DIPLOMARBEIT

Titel der Diplomarbeit

The Danger of Tornadoes in the United States –
a Spatial and Temporal Analysis of Tornado Touchdown Points using Geographic Information Systems and Spatiotemporal Statistics

Verfasser

Philip Glasner

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Abstract

This diploma thesis contributes to the retrospective analysis of tornado occurrences in the United States from 1950 to 2009. The spatial and temporal analysis is carried out with Geographic Information Systems (GIS) and spatiotemporal statistics. At the beginning an extensive overview about the genesis and composition of tornadoes is given, followed by a comprehensive discussion of previous studies about tornado occurrences in the United States. Data and the methodology that will be used for the analysis are the content of Chapter 2. Different mapping principles are presented and compared for the suitability in spatial cluster analysis. Then, the basics of spatial and temporal statistics are discussed. The chapter concludes with the presentation of four selected spatial and spatiotemporal statistics and how they can be applied for a space-time analysis of events. The focus of discussion in Chapter 3 is on spatial and spatiotemporal statistics that are available in open source software packages. For the spatial and temporal analysis of tornado touchdown points the kernel density estimation technique, the Nearest Neighbor Hierarchical Clustering (NNHC) routine, the Local Moran's I as Local Indicators of Spatial Association (LISA) method, and the space-time permutation model as space-time scan statistic are applied. The entire tornado dataset, tornadoes by F-Scale, monthly maxima in tornado occurrences, and tornado fatalities are being analyzed by using a combination of these statistical techniques. Finally, the results from the different statistics are compared with each other and with related studies. In general, the results of the spatial analysis of tornado touchdown points in this thesis show similar outcomes compared to previous studies. Higher concentrations of tornado occurrences which have not been detected in previous studies can be found in the south of the United States, especially in Mississippi and Florida. Since the previous studies did not contain temporal variations of tornado patterns, these new results in this thesis are very insightful. High increases in tornado intensity between two defined time periods have been detected around Denver, CO, Houston, TX, and St. Petersburg, FL, whereas decreases in the intensity of significant tornadoes (rated F2 and higher) have been identified in the area of the Great Plains, especially in northern Texas and Oklahoma.

Zusammenfassung

Die vorliegende Diplomarbeit soll der retrospektiven Analyse von Tornados in den Vereinigten Staaten von 1950 bis 2009 beitragen. Die räumliche und zeitliche Analyse wird unter der Verwendung von Geographischen Informationssystemen (GIS) und raumzeitlichen Statistiken durchgeführt. Zu Beginn wird ein umfangreicher Überblick über der Entstehung und die Struktur von Tornados geboten, dem vorangegangene Studien über die Tornadoaktivität in den Vereinigten Staaten folgen. In Kapitel 2 werden der für die Analyse verwendete Datensatz und Methoden zur Analyse des Datensatzes vorgestellt. Verschiedene Kartierungstechniken werden im Sinne einer Einsetzbarkeit in der räumlichen Clusteranalyse diskutiert. Im Anschluss daran werden die Grundlagen von räumlichen und raumzeitlichen Statistiken erörtert. Das Kapitel schließt mit der Vorstellung von vier gewählten Statistiken und deren Anwendung in der raumzeitlichen Analyse. Der

Fokus wurde hierbei auf Statistiken gesetzt, die in frei verfügbaren Softwarepaketen enthalten sind. In der räumlichen und zeitlichen Analyse von Tornados werden die Kerndichteschätzung, die Nächste Nachbar Hierarchische Clusterungtechnik, der Lokale Moran's I als Local Indicator of Spatial Association (LISA) und das raumzeitliche Permutationsmodell als raumzeitliche Scan Statistik verwendet. Es werden der gesamte Datensatz, Tornados gegliedert nach der F-Skala, monatliche Maxima in der Tornadointensität und die Anzahl von Personen, die während eines Tornados verunglückt sind, analysiert, wobei eine Kombination von den statistischen Methoden herangezogen wird. Die erhaltenen Ergebnisse von den verschiedenen angewendeten Techniken werden folglich zuerst untereinander als auch zu den Ergebnissen vorangegangener Studien verglichen. Generell gleichen die in dieser Diplomarbeit erhaltenen Ergebnisse der räumlichen Analyse der Tornados den Resultaten vorangegangener Studien. Höhere Konzentrationen von Tornados, welche in vorangegangenen Studien unentdeckt blieben, wurden im Süden der Vereinigten Staaten, speziell in Mississippi und Florida, gefunden. Da frühere Studien keine zeitlichen Veränderungen in räumlichen Mustern behandelt haben, sind diese Ergebnisse in dieser Diplomarbeit sehr aufschlussreich. Erhöhte Tornadointensitäten zwischen zwei definierten Zeiträumen wurden in der Nähe von Denver, CO, Houston, TX, und St. Petersburg, FL, identifiziert. Verminderte Intensitäten von signifikanten Tornados (die als F2 oder höher klassifiziert wurden) wurden in der Region der Great Plains, besonders im nördlichen Texas und Oklahoma, aufgezeichnet.

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Preface

During the spring term 2009 Dr. Michael Leitner, Associate Professor at the Department of Geography and Anthropology at Louisiana State University in Baton Rouge, LA, U.S.A., taught the class "Advanced Methods in Spatial Statistics" at the Department of Geography and Regional Research at the University of Vienna. For me, it was the first time during my studies to analyze spatial data with spatial statistics to search for local concentrations of events or so-called hot spots. In this class, I chose to spatially analyze tornado touchdown points in the United States for the year 2004 for my term paper. During the completion of the final paper for this class I got more and more involved in research about tornadoes. Since I was interested in hot spot analysis, I asked Michael Leitner to supervise my diploma thesis, which he gladly agreed that he would do. I decided to analyze tornado touchdown points in the United States during the entire period from 1950 to 2009, since there has not been done much research on this topic.

Spatial statistics was introduced into geography by the "quantitative revolution" in the early 1960s. Subsequently other paradigms became important in geography and partially replaced the quantitative approaches in spatial research. In the last decades – since data processing of geographic data developed immensely – the application and research in spatial statistics experienced a "renaissance". Nowadays, spatial statistics are a very common and useful tool in, for example, crime analysis or epidemiology in the Anglo-American countries.

The development of Geographic Information Systems (GIS) progressed enormously during the last 30–40 years. However, researchers identified numerous challenges for GIS in the future. One major challenge that has been identified relates to the integration of time as a third dimension in addition to longitude and latitude. The analysis and visualization of both space and time is a rapidly growing research frontier in geography, GIS and GIScience. Two conferences on that topic should exemplify the broad interest.

- The Association of American Geographers (AAG) identifies particularly relevant themes to feature during its Annual Meetings. This year, a special symposium focused on the research status, recent advances, and research needs of space-time integration, modeling, and analysis in geography and GIScience will be organized within the AAG Annual Meeting in Seattle, April 12–16, 2011.
- The 1st Conference on Spatial Statistics with its subtitle Mapping Global Change will be held at the University of Twente in Enschede, Netherlands, March 23–25, 2011.

In the spatial research of tornado events papers that use spatial statistics are rare. Among the few studies are KELLY et al. (1978), who did research on tornado occurrences in the United States for the period 1950 to 1976, whereas BROOKS et al. (2003) analyzed data in the United States from 1980 to 1999. Both analyzed aggregated data for these periods, but did not include space-time interactions or differences in space and time. This diploma thesis will conduct both spatial and temporal analyses of tornado touchdown points in the United States from 1950 to 2009. "Cutting-edge" spatial and temporal techniques will be applied and results compared. This dataset is made available by the

Storm Prediction Center (SPC) of the National Oceanic and Atmospheric Administration (NOAA) free of charge.

The following research questions will be addressed in this thesis:

- Will recently developed statistical techniques result in more accurate analysis than classic methods?
- Do different hot spot analysis techniques provide the same or different results? What techniques are most useful for the spatial and temporal analysis?
- Did the locations of spatial concentrations of tornadoes in the United States change over time? Is there a general pattern in the spatial variation or is the F-Scale an influencing factor for spatial and temporal variability?
- Is the pattern of BROOKS et al. (2003) who analyzed tornadoes from 1980 to 1999 (dis)similar to the monthly maxima pattern of the tornado occurrences from 1950 to 2009?
- What are the relative risks of fatalities due to tornado touchdowns in the United States? How did these rates change over time?

The aim of this thesis is to analyze and visualize tornado occurrences in the United States using GIS and state-of-the-art spatiotemporal statistics. Methods such as the kernel density estimation approach as an interpolating approach, the Nearest Neighbor Hierarchical Clustering routine, and the Space-Time Permutation Model that group events to clusters and the Local Indicators of Spatial Association technique to look for spatial autocorrelation in neighboring values will be introduced to thoroughly analyze the tornado dataset. This thesis should be of interest to researchers in various fields that use spatial and temporal methods to analyze point patterns. Each proposed method in this thesis will be explained and their strengths and drawbacks evaluated.

In the first chapter the meteorological phenomenon called “tornado” will be explained and discussed briefly. The focus of this chapter will be on the spatial distribution of tornadoes in the United States. In addition, previous research on tornado occurrences will be shown and evaluated.

The second chapter starts with an introduction to the tornado dataset that will be used in this study. In the methodological part of this chapter, the basics of point pattern analysis will be explained comprehensively. Then, conventional mapping techniques as well as mapping techniques based on spatial statistics will be presented and compared. Methods to check for space-time interaction and cluster persistence will be addressed afterwards. Freely available software packages that provide various spatial and temporal statistics will then be introduced. From these software tools four statistical methods are chosen to comprehensively analyze the tornado dataset. The proposed techniques are explained and evaluated subsequently.

The third chapter contains the spatial and temporal analysis of tornado touchdown points in the United States in the period 1950 to 2009. Herein, numerous maps, charts and tables will be provided to visualize the resulting outputs.

The thesis concludes with a summary and possibly future research areas on these topics.

1. The Phenomena of Tornadoes

In this chapter the phenomena of tornadoes will be presented beginning with a definition and explanation of the meteorological basics. As already mentioned in the Preface, this diploma thesis will not discuss the meteorological requirements of the development of tornadoes in detail. Furthermore, there will be a discussion of how tornadoes are different from other whirling storms before the spatial component of tornado touchdown points is discussed. The distribution of tornadoes in the world will be presented first, followed by focusing on the distribution of tornadoes in the contiguous United States. Much work has been done by the Storm Prediction Center as part of the National Oceanic and Atmospheric Administration (NOAA) in collecting data from tornado touchdown points. The extensive database with several indicators related to tornadoes will be discussed, including the database's benefits and limitations. In the database the F-Scale is used to classify tornadoes in terms of the typical damage pattern. Historical classification methods, the proposed F-Scale, and the recently introduced Enhanced F-Scale (EF-Scale) will be explained one by one.

This chapter will also include a literature review of spatial and temporal analyses of the distribution of tornado touchdown points. In this context and due to the high frequency of tornadoes in the Great Plains an area named "Tornado Alley" has been established.

1.1. Characteristics of Tornadoes

A tornado (from the Latin word "tornare" – "to turn") is the most violent storm that occurs in the atmosphere. It is much stronger compared to other cyclones, dust whirls, waterspouts, hurricanes, and typhoons. Each of these is a whirling storm, but all of them, except of waterspouts, have different characteristics from those of a tornado (FLORA 1953).

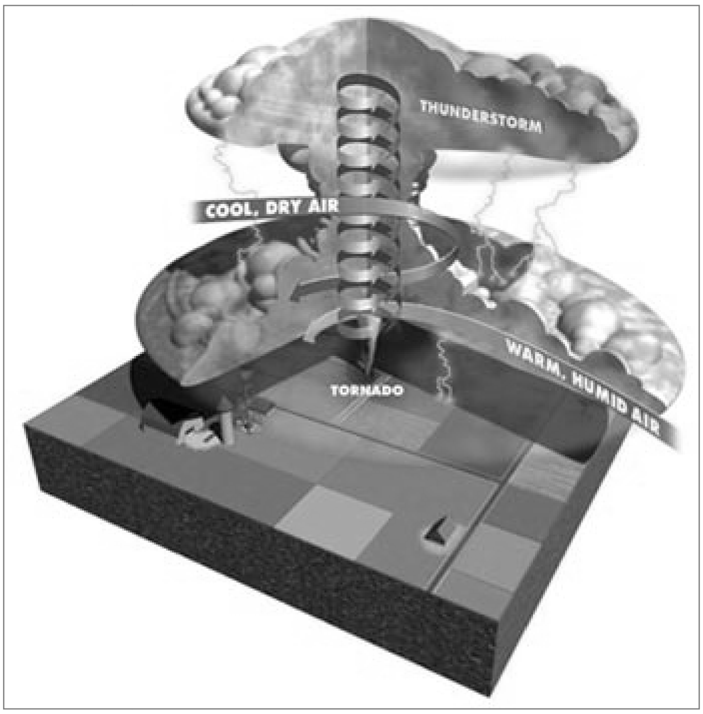
The difference to cyclones is the non-existent funnel-shaped cloud. Another characteristic is the duration: most cyclones last for several days while tornadoes last only few hours at the most. While such cyclones do not have the same common characteristics of a tornado, a true waterspout is actually a tornado over a water surface. Hence, if a waterspout passes from water to land it becomes a tornado and vice versa. As mentioned in the word "true" waterspout there are some "untrue" waterspouts known as the "fair-weather spout". The difference is that a fair-weather spout starts from a water surface and develops upward like the familiar dust whirl or "dust devil" on land. A true waterspout develops in the clouds and forms downward (FLORA 1953).

People often do not know the difference between tornadoes and hurricanes. A hurricane is a violent tropical cyclone with approximately 100 to 500 miles in diameter. American hurricanes usually originate during July to October. Their familiar counterpart at the eastern coast of Asia is called Typhoon. The two most important characteristics of these violent storms are the area that they cover and their duration in comparison to tornadoes. First, a hurricane covers a large area and is the most destructive of all storms. The paths of tornadoes cover only a part of a hurricane's area but the winds of a tornado are more violent. Second, a hurricane has an average life of nine and one-half days. In comparison, the duration of tornadoes – as mentioned above – it is only a fractional part of duration of a hurricane (FLORA 1953). It should be noted that tornadoes occasionally accompany hurricanes, when they make landfall along the Gulf of Mexico or the southeastern Atlantic coast of the U.S. (BLUESTEIN 1999, NOAA 1995).

Now that the difference between a hurricane and a tornado has been made it is necessary to define a tornado and to explain its meteorological structure. In the literature several definitions of tornadoes are given. The National Oceanic and Atmospheric Administration (NOAA) defines a tornado as "a violently rotating column of air extending from a thunderstorm to the ground" (NOAA 1995). Howard B. BLUESTEIN (1999) argues that meteorologists are still trying to answer the question what a tornado exactly is. Not every tornado occurs within powerful thunderstorms, and not all tornadoes are spawned by thunderstorms. As mentioned before, hurricanes and typhoons can spawn tornadoes. Considering these circumstances, Bluestein introduces the following definition of a tornado: "It is a violently rotating column of air, which may not be oriented vertically, that comes from beneath the base of a thunderstorm or a rapidly growing towering cumulus cloud" (BLUESTEIN 1999).

EAGLEMAN et al. (1975) state that a typical tornado day starts with very humid and warm air at ground level (Figure 1). Large cumulonimbus clouds and furthermore thunderstorms develop due to the progressing solar heating on the ground and the eastward-moving cold fronts in advance (EAGLEMAN et al. 1975, NOAA 1995). These thunderstorms often produce large hail, strong winds, and tornadoes.

Figure 1: Development of tornadoes



Source: http://teacher.scholastic.com/activities/wwatch/tornadoes/images/tornado_map.jpg

Tornadoes are rotating vortices that extend from the bottom of the thunderstorm cloud to the earth's surface. A vortex is composed of circulating air around a central core. If the vortex does not reach the ground it is designated a funnel cloud. The visibility of the funnel clouds is given because of condensation in the lower pressure within the vortex. Due to this lower pressure within the funnel water vapor condenses into cloud droplets. As the funnel reaches the ground it becomes a tornado and its appearance is affected by dust, water, or debris that is picked up from the surface (EAGLEMAN et al. 1975).

All tornadoes have in common that a loud noise is accompanying them. The noise is described as the roar of many trains or jets (EAGLEMAN et al. 1975). Tornadoes vary in intensity and much progress has been made recently to assign a scale to tornadoes on the basis of the types of damage tornadoes can cause (see subchapter 1.2.). Additionally, tornadoes develop into a variety of shapes as well as sizes (for more details and pictures see BLUESTEIN 1999, EAGLEMAN et al. 1975).

1.2. Classification of Tornadoes

First attempts toward a useful method to classify tornadoes by size and intensity were made in the 19th century. HAZEN (1890) presented Hinrich's method to classify tornadoes:

Table 1: Hinrich's method of tornado classification (HAZEN 1890)

A. Notable Tornadoes
   - Class I: Multiple
     - (a) Large
     - (b) Small
   - Class II: Single
     - (a) Large
     - (b) Small

B. Minor and Doubtful Tornadoes

Clearly, this rudimentary method was not very satisfying. Although it was certainly known that tornadoes are not uniformly intense, there had been no formal attempt for some time to differentiate tornado occurrence by intensity (DOSWELL et al. 2009). In 1971 it was Tetsuya "Ted" Fujita, a meteorologist at the University of Chicago, who developed the Fujita scale to provide a method to rate the intensity of tornadoes (FUJITA 1971, 1981). His intention was to distinguish between weak tornadoes and strong tornadoes because there was a need to rate historical tornadoes as well as future tornadoes. The Fujita scale was immediately accepted by the meteorological and engineering communities (MCDONALD and MEHTA 2006).

The scale rates tornadoes from F1 to F6. Although the scale was created as a wind speed scale, the tornado intensity is based only on the degree of damage caused by tornadoes. Basically the scale was designed to connect smoothly with the Beaufort scale, devised in 1806 by Sir Francis Beaufort, a

British naval officer. The Beaufort scale is a measure for describing wind speed from 0 (calm) to 12 (hurricane-force winds). The Fujita scale picks up where the Beaufort scale ends and eventually reaches the speed of sound (Mach 1). As proposed by Fujita, an F6 tornado is “inconceivable” (BLUESTEIN 1999). Tornadoes rated as F0 are winds weaker than hurricane force.

Table 2: The Fujita F Scale (BLUESTEIN 1999)

F number	F-scale damage specification
F0	<72 mph - Light damage: some damage to chimneys; break branches off trees; push over shallow-rooted trees; damage signboards
F1	73–112 mph - Moderate damage: peels surface off roots; mobile homes pushed off foundations or overturned; moving autos pushed off the road
F2	113–157 mph - Considerable damage: roofs turn off frame houses; mobile homes demolished; boxcars pushed over; large trees snapped or uprooted; light-object missiles generated
F3	158–206 mph - Severe damage: roofs and some walls torn off well-constructed houses; trains overturned; most trees in forest uprooted; heavy cars lifted off ground and thrown
F4	207–260 mph - Devastating damage: well-constructed houses leveled; structures with weak foundation blown off some distance; cars thrown and large missiles generated
F5	261–318 mph - Incredible damage: strong frame houses lifted off foundations and carried considerable distance to disintegrate; automobile-sized missiles fly through the air in excess of 100 meters; trees debarked; incredible phenomena will occur

Although the Fujita scale has been in use for 33 years, its limitations are well known. In fact, damage and wind speed are not unrelated (SCHAEFER et al. 1986), but it is risky to estimate the tornado intensity on damage alone, without any actual wind measurements. The Fujita scale does not account for different construction qualities. Well-built structures can withstand strong winds, while a poorly built structure can suffer devastating damage even from less intense winds. BLUESTEIN (1999) argues that the most tornado damage is a result of pressure induced by the wind. Furthermore, the damage is related to different angles of the wind: two identical objects that feel the wind from different angles may suffer different amounts of damage. And of course, if tornadoes occur over open country no damage occurs and an adequate classification will not be possible. Currently, instruments to measure wind speed directly have never survived a strong tornado (BLUESTEIN 1999).

DOSWELL and BURGESS (1988) explain another peculiarity of tornado rating: The Fujita scale rating is determined by the maximum observed damage at a point anywhere within the total path of the tornado. Hence, a single occurrence of the highest damage level determines the rating for the entire path. Another important aspect can be seen in the individual reasoning of human beings. Fujita scale ratings are dependent upon the person reviewing the damage. A person with experience and knowledge of building structures (e.g., a structural engineer) would probably rate the damage differently than a person without that knowledge (MARSHALL 2002).

All those mentioned limitations and drawbacks have led to inconsistent rating of tornadoes and in some cases to an overestimation of tornado wind speeds (McDonald and Mehta 2006). Accordingly, there was the need to revisit the concept of the Fujita scale and to improve and eliminate some of the limitations and drawbacks.

In 1970 a strong tornado passed near the campus of Texas Tech University (TTU). As a result of that devastating event, the TTU created a wind engineering research program with an emphasis on structural engineering issues. Researchers tried to further explore the relationship between wind speed and damage and to answer questions about how to design structures to resist tornadic winds. In the last decade, structural engineers led by the TTU group initiated a series of discussions based on their individual experience on tornado intensity ratings to enhance the Fujita scale. It is possible to measure wind speeds using the Doppler principle (mobile Doppler radar). However, there are some physical limitations that make the possibility of obtaining useful tornado wind speed measurements using the mobile Doppler radar quite unlikely. As a consequence, damage continues to be the most useful indicator of tornado intensity rating (Doswell et al. 2009).

The efforts of the group of experts at TTU resulted in the adoption of the Enhanced Fujita (EF) scale by the National Weather Service (NWS) in 1 February 2007. The most important difference is the identification of damage indicators. These indicators were created additionally to the "well-constructed" frame home as the primary indicator of the original Fujita scale. In total, the experts created a list of 28 damage indicators to allow the members of a local National Weather Service team to estimate the wind speeds associated with an observed degree of damage for each indicator. The TTU team of scientists and engineers assigned a wind speed estimate to each degree of damage for every damage indicator. They also adjusted the EF-scale ratings to be identical to the F-scale ratings from the past, in order to maintain historical continuity (Doswell et al. 2009). A correlation analysis of the F-scale ratings and the EF-scale ratings showed that there is a high correlation of R^2=0.91 (McDonald and Mehta 2006).

In their conclusion, Doswell et al. (2009) compare the early beginnings of the measurements of earthquake intensities to the tornado intensities. Before the adoption of the Richter scale, which measures the magnitude of earthquakes by the energy released, a subjective, damage-based intensity scale was used instead. The authors believe that ultimately some objective measure of tornado wind speeds will be developed in the future.

1.3. Distribution of Tornadoes

In this subchapter a general discussion of the spatial distribution of tornadoes in the world as well as in the United States will be given. Then, factors that influence the locations of tornado occurrences will be presented, followed by an analysis of an area named "Tornado Alley", where the most tornadoes occur. In this subchapter existing research related to tornado touchdown points will be introduced and discussed.

1.3.1. Distribution in the World

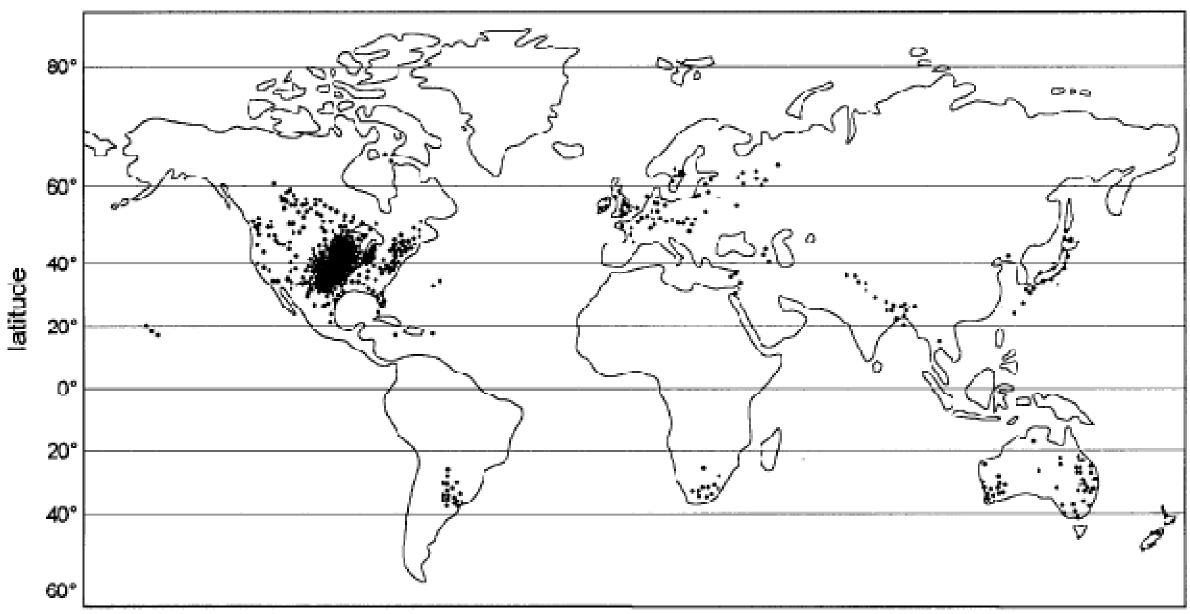
Tornadoes occur in all parts of the world except the Antarctica. Their occurrence in the world is more frequently than is commonly assumed. In terms of tornado frequency Australia is second to the United States (FUJITA 1973). While large amounts of data are available about tornadoes in the United States, for many other countries the information on tornado touchdown points are fragmented and in some cases contradictory (GOLIGER and MILFORD 1998).

Tornadoes throughout the world are concentrated in both hemispheres between the latitude 20° and 60° but predominantly in the United States. These belts on both sides of the equator correspond to the zones of the jet streams and the presence of contrasting air masses (EAGLEMAN et al. 1975). Figure 2 shows a map of expected events for a 4-year period.

1.3.2. Distribution in the United States

Tornadoes have been recorded in every state of the United States including Alaska and Hawaii. As can be seen in Figure 2 tornadoes are much more frequent in the Great Plains region east of the Rocky Mountains. In the central United States the tornado activity is more frequent because of its unique geographical setting, where unstable atmospheric characteristics are present. The atmosphere becomes less stable and this is a requirement for large thunderstorm development. In the Great Plains tornado outbreaks are often associated with the southeastward flow of cool, dry air over the Rocky Mountains to the Gulf of Mexico. From the opposite direction warm, moist air is flowing northward at the same time. Atmospheric instability occurs when the cool, dry air from the west is overriding the warm, moist air from the south. This leads to an easier development of thunderstorms and therefore the central United States has the greatest tornado activity (EAGLEMAN et al. 1975).

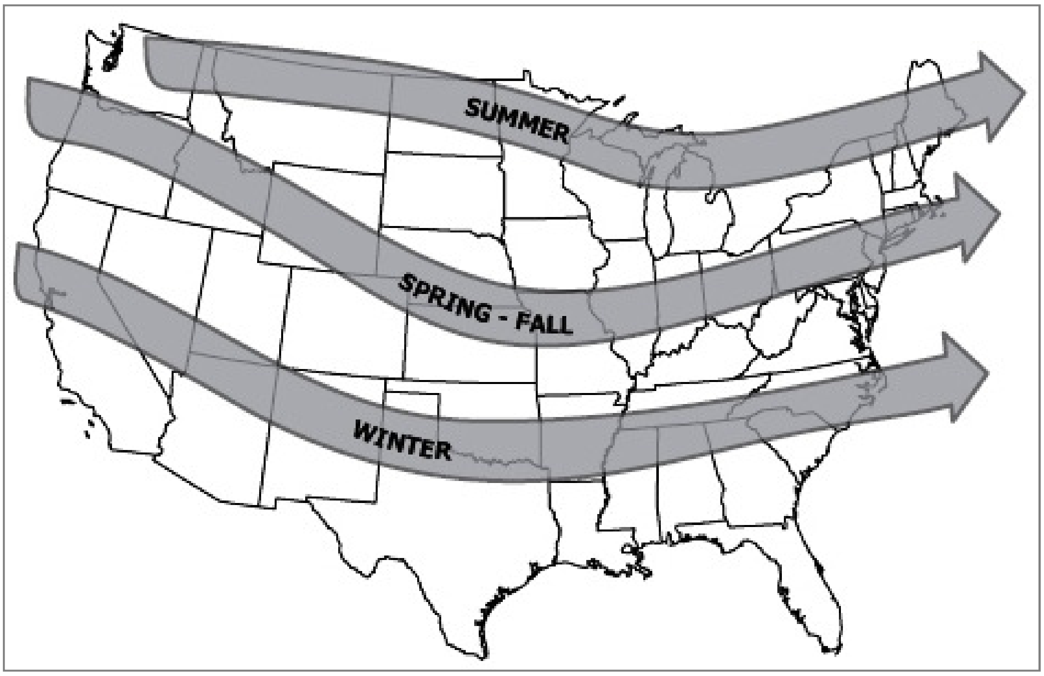
Figure 2: Tornado occurrence in the world expected for about a four-year period



Source: FUJITA (1973)

The monthly distribution of tornadoes is known to be associated with the jet streams. The jet streams – a high velocity stream of air – flow from west to east at different latitudes during different seasons of the year. Their positions shift northward during the summer months and southward during the winter (Figure 3), where they separate the cold air from the north from the warm air to the south. If the jet streams are flowing to the southern part of the United States, tornadoes are more likely to occur in these regions. As the jet streams move northward during the spring months the tornado activity also moves northward. Generally, it has to be noted that the most tornadoes occur in May although tornadoes are known to happen during all months of the year (EAGLEMAN et al. 1975).

Figure 3: The general position of the polar jet streams during different seasons of the year

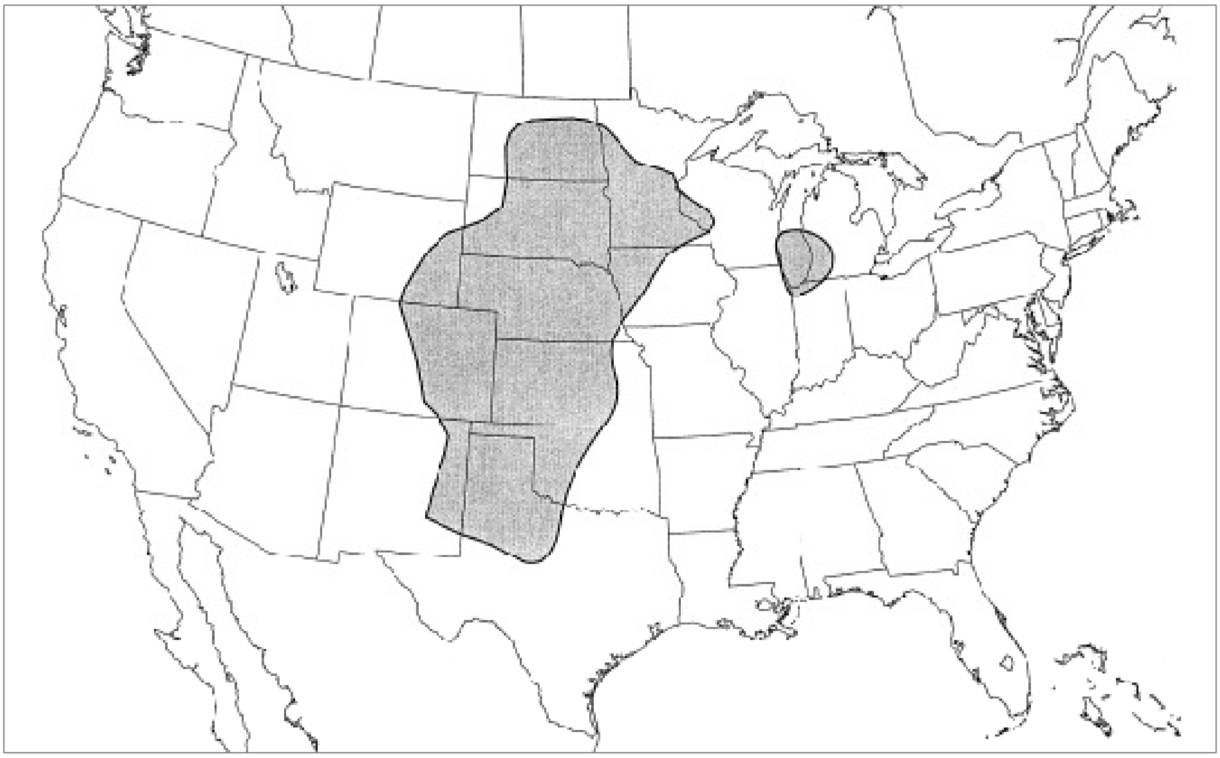


Adapted from EAGLEMAN et al. (1975)

The region in the central United States where most tornadoes occur is called "Tornado Alley" (KELLY et al. 1978). In their study, the authors collected tornado reports from 1950 to 1976, removed "doubtful" reports, and generated national annual cycles, diurnal cycles normalized by local solar time and maps of the annual-averaged tornado reports. The Tornado Alley they identified runs between 97° and 98°W, with a secondary axis curving northeastward from the Texas Panhandle through Missouri and eastward into north-central Indiana. BROOKS et al. (2003) criticized the concept of the Tornado Alley. Although it is a popular concept of a geographical demarcation, the authors see it as historically ill-defined. BROOKS et al. (2003) argue that the concept refers most often only to the frequency of events but it should additionally include the temporal autocorrelation of the seasons. Based on the combination of the frequency of occurrence and the reliability of the season, BROOKS et al. (2003) used at least 0.5 tornado touchdown days per year and a variability measure (trimmed standard deviation) in the timing of the peak threat of less than 20 days to define their Tornado

Alley. The result (Figure 4) shows similar boundaries as the one from KELLY et al. (1978). In addition, there is a small region near southern Lake Michigan that is separated from the main region and which also shows a high occurrence of tornadoes (BROOKS et al. 2003). BROOKS et al. (2003) used tornado days (days with tornadoes) from 1980 to 1999 to produce the following map.

Figure 4: Updated Tornado Alley as defined by BROOKS et al. (2003)



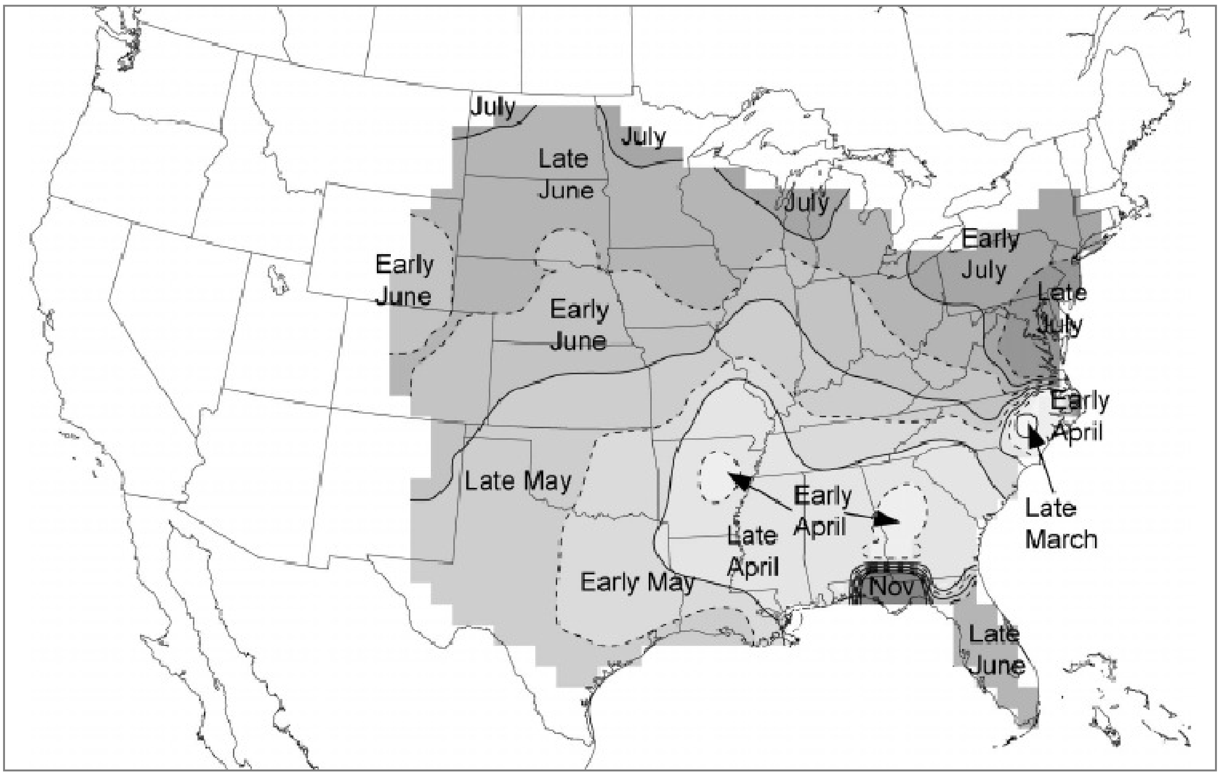
Source: BROOKS et al. (2003)

The total amount of tornado reports varies from approximately 800 to 1,400 in any given year. The first map of the tornado occurrence in the United States was published by FINLEY (1887). He displayed the locations of approximately 1,300 tornadoes from 1760 to 1885. Due to the low population density in Oklahoma and western Texas, there were no reported tornadoes in Finley's map. A more precise and accurate map using data from 1916 to 1955 has been presented by WOLFORD (1960), where a maximum of tornado occurrence has been identified in the region of the Tornado Alley.

The first statistical attempt to estimate tornado probabilities was made by THOM (1963). He used data from 1953 to 1962, and smoothed the values over a grid box. KELLY et al. (1978) presented some statistical analyses using a dataset of tornado touchdown points from 1950 to 1976. First of all, KELLY et al. (1978) investigated the average annual diurnal distribution of tornadoes. The result was that the peak occurrence is during the late afternoon, while minimum occurrence is just prior to sunrise. In addition they investigated the diurnal occurrence of tornadoes by the tornado intensity (F-Scale). They concluded that weak tornadoes (F0 and F1) maximize at midday, while strong tornadoes (F2 and F3) have their maximum in the late night.

In agreement with previous tornado studies (e.g., LOOMIS 1842), KELLY et al. (1978) report that the highest tornado frequency occurs during the four-month period March to June. Approximately 40 percent of all tornadoes are found during May and June. Geographical distributions have been constructed by aggregating the counts of tornadoes in a grid. KELLY et al. (1978) produced smoothed intensity maps for weak, strong, and violent (F4 and F5) tornadoes for the period 1950 to 1976.

Figure 5: Geographical distribution of the date of maximum tornado threat

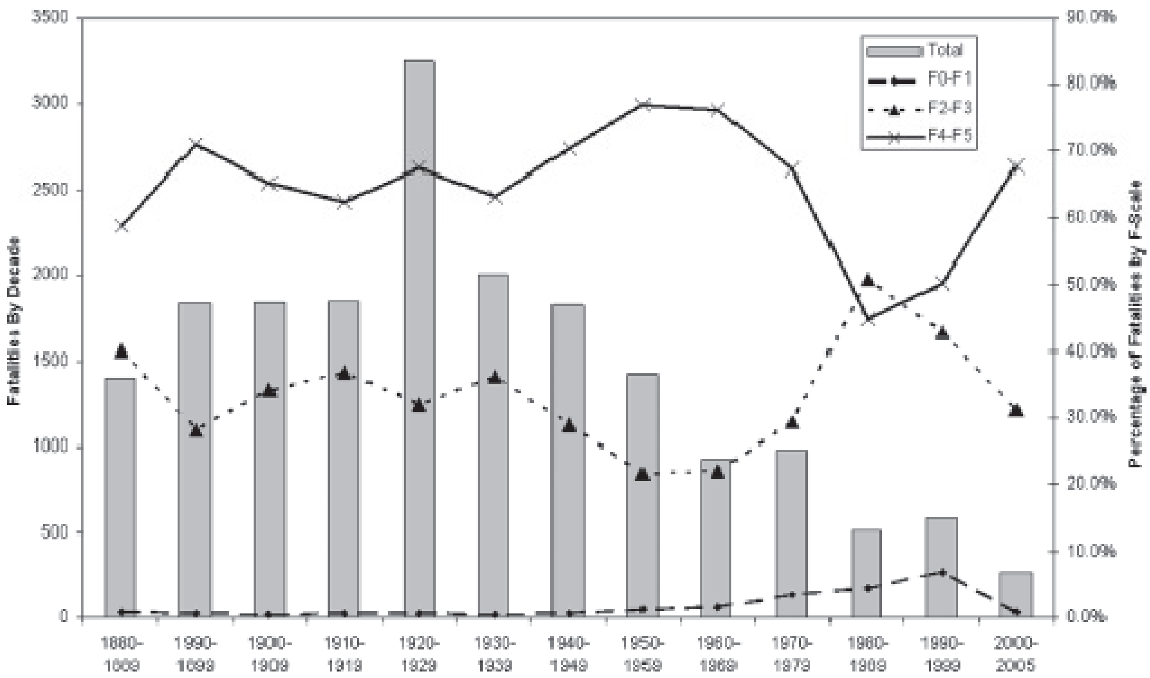


Source: BROOKS et al. (2003)

The spatial variability in the variation of the threat during the year has been investigated by BROOKS et al. (2003). Figure 5 shows the location of maximum tornado threat in the United States for the period 1980–1999 with at least 0.25 tornado days per year. According to the explained concept of the jet stream, the maximum threat occurs in April over much of the southeastern United States (except Florida). The peak threat moves westward toward Texas, and almost all locations between the Rocky Mountains and the Appalachians have their peak threat till the end of May. Locations in the north have their peak threat in later months. States at the Atlantic coast, east of the Appalachians, have their peak threat in July. As can be seen, there are two regions depart from this general pattern: peninsular Florida, where the summer peak is associated with nonsupercellular – a supercell is a rotating thunderstorm with a well-defined radar circulation – convection, and the Gulf Coast near Tallahassee, FL, with a peak threat in late November (BROOKS et al. 2003).

Only a small percentage of tornadoes in any given year produce casualties. Although there have been considerably advances in tornado detection, warning dissemination, and public awareness, tornado casualties cannot be prevented entirely. The number of tornado fatalities declined in the last years (Figure 6) but such killer tornadoes have been reported recently (ASHLEY 2007).

Figure 6: Total number of tornado fatalities (solid bar) by decade (except for 2000–05) during the period of record and percentage of fatalities due to weak, significant, and violent tornadoes by decade (lines)



Source: ASHLEY (2007)

Numerous studies have investigated tornadoes as a hazard to life and property throughout the United States. KELLY et al. (1978) made a statistical analysis of the percentage of tornadoes by F-Scale and the percentage of fatalities associated with each category. In the period 1950 to 1976 there have been 3,092 tornado fatalities. The majority (61.7 percent) of the tornadoes were weak (F0 and F1). Weak tornadoes resulted in only 2.5 percent of all tornado fatalities. Strong tornadoes (F2 and F3) have a proportion of 36.0 percent of all tornadoes and produce 29.6 percent of all fatalities. Only 2.3 percent of tornadoes are violent (F4 and F5) but they cause 68.0 percent of all tornado fatalities. An extension of the work of KELLY et al. (1978) was made by ASHLEY (2007). He analyzed the percentages of weak, strong, and violent tornadoes by decade from 1880 to 2005 (Figure 6). The figure shows that violent tornadoes account for approximately 70 percent of all fatalities throughout this period. An exception can be determined in the decades 1980-1989 and 1990-1999, where the percentage of fatalities occurred from violent tornadoes was as high as the percentage from strong tornadoes. A reason of the slightly increase of fatalities occurred from weak tornadoes can be seen in the increased proportion of mobile homes in the United States. The percentage of mobile home fatalities from weak tornadoes is significantly higher compared to the percentage of permanent home fatalities (SUTTER and SIMMONS 2010). The authors as well as BROOKS and DOSWELL (2002) argue that the probability of a tornado fatality in mobile homes is estimated to be 10–15 times higher than in permanent homes.

ASHLEY (2007) investigated the spatial and temporal distribution of tornado fatalities in the contiguous United States from 1880 to 2005. Only four states of the conterminous 48 states – California, Nevada, Rhode Island, and Vermont – never experienced a killer tornado during the mentioned period. In terms of a standardized fatalities rate (deaths per square kilometer) the three southern states – Mississippi, Alabama, and Arkansas – are leading. ASHLEY (2007) listed nine possible climatological and nonclimatological reasons for an increased vulnerability to the greater concentration of tornado fatalities and killer events within this region. One possible reason is the fact that tornadoes within this region tend to occur during the cool and transition seasons when day length is at a minimum, increasing the likelihood of nighttime tornadoes. Another reason is the large percentage of mobile home and weak-frame housing stock in comparison to other parts of the United States that experience tornadoes. An important aspect is the population density which is much higher in the South in comparison to the Midwest and the Great Plains. In contrast, the tornado season in the Great Plains is much more concentrated and peaked (BROOKS et al. 2003), which leads to an enhanced period of awareness and preparedness of the population to reduce the vulnerability to a tornado hazard. In addition, the population has a “greater” experience with tornadoes which leads to more awareness of what to do during a tornado situation (ASHLEY 2007).

1.4. The History of the Storm Prediction Center

The first attempt in tornado forecasting was made in the mid-1880s, when the meteorologist J. P. Finley from the U.S. Army Signal Service dared to suggest that tornadoes were predictable. In 1883, the U.S. Government banned the word “tornado” from forecasts to avoid panicking the masses. The explanation of the chief Signal Officer in his report was: “It is believed that the harm done by such a prediction would be greater than that which results from the tornado itself.” (U.S. ARMY 1887, BLUESTEIN 1999).

The reestablishment of a centralized severe weather forecasting program in the United States happened due to a fortuitous occurrence of two tornadoes at the same place in less than a week. On March 20, 1948, a tornado struck Tinker Air Force Base, near Oklahoma City. Five days later, with similar atmospheric conditions, two meteorologists at Tinker, Major Ernest Fawbush and Captain Robert Miller, issued a tornado warning, although it was not made public. The actions by Fawbush and Miller led to first attempts of a civilian tornado forecasting program (CORFIDI 1999, BLUESTEIN 1999, DOSWELL et al. 1993).

Further efforts by Fawbush and Miller led the Weather Bureau (predecessor of the National Weather Service) to establish its own severe weather unit on a temporary basis in the Weather Bureau-Army-Navy (WBAN) Analysis Center Washington, D.C., in March 1952. From now on the permanently five-man operation group of the WBAN severe weather unit was responsible for the issuance of “bulletins” (watches) for tornadoes, high winds, and/or damaging hail. In June 1953 the unit was renamed the Severe Local Storms Warning Service (SELS) and moved from Washington, D.C. to Kansas City, MO in September 1954 in part to be closer to the Tornado Alley. Over the years the Severe Local Storms Warning Service fostered the development of a separate research and development unit, and continued to grow as additional forecast and staff were added. Once it also resumed the responsibility of local and regional forecast duties it was renamed the National Severe Storms Forecast Center (NSSFC) in 1966. At this time the research group (of the former Severe Local Storms Warning Service) merged with the Weather Bureau's Weather Radar Laboratory to form the National Severe Storms Laboratory (NSSL) in Norman, Oklahoma, in 1964. The severe weather function of the National Severe Storms Forecast Center was renamed the Storm Prediction Center in 1995. In 1997 the Storm Prediction Center joined the National Severe Storms Laboratory and moved from Kansas City to Norman, Oklahoma (CORFIDI 1999).

2. Data and Methodology

In this chapter the dataset of the tornado touchdown points from 1950 to 2009 is explained and discussed. Afterwards, principles of the spatial and spatiotemporal cluster analysis as well as mapping techniques will be thoroughly presented. The section about the mapping techniques includes traditional techniques, as well as statistical approaches to display and analyze spatial data. These statistical techniques are then the basis of space-time approaches that will be subsequently applied in the analysis in the next chapter.

Then, a review of software packages that are available for spatial and spatiotemporal cluster analysis will be discussed. The focus will be on non-commercial, open-source software tools, which are available at the web free of charge.

The last subchapter explains techniques, which are used to analyze the tornado dataset from 1950 to 2009. These techniques will be discussed and compared with each other and the advantages as well as the drawbacks will be explained.

