Local Impacts of Tornadoes

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Abstract

This study provides an analysis of the new Visible Infrared Imaging Radiometer Suite (VIIRS) lights data to examine whether it delivers accurate data on economic changes following a natural disaster. Obtaining data on economic changes can be challenging, especially if disasters occur on a local level, as conventional measurements are not often collected on such a small scale. Therefore, night light data from the VIIRS offered an interesting approach to solving this problem, even more so as they have global ubiquity and hence independence.

In this study, tornadoes were selected because these natural disasters occur locally. Fixed effects regressions were run using R and, more specifically, the felm function.
The results indicate that the VIIRS light data capture a change in economic activity after a tornado. The night light brightness decreases in the aftermath of a tornado and recovers after a short time. This pattern is repeated after a few months. The stronger a tornado is, the stronger the effect. However, the effects are generally small.
Further investigations must be conducted to determine what might influence the VIIRS night light data and disentangle the various influences on the night light brightness. Thus, it is of interest to analyze this above-mentioned pattern of decreasing and increasing night light brightness after a tornado.

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1 Introduction

It is not without reason that tornadoes are called the most violent storms in nature. During their lifetime, they can gain enormous force and leave a trail of destruction and damage. Although tornadoes have such destructive power and much research has been conducted, many unsolved questions remain regarding their formation. To date, almost every country has registered tornadoes; however, large gaps exist concerning their frequency and number. With around 75% of all reported tornadoes worldwide, the US has the highest number and frequency of tornadoes, while only Antarctica has zero registered tornadoes (Goliger and Milford, 1998). Great Britain has the most tornadoes based on country size; however, they are mainly low-strength, especially compared to the US (NASA, 2019).

Field of Study:
On average, 1,200 tornadoes occur in the US per year. This imposes various challenges on the country. Since the official tornado recording was established in the US in 1950, over 5,000 fatalities and 85,000 injuries alone were reported (Simmons and Sutter, 2012).

In addition to the fatalities and injuries tornadoes can inflict, they also cause much damage and disruption, impacting the people living in the affected areas. Among others, damage and disruption of transport and utilities, as well as reduced traffic and employee productivity, might occur in the aftermath and thus severely harm the local economy. Compared to other natural hazards, tornadoes cause the third-highest number of fatalities and dollar losses (Boruff et al., 2003; Martinez, 2009). On average, 39.9% of insured catastrophic losses originate from tornadoes (1997–2016, inflation-adjusted), and the average annual loss adds up to $11.23 billion (in 2016, U.S. dollars; III, 2019). The tornado that hit Oklahoma on the 3rd of May 1999 caused damage of $1.2 billion (Ewing, Kruse and Wang, 2006). And in 2011, a series of tornadoes led to 552 fatalities and over $27 billion worth of insured property loss. Compared to Hurricane Irene, the most damaging hurricane of that year, the loss was approximately five times higher. These numbers illustrate the tremendous damage tornadoes can cause today (Simmons and Sutter, 2012; Romanic et al., 2016).

Night Lights: A New Approach:
A huge challenge in analyzing the implication of tornadoes is the lack of uniformity of data collection. Therefore, comparisons within the same country, let alone between different countries, and over time are difficult if not impossible to reach (Brooks, Lee, Craven, 2003). Over the years, new measurement approaches have been developed. Among the newer approaches to solving the problem of uniformity over space is the use of night light data from the new Visible Infrared Imaging Radiometer Suite (VIIRS).

Night lights are a suitable proxy for local-scale economic activity. When considering night light images (see Image 1), it is evident that higher night light intensities accompany a higher population density and, therefore, often increased economic activity (Henderson, Storeygard and Weil, 2011).

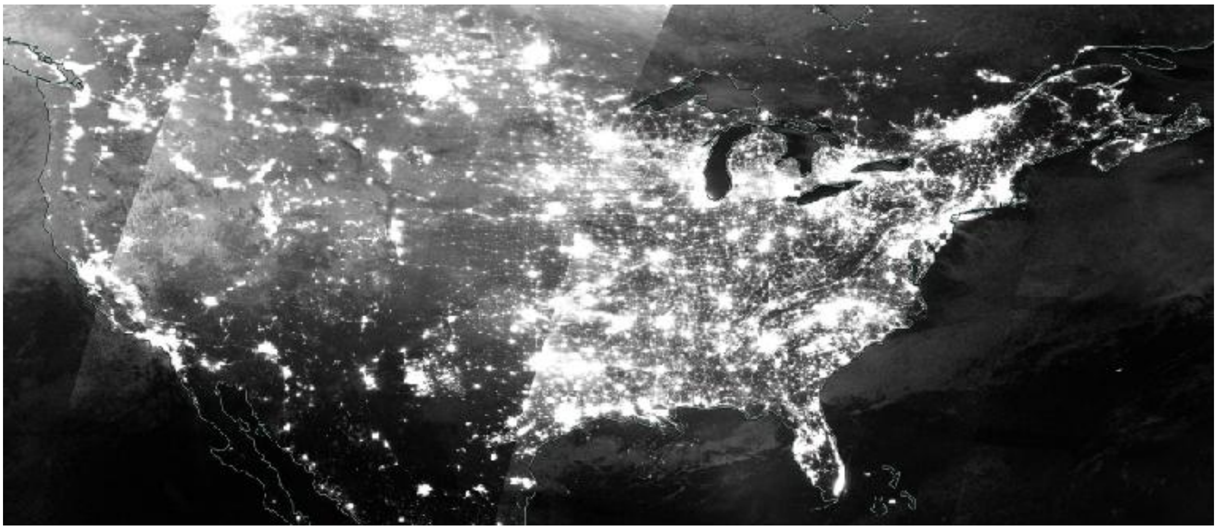


Image 1. VIIRS Image of the U.S. at nighttime, 2017 Feb. 04. (Source: NASA Worldview, https://worldview.earthdata.nasa.gov)

The concept of using night lights to predict economic activities is not new, and many scientists have used this approach to investigate war, genocides, income, poverty, emissions, electricity and many others (Donaldson and Storeygard, 2016). Overall, they illustrate people's nocturnal activity and are a suitable index of the economic wealth of a region (Bertinelli and Strobl, 2013). Therefore, changes in night light are a useful indicator of how much a region has suffered from a disaster, how fast it has recovered and whether an activity shift occurred (e.g. whether some regions are more or less active than before and whether some areas are more or less connected). Because night light data are available in high geographic detail (up to one square kilometre), they are suitable for mapping local economic activity trends. This is a major advantage compared to using GDP changes as a measurement since almost no country has GDP data on a city level; therefore, local effects are difficult to detect (Henderson, Storeygard and Weil, 2011). Additional advantages of using night lights are that in contrast to conventional statistical measures, they are collected independently, objectively, at a high frequency and worldwide (except at high latitudes) and thereby avoid problems associated with conventional standard measurements. They are also affordable for the public as one can extract them for free from the NASA's Earth Science Data Systems (Chen and Nordhaus, 2019; Henderson, Storeygard and Weil, 2011 and 2012).

Generally, studies examining night lights as a proxy for GDP concluded that, at least on a national level, this is a valid method (Chen and Nordhaus, 2011 and 2015; Henderson, Storeygard and Weil, 2012; Gillespie et al., 2014; Hodler and Raschky, 2014; Michalopoulos and Papaioannou, 2013; World Bank, 2017; Pinkovskiy and Sala-i-Martin, 2016). However, on a local level, as is the case for tornadoes, only a moderate correlation between night light brightness and economic activity was found (Doll, 2008; Ghosh et al., 2013; Mellander et al., 2015).

The VIIRS measurement has many advantages over earlier measurement instruments, enabling more precise data analysis on a local scale. Recent studies suggest that data from the VIIRS are more meaningful than those from its predecessors regarding prediction when used for estimating economic data (Chen and Nordhaus, 2015).
However, night lights might not be a suitable proxy for some economic activities, such as agricultural cropland production (Mohan and Strobl, 2017).

Structure of the Study:
Only a limited number of studies have examined the impact of tornadoes on the local economy in the US. Research is mainly performed on the implications of tornadoes at a higher level (e.g. national level). However, the impacts of tornadoes vary greatly between different regions, and their shocks occur locally. Therefore, this study aims to illuminate the impact of tornadoes on the economy on a local level. This is achieved using night light data to detect these local implications of tornadoes.

First, a literature review was conducted. The literature research focuses on the climatology of tornadoes as well as their local economic impacts. Although relevant studies from different countries are included, the main focus is the US. It is the country with the highest tornado frequency and also the one conducting the most tornado research. Much remains unclear about the impact of a tornado on the local economy. This study aimed to identify common ground and highlight different views by reviewing and summarizing the relevant literature. Additionally, some maps were created, illustrating the climatology of tornadoes in the US.

Second, a data analysis was conducted regarding the impacts of tornadoes on the US economy on a local scale. The tornado tracks and night light data used are solely from the US. Therefore, the second part of the thesis only focuses on that country. The main goal of the panel data analysis was to study the impact tornadoes have on local economies in the US using night light data obtained by the VIIRS. The change in the night light intensity around tornado paths compared to that before the storm should indicate changes in economic activity on a local scale. Additionally, lagged effects were examined to analyze the duration of the effect of tornadoes on night lights. Fixed effects regressions were created using R and, more specifically, the felm function to calculate these changes. The hypothesis is, that tornadoes do lead to a change in the night light brightness, at least in the short term. Furthermore, several relationships were of interest:

1. Does the number of injured depend on the magnitude of a tornado?
2. Does the number of fatalities depend on the magnitude of a tornado?
3. Does the amount of property loss depend on the magnitude of a tornado?
4. Does the amount of crop loss depend on the magnitude of a tornado?

This paper is organized as follows. Sections 2 and 3 outline the climatology of tornadoes and their impact on the economy, with the main focus on the US. Section 4 describes the data and methods used in this thesis. Section 5 presents the results of the statistical analysis. The results from the analysis and the findings obtained from the literature review are then discussed in Section 6. This paper ends with Section 7, which presents a conclusion.

2 Tornadoes

2.1 Tornado Appearance

Tornadoes can last from under 10 seconds to over 2 hours. In that time, their funnels can vary in many ways: the forward speed, direction, path width, path length, colour, wind speed, movement, sound and many more attributes can change. Some tornadoes may even remain invisible (Grazulis, 2001; Ahrens, 2008). The average diameter of a tornado is between 100 and 600 m. However, the path width can vary strongly, with some having diameters of only a few metres, while others may have diameters exceeding 1,600 m. The speed of a tornado is usually between 35 and 75 km/h, with some exceeding 130 km/h.

Tornadoes generally only last a few minutes; therefore, their path length is relatively short (on average about 7 km). However, this can vary widely; in extreme cases, tornadoes have lasted for hours and travelled hundreds of kilometres during this time (Doswell III. and Burgess, 1988; Ahrens, 2008; Encyclopaedia Britannica, 2019). The damage path of a tornado is often not particularly wide, leaving devastation in a compact area. Simultaneously, the surrounding neighbourhoods can remain undamaged (Smith and Sutter, 2013; Hatzis, Koch and Brooks, 2019; Ahrens, 2008; Encyclopaedia Britannica, 2019).

The potentially harmful impact is especially high for tornado outbreaks. According to Grazulis (2001), a tornado outbreak occurs when a single weather system produces six or more tornadoes whose activity lasts over 6 hours (Grazulis, 2001). A national tornado outbreak causes the highest number of deaths and injuries. Roughly every 10 to 15 years, the weather patterns over the US are such that they could produce a national outbreak. The largest outbreak occurred in April 2011, when over 300 tornadoes hit the eastern US within 2 days (Henson and Ahrens, 2016; Encyclopaedia Britannica, 2019).

2.2 Tornado Formation

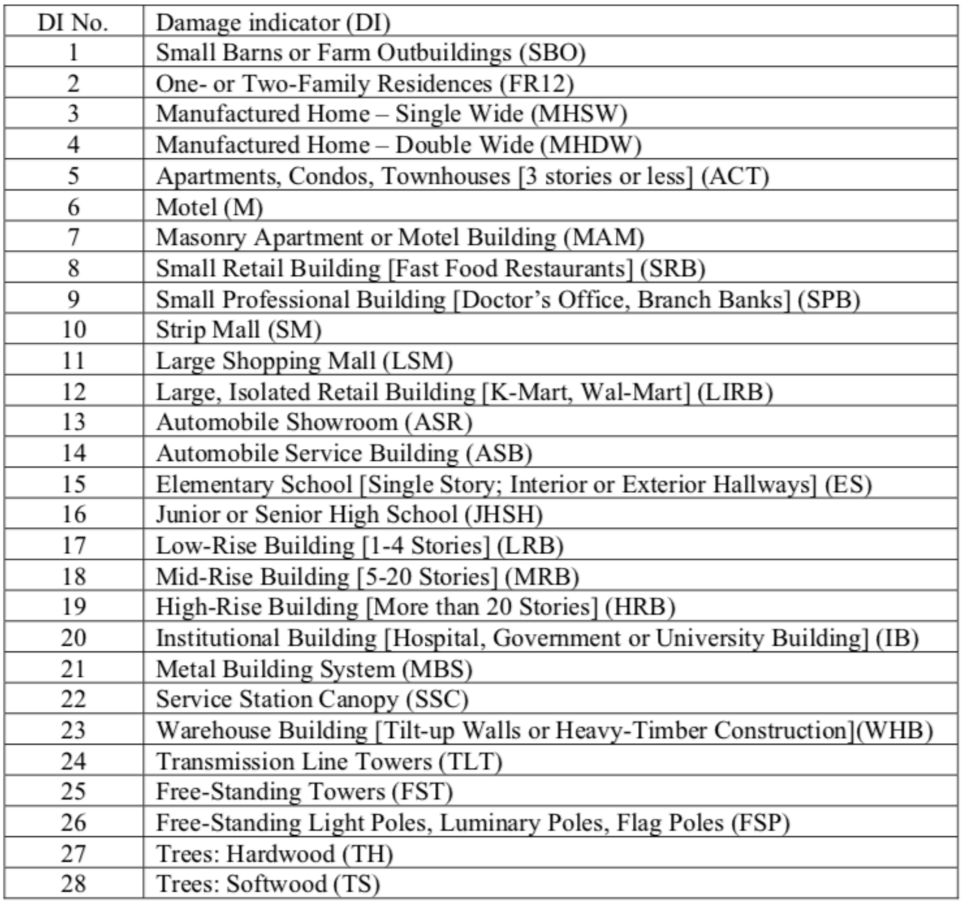
Although tornadoes are violent storms and can have tremendous impacts on the places they strike, understanding is lacking on their formation, magnitude, frequency and structure (Edwards, 2003; Womble, Wood and Mohammadi, 2018; Grazulis, 2001). A major reason why some aspects of tornado genesis remain poorly researched is that measurements of tornadoes are difficult to obtain and therefore rare. Additionally, storms are often too complex to fully understand all the processes occurring, much less measure them (Grazulis, 2001). Generally, tornadoes form within intense thunderstorms. The unstable atmospheric conditions they require for their development are the same as for any other severe storm (Aguado and Burt, 2007; Key, 2015). Under the appropriate atmospheric conditions, tornadoes can form anywhere and at any time of the year. Nevertheless, spatial as well as seasonal and daily patterns exist. Generally, a tornado is a rapidly rotating column of air with a circulation that reaches the ground and blows around an area of intense low pressure. Tornadoes occur with convective cells; however, they are not always accompanied by thunderstorms. Tornadoes are also known as twisters and cyclones (Keller and Blodgett, 2008; Key, 2015; Markowski and Richardson, 2014; Ahrens, 2008; Henson and Ahrens, 2016; Lozán et al., 2018; Cooley, 1978; Burgess and Donaldson, 1979; Ahrens, 2008; NSSL and NOAA, 2019; Etkin et al., 2001).

