Identifying United States Hurricane Risk With Changing Climate

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i. Personal Section

W. Clement Stone once claimed, “you are a product of your environment.” Although I agree with his statement, I feel that it needs a slight modification for the context of this journal: *your research* is a product of your environment. Many high school students who have the opportunity to pursue scientific research choose to complete a project they are personally connected to, no matter the field. Through their research, these students are able to solve problems plaguing their community. They are able to delve into a passion unlike ever before. This especially holds true for me. As someone who grew up near the water on Long Island, and someone who frequently visits relatives along the coasts of North Carolina, South Carolina, and Florida, it is no wonder why I became interested in studying climate change. When I was in 9th grade, I first saw the grim map depicting sea level rise into the late 21st- century. My house, my grandparents’ house, and my cousins’ house are all expected to be underwater or severely flooded. I took this epiphany as a call to action. Through education and scientific investigation, I planned to help humanity find a way to better understand and adapt to the changes in our natural world.

I was just 10 years old when Hurricane Irene hit New York and 11 years old when Hurricane Sandy hit. I witnessed these storms ravage my community first-hand, and I remember hearing of my cousin’s house flooding in nearby Long Beach, New York. She was forced to uproot and relocate elsewhere temporarily. These storms wreaked havoc; I was out of school for more than a week, and many of my neighbors went without electricity for many days. Even though I was a child at the time, I can still remember the chaos that ensued in the aftermath of these storms. When it came time to find a mentor outside of my high school with whom I could complete climate research, I knew I wanted research hurricanes, weather and climate. Having had personal experience with hurricanes continued to motivate me throughout the research process.

In 2017, as a sophomore, my quest to find a mentor who would guide me in the field of climate science was difficult. I sent emails to many, many local professors specializing in climate change and extreme weather. Although my search for guidance was initially a failure, reading one research paper changed my course for the better. As I tried to delve into the field as much as I could, this particular research paper repeated an acronym several times: GFDL. It turned out that GFDL was the National Oceanic and Atmospheric Administration's Geophysical Fluid Dynamics Laboratory in New Jersey that generates many U.S. global climate models. With a surge of confidence, I reached out to researchers there, and was ultimately connected with Dr. Hiroyuki Murakami. Had I not sent those emails out of fear, I would have never had the experience of a lifetime completing hurricane research for two years at GFDL with Dr. Murakami's guidance. It is critical for young researchers to understand that they should never feel scared or intimidated in reaching out to others for help.

To this day, I am incredibly appreciative of the opportunity Dr. Murakami gave me at GFDL during my two summers working there. He gave me freedom to explore my own research project, but always had his door ajar if I needed to ask for help. He treated me with respect; I did not feel like a high school student working alongside him. Dr. Murakami made me feel confident in my abilities and talents, and it was our experience working together that made me so eager to continue to pursue climate science as a life-long career.

Because the climate models used at GFDL are accessible on a computer, I began to teach myself Python and the Unix/Linux systems to understand how to access the model data. Free online resources were a tremendous help for me as I began to comprehend these systems. As online learning becomes more and more accessible, it so easy to learn a new skill. As I generated data for my project, I began to realize how much I truly loved the work. I completely immersed myself in it, reading articles in science magazines and watching videos online. Not only did I begin to understand just how important this work truly is (the fate of humanity rests on how we deal with climate change- no big deal), but I also love the work itself. This is especially true as my computer skills improved and I was able to extract images from the models. Being able to use the computer to spit out global images, I felt like I had the whole earth at my fingertips; I felt godly. With this work, I felt more and more like my education in my high school classrooms was being put to use. Especially in the field of climate science, the research is undeniably interdisciplinary. I found myself invoking earth science, math, physics, chemistry, computer science, geography, sociology, and economics that I learned throughout high school.

