MATH 370 FINAL - CATASTROPHE MODELING

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Contents

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1. Introduction to Catastrophe Modeling

Origins of Catastrophe Models

The origins of catastrophe modeling can be traced back all the way to the early 1800s residential insurers covering fire and lightning risk used pins on a wall-hung map to visualise concentrations of exposure. The use of mapping ended around the 1960s when it became too cumbersome and time consuming to execute, however, the practice of catastrophe modeling never ceased to exist [LS08].

As data collection and processing technology has improved, insurance companies have been eager to utilize this new technology to better predict their risk. Specifically, once GIS software became available, insurers could combine data connecting natural disasters to specific locations with the properties that are in those locations. In the 1980s and 1990s, this advanced computing capability made it possible to model these historical disaster occurrences and trends based on location, and use these models to assess risks for the insured properties.

One of the most important predictors in these models is the strength of the natural disaster. The magnitude of the earthquake, category of the hurricane, or intensity of the tornado is the defining factor of the occurrence that is used to describe how serious it is. However, these scales to define the strength of the disaster

Well-known Catastrophe Modeling Companies

The field of catastrophe modeling, while often unheard of, is a huge field, employing thousands of people in jobs such as engineers and data analysts and having a multi-billion dollar annual revenue. Insurance companies and government agencies are constantly looking to hire new people to fill new positions. A quick search on LinkedIn found nearly 500 unfilled catastrophe modeling jobs, many of which pay a very handsome salary. As modeling techniques and technology continue to develop, employers are hungry to snatch up people who have the relevant skills making catastrophe modeling a very good field to work in. We'll be discussing the three biggest catastrophe modeling companies.

1.2.1 *Verisk:* Founded as AIR Worldwide in 1985, American risk modeling and data analytics company headquartered in Boston, MA, and changed their name to Verisk in January of 2022. They report \$3 billion in revenue and \$666 million in net income on a yearly basis.

1.2.2 *RMS:* Founded in 1988 and headquartered in Newark, CA, Risk Management Solutions has helped lead the way in transforming the catastrophe risk industry, helping organizations make better decisions to improve human and environmental outcomes. They work in over 120 countries and have very extensive workings. They have over 18 million simulated fires in their wildfire model as well as more than 60 trillion data points in their API.

1.2.3 *EQE:* EQECAT was founded in 1994 under the parent company ABS Group and acquired by CoreLogic in 2013. They have reported over \$1.5 billion in operating revenue making them one of the most profitable catastrophe modeling corporations.They tend to focus on property-specific data and models and boast that they have nearly 200 different models for their clients.

2. Concepts and Applications

Data Acquisition

Much of the data used in catastrophe modeling is from historical events, and can be found in public databases such as those provided by NOAA. This information is one of the most valuable aspects of catastrophe modeling, primarily because, relative to more common occurrences of insurance claims such as theft, fire, flood, etc., these disasters are rare and specific location-based data accompanying the information on the disaster is some of the best material for producing these models. When an opportunity arises to collect data not only on a natural catastrophe, but on the damages associated with that catastrophe (with more detailed breakdowns of the damages being preferred), acquiring as much accurate data as possible is a very high priority for insurers and other builders of catastrophe models [DFBD15] [Dat19].

Quality of Data

Building an effective model relies on taking as many consistently measurable variables into account as possible, which is why the quality of data is crucial for catastrophe modeling. Since an emphasis is placed on collecting local data (so as to increase the resolution of the model and reduce uncertainty [Whi16]), much of the information in these databases is recorded by the policyholders themselves. There is no uniform way of collecting and organizing the relevant property information. This leads to a multitude of problems: many policyholders do not have accurate knowledge of these details; a lot of data – such as home value – quickly becomes inaccurate over time and may not be frequently updated; as companies re-organize and merge, information may get lost in the shuffle. The information that is missing is often the most important and basic details of the property, such as location (street address or latitude/longitude), the number of occupants in the building, year and type of construction, and the height of the building, These, among other reasons, help to explain why much of the data held and used by insurance companies is not completely precise and accurate.

Nonetheless, improvements have been made with regards to the quality of data collection, especially in recent years. The amount of resources devoted to the collection of high-quality data has been increased across the industry. Many firms are realizing that the short-term costs of employing more risk-assessment experts and knowledgeable engineers is outweighed by the long-term savings that are achieved through the assistance accurate models helping to forecast potential losses [DFBD15].

Four Steps to Catastrophe Modeling

When modeling catastrophes, there are four main steps [DFBD15] that are included in the modeling process:

- Event
- Hazard
- Vulnerability
- Financial Risk

Some catastrophe models combine the "Event" and "Hazard" modules, but there are enough distinctions between them that they can be considered separately. The event step describes the specific characteristics of the catastrophe that is occurring. The hazard step analyzes what the dangers of that particular catastrophe are. The vulnerability step assesses the specific property in question, and what parts of it are most susceptible to the disaster. The financial risk step is the final step, and it takes into account the policy details when describing, in monetary terms, what the potential damages could amount to.