2.3 The Enhanced Fujita Scale

In 2007, the original Fujita scale to measure the magnitude of tornadoes was improved, and the Enhanced Fujita (EF) scale was adopted (Womble, Wood and Mohammadi, 2018; Henson and Ahrens, 2016). The new scale includes 28 different damage indicators (see Table 1) to estimate the wind speed, such as small barns, townhouses, and electrical transmission lines, to name a few. Overall, it considers how many damage indicators were affected and the degree of damage to them. This provides the wind speed and, therefore, the EF rating of the tornado. The EF scale includes six classes (EF0–EF5), whereby a larger EF number indicates a higher wind intensity (see Table 2). The EF scale aims to combine the observed tornado damage with wind speeds estimated by experts. However, except for two indicators, only damage caused to structures is captured. The absence of non-structural indicators makes the location of a tornado extremely important. Additionally, the EF scale does not cover the path length or width of a tornado. These are important features when reconstructing the events (Womble, Wood and Mohammadi; 2018; Henson and Ahrens, 2016; Doswell III., Brooks and Dotzek, 2009; McCarthy, 2003; Reeves, 2015; Doswell III. and Burgess, 1988).

Table 1 lists the 28 damage indicators. The wind speed and resulting EF class are evaluated by determining which indicators have suffered damage during a tornado.

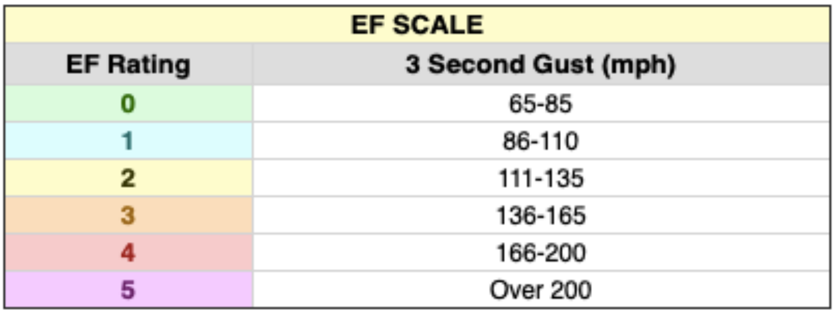
Table 1. Damage indicators of tornadoes. (Source: Wind Science and Engineering Center at Texas Tech University)



DI No.	Damage indicator (DI)
1	Small Barns or Farm Outbuildings (SBO)
2	One- or Two-Family Residences (FR12)
3	Manufactured Home – Single Wide (MHSW)
4	Manufactured Home – Double Wide (MHDW)
5	Apartments, Condos, Townhouses [3 stories or less] (ACT)
6	Motel (M)
7	Masonry Apartment or Motel Building (MAM)
8	Small Retail Building [Fast Food Restaurants] (SRB)
9	Small Professional Building [Doctor's Office, Branch Banks] (SPB)
10	Strip Mall (SM)
11	Large Shopping Mall (LSM)
12	Large, Isolated Retail Building [K-Mart, Wal-Mart] (LIRB)
13	Automobile Showroom (ASR)
14	Automobile Service Building (ASB)
15	Elementary School [Single Story; Interior or Exterior Hallways] (ES)
16	Junior or Senior High School (JHSH)
17	Low-Rise Building [1-4 Stories] (LRB)
18	Mid-Rise Building [5-20 Stories] (MRB)
19	High-Rise Building [More than 20 Stories] (HRB)
20	Institutional Building [Hospital, Government or University Building] (IB)
21	Metal Building System (MBS)
22	Service Station Canopy (SSC)
23	Warehouse Building [Tilt-up Walls or Heavy-Timber Construction](WHB)
24	Transmission Line Towers (TLT)
25	Free-Standing Towers (FST)
26	Free-Standing Light Poles, Luminary Poles, Flag Poles (FSP)
27	Trees: Hardwood (TH)
28	Trees: Softwood (TS)

Table 2 shows the six different EF classes according to the wind speed.

Table 2. EF Scale. (Source: National Weather Service. https://www.weather.gov/oun/efscale)



EF SCALE	
EF Rating	**3 Second Gust (mph)**
0	65-85
1	86-110
2	111-135
3	136-165
4	166-200
5	Over 200

3 Impacts of Tornadoes on the Local Economy

Different methods exist for distinguishing the damage caused by natural disasters as to where they strike (e.g. direct, indirect, short-term and long-term; Cavallo and Noy, 2011; Shabnam, 2014). In the Storm Prediction Center (SPC) database for 1950 to 2011, over 56,457 tornado reports are documented in the US; 33,756 of these tornado events resulted in reported damage. However, most of them did not result in large damage costs. Nonetheless, some single events or outbreaks cause tremendous harm. In 2011, one tornado alone led to damage of $3 billion. However, this was also the highest ever measured damage caused by a tornado (Simmons, Sutter and Pielke, 2013). During the period studied in this thesis (2007–2017), 64 severe storms resulted in losses of US$ 151.5 billion (Consumer Price Index adjustment (CIP) adjusted) and took 955 lives (NOAA and NCEI, 2019).

The following sections discuss some of the potential impacts of tornadoes on the local economy. In addition to the economic point of view, there is also an ethical aspect (e.g. 3.6. Value of Life). However, this is neglected here.

3.1 Employment Growth

Employment growth and its stability are used to indicate how well the economy is developing. Therefore, it is interesting to observe whether and how tornadoes influence this. Ewing, Kruse and Thompson (2003; 2004; 2009) conducted three studies on this topic. They selected three tornadoes and cities (Oklahoma City, Nashville, Fort Worth/Arlington). They then used different sectors (such as construction, finance, government and transport) to examine how their employment growth changed compared to the pre-disaster condition.

Overall, the changes in employment growth after the tornadoes were only transitory. However, in the short term, different sectors and cities responded differently. Some had experienced a transitory economic boost, such as with public transport and utilities. This is probably because they provide essentials for rebuilding. The construction and mining sectors also experienced an increase as they were highly important for the rebuilding. Other sectors were unaffected or briefly decreased before returning to their normal state within a short time. Among these were the manufacturing and service sectors. With time, the employment growth rate receded to its unconditional mean.

However, it is challenging to predict the impact of tornadoes on employment, as many aspects must be considered. The strength of the tornado, the pre-disaster economic condition of a city, and the main economic sectors of this area play an important role and can lead to diverse results. Ewing, Kruse and Thompson (2004) even concluded that the volatility of the labour market is decreasing in the long term, thus increasing its stability. This can be considered an improvement in economic activity (Ewing, Kruse and Thompson, 2004 and 2009).

3.2 Property Market Value

After heavy storms, the most visible damage is observed in real estate. Damage to structures and the resulting renovation measures are likely to impact the prices of the properties and the growth of the housing market. Therefore, the local housing market can indirectly measure the impact of disasters on the local economy (Ewing, Kruse and Wang, 2006).

De Silva, Kruse and Wang (2006) used the Oklahoma tornado of 1999 to examine the relationship between the magnitude of tornadoes (according to the Fujita scale) and a possible reduction in property market value. They studied the values of 89 properties before and after a tornado. Three years later, the damaged properties had lost approximately 76% of their initial value. The stronger a tornado is, the higher the market value reduction. However, stronger tornadoes result in many new buildings or at least fundamentally renovated houses. This accompanies an upgrade of some properties. Hence, within 3 years, these properties have exceeded their pre-disaster value by around 32% in terms of the tax base. Conversely, undamaged properties only showed a rise in property value of approximately 23% for the same time (De Silva, Kruse and Wang, 2006).

However, Ewing, Kruse and Wang (2006) observed that, on average, the immediate response in the aftermath of a tornado results in a 0.5%–1.2% reduction in the housing price index. Nonetheless, the estimations of the duration of a tornado's effect are inconsistent among cities and might vary greatly. However, it appears that most of the decrease occurs within 1 year of a severe windstorm. Subsequently, the change in the housing price index is only 0.19%–0%. It is likely that the more resilient the housing values were before the disaster, the shorter the impact of a tornado on the housing price (Ewing, Kruse and Wang, 2006).

3.3 Farmland Value and Crop Insurance

The United States Department for Agriculture (USDA) states that most crop producers choose a crop yield coverage of 70%. Consequently, the producers must pay for the first 30% of crop losses (Smith and Matthews, 2015). Massetti and Mendelson (2016) examined the effects of extreme events on agriculture in the US. They concluded that extreme events such as tornadoes, heat and cold waves do not affect the farmland value. This is due to subsidized public crop insurance. Hence, the premiums for the insurance are the same apart from the level of risk for an extreme event. A moderate tornado (<EF3) reduces corn crop yields by approximately 1.3% and soybean yields by approximately 1.7%, while strong tornadoes (≥EF3) reduce corn crop yields by approximately 1.7% and soybean yields by approximately 4.7%. However, all these effects are not statistically significant. One can expect tornadoes to cause damage to corn of about 0.07% and to soybeans of about 0.12% in a year on average (Massetti and Mendelson, 2016).

3.4 Insurance

In the US, tornado damage is covered by a standard homeowner's policy; therefore, most homes are insured. Homes with a mortgage are even required to carry such insurance. The Insurance Information Institute (III, 2019) claims that tornadoes count among the highest insured losses, amounting to 39.9% of all insured losses from 1997 to 2016. Insured losses due to severe storms (tornadoes, thunderstorms) average around $11.23 billion per year. The Swiss Re Institute (2018) analyzed the 20 costliest insurance losses in 2017. Six of them were tornado events (accompanied by hail, thunderstorms and others). All of them occurred in the US (Courbage and Stahel, 2012; The Insurance Information Institute III, 2019; Changnon et al., 2000; Smith and Sutter, 2013; Alabama Media Group, 2019; Swiss Re Institute, 2018).

Kunreuther and Roth (1998) claim that insurance companies are slowly trying to reduce their activities and increase insurance rates for regions experiencing many natural disasters (e.g. Florida and California). Consequently, some companies have complained that the risk of insolvency is too high for them to settle in such regions if they sustain such small amounts of

reinsurance, especially with an additional high risk of experiencing a natural disaster. Property owners in at-risk regions must not only pay significantly higher rates but generally have more problems acquiring insurance. A study conducted by Quote Wizard (2019), a private company that conducts insurance comparisons, found that natural disasters have increased insurance rates in each state of the US on comparing 2007 with 2016.
Of the 15 states with the highest increase in home insurance rates, 11 are in the so-called Tornado Alley (Arkansas, Colorado, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Nebraska, Oklahoma, South Dakota and Texas). On average, the home insurance rate increased by $580 for these states, equal to a 67% rise.

Additionally, many of these tornado-prone areas (such as Mississippi and Arkansas) are those with the highest number of uninsured homes. This is directly linked to the homes, which have no mortgages; therefore, the bank does not require coverage (Polygon, 2019; Insurance Journal, 2011).

For businesses and farmers, an additional problem arises. As mentioned above, most properties, businesses and farmland are sufficiently insured. However, only between 32% and 48% of firms have business interruption insurance that covers losses from missed economic activities in the aftermath of a natural disaster. Furthermore, 75% of commercial buildings are underinsured by around 40% (Smith and Matthews, 2015). The Federal Emergency Management Agency (FEMA) stated that immediately after a natural disaster, around 40% of small businesses will not reopen, and within 1 year, another 25% will shut in the US (FEMA and FLASH, 2019).

3.5 Population Change

The change in the population of a region illustrates the well-being of an economy. Therefore, it is interesting to examine how communities change after a significant tornado. A stable community with successful businesses, attractive living spaces, neighbourhoods and schools attracts people to settle or residents to stay. However, communities that cannot provide or have lost these facilities (e.g. due to a natural disaster) probably find it harder to attract people or even experience out-migration (due to loss of home, income, livelihoods or fear). Tornadoes make assessing such aspects more difficult, as they occur locally and often impact only a small part of a community. People moving inside the state borders are often not registered, which negatively impacts the local economy of the affected area. Poorer people settle and spend less; therefore, the local economic revenues might decrease (Simmons and Sutter, 2012).

Simmons and Sutter (2012) identified 141 tornadoes that killed 20 or more people, with the highest fatality rate of 695 (Tri-State Tornado, 1925), since the beginning of 1900 in the US. They analyzed the impact of the 35 tornadoes with the highest number of fatalities compared to the 35 tornadoes with the lowest fatality rates. On average, the population increased by 8.4% in the first decade after the tornado when considering the tornadoes with the highest death toll. Twenty years later, the average population growth was 15.5%. However, areas hit by tornadoes with the lowest death tolls registered average population increases of about 17.9% in the first decade after the tornado and 23.3% 20 years afterwards. Hence, it appears that tornadoes causing a higher number of fatalities, for example, those of a higher magnitude, slow the population growth.

However, overall, the magnitude of tornadoes is only one of many factors inducing people to stay or out-migrate. Many other factors play an important role (including rural areas vs urban areas, age of population and renters vs homeowners). Hoisington experienced a devastating tornado in 2001 that led to some out-migration to the surrounding communities. However, when an EF5 tornado hit Missouri (Joplin) in 2011, almost no out-migration was observed (Paul and Leven, 2002; Paul et al., 2003; Simmons and Sutter, 2012; Smith and Sutter, 2013; Boustan et al., 2017; Cong et al., 2018). Therefore, no clear conclusion can be drawn regarding whether tornadoes lead to out-migration.

3.6 Value of Life

Generally, the economic value of life tries to quantify the benefits of lives, respectively avoiding fatalities. Two approaches exist for calculating the value of a life regarding disasters. First, one can consider the human capital. Thereby the future of a human is considered in terms of production capacity and output. Second, one can consider the willingness of people to pay for changes that increase their probability of survival (Daniell et al., 2015). An example concerning tornadoes would be installing safe rooms or shelters.

Simmons and Sutter (2011) achieved this by calculating how high the value of a life must be rated to install shelters in all houses of the US. They took the tornado-prone state of Alabama as a basis for their calculation. They concluded that installing shelters in every permanent home would cost US$32 million for one saved life. As mobile homes are more prone to tornadoes, making a similar calculation for them would lead to costs of US$4 million for one saved life. Therefore, this approach appears to be more promising (Simmons and Sutter, 2011).

Older people (>65) appear more likely to die in tornadoes (Paul and Stimers, 2014). This would decrease the loss of human capital due to killer tornadoes, as the production capacity of people over 65 is smaller than that of younger working people.