During my first summer at GFDL, as I was getting acclimated to the new technology, I simply looked at a cause and effect relationship between anthropogenic climate change and major hurricane landfall frequencies in the United States (https://www.mdpi.com/2077-1312/7/5/135). At that time, we were in the midst of a 12-year period during which no major hurricanes made landfall in the United States (that ultimately ended during the 2017 hurricane season), which is only expected to occur once every 400 years (Hall et al. 2015). It seemed interesting to look at the effects of warmer global temperatures on these catastrophic events; after all, intense storms that cross the coastline are going to be the most detrimental to coastal communities. Using QGIS (a free software that I also learned to use through online coursework) with our project, Dr. Murakami and I came up with some interesting results. In most scenarios, the climate models depicted an increase in the frequency of major hurricanes to make landfall in the United States with warmer models projecting future conditions. My immediate reaction was alarm. After witnessing the utter destruction hurricanes can cause firsthand, I did not want others in the future to lose their homes and livelihoods. After reflecting on the results, I realized I had many more follow-up questions. Where will these major hurricanes make landfall in the future? Who in particular will be affected? When will these storms cause the most damage to Long Island and the New York metropolitan area? As I thought of the questions I was asking, I understood that there was one common thread running through them: I needed more specific information. In order to answer my questions, I needed to focus my attention geographically on smaller regions, not the country as a whole.

These questions were the foundation of the project I submitted to the Regeneron Science Talent Search. Dr. Murakami and I conceived of the project that I would complete during the summer of 2018 on the chalk board in his office. I sought to create a novel risk index that could pinpoint regions of the country expected to experience the most monetary and life losses due to hurricane activity. I desired to continue to use GIS software to visually represent the data, so laypeople could simply look at a map and understand whether or not their homes were predicted to be in danger.

Ultimately, the project was a success because of the help I received. Had I not utilized the resources at GFDL and asked for help, my project would have fallen apart. I could not be more appreciative of the scientists at GFDL, especially Dr. Hiroyuki Murakami, who took their time to assist me, my teachers, especially my high school research teacher, Mr. John Schineller, who continuously challenged me throughout the process, and my family for encouraging me to do my research out of passion and love.

ii. My Research

1. Introduction

Heightened tropical cyclone (TC) risk is becoming a pressing issue as anthropogenic forcing and U.S. coastal population density increases (Ashley et al. 2014). Several studies quantified local U.S. TC risk by utilizing varied physical storm attributes and characteristics of the region affected. Huang et al. (2000) used measures like radius of maximum wind speed, central pressure difference, landfall location, storm track, and decay rate to identify TC risk on a zip-code scale over a 50-year interval. Similarly identifying TC risk on a zip-code scale, the risk index developed by Vigh et al. (2018) uses wind speed and storm surge height during specific storm events to provide warnings to individuals. To build upon these risk indexes, I developed a wind-based and rain-based TC risk index using a Geographic Information System (GIS)-based approach, which can calculate TC risk for a multitude of timeframes and regions of interest.

Additionally, previous studies propose an increase in anthropogenic climate change and radiative forcing is associated with an increase in sea surface temperature (SST) in the North Atlantic (NA) main development region (MDR) and an increase in the proportion of the NA basin's intense TC activity (Daloz et al. 2015). With a weakening of subtropical easterlies and an eastward shift in TC genesis location, storm tracks are predicted to curve eastward more frequently, increasing the TC density in the central and northern NA and increasing risk in the northeastern U.S. (Colbert et al. 2013). Additionally, Kossin (2018) found that TCs have slowed down in translational speed by 10% in the last half century and continue to do so, which will correspond with an increase in related TC accumulated rainfall affecting U.S. coastal communities.

I utilized the devised risk index to assess the effects of anthropogenic climate change on hurricane risk in U.S. counties.

2. Methods

2.1 Modeling Hurricane Windspeed Zones 6-hourly and Symmetrically

Essentially, I sought to run global climate model-generated hurricane projections through my risk indexes, that could, in turn, provide a bit more insight as to the areas in the U.S. that are projected to experience the most hurricane-related economic and life loss. I intended for the index to contain values explicitly from the climate models (such as storm frequency, intensity, and precipitation), as well as values that are indicative of the demographics of the region of interest (such as population and infrastructure). In order to run the climate model information through my risk index, I needed to make sure I was familiar with the structure of climate model data, and that it would be easily compatible with the risk index formulas.

