

SPATIAL VARIABILITY OF TORNADO
TRACK LOCATIONS

by

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ABSTRACT

Despite the danger they present to communities, there is still a notable lack of knowledge of how violent tornadoes (VTs) vary on a small spatial scale, such as county or citywide. Moore, OK, has seen an abnormally high number of VTs (three) compared to neighboring towns since the beginning of the historic record in 1950. The primary goal of this research was to determine if the atypical pattern of VTs in cities like Moore can be replicated by random chance. This was done using sets of Monte-Carlo style simulations to replicate each city's historic tornado record. To explain these anomalous patterns, a secondary goal was formed with the intention of determining if large-scale climate indices could play a role in regional, state, or even county and city scale VT variability. Pearson correlation tests and generalized linear modeling were used to explore the potential relationship between various climate indices and multi-scale tornado variability.

Results show how difficult it is to replicate these cities' numbers of VTs, suggesting these patterns have not occurred strictly by random chance. In five of the six trials, the model was unable to replicate Moore's actual number of historic VTs (<0.01%), with the largest rate of replication occurring when simulating only VTs (0.5%), indicating that the odds of a similar number of tornadoes reoccurring in Moore are low. The number of VTs in Birmingham and Tanner, AL, were also notably difficult to replicate in all six trials. However, in the last trial, Birmingham and Tanner's actual number of VTs were recreated at rates of 1.2% and 3.6%, respectively. Further results show that climate indices like the El Niño–Southern Oscillation (ENSO) might play a role in affecting tornado activity at multiple scales.

LIST OF ABBREVIATIONS AND SYMBOLS

AO	Arctic Oscillation
EF	Enhanced-Fujita scale
ENSO	El Niño–Southern Oscillation
SOI	Southern Oscillation Index
NAO	North Atlantic Oscillation
ONI	Oceanic Niño Index
PDO	Pacific Decadal Oscillation
MJO	Madden-Julien Oscillation
MLD	Mean Linear Direction
NE	Northeast
SST	Sea-surface temperature
SW	Southwest
<	Less Than
>	Greater Than
=	Equal To

α Significance/Confidence Interval

μ Mean

$A\mu$ Actual Mean

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CHAPTER 1

INTRODUCTION

More tornadoes occur in the United States (U.S.) than any other country in the world. Although the majority of these tornadoes are relatively weak and rated low on the Enhanced-Fujita (EF) scale (EF0 and EF1), a select few result in mass destruction of property and loss of human life. Of all the tornadoes that have touched down in the continental U.S. since the beginning of the historic record in 1950, less than 1% have been categorized as a violent tornado, which the National Weather Service (NWS) defines as an EF4 or EF5. Although exceedingly rare, many VTs have tracked through populated areas (Hatzis et al 2019).

Furthermore, when analyzing the National Ocean Atmospheric Administration's (NOAA) historic tornado track dataset (1950-2020), it appears that certain cities are hit more frequently than their neighboring locations. For example, Tanner, Alabama has been hit by three EF5 tornadoes since 1974, while its neighboring city Madison, Alabama has not seen a tornado with a magnitude greater than an EF3 since at least 1950. Similarly, Moore, Oklahoma, has been hit by three VTs, while downtown Oklahoma City has not experienced a tornado with a magnitude greater than an EF1 since at least 1950. Are these examples evidence of small-scale, or localized tornado alleys? If so, then what explains why some locations are hit at what appears to be statistically anomalous rates? These are questions that deserve increased scrutiny in order

to understand the spatial variability of tornadoes at smaller scales, such as a county-wide or in cities of various sizes.

There is a notable research gap in the study of small-scale tornadic spatial variability; and there is little to no insight into whether this spatial variability is due to random chance or if underlying meteorological or geographical factors are responsible. Such questions are of great importance to the field of severe weather climatology, as answering them would add to our understanding of tornado track variability and VT probability. Furthermore, this understanding would aid communities that get hit disproportionately by VTs by providing a better estimation of the odds of certain tornado events. This knowledge is crucial given how urban areas are expanding, which increases damage and casualty potential from tornadoes among other natural disasters (Ashley et al. 2014; Strader et al. 2017; Strader et al. 2018 Fricker & Friesenhahn 2022).

With this in mind, the primary concern of this research was to determine if the anomalously-high number of VTs seen in cities like Tanner and Moore can be replicated using Monte-Carlo-style simulations of random tornado initial points. Here, it was important to replicate each city and surrounding area's actual number of tornadoes from multiple categories (EF0-EF5, > EF0, and VTs). This was done in separate trials to determine how rare it was to replicate not only each studied city's number of VTs, but also their number of total tornadoes. If each city's actual number of tornadoes from any category could not be replicated by random chance, certain meteorological factors, like ocean-atmospheric oscillations, may be responsible.

The second portion of this research was executed to find the variables potentially linked to small-scale tornado variability. Many climatic factors play a role in the variance of tornado frequency year-to-year, but much of the research done on this topic has explored the relationship

between tornadoes and ocean-atmospheric oscillations (Barrett & Gensini 2013; Moore 2019; Brown & Nowotarski 2020). Ocean-atmospheric oscillations are naturally-occurring climate cycles classified by oscillating pressure fields or sea surface temperatures (SSTs) that impact the global and regional climates. Annual and seasonal weather patterns or anomalies caused by these climate phenomenon are known as teleconnections (Barrett & Gensini 2013; Brown & Nowotarski 2020).

Previous research has determined that certain teleconnections influence the frequency of weather hazards in addition to temperature and precipitation patterns (Brown & Nowotarski 2020). For instance, a negative Ocean Niño Index (ONI) value, classified as La Niña, has been associated with increased tornado frequency throughout the Midwestern U.S. (MWUS) and parts of the Southeastern U.S. (SEUS), with some of the worst tornado seasons being during a La Niña-dominant year (Lee et al. 2013; Allen et al. 2015; Cook et al. 2017; Lepore et al. 2017; Moore 2018; Moore 2019).

La Niña is known to weaken both the polar and subtropical jet streams, which can result in more baroclinic zones developing east of the Rocky Mountains (Allen et al. 2015, Cook et al. 2017). The high-pressure zone which dominates the northern Pacific ocean during a La Niña year leads to a weaker, “wavy” subtropical jet stream (Allen et al. 2015, Cook et al. 2017). A persistent, strong meridional jet stream creates separate pressure zones which influence surface-level conditions like temperature and humidity, but a “wavy” meridional jet stream separates these conditions at similar latitudes, pulling warm air from the south and cool air from the north. (Liu et al. 2002; Shepard et al. 2009; Muñoz & Enfield 2011; Weaver et al. 2012; Moore 2018). This inflow of warm, humid air masses inland from the Gulf of Mexico is often associated with a

heightened risk of severe weather throughout the U.S., as moisture is a key component in the creation of violent storm systems (Lee et al. 2012).

Links like these are typically discovered using climate indices that numerically track the phases of a particular ocean-atmospheric oscillation (Liu et al. 2002; Shepard et al. 2009; Brown & Nowotarski 2020). Other oscillations such as the Arctic Oscillation (AO), Madden-Julien Oscillation (MJO), and the North Atlantic Oscillation (NAO), have also been found to be related to annual and seasonal tornado frequency in the U.S. due to their similar effects on SST and pressure gradients (Shepard et al. 2009; Muñoz & Enfield 2011; Weaver et al. 2012; Barrett & Gensini 2013; Thompson & Roundy 2013; Moore et al. 2018; Brown & Nowotarski 2020). However, the scale of each influencing teleconnection varies both spatially and temporally across the U.S. (Cook & Schaefer 2007; Barrett & Gensini 2013; Moore 2019 Brown & Nowotarski 2020).

Despite our expansive understanding of the correlation between ocean-atmospheric oscillations and large-scale tornadic variability, there is a noteworthy research gap in the studying of teleconnective relationships with tornadic spatial variability on a smaller scale. There are limitations when comparing disparate scales of global or continental teleconnections to small units like counties; nevertheless, exploring potential patterns of tornado occurrences may reveal novel results. Since there is a conspicuous relationship between certain climate indices and large-scale tornadic variability, it is possible this link extends to small-scale variability. This study will examine this potential link.

Overall, three research questions and subquestions will be answered in this thesis:

1. Can the actual total number of all tornadoes (EF 0/1-EF 5) or VTs (EF 4 and EF 5) seen in the chosen cities be replicated strictly by random chance?

- a. Can this number be replicated when simulating all tornadoes (EF 0/1-EF 5)?
 - b. Can this number be replicated when simulating just VTs
2. Is there a significant relationship between the chosen climate indices and tornadic/VT variability in several regions within the Eastern U.S.?
 3. Is there a significant relationship between the chosen climate indices and tornadic/VT variability in the chosen cities?
 - a. How do results vary between each city and its adjacent region?

Research question one will be addressed in Chapters 2 and 3. The remainder will be answered in Chapters 4 and 5. Chapter 2 will discuss the selection methods of the studied cities and outline the model used to simulate hypothetical tornado initial points. This chapter will also cover how the hypothetical number of VTs for each simulation were calculated. Chapter 3 will discuss the results from Chapter 2, following a similar format. Here, the statistics from the previous chapter will be analyzed for each of the studied cities, with all cities referenced in Chapter 2 being included in the final analysis. Chapter 4 will cover the methods used in the study's second research stage. This chapter will be dedicated to the analysis of chosen climate indices with regional tornado statistics. Each of the chosen ocean-atmospheric oscillations are listed alongside their particular climate index that was used for calculations. The next section in this chapter will discuss the statistics and techniques used to examine the links between these variables and tornadic variability. Chapter 5 will follow the formatting of the previous chapter, first discussing the trial results for each climate index. The final chapter, Chapter 6, will cover the most important conclusions from each chapter and examine the potential for future research.

CHAPTER 2

ARE SOME CITIES TORNADO MAGNETS? METHODOLOGY

a. City Selection

In total, seven cities were selected for this analysis. These cities were Birmingham, Tanner, and Tuscaloosa, Alabama; Cincinnati, Ohio; Kansas City, Kansas/Missouri; Moore, Oklahoma; and Wichita, Kansas (Fig. 1). These cities are all located within the Eastern U.S. (EUS), the most tornado-prone half of the country. All seven have been directly affected by multiple VTs tracking into developed areas. These seven cities were tested alongside adjacent cities or metropolitan areas within the same study area that have seen notably fewer VTs.

Chosen Cities in the Eastern U.S.

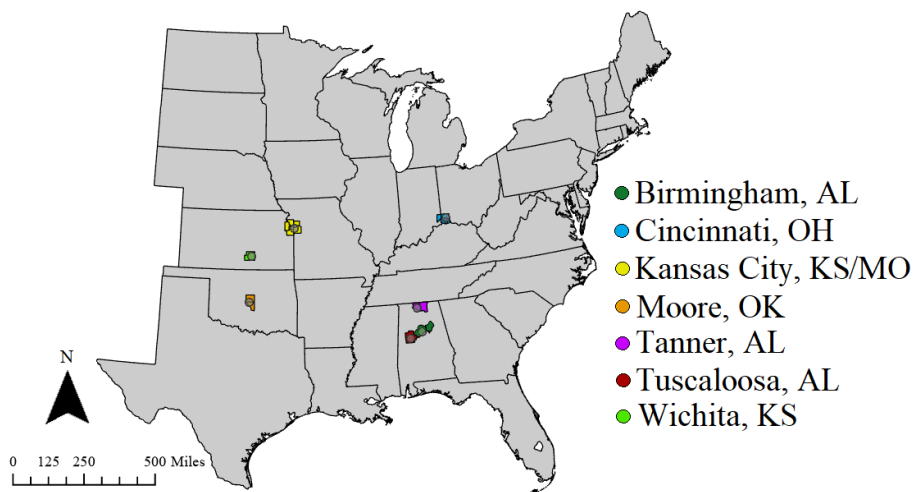


Figure 1. The selected cities within the EUS

These adjacent cities were Vestavia Hills/Hoover, Alabama, (Birmingham); Covington, Kentucky, (Cincinnati); Platte City, Kansas/Missouri (Kansas City); Norman, Oklahoma (Moore); Madison, Alabama (Tanner); Northport, Alabama (Tuscaloosa); and Goddard, Kansas (Wichita) (Table 1.)

Table 1. The chosen cities

The Chosen Cities	
Primary Cities	Adjacent Cities
Birmingham	Vestavia Hills-Hoover
Cincinnati	Covington
Kansas City	Platte City
Moore	Norman
Tanner	Madison
Tuscaloosa	Northport
Wichita	Goddard

To be selected, a city had to meet a specific set of parameters. Most importantly, a chosen city had to be hit by an anomalously high total of VTs relative to nearby cities between 1950 and 2020. Anomalously high was defined as a city seeing >40% of all VTs and/or at least 50% of all EF5s which passed through the city’s county and/or surrounding counties. These data were obtained from the SPC’s SVRGIS (<https://www.spc.noaa.gov/gis/svrgis/>) historic tornado track dataset, a polyline dataset that displays both the initial and endpoint coordinates for every recorded tornado since 1950.

Location was most important when selecting the adjacent cities. Although these cities were not equal in size to the primary cities (some larger, some smaller), equal area was assumed to reduce possible confounding variables introduced by varying city sizes within the same study area or county. A primary city and its adjacent city shared the same study area, which was confined to each pair’s encompassing county or counties. City buffers were created for each pair as a substitute for the cities’ actual boundaries to simplify each city’s area. This meant that the

city buffers created for the primary cities were reused for their adjacent cities. It should be assumed that, if tornadoes occur randomly across space, adjacent cities larger than their primary cities should, theoretically, have seen more tornadoes in every category due to a greater land area. In contrast, adjacent cities smaller than their primary cities should have seen fewer total tornadoes, > EF0s, and VTs.

Diversity of city location was also important in the selection process. In this case, diversity was defined in terms of the location within the Eastern U.S., overall size, size relative to their county and surrounding counties, and their positioning inside their enveloping county boundaries (centered, westside, split in between one or more counties/states, etc.). Spatial diversity was necessary for reducing confounding variables like regional climate and city size (Daneshvaran and Morden 2007; Deng et al. 2016). It is predicted that city size would be the most important variable for the number of intersecting tornadoes produced in each simulation, so assessing how the model's predictions varied with city size will also be useful for selecting cities for future projects (Ashley et al. 2014; Fan and Pang 2019).

The chosen cities for the SEUS were Birmingham, AL, Tanner, AL, and Tuscaloosa, AL. These three cities are all located within or on the border of the region with the highest risk for significant tornadoes (Dixon et al. 2011; Coleman and Dixon 2014; Long et al. 2018; Cao et al. 2021). Despite all being in Alabama, each city had a varying rate of VTs to total tornadoes and an anomalous presence of VTs in the studied city. Birmingham has seen five VTs, with two being EF5s, accounting for 55% of all local VTs and 100% of all EF5s. Tanner has seen three VTs, all being EF5s, making up 50% of all VTs and 100% of all EF5s. Lastly, Tuscaloosa has had three VTs, accounting for 43% of all surrounding VTs in that study area (Table 2). In the MWUS, Cincinnati, OH, was chosen. The study area surrounding Cincinnati has the highest ratio

of VTs to total tornadoes, at 14.6%. The city itself has seen two VTs, with one being an EF5, accounting for 30% of all surrounding VTs and 100% of all EF5s (Table 2).

Table 2. Simulated study area and city size

Study Area and City Size					
	<i>Simulated Land Area (Km²)</i>	<i>Simulated City Area (Km²)</i>	<i>% Of Simulated Land Area</i>	<i>SW-NE Track Buffer Area (Km²)</i>	<i>% Of Simulated Land Area</i>
Birmingham, AL	4875	436	8.90	1042	21.37
Cincinnati, OH	3246	207	6.40	672	20.70
Kansas City, KS/MO	5899	724	12.23	2225	37.77
Moore, OK	1389	57	4.16	98	7.05
Tanner, AL	1761	114	6.50	231	12.50
Tuscaloosa, AL	3029	222	7.30	537	17.80
Wichita, KS	2626	558	21.30	1012	38.60

In the Great Plains U.S. (GPUS), Kansas City, KS/MO, Moore, OK and Wichita KS were chosen. It should be noted that a portion of the study area for Kansas City KS/MO does fall in between the MWUS and Great Plains U.S. (GPUS) regional boundaries used in the later chapters of this research. However, because the majority of the study area falls into Kansas, this city was sorted into the GPUS. Kansas City has seen four VTs, which is 50% of the total surrounding VTs. Moore has experienced three VTs with all being EF5s, accounting for 30% of the total surrounding VTs and 100% of the EF5s in that study area. Wichita has the lowest rate of VTs to total tornadoes, at 3.3%. The city itself has seen two VTs, with one being an EF5, accounting for 66.7% of the total surrounding VTs and 100% of the total surrounding EF5s (Table 2). When adjusted to the sizes of the chosen cities, the number of VTs in each of the adjacent cities varied from zero to two.

b. Model Structure

ModelBuilder in ArcGIS Pro was used to create the model for the first research stage. This tool also automated the simulation process. For each simulation, a set of points equal to the actual number of tornadoes in a study area was randomly generated using the Create Random Points tool. These points were generated within a constraint in the southwestern portion of a particular study area. This was a circular constraint where the edge of its radius connected either from the study area's centroid or the northeastern-most initial points of a VT in that study area, whichever was furthest northeast (NE). The centroid of the constraint was the initial point of the tornado that spawned farthest southwest (SW) of the study area but still tracked through it. For example, Tanner, AL's circular SW constraint was formed using the initial coordinates of the town's intersecting 2011 EF5 tornado and the centroid of Limestone and Madison County, AL, the two counties encompassing Tanner and its adjacent city, Madison, AL. These two counties made up Tanner's entire study area. (Figure 3.)

Each constraint was then cut off at the county boundary, so the created points were all generated within the southwestern portion of the study area. The area within the constraint was used and defined as the simulated land area. The SW portion of the study area was used as the simulated land area as opposed to the entire study area to account for the fact that the model is producing tornado initial points, and tornadoes typically track SW to NE (Allen et al. 2021). This is especially true for VTs (Senkbeil et al. 2022). It should be noted that average track direction does vary spatially across the EUS, but the mean linear direction (MLD) of VTs in all the chosen study areas is SW to NE (Figure 4) (Suckling and Ashley 2006). In using this constraint for the simulated land area, all tornadoes' initial points were generated to the SW so a northeastern track can be assumed.

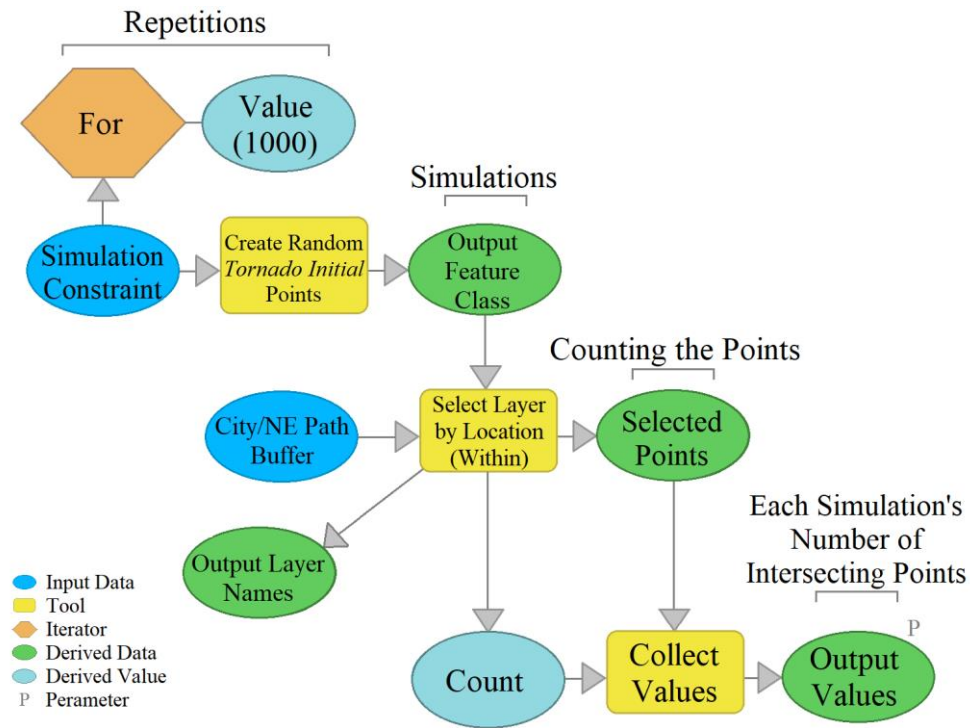


Figure 2. Model framework

This simulation process was replicated 1000 times for each city in each of the six trials. The model then counted the number of points that intersected the specified buffer zone for each trial. These values were used to calculate the simulated number of VTs using a study area's ratio of actual VTs to actual total tornadoes. For half of the trials, this zone was a circular buffer with an area equal to the particular city. Each circular buffer was centered over the centroid of its adjacent city. A circular buffer was used in place of the actual cities' borders to simplify each city's shape and put more emphasis on a city's total size (km²).

For the proceeding half of trials, the circular city buffer was extended to the western edge of a study area. The extending lines connected the outside of the circular buffer to the western boundary of the SW constraint at a degree equal to the mean linear direction of a study area's intersecting VTs (Figure 3). Trials using this method were used to account for tornado tracks,

since the model simulates just tornado initial points and not entire tracks. Because tornadoes generally move SW to NE, it's possible that a tornado would track into a city if its initial points were generated SW of a city's buffer zone (Allen et al. 2021).

It should be noted that, while VTs typically track SW to NE, the degree of track direction varies both seasonally and regionally (Suckling and Ashley 2006). It is because of this variation that each SW to NE track buffer was made specially for each study location. As stated previously, the MLD of VTs for each studied location was roughly SW to NE despite this known variability (Figure 4). Because equal area was assumed between city pairs, the model was not run separately for the adjacent cities. Instead, trial results for each of the primary cities were also used with their paired adjacent city. This was done to determine whether the model was underpredicting tornado quantities in all cities, both with anomalously high tornado numbers and those with comparatively low tornado numbers.