2.1. Tornado Touchdown Points

This thesis applies tornado touchdown points from 1950 to 2009 from the Storm Prediction Center's Severe Weather Database Files (hereafter tornado database). The data are available for free and accessible at http://www.spc.noaa.gov/wcm/. Tornado reports in the dataset are available since 1950, and therefore 1950 was chosen as the starting year for this study. The end of this dataset in 2009 was determined by the last full year the tornado reports were available. There may be some problems during the first few years of this database due to the unorganized manner in which the reporting of tornadoes was conducted and documented (GRAZULIS et al. 1993). Understandably, many tornadoes have not been reported in these early years, but the underreporting has been reduced in recent decades (BROOKS and DOSWELL 2002).

DOSWELL and BURGESS (1988) illustrated some limitations of the database. They argued that much of the information about tornadoes comes from untrained witnesses, and there might be ample reasons to question the quantitative aspects of the database. Additional limitations include basic errors in reporting and/or recording of time and location. Other limitations relate to the spatial and temporal variability in the collection efforts for warning verification, changes in damage survey procedures, population increase and migration, and storm spotter network creation (DOSWELL and BURGESS 1988, GRAZULIS 1993 and VERBOUT et al. 2006).

Alternative data sources are listed in GRAZULIS (1993, 1997) and in the National Climatic Data Center's Storm Data and "Storm Events" database (available online at http://www4.ncdc.noaa.gov/cgi-win/wwcgi.dll?wwevent~storms). The dataset of Grazulis includes "significant" tornadoes, including all known tornadoes that produced fatalities, from 1680 to 1995. The Storm Data contains tornado events from 1950 to 1992. According to the Storm Prediction Center a tornado is "significant" if it is rated EF2 or greater (F2 or greater on the former Fujita scale). It should be noted, that this definition is arbitrary. There is no scientific research about "significant" tornadoes, since any tornado can kill or cause damage.

As mentioned before, the tornado database contains tornado touchdown points from 1950 to 2009 from the contiguous United States. This dataset and this period was chosen because this period is the start of a large increase in the number of reported tornadoes. This tornado dataset contains several parameters like the geographic coordinates from each tornado's starting and ending point, the exact date of the event, the F-Scale and the EF-Scale rating (after January 2007), respectively, the total number of injuries and fatalities, and estimated property loss information. There are more parameters available in the dataset but they are not of interest to this thesis. Further information is available in the description of the Severe Weather Dataset, available online at http://www.spc.noaa.gov/wcm/data/SPC_severe_database_description.pdf.

Table 3: Basic statistics of the tornado database, 1950–2009

F-/EF-Scale	Events	Fatalities	Fatalities per Events	Events (%)	Fatalities (%)
0	23,142	20	0.001	42.9	0.3
1	17,465	208	0.012	32.4	3.6
2	8,461	538	0.064	15.7	9.3
3	2,365	1,261	0.533	4.4	21.8
4	612	2,398	3.918	1.1	41.4
5	72	1,361	18.903	0.1	23.5
-9	1,843	6	0.003	3.4	0.1
Total	53,960	5,792	0.107	100.0	100.0

Note: -9 means the rating of the tornado was undefined.

Table 3 contains general absolute and relative statistics of the tornado database used in this thesis. In total, 53,960 tornado events were reported in the period 1950–2009. This number resulted in 5,792 fatalities. The average count of tornado events per year was 899. The average annual number of injured people was 1,607, and the average number of fatalities per year was almost 97. As can be seen in Table 3, the two mentioned indicators, events and fatalities, are structured by the F-/EF-Scale in cross tables. The ratings of some tornadoes were undefined and their ratings were set to "-9". Almost every second reported tornado is rated as F0. In comparison only 0.1 percent of all recorded tornadoes are rated as F5 tornadoes. This means that the annual average occurrence of a F5 tornado was 1.2. Generally, it can be argued that the higher the rating, the lower the occurrence of tornadoes. Considering the absolute numbers of fatalities, one would believe that the higher the tornado rating, the higher the casualties. In fact this rule works well for tornadoes rated F0 to F4. Due to the low absolute number of F5 tornadoes, the total number of fatalities is comparably low compared to lower rated tornadoes. Therefore, a relative measurement, namely the number of fatalities per events is calculated and added to the table. Based on relative measurements, it can now be stated that the higher the rating, the higher the relative number of fatalities per tornado event. As an example see the relative number of tornadoes rated with incredible damage (F5). A single F5 tornado results in an average number of approximately 19 fatalities.

In addition, tornado events are aggregated based on classifications taken from the literature. The classification of significant tornadoes rated F2 or higher (GRAZULIS 1993), and the three classifications proposed by KELLY et al. (1978) and ASHLEY (2007) are listed in Table 4.

Only one fifth of the reported tornadoes were rated as significant, meaning the rating was at least F2. But these 21.3 per cent of the total amount of tornado events resulted in 96.0 percent of the total amount of fatalities. Therefore it is legitimate to use the term “significant tornado” due to the amount of fatalities.

Regarding the three categories – weak (F0 and F1), strong (F2 and F3), and violent (F4 and F5) – used in the studies of KELLY et al. (1978) and ASHLEY (2007), one can confirm the pattern described above: The stronger the tornadoes, the lower their numbers. The total number of weak tornadoes was approximately 60 times higher than the total number of violent tornadoes. In contrast, the total number of fatalities is 16 times higher for violent tornadoes compared to weak tornadoes.

Table 4: Basic statistics of the tornado database based on classified tornadoes, 1950–2009

F-/EF-Scale	Events	Fatalities	Fatalities per Events	Events (%)	Fatalities (%)
Significant (F2+)	11,510	5,558	0.483	21.3	96.0
Weak (F0–F1)	40,607	228	0.006	77.9	3.9
Strong (F2–F3)	10,826	1,799	0.166	20.8	31.1
Violent (F4–F5)	684	3,759	5.496	1.3	65.0
Total (F0-F5)	52,117	5,786	0.111	100.0	100.0

An advantage of the tornado dataset is the data format. Its CSV-File can be read easily by a Geographic Information System (GIS), where the dataset can be manipulated and analyzed. Generally, a GIS can perform four basic functions on spatial data: Input, storage, analysis, and output (GOODCHILD 1987). The combination of a GIS and spatial data analysis is an important aspect of a GIS as a research tool to explore and analyze spatial relationships. VANN and GARSON (2001) argued that “spatial analysis using GIS is not synonymous with statistical analysis”. WILSON (2007) differentiates these various techniques: A GIS is simply a geographic data visualization and manipulation tool. It is used to prepare data for statistical analysis and to display the output from analysis. Spatial analysis represents the (spatial) analysis of geographic objects to other geographic objects across space. Spatial data analysis is seen as the combination of the spatial analysis techniques with associated attribute data of the geographic objects.

2.2. Spatial and Spatiotemporal Cluster Analysis

Due to the increasing use of GISs and its combination with modern data capturing methods (e.g., GPS, satellite imagery, etc.), the number of available spatial data has risen in recent decades. Spatial cluster analysis plays an increasing role in quantifying geographic variation in patterns. The techniques are commonly used in disease surveillance, spatial epidemiology, population genetics, landscape ecology, crime analysis, and many other fields, but the underlying principles are still the same (JACQUEZ 2008). The origins of the techniques used nowadays in the statistical analysis of spatial point data arose almost 80 years ago in plant ecology. In the early 1960s, geography in the United States experienced the "quantitative revolution" when the techniques developed by ecologists were introduced into geography. At first they were used to refine and substantiate previous qualitative descriptions, particularly of settlement patterns. In further consequence, point pattern techniques were extended to the analysis of various phenomena in the field of geography and subsequently to other sciences (BOOTS and GETIS 1988). As many academic movements, the "quantitative revolution" in geography experienced a slow decline after its popular peak, and died out in the late 1960s and early 1970s. In the last two decades the field of spatial analysis rose to a point, where the methods and concepts are becoming fundamental to researchers in a host of disciplines (GETIS 2008). Reasons for that increasing usage of statistical analysis methods of spatial data processes can be found in GATRELL et al. (1996) and LORUP and LEITNER (2000). Both publications mention the development of GISs and its capability to store and analyze a huge amount of geographic data to be the main reason. In addition, GISs have the capability to visualize the results of the analysis. Another reason can be seen in the increased availability and collection of spatial data (GATRELL et al. 1996, LORUP and LEITNER 2000).

Spatial data can be divided by the type of spatial data, namely point and area data. Individual events, such as tornado touchdown points or street addresses of patients, can be represented as points. Area data result from aggregating individual data points by administrative units, or areal units, and are expressed as a count of events, or as a rate or proportion (e.g., tornado fatalities by population, or cancer death rates) (ANSELIN 2004).

In general, both point and area data would be referred to as "individual event data", but the type of analysis and interpretation of the results are slightly different. The analysis of point data is based on its proximity to each other and to what extent points are "closer to each other" than they would be compared to a reference situation. A cluster of aggregated data refers to the situation where an areal unit is surrounded by other units that are more similar to it than it would be in the case of a random distribution. This concept is termed positive spatial autocorrelation (ANSELIN 2004). A spatial cluster might be defined as an excess of events or values in geographic space. Cluster analysis plays an important role in Exploratory Spatial Data Analysis (ESDA). ESDA involves the identification and description of spatial patterns (such as spatial hotspots, spatial coldspots, and spatial outliers), and has two primary objectives (JACQUEZ 2008):

- Objective 1: Recognize patterns using visualization, spatial statistics, and geostatistics to identify the locations, magnitudes, and shapes of statistically significant pattern descriptors.
- Objective 2: Generate hypothesis to specify realistic and testable explanations for the geographic patterns found under Objective 1.

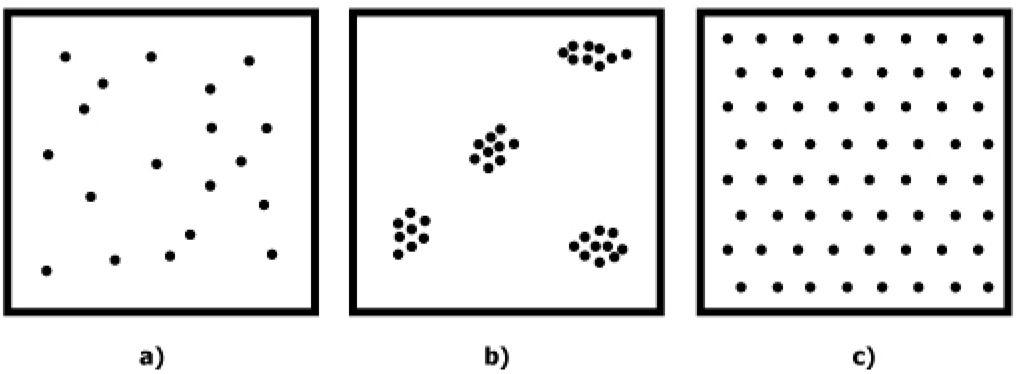
2.2.1. Fundamental Types of Point Patterns

A point pattern contains two major types of components: The points representing the objects being analyzed and the geographical area in which they are located. The main reason for the examination of point patterns is to learn something of the processes that generated the pattern. A basic question is, whether the spatial point distribution shows a systematic or a random pattern. Researchers have most often defined a theoretical pattern which is compared to the observed point pattern. An operation process called a homogeneous planar Poisson point process results in finding a theoretical pattern. In this process points are produced in a study area underlying two requirements (BOOTS and GETIS 1988):

- Uniformity: Each location in the study area has an equal chance of receiving a point,
- Independence: The selection of a location for a point in no way influences the selection of locations for any other points.

These two conditions can be interpreted that there is no interaction between the points and the study area is regarded as completely homogeneous. Such a pattern is considered as one that would occur by chance in a completely undifferentiated environment. DIGGLE (1983) calls such a pattern complete spatial randomness (CSR). An example of a complete spatial random distribution is shown in Figure 7a. Due to the conditions of a complete spatial random pattern, it is unlikely that a true complete spatial random distribution occurs in any real-world situation (BOOTS and GETIS 1988).

Figure 7: Fundamental Types of Patterns



(a) Complete spatial randomness (CSR), (b) clustered pattern, and (c) regular pattern
Adapted from BOOTS and GETIS (1988)

The pattern of a complete spatial randomness is considered to be an idealized standard. Such a pattern is used to compare it with the observed or empirically collected pattern from the real world and testing the hypothesis whether the observed pattern is similar or significantly different from a complete spatial randomness produced by a homogeneous planar Poisson point pattern. This leads to the exploration of a set of point data, and often to the formulation of other geographically relevant hypotheses. At the minimum, a description of the point pattern is conducted, whether or not the initial hypothesis relating to complete spatial randomness is rejected. Observed spatial point patterns which deviate from complete spatial randomness appear as clustered or as regular patterns. Clustered patterns show points that are significantly closer to each other in the study area than they would be in complete spatial randomness (see the example in Figure 7b). Regular patterns show points that are more spread out in the study area than they would be in complete spatial randomness (see Figure 7c). Clustered and regular patterns can result as a violation of one or both conditions underlying the homogeneous planar Poisson point process (BOOTS and GETIS 1988).

Basically, the most common techniques used in spatial cluster analysis are founded on statistical pattern recognition. Spatial pattern recognition proceeds by calculating a statistic (e.g., spatial cluster statistic, autocorrelation statistic, etc.) that quantifies a relevant aspect of a spatial pattern in spatial data. In addition, the numerical result of this statistic is compared to the distribution of that statistic's value under a null spatial model (JACQUEZ 2008). Hence, probability estimation is made of how unlikely an observed spatial pattern is under the null hypothesis that the observed pattern is not different from spatial randomness (GUSTAFSON 1998). Following WALLER and JACQUEZ (1995), a test of a spatial pattern consists of five components:

- Test statistic: It quantifies a relevant aspect of spatial pattern (e.g., Moran's I, Local Indicator of Spatial Association (LISA), etc.).
- Alternative hypothesis: Describes the spatial pattern that the test is designed to detect. This could be a specific alternative, or just be "not the null hypothesis".
- Null hypothesis: Describes the expected spatial pattern when the alternative hypothesis is false.
- Null spatial model: This mechanism is responsible for generating the reference distribution. It is either based on a distribution theory, or it may use randomization techniques (e.g., Monte Carlo). Many cluster tests employ heterogeneous Poisson models for specifying the null hypothesis.
- Reference distribution: It is the distribution of the test statistic, when the null hypothesis is true.

Statistical significance is achieved by the comparison of the test statistic to the reference distribution. The probability of observing the value of the test statistic under the null hypothesis of no clustering is calculated (JACQUEZ 2008).

Actually, there is still some discussion of how to specify the null hypothesis and the null spatial model. Many spatial cluster tests use the null hypothesis of complete spatial randomness, as explained above. In fact, most geographic systems are highly complex and therefore a null hypothesis of complete spatial randomness is rarely suitable (if ever). Complete spatial randomness does not describe any plausible state of the system but it can be used as a reasonable null hypothesis (JACQUEZ 2008).

In 1996, GATRELL et al. (1996) argued that the development of null hypotheses other than complete spatial randomness was one (and probably the more significant) reason why spatial analysis techniques have been neglected in geography in former times. This is certainly not true anymore: Different spatial analysis techniques are found in various application fields in the recent years. Other reasons for the push of spatial analysis methods in geography are the development of powerful soft- and hardware, especially the development of Geographic Information Systems as has already been mentioned above.

2.2.2. Identification of Spatial and Spatiotemporal Clusters

Besides the general identification of spatial point patterns, the identification of spatial and spatiotemporal clusters (so called hotspots) is a common and important task in point pattern analysis. Spatial and spatiotemporal cluster techniques are commonly used in various disciplines like criminology, urban planning, epidemiology, or econometrics. In the spatial and spatiotemporal analysis of tornadoes, statistical methods for cluster detection have rarely been used, although tornado touchdown points are easily accessible in the form of spatial point data. In the following section several possibilities of the identification and visualization of local concentrations of point events are discussed. Afterward, the basics of the identification of spatial and spatiotemporal clusters are explained in more detail.

2.2.2.1. Mapping Techniques

A basic task in the analysis of spatial point patterns is the identification and visualization of local spatial concentrations of events. It is then possible to organize the point dataset to detect possible structures in the spatial distribution of events. In addition, the knowledge of the location and the distribution of local spatial concentrations are important and necessary for further in-depth analysis of the point dataset (BLOCK 1994). The latter allows further analysis of the underlying processes which may have caused these anomalies in the first place. Therefore, the identification of areas with a high concentration of events leads to further, more focused analysis of spatial patterns (MEẞNER 2004).

Several different mapping techniques have been used to identify and explore patterns of events. The simplest technique is to represent each single event as a point and to observe the geographic distribution of these points. GIS can be used to aggregate these points to administrative areas, or to interpolate the points to create a continuous surface that can be interpreted as the volumetric densities of the geographic distribution of events (CHAINEY et al. 2008).

Most often, a first attempt to visualize geographic patterns is **by common dot mapping**. Mainly due to its simplicity it is very popular. Originally, this technique simply placed pins representing events on a wall map. Today, computers and GIS have replaced the familiar and traditional analogue version of the so-called pin map. One benefit of a GIS is the inclusion of further attribute information in addition to individual events, such as time of occurrence, F-scale, or fatalities, in the case of the individual events being tornado touchdown points. With this additional information, touchdown points can be simply and quickly queried, if they meet particular conditions (e.g., select all tornadoes rated F4 or higher or select all tornadoes within the year 2000). As a consequence, these selected events can be displayed using suitable symbology. However, the interpretation of spatial patterns and hot spots simply from common dot maps can be difficult, particularly if the datasets are large (CHAINEY 2005). Common dot maps should be used if the map reader needs locational details. If the map reader wants information summarized by geographic areas, then the point data can be aggregated to the areas of interest (HARRIES 1999).

Figure 8: Common dot map of tornado touchdown points, May 2005–2009

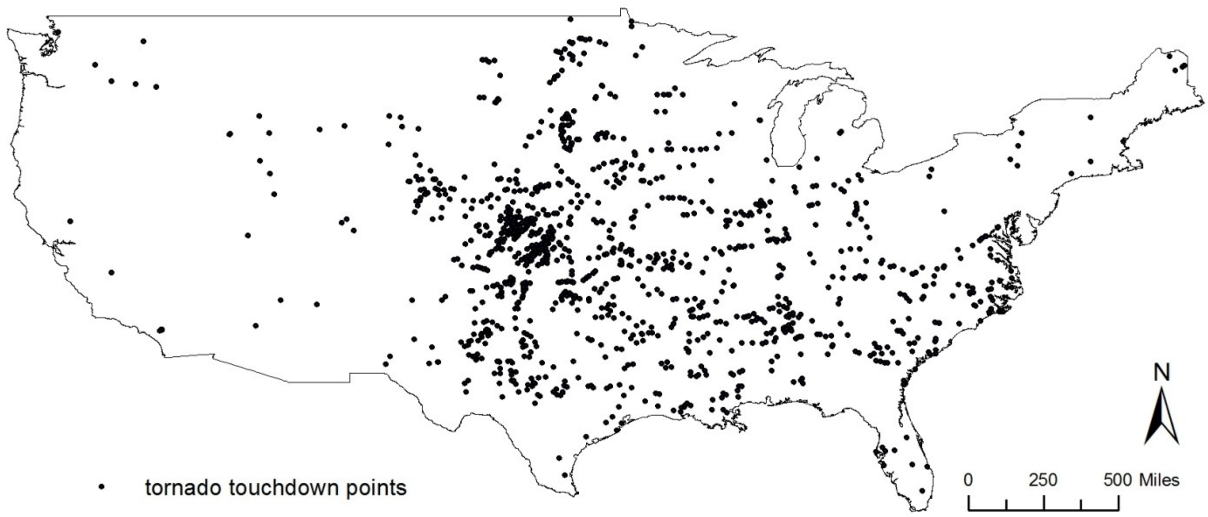
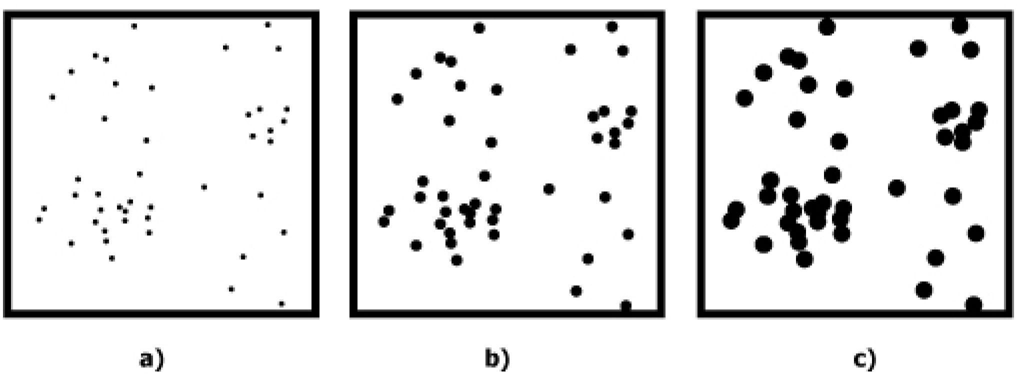


Figure 8 shows 1,197 tornado touchdown points that occurred in May during a five-year-period from 2005 to 2009. The large volume of points shown in the map makes it difficult to clearly identify the hot spots of tornado touchdown points.

Figure 9: Spatial distribution of point events under varying point sizes

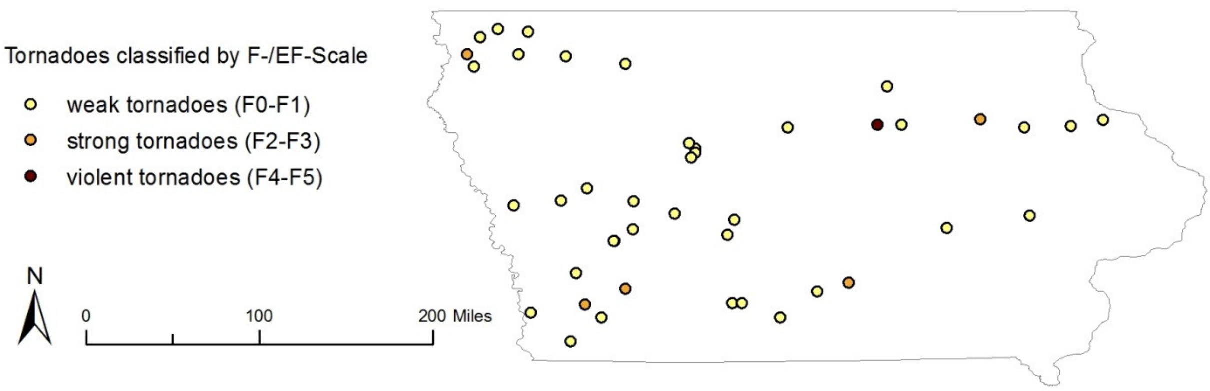


Point size: (a) too small, (b) appropriate size, (c) too large
Adapted from SADAHIRO (1997)

The influence of the size of points needs to be considered, when visually identifying local clusters (see Figure 9). If the size of the points is too small, then the spatial distribution of points seems to be nearly regularly and therefore, a visual identification of local concentrations is more difficult. However, if the size of the points is too large then the user may detect too many local concentrations due to overlapping point events (SADAHIRO 1997).

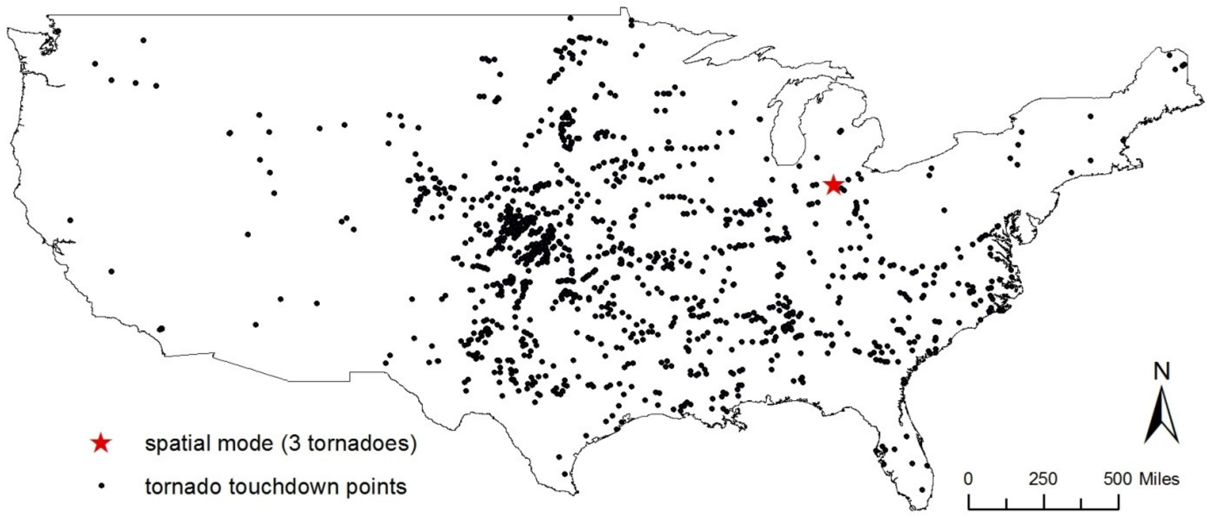
CHAINEY (2005) analyzed the spatial distribution of vehicle crime. He asked three different crime analysts, who were not familiar with the study area to draw the location of the top three hot spots of vehicle crime in that given common dot map. Although some similarities between the hot spot locations among these three analysts existed, the hot spots differed in size and shape. The question, which analyst is correct, could not be answered, because each hot spot that was drawn seemed plausible to each analyst. But in fact, CHAINEY (2005) argued that neither of these hot spots was completely correct. This example demonstrates how difficult it is to identify hot spots from point data only by visual means. One reason is that points can be located exactly on top of each other and what appears to be a single tornado point may be actually more than one tornado point. As can be seen in Figure 8 more than one point at the same location is impossible to identify visually using common dot maps. In conclusion, common dot maps are useful for mapping of individual events (e.g., tornadoes), as long as the number of events is small. Events that fall on the same location can be better represented through the use of graduating symbol sizes, or the use of the same symbol sizes that are differently colored. However, the latter two visualization methods are less effective for identifying hot spots of point data, particularly from large datasets (CHAINEY 2005). Figure 10 represents the distribution of tornado touchdown points in the state of Iowa from May 2005–2009. The point data are classified using different color hues.

Figure 10: Tornado touchdown points in Iowa in May 2005–2009, classified by F-/EF-scale



A simple method to detect spatial concentrations of events from a point dataset is the detection of locations with a very high amount of events. One method which does this is referred to as the **spatial mode** of events. The spatial mode is defined as location with the largest number of incidents (e.g., tornado touchdown points). The results from the spatial mode depend on the spatial accuracy of the locations of the events. For example, if events are determined very precisely it could happen that each event has a different location, which means that the spatial mode equals one for each event. In other words, no high-order spatial modes are found, and only 1-order spatial modes are detected. When the goal is to identify locations with a high amount of events, 1-order spatial modes are not a very useful result. A spatial mode does not aggregate events within a close distance to each other to a single spatial mode. Therefore, this method is not very useful to detect local concentrations, but it is useful to identify overlapping events on identical locations, which cannot be detected purely by visual inspection of events in a common dot map (LEVINE 2010). Figure 11 contains the spatial mode for the 1,197 tornado touchdown points for May 2005–2009. As can be seen, one location with a frequency of three tornado touchdown points is found.

Figure 11: Spatial mode of tornado touchdown points, May 2005–2009



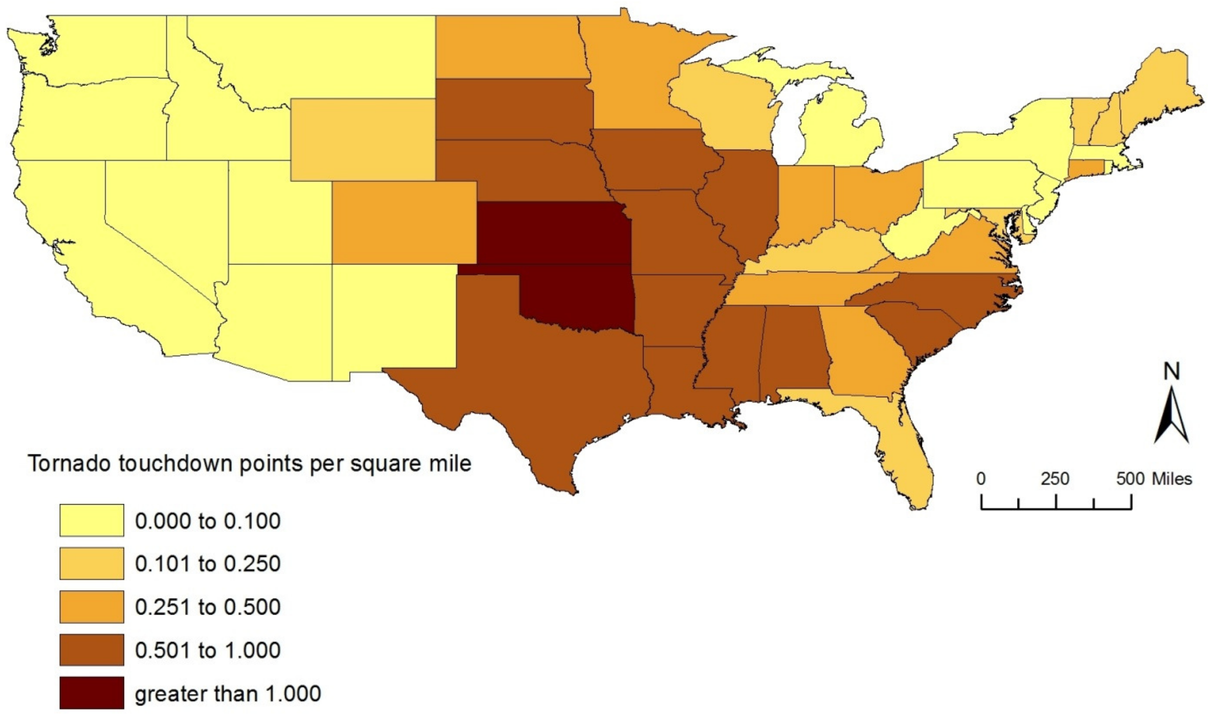
A popular method to represent spatial distributions of point data that have been aggregated to enumeration units is **the choropleth map**. Examples for enumeration units are administrative or political areas such as beats, census blocks, polling districts, wards, boroughs, counties, states, or country boundaries. Events mapped as points can be aggregated to any of these geographic areas (CHAINEY 2005). A choropleth map can be used to visualize spatial patterns of events that have been standardized or normalized by their geographic areas (event densities) or their underlying population (even rate).

When choropleth maps are created, the cartographer is required to select an appropriate classification method to represent the distribution of events. Examples of classification methods are quantiles, equal steps, natural breaks, standard deviations, or custom classes. For more details see HARRIES (1999), who offers a good overview of these different classification methods. It should be noted that the choice of the classification method creates differently looking choropleth maps and often also different sets of hot spots. The question arises, which classification method is most appropriate for identifying existing hot spots in the study area (CHAINEY 2005). In other words: “When is a hot spot a hot spot?” (CHAINEY 2005).

For the cartographer it is important to know the application and the target audience of the map that is being produced. If the application of the map is to detect hot spots of events, a classification method should be chosen to focus on revealing the locations of high-volume event areas. The analysts should consider using certain class boundaries that are easy for the audience to understand. The map itself should be the interesting part in the foreground, and the class boundaries should follow in a logical sequence. Therefore, if the class boundaries require further explanation or confuse the audience, the analysts failed the opportunity to transfer the central message to map and to display hot spots of events. The first version of a map is usually not the final version, because mapping is considered to be an iterative process. For this reason, different class boundaries need to be tested to achieve the aim of transferring the central message of the map (CHAINEY 2005).

Thematic maps which use absolute values (e.g., tornado counts) usually tend users to attract the largest areas shaded in the top threshold color range. This results in a problematic feature of geographic boundary thematic maps to identify hot spots of events in general. In fact, thematic shading of geographic boundaries can mislead the audience in identifying hot spots due to the varying size and shape of geographic boundaries (CHAINEY 2005).

Figure 12: Density of tornado touchdown points, May 2005–2009

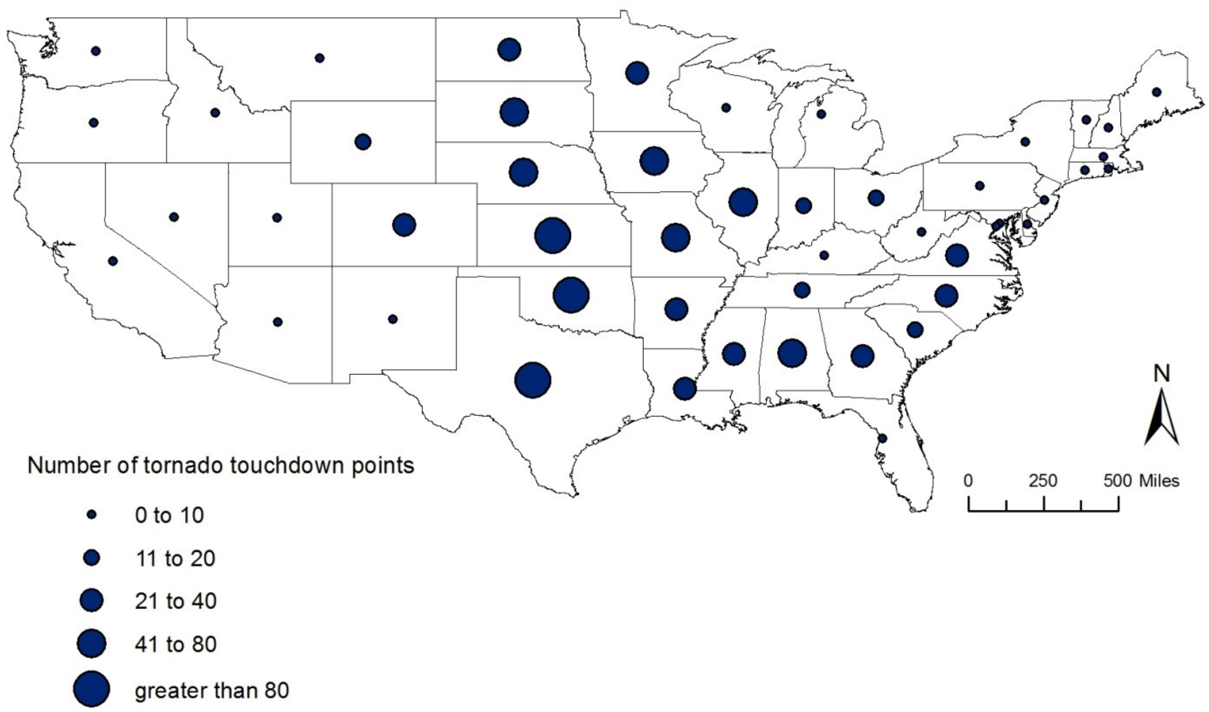


IMHOF (1972) argues that it is absolutely wrong to use absolute, non-relative values in choropleth maps. In his publication IMHOF (1972) refers to the common use of applying this inappropriate technique (i.e., using absolute data values in choropleth maps) which misleads the audience. Thus, **choropleth maps** displaying relative values (e.g. densities) should be used instead of absolute values. If one considers using absolute values instead of (relative) densities the use of, for example, graduated map symbols, or the use of absolute values based on uniform grids are recommended. Figure 12 shows a choropleth map with the number of tornado touchdown points divided by its geographic area. Many small states which have not experienced as much tornadoes as Texas in this period have a higher density because of the comparable small area. Examples of such states are

Louisiana, Missouri, Mississippi, North Carolina, and especially South Carolina. In the latter state a number of twenty tornadoes occurred during the observation period. This count puts South Carolina into the second lowest class range in Figure 12. Due to the relatively small area of this state, the dominator of the ratio is low and therefore the density results in a relatively high value. 0.227 tornadoes per square kilometers moves South Carolina now into the second highest class range.

In addition, OPENSHAW (1984), and BAILEY and GATRELL (1995) identified a problem with mapping spatial data based on enumeration units, which is referred to as the Modifiable Area Unit Problem (MAUP). This problem refers to the change in the sizes and shapes of enumeration units used to thematically represent the distribution of events which can effect and mislead the interpretation of maps. Despite of this problem, the choropleth mapping technique remains important and should not be completely neglected. Choropleth maps are a popular map type, because the areas used are often based on political or administrative boundaries. For example, the knowledge of the occurrence of tornado touchdown points inside administrative areas is important for emergency response. Considering the devastation of tornadoes it is necessary to know where they occur to establish, for example, evacuation routes, special facilities for tornado watches, and tornado warnings[1], or to build places of safety. Therefore, choropleth maps are important for providing summarized information across political and administrative areas. They may however, distort results because of failing to reveal patterns within individual enumeration units (CHAINEY 2005).

Figure 13: Tornado touchdown points using graduated map symbols, May 2005–2009



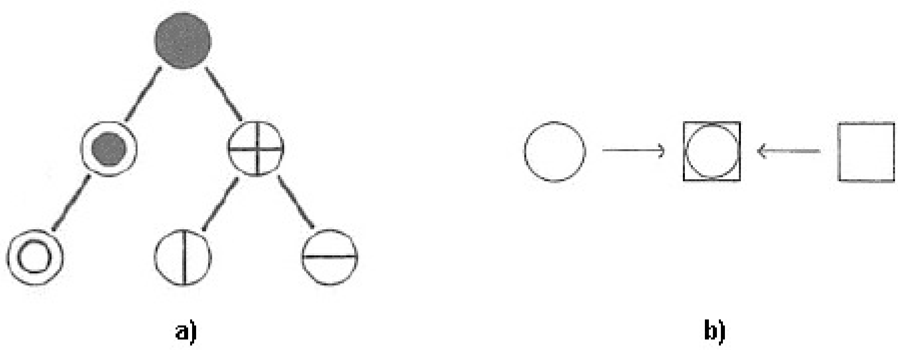
As mentioned before, an alternative method to represent absolute counts per geographic area is to

[1] Tornado watches refer to the possibility of a tornado in a specific area. In contrast, a tornado warning indicates that a tornado has been sighted or detected by weather radar (NOAA 1995).

use **graduated map symbols**. With this technique individual point data are aggregated to an absolute count. This count represents the number of events that occurred inside a geographic area or at a specific location. The final counts are subsequently classified and represented by graduated symbols. The choice of the size of each graduated symbol is crucial. If the size differences between all graduated symbols are too small, it is difficult for the map reader to extract the meaning of the map. A disadvantage of graduated map symbols is that they may overlap, which reduces the readability of the map (HARRIES 1999). Due to the aggregation of the results by geographic areas and the visualization of the results using these so-called proportional symbol maps, it is possible to offer a quick and fast overview of the spatial distribution of the results. One can thus easily identify areas with a higher concentration of events as well as areas with a lower concentration of events (LEITNER 1998).

Figure 13 shows a proportional symbol map of tornado touchdown points from May 2005 to 2009. In a proportional symbol map, two different types of map symbols can be distinguished: Pictorial and abstract map symbols. Pictorial map symbols look like the features they represent, and are often used to determine locations of events, or facilities (e.g., a symbol of an airplane is used to show the location of an airport). However, abstract map symbols are usually based on geometrical shapes (e.g., circles, squares, rectangles, triangles, etc.) and they are used to represent quantitative data. The benefits of abstract map symbols are their ability of grouping and combining them together. When abstract map symbols are grouped, then they can vary their meaning, while not changing their geometrical shape. Figure 14a shows an example of grouping using a point symbol, where its filling varies to indicate a hierarchical structure. When abstract map symbols are combined, the combination of two different map symbols indicates the co-occurrence of two different qualitative events at the same location. Figure 14b shows an example of combining a circle and a square (ARNBERGER 1977).

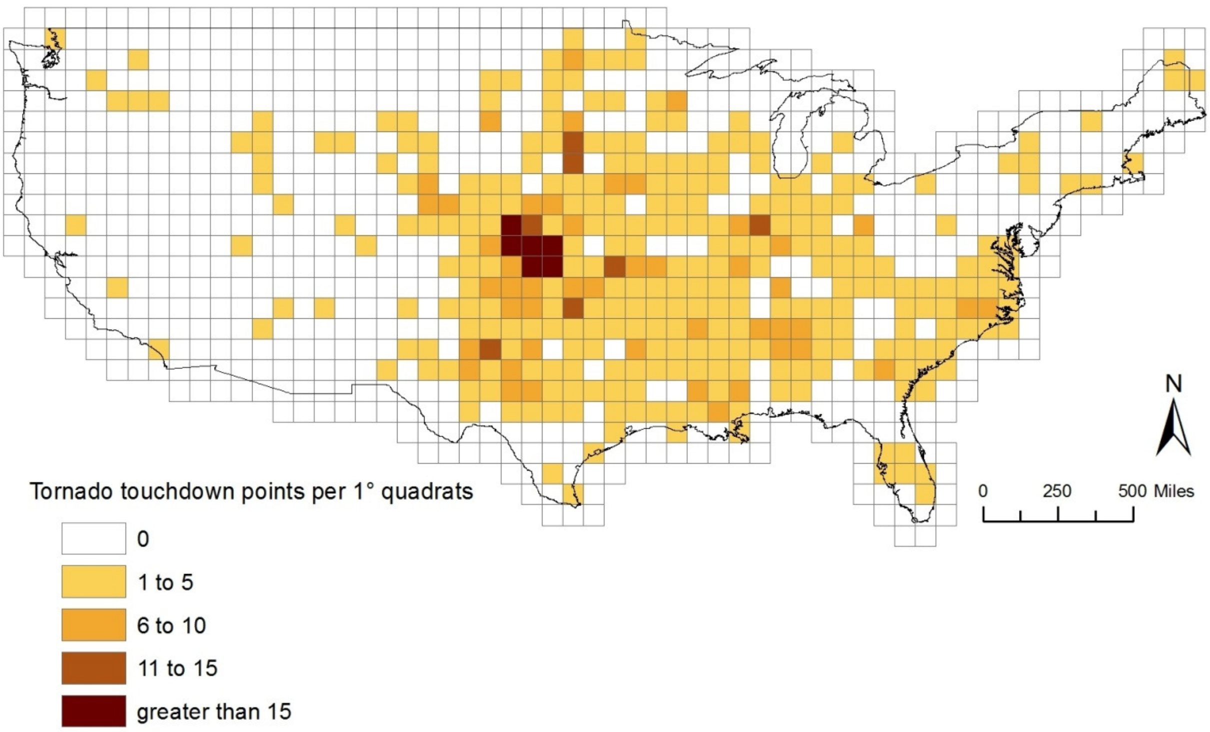
Figure 14: Principles of grouping and combining abstract map symbols



(a) An example for grouping abstract map symbols, and (b) for combining abstract map symbols
Adapted from ARNBERGER (1977)

Another alternative solution to avoid the varying sizes and shapes of administrative units is the technique called **quadrate thematic mapping**. Uniform grids are drawn across the study area and can then be shaded, using the same concept when constructing a choropleth map. The data to be mapped in these grids could be either absolute or relative. On the one hand it is possible to use absolute values (counts of events) because the size of each cell is the same. On the other hand relative values, expressed as counts per area, are applicable, as well due to the same size of each grid cell, which makes the relative values (ratios) comparable. Crucial for the detection of hot spots is the size of the grid cells. It is necessary that the cells are small enough so that high event densities can still be properly analyzed and displayed. Figure 15 shows a thematic map of tornado touchdown counts with 1° grid cell sizes. In comparison to the thematic map based on enumeration units (Figure 12) some differences can be detected. As mentioned before, events may be evenly spread across the whole area of large states. For example, Texas has a large number of tornado touchdown points that were observed from May 2005 to 2009. In comparison, Texas is not in the highest class, when relative counts (number of tornado touchdown points per area) were visualized in Figure 12. Finally, the quadrate mapping technique shows that there is just one hot spot in the Texas Panhandle, located close to Lubbock, TX. However, just a few tornadoes occurred in the southern part of Texas. The large number of tornadoes in Texas is generally spread across the northern part of the state. Therefore, quadrate thematic mapping appears to offer a more accurate technique for identifying hot spots of point events. In particular the method is useful to detect local hot spots (CHAINEY 2005).

Figure 15: Quadrate thematic map of tornado touchdown points, May 2005–2009



As discussed above, the usage of shaded grid cells (and the usage of choropleth maps, in general) often results in loss of spatial detail within each quadrate and across quadrate boundaries. Thus, inaccurate interpretation is a problem. Generally, quadrate thematic maps look blocky and do not entirely invoke interest. A common solution is the reduction of the cell size. Speckled maps of small, shaded grid cells are produced then. For users these maps are more or less useless because the sizes, shapes, and locations of possible hot spots cannot be detected accurately. It should be added that the issues related to the chosen classification method and the Modifiable Area Unit Problem need to be considered, as well, when using the technique of quadrate thematic mapping (CHAINEY 2005).

The above discussed techniques to represent spatial point data have shown that they do not really represent the real spatial distribution of events. For that reason certain spatial locations of hot spots can be hidden. This drawback makes it necessary to use statistical techniques to identify and visualize local concentration of events.

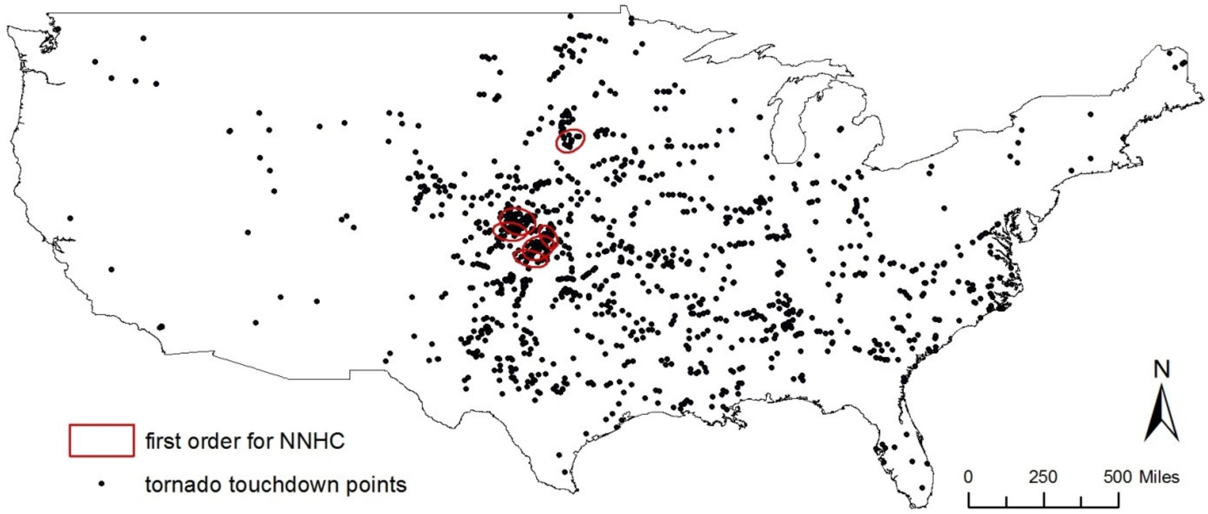
Spatial ellipses can also be used to identify hot spots. Although spatial ellipses have a long tradition in, for example, crime mapping, the technique has not been used in the detection of, for example, significant tornado touchdown clusters. Different techniques to create standard deviational ellipses around point clusters exist. The software CrimeStat III offers the Nearest Neighbor Hierarchical Clustering (NNHC), K-means clustering, and the Spatial and Temporal Analysis of Crime (STAC) methods, which all produce spatial ellipses, identifying significant hot spots. All of these techniques can be applied to analyze tornado touchdown points (CHAINEY 2005). It has to be noted that none of these techniques can identify spatiotemporal ellipses. Nevertheless, two different approaches for the construction of purely spatial ellipses will be explained briefly.

A nearest neighbor analysis technique such as the Nearest Neighbor Hierarchical Clustering (NNHC) technique identifies groups of clusters that contain a minimum number of user-defined points. The concept of spatial randomness is used to group only those points into clusters that are closer together than would be expected by chance alone. The first outputs of this method are the so-called first-order-ellipses, which cluster together the original point locations. If certain conditions apply first-order ellipses are grouped to second-order clusters. Higher-order clusters can be repeatedly created until all events fall into a single cluster or when the grouping criterion fails. A nearest neighbor analysis technique can be termed a hierarchical technique due to the characteristic of aggregating low-order clusters to high-order clusters (LEVINE 2010). Figure 16 shows an example of the NNHC technique applied to the example dataset of tornadoes May 2005–2009.