What is most noticeable about most global climate models used throughout the world is that they project hurricane points on a 6-hourly basis. Therefore, with the risk index formulas, I treated each 6-hourly projection of a storm as an individual event. Frequency values in the formulas represent the frequency of 6-hourly events, not total hurricanes, to hit each U.S. county.

Additionally, to separate each event into different zones of wind-speed intensity, this study utilizes the devised symmetric hurricane wind model of Xie et al. (2006), a model that assumes the wind speeds of a TC event to be distributed concentrically symmetric about the storm's center. I utilized four wind-speed azimuthal radii output measures from the climate models [34 kt (R34), 50 kt (R50), 64 kt (R64), and radius of maximum intensity (RMI)] to separate each event into four zones of uniformly distributed intensity. I assumed the wind speed of each event to be uniformly distributed such that the ring between the R50 and R34 is considered to have a uniform wind intensity of 34 kt, the ring between R64 and R50 is considered to have a uniform wind intensity of 50 kt, the ring between RMI and R64 has a uniform wind intensity of 64 kt, and the circle encompassing the RMI has a uniform intensity of the maximum intensity (figure 1). If an event's wind speed does not reach 34 kt, 50 kt, or 64 kt, the respective R34, R50, and R64 values are set at zero.

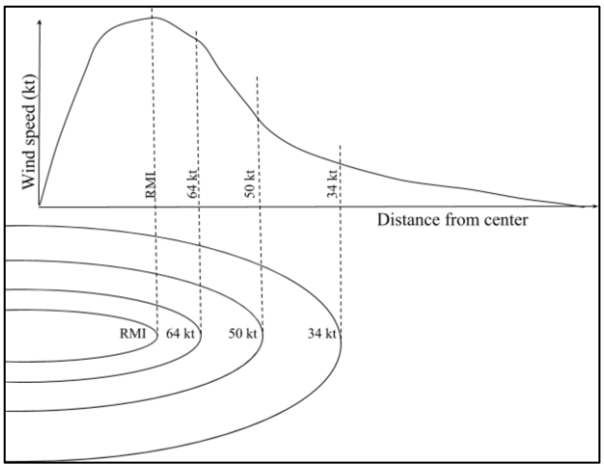

FIG. 1. A cross-sectional view of a tropical cyclone's radial wind speed and the corresponding zones of intensity through a symmetric, circular model. Note: this depiction of the tropical cyclone and its symmetric representation are not drawn to scale.

Assuming the precipitation of each event is symmetric and uniform as well, I calculated the average rainfall in each intensity zone (34 kt, 50 kt, 64 kt, and RMI) for the HiFLOR model simulations by applying the work of Lonfat et al. (2007).

2.2 Risk Indexes

To quantify annual hurricane risk for a given county on an annual basis, I utilized two independent models that identify hurricane risk based on storm wind intensities and rainfall. The wind-based risk index is detailed below:

$$WRIDX = (f_{34kt} \times 34^3 \times pop) + (f_{50kt} \times 50^3 \times pop) + (f_{64kt} \times 64^3 \times pop) + \sum_{i=1}^{f_{RMI}} (RMI_i{}^3 \times pop)$$

where WRIDX is the total wind risk index of the county in the given time frame. f_{34kt}, f_{50kt}, and f_{64kt} correspond to the frequency of all the 34kt, 50kt, and 64kt zones of an event that physically overlap the county boundaries of the county of interest in the given year. If a county intersects two separate wind zones of an individual storm event, the county is considered to have experienced the higher-wind speed event. Intensity measurements are raised to the third power (ex. 34^3) to maintain consistency with Bruyère et al. (2012) and their use of a Genesis Potential Index to convert cubed storm speed to a unit of energy. pop represents the population of the individual county being examined, or the affected population by each event. Because each event's RMI is unique, $\sum_{i=1}^{f_{RMI}}({RMI_i}^3 \times pop)$ represents the summation of all RMI intensities cubed that intersect the county in a given year multiplied by the county population. For all simulations and observed data, I calculated the WRIDX for each county on an annual basis, where f_{34kt}, f_{50kt}, and f_{64kt} represent frequencies of events that occurred in the county of interest for a duration of one year.