3.7 Tornadoes as the Cause of Economic Boom: Theory of Creative Destruction

The theory of creative destruction is controversial. The basic concept is that a disaster leads to an increase in economic activity due to recovery processes. Furthermore, the destroyed infrastructure might be replaced by one of higher quality. Skidmore and Toya (2002) found that hurricanes and a higher rate of national economic growth are linked for many countries. Miao, Hou and Abrigo (2018) and Thompson et al. (2005a) found positive impacts on the economy in the long term for various disasters in the US.

Conversely, Addy and Ijaz (2011) investigated the economic consequences of a tornado that struck Alabama on April 27, 2011. They concluded that economic declines occurred in some important sectors (such as employment, state tax revenue, local sales tax revenue and gross domestic product GDP) of Alabama in 2011.

Similarly, Simmons and Sutter (2011) argue that tornadoes might increase the economic activity of the struck area; however, this does not indicate that the local community benefits from it. One must consider that people might need to spend more on conventional goods in the aftermath, which is associated with a high level of economic activity. However, many purchases people would make under normal circumstances become unaffordable after a disaster. Therefore, the unseen or diverted economic activity must be remembered. A balance normally exists between stocks (e.g. durable goods such as homes and infrastructure) and flows (e.g. income, spending) in the economy. After a disaster, the economic flow activity increases to restore the stock. However, this increase is temporary and thus cannot be compared to an increase in economic activity under normal circumstances. Thus, it is not a reliable measure of the well-being of the economy. Moreover, tornadoes can have a distributional effect. Some people are richer (e.g. those working in construction), while others are poorer (e.g. those losing their homes). Depending on how strong these voices are, the local economy might appear to have benefited from the disaster, while the reality might differ.

Miao, Hou and Abrigo (2018) analyzed 50 U.S. states from 1970–2013 for natural catastrophes (hurricanes, tornados, flooding etc.) and their impacts on spending, revenue, debt issuance and intergovernmental transfer. They found that states increased public spending in the aftermath. Simultaneously, nonetheless, they receive more federal transfers. This usually exceeds the expenditure of the states. Therefore, the negative impacts of a natural disaster were transitory and were outweighed by the positive ones.

Different results emerged from a study by Addy and Ijaz (2011) investigating the economic consequences of the tornado that struck Alabama on April 27, 2011. They concluded that economic declines occurred in some important sectors (such as employment, state tax revenue, local sales tax revenue and GDP) of Alabama in 2011. Although it is expected that sufficient revenues are generated to cover damage-related government expenditure, the surrounding areas rather than the affected communities probably profit the most from the positive economic impact of recovery activities.

Thompson et al. (2005b) examined the impacts of a devastating EF5 tornado that struck Oklahoma City in 1999. After the Oklahoma tornado, a shift in the relationships and linkages between the labour markets of the surrounding region and that of Oklahoma City could be observed. Oklahoma City developed stronger labour market linkages to the cities nearby while the linkages between these cities loosened. This was probably due to the higher labour market exchange due to an increased need for a labour force in Oklahoma City in the aftermath of the tornado (e.g. construction, rebuilding processes and clean-up efforts).

3.8 Conclusion

The impacts of natural disasters on the local economy are diverse and complex. However, tornadoes usually appear to have too small an impact to consider the economy of an entire region. Nonetheless, certain trends are observed that are probably related to high tornado activity (e.g. higher insurance rates). Additionally, many factors play a role in how a tornado affects the economy. Tornadoes are apparently a larger threat to small economies, while large metropolitan economies have usually shown resilience in recent years. Although metropolises are more densely populated, they have the resources to deal with natural hazards, both for preparing for and managing the consequences (Simmons and Sutter, 2012; Martinez, 2009).

Sutter, De Silva and Kruse (2009) claim that, at least for tornado-prone states, wind-resistant construction may not only be an efficient mitigation measure but also cost-efficient. For violent tornadoes, strengthening construction has minimal to no effect. However, as most tornadoes are of weaker magnitudes, EF0 and EF1, this strengthening of construction might have a significant effect. They conclude that wind-resistant construction worth $500 can reduce insured losses caused by tornadoes by 30%. However, this only holds for the most tornado-prone regions. For all the others, damage from tornadoes is too infrequent; therefore, this would not be cost-efficient.

Considering individuals, the losses and economic consequences of tornadoes might be substantially higher than when examining their impact on a national level. Hong, Kim and Lee et al. (2021) determined the long-term effects of foetal exposure to a super outbreak (148 tornados over 2 days in 1974). They found that foetal exposure increased the likelihood of sensory and cognitive difficulties by 17% and 8%, respectively, and reduced socioeconomic status by 1% (according to the late 30s of the individuals affected). According to Hong, Kim and Lee (2020), the annual income gap between those with and without sensory or cognitive difficulties is estimated at $36,120. Therefore, it is estimated that the total annual cost of physical health impairment was approximately $136 million in 2014 alone. This rough estimate is limited to the annual income gap and would be larger when considering the costs of a whole lifetime (Hong, Kim and Lee, 2020).

This illustrates that the research time plays a major role in assessing the impacts of tornadoes. Although the short-term effects may not be classified as serious, they may increase in importance in the long term (physical and psychological damage, decrease in property value, loss of tourist revenues and migration). Similarly, losses assessed as high in the short term can lead to a long-term economic upswing (improved reconstruction of industries and increased economic linking).

Research on how tornadoes affect the local population and consequently the local economy is minimal. Studies usually refer to an entire state or county due to data availability. This imposes some difficulties as, on a regional or national level, a disaster can lead to economic enhancement while the consequences for the affected community can diverge strongly. The Tornado Alley comprises many such small communities (Cross, 2001; Martinez, 2009). Hence, further research examining the impacts tornadoes have on local economies is needed.

4 Data and Methods

4.1 Night Light Data

The night light data are provided by the Earth Observation Group at the NOAA National Centers for Environmental Information (NCEI). These data originate from the VIIRS, specifically its panchromatic day/night band (DNB). The satellite (Suomi NPP) carrying the VIIRS was launched at the end of October 2011, and its data have been available since April 2012. The VIIRS is one of five sensors on board the satellite. The VIIRS instrument is a further development of some of the most important operational and research instruments dating back to the 1970s. Among others, these aged instruments included the MODIS, the OLS, the SeaWiFS and the AVHRR. With the improved VIIRS instrument, attempts are made to overcome some of the disadvantages of these instruments (Cao et al., 2013).

The VIIRS has a large swath width of 3,060 km at a nominal altitude of 829 km. An on-board aggregation scheme is used to ensure a constant spatial resolution. The high resolution and swath width allow full coverage of the world every 12 hours, at the day and night sides. The VIIRS has a scanning radiometer with 22 channels, with a wavelength between 0.412 and 12.01 µm. The channels contain 16 moderate-resolution bands (M-bands), five imaging resolution bands (I-bands) and one panchromatic band (DNB). The main goal of the VIIRS is to observe and measure cloud and Earth surface variables. With its unique approach to pixel aggregation, the VIIRS is able to control the pixel growth towards the end of the scan, resulting in more comparable spatial resolution data for the nadir and edge-of-scan. In more detail, the pixel footprint of the VIIRS data is approximately 0.75 × 0.75 km. Thus, it is a major improvement compared to its ancestor, the DMSP OLS, whose pixel footprint data are only 5 × 5 km at the nadir and 7 × 7 km at the scan edge. Therefore, the VIIRS data are stored at higher spatial resolution than those of the DMSP OLS, and the various channels can measure dimmer lights than those of its predecessor. The pixel values are given in radiance (nW cm^{-2} sr^{-1}). The wider radiometric detection range (due to the rotating telescope) and the calibration implemented on board the satellite avoids light saturation problems for the image data, which were a major concern for its predecessors (Chen and Nordhaus, 2015; Cao et al., 2013; Zhao et al., 2017).

The data used in this thesis originate from the VIIRS panchromatic DNB radiometer and can be downloaded for free from NOAA's NCEI (available online at http://ngdc.noaa.gov/eog/viirs/download_monthly.html[1]). The main objective of the DNB is to produce visible and near-infrared spectral imagery of the Earth during day and night. Traditionally, at night, the measurements were limited to the thermal infrared emissions, which contain minimal information regarding climate and weather. However, due to its large dynamic range (45,000,000:1), the DNB measures visible and near-infrared light even for extremely low levels at night. Therefore, reflected signals as low as a quarter moon illumination and up to the brightest daylight are detectable. This is a major improvement, considering that at night, the visible moonlight is up to six times fainter than sunlight. Hence, the DNB enables measurement of the full diurnal behaviour as well as processes of weather and climate variables (Cao et al., 2013). Additionally, it is a useful tool to detect natural and artificial night light emissions since they are stable, and a sudden change can often be linked to power outages. Therefore, satellite imagery is an important tool to assess post-disaster impacts by comparing before and after satellite images (Miller et al., 2013; Hultquist et al., 2015).

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[1] Accessed 10/08/2019. As of October 2021, this link does no longer work.

The NOAA's Earth Observation Group has already prepared the DNB data (Cao et al., 2013). Hence, impacts such as lunar illumination, stray light or cloud coverage that could interfere with this study are excluded. The data are a monthly average for the measured night lights from each recorded grid cell. Therefore, the night light data used in this thesis are averaged monthly data for the US from 2012 to 2017.

The data were fed into R, where they were cleaned, and statistical analyses were conducted.

4.2 Tornado Database and Urban Layer Database

The database for the tornadoes was obtained by NCDC and the SPC. These two centres have gathered and reviewed tornado data back to 1950 for the US, resulting in an extensive database. Among others, their data include the number of tornadoes occurring each year, the exact date and specific time they occurred, the states they occurred in and the F/EF scale. They also include the longitude and latitude values of the start and end points of a tornado track and the path's length and width. Moreover, data about property and crop loss and the numbers of injured and fatalities were collected. The data are accessible to the public for free. Therefore, the data needed for the descriptive statistics and the tornado maps could be extracted from this source (available online at https://www.spc.noaa.gov/wcm/#data[2]). Data about tornadoes in the US that occurred between 2007 and 2017 were analyzed.
Some limitations apply when using this dataset; however, few were relevant for the analysis conducted in this thesis. One disadvantage was that the NCDC records the tornado data in state segments and not in tornado tracks. Thus, tornadoes crossing state borders are counted multiple times. However, this problem was minimized, as every tornado has a single identification number. Therefore, by considering this number, multi-counting of the same tornado could be avoided. Other limitations, such as the change in the tornado magnitude scale, were not relevant to this thesis as only recent years were examined.

Only the impacts of tornadoes on urban and built-up areas of the US are examined since rural areas might be largely unaffected by their implications. Therefore, the data for the urban and built-up areas, according to the National Land Cover database from the U.S. Census Bureau, are extracted (available online at https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2010&layergroup=Urban+Areas[3]). The last update of the database was in 2010. They classified all units (e.g. population, territory) within urbanized areas (UAs, containing at least 50,000 people) as built-up and those within the urban clusters (UCs, containing between 2,500 and under 50,000 people) as urban. Additionally, the unit must show a population density of 1,000 people per square mile. Among many variables, the database includes the state's name, whether it is classified as urban/built-up and its area type. Rural areas are all those not classified as urban or built-up (Census Bureau, 2019).

4.3 Data and Method for the Tornado Track Maps

The tornado tracks were classified using the EF scale to map them according to their magnitude. A state layer was used to map the frequency of tornadoes per state, and the tracks were then counted for each state. This is how the frequency of tornadoes per state was calculated.

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[2] Accessed 10/10/2019
[3] Accessed 10/10/2019

The data used to map the geographical features (such as state names and boundaries) contain information about the states of the US, such as their longitude and latitude, name and the Federal Information Processing Series (FIPS) codes.

The free software QGIS 3.8.1 was used to create the maps. The same data were used to create the tornado track map per state and the EF tornado track map. The tornado data were summarized on the U.S. state level to create the tornado track map per state. This was achieved by counting all tornado points from 2007 until 2017 for each U.S. state. Each state was then coloured according to the number of tornadoes occurring in that state. Therefore, one can examine the frequency of tornadoes per U.S. state.

Data on the lengths of each tornado were taken and mapped to illustrate the EF tornado tracks from 2007 to 2017. The tornadoes were then classified according to their magnitude. Therefore, the frequency of the tornadoes could be observed based on their magnitude.

4.4 Statistical Analysis

The statistics programs R and RStudio and various packages of these programs were used to conduct the statistical analysis. The first step of conducting a statistical analysis is to create a reliable database. Therefore, corrections and bug fixes were performed to generate a clean and thereby reliable database. As the data set contained many variables that were irrelevant to this thesis, those required were selected, and all the others were omitted. The variables were then renamed and converted into factors.

The monthly VIIRS night lights have a noise floor (due to snow-covered mountains and volcanoes) that was not removed from the data. Consequently, some night light data had a small negative value. To address this, an inverse hyperbolic sine transformation, defined as $log(y_i + (y_i^2 + 1)^{1/2})$, was applied to the night light data (Aihounton and Henningsen, 2021).

The SPC has assigned each tornado its own identification number. As the same tornado sometimes appeared several times (e.g. when the same tornado crossed states), the tornadoes were grouped according to their identification number. Thus, multiple appearances of the same tornado could be avoided.

As some months experienced more than one tornado, every regression was run once with the mean magnitude of tornadoes and once with the maximum value of tornados. The grid points of the tornado tracks were then matched with those of the previously extracted night light data. Finally, the night light intensities along a tornado track before and after the tornado were compared. Thus, it could be determined how much the economy of this region was affected by the incident.

In a second step, the descriptive statistics were calculated. As the data were not normally distributed, a Spearman rank-order correlation coefficient (r_s) was used to determine relationships between the variables with a linear regression using the lm package in R. Multiple graphs were generated to illustrate further relationships as well as trends and seasonality.

In a third step, linear fixed effect models using the felm function in R were constructed with the night light intensity as a function of the tornado magnitude. The felm function allowed the inclusion of fixed effects and multiple group fixed effects to account for the effect of the year, month and location of the tornado as well as the cloud coverage. Standard errors were robust over the point ID.

The outcome of the fixed linear model illustrated the relationship between tornadoes and the night light brightness. The remaining coefficients were estimated using ordinary least squares (OLS).

In a fourth step, the lag function was used to determine the effect of tornadoes on the night light brightness.

4.5 Regression Specifications

Impact of Tornadoes on the Night Light Brightness

It is assumed that a relationship exists between a tornado and the brightness of the night lights in its aftermath compared to the brightness of the night lights before the tornado.
The data used are clustered panel data as the same data units were observed over a given time in the same space (the US). The following regression served as a baseline:

$$Y_{it} = \beta 0 + X_{it}\beta_{ft} + \beta_y + \beta_m + \beta_c + \varepsilon_{it}$$

On the left side of the regression stands the night light intensity for cluster i at time point t. On the right side, β is the coefficient of interest and ε is the random error term. X_{it} is a matrix of the time/point ID combination. β_f is the coefficient for the tornado magnitude and is time-variant. β_y and β_m are the coefficients for the year and month, respectively. β_c indicates the weather during which the sky was covered in clouds. By controlling for the year, year-specific effects for all grid points were included. This could have been, for example, a change in satellite data measurement, economic changes or energy cost changes. By including a month control variable, one could control for seasonality.