The second technique to construct spatial ellipses is the K-means clustering technique. In this technique a user-defined number (K) of ellipses is created by partitioning the point data into groupings. Then the best positioning of the K centers are found and each point is assigned to the center that it is nearest. This method belongs to the group of partitioning techniques due to the feature of partitioning events to a defined number of spatial clusters (CHAINEY 2005).

Both methods show how spatial ellipses are useful for identifying event clusters, which can subsequently be selected for closer inspection. A well-known weakness of these methods is the fact, that analysts are not possible to accurately identify the boundaries of hot spots. Usually, event hot spots do not naturally form spatial ellipses. Therefore, the outputs of these methods do not represent the actual spatial distribution of events and can often mislead analysts to focus on areas with low event importance within an ellipse. In addition, all of these methods require detailed knowledge about them in order to appropriately select a number of required parameters. Users with little knowledge of these statistical methods are given few rules to enter suitable parameters, thus introducing ambiguity and influencing variability in the final output. For example, different analysts investigating tornado hot spots from the same data may produce different results because of the different choices of input parameters that are being used (CHAINEY 2005).

Figure 16: Nearest neighbor hierarchical clusters for tornado touchdown points, May 2005–2009

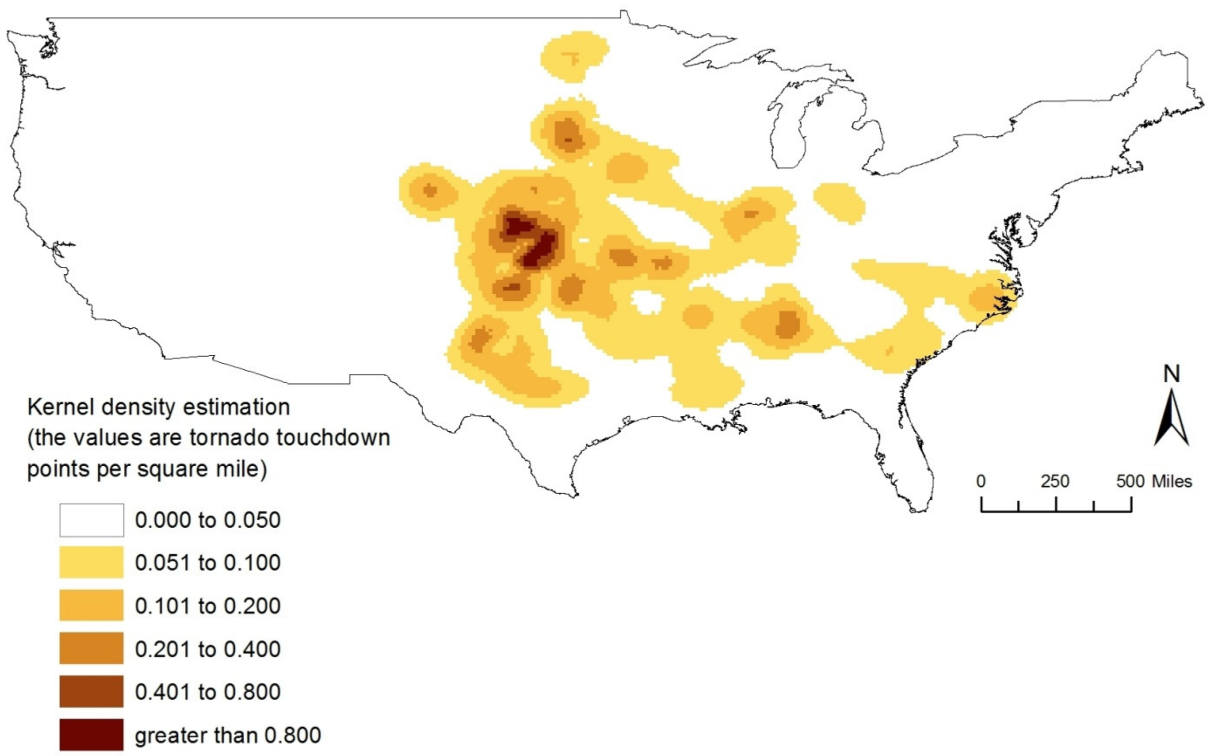


Techniques that consider concentrations of events across the entire study area are the so-called **interpolation and continuous surface smoothing methods**. Interpolation methods experience an increasing popularity and application for visualizing the distribution of events and identifying hot spots. These methods aggregate points within a specified search radius and create a smooth, continuous surface. This surface represents the density or volume of events across the area. Common interpolation techniques use an intensity, population, or “z” value taken from event locations to estimate values for all locations across the study area. These interpolation techniques, such as inverse distance weighting, kriging, triangulation with smoothing, and splining are classified as geostatistical techniques. An example for the usage of interpolation techniques is the creation of surfaces representing the distribution of rainfall. Therefore, values between and at rain gauges are estimated from a function considering the rainfall readings and the distribution of rain gauges. Within the tornado touchdown data set, collection sites do not exist. Therefore, it would not make sense to apply one of these techniques to estimate the number of tornado touchdowns that may have occurred between the locations of the existing tornado touchdown points. No tornadoes have been reported in the areas between actual tornado touchdown points, so the analyst should avoid using methods to interpolate tornadoes, where there are no tornadoes occurring. Instead, methods should represent a continuous surface of the relationships or densities between event point distributions (CHAINEY 2005).

The most useful technique for visualizing events like tornado touchdown points as a continuous surface is the kernel density estimation method. This method creates a smooth surface of the variation in the density of points across a geographic area. The first step to construct a continuous surface is to define a fine grid which is laid on top of the point distribution. Users usually define the size of the grid as well as the size of the grid cell. Then, a three-dimensional kernel function calculates weights for each grid cell inside a defined kernel's radius (bandwidth). Points that are closer to the center of the kernel function receive a higher weight and higher weights result in a higher total density value of a cell. Finally, all circle surfaces which are calculated for each grid cell are summed to generate the final grid cell values (CHAINEY 2005). These different steps to calculate a kernel density estimate will be explained in more detail in the next subchapter.

The output of kernel density estimations are easy to interpret and to understand by the lay person. This makes the method very useful to an audience which is not very familiar with statistical techniques. An advantage of this method is that density values are estimated at all locations within the study area. These continuous density surface maps allow for easier interpretation of local clusters which makes the method very useful in various application fields (CHAINEY 2005). For example, this technique reflects the locations and spatial distribution of high density values (i.e., hot spots) more accurately compared to other mapping techniques (e.g. quadrate thematic mapping). The different types of kernel density estimation techniques, as well as their advantages and drawbacks, will be explained in the next subchapter in more detail. As a quick example, Figure 17 shows a kernel density estimation result for tornado touchdown points from May 2005 to 2009. The figure below shows kernel density estimation results of tornado touchdown points in the mid-west of the coterminous United States. In comparison the output of kernel density estimations are not as speckled as the output of the quadrate thematic mapping technique (as can be seen in Figure 15). In the following figure, grid cells with density values from 0 to 0.3 are filled with a white color in order to show a better visibility of the higher density values and clusters.

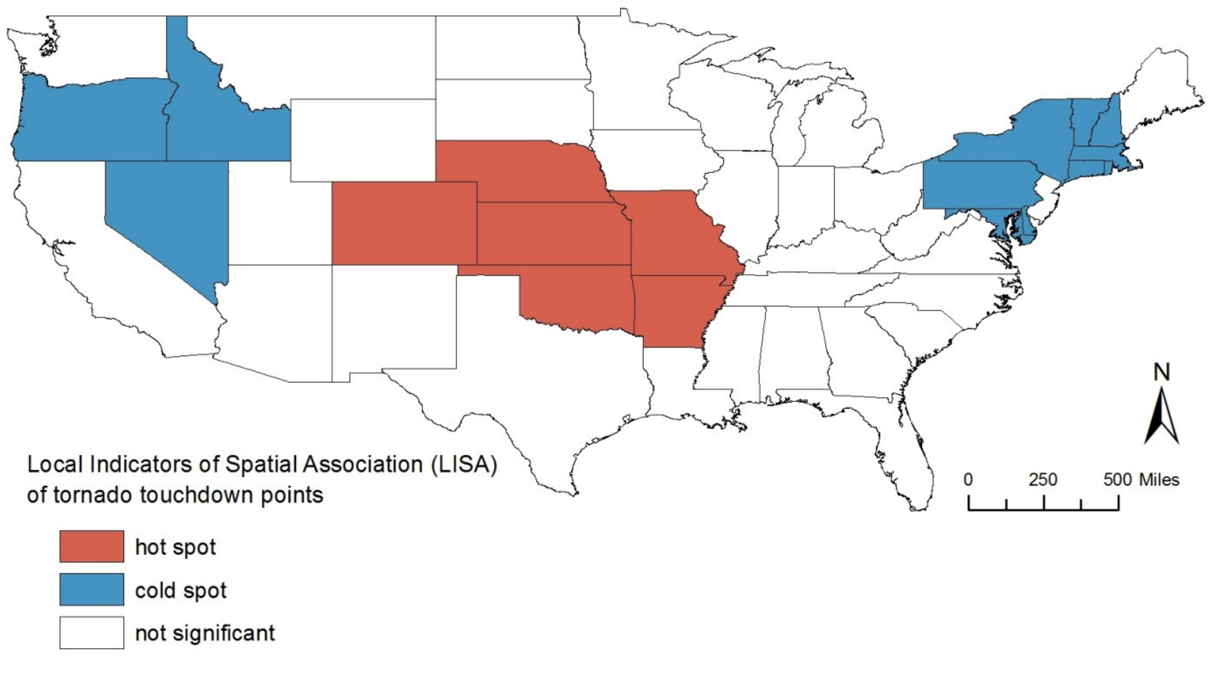
Figure 17: Kernel density estimation of tornado touchdown points, May 2005–2009



The two latter techniques analyzed point data. In the analysis of areal data the concept of spatial autocorrelation is commonly used. Positive spatial autocorrelation indicates cases where a polygon and its spatial neighbors have similar values. This results in clusters of high values (hot spots), low values (cold spots), and medium values ("average" spots). Contrasting values between a polygon and its spatial neighbors indicate negative spatial autocorrelation (LEITNER and BRECHT 2007). These spatial outliers indicate areas of high tornado occurrence surrounded by low tornado occurrence and vice versa. Local Indicators of Spatial Association (LISA) can be used to identify significant patterns of spatial association around individual locations, resulting in spatial hot spots, spatial cold spots, or spatial outliers (ANSELIN 1995). An appropriate visualization method to measure local spatial autocorrelation is a LISA Local Moran map. Additionally, a Moran Significance map can be visualized to show the significance of the clusters (LEITNER and BRECHT 2007). The Local Moran map in Figure 18 shows that a significant cluster of high tornado occurrences is present in the center of the United States. In addition, two cold spots with low tornado occurrences are also identified in the Local Moran map. The first cold spot cluster can be found in the western part of the United States and second cluster in the Northeast.

The Local Moran's I statistic is a useful tool for identifying areas which are dissimilar from their neighborhood. In comparison to the previous techniques, the Local Moran's I statistic is the only statistic that demonstrates dissimilarity. The other techniques only identify areas with high concentrations. A peculiarity of the Local Moran's I statistic is that the data need to be summarized into areas in order to produce the necessary Local Moran's I value (LEVINE 2010). This can be seen as a drawback of the technique due to the loss of spatial detail.

Figure 18: Local Indicators of Spatial Association (LISA) of tornado touchdown points, May 2005–2009



In this section different techniques to map events such as tornado touchdown points have been explained and discussed. The techniques range from simple and easy to understand methods such as the proposed point mapping technique to more complex techniques, which offer more accurate results of cluster detection such as spatial ellipses or the kernel density estimation. The use of the latter techniques requires statistical knowledge to appropriately select parameter settings. The choropleth mapping methods are simple to apply, but do not necessarily lead to objective interpretations. Therefore, the use of objective techniques to determine hot spots of events should be considered. The following section discusses the basics of statistical techniques to detect hot spots, as well as the differences of approaches to cluster point events.

2.2.2.2. Basics of the Identification of Spatial and Spatiotemporal Clusters

The search for higher concentrations of events within a geographical area is important in the analysis of spatial point data. These spatial analysis methods are used to detect anomalies and conspicuous structures in the spatial point dataset and they indicate the processes which might have caused these irregularities. The exploratory identification of areas with a high concentration of events is the basis of further analysis of spatial point patterns. The morphology of clusters plays an important role since they can take on a variety of different shapes. Usually, different cluster tests are sensitive to different aspects of cluster morphology: some detect boundaries, some detect outliers, some detect elliptical clusters, some detect circular clusters, etc. Hot spots can take many shapes, while statistical techniques usually use geographical templates such as a circular scanning window (e.g. the scan statistic as proposed by KULLDORFF and NAGARWALLA (1995)). The techniques which use specific geographic templates are most sensitive to cluster shapes they employ. In fact, cluster morphology in geographic systems is highly complex and a simple description by a single geographic template is not appropriate (JACQUEZ 2008).

At first, the terms for spatial, temporal, and spatiotemporal techniques will be explained and defined. Traditional or non-spatial statistics analyze large datasets which do not contain any spatial component like geographic coordinates. Purely spatial statistics are specifically designed to analyze purely spatial data, whereas purely temporal statistics analyze temporal data. GRUBESIC and MACK (2008) argue that previous analyses for clustering and clusters treat space and time as separate components, and largely ignoring the interaction of events in time and space. RATCLIFFE (2010) calls it a "shame", since the understanding of interactions of spatiotemporal data can offer a wealth of information. Spatiotemporal interaction arises when events are located relatively close in geographic space and when these events occur also at about the same time (JACQUEZ 1996, KULLDORFF and HJALMARS 1999). Recent works suggested space-time statistics as a useful tool in, for example, crime analysis (e.g. GRUBESIC and MACK 2008) or epidemiology (e.g. KULLDORFF and HJALMARS 1999).

In the usage of statistical methods to identify spatial, temporal, and spatiotemporal clusters one can distinguish between tests for clustering and tests for clusters. The former term refers to global tests, whereas the latter to local and focal tests (ANSELIN 2004).

Global tests are designed to reject the null hypothesis of complete spatial randomness for the dataset as a whole. The objective of a global test is to find evidence of significant patterning (ANSELIN

2004). Hence, global statistics have the ability to identify whether spatial structure (e.g. clustering, autocorrelation, uniformity) exists, but they do not identify where the locations of clusters are, nor do they quantify how spatial dependency varies from one place to another (JACQUEZ 2008). Examples of global tests for purely spatial data are the Moran's I statistic (MORAN 1950) or the Geary's C statistic (GEARY 1950), and for space-time interaction the Knox test (KNOX 1964) or the Mantel test (MANTEL 1967).

Instead, focused statistics quantify clustering around a specific location called a focus. A typical application field is the analysis of clusters or disease sources of environmental pollutants (JACQUEZ 2008). An example of a focused test is the Lawson-Waller local score test (LAWSON 1993, WALLER et al. 1992).

In contrast, local tests are designed to identify the locations of clusters (or of spatial outliers). Many global statistics have local counterparts. As an example, the global Moran's I statistic is the scaled sum of the local indicators of spatial association (LISA) statistic (ANSELIN 1995). A recently developed test named spatial scan statistic is very popular and powerful and can be used in both spatial and spatiotemporal analysis (KULLDORFF 2010).

With local tests it is possible to detect local spatial concentrations of events, while global tests do not detect any spatial interaction in the same dataset. FOTHERINGHAM et al. (2000) favor the application of local spatial statistics. Therefore, only tests to detect local clusters will be discussed and applied in this thesis.

Local areas with an unusually high occurrence of events are called **spatial clusters** or **hot spots**. Unfortunately, there is no clear definition for what exactly constitutes a spatial cluster. Hot spots could either be based on point data, or on point data that have been aggregated to areas (LU 2000). Hot spot analysis techniques aim to identify locations with unusual high concentrations of event occurrences. Since hot spots do not have clear boundaries and they may not exist in reality the user's delimitation of the hot spots is more or less subjective and therefore arbitrary (LEVINE 2010).

Measuring a hot spot is a complicated problem. Due to the technical improvements in information technology dozens of different statistical techniques have been developed to identify hot spots or hot spot areas (EVERITT 1974). Not all of these techniques are generally known for spatial cluster analysis. These statistical techniques have in common that each of them aims at grouping cases together into relatively coherent clusters. But there are differences in the methodology as well in the criteria used for identification. LEVINE (2010) describes hot spots as perceptual constructs, and therefore the different techniques refer to their approximation how someone would perceive an area. Thus, the techniques use various mathematical criteria (LEVINE 2010).

In general, tests can be distinguished by type of data. First, tests for clustering and clusters of point events are described, and then cluster tests based on areal units are explained. Afterwards different techniques of local cluster or hot spot analysis will be distinguished using typical characteristics and typologies (EVERITT 1974, ÇAN and MEGBOLUGBE 1996). This thesis will apply different methods to detect spatiotemporal hot spots in the tornado touchdown dataset for the study area discussed above. Therefore, the different types of spatiotemporal hot spots will be explained briefly.

Tests for clustering and clusters of point events which are commonly used tend to be either based on inter-point distances, or on the number of events within a so-called quadrate (e.g. a grid cell, a circle, or ellipse). The tests consist of the comparison of the distances, functions of distances, or the density of points in a quadrate to what they would be under a null hypothesis of spatial randomness. When the inter-point distances tend to be shorter, or when the number of points in the quadrate is higher than expected under randomness, the declaration of significant clusters is the result (ANSELIN 2004).

Cluster tests based on areal units can be divided into two types. First, the area is simplified to a point (e.g. the center of gravity, or centroid of an area) and all the events of that areal unit are aggregated to that single point. The so-formed points can be analyzed using a quadrate method (e.g. a spatial scan statistic) as if it was a collection of individual points. An alternative approach to detect clusters from areal units (whether they are represented as points or polygons) is the use of spatial autocorrelation tests. These consist of a combined evaluation of locational similarity (neighbors) and attribute similarity (e.g. cross-product correlation). The definition of neighbors is an important aspect in using spatial autocorrelation statistics. Common solutions are the consideration of points to be neighbors when they are within a certain distance, or to take polygons as neighbors when they share a common boundary (ANSELIN 2004). The latter definition of contiguity is furthermore divided in two commonly used options: the so-called rook contiguity uses only common boundaries, while the so-called queen contiguity uses all common points (boundaries and vertices) in the definition of contiguity (ANSELIN 2003).

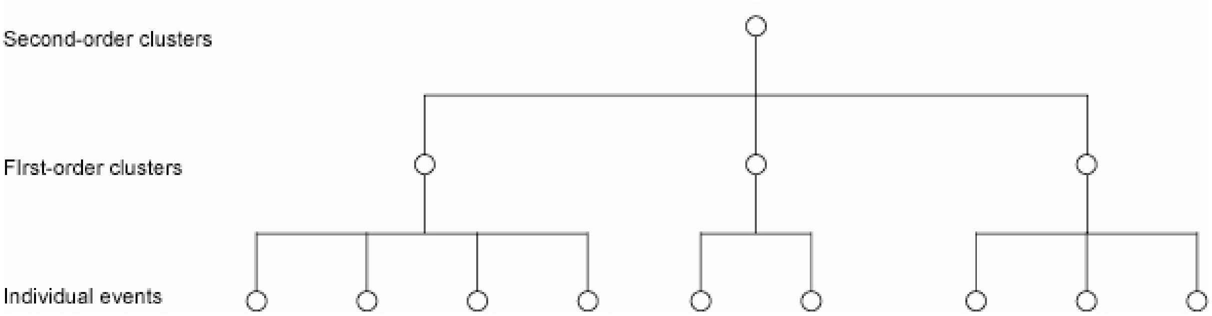
As proposed by EVERITT (1974), and ÇAN and MEGBOLUGBE (1996) several general categories of cluster routines have been established in spatial cluster analysis:

- Point locations
- Hierarchical techniques
- Partitioning techniques
- Density techniques
- Clumping techniques
- Risk-based techniques
- Miscellaneous techniques
- Hybrid techniques

Point locations simply identify locations with a sum of the occurrences at these locations. Thus, locations with the most number of event occurrences are identified as hot spots. Examples are, for example, the spatial mode (LEVINE 2010). The spatial mode is explained in Section 2.2.2.1. (Page 38 and Figure 11)

Hierarchical techniques are based on the grouping of incidents to (first-order) clusters which have some criteria in common (e.g. nearest neighbor). Usually, first-order clusters are then grouped to second-order clusters, and these in turn are grouped to third-order clusters. This process is repeated until either all events fall into a single cluster or the criteria for the grouping fail. The hierarchy of the resulting clusters can be shown in a dendrogram (for an example see Figure 19). However, many hierarchical techniques do not necessarily group clusters into the next highest level. In the section about mapping techniques (2.2.2.1., page 44) the method called nearest neighbor hierarchical clustering (NNHC) is an example of a hierarchical technique (LEVINE 2010).

Figure 19: Hierarchical clustering technique



Adapted from LEVINE (2010)

Partitioning techniques partition the events into a specified number of clusters. Usually, this number of groupings is defined by the user. The points are then assigned to one, and only one, group (LEVINE 2010). An example is the K-means clustering technique.

Density techniques identify hot spots by searching for dense concentrations of events (LEVINE 2010). As proposed in Section 2.2.2.1., a single kernel density estimation (page 45 and Figure 17) is a representative of this type of cluster analysis.

Clumping techniques partition events to clusters or groups but allow overlapping membership (LEVINE 2010).

Risk-based techniques search for hot spots in relation to an underlying variable which represents, for example, populations or employment at risk (LEVINE 2010). Commonly used risk-based techniques, which will be explained in a comprehensive manner in the following subchapter, are the risk-adjusted nearest neighbor hierarchical clustering (Ra-NNHC) method, a dual kernel density estimation method, or the spatial scan statistic.

Miscellaneous techniques are less commonly used methods, which are applied to detect areal clusters, not events (LEVINE 2010). An example is the local indicator of spatial association (LISA) technique. In this thesis a Local Moran's I will be applied to the spatiotemporal analysis of tornado touchdown points.

Some statistical techniques could not be assigned to one single type of cluster analysis methods. These **hybrid techniques** are a combination of the methods explained above. For example, the risk-adjusted nearest neighbor clustering technique is primarily risk-based but involves elements of the clumping approach (LEVINE 2010).

As can be seen, many statistical techniques based on different criteria exist for the exploration of hot spots. All of these methods have their advantages as well as their limitations. It is quite impossible that only one technique shows the correct existence of spatial hot spots. Furthermore, there are different possible results in the identification of spatial clusters. Therefore, it is important that users take into consideration that the techniques for the detection of spatial hot spots are just explorative tools which support the user in the analysis of spatial point data. The interpretation of the results and further analysis of the hot spots rests on the user. Thus, it is necessary to know the characteristics of the spatial point pattern and the aim of the analysis to apply the appropriate statistical techniques (LU 2000, LEVINE 2010).

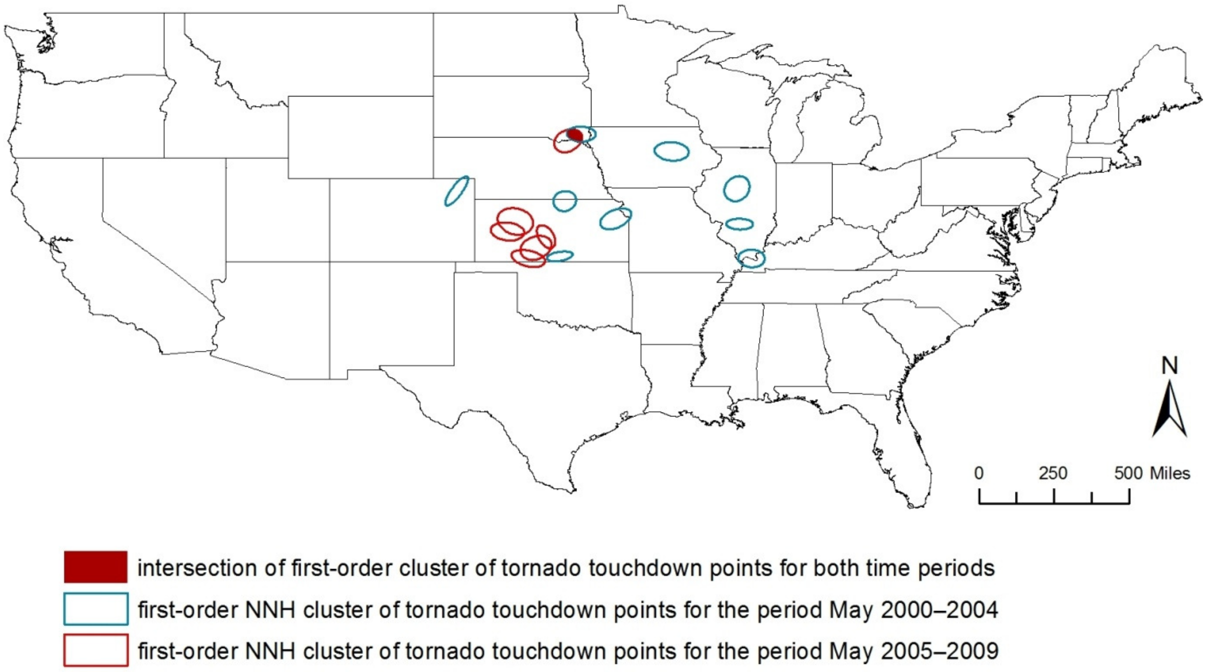
Furthermore, it is important to notice that within the identification of spatial clusters most often only the point events are regarded without any consideration of possible underlying variables which may influence the formation of local concentrations. Spatial distributions of events are affected by certain influencing variables. Tornado fatalities are usually higher in areas where the size of the population is higher. Thus, it is necessary to relate the fatalities to the population size. The results are spatial hot spots where the influence of the population size is regarded as an equalizing factor. Statistical techniques which take an underlying variable into consideration have been proposed as risk-based methods (LEVINE 2010).

2.2.2.3. Temporal Variation in Spatial Clusters

The environment of our dynamic world changes constantly. It is important to examine not only patterns over space. Furthermore, it is necessary to analyze how those patterns change over time to fully understand spatial phenomena. The analysis of cluster changes over time results in finding temporal patterns (e.g., cycles and rhythms of occurrence). Initially, GIS were used to represent and analyze spatial phenomena but recently the representation of temporal dynamics within GIS evolved as a significant challenge (PEUQUET 2006). Two aspects of cluster change and persistence will be discussed and subsequently applied in the spatiotemporal analysis in this thesis. The first aspect discusses temporal changes in the spatial distribution of clusters, and the second aspect considers clustering of attributes from two different time periods (JACQUEZ 2008). Finally, a space-time scan statistic which automatically adjusts for both purely spatial and purely temporal clusters will be explained briefly.

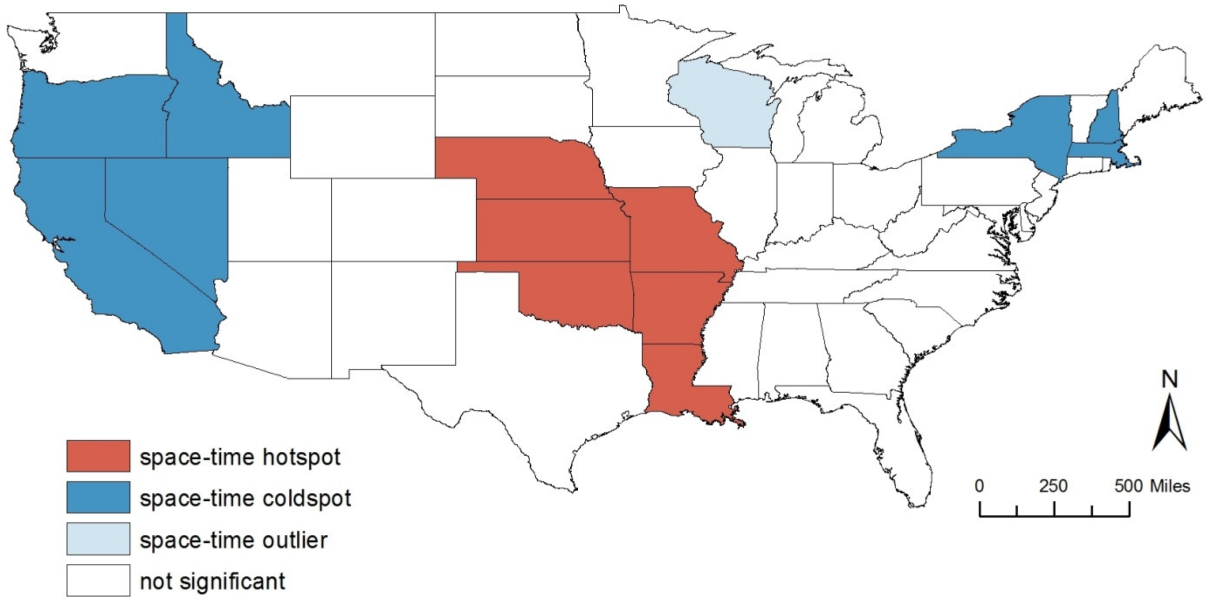
A first approach in the exploration of cluster change and persistence is to explore **temporal changes in the spatial distribution of clusters**. Therefore, a spatial distribution of clustered attributes at time t is compared to those clusters obtained for that attribute at time t+1. JACQUEZ (2008) proposes boundary and overlay statistics to determine the amount of association between the clusters at the different time periods, t and t+1. Alternatively, the intersection of first-order NNHC ellipses can be used to control for cluster persistence. Figure 20 shows an example where cluster existence changes through time and where clusters are persistent. There are several first-order NNHC ellipses for both periods but there is only one temporal intersection of these first-order NNHC ellipses. This area indicates a significantly high tornado occurrence at both time periods May 2000–2004 and May 2005–2009 and therefore, this approach is useful to check for temporal cluster persistence.

Figure 20: Space-time NNH clusters of tornado touchdown points for May 2000–2004 and May 2005–2009



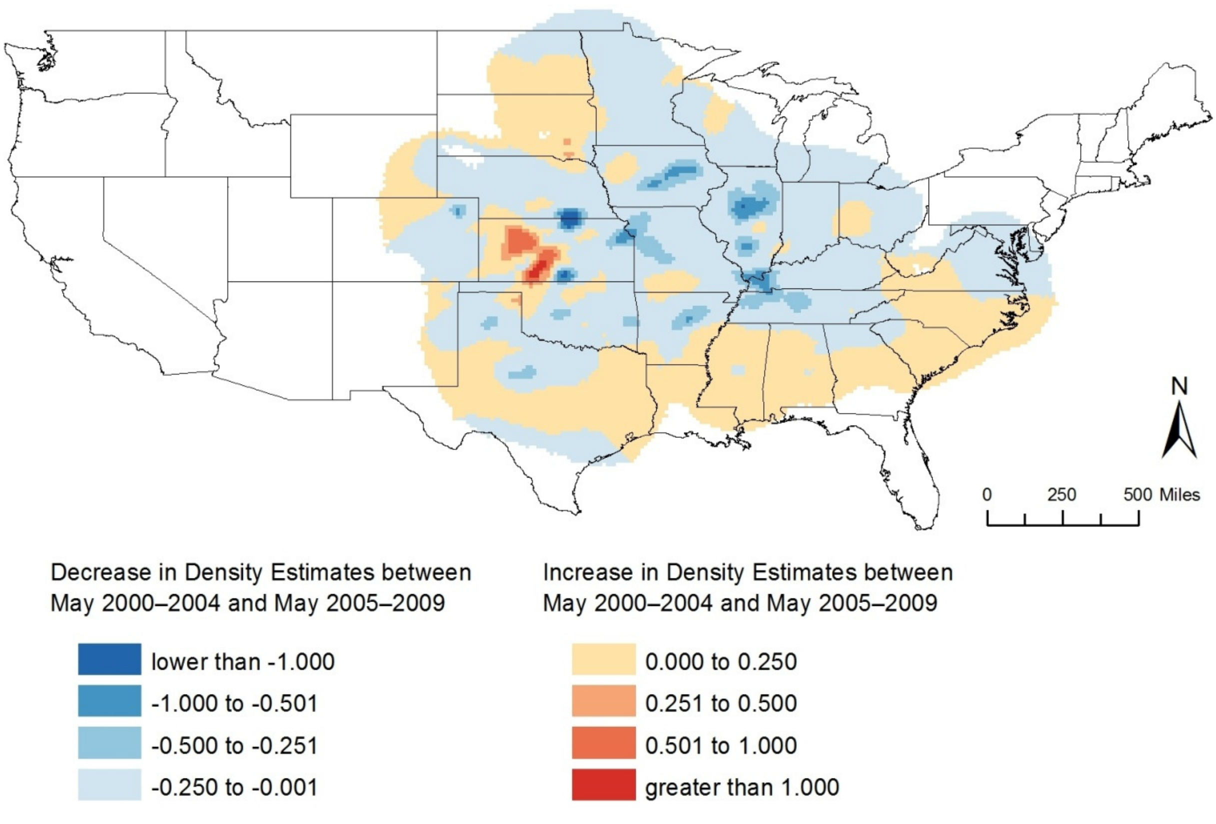
A second approach considers the **clustering of attributes at two different time periods**. Bivariate LISA statistics can be used for identifying areas with high values at time t that are surrounded by areas with high values at time t+1 (JACQUEZ 2008). Although this space-time approach is not used very often in the literature, JACQUEZ (2008) quotes that this tool is useful for gaining insights into cluster persistence. An example of clustering attributes at two different time periods is shown in Figure 21. This space-time LISA identified significant states with high (respective low) tornado occurrences in the period May 2000–2004 that are surrounded by states with high (respective low) tornado occurrences in the period May 2005–2009. In the center of the United States a space-time hotspot of high values has been detected. Space-time cold spots with low values at both time periods are located in the western part and in the Northeast of the United States. Additionally, there is one spatiotemporal outlier (Wisconsin) with a low value in the period May 2000–2004 that is surrounded by states with high values in the period May 2005–2009.

Figure 21: Space-time LISA of tornado touchdown points between May 2000–2004 and May 2005–2009



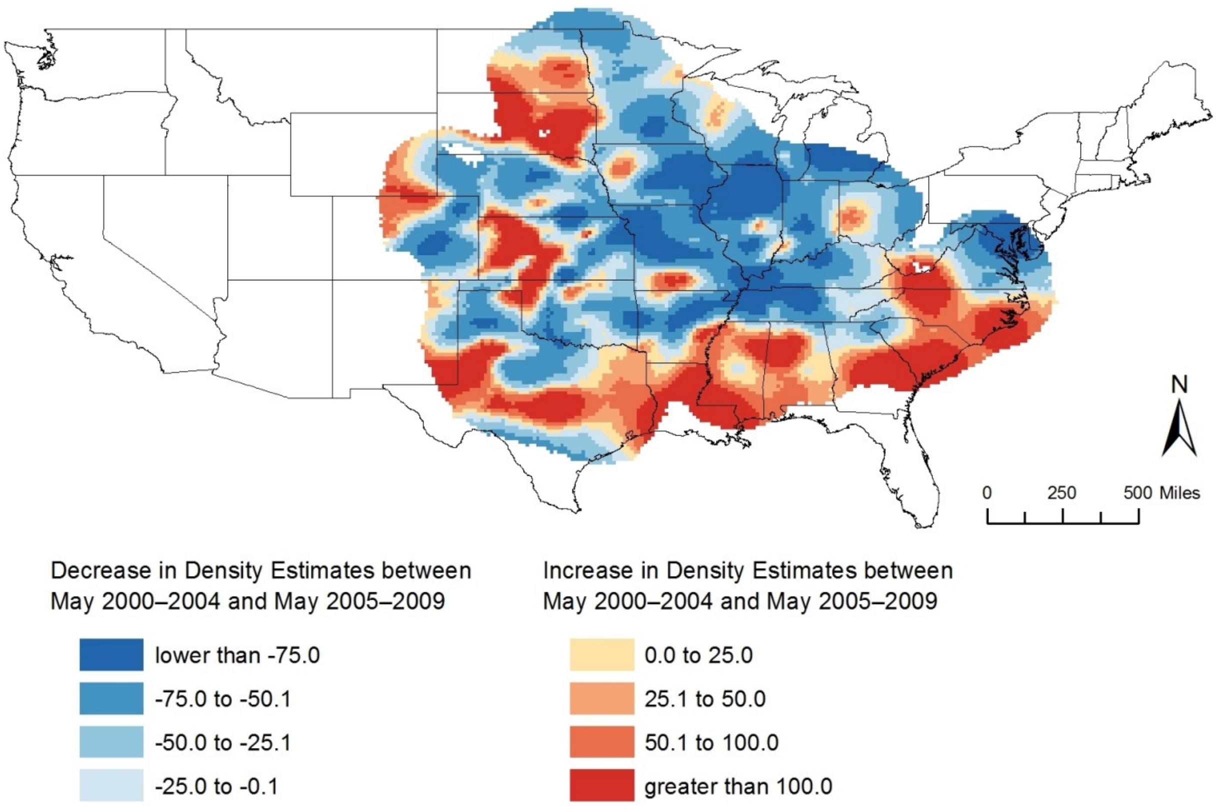
A third approach is to **cluster temporal differences**. This technique uses difference maps instead of working with maps showing attributes at time t and t+1 (see the second approach). These difference maps subtract the value at time t from the value at time t+1. The approach is useful to locate areas where the temporal difference of the attribute values is stable or changes dramatically (JACQUEZ 2008).

Figure 22: Differences of absolute density estimates of tornado touchdown points between May 2000–2004 and May 2005–2009



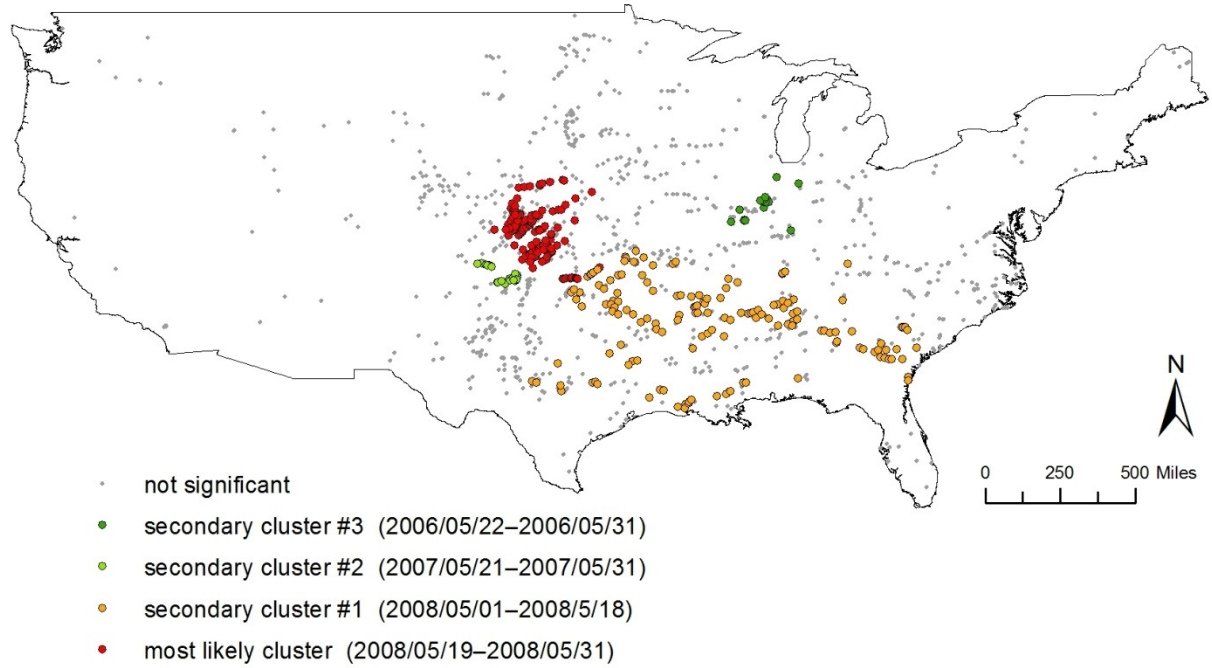
As an alternative the proportion of the difference to the base time t (relative difference) can be calculated and visualized. Both methods belong to the dual kernel density estimations method. Figure 22 shows an example where temporal differences of absolute density estimations are clustered. The values can be interpreted as follows: A value of 1 means that the density value of tornado touchdown points per square mile increased by 1 from 2000–2004 to 2005–2009. In comparison, Figure 23 uses differences of relative kernel density estimations of tornado touchdown points. Here, a value of 100 means that the density value increased by 100 percent from 2000–2004 to 2005–2009. These maps should be interpreted as follows: Red shaded areas indicate locations where the number of tornadoes was higher in May 2005–2009 than in May 2000–2004. In contrast, blue shaded areas experienced more tornadoes during the earlier period from May 2000–2004. For a better visualization only areas with an absolute density estimation of >= 0.01 tornado touchdown points per square mile at both periods are shown.

Figure 23: Differences of relative density estimates of tornado touchdown points between May 2000–2004 and May 2005–2009



So far, each hot spot map considered in this section accounts for the combination of hot spot maps at two different snapshot periods in time. New areas of research have started the exploration of space-time interaction. Test statistics such as the Knox test (KNOX 1964) or the Mantel test (MANTEL 1967) are appropriate tests for space-time interaction. These tests are global in nature and therefore useful, if the analyst wants to see if there is clustering throughout the entire study region and the whole time period. Hence, these tests are unable to find specific locations and sizes of clusters. Therefore, as a fourth set of approaches, scan statistics will be applied in this thesis. Such statistics are commonly used to detect und evaluate clusters of cases in either a purely spatial, purely temporal or space-time setting. The **space-time scan statistic** gradually scans a window across space and time, and noting the number of observed and expected observations inside the window at each location. As a result, the most likely cluster is the window with the maximum likelihood. This is the cluster least likely to be due to chance and an appropriate p-value is assigned to this cluster (KULLDORFF 2010). Figure 24 shows the results of a space-time scan statistic applied to the tornado touchdown points in the period May 2005–2009. Four space-time clusters were identified, each with a p-value of 0.001. The most likely cluster contains 143 tornadoes that occurred in the period 2008/05/19 to 2008/05/31. As can be seen in Figure 24, the different clusters differ in their morphology in regards to their spatial and temporal extends.

Figure 24: Space-time scan statistic of tornado touchdown points, May 2005–2009



The following subchapter discusses software for cluster analysis. Freely available software packages, which include these space-time approaches, will be presented.

2.3. Cluster Analysis Software

The increasing application of statistical techniques for the analysis of spatial patterns is the result of developments in the hard- and software industry. Although techniques of spatial pattern analysis are well known over decades, the development of specific software packages did not start until the early 1990s. Most statistical tests are very processor-intensive because of large datasets. For this reason, the application of statistical techniques for spatial data analysis needed computers with increased computational power (LORUP and LEITNER 2000).

There are several software packages available nowadays. Besides commercial products such as ClusterSeer (http://www.terraseer.com), various freely available software packages are commonly used. These software packages (e.g., GAM, CrimeStat, GeoDA, SatScan) are based on common scripting languages and are mostly developed by the public sector (LORUP and LEITNER 2000). In the application of cluster analysis software it is necessary that some basic GIS infrastructure exists. Inside this GIS infrastructure, the data of interest need to be geo-coded as points on a map, or have been aggregated to areal units. Therefore, spatial statistics software should have an efficient interface to GIS to extract the relevant data and to feed back the results for map display. Although statistical software sometimes contains some GIS-functionalities, the functions are typically less efficient in comparison to purely GIS software. For this reason, ESRI's ArcGIS 9.3 is used in this thesis to initially prepare the tornado data and finally to visualize the outputs of the statistical analysis (ANSELIN 2004).

This subchapter includes a review of three selected software for the analysis of spatial clusters. The software should provide techniques to find potential tornado clusters in a given dataset. Furthermore, the software should include techniques which can be applied to the space-time approaches explained above.

The software should at least meet the following requirements. First of all, the focus should be on non-commercial, open-source software tools, which are available at the web free of charge. The software needs to be up to date and has to work in a Microsoft Windows operating system.

This selection is limited to three packages that have been established to implement techniques for spatial and spatiotemporal data analysis of tornado touchdown points in the United States. *CrimeStat*, *GeoDa* and *SaTScan* are freestanding tools which can be downloaded and installed directly in a Microsoft Windows environment.

- *CrimeStat* 3.3. A Spatial Statistics Program for the Analysis of Crime Incident Locations. Developed by Ned Levine & Associates, with support from the National Institute of Justice, Washington, DC.
    - Available at http://www.icpsr.umich.edu/CrimeStat/.
- *GeoDa* 0.9.5-i. Developed by Luc Anselin through the Center for Spatially Integrated Social Science at the University of Illinois, Urbana-Champaign.
    - Available at http://geodacenter.asu.edu/.
- *SaTScan* 9.1.0. Software for the Spatial and Space-Time Scan Statistics. Developed by Martin Kulldorff together with Information Management Services Inc.
    - Available at http://www.satscan.org/.

ANSELIN (2004) addresses the following essential requirements of a software tool for exploratory analysis of event clusters:

- Data input: X- and y-coordinates of event locations and digital boundaries of areal units (polygons);
- Spatial information: Spatial weights construction and distance computations;
- Descriptive statistics: Identification of "extreme" values and outlier detection;

- Point pattern analysis: Statistics to identify locations that are more clustered than likely under the null hypothesis;
- Spatial autocorrelation analysis: Measures of global and local spatial autocorrelation (LISA) to identify areas which are surrounded by areas with similar values, or to identify spatial outliers;
- Visualization of results: Indicate outliers and significant clusters in maps and/or graphs;
- Program output: Save and store results in a way that can be integrated within other software such as GIS;

None of the three packages proposed for the statistical analysis in this thesis satisfies all these criteria. In the following sections the features as well as the benefits and the drawbacks of the three implemented software packages will be considered.

2.3.1. CrimeStat

CrimeStat was originally developed for the analysis of crime incident locations. However, the software and its statistical techniques can be used to analyze any point pattern data, such as patterns of locations of tornado touchdown points. An advantage of *CrimeStat* is the ability to read data from a wide range of formats, although only point data (no polygons or lines) can be read. The program is organized along five main sets of functions, including data setup, spatial description, spatial modeling, crime travel demand, and options. ANSELIN (2004) evaluates the data input as the most flexible of the proposed software packages. This includes the selection of a primary file, a secondary file (if applicable) and a reference grid for kernel density estimation.

The statistical functions in *CrimeStat* are structured in "description" and "modeling". In the description tab most of the functions are relevant to cluster analysis respectively the so-called "hot spot" analysis. It contains clustering methods such as the Nearest Neighbor Hierarchical Clustering (NNHC) technique, the Local Moran, as well as the STAC method of Block and Block (Space Time Analysis of Crime). The latter technique is similar to Kulldorff's scan statistic, but is not based on a likelihood criterion. The techniques in the modeling tab include the kernel density estimation as "cutting edge" interpolation routine and the Knox and Mantel tests for space-time analysis. ANSELIN (2004) argues that both tests are essential tools in a space-time analysis of clustering of events. The Knox and Mantel test both refer to local tests and do not find an application in this thesis. Finally, *CrimeStat* contains the so-called Journey-to-Crime function. This function is a specialized technique used in crime analysis and therefore less applicable to tornado touchdown studies (ANSELIN 2004).

The analysis in *CrimeStat* runs off in two stages. At the beginning, the analyst sets the dataset, options, and type of analysis. Then, the chosen computations are carried out and the results are shown on the screen. For the different statistical techniques various output options exist (e.g., ellipses and/or convex hulls for NNHC) to export the results in an appropriate format for GIS and mapping packages. *CrimeStat* does not include any mapping capabilities (ANSELIN 2004).

CrimeStat includes statistical tests which are the current standard for point pattern analysis. Most of the methods use Monte Carlo randomization to assess significance. The software is available with an extensive manual of 954 pages (Levine 2010) with several case studies and examples. Some understanding of the cluster statistics is required. In the manual and examples the statistical background of the various tests are explained comprehensively for first-time users (ANSELIN 2004).