In using the measured precipitation that falls in the 34 kt zone, 50 kt zone, 64 kt zone, and RMI zone for each event, I created a rain-based risk index (RRIDX) that I used to calculate annual risk on a county-scale:

$$RRIDX = f \times \sum_{i=1}^{f} p \times pop$$

where RRIDX is the annual rain-based risk index the county faces in a given time frame. f represents the total number of events that physically intersect the county in a year. p represents the average accumulated rainfall from the wind speed zone of the event that intersects the county. pop is the population of the county in the given year of analysis, which represents the population affected by each event. For all simulations and observed data, I calculated the RRIDX for each county on an annual basis, where f represents the frequency of events that occurred in the county of interest for a duration of one year.

2.3 GIS Methodology

To map the symmetric, circular wind speed zones for each event and determine the frequency of 34 kt, 50 kt, 64 kt, and RMI events that physically intersect U.S. counties, I utilized ArcGIS Pro 2.1 (©ESRI) to create circular, vector buffers corresponding with the R34, R50, R64, and RMI zones of the storm. Using the ModelBuilder function (figure 2), the steps to determine which counties intersect the wind speed zone of each event are as follows:

1. Project each event with corresponding latitude and longitudinal coordinates. The projections are completed with an input file (climate model data).
2. Create each wind speed zone, a fixed-distance buffer around each event that corresponds to the R34, R50, R64, and RMI. If an event's wind speed did not reach any of these threshold speeds, the fixed-distance buffer is set to zero.
3. Determine the counties that intersect each zone of each event. The input file for this step in all cases is the 2015 United States county shapefile. The county intersection data becomes an output file.

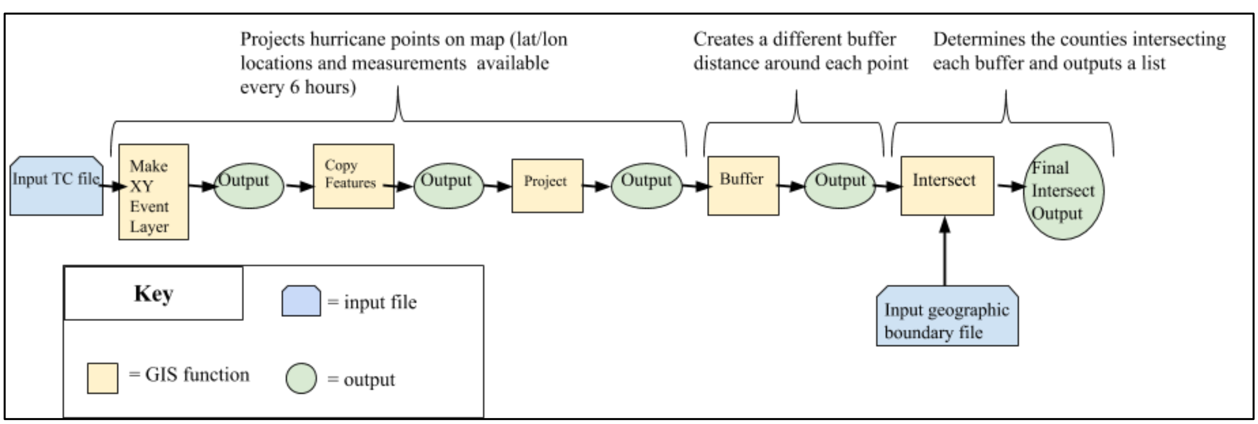

FIG. 2. Chart of ArcGIS Pro ModelBuilder function to calculate the frequency of 34kt, 50kt, 64kt events, and the counties affected by each event's RMI. Input TC file is the model output file listing each event's coordinate points, and the input geographic boundary file is the 2015 U.S. county shapefile. I utilized the final intersection output data in the final calculation of WRIDX and RRIDX.