Process for Creating the Study Areas' Simulation Constraint and Buffers

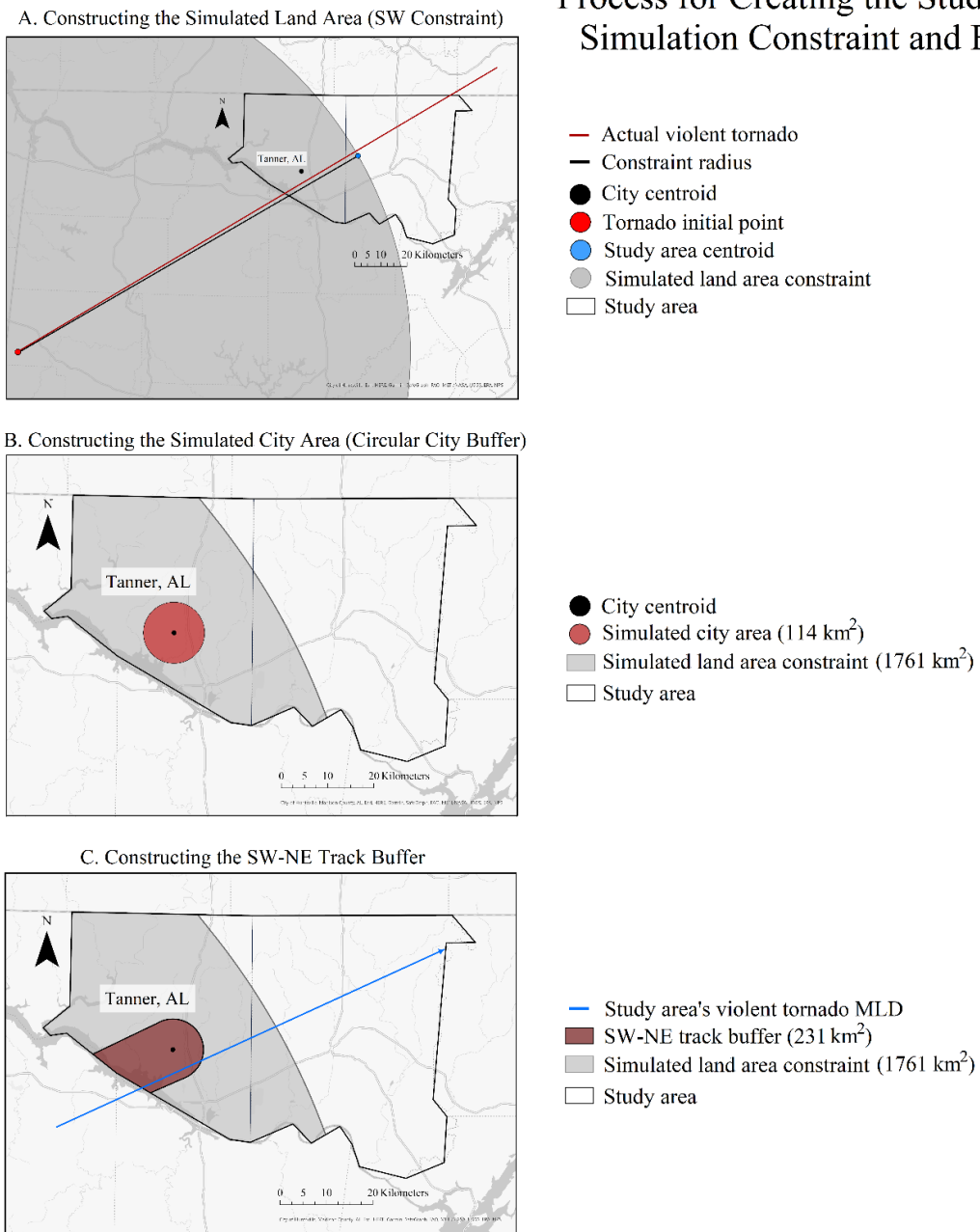


Figure 3. The process for creating each study area's simulation constraint and buffers

The Chosen Cities' Constraints and Buffers Relative to each Study Area's Mean Linear Direction of Violent Tornadoes

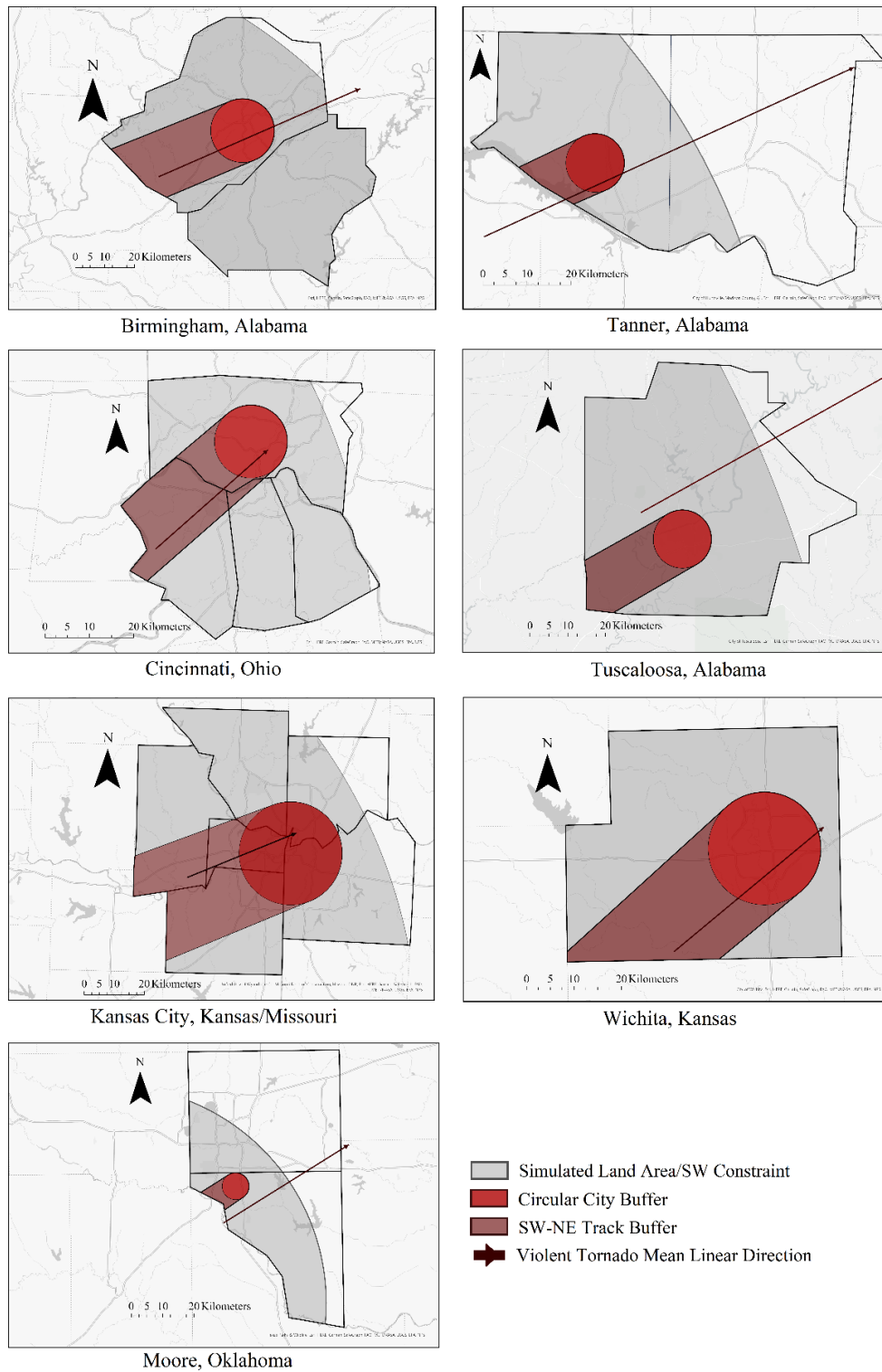


Figure 4. City constraints and buffers relative to their adjacent study area's VT MLD

c. Data Analysis

For all six trials, defined by the types of tornadoes analyzed, quantitative methods were used to assess the likelihood of the model replicating each city's actual number of tornadoes. This likelihood was determined using the rate of accurate simulations to the total number of simulations (1000). The mean (μ) and 99th percentile of each city's simulated tornadoes were also used to assess the results and compare them with the actual number of tornadoes in each city. The calculated μ values were compared alongside the actual number of tornadoes (A_μ) in a series of one sample t-tests.

Because of their rarity and the danger they present to communities, the replicability of VTs was of the greatest level of interest. However, replicating a city's total number of tornadoes was also necessary in determining if a city is being hit by more total tornadoes than what the model deems random. For each simulation, the model generated a number of points equal to the number of actual tornadoes from a study area into its simulated land area using the SW constraint. This number was either the complete number of total tornadoes (EF0-EF5), > EF0 tornadoes, or VTs. A study area's actual rate of VTs (%) was used to calculate a simulation's predicted number of VTs when simulating either total tornadoes or tornadoes with a magnitude > EF0.

The numbers of simulated tornadoes were used to quantify how likely it is for the model to replicate each city's historic number of all tornadoes, > EF0s, or VTs. For a single simulation to count as a duplicate of a city's historic record, it had to have an equal or greater number of simulated tornadoes within the chosen buffer. The location of each point within the buffer was not important. For Kansas City, Moore, and Wichita, their SW-NE track buffer intersected with more historic VTs than their circular city buffer. Because these historic VTs did not intersect

with the city, they were not included in the final analyses. Common, weaker tornadoes (EF0-EF1) typically have shorter tracks (Allen et al. 2021; Suckling and Ashley 2006). Thus, there is a lower possibility that if one were to touch down outside of the city, that it would track through. Because of this, the predicted number of total tornadoes was not analyzed in trials using the SW-NE track buffer, as the likelihood of the model overpredicting the total number of tornadoes in these cities when using this buffer was high.

i. Trial 1-2: Simulating all tornadoes

The first trial consisted of simulating a number of points within the SW constraint equal to the total number of tornadoes which tracked through a particular study area. The number of points generated within the city buffer were used to calculate the number of VTs. This number was calculated using the specific study area's actual ratio of VTs to total tornadoes. For example, when simulating Tanner Alabama's tornado record, 133 points were generated in each simulation, as this number of tornadoes EF0-EF5 have intersected Tanner's study area since 1950. The study area used for Tanner has experienced six VTs since 1950, so the ratio of VTs to total tornados here is six to 133 or 4.51%. So, for a simulation to produce one VT in Tanner, it needed to generate 23 points in the city's buffer zone. Tornadoes cannot exist in fractions or percentages because there cannot be half, or even 99% of a tornado. Due to this, all resulting VT estimations were rounded down to the nearest whole number.

The second trial replicated the processes of the first trial, with the only difference being the buffer zone. In this trial, the SW-NE track buffer was used in place of the city buffer. In all cases, this buffer is larger than its adjacent city buffer, so it was likely that this trial would see higher predictions of VTs compared to the previous trial.

ii. Trial 3-4: Simulating > EF0 tornadoes

The only difference between trials three and four and the previous trials are that EF0s were excluded from the former's tests. The testing process was the same, though it should be noted that all study areas had a higher rate of VTs to total tornadoes due to this exclusion. For Tanner, the total number of tornadoes was 79, with a VT rate of 7.59%. Separate trials excluding EF0s were conducted to test if their exclusion heavily impacted the results. EF0s are the most common type of tornado, with approximately 44.3% of all tornadoes having occurred in the EUS since 1950 falling into this category. EF0s can be problematic and sometimes difficult to identify and separate from straight line winds when studying tornado patterns and outbreaks (Foglietti et al. 2020). Furthermore many EF0s are short duration events associated with tropical cyclones (Fuhrmann et al. 2014; Foglietti et al. 2020). The emphasis of this research is on baroclinic tornadoes initiated by synoptic or regional scale meteorological processes with frontal systems moving from some component of westerly to easterly motion. The exclusion of EF0s from these trials was an attempt to reduce the level of tropical influence on the cities', (particularly those in the Southeastern U.S. SEUS region), total number of tornadoes, one of the most important parameters in creating the model.

iii. Trial 5-6: Simulating VTs

Trials 5 and 6 replicated the same process as the previous two trial groups, with the only difference being the exclusion of all tornadoes rated < EF4. In the case of Tanner, this meant that each simulation generated six VT initial points within the SW constraint and counted how many VTs intersected with the specified buffer. For these trials, the ratio of VT to total tornadoes was not needed, as only VTs were generated.

iv. *One sample t-tests*

One sample t-tests were run to statistically compare the simulated averages of tornadoes (μ) with the actual number of tornadoes seen in each study area (A_μ). This was done to further validate the significance of the trials' results. For these tests, an alpha level of 0.01 was used, so p-values < 0.01 were considered statistically significant. T-tests were run with both the exact and adjusted μ . The exact μ is the raw average of predicted tornadoes, while the adjusted μ was rounded down to the nearest whole number. As explained before, this is because tornadoes cannot feasibly exist as fractions of a whole number. However, this does not diminish the importance of the exact μ , as the t-tests using these μ values yielded more precise p-values.

v. *Replicability of tornadoes in the chosen cities vs. their adjacent cities*

One sample t-tests were done on the adjacent cities using the same data gathered in trials 1-6. P-values from these tests were compared with those from the tests done on the primary cities. These comparisons further elaborate on how unique the primary cities are relative to neighboring locations. Additionally, these results provide supplemental insight on how accurate the model is in predicting typical tornado patterns, especially patterns of VTs.

CHAPTER 3

ARE SOME CITIES TORNADO MAGNETS? RESULTS

a. City tornado statistics

Once cities were selected, the simulated land area and city area was documented and compared between the chosen cities along with each city's SW-NE track buffer area (Table 2.) The total area of both the city buffer and SW-NE track buffer relative to the total simulated land area (%) was documented to quantify the buffers by size. This was important for determining how buffer size impacts the number of simulated, intersecting tornadoes.

The size of the simulated land areas ranged from 1300 to 5900km², while the simulated city areas ranged from 50 to 725km². In all cases, the SW-NE track buffer was larger than the simulated city area, ranging from 100 to 2225km² greater. The cities' SW-NE track buffers varied greatly in size due to each city's positioning within the surrounding county or counties. However, the ratio of a SW-NE track buffer area to total simulated land area was never greater than 40% (Table 2.)

Each city's tornado statistics were also recorded (Table 3.) The μ number of total tornadoes for the study areas was 136, with the μ number of VTs being 7.71. The μ rate of VTs to total tornadoes was 6.19%. Cincinnati's study area has the largest rate of VTs 14.63%, over

seven times greater than the national μ of 2%, with all other study areas' VT rates also being larger than the national μ (Moore 2019).

The μ number of intersecting tornadoes (EF0-EF5) for the cities was 18.86, with the μ number of > EF0s being 14.29 (Table 3.) Birmingham had the greatest number of both all tornadoes and > EF0s, with 32 and 28, respectively. The number of historic VTs seen in the chosen cities ranged between two and five, averaging at 3.14. Birmingham also had the greatest number of VTs in its record at five, followed by Kansas City with four. All other cities have seen either two or three VTs since 1950 (Table 3.)

Table 3. Tornado statistics for the seven chosen cities

City Tornado Statistics					
	<i>All Tornadoes in Study Area</i>	<i>> EF0s in Study Area</i>	<i>All Intersecting Tornadoes (% Total Tornadoes)</i>	<i>Intersecting > EF0s (% Total >EF0s)</i>	
Birmingham, AL	140	109	32 (22.9%)	28 (25.7%)	
Cincinnati, OH	41	31	6 (14.6%)	4 (12.9%)	
Kansas City, KS/MO	163	94	23 (14.1%)	17 (18.1%)	
Moore, OK	207	145	17 (8.21%)	14 (9.65%)	
Tanner, AL	133	79	12 (9%)	7 (8.9%)	
Tuscaloosa, AL	75	52	13 (17.3%)	11 (21.2%)	
Wichita, KS	91	40	31 (34%)	20 (50%)	
City VT Statistics					
	<i>VTs in Simulated Land Area</i>	<i>Rate of VTs (%) (EF0-EF5)</i>	<i>Rate of VTs (%) (> EF0)</i>	<i>VTs in City Area (%Total VTs)</i>	<i>EF5s in City Area (%Total EF5s)</i>
Birmingham, AL	9	6.43	8.26	5 (55%)	2 (100%)
Cincinnati, OH	6	14.63	19.35	2 (30%)	1 (100%)
Kansas City, KS/MO	8	4.91	8.51	4 (50%)	0 (0%)
Moore, OK	10	4.83	6.90	3 (30%)	2 (100%)
Tanner, AL	6	4.51	7.59	3 (50%)	3 (100%)
Tuscaloosa, AL	7	9.33	13.46	3 (43%)	0 (0%)
Wichita, KS	3	3.30	7.50	2 (66.7%)	1 (100%)

b. Trials 1-2: Simulating all tornadoes

Trial one simulated all tornadoes (EF0-EF5), utilizing the circular city buffer to count intersecting tornado points. For all cities, the μ was < A_μ , with A_μ being the actual number of

intersecting tornadoes for each city. For Birmingham, Tuscaloosa, and Wichita the 99th percentile of simulated tornadoes was still less than their A_{μ} values (Table 4.) In contrast, Cincinnati, Kansas City, and Tanner’s number of total tornadoes were replicated at high rates of 12.5, 29.9, and 34.6% respectively. This could be a result of fewer, weaker tornadoes (EF0-1) intersecting these cities compared to their entire study area.

In trial one, there was a $< 0.1\%$ chance that a simulation matched the same number of VTs seen in that area for all cities (Table 4.) In other words, no simulation for any city replicated that city’s actual number of VTs. Moore and Tuscaloosa had the lowest μ prediction of simulated VTs at 0.42 and 0.43, respectively. For all cities except Kansas City, the μ number of simulated VTs was less than one, which contrasts from each city’s actual number (2-5). For Moore, Tanner, Tuscaloosa, and Wichita, the 99th percentile of simulated VTs was still less than one.

Table 4. Simulating all tornadoes and counting those that intersect a city’s circular buffer

Simulating All Tornadoes (City Buffer)					
Simulated Tornadoes (EF0-EF5)					
	Historic Record		# of Simulated Tornadoes		
	<i>Total Tornadoes</i>	<i>Intersecting Tornadoes</i>	<i>Mean</i>	<i>99th Percentile</i>	<i># of Replications</i>
Birmingham, AL	137	32	10.46	18	0
Cincinnati, OH	55	6	3.45	8	125
Kansas City, KS/MO	163	23	20.30	31	299
Moore, OK	207	17	8.69	16	25
Tanner, AL	133	12	10.36	18	346
Tuscaloosa, AL	166	13	4.60	10	0
Wichita, KS	91	31	19.39	29	2
Simulated VTs					
	Historic Record		# of Simulated VTs		
	<i>Total Tornadoes</i>	<i>VTs (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>
Birmingham, AL	137	5.84	5	0.67	1.16
Cincinnati, OH	55	12.73	2	0.50	1.17
Kansas City, KS/MO	163	4.91	4	1.00	1.52
Moore, OK	207	4.83	3	0.42	0.77
Tanner, AL	133	4.51	3	0.47	0.81
Tuscaloosa, AL	166	7.23	3	0.43	0.93
Wichita, KS	91	3.30	2	0.64	0.96

Trial two simulated all tornadoes (EF0-EF5) but utilized the SW-NE track buffers to count intersecting tornado points. The results for calculating VTs in trial two were similar to those of the previous trial. Like trial one, there was a < 0.1% chance that a simulation matched the same number of VTs seen in that area for Birmingham, Kansas City, Moore, Tanner, Tuscaloosa and Wichita. However, the model was able to simulate a number of VTs equal to or greater than Cincinnati’s actual number of VTs at a rate of 17.3%. The highest number of simulated VTs for Cincinnati was 3.07, which is greater than the number of actual VTs in this city’s historic record, two.

Moore and Tanner had the lowest μ prediction of VTs at 0.80 and 0.76, respectively. All other cities had a μ prediction value greater than one. However, the 99th percentile of simulated VTs was still less than one for all cities. Overall, the μ VT predictions for all cities were higher in trial two compared to those in the previous trial (Table 5.) Again, the calculations of total tornadoes were left out of this trial due to weaker tornadoes having shorter tracks (Allen et al. 2021; Suckling and Ashley 2006).

Table 5. Simulating all tornadoes and counting those that intersect a city’s SW-NE track buffer

Simulating All Tornadoes (SW-NE Track Buffer)							
	Historic Record			# of Simulated VTs			
	<i>Total Tornadoes</i>	<i>VTs (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>	<i># of Replications</i>	
Birmingham, AL	137	5.84	5	1.90	2.57	0	
Cincinnati, OH	55	12.73	2	1.62	2.63	173	
Kansas City, KS/MO	163	4.91	4	2.65	3.34	0	
Moore, OK	207	4.83	3	0.80	1.26	0	
Tanner, AL	133	4.51	3	0.76	1.17	0	
Tuscaloosa, AL	166	7.23	3	1.22	2.05	0	
Wichita, KS	91	3.30	2	1.35	1.72	0	

c. Trials 3-4: Simulating $> EF0$ tornadoes

Excluding EF0s from these trials greatly decreased the total number of points the model was generating (Table 3.) For Tuscaloosa, this number decreased by 68.67%. However, this also meant that the ratio of VTs to all other tornadoes was increased. For Tuscaloosa, this rate increased by 6.23%. Cincinnati had the highest ratio of VTs to total tornadoes for this trial, at 19.35%, more than double all other rates besides Tuscaloosa's.

Trial two simulated all $> EF0$ tornadoes, utilizing the circular city buffer to count intersecting tornado points. For all cities, the μ was less than A_μ , with A_μ being the actual number of intersecting $> EF0$ s for each city. For Birmingham, Moore, Tuscaloosa, and Wichita, the 99th percentile of simulated tornadoes was still $< A_\mu$. Cincinnati, Kansas City, and Tanner's number of tornadoes $> EF0$ were replicated at high rates of 26.5, 6.5, and 40.7%, respectively. Trial three also simulated only tornadoes $> EF0$ but utilized the SW-NE track buffer to count intersecting tornado points. In trial three, there was a $< 0.1\%$ chance that a simulation matched the same number of VTs seen in that area for all cities. Additionally, the μ number of simulated VTs for all cities was $\mu < 1$. This includes Kansas City, which had the highest μ , 0.99. This was lower than its μ in trial one by 0.01. Moore and Tuscaloosa had the lowest μ number of simulated VTs at 0.40 and 0.43, respectively. In this trial, no simulation replicated any city's actual number of VTs. Furthermore, even the top 1% of values were up to four times lower than the cities' actual number of VTs (Table 6.)

Table 6. Simulating > EF0 tornadoes and counting those that intersect a city’s circular buffer

Simulating > EF 0 Tornadoes					
Simulated > EF0 Tornadoes (City Buffer)					
	Historic Record		# of Simulated Tornadoes		
	<i>Total Tornadoes</i>	<i>Intersecting Tornadoes</i>	<i>Mean</i>	<i>99th Percentile</i>	<i># of Replications</i>
Birmingham, AL	109	28	8.25	15	0
Cincinnati, OH	31	4	2.63	6	259
Kansas City, KS/MO	94	17	11.61	20	65
Moore, OK	145	14	5.85	12	3
Tanner, AL	79	7	6.04	12	407
Tuscaloosa, AL	52	11	3.20	8	1
Wichita, KS	40	20	8.54	15	0
Simulated VTs (City Buffer)					
	Historic Record			# of Simulated VTs	
	<i>Total Tornadoes</i>	<i>VTs (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>
Birmingham, AL	109	8.26	5	0.68	1.24
Cincinnati, OH	31	19.35	2	0.51	1.16
Kansas City, KS/MO	94	8.51	4	0.99	1.70
Moore, OK	145	6.90	3	0.40	0.83
Tanner, AL	79	7.59	3	0.46	0.91
Tuscaloosa, AL	52	13.46	3	0.43	1.08
Wichita, KS	40	7.50	2	0.64	1.13

Trial four produced simulations that replicated both Cincinnati and Kansas City’s historic VT count. Cincinnati’s actual number of VTs was replicated at a rate of 21.3%, higher than in trial two (Table 7.) Additionally, the model produced four simulations where Cincinnati had three VTs (0.4%), which is greater than the city’s actual number of VTs, two. While Kansas City’s historic VT count was also replicated, this was only the case for seven simulations, or at a rate of 0.7%.

For all other cities, the model was unable to generate a simulation that replicated the number of VTs in their historic record (< 0.01%), with only Cincinnati’s number of actual VTs being met or surpassed by this trial’s set of 99th percentile values. This includes Tuscaloosa, despite its study area having the second highest rate of VTs at 13.46%. Overall, Tanner and

Moore had the lowest μ number of simulated VTs at 0.74 and 0.81, respectively, the only value less than one.

Table 7. Simulating > EF0 tornadoes and counting those that intersect a city’s SW-NE track buffer

Simulating > EF0 Tornadoes (SW-NE Track Buffer)						
		Historic Record		# of Simulated VTs		
	<i>Total Tornadoes</i>	<i>VTs (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>	<i># of Replications</i>
Birmingham, AL	109	8.26	5	1.92	2.81	0
Cincinnati, OH	31	19.35	2	1.65	2.71	213
Kansas City, KS/MO	94	8.51	4	3.03	3.91	7
Moore, OK	145	6.90	3	0.81	1.38	0
Tanner, AL	79	7.59	3	0.74	1.29	0
Tuscaloosa, AL	52	13.46	3	1.26	2.15	0
Wichita, KS	40	7.50	2	1.16	1.73	0

d. Trials 5-6: Simulating VTs

In trial five, when simulating just VTs using the circular city buffers, Moore had the lowest μ number of simulated VTs, at 0.18, while Tuscaloosa and Tanner had the second and third lowest μ values at 0.42 and 0.48, respectively. This is similar to the results of trials 1-4. However, when compared to the previous trials, trial five saw a higher degree of replication for all cities except Birmingham and Moore. The cities of Cincinnati, Kansas City, and Wichita had simulations that replicated an equal or greater number of VTs relative to their historical record at a rate >1% (Table 8). Cincinnati’s record was replicated at a rate of 10.3%, Kansas City at 1.1%, and Wichita at 10.4%. The model was unable to replicate Birmingham, Moore, Tanner, or Tuscaloosa’s actual number of VTs at a rate >1%, with not a single simulation replicating Birmingham or Moore’s actual number of VTs (<0.01%). For Tanner and Tuscaloosa, it did so at a rate of 0.5%.

Table 8. Simulating VTs and counting those that intersect a city’s circular buffer

Simulating VTs (City Buffer)					
	Historic Record			# of Simulated VTs	
	<i>VTs</i>	<i>VTs in Buffer (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>
Birmingham, AL	8	0.63	5	0.69	3
Cincinnati, OH	7	0.29	2	0.53	3
Kansas City, KS/MO	8	0.50	4	1.02	4
Moore, OK	10	0.30	3	0.18	2
Tanner, AL	6	0.50	3	0.48	2
Tuscaloosa, AL	12	0.25	3	0.42	2
Wichita, KS	3	0.67	2	0.62	2

In trial six, when simulating just VTs using the SW-NE track buffer, the model was able to replicate an equal or greater number of VTs for all cities (Table 9.) Similar to the previous trial, Cincinnati, Wichita, and Kansas City had the greatest rate of replication at 50.6, 41.5, and 26.2%, respectively. Tuscaloosa, Tanner, and Birmingham were also replicated at rates greater than 1%. Tuscaloosa was replicated at a rate of 12.6%, but Tanner and Birmingham were replicated less frequently at rates of 3.5 and 1.2%, respectively. Although these rates exceed 1%, they are still notably low.

Moore had simulations that replicated its actual number of VTs, but they occurred at the lowest rate of 0.5%. Concurrently, Moore had the lowest μ number of simulated VTs, at 0.45, 2.5 times larger than the city’s μ in the previous trial. Tanner had the second lowest μ at 0.81, the only other μ value less than one. Each of the cities’ 99th percentiles were greater than one, with Moore having the lowest value, two. All other 99th percentile values aside from Moore’s were equal to or greater than their city’s actual number of VTs.