2.3.1 *Event:* Before considering anything else, the first step when modeling catastrophes and their potential effects is to consider what disaster is actually occurring. This includes taking into account the measurable and descriptive details, such as size/strength, expected duration, and location, among other factors [DFBD15]. Within the model itself, an event database is formed. The database is composed of a combination of historical events and "synthetic" events. The creation of the synthetic events is a remarkable addition to the model, because even the inclusion of all recorded historical occurrences of a given type of catastrophe (be it hurricanes, tornadoes, earthquakes, or another) does not give enough data points for an accurate model. For this reason, it is necessary to create events that did not actually occur, but fall into the parameters of events that reasonable could have occurred. Using the probabilities of a given variable occurring at a certain value (from the historical data), a random sampling of these probabilities is done to create these synthetic events and fill in the characteristics based on those probabilities [Whi16]. Using this event database, the characteristics of an event that are occurring can be recognized and related to events within the model.

2.3.2 *Hazard:* Following the assessment of the catastrophe that is occurring, next the model must consider what dangers this catastrophe could bring. In this module, the severity of the disaster is related to the specific site that is insured. For example, if a specific site is located in an area with a high water table, then a prolonged hurricane with sustained rain would be especially dangerous. This particular hurricane may not pose a flood risk to most areas, but for that specific area, the storm is a significant hazard. Other site factors that are taken into consideration are its location relative to bodies of water (with different hazards associated with different types of water bodies, and with varying levels of significance), the condition of the soil, elevation, proximity to fault lines (which is relevant for earthquakes), and weather patterns [DFBD15].

As was previously mentioned, this module is often combined with the "Event" module due to both modeling steps being related to factors outside of human control. For the final two modules, the variables that are modeled are primarily decided by human actions, whereas the details of specific disasters and the natural conditions of a location are existent regardless of humans. Although humans may actually be having long-term impacts on these phenomena and locations – due to human intervention in the natural environment – for the purposes of modeling catastrophes it is suitable to consider the "events" and "hazards" to be products of nature rather than products of humans.

2.3.3 *Vulnerability:* The "Vulnerability" module seems similar to the "Hazard" module, but there is a distinct difference: the hazards are considered to be innate attributes of the location, while the vulnerabilities are related to the man-made structures on the site. This property-centric data – necessary to assess vulnerability – consists of factors such as quality of building materials, design of construction, and status of inspection (and what the criteria of that inspection are).

This step can be quite complex to model because these variables are not always easy to quantify. As Dickie Whitaker states in his report "Catastrophe Modeling", there are three types of information that are collected to help assess vulnerability: empirical data, engineering consensus, and engineering reliability analysis. Empirical data is the numerical data that is based on historical events, where information on damage costs and building type can be connected to the strength of the disaster. When considering similar future disasters of the same strength, the damages and associated building type for all instances in the past will aid the model in predicting the future damages. Engineering consensus is simply the professional opinion from experts in a certain field of engineering – either individually or through an organization – that makes recommendations and supplies data. Lastly, engineering reliability analysis uses sophisticated computer models specific to each individual structure (down to details such as design, building materials, age, etc.) to test how much of a given catastrophe the structure could withstand, be it a tornado, hurricane, earthquake, or another type. These can be very helpful for modeling potential future losses on a given building, but these models are expensive and still based on insufficient data, while also not being completely comprehensive since no building is constructed exactly as it is designed with every specification as predicted.

One final aspect of vulnerability that many of these models consider is the interruption of business that often accompanies damage to structures. Certain businesses, such as those that rely on specialty machinery, may not be able to continue business for a length of time after the catastrophe damages their property. Some insurance policies cover these business interruptions in addition to the material damages of the catastrophe. Thus, when modeling potential losses for structures that are covered by this kind of policy, it is important to take these potential interruptions of business into account as well [Whi16].

2.3.4 *Financial Risk:* The final step of a standard catastrophe model is assessing the financial risk that the insurance provider faces (or whatever other entity has money at stake). The first three steps are all used to calculate the potential monetary impact of a certain catastrophe, given the specific details of the catastrophe, the site in question, and the structures and property located at that site. However, this is not translated into financial risk until the relevant financial details are considered. For example, some policies may have deductibles, so damages that do not surpass that amount are of no concern for the insurance provider. Similarly, a policy may have a limit, and for any claim that surpasses that amount, the payout will not be greater than the insurance limit [Whi16]. In these ways, insurance companies mitigate their financial risk, but these deductibles, limits, and other policies are often very specific. These policy details may differ depending on the exact type of disaster, and policies also differ from location to location, so the same company with multiple sites may have different coverages depending on the exact site. This is why the models must consider all four of these steps – so that the risk to the insurance company can be modeled as accurately as possible when taking all possible variables into consideration.