3. Results

3.1 Validation

To assess the validity of the formulas listed above, instead of using climate model projections, I ran observed conditions between 2004 and 2017 through the formulas. This dataset, the NHC "best track" HURDAT2 dataset (Landsea and Franklin 2013), was collected by compiling observations from satellites, aircraft reconnaissance missions, weather surveillance dopplers, and buoys; like the climate model data, it projects hurricanes on a 6-hourly time scale. I was only able to validate the WRIDX, as the HURDAT2 dataset does not include precipitation information.

Visually, the WRIDX formula accurately depicts relative losses due to hurricane activity. Figure 3 depicts the WRIDX values for the 2012 hurricane season, which are noticeably clustered around the New York metropolitan area in the wake of Hurricane Sandy. Additionally, Kings County, Queens County, Suffolk County, New York County, Nassau County, and Bronx County, all in the New York metropolitan region, were listed among the counties with the ten highest WRIDX of all U.S. counties that year, demonstrating accuracy in the risk index formulas.

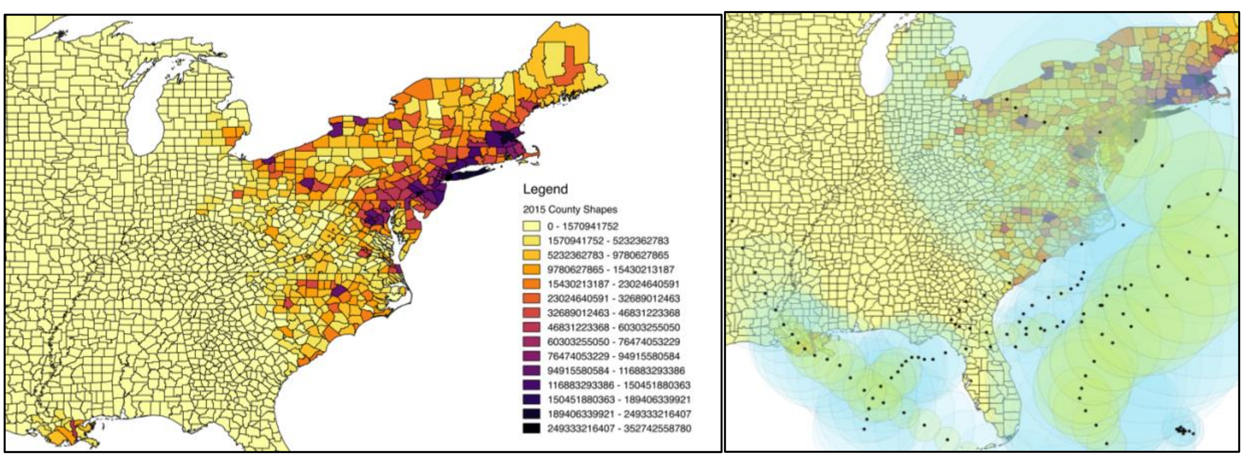

FIG. 3. (left) The county level WRIDX of 2012. the WRIDX of 2012 with blue circles representing R34 of each event and the yellow circles represent the R50 of each event during the 2012 hurricane season. The tracks of storms Alberto, Debby, Isaac, and Sandy are plotted in black, with each dot representing an event.

Table 1 shows the correlation between the components of the total annual United States WRIDX computed from the HURDAT2 dataset and the annual hurricane frequencies and climate indexes. The statistically significant correlations between average annual WRIDX and hurricane activity/climate indexes/economic losses suggest the WRIDX has high capabilities in addressing climatological conditions in the NA and storm risk.