Table 9. Simulating VTs and counting those that intersect a city's SW-NE track buffer

Simulating VTs (SW-NE Track Buffer)	Historic Record			# of Simulated VTs	
	<i>VTs</i>	<i>VTs in Buffer (%)</i>	<i>Intersecting VTs</i>	<i>Mean</i>	<i>99th Percentile</i>
Birmingham, AL	8	0.63	5	1.74	5
Cincinnati, OH	7	0.29	2	1.58	4
Kansas City, KS/MO	8	0.50	4	2.66	6
Moore, OK	10	0.30	3	0.45	2
Tanner, AL	6	0.50	3	0.81	3
Tuscaloosa, AL	12	0.25	3	1.27	4
Wichita, KS	3	0.67	2	1.33	3

Simulating Violent Tornadoes in Tanner, AL

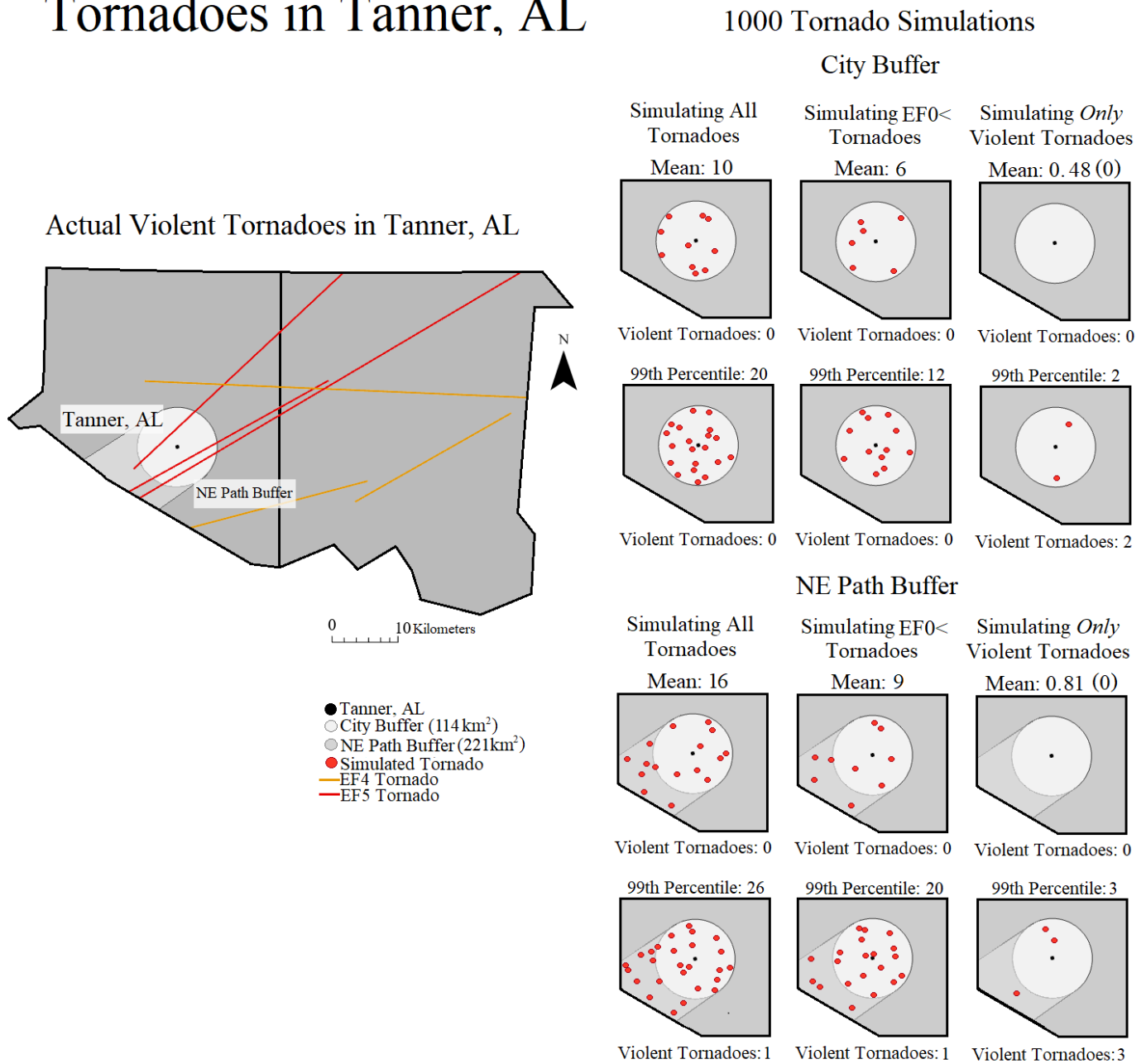


Figure 5. Simulating VTs: Trials 1-6 results from 6000 simulations (Tanner, AL)

e. One sample t-tests

One sample t-tests were performed to compare the actual and adjusted μ values with the real number of total tornadoes (EF0-EF5), > EF0s, and VTs (A_μ). These tests were run for each city in each trial, with tests rerun on trials simulating more than just VTs. This was to compare the accuracy of the model's simulations in regards to each city's historic record of tornadoes in each of the three categories (EF0-EF5, > EF0, and EF4-EF5). The test results provide a deeper insight on the model's capability to reproduce anomalous tornado patterns. For these tests, p-values < 0.01 were considered statistically significant, as the 99th confidence interval was used to confirm dissimilarity between the μ and A_μ values ($\alpha = 0.01$).

T-tests comparing trial one's results using the actual μ of total simulated tornadoes (EF0-EF5) with the A_μ values yielded p-values < 0.01 (Table 10.) These results were the same for the comparison between the adjusted μ of simulated EF0-EF5 tornadoes and the A_μ values (Table 10.) All μ values were lower than the real number of total tornadoes seen by each city, showing that the model's simulated μ number of tornadoes was underpredicted for all cities despite accurate replications for Cincinnati, Kansas City, Moore, and Tanner. These dissimilarities between the μ and A_μ values were enough to be considered statistically significant.

Birmingham's number of EF0-EF5 tornadoes was the most underpredicted, with its μ accounting for only 31.25% of the real number of EF0-EF5 tornadoes seen in that city since 1950. Tuscaloosa's μ number of EF0-EF5s was also greatly underpredicted, at four instead of 13. Tanner's number of predicted EF0-EF5 tornadoes was the closest to what the city has seen historically, but still lower, at ten as opposed to 11. For all cities, adjusting the μ values led to lower t-statistic values, increasing the dissimilarity between the μ and A_μ values.

Table 10. One sample t-test results for simulating all tornadoes (EF0-EF5) in the primary cities

Actual Mean (EF0-EF5s)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	10.456	3.455	20.305	8.691	10.359	4.597	19.392
Standard Deviation	2.996	1.746	4.233	2.835	3.150	2.012	4.025
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.095	0.055	0.134	0.090	0.100	0.064	0.127
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	32	5	23	17	11	13	31
T-statistic	-227.537	-27.997	-20.146	-92.711	-6.442	-132.120	-91.254
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Adjusted Mean (EF0-EF5s)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	10	3	20	8	10	4	19
Standard Deviation	2.996	1.746	4.233	2.835	3.150	2.012	4.025
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.095	0.055	0.134	0.090	0.100	0.064	0.127
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	32	5	23	17	11	13	31
T-statistic	-232.349	-36.231	-22.423	-100.425	-10.044	-141.514	-94.332
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001

Similarly, the t-tests comparing trial three’s results, or the μ of simulated tornadoes > EF0 with each city’s A_μ also yielded significant p-values (Table 11.) As expected, this was also true for the comparison between the adjusted μ of simulated tornadoes > EF0 and the corresponding A_μ values (Table 11.) All μ values were smaller than the real number of tornadoes > EF0 seen by each city’s historic record, meaning the model also greatly underpredicted the number of EF1-EF5 tornadoes for all cities. Again, the dissimilarity between all μ and A_μ values were enough to be considered statistically significant.

Similar to the first series of t-tests, Birmingham’s number of simulated tornadoes was the most underpredicted. Birmingham’s μ number of simulated tornadoes accounted for only 28.57% of the city’s real number of tornadoes > EF0, a percentage slightly smaller than that in trial one. Like trial one, both Tanner’s actual and adjusted μ number of simulated EF1-EF5 tornadoes were closest to its A_μ value, though still smaller, at 6.043/6 compared to 7, respectively. Adjusting the μ values from trial two also led to lower t-statistic values, increasing the dissimilarity between the μ and A_μ values (Table 11.) Regardless, all resulting p-values were

far < 0.01, showing statistical significance in the difference between corresponding μ and A_μ values.

Table 11. One sample t-test results for simulating tornadoes > EF0 in the primary cities

Actual Mean (> EF0s)							
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	8.254	2.631	11.608	5.852	6.043	3.204	8.549
Standard Deviation	2.712	1.490	3.093	2.398	2.439	1.707	2.615
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.086	0.047	0.098	0.076	0.077	0.054	0.083
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	28	3	17	14	7	11	20
T-statistic	-230.322	-7.826	-55.157	-94.309	-12.412	-144.510	-138.522
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Adjusted Mean (> EF0s)							
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	8	2	11	5	6	3	8
Standard Deviation	2.712	1.490	3.093	2.398	2.439	1.707	2.615
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.086	0.047	0.098	0.076	0.077	0.054	0.083
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	28	3	17	14	7	11	20
T-statistic	-233.282	-21.230	-61.381	-105.553	-12.969	-148.291	-145.163
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001

One sample t-tests were run for every trial’s actual and adjusted μ number of simulated VTs for all cities, comparing them with each city’s real number of VTs (A_μ). When using the actual μ number of VTs, all p-values for every trial and city were statistically significant (Table 12.) While trials using the SW-NE track buffer (trials two, four, and six) had the largest predictions of VTs, the μ and A_μ number of VTs in all three trials were still notably dissimilar. Overall, the model greatly underpredicted all cities μ number of VTs relative to each one’s historic number of VTs.

Table 12. One sample t-test using the actual mean of simulated VTs in the primary cities

Actual Mean (VTs)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0.672	0.504	0.997	0.420	0.467	0.429	0.640
Standard Deviation	0.193	0.255	0.208	0.137	0.142	0.188	0.133
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.006	0.008	0.007	0.004	0.004	0.006	0.004
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-710.828	-185.578	-457.142	-596.084	-564.080	-433.299	-323.988
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 2: Simulating All Tornadoes (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1.905	1.625	2.655	0.801	0.761	1.224	1.352
Standard Deviation	0.290	0.386	0.286	0.183	0.165	0.317	0.157
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.009	0.012	0.009	0.006	0.005	0.010	0.005
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-332.006	-30.743	-146.362	-374.768	-423.916	-174.702	-127.872
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0.682	0.509	0.988	0.404	0.459	0.431	0.641
Standard Deviation	0.224	0.288	0.263	0.165	0.185	0.230	0.197
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.007	0.009	0.008	0.005	0.006	0.007	0.006
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-609.786	-163.566	-362.101	-496.441	-434.248	-353.367	-219.168
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 4: Simulating > EF0 Tornadoes (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1.922	1.651	3.028	0.809	0.744	1.258	1.157
Standard Deviation	0.356	0.462	0.395	0.227	0.215	0.364	0.225
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.011	0.015	0.012	0.007	0.007	0.012	0.007
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-267.381	-23.943	-76.779	-300.181	-326.788	-149.591	-117.438
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 5: Simulating VTs (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0.691	0.524	1.013	0.178	0.484	0.422	0.617
Standard Deviation	0.820	0.710	0.949	0.425	0.651	0.615	0.693
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.0259	0.0224	0.0300	0.0134	0.0206	0.0194	0.0219
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-166.342	-65.781	-99.571	-210.255	-122.276	-132.670	-63.109
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 6: Simulating VTs (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1.746	1.584	2.667	0.446	0.810	1.277	1.329
Standard Deviation	1.127	1.086	1.307	0.650	0.834	1.050	0.857
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.036	0.034	0.041	0.021	0.026	0.033	0.027
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-91.341	-12.133	-32.268	-124.309	-83.098	-51.902	-24.750
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001

Tests using each of the six trials' adjusted μ number of simulated VTs yielded p-values of the same significance as tests using the actual μ values (Table 13.) Again, trials using the SW-NE track buffer (trials two, four, and six) predicted the greatest number of VTs in each city, but the μ and A_μ number of VTs were still statistically dissimilar, with the μ values being much lower. Using the adjusted μ values led to even smaller t-statistic values, causing the resulting p-values to also be smaller and more significant. The adjusted μ number of simulated VTs was greatest for Kansas City, at three in trial four. No other adjusted μ number of simulated VTs aside from this value was greater than two (Table 13.) Overall, one sample t-tests for all trials simulating VTs show that the model's simulated μ number of VTs all cities was significantly lower than each city's actual number of VTs. This was despite all cities' VT patterns being accurately replicated in at least one trial.

Table 13. One sample t-test using the adjusted mean of simulated VTs in the primary cities

Adjusted Mean (VTs)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0	0	0	0	0	0	0
Standard Deviation	0.193	0.255	0.208	0.137	0.142	0.188	0.133
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.006	0.008	0.007	0.004	0.004	0.006	0.004
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-821.252	-248.160	-608.906	-693.064	-668.123	-505.587	-476.426
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 2: Simulating All Tornadoes (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1	1	2	0	0	1	1
Standard Deviation	0.295	0.391	0.291	0.186	0.167	0.322	0.161
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.009	0.012	0.009	0.006	0.005	0.010	0.005
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-428.835	-80.863	-217.421	-511.022	-567.719	-196.488	-197.036
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0	0	0	0	0	0	0
Standard Deviation	0.224	0.288	0.263	0.165	0.185	0.230	0.196
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.007	0.009	0.008	0.005	0.006	0.007	0.006
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-706.058	-219.662	-480.858	-573.655	-512.620	-412.624	-322.585
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 4: Simulating > EF0 Tornadoes (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1	1	3	0	0	1	1
Standard Deviation	0.361	0.467	0.400	0.230	0.218	0.368	0.227
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.011	0.015	0.013	0.007	0.007	0.012	0.007
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-350.280	-67.804	-79.160	-413.030	-436.112	-172.099	-139.598
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 5: Simulating VTs (City Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	0	0	1	0	0	0	0
Standard Deviation	0.820	0.710	0.949	0.425	0.651	0.615	0.693
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.0259	0.0224	0.0300	0.0134	0.0206	0.0194	0.0219
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-193.031	-89.163	-100.004	-223.503	-145.769	-154.361	-91.289
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Trial 6: Simulating VTs (SW-NE Track Buffer)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Mean	1	1	2	0	0	1	1
Standard Deviation	1.131	1.086	1.307	0.650	0.834	1.050	0.857
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.036	0.034	0.041	0.021	0.026	0.033	0.027
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	5	2	4	3	3	3	2
T-statistic	-111.881	-29.137	-48.401	-146.042	-113.823	-60.256	-36.904
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001

f. Replicability of tornadoes in the chosen cities vs. their adjacent cities

The same series of one sample t-tests were performed on the adjacent cities comparing the actual and adjusted μ values with their real number of total tornadoes, > EF0s, and VTs (A_μ). This was done to determine the model's level of accuracy in predicting seemingly normal tornado patterns in locations neighboring cities with an anomalous level of tornado activity. Like with the previous tests, p-values < 0.01 were considered statistically significant, with the 99th confidence interval being used to confirm dissimilarity between the μ and A_μ values ($p < \alpha = 0.01$).

Trial one, simulating all tornadoes (EF0-EF5) in the adjacent cities, yielded results differing from those performed on the primary cities. The number of total tornadoes for Covington, Platte City, and Goddard were greatly overpredicted, as shown by the positive t-statistic values (Table 14.) Dissimilarity between the μ and A_μ values decreased when adjusting the μ values for these three cities. All other cities' tornado quantities were underpredicted to a significant degree, with dissimilarity increasing when using the adjusted μ values.

Table 14. One sample t-test results for simulating all tornadoes (EF0-EF5) in the adjacent cities

Actual Mean (EF0-EF5s)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	10.456	3.455	20.305	8.691	10.359	4.597	19.392
Standard Deviation	2.996	1.746	4.233	2.835	3.150	2.012	4.025
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.095	0.055	0.134	0.090	0.100	0.064	0.127
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	20	2	8	10	11	10	14
T-statistic	-100.802	26.350	91.969	-14.603	-6.442	-84.949	42.384
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Adjusted Mean (EF0-EF5s)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	10	3	20	8	10	4	19
Standard Deviation	2.996	1.746	4.233	2.835	3.150	2.012	4.025
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.095	0.055	0.134	0.090	0.100	0.064	0.127
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	20	2	8	10	11	10	14
T-statistic	-105.613	18.116	89.692	-22.317	-10.044	-94.343	39.305
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001

Tests performed on trial three, simulating tornadoes > EF0 in the adjacent cities produced smaller t-statistic values than those for the primary cities. Covington, Platte City, and Goddard’s number of > EF0 tornadoes was still overpredicted, but to a lesser degree. Using the adjusted μ value for Goddard gave a p-value equal to one, the first insignificant p-value calculated from these tests (Table 15.) Thus, the model accurately predicted the μ number of tornadoes > EF0 in trial three for Goddard, the city adjacent to Wichita.

Table 15. One sample t-tests for simulating tornadoes > EF0 in the adjacent cities

Actual Mean (> EF0s)							
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	8.254	2.631	11.608	5.852	6.043	3.201	8.541
Standard Deviation	2.712	1.490	3.093	2.398	2.439	1.709	2.625
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.086	0.047	0.098	0.076	0.077	0.054	0.083
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	15	1	7	8	8	9	8
T-statistic	-78.689	34.634	47.145	-28.339	-25.381	-107.361	6.526
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001
Adjusted Mean (> EF0s)							
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	8	2	11	5	6	3	8
Standard Deviation	2.712	1.490	3.093	2.398	2.439	1.709	2.580
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.086	0.047	0.098	0.076	0.077	0.054	0.082
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	15	1	7	8	8	9	8
T-statistic	-81.649	21.230	40.921	-39.582	-25.939	-111.078	0
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	1

Results from the one sample t-tests run on the model’s VT predictions for the adjacent cities varied from those done on the primary cities. These were also run for every trial’s μ prediction of VTs in each of the chosen cities. Insignificant p-values from simulating VTs in trial one and five show that the model accurately predicted Platte City’s real number of VTs (Table 16.) All of the adjacent cities besides Madison had their actual number of VTs overpredicted in at least one trial, with Covington and Norman’s μ prediction of VTs being overpredicted in every trial. Results from the previous series of t-tests run on the primary cities showed strictly underpredicted quantities of VTs for all cities. The results here are far more varied between accurately predicted, overpredicted, and underpredicted in the number of simulated VTs.

Table 16. One sample t-tests using the actual mean of simulated VTs in the adjacent cities

Actual Mean (VTs)								
Trial 1: Simulating All Tornadoes (City Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	0.672	0.504	0.997	0.420	0.467	0.429	0.640	
Standard Deviation	0.193	0.255	0.208	0.137	0.142	0.188	0.133	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.006	0.008	0.007	0.004	0.004	0.006	0.004	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	-53.826	62.581	-0.463	96.981	-118.664	-96.241	-85.775	
P-value	<.00001	<.00001	0.641	<.00001	<.00001	<.00001	<.00001	
Trial 2: Simulating All Tornadoes (SW-NE Track Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	1.903	1.623	2.654	0.800	0.760	1.222	1.351	
Standard Deviation	0.295	0.391	0.291	0.186	0.167	0.322	0.161	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.009	0.012	0.009	0.006	0.005	0.010	0.005	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	96.828	131.222	179.770	136.253	-45.437	21.786	69.164	
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	
Trial 3: Simulating > EF0 Tornadoes (City Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	0.682	0.509	0.988	0.404	0.459	0.431	0.641	
Standard Deviation	0.224	0.288	0.263	0.165	0.185	0.230	0.196	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.007	0.009	0.008	0.005	0.006	0.007	0.006	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	-44.939	55.863	-1.458	77.214	-92.501	-78.285	-57.876	
P-value	<.00001	<.00001	0.147	<.00001	<.00001	<.00001	<.00001	
Trial 4: Simulating > EF0 Tornadoes (SW-NE Track Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	1.919	1.648	3.025	0.807	0.743	1.256	1.156	
Standard Deviation	0.361	0.467	0.400	0.230	0.215	0.364	0.227	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.011	0.015	0.013	0.007	0.007	0.012	0.007	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	80.457	111.749	160.320	111.149	-37.415	22.044	21.763	
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	
Trial 5: Simulating VTs (City Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	0.691	0.524	1.013	0.178	0.484	0.422	0.617	
Standard Deviation	0.820	0.710	0.949	0.425	0.651	0.615	0.693	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.026	0.022	0.030	0.013	0.021	0.019	0.022	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	-11.917	23.382	0.433	13.248	-25.096	-29.762	-17.464	
P-value	<.00001	<.00001	0.665	<.00001	<.00001	<.00001	<.00001	
Trial 6: Simulating VTs (SW-NE Track Buffer)								
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard	
Mean	1.742	1.580	2.661	0.446	0.808	1.275	1.327	
Standard Deviation	1.131	1.089	1.318	0.649	0.834	1.051	0.860	
Count	1001	1001	1001	1001	1001	1001	1001	
Standard Error of Mean	0.036	0.034	0.042	0.021	0.026	0.033	0.027	
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000	
Hypothesized Mean	1	0	1	0	1	1	1	
T-statistic	20.761	45.919	39.891	21.719	-7.278	8.267	12.013	
P-value	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	<.00001	

One sample t-tests run using the adjusted μ prediction of VTs in the adjacent cities yielded the greatest number of insignificant results compared to all other series of tests (Table 17.) Covington's μ number of VTs was either accurately predicted or overpredicted in each trial, with Norman's μ being accurately predicted in all six trials. Trials using the SW-NE track buffer were the most likely to either accurately predict or overpredict each of the adjacent city's historic number of VTs. Only Madison's μ number of VTs was significantly dissimilar to its A_μ in all six trials (Table 17.)

Overall, the t-statistics resulting from t-tests done on the adjacent cities' simulated VT μ values were much higher than those from tests done on the primary cities. In all trials, the μ number of simulated VTs in the primary cities were significantly underpredicted. While the μ number of simulated VTs were underpredicted for some of the adjacent cities, such as Madison, most of the resulting t-statistic values were closer to zero. This shows a lower degree of dissimilarity between the adjacent cities' μ number of simulated VTs and the A_μ values for each city. Thus, the model was more capable of reproducing the actual number of VTs in the adjacent cities than in the primary cities.

Table 17. One sample t-tests using the adjusted mean of simulated VTs in the adjacent cities

Adjusted Mean (VTs)							
Trial 1: Simulating All Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	0	0	0	0	0	0	0
Standard Deviation	0.193	0.255	0.208	0.137	0.142	0.188	0.133
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.006	0.008	0.007	0.004	0.004	0.006	0.004
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	-164.250	0	-152.226	0	-222.708	-168.529	-238.213
P-value	<.00001	1	<.00001	1	<.00001	<.00001	<.00001
Trial 2: Simulating All Tornadoes (SW-NE Track Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	1	1	2	0	0	1	1
Standard Deviation	0.289	0.391	0.291	0.183	0.167	0.317	0.157
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.009	0.012	0.009	0.006	0.005	0.010	0.005
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	0	80.863	108.711	0	-189.240	0	0
P-value	1	<.00001	<.00001	1	<.00001	1	1
Trial 3: Simulating > EF0 Tornadoes (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	0	0	0	0	0	0	0
Standard Deviation	0.224	0.288	0.263	0.165	0.185	0.230	0.197
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.007	0.009	0.008	0.005	0.006	0.007	0.006
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	-141.212	0	-120.214	0	-170.873	-137.541	-161.292
P-value	<.00001	1	<.00001	1	<.00001	<.00001	<.00001
Trial 4: Simulating > EF0 Tornadoes (SW-NE Track Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	1	1	3	0	0	1	1
Standard Deviation	0.356	0.462	0.395	0.227	0.215	0.364	0.225
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.011	0.015	0.012	0.007	0.007	0.012	0.007
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	0	67.804	158.320	0	-145.371	0	0
P-value	1	<.00001	<.00001	1	<.00001	1	1
Trial 5: Simulating VTs (City Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	0	0	1	0	0	0	0
Standard Deviation	0.820	0.710	0.949	0.425	0.651	0.615	0.693
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.026	0.022	0.030	0.013	0.021	0.019	0.022
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	-38.606	0	0	0	-48.590	-51.454	-45.645
P-value	<.00001	1	1	1	<.00001	<.00001	<.00001
Trial 6: Simulating VTs (SW-NE Track Buffer)							
	Vestavia Hills-Hoover	Covington	Platte City	Norman	Madison	Northport	Goddard
Mean	1	1	2	0	0	1	1
Standard Deviation	1.127	1.089	1.318	0.650	0.834	1.050	0.857
Count	1001	1001	1001	1001	1001	1001	1001
Standard Error of Mean	0.036	0.034	0.042	0.021	0.026	0.033	0.027
Degrees of Freedom	1000	1000	1000	1000	1000	1000	1000
Hypothesized Mean	1	0	1	0	1	1	1
T-statistic	0	29.055	24.01	0	-37.946	0	0
P-value	1	<.00001	<.00001	1	1	1	1

CHAPTER 4

CLIMATE INDICES AND TORNADO SPATIAL VARIABILITY METHODOLOGY

a. Study area

For testing the relationship between climate indices and tornado frequency in the U.S., the Eastern United States (EUS) was divided into three regions, the Great Plains (GPUS), Midwest (MWUS), and Southeast (SEUS) (Figure 6.) The entire EUS was tested alongside these regions to assess the variance of effects between the larger region and its subdivisions.