Risk Management and Catastrophe Models

While one of the most common and important uses of catastrophe models is to predict the potential losses of an insurance company. However, because these models are so comprehensive and the dependent variable is modifiable, there are other uses that illustrate the contributions of catastrophe models in society. Grossi, Kunreuther, and Windeler explore the application of these models to disaster management [GKW05]. Using the open-source Hazus software, they use available data to model the displacement of people in the Charleston, SC area from their homes following a potential 7.3 magnitude earthquake.

As can be seen from the image, the number of displaced households diminishes as the locations are farther away from the epicenter. FEMA is the governmental department in charge of federal disaster response, and they maintain the Hazus program with specific data, down to the town/city level. Using the created model, and only inputting the epicenter and magnitude of the earthquake, maps such as the one above can be quickly generated to provide immediate support to first responders [GKW05].

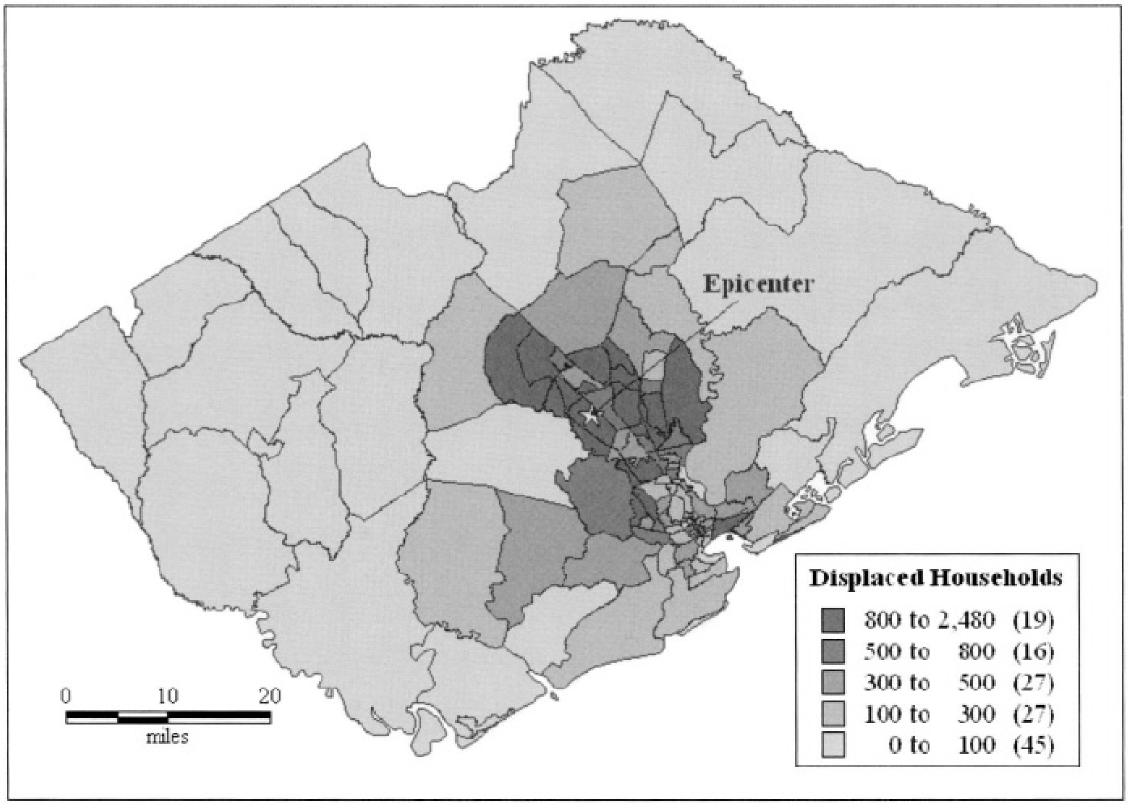

FIGURE 1. Displaced Households based on Hazus data [GKW05]

3. Importance of Updating Models

Catastrophe modelling has proven itself to be a critical tool in mitigating disasters and saving lives. However, it has also been shown that the models need to be kept up to date to maintain their efficacy [RRL13]. This can most clearly be seen looking at the aftermath of Hurricane Katrina.

To this day, Hurricane Katrina is still the most destructive hurricane recorded in the United States, causing approximately \$108 billion in damages [MBB+16]. The high winds and heavy rainfalls caused a storm surge of of over 14 feet, flooding low-lying areas. The storm cost insurance companies more than \$41 billion [DFBD15], and they used Hurricane Katrina as an opportunity to learn from past mistakes and were better prepared for future storms.