2.3.2. GeoDa

The intention of the software package *GeoDa* is to introduce the user to spatial data analysis in combination with some minimal mapping functionality. *GeoDa* does not include wide-ranging GIS tools. The emphasis lies on data visualization and interactive data analysis. The latter is implemented by dynamically linked windows to use linking and brushing of all statistical graphs and maps. The primary data input type is polygon data, although points which represent areas can be used as well. *GeoDa* includes several functions to manipulate spatial data, such as the computation of centroids or the conversion of data from various input files to point shape files. Spatial analysis is focused on statistical graphs, autocorrelation statistics, and maps (ANSELIN 2004, LEITNER and BRECHT 2007).

GeoDa is the only package of the three that includes mapping functionality and does not necessarily require a GIS for visualization. As the main input format ESRI's shape files are required. Several map types such as choropleth maps or outlier maps (e.g., box maps as a spatial equivalent of a box plot) as well as cartograms can be visualized (ANSELIN 2004). The maps can be saved as bitmap files. In newer versions it is possible to save the results in the PostScript format. Once an analysis or a specific map have been completed in *GeoDa*, it is possible to save the results and export the updated data table to a shape file.

The main analytical focus of *GeoDa* is on ESDA. This includes a variety of statistical graphs, such as a histogram, boxplot, scatterplot, and a parallel coordinate plot, as well as the investigation of spatial autocorrelation. For the analysis of the latter a Moran scatterplot for the global Moran's I, and LISA significance and cluster maps for the Local Moran's I are implemented. The results of the Local Moran's I can be saved in the input table and exported to further analyze or visualize them in a GIS or in another software. As already proposed, the Local Moran's I can be extended to a bivariate case for space-time analysis. For the usage of the concept of spatial autocorrelation in *GeoDa* it is necessary to construct spatial weights, which are based on either the contiguity between polygons or the distance between points. These weights files can be created and used in *GeoDa* but can also be used by other software (ANSELIN 2004).

Generally, *GeoDa* can be used by a broad audience that needs not to be GIS experts. The user does not need much statistical prerequisites for the implemented descriptive statistics and basic statistical inferences. The software package comes with a user's guide and the current software version release notes, as well as several sample data sets and tutorials (ANSELIN 2004).

2.3.3. SaTScan

The software *SaTScan* is a very specialized package. It only implements Kulldorff's scan statistic for temporal, spatial, and spatiotemporal cluster detection. This technique is most often used in public health to detect disease clusters. So far, this technique was not applied to tornado touchdown points. The basis of this statistic is a combination of a quadrat-like counting of cases in a circular area. A likelihood ratio test is used to identify the most likely cluster. The statistic can be applied to individual case locations, or to the aggregation of event counts associated with points (ANSELIN 2004). By 2005, all scan statistics available needed data that provide information about spatial and temporal distribution of the underlying population-at-risk. Census data can be an appropriate denominator for tornado fatalities, where the expected number of fatalities is then estimated based on the underlying population (KULLDORFF et al. 2005). Recently, KULLDORFF et al. (2005) proposed the so-called space-time permutation model which uses only events with no need for population-at-risk data.

The analysis in *SaTScan* is made in two steps. First, the user sets the parameters for the intended analysis technique, such as the input data files, the output location and output file, and various settings for the statistical computation. Afterwards, the analysis will be executed and the results are shown on the screen. Additionally, the results will be written to output files, if specified. ANSELIN (2004) argues that system of data input is somewhat rigid. The software requires separate files for cases, controls (population-at-risk), and location coordinates of the events. In addition, the usage of the ascii file format is peculiar (ANSELIN 2004).

The output results consist of cluster locations for the most likely cluster and additional clusters as well as their likelihood and significance. *SaTScan* does not possess any built-in visualization options. This makes the software rather limited in regard to its combination with GIS and other software. The scan statistic is the only technique implemented in *SaTScan* and requires detailed statistical knowledge in order to appropriately set the parameters and to intelligently interpret the clusters (ANSELIN 2004).

2.3.4. Software Summary Evaluation

All of the three proposed software packages are free, so monetary constraints do not play a role in their assessment. The software packages differ in the range of functionality, in terms of its handling, and in the statistical background required from the user. None of these packages meets the software requirements proposed by ANSELIN (2004). It is notable, that to some extent the software packages are complementary to each other. Therefore, it is recommended to use a combination of several packages to implement an effective cluster analysis in the real world. *CrimeStat* and *SaTScan* additionally need separate GIS or mapping software to appropriately visualize the results (ANSELIN 2004).

Due to the increasing popularity of Kulldorff's scan statistic, ANSELIN (2004) suggests that the *SaTScan* package should be part of any software collection, since this technique is not included in any other packages which are free of charge. The scan statistic should at the minimum be supplemented with the Local Moran's I statistic as ANSELIN (2004) proposes. The Local Moran's I statistic is available in both *CrimeStat* and *GeoDa*.

CrimeStat and *GeoDa* overlap only to a small extent. They are mainly complementary to each other. *CrimeStat* offers extensive functionalities for point pattern analysis, whereas *GeoDa* focuses on interactive data exploration and visualization, and provides a wider variety of options for local autocorrelation statistics. Both packages can be used with basic understanding in cluster analysis and spatial association (ANSELIN 2004).

Annex A shows an overview of current specific cluster statistics in each of the proposed packages. As can be seen a huge number of different cluster analysis techniques are offered in freely available software. For this reason, only a few statistical tests will be selected for the spatial and spatiotemporal analysis of tornado touchdown points. These techniques will be explained in the next subchapter.

2.4. Selected Techniques for the Identification of Spatial and Spatiotemporal Clusters

Many different statistical tests for spatial data analysis have been developed recently. Due to the huge number of techniques researchers often deliberate which spatial cluster statistic to use. Online cluster analysis advisors, such as the one at http://www.terraseer.com/products_clusterseer_advisor.php provide help in this regard (JACQUEZ 2008).

It is difficult to find the "one" cluster test which is appropriate for the spatial data analysis. This should only be done when the analyst has prior knowledge of the cluster shape. JACQUEZ (2008) argues that prior knowledge of cluster shape is lacking because analysts usually do cluster analysis to locate and describe clusters.

Only a few selected techniques will be applied to the tornado touchdown points in the United States. These methods are the NNHC technique, the kernel density estimation, the Local Moran's I, and the space-time permutation model. The NNHC technique is useful for the detection of spatial ellipses or convex hulls at a small scale. In contrast, the kernel density estimation calculates density values for the whole study area. In addition to these techniques the Local Moran's I and Kulldorff's scan statistic will be applied as proposed by ANSELIN (2004). The Local Moran's I is based on the concept of spatial autocorrelation which compares values at each location with values in close proximity. Various scan statistics (see Annex A) are provided in the *SaTScan* package. In line with the focus of this thesis, only the space-time permutation model will be applied. This state-of-the-art method searches for clusters in both space and time. The space-time permutation model is the only scan statistic which solely analyzes events and does not need a population-at-risk. These four techniques will be used for the spatial and spatiotemporal analysis of tornado touchdown points in the United States. As proposed in Section 2.2.2.3 all of these techniques include have a space-time approach. While the space-time permutation model is the only approach which accounts for both spatial and temporal interaction, the techniques selected above can be used to analyze cluster persistence or cluster changes. In the following sections the statistical background of these four techniques will be discussed in detail.

2.4.1. Nearest Neighbor Hierarchical Clustering

Generally speaking, the NNHC technique identifies groups of events that are in close spatial proximity. As has been said in Section 3.2.2, this routine is a hierarchical technique that clusters points based on various criteria. The process of clustering is repeated until either all points fall into a single cluster or the clustering criteria fail. The method uses a defined threshold distance and compares it to the distances between all pairs of points. Points that are closer to other points than the threshold distance are considered for clustering. The second parameter in the NNHC method is a minimum number of points which are included in a cluster. If points fulfill both criteria, clusters at the first level – so-called first-order clusters – are calculated. First-order clusters are subsequently clustered into second-order clusters. Again, if the centers (seeds) of first-order clusters are spatially closer than a threshold value these first-order clusters are grouped together. According to this hierarchy of clustering, second-order clusters are grouped into third-order clusters. This re-clustering process is continued until either all clusters are grouped into one single cluster or the clustering criteria fail (LEVINE 2010).

The first criterion in the identification of clusters is whether points are in close proximity than a selected threshold distance. In *CrimeStat* two different choices exist in selecting the threshold distance: first, a random nearest neighbor distance and second, a fixed distance. The random nearest neighbor distance is the default parameter in the software package. In *CrimeStat* the user needs to specify a one-tailed confidence interval around the random expected nearest neighbor distance. With the confidence interval a probability for the distance between any pairs of points is defined. For a specific one-tailed probability p, less than p-percent of the incidents would have nearest neighbor distances smaller than the specified limit if the spatial distribution was random. For example, for randomly distributed data, if p is set to 0.05, then only 5 percent of pairs would be closer than the threshold distance. If a 0.5-level (the default value) is taken for p, then 50 percent of the pairs would be closer than the threshold value. In conclusion, the threshold distance is a probability value for selecting pairs of points based on a chance distribution. *CrimeStat* provides a slide bar with 12 levels, each referring to a specific probability value. (LEVINE 2010).

The selection of a fixed distance is the second choice in determining a threshold value. The main benefit of this method is the exact specification of the search radius. LEVINE (2010) argues for its usefulness in the comparison of the number of clusters for different distributions. However, the main drawback of this approach is the subjective choice of a threshold. Generally, the larger the selected threshold distance the greater the likelihood that clusters will be found (LEVINE 2010).

The second criterion is the selection of a minimum number of points that are aggregated to the same single cluster. This criterion is usually used to reduce the possibility of finding very small clusters as well as to reduce the likelihood that clusters are found by chance. *CrimeStat* uses a default value of 10 points. If this number is decreased, more clusters are found. By increasing the minimum number of points, fewer clusters are selected (LEVINE 2010).

CrimeStat then calculates first-order ellipses using these criteria. As described above, higher-order clustering of the previously detected lower-order cluster centers is done if necessary. The results can be saved as either ellipses, convex hulls, or both. Standard deviational ellipses are calculated for the clusters. The user is able to choose between 1X, 1.5X, and 2X standard deviations. One standard deviation typically includes more than 50 percent of the cases, one and a half standard deviations covers more than 90 percent of the cases, and two standard deviations contain more than 99 percent of the cases. After this specification the user can save the ellipses in various output formats of common GISs (e.g., ESRI's *.shp). LEVINE (2010) proposes to use a 1X standard deviational ellipse. 1.5X and 2X standard deviations may result in an exaggerated view of the clusters. However, for a regional view, a 1X standard deviational ellipse may be too small and thus not recognizable. Alternatively, clusters can also be visualized by convex hulls. A convex hull draws a boundary around the points in the clusters. At a regional view, ellipses are more useful and preferable since a viewer can quickly capture the distributions of the hotspots. If the purpose of the application is based on detailed neighborhood-level work, convex hulls are recommended since the actual locations of the incidents are shown (LEVINE 2010).

LEVINE (2010) provides some guidelines for selecting the parameters appropriately. The smaller the threshold distance, the fewer and (usually) smaller clusters are found. Therefore, the slide bar can be seen as a filter for generating clusters. The probability that will be used has some effect on the final number of clusters. Generally, the minimum number of points to be clustered has more influence on the result. A hot spot with a very low size of two or three incidents is typically not very useful. For this reason, users should consequently increase the minimum number of events to ensure that the clusters are represented by a meaningful number of cases. It seems understandably that users may have to experiment with several runs using different combinations of probability threshold distances and minimum numbers of points to get an appropriate and convincing result. LEVINE (2010) proposes to start the analysis with the default settings (threshold distance of 5 percent and a minimum number of 10 points). If the output shows too many clusters, one can decide to select a lower probability (e.g., shift the slide bar to the left) and/or to increase the minimum number of events required to define a cluster (e.g., from 10 to 20). Conversely, if the result appears to include too few clusters, try to select a higher probability (e.g., increase the threshold value by shifting the slide bar to the right) and/or decrease the minimum number of points to be clustered (e.g., from 10 to 5). If finally an adequate solution has been found, fine tuning can be done by slightly changing the parameters. Generally, the minimum number of points is a more influencing factor on the number of clusters than the threshold distance. The latter factor can also influence the results, though (LEVINE 2010).

Four advantages to this technique are listed by LEVINE (2010). The first advantage can be seen in the detection of small geographical environments where concentrated locations exist. This identification can be useful for specific targeting. Small clusters can be achieved by a low probability and a high minimum number of points. Second, the statistic can be used with any data set and need not to be considered only for small geographical areas. This makes the usage easier for analysts. In addition, it facilitates comparisons between different areas without the need of limiting or splitting the data set. Third, there are different geographical levels of clustering of points and/or lower-order clusters. Several small clusters can be aggregated to higher-order clusters. Frequently, hot spots are located near other hot spots. The fourth advantage considers the implication of different policing strategies to each of the levels. In crime analysis, first-order clusters can be used for interventions in small neighborhoods. Second-order clusters can be appropriate for patrol areas, and so on. For the occurrences of tornado touchdown points, the different levels can be used to define different security strategies or to establish specific tornado awareness programs for the population (LEVINE 2010).

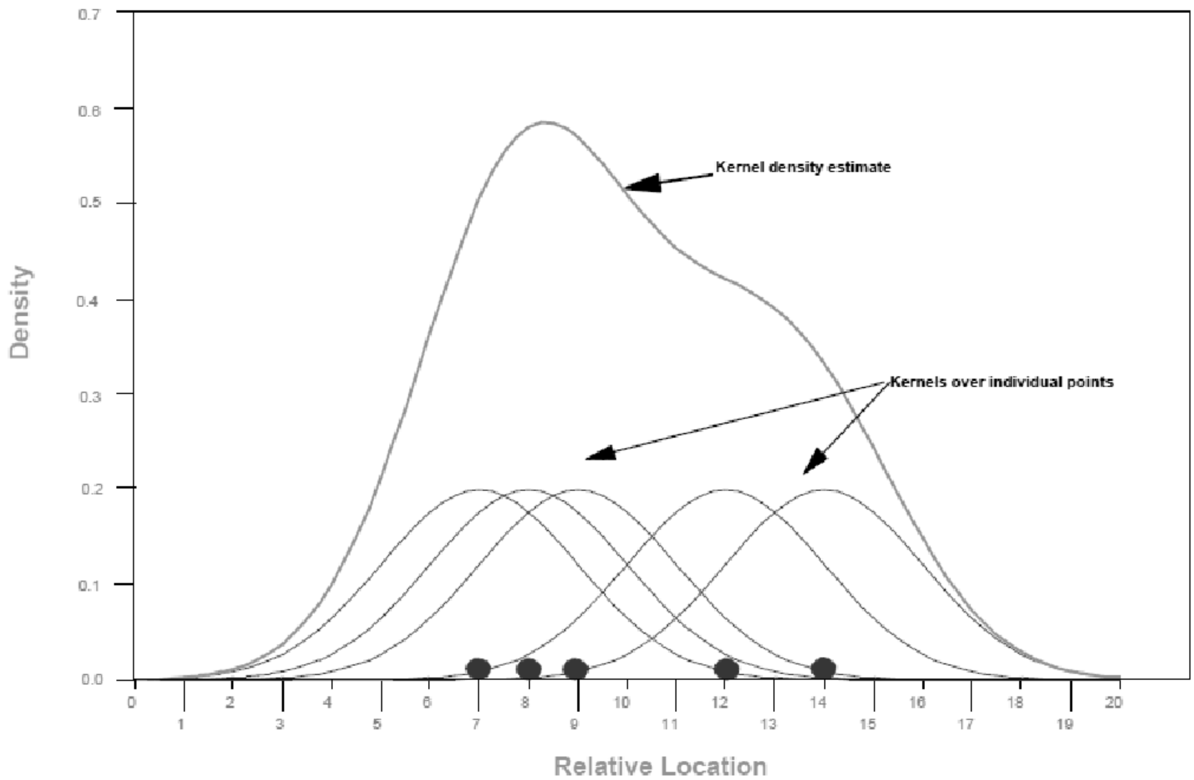
There are several limitations to this technique which need to be considered also. First, the method only clusters points and therefore, weighting a variable does not have any effect. Second, when the random nearest neighbor distance is used as the threshold distance, the size of the cluster is dependent on the sample size. Theoretically, a hot spot is dependent on an environment and not on the number of events. Therefore, the random nearest neighbor distance does not produce a consistent definition of a hot spot. The usage of a fixed distance for the threshold value can only partly overcome this. Third, the technique considers an arbitrary choice of the minimum number of points. The definition of patterns is, to some extent, made by human beings. In fact, this can lead to arbitrary results when two different users interpret the size of a hot spot differently. Additionally, the choice of the p-value allows some variability between users. In conclusion, the technique produces constant results but it involves subjectivity across users. Finally, the technique does not have any theory behind the creation of its clusters. Like many other clustering techniques empirical derivatives are produced which are not based on any explanatory theory (LEVINE 2010).

2.4.2. Kernel Density Estimation

The kernel density estimation technique interpolates event locations to an entire area. While the previously introduced NNHC routine provides statistical summaries for the incidents themselves, the kernel density interpolation technique generalizes those incidents to the entire region. These density estimates are intensity variables, a so-called Z-value, which is estimated at a certain location. Thus, these Z-values can be displayed by either contour maps or surface maps to show the intensity across the entire area (LEVINE 2010).

Several interpolation techniques exist, such as kriging, trend surfaces, or local regression models. Most of these methods estimate a variable as a function of location. In contrast, kernel density estimation is suitable for the interpolation of individual point locations. This technique places a symmetrical surface over each incident point, analyzing the distance from the point to a reference location derived from a mathematical function. Then, the values of all surfaces for that reference location are summed. The technique was developed in the late 1950s as an alternative approach for estimating the density of a histogram. Due to some statistical problems the kernel density method was introduced to handle these problems (although not all of the problems have been solved). Figure 25 shows how a symmetrical kernel function is placed over each point. Symmetrical in this context means that the function falls off with distance at an equal rate in both directions. The function used in Figure 25 is a normal distribution function, but other types of distributions have been used and will be proposed. The density distribution is then estimated by summing the kernel functions at all locations to generate a smooth cumulative density surface. Two main advantages of this technique are, first, the fact that each point equally contributes to the density surface and, second, that at all points the resulting density surface is continuous. For spatial data analysis purposes the kernel function is expanded to three dimensions. Thus, this approach is particularly suitable for geographical data (LEVINE 2010).

Figure 25: Summing of normal kernel functions for 5 points



Adapted from LEVINE (2010)

As mentioned above there is still one problem that exists in using a kernel function. This problem is related to the choice of the kernel function's bandwidth (i.e., width of the kernel function) that the user decides upon. Different choices of the bandwidth size produce different results. Thus, the smoothness of the resulting density estimate surface is a consequence of the bandwidth size (LEVINE 2010).

Users can decide between various kernel functions to interpolate the data to the grid cells. In *CrimeStat* five different functions are available. The normal kernel function weighs all points, although near points are weighted more than distant points. The normal distribution, similar to the other four types of distributions, can cause some edge effects, if there are many points close and on either side of the boundary of the study area. In contrast to the normal function, the other four functions use a delimitated circle around each point location. The usage of these four functions leads to less edge effects as the normal distribution. First, the uniform function weighs all points within the circle equally. Second, the quartic distribution weighs near points more than distant points but the weight falls off gradually. Third, the triangular function is equal to the quartic function but the fall off is more rapidly. Fourth, the negative exponential function weighs near points much higher than far points within the circle (LEVINE 2010).

The usage of any of these functions depends on the weights a user wants to apply to near points in comparison to distant points. While functions with big differences in the weights of near and far points (e.g., negative exponential or the triangular) tend to produce finer variations within the surface, more evenly weighted functions (e.g., the normal distribution, the quartic, or the uniform) tend to smooth the distribution much more. There are small differences in the results when applying the different kernel functions. Users should start their analysis with the default normal function and adjust the parameters accordingly (LEVINE 2010).

As a second criterion, users need to indicate what type of bandwidth is used for the estimation. In *CrimeStat*, the fixed and the adaptive bandwidth approaches are available. In using a fixed bandwidth, the bandwidth length as well as the units of measurement needs to be specified. Usually, a narrower bandwidth length results in a finer mesh density estimate. In contrast, a larger bandwidth will lead to a smoothed surface and therefore, less variability between peaks and valleys. One should keep in mind that the usage of a narrow bandwidth can lead to imprecision in the estimates, if the sample size is not very large. Then, peaks and valleys could be an effect of random variation. If the sample size is large, a finer density estimate can be produced (LEVINE 2010).

The second type of bandwidth, the adaptive bandwidth, adjusts the bandwidth interval so that a minimum number of events are found. Therefore a constant precision of the estimate over the entire area is provided. In areas where the concentration of points is sparse, the bandwidth will be larger, and vice versa. The precision of the surface is dependent on the chosen number of points. If the user wants to have a finer mesh density surface, a smaller number of points should be considered. In general, that would translate into a shorter bandwidth length. Should the density surface be more smoothed, a larger number of points (results in a longer bandwidth length) should be chosen. Again, the user needs to experiment to see which results make the most sense (LEVINE 2010).

Finally, the user needs to choose the type of output for the density estimates. *CrimeStat* offers three different types of how the kernel density estimate can be calculated. First, it is possible to calculate absolute densities. With this approach the sum of the densities over the whole grid equals to the total number of events. This is done by re-scaling the estimates at each reference cell. Second, the kernel density estimates can be represented as relative density estimates. This is done by dividing the absolute densities by the area of the grid cell. This could be interpreted as follows: Instead of calculating the number of points per grid cell, the relative densities indicate points per, for example, square mile. Third, the densities can be shown as probabilities by dividing the density value at each cell by the total number of events. Since these three calculations are directly interrelated with each other, it is obvious that the final density estimate does not change irrespective of which output type (absolute, relative densities, or probabilities) was chosen. The type of output selected depends on the type of research questions to be answered. For display purposes only, it does not make any difference as all different output types look the same (LEVINE 2010).

LEVINE (2010) argues that the kernel density estimate is more suitable for identifying hot spots than a cluster analysis routine such as the NNHC method. Typically, cluster analysis routines group events into clusters and differentiate between events which belong to clusters and those which do not belong to clusters. Generally, different mathematical clustering algorithms are used which produce different allocations of points to clusters. In comparison, the kernel density estimation is a continuous surface where densities are calculated at all locations. For this reason, the user is able to make a visual decision what to call a hot spot because there is no arbitrary definition where to cut off the hot spot zone (LEVINE 2010).

In *CrimeStat* there is the possibility to choose either a single kernel density estimate or a dual kernel density estimation. The difference is simple. While a single kernel estimate only uses one point data set, the dual variant is applied to two different point distributions at the same time. For example, the primary file could be the location of tornado touchdown points with the number of fatalities as the intensity variable, and the secondary file could be the centroids of counties with the population being chosen as the intensity variable. Thus, both of the point distributions are interpolated onto the same reference grid. The two kernel density estimations can then be related through some algebraic operations, such as dividing, subtracting, or summing. Therefore, this dual kernel density approach is useful to examine the risk and not just the concentration of cases (LEVINE 2010). Additionally, the dual kernel density method is useful for a space-time approach as proposed in Section 2.2.2.1. This is accomplished by interpolating the same attribute at times t and t+1 and subsequently calculating the difference between the two kernel density estimates to show temporal changes t to t+1.

2.4.3. Local Indicators of Spatial Association (LISA)

ANSELIN (1995) developed the LISA approach, as a statistic that satisfies two requirements. First, the LISA for each incident returns a value of the extent of significant spatial clustering of similar values around that incident. Second, the sum of the LISA's at all locations of incidents refers to a global indicator of spatial association (ANSELIN 1995).

For the analysis the user needs to choose a spatial attribute and a definition of spatial contiguity. The input values can either be the original absolute values (e.g., number of tornado fatalities) or, more appropriately, a standardization of the absolute values to avoid scale dependence of the local indicators. The neighborhood for each observation can be formalized using a spatial weights or contiguity matrix (ANSELIN 1995). Spatial weights are necessary for the calculation of spatial autocorrelation statistics. Weights can be built based on contiguity from polygon boundary files (e.g., counties), or calculated from the distance between events displayed as points. To distinguish the output files in *GeoDa*, spatial weights files which use the contiguity criterion are saved in a *.gal-extension, and those which use distance as criterion are saved in *.gwt-extension. Contiguity based weights offer the choice between two contiguity criteria. While rook contiguity uses only common boundaries of polygons to define neighbors, queen contiguity includes all common boundaries and all common vertices in the definition (ANSELIN 2003).

The second requirement of a LISA statistic is that a global counterpart of the statistic exists. *GeoDa* uses the Local Moran's I as LISA, whereas its global counterpart, the Moran's I is also included in the software package. This requirement is not compulsory for the exploration of significant local spatial clusters. Local spatial clusters which can be referred to as spatial hot spots are defined as those locations where the LISA statistic is significant. The values of the Local Moran's I are positive, if there are similar values that are clustered (either high or low). Alternatively, negative values indicate spatial clustering of dissimilar values (e.g., a location with low values that is surrounded by neighbors with high values) (ANSELIN 1995).

In *GeoDa*, four different output options can be generated, including the box plot, the Moran scatter plot, the significance map, and the cluster map. The most important outputs are the significance map and the cluster map. The cluster map is a special choropleth map which shows locations of significant Local Moran's I statistics. These are classified by type of spatial autocorrelation. Positive spatial autocorrelation indicate observations where both a location and its neighbors have similar values. A bright red color is used if the values are similar high, whereas a bright blue is used if the values are similar low. A bright red cluster is also referred to as a "hot spot", whereas a bright blue cluster is referred to as a "cold spot". Spatial outliers are shown by a light red (location with a high value surrounded by neighbors with low values) or by a light blue (location with a low value surrounded by neighbors with high values). The significance map shows locations with a significant Local Moran's I statistic. Based on the different significance levels the locations are shaded in different shades of green. The level of significance depends on the number of replications. With a low number of replications (e.g., 99), extreme significance levels will never appear (ANSELIN 2003).

The LISA approach is easy to implement und its interpretation does not require much statistical knowledge. ANSELIN (1995) argues that it serves a useful purpose in an exploratory spatial data analysis, particularly in the detection of local spatial clusters. As proposed in Section 3.2.2.1, a bivariate LISA is suitable for the exploration of cluster persistence in both space and time.

2.4.4. Space-Time Scan Statistic

Nowadays, users have many statistical tests available for spatial clustering. Behind these, well-developed mathematical theories of spatial clustering are available. Software tools for space-time clustering are not very common, nor are tests for space-time interaction well developed (BLOCK 2007).

The standard purely spatial scan statistic uses a circular window for each incident. The space-time scan statistic can be seen as an extension of the purely spatial approach. It is defined by a cylindrical window with a circular geographic base and the height corresponding to time. While the base is exactly defined as the spatial scan approach, the height indicates the time period. The cylindrical window is moved in both time and space, so that for each geographical location and size, it visits each possible time period. Thus, an infinite number of overlapping cylinders of different sizes is obtained. By doing so, the entire study region is covered where each cylinder could be a possible cluster. Finally, all of these clusters are compared to a Monte Carlo distribution to control for deviation from randomness. The resulting output then contains the identification of spatial clusters of high and/or low incidents at concrete time periods (KULLDORFF 2010).

Scan statistics are commonly used for disease cluster detection and evaluation (e.g., KULLDORFF et al. 2005) and in crime analysis (e.g., LEITNER and HELBICH 2009). In the analysis of tornado touchdown points, the scan techniques have not been used in the literature so far. While most of the scan statistics require either a population-at-risk or control group data, the space-time permutation model is the only scan statistic which requires only case data. For this statistic, the spatial location and time of occurrence are needed to perform the test. Then, for each cylindrical window, the observed number of cases is compared to the expected number of cases. The expected number is based on the assumption that the spatial and temporal locations of all cases were independent of each other. Under such an assumption, space-time interaction would not exist. In general, space-time interaction can be defined as follows: When an existing cluster in a geographical area has a higher proportion of incidents during a specific time period compared to the remaining regions in that time period. If, for example, all of the regions have twice the number of incidents as normal, no space-time cluster will be detected. In contrast, if one specific area has twice the number of events during a specific week compared to the remaining areas, then there will be a space-time cluster in that one specific area. It is important to mention that space-time permutation clusters may be found due to an increased population-at-risk. This should be taken into consideration when the space-time test is carried out over a time period of several years. In the analysis of tornado touchdown points this problem does not play a role since tornado probability is not influenced by an underlying population (KULLDORFF 2010).

When using likelihood functions which are maximized over all window locations and sizes, the most likely cluster is found. In the space-time analysis, the software *SaTScan* also identifies secondary clusters in addition to the most likely clusters. The secondary clusters are then ordered by the associated likelihood ratio test statistic. Various analysis parameters can be set to run the scan statistics. First of all, the user can choose a maximum spatial cluster size and a maximum temporal cluster size. In the analysis of secondary cluster locations the analyst can decide about the criterion of geographical cluster overlap. The user can choose between no overlap and no restrictions in the cluster definition (KULLDORFF 2010).

The scan statistics have the strength to scan a geographic area over time without any spatial and temporal constraints. The identification of which areas and what time periods are involved in each cluster is unique and not available in any other scan methods. Therefore, the scan statistics should be part of a spatial data analyst's toolbox (BLOCK 2007).

3. Spatial and Temporal Analysis of Tornado Touchdown Points

Numerous aspects related to tornado touchdown points have been analyzed in the literature. Research topics reach, for example, from spatial aspects of tornado occurrence, to principles of tornado safety or to climatological requirements of the development of tornadoes. In this chapter the proposed hot spot analysis techniques will be applied to the tornado dataset from 1950 to 2009. Thus, this thesis clearly contributes to the research of the spatial and temporal occurrence of tornadoes in the United States. There will not be any research included in this thesis about tornado safety or about the changes of climatological parameters.

The following research questions will be addressed in this chapter:

- Will recently developed statistical techniques result in more accurate analysis than classic methods?
- Do different hot spot analysis techniques provide the same or different results? What techniques are most useful for the spatial and temporal analysis?
- Did the locations of spatial concentrations of tornadoes in the United States change over time? Is there a general pattern in the spatial variation or is the F-Scale an influencing factor for spatial and temporal variability?
- Is the pattern of BROOKS et al. (2003) who analyzed tornadoes from 1980 to 1999 (dis)similar to the monthly maxima pattern of the tornado occurrences from 1950 to 2009? Is the pattern of monthly maxima of tornado occurrences congruent with the locations of the jet streams?
- What are the relative risks of fatalities due to tornado touchdowns in the United States? How did these rates change over time?

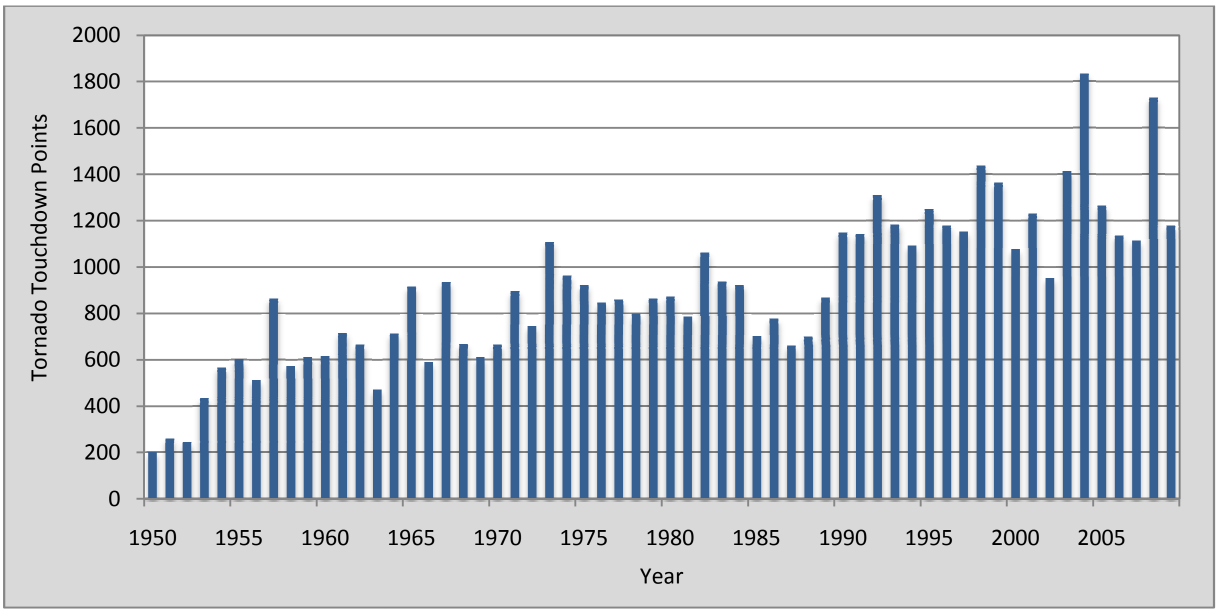
But this thesis does not only discuss these research questions. Numerous statistical analyses, maps, charts, and tables will lead to a comprehensive spatial and temporal analysis of tornado touchdown points in the United States. This thesis should therefore contribute to a better knowledge of spatial and temporal occurrences of tornadoes as well as the associated risk to the underlying population. The extension of the spatial analysis with the temporal component should identify changes of the climatological requirements for tornado development. This thesis will not only focus on tornado touchdown points. An important aspect is the comparison of different mapping techniques associated with different statistical methods. More specifically, a selected group of four statistical tests will be applied and compared. Each of the four tests (see Subchapter 2.4. for more details) uses a different statistical approach and outputs the results in different ways. Thus, these techniques should not be seen as being contrary to each other, rather than being supplementary.

In the following subchapters different parts of the entire dataset will be analyzed. First, all recorded tornadoes in the coterminous 48 states of the United States will be analyzed. Then, only “significant” tornadoes rated F2 and higher will be analyzed in space and time. The entire dataset will be classified again, but this second time using the classification of KELLY et al. (1978) who classifies weak (F0–F1), strong (F2–F3) and violent (F4–F5) tornadoes. Then, monthly tornado touchdown patterns over the entire period will be used to create a map that shows for every month the maximum tornado threat. This map will be compared with a similar map in BROOKS et al. (2003), who used tornado data from 1980 to 1999. The last part of the analysis focuses on tornado fatalities. A comprehensive spatial and temporal analysis will be presented. In addition, the underlying population-at-risk will be introduced to calculate fatality rates for different geographical areas.

3.1. Analysis of Tornado Touchdown Points from 1950 to 2009

The first analysis considers all tornado touchdown points that occurred in the contiguous 48 states between 1950 and 2009. Table 3 in Subchapter 2.1 (page 30) listed all recorded tornadoes in this period. In total, a number of 53,960 tornadoes were reported in the United States between 1950/1/1 and 2009/12/31. Since the annual tornado occurrence is not the same over the entire period, Figure 26 indicates the annual variability of tornadoes. As can be seen, the annual number of reported tornadoes increased over time. Possible reasons for the observed increase could include population growth in sparsely populated areas that results in a greater chance to register a tornado or improved tornado detection systems. A third reason for the increase in tornado occurrences may be due to climate change during the observation period. The lowest number of tornado events was recorded in 1950 due to the low number of detection systems. In recent times (since 1990) the number of tornadoes is somehow constant although the annual number fluctuates. During that time-period the maximum number of tornado occurrences (1,835) was reported in 2004, whereas the minimum number of tornadoes (953) was recorded only two years earlier in 2002. The relative difference in these numbers is almost 100 percent. Thus, there is not a constant annual tornado occurrence that can be observed in the last two decades.

Figure 26: Annual occurrence of tornado touchdown points from 1950 to 2009

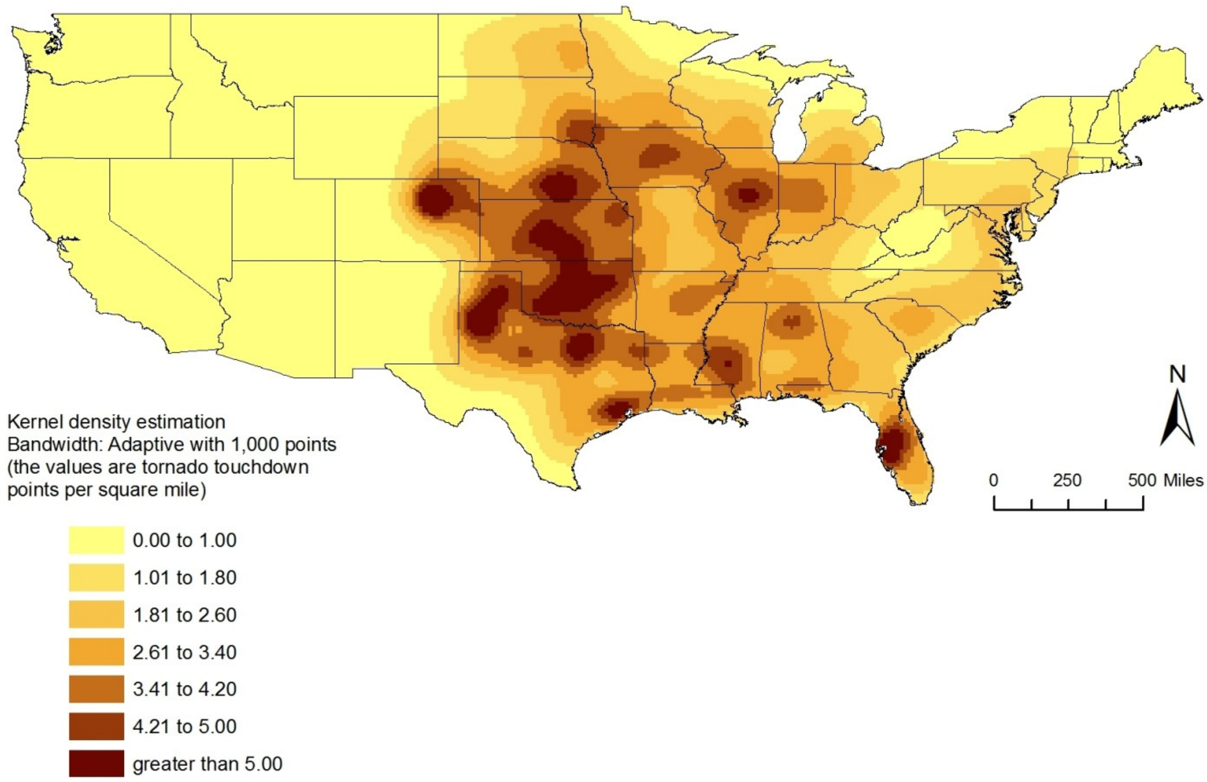


The following sections will analyze the spatial distribution of all recorded tornadoes. Furthermore, the tornado dataset will be divided in two different time periods to analyze temporal changes in the spatial locations of tornado concentrations.

3.1.1. Analysis of all recorded Tornadoes aggregated from 1950 to 2009

This first spatial analysis of tornado touchdown points considers all recorded tornadoes during the entire period from 1950 to 2009. Two different techniques of spatial clustering will be applied. The kernel density estimation technique will be used first, followed by the NNHC method. For both techniques different parameter settings will be applied and the outputs will be compared with each other.

Figure 27: Kernel density estimation of tornado touchdown points from 1950 to 2009 (version 1)



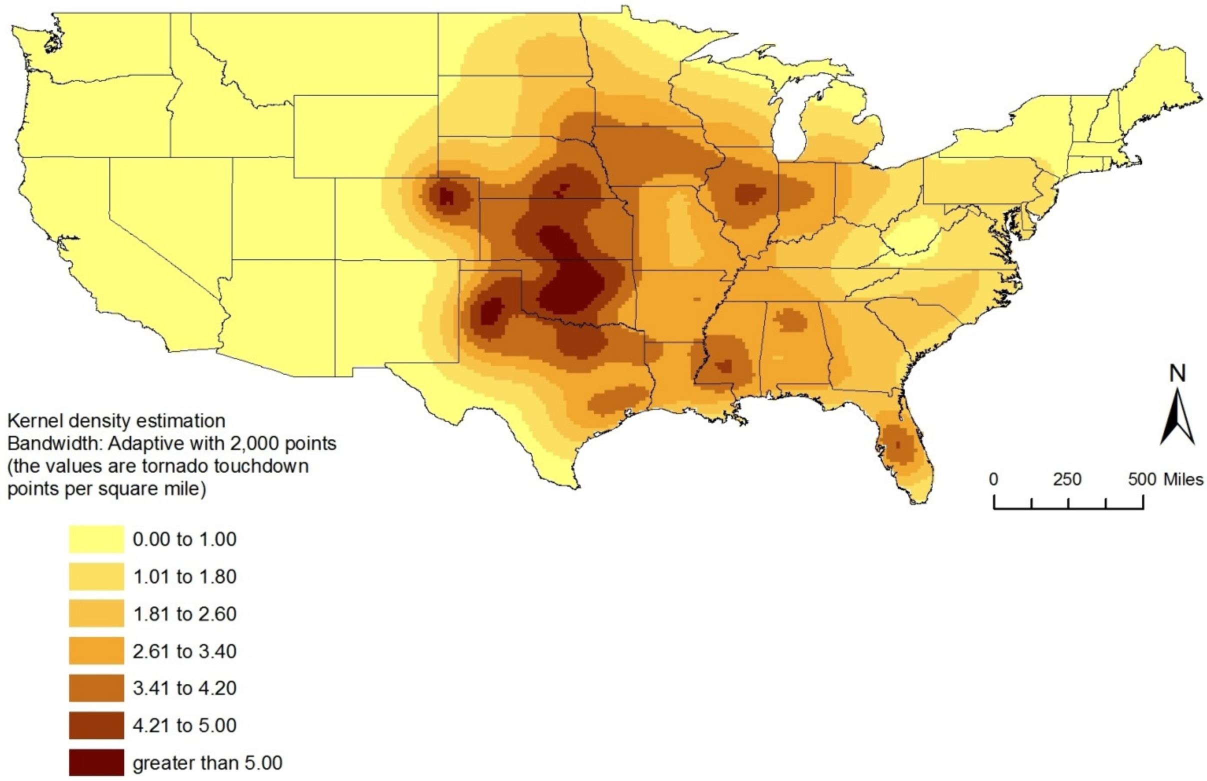
The first map (Figure 27) represents the absolute frequencies of tornado touchdown points for the entire period from 1950 to 2009. This analysis was realized using the kernel density estimation to interpolate the data over the entire area. Since tornadoes only occur over land, only values in the United States are shown in the map. In the application of the kernel density estimation only the quartic kernel function was used to make the results comparable with each other. The quartic distribution weighs near points more than distant points while the weight falls off gradually (LEVINE 2010).

Since the entire tornado dataset contains a lot of points (53,960 tornadoes) a simple dot map would not make sense in this context. The points would overlap in most areas of the United States which makes it impossible to detect a spatial pattern. Therefore the kernel density estimation is a useful technique to interpolate the data over the entire study area. The results are easy to interpret and to understand. The most important and influencing parameter is the specification of the type of bandwidth. All kernel density maps in this analysis use an adaptive bandwidth with a minimum point size that differs between maps. Figure 27 uses an adaptive bandwidth with 1,000 points, whereas Figure 28 uses an adaptive bandwidth with 2,000 points. Generally, it can be said that the fewer the number of points, the more “speckled” the density estimation looks like. In Figure 27 there are more local concentrations of tornadoes, whereas in Figure 28 the density estimation is more generalized. It is important that users specify the intention of the density estimation map. If the purpose is a map for a quick overview of point densities, then the user should prefer a larger number of points. Is the purpose a map with small local concentrations of events, then the user should consider fewer number of points.

After the reasoning for the parameter selection was discussed in detail, a discussion of the results of the two kernel density maps follows. As can be seen in Figure 27 the highest concentrations of tornado touchdown points can be found in the Great Plains (Annex B contains a map of the physical regions as well as important cities mentioned in this chapter). Nearly the entire state of Oklahoma is covered by the highest concentration of tornadoes. This largest hot spot is located from Oklahoma to Kansas in the north. A further local hot spot was detected around Hastings, NE. The far most western cluster was detected around Denver, CO, where the density values rapidly decline in the Rocky Mountains. The state of Texas contains three clusters with the highest concentrations of tornado touchdown points. These can be located in the Texas Panhandle from Lubbock, TX, to Amarillo, TX. The second hot spot is located in the area around Dallas, TX, and Fort Worth, TX. The third cluster, which is close to the Gulf of Mexico, is located around the area of Houston, TX. A small hot spot is detected around Jackson, MS. North of this cluster the density declines but further north there is a local concentration in the center of Illinois. Generally, the shape of these highest concentrations can be identified as a “C”. In addition, there is a “spatial outlier” found in Florida. This hot spot reaches from St. Petersburg, FL to Orlando, FL. There are not much tornadoes west of the Rocky Mountains. In the northeastern part of the United States the density values are very low, as well. In West Virginia and Virginia the density values are low, as well. Here, the presence of the Appalachians could be a reason for such low values.

Figure 28 shows similar results since the same tornado touchdown dataset was used as in Figure 27. As has been said above, the greater the minimum point size the more generalized the density becomes. In comparison to Figure 27, the kernel density results in Figure 28 show fewer areas with the highest concentrations of tornado touchdown points. The large area in Oklahoma and Kansas, the small cluster in Denver, CO, the cluster around Lubbock, TX, and some small hot spots in Nebraska were detected as highest concentrations of tornado touchdown points in Figure 28.

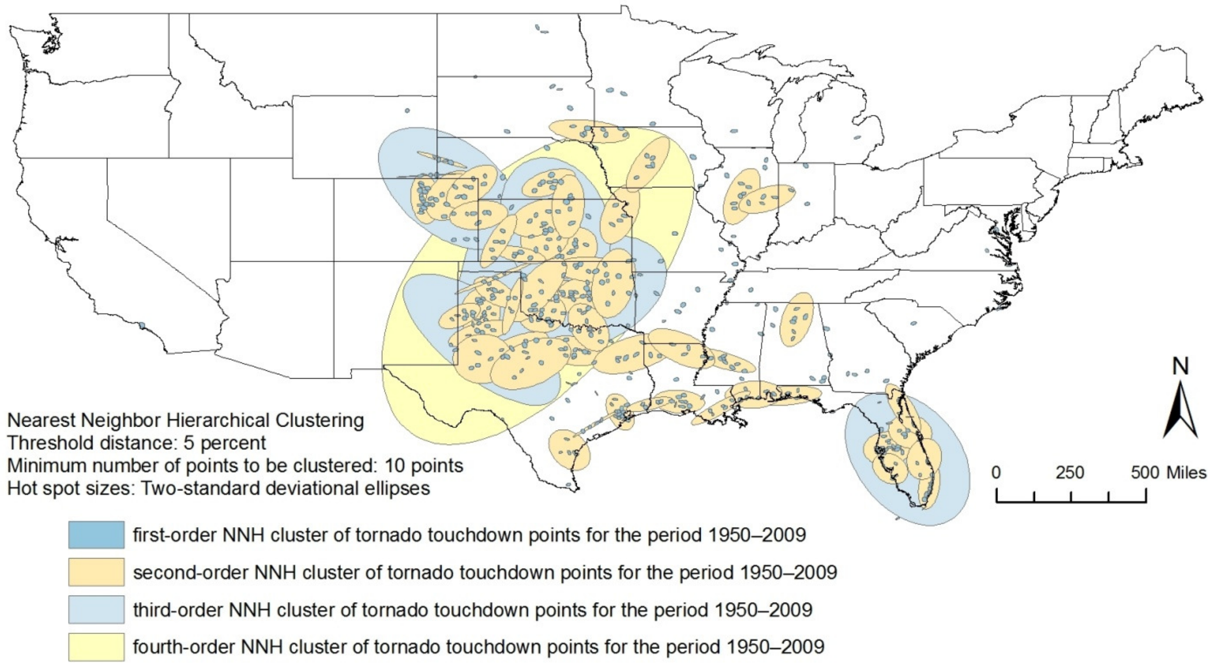
Figure 28: Kernel density estimation of tornado touchdown points from 1950 to 2009 (version 2)



The kernel density estimation method is a useful technique to detect hotspots. The main advantage is that the density surface is interpolated over the entire area. Therefore analysts can detect hot spots as well as cold spots (areas with a low concentration of events). The next technique that will be applied to the entire dataset from 1950 to 2009 is the NNHC technique. This technique was discussed in detail in Subchapter 2.4.1. In general, the NNHC technique clusters a minimum number of points which are in close proximity. This distance is expressed by a threshold value. The NNHC technique only clusters points to hot spots – say that starting with the second order, lower order clusters are clustered to higher order clusters.

