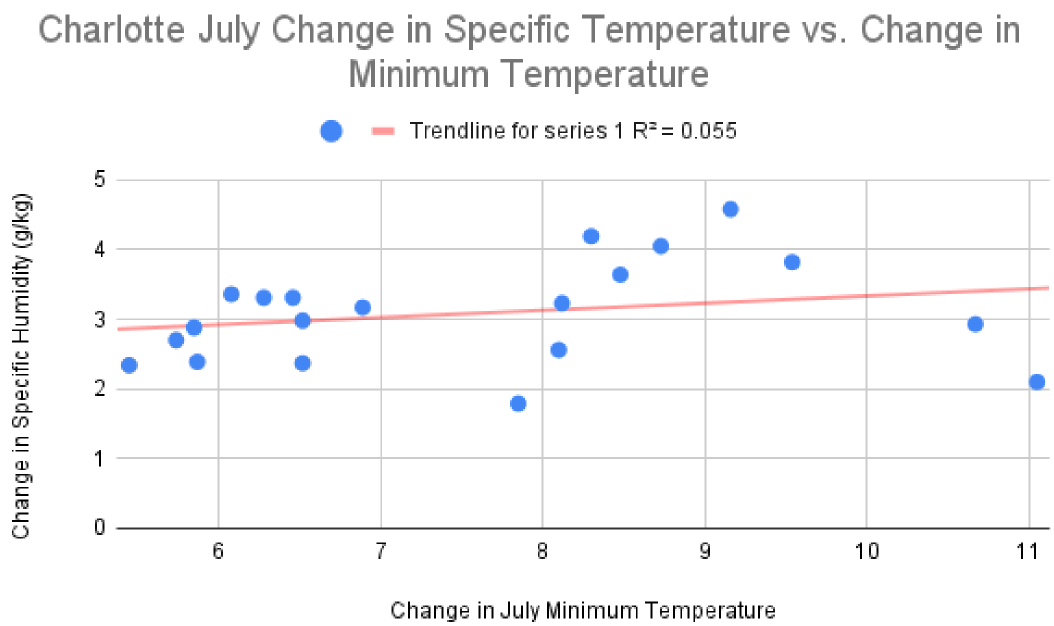


Figure 4.3.b. Shows the R^2 value of 0.055 for for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Charlotte.

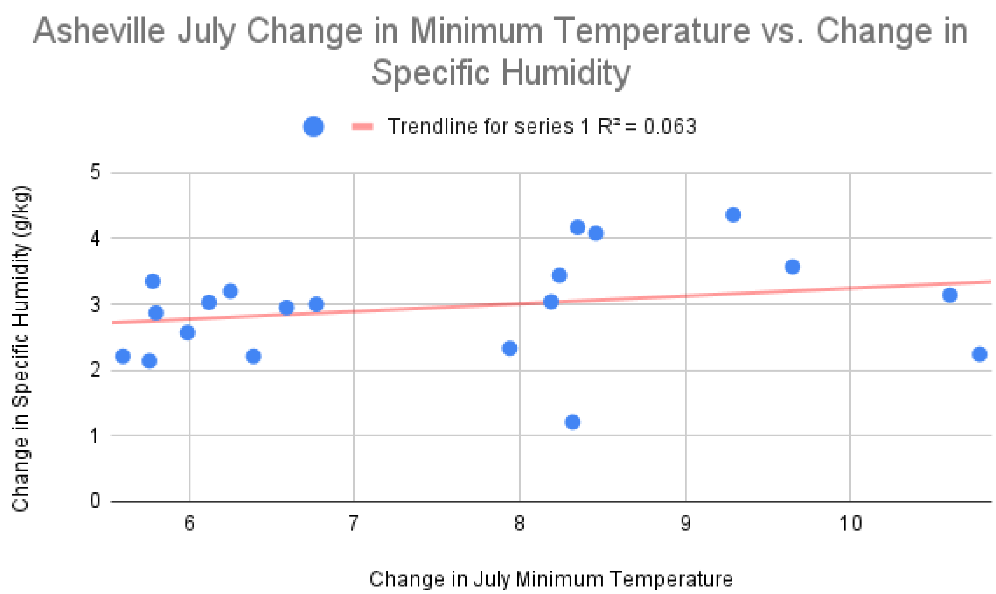


Figure 4.3.c. Shows the R^2 value of 0.063 for the relationship between the change in Minimum Temperatures and Specific Humidity across the 20 models (blue points) in July in Asheville.

These results agree with the results presented by the NCCSR where the rise in humidity is directly correlated to the rise in temperature at the ocean (Kunkel et al., 2020). These results indicate that projections of humidity and temperature at the ocean are separate from inland. This could be because Wilmington's main source of atmospheric moisture is essentially unlimited coming from the Atlantic Ocean and the moisture for the rest of the state is limited because it comes from both the Atlantic and the Gulf of Mexico. This means just because the capacity of the atmosphere to hold moisture increases, does not mean the moisture is available in the piedmont and the mountains as it depends on flow from these two sources of moisture.

Changes in summer precipitation had almost no statistical correlation with changes in other variables. This could be because changes in precipitation had the widest range of possible outcomes across models. Summertime precipitation in the Southeastern US is driven by convection (Sayemuzzaman and Jha, 2014; Boyles and Raman, 2003), which low spatial resolution climate models have difficulty resolving (Maher et al., 2018; Becker et al., 2009). In a basic sense, climate models do not simulate thunderstorms. While MACA downscaling produces data with a 4 km spatial resolution, the input data is still from low spatial resolution climate model output and MACA downscaling does not include any additional physics that would mimic higher spatial and temporal resolution convection. In order to more accurately predict convective rainfall in North Carolina in the future, we would need to incorporate convection into the downscaling method, or have climate model inputs that have more physically realistic convection.

The previous 20 year average of January precipitation in North Carolina is 3.3 inches (NOAA NCEI, 2022), so our results indicate a possible change of 23% decrease to 46% increase. This large range of possible winter precipitation outcomes indicates a need to prepare for both ends of the extreme scenarios. The percentage changes in winter precipitation are similar to the percentage changes in summer, but importantly, the magnitudes of the range are much different (-0.75 to 1.52 inches in winter, versus -2.47 to 1.53 inches in summer). This wide range could be due to the change in position of the jet stream which will have a large effect on midlatitude winter storm track. This is the main driver for North Carolina's winter precipitation.

The North Carolina Climate Science Report analyzed downscaled precipitation at the daily timescale and concluded that precipitation events that are currently considered statistical outliers in terms of magnitude will become more frequent in the future of North Carolina climate (Kunkel et al., 2020), consistent with larger-scale climate model findings (IPCC, 2021). While we looked at total rainfall in January and July, the prediction of the magnitude and frequency of sub-monthly events is important for flood forecasting to allow for better hazard mitigation, but the monthly results here suggest our winters will become wetter across the state and our summers will become wetter with the exception of the coast. Agriculture would also be affected because an increase or decrease in monthly precipitation affects crop yield over the course of a growing season. Crops grown in North Carolina such as corn can be destroyed by severe flooding events (Ali et al., 2017), but also because of drought. My results show a wide range of variability across the models, leading to uncertainty in planning.