A Model Depends on the Data you Feed It

One of the biggest mistakes made in the lead-up to Hurricane Katrina was the use of inaccurate data in the insurance company models. Things like the year a house is built, its construction type, how many people are living there, and the physical location of the house can all dramatically effect the total value of the property, and therefore how much damage can potentially occur. Prior to Hurricane Katrina, most of this information was self-reported by policy-holders, and could be filled with mistakes. These mistakes can happen for a variety of reasons: the data could be not readily available, or the information available might be out of date. But regardless of the reason for it, bad data can cause otherwise good models to give bad results. Hurricane models of the time severely underestimated the potential losses; initial damage estimates were only a quarter of the actual damage caused [DFBD15]. Insurance companies were operating without knowing the true value of the properties they were insuring.

Inaccurate data may have lead to the inaccuracies in property values, but models based on bad assumptions were unable to predict how destructive the hurricane could be. The models in use for Hurricane Katrina made several assumption about the buildings in the area. It was assumed that all of the buildings were built to meet existing codes. This means that the models assumed all of the buildings would be able to withstand certain wind forces, and that failures would occur in predictable ways. In reality, not all of the buildings were able to withstand some of the forces they were expected to, or they reacted to flooding in unexpected ways, so the amount of actual damage done was greater than the models had predicted.

Both of these problems together caused insurance companies to undervalue the properties they insured, and underestimate how much damage that a storm could cause.

Climate Change Will Impact Every Weather Event

As climate change continues to progress, we are seeing its effects all around the world. For large and infrequent storm systems, it can be difficult to track long-term trends given the natural variability they posses, and even more difficult to adequately explain any differences. However, that does not mean predictions can not be made. For example, due to the rising sea level, we can expect to see higher levels of coastal inundation (seeing water above normally dry land) [Knu22]. Experts have also predicted that we are likely to see increases in the amount of rainfall around hurricanes along with increases in their overall severity, although interestingly the total number of hurricanes is expected to either stay the same or even decrease slightly [MDZP+21]. All of this is to say that climate change will bring about changes to our environment, sometimes in ways that might at first seem counter-intuitive.

3.2.1 *Tornado patterns in the U.S. are already changing:* Tornadoes are quick-forming, short-lived events that can be very difficult to accurately predict. They are usually formed near thunderstorms, when there are winds blowing in different directions or at different speeds at different altitudes. This phenomenon of crosswinds is called "wind shear" and is the first step in the formation of a tornado. Between these two layers, a spinning column of air can form. Because the original layers of air causing the wind shear often have different temperatures and humidity levels, the temperature differential within the column of air can cause it to become vertical. If it continues spinning, it can extend down below the storm, and if the funnel makes it to the ground it is a tornado [OAa].

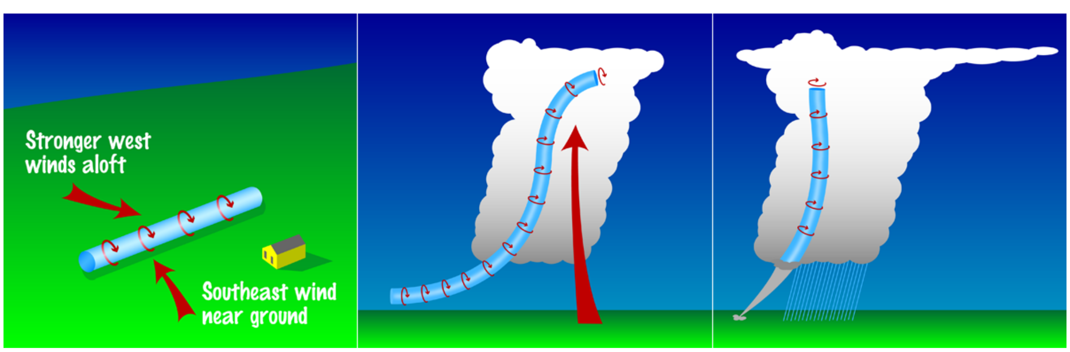

FIGURE 2. Simple diagram of how tornadoes are formed from the National Oceanic and Atmospheric Administration

The vast majority of tornadoes occur in clusters, appearing at similar times in similar places. Around 60% of tornadoes occur within 100 km and 3 hours of at least three other tornadoes, and around 80% of tornadoes are clustered with at least one other tornado [Mun22]. However, tornadoes are not just clustered by time and place, but also by intensity. "Beyond clustering in time and space, if we turn now to tornado intensity, our analysis also showed that 9 – i.e. almost half – of the 20 EF-5 (incredible damage) tornadoes from the period 1997-2020 occurred in a single outbreak, the outbreak of April 25-28, 2011" [Mun22]. This means that when a severe tornado occurs, there are likely to be multiple severe tornadoes happening within a relatively short span of time.