TABLE 1. r values between components of WRIDX and NA basin characteristics. Variables include mean annual WRIDX in the U.S. (WRIDX), mean annual frequency of events in all U.S. counties (Freq), mean annual wind speed of all events in the U.S. (MeanWS), total hurricane frequency in the NA basin (AHF), total hurricane landfall frequency in the NA basin (AHL), total MH frequency in the NA basin (MHF), and total MH landfall frequency in the NA basin (MHL), mean JASON (July-November) Pacific Decadal Oscillation index (PDO), mean JASON Atlantic Multidecadal Oscillation index (AMO), mean MDR JASON SST (20°W−80°W, 10°N−25°N), and total annual U.S. TC-related CPI-adjusted loss (Loss). Coefficients in bold show statistically significant correlations

	AHF	AHL	MHF	MHL	PDO	AMO	MDR SST	Loss
WRIDX	**0.358**	**0.397**	**0.226**	**0.402**	**0.294**	**0.678**	0.109	**0.537**
Freq	0.076	0.096	0.127	0.035	**0.464**	**0.573**	0.167	**0.574**
MeanWS	0.119	**0.395**	**0.279**	**0.345**	-0.183	-0.272	**0.705**	0.028

3.2 Future Projections

To assess projected changes in climate, I ran three RCP4.5 simulations through the risk index formulas. These three simulations come from the GFDL HiFLOR global climate model and represent the following projected time periods: 1986-2005 (CLIMO), 2016-2035 (EARLY), and 2081-2100 (LATE).

Figure 4 depicts the difference in average county WRIDX and RRIDX for the CLIMO, EARLY, and LATE simulations. The anomaly of the CLIMO and EARLY simulations (8a and 8b) depict two distinct regions of amplified risk as the simulations become warmer and later in start time: the New York tri-state area and coastal New England as well as the state of Florida. However, the rest of the United States coastline, as well as many inland counties, are projected to experience a decrease in risk index from the CLIMO simulation to the EARLY simulation, indicating an eastward shift in track location. These anomalies suggest that as radiative forcing increases, NA hurricane tracks shift eastward, complementing the results of Colbert et al. (2013) and Murakami and Wang (2010). Figures 8c and 8d suggest this eastward shift in hurricane tracks through the late 21st century, as the LATE simulation shows a greater WRIDX and RRIDX in counties adjacent to the east coast of the United States. Throughout all the anomalies, Florida is consistently projected to experience the greatest hurricane-related damages. State governmental county population projections were utilized in these calculations.

