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The Importance and Development of Catastrophe Models

Kevin Schwall
kjs123@zips.uakron.edu

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Honors Research Project

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A key component of the insurance industry operating successfully is the company's ability to accurately predict the risks that they are taking on when they agree to insure against possible losses to their clients. Hurricanes, tornados, and other natural events can be tricky to predict, but often can cause substantial damage, which in turn will lead to a large number of insureds filing a claim with their insurance company. In 2017, $306 billion of damages was caused by storms and other natural disasters, which was the most expensive year for natural disaster related damage in United States history (Mooney & Dennis, 2018). This shows that it is very important for insurers and reinsurers to have as great of an understanding on their potential exposures as possible, in order to maintain profitability as a business. This is where catastrophe models are being used to try to more accurately make predictions on the frequency, severity, and location of possible storms.

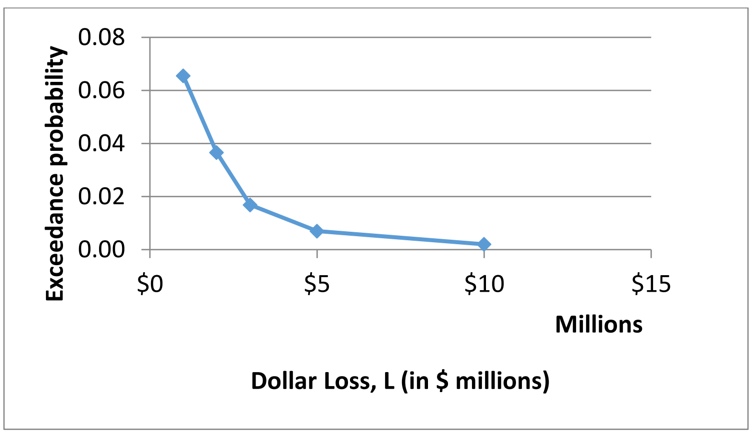
AIR Worldwide began developing catastrophe models in 1987 and have since established themselves as one of the premiere providers in the catastrophe modelling industry ("About Catastrophe Risk Modeling", 2018). Their models use computer simulations to try to estimate all plausible catastrophic events. These models are now very advanced and include a tremendous amount of data. The models essentially look to make predictions for a wide variety of factors that collectively contribute to the damage amounts and any insured loss that the insurance or reinsurance company would be liable to payout in claims. To make these predictions, historical information is used as a basis for the simulation that the model will run. It is important to note that catastrophe models aren't designed to make predictions of specific future events, but rather to estimate the probability of future loss (Wang, 2012). These simulations are over many years and help to create probabilities for all sorts of natural disasters occurring in a given area at a given severity. This is much better than relying solely on the historical information because as you go further into the past, the quality and quantity of available data can be diminished. Also, there are changes occurring in many other aspects related to storm damage, such as development of cities, population shifts, and changing climate conditions. One way that AIR tries to account for this uncertainty is to include climate data along with the historical occurrence of storms to create probability distribution functions of the storms. These are then used to create a portfolio of all physically plausible events ("Casualty Actuarial Society", 2010).

Frequency and severity of catastrophes are two pieces of these models, which estimate how many and how strong a potential event is likely to be. This information, combined with detailed information about the property and structures in the theoretical area and the policy terms, allows the catastrophe model to predict insured loss. This exposure information is extremely important to the accuracy of the model. The model is only as good as the data allows it to be, so ideally, it will have very detailed, possibly address specific, information about building values and structural integrity. Without this information, the utility of the model will be limited. If the information about building values is limited to citywide or zip codes, then the model will be unable to make as accurate of predictions as it otherwise would've. This can be combined with detailed insurance policy information, which will allow the model to create loss probabilities for insurers.