Contrary to what one might expect, there has not been any significant change in the average number of tornadoes per year [Hen21]. There are more EF-0 tornadoes reported in recent years compared to the earliest days of keeping records of tornadoes, but that can be explained by better equipment and monitoring practices that more easily identify small, non-destructive tornadoes. Limiting the count to only EF-1 tornadoes and above, there has not been a significant change in the total number of tornadoes recorded per year. Instead, what we are seeing is an increase in the variability of tornadoes. This means that we can see a record number of tornadoes in May of 2019 [fEI19], followed by the first May in recorded history with no EF-3+ tornadoes in 2021 [fEI21] for example. An increase in variability means that more extreme scenarios are likely to be seen, larger clusters of tornadoes and more periods of relative calm.

Along with the changes in tornado variation, we are also seeing shifts in where geographically tornadoes occur. There has been a significant decrease in the number of tornadoes in Texas and Oklahoma, while Alabama, Arkansas, Illinois, Indiana, Kentucky, Mississippi, Missouri, and Tennessee have seen an increase. Texas and Oklahoma have seen a decrease in the average number of days favorable to tornadoes, while the states to their East have seen an increase [Hen21]. The old "Tornado Alley" has been gradually moving both East and North [GB18].

This section has discussed some of the changes being observed in yearly tornado patterns in the context of climate change, but each tornado is very localized event. It is very difficult to attribute any individual tornado to climate change, all we can do is point to any overarching trends. Still, it is important to recognize these trends and update any models accordingly.

4. Our Tornado Model

Model Data

For our model we used data from the NOAA database of Storm Event data [OAb], specifically looking at tornado events. We aimed to predict the total damages caused by a tornado, in dollars.

Data Analysis

Initially when making our model, we explored the correlation between our response variable, total damages, and our selected explanatory variables, the tornado's path width, the tornado's path length, the tornado's F-Scale rating, and the Rural Urban Continuum Code classification for the location of the tornado. Using our data we found the correlations in the following subsections.

Distribution of Total Damages

When we initially generated the following distribution:

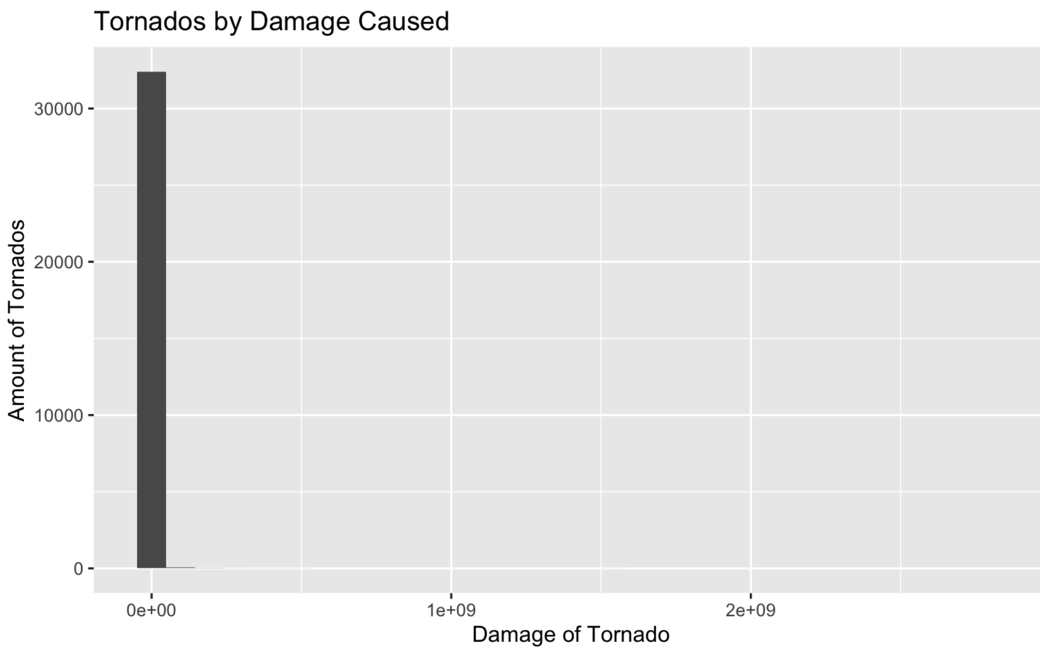

FIGURE 3. Distribution of damage caused by tornadoes in the US (2000 - 2021)

This distribution doesn't give much information other than that the majority of tornadoes don't cause damage, but if we filter out the tornadoes that caused 0 damage we a find distribution that is slightly more interesting, showing a normal distribution of the damage of tornadoes.