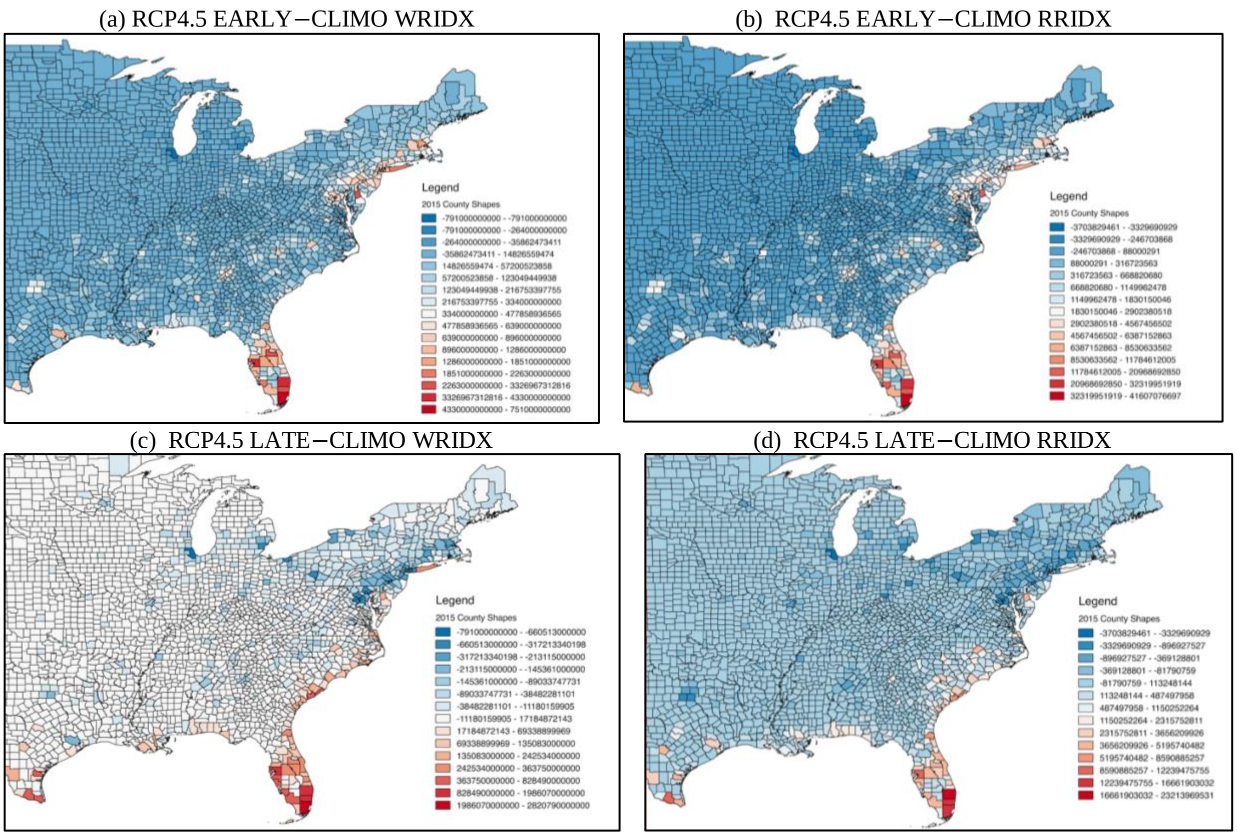

FIG. 4. RCP4.5 comparison of simulations: (a) EARLY−CLIMO WRIDX (b) EARLY−CLIMO RRIDX (c) LATE−CLIMO WRIDX (d) LATE−CLIMO. Several states are not included (white) due to a lack of data for state population projections (years 2024-2030) in western states. This only occurs for these figures because these anomalies are the only to include solely population projections. All other anomalies include CLIMO data, with which the entire U.S. 2015 county population data was used.

4. Conclusion

This study outlines a flexible, wind-based and rain-based risk index for TC activity. Although the indexes were utilized to identify observed risk using HURDAT2 data and HiFLOR model output, they can be utilized with most climate model output and forecasts, whether century projections or seasonal forecasts. The use of the HURDAT2 dataset allowed me to deem the WRIDX a sound measure of hurricane-related losses to U.S. counties.

The RCP4.5 simulations indicate that an eastward shift in storm tracks shows heightened risk in the counties adjacent to the U.S. east coast. RCP4.5 model projections of the late 21st century anticipate wind and rain risk in Florida. Although these projections predict an increase in risk in certain regions of the country, they do not predict a complete absence of hurricanes affecting other areas of the U.S.

Using the WRIDX and RRIDX, citizens can be alerted about what precautions need to be taken in the case of a hurricane. The predicted hurricane wind and rain risk indexes, providing a singular quantity that account for both the characteristics of the storm and details of the potential area affected, can be used by government agencies and disaster preparation teams for short-term preparation or by real estate and insurance companies for long-term decision making. The risk indexes can be used for smaller areas, such as street blocks, or scaled from a county-scale to a state, regional, or country-wide scale. The indexes can be applied in any global region to address potential typhoon damage.

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iii. **The Future**

Hopefully, this hurricane risk model can be utilized to help others prepare for any catastrophic events in the future or inspire meteorologists to use GIS software in new and creative ways to assess hurricane activity. Because I found this research so fun, interesting, and important, I plan to continue studying climate change. My goal is to obtain a PhD in Atmospheric and Oceanic Sciences, which I plan to use to help others as our climate continues to change. I am not exactly sure how I will make a difference, but I am excited to see where my journey takes me.

My message to others pursuing STEM (not necessarily climate science): find something you love. Never force yourself to complete work that is dull or boring to you. High school research is about discovery, not just in the realms of the laboratory, but internal, personal discovery. In order to find a topic you love, take a look around at the problems in your world. Never be scared to reach out to experts. If I had not sent that initial email to GFDL, who knows if I would still be conducting research. Another piece of advice is to find research that helps make the world a better place. It feels so rewarding in the end to know that the work I did has the potential to save lives. I wish anyone hoping to pursue STEM the best of luck in their future endeavors. I hope you find something to pursue that changes your perspective on the world and captivates you, just as my research did for me.