The states in each region aside from the EUS were:

- GPUS: Kansas, Nebraska, North Dakota, Oklahoma, South Dakota, and Texas
- MWUS: Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin
- SEUS: Alabama, Arkansas, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Tennessee, and South Carolina

Florida was excluded from this analysis because of its unique climatology influenced by its proximity with both the Gulf of Mexico and Atlantic ocean. Florida experiences year round tropical influence, coastal thunderstorms, and it is vulnerable to tropical cyclones, all of which can produce waterspouts that move inland (Brooks and Doswell 2001). Because of this, Florida was left out of the tests to avoid confounding variables introduced by tropical activity.

Climate Indices and Tornado Spatial Variability: Study Regions

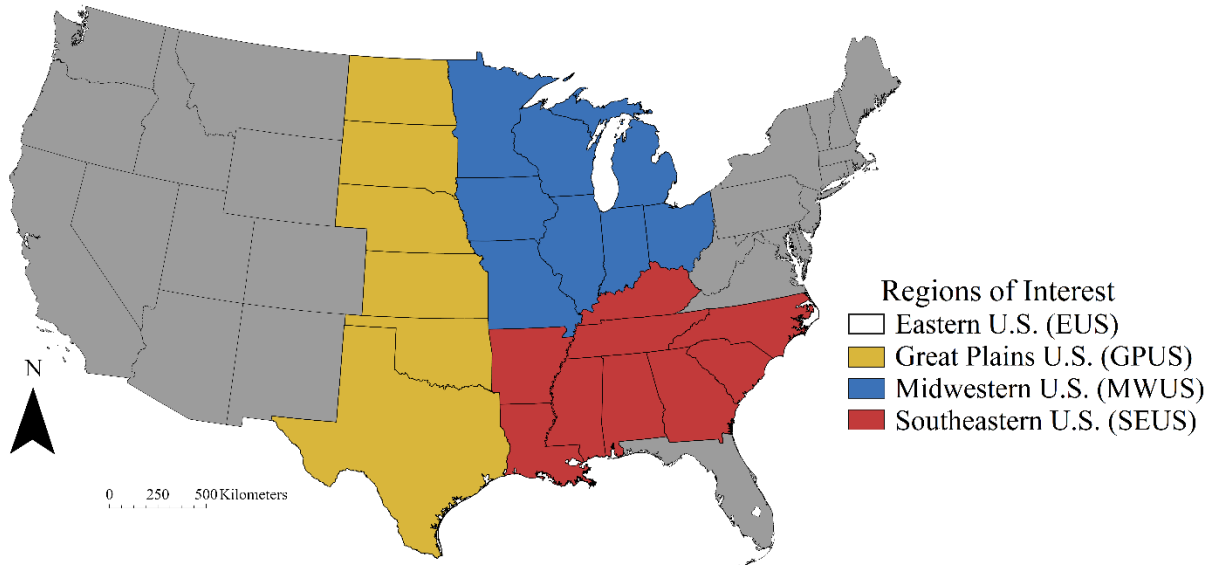


Figure 6. Regions used to examine climate indices' impact on tornado frequency

b. Chosen climate indices

The climate indices of interest are:

- Arctic Oscillation (AO)
- El Niño–Southern Oscillation (ENSO)
- North Atlantic Oscillation (NAO)
- Pacific Decadal Oscillation (PDO)
- Pacific-North American Pattern (PNA)
- Madden-Julien Oscillation (MJO)

It was important to choose climate indices with the highest likelihood of influence on tornado frequency over the EUS. This likelihood was determined through the review of related scientific literature (Marzban & Schaefer 2001; Allen et al. 2015; Brown & Nowotarski 2020)

All climate variables were quantified using their indices. All indices aside from the Madden-Julian Oscillation (MJO) were obtained from NOAA's Climate Monitoring data depository (<https://www.ncei.noaa.gov/access/monitoring>). The MJO was taken from the Australian Government's Bureau of Meteorology (<http://www.bom.gov.au/climate/mjo/>). For some climate indices, there are multiple datasets available to analyze parameters of the same variable. This is the case for ENSO and the MJO. For ENSO, this study utilizes the Southern Oscillation Index (SOI) and the Oceanic Niño Index (ONI) due to their wide use among the scientific community and use for defining significant ENSO events (Tippett et al. 2016). For the MJO, the RMM was selected because of its previous utilization in tornado analyses (Moore et al. 2018).

The climate indices vary in format and record length, so it was necessary to reorganize them to match the historic tornado dataset. Teleconnections do not typically occur simultaneously with shifts in the phase of the climate index, resulting in a lag of their impact on the global and regional hydroclimates (Switanek et al. 2009; Shah et al. 2022). Because of this, all climate indices were reformatted into a tri-monthly index to account for the latency effect. This meant that the quantity of tornadoes or VTs in each month were correlated alongside indices that were the mean (μ) values of the previous three months.

Table 18. Climate indices used and their record length

Climate Indices	
Index	Record Length
AO	1950-2020
NAO	1950-2020
ONI (ENSO)	1950-2020
PDO	1950-2020
PNA	1950-2014
RMM (MJO)	1975-2025
SOI (ENSO)	1951-2020

c. Data analysis

The indices and historic tornado datasets were all tested and confirmed to be normally distributed using the Kolmogorov-Smirnov test. Correlation tests were used to determine the statistical significance of the relationships between the selected climate indices and regional tornado and VT frequency. The same series of tests were used to determine the relationship between these factors countywide in the cities' study areas. These correlations will be compared to determine how they vary between different spatial scales. For both trials, the tornado counts were correlated alongside their adjacent tri-monthly index values. Only each region's most active tornado months were tested. These months were chosen quantitatively through each month's μ number of total tornadoes (> EF0) or VTs. In the case that two or more months were equal in tornadic activity, all were included in the tests. It should be noted that these μ values have likely shifted throughout the historic tornado record due to advancements made in radar and rating tornadoes (Brown and Nowotarski 2020; Edwards et al. 2021). Because of this, notable events in tornado research between 1950 and 2020 were considered when ranking the months by tornadic activity.

i. Monthly > EF0 and VT frequency for the regions and cities of interest

Monthly > EF0 and VT frequency were analyzed for both the chosen regions and the study areas surrounding the cities of interest. Graphs displaying these trends were created to examine how tornado frequency varies spatially throughout the EUS. Of greatest interest was if monthly tornado frequency varies between the smaller study areas and their encompassing regions.

ii. Pearson Correlation: climate indices and regional tornado frequency

For these tests, the four regions were analyzed separately. Pearson correlation tests were done in Excel for both > EF0 and VT counts within the three most active > EF0/VT months for each region. Again, if multiple months tied, all were included in the tests. Together, these months were defined as an area's tornado season. If one month was separated temporally from the others by three or more months, it was analyzed separately. These methods were the same for all proceeding tests. Only > EF0s were included in the total monthly tornado count due to EF0s relationship with tropical activity and other non-synoptic systems (Fuhrmann et al. 2014; Foglietti et al. 2020). The entire EUS was compared with the other three regions to determine if and to what degree the correlation between climate indices and tornado frequency varies between the primary region and its subregions. Only Pearson correlation coefficients $r > 0.250$ were considered statistically significant (Gibbs 2021).

iii. Generalized linear models: climate indices and regional tornado frequency

Generalized linear models were used to further analyze the relationships between climate indices and > EF0/VT frequency in the selected regions. The models' probability distribution and link function varied for each region, as it was necessary to select the parameters that resulted in the model being a good fit for a particular dataset. Goodness of fit was determined by the

calculated Pearson Chi-Square value, which needed to be within 0.05 of one for the model to be considered a good fit (McCullagh 2019). The Omnibus Test value ($\alpha < 0.05$) was then used to determine if the resulting model performed better than the null. Multicollinearity is a concern when using generalized linear models, so the SOI standardized index was left out of these analyses. The SOI anomaly index was used instead, as it was found to more-correlated to monthly tornado frequency in the preliminary tests than the standardized index. Relationship values $\alpha < 0.05$ between climate indices and tornado frequency were considered statistically significant.

iv. *Pearson Correlation: Climate indices and countywide tornado frequency*

Pearson correlation was also used to test the relationship between each of the climate indices and tornado frequency in the chosen cities. For these tests, the study areas for the seven cities in the first chapter were used in place of the chosen regions. Datasets containing monthly EF0 and VT counts were created for each study area. Here, EF0s were also excluded from the datasets containing the total monthly tornado counts. Tornadoes from the three most active tornado months for each study area were defined as that area's tornado season. As with the regional tests, if multiple months tied, all were included in the analyses.

Tests were run on the annual sums of tornadoes from each season, not by month. This was done both to make the data normally distributed, and account for the longer duration of some climate indices' effects, which may last longer than a month. Seasons without tornadoes before the start of 1992 were left out of the datasets, due to the possibility of a greater number of missed tornadoes before Next-Generation Radar systems (NEXRAD) was deployed (Ryzhkov et al. 2005). The resulting correlation coefficients were compared between the cities in addition to the results for the EUS and the three smaller regions. The comparison between the results of the

cities and the region that contains them was of the greatest interest. The secondary focus was on the similarity in the results of the cities and the whole EUS region. Again, Pearson correlation coefficients $r > 0.250$ were considered statistically significant (Gibbs 2021).

v. *Generalized linear models: climate indices and countywide tornado frequency*

Generalized linear models were also used to further analyze the relationship between $> EF0/VT$ frequency in each of the chosen cities. Despite these datasets being much smaller, the models' goodness of fit was still important. Again, this was measured by the calculated Pearson Chi-Square value, which needed to be within 0.05 of one for the model to be considered a good fit (McCullagh 2019). The datasets used for countywide VT frequency were much smaller with little variation, so models with Pearson Chi-Square within 0.3 of one were considered in the final analysis (McCullagh 2019). Significant Omnibus Test values ($\alpha < 0.05$) were needed to determine if the resulting model performed better than the null. Here, the SOI standardized index was also left out to reduce multicollinearity. Again, relationship values $\alpha < 0.05$ between climate indices and tornado frequency were considered statistically significant.

vi. *Summary of climate indices' influence on $> EF0$ and VT activity in the chosen regions and cities of interest*

Overall influence of climate indices over $> EF0$ and VT activity in the chosen regions and cities of interest was determined using the total number of significant relationships from all tests ($\alpha < 0.05$ or $r > 0.250$). Here, it was important to analyze how the relationships between certain climate indices varied by region and city; most importantly, if the dominant climate indices varied between each city's study area and that city's encompassing region.

CHAPTER 5

CLIMATE INDICES AND TORNADO SPATIAL VARIABILITY RESULTS

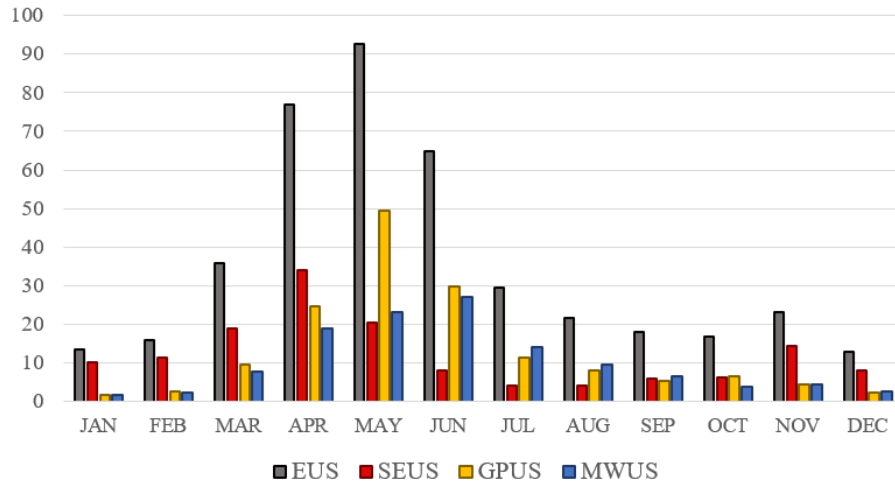
a. Monthly > EF0 and VT frequency for the regions and cities of interest

Over the entire EUS and in the GPUS, total tornado (> EF0) frequency peaks in the springtime, with the most active month being May (Figure 7.) > EF0 activity in the MWUS is also greatest in spring, but peaks later, with the most active month here being June. In contrast, tornado season begins earlier in the SEUS, with its most active month being April. The SEUS also sees a second spike in > EF0 frequency towards the end of the of the fall and in the winter, from November to February. These results match with those found in established tornado seasonality literature (Tippett et al. 2012; Moore 2019). For the GPUS and SEUS, VT activity by month varied little from the regions' monthly total > EF0 activity. However, for the EUS and MWUS, the peak for VT activity appears to occur earlier in the year compared to the regions' > EF0 activity.

> EF0 activity by month in the cities' study areas was most similar to the tornado seasonality of their encompassing regions, and not the entire EUS (Figure 8.) There was some variance in which months were the most active, but this could be a result of a singular tornado outbreak. This is because the quantity of data for the cities' study areas was much smaller, so it's possible the datasets' trends have been swayed by one or more tornadic events (Foglietti et al.

2020). This is also the case for each study area’s VT datasets, which were even smaller. Even so, there does not appear to be much variance in monthly $\mu >EF0$ and VT activity between the cities’ study areas and their regions (Figure 9.)

Monthly Averages of **Total Tornadoes (> EF0)** by Region (1950-2020)



Monthly Averages of **Violent Tornadoes** by Region (1950-2020)

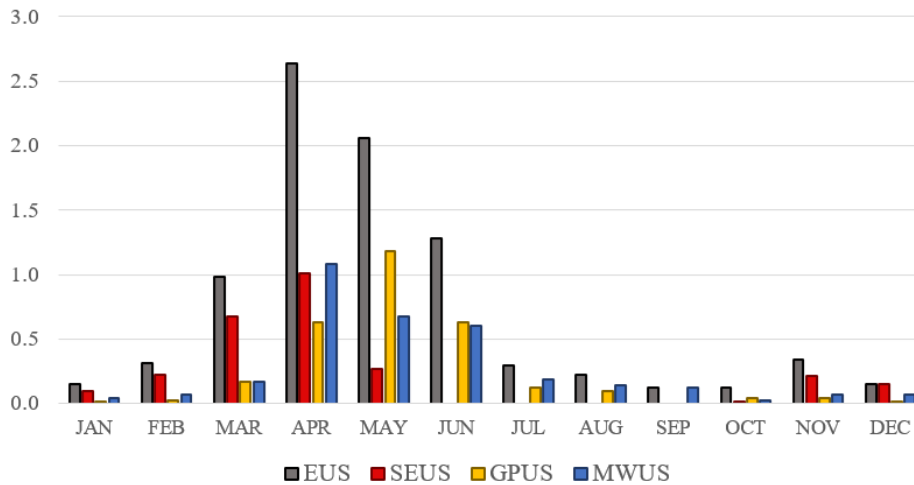


Figure 7. The most active tornado months by region in the EUS

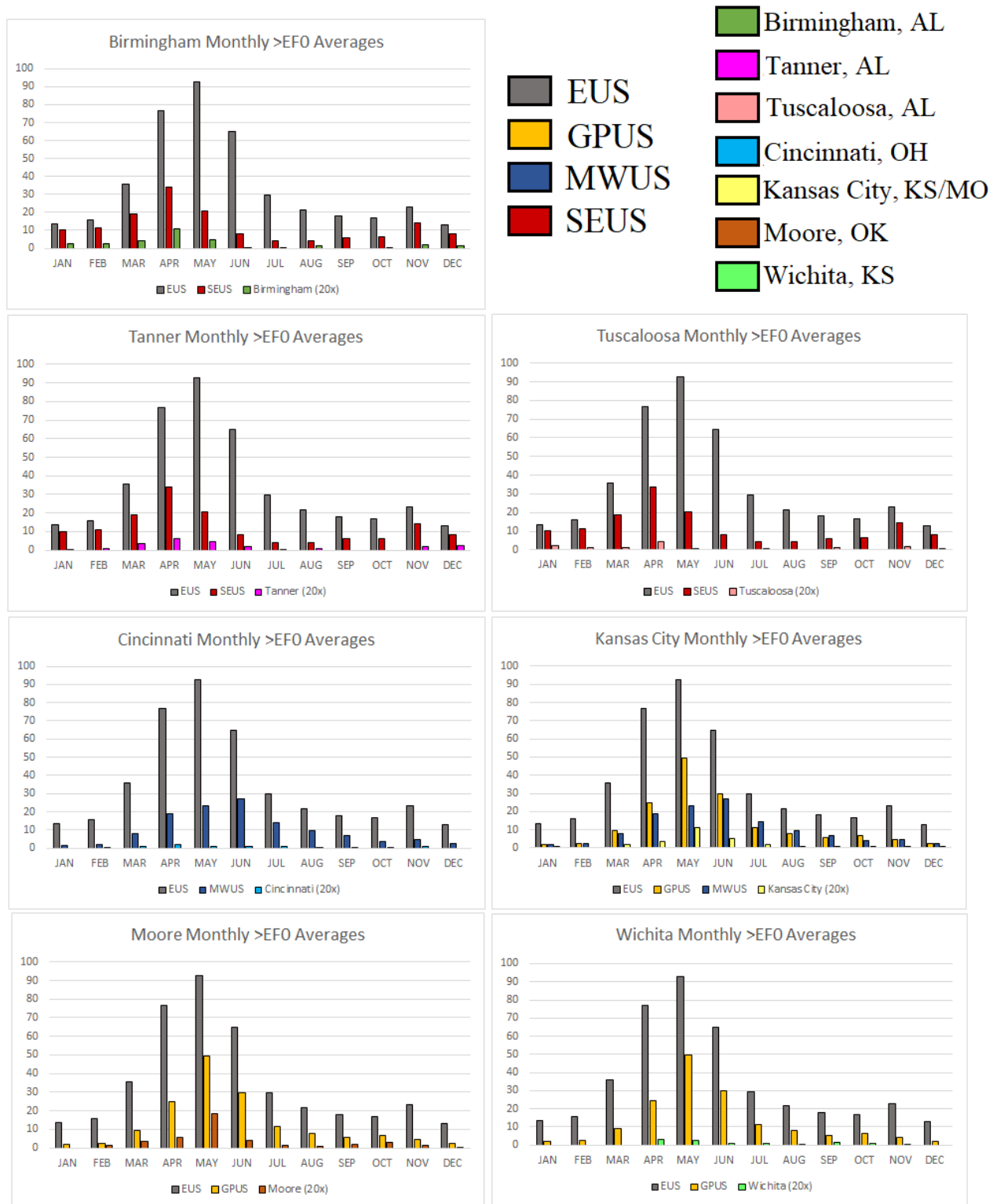


Figure 8. Monthly > EFO averages for the seven city’s study areas

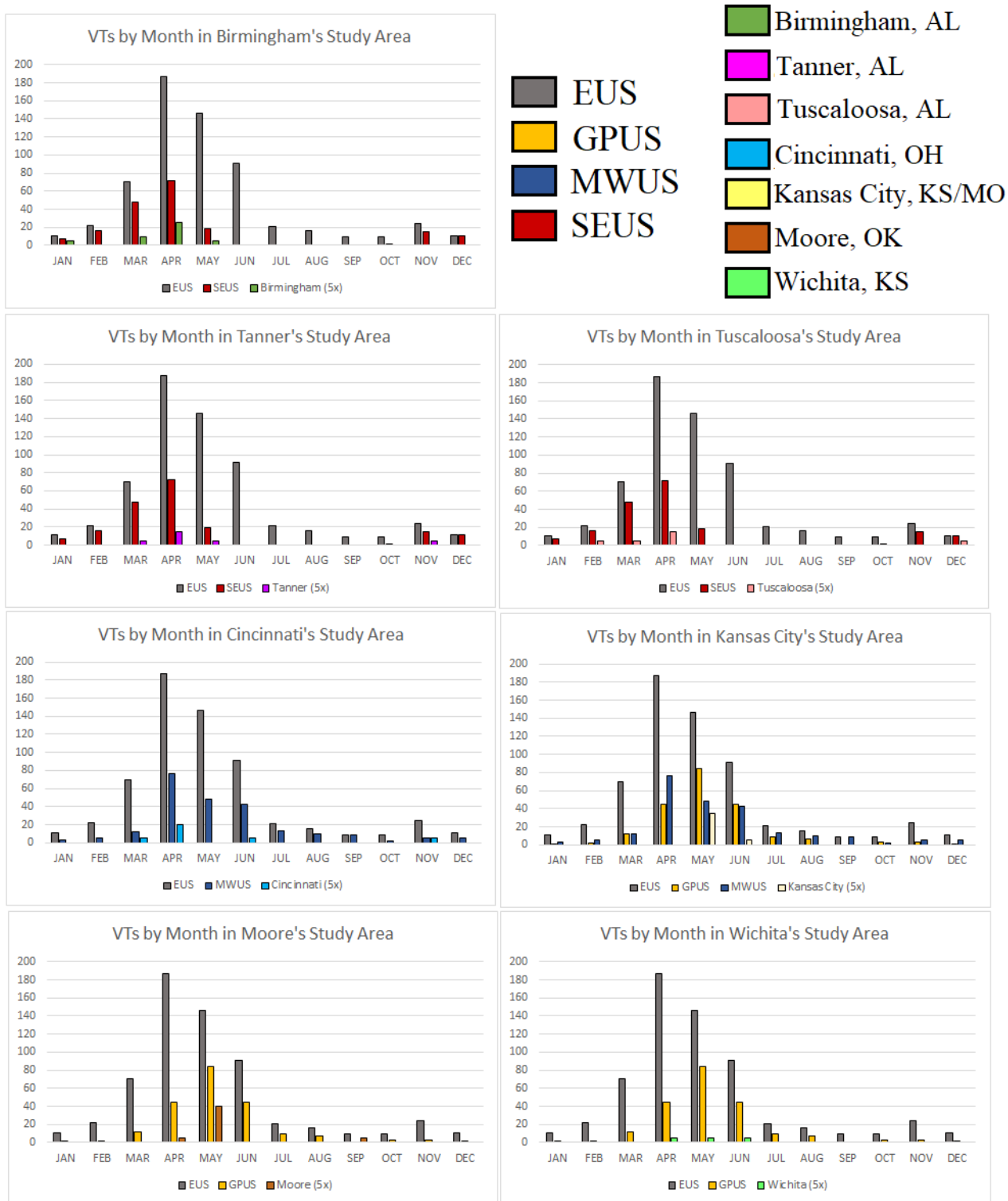


Figure 9. Monthly VT averages for the seven city's study areas

b. Pearson Correlation: climate indices and regional tornado frequency

i. *Results for > EF0 tornado frequency*

The entire EUS was tested alongside the climate indices first to establish a baseline relationship between each climate index and > EF0 frequency for the whole study area (Table 19.) The greatest level of significance was found between tornado frequency in April and the ONI. This significance was present between tornadic frequency and both the anomaly and standardized ONI datasets, with the correlations for the latter being only 0.001-0.002 lower. The ONI anomaly tri-monthly index values for April (JFM) and May (FMA) had the greatest impact on > EF0 tornado frequency in April (0.427). This significance was not present for the remaining two months, May and June. The greatest correlation coefficient for May in the EUS was found using the AO tri-monthly index for May (FMA), 0.204. In contrast, June tornadoes had the greatest relationship with the June (MAM) RMM index value.

It should be noted that the significance is not always greatest between a tornado month and its adjacent tri-monthly index. For example, the relationship between the PNA index value for June (MAM) has a more-significant relationship with April tornado frequency (-0.269) than the April (JFM) index (-0.231) (Table 19.) Thus, it's possible that the monthly value or phase of a climate index early on in the month impacts regional climatology later in that same month.

The GPUS' most significant correlation was between its tornado frequency in April and the PNA May (FMA) index, -0.390. For May, there was no relationship with any of the indices' tri-monthly values > 0.20. June's largest coefficient was -0.294 for its correlation with the RMM's April (JFM) index. Its relationship with the June (MAM) index for this dataset was slightly less significant, at 0.278. Regardless, only the GPUS' frequency of tornadoes in April had coefficient values > 0.3 (Table 19.)