Analogous to the previous analysis using kernel density estimation, the following analysis compares two different versions of NNH clustering. First, Figure 29 uses ten tornado touchdown points as the minimum number of points to be clustered. In contrast, Figure 30 uses 20 tornado touchdown points as the minimum number of points to be clustered. These numbers of points were chosen since the analysis using more points to be clustered resulted in only one cluster. Both statistics were applied using a threshold distance of 5 percent and the resulting clusters are shown with two standard deviational ellipses. Generally, the higher the threshold value and the lower the minimum number of points to be clustered, the more clusters are found (and vice versa).

Figure 29: NNH clusters of tornado touchdown points from 1950 to 2009 (version 1)

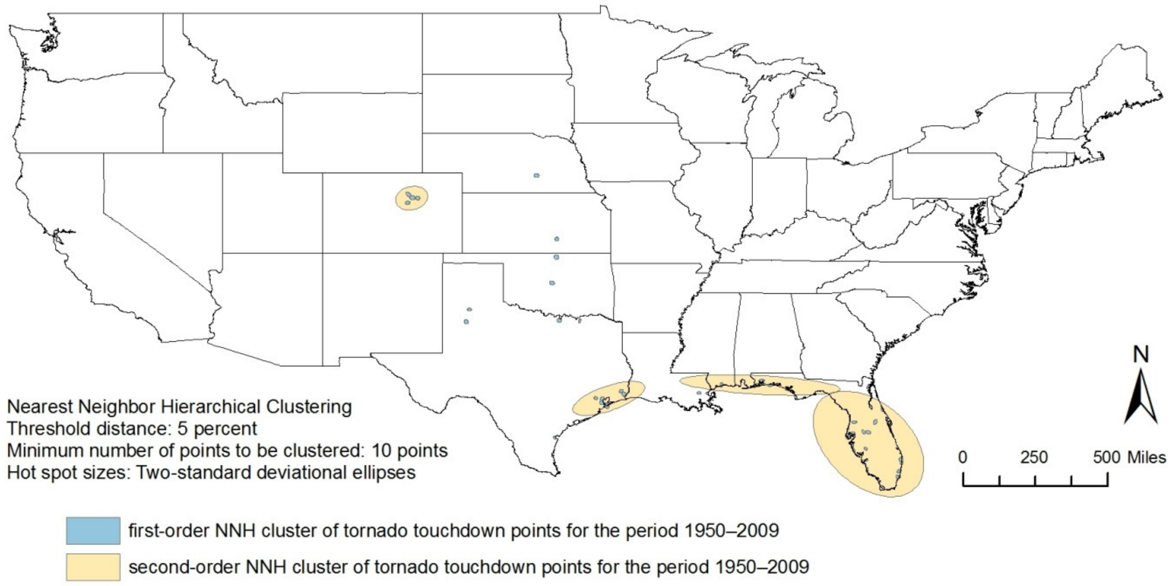


Such an analysis was realized in Figure 29, where a huge number of clusters was found. In total, 479 first-order NNH clusters of tornado touchdown points from 1950 to 2009 were detected. Due to the hierarchical principle of the NNH technique, the first-order ellipses are clustered into second-order clusters and so on. These 479 first-order clusters are grouped into 53 second-order ellipses. These are further grouped to six third-order clusters and one fourth-order cluster. The first-order clusters represent local concentrations of events. In comparison to the kernel density estimates, a user cannot generally identify areas with a low concentration of tornadoes. Most of the second-order clusters are congruent with the highest concentration of the kernel density surface in Figure 27. Since the resulting clusters are visualized in form of ellipses the third- and fourth-order ellipses cover both areas of high and low concentrations of tornadoes, when compared to the kernel density results.

In comparison to Figure 29, a second analysis using the same parameters except the number of minimum points to be clustered, namely 20, was applied. In Figure 30, fewer clusters are found because of the increased minimum number of points. 48 first-order ellipses were found, which are further clustered into four second-order clusters. From a visual point of view, the results of Figure 30 are easier to comprehend, since Figure 29 includes too much information and thus, the map reader may not be able to correctly interpret the results shown in Figure 29.

The first-order clusters in Figure 30 are located in Denver, CO, Nebraska, Kansas, Oklahoma, Texas, Louisiana, Mississippi, Florida and North Carolina. The highest number of clusters is found in Florida, followed by Texas. The second-order clusters are located around Denver, CO, in the South from Houston, TX, to Louisiana, from Louisiana to the Florida Panhandle and one big cluster covering almost the entire state of Florida. In comparison to the kernel density estimates, the cluster results in Figure 30 are very similar. Hence, the outputs in Figures 28 and 30 are both comparable and supplementary, since the kernel density technique did not detect hot spots in Louisiana, Mississippi and North Carolina, but the cluster method did.

Figure 30: NNH clusters of tornado touchdown points from 1950 to 2009 (version 2)



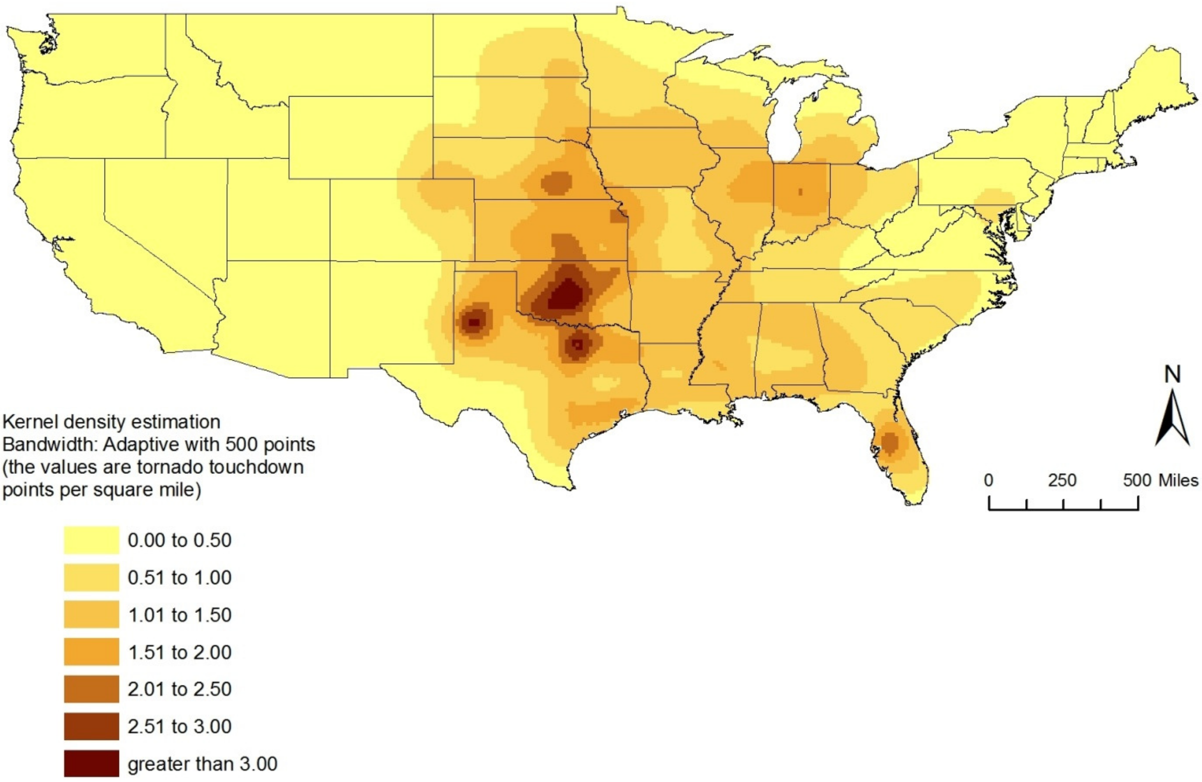
3.1.2. Analysis of Tornadoes separated into Two different Time Periods

In this section the dataset of tornado touchdown points from 1950 to 2009 will be divided into two time periods to compare the spatial patterns for each period and to measure possible variability in cluster change and cluster persistence. The entire dataset (from 1950 to 2009) contains data over a 60 year time-period. Thus, the entire dataset was divided in two time periods with covering 30 years each. The first time period is from 1950 to 1979 and contains 20,460 tornado touchdown points or 37.9 percent of the total number of tornadoes in the entire dataset. The second time period is from 1980 to 2009 and contains 33,500 tornado touchdown points or 62.1 percent of the total number of tornadoes in the entire dataset.

Two approaches to measure variability in cluster persistence and cluster change (for the theory behind this see Section 2.2.2.3.) will be presented and discussed in this section. Analogous to the previous discussion, kernel density estimates and NNH clusters are used to check for space-time patterns in the tornado dataset.

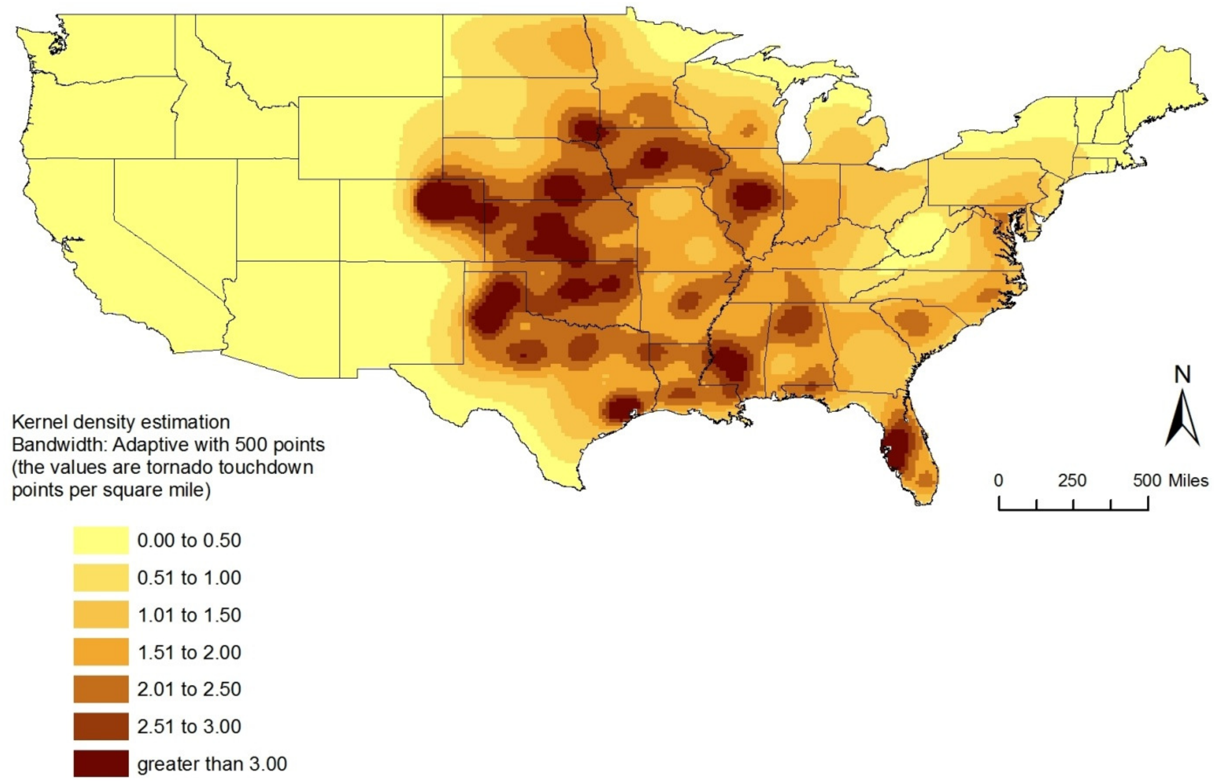
The conceptual background of space-time patterns using kernel density estimates is based on two maps at different time periods. The difference is then calculated to check for temporal variability in each location. Figures 31 and 32 show kernel density estimations of tornado touchdown points for the two proposed time periods. Each of the maps is calculated using the same statistical parameters and the same mapping principles (number of classes, classification method, and color scheme) to make the maps comparable and easy to read. Similar to above, the quartic kernel function and an adaptive bandwidth is used. Since the adaptive bandwidth with 1,000 points showed the best results for the entire dataset (see Figure 27), a sample size of 500 points is selected to the analysis of the two periods. Figure 31 contains the kernel density estimation of tornado touchdown points from 1950 to 1979. The highest concentrations of tornadoes (i.e., more than three tornadoes per square mile) during this period can be detected around Oklahoma City, OK, around Lubbock, TX, and in the area of Dallas, TX, and Fort Worth, TX. Other higher concentrations are found at the border area of Kansas and Missouri. In addition, there is a hot spot in southern Nebraska and in central Florida.

Figure 31: Kernel density estimation of tornado touchdown points from 1950 to 1979



When doing a quick comparison between the kernel density results from the first time period (1950 to 1979) with the second time period (1980 to 2009), a map reader can detect many more hot spots over the entire study area for the second period. Since the number of reported tornadoes from 1950–1979 to 1980–2009 increased by 50 percent and the mapping principles (number of classes, classification method, and color scheme) are the same for both maps, it is clearly understandable that the kernel density results for 1980-2009 needs to show more areas of the highest class range. Areas with the highest tornado occurrences in Figure 32 are central Oklahoma, central Kansas, northeast Colorado, southern Nebraska, southeast of South Dakota, central Iowa, central Illinois, the Texas Panhandle and the Houston area, TX, central Mississippi and the St. Petersburg area, FL. In comparison to Figure 31 which mapped the tornado occurrences from 1950 to 1979, some similarities of tornado densities can be detected. The hot spots in Oklahoma, southern Nebraska, in the Texas Panhandle, around Dallas, TX, and in central Florida are found during both time periods. Since this analysis is a purely visual comparison no statement about quantitative changes in spatial tornado occurrences can be made. In the following, an assessment about the quantitative change in tornado densities between 1950 to 1979 and 1980 to 2009 will be conducted.

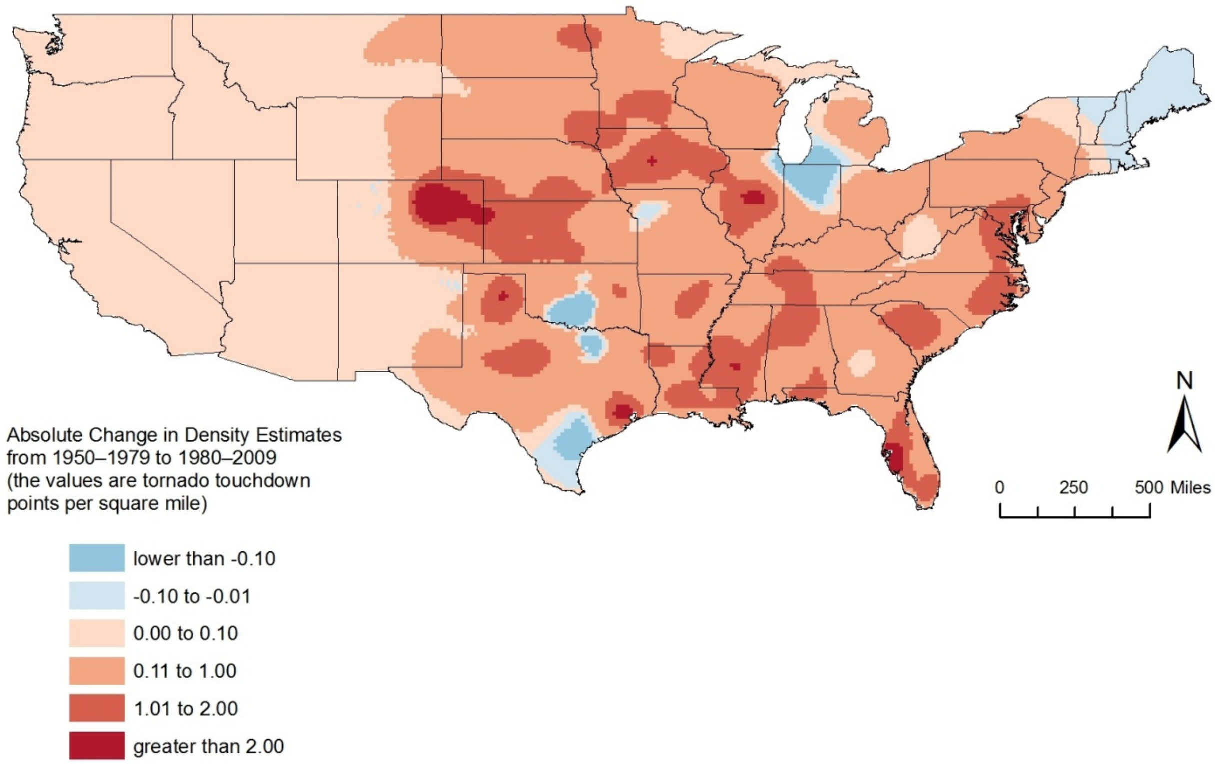
Figure 32: Kernel density estimation of tornado touchdown points from 1980 to 2009



As already discussed in Section 2.2.2.3 about the principles of cluster change and persistence, space-time kernel density estimation shows good results for the entire study area. Figure 33 shows the absolute change in density estimates of tornado touchdown points from 1950–79 to 1980–2009. In this figure, a value of 1.0 means that the number of tornado touchdown points per square mile increased by 1.0 from 1950–79 to 1980–2009. As has been said previously, the number of tornadoes increased significantly between these two time periods. Therefore, areas with increases are expected to dominate that for most of the conterminous 48 states. The highest increases in the tornado intensity between these two time periods can be detected in northeastern Colorado, in the Texas Panhandle, in the area of Houston, TX, in the area of St. Petersburg, FL, in central Illinois, and in small clusters in Iowa and Mississippi. Areas with a decrease in tornado occurrences are very sparse as can be seen in Figure 33. The most interesting areas with a decrease in tornado intensity are the areas in central Oklahoma and around Dallas, TX, where the highest concentrations of tornadoes have been measured in the time period from 1950-79. Nevertheless, there have been high intensities in the time period from 1980-2009, as well. Thus, single kernel density estimates (at both time periods) should always be considered in addition to a dual-kernel density estimate. It is also important to know the individual underlying kernel intensities that created the differences. For example, the decrease in densities in Oklahoma and in southern Texas show similar values but the underlying individual kernel intensities that result in those decreases are very different from each other.

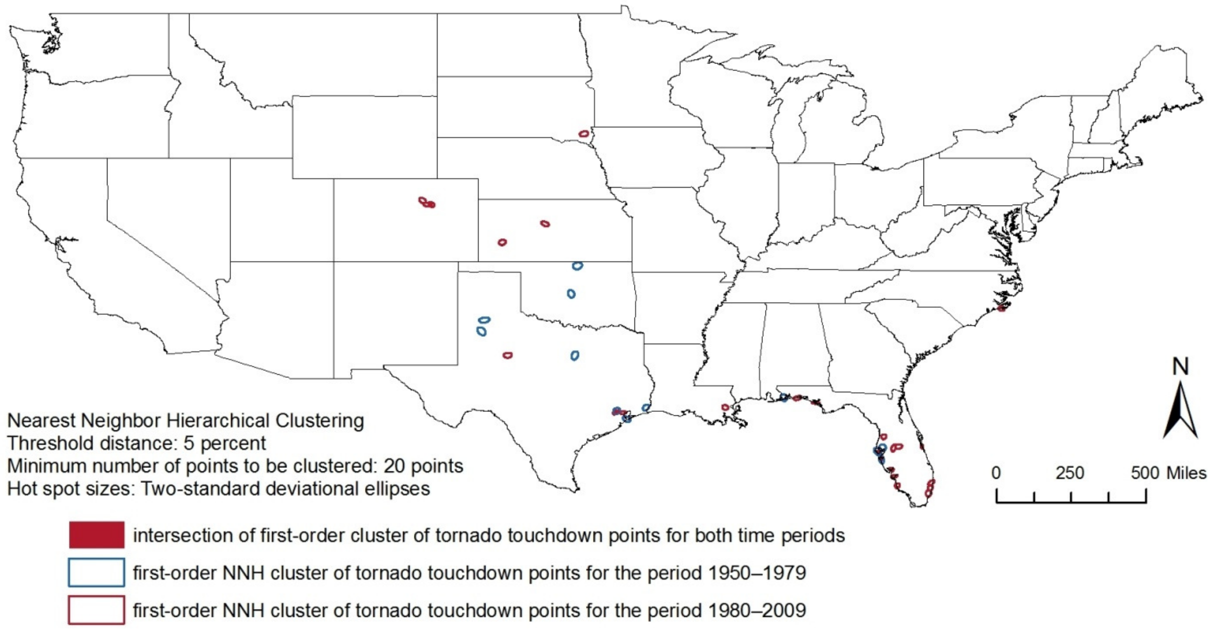
Absolute differences in kernel density estimates are a useful technique to measure event densities over time. It needs to be said that both individual kernel density estimates are calculated with the same parameter settings. In addition, a space-time kernel density map does not reveal spatial hot spots occurring in the study area. Therefore, single kernel density estimations should always be provided together with the space-time map to show spatial hot spots as well as their temporal deviation.

Figure 33: Absolute change in density estimates of tornado touchdown points from 1950–79 to 1980–2009



The second approach to measure cluster change and persistence over time is the space-time NNHC technique. In this approach, two NNHC routines with the same parameter settings are calculated using related tornado data for each time period. Then, the spatial ellipses are integrated in a GIS to calculate the intersections. These intersections represent areas of cluster persistence with significant clusters being found during both time periods. In Figure 34 the final ellipses of both NNHC analyses as well as their intersections are displayed. As already discussed in the previous section, the first-order NNH clusters are preferable to detect hot spots at a small scale. In the period from 1950 to 1979 a number of 12 hot spots are found (blue ellipses), whereas 25 ellipses are identified in the period from 1980 to 2009. Six respectively four of the 12 ellipses at the earlier time period are located in Texas respectively in Florida. In the period from 1980 to 2009 a number of 14 out of 25 clusters are located in Florida. Three clusters are found in each Colorado and Texas. Four intersections, indicating cluster persistence, have been found. Florida and Texas possess two intersections each. The intersection with the most tornado occurrences found in the two ellipses at both time periods is located at a peninsula near St. Petersburg, FL. The NNH cluster from 1950 to 1979 found 32 tornadoes and the NNH cluster from 1980 to 2009 found 40 tornadoes. The second intersection in Florida is found south of the first intersection. The two intersections in Texas are located in the area of Pasadena, TX, near Houston, TX, where two ellipses from the period 1980 to 2009 overlap with one ellipse from the tornado data from 1950 to 1979.

Figure 34: Space-time NNH clusters of tornado touchdown points for 1950–79 and 1980–2009



3.2. Analysis of Significant Tornadoes

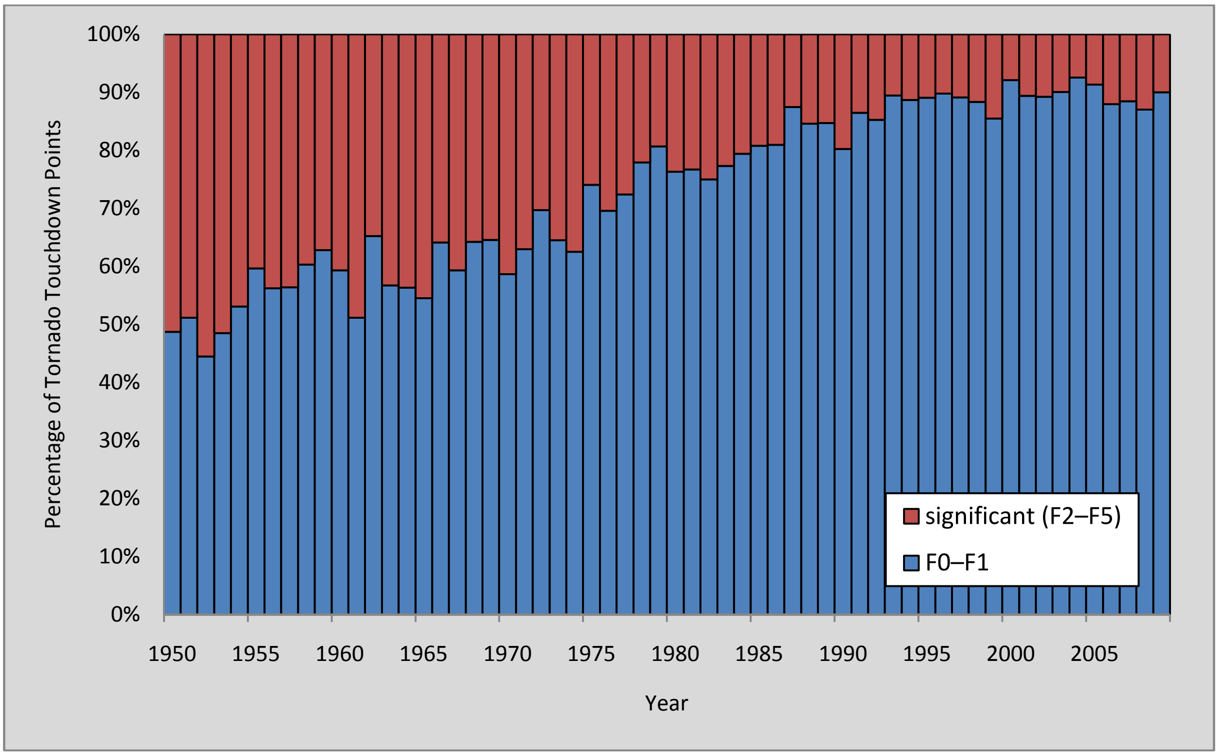
The first subchapter analyzed and discussed all recorded tornadoes in the coterminous United States. Numerous factors played an important role in the detection of tornadoes in earlier decades. Sparse population is one of those factors. Small tornadoes which did not cause much damage were not detected or reported. Hence, significant tornadoes rated F2 or higher were more likely to be detected since they caused bigger and more visible damage. This subchapter analyzes significant tornadoes rated F2 or higher. Thus, tornadoes rated F0 or F1 as well as tornadoes which have not been rated are excluded from the dataset and the following analysis. Table 5 shows basic statistics of the dataset of significant tornadoes. Over the entire time period from 1950 to 2009, only 11,510 reported tornadoes were rated F2 or higher. This number is about one fifth (21.3 percent) of all recorded tornadoes. Over time a strong decline of significant tornadoes can be observed. The absolute number of significant tornadoes decreased from 6,960 tornadoes in 1950–79 to 4,550 tornado touchdown points in the period from 1980–2009. The relative proportion decreased even more dramatically. This is mainly due to the fact that weak tornadoes rated F0 and F1 increased by more than 100 percent.

Table 5: Basic statistics of significant tornadoes

	Total	Significant (F2–F5)	F0–F1 and unrated	Significant (F2–F5) (%)	F0–F1 and unrated (%)
1950–79	20,460	6,960	13,500	34.0	66.0
1980–2009	33,500	4,550	28,950	13.6	86.4
Total (1950–2009)	53,960	11,510	42,450	21.3	78.7

When comparing the proportion of significant (F2–F5) and weak (F0–F1) tornadoes with each other, then a constant decline of significant tornadoes over time can be observed (Figure 35). The influence of recent achievements, such as the introduction of the EF-Scale, has had an important impact on tornado rating. Since the EF-rating was only used for the last three years from 2007 to 2009, a temporal trend cannot be observed in such a short time period. Since the 1990s the proportion of significant tornadoes compared to all tornadoes can be interpreted as stable. The annual number of significant tornadoes does not fluctuate that strongly as compared to the numbers from earlier years.

Figure 35: Percentage of significant tornado touchdown points from 1950 to 2009

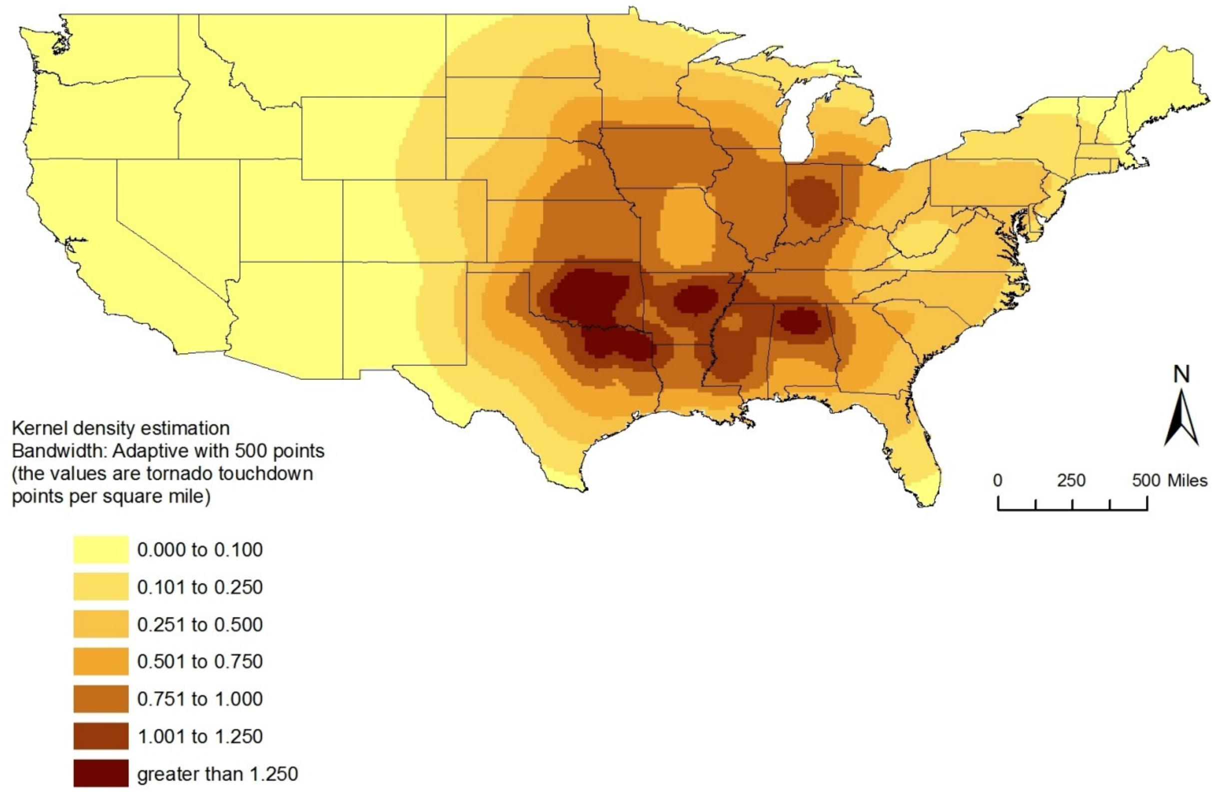


First, significant tornadoes from 1950 to 2009 will be analyzed. Then, the tornadoes during the same two time periods as above and their spatial and temporal differences will be analyzed. In this subchapter the kernel density estimates, the NNHC routine, and the space-time permutation model, as a both spatial and temporal statistic, will be used to analyze data of significant tornadoes.

3.2.1. Analysis of Significant Tornadoes from 1950 to 2009

The analysis in this subchapter is limited to a kernel density estimate. For the purpose of space-time analysis it is necessary to have an overview about a general pattern of tornado occurrences. Therefore, a kernel density surface is appropriate. Significant tornadoes (see Figure 36) occur preferably in the states of Oklahoma, northern Texas, in Arkansas, and in the northern Alabama. Higher concentrations of significant tornado occurrences can also be detected in Indiana, Mississippi and in areas of northern Louisiana. In comparison to Figure 28 (page 73), which represented a density surface of all recorded tornadoes from 1950 to 2009, there are differences that can be identified. Whereas the general pattern of occurrences of significant and all tornadoes is somewhat similar, differences can be seen in Colorado, in the areas of Houston, TX, and Lubbock, TX, and in Florida. Since there are no distinctive hot spots in these areas in Figure 36, it can be concluded that tornado occurrences in these areas are mainly restricted to tornadoes rated F0 or F1. BROOKS et al. (2003) confirms this finding, when they argue that tornado occurrences in Florida are predominantly associated with nonsupercellular convection, which does not produce such strong tornadoes.

Figure 36: Kernel density estimation of significant tornado touchdown points from 1950 to 2009



3.2.2. Analysis of Significant Tornadoes between 1950–1979 and 1980–2009

In the analysis of significant tornadoes during the two time periods (1950–1979 and 1980–2009) the kernel density estimates, the NNHC routine and, for the first time, the space-time permutation model will be applied.

The difference map of density estimates is based on kernel density estimates of significant tornadoes during the two time periods. These underlying maps are integrated in Annex C (Figures C-1 and C-2). Figure 37 shows the absolute changes in density estimates of significant tornado touchdown points between the two time periods, 1950–79 and 1980–2009. The largest decline can be observed in the area where the most significant tornadoes occur: Oklahoma, northern Texas and Indiana (for the comparison see Figure 36). A cluster of decrease can be detected in the area of Kansas City, MO. Areas of increasing intensity of significant tornadoes can be detected in the area of Nashville, TN, and in the states of the East Coast of the United States. Figure 37 is barely comparable to Figure 33 where absolute changes of all recorded tornado intensities between the two time periods are mapped. Generally, it can be said that areas that experienced increases within all tornado occurrences and decreases within significant tornadoes are a result of the increasing intensity of tornadoes rated F0 or F1 (e.g., the state of Florida).

Figure 37: Absolute change in density estimates of significant tornado touchdown points between 1950–79 and 1980–2009

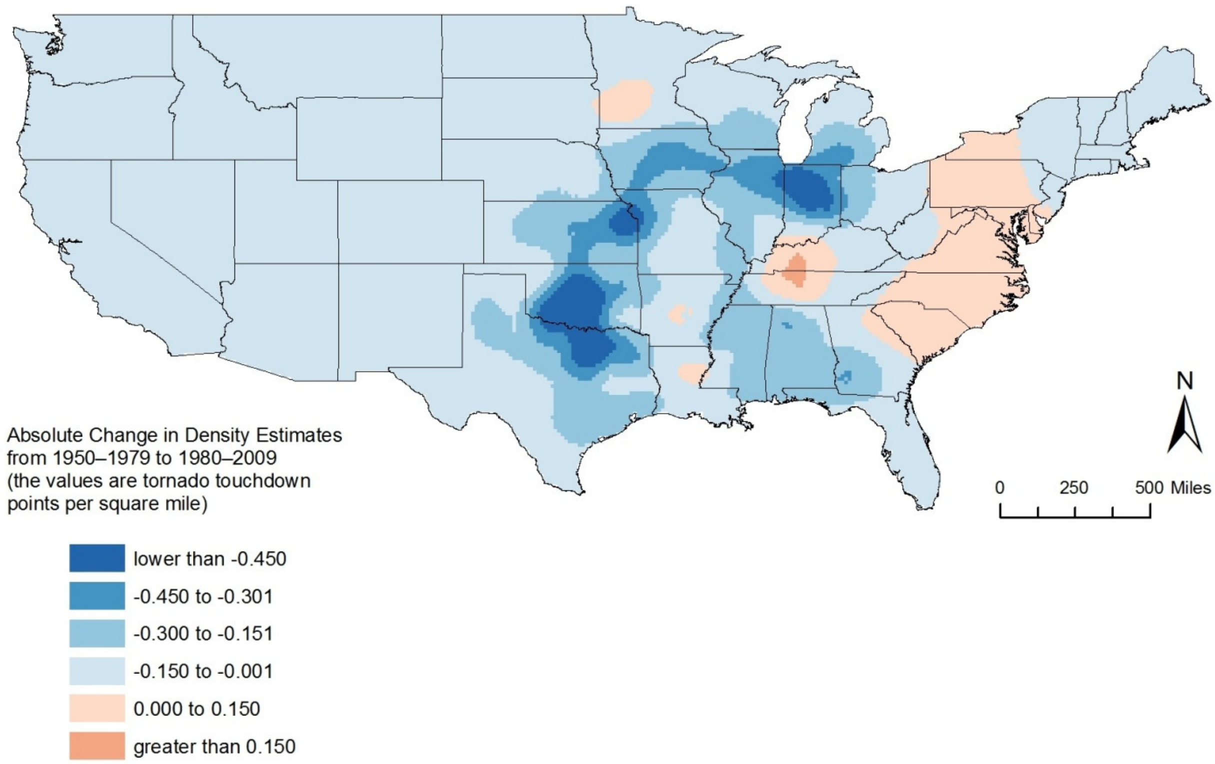
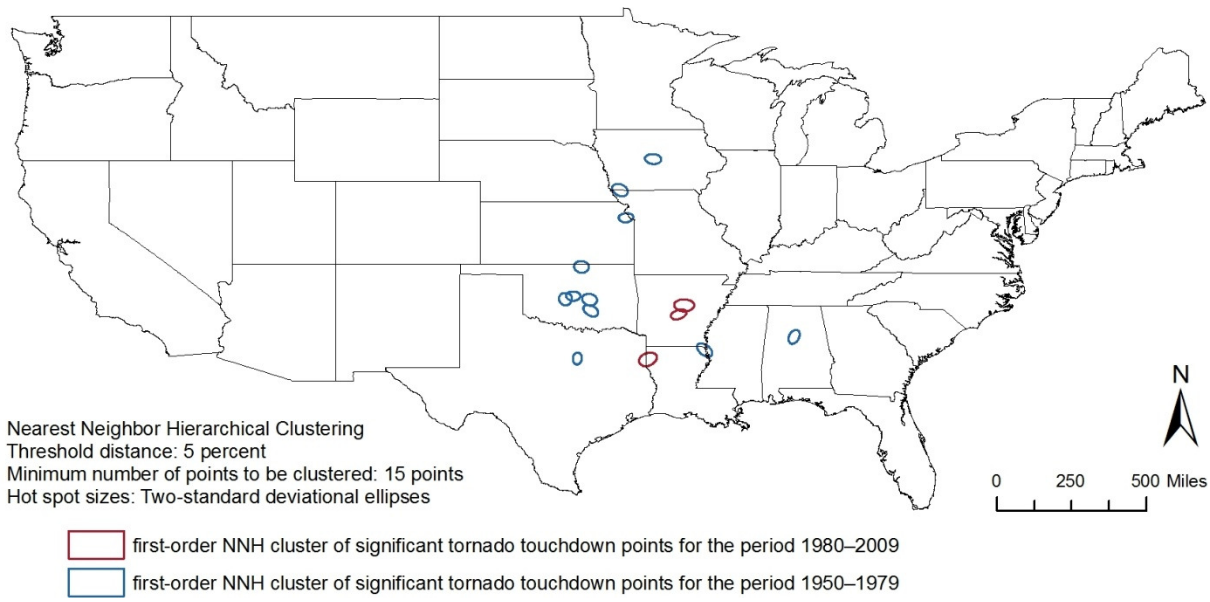


Figure 38 represents the spatial locations of first-order NNHC ellipses of significant tornado touchdown points for 1950–79 and 1980–2009. The parameters of the analysis have been set to a threshold distance of five percent (as for the previous analyses) and to 15 points to be grouped to receive only a few clusters. For the earlier time period eleven ellipses are found of which five are located within the state of Oklahoma. The NNHC analysis of the more recent time period resulted in only three ellipses of which two are located in Arkansas. There are no spatial overlaps in the ellipses detected. When comparing the kernel density results (Figure 37) with NHHC ellipses, similar pattern become apparent. In areas of decline of significant tornado intensity, NNHC ellipses of the earlier time period can also be found (e.g., the ellipses in central Oklahoma). In contrast, the two spatial ellipses in Arkansas is similar to a small area of increasing intensity of significant tornadoes during the two time periods, as can be seen in Figure 37.

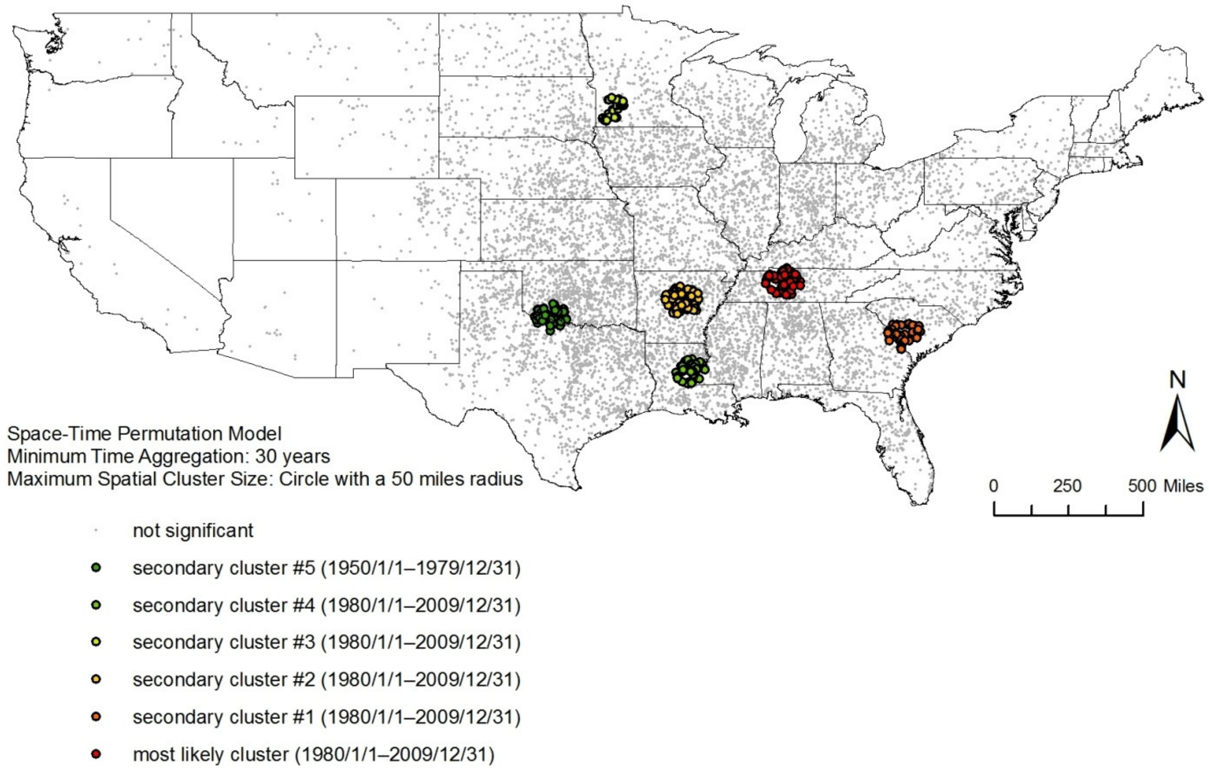
As an alternative and additional technique, the space-time permutation model in form of the scan statistic is introduced. The space-time permutation model requires only data about cases (or events) such as the tornado touchdown points. The model then searches for significant hot spots in both space and time. This search is conducted by a cylindrical window with a circular geographic base and the height corresponding to time. While the base is defined similar to the spatial scan approach, the height indicates the time period (KULLDORFF 2010). In this analysis, the spatial extent of a space-time hot spot is restricted to a radius of 50 miles. This radius was set 50 miles in order to avoid large clusters. In the analysis of significant tornadoes two different minimum temporal extents are applied, namely 30 and five years.

Figure 38: Space-time NNH clusters of significant tornado touchdown points for 1950–79 and 1980–2009



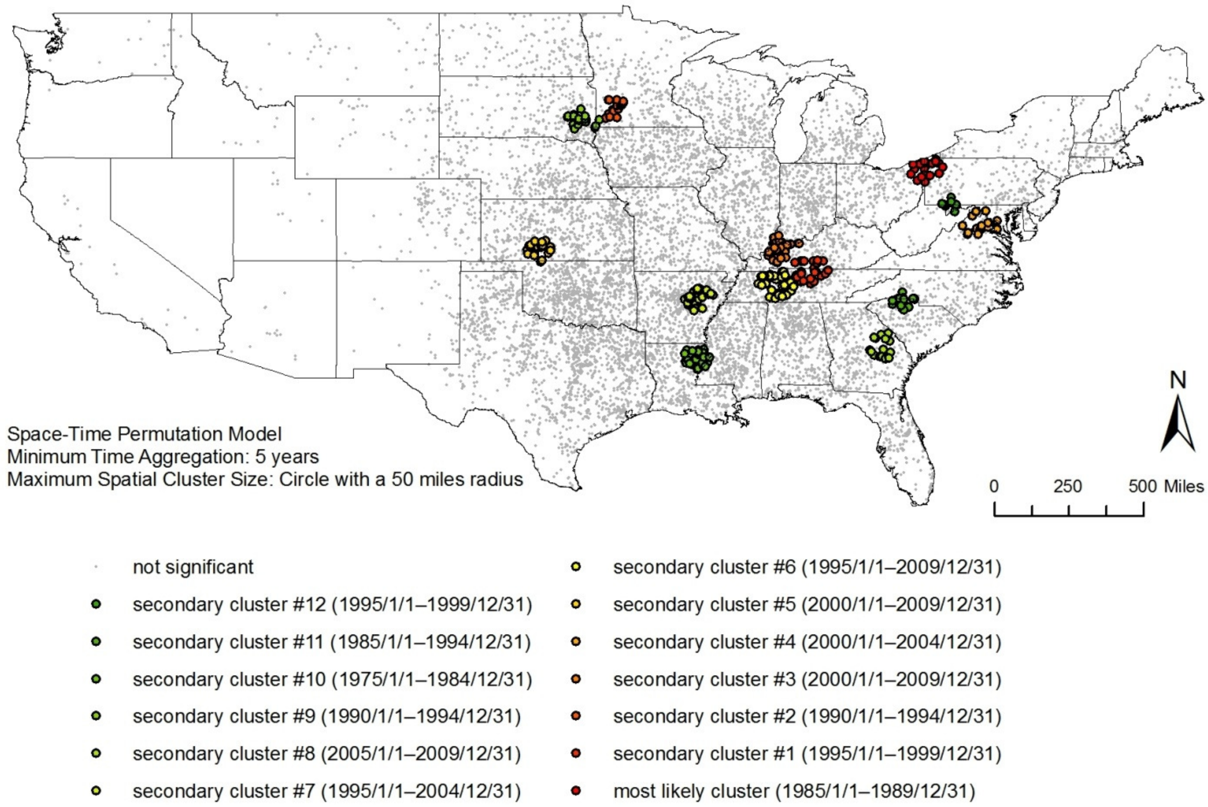
First, the minimum time aggregation is set to 30 years to check for long-term space-time clusters. With this setting, a total number of 39 spatiotemporal clusters have been detected in the United States.

Figure 39: Space-time permutation model of significant tornado touchdown points from 1950 to 2009 (version 1)



In Figure 39 only space-time hot spots below a significance level of p<0.01 have been visualized. Only six out of 39 hot spots fulfill this criterion. The location of the most likely cluster was found in the area of Nashville, TN, in the time period from 1980 to 2009. In comparison to Figure 37 it can be said, that in this area there has been an increase in the intensity of significant tornadoes. The same is true for the secondary clusters #1 to #4, where increases have also been detected in Figure 37. When using likelihood functions which are maximized over all window locations and sizes, the most likely cluster is found. In the space-time analysis, the software *SaTScan* also identifies secondary clusters in addition to the most likely clusters. The secondary clusters are then ordered by the associated likelihood ratio test statistic (KULLDORFF 2010). The only significant cluster in the period from 1950 to 1979 was found in the border area between Oklahoma and Texas. As a result, the significant tornado intensity in this area is significantly different from the significant tornado intensity in the areas from the period 1980 and 2009.