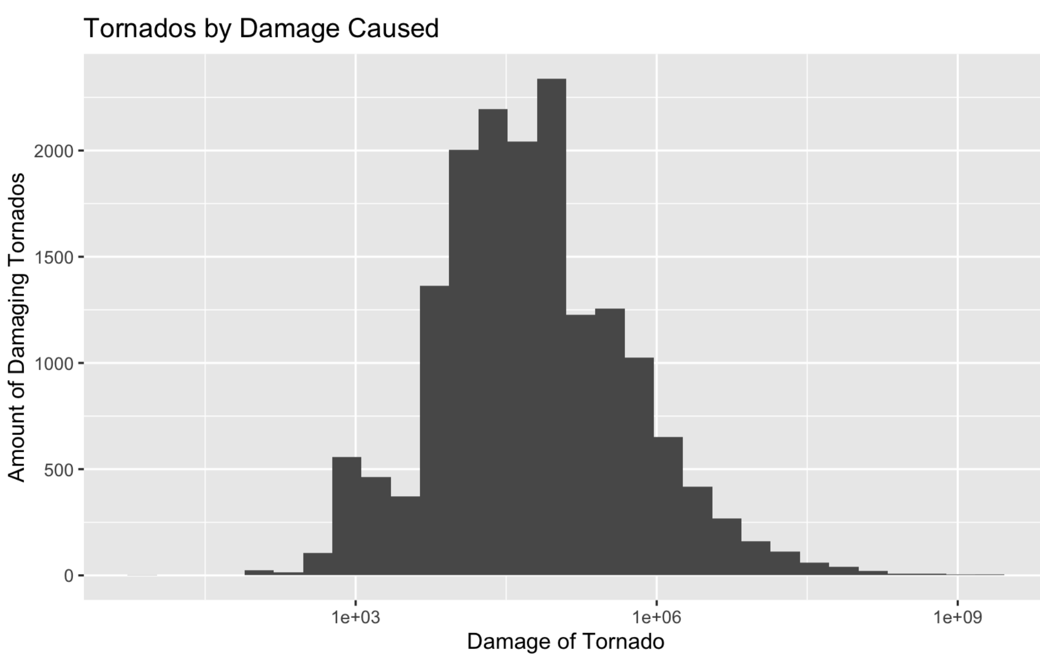

FIGURE 4. Distribution of damage caused by tornadoes in the US (2000 - 2021)

Correlation between total damage and other variables

When we further explore the data set we can find some interesting correlations between our selected variables and the amount of damage caused. First, looking at the F-Scale rating of the tornadoes, we found that there is a positive correlation between the F-Scale rating of a tornado, and the total damage caused by a tornado, shown by the graph below.

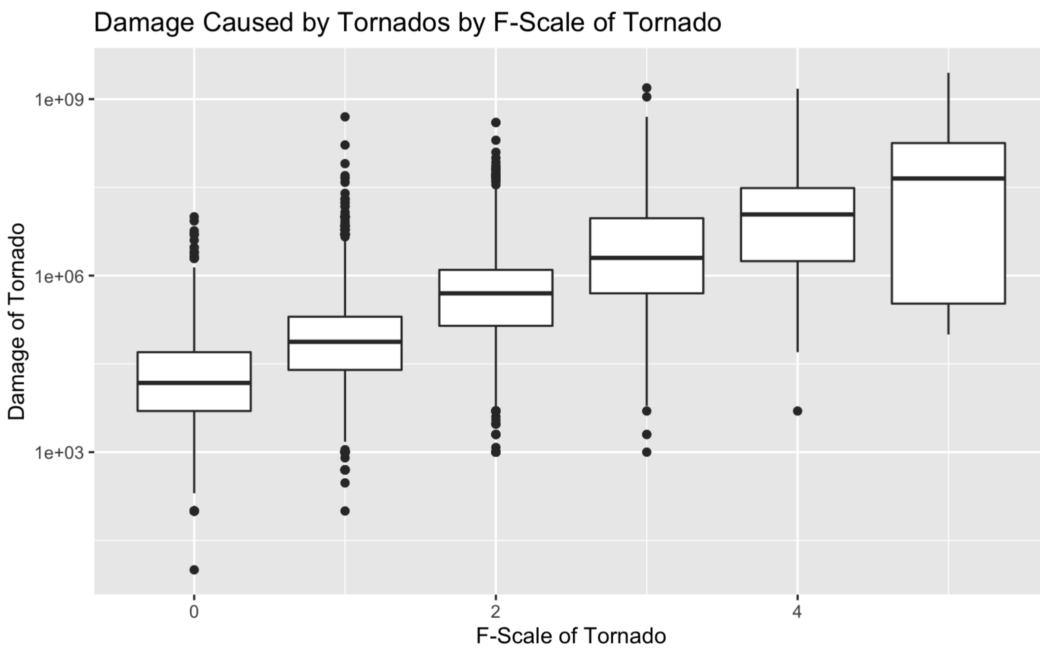

FIGURE 5. Damage caused by tornadoes by F-Scale rating

Next, looking at the correlation between the Rural Urban Continuum Code classification, or RUCC classification, of the county where the tornado occurred and the damage caused by the tornado. Somewhat surprisingly, we found almost no correlation between them, only a very small positive correlation, as shown in the following graph.