Table 19. The relationship between the chosen climate indices and > EF0 tornado frequency in the EUS and GPUS using correlation analyses

EUS EF0< Tornadoes and Climate Indices				GPUS EF0< Tornadoes and Climate Indices			
<i>Index</i>	<i>Tri-Monthly Index Value</i>			<i>Index</i>	<i>Tri-Monthly Index Value</i>		
<i>AO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.138	0.274	0.251	April Tornadoes	0.047	0.048	0.095
May Tornadoes	0.202	0.204	0.069	May Tornadoes	0.119	0.183	0.079
June Tornadoes	0.070	0.034	-0.009	June Tornadoes	0.063	-0.046	-0.098
<i>NAO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>NAO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.041	0.164	0.080	April Tornadoes	-0.034	-0.008	-0.024
May Tornadoes	0.112	0.144	-0.054	May Tornadoes	0.028	0.144	-0.017
June Tornadoes	-0.041	0.023	-0.045	June Tornadoes	-0.151	-0.126	-0.076
<i>ONI (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>ONI (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.257	-0.249	-0.233	April Tornadoes	-0.130	-0.135	-0.140
May Tornadoes	0.077	0.052	0.022	May Tornadoes	0.092	0.117	0.154
June Tornadoes	0.157	0.159	0.165	June Tornadoes	0.083	0.089	0.096
<i>PDO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>PDO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.229	-0.216	-0.184	April Tornadoes	-0.265	-0.279	-0.288
May Tornadoes	0.064	0.075	0.071	May Tornadoes	0.056	0.074	0.084
June Tornadoes	0.062	0.070	0.115	June Tornadoes	-0.105	-0.114	-0.083
<i>PNA</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>PNA</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.231	-0.309	-0.269	April Tornadoes	-0.319	-0.390	-0.344
May Tornadoes	0.034	-0.050	-0.093	May Tornadoes	-0.075	-0.132	-0.104
June Tornadoes	0.141	0.166	0.207	June Tornadoes	-0.042	-0.016	0.045
<i>RMM (MJO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>RMM (MJO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.114	0.169	0.171	April Tornadoes	0.310	0.298	0.111
May Tornadoes	-0.061	-0.055	-0.010	May Tornadoes	-0.094	-0.083	-0.053
June Tornadoes	-0.350	-0.089	0.235	June Tornadoes	-0.294	0.010	0.278
<i>SOI Anomaly (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>SOI Anomaly (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.427	0.427	0.383	April Tornadoes	0.247	0.227	0.171
May Tornadoes	-0.012	0.025	0.094	May Tornadoes	-0.071	-0.071	-0.033
June Tornadoes	-0.167	-0.140	-0.024	June Tornadoes	-0.063	-0.032	0.038
<i>SOI Standardized (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>SOI Standardized (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.426	0.426	0.385	April Tornadoes	0.245	0.223	0.164
May Tornadoes	-0.013	0.023	0.096	May Tornadoes	-0.072	-0.074	-0.030
June Tornadoes	-0.169	-0.139	-0.022	June Tornadoes	-0.063	-0.029	0.041

For the MWUS, tornado frequency in April and July were significantly correlated with the three indices used for ENSO (Table 20.) All of the ONI tri-monthly indices used, April (JFM), May (FMA), and June (AMJ) had a significant relationship with tornado frequency in July ($r > 0.430$). April tornado frequency had a greater relationship with the SOI anomaly and standardized datasets, with the greatest value being with the April (JFM) tri-monthly index for

the latter ($r = 0.458$). However, April correlates positively to the SOI, while July correlates negatively. The tornado frequency for July also correlates positively with all tri-monthly indices for the PDO and PNA ($r > 0.327$). June's also has a positive relationship with the April (JFM), May (FMA), and June (MAM) indices for the PNA ($r > 0.332$) and the July (AMJ) index for the RMM (0.425). May's greatest coefficient value is with the June (MAM) index for the standardized SOI dataset (0.244). None of May's other coefficients were > 0.2 .

In the SEUS, overall the results were less significant, with few correlation coefficients being > 0.3 (Table 20.) March's tornado frequency had the greatest relationship with the March (DJF) trimonthly index for the SOI anomaly dataset (0.296). This month also had a positive relationship with the April (JFM) indexes for the AO and NAO. April's tornado frequency was most correlated with the May (FMA) index for the AO (0.330). This month also positively correlated with the March (DJF), April (JFM), and May (FMA) indices for the SOI anomaly dataset. May had a positive relationship with the AO's March (DJF) and April (JFM) indices and NAO's April (JFM) index, with no other values > 0.2 . Tornado frequency in November had the greatest correlation to the SOIs' March (DJF) index and the March (DJF), April (JFM), and May (FMA) indices for the ONI. No significant relationship existed between November's tornado frequency and the November (ASO) variable for any climate index.

Table 20. The relationship between the chosen climate indices and > EF0 tornado frequency in the MWUS and SEUS using correlation analyses

MWUS EF0< Tornadoes and Climate Indices					SEUS EF0< Tornadoes and Climate Indices				
<i>Index</i>	<i>Tri-Monthly Index Value</i>				<i>Index</i>	<i>Tri-Monthly Index Value</i>			
<i>AO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>AO</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.064	0.074	0.103	0.240	March Tornadoes	0.236	0.244	0.239	0.147
May Tornadoes	0.105	0.147	0.083	-0.133	April Tornadoes	0.072	0.202	0.330	0.080
June Tornadoes	-0.044	-0.014	-0.017	-0.064	May Tornadoes	0.223	0.222	0.100	0.216
July Tornadoes	-0.069	-0.067	-0.074	-0.119	November Tornadoes	0.087	0.043	-0.078	0.146
<i>NAO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>NAO</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.133	-0.008	0.030	0.135	March Tornadoes	0.192	0.240	0.119	0.093
May Tornadoes	-0.006	0.091	0.008	-0.095	April Tornadoes	0.004	0.128	0.234	0.011
June Tornadoes	-0.037	0.037	-0.094	-0.125	May Tornadoes	0.145	0.226	0.059	0.026
July Tornadoes	0.013	0.113	0.178	0.165	November Tornadoes	0.267	0.177	0.142	-0.167
<i>ONI (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>ONI (ENSO)</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.306	-0.312	-0.301	-0.230	March Tornadoes	-0.250	-0.256	-0.236	0.036
May Tornadoes	0.066	0.021	-0.028	-0.102	April Tornadoes	-0.166	-0.175	-0.159	-0.198
June Tornadoes	0.189	0.174	0.156	0.079	May Tornadoes	0.040	-0.005	-0.064	-0.245
July Tornadoes	0.439	0.473	0.471	0.432	November Tornadoes	0.275	0.278	0.277	-0.033
<i>PDO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>PDO</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.054	-0.085	-0.130	-0.153	March Tornadoes	-0.101	-0.080	-0.077	-0.069
May Tornadoes	0.014	0.029	0.029	0.019	April Tornadoes	-0.196	-0.194	-0.156	-0.168
June Tornadoes	0.187	0.201	0.229	0.215	May Tornadoes	0.061	0.061	0.051	-0.032
July Tornadoes	0.327	0.366	0.383	0.373	November Tornadoes	0.134	0.202	0.221	0.111
<i>PNA</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>PNA</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.202	-0.292	-0.342	-0.391	March Tornadoes	-0.015	-0.090	-0.078	0.174
May Tornadoes	0.006	-0.081	-0.161	-0.131	April Tornadoes	-0.134	-0.111	-0.154	0.111
June Tornadoes	0.300	0.320	0.296	0.085	May Tornadoes	0.110	0.158	0.115	0.100
July Tornadoes	0.400	0.404	0.332	0.411	November Tornadoes	0.189	0.283	0.249	-0.140
<i>RMM (MJO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>RMM (MJO)</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	-0.125	0.051	0.079	0.103	March Tornadoes	0.035	-0.039	-0.055	0.043
May Tornadoes	0.150	0.137	0.098	-0.095	April Tornadoes	0.037	0.090	0.112	0.203
June Tornadoes	-0.269	-0.132	0.156	0.424	May Tornadoes	-0.002	-0.130	-0.121	0.300
July Tornadoes	-0.053	-0.122	-0.238	-0.067	November Tornadoes	-0.122	-0.087	-0.070	0.046
<i>SOI Anomaly (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>SOI Anomaly (ENSO)</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	0.457	0.426	0.354	0.227	March Tornadoes	0.296	0.229	0.174	-0.002
May Tornadoes	0.087	0.163	0.243	0.123	April Tornadoes	0.301	0.300	0.320	0.172
June Tornadoes	-0.201	-0.177	-0.062	0.136	May Tornadoes	-0.023	0.004	0.034	0.252
July Tornadoes	-0.365	-0.359	-0.425	-0.424	November Tornadoes	-0.284	-0.242	-0.250	-0.001
<i>SOI Standardized (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>	<i>AMJ</i>	<i>SOI Standardized (ENSO)</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
April Tornadoes	0.458	0.429	0.356	0.227	March Tornadoes	0.279	0.228	0.172	-0.004
May Tornadoes	0.088	0.162	0.244	0.119	April Tornadoes	0.285	0.299	0.320	0.172
June Tornadoes	-0.204	-0.178	-0.061	0.140	May Tornadoes	-0.032	0.004	0.033	0.252
July Tornadoes	-0.365	-0.359	-0.422	-0.422	November Tornadoes	-0.286	-0.243	-0.251	0.000

ii. Results for VT frequency

Similar to the previous trial, the EUS was tested first to determine the relationship between climate indices and VT frequency over the whole study area. Like the prior results, April tornado frequency over the entire EUS appears to have the greatest relationship with ENSO, as suggested by the correlation results with the SOI datasets (Table 21.) The correlation coefficient is highest between April VT frequency and the April (JFM) SOI indices (0.360), followed by the May (FMA) and June (MAM) indices from the same dataset (0.331 and 0.310, respectively). While significant, these variables are lower than the correlation between the same indices and > EF0 tornado frequency during these months (Table 19.) In contrast, the relationship between the PDO's June (MAM) index and April tornadoes increased -0.216. Similarly, the coefficient between NAO's May (FMA) index and April VT frequency increased (-0.238). No other months had coefficients > 0.2.

The correlation tests between GPUS' VT frequency and climate indices did not yield any coefficients > 0.3 (Table 21.) Unlike the previous trial, there was not a significant correlation between April tornado frequency and the PNA's May (FMA) index, which was the most significant relationship in the previous test (Table 19.) However, tests yielded higher r-values for May's VT frequency. The highest value was between May and the June (MAM) index for AO (-0.269). Also higher was the relationship between May and the April (JFM) index for the RMM. June's largest r-value was lower in this trial than in the previous, but for the same tri-monthly index value, PNA's JFM (0.212). No other r-values for June were > 0.2.

Table 21. The relationship between the chosen climate indices and VT frequency in the EUS and GPUS using correlation analyses

EUS VTs and Climate Indices				GPUS VTs and Climate Indices			
Index	Tri-Monthly Index Value			Index	Tri-Monthly Index Value		
	JFM	FMA	MAM		JFM	FMA	MAM
April Tornadoes	-0.028	0.044	0.090	April Tornadoes	-0.055	-0.121	-0.077
May Tornadoes	-0.021	-0.018	-0.115	May Tornadoes	-0.170	-0.171	-0.269
June Tornadoes	0.021	0.052	0.040	June Tornadoes	0.057	0.048	0.040
NAO				NAO			
April Tornadoes	-0.162	-0.238	-0.170	April Tornadoes	-0.189	-0.071	-0.044
May Tornadoes	-0.073	-0.032	0.086	May Tornadoes	-0.042	-0.028	0.037
June Tornadoes	-0.027	0.099	0.074	June Tornadoes	0.137	0.120	0.150
ONI (ENSO)				ONI (ENSO)			
April Tornadoes	-0.280	-0.265	-0.238	April Tornadoes	-0.004	0.037	0.074
May Tornadoes	-0.039	-0.075	-0.102	May Tornadoes	-0.016	-0.062	-0.119
June Tornadoes	0.120	0.148	0.149	June Tornadoes	-0.037	-0.019	0.005
PDO				PDO			
April Tornadoes	-0.179	-0.185	-0.216	April Tornadoes	0.007	0.004	0.041
May Tornadoes	-0.122	-0.061	-0.006	May Tornadoes	-0.144	-0.106	-0.102
June Tornadoes	-0.117	-0.129	-0.151	June Tornadoes	-0.068	-0.060	-0.048
PNA				PNA			
April Tornadoes	-0.101	-0.088	-0.112	April Tornadoes	0.126	0.094	0.078
May Tornadoes	-0.076	-0.019	-0.034	May Tornadoes	-0.076	-0.126	-0.140
June Tornadoes	-0.167	-0.127	-0.144	June Tornadoes	-0.212	-0.113	-0.018
RMM (MJO)				RMM (MJO)			
April Tornadoes	-0.089	-0.032	0.054	April Tornadoes	0.073	0.030	-0.080
May Tornadoes	-0.107	0.045	-0.017	May Tornadoes	-0.256	0.003	0.035
June Tornadoes	0.007	0.067	0.333	June Tornadoes	0.012	0.061	0.036
SOI Anomaly (ENSO)				SOI Anomaly (ENSO)			
April Tornadoes	0.360	0.331	0.308	April Tornadoes	-0.002	-0.057	-0.095
May Tornadoes	0.104	0.146	0.136	May Tornadoes	0.034	0.084	0.137
June Tornadoes	-0.115	-0.065	-0.025	June Tornadoes	0.025	0.039	-0.003
SOI Standardized (ENSO)				SOI Standardized (ENSO)			
April Tornadoes	0.360	0.331	0.310	April Tornadoes	-0.003	-0.062	-0.100
May Tornadoes	0.101	0.145	0.135	May Tornadoes	0.028	0.080	0.134
June Tornadoes	-0.116	-0.063	-0.024	June Tornadoes	0.026	0.044	-0.002

VT frequency in the MWUS was less correlated to the ENSO than was > EF0 tornado frequency, with the largest r-values being < 0.270 for tests using the SOI datasets. April's VT frequency had a greater correlation to the RMM's April (JFM) index (-0.371), larger than for April's > EF0 frequency (-0.125) (Table 22.) May's most significant correlation was with the NAO's April (JFM) index (-0.167). This was much larger than the correlation between the latter and May's > EF0 tornado frequency (-0.006) (Table 20.) June's correlation with this index was -0.167, larger than the value in the previous trial (-0.037). However, no coefficients for May or June were > 0.2 . (Table 22.) Although these relationships were statistically insignificant, it's possible the MJO and NAO play a larger role in VT frequency than in > EF0 tornado frequency in the MWUS

Table 22. The relationship between the chosen climate indices and VT frequency in the MWUS using correlation analyses

MWUS VTs and Climate Indices			
<i>Index</i>	<i>Tri-Monthly Index Value</i>		
<i>AO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.028	0.020	0.067
May Tornadoes	0.031	0.084	0.072
June Tornadoes	-0.043	0.012	0.023
<i>NAO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.196	-0.242	-0.159
May Tornadoes	-0.167	-0.122	0.047
June Tornadoes	-0.167	0.010	-0.034
<i>ONI (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.207	-0.209	-0.179
May Tornadoes	-0.017	-0.008	0.026
June Tornadoes	0.183	0.205	0.173
<i>PDO</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.131	-0.132	-0.158
May Tornadoes	0.038	0.088	0.151
June Tornadoes	-0.059	-0.087	-0.139
<i>PNA</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.118	-0.102	-0.113
May Tornadoes	0.068	0.122	0.076
June Tornadoes	-0.048	-0.075	-0.153
<i>RMM (MJO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	-0.371	-0.206	-0.136
May Tornadoes	0.113	0.073	-0.124
June Tornadoes	0.001	0.046	0.429
<i>SOI Anomaly (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.264	0.227	0.177
May Tornadoes	0.086	0.097	-0.008
June Tornadoes	-0.182	-0.113	0.015
<i>SOI Standardized (ENSO)</i>	<i>JFM</i>	<i>FMA</i>	<i>MAM</i>
April Tornadoes	0.266	0.231	0.182
May Tornadoes	0.087	0.098	-0.006
June Tornadoes	-0.183	-0.113	0.016

The results for the SEUS were similar to those of the prior trial using $> EF0$ tornadoes, with ENSO appearing to have the greatest influence over VT frequency. However, there were still few r -values over 0.3. (Table 23.) February's VT frequency in the SEUS appears to correlate most with the April (JFM) and May (FMA) indices for the PDO and ENSO ($r > -0.215$), and the February (NDJ) index for the PNA (-0.216). The highest coefficient for February was with the May (FMA) ONI index, at -0.274.

VT frequency in April had the highest correlation to the February (NDJ), March (DJF), April (JFM), and May (FMA) indices for the SOI anomaly dataset (0.374, 0.354, 0.357, and 0.358, respectively). These values were higher than those for the same variables in the previous tests with $> EF0$ frequency (Table 20.) Thus, it's possible that the ENSO has a greater influence over VT frequency than $> EF0$ frequency in April throughout the SEUS. However, unlike April, March's relationship with the SOI is less evident in this trial than the previous, with no r -value surpassing -0.2.

May's VT frequency had the greatest correlation to the AO's April (JFM) index (0.240), with no other values > 0.2 . VT frequency in November correlated negatively to the RMM's February (NDJ) index (-0.256). November was also found to correlate with ENSO, with the greatest correlation being between this month's VT frequency and ONI's May (FMA) index (0.211). In contrast, it correlated negatively with all SOI indices except for the SOIs' November (ASO) indices (Table 23.) Furthermore, November's correlation coefficients are more significant between the month and the February (NDJ) and/or March (DJF) trimonthly climate indices compared to the November (ASO) values for all climate variables except the PDO.

Table 23. The relationship between the chosen climate indices and VT frequency in the SEUS using correlation analyses

SEUS VTs and Climate Indices					
<i>Index</i>	<i>Tri-Monthly Index Value</i>				
<i>AO</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	0.079	0.074	0.005	-0.047	0.205
March Tornadoes	0.129	0.125	0.041	-0.006	-0.024
April Tornadoes	-0.127	-0.093	0.002	0.093	-0.117
May Tornadoes	0.045	0.175	0.240	0.138	0.152
November Tornadoes	0.091	0.096	0.061	-0.017	0.075
<i>NAO</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	0.031	0.001	-0.065	-0.122	0.073
March Tornadoes	0.047	0.106	0.075	0.001	0.004
April Tornadoes	-0.206	-0.105	-0.017	0.024	0.029
May Tornadoes	-0.068	0.052	0.172	0.039	-0.008
November Tornadoes	0.045	0.100	0.069	0.096	-0.089
<i>ONI (ENSO)</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	-0.166	-0.219	-0.247	-0.274	-0.072
March Tornadoes	-0.020	-0.018	-0.011	0.013	0.122
April Tornadoes	-0.280	-0.258	-0.267	-0.253	-0.160
May Tornadoes	0.003	0.002	-0.023	-0.062	-0.194
November Tornadoes	0.119	0.149	0.179	0.211	-0.065
<i>PDO</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	-0.149	-0.190	-0.217	-0.235	-0.194
March Tornadoes	0.048	0.026	0.022	0.032	0.113
April Tornadoes	-0.191	-0.199	-0.186	-0.161	-0.079
May Tornadoes	-0.050	-0.075	-0.058	-0.062	-0.095
November Tornadoes	-0.023	0.003	0.036	0.054	0.084
<i>PNA</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	-0.216	-0.185	-0.135	-0.045	0.086
March Tornadoes	-0.096	-0.065	-0.011	0.103	0.123
April Tornadoes	-0.151	-0.108	-0.117	-0.080	0.183
May Tornadoes	-0.030	0.021	0.016	0.054	-0.013
November Tornadoes	0.180	0.096	0.179	0.124	-0.033
<i>RMM (MJO)</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	-0.037	-0.076	-0.114	-0.149	0.244
March Tornadoes	-0.145	0.049	-0.115	-0.135	-0.103
April Tornadoes	0.003	0.000	0.010	0.032	-0.159
May Tornadoes	0.046	-0.004	-0.076	-0.018	-0.064
November Tornadoes	-0.256	-0.160	-0.083	0.112	0.130
<i>SOI Anomaly (ENSO)</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	0.146	0.201	0.224	0.256	0.225
March Tornadoes	-0.057	0.006	-0.009	-0.016	-0.119
April Tornadoes	0.374	0.354	0.357	0.358	0.209
May Tornadoes	0.021	0.006	0.079	0.095	0.120
November Tornadoes	-0.123	-0.152	-0.167	-0.142	0.007
<i>SOI Standardized (ENSO)</i>	<i>NDJ</i>	<i>DJF</i>	<i>JFM</i>	<i>FMA</i>	<i>ASO</i>
February Tornadoes	0.145	0.197	0.222	0.255	0.226
March Tornadoes	-0.060	0.003	-0.008	-0.017	-0.118
April Tornadoes	0.355	0.342	0.355	0.357	0.210
May Tornadoes	0.013	-0.001	0.079	0.097	0.123
November Tornadoes	-0.127	-0.156	-0.169	-0.143	0.010

c. Generalized linear models: climate indices and regional tornado frequency

i. *Results for > EF0 tornado frequency*

Unlike the results of the Pearson’s Correlation tests done on the EUS, generalized linear modeling showed mostly insignificant relationships between monthly total tornado (> EF0) frequency and the chosen climate indices. For this analysis, only the model for April had a significant Omnibus Test value ($\alpha < 0.05$), indicating this model is a better fit than the null model, or intercept. The only significant relationship was between > EF0 tornado frequency in June and the April MJO tri-monthly index ($\alpha < 0.05$) (Table 24.) The relationship between April > EF0 frequency and the April MJO tri-monthly index was only slightly above the significance threshold, at 0.052.

Table 24. The relationship between seasonal climate indices and > EF0 frequency in the EUS using generalized linear modeling

Model (Omnibus Test Sig.)	EUS (Tornado Month VS Seasonal Climate Indices)		
	April	May	June
	Tweedie 1.75 (0.004)	Tweedie 1.77 (0.376)	Tweedie 1.75 (0.121)
	Significance	Significance	Significance
AO (JFM)	0.203	0.249	1
AO (FMA)	0.971	0.886	0.388
AO (MAM)	0.072	0.335	0.727
NAO (JFM)	0.357	0.576	0.891
NAO (FMA)	0.743	0.319	0.727
NAO (MAM)	0.491	0.675	0.561
MJO (JFM)	0.051	0.568	0.013
MJO (FMA)	0.212	0.430	0.146
MJO (MAM)	0.554	0.194	0.672
ONI (JFM)	0.226	0.185	0.470
ONI (FMA)	0.412	0.598	0.511
ONI (MAM)	0.564	0.886	0.300
PDO (JFM)	0.329	0.904	0.385
PDO (FMA)	0.300	0.879	0.393
PDO (MAM)	0.311	0.632	0.551
PNA (JFM)	0.659	0.113	0.539
PNA (FMA)	0.745	0.692	0.395
PNA (MAM)	0.276	0.074	0.274
ASOI (JFM)	0.074	0.485	0.157
ASOI (FMA)	0.250	0.552	0.120
ASOI (MAM)	0.181	0.053	0.073

In models using only the corresponding tri-monthly indices, their relationship with monthly > EF0 tornado activity was more apparent. The results here were also more similar with trends seen in the correlation analyses, with significant relationships between tornado activity and the AO, PNA and SOI anomaly indices (Table 25.) In all cases, a single significant relationship with a certain climate index was not apparent for all months. Regardless, only the model for month of April had a significant Omnibus Test value.

Table 25. The relationship between monthly climate indices and > EF0 frequency in the EUS using generalized linear modeling

EUS (Tornado Month VS Corresponding Tri-monthly Indices)			
	April (JFM)	May (FMA)	June (MAM)
Model (Omnibus Test Sig.)	Tweedie 1.75 (0.004)	Tweedie 1.77 (0.655)	Tweedie 1.70 (0.077)
	Significance	Significance	Significance
AO	0.505	0.319	0.046
NAO	0.962	0.524	0.104
MJO	0.546	0.426	0.82
ONI	0.421	0.116	0.162
PDO	0.488	0.613	0.822
PNA	0.572	0.649	0.029
ASOI	0.042	0.063	0.18

Model results for the GPUS yielded more significant values between > EF0 tornado activity and seasonal tri-monthly indices. For this test series, only June’s model had a significant Omnibus Test value. In contrast to the previous analyses using correlation, tornado activity in June appears to be heavily influenced by climate indices, having significant relationships with tri-monthly indices from the AO, NAO, ONI, PDO and PNA (Table 26.) Here, May is also significantly related to the NAO and PNA. Like with the EUS’s models, April had the fewest significant values.