There is a clear need to prepare for increased climatological temperatures and humidity in our major population hubs, especially when combined with the documented urban heat island effect (Eastin et al., 2017), and even though changes in precipitation are not clear, our results suggest that extremes (either more or less rain in a month) are within the realm of possibilities. Green space (parks, tree canopy) in cities serves to cool the city and also slow stormwater runoff from extreme precipitation events (Mukherjee et al., 2018). Infrastructure such as cool roofing, concrete road surfaces, and energy efficient buildings can also be used to cool off our population centers as the climate warms (Macintyre and Heaviside, 2013). Some of these measures will also help with potential flash flooding events in our cities. By reducing the amount of impermeable surfaces and increasing the amount of green spaces and green infrastructure we can reduce the amount of rapid runoff and flash flooding caused by the impermeable surfaces in our cities today (Mukherjee et al., 2018).

Rural spaces require planning as well, and my results show how North Carolina minimum and maximum temperature will increase alongside an increase in humidity across the state, and in both seasons. Again, precipitation changes are widely variable depending on the region and model, but this suggests that both dry and wet extremes in a month will be important to prepare for. Agriculture is a huge industry in North Carolina and this takes place mostly in rural areas (Figure 4.3). While flooding and extreme precipitation will be of concern here, the most pressing issues facing farmers is likely to be summertime temperature increases and the drought driven by increased evaporation (Kunkel et al., 2020). Our composite mean predicts the largest maximum and minimum temperature increases in the Piedmont region and just away from the coast (Figure 3.1 and Figure 3.3), where significant agriculture takes place.

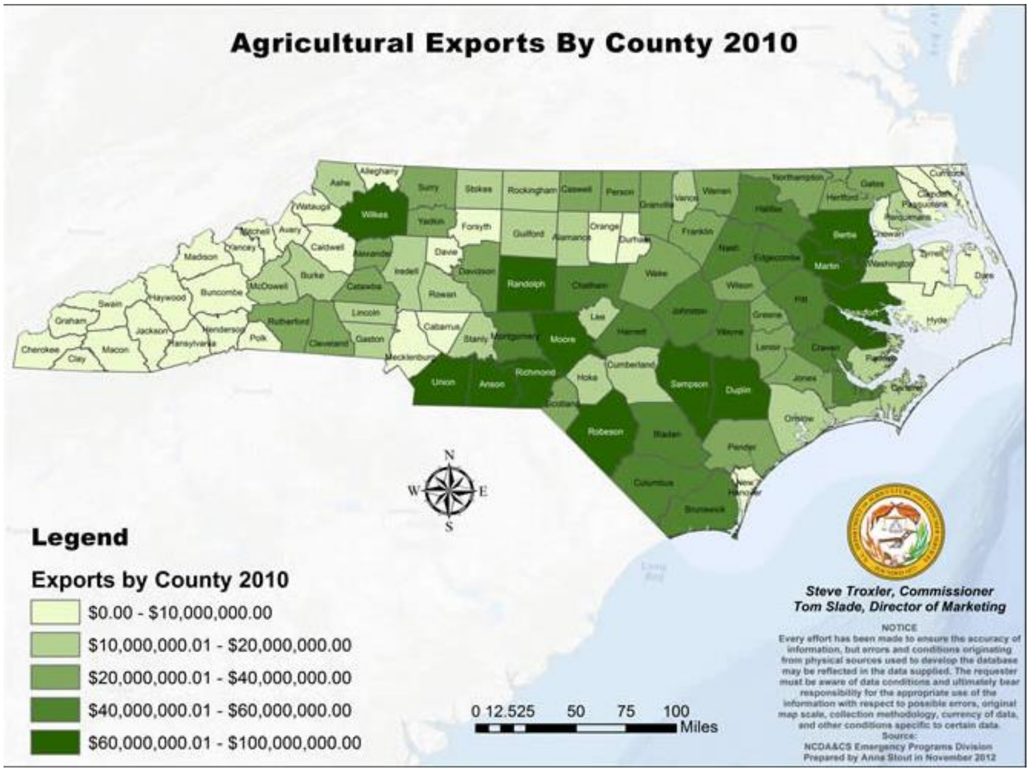


Figure 4.4. A large portion of North Carolina agriculture falls within the area of higher warming in the state. Compare to figure 3.1. Figure retrieved from [*https://ncmepsummercurriculum.wordpress.com/about-nc-migrant-farmworkers/nc-agriculture-info/*](https://ncmepsummercurriculum.wordpress.com/about-nc-migrant-farmworkers/nc-agriculture-info/)

Higher than average growing season temperatures along with drought could reduce crop yield in North Carolina (Raza et al., 2019). Strategies to fight this will be different than those implemented in our urban areas and should be formulated prior to the largest portion of the changes we are expected to see in order to avoid the brunt of their impacts. Better irrigation and farming methods could be a potential solution for the droughts North Carolina is likely to face over the coming decades (Raza et al., 2019). The use of genetically modified organisms in our crops could help mitigate some of the crop losses by making main crops like corn more resistant to drought and higher than average growing season temperatures (Poumadère et al., 2011).

Our winters will also become notably warmer as the composite mean model suggests a warming of almost 6 degrees across the state for January maximum temperatures. While this outcome may seem desirable, an increase in winter temperatures has other effects as well. North Carolina is often on the rain/snow boundary and a temperature increase could cause North Carolina to receive more rain rather than snow. This could have economic impacts on the ski industry in Western North Carolina. Farmers also rely on the winter freeze to kill off crop pests before the spring planting (Andreadis et al., 2017). With warmer winter temperatures it stands to reason that not as many pests would be terminated by the cold.

While there is a rise in specific humidity in January, it is not as large of an increase as summer. This is logical as the atmosphere's moisture capacity is exponentially related to its temperature and the summer temperature is slated to increase more in addition to it already being the naturally warmer season.

By using 20 downscaled climate models to predict future climate in North Carolina and major cities within three of the state's geographic regions, it can be projected how each place will change independently of each other. This will help understand the future of changes in our ecosystems, weather patterns, and growing seasons. By looking at where and how climate shifts in North Carolina it will give the state an extra advantage in preparing for the future. If citizens and government officials see the localized effects of climate change perhaps they will take action. If this project affects any sort of change in these areas, that is a positive outcome.

The methods outlined here can be used on any area within the continental United States where MACA has compiled data. For future work, any space could be studied to examine what climate could look like across models. The only thing that would need to be altered is the spatial domain. Perhaps looking at the spaces at the county level could provide more actionable results in terms of policy making. In the future, we would like to automate this process more by incorporating a coding language such as Python rather than Arcmap. This would allow for rapid processing of downscaled climate model output across different spatial domains.

CHAPTER 5: CONCLUSIONS

North Carolina is projected to warm in every spatial domain and both the summer and winter, and the atmosphere is also projected to become more humid throughout the state. This has been a hallmark of climate change across the globe and is easily understood based on the climate models.