Today, AIR models include a variety of statistics that assist companies in properly assessing their risk. These include: average annual loss, exceedance probability, probable maximum loss, and tail value at risk. Average annual loss is simply the amount of predicted loss per year by the model, which can be calculated from the exceedance probability ("About Catastrophe Risk Modeling", 2018). Insurance companies can use the average annual loss to price their premiums at a level that should help them reach a desired level of profit. This is just an average annual loss, predicted over the course of multiple years, and obviously won't always be a good estimator for the loss in any given individual year, however, in the long run it should be fairly accurate. The exceedance probability is the probability that a catastrophe will occur in the coming year that produces a loss that is greater than or equal to a given value and is the most often used metric from catastrophe models. This is where the term "1 in 200 year storm" comes from that is often used to describe major hurricanes. For example, the aforementioned 1 in 200 year storm would have an exceedance probability of 0.5%. This doesn't mean, however; that there will be an event in the 200 year period that produces damages to that level. There may be multiple events or there could be none. It simply is saying that the annual probability that an event produces damages in excess of that value is 0.5%.

Below is an example of exceedance probability calculations and a graphical representation using made up figures just to display how the calculations are developed. To calculate the exceedance probability for a Category 1 hurricane, you would first need to get (1-annual probability of occurrence for each of the 5 categories). This gives you the probability of there being zero hurricanes in each given category in the coming year, which is what we are looking for to calculate the lowest exceedance probability in the chart, since if any of the events occurred the expected loss would be at or over the given exceedance probability. You then take the probability of there not being a hurricane in each of the five categories and multiply those figures together to get the probability of there being zero hurricanes overall in a given year. That number is then subtracted from 1 to give you the probability of an individual event occurring with damages in excess of $1 million in this example. As you move up to the exceedance probabilities of the other categories, you simply remove the probability of the prior categories event occurring, for example, a Category 1 hurricane could occur and not be above the $2 million level, so the probability of a category 1 storm isn't used in the calculation of the exceedance probability.

Event (E_i)	Description	Annual probability of occurrence (p_i)	Loss (L_i)	Exceedance probability	E[L]
1	Category 5 Hurricane	0.002	$10,000,000	0.0020	$20,000
2	Category 4 Hurricane	0.005	$5,000,000	0.0070	$25,000
3	Category 3 Hurricane	0.010	$3,000,000	0.0169	$30,000
4	Category 2 Hurricane	0.020	$2,000,000	0.0366	$40,000
5	Category 1 Hurricane	0.030	$1,000,000	0.0655	$30,000



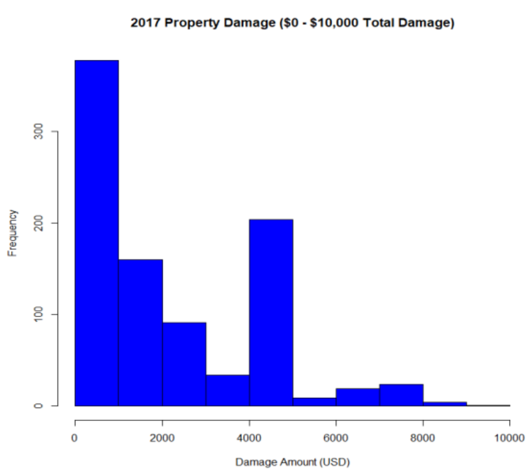
Possible maximum loss looks at the "worst case scenario" and represents the maximum loss that the company could theoretically take on that specific exposure. It is very unlikely that the company will experience a total loss on an exposure as many structures have measures in place to protect against and mitigate any damage. Therefore, many commercial insurers will choose to view probable maximum loss instead as the highest maximum claim as a more useful figure than possible maximum loss (Boggs, 2008).