Table 26. The relationship between seasonal climate indices and > EF0 frequency in the GPUS using generalized linear modeling

GPUS (Tornado Month VS Seasonal Tri-monthly Indices)			
	April	May	June
Model (Omnibus Test Sig.)	Tweedie 1.77 (0.403)	Tweedie 1.68 (0.077)	Tweedie 1.5 (0.001)
	Significance	Significance	Significance
AO (JFM)	0.870	0.117	0.000
AO (FMA)	0.231	0.524	0.001
AO (MAM)	0.199	0.441	0.064
NAO (JFM)	0.396	0.001	0.000
NAO (FMA)	0.462	0.077	0.001
NAO (MAM)	0.348	0.248	0.296
MJO (JFM)	0.943	0.665	0.116
MJO (FMA)	0.422	0.935	0.283
MJO (MAM)	0.994	0.065	0.081
ONI (JFM)	0.988	0.430	0.315
ONI (FMA)	0.994	0.371	0.045
ONI (MAM)	0.954	0.487	0.003
PDO (JFM)	0.177	0.090	0.070
PDO (FMA)	0.132	0.188	0.007
PDO (MAM)	0.166	0.508	0.005
PNA (JFM)	0.910	0.023	0.162
PNA (FMA)	0.906	0.039	0.139
PNA (MAM)	0.156	0.485	0.010
ASOI (JFM)	0.288	0.236	0.788
ASOI (FMA)	0.101	0.759	0.266
ASOI (MAM)	0.044	0.733	0.913

Unlike the results from EUS models, using only the corresponding tri-monthly indices as independent variables in the GPUS models resulted in less-significant values compared to those using all seasonal tri-monthly indices (Table 27.) Furthermore, none of the models had a significant Omnibus Test value. Here, the only significant relationship was between May and the PNA, quantified at 0.047. In contrast to the previous test, June was not influenced by any of the corresponding tri-monthly climate indices (Tables 26 & 27.)

Table 27. The relationship between monthly climate indices and > EF0 frequency in the GPUS using generalized linear modeling

GPUS (Tornado Month VS Corresponding Tri-monthly Indices)			
	April (JFM)	May (FMA)	June (MAM)
Model (Omnibus Test Sig.)	Tweedie 1.77 (0.717)	Tweedie 1.68 (0.143)	Tweedie 1.63 (0.884)
	Significance	Significance	Significance
AO	0.988	0.807	0.659
NAO	0.829	0.842	0.372
MJO	0.735	0.838	0.535
ONI	0.658	0.856	0.317
PDO	0.951	0.18	0.159
PNA	0.389	0.047	0.81
ASOI	0.550	0.076	0.529

MWUS models show a large amount of influence of tri-monthly climate indices over seasonal > EF0 frequency. However, the primary influencers and degree of influence varied by month (Table 28.) The models for all months had significant Omnibus Test values. Furthermore, both April and July were significantly correlated to at least one tri-monthly variable for every climate index. > EF0 frequency in May was found to be significantly related to the NAO, MJO, ONI, PNA and SOI anomaly indices. June was the least-influenced month, with significant relationships only to the NAO and PDO.

Table 28. The relationship between seasonal climate indices and > EF0 frequency in the MWUS using generalized linear modeling

MWUS (Tornado Month VS Seasonal Tri-monthly Indices)				
	April	May	June	July
Model (Omnibus Test Sig.)	Tweedie 1.76 (0.000)	Tweedie 1.96 (0.008)	Tweedie 1.83 (0.001)	Tweedie 1.39 (0.000)
	Significance	Significance	Significance	Significance
AO (JFM)	0.457	0.151	0.792	0.020
AO (FMA)	0.017	0.168	0.810	0.000
AO (MAM)	0.069	0.072	0.392	0.339
AO (AMJ)	0.110	0.779	0.630	0.013
NAO (JFM)	0.271	0.088	0.043	0.688
NAO (FMA)	0.000	0.340	0.023	0.003
NAO (MAM)	0.041	0.016	0.100	0.296
NAO (AMJ)	0.099	0.622	0.873	0.000
MJO (JFM)	0.045	0.645	0.362	0.019
MJO (FMA)	0.397	0.117	0.729	0.013
MJO (MAM)	0.506	0.014	0.214	0.731
MJO (AMJ)	0.016	0.571	0.522	0.000
ONI (JFM)	0.164	0.013	0.303	0.304
ONI (FMA)	0.476	0.007	0.571	0.488
ONI (MAM)	0.041	0.006	0.564	0.142
ONI (AMJ)	0.003	0.013	0.532	0.000
PDO (JFM)	0.640	0.518	0.001	0.047
PDO (FMA)	0.041	0.500	0.001	0.297
PDO (MAM)	0.000	0.638	0.006	0.000
PDO (AMJ)	0.040	0.377	0.009	0.000
PNA (JFM)	0.002	0.248	0.051	0.006
PNA (FMA)	0.517	0.648	0.840	0.068
PNA (MAM)	0.000	0.002	0.234	0.128
PNA (AMJ)	0.000	0.995	0.393	0.010
ASOI (JFM)	0.833	0.142	0.278	0.002
ASOI (FMA)	0.037	0.058	0.290	0.002
ASOI (MAM)	0.026	0.039	0.496	0.238
ASOI (AMJ)	0.002	0.960	0.107	0.204

In contrast to the MWUS models using all seasonal tri-monthly indices, models using tri-monthly indices corresponding to the chosen months saw a greater number of significant relationships between the independent variables with May and June (Table 29.) For these tests, only May’s model did not have a significant Omnibus Test value. Here, June was significantly related to the AO, NAO, and PNA, with May being significantly related to only the ONI and SOI anomaly indices. April was only significantly related to the SOI anomaly, with July only being significantly related to the NAO.

Table 29. The relationship between monthly climate indices and > EF0 frequency in the MWUS using generalized linear modeling

MWUS (Tornado Month VS Corresponding Tri-monthly Indices)				
	April (JFM)	May (FMA)	June (MAM)	July (AMJ)
Model (Omnibus Test Sig.)	Tweedie 1.84 (0.026)	Tweedie 1.82 (0.162)	Tweedie 1.78 (0.044)	Tweedie 1.65 (0.001)
	Significance	Significance	Significance	Significance
AO	0.224	0.78	0.028	0.083
NAO	0.374	0.999	0.005	0.042
MJO	0.104	0.864	0.469	0.181
ONI	0.244	0.011	0.646	0.172
PDO	0.134	0.259	0.964	0.656
PNA	0.311	0.898	0.014	0.966
ASOI	0.023	0.003	0.546	0.564

For models analyzing the SEUS using all tri-monthly indices, there was a clear relationship between the region's > EF0 activity in April and May and the AO (Table 30.) However, only May's model had a significant Omnibus Test value. Both months also appear to be related to the NAO. March was only found to be significantly related to the tri-monthly PDO index for April but had the least significant Omnibus Test value of the three models.

Table 30. The relationship between seasonal climate indices and > EF0 frequency in the SEUS using generalized linear modeling

SEUS (Tornado Month VS Seasonal Tri-monthly Indices)			
	March	April	May
Model (Omnibus Test Sig.)	Tweedie 1.78 (0.318)	Tweedie 1.77 (0.191)	Tweedie 1.87 (0.002)
	Significance	Significance	Significance
AO (DJF)	0.114	0.005	0.014
AO (JFM)	0.214	0.001	0.020
AO (FMA)	0.152	0.010	0.013
NAO (DJF)	0.511	0.007	0.021
NAO (JFM)	0.752	0.001	0.014
NAO (FMA)	<i>0.098</i>	0.007	<i>0.056</i>
MJO (DJF)	0.899	0.648	0.441
MJO (JFM)	0.468	0.771	<i>0.060</i>
MJO (FMA)	0.349	0.951	0.006
ONI (DJF)	0.861	0.121	0.735
ONI (JFM)	0.817	0.332	0.416
ONI (FMA)	0.512	0.997	0.146
PDO (DJF)	<i>0.092</i>	0.852	<i>0.090</i>
PDO (JFM)	0.026	0.797	0.258
PDO (FMA)	<i>0.051</i>	0.546	0.969
PNA (DJF)	0.149	0.678	0.500
PNA (JFM)	<i>0.073</i>	0.163	0.299
PNA (FMA)	0.138	0.804	0.112
ASOI (DJF)	0.972	0.850	0.132
ASOI (JFM)	0.306	0.192	0.364
ASOI (FMA)	<i>0.054</i>	<i>0.055</i>	0.403

November's model for the SEUS included the November (ASO) indices, so it was created separately from the other three months' models. For November's model, the Omnibus Test was significant. However, there were no significant relationships between > EF0 activity in November and any of the tri-monthly climate indices (Table 31.) This suggests that springtime climate indices do not have a significant impact on > EF0 tornado activity in November, contrasting previous tests (Table 23.)

Table 31. The relationship between seasonal climate indices and November > EF0 frequency in the SEUS using generalized linear modeling

SEUS (VT Month VS Seasonal Tri-monthly Indices)	
	November
Model (Omnibus Test Sig.)	Negative Binomial 0.85 (0.004)
	Significance
AO (DJF)	0.744
AO (JFM)	0.550
AO (FMA)	0.444
AO (ASO)	0.791
NAO (DJF)	0.568
NAO (JFM)	0.309
NAO (FMA)	0.327
NAO (ASO)	0.057
MJO (DJF)	0.174
MJO (JFM)	0.421
MJO (FMA)	0.510
MJO (ASO)	0.712
ONI (DJF)	0.798
ONI (JFM)	0.759
ONI (FMA)	0.951
ONI (ASO)	0.765
PDO (DJF)	0.493
PDO (JFM)	0.671
PDO (FMA)	0.884
PDO (ASO)	0.416
PNA (DJF)	0.377
PNA (JFM)	0.091
PNA (FMA)	0.057
PNA (ASO)	0.714
ASOI (DJF)	0.283
ASOI (JFM)	0.905
ASOI (FMA)	0.647
ASOI (ASO)	0.053

SEUS Models calculating the relationship between monthly > EF0 activity and their corresponding climate indices indicate a fluctuation in the dominance of certain climate indices temporally (Table 32.) However, the only two months with significant Omnibus Test values were November and May. In contrast to the previous test, here November's > EF0 activity was significantly related to the AO, NAO and PDO, not the PNA. Furthermore, May's > EF0 activity

appears to be primarily influenced by the MJO, PNA, and SOI anomaly. April was not found to be significantly correlated to any index.

Table 32. The relationship between monthly climate indices and > EF0 frequency in the SEUS using generalized linear modeling

SEUS (Tornado Month VS Corresponding Tri-monthly Indices)				
	March (DJF)	April (JFM)	May (FMA)	November (ASO)
Model (Omnibus Test Sig.)	Tweedie 1.80 (0.262)	Tweedie 1.76 (0.461)	Tweedie 1.84 (0.001)	Negative Binomial 0.85 (0.001)
	Significance	Significance	Significance	Significance
AO	0.593	0.075	0.221	0.019
NAO	0.538	0.107	0.489	0.002
MJO	0.579	0.995	0.018	0.34
ONI	0.035	0.836	0.092	0.371
PDO	0.434	0.507	0.37	0.008
PNA	0.083	0.081	0.002	0.874
ASOI	0.938	0.410	0.011	0.114

ii. Results for VT frequency

Models analyzing EUS VT activity during the region’s most-active months yielded more significant values than those using tornadoes > EF0 (Tables 24 & 33.) However, only the month of June had a significant Omnibus Test value. June also had the greatest number of significant relationships, including with tri-monthly indices from the NAO, ONI, PNA, and SOI anomaly. A relationship between June VT frequency and the June SOI anomaly index was the only common denominator between these models and those analyzing > EF0 frequency.

Table 33. The relationship between seasonal climate indices and VT frequency in the EUS using generalized linear modeling

EUS (VT Month VS Seasonal Tri-monthly Indices)			
Model (Omnibus Test Sig.)	April	May	June
	Negative Binomial 1.35 (0.760)	Negative Binomial 1.2 (0.441)	Normal Identity (0.000)
	Significance	Significance	Significance
AO (JFM)	0.471	0.897	0.429
AO (FMA)	0.472	0.074	0.992
AO (MAM)	0.701	0.025	0.090
NAO (JFM)	0.854	0.187	0.065
NAO (FMA)	0.460	0.594	0.019
NAO (MAM)	0.892	0.958	0.000
MJO (JFM)	0.040	0.220	0.678
MJO (FMA)	0.329	0.251	0.255
MJO (MAM)	0.470	0.284	0.154
ONI (JFM)	0.637	0.693	0.000
ONI (FMA)	0.476	0.477	0.000
ONI (MAM)	0.638	0.101	0.012
PDO (JFM)	0.385	0.894	0.208
PDO (FMA)	0.401	0.650	0.127
PDO (MAM)	0.375	0.466	0.369
PNA (JFM)	0.704	0.601	0.506
PNA (FMA)	0.613	0.360	0.009
PNA (MAM)	0.950	0.164	0.616
ASOI (JFM)	0.240	0.721	0.820
ASOI (FMA)	0.252	0.632	0.283
ASOI (MAM)	0.563	0.734	0.008

Models analyzing VT months to their corresponding tri-monthly indices yielded a fewer number of significant relationships. Again, only June’s model had a significant Omnibus Test result. Still, none of the climate indices were found to be related to June at the chosen confidence interval (Table 34.) Despite its insignificant Omnibus Test value, April’s model was found to have a significant relationship between that month’s VT activity and the MJO. May’s model had neither a significant Omnibus Test value nor any significant relationships.

Table 34. The relationship between monthly climate indices and VT frequency in the EUS using generalized linear modeling

EUS (VT Month VS Corresponding Tri-monthly Indices)			
	April (JFM)	May (FMA)	June (MAM)
Model (Omnibus Test Sig.)	Negative Binomial 0.95 (0.137)	Negative Binomial 1.05 (0.470)	Negative Binomial 1.05 (0.034)
	Significance	Significance	Significance
AO	0.696	0.472	0.073
NAO	0.853	0.468	0.084
MJO	0.021	0.934	0.472
ONI	0.127	0.324	0.188
PDO	0.337	0.271	0.559
PNA	0.967	0.844	0.165
ASOI	0.099	0.063	0.267

None of the models analyzing monthly VT activity in the GPUS with seasonal tri-monthly indices yielded significant Omnibus Test values. Unlike the tests done on > EF0 activity for this region, June’s model had the highest Omnibus Test value and the fewest number of significant relationships with the seasonal tri-monthly indices (Tables 26, 27 & 35.) In contrast, May was found to be significantly related to the AO, and NAO, with April being linked to the NAO, and SOI anomaly indices.

Table 35. The relationship between seasonal climate indices and VT frequency in the GPUS using generalized linear modeling

GPUS (VT Month VS Seasonal Tri-monthly Indices)			
Model (Omnibus Test Sig.)	April	May	June
	Normal Identity (0.120)	Normal Identity (0.129)	Normal Identity (0.229)
	Significance	Significance	Significance
AO (JFM)	0.757	0.045	0.283
AO (FMA)	0.186	0.827	0.403
AO (MAM)	0.689	0.024	0.229
NAO (JFM)	0.018	0.014	0.125
NAO (FMA)	0.761	0.696	0.362
NAO (MAM)	0.723	0.489	0.819
MJO (JFM)	0.106	0.408	0.072
MJO (FMA)	0.353	0.452	0.555
MJO (MAM)	0.537	0.656	0.149
ONI (JFM)	0.530	0.144	0.815
ONI (FMA)	0.473	0.128	0.575
ONI (MAM)	0.613	0.230	0.334
PDO (JFM)	0.063	0.993	0.839
PDO (FMA)	0.133	0.723	0.240
PDO (MAM)	0.554	0.557	0.069
PNA (JFM)	0.583	0.138	0.969
PNA (FMA)	0.466	0.051	0.615
PNA (MAM)	0.100	0.448	0.652
ASOI (JFM)	0.050	0.709	0.251
ASOI (FMA)	0.010	0.471	0.955
ASOI (MAM)	0.044	0.733	0.913

GPUS models analyzing the relationship between monthly VT activity and each month's corresponding tri-monthly climate indices yielded no significant values (Table 36.) Additionally, none of the models had significant Omnibus Test values. These results were similar to those from the same series of tests done on the GPUS region's monthly > EF0 activity (Table 26.)

Table 36. The relationship between monthly climate indices and VT frequency in the GPUS using generalized linear modeling

GPUS (VT Month VS Corresponding Tri-monthly Indices)			
Model (Omnibus Test Sig.)	April (JFM)	May (FMA)	June (MAM)
	Negative Binomial 1.5 (0.735)	Negative Binomial 1.4 (0.918)	Negative Binomial 1.3 (0.614)
	Significance	Significance	Significance
AO	0.305	0.412	0.604
NAO	0.263	0.620	0.764
MJO	0.614	0.901	0.159
ONI	0.605	0.711	0.959
PDO	0.574	0.362	0.833
PNA	0.601	0.888	0.620
ASOI	0.844	0.823	0.211

MWUS models analyzing VTs for the most active months alongside seasonal tri-monthly climate indices yielded significant results for both May and June (Table 37.) The models for

these two months also had significant Omnibus Test values, further adding to the confidence in the effect of certain climate indices on VT activity in the latter half of the MWUS’s tornado season. May had significant relationships with one or more tri-monthly indices the MJO, ONI, and PNA, while June was significantly related to the NAO, ONI, and PNA.

Table 37. The relationship between seasonal climate indices and VT frequency in the MWUS using generalized linear modeling

MWUS (VT Month VS Seasonal Tri-monthly Indices)			
	April	May	June
Model (Omnibus Test Sig.)	Normal Identity (0.469)	Normal Identity (0.005)	Normal Identity (0.002)
	Significance	Significance	Significance
AO (JFM)	0.464	0.121	0.554
AO (FMA)	0.205	0.765	0.571
AO (MAM)	0.318	0.541	0.303
NAO (JFM)	0.884	0.435	0.145
NAO (FMA)	0.685	0.425	0.163
NAO (MAM)	0.443	0.231	0.009
MJO (JFM)	0.468	0.198	0.338
MJO (FMA)	0.673	0.022	0.440
MJO (MAM)	0.860	0.030	0.585
ONI (JFM)	0.266	0.296	0.000
ONI (FMA)	0.190	0.366	0.000
ONI (MAM)	0.417	0.021	0.040
PDO (JFM)	0.319	0.086	0.234
PDO (FMA)	0.558	0.074	0.196
PDO (MAM)	0.777	0.532	0.645
PNA (JFM)	0.460	0.135	0.389
PNA (FMA)	0.864	0.243	0.019
PNA (MAM)	0.437	0.017	0.755
ASOI (JFM)	0.713	0.215	0.228
ASOI (FMA)	0.671	0.589	0.790
ASOI (MAM)	0.735	0.613	0.211

MWUS models testing the relationship between monthly VT activity and corresponding tri-monthly climate indices for those months also yielded significant Omnibus Test values for May and June (Table 38.) However, only May’s model yielded any significant relationship values. Specifically, VT frequency in May was found to be significantly related to the PDO and SOI anomaly indices.

Table 38. The relationship between monthly climate indices and VT frequency in the MWUS using generalized linear modeling

MWUS (VT Month VS Corresponding Tri-monthly Indices)			
	April (JFM)	May (FMA)	June (MAM)
Model (Omnibus Test Sig.)	Negative Binomial 1.6 (0.079)	Negative Binomial .99 (0.009)	Negative Binomial 1.65 (0.003)
	Significance	Significance	Significance
AO	0.791	0.187	0.950
NAO	0.463	0.563	0.391
MJO	0.076	0.796	0.065
ONI	0.759	0.108	0.627
PDO	0.342	0.009	0.560
PNA	0.463	0.501	0.108
ASOI	0.247	0.032	0.251

Overall, the SEUS VT models pointed to a large influence of seasonal tri-monthly indices over monthly VT frequency in that region (Table 39.) While every month had significant relationship values, only the models for February, April, and May had significant Omnibus Test values. VTs in February were significantly related to one or more seasonal tri-monthly indices from the NAO, PDO, PNA, and SOI anomaly datasets. April had a greater number of significant relationships, namely to the AO, NAO, MJO, ONI, PDO, and SOI anomaly. June, too, had multiple significant relationships, specifically with the AO, NAO, MJO, and ONI.

Table 39. The relationship between seasonal climate indices and VT frequency in the SEUS using generalized linear modeling

SEUS (VT Month VS Seasonal Tri-monthly Indices)				
	Feburary	March	April	May
Model (Omnibus Test Sig.)	Normal Identity (0.020)	Normal Identity (0.112)	Normal Identity (0.002)	Normal Identity (0.003)
	Significance	Significance	Significance	Significance
AO (NDJ)	0.089	0.720	0.009	0.000
AO (DJF)	0.433	0.017	0.002	0.150
AO (JFM)	0.938	0.002	0.001	0.003
AO (FMA)	0.179	0.002	0.435	0.000
NAO (NDJ)	0.837	0.514	0.001	0.034
NAO (DJF)	0.111	0.816	0.000	0.042
NAO (JFM)	0.042	0.113	0.001	0.881
NAO (FMA)	0.366	0.000	0.424	0.044
MJO (NDJ)	0.207	0.279	0.174	0.492
MJO (DJF)	0.154	0.499	0.000	0.464
MJO (JFM)	0.299	0.921	0.002	0.020
MJO (FMA)	0.539	0.755	0.296	0.049
ONI (NDJ)	0.072	0.234	0.000	0.281
ONI (DJF)	0.375	0.503	0.000	0.383
ONI (JFM)	0.908	0.872	0.000	0.245
ONI (FMA)	0.503	0.995	0.001	0.008
PDO (NDJ)	0.011	0.101	0.131	0.173
PDO (DJF)	0.005	0.195	0.015	0.108
PDO (JFM)	0.082	0.658	0.001	0.129
PDO (FMA)	0.228	0.035	0.145	0.174
PNA (NDJ)	0.567	0.149	0.411	0.129
PNA (DJF)	0.934	0.105	0.177	0.101
PNA (JFM)	0.850	0.096	0.696	0.860
PNA (FMA)	0.005	0.000	0.343	0.565
ASOI (NDJ)	0.484	0.005	0.184	0.605
ASOI (DJF)	0.153	0.529	0.068	0.121
ASOI (JFM)	0.053	0.010	0.404	0.710
ASOI (FMA)	0.021	0.036	0.032	0.225

Again, November was tested separately from the months in the SEUS’ primary tornado season. November’s model performed significantly better than the null, as indicated by the highly-significant Omnibus Test value (Table 40.) The model showed significant relationships between November VT frequency and one or more seasonal tri-monthly indices from the AO, NAO, MJO, ONI, and SOI anomaly. This contrasts with the tests done on November’s > EF0 frequency in the SEUS (Table 31.)

Table 40. The relationship between seasonal climate indices and November VT frequency in the SEUS using generalized linear modeling

SEUS (November VTs VS Seasonal Tri-monthly Indices)	
Model (Omnibus Test Sig.)	November
	Normal Identity (0.000)
	Significance
AO (NDJ)	0.335
AO (DJF)	0.974
AO (JFM)	0.014
AO (FMA)	0.025
AO (ASO)	0.337
NAO (NDJ)	0.785
NAO (DJF)	0.636
NAO (JFM)	0.314
NAO (FMA)	0.207
NAO (ASO)	0.024
MJO (NDJ)	0.180
MJO (DJF)	0.711
MJO (JFM)	0.258
MJO (FMA)	0.048
MJO (ASO)	0.966
ONI (NDJ)	0.077
ONI (DJF)	0.145
ONI (JFM)	0.156
ONI (FMA)	0.034
ONI (ASO)	0.968
PDO (NDJ)	0.313
PDO (DJF)	0.075
PDO (JFM)	0.191
PDO (FMA)	0.605
PDO (ASO)	0.802
PNA (NDJ)	0.639
PNA (DJF)	0.609
PNA (JFM)	0.891
PNA (FMA)	0.434
PNA (ASO)	0.111
ASOI (NDJ)	0.242
ASOI (DJF)	0.051
ASOI (JFM)	0.229
ASOI (FMA)	0.922
ASOI (ASO)	0.014

Contrary to the previous SEUS VT models, for those testing monthly VT frequency alongside the months' corresponding tri-monthly indices, only April's model had a significant Omnibus Test value (Table 41.) Despite this test value, April's only significant relationship was with the ONI. Although May had an insignificant Omnibus Test value, it was found to be significantly related to the AO, PDO, and PNA climate indices. No other models had any significant relationships between VT frequency in the SEUS and climate indices.

Table 41. The relationship between monthly climate indices and VT frequency in the SEUS using generalized linear modeling

SEUS (VT Month VS Corresponding Tri-monthly Indices)					
Model (Omnibus Test Sig.)	February (NDJ)	March (DJF)	April (JFM)	May (FMA)	November (ASO)
	Normal Identity (0.600)	Negative Binomial 4.25 (0.916)	Negative Binomial 1.35 (0.000)	Normal Identity (0.183)	Normal Identity (0.613)
	Significance	Significance	Significance	Significance	Significance
AO	0.454	0.640	0.063	0.042	0.328
NAO	0.199	0.688	0.595	0.411	0.590
MJO	0.330	0.588	0.655	0.657	0.383
ONI	0.718	0.854	0.001	0.464	0.101
PDO	0.369	0.579	0.520	0.041	0.457
PNA	<i>0.093</i>	0.590	0.646	0.015	0.920
ASOI	0.414	0.745	0.308	0.391	0.875

d. Pearson Correlation: Climate indices and countywide tornado frequency

i. *Results for > EF0 tornado frequency*

As expected, when correlating seasonal total tornadoes > EF0 for each of the seven chosen study areas alongside tri-monthly climate indices, there was a decent level of variation between the cities (Table 42.) The test on Birmingham indicates some degree of influence of ENSO on >EF0 activity, as shown by the correlation coefficients for both SOI datasets ($r > 0.250$). When including November in Cincinnati’s correlation test alongside all tri-monthly indices, only the June (MAM) ONI index was calculated to have a significant affect over the study area’s > EF0 activity. When excluding November in the test, this relationship was no longer present. Instead, the dominant influencers were the June (MAM) MJO and April (JFM) PNA indices.