Figure 40: Space-time permutation model of significant tornado touchdown points from 1950 to 2009 (version 2)

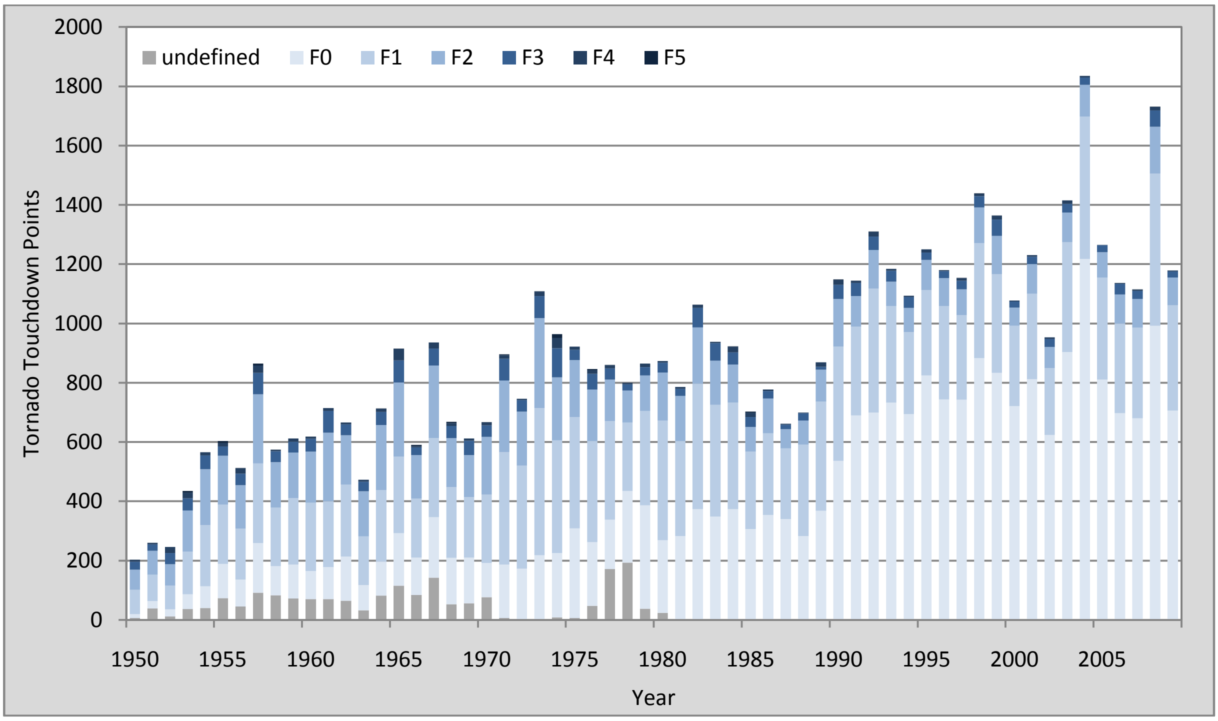


The second analysis using the space-time permutation model uses the same spatial extent as in the first analysis (Figure 39). The difference to the first analysis is the selected minimum time aggregation, which was set to five years. It is expected that the reduction of the time aggregation results in more spatiotemporal clusters since the length of the time aggregation has been decreased. The shorter time aggregation results in 13 spatiotemporal clusters of significant tornado touchdown points, which are all significant at the p=0.001-level (Figure 40). In total, a number of 92 spatiotemporal clusters have been found. According to Figure 40, the clusters occur at very different time periods and are not restricted to a temporal extent of five years (For example, see secondary cluster #3. Herein, the tornado occurrences both in space and time are significantly increased over ten years from 2000 to 2009). As can be seen in Figure 40, the spatiotemporal hot spots do not necessarily occur in the so-called "Tornado Alley". For example, significant tornadoes rated F2 or higher occur in almost every season in the Great Plains, which is not part of the Tornado Alley. Space-time interaction is characterized by a greater occurrence of events in both space and time. This means that there was a significantly higher occurrence of significant tornadoes in comparison to other time periods and other areas. Therefore, space-time hot spots are detected in somewhat "unusual" locations in addition to the areas where significant tornadoes occur. For example, the most likely cluster was found in the border area of Ohio and Pennsylvania and contains 28 significant tornadoes from 1985 to 1989. However, the value of expected cases calculated for this area and this time period should have only been 3.06 tornadoes.

3.3. Analysis of Tornado Touchdown Points by F-Scale

The third analysis of tornado touchdown points focuses on their classification on the F-Scale. Figure 41 shows all recorded tornado touchdown points by F-Scale from 1950 to 2009. It is worthwhile mentioning that the number of tornadoes increased over time. Also, the number of unrated tornadoes ceased to exist after 1981. The number of tornadoes rated F0 increased over time but has remained stable since the early 1990s. In contrast, the number of F1-tornadoes has remained stable since the early 1970s. The number of tornadoes rated F2 has declined considerably. In contrast, the absolute numbers of tornadoes rated F3, F4, and F5 declined only slightly. In 1974, 13 tornadoes rated F5 have been reported, which makes 1974 the year with the highest number of devastating tornadoes in the data series.

Figure 41: Annual tornado occurrences by F-Scale from 1950 to 2009



In addition to analyzing tornadoes by each F-Scale category, the tornadoes are also analyzed as a group using the classification, first used by KELLY et al. (1978). They grouped tornadoes rated F0 or F1 to "weak" tornadoes, tornadoes rated F2 or F3 to "strong" tornadoes, and tornadoes rated F4 or F5 to "violent" tornadoes. Table 6 contains basic statistics of tornado touchdown points by the classification of weak, strong, and violent tornadoes. Absolute numbers of tornadoes as well as their proportions are listed for the entire time period and for the two time periods, which will be compared in the next section. In Table 6 unrated tornadoes are not included.

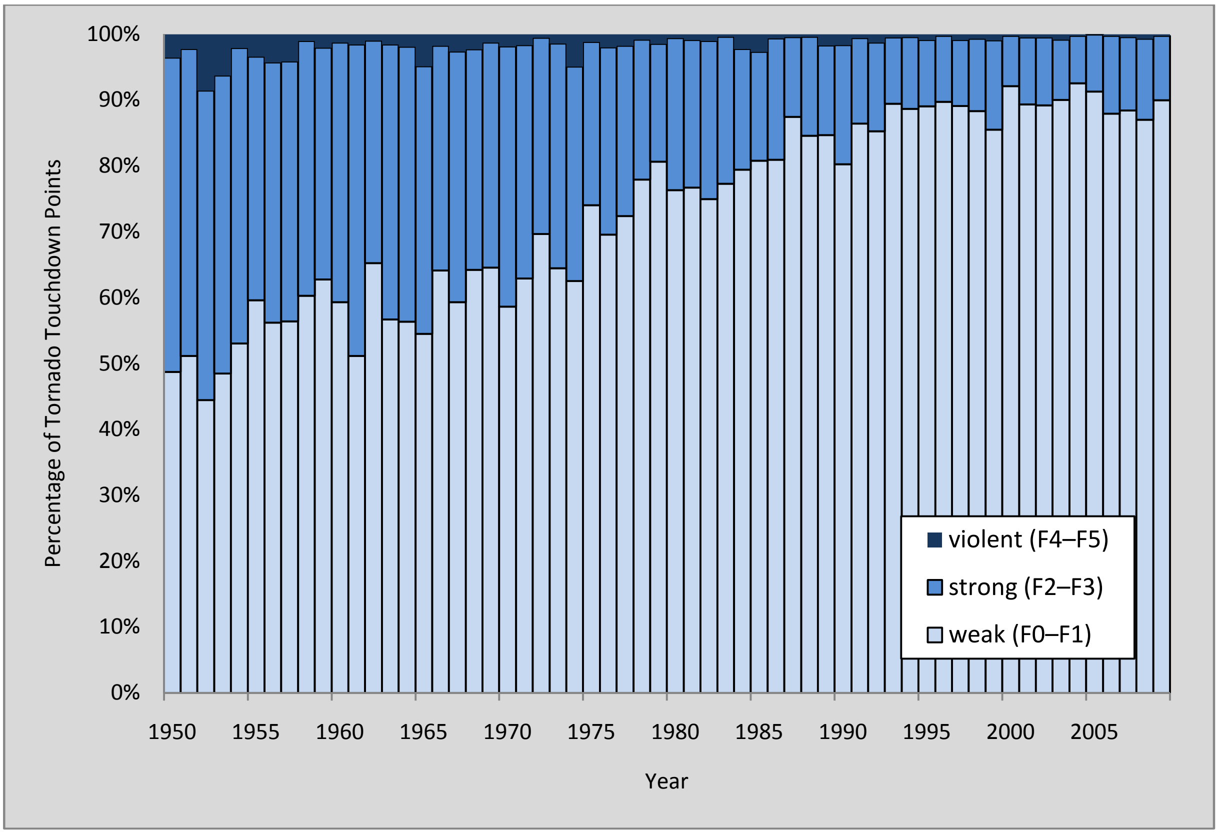
More than three out of four tornadoes are weak tornadoes. One out of five tornadoes is classified as a strong tornado. The proportion of violent tornadoes is only 1.3 percent and thus very low. The number of weak tornadoes rated F0 and F1 increased by nearly 150 percent over the two time periods, whereas the numbers of strong (-34%) and violent (-43%) tornadoes declined.

Table 6: Basic statistics of weak, strong, and violent tornadoes, 1950–2009

	weak	strong	violent	weak (%)	strong (%)	violent (%)
1950–79	11,682	6,525	435	62.7	35.0	2.3
1980–2009	28,925	4,301	249	86.4	12.8	0.7
Total (1950–2009)	40,607	10,826	684	77.9	20.8	1.3

The grouping to weak, strong, and violent tornadoes is further visualized in Figure 42. In this figure, the absolute numbers of tornadoes are set to 100 percent in every year to make the proportions comparable. It can be seen that in 1950 only 50 percent of all tornadoes are rated as weak. Since then however, the proportion of weak tornadoes increased constantly. In recent years the proportion of weak tornadoes reaches approximately 90 percent. The proportion of strong tornadoes declined from approximately 45 percent in 1950 to 10–15 percent in 2009. The percentage of violent tornadoes declined as well. The largest proportion of violent tornadoes was recorded in 1953 when nearly 10 percent of all tornadoes were rated as F4 or F5.

Figure 42: Percentage of weak, strong, and violent tornado touchdown points from 1950 to 2009



3.3.1. Analysis of Tornadoes by F-Scale from 1950 to 2009

In this section, kernel density estimations of weak, strong, and violent tornadoes from 1950 to 2009 will be carried out. Figure 43 shows the result of a kernel density estimation of weak tornado touchdown points rated F0 or F1. There are several hot spots that can be identified. These hot spots are located throughout the states, especially in the Great Plains. The largest clusters can be seen in Oklahoma, in Kansas, in Colorado, in Nebraska, in Illinois, in the Texas Panhandle, around Dallas, TX, Houston, TX, and St. Petersburg, FL. Additional hot spot areas, which have not been detected in previous, similar analysis in this thesis are located around Sweetwater, TX, Lafayette, LA, Pensacola, FL, Miami, FL, and Sioux Falls, SD.

Figure 43: Kernel density estimation of weak tornado touchdown points from 1950 to 2009

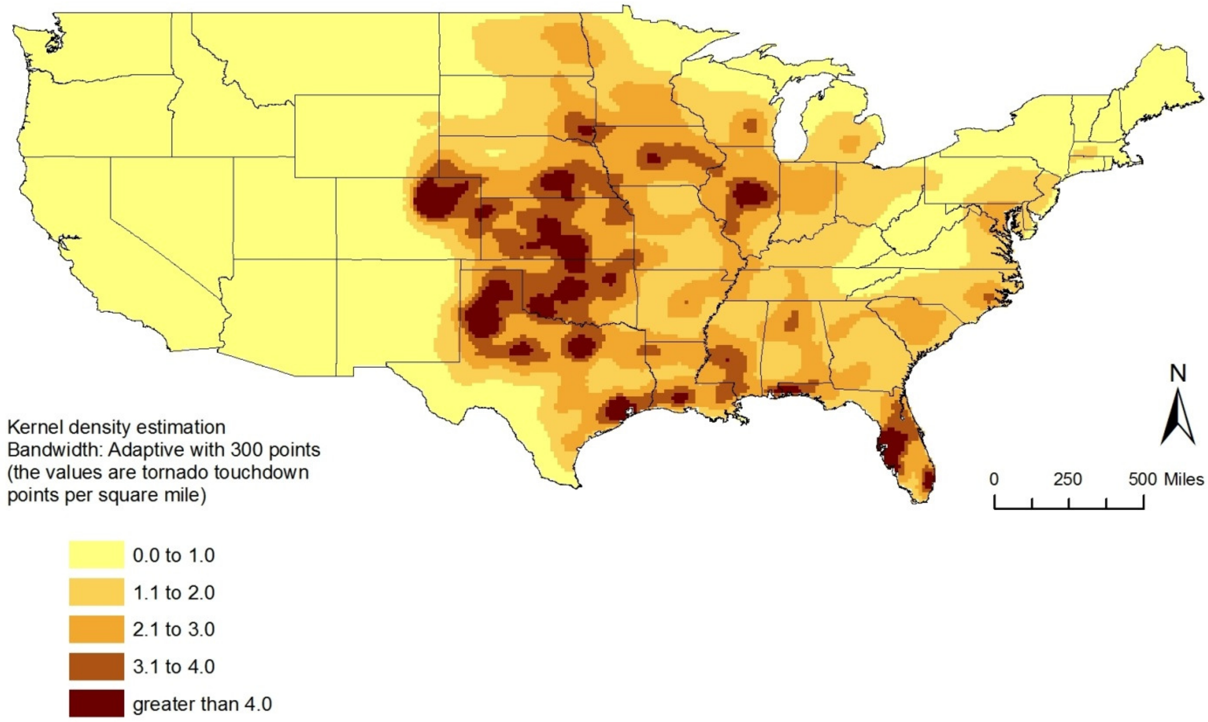
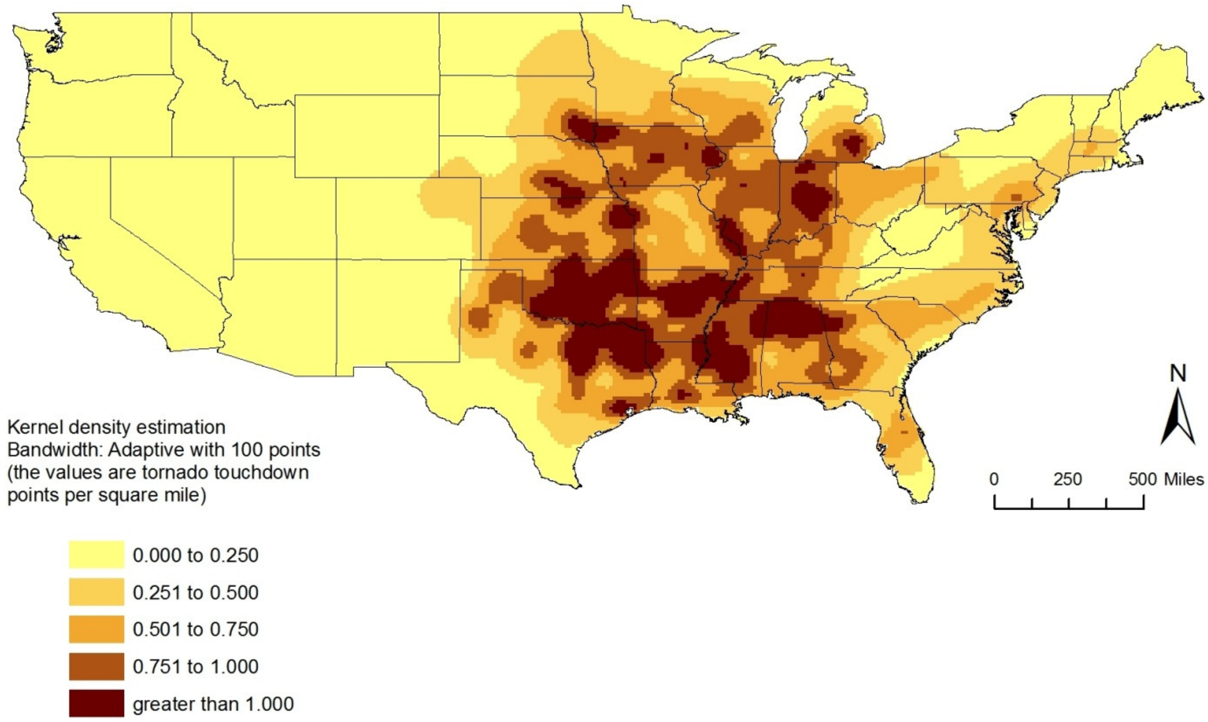


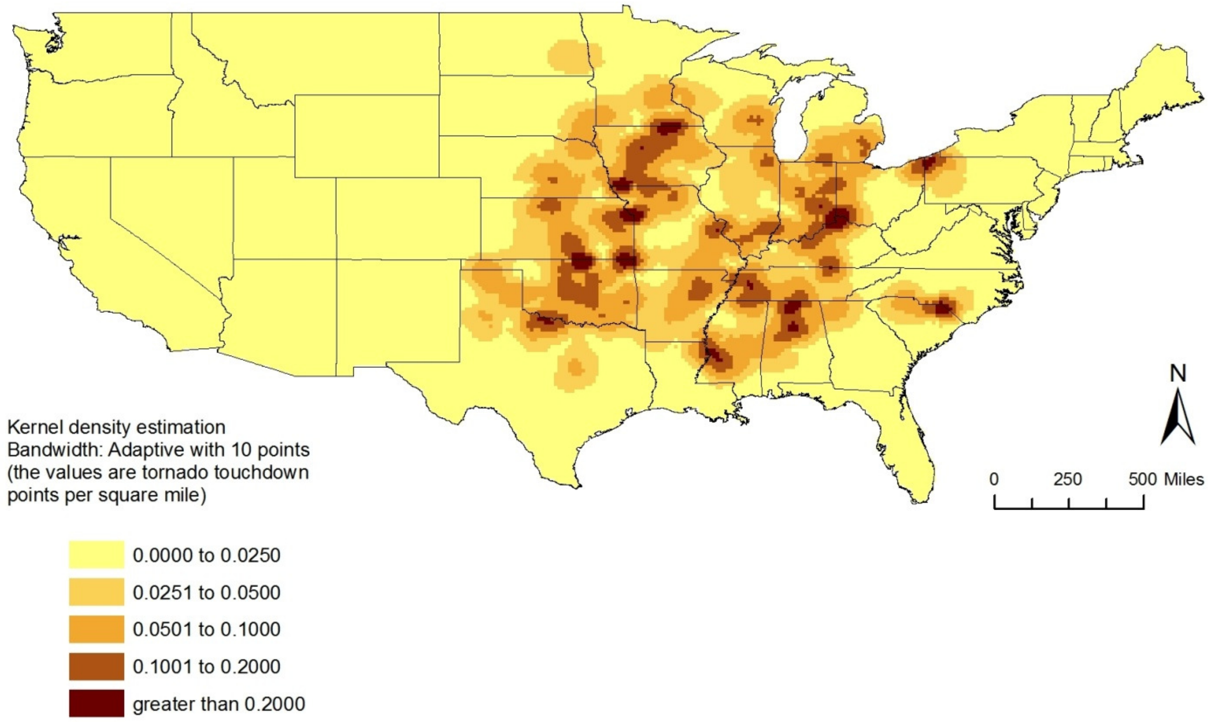
Figure 44 shows the spatial intensities of strong tornadoes (F2 or F3) in the contiguous 48 states of the United States using the kernel density estimation technique. Locations where strong tornadoes predominantly occur can be detected in a large area which extends from northern Texas to nearly the whole state of Oklahoma. Further hot spots can be detected in the southern United States in the states of Arkansas, Louisiana, Mississippi, Alabama, Georgia, and Tennessee. Strong tornadoes do also occur frequently in parts of Kansas, Nebraska, South Dakota, Iowa, Illinois, Indiana, and Michigan. In this analysis, the cluster in the state of Michigan has been identified for the first time compared to previous studies in this thesis. In comparison to Figure 43, which analyzed weak tornadoes, it can be seen that the clusters of weak tornadoes in Florida, in the Texas Panhandle and in Colorado and in central Kansas are not areas, where also strong tornadoes occur frequently. The spatial pattern in Figure 44 shows an interesting pattern. All states located around the state of Missouri experienced a high intensity of strong tornadoes whereas Missouri itself is a spatial outlier with comparable low intensities.

Figure 44: Kernel density estimation of strong tornado touchdown points from 1950 to 2009



The third kernel density estimation was carried out for the violent tornado touchdown points rated F4 or F5 from 1950 to 2009. Since the number of violent tornadoes is small in comparison to weak and strong tornadoes, the density surface looks speckled. The pattern is characterized by small spatial hot spots. It is interesting that these clusters are predominantly located in border areas between different U.S. states. The most clusters can be detected along border areas in the Great Plains (e.g., along the border between Oklahoma to Kansas). A new cluster, not found in the analysis of weak or strong tornadoes, is found along the border area of Indiana, Ohio, and Kentucky. Other "new" clusters are found along the border area between Ohio and Pennsylvania, and between North Carolina and South Carolina.

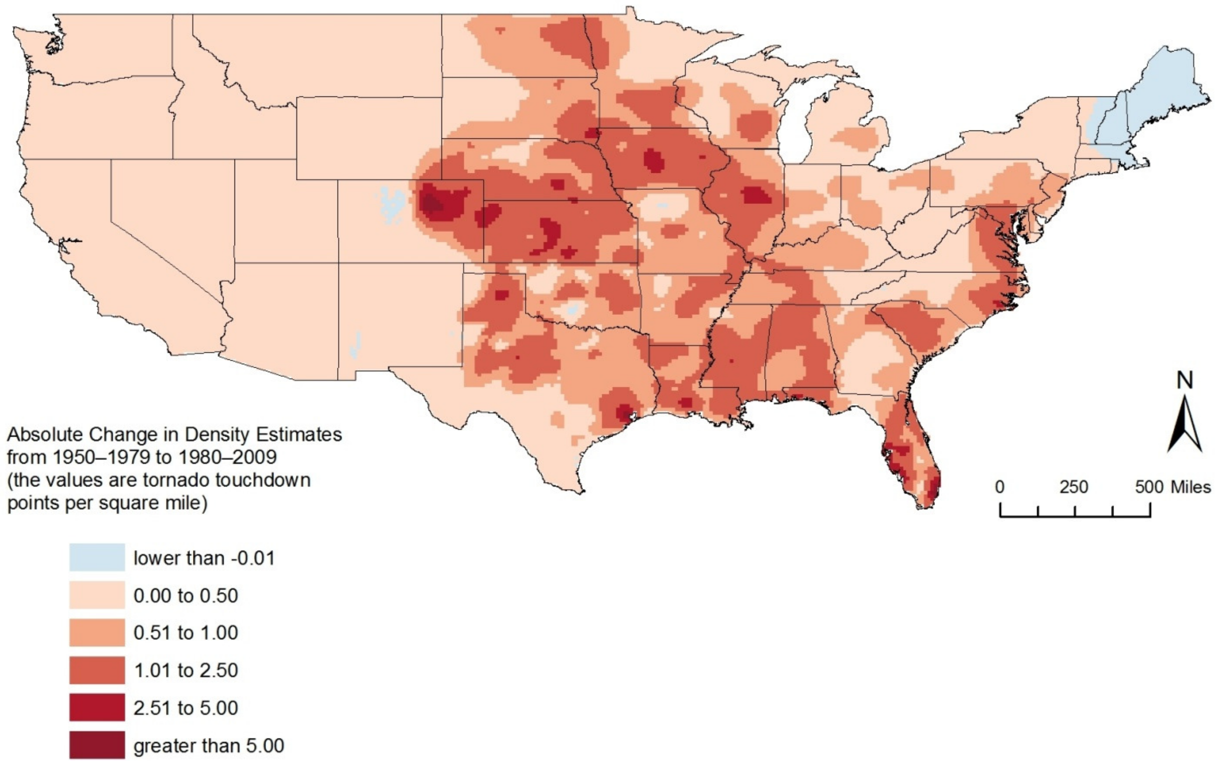
Figure 45: Kernel density estimation of violent tornado touchdown points from 1950 to 2009



3.3.2. Analysis of Tornadoes by F-Scale between 1950–1979 and 1980–2009

In this section the absolute changes in density estimates of weak, strong, and violent tornadoes are discussed. The focus will be on violent tornadoes, which will be analyzed in more detail. In this analysis kernel density estimates will be compared with NNHC ellipses. This section concludes with a space-time permutation analysis of violent tornadoes.

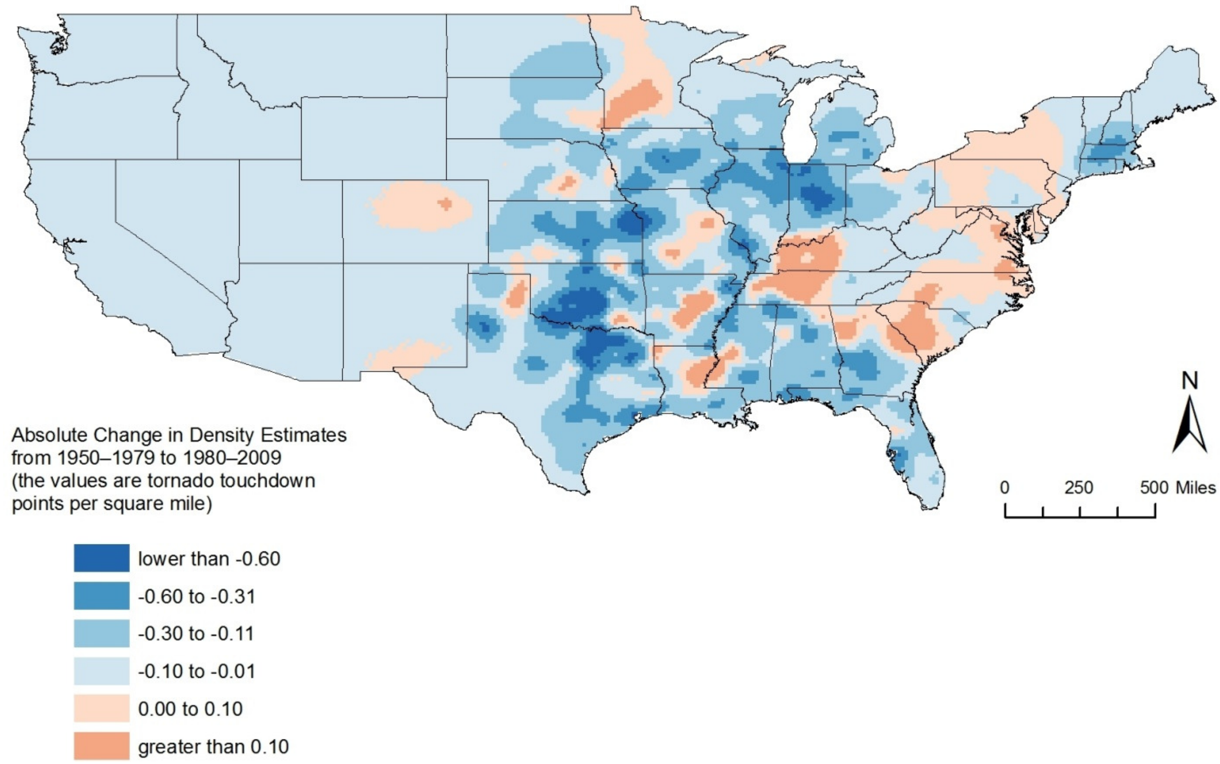
Figure 46: Absolute change in density estimates of weak tornado touchdown points from 1950–79 to 1980–2009



The following maps of absolute changes in density estimates of weak (Figure 46) and strong (Figure 47) tornadoes are based on kernel density estimates for two selected time periods. The kernel densities for each of the two individual time periods can be found in Annex D (Figures D-1 and D-2 respectively Figures D-3 and D-4).

Weak tornadoes increased immensely between the two time periods from 1950–79 to 1980–2009. Therefore it can be expected that the overall intensity also increased throughout the entire area of the United States. As can be seen in Figure 46 there are very few areas, where the tornado intensity declined between the two selected time periods. Among the regions with a declining tornado intensity is a small area in Oklahoma. The biggest increases can be identified around Denver, CO, and Houston, TX.

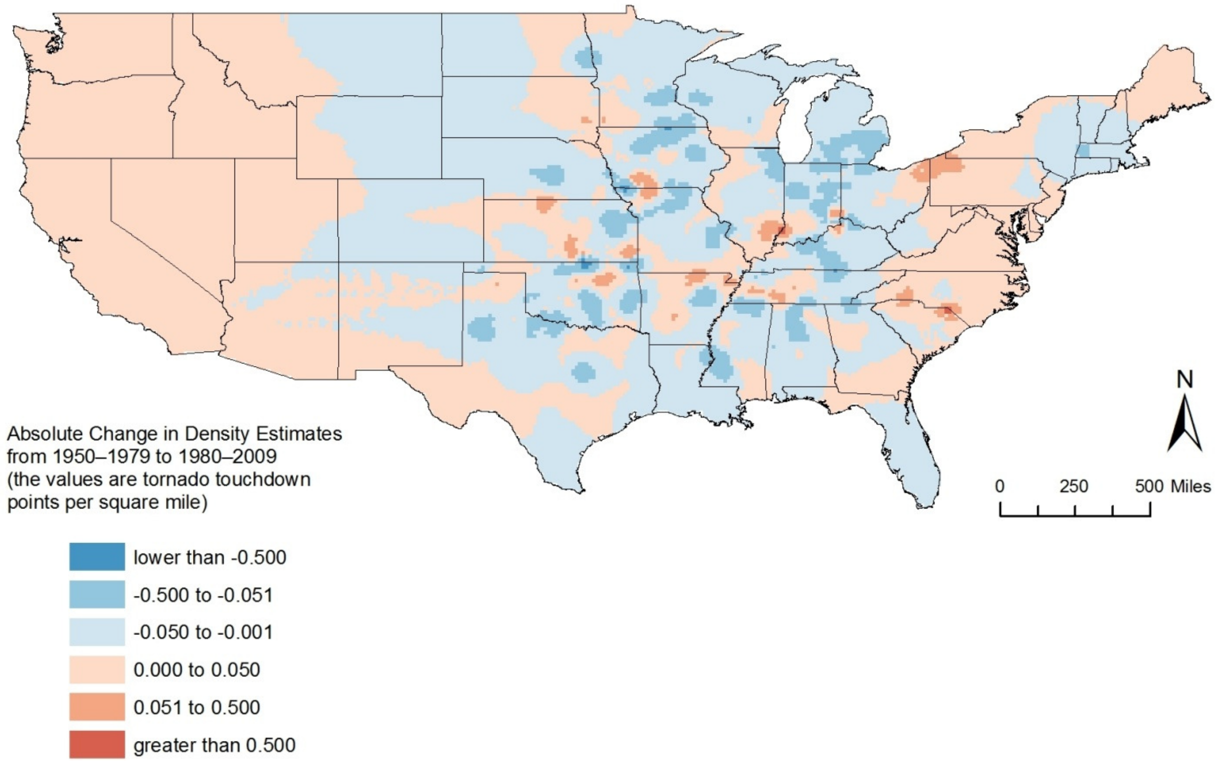
Figure 47: Absolute change in density estimates of strong tornado touchdown points from 1950–79 to 1980–2009



Since overall the total number of strong tornadoes declined, the blue shaded areas of decline outweigh the red shaded areas of increase in Figure 47. The largest area of increase of strong tornado intensities can be found in the western parts of Kentucky and Tennessee. Increases can also be identified in parts of the East Coast and in areas in Louisiana, Arkansas, and Minnesota. Large areas of decrease can be identified in central Oklahoma, northern Texas, eastern Kansas, and central Indiana. These areas are characterized by a high intensity of strong tornadoes over the entire time period (Figure 44). Since there is an overall decline in these areas over the entire time period, most of the strong tornadoes in these areas occurred in the first time period from 1950 to 1979.

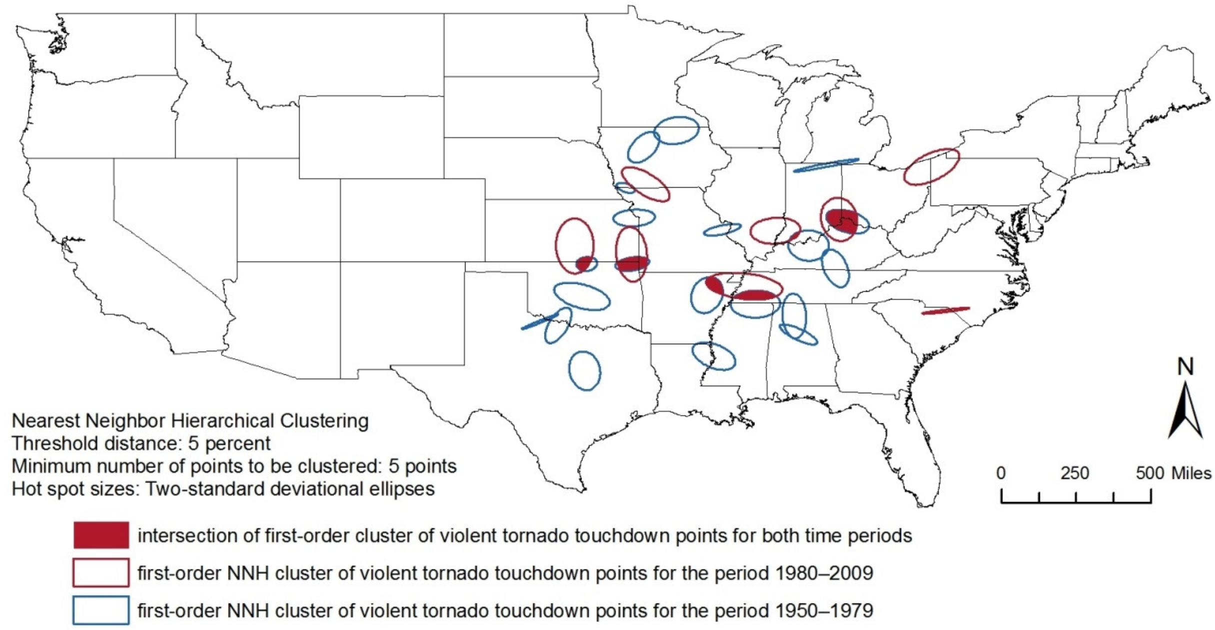
When considering absolute changes of violent tornadoes rated F4 or F5 (Figure 48), relatively small clusters of increase respectively of decrease can be identified. However, no general pattern can be observed. Generally, it can be said that there are more areas of decrease than increase in the Great Plains, where the most violent tornadoes occur. Areas of increases of 0.5 violent tornadoes per square mile can be detected in the border area of North Carolina and South Carolina. Another area of increase by 0.5 violent tornadoes per square mile is identified in the border area of Illinois and Indiana.

Figure 48: Absolute change in density estimates of violent tornado touchdown points from 1950–79 to 1980–2009



For comparison purposes, absolute changes in kernel density estimates of violent tornado touchdown points rated F4 and F5 are analyzed using both the NNHC technique and the space-time permutation model. The NNHC routine is useful to detect hot spots of a minimum number of points that are close to each other. Therefore, this method is suitable to analyze the small dataset of violent tornadoes. For the analysis of violent tornadoes for the two time periods from 1950–79 and 1980–2009 a minimum number of five points to be clustered and a threshold distance of five percent were chosen. Then, the intersection of the resulting NNHC ellipses was calculated to check for cluster persistence. Figure 49 shows spatial cluster ellipses for the two time periods as well as their intersections. For the period 1950 to 1979 twenty ellipses were found. These NNH clusters are located in the states of Texas, Oklahoma, Kansas, Minnesota, Iowa, Missouri, Arkansas, Louisiana, Mississippi, Alabama, Tennessee, Kentucky, Illinois, Indiana, Ohio, and Michigan. In contrast, eight NNH clusters are found for violent tornadoes from 1980 to 2009. These are located in Oklahoma, Kansas, Iowa, Missouri, Arkansas, Tennessee, Illinois, Indiana, Ohio, Kentucky, Pennsylvania, New York, North Carolina, and South Carolina. In general, the hot spot ellipses for the period 1980 to 2009 are located farther north and farther east than the hot spot clusters from the previous time period. There are no clusters from 1980 to 2009 located in the southern states of Texas, Louisiana, Mississippi, and Alabama. In total, six cluster intersections have been identified. Two of them are along the border area of Oklahoma and Kansas. Further cluster intersections are found in Arkansas, Tennessee, and Indiana, with the largest area of overlapping clusters is found along the border area of Indiana, Ohio, and Kentucky. Overall, the areas of intersecting clusters are congruent with hot spot areas from the kernel density estimation of violent tornadoes mapped in Figure 45.

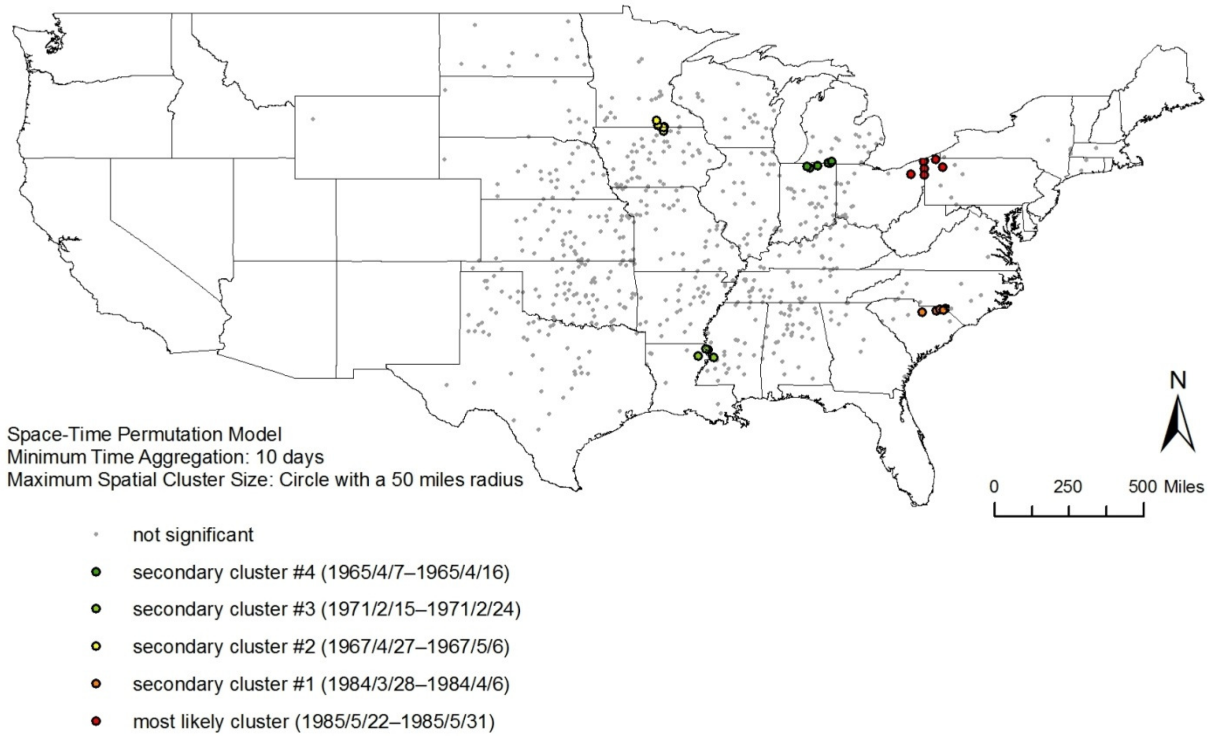
Figure 49: Space-time NNH clusters of violent tornado touchdown points for 1950–79 and 1980–2009



The space-time permutation model of violent tornado touchdown points in the period from 1950 to 2009 concludes the subchapter of tornadoes analyzed by the F-Scale. Similar to the space-time permutation analyses in Subchapter 3.2 the radius of the maximum spatial cluster size does not extent 50 miles. In addition, a minimum time aggregation unit of ten days was chosen.

Figure 50 shows an analysis of violent tornado touchdown points using a space-time permutation model. The application of a minimum time aggregation of ten days allows a retrospective analysis of so-called tornado outbreaks of violent tornadoes. Tornado outbreaks are characterized by a large number of tornadoes in a relatively short time period [e.g., the tornado outbreak on May 3, 1999 in Oklahoma City, OK (BROOKS and DOSWELL 2002)]. This analysis excluded clusters, which do not contain at least five violent tornadoes and where the according significance value is greater than 0.001. Overall, 72 space-time hot spots have been detected by this method but only five satisfy the aforementioned criteria. There have not been any violent tornado outbreaks since the 1980s. The most likely cluster of violent tornadoes occurred from May 22, 1985 to May 31, 1985 around Erie, PA. This cluster contains 12 violent tornadoes that occurred during this period. This cluster has also been detected by the NNH routine (see Figure 49). All other space-time hot spots of the space-time permutation model have also been detected by the NNHC technique (see Figure 49). The space-time permutation model did not find any clusters from Oklahoma to Kansas or in Indiana, Ohio, and Kentucky. In these areas violent tornadoes occur more or less regularly distributed over the entire time period, but not as space-time clusters. The application of the space-time permutation model using a small temporal aggregation unit (such as ten days) requires a long time of data processing. Due to the 999 Monte Carlo simulation runs the spatiotemporal analysis of 648 violent tornadoes (Figure 50) lasted 17 hours 2 minutes and 31 seconds (Intel® Core™2 Duo CPU T5550 1.83 GHz; 3.00 GB RAM).

Figure 50: Space-time permutation model of violent tornado touchdown points from 1950 to 2009



3.4. Analysis of Tornado Touchdown Points by Month

In this subchapter the analysis focuses on the monthly variations of all recorded tornado touchdown points and then only on the group of significant tornadoes.

3.4.1. Analysis of all recorded Tornado Touchdown Points by Month

The variation of tornado touchdown points in any given year follows a usual pattern. During the winter months January and February only a small number of tornadoes occur in the United States. According to LOOMIS (1842) and KELLY et al. (1978) the highest tornado frequency occurs during the four-month period from March to June. Then the tornado intensity declines from July to December and experiences the annual minima in December and January.

Figure 51 shows all recorded tornado touchdown points from 1950 to 2009 aggregated by month. The bars are divided into the number of tornadoes from the two selected time periods to identify changes in monthly tornado occurrences. As can be identified very quickly, the most tornadoes occur in May and June. In agreement to KELLY et al. (1978) approximately 40 percent of all tornadoes are found during May and June. In this dataset from 1950 to 2009 a proportion of 41.7 percent of all tornadoes are found in May and June. Comparing the two selected time periods with each other, it can generally be said that the tornado frequency increased in each month in the more recent time period. The frequencies increased on average by 64 percent. The tornado occurrences during February, April, and March show the lowest increases with about 40 percent, whereas the occurrences during October and November increased by more than 100 percent (October: 125 percent; November: 146 percent).

Figure 51: Changes in monthly tornado occurrences between 1950–79 and 1980–2009

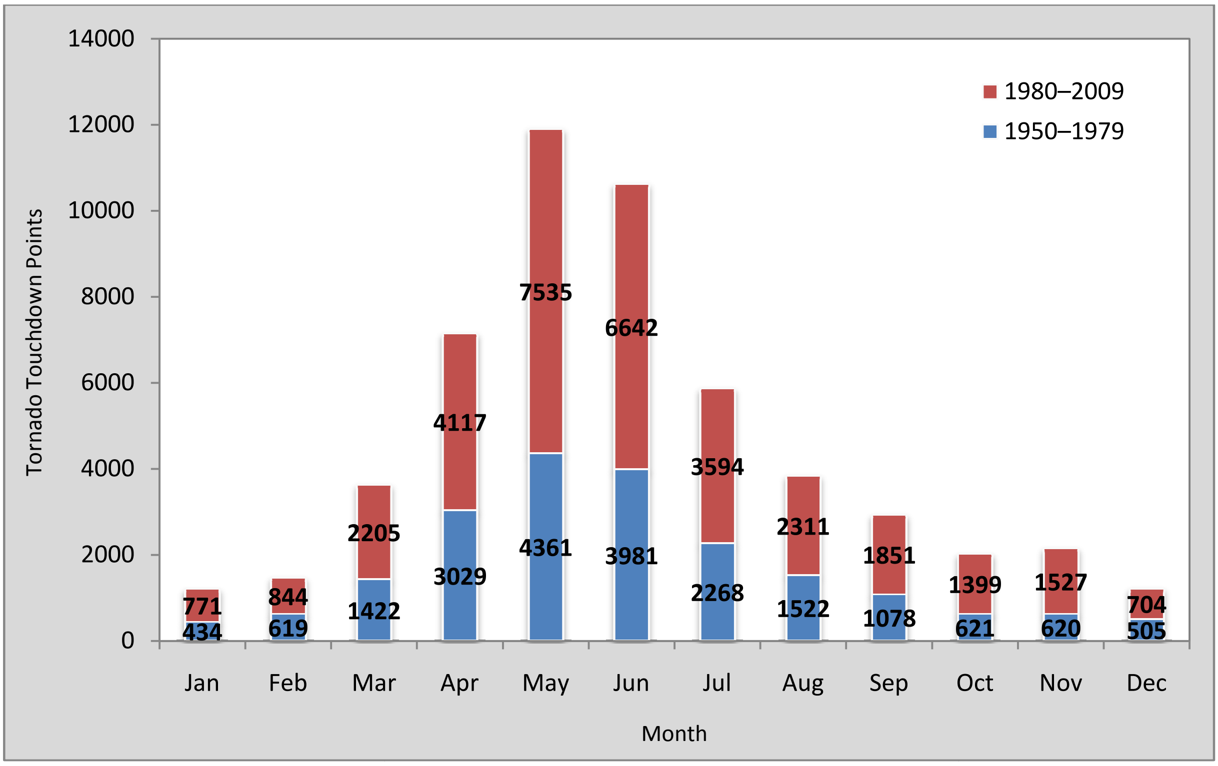
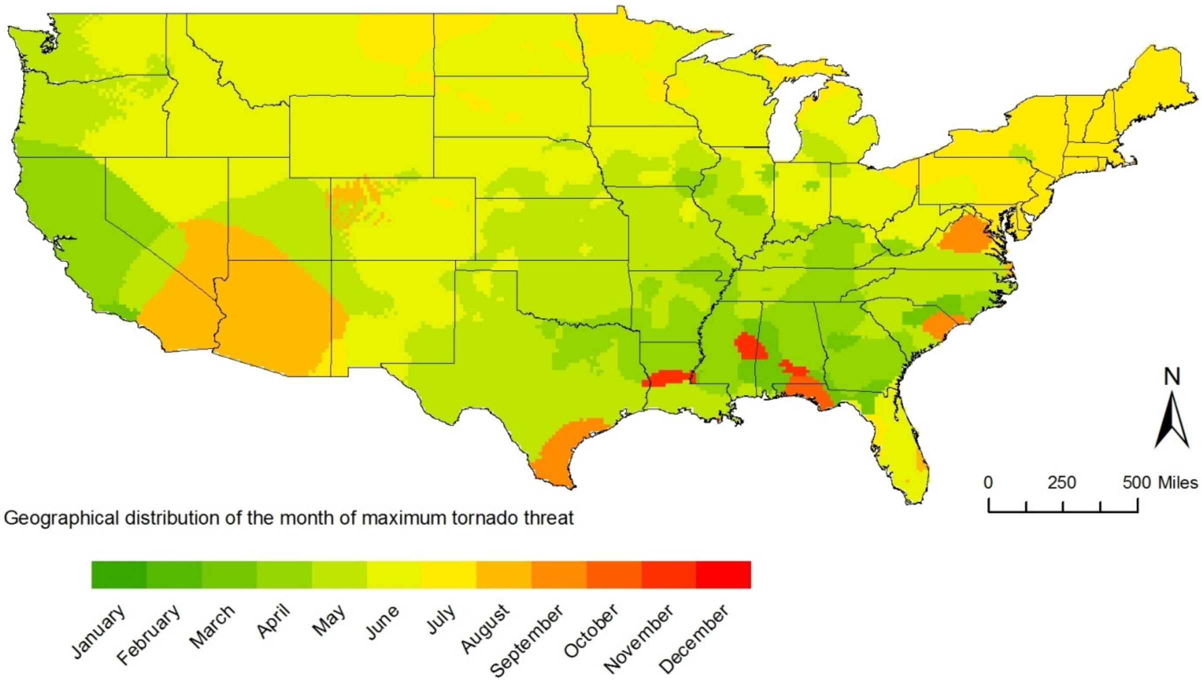


Figure 51 represented the absolute frequencies of tornado touchdown points aggregated by month. This was a purely temporal analysis, neglecting the spatial component. In contrast, Figure 52 shows the geographical distribution of the month with the maximum tornado threat. As has been said in Section 1.3.2, the monthly distribution of tornadoes is known to be associated with the jet streams. During the winter months the position of the jet stream shifts southward and northward during the summer months. According to the position of the jet stream, tornadoes are more likely to occur in these regions.