Lastly, we examined the correlation between the length of the path of a tornado and the damage caused, finding another positive correlation between them, as shown in the graph below.

The Model

After we have explored the data, we can now construct our model. First, we transformed the total damages into log_DAMAGE, which is equivalent to $log_{10}(damage)$, as the correlation between the the amount of damage and the selected explanatory variables is exponential, hence why all of the scales in the earlier graphs have a y-scale measuring the magnitude of the damage. Once we fit the model, we obtain the following summary table.

This model shows that the formula for the total damage as

$$damage = 10^{2.251463+1.289463*(\text{Strength of Tornado})+0.019939*(\text{Tornado Length})-0.121132*(\text{RUCC})}$$

with an R^2 value of .2111, meaning these variables with these coefficients explain about 21% of the damage caused by the tornadoes using these variables.

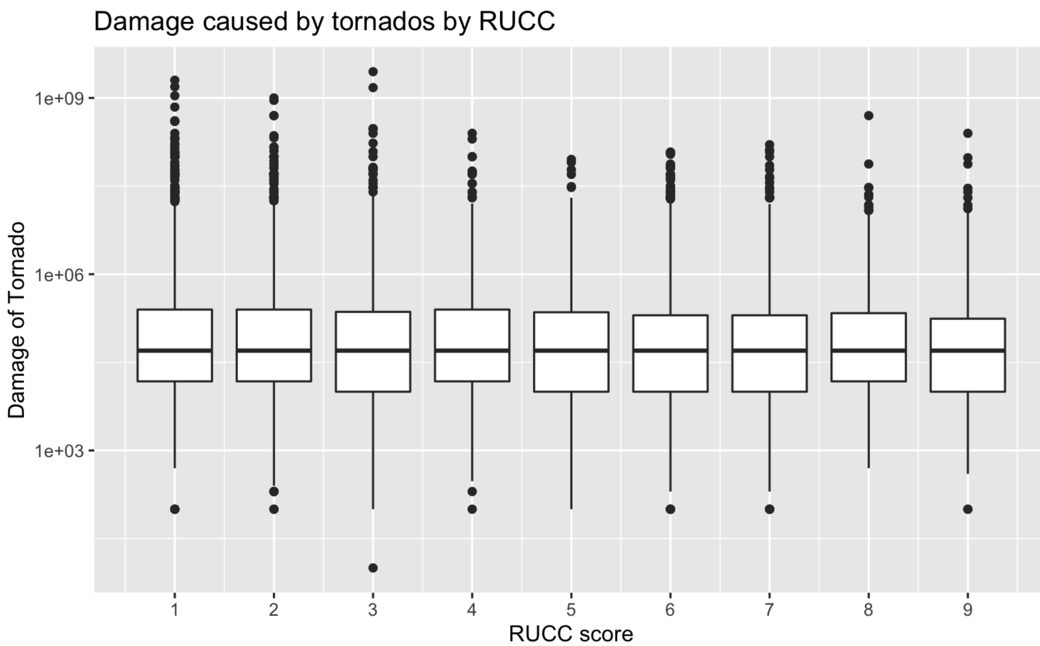

FIGURE 6. Damage caused by tornadoes by RUCC classification

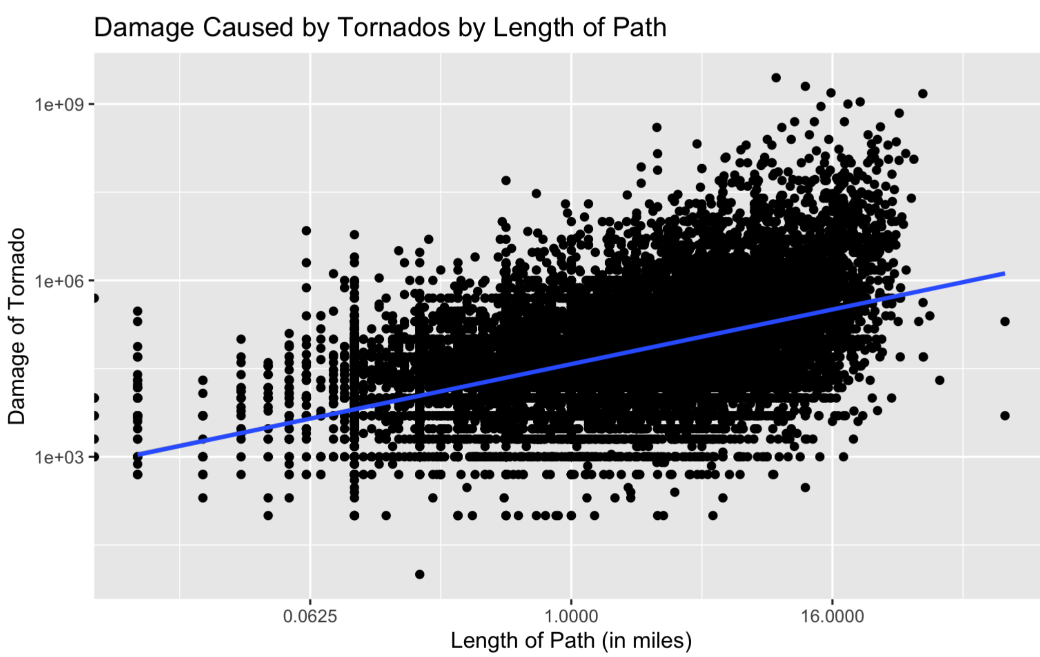

FIGURE 7. Damage caused by tornadoes by path length

Interpretations of Model

After the creation of our model, we were able to compare the independent variables of strength of the tornado, length of the tornado, and urbanization of the county in which the tornado struck with the damage caused by the tornado. We were able to conclude that as the strength of the tornado increases, the damage caused by the tornado increases. The

```
Call:
lm(formula = log_DAMAGE ~ TOR_F_SCALE + TOR_LENGTH + TOR_WIDTH +
    RUCC_2013, data = .)

Residuals:
    Min      1Q  Median      3Q     Max
-9.4316 -1.7928  0.3852  1.9831  5.8813

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.249e+00  2.706e-02  83.120   <2e-16 ***
TOR_F_SCALE  1.272e+00  1.912e-02  66.526   <2e-16 ***
TOR_LENGTH   1.928e-02  2.174e-03   8.868   <2e-16 ***
TOR_WIDTH    1.021e-04  5.762e-05   1.771   0.0765 .
RUCC_2013   -1.214e-01  4.581e-03 -26.498   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.197 on 31850 degrees of freedom
  (648 observations deleted due to missingness)
Multiple R-squared:  0.2112,    Adjusted R-squared:  0.2111
F-statistic:  2131 on 4 and 31850 DF,  p-value: < 2.2e-16
```

FIGURE 8. Summary table of our model

strength of the tornado is measured by the Enhanced Fujita scale, which is a scale that is used to assess the strength of the tornado. Another conclusion we drew was as the length of the tornado increases, the damage caused by the tornado increases. The length covered by the tornado was measured in miles. Our final conclusion was that as the urbanization of the county increases, or in other words, a more highly developed county will result in less damage caused by the county. The correlations between the strength of the tornado and damaged caused and between the length of the tornado and the