Kansas City’s > EF0 frequency appears to be affected by one or more tri-monthly indices from the AO, NAO, MJO, and PNA (Table 42.) Tests done on Moore yielded the greatest correlation coefficients, the highest being -0.503 for the April (JFM) AO index and seasonal > EF0 activity in the study area. Moore’s tornado activity also appears to be affected by other tri-monthly indices from the AO, NAO, MJO, and SOI datasets. For Tanner, > EF0 tornado frequency was significantly correlated with the NAO, PNA, and SOI datasets. In contrast,

Tuscaloosa's > EF0 tornado frequency had significant correlations with one or more tri-monthly indices from the NAO, ONI, PDO, PNA, and SOI datasets. When including September in Wichita's tests, > EF0 tornado frequency is mostly correlated with at least one tri-monthly indices from the AO, MJO, or SOI datasets (Table 42.) When September was excluded, significant correlations were calculated between seasonal > EF0 activity and the AO and NAO.

Table 42. Seasonal > EF0 totals in cities vs tri-monthly climate indices

Seasonal > EF0 Totals vs Tri-monthly Climate Indices																	
Birmingham		Cincinnati		Cincinnati (W/Nov)		Kansas City		Moore		Tanner		Tuscaloosa		Wichita		Wichita (W/Sep)	
AO-DJF	-0.049	AO-DJF	0.210	AO-DJF	0.108	AO_JFM	-0.319	AO_JFM	-0.503	AO-DJF	-0.232	AO-OND	-0.040	AO-JFM	-0.224	AO-JFM	-0.299
AO-JFM	0.042	AO_JFM	0.132	AO_JFM	0.055	AO_FMA	-0.277	AO_FMA	-0.464	AO_JFM	-0.139	AO-JFM	0.161	AO-FMA	-0.325	AO-FMA	-0.414
AO-FMA	0.211	AO_FMA	0.166	AO_FMA	0.151	AO_MAM	-0.147	AO_MAM	-0.332	AO_FMA	0.094	AO-ASO	-0.013	AO_MAM	-0.173	AO_MAM	-0.274
NAO-DJF	-0.157	AO_MAM	0.016	AO_MAM	0.028	NAO_JFM	-0.463	NAO_JFM	-0.485	NAO-DJF	-0.283	NAO-OND	-0.253	AO-JJA	0.057	NAO-JFM	-0.183
NAO-JFM	-0.092	AO_AMJ	-0.044	AO_AMJ	-0.015	NAO_FMA	-0.348	NAO_FMA	-0.493	NAO_JFM	-0.167	NAO-JFM	0.094	NAO-JFM	-0.199	NAO-FMA	-0.338
NAO-FMA	0.116	AO-ASO	-0.033	NAO-DJF	0.042	NAO_MAM	-0.174	NAO_MAM	-0.183	NAO_FMA	0.069	NAO-ASO	-0.105	NAO-FMA	-0.223	NAO_MAM	-0.180
MJO-DJF	0.020	NAO-DJF	0.106	NAO_JFM	0.074	MJO_JFM	-0.154	MJO_JFM	-0.322	MJO-DJF	-0.012	MJO-OND	0.105	NAO_MAM	0.024	MJO-JFM	-0.230
MJO-JFM	-0.077	NAO_JFM	0.120	NAO_FMA	0.102	MJO_FMA	-0.195	MJO_FMA	-0.376	MJO_JFM	-0.141	MJO-JFM	-0.076	NAO-JJA	0.161	MJO-FMA	-0.206
MJO-FMA	-0.013	NAO_FMA	0.167	NAO_MAM	0.041	MJO_MAM	-0.259	MJO_MAM	0.140	MJO_FMA	-0.173	MJO-ASO	-0.050	MJO-JFM	-0.328	MJO_MAM	-0.224
ONI-DJF	-0.088	NAO_MAM	0.114	NAO_AMJ	-0.035	ONI_JFM	0.109	ONI_JFM	-0.010	ONI-DJF	-0.224	ONI-OND	-0.360	MJO-FMA	-0.095	ONI-JFM	0.106
ONI-JFM	-0.109	NAO_AMJ	0.073	MJO-DJF	-0.018	ONI_FMA	0.087	ONI_FMA	-0.033	ONI_JFM	-0.232	ONI-JFM	-0.349	MJO_MAM	-0.063	ONI-FMA	0.093
ONI-FMA	-0.134	NAO-ASO	0.128	MJO_JFM	0.212	ONI_MAM	0.073	ONI_MAM	-0.116	ONI_FMA	-0.230	ONI-ASO	-0.010	MJO-JJA	0.508	ONI_MAM	0.055
PDO-DJF	-0.189	MJO-DJF	-0.189	MJO_FMA	-0.023	PDO_JFM	-0.094	PDO_JFM	0.109	PDO-DJF	-0.143	PDO-OND	-0.374	ONI-JFM	0.217	PDO-JFM	0.010
PDO-JFM	-0.151	MJO_JFM	0.017	MJO_MAM	0.294	PDO_FMA	-0.155	PDO_FMA	0.063	PDO_JFM	-0.125	PDO-JFM	-0.386	ONI-FMA	0.238	PDO-FMA	-0.037
PDO-FMA	-0.114	MJO_FMA	-0.088	MJO_AMJ	-0.027	PDO_MAM	-0.234	PDO_MAM	-0.022	PDO_FMA	-0.117	PDO-ASO	-0.230	ONI_MAM	0.226	PDO_MAM	-0.120
PNA-DJF	-0.057	MJO_MAM	0.302	ONI-DJF	-0.117	PNA_JFM	-0.313	PNA_JFM	0.178	PNA-DJF	-0.088	PNA-OND	-0.144	ONI-JJA	0.205	PNA-JFM	0.088
PNA-JFM	-0.054	MJO_AMJ	0.195	ONI_JFM	-0.080	PNA_FMA	-0.263	PNA_FMA	0.113	PNA_JFM	-0.183	PNA-JFM	-0.314	PDO-JFM	0.007	PNA-FMA	0.133
PNA-FMA	-0.104	MJO-ASO	-0.248	ONI_FMA	-0.077	PNA_MAM	-0.289	PNA_MAM	-0.026	PNA_FMA	-0.349	PNA-ASO	0.524	PDO-FMA	0.000	PNA_MAM	-0.036
ASOI-DJF	0.225	ONI-DJF	0.013	ONI_MAM	-0.088	ASOI_JFM	0.003	ASOI_JFM	-0.037	ASOI-DJF	0.392	ASOI-OND	0.586	PDO_MAM	-0.050	ASOI-JFM	-0.173
ASOI-JFM	0.238	ONI_JFM	0.035	ONI_AMJ	-0.055	ASOI_FMA	0.074	ASOI_FMA	0.028	ASOI_JFM	0.367	ASOI-JFM	0.443	PDO-JJA	-0.029	ASOI-FMA	-0.018
ASOI-FMA	0.290	ONI_FMA	0.027	PDO-DJF	-0.156	ASOI_MAM	0.058	ASOI_MAM	0.275	ASOI_FMA	0.395	ASOI-ASO	0.164	PNA-JFM	0.143	ASOI_JFM	-0.057
SSOI-DJF	0.223	ONI_MAM	-0.013	PDO_JFM	-0.173	SSOI_JFM	0.002	SSOI_JFM	-0.040	SSOI-DJF	0.387	SSOI-OND	0.585	PNA-FMA	0.142	SSOI-JFM	-0.175
SSOI-JFM	0.235	ONI_AMJ	-0.017	PDO_FMA	-0.153	SSOI_FMA	0.072	SSOI_FMA	0.026	SSOI_JFM	0.363	SSOI-JFM	0.439	PNA_MAM	0.009	SSOI-FMA	-0.016
SSOI-FMA	0.292	ONI-ASO	-0.108	PDO_MAM	-0.214	SSOI_MAM	0.057	SSOI_MAM	0.273	SSOI_FMA	0.393	SSOI-ASO	0.165	PNA-JJA	0.050	SSOI_MAM	-0.060
		PDO-DJF	-0.053	PDO_AMJ	-0.232									ASOI-JFM	-0.269		
		PDO_JFM	-0.066	PNA-DJF	-0.196									ASOI-FMA	-0.136		
		PDO_FMA	-0.055	PNA_JFM	-0.294									ASOI_MAM	-0.166		
		PDO_MAM	-0.116	PNA_FMA	-0.061									ASOI-JJA	0.042		
		PDO_AMJ	-0.122	PNA_MAM	-0.172									SSOI-JFM	-0.269		
		PDO-ASO	0.055	PNA_AMJ	-0.083									SSOI-FMA	-0.136		
		PNA-DJF	-0.098	ASOI-DJF	0.155									SSOI_MAM	-0.162		
		PNA_JFM	-0.138	ASOI_JFM	0.142									SSOI-JJA	0.043		
		PNA_FMA	0.046	ASOI_FMA	0.094												
		PNA_MAM	-0.026	ASOI_MAM	0.188												
		PNA_AMJ	0.026	ASOI_AMJ	0.108												
		PNA-ASO	0.119	SSOI-DJF	0.157												
		ASOI-DJF	0.029	SSOI_JFM	0.144												
		ASOI_JFM	0.011	SSOI_FMA	0.097												
		ASOI_FMA	-0.037	SSOI_MAM	0.187												
		ASOI_MAM	0.082	SSOI_AMJ	0.100												
		ASOI_AMJ	0.117														
		ASOI-ASO	0.063														
		SSOI-DJF	0.029														
		SSOI_JFM	0.012														
		SSOI_FMA	-0.036														
		SSOI_MAM	0.081														
		SSOI_AMJ	0.114														
		SSOI-ASO	0.066														

Correlation tests that utilized the seasonal climate indices yielded results similar to those from the previous test. Here, > EF0 activity in Birmingham was also found to be correlated to the SOI indices (Table 43.) When including November's > EF0s in Cincinnati's correlation test, there were no significant relationships with climate indices. However, when excluding

November, > EF0 frequency was significantly correlated to the AO with a coefficient of one. However, this is likely overestimated due to the lack of tornado data from Cincinnati's study area without November's total.

Similar to the previous trial, Kansas City's > EF0 frequency was found to be significantly correlated to the AO, NAO, MJO, and PNA (Table 42 & 43.) Moreover, > EF0 tornado frequency in Moore was calculated to be significantly correlated to the AO, NAO, and MJO, but not the SOI indices like the previous trial. The results for Tanner were also slightly different from the previous test. Here, > EF0 frequency in Tanner's study area was only significantly correlated to the SOI indices (Table 43.) Furthermore, Tuscaloosa's > EF0 frequency was correlated to the ONI, PDO, and SOI indices, but not the PDO and PNA like in the previous test. Results for Wichita were also largely different, with tests including September only correlating > EF0 frequency to the AO and ONI. Tests excluding September correlated > EF0 frequency to the AO, NAO, and MJO.

Table 43. Seasonal > EF0 totals in cities vs seasonal tri-monthly climate indices

Seasonal > EF0 Totals vs Seasonal Tri-monthlies									
Birmingham		Cincinnati		Cincinnati (W/Nov)		Kansas City		Moore	
AO	0.240	AO	0.145	AO	1.000	AO	-0.285	AO	-0.486
NAO	0.161	NAO	0.176	NAO	0.063	NAO	-0.386	NAO	-0.450
MJO	-0.069	MJO	-0.004	MJO	0.154	MJO	-0.265	MJO	-0.259
ONI	-0.244	ONI	-0.008	ONI	-0.092	ONI	0.094	ONI	-0.046
PDO	-0.177	PDO	-0.067	PDO	-0.197	PDO	-0.167	PDO	0.052
PNA	-0.064	PNA	-0.053	PNA	-0.210	PNA	-0.320	PNA	0.115
ASOI	0.362	ASOI	0.038	ASOI	0.151	ASOI	0.044	ASOI	0.071
SSOI	0.361	SSOI	0.039	SSOI	0.152	SSOI	0.042	SSOI	0.067
Tanner		Tuscaloosa		Wichita		Wichita (W/Sep)			
AO	-0.109	AO	0.085	AO	-0.255	AO	-0.361		
NAO	-0.149	NAO	-0.142	NAO	-0.088	NAO	-0.268		
MJO	-0.117	MJO	-0.017	MJO	0.003	MJO	-0.301		
ONI	-0.230	ONI	-0.353	ONI	0.272	ONI	0.091		
PDO	-0.132	PDO	-0.392	PDO	-0.021	PDO	-0.053		
PNA	-0.214	PNA	-0.185	PNA	0.117	PNA	0.072		
ASOI	0.391	ASOI	0.532	ASOI	-0.201	ASOI	-0.105		
SSOI	0.388	SSOI	0.531	SSOI	-0.201	SSOI	-0.106		

ii. Results for VT frequency

The results for correlation tests done on the chosen cities' VT frequency alongside all tri-monthly climate indices varied from the previous tests analyzing the cities' > EF0 frequency. Seasonal VT frequency in Birmingham was found to be correlated with one or more tri-monthly indices from the AO, NAO, MJO, and PNA, but not the SOI indices as calculated previously (Tables 42, 43 & 44). Similar to before, when including November in Cincinnati's correlation tests, the only significant relationship was with the June (MAM) MJO index. Excluding November resulted in multiple significant correlations, including one or more tri-monthly indices from the ONI and SOI indices, suggesting an influence of ENSO over VT frequency in

Cincinnati. In contrast, there were no obvious trends between Kansas City’s seasonal VT frequency and any of the climate indices.

Unlike the previous tests with Moore’s > EF0 frequency, there was no clear relationship between the AO and the city’s VT frequency (Table 44.) When excluding September VTs in Moore’s test, there was also present correlation between VT frequency in that study area and the SOI indices. In contrast, a relationship between the SOI indices and VT frequency in Tanner was present both when including and excluding November. For the tests including November, a significant correlation between the PDO and seasonal VT frequency in Tanner was present, with influence from the MJO also present when excluding November’s VTs. Tuscaloosa was calculated to be correlated with one or more tri-monthly indices from the PDO and SOI indices. Wichita had no significant relationships between seasonal VT frequency and any of the climate indices.

Table 44. Seasonal VT totals in cities vs tri-monthly climate indices

Seasonal VT Totals vs Tri-monthly Climate Indices																			
Birmingham	Cincinnati		Cincinnati (W/Nov)		Kansas City		Moore		Moore W/Sep		Tanner		Tanner (W/Nov)		Tuscaloosa	Wichita			
AO-OND	-0.488	AO-DJF	0.159	AO-DJF	0.120	AO_FMA	-0.043	AO-JFM	-0.198	AO-JFM	-0.196	AO-DJF	0.161	AO-DJF	0.045	AO-NDJ	-0.089	AO_JFM	-0.146
AO-DJF	-0.112	AO_JFM	0.123	AO_JFM	0.092	AO_MAM	-0.011	AO-FMA	-0.182	AO-FMA	-0.151	AO_JFM	0.132	AO_JFM	0.021	AO-DJF	0.001	AO_FMA	-0.124
AO-JFM	0.243	AO_MAM	0.081	AO_MAM	0.052	NAO_FMA	-0.074	AO-JJA	0.008	AO-JJA	0.042	AO_FMA	0.116	AO_FMA	0.044	AO-JFM	0.057	AO_MAM	-0.088
AO-FMA	0.518	AO-ASO	-0.169	NAO-DJF	0.150	NAO_MAM	-0.156	NAO-JFM	-0.192	NAO-JFM	-0.191	AO-ASO	-0.026	NAO-DJF	0.095	AO-SON	0.145	NAO_JFM	-0.062
NAO-OND	-0.388	NAO-DJF	0.160	NAO_JFM	0.155	MJO_FMA	-0.060	NAO-FMA	-0.187	NAO-FMA	-0.175	NAO-DJF	0.155	NAO_JFM	0.065	NAO-NDJ	-0.152	NAO_JFM	-0.064
NAO-DJF	-0.279	NAO_JFM	0.173	NAO_MAM	0.068	MJO_MAM	-0.060	NAO-JJA	-0.069	NAO-JJA	-0.038	NAO_JFM	0.155	NAO_FMA	0.074	NAO-DJF	-0.021	NAO_MAM	0.028
NAO-JFM	0.108	NAO_MAM	0.172	MJO-DJF	-0.019	ONI_FMA	0.198	MJO-JFM	-0.123	MJO-JFM	-0.123	NAO_FMA	0.155	MJO-DJF	0.265	NAO-JFM	-0.001	MJO_JFM	0.004
NAO-FMA	0.399	NAO-ASO	0.039	MJO_JFM	0.151	ONI_MAM	0.177	MJO-FMA	-0.187	MJO-FMA	-0.187	NAO-ASO	0.098	MJO_JFM	0.222	NAO-SON	0.129	MJO_FMA	0.110
MJO-OND	0.751	MJO-DJF	-0.157	MJO_MAM	0.229	PDO_FMA	0.082	MJO-JJA	-0.361	MJO-JJA	-0.361	MJO-DJF	0.120	MJO_FMA	0.078	MJO-NDJ	0.010	MJO_MAM	-0.075
MJO-DJF	0.955	MJO_JFM	0.053	ONI-DJF	-0.264	PDO_MAM	0.040	ONI-JFM	0.027	ONI-JFM	0.024	MJO_JFM	0.053	ONI-DJF	-0.159	MJO-DJF	0.075	ONI_JFM	0.008
MJO-JFM	0.703	MJO_MAM	0.313	ONI_JFM	-0.264	PNA_FMA	-0.082	ONI-FMA	-0.006	ONI-FMA	-0.026	MJO_FMA	0.011	ONI_JFM	-0.174	MJO-JFM	-0.002	ONI_FMA	-0.001
MJO-FMA	-0.140	MJO-ASO	-0.099	ONI_MAM	-0.258	PNA_MAM	-0.086	ONI-JJA	-0.221	ONI-JJA	-0.295	MJO-ASO	-0.100	ONI_FMA	-0.167	MJO-SON	-0.132	ONI_MAM	0.008
ONI-OND	0.123	ONI-DJF	-0.199	PDO-DJF	-0.176	ASOI_FMA	-0.146	PDO-JFM	-0.078	PDO-JFM	-0.048	ONI-DJF	-0.221	PDO-DJF	-0.242	ONI-NDJ	-0.242	PDO_JFM	-0.174
ONI-DJF	0.151	ONI_JFM	-0.193	PDO_JFM	-0.184	ASOI_MAM	-0.194	PDO-FMA	-0.065	PDO-FMA	-0.041	ONI_JFM	-0.233	PDO_JFM	-0.192	ONI-DJF	-0.230	PDO_FMA	-0.196
ONI-JFM	0.130	ONI_MAM	-0.174	PDO_MAM	-0.145	SSOI_FMA	-0.147	PDO-JJA	-0.175	PDO-JJA	-0.222	ONI_FMA	-0.227	PDO_FMA	-0.139	ONI-JFM	-0.238	PDO_MAM	-0.221
ONI-FMA	0.051	ONI-ASO	-0.077	PNA-DJF	-0.124	SSOI_MAM	-0.192	PNA-JFM	0.140	PNA-JFM	0.198	ONI-ASO	-0.133	PNA-DJF	-0.122	ONI-SON	-0.222	PNA_JFM	-0.060
PDO-OND	-0.107	PDO-DJF	-0.160	PNA_JFM	-0.178			PNA-FMA	0.046	PNA-FMA	0.085	PDO-DJF	-0.258	PNA_JFM	-0.140	PDO-NDJ	-0.212	PNA_FMA	0.057
PDO-DJF	0.081	PDO_JFM	-0.163	PNA_MAM	-0.086			PNA-JJA	-0.222	PNA-JJA	-0.242	PDO_JFM	-0.224	PNA_FMA	-0.069	PDO-DJF	-0.241	PNA_MAM	0.005
PDO-JFM	0.108	PDO_MAM	-0.106	ASOI-DJF	0.262			ASOI-JFM	-0.008	ASOI-JFM	-0.010	PDO_FMA	-0.160	ASOI-DJF	0.225	PDO-JFM	-0.231	ASOI_JFM	0.025
PDO-FMA	0.061	PDO-ASO	-0.010	ASOI_JFM	0.255			ASOI-FMA	0.040	ASOI-FMA	0.044	PDO-ASO	-0.009	ASOI_JFM	0.279	PDO-SON	-0.232	ASOI_FMA	0.011
PNA-OND	0.271	PNA-DJF	-0.088	ASOI_MAM	0.254			ASOI-JJA	0.237	ASOI-JJA	0.253	PNA-DJF	-0.169	ASOI_FMA	0.268	PNA-NDJ	-0.113	ASOI_MAM	-0.047
PNA-DJF	0.335	PNA_JFM	-0.116	SSOI-DJF	0.268			SSOI-JFM	-0.011	SSOI-JFM	-0.013	PNA_JFM	-0.190	SSOI-DJF	0.231	PNA-DJF	-0.142	SSOI_JFM	0.026
PNA-JFM	0.096	PNA_MAM	-0.022	SSOI_JFM	0.256			SSOI-FMA	0.035	SSOI-FMA	0.040	PNA_FMA	-0.098	SSOI_JFM	0.279	PNA-JFM	-0.130	SSOI_FMA	0.013
PNA-FMA	-0.231	PNA-ASO	0.133	SSOI_MAM	0.250			SSOI-JJA	0.238	SSOI-JJA	0.254	PNA-ASO	0.148	SSOI_FMA	0.267	PNA-SON	-0.035	SSOI_MAM	-0.048
ASOI-OND	-0.027	ASOI-DJF	0.188									ASOI-DJF	0.264			ASOI-NDJ	0.289		
ASOI-DJF	0.118	ASOI_JFM	0.175									ASOI_JFM	0.311			ASOI-DJF	0.329		
ASOI-JFM	0.128	ASOI_MAM	0.187									ASOI_FMA	0.309			ASOI-JFM	0.321		
ASOI-FMA	0.102	ASOI-ASO	0.091									ASOI-ASO	0.140			ASOI-SON	0.270		
SSOI-OND	-0.025	SSOI-DJF	0.192									SSOI-DJF	0.270			SSOI-NDJ	0.298		
SSOI-DJF	0.114	SSOI_JFM	0.175									SSOI_JFM	0.311			SSOI-DJF	0.336		
SSOI-JFM	0.121	SSOI_MAM	0.184									SSOI_FMA	0.308			SSOI-JFM	0.321		
SSOI-FMA	0.101	SSOI-ASO	0.092									SSOI-ASO	0.144			SSOI-SON	0.275		

Correlating seasonal VT totals with tri-monthly index μ values greatly swayed the results of the tests (Table 45.) When using these parameters, Birmingham's VT frequency was only found to be significantly correlated with the MJO. When including November's VTs, Cincinnati also had fewer correlated climate indices, with only a slight significant relationship to the ONI. When excluding November, this relationship was stronger. Cincinnati was also found to be significantly correlated to the SOI indices. Neither VT frequency for Kansas City nor Wichita had any significant correlations to the climate indices.

Similarly, only when including September was Moore's VT frequency correlated to any climate indices, namely the MJO (Table 45.) In contrast, Tanner's VT frequency was correlated to the SOI indices both when including and excluding November. However, only when including November was Tanner's seasonal VT frequency found to be related to the ONI. Furthermore, Tuscaloosa's VT frequency was found to be significantly correlated to the ONI, PDO, and both SOI indices.

Table 45. Seasonal VT totals in cites vs seasonal tri-monthly climate indices

Seasonal VT Totals vs Seasonal Tri-monthlies									
<i>Birmingham</i>		<i>Cincinnati</i>		<i>Cincinnati (W/Nov)</i>		<i>Kansas City</i>		<i>Moore</i>	
AO	0.099	AO	0.114	AO	0.107	AO	-0.031	AO	-0.190
NAO	-0.058	NAO	0.196	NAO	0.155	NAO	-0.121	NAO	-0.211
MJO	0.796	MJO	0.031	MJO	0.157	MJO	-0.069	MJO	-0.402
ONI	0.123	ONI	-0.212	ONI	-0.273	ONI	0.191	ONI	-0.069
PDO	0.035	PDO	-0.129	PDO	-0.177	PDO	0.061	PDO	-0.119
PNA	0.168	PNA	-0.078	PNA	-0.159	PNA	-0.088	PNA	0.072
ASOI	0.087	ASOI	0.207	ASOI	0.279	ASOI	-0.174	ASOI	0.091
SSOI	0.084	SSOI	0.208	SSOI	0.280	SSOI	-0.174	SSOI	0.087
<i>Moore W/Sep</i>		<i>Tanner</i>		<i>Tanner W/Nov</i>		<i>Tuscaloosa</i>		<i>Wichita</i>	
AO	-0.181	AO	0.140	AO	0.039	AO	0.019	AO	-0.134
NAO	-0.194	NAO	0.188	NAO	0.086	NAO	-0.022	NAO	-0.042
MJO	-0.170	MJO	0.040	MJO	0.226	MJO	-0.051	MJO	0.020
ONI	0.002	ONI	-0.262	ONI	-0.168	ONI	-0.305	ONI	0.005
PDO	-0.045	PDO	-0.190	PDO	-0.195	PDO	-0.275	PDO	-0.202
PNA	0.154	PNA	-0.153	PNA	-0.124	PNA	-0.151	PNA	-0.004
ASOI	0.015	ASOI	0.321	ASOI	0.264	ASOI	0.377	ASOI	0.002
SSOI	0.011	SSOI	0.323	SSOI	0.265	SSOI	0.382	SSOI	0.002

e. Generalized linear models: Climate indices and countywide tornado frequency

i. Results for > EF0 tornado frequency

Generalized linear modeling calculated even fewer relationships between seasonal > EF0 frequency in the chosen study areas compared to the Pearson correlation tests. Only Tuscaloosa and Wichita’s models had significant Omnibus Test values indicating they were a good fit for the input data (Table 46.) Tuscaloosa’s model showed significant relationships between the study area’s seasonal VT frequency and the AO, NAO, MJO, PNA, and SOI anomaly indices. However, these values were extremely low for such a small amount of data, suggesting some degree of overestimation. Significant relationships in Wichita’s VT frequency model were more

reasonable. These significant relationships were with the AO, PDO, PNA, and SOI anomaly indices.