What is not as clearly understood, but could have just as large an impact is the changes we could experience in precipitation. It is fairly conclusive from the models that precipitation should increase in the month of January across North Carolina. While not all models agree on this increase, the composite mean model suggests an increase of 0.49 inches of precipitation across the state in the month of January. With January maximum and minimum temperature increases of 5.58 and 5.71 °F (respectively) across North Carolina, more precipitation is likely to fall as rain than snow. July precipitation is unclear as there is such a wide range of possible outcomes. The composite mean suggests a slight increase in precipitation across the mountain (Asheville) and Piedmont (Charlotte) and actually a slight decrease in the coastal plain (Wilmington). Precipitation is a particularly hard variable to resolve given the convective and complex nature of summertime thunderstorms in the southeastern United States.

One thing the models are clear about is an increase in specific humidity across the state in both months. While January is slated to only see a small increase in specific humidity (0.77 g/kg), July is predicted to receive an increase of over four times that of the winter month (3.15 g/kg). This is likely because as temperature increases, the atmosphere's ability to hold moisture increases at an exponential rate.

Overall, the end of century changes in summer and winter that we summarize, suggest that planning is imperative. It will be far costlier, both from an economic and morbidity standpoint to react to these changes as they happen rather than get in front of them with action in our urban and rural communities. The climate is warming and getting more humid and we must be ready for periods of heavy precipitation leading to flooding followed by periods of extreme heat and drought. It is important to connect these climate projections to meaningful actions in order to prevent worst case social outcomes.

This work only touches on the possibilities for the MACA downscaled climate model output. This study looked at the two most extreme (hottest and coldest) months of the year to see how they would change in North Carolina. In order to build a more complete climate projection for North Carolina, every month would need to be considered. MACA also offers daily model output. This could be useful to estimate flood risk in North Carolina as it would project individual days with extreme precipitation events. Daily data would also allow us to project extreme heat waves in the future (e.g. 5 days in a row with temperatures 5 degrees above the mean). This is similar to what the NCCSR did with the LOCA downscaling data. A direct comparison of LOCA versus MACA using daily data over the shorter time scale (NCCSR studied a future defined as 2040-2060) could be useful. If CMIP6 climate models (IPCC, 2021; IPCC, 2022) are successfully downscaled, that would provide an updated look at how North Carolina climate could look in the future. Other possibilities include examining different spatial domains within the CONUS (e.g. every major city or every county), and looking at all of the variables contained within the MACA method.

REFERENCES

Abatzoglou, J.T. (2013), Development of gridded surface meteorological data for ecological applications and modeling. Int. J. Climatol., 33: 121-131. https://doi.org/10.1002/joc.3413

Abatzaglou, J. T. (n.d.). Maca statistical downscaling method. Retrieved April 25, 2022, from https://climate.northwestknowledge.net/MACA/data_portal.php

Abatzoglou, J. T., and T. J. Brown, 2012: A comparison of statistical downscaling methods suited for wildfire applications. International Journal of Climatology, 32, 772-780. [Available online at https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/joc.2312.]

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas, A., & Din, I. (2017). Climate change and its impact on the yield of major food crops: Evidence from Pakistan. *Foods*, *6*(6), 39. https://doi.org/10.3390/foods6060039

Anderson, G. B., Bell, M. L., & Peng, R. D. (2013). Methods to calculate the heat index as an exposure metric in environmental health research. *Environmental Health Perspectives*, *121*(10), 1111–1119. https://doi.org/10.1289/ehp.1206273

Andreadis, S. S., & Athanassiou, C. G. (2017). A review of insect cold hardiness and its potential in stored product insect control. *Crop Protection, 91*, 93–99. https://doi.org/10.1016/j.cropro.2016.08.013

Barreca A. I. (2012). Climate change, humidity, and mortality in the United States. *Journal of environmental economics and management*, *63*(1), 19–34. https://doi.org/10.1016/j.jeem.2011.07.004

Becker, E. J., Berbery, E. H., & Higgins, R. W. (2009). Understanding the Characteristics of Daily Precipitation over the United States Using the North American Regional Reanalysis, Journal of Climate, 22(23), 6268-6286. Retrieved Apr 18, 2022, from https://journals.ametsoc.org/view/journals/clim/22/23/2009jcli2838.

Boyles, R. P., & Raman, S. (2003). Analysis of Climate Trends in North Carolina (1949–1998). *Environment International*, *29*(2-3), 263–275. https://doi.org/10.1016/s0160-4120(02)00185-x

Dahl, K., Licker, R., Abatzoglou, J. T., & Declet-Barreto, J. (2019). Increased frequency of and population exposure to extreme heat index days in the United States during the 21st Century. *Environmental Research Communications*, *1*(7), 075002. https://doi.org/10.1088/2515-7620/ab27cf

Diem JE, Stauber CE, Rothenberg R (2017) Heat in the southeastern United States: Characteristics, trends, and potential health impact. PLoS ONE 12(5): e0177937. https://doi.org/10.1371/journal.pone.0177937

Eastin, M. D., Baber, M., Boucher, A., Di Bari, S., Hubler, R., Stimac-Spalding, B., & Winesett, T. (2018). Temporal variability of the Charlotte (sub)urban Heat Island. *Journal of*

Applied Meteorology and Climatology, *57*(1), 81–102. https://doi.org/10.1175/jamc-d-17-0099.1

Golledge, N. R., Keller, E. D., Gomez, N., Naughten, K. A., Bernales, J., Trusel, L. D., & Edwards, T. L. (2019). Global environmental consequences of twenty-first-century ice-sheet melt. *Nature, 566*(7742), 65–72. https://doi.org/10.1038/s41586-019-0889-9

Hausfather, Z., & Peters, G. P. (2020, January 29). *Emissions – the 'business as usual' story is misleading*. Nature News. Retrieved April 15, 2022, from https://www.nature.com/articles/d41586-020-00177-3

Hausfather, Z. (2021, October 11). *Explainer: The high-emissions 'RCP8.5' global warming scenario*. Carbon Brief. Retrieved April 9, 2022, from https://www.carbonbrief.org/explainer-the-high-emissions-rcp8-5-global-warming-scenario

Hausfather, D. Z. (2021, February 25). When climate scientists try and project how much the Earth will warm in the future, we have to deal with three different types of uncertainties:The magnitude of future HUMAN EMISSIONS.THE sensitivity of the climate to CO2.The degree to which carbon cycle feedback will change. pic.twitter.com/yzvK2skC2E. Twitter. Retrieved September 23, 2021, from https://twitter.com/hausfath/status/1365067715312971779.

Hausfather, Z. (2021, August 19). *Explainer: The high-emissions 'RCP8.5' global warming scenario*. Carbon Brief. Retrieved September 23, 2021, from https://www.carbonbrief.org/explainer-the-high-emissions-rcp8-5-global-warming-scenario.

Heidari, H., Arabi, M., Warziniack, T., & Kao, S.-C. (2021). Shifts in hydroclimatology of US megaregions in response to climate change. *Environmental Research Communications*, *3*(6), 065002. https://doi.org/10.1088/2515-7620/ac0617

Howe, P. D., M. Mildenberger, J. R. Marlon, and A. Leiserowitz, 2015: Geographic variation in opinions on climate change at state and local scales in the USA. Nature Climate Change, 5, 596. [Available online at http://dx.doi.org/10.1038/nclimate2583, accessedSeptember 2021]

Huntingford, C., Lowe, J. A., Booth, B. B., Jones, C. D., Harris, G. R., Gohar, L. K., & Meir, P. (2009). Contributions of carbon cycle uncertainty to future climate projection spread. *Tellus B*, *61*(2). https://doi.org/10.3402/tellusb.v61i2.16834

IPCC, 2021: Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [MassonDelmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press.