In general, the geographical distribution of the month with the maximum tornado threat (seen in Figure 52) follows the position of the jet stream (Figure 3). This map was created using twelve kernel density estimations for each month. Then the highest value in each location was selected representing the month with the maximum tornado threat. During spring and fall the position of the jet stream flows in the central United States. Since there are no areas with a maximum tornado threat in January and February in the entire United States, the green shaded areas indicate the spring months March, April, and May. In March and April the most tornadoes occur in the southeast of the United States. In the month of May a large area from Texas to Oklahoma, Kansas, Nebraska, Missouri, southern Iowa, Illinois, southern Virginia, and North Carolina experiences the maximum tornado frequency throughout the year. Regions north of the area with a peak tornado frequency in May have their maximum tornado frequency in the summer months June and July (e.g., in the northeast of the United States). Florida is an exception from the general pattern that the distribution of the highest monthly frequency of tornado occurrences follows the position of the jet stream. Almost the entire area of Florida experiences its maximum number of tornadoes in June. Areas north of St. Petersburg, FL, have their maximum number of tornadoes in July, whereas areas on the eastern part of Florida experience their highest number of tornadoes in August. This exception of not following the jet stream pattern is associated with the nonsupercellular convection (BROOKS et al. 2003). Tornado maxima during fall months can be identified in Virginia as well as in South Carolina, where tornado frequencies show their maxima in September. In the Florida Panhandle around Panama City, FL, the annual tornado peak frequency reaches its maximum in October. Three areas can be further identified to have their maxima tornado frequencies in winter, when the jet stream moves southward. These areas include southern Alabama, the border area between Alabama and Mississippi, and central Louisiana, where the maximum tornado threat was found in November. There is no region in the entire United States which has its maximum tornado frequency in the month of December.

Figure 52: Geographical distribution of the month with the maximum tornado threat



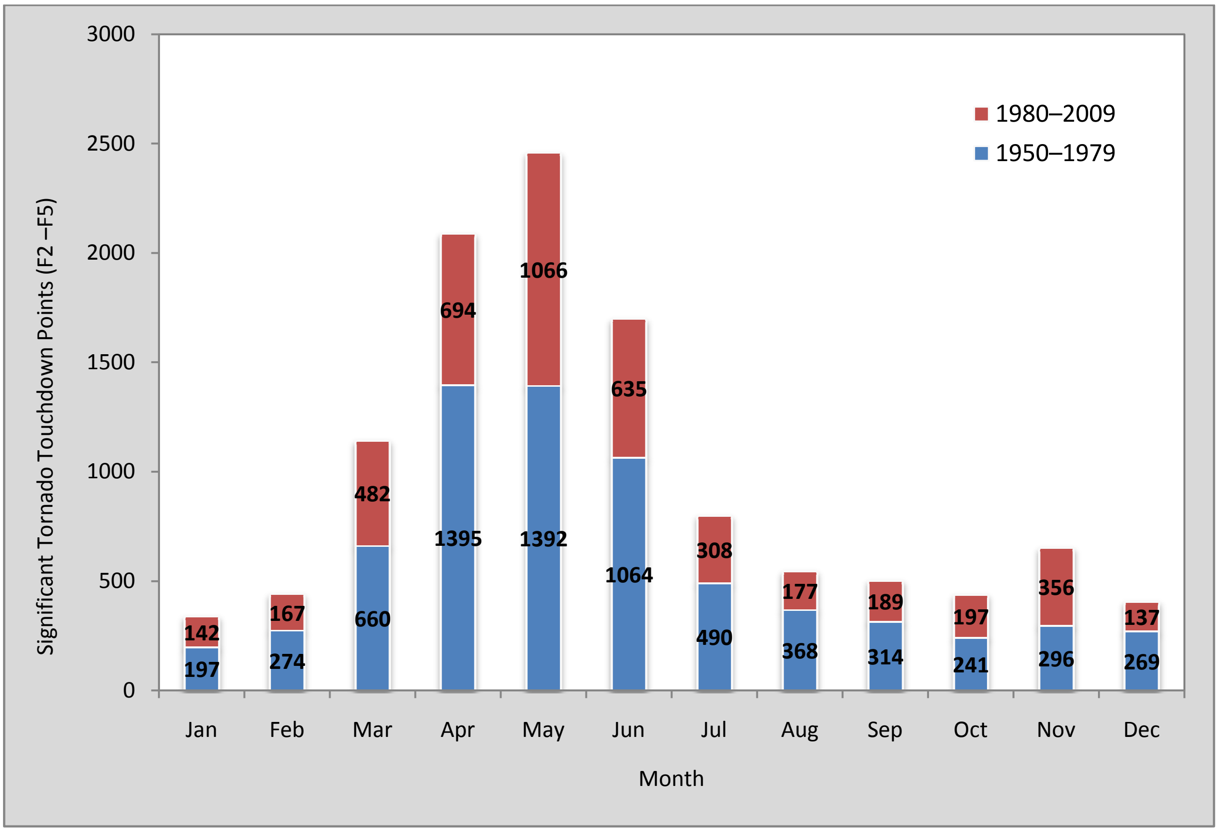
In comparison to the map of BROOKS et al. (2003) (see Figure 5, page 25), some differences to the map shown in Figure 52 can be identified. BROOKS et al. (2003) used data from 1980 to 1999 to produce the map. In general, the contour lines in Figure 5 (page 25) representing the date of the maximum tornado threat is smoothed and thus neglects local variations. For example, areas of monthly maxima of tornado occurrences in July and August as shown in Figure 52 are not represented in Figure 5. A possible reason can be the smoothed analysis in the map by BROOKS et al. (2003), or the fact that there were no tornado peaks in Florida in July and August during the period from 1980 to 1999. BROOKS et al. (2003) identified a peak number of tornado occurrence in November in the Florida Panhandle. In the analysis from 1950 to 2009, the peak number of tornado occurrence in the Florida Panhandle was found in October. In comparison to Figure 5 (page 25), the peak number of hurricane occurrences in the months September (Virginia and South Carolina) and November (Alabama, Mississippi, and Louisiana) have not been identified in the map in Figure 52.

3.4.2. Analysis of Significant Tornado Touchdown Points by Month

In this section the same analysis as in Section 3.4.1 will be done. Instead of using all recorded tornado touchdown points, only significant tornadoes will be analyzed to identify the month with the highest tornado frequency in different regions across the United States.

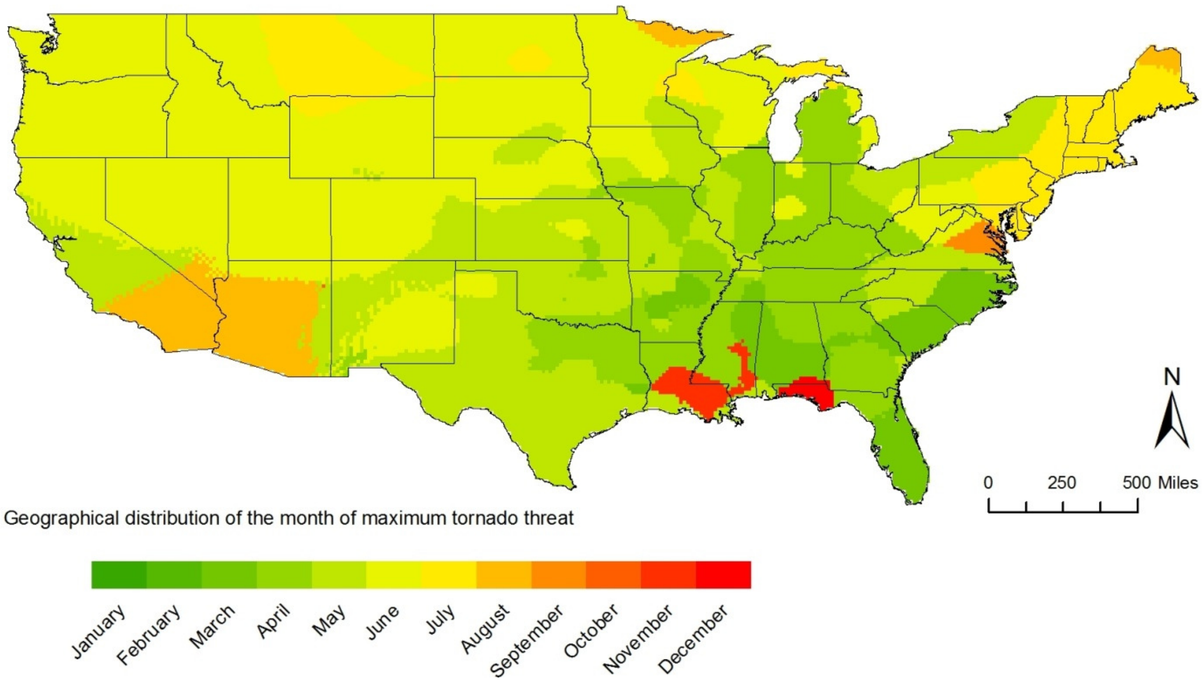
As has been discussed in previous sections, the number of significant tornadoes is small in comparison to the total number of tornado touchdown points that occurred between 1950 and 2009. Only 21.3 percent of all tornadoes were rated as F2 or higher. Figure 53 shows a chart representing the monthly occurrences of significant tornadoes in the contiguous 48 states. In general, the pattern looks pretty much the same as in Figure 51 (page 97), with all recorded tornadoes being included. May shows the highest number of significant tornadoes and the highest number of all recorded tornadoes. The second-highest number is in April, followed by June. When considering all recorded tornadoes (Figure 51, page 97), the second-highest frequency was found in June, followed by April. Since the absolute number of significant tornadoes decreased over time, the tornado occurrences decreased in each month except for November, with an increase in the tornado frequency by 20 percent. On average the tornado frequency for significant tornadoes decreased by 35 percent. The largest decreases can be identified in April and August, with a frequency decline by approximately 50 percent.

Figure 53: Changes in monthly occurrences of significant tornadoes between 1950–79 and 1980–2009



In the following map, the geographical distribution of the month with the maximum threat of significant tornadoes rated F2 or higher is shown. In general, there are not many differences in Figure 54 when compared to Figure 52 (page 98). One significant difference is that in Florida the month with the highest tornado threat of significant tornadoes is in March. In Figure 52 (page 98) the month with the maximum tornado threat was in June. In conclusion, the most tornadoes rated F0 and F1 occur in June, whereas significant tornadoes rated F2 or higher occur in March. The local peak of significant tornadoes in September in South Carolina cannot be detected in Figure 54. In the same region, the highest number of significant tornadoes was identified in March. Both Figures 52 and 54 show the month with the maximum number of (significant) tornadoes in September in Virginia. This means that in this region not only weak, but also significant tornadoes occur. The local "annual outlier" detected in November in Figure 52 (page 98) in Alabama disappeared in Figure 54. In contrast, the area of maximum tornado threat in November increased in Louisiana. In the Florida Panhandle the highest monthly number of significant tornadoes can now be found in December.

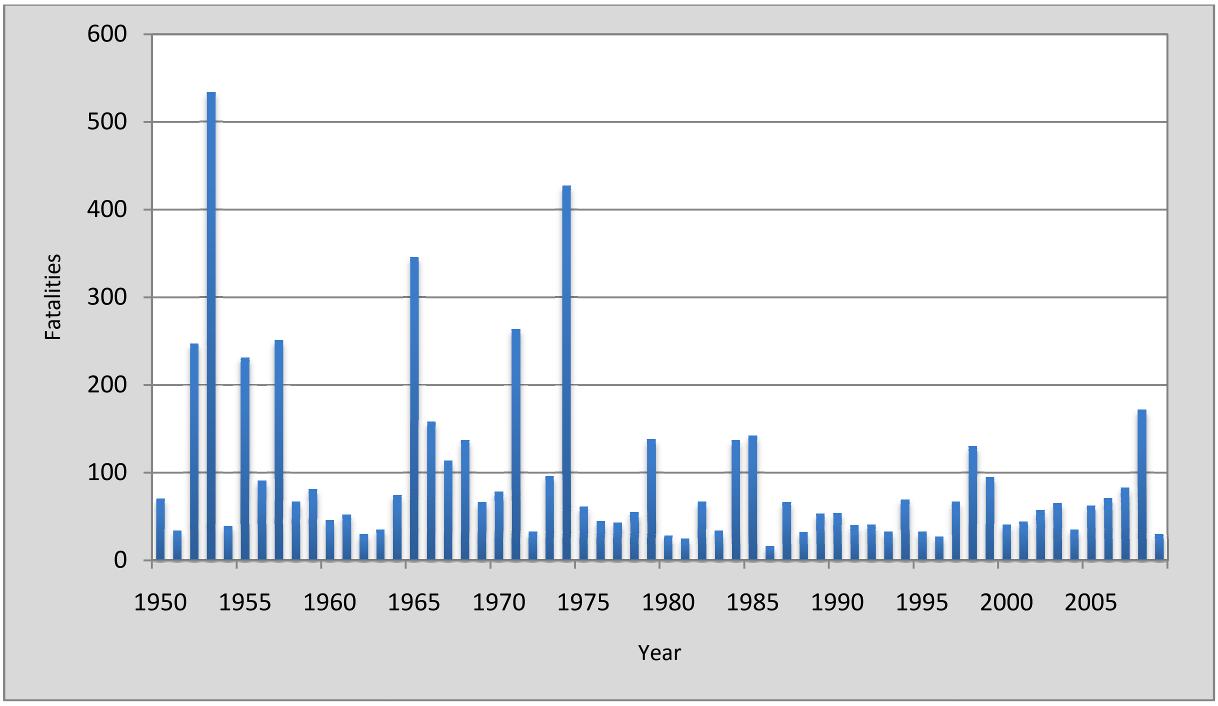
Figure 54: Geographical distribution of the month of maximum significant tornado threat



3.5. Spatial and Temporal Analysis of Tornado Fatalities

The final spatial and temporal analysis deals with tornado fatalities in the United States from 1950 to 2009. During this sixty year period, a total number of 5,792 tornado fatalities has been recorded. As can be seen in Figure 55, the annual number of tornado fatalities declined over time. However, the number of tornado fatalities has increased slightly since 2000. Since 1950 "killer tornadoes" (tornadoes that kill people) have been reported in every single year. The maximum number of fatalities was reported in 1953 with 534. In 1986 the lowest number of 16 tornado fatalities was identified. During the period from 1950 to 1979 a total number of 3,943 tornado fatalities was recorded. In the last thirty-year-period from 1980 to 2009 the number of tornado fatalities decreased by more than 50 percent resulting in 1,849 casualties.

Figure 55: Annual tornado fatalities from 1950 to 2009

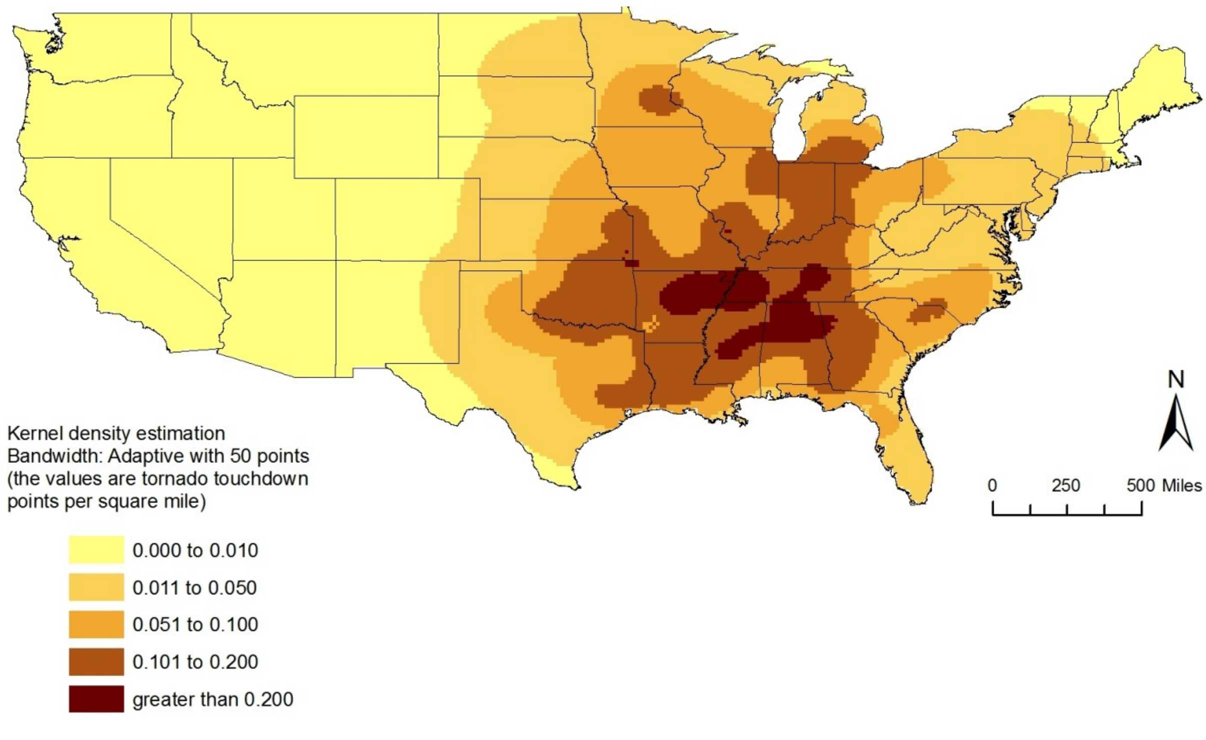


Possible reasons for the decline of tornado fatalities were discussed by DOSWELL et al. (1999) and BROOKS and DOSWELL (2002). These include the initial development and advancement of tornado forecasting, improved communication, spotter networks, better construction techniques, installation of radar, and the establishment of the watch-warning process. BROOKS and DOSWELL (2002) argued that the decreasing trend of the rate of tornado fatalities per one million residents is unlikely to continue. Despite improved detection methods and watch-warning operations, the growing vulnerability brought about by demographic changes influences the tornado fatality rates (BROOKS and DOSWELL 2002, ASHLEY 2007).

Numerous factors impact the amount of risk to individuals during a tornado. These factors include technology (e.g., detection and warning systems), characteristics of the tornado (e.g., magnitude, intensity, time of day, duration, and geography), social aspects (e.g., population trends and urbanization), personal attributes (e.g., perception and preparedness), and location (e.g., type of shelter or the lack thereof) (HAMMER and SCHMIDLIN 2001, ASHLEY 2007).

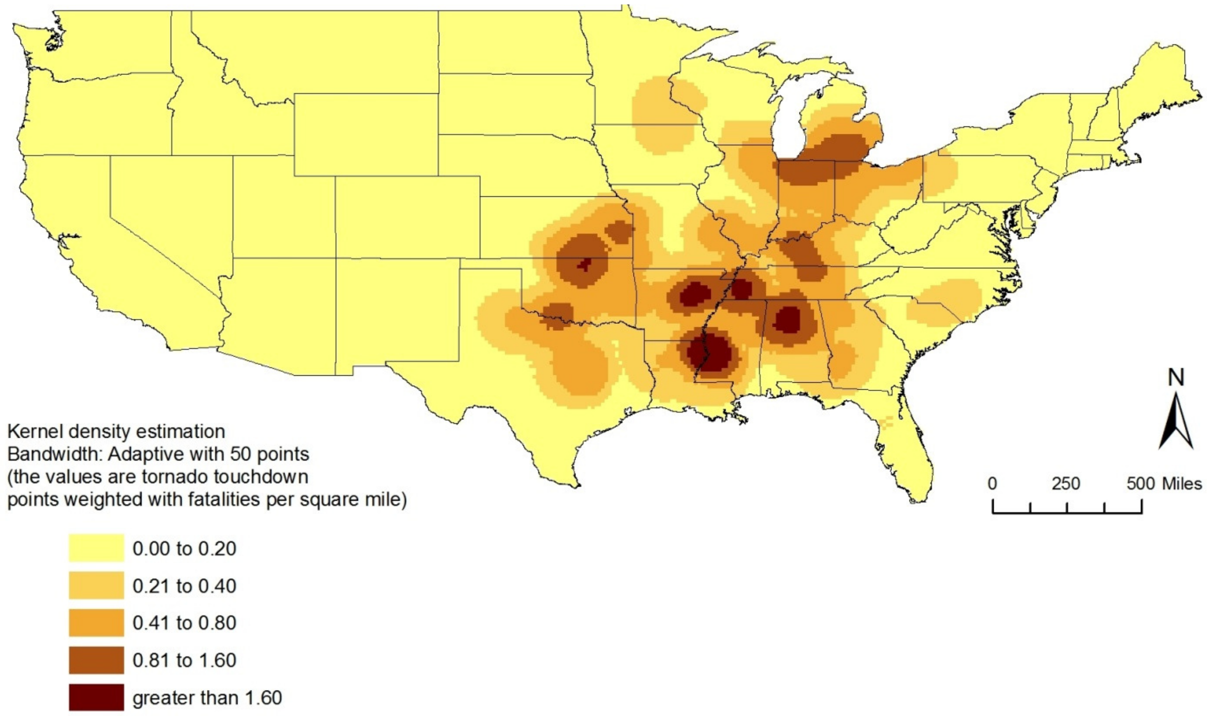
During the entire time period from 1950 to 2009 a total number of 1,434 killer tornadoes were reported. The most killer tornadoes are located in Texas (137), followed by Arkansas (99), Alabama (86), Tennessee (86), and Missouri (80). Figure 56 shows a kernel density estimation of killer tornadoes from 1950 to 2009. As can be seen, the highest densities can be found in Arkansas, Tennessee, Mississippi, Alabama, and Georgia. When comparing the results in Figure 56 with Figures 27 (page 71) and 36 (page 81), which analyzed all recorded tornadoes (Figure 27, page 71) as well as only significant tornadoes (Figure 36, page 81), a map reader can identify differences in the spatial locations of the hot spots. Most killer tornadoes occur in the south, whereas the most tornadoes overall can be detected in the Great Plains, where the so-called Tornado Alley is located. The analysis of killer tornadoes is thus comparable to the analysis of ASHLEY (2007), who argued that the region centered on the lower-Arkansas, Tennessee, and lower Mississippi River Valleys has the greatest concentration of killer events and tornado fatalities, as well. As has been already discussed in Section 1.3.2, ASHLEY (2007) listed climatological and nonclimatological reasons as possibilities for an increased vulnerability of a greater concentration of tornado fatalities and killer events within this region. First, as has already been mentioned before, while the overall intensity of tornadoes in this region (lower-Arkansas, Tennessee, and lower Mississippi River Valleys) is not as high as in the Tornado Alley, a large number of significant tornadoes can be detected in this region. Second, tornadoes occur more likely during cool and transition seasons (BROOKS et al. 2003), when day length is at a minimum, which increases the likelihood of nighttime tornadoes. Third, a large percentage of mobile home and weak-frame housing stock is available in this particular region compared to other regions of the United States. Fourth, the population density of this region is much higher compared to the Midwest and the Great Plains. Fifth, there is a lack of a concentrated "tornado season" in the South, which can lead to complacency among the population (DOSWELL 2003).

Figure 56: Kernel density estimation of killer tornadoes from 1950 to 2009



In the consideration of the spatial distribution of tornado fatalities the kernel density estimate was used to locate areas with high tornado fatalities. The kernel density estimation is useful, because it is possible to use an intensity or weighting variable. Thus, the NNHC routine has not been used, since, with this method, it is not possible to weigh the killer events by the number of tornado fatalities. Figure 57 shows the kernel density estimation of killer tornadoes weighted with the number of fatalities from 1950 to 2009. It can be seen that the hot spot areas are more concentrated in comparison to the previous analysis, where the locations of killer tornadoes were not weighted (Figure 56). Hot spot areas are located in Louisiana, Arkansas, Mississippi, Tennessee, Alabama, and in a small cluster in Oklahoma. The largest hot spot of tornado fatalities is identified in the area around Vicksburg, MS. In fact, this area did not show the highest rates of killer tornadoes per square mile in Figure 56. This means that the killer tornadoes caused a higher number of fatalities as compared to the three hot spots that can be identified in Arkansas, Tennessee, and Alabama (Figure 57). In numbers, the states Texas (610), Mississippi (545), Oklahoma (406), Alabama (405), and Arkansas (370) are the leading states in terms of tornado fatalities over the entire time period from 1950 to 2009.

Figure 57: Kernel density estimation of killer tornadoes weighted with the number of fatalities from 1950 to 2009

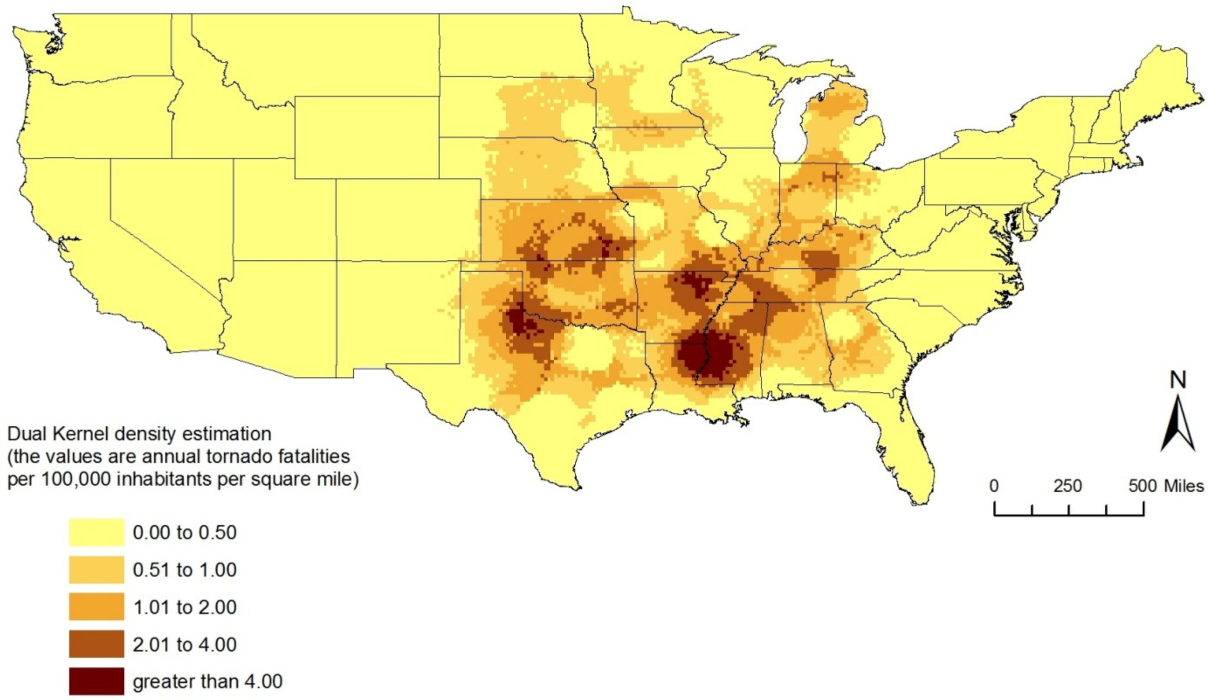


In the following analysis, the number of tornado fatalities is standardized by the underlying population-at-risk. Population data needed for this analysis was collected from the Minnesota Population Center, National Historical Geographic Information System: Pre-release Version 0.1, University of Minnesota. The data are freely available on the web (http://www.nhgis.org). Similar to before, two time periods (1950-1979 and 1980-2009) were analyzed separately. The number of fatalities for the first time period (1950-1979) was standardized with the 1965 population, whereas the number of fatalities for the second time period (1980-2009) was standardized with the 1995 population data. Both the 1965 and 1995 population data were derived through interpolation. These interpolated population sizes for each county were then used to create a kernel density surface over the entire United States (refer to Annex E, pages 131 and 132, for (1) maps of the interpolated population densities and (2) maps of the kernel density estimates of the distribution of tornado fatalities for the time periods 1950 to 1979 and 1980 to 2009). Both the tornado fatalities and the population surfaces are used to create dual kernel density estimates for both time periods. Afterwards, a difference map between the two time periods was created and visualized to check for temporal changes in the rates of tornado fatalities per 100,000 residents per square mile.

The following two maps (Figures 58 and 59) show dual kernel density estimations of killer tornadoes weighted with the number of tornado fatalities standardized by the underlying population for the two time periods.

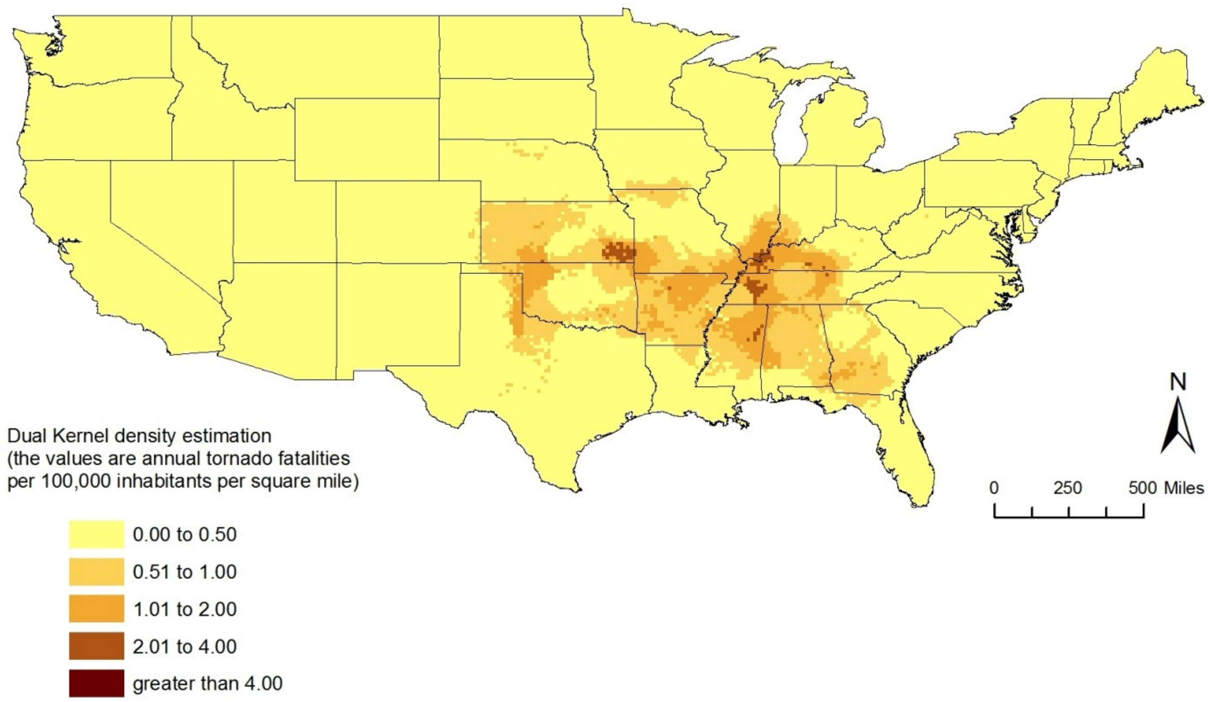
The dual kernel density estimation was calculated by dividing the number of tornado fatalities with the population size per square mile. The resulting values were then divided by 30 to obtain annual tornado fatality rates. Subsequently, these values were multiplied by 100,000 to receive annual tornado fatality rates per 100,000 residents per square mile.

Figure 58: Dual kernel density estimation of tornadoes weighted with the number of fatalities from 1950 to 1979 standardized by the 1965 population



In the analysis of the tornado fatalities from 1950 to 1979 (Annex D), the hot spots have been detected in the areas of Louisiana, Mississippi, Arkansas, and Alabama. Further areas of high densities of tornado casualties were recorded in Texas, in Oklahoma, in Kansas, around the Great Lakes, in Kentucky, and in Tennessee. The dual kernel density estimation of annual rates of tornado fatalities from 1950 to 1979 per 100,000 residents (Figure 58) shows a similar pattern as the map for the single kernel density estimation of tornado fatalities from 1950 to 1979 (Figure E-3 in Annex E, page 132). However, a comparison reveals some differences. Since the population density is somewhat low in Louisiana and Mississippi, the hot spot of the highest tornado fatality rates can again be seen in both states according to Figure 58. The cluster in Arkansas can be identified as well in the dual kernel density estimation. In contrast, the cluster of highest tornado fatalities located in Alabama disappeared from Figure 58, due to the higher population density in Birmingham, AL. In addition, the large cluster around the Great Lakes disappeared as well in Figure 58, since the population density was very high in this region, especially in Chicago, IL and Detroit, MI. In addition, areas with very high tornado fatality rates can be identified in northern Texas, northern Oklahoma, and southern Kansas. According to Figure E-3 in Annex E, page 132, the number of tornado fatalities in these areas was not as high as in other areas of the United States. Instead, the population density (the denominator of the ratio) is very low, which results in higher tornado fatality rates. For example, the cluster identified in Texas (Figure 58) is only located in the third class range in the density map of tornado fatalities (Figure E-3, Annex E, page 132).

Figure 59: Dual kernel density estimation of tornadoes weighted with the number of fatalities from 1980 to 2009 standardized by the 1995 population

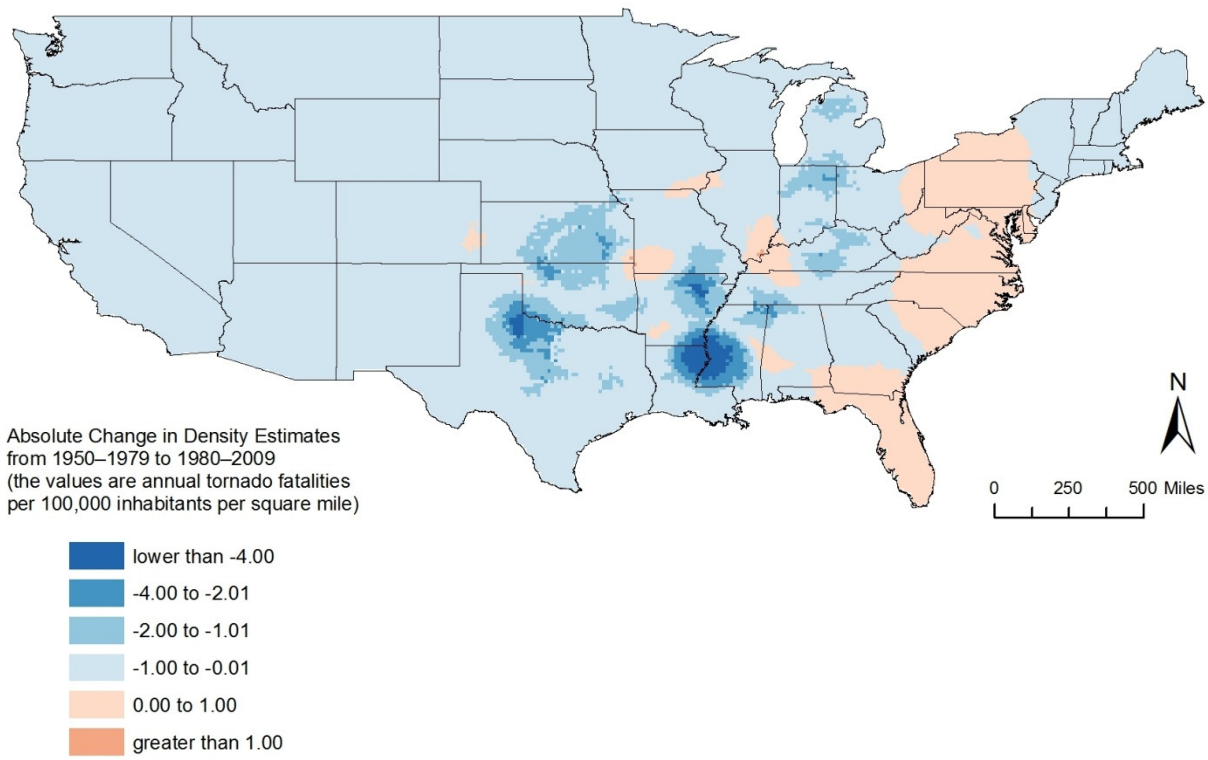


The analysis of the tornado fatality rates for the period from 1980 to 2009 does not have such distinctive hot spot areas compared to the period from 1950 to 1979. The reasons are as follows: The parameter settings for the kernel density estimation remained the same for the killer tornadoes at both time periods. Since the number of tornado fatalities declined over time and the class ranges remained the same for both maps, no hot spots appear in the period from 1980 to 2009. However, the only higher concentration of tornado fatalities can be seen in Alabama (Figure E-4 in Annex D, page 132). In the same area there has been a cluster in the earlier time period, as well. Since the population density was not as low as in other areas, where killer tornadoes occur, this cluster disappeared in the most recent time period, as can be seen in Figure 59. Areas of increased tornado fatality rates can be identified in Lincoln, NE, in western Tennessee, and in western Kentucky. The same hot spot areas of tornado fatality rates that were found during the time period from 1950 to

1979 cannot be detected any more during the time period from 1980 to 2009. The clusters in Louisiana and Mississippi as well as the cluster in Texas disappeared almost completely.

The following map (Figure 60) shows absolute changes of the tornado fatality rates from 1950–1979 to 1980–2009. As has been said before, the number of tornado fatalities declined between the two time periods. The large clusters in Louisiana and Mississippi disappeared over time, resulting from a decrease of about more than four annual tornado fatalities per 100,000 residents per square mile. Additional clusters showing decreases are located in Texas and Arkansas. In the remaining areas the absolute changes of tornado fatality rates are somewhat constant over time. Areas of increasing tornado fatality rates are sparse. There are small areas, where the absolute changes in density estimates increased by more than one annual tornado fatality per 100,000 residents. These are located along the border area between southern Illinois and Kentucky, and along the border area between Kansas and Missouri.

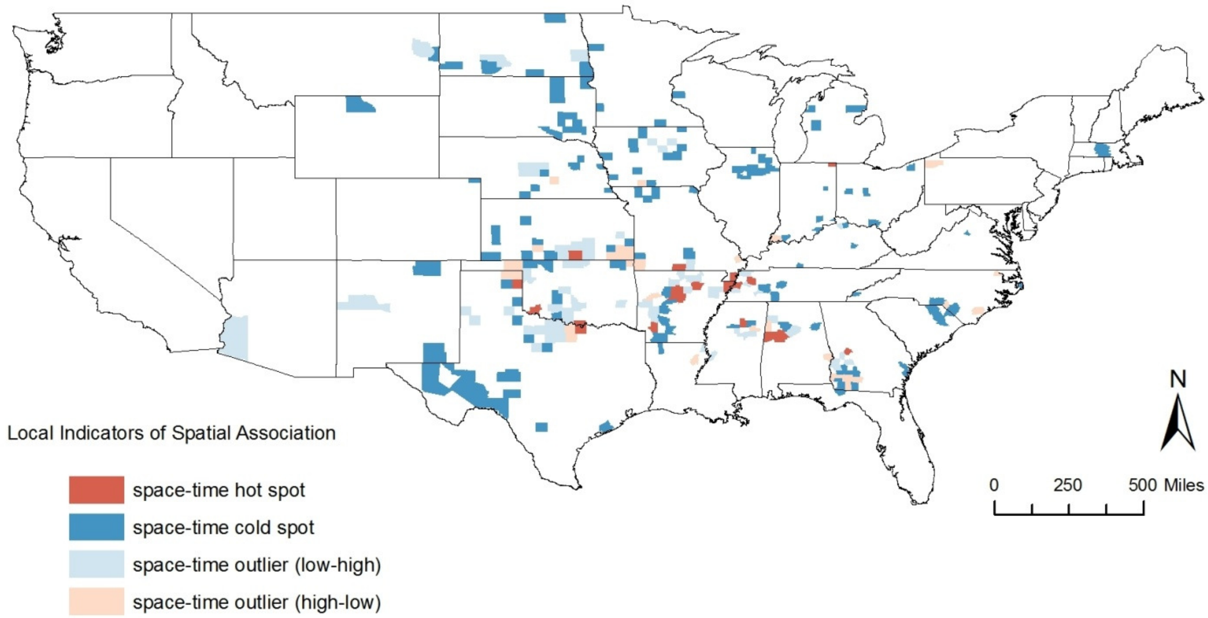
Figure 60: Absolute change of tornado fatality rates from 1950–79 to 1980–2009



The last map in this chapter introduces a technique that is based on the concept of spatial autocorrelation. The LISA routine compares neighboring values. If they are both high, a hot spot is identified. If the neighboring values are both low, a cold spot is identified. If the values are different (one high, the other low), spatial outliers are detected. The routine then calculates the level of significance for this relationship between neighboring polygons (ANSELIN 2003). In the following analysis, 999 replications (i.e., Monte Carlo simulations) were applied to calculate the level of significance.

Figures E-5 and E-6 in Annex E, pages 133, shows the LISA results for the two time periods from 1950 to 1979 and from 1980 to 2009. A combined approach is the space-time LISA, where a polygon with a tornado fatality rate from the period 1950 to 1979 is compared with polygons with tornado fatality rates from the period 1980 to 2009. Therefore, the spatial and temporal persistence of similar values (space-time hot spots or space-time cold spots) is identified. Figure 61 shows the space-time LISA of tornado fatality rates of tornado touchdown points for 1950 to 1979 and 1980 to 2009. There are some counties that are identified as space-time hot spots at a significance level of p<=0.05. These are located along the border area between Texas and Oklahoma, in southern Kansas, in northern Indiana, in southern of Missouri, in Arkansas, in the western part of Tennessee, in the northern parts of Mississippi and Alabama, as well as in one county in Georgia. The largest space-time hot spot areas of tornado fatality rates can be identified in central Arkansas, along the border between Arkansas, Missouri, and Tennessee and in northern Alabama.

Figure 61: Space-time LISA of tornado fatality rates of tornado touchdown points for 1950–79 and 1980–2009



4. Conclusion

In this diploma thesis an extensive analysis of the geographic patterns of tornadoes and of tornado fatalities has been conducted. In addition, the spatial data analysis has been extended to also investigate temporal patterns, such as cluster persistence or cluster change of tornadoes and their fatalities. The spatial data analysis has been conducted by "state-of-the-art" spatial statistics. The outputs of these statistical analyses have been compared to more "traditional" mapping techniques, such as the common dot map or the choropleth map. It has been argued that spatial statistics result in more accurate and statistically significant outputs. In general, the following spatial statistics have been applied to analyze the dataset of tornado touchdown points in the United States from 1950 to 2009. First, an interpolating technique using a kernel function is applied to calculate a (kernel) density surface. Thus, locations of high as well as low tornado occurrences are shown over the entire study area. Second, the NNHC routine groups a certain minimum number of events to clusters, which are in close proximity. This routine only identifies hot spots but no cold spots. Third, the Local Moran's I (LISA) approach has been introduced. This method compares values of neighboring polygons for similarity or dissimilarity. High neighboring values are referred to as "hot spots", whereas low neighboring values are referred to as "cold spots". JACQUEZ (2008) proposed different approaches to check for temporal variations in the spatial patterns of events, such as cluster change or cluster persistence. These attempts have been applied in the analysis and later discussed in their suitability for a spatiotemporal analysis. As a fourth technique, the space-time permutation model in the form of a spatial scan statistic is used to analyze the dataset. This technique adjusts for both spatial and temporal interaction, in other words, an existing cluster in a geographical area has a higher proportion of incidents during a specific time period compared to the other regions in that time period. This method only shows spatiotemporal hot spots, whereas areas of low concentrations or insignificant clusters are not shown.

4.1. Research Questions

Several research questions have been investigated in this thesis (see page 16 or 69). The first research question addresses the application of modern statistical techniques compared to traditional techniques. This comparison has been discussed in Section 2.2.2.1. Various traditional techniques, such as the common dot map, the choropleth map, or the quadrate thematic map result in more or less satisfying outcomes. Choropleth maps are inappropriate in showing hot spots, especially when those hot spots cover only a small portion inside a polygon. The quadrate thematic map solves this problem by using a grid, where values are totaled in each quadrate. This map type looks somewhat "speckled", especially with larger grid cell sizes. Since the quadrate thematic map is purely a visualization method, it cannot account for spatial autocorrelation. The concept of spatial autocorrelation was introduced as the "first law of geography", meaning that "everything is related to everything else, but near things are more related than distant things" (TOBLER 1970). Spatial statistics make use of this concept. Therefore they are more appropriate to analyze spatial data and their spatial interactions and thus, the results are more accurate in comparison to the proposed traditional, rather visual techniques.

As has been said previously in this chapter, the four statistical techniques result in different outputs. The kernel density estimation is the only technique which provides an estimated value at each location and therefore, areas of high, medium, as well as low occurrences of events are shown. The NNHC routine and the space-time permutation model are useful, when events need to be grouped to clusters and areas of low concentrations are not the main interest. The LISA statistic has been used for the analysis of tornado fatality rates, since the statistic analyzes values of neighboring polygons in which the population size is known. In the application of these techniques for spatial and temporal analysis, different results were yielded due to different underlying principles. The dual kernel density estimation as the space-time approach creates difference maps of density estimates of two different time periods. Thus, locations of cluster change and cluster persistence are visible. The space-time NNHC approach uses (spatial and temporal) intersections of spatial cluster ellipses from two different time periods. It is understandable that these spatial and temporal intersections point to cluster persistence. Space-time LISA statistics analyze neighboring values at two different time periods. Statistically significant space-time hot spots and space-time cold spots signify cluster persistence, whereas spatiotemporal outliers account for cluster change. The space-time permutation model is somewhat special, since it adjusts for both purely spatial und purely temporal interactions in the dataset. Thus, this statistic is hardly comparable to the other space-time approaches which do not account for both spatial and temporal interaction. Hence, these space-time approaches account for temporal variations of spatial patterns.

The question of which technique is most useful for the spatial and temporal analysis cannot be answered explicitly. It depends on the purpose of the analysis. In this spatial and temporal analysis of tornado touchdown points the kernel density estimation is the only technique which has been applied to each analysis since the technique is easy to interpret and allows for an extensive interpretation. This technique provides a useful space-time approach and allows the application of weights (e.g., the number of tornado fatalities), which has been applied in the calculation of tornado fatality rates. The space-time permutation model is a special case, since none of the proposed space-time approaches adjust for both spatial and temporal interaction. In the analysis of tornado touchdown points, the space-time permutation model can be useful for a retrospective analysis of tornado outbreaks in a short time period.

The spatial and temporal analysis of tornado touchdown points resulted in outputs similar to KELLY et al. (1978), BROOKS et al. (2003), and ASHLEY (2007). However, the authors of these research papers used tornado data during a different time period. The spatial analysis of all recorded tornadoes in the period from 1950 to 2009 showed that a high number of tornadoes overlap with the boundaries of the "Tornado Alley". Since the number of tornadoes increased immensely during the periods from 1950–79 to 1980–2009 the temporal variation of the spatial patterns showed increasing tornado occurrences in almost each of the 48 contiguous states of the United States. The biggest increases have been detected in Denver, CO, Houston, TX, and St. Petersburg, FL. In the analysis of only significant tornadoes rated F2 or higher the visual interpretation was almost the opposite, since the number of significant tornadoes declined over the same time period. In this analysis, the border areas between Texas and Oklahoma, as well as between Kansas and Indiana have been identified as those areas, where the occurrences of significant tornadoes declined the most. However, there are a few areas of increase during this time period. In the analysis of violent tornadoes rated F4 or F5 no general pattern was detectable. The space-time NNHC analysis resulted in spatial and temporal intersections indicating cluster persistence along the border areas of Indiana, Ohio, and Kentucky, in Tennessee and Arkansas and along border areas of Oklahoma and Kansas. In comparison to all recorded tornadoes it can be argued that violent tornadoes do not necessarily occur in the area of the Tornado Alley.

BROOKS et al. (2003) analyzed the maximum monthly frequency of tornadoes from 1980 to 1999. The resulting map can be seen in Figure 5 (page 25). In the analysis of the maximum monthly frequency of tornadoes from 1950 to 2009, the monthly frequency shows some differences to the map of BROOKS et al. (2003). In general, both monthly frequencies follow the position of the jet stream. In the analysis of BROOKS et al. (2003) the contour lines are more smoothed and do not show local variations. For example, areas of monthly maxima in July and August (see Figure 52, page 98) are not represented in Figure 5 (page 25). A possible reason can be the rather smoothed analysis or visualization, or the fact that Florida did not have monthly maxima in July and August during the period from 1980 to 1999. BROOKS et al. (2003) identified a monthly maximum in November in the Florida Panhandle. In the analysis in this thesis from 1950 to 2009, the monthly maximum was found in October. In comparison to Figure 5 (page 25), the monthly maxima in the months September (Virginia and South Carolina) and November (Alabama, Mississippi and Louisiana) have not been identified in this thesis.