The tornadoes were grouped according to their magnitude. Hence, one could study whether different magnitudes had different impacts on the night light brightness. The single EF5 and all the EF4 tornadoes were combined in one group since a group with only one value would not be representative. Additionally, the above formula was extended by including lagged effects of tornado intensity in previous months.

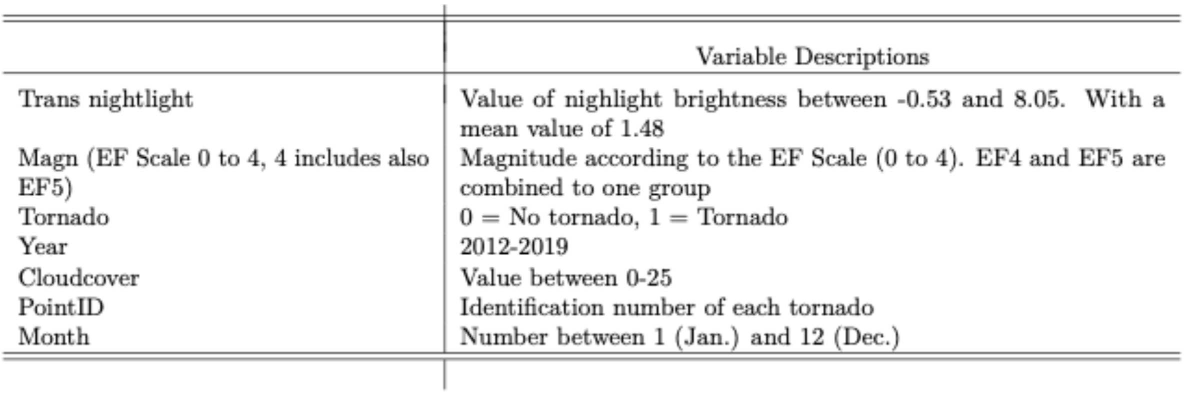
By including X_{it}, one can consider that some areas might have already taken mitigation or adaptation strategies against a tornado. This will probably weaken the impact a tornado could have on this gridded area. In our case, X_{it} represents the different point IDs.

A more detailed description of the variables used is presented in Table 2.

As we were only interested in populated areas, the urban layer used needed to contain over 2,500 people and show a population density of at least 1,000 people per square mile.
The felm function of RStudio was used to calculate the regression, as we had a linear model with multiple group fixed effects.

Table 3 explains the variables in greater detail.

Table 3. Descriptive Statistics. Description of Variables.



	Variable Descriptions
Trans nightlight	Value of nighlight brightness between -0.53 and 8.05. With a mean value of 1.48
Magn (EF Scale 0 to 4, 4 includes also EF5)	Magnitude according to the EF Scale (0 to 4). EF4 and EF5 are combined to one group
Tornado	0 = No tornado, 1 = Tornado
Year	2012-2019
Cloudcover	Value between 0-25
PointID	Identification number of each tornado
Month	Number between 1 (Jan.) and 12 (Dec.)

Three different calculations were run using the following regression:

1. Calculating a linear regression by only considering whether there was a tornado (1) or no tornado (0).
2. Calculating a linear regression by taking the magnitude scale (EF0–4) as a continuous scale.
3. Calculating the polynomial regression in case the relationship between the magnitude and the night light brightness was not linear.

Every calculation was run twice: once using the maximum magnitude (e.g. only the strongest tornado in that month and for the same location was counted) and a second time using the mean magnitude (e.g. the mean magnitude of all tornadoes appearing in the same month was taken).

Lagged Effects

A felm function with lagged magnitude variables was created to obtain a deeper understanding of how long a tornado impacted the brightness of night lights.
A time series of several months was generated. Hence, one could study the effects of tornadoes on the night light brightness for the first few months following a tornado. As the impacts of tornadoes are mainly local, it was assumed that, at least for a developed country such as the US, the economy would have recovered sufficiently that no effect on the night light intensity could be measured after the first few months. Therefore, the time series ended after 12 months. As a control, night light data where no tornado occurred were included in the regression. Therefore, the variable 0 was added as a control factor for no tornado. As a tornado magnitude EF0 exists, the whole EF scale was shifted by adding 1 to each value. Hence, a tornado of group EF0 was assigned the value 1, tornado group EF1 was assigned the value 2, tornado group EF2 was assigned the value 3 and tornado group EF3 was assigned the value 4. The value 5 was assigned to the combined tornado group containing EF4 and EF5.

Relationship Between Injured, Fatalities, Crop Loss, Property Loss and Length, Width and Magnitude of a Tornado

A linear regression using the lm package in R was used to illustrate the linear relationship between different variables. Again, the tornadoes were grouped according to their magnitude, and the EF4 and the single EF5 tornadoes were combined in one group. The linear regression constructed resembled the following:

$Y_{it} = \alpha + \beta_k \text{Tornado}_{it-k} + \mu_i + \varepsilon_{it}$

Variable Y is the dependent variable of interest at time t and for grid point i. The independent variable Tornado is the EF magnitude of tornadoes at grid point i and time t (this holds as an indicator of the potential tornado damage); β is the coefficient of interest, μ stands for the width and length of the tornado and ε is the error term. Again, the regression was always conducted twice. The first time involved taking the mean magnitude and the second time involved taking the maximum magnitude. The length and width were not necessarily independent of each other. Year and month variables were again taken as a control factor.

Several relationships were of interest. Hence, different variables were set as Var Y.

5 Results

5.1 Descriptive Statistics

The data series ranged from 2007 to 2017 and contained data on 9,606 tornadoes classified on the EF scale. All tornadoes not classified on the EF scale were excluded from the study. However, this only affected a small number of tornadoes. Table 4 gives an overview of some of the most important parameters examined in the descriptive part of this thesis. The night light values were transformed using a hyperbolic sine transformation.

Table 4. Descriptive Statistics. Variables. Rounded to two decimal places.

	Mean	SD	Median	Min	Max
Magnitude (EF Scale)	0.71	0.85	1.00	0.00	5.00
Injuries	1.02	20.95	0.00	0.00	1500.00
Fatalities	0.08	1.87	0.00	0.00	158.00
Property loss (in Mio $)	0.08	0.325	0.01	0.00	310.30
Crop loss (in Mio $)	0.00	0.08	0.00	0.00	7.5
Width (in yards)	161.35	243.28	75.00	1.00	4575.00
Length (in miles)	3.47	5.61	1.63	0.01	82.52
Nightlight	1.48	1.36	0.96	−0.53	8.05

While 4,696 EF0 tornadoes were observed during this time, only nine tornadoes with the strong EF5 magnitude occurred. For more details, see Figure 4 of Section 5.1.2, ‘Tornadoes in the US’. There were two peak years regarding the number of tornadoes: 2008 (1,495) and 2011 (1,692). Conversely, 2012 (938), 2013 (906) and 2014 (886) had significantly fewer tornadoes. For more details, see Figure 2 in the section ‘Tornadoes in the US’.

It is striking that six EF5 tornadoes occurred in the same year, 2011. A further two EF5 tornadoes occurred in 2008. Therefore, of these nine EF5 tornadoes occurring from 2007–2017, eight appeared in these 2 years alone.

Injuries and Fatalities

Although tornadoes can cause injuries and deaths, the data indicate that this is not the norm. As Table 4 illustrates, means of only around 1.02 injured and 0.08 fatalities are expected from a tornado. This indicates that tornadoes are not often fatal.

The number of fatalities and injured appears to depend heavily on the magnitude of the tornado. In almost all cases, a tornado of the weakest magnitude, EF0, resulted in no injuries (98.8%). In only 27 cases (0.6%), more than one person was injured by a tornado of this magnitude. Conversely, an EF4 tornado injured people in 77.5% of all cases. However, this number varied considerably, ranging from zero to a maximum of 1,500 injured people.

The trend for the number of fatalities was similar. Around 63.4% of all EF4 tornadoes caused deaths, while only two (0.04%) EF0 tornadoes caused one death (there was never more than one fatality caused by an EF0 tornado). Nine EF5 tornadoes caused zero to 1,150 injured. Again, this illustrates the large variation in the number of injured caused by an EF5 tornado. A similar trend was observed for the number of fatalities: between two and 158 fatalities were caused by an EF5 tornado.

Width and Length of Tornadoes

The width of tornadoes differs relatively strongly, as shown in Table 4. However, around 64.1% of all tornadoes did not exceed the mean value of 161.35 yards (147.54 meters). Like the tornado width, the tornado length can also differ greatly, as shown again in Table 4. The mean length was 3.47 miles (5.58 kilometres), with around 57.8% of all tornadoes not exceeding this value. As the strength of a tornado increases, its length normally also increases. A similar trend exists for the relationship between tornado strength and width. However, this positive relationship appears to disappear as a tornado increases in strength; therefore, no statistical significance exists between the width of a tornado and its magnitude when the magnitude exceeds EF3.

Property Losses

On average, a tornado results in property losses of approximately $83,223. More details are provided in Table 4. The highest property loss was caused by EF3 tornadoes ($310,300,000). Remarkably, the 10 tornadoes resulting in the highest property loss were all EF3 and EF2 tornadoes, except for one EF4 tornado. The high standard deviation suggests that large differences exist in how much property loss a tornado causes.

Crop Losses

On average, the crop loss caused by one tornado was $2,019. An EF1 tornado caused the most crop damage ($7,500,000). Of the top 10 tornadoes causing the most crop damage, only those of EF magnitudes 1 to 3 were found. More details are provided in Table 4. Again, the standard deviation was high.

When considering the data, it was striking that the strength of the tornadoes appeared decisive regarding the number of casualties and injured. Conversely, regarding property and crop loss, this appeared to play a minor role. However, since only data from built-up and urban areas were used, no reliable conclusions on farmland and crop loss could be drawn.

Night Light Values

Frequency:

After performing the inverse hyperbolic sine transformation, the spectrum of the night light values appeared, as shown in Figure 1. The lowest night light value was −0.53 cm^2 × sr, while the highest was 8.05 cm^2 × sr. Overall, 8,209,866 night light values were recorded.

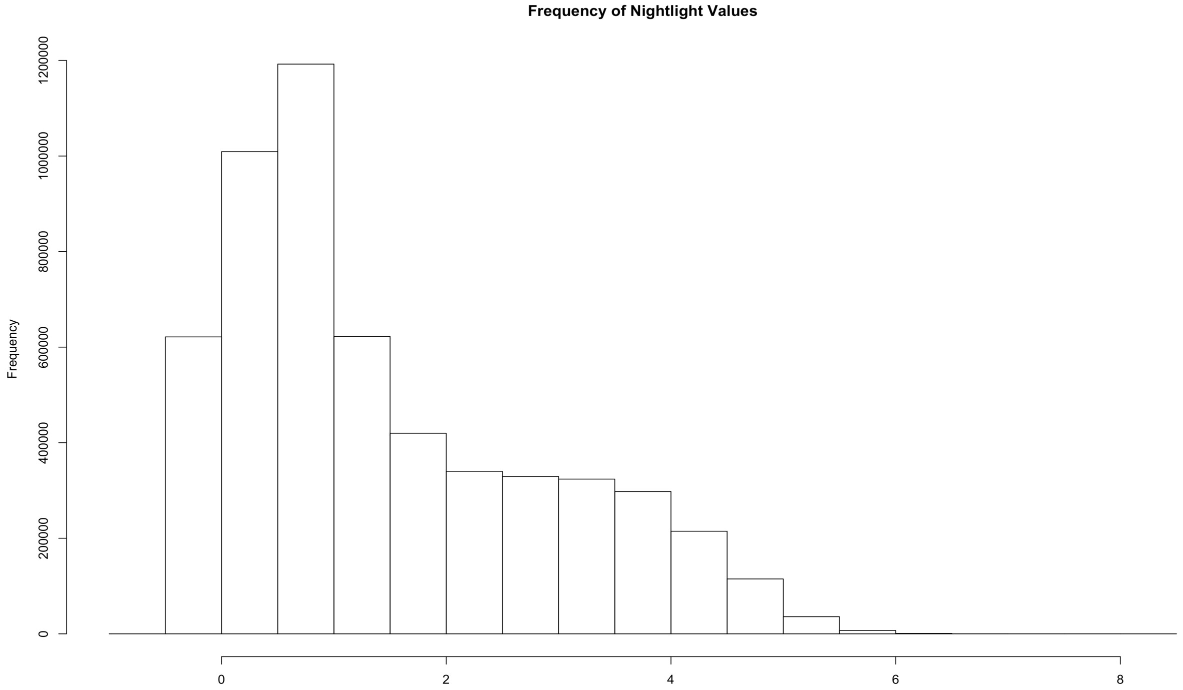


Figure 1. Night Light Values After Inverse Hyperbolic Sine Transformation

Monthly Trends in Night Light Intensity:
A Kruskal-Wallis test in the form of a box plot was performed to determine the seasonality of the night lights. The more stars a month had, the smaller the calculated p-value.
A significant p-value indicated that the central tendency of night light intensity differed between two adjacent months.

Night light values appeared lower in the summer, with June and July having the smallest night light values. However, exceptions existed, such as August and September, in which the night light values increased considerably, even compared to the months occurring later in the year. Figure 2 illustrates the night light values for every month of the year in more detail.

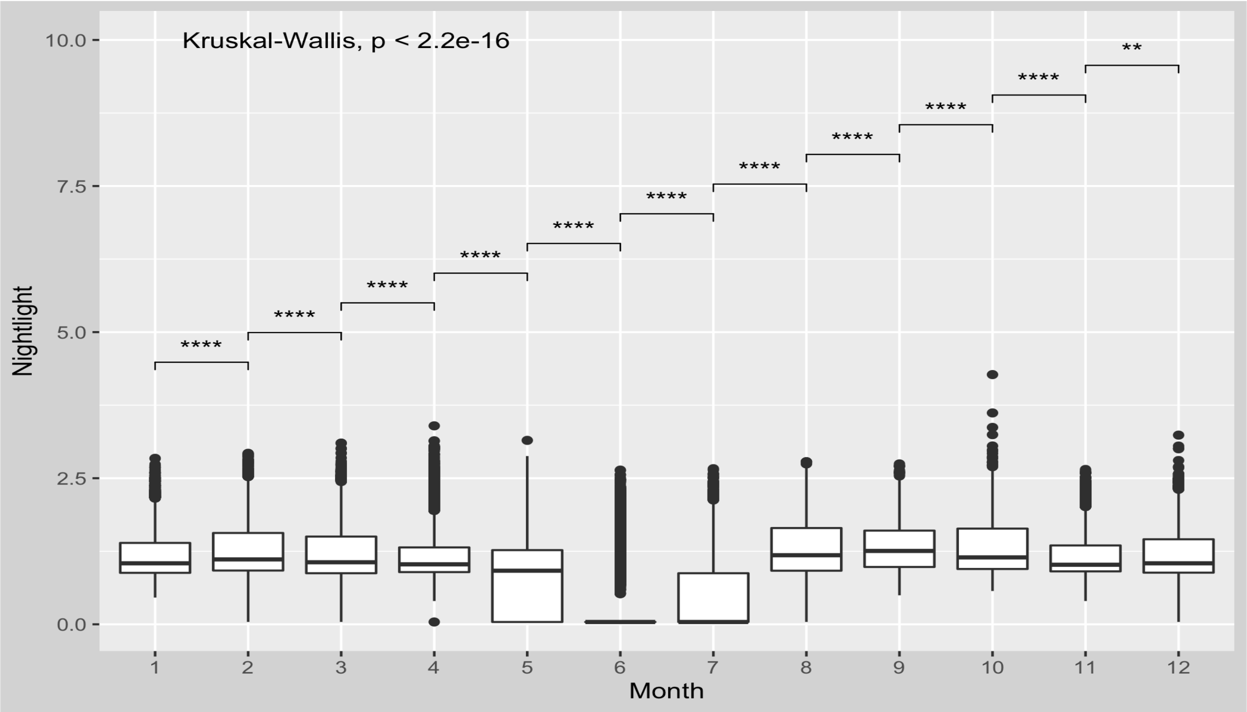


Figure 2. Monthly Trends in Night Light Intensity

5.2 Study Area: Tornadoes in the US

With approximately 75% of all tornadoes recorded worldwide, the US is the country where the most tornadoes occur. This high number of tornadoes is a consequence of the meteorologically favourable conditions for the formation of tornadoes to which the US is exposed. A major cause is the warm and humid air masses from the Gulf region flowing unhindered to the northeast of the Rocky Mountains where, consequently, violent thunderstorms can form. On average, 1,253 tornadoes are recorded each year in the US (considering 1991–2010). However, this number can vary greatly from year to year. Approximately 1,700 tornadoes occurred in 2011, while only about 900 tornadoes appeared in 2013 (NOAA, 2019; NASA, 2019; Lozán et al., 2018). The reason behind these large annual differences is that favourable and less favourable conditions exist for tornado development. It has been shown that a La Niña year leads to an above-average number of tornadoes, while El Niño years tend to lead to a below-average number of tornadoes. For example, 2011 was a strong La Niña year (Allen, Molina and Gensini, 2018; Cook et al. 2017; Lee et al., 2013; Lee et al., 2021).