IPCC, 2022: Summary for Policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A.Alegría, M. Craig, S. Langsdorf, S.

Löschke, V. Möller, A. Okem (eds.)]. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. In Press.

Jay, A., D.R. Reidmiller, C.W. Avery, D. Barrie, B.J. DeAngelo, A. Dave, M. Dzaugis, M. Kolian, K.L.M. Lewis, K. Reeves, and D. Winner, 2018: Overview. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 33–71. doi: 10.7930/NCA4.2018.CH1

Kau, G. (2021, February 23). *When fossil fuels run out, what then?*MAHB. Retrieved September 28, 2021, from https://mahb.stanford.edu/library-item/fossil-fuels-run/.

Kunkel, K.E., D.R. Easterling, A. Ballinger, S. Bililign, S.M. Champion, D.R. Corbett, K.D. Dello, J. Dissen, G.M. Lackmann, R.A. Luettich, Jr., L.B. Perry, W.A. Robinson, L.E. Stevens, B.C. Stewart, and A.J. Terando, 2020: North Carolina Climate Science Report. North Carolina Institute for Climate Studies, 233 pp. https://ncics.org/nccsr

Lashof, D. (2018, August 20). *Why positive climate feedbacks are so bad*. World Resources Institute. Retrieved September 24, 2021, from https://www.wri.org/insights/why-positive-climate-feedbacks-are-so-bad.

Macintyre, H., & Heaviside, C. (2019). Potential benefits of cool roofs in reducing heat-related mortality during heatwaves in a European City. *Environmental Epidemiology, 3*, 254–255. https://doi.org/10.1097/01.ee9.0000608692.75541.67

Moss, R., Edmonds, J., Hibbard, K. et al. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756 (2010). https://doi.org/10.1038/nature08823 https://www.nature.com/articles/nature08823

Mukherjee, M., & Takara, K. (2018). Urban green space as a countermeasure to increasing urban risk and the UGS-3CC resilience framework. *International Journal of Disaster Risk Reduction*, *28*, 854–861. https://doi.org/10.1016/j.ijdrr.2018.01.027

NC Agriculture Data. MEP Summer Curriculum. (2013, July 24). Retrieved April 15, 2022, from https://ncmepsummercurriculum.wordpress.com/about-nc-migrant-farmworkers/nc-agriculture-info/

NOAA National Centers for Environmental information, Climate at a Glance: Statewide Time Series, published April 2022, retrieved on April 18, 2022 from https://www.ncdc.noaa.gov/cag/

Maher, P., Vallis, G. K., Sherwood, S. C.,Webb,M.J.,& Sansom,P.G.(2018). The impact of parameterized convection on climatological precipitation in atmospheric global climate models. Geophysical Research Letters 45, 3728–3736. https://doi.org/10.1002/2017GL076826

Sayemuzzaman, M., & Jha, M. K. (2014). Seasonal and annual precipitation time series trend analysis in North Carolina, United States. *Atmospheric Research*, *137*, 183–194. https://doi.org/10.1016/j.atmosres.2013.10.012

Schwartz, S. E. (2004). Uncertainty requirements in radiative forcing of climate change. *Journal of the Air & Waste Management Association*, *54*(11), 1351–1359. https://doi.org/10.1080/10473289.2004.10471006

de Sherbinin, A., Carr, D., Cassels, S., & Jiang, L. (2007). *Population and environment*. Annual review of environment and resources. Retrieved September 23, 2021, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2792934/.

Sherwood, S.C. Webb, M.J., Annan, J.D., Armour, K.C., Forster, P.M, Hargreaves, J.C., et al. (2020). An assessment of Earth's climate sensitivity using multiple lines of evidence. Reviews of Geophysics, 58, e2019RG000678. https://doi.org/10/1029/2019RG00678

Petitti, D. B., Hondula, D. M., Yang, S., Harlan, S. L., & Chowell, G. (2016). Multiple trigger points for quantifying heat-health impacts: New evidence from a hot climate. *Environmental Health Perspectives*, *124*(2), 176–183. https://doi.org/10.1289/ehp.1409119

Pierce, D. W., D. R. Cayan, and B. L. Thrasher, 2014: Statistical downscaling using Localized Constructed Analogs (LOCA). Journal of Hydrometeorology, volume 15, page 2558-2585. http://loca.ucsd.edu/

Poumadère, M., Bertoldo, R., & Samadi, J. (2011). Public perceptions and governance of controversial technologies to tackle climate change: Nuclear power, carbon capture and storage, wind, and geoengineering. *Wiley Interdisciplinary Reviews: Climate Change*, *2*(5), 712–727. https://doi.org/10.1002/wcc.134

Raza, A., Razzaq, A., Mehmood, S., Zou, X., Zhang, X., Lv, Y., & Xu, J. (2019). Impact of climate change on crops adaptation and strategies to tackle its outcome: A Review. *Plants*, *8*(2), 34. https://doi.org/10.3390/plants8020034

Raymond, C., Matthews, T., & Horton, R. M. (2020). The emergence of heat and humidity too severe for human tolerance. *Science Advances*, *6*(19). https://doi.org/10.1126/sciadv.aaw1838

Representative concentration pathways. ...and Then There's Physics. (2015, August 24). Retrieved April 17, 2022, from https://andthentheresphysics.wordpress.com/2015/08/14/representative-concentration-pathways/

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., & Rafaj, P. (2011). RCP 8.5—a scenario of comparatively high greenhouse gas emissions. *Climatic Change*, *109*(1-2), 33–57. https://doi.org/10.1007/s10584-011-0149-y

Tan, J., Zheng, Y., Tang, X., Guo, C., Li, L., Song, G., Zhen, X., Yuan, D., Kalkstein, A. J., Li, F., & Chen, H. (2009). The urban heat island and its impact on heat waves and human health in Shanghai. *International Journal of Biometeorology*, *54*(1), 75–84. https://doi.org/10.1007/s00484-009-0256-x

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society, 93, 485-498. [Available online at https://journals.ametsoc.org/view/journals/bams/93/4/bams-d-11-00094.1.xml.]