The last analysis focused on killer tornadoes and tornado fatalities. In this analysis, the rates of tornado fatalities are calculated using an interpolated underlying population. The highest concentrations of killer tornadoes have been detected outside of the Tornado Alley, where most of the tornadoes occur. Killer tornadoes occur preferably in the interior southeast and in the south-central United States. The most tornado fatalities have been detected in the states of Arkansas, Louisiana, Mississippi, Tennessee, Alabama, and in a small area in Oklahoma. The dual kernel density estimation uses a density estimate of killer tornadoes weighted with the number of tornado fatalities standardized by the underlying population. Since the number of tornado fatalities was higher and the population densities lower during the earlier time period, more distinctive hot spots with high tornado fatality rates were found in the period from 1950 to 1979. These hot spots can be identified in Louisiana and Mississippi, as well as in Arkansas, and in northern Texas. During the two time periods the number of tornado fatalities decreased, while the population density increased. This resulted in lower tornado fatality rates. Thus, the difference map of absolute changes between the density estimates shows decreases in almost all areas. The biggest declines were detected in Louisiana and Mississippi, Arkansas, and Texas. Slight increases of more than one tornado fatality per year per 100,000 inhabitants have been identified along the border area between southern Illinois and Kentucky, and along the border area between Kansas and Missouri.

4.2. Future Prospects

Numerous analyses have been made using the dataset of the Storm Prediction Center (SPC). I am in agreement with ASHLEY (2007) who argues that the information of the data needs to be improved. Since the mid-1980s data descriptions of how and where tornado fatalities occur have advanced, however, the data still needs much improvement in the information provided for future damage and casualty assessments. In the verification of tornado damage and effort should be made to determine the location of the casualty and the type of structure in which the fatality occurred (ASHLEY 2007).

In the application and comparison of various statistical techniques to test for space-time interaction, some limitations arose in the analysis of the dataset of tornado touchdown points. In the analysis the kernel density estimation showed the best results since density values are calculated across the whole country. This technique allows the detection of hot spots and a comparison with the NNHC routine. The NNHC technique produces spatial ellipses around events, which define hot spots. The space-time permutation model provides circular clusters of events, in both space and time. For this reason, the results of the kernel density estimate and the NNHC are not completely comparable with the outputs of the space-time permutation model. There might be some similarities in the locations of the clusters, however the kernel density estimation as well as the NNHC technique do not account for both spatial and temporal interaction. The Local Moran's I as the fourth technique uses areal data. With this technique, neighboring tornado fatality rates based on counties have been analyzed for spatial as well as space-time hot spots and cold spots. The outputs of the space-time LISA showed cluster persistence over time and has been subsidiary to the space-time analysis using kernel density estimations, since the latter shows cluster changes and cluster persistence. The space-time kernel density estimation should always be provided together with the single kernel density estimation, since the dual kernel density map does not make a statement about high respectively low densities. It only shows differences between two time periods.

However, numerous challenges for GIS in the future can be identified. One major challenge that has been identified relates to the integration of time as a third dimension in addition to longitude and latitude. The analysis and visualization of both space and time is a rapidly growing research frontier in geography, GIS, and GIScience.

Future research should therefore focus on the development and improvement of spatial statistics and especially on techniques to analyze correlations in both time and space. An important first attempt has been made with the development of the space-time scan statistic. Future research about tornado occurrences in the United States should focus on the improved collection of information. In the future, the analysis presented in this thesis should be repeated to see whether further changes in the locations of tornado occurrences have happened. For a future analysis, data before the mid-1980s should be excluded, since the reporting systems improved significantly since then.

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List of Abbreviations

AAG	Association of American Geographers
ESDA	Exploratory Spatial Data Analysis
GIS	Geographic Information Systems
LISA	Local Indicators of Spatial Association
NNHC	Nearest Neighbor Hierarchical Clustering
NOAA	National Oceanic and Atmospheric Administration
Ra-NNHC	Risk-adjusted Nearest Neighbor Hierarchical Clustering
SPC	Storm Prediction Center
STAC	Spatial and Temporal Analysis of Crime

List of Abbreviations of U.S. States

AL	Alabama
CO	Colorado
FL	Florida
IL	Illinois
LA	Louisiana
MI	Michigan
MO	Missouri
MS	Mississippi
NE	Nebraska
OK	Oklahoma
PA	Pennsylvania
SD	South Dakota
TN	Tennessee
TX	Texas

Annex A

Overview of specific cluster statistics in the selected software packages used in this thesis

CrimeStat

- Moran's I
- Geary's C
- Getis-Ord's G
- Nearest neighbor index and K-th order nearest neighbor index
- Ripley's K
- Spatial Mode
- Spatial Fuzzy Mode
- Nearest neighbor hierarchical clustering
- Risk-adjusted nearest neighbor hierarchical clustering
- STAC (spatial and temporal analysis of crime)
- K-means clustering
- Local Moran's I
- Getis-Ord Local G
- Single kernel density estimation
- Dual kernel density estimation
- Knox Index (space-time)
- Mantel Index (space-time)

GeoDa

- Outlier detection
- Global Moran's I
- Global Moran's I for rates with Empirical Bayes correction
- Local Moran's I
- Local Moran's I for rates with Empirical Bayes correction
- Bivariate (space-time) Moran's I
- Bivariate (space-time) Local Moran's I

SaTScan

- Retrospective purely spatial scan statistic
    - Bernoulli model
    - Poisson model
    - Multinomial model
    - Ordinal model

    - Exponential model
    - Normal model
- Retrospective purely temporal scan statistic
    - Bernoulli model
    - Poisson model
    - Multinomial model
    - Ordinal model
    - Exponential model
    - Normal model
- Prospective purely temporal scan statistic
    - Bernoulli model
    - Poisson model
    - Multinomial model
    - Ordinal model
    - Exponential model
    - Normal model
- Retrospective space-time scan statistic
    - Bernoulli model
    - Poisson model
    - Multinomial model
    - Ordinal model
    - Exponential model
    - Normal model
    - Space-time permutation model
- Prospective space-time scan statistic
    - Bernoulli model
    - Poisson model
    - Multinomial model
    - Ordinal model
    - Exponential model
    - Normal model

Annex B

Figure B-1: Topographic map of the United States

Adapted from http://www.usgs.gov/

Annex C

Figure C-1: Kernel density estimation of significant tornado touchdown points from 1950 to 1979

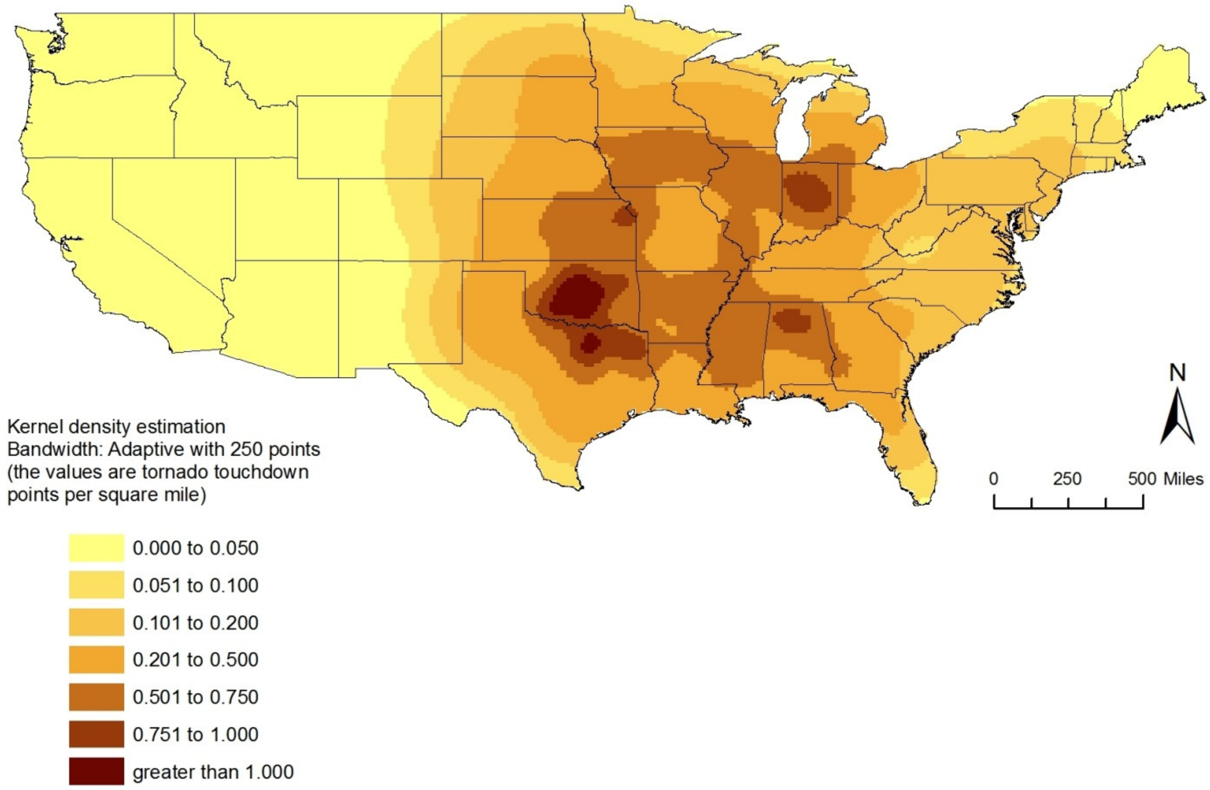
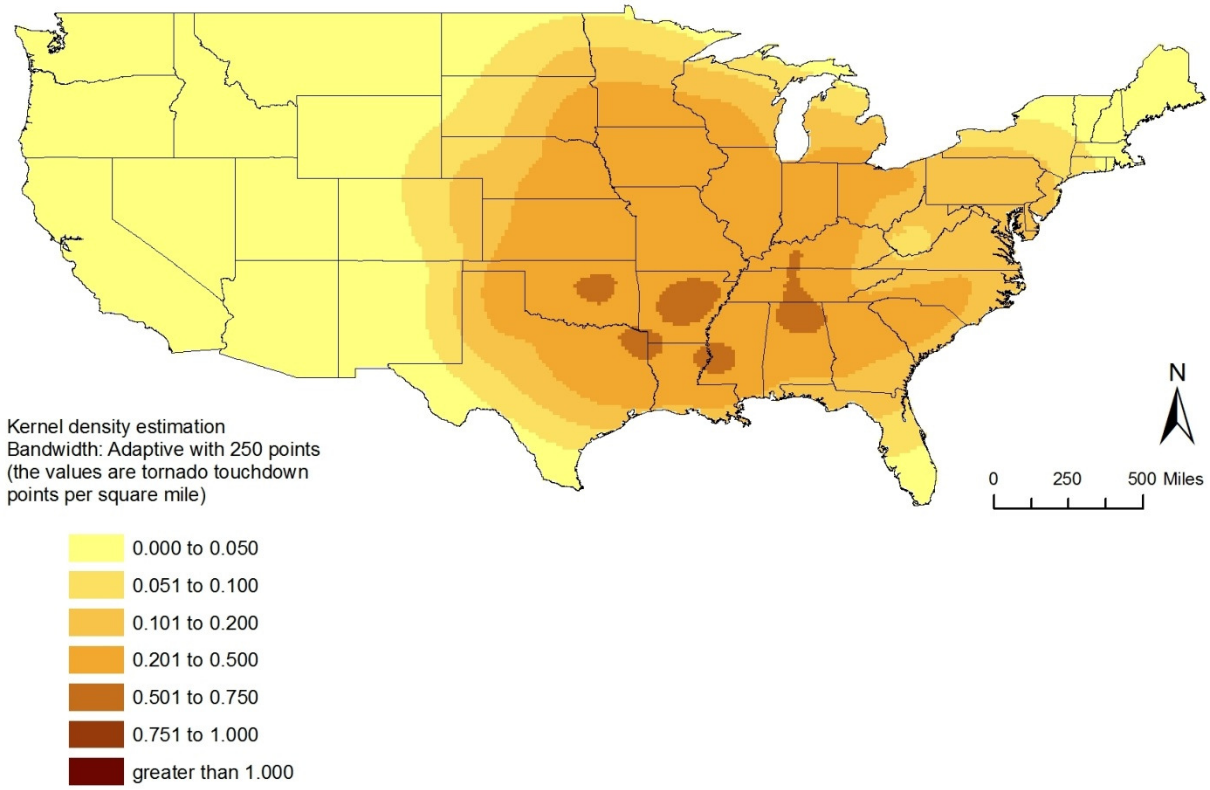


Figure C-2: Kernel density estimation of significant tornado touchdown points from 1980 to 2009



Annex D

Figure D-1: Kernel density estimation of weak tornado touchdown points from 1950 to 1979

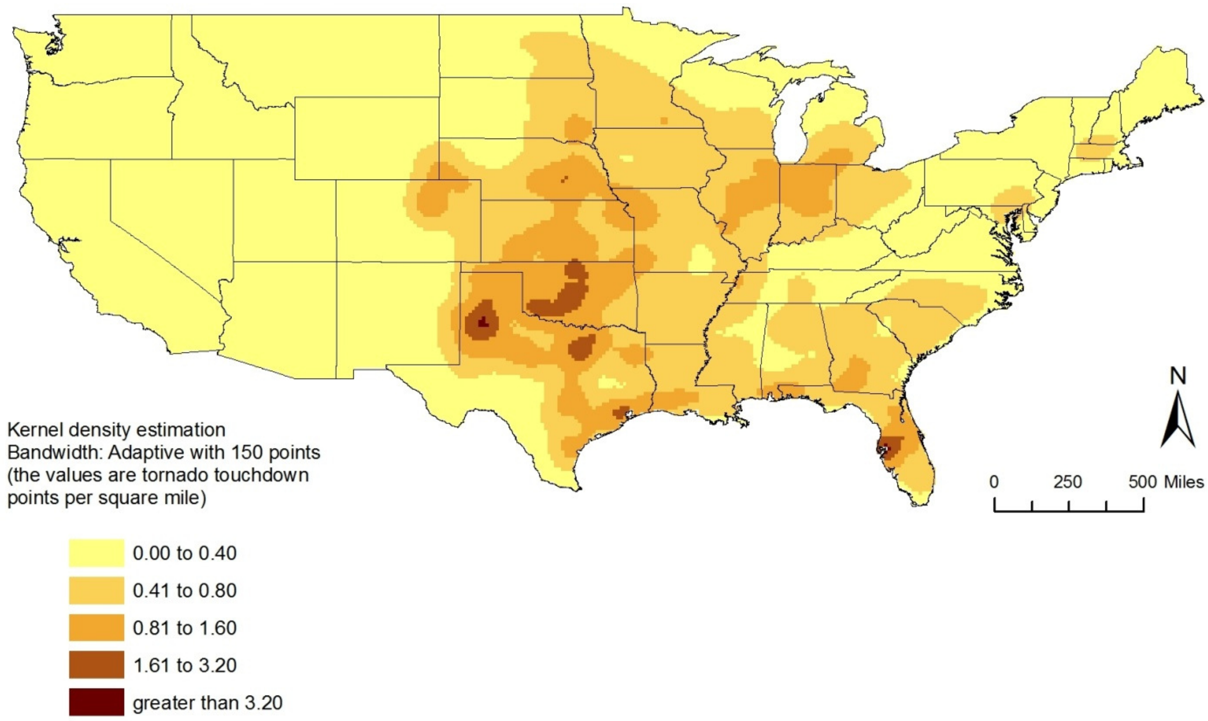


Figure D-2: Kernel density estimation of weak tornado touchdown points from 1980 to 2009

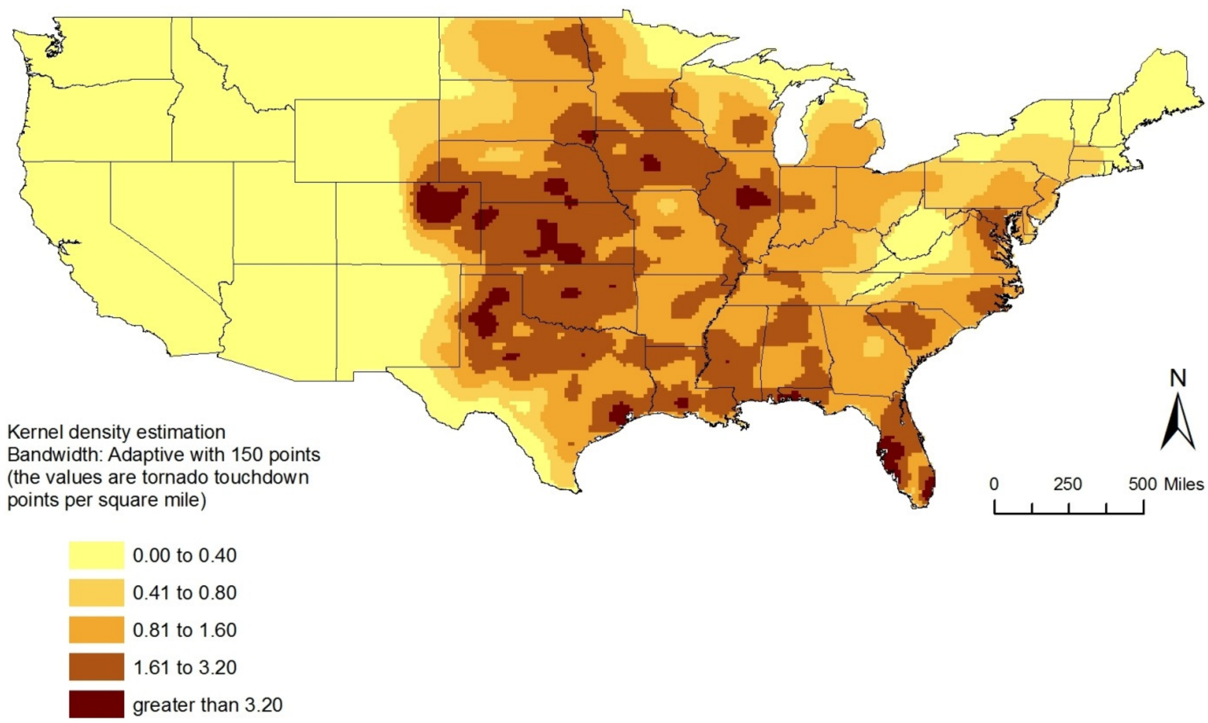


Figure D-3: Kernel density estimation of strong tornado touchdown points from 1950 to 1979

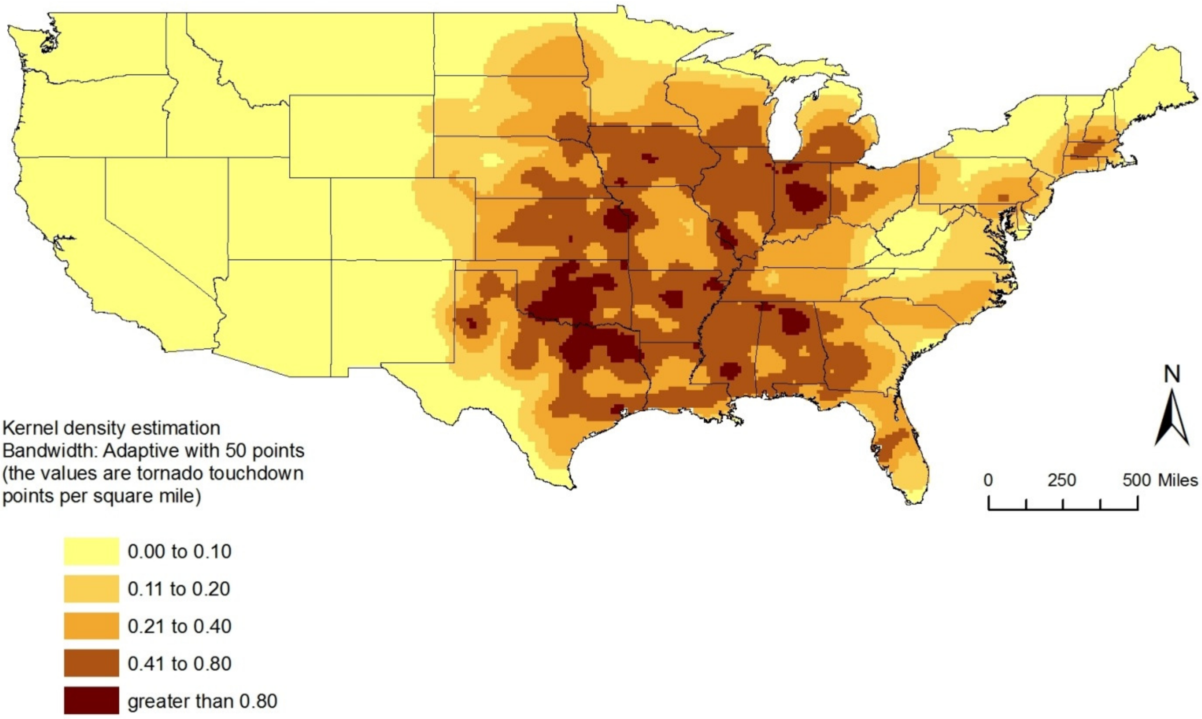


Figure D-4: Kernel density estimation of strong tornado touchdown points from 1980 to 2009

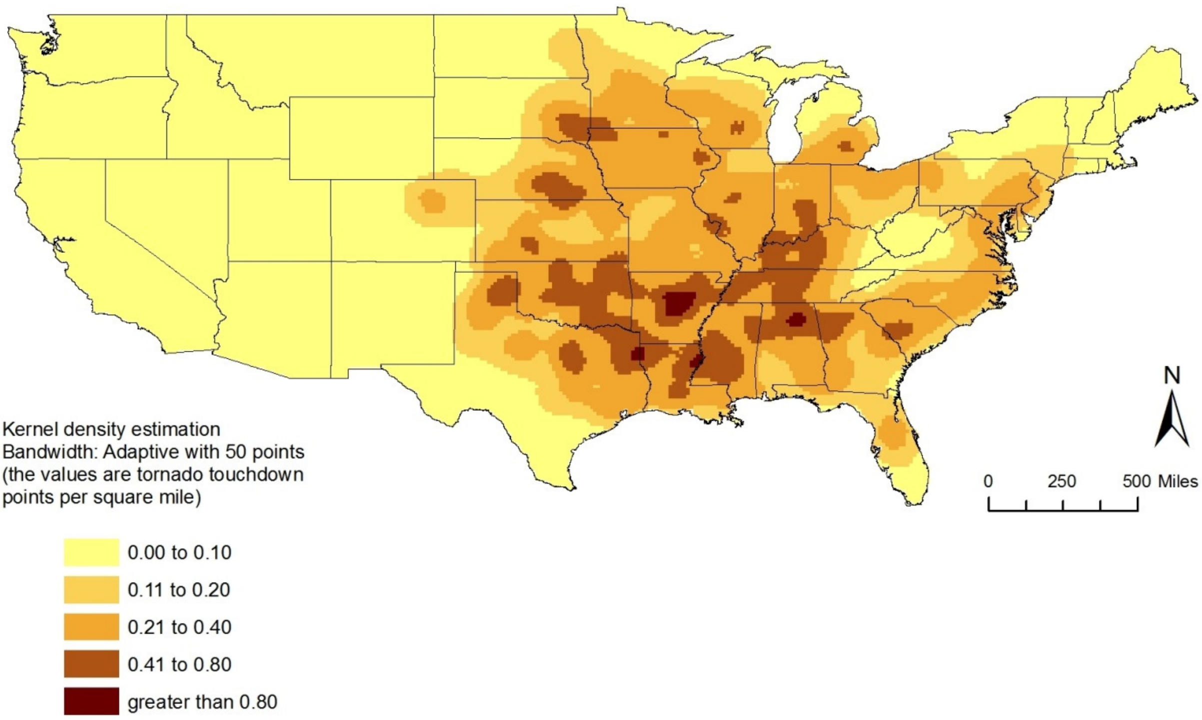


Figure D-5: Kernel density estimation and NNH clusters of violent tornado touchdown points from 1950 to 1979

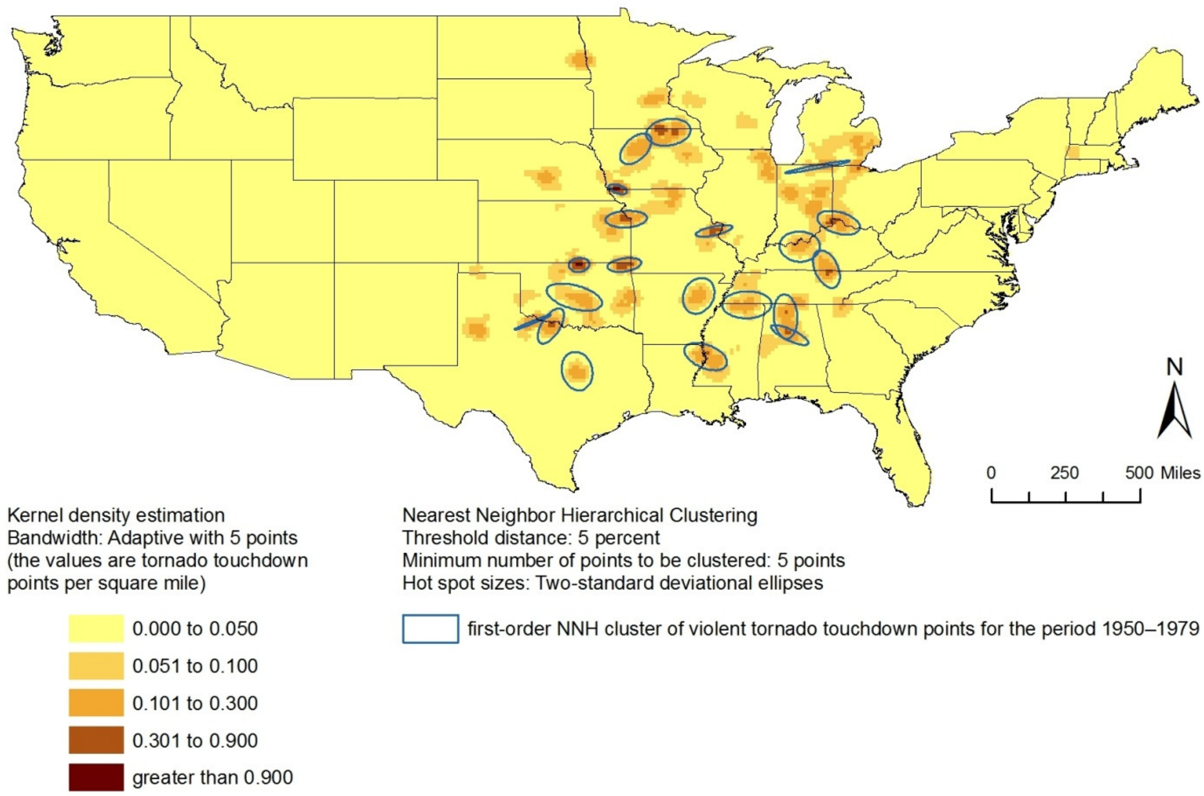
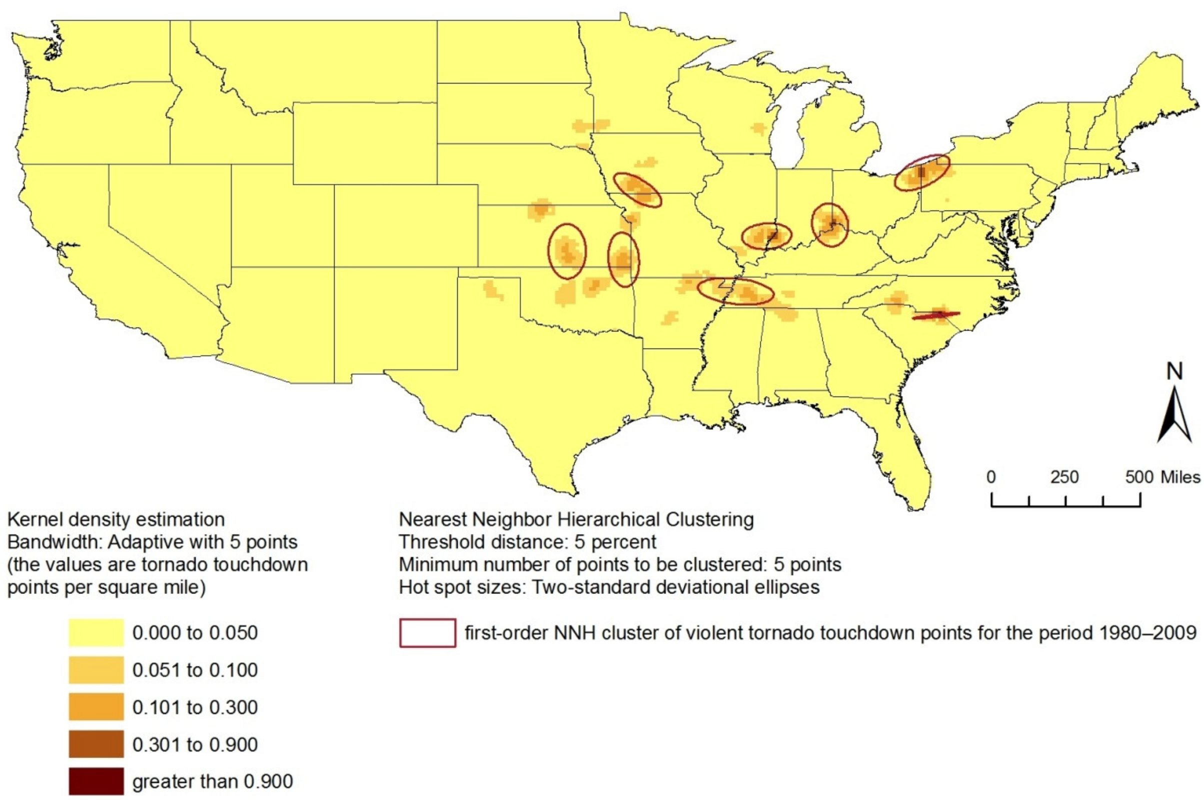


Figure D-6: Kernel density estimation and NNH clusters of violent tornado touchdown points from 1980 to 2009



Annex E

Figure E-1: Kernel density estimation of the estimated population in 1965

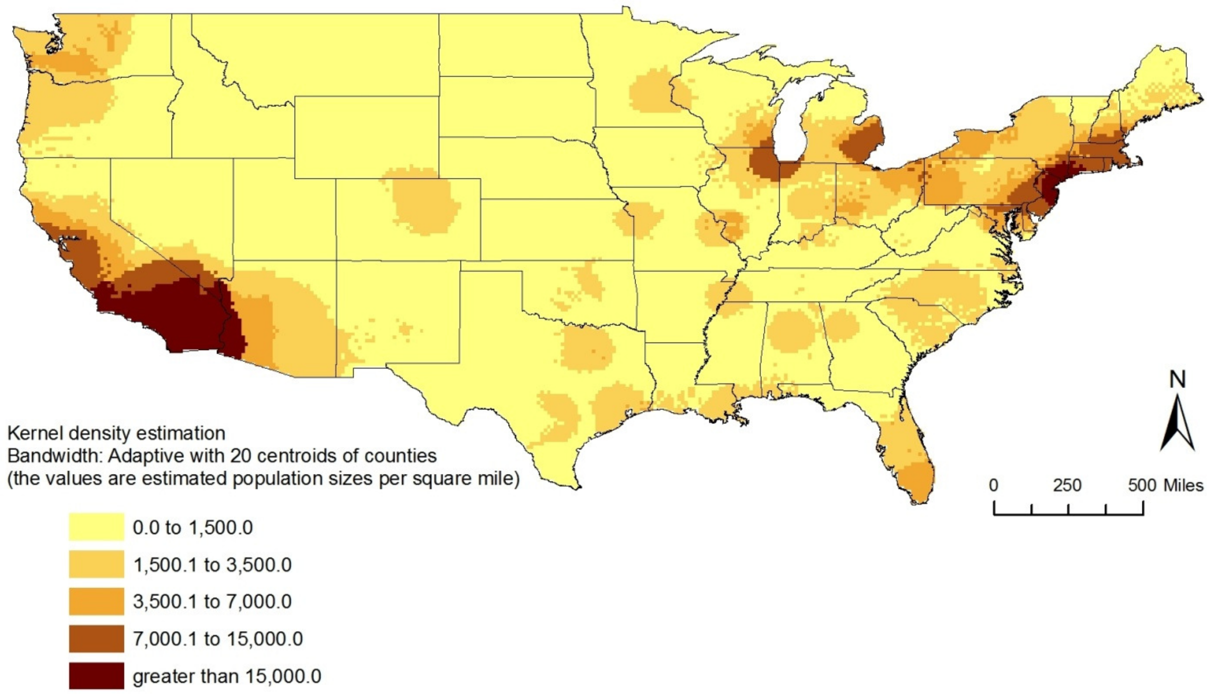


Figure E-2: Kernel density estimation of the estimated population in 1995

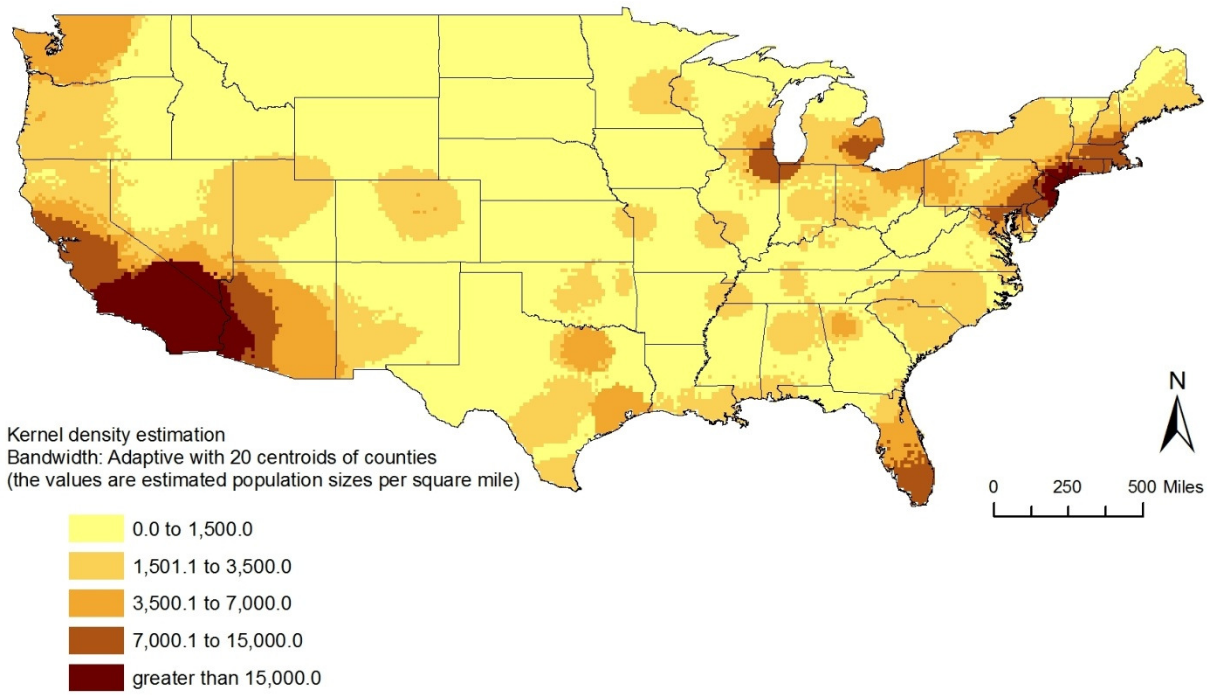


Figure E-3: Kernel density estimation of tornadoes weighted with the number of fatalities from 1950 to 2009

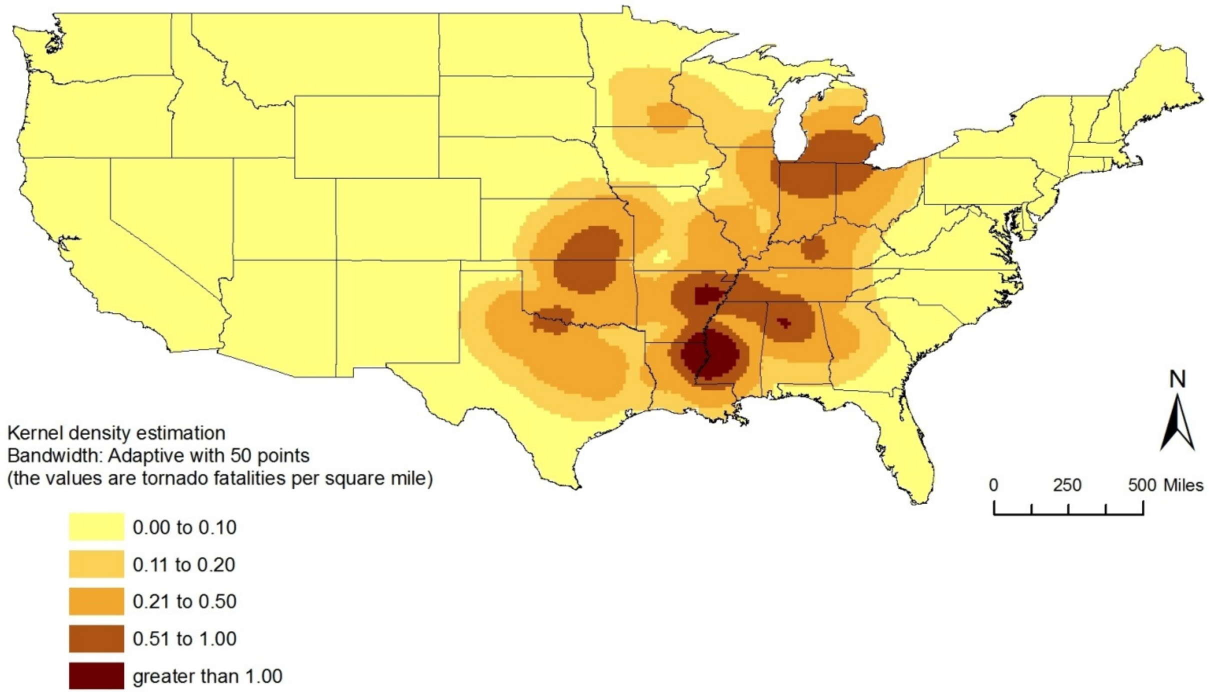


Figure E-4: Kernel density estimation of tornadoes weighted with the number of fatalities from 1980 to 2009

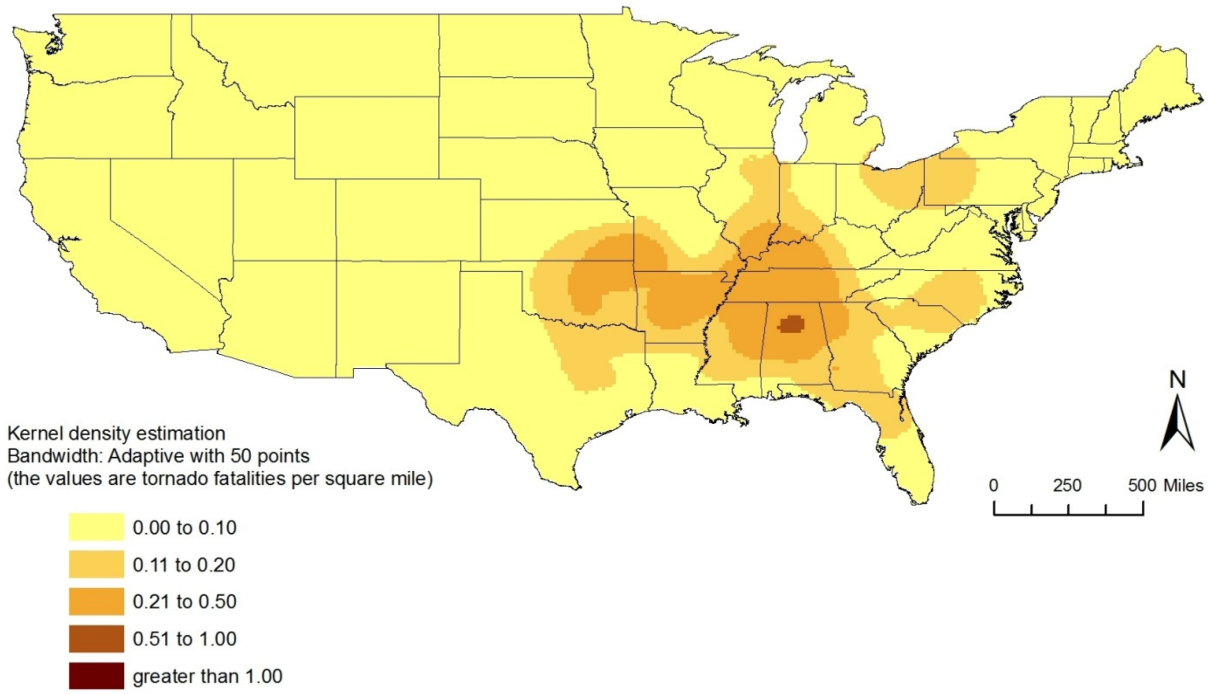


Figure E-5: LISA of tornado fatality rates for 1950 to 1979

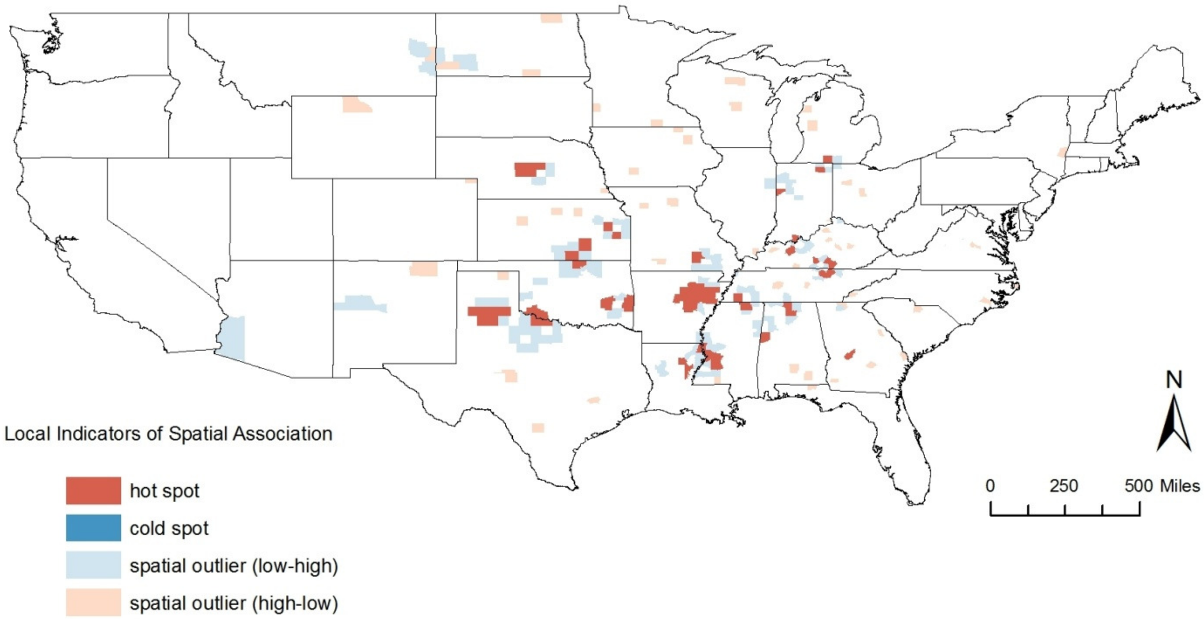
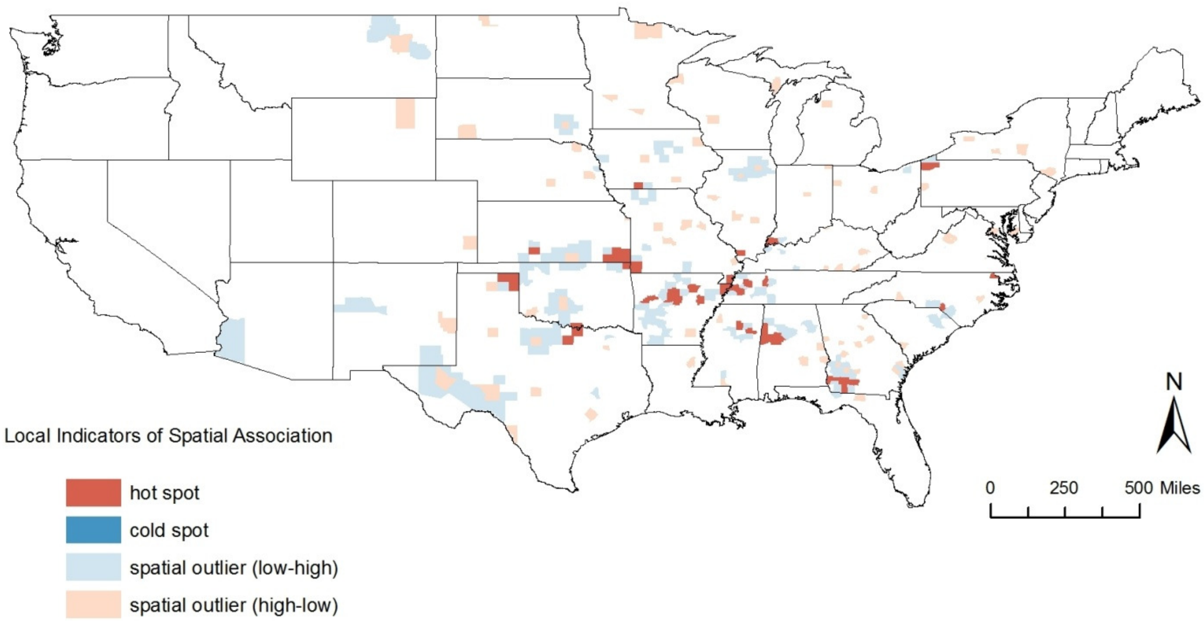


Figure E-6: LISA of tornado fatality rates for 1950 to 1979



CURRICULUM VITAE

March 2011

First Name/ Last Name	**PHILIP GLASNER**
Addresses	Lärchenweg 14, 7511 Mischendorf Pezzlgasse 72/2, 1170 Vienna
Phone	+43 664 523 83 38
E-mail	philip.glasner@univie.ac.at
Nationality	Austrian
Date of Birth	March 3rd, 1985

EDUCATION

Since 2007	Studies of Geography at the University of Vienna Branches of Study in Level 2 of the Diploma Degree Program: - Cartography and Geographic Information Science - Population Research/ Regional Demography
08/2010-12/2010	Research for the Diploma Thesis at the Department of Geography and Anthropology, Louisiana State University in Baton Rouge, LA, U.S.A.

PRACTICAL EXPERIENCE

07/2010	Project about Labor Force Participation in Austria, Statistics Austria
09/2009-08/2011	Teaching Assistant for Regional Geography (Univ.-Prof. H. Wohlschlägl), Department of Geography and Regional Research, University of Vienna
03/2008-09/2009	Teaching Assistant for eLearning, Faculty of Earth Sciences, Geography and Astronomy, University of Vienna
Summer 2008	Intern at the Vienna Institute of Demography, Austrian Academy of Sciences

GRANTS

2010	Performance Scholarship offered by the Austrian Federal Ministry for Education, Arts and Culture
2009	Performance Scholarship offered by private institutions
2009	Performance Scholarship offered by the Austrian Federal Ministry for Education, Arts and Culture
2008	Performance Scholarship offered by private institutions

Declaration

Herewith I affirm,

- That this diploma thesis was written by me.
  I did not use any sources besides those cited as references.

- That this diploma thesis was not submitted prior to this
  as an examination paper in any form.

- That this thesis is identical with the version evaluated by the advisor.

Erklärung

Hiermit versichere ich,

- dass ich diese Diplomarbeit selbständig verfasst habe, keine anderen als die angegebenen
  Quellen und Hilfsmittel benutzt und mich auch sonst keiner unerlaubten Hilfe bedient habe.

- dass ich dieses Diplomarbeitsthema bisher weder im In- noch im
  Ausland in irgendeiner Form als Prüfungsarbeit vorgelegt habe.

- dass diese Arbeit mit der vom Begutachter beurteilten Arbeit übereinstimmt.

Wien, im April 2011

Philip Glasner