Figure 3 illustrates the number of tornadoes, classified using the EF scale, for 2007–2017.

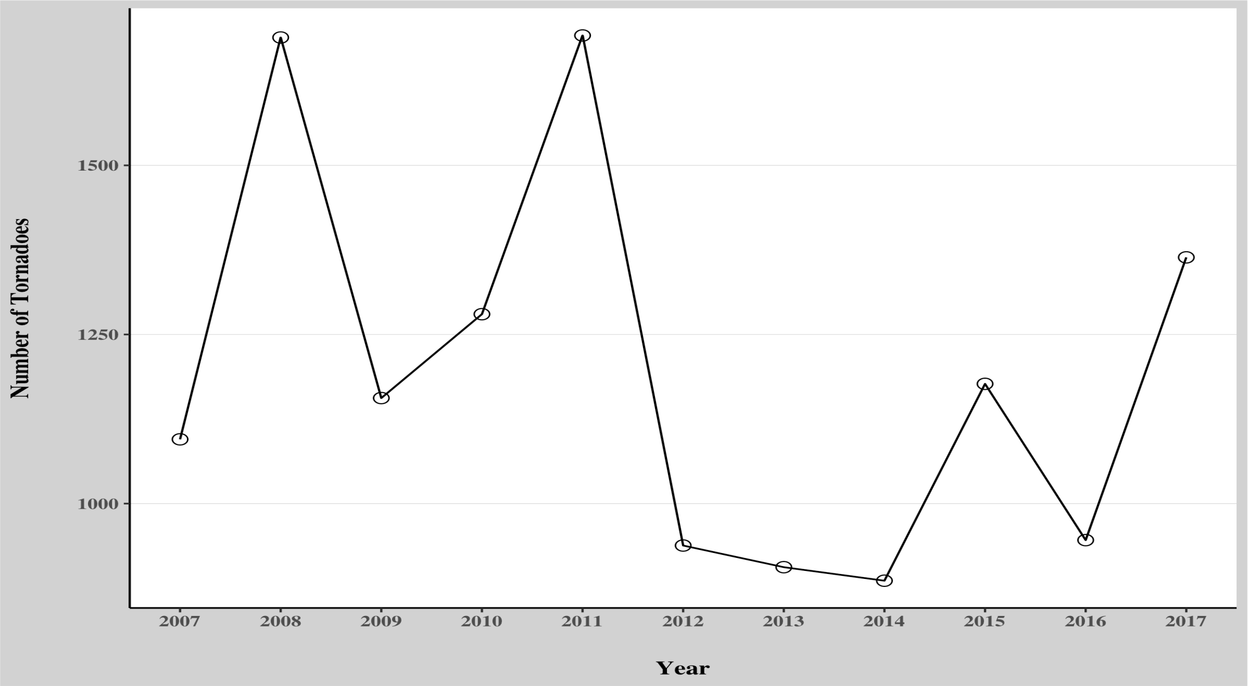


Figure 3. Number of Tornadoes 2007–2017.

Like all disasters, tornadoes can cause much harm. Since the official tornado recording was established in the US in 1953, over 5,000 fatalities and 85,000 injuries were reported. Compared to other natural hazards, tornadoes cause the third-highest number of fatalities and dollar losses. However, over 95% of all tornadoes result in no deaths. Between 1950 and 2010, only 106 tornadoes caused 10 or more fatalities.

Most tornadoes are in categories EF0 and EF1 (88%), and only about 1% are in categories EF4 and EF5 (Simmons and Sutter, 2012; Mihajlovic, Ducic and Buric, 2015). Simmons and Sutter (2012) illustrate that EF5 tornadoes are by far the fewest but rank highest in terms of fatalities and damage. While an EF5 tornado results in damage of around $300 million on average, an EF4 tornado results in around $45 million worth in damage and an EF3 tornado in $14 million. However, EF3 tornadoes are around 56 times more frequent than EF5 tornadoes.

Figure 4 illustrates the numbers of tornadoes from 2007–2017 according to their magnitude.

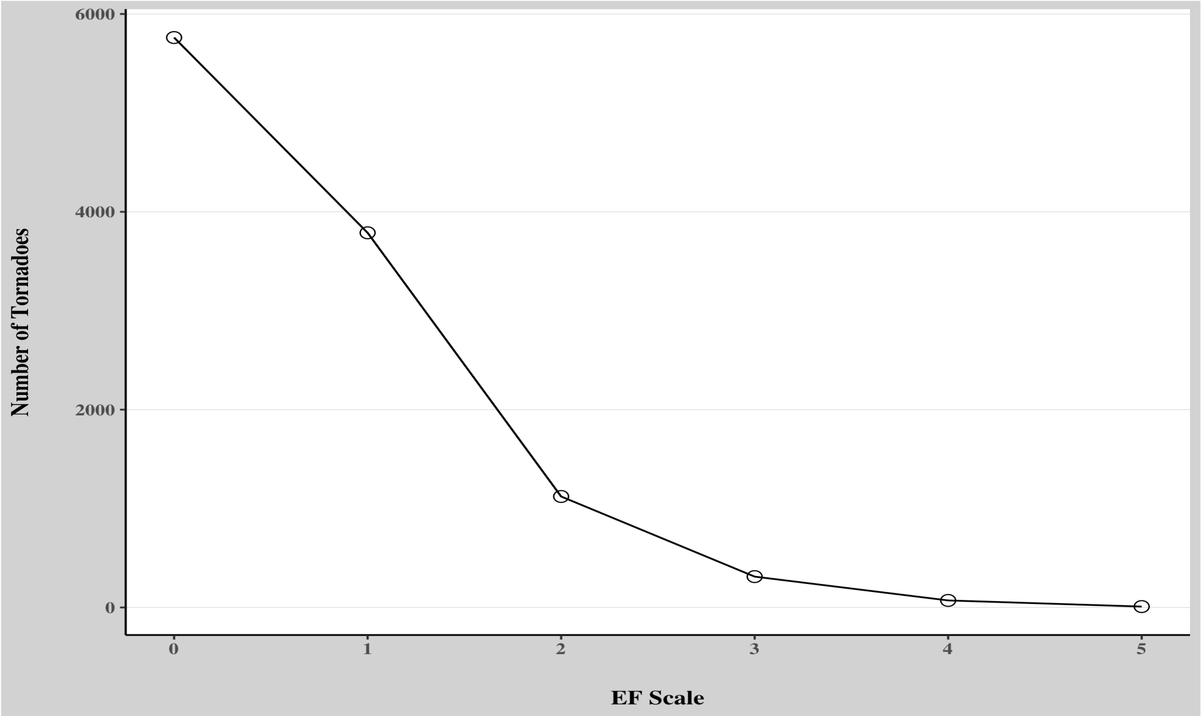


Figure 4. Frequency of Tornadoes Based on Their Magnitude (2007-2017).

5.3. Tornado Season

The most active tornado season lasts from May to July as the development of thunderstorms requires warm, humid surface air. Approximately 70% of all tornadoes occur during this period. April, with an average of 219 tornadoes, and May, with an average of 234, are the months with the highest numbers of tornadoes. This could be due to the vertical and horizontal temperatures and the differences in moisture, which are large in April, although the reasons are not yet fully understood (Simmons and Sutter, 2012). December is the month with the fewest tornadoes, with an average of about 33. However, October appears to have more tornadoes (with an average of 55 tornadoes) than September (with an average of 44 tornadoes) or November (with an average of 38 tornadoes), indicating a small peak in tornado activity in the fall. In 2011, April had the highest number of tornadoes for the examined period, with 758 tornadoes occurring in that month alone. Yet, this can vary greatly.

However, a regional pattern of tornado seasonality also exists. In the Midwest, the tornado peak usually occurs in spring. The further north, the later the main tornado activity occurs. Additionally, the south-eastern states experience two tornado seasons (late winter/early spring and autumn) while the Midwestern states normally experience only one (in spring; Brooks, Lee and Craven, 2003). These differences are explained by the weather pattern of the US (Henson and Ahrens, 2016; Encyclopaedia Britannica, 2019; Lozán et al., 2018).

Figure 5 illustrates the tornado seasonality for 2007–2017.

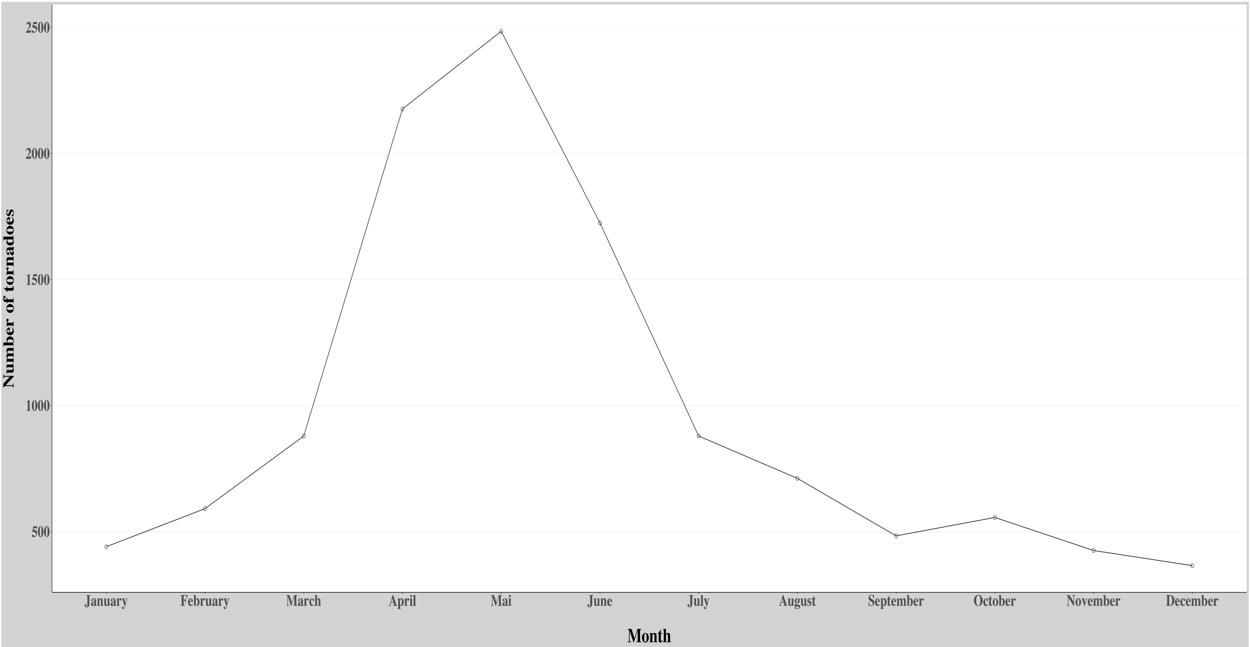
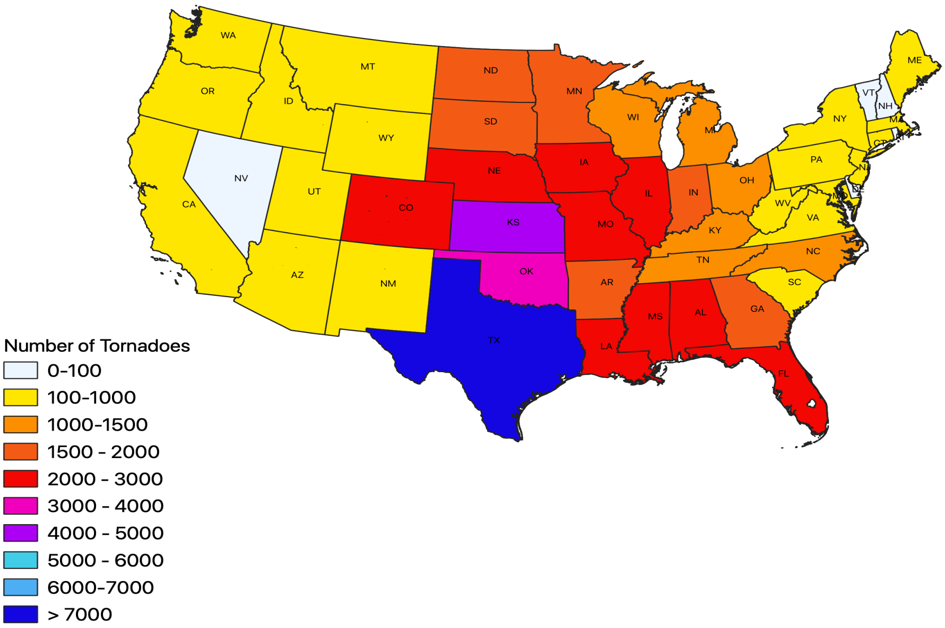


Figure 5. Tornado Frequency per Month (2007–2017)

5.4 Regional Pattern

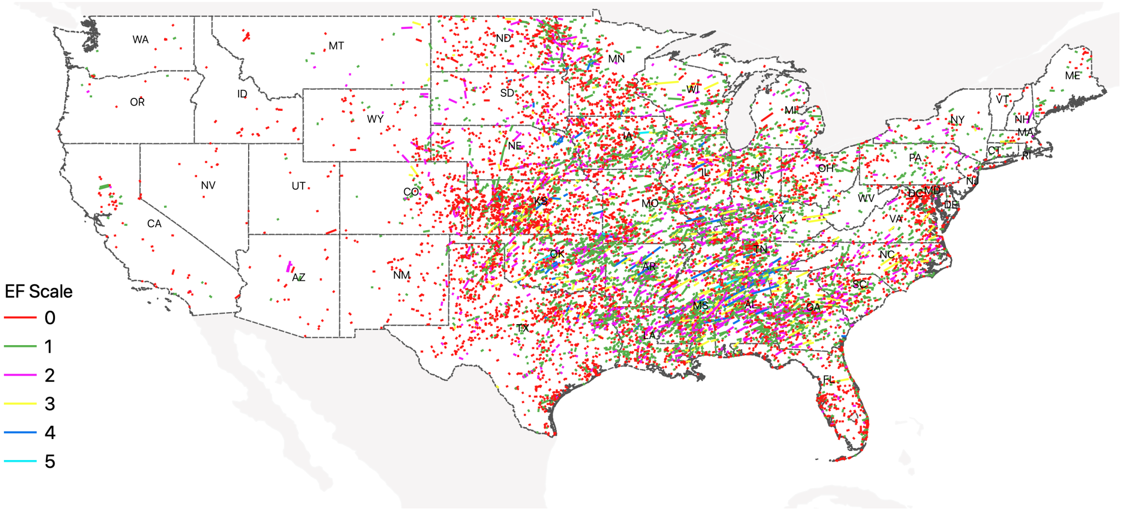
Although large differences exist between the U.S. states regarding tornado frequency, tornadoes have occurred in all states. Two maps were created to illustrate the regional patterns of tornadoes. Map 1 shows that two regions in the US experience an over proportionate number of tornadoes: the state of Florida and the so-called ‘Tornado Alley’, an area in the southern plains of the US. From a meteorological viewpoint, these two areas are ideally situated for the formation of thunderstorms, which can produce violent tornadoes. However, the tornadoes in Florida tend to be weaker than those in Tornado Alley (NOAA, NWS and NCEI, 2019; Reeves, 2015; Encyclopaedia Britannica, 2019; Bohonos and Hogan, 1999).