Webster, M. D., Babiker, M., Mayer, M., Reilly, J. M., Harnisch, J., Hyman, R., Sarofim, M. C., & Wang, C. (2002). Climate change projections: Characterizing uncertainty using climate models. *SpringerReference*. https://doi.org/10.1007/springerreference_305848

Wilhelmi, O. V., Howe, P. D., Hayden, M. H., & O'Lenick, C. R. (2021). Compounding hazards and intersecting vulnerabilities: experiences and responses to extreme heat during COVID-19. *Environmental Research Letters*, *16*(8), 084060. https://doi.org/10.1088/1748-9326/ac1760

Williams, P. A., Ng'ang'a, S. K., Crespo, O., & Abu, M. (2020). Cost and benefit analysis of adopting climate adaptation practices among smallholders: The case of five selected practices in Ghana. *Climate Services*, *20*, 100198. https://doi.org/10.1016/j.cliser.2020.100198

Vaidyanathan A, Malilay J, Schramm P, Saha S. Heat-Related Deaths — United States, 2004–2018. MMWR Morb Mortal Wkly Rep 2020;69:729–734. DOI: http://dx.doi.org/10.15585/mmwr.mm6924a1

van Vuuren, D.P., Edmonds, J., Kainuma, M. *et al.* The representative concentration pathways: an overview. *Climatic Change* 109, 5 (2011). https://doi.org/10.1007/s10584-011-0148-z

Zhang, K., Rood, R. B., Michailidis, G., Oswald, E. M., Schwartz, J. D., Zanobetti, A., Ebi, K. L., & O'Neill, M. S. (2012). Comparing exposure metrics for classifying 'dangerous heat' in heat wave and Health Warning Systems. *Environment International*, *46*, 23–29. https://doi.org/10.1016/j.envint.2012.05.001

APPENDIX A: MODEL OUTPUT

Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
CCSM4	*NC*	*7.94*	*6.30*	*6.32*	*6.50*	*0.23*	*1.38*	*2.46*	*1.01*
CCSM4	*Asheville*	*7.96*	*6.39*	*6.53*	*6.80*	*1.74*	*1.78*	*2.21*	*0.98*
CCSM4	*Charlotte*	*8.39*	*6.52*	*6.26*	*6.53*	*0.97*	*1.31*	*2.37*	*1.02*
CCSM4	*Wilmington*	*5.94*	*4.82*	*5.62*	*6.05*	*-2.05*	*1.03*	*2.81*	*1.02*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
NorESM1-M	*NC*	*7.88*	*5.85*	*3.92*	*3.51*	*1.53*	*0.49*	*2.58*	*0.39*
NorESM1-M	*Asheville*	*8.41*	*5.76*	*4.39*	*3.64*	*0.60*	*0.29*	*2.14*	*0.37*
NorESM1-M	*Charlotte*	*8.62*	*5.87*	*4.45*	*3.73*	*1.30*	*0.51*	*2.39*	*0.39*
NorESM1-M	*Wilmington*	*5.98*	*4.68*	*3.01*	*2.84*	*1.29*	*0.58*	*2.78*	*0.43*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
bcc-csm1-1	*NC*	*8.87*	*7.15*	*4.48*	*5.02*	*-0.35*	*1.42*	*2.26*	*0.74*
bcc-csm1-1	*Asheville*	*10.39*	*8.32*	*4.12*	*4.93*	*-0.97*	*1.56*	*1.21*	*0.69*
bcc-csm1-1	*Charlotte*	*10.04*	*7.85*	*4.70*	*4.70*	*-0.64*	*1.47*	*1.79*	*0.74*
bcc-csm1-1	*Wilmington*	*6.32*	*5.36*	*4.79*	*5.13*	*0.63*	*1.35*	*3.11*	*0.84*

Model	Spatial Domain	Jul Max Temp	Jul Min Temp	Jan MaxTemp	Jan Min Temp	Jul Precip	Jan Precip	Jul Huss	Jan Huss
MRI-CGCM3	NC	5.13	5.80	4.72	4.52	0.67	1.24	3.18	0.87
MRI-CGCM3	Asheville	4.61	5.78	4.77	3.78	0.56	1.04	3.35	0.83
MRI-CGCM3	Charlotte	5.15	6.28	4.79	3.87	0.34	1.14	3.31	0.88
MRI-CGCM3	Wilmington	5.13	4.86	4.57	4.48	0.34	1.44	3.26	0.86
Model	Spatial Domain	Jul Max Temp	Jul Min Temp	Jan MaxTemp	Jan Min Temp	Jul Precip	Jan Precip	Jul Huss	Jan Huss
MIROC5	NC	6.82	5.94	7.70	6.64	0.59	0.34	2.88	0.86
MIROC5	Asheville	6.28	5.80	8.01	6.48	0.29	0.13	2.87	0.86
MIROC5	Charlotte	6.91	5.85	7.96	6.28	0.47	0.44	2.88	0.9
MIROC5	Wilmington	5.67	4.93	6.59	6.52	0.97	0.56	3.07	0.88
Model	Spatial Domain	Jul Max Temp	Jul Min Temp	Jan MaxTemp	Jan Min Temp	Jul Precip	Jan Precip	Jul Huss	Jan Huss
inmcm4	NC	4.10	5.58	1.96	4.00	-0.12	0.54	2.78	0.47
inmcm4	Asheville	4.09	5.99	1.85	3.83	-0.18	0.67	2.57	0.46
inmcm4	Charlotte	4.00	5.74	1.76	3.96	0.16	0.43	2.7	0.49
inmcm4	Wilmington	3.53	3.73	1.91	3.11	-1.00	0.63	2.83	0.49
Model	Spatial Domain	Jul Max Temp	Jul Min Temp	Jan MaxTemp	Jan Min Temp	Jul Precip	Jan Precip	Jul Huss	Jan Huss

MIROC-ESM	*NC*	*8.51*	*8.17*	*7.69*	*7.63*	*0.20*	*0.77*	*4.1*	*1.07*
MIROC-ESM	*Asheville*	*8.32*	*8.35*	*9.13*	*7.97*	*0.44*	*0.62*	*4.17*	*1.04*
MIROC-ESM	*Charlotte*	*8.60*	*8.30*	*9.05*	*7.40*	*0.24*	*0.64*	*4.19*	*1.03*
MIROC-ESM	*Wilmington*	*7.49*	*6.79*	*6.46*	*7.15*	*-0.62*	*0.62*	*4.13*	*1.18*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
BNU-ESM	*NC*	*6.62*	*6.41*	*7.88*	*8.55*	*1.50*	*-0.64*	*3.45*	*1.19*
BNU-ESM	*Asheville*	*6.14*	*6.25*	*9.14*	*9.14*	*0.82*	*-0.16*	*3.2*	*1.29*
BNU-ESM	*Charlotte*	*6.43*	*6.46*	*8.55*	*8.87*	*1.22*	*-0.42*	*3.31*	*1.27*
BNU-ESM	*Wilmington*	*5.90*	*5.27*	*6.35*	*7.31*	*1.78*	*-0.93*	*3.58*	*1.22*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
GFDL-ESM2G	*NC*	*6.48*	*5.87*	*2.41*	*2.72*	*1.19*	*0.72*	*3.35*	*0.44*
GFDL-ESM2G	*Asheville*	*6.91*	*6.12*	*2.32*	*2.75*	*0.04*	*0.67*	*3.03*	*0.4*
GFDL-ESM2G	*Charlotte*	*6.57*	*6.08*	*2.63*	*2.92*	*0.73*	*0.88*	*3.36*	*0.42*
GFDL-ESM2G	*Wilmington*	*5.49*	*4.79*	*2.21*	*2.41*	*2.38*	*0.18*	*3.57*	*0.46*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
GFDL-ESM2M	*NC*	*6.73*	*5.29*	*4.18*	*3.38*	*0.09*	*-0.75*	*2.39*	*0.58*