damage caused are directly proportional to each other, while the correlation between the urbanization of a county and the damage caused by the tornado are inversely proportional. The first two correlations were no surprise, but the relationship between urbanization and damage caused came across as a surprise because it seemed counter intuitive. We originally thought that with a higher development comes more buildings, population, and other factors which allow for more opportunity for damage. After additional research, it was discovered that higher urbanization, in general, corresponds with stronger built buildings and better preparation for natural disasters, so this misunderstanding was resolved.

Shortcomings of Model

While we attempted to create a model to the most accurate extent of predicting damages caused by tornadoes, we were definitely faced with some limitations which prevented us from a better model. While the data sets we used had a plethora of data points to work with, these sets only provided us with very basic meteorological data. Most of the data points seem to be estimations, which definitely could hinder the accuracy of our model. Insurance firms and catastrophe modeling companies have exclusive access to resources or data that is only available to these companies in addition to what we were provided with, which enables them to be able to build more accurate models. Insurance firms have access to information that includes the exact values of specific property or destroyed in a tornado; this information is not available to the general public. Information such as that would be much more helpful in the creation of a more accurate catastrophe model. Insuring property comes with specific details regarding the price and location of this property, which would be a much greater help in building our model.

5. Conclusion

Catastrophe modeling is an important tool for insurance companies because without these models, insurers would be more likely to go bankrupt since they would not be able to accurately estimate amounts of money needed based on the damages from past disasters. The inability to do this would interrupt and hold off on payments back to buyers of the insurance firm. Despite its shortcomings and the limitations we faced in the data sets we were provided with, we were still able to develop a rudimentary catastrophe model that estimated the amount of damage caused by a tornado by looking at the strength of the tornado and the path size and basing it off of tornadoes that occurred in the past. Insurance companies that have access to more specific details and can account for location and property data are able to more effectively predict these losses caused by natural disasters. In doing so, these companies are able to minimize the losses faced by the insurance company and allows them to properly insure their costumers.

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