Map 1 illustrates the frequency of tornadoes per state for 2007–2017.



Map 1. Tornado Frequency per U.S. State (2007–2017)

Map 2 illustrates all the tornado tracks for 2007–2017. The tornado tracks are grouped according to their EF scale (EF0–EF5) for the tornadoes occurring between 2007 and 2017 in the US.



Map 2. Tornado Tracks in the US (2007–2017). EF scaled.

5.5 Results Regression

The change in night light brightness was estimated for up to 12 months after a tornado by lagging the impact of tornadoes on the night light brightness to analyze how long the effect of the tornadoes on the night light brightness lasts. The regression using the continuous magnitude and the polynomial regression were calculated for a tornado of magnitude EF1, one of magnitude EF3 and one of magnitude EF5 to analyze how the magnitude impacts the change in night light brightness.

Linear Regression With/Without Tornado:
A linear regression was calculated with

- 0 = no tornado occurred
- 1 = a tornado has occurred

A tornado leads to an immediate reduction in the night light brightness. Shortly afterwards, the night light brightness rises again steadily. So much so, from a certain point, the lights shine brighter than before the tornado. At around month 9, the night light brightness decreases again. Figure 6 illustrates these results in more detail.

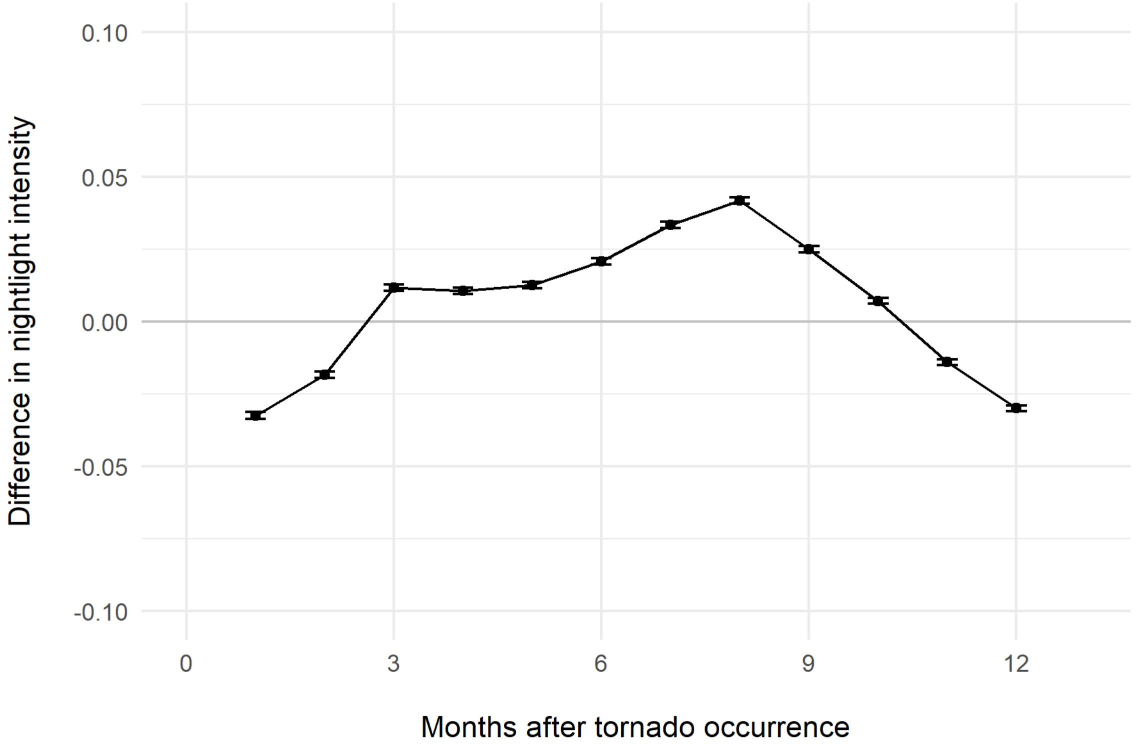


Figure 6. Linear Regression With/Without Tornado

Linear Regression with a Continuous Magnitude Scale:
A linear regression was calculated by taking the strength of the tornadoes as a continuous scale.

In the first month following a tornado, the night light brightness was slightly reduced, only to slowly increase again thereafter. In month 2, the night light brightness reached a positive value, meaning that all three tornado magnitudes led to brighter night lights in the second month after the incident. After 2 months, the night lights shine brighter than before the tornado, and at around month 8, a sudden decrease in the night light brightness was observed. However, the night lights appeared to recover in month 12. Figure 7 provides more details concerning the results. The results resemble those calculated in the regression above with/without a tornado. The main difference was that the values were smaller when using the continuous scale.

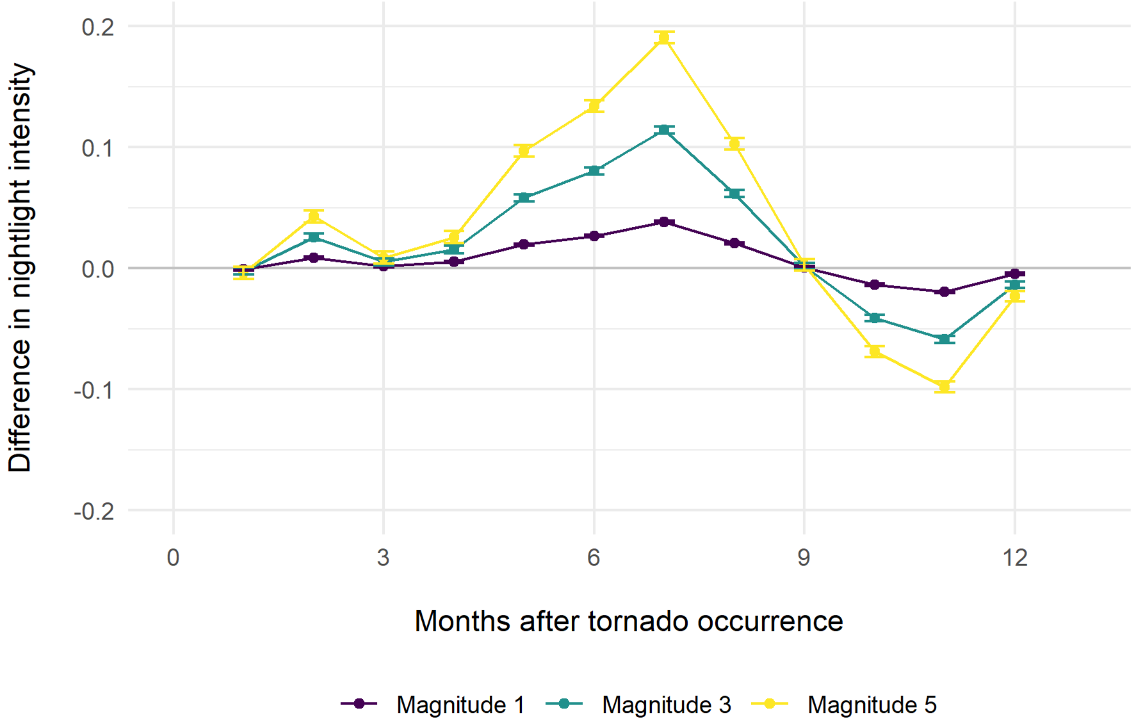


Figure 7. Linear Regression Continuous Scale

Polynomial Regression:
As with the above regression, the maximum and average strengths of the tornadoes per month were calculated. Slight differences were observed between these two regressions, with one regression sometimes showing slightly higher values and then vice versa. However, the differences remained within a small range.

Generally, it was noticeable that tornadoes in categories EF1, EF3 and EF5 had similar effects on the night lights. Conversely, the EF3 tornadoes had a slightly stronger effect than EF1, and the EF5 tornadoes had a stronger effect than the EF1 and the EF3 tornadoes. In the 1st and 2nd months after a tornado, the night lights decreased. Afterwards, the brightness increased again. In month 9, a second attenuation of the night lights began, reaching the lowest night light value in month 12. The effects of the EF5 tornadoes were much stronger than for the two lower magnitudes. The results resemble those calculated in the linear regression with/without tornado.

More details are provided in Figure 8.

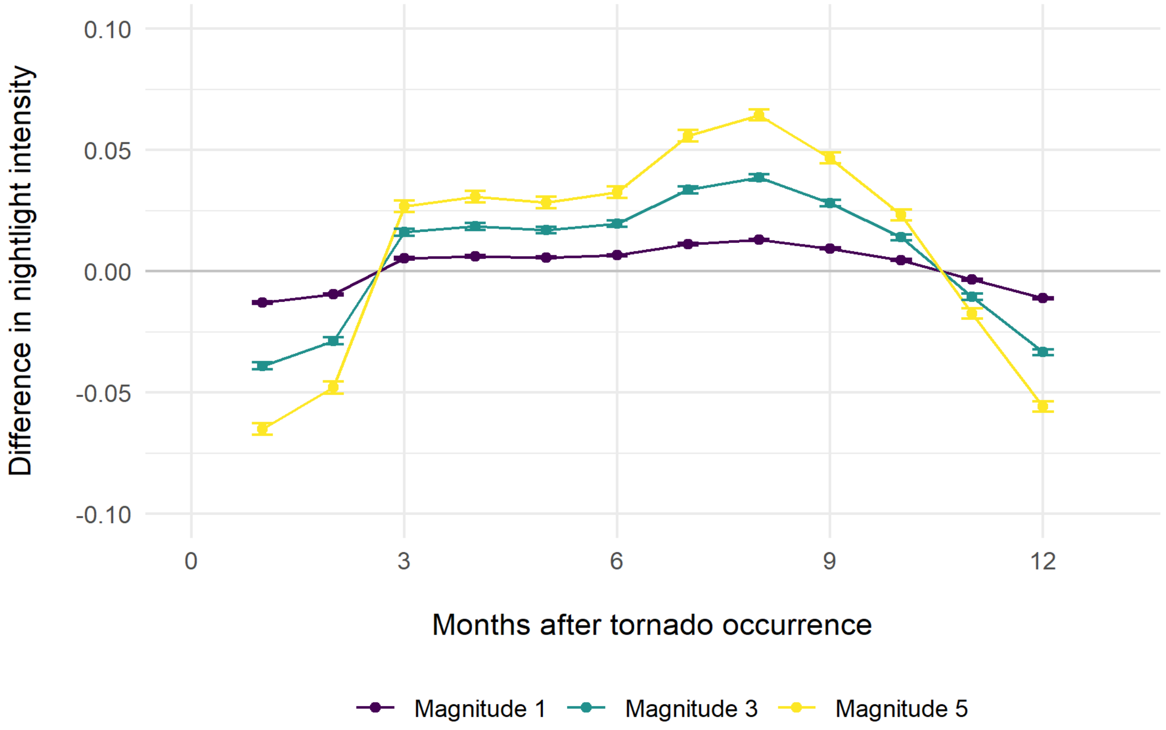


Figure 8. Polynomial Regression

Overall, all three models showed similar results. Given the consistency of the results, the models appeared robust. The R^2 value of the models was 0.957.

Generally, the effects using the mean magnitude appeared slightly lower than those using the maximum magnitude. However, the difference was negligible. More so polynomial models tend to overfit; thus, it is difficult to make predictions using such a model.

5.6 Changes in the Night Light Values After a Tornado

Five different and diverse cities were chosen to analyze how night lights change after a tornado (including topography, geography and size). The mean brightness of the night lights was calculated. The average night light value for several years was calculated to ensure that no external factors (e.g. seasonality) distorted the night light values. The results illustrate the change in night light brightness compared to the mean night light value as a percentage change. All values were rounded to decimal places. The post-tornado night light values were calculated by the linear regression with the continuous scale, as this model allows a distinction between the different tornado magnitudes. As a control, all the calculations were also performed using the results from polynomial regressions.

Image 2 illustrates the nightly radiance for the four chosen cities on the night of the 21st of March, 2021. This was downloaded for free from the NOAA National Centers for Environmental Information VIIRS DNB. Maps 1 and 2 in Chapter 5.1.4 provide more detail concerning how prone the different states are to tornadoes.