GFDL-ESM2M	*Asheville*	*6.79*	*5.60*	*4.48*	*3.28*	*-0.09*	*-0.22*	*2.21*	*0.6*
GFDL-ESM2M	*Charlotte*	*7.06*	*5.45*	*4.59*	*3.40*	*0.43*	*-0.58*	*2.34*	*0.63*
GFDL-ESM2M	*Wilmington*	*6.03*	*4.39*	*3.53*	*3.31*	*-0.12*	*-0.79*	*2.81*	*0.6*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
CAN-ESM2	*NC*	*7.96*	*7.63*	*4.88*	*5.35*	*-0.82*	*0.69*	*3.42*	*0.85*
CAN-ESM2	*Asheville*	*7.96*	*8.19*	*5.33*	*5.90*	*-0.74*	*0.95*	*3.04*	*0.88*
CAN-ESM2	*Charlotte*	*8.37*	*8.12*	*5.35*	*5.89*	*-0.36*	*0.45*	*3.23*	*0.88*
CAN-ESM2	*Wilmington*	*6.57*	*5.76*	*4.37*	*4.75*	*-2.35*	*0.30*	*3.66*	*0.88*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
IPSL-CM5A-LR	*NC*	*7.34*	*8.44*	*7.58*	*7.61*	*0.64*	*-0.65*	*3.76*	*0.64*
IPSL-CM5A-LR	*Asheville*	*7.36*	*8.24*	*8.03*	*8.42*	*0.21*	*-0.34*	*3.44*	*0.63*
IPSL-CM5A-LR	*Charlotte*	*7.24*	*8.48*	*7.81*	*7.74*	*0.35*	*-0.48*	*3.64*	*0.62*
IPSL-CM5A-LR	*Wilmington*	*6.64*	*6.91*	*6.26*	*6.59*	*1.05*	*-0.95*	*4.2*	*0.66*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
IPSL-CM5A-MR	*NC*	*8.48*	*9.29*	*6.25*	*6.66*	*0.52*	*-0.18*	*4*	*0.5*
IPSL-CM5A-MR	*Asheville*	*8.64*	*9.65*	*6.28*	*6.55*	*0.12*	*-0.46*	*3.57*	*0.44*

IPSL-CM5A-MR	*Charlotte*	*8.62*	*9.54*	*6.44*	*6.55*	*0.43*	*-0.27*	*3.82*	*0.49*
IPSL-CM5A-MR	*Wilmington*	*7.04*	*6.91*	*5.18*	*5.89*	*1.14*	*0.13*	*4.48*	*0.62*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
bcc-csm1-1-m	*NC*	*7.65*	*7.36*	*2.48*	*3.26*	*-0.93*	*1.00*	*2.9*	*0.46*
bcc-csm1-1-m	*Asheville*	*8.48*	*7.94*	*2.23*	*3.37*	*-0.47*	*0.57*	*2.33*	*0.41*
bcc-csm1-1-m	*Charlotte*	*8.75*	*8.10*	*2.48*	*3.29*	*-0.39*	*0.81*	*2.56*	*0.45*
bcc-csm1-1-m	*Wilmington*	*4.64*	*4.59*	*2.57*	*2.88*	*-2.87*	*1.75*	*3.31*	*0.53*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
MIROC-ESM-CHEM	*NC*	*9.20*	*8.42*	*7.40*	*7.90*	*-1.47*	*0.39*	*4.02*	*1.01*
MIROC-ESM-CHEM	*Asheville*	*8.24*	*8.46*	*7.96*	*8.44*	*-0.74*	*0.52*	*4.08*	*1.01*
MIROC-ESM-CHEM	*Charlotte*	*9.11*	*8.73*	*7.76*	*8.03*	*-0.80*	*0.43*	*4.05*	*1.03*
MIROC-ESM-CHEM	*Wilmington*	*8.46*	*7.11*	*6.71*	*7.29*	*-2.75*	*0.25*	*4.07*	*1.12*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
IPSL-CM5B-LR	*NC*	*6.84*	*6.39*	*5.60*	*5.81*	*0.50*	*1.18*	*3*	*0.67*
IPSL-CM5B-LR	*Asheville*	*6.68*	*6.59*	*5.24*	*5.56*	*-0.11*	*0.53*	*2.95*	*0.59*

IPSL-CM5B-LR	*Charlotte*	*6.62*	*6.52*	*5.33*	*5.35*	*0.63*	*0.95*	*2.98*	*0.63*
IPSL-CM5B-LR	*Wilmington*	*5.71*	*5.04*	*4.95*	*5.35*	*0.95*	*1.79*	*3.25*	*0.74*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
HadGEM2-ES365	*NC*	*12.02*	*10.04*	*5.42*	*5.02*	*-2.47*	*-0.43*	*2.42*	*0.53*
HadGEM2-ES365	*Asheville*	*12.60*	*10.78*	*6.10*	*5.47*	*-1.34*	*-0.93*	*2.24*	*0.63*
HadGEM2-ES365	*Charlotte*	*13.39*	*11.05*	*5.99*	*4.93*	*-1.86*	*-0.69*	*2.1*	*0.54*
HadGEM2-ES365	*Wilmington*	*8.39*	*7.07*	*4.12*	*4.59*	*-3.15*	*0.46*	*3.33*	*0.46*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
HADGEM2-CC 365	*NC*	*10.37*	*9.79*	*6.55*	*7.00*	*-1.20*	*1.52*	*2.97*	*1.07*
HADGEM2-CC 365	*Asheville*	*11.09*	*10.60*	*6.57*	*7.40*	*0.08*	*1.41*	*3.14*	*1.14*
HADGEM2-CC 365	*Charlotte*	*11.11*	*10.67*	*6.79*	*7.29*	*-0.60*	*1.94*	*2.93*	*1.16*
HADGEM2-CC 365	*Wilmington*	*6.89*	*6.50*	*5.83*	*6.30*	*-3.24*	*1.20*	*3.45*	*1.03*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
CSIRO-Mk3-6-0	*NC*	*7.70*	*8.60*	*7.63*	*5.67*	*1.31*	*0.13*	*4.59*	*1.13*
CSIRO-Mk3-6-0	*Asheville*	*7.72*	*9.29*	*7.79*	*4.86*	*1.10*	*-0.14*	*4.36*	*1.02*

CSIRO-Mk3-6-0	*Charlotte*	*8.15*	*9.16*	*7.83*	*4.84*	*0.68*	*0.19*	*4.58*	*1.07*
CSIRO-Mk3-6-0	*Wilmington*	*6.79*	*6.97*	*6.68*	*5.74*	*2.20*	*0.70*	*4.85*	*1.23*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
CNRM-CM5	*NC*	*5.85*	*6.52*	*6.07*	*6.88*	*-0.31*	*0.61*	*3.05*	*0.98*
CNRM-CM5	*Asheville*	*5.80*	*6.77*	*6.44*	*7.47*	*-0.25*	*0.35*	*3*	*1.01*
CNRM-CM5	*Charlotte*	*5.85*	*6.89*	*6.23*	*6.86*	*-0.06*	*0.38*	*3.17*	*1.03*
CNRM-CM5	*Wilmington*	*5.08*	*5.18*	*5.69*	*6.44*	*-0.27*	*0.63*	*3.11*	*0.99*
Model	*Spatial Domain*	*Jul Max Temp*	*Jul Min Temp*	*Jan MaxTemp*	*Jan Min Temp*	*Jul Precip*	*Jan Precip*	*Jul Huss*	*Jan Huss*
Composite	*NC*	*7.63*	*7.24*	*5.58*	*5.71*	*0.06*	*0.49*	*3.15*	*0.77*
Composite	*Asheville*	*7.70*	*7.54*	*5.87*	*5.80*	*0.06*	*0.44*	*2.93*	*0.76*
Composite	*Charlotte*	*7.96*	*7.56*	*5.83*	*5.65*	*0.16*	*0.48*	*3.06*	*0.78*
Composite	*Wilmington*	*6.19*	*5.58*	*4.88*	*5.20*	*-0.28*	*0.55*	*3.45*	*0.82*

Appendix A. Shows the differences in NC and Regional Climate across models, seasons, and variables.