Table 46. The relationship between seasonal climate indices and > EF0 frequency in the chosen cities’ study areas using generalized linear modeling

Chosen Study Areas (Seasonal >EF0 totals vs. Seasonal Tri-monthlies)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Model (Omnibus Test Sig.)	Neg. Binomial 1.25 (0.634)	Neg. Binomial 1.01 (0.968)	Neg. Binomial 1.001 (0.682)	Neg. Binomial 1.15 (0.432)	Neg. Binomial 1.001 (0.614)	Tweedie 1.001 (0.000)	Poisson Log (0.000)
	Significance	Significance	Significance	Significance	Significance	Significance	Significance
AO	0.723	0.937	0.461	0.481	0.809	0.000	0.032
NAO	0.775	0.540	0.821	0.466	0.655	0.000	0.051
MJO	0.627	0.588	0.928	0.714	0.421	0.000	0.054
ONI	0.861	0.910	0.921	0.764	0.083	0.000	0.283
PDO	0.495	0.665	0.121	0.850	0.902	0.583	0.004
PNA	0.504	0.655	0.716	0.925	0.429	0.000	0.013
ASOI	0.360	0.997	0.754	0.693	0.109	0.000	0.028

ii. Results for VT frequency

Even smaller pools of data further complicated the making of generalized linear models for the cities’ VT frequency. Only two of the seven city models had Pearson Chi-squared values within 0.3 of one, indicating these models, overall, were not a good fit for analyzing the effect of climate indices on small-scale VT frequency (Table 47.) Still, Moore’s model had a significant Omnibus Test value, suggesting its model did perform better than the null.

Birmingham VT frequency was calculated to be significantly related to the AO and NAO (Table 47.) Despite multiple degrees on unfitness, Kansas City, Moore, and Wichita’s models all found seasonal VT frequency to be significantly related to the PDO, with Moore’s frequency also being significantly related to the MJO. Furthermore, Tanner’s VT frequency was found to be influenced by the SOI anomaly index, as seen in previous tests (Tables 42-45.)

Table 47. The relationship between seasonal climate indices and VT frequency in the chosen cities’ study areas using generalized linear modeling

Chosen Study Areas (Seasonal VT totals vs. Seasonal Tri-monthlies)							
	Birmingham	Cincinnati	Kansas City	Moore	Tanner	Tuscaloosa	Wichita
Model (Omnibus Test Sig.)	Normal Identity (0.115)	Normal Identity (0.782)	Normal Identity (0.305)	Normal Identity (0.007)	Normal Identity (0.063)	Normal Identity (0.071)	Normal Identity (0.187)
	Significance	Significance	Significance	Significance	Significance	Significance	Significance
AO	0.006	0.875	0.317	0.217	0.490	0.703	0.083
NAO	0.028	0.245	0.285	0.881	0.411	0.886	0.245
MJO	0.406	0.197	0.928	0.007	0.866	0.318	0.611
ONI	0.300	0.982	0.941	0.483	0.208	0.746	0.222
PDO	0.097	0.591	0.035	0.012	0.738	0.126	0.006
PNA	0.205	0.750	0.056	0.271	0.161	0.254	0.908
ASOI	0.563	0.769	0.718	0.538	0.019	0.186	0.119

- f. Summary of climate indices' influence on > EF0 and VT activity in the chosen regions and cities of interest

For every region except the EUS and GPUS, all climate indices appeared to have some effect on total tornado (> EF0) and VT frequency, with ENSO appearing to have the greatest effect on tornado frequency in both categories (Figure 10.) Furthermore, the dominate climate indices varied by region and tornado intensity (> EF0s vs VTs). For the EUS, the AO, ENSO, and PNA appear to have the greatest effect on > EF0 activity. In contrast, the ENSO, MJO, and NAO were found to be the most important variables for the EUS' VT activity. For the GPUS, the PNA, PDO, ENSO and MJO were the most important variables for > EF0 activity. For VT activity in this region, these variables were the AO, ENSO, and NAO. > EF0 activity in the MWUS appears to be greatly affected by all climate indices, but mostly by the ENSO, PNA, and PDO. VT activity in the MWUS is less affected, but still had a number of significant relationships with the ENSO, MJO, NAO, and PNA. In the SEUS, the AO, NAO, and ENSO were the most important variables for both > EF0 and VT frequency, but in a different order of significance.

The ENSO, MJO, and AO had the greatest total number of significant relationships with tornado frequency (>EF0s and VTs) in the cities' study areas (Table 10.) ENSO had the greatest level of influence over > EF0 activity in Tanner and Tuscaloosa, and the largest influence over VT activity in Cincinnati, Tanner, and Tuscaloosa, while MJO's effect on the cities' tornado activity was relatively level for both categories. The AO had a clear effect on > EF0 frequency in Kansas City, Moore, and Wichita in multiple tests. Interestingly, there were notable relationships between the PNA and PDO on > EF0 frequency in Tuscaloosa, despite them having a minimal effect on > EF0 frequency in the SEUS, Birmingham and Tanner. In contrast, there were

multiple significant relationships between VT activity in Birmingham and the AO, MJO, NAO, and PNA. The PNA was also found to effect > EF0 frequency in Kansas city and Tuscaloosa.

The effect of all other climate indices for both tornado categories was sparse.

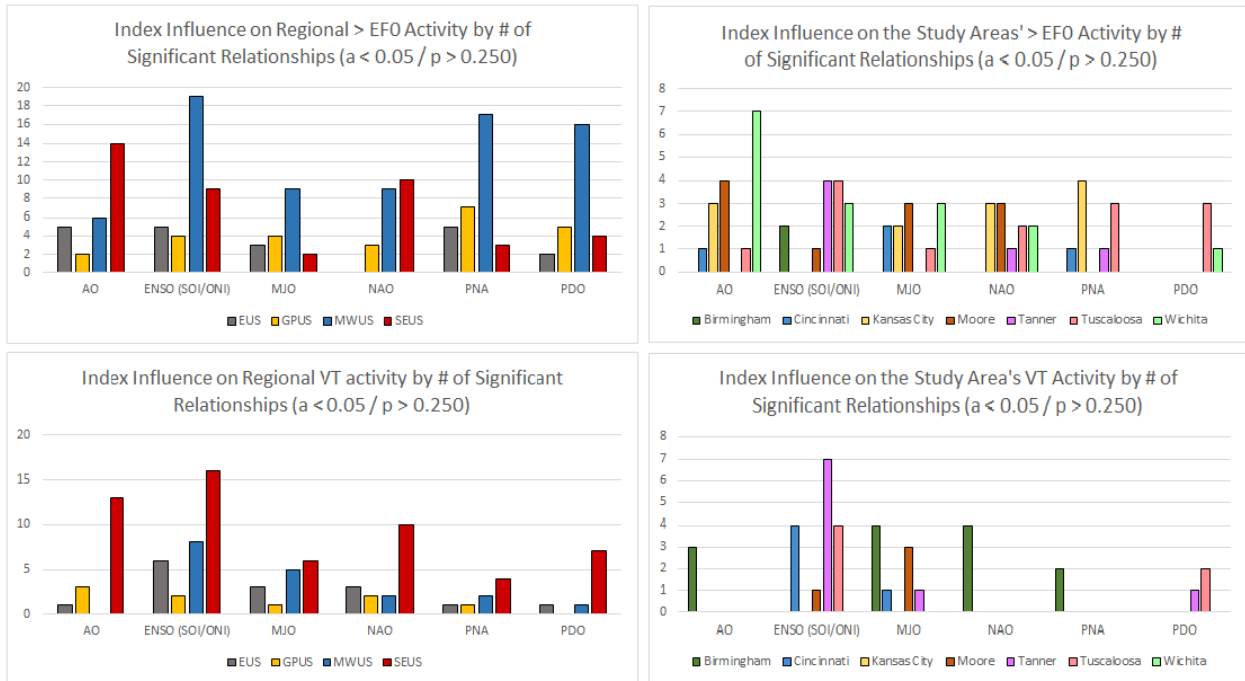


Figure 10. Climate indices' influence over total (> EF0) and VT frequency in the regions and cities' study areas by number of significant relationships ($\alpha < 0.05 / r > 0.250$)

CHAPTER 6

DISCUSSION AND CONCLUSION

Previous research has established how tornado magnitude and frequency varies across the EUS (Suckling & Ashley 2006; Daneshvaran & Morden 2007; Dixon et al. 2011; Coleman & Dixon 2014; Foglietti et al 2020). However, our understanding of tornadic spatial variability on a smaller scale is limited. This research sought to determine if certain anomalous tornado patterns in cities could be replicated strictly by random chance. Tornado patterns in cities were chosen due to the devastating impact tornadoes, especially violent tornadoes (VTs), can have in populated areas. Unfortunately, this issue only grows more important as cities continue to expand in population and size (Ashley et al. 2014; Strader et al. 2017; Strader et al. 2018 Fricker & Friesenhahn 2022). Thus, understanding if certain cities are of higher risk for VTs relative to surrounding areas would be beneficial to their communities and officials responsible for planning and disaster mitigation.

An automated Monte-Carlo-style model was used to generate random tornado initial points equal in quantity to the actual number of tornadoes seen in each of the seven study areas: Birmingham, Tanner and Tuscaloosa, AL; Cincinnati, OH; Kansas City, KS/MO; Moore, OK; and Wichita, KS. The μ number of simulated total tornadoes, >EF0s, and VTs that intersected the seven cities of interest were used to determine the accuracy of the model in replicating each city's actual historic tornado count. These μ values were also used to determine the model's

accuracy in predicting the tornado patterns within cities adjacent to the primary cities. The μ values were then analyzed alongside each city's actual number of tornadoes using one sample t-tests to determine the level of statistical variance present between the latter and the model's predictions.

No simulation replicated the actual number of total tornadoes or >EF0 tornadoes in Birmingham or Wichita with only a single simulation replicating Tuscaloosa's number of tornadoes > EF0. Furthermore, when only counting the generated tornado initial points that fell into the city buffer as "intersecting tornadoes", the mean number of simulated VTs was less than one for all cities except Kansas City. Although the model was able to replicate Moore's number of total tornadoes at a rate >1%, it was not able to replicate its actual number of > EF0s or VTs at a rate >1% in any trial. Additionally, while Tanner's number of VTs was only replicated at a rate >1% in the final trial, both its number of total tornadoes and >EF0s were frequently replicated (34.6% and 40.7%, respectively). This is likely a combination of the study areas for Moore and Tanner having smaller ratios of VTs to total tornadoes relative to all other study areas beside Tuscaloosa's and the smallest percentage of intersecting total tornadoes and > EF0s relative to their study areas (Table 3).

One sample t-tests comparing the simulated total tornado, >EF0, and VT μ values with the actual number of tornadoes from these categories in each city in each trial all yielded values $p < 0.01$. In contrast, t-tests done on the adjacent cities all yielded t-statistic values closer to one. Thus, the model was much more capable of predicting the number of total tornadoes, >EF0s, and VTs in cities adjacent to those with anomalous tornado patterns relative to the entire study area. Overall, results from these tests reveal that the number of tornadoes, specifically VTs, hitting the primary cities is significantly greater than what the model predicted. This was despite the model

being able to replicate these patterns at a rate $>1\%$ in at least one trial for all cities except Moore.

Previous research has established a relationship between certain climate indices and regional tornado and VT activity in the US (Barrett & Gensini 2013; Allen et al. 2015; Brown & Nowotarski 2020) Because these patterns were difficult to replicate randomly, it was suggested that major climate indices effects might fluctuate on a smaller-scale, influencing the level of tornadic frequency seen in the chosen study areas. To investigate this idea, each region's (EUS, GPUS, MWUS and SEUS) three most active tornado and VT months, defined as its tornado season, were tested alongside a series of climate indices using Pearson's Correlation and generalized linear modeling. These indices were the AO, ENAO, NAO, MJO, PDO, and PNA all having been demonstrated to influence regional tornado activity in previous research (Marzban & Schaefer 2001; Barrett & Gensini 2013; Allen et al. 2015; Brown & Nowotarski 2020). The same series of tests were done on all of the chosen cities' study areas using their total number of tornados $> EF0$ /VTs in each tornado season instead of month to account for smaller data pools.

Overall, ENSO was calculated to have the largest effect on both $> EF0$ and VT frequency over studied regions, followed in order of influence by the AO, PNA, NAO, PDO, and MJO (Table 10.) However, the primary influencing climate indices varied by region, month, and tornado category. Compared to other regions, $> EF0$ frequency in the MWUS appears to be the most dependent on climate indices. For VT frequency, climate indices were found to have the greatest impact on the SEUS. For both categories, tornado frequency in the EUS had the smallest number of relationships with climate indices, further suggesting these effects vary regionally across this portion of the U.S.

Analysis done on the cities' study areas showed ENSO as having the greatest relationship with both > EF0 and VT frequency, followed in order of influence by the MJO, AO, NAO, PNA, and PDO (Table 10.) Aside from the ENSO and AO being at the top of both lists, the order of importance is notably different. While > EF0 frequency in the MWUS was found to be the most dependent upon climate indices in the previous tests, here Tuscaloosa and Wichita had the greatest number of significant relationships with the chosen climate indices ($\alpha < 0.05/ r > 0.250$). Cincinnati fits well within the boundaries of the defined MWUS region yet had the fewest significant relationships in total between seasonal > EF0 frequency and the climate indices. In contrast, Cincinnati had the second greatest number of relationships between the later and VT frequency, with Tanner having the most.

Pearson correlation and generalized linear modeling were likely not efficient tools for analyzing relationships with small-scale VT variability, as the vast number of zeros resulted in datasets that were not normally distributed like the others, possibly making any relationships nonlinear. Furthermore, a smaller pool of tornado data from each of the study areas likely contributed to a portion of the variance in calculation of influence over tornado frequency compared to the regional tests. Overall, there was a decent level of variation between the correlation tests analyzing > EF0 tornado frequency in the seven chosen study areas and the regional tests. This was especially true when comparing the correlation coefficients between the study areas and the entire EUS. Although the lack of data is apparent, the results indicate similar relationships between > EF0 and VT frequency and climate indices for the smaller study areas and their overlying regions.

Difficulty in replicating the chosen cities' tornado patterns in chapter three suggest that the number of total, > EF0, and VT patterns in these cities are not random. Further analysis must

be done on the effect of climate indices, but these patterns could also be related to the effects of other synoptic meteorological conditions and/or local land-surface heterogeneity. Moving forward, it would be beneficial to test more cities to broaden the scope of the research.

Regardless, future research on this topic would yield a better understanding of how tornado patterns vary county or citywide, knowledge important to both storm prediction sciences and these cities' communities.

REFERENCES

- Allen, M. J., Allen, T. R., Davis, C., & McLeod, G. (2021). Exploring spatial patterns of Virginia tornadoes using kernel density and space-time cube analysis (1960–2019). *ISPRS International Journal of Geo-Information*, 10(5), 310.
- Allen, J. T., Tippett, M. K., & Sobel, A. H. (2015). Influence of the El Niño/Southern Oscillation on tornado and hail frequency in the United States. *Nature Geoscience*, 8(4), 278-283.
- Ashley, W. S., Strader, S., Rosencrants, T., & Krmenc, A. J. (2014). Spatiotemporal changes in tornado hazard exposure: The case of the expanding bull's-eye effect in Chicago, Illinois. *Weather, Climate, and Society*, 6(2), 175-193.
- Barrett, B. S., & Gensini, V. A. (2013). Variability of central United States April–May tornado day likelihood by phase of the Madden-Julian Oscillation. *Geophysical Research Letters*, 40(11), 2790-2795.
- Brooks, H., & Doswell III, C. A. (2001). Some aspects of the international climatology of tornadoes by damage classification. *Atmospheric Research*, 56(1-4), 191-201.
- Brown, M.C., & Nowotarski, C.J. (2020). Southeastern U.S. Tornado Outbreak Likelihood Using Daily Climate Indices, *Journal of Climate*, 33(8), 3229-3252.
- Cao, Z., Cai, H., & Zhang, G. J. (2021). Geographic shift and environment change of US tornado activities in a warming climate. *Atmosphere*, 12(5), 567.
- Coleman, T. A., & Dixon, P. G. (2014). An objective analysis of tornado risk in the United States. *Weather and Forecasting*, 29(2), 366-376.
- Cook, A.R., Leslie, L.M., Parsons, D.B., & Schaefer, J. T. (2017). The Impact of El Niño–Southern Oscillation (ENSO) on Winter and Early Spring U.S. Tornado Outbreaks, *Journal of Applied Meteorology and Climatology*, 56(9), 2455-2478.
- Cook, A.R., & Schaefer, J.T. (2008). The Relation of El Niño–Southern Oscillation (ENSO) to Winter Tornado Outbreaks, *Monthly Weather Review*, 136(8), 3121-3137.

- Daneshvaran, S. and Morden, R.E. (2007), "Tornado risk analysis in the United States", *Journal of Risk Finance*, Vol. 8 No. 2, pp. 97-111. <https://doi.org/10.1108/15265940710732314>
- Deng, Y., Wallace, B., Maassen, D., & Werner, J. (2016). A few GIS clarifications on tornado density mapping. *Journal of Applied Meteorology and Climatology*, 55(2), 283-296.
- Dixon, P. G., Mercer, A. E., Choi, J., & Allen, J. S. (2011). Tornado risk analysis: is Dixie Alley an extension of Tornado Alley?. *Bulletin of the American Meteorological Society*, 92(4), 433-441.
- Edwards, R., Brooks, H. E., & Cohn, H. (2021). Changes in Tornado Climatology Accompanying the Enhanced Fujita Scale, *Journal of Applied Meteorology and Climatology*, 60(10), 1465-1482.
- Fan, F., & Pang, W. (2019). Stochastic track model for tornado risk assessment in the US. *Frontiers in built environment*, 5, 37.
- Foglietti, R. V., Mitchell, T. J., & Ortegren, J. T. (2020). US tornado outbreak climatologies based on different definitions of “outbreak,” 1975–2014. *southeastern geographer*, 60(1), 6-22.
- Fricker, T., & Friesenhahn, C. (2022). Tornado fatalities in context: 1995–2018. *Weather, climate, and society*, 14(1), 81-93.
- Fuhrmann, C. M., Konrad, C. E., II, Kovach, M. M., McLeod, J. T., Schmitz, W. G., & Dixon, P. G. (2014). Ranking of Tornado Outbreaks across the United States and Their Climatological Characteristics, *Weather and Forecasting*, 29(3), 684-701.
- Hatzis, J. J., Koch, J., & Brooks, H. E. (2019). Spatiotemporal analysis of near-miss violent tornadoes in the United States. *Weather, climate, and society*, 11(1), 159-182.
- Gibbs, J. G. (2021). Evaluating precursor signals for QLCS tornado and higher impact straight-line wind events.
- Lee, S. K., Atlas, R., Enfield, D., Wang, C., & Liu, H. (2013). Is there an optimal ENSO pattern that enhances large-scale atmospheric processes conducive to tornado outbreaks in the United States?. *Journal of Climate*, 26(5), 1626-1642.
- Lepore, C., Tippet, M. K., and Allen, J. T. (2017), ENSO-based probabilistic forecasts of March–May U.S. tornado and hail activity, *Geophys. Res. Lett.*, 44, 9093– 9101 [doi:10.1002/2017GL074781](https://doi.org/10.1002/2017GL074781)

- Liu, J., Yuan, X., Rind, D., & Martinson, D. G. (2002). Mechanism study of the ENSO and southern high latitude climate teleconnections. *Geophysical Research Letters*, 29(14), 24-1.
- Long, J. A., Stoy, P. C., & Gerken, T. (2018). Tornado seasonality in the southeastern United States. *Weather and climate extremes*, 20, 81-91.
- Marzban, C. & Schaefer, J. T., (2001) The correlation between U.S. tornadoes and Pacific sea surface temperatures. *Mon. Weath. Rev.* 129, 884–895
- McCullagh, P. (2019). *Generalized linear models*. Routledge.
- Moore, T. W. (2018). Annual and seasonal tornado activity in the United States and the global wind oscillation. *Climate Dynamics*, 50(11-12), 4323-4334.
- Moore, T.W., (2019) Seasonal Frequency and Spatial Distribution of Tornadoes in the United States and Their Relationship to the El Niño/Southern Oscillation, *Annals of the American Association of Geographers*, 109:4, 1033-1051 DOI: 10.1080/24694452.2018.1511412
- Moore, T. W., St Clair, J. M., & DeBoer, T. A. (2018). An analysis of anomalous winter and Spring Tornado frequency by phase of the El Niño/Southern Oscillation, the Global wind oscillation, and the Madden-Julian oscillation. *Advances in Meteorology*, 2018.
- Moore, T. W., & DeBoer, T. A. (2019). A review and analysis of possible changes to the climatology of tornadoes in the United States. *Progress in Physical Geography: Earth and Environment*, 43(3), 365–390.
- Muñoz, E., Enfield, D. (2011). The boreal spring variability of the Intra-Americas low-level jet and its relation with precipitation and tornadoes in the eastern United States. *Clim Dyn* 36, 247–259
- Ryzhkov, A. V., Schuur, T. J., Burgess, D. W., & Zrnich, D. S. (2005). Polarimetric tornado detection. *Journal of Applied Meteorology and Climatology*, 44(5), 557-570.
- Senkbeil, J. C., Sherman-Morris, K., Skeeter, W., & Vaughn, C. (2022). Tornado radar images and path directions: An assessment of public knowledge in the southeastern United States. *Bulletin of the American Meteorological Society*, 103(7), E1669-E1683.
- Shah, L., Arnillas, C. A., & Arhonditsis, G. B. (2022). Characterizing temporal trends of meteorological extremes in Southern and Central Ontario, Canada. *Weather and Climate Extremes*, 35, 100411.

- Shepherd, M., Niyogi, D., & Mote, T. L. (2009). A seasonal-scale climatological analysis correlating spring tornadic activity with antecedent fall–winter drought in the southeastern United States. *Environmental Research Letters*, 4(2), 024012.
- Strader, S. M., Ashley, W. S., Pingel, T. J., & Kremenec, A. J. (2017). Observed and Projected Changes in United States Tornado Exposure, *Weather, Climate, and Society*, 9(2), 109-123. Retrieved Mar 18, 2022, from https://journals.ametsoc.org/view/journals/wcas/9/2/wcas-d-16-0041_1.xml
- Strader, S. M., & Ashley, W. S. (2018). Finescale Assessment of Mobile Home Tornado Vulnerability in the Central and Southeast United States, *Weather, Climate, and Society*, 10(4), 797-812.
- Suckling, P. W., & Ashley, W. S. (2006). Spatial and temporal characteristics of tornado path direction. *The Professional Geographer*, 58(1), 20-38.
- Switanek, M. B., Troch, P. A., & Castro, C. L. (2009). Improving seasonal predictions of climate variability and water availability at the catchment scale. *Journal of Hydrometeorology*, 10(6), 1521-1533.
- Thompson, D.B., and Roundy, P.E., (2013) The relationship between the Madden–Julian Oscillation and US violent tornado outbreaks in the spring Mon. *Weather Rev.* 141 2087–95
- Tippett M K, Sobel A H and Camargo S J (2012) Association of US tornado occurrence with monthly environmental parameters, *Geophys. Res. Lett.* 39 L02801
- Tippett, M. K., Lepore, C., & Cohen, J. E. (2016). More tornadoes in the most extreme U.S. tornado outbreaks. *Science*, 354(6318), 1419– 1423. <https://doi.org/10.1126/science.aah7393>
- Weaver, S. J., Baxter, S., & Kumar, A. (2012). Climatic Role of North American Low-Level Jets on U.S. Regional Tornado Activity, *Journal of Climate*, 25(19), 6666-6683.