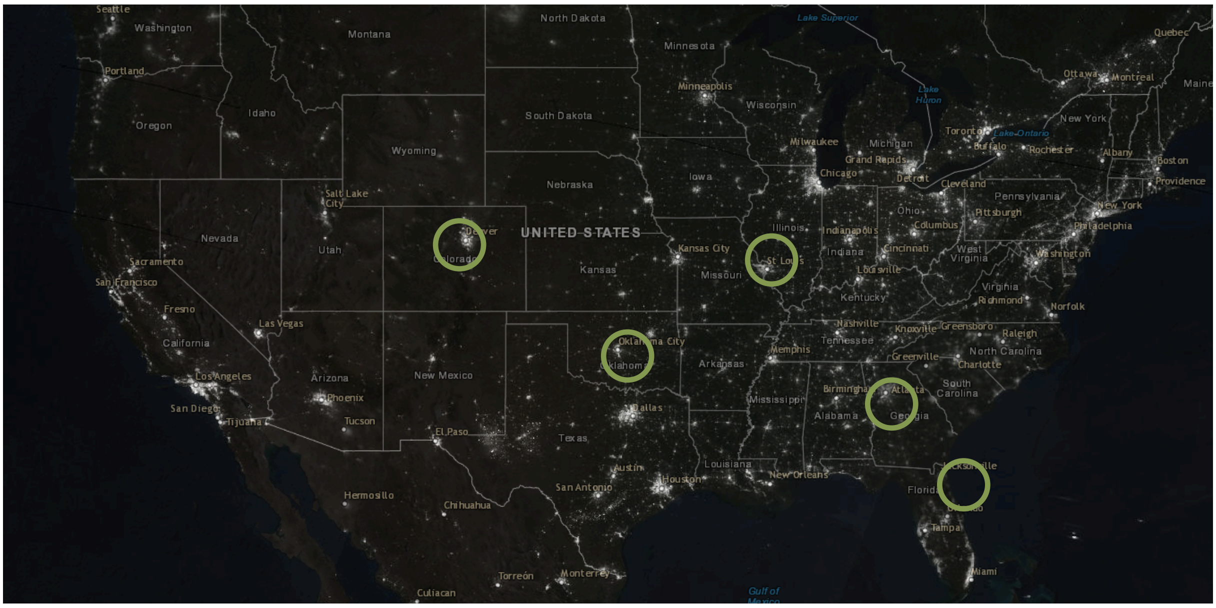


Image 2. The Nightly Radiance for Different US Cities, 03.21.2021
Source: https://maps.ngdc.noaa.gov/viewers/VIIRS_DNB_nighttime_imagery/index.html

Oklahoma City

Oklahoma City is the capital of the federal state of Oklahoma. Oklahoma is in the heart of Tornado Alley. Therefore, the state has suffered many tornadoes.

Figure 9 shows how the brightness of night lights in Oklahoma City changed when tornadoes of varying magnitudes hit the city during 2012 and 2017. The mean night light vale of this time period is 3.36 for Oklahoma City.

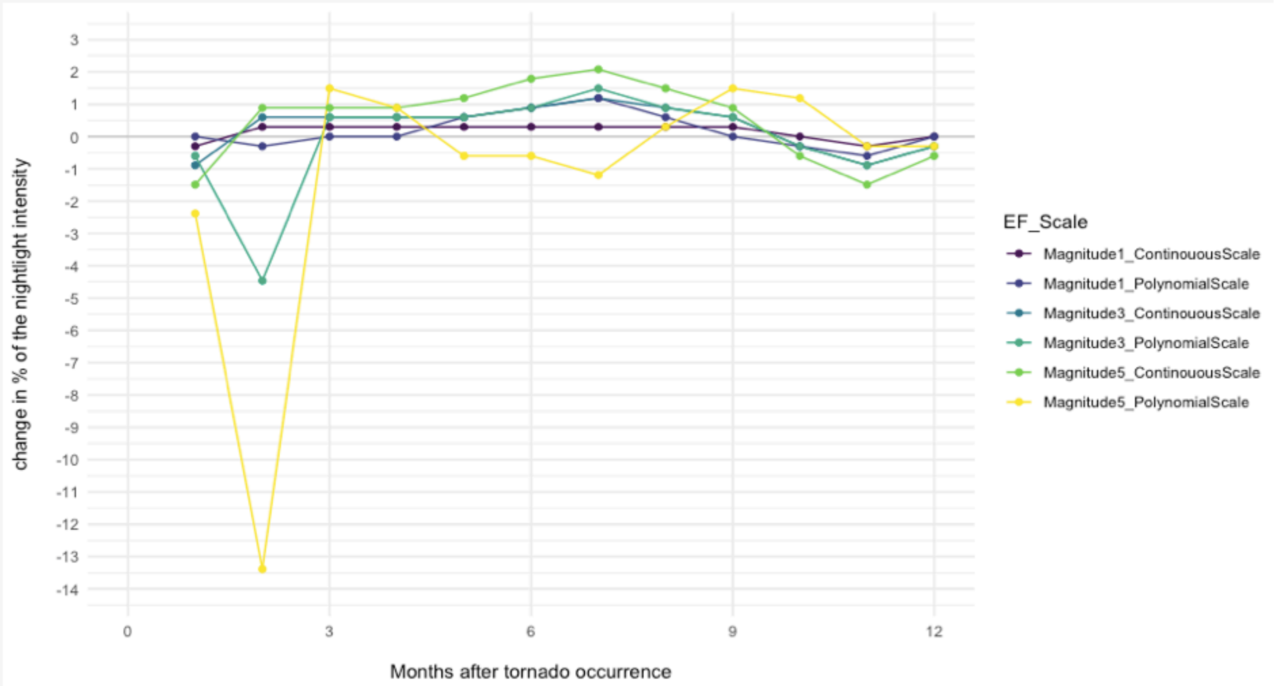


Figure 9. Changes in Night Light After Tornadoes of Different Magnitudes in Oklahoma City

Denver

Denver is the capital and most populated city in the state of Colorado. The Rocky Mountains are in the west and the High Plains in the east. The elevation of the city is around 1,609 m (USGS, 2015) above sea level.

Figure 10 shows how the brightness of night lights in Denver changed when tornadoes of varying magnitudes hit the city during 2015 to 2017. The mean night light value of this time period is 3.39 for Denver.

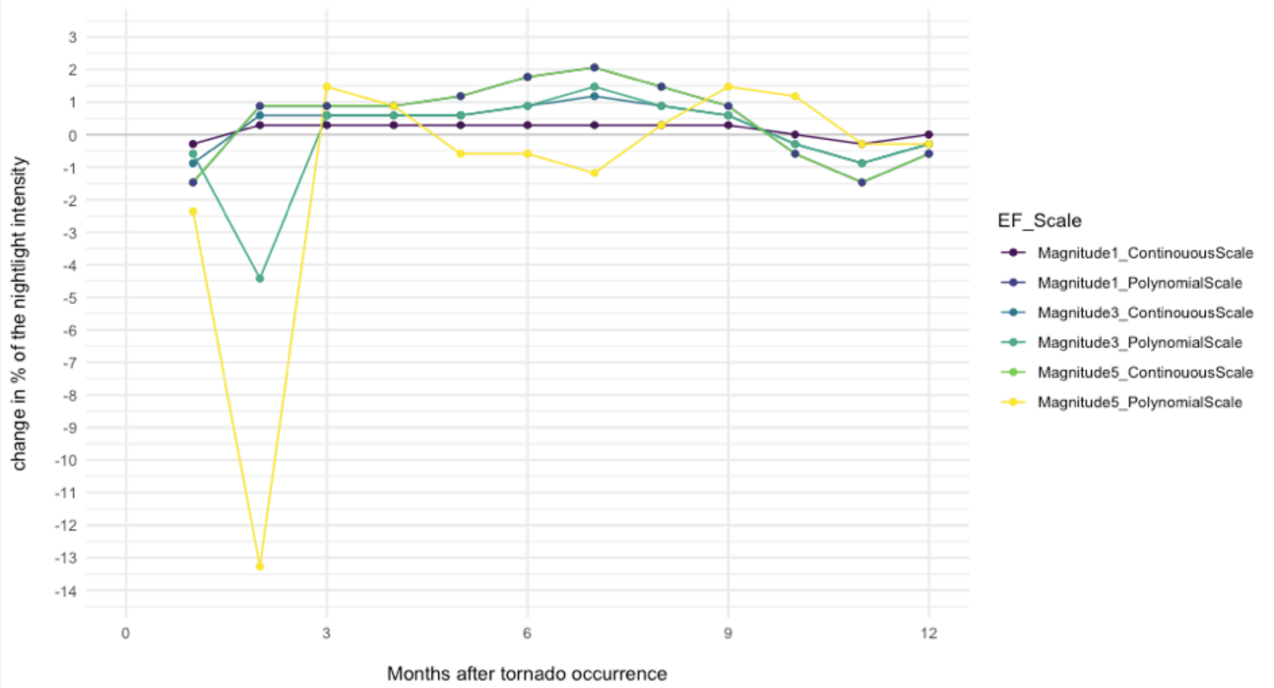


Figure 10. Changes in Night Light After Tornadoes of Different Magnitudes in Denver

Atlanta

Atlanta is the capital and most populated city of the state of Georgia. The city is in the Piedmont, which is a plateau-shaped region in the east of the US. Atlanta experiences regular tornadoes.

The mean night light value for 2013 to 2017 is 2.95.

Figure 11 shows how the brightness of night lights in Atlanta changed when tornadoes of varying magnitudes hit the city during 2013 to 2017. The mean night light value of this time period is 2.95 for Atlanta.

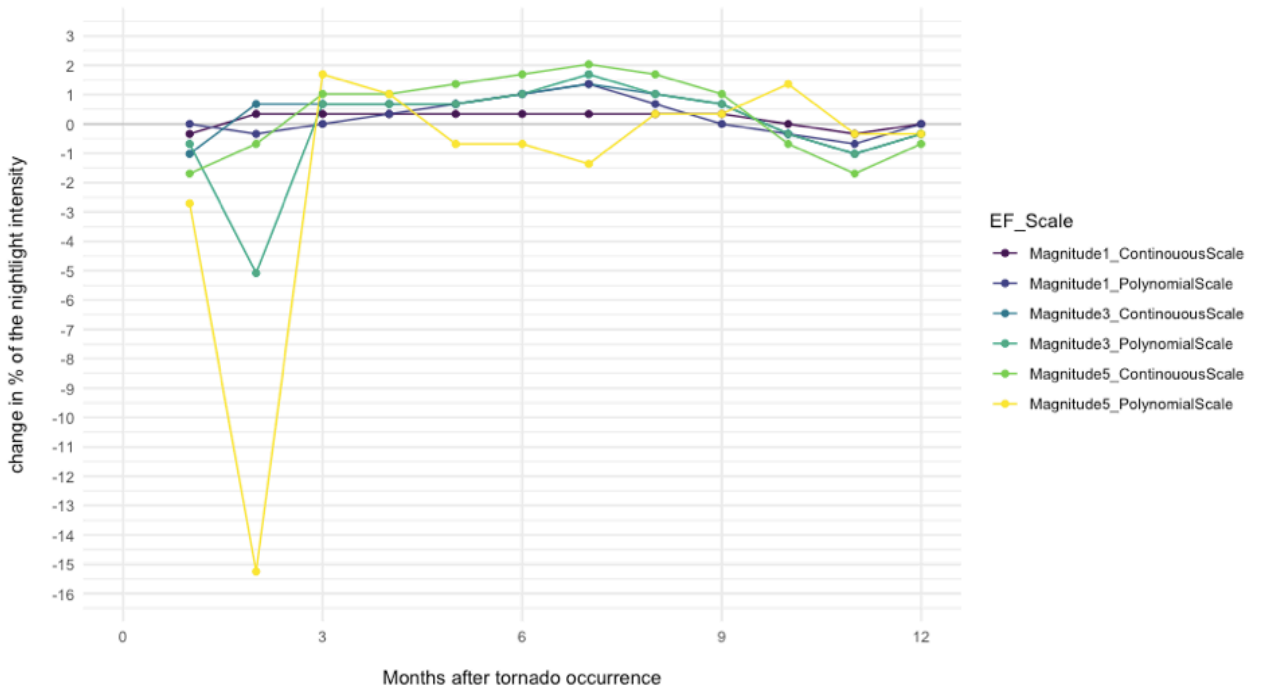


Figure 11. Changes in Night Light After Tornadoes of Different Magnitudes in Atlanta

St. Augustine

St. Augustine is a small city in the state of Florida. It is on the Matanzas River and close to the Atlantic coast. It has an average elevation of 0 m. As the state of Florida experiences many tornadoes, so does St. Augustin.

When calculating the mean night light value, only a value for 1 year could be calculated, namely for 2017, with a mean night light value of 2.48.

Figure 12 shows how the brightness of night lights in St. Augustin changed when tornadoes of varying magnitudes hit the city in 2017.

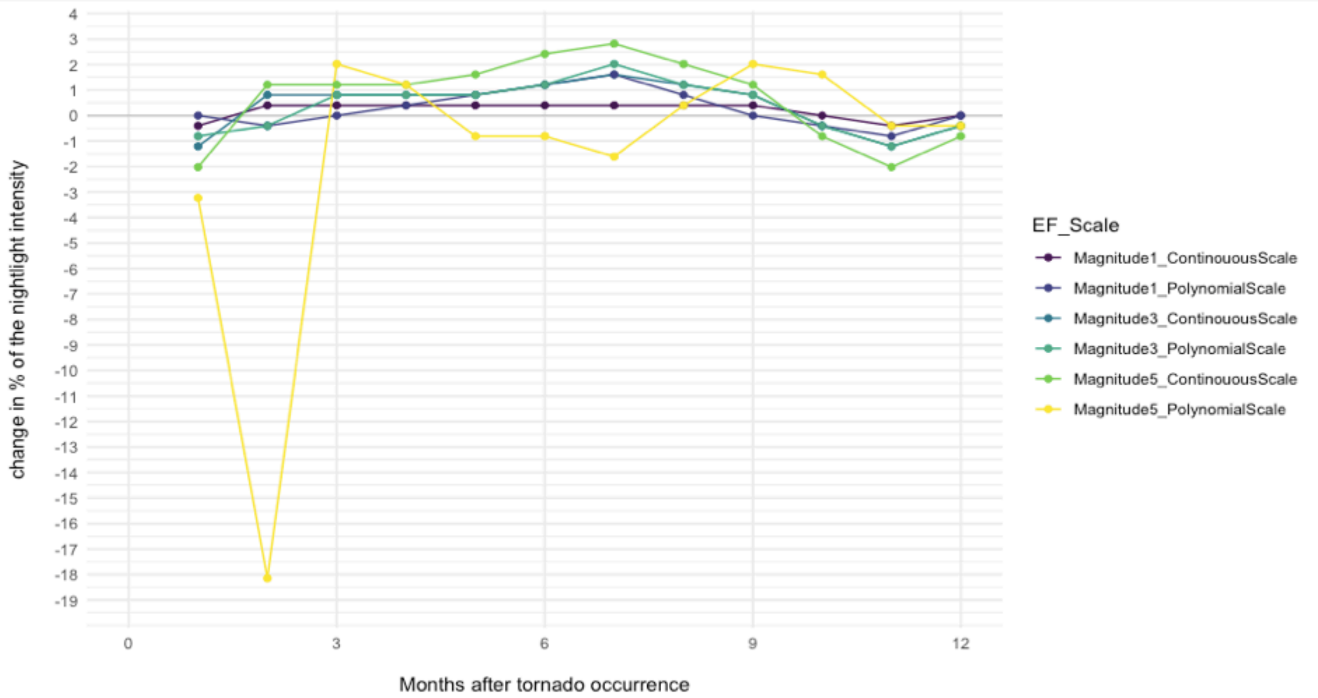


Figure 12. Changes in Night Light After Tornadoes of Different Magnitudes in St. Augustin

St. Louis

St. Louis is in the state of Missouri, next to the Mississippi River. St. Louis has experienced many tornadoes in the past, some of them extremely heavy and with fatal consequences.

The mean night light value for 2012 to 2017 is 2.94.
Figure 13 shows how the brightness of night lights in St. Louis changed when tornadoes of varying magnitudes hit the city during this time.