APPENDIX B: FIGURE SCRIPT

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

#-------------------------------------------------------------------------------
# Begin: Import External Libraries
#-------------------------------------------------------------------------------

# os provides Operating System tools
import os

# NumPy provides array management tools
import numpy as np

# netCDF4 provides tools to work with netCDF4 data
import netCDF4 as nc

# datetime is used to calculate script runtime
from datetime import datetime

# matplotlib is the primary tool for constructing plots in python
import matplotlib.pyplot as plt

# ncdump is an external script to read and report netcdf metadata
from ncdump import ncdump

# cartopy.crs is used to assign coordinate reference systems to plots
import cartopy.crs as ccrs

# cartopy.feature is used to download shapefiles for plotting
import cartopy.feature as cfeat

# matplotlib tool to add halos to any annotations
import matplotlib.patheffects as PathEffects
```

```
#------------------------------------------------------------------------------
# End: Import External Libraries
#------------------------------------------------------------------------------


#------------------------------------------------------------------------------
# Begin: User-Modfiable Variables
#------------------------------------------------------------------------------

# Path to the data (You will need to change this!)
main_directory = '/Users/rodneyrobinson/Desktop/help_andrew/'

# Path to model data (Should not need to change if following my directory structure)
data_directory = main_directory + 'data/'

# Path to store finalized figures (Should not need to change if following my directory structure)
plot_directory = main_directory + 'figures/'

# Variable of interest (Should just need to add additional variables to the list)
var = [ 'tasmax', 'tasmin', 'huss', 'precip' ]
var_name = [ 'Maximum Temperature', 'Minimum Temperature', 'Specific Humidity',
'Precipitation' ]

# Month of interest (Should just need to add additional months to the list)
month = ['Jul','Jan' ]
month2 = [ 'jul','jan' ]

# Month name for plot title
month_name = [ 'July','January' ]

# Model of interest (Output files need to named in an identical manner to these model name
strings)
model = [
        'CCSM4', 'NorESM1-M', 'bcc-csm1-1', 'MRI-CGCM3',
        'Miroc5', 'inmcm4', 'MIROC-ESM', 'BNU-ESM',
        'GFDL-ESM2G', 'GFDL-ESM2M', 'CanESM2', 'IPSL-CM5A-LR',
        'IPSL-CM5A-MR', 'bcc-csm1-1-m', 'MIROC-ESM-CHEM', 'IPSL-CM5B-LR',
        'HadGEM2-ES365', 'HadGEM2-CC365', 'CSIRO-Mk3-6-0', 'CNRM-CM5',
        'Composite'
```

```
    ]

# BB_Box Coordinates Northern Lat (No need to change)
y1 = 37.0

# BB_Box Coordinates Eastern Lon (No need to change)
x1 = -75.1

# BB_Box Coordinates Southern Lat (No need to change)
y2 = 33.6

# BB_Box Coordinates Western Lon (No need to change)
x2 = -84.6

# Consolidate BB_Box coordinates into a list for future calling (No need to change)
bb_box = [ x2, x1, y2, y1 ]

# Map projection (No need to change)
proj = ccrs.PlateCarree()

# Download and save the state boarder shapefile from Natural Earth Database for plotting (No
need to change)
state_borders = cfeat.NaturalEarthFeature(
                        category = 'cultural',
                        name = 'admin_1_states_provinces_lakes',
                        scale = '10m',
                        facecolor = 'none'
                       )

# Run ncdump on netcdf file? (Boolean, make true if you want to see netCDF metadata)
header = False

# Set fontsize for subplot titles
title_font = 28

# Colormap schema for plotting (May want to change or convert into lists when adding
additional variables)
colormap = [
        plt.cm.get_cmap( 'gist_heat' ).reversed(),
        plt.cm.get_cmap( 'gist_heat' ).reversed(),
```

```
            plt.cm.get_cmap( 'Purples' ) ,
            plt.cm.get_cmap( 'terrain' ).reversed()
           ]

var_min = [ 3, 3, 0, -1.0 ]
var_max = [ 9, 9, 4.2, 1.0 ]


var_label = [
             "Temperature Change (\u00b0F)",
             "Temperature Change (\u00b0F)" ,
             "Specific Humidity Change (gkg$^{-1}$)",
             "Precipitation Change (in.)"
            ]

# Contour increments (Controls contour interval for variable plotting)
inc = [ 0.25, 0.25, 0.1, 0.1 ]

#-----------------------------------------------------------------------------
# End: User-Modfiable Variables
#-----------------------------------------------------------------------------



#----------------------------------------------------------------------------
# Begin: Main Script ( DO NOT CHANGE ANYTHING BELOW HERE!)
#----------------------------------------------------------------------------



#----------------------------------------------------------------------------
# Begin 1: Set Working Directory
#----------------------------------------------------------------------------

# Record Script start time
startTime = datetime.now()

# Loop through each month of data
#----------------------------------------------------------------------------
for k in range( 0, len( month ) ):

    # Loop through each provided variable
```

```
    #----------------------------------------------------------------------------
    for j in range( 0, len( var ) ):

        # Report program status to terminal
        print( "\nBegin main program..." )

        # Create a new directory for plots if it does not exist
        if( os.path.isdir( plot_directory ) == False ):

            # Report to terminal
            print( "\nCreating directory to store plots..." )

            # Create directory
            os.mkdir( plot_directory )

        # Report to terminal
        print( "\nChanging working directory to model output location..." )

        # Change the working directory to the provided path
        os.chdir( data_directory )

        # Retrieve the current directory
        cwd = os.getcwd()

        # Report CWD to terminal
        print('\nCurrent Working Directory: \n {}'.format(cwd) )

#----------------------------------------------------------------------------
# End 1: Set Working Directory
#----------------------------------------------------------------------------


#----------------------------------------------------------------------------
# Begin 2: Set-up Figure
#----------------------------------------------------------------------------

        # Report to terminal
        print( "\n\tConstructing new plot..." )
```

```
    # Representative of the individual plots that compose the figure (Each letter is a separate
subplot and . skips that position)
    figure_mosaic = """
            ABCD
            EFGH
            IJKL
            MNOP
            QRST
            .UU.
            .UU.
           """

    # List of subplot position to call during loop
    current_fig = [
           'a','b','c','d',
           'e','f','g','h',
           'i','j','k','l',
           'm','n','o','p',
           'q','r','s','t',
           'u'
          ]

    # Create figure and axes objects
    fig, axes = plt.subplot_mosaic(
                    mosaic = figure_mosaic,
                    figsize = (30,20),
                    constrained_layout = True,
                    subplot_kw = { 'projection': proj }
                   )

    # Set Main Plot Title
    fig.suptitle(
          '{} {} Difference (2080-2099) - (2006-2025)'.format( month_name[k], var_name[j]
),
          fontsize = title_font + 18,
          fontweight = 'bold'
         )

    # Loop through each model output file
    #----------------------------------------------------------------------------
```

```
    for i in range( 0, len(model) ):

        # Construct axis objects for row one
        ax = fig.add_subplot( axes[current_fig[i].upper() ], projection = proj )

         # Titles for each subplot
        ax.set_title ( model[i], fontsize = title_font, fontweight = 'bold' )

        # Draw the US state borders on all panels
        ax.add_feature( state_borders, linestyle = '-', edgecolor = 'black' )

        # Zoom in on the specified extent on all panels
        ax.set_extent( bb_box )

        # Add background images
        ax.add_feature( cfeat.LAND )
        ax.add_feature( cfeat.OCEAN )

#------------------------------------------------------------------------
# End 2: Set-up Figure
#------------------------------------------------------------------------



#------------------------------------------------------------------------
# Begin 3: Read NetCDF
#------------------------------------------------------------------------

        # Construct the filename
        filename = 'difference_{}_{}_{}.nc'.format( var[j], model[i], month[k] )

        # Open the netCDF file with netCDF4 module
        data = nc.Dataset( filename, 'r', format = "NETCDF4" )

        # Report function status to terminal
        print( "\n{} has been successfully opened...".format( filename ) )

        # Print out variable info (Requires ncdump.py to be in same directory)
        if( header == True ):

            # Report function status to terminal
```

```
            print( "\n\tRunning ncdump on {}...".format( filename ) )

            # Run ncdump on current netcdf file
            ncdump( data )

        # Read in netcdf data
        lon = data[ 'lon' ][:]
        lat = data[ 'lat' ][:]

        # Variable longname (Comes from netCDF metadata)
        longname = 'difference_{}_{}_{}'.format( var[j], model[i], month[k] )

        # Logic to read in model data from netCDF file (Required atm due to inconsistent naming
conventions)
        if( i == 20 ):
             longname = 'Difference_{}_{}_{}'.format( var[j], model[i], month[k] )
        try:
            variable = data[ longname ][:]
        except:
            longname = 'difference_{}_{}_{}'.format( var[j], model[i], month2[k] )
            variable = data[ longname ][:]

        # Unit conversions based on variable type
        if( var[j] == 'tasmax' or var[j] == 'tasmin' ):
            variable = variable * 1.8
        if( var[j] == 'precip' ):
            variable = variable / 25.4
        if( var[j] == 'huss' ):
            variable = variable * 1000.0

        # Close the current netCDF file
        data.close()

        # Report function status to terminal
        print( "\n{} has been successfully closed...".format( filename ) )

#-----------------------------------------------------------------------------
# End 3: Read NetCDF
#-----------------------------------------------------------------------------
```

```
#---------------------------------------------------------------------------
# Begin 4: Plot current netCDF data
#---------------------------------------------------------------------------

        # Report to terminal
        print( "\n\tGenerating current plot ( {}_{} )...".format( var[j], model[i]) )

        # Create a plotting grid
        lon2d, lat2d = np.meshgrid(lon, lat)

        # Add model data as a filled contour over the plotting grid
        cf = ax.contourf(
                    lon2d, lat2d, variable,
                    levels = np.arange( var_min[j], var_max[j] + inc[j], inc[j] ),
                    cmap = colormap[j],
                    transform = proj
                    )

        # Add model data as contour lines over the plotting grid (Every other filled contour is
complimented by a line)
        c = ax.contour(
                  lon2d, lat2d, variable,
                  levels = np.arange( var_min[j], var_max[j] + inc[j]*2, inc[j]*2 ),
                  colors = 'w',
                  linestyles = '--',
                  linewidths = 0.75,
                  transform = proj
                 )

        # Logic to control fontsize between individual model plots and composite plot
        if( i < 20 ):
           c_font = 18
        else:
           c_font = 24

        # Label the contour lines
        clab = ax.clabel( c, fontsize = c_font - 2, inline = True ,fmt = '%1.1f' )

        # Plot Charlotte, NC Location
```

```
        clt = ax.text( -80.943054, 35.213890, s = 'CLT', color = 'lightgrey', fontsize = c_font )

        # Plot Asheville, NC Location
        ash = ax.text( -82.55176, 35.595009, s = 'AVL', color = 'lightgrey', fontsize = c_font )

        # Plot Wilmington, NC Location
        wil = ax.text( -77.944710, 34.225727, s = 'ILM', color = 'lightgrey', fontsize = c_font )

        # Add a halo around all annotations
        # plt.setp(
        #       [ clab, ash, clt, wil  ],
        #       path_effects=[ PathEffects.withStroke( linewidth = 1.5, foreground = "k", alpha
= 0.85 ) ]
        #     )

        # Include color bar legend at the end of the loop cycle on a new axis
        if( i == 20 ):

          # Create a new axis object for the colorbar
          cb_ax = fig.add_axes( [0.999, 0.15, 0.05, 0.7] )

          # Construct axis objects for row one
          cbar = fig.colorbar(
                    cf,
                    fraction = 0.046,
                    pad = 0.04,
                    cax = cb_ax
                   )

          # Set colorbar label
          cbar.set_label( label = var_label[j], fontsize = title_font, fontweight = 'bold' )

          # Set colorbar axes labels
          cb_ax.tick_params( axis = 'y', labelsize = title_font )

        # Report to terminal
        print( "\n\tPlot {}_{} is completed...".format( var[j], model[i]) )

      # End Model output loop
      #--------------------------------------------------------------------------
```

```
#---------------------------------------------------------------------------
# End 4: Plot current netCDF data
#---------------------------------------------------------------------------


#---------------------------------------------------------------------------
# Begin 5: Save current plot
#---------------------------------------------------------------------------

        # String for fille name of current plot
        plot_file = plot_directory + '{}_{}_summary_fig.jpeg'.format( var[j], month[k] )

        # Create a new directory for plots if it does not exist
        if( os.path.isfile( plot_file ) == True ):

            # Report to terminal
            print( "\nDeleting previous version of figure..." )

            # Create directory
            os.remove( plot_file )

        # Save the current radar plot
        fig.savefig(
                    fname = plot_file,
                    dpi = 300,
                    bbox_inches = "tight"
                    )

        # Report to terminal
        print( "\nNew figure succesfully saved..." )

    # End variable loop
    #---------------------------------------------------------------------------

# End month loop
#---------------------------------------------------------------------------


#---------------------------------------------------------------------------
```

```
# End 5: Save current plot
#-----------------------------------------------------------------------------


#-----------------------------------------------------------------------------
# End: Main Script ( DO NOT CHANGE ANYTHING ABOVE HERE!)
#-----------------------------------------------------------------------------

# Report the time required to run the function
print( "\nScript successfully completed!" )
print( "\nScript Total Runtime: {}".format( datetime.now() - startTime ) )
```

Appendix B. Contains the Python Script used in the multimodel map layouts in Chapter 3.