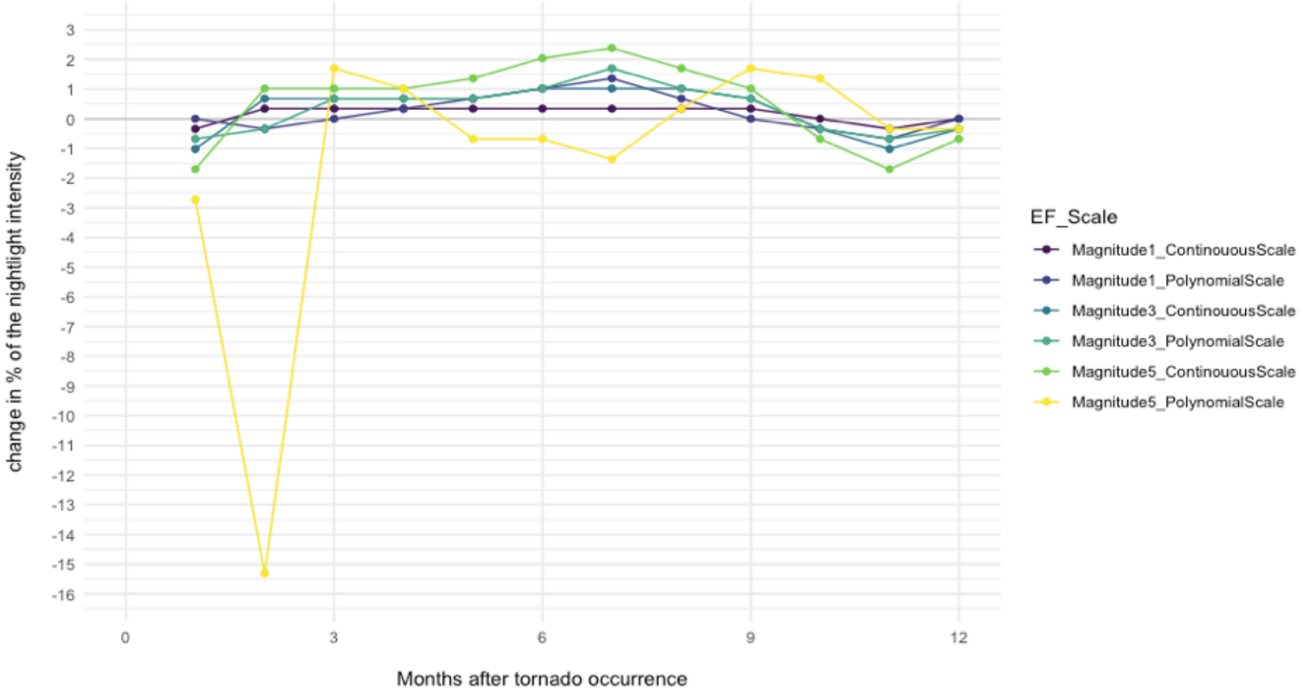


Figure 13. Changes in Night Light After Tornadoes of Different Magnitudes in St. Louis

6 Discussion

This thesis hypothesized that tornadoes lead to a decrease in the night light brightness, at least in the short term. This chapter provides some possible explanations for the observed patterns and offers room for interpretation. As night lights and their brightness are correlated with economic activity, it is assumed that if the night light brightness decreases in the aftermath of a tornado, tornadoes negatively impact the economy.

The R^2 value of the three models is 0.957. However, the calculation incorporates the specific coordinates and therefore alone providing much information on the lights.
Almost all the results were significant, indicating a correlation. However, the size of the data set, which was large in this calculation (over 12 million data points), plays an important role.

The outcomes of the three different calculations all show that tornadoes lead to a significant change in the night light brightness, although a small one. A general pattern was observed when the three models were interpreted. First, a decrease in the night light brightness in the aftermath was observed. As tornadoes destroy houses, factories, supermarkets and infrastructure, which are all sources of lights, the immediate decrease in the night light brightness might be a consequence of their destruction. However, this decrease was only transitory. A possible explanation for this transitory decrease might be that the aftermath of disasters is categorized in different post-disaster periods, which all require light: emergency, restoration, reconstruction and commemoration (Kates et al., 2006). Governmental and non-governmental organizations provide relief assistance (such as the American Red Cross and the United Way), and volunteers offer support (Paul et al., 2007; Smith and Sutter, 2013). Activities such as removing debris, installing temporary shelters and reparation work lead to an increase in light sources. This is then captured by the DNB images. How long these different phases last strongly depends on the magnitude of the damage and the assistance responses (Kates et al., 2006). Sarasota County in Florida analyzed how long this effect lasted and calculated that the short-term recovery plateaus after the first 3 months. However, the graph also analyzes the long-term redevelopment, which begins 3 months after the incident and can last for up to 5 years, peaking after 1 year (see Figure 14).

The results of the models calculated in this thesis show an increase in night lights after the first few months. Since the night light sources cannot be analyzed, it cannot be determined whether this is due to activity belonging to the short-term recovery or the long-term redevelopment phase. The peak of the night light brightness is reached between 7 and 8 months (depending on the model) and therefore does not appear consistent with the peaks of the graph below (after 2 months and after 1 year). The results show a significant decrease in the night lights lasting from month 8/9 to month 11/12 (depending on the model). However, the night lights may not capture the long-term redevelopment phase but another phenomenon covering this phase. Hence, it would be interesting to identify the cause of the night light brightness in the aftermath. It might be that the economy has already recovered or that reconstruction efforts, which generally are in need of light are the reason of this increase in the night light brightness. However, there might be a completely different reason causing this increase.

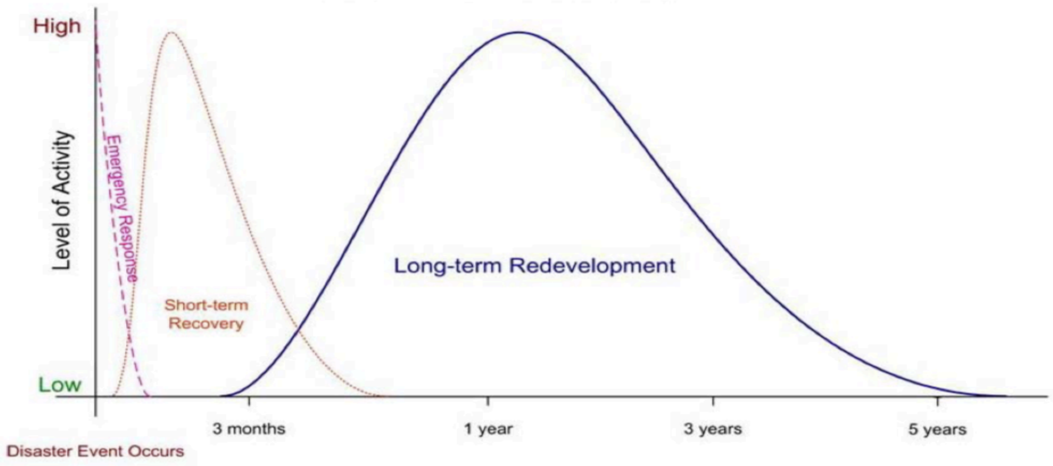


Figure 14. Post-Disaster Recovery Phases and Level of Activity: Post-Disaster Phased Activity for a Major Disaster Scenario (Source: https://www.scgov.net/Home/ShowDocument?id=34546)

The results show that tornadoes with a higher magnitude lead to a larger decrease in night light values. Stronger tornadoes probably lead to more destruction; therefore, the night lights are lower than after a weaker tornado.

However, as the felm function was used to calculate the models, the night light brightness before could not be compared with the night light brightness after a tornado. Therefore, the mean night light values for different and diverse U.S. cities were taken and compared with the calculated coefficient of the models. This allowed comparison between the night light brightness before a tornado and that after a tornado.

There are many reasons why the night lights might be lower at around month 8/9 after a tornado. This might be because the immediate emergency responses, which lead to an increase in activity and consequently an increase in night light brightness, slowly decrease. Simultaneously, reconstruction of infrastructure and larger buildings might take longer than a few months. Hence, important sources of lights are still not operating. Some people whose houses were destroyed would rather move away than rebuild them. This might be the case when rebuilding costs are too high. Moreover, when landlords must rebuild their houses – often in a better condition – rents may rise and become unaffordable for the former residents. Additionally, the region's economic landscape might change in the aftermath so that workers find no work. However, some former employees do not return because they settled elsewhere after the disaster, potentially leading to a shortage of employees (Paul and Che, 2011; Paul et al., 2007; Smith and Sutter, 2013). The recovery process can last from several months to years (Paul et al., 2007). Therefore, the number of light sources could be lower or higher for a long time after a disaster.

Another reason might be that an older infrastructure damaged during the tornado was replaced by a newer one, which normally emits a smaller fraction of light (e.g. street lamps). However, due to a disaster, the vegetation of a city (e.g. tree cover) might be less abundant, as trees and vegetation are destroyed. This would lead to an increase in night light brightness (Kyba et al., 2015).

Interestingly, a few months after a tornado, a further decrease in night light brightness was observed, almost as large as in the first months afterwards. One explanation is that this is when the effects of tornadoes on the night light brightness are most noticeable. However, the question then arises of whether this might be a seasonal phenomenon. It might be that the same areas experience the same weather phenomenon more often than do other areas. By creating a map (See Chapter 5.1.4), one can observe that the US has areas prone to the development and thus occurrence of tornadoes. Certain weather conditions must exist for the formation of tornadoes (so that thunderstorms can form). Hence, tornadoes have a seasonality lasting from May to July. However, the most violent tornadoes occur in April, and the seasonality can shift depending on the region (see Chapter 5.1.3). Therefore, the same areas may experience tornadoes around the same season year after year (Long, Stoy and Gerken, 2018; Brooks, Doswell and Kay, 2003; Moore, 2017; Lee et al., 2016; Gensini and Brooks, 2018; NSSL and NOAA, accessed 14 February 2021).

Since tornadoes occur locally, they generally have a mild effect on the labour and housing markets (Simmons and Sutter, 2011). The destruction is local, and repair works might therefore be able to start immediately after the event. However, this makes it even more surprising, that tornadoes have a significant effect almost every month and that this effect can still be captured months in the aftermath. Initially, it is unexpected that tornadoes have such a long-lasting effect in a rich country such as the US, especially as tornadoes are a relatively small hazard and only occur locally, for example, destroying one house and leaving the one next door untouched. Some of the causes were discussed earlier in this thesis (e.g. people moving away, rent increases, and changes in the working landscape). Additionally, the dataset used in this thesis is large (12,245,870 values), and results are more likely to be significant with a large sample size (Frost, 2017; Kaplan, Chambers and Glasgow, 2014).

Limitations of this Study:
It is possible that the regression specification could not capture and quantify the full relationship between night light brightness and economic activity in the aftermath of tornadoes in the US. Variables having an effect may not have been included in the calculation; therefore, tornadoes may have a weaker or stronger effect than calculated here.

The VIIRS sensor has a noise floor originating partially from stray light corrections. This noise floor is calibrated to set the average value to zero. This can lead to small negative values. Additionally, resampling of the VIIRS data occurs. Although the images comprise 15 arc-second grids, the underlying data used to construct these images have a resolution of 750 by 750 m. Due to this additional resampling, noise was added to the data (Skoufias, Strobl and Tveit, 2021).

As only data from urban and built-up areas were used in this study, noise from rural areas was removed (for example, forest fires). However, this also means that some losses might remain undetected, such as damage to the agricultural sector. However, it is assumed that the overall well-being of the economy of a region was captured.

Night light data undergo seasonality. In summer, less light is used than during winter. However, this should not be an issue, as the months were included in the regression calculations. Nonetheless, using the DNB, one major disadvantage is the cloud coverage. Storms such as tornadoes are often accompanied by rainfall and cloud coverage. Therefore, it is difficult to detect the short-term impact of tornadoes (Zhao et al., 2018).

The results do not show the factors influencing the brightness of the night lights. For example, no conclusion can be drawn regarding whether the night lights are brighter after a tornado due to reconstruction work or because the effect of the tornado is no longer visible. Likewise, spill-over effects cannot be detected. These are interesting future research areas.

As tornadoes usually cause a local and sudden shock, which is mainly only transitory (especially for rich countries such as the US), it could have been preferable to use daily data rather than monthly data, as in this thesis. Emergency aid (and with it new light sources) arrives within days, distorting the image of the damage that the tornado caused. Unfortunately, it is impossible to conduct a statistical analysis with such a huge number of data points because it would exceed the capacity of my computer.

Future Research:

The results of this thesis show a correlation between night lights and the impact of tornadoes on the local economy. Therefore, using the night light data from the VIIRS sensor is a promising method if other data are missing for the specific region.

It is challenging to determine the exact effect of different factors on night lights. However, only by disentangling the different influences can one determine which effects on the night light brightness result from tornadoes, cloud coverage, repair works and other factors. Further research might identify the different relationships.

Testing new methods, especially different regression methodologies, might improve the analysis. A different function could be used to calculate the impact of tornadoes on the night light data. A different function could also capture the night light values immediately before a tornado. Therefore, it could be more accurate to compare that value with the night light values in the aftermath rather than tracking, as here, the average night light value for several years for a certain city. Moreover, more data from other sources could be included to make the results more reliable and stable. It could also be beneficial to use daily data rather than monthly data.

Further research could also analyze the spill-over effect of tornadoes. Disasters can lead to changes in the social or political structures of nearby regions (Kates et al., 2006). It would be of great interest to observe these effects.

Additionally, further research must be conducted to analyze the recurring pattern in the night light data captured by this thesis and determine whether this is caused by tornado cycles (e.g. seasonality) as assumed or is due to a different cause.

7 Conclusion

The outcomes of the three different calculations all show that tornadoes lead to a significant change in the night light brightness, although a small one. The hypothesis, drawn in the beginning of this study, that tornadoes do lead to a change in night light brightness was confirmed by the results of this thesis. A general pattern was observed when the three models were interpreted. First, a decrease in the night light brightness in the aftermath was observed. However, this decrease was only transitory, and the brightness increased again. The peak of the night light brightness was reached after about 7 to 8 months. A significant decrease in night lights was then captured. However, depending on the model and city, in month 12, an increase in the brightness was observed.

Furthermore, the results show that stronger tornadoes lead to a larger decrease in night light values than weaker tornadoes. The results of this study also suggest a correlation between the magnitude of a tornado and the number of injuries and fatalities. Weaker tornadoes lead to fewer incidents than stronger tornadoes. Yet, the results also show that crop and property losses do not increase with the strength of a tornado. In fact, the greatest losses stem from tornadoes of the magnitude EF1 to EF3.

Overall, research using remote sensing to detect the impacts of severe storms could gain importance in the future as a debate is occurring regarding whether climate change leads to an increase in extreme weather (Christensen et al., 2007; Mihajlovic, Ducic and Buric, 2015; Marsh, Brooks and Karoly, 2007; Trapp et al., 2007; Trapp, Halvorson and Diffenbaugh, 2007; Gensini and Mote, 2015; Elsner and Jagger, 2015; Hatzis, Koch and Brooks, 2019).

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