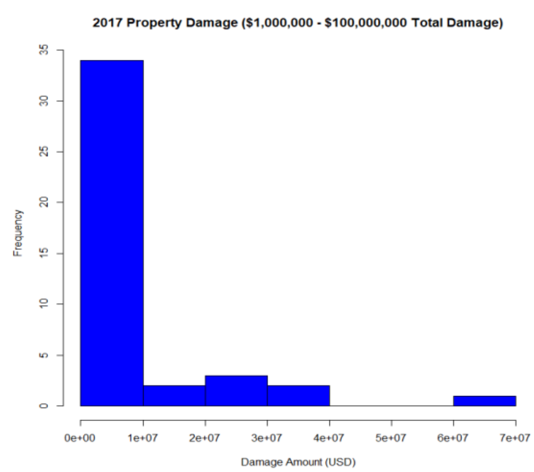
The tail value at risk measure is an estimate of the expected value of loss given that you are already passed some exceedance probability. This is often used to estimate large losses, which are becoming increasingly frequent, with 16 events that caused over $1 billion in damage in 2017 alone (Mooney & Dennis, 2018). I think that tail value at risk data could be especially useful for reinsurers, as they would be interested in the possibility of very large damage amounts coming from catastrophic events. Even large insurance companies frequently use reinsurance companies to hedge some of their risk on large exposures, so these large damage events are the ones that would be the most relevant to reinsurance companies.

The data that I used for this project was gathered from the National Oceanic Atmospheric Administration. They had detailed storm data from the 1950 through 2017. I chose to focus on the data from 2008-2017 in my analysis of overall storm damage in the United States. This dataset was an aggregation of damage reports for property and crop damage resulting from a wide range of weather events including: minor thunderstorms, droughts, floods, and hurricanes. The data was broken down into these damage amounts by county, so I was able to sum the figures in order to get a per storm total. From my analysis I was able to see that the vast majority of storms produced little to no damage. However, the tails of the distribution were often quite extreme, with storms causing billions of dollars of property damage. I think that this is really what insurers worry about, obviously all losses are important and need to be considered, but many just don't carry the same weight as some more costly events such as, Hurricane Katrina, which caused an estimated total of $160 billion in damages ("New list of the Costliest", 2018). As evidence for this assertion, according to an AIR Worldwide study, there were 3 cases of insurance company insolvencies after Katrina hit New Orleans. For comparison, Hurricane Andrew, another storm that caused well over $100 billion in 1992, resulted in 11 insolvencies (Wang, 2012). I think that one factor that helped to reduce the number of insolvencies among insurance companies after another extreme hurricane is the emergence of catastrophe models.

These models are constantly improving, as the exposure data gets better and industry experts are continually looking for ways to better quantify the total risk that a company could be exposed to. It also seems that the industry does a good job of learning from their mistakes, so to say. For example, following Hurricane Katrina, hurricane models started to be conditioned on warm sea temperatures, to more accurately reflect rising ocean temperatures over time. Another example of this is terrorism models were never considered until after 9/11, but are now something that absolutely needs to be accounted for as insurers (Wang, 2012).

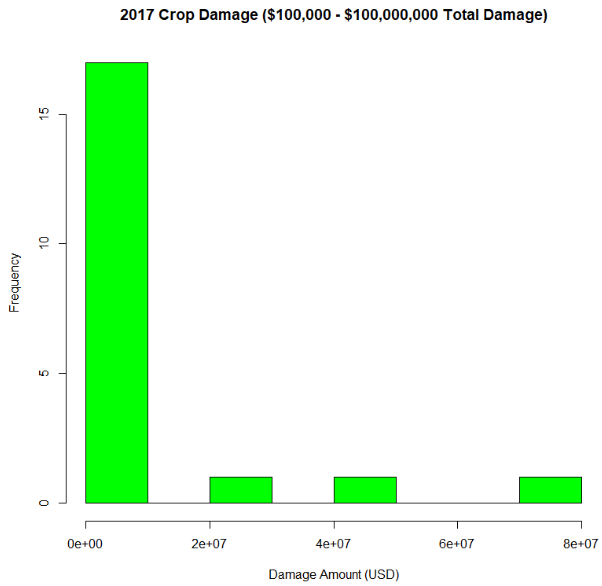
Here, I will discuss some of my findings from analyzing the NOAA dataset. One noteworthy item was that the vast majority of reported weather events had very little to no damage to property or crops associated with them. When looking at the 2017 event data, I found that over 78% of the 8093 reported weather events resulted in $0 of property damage. This is not surprising, because the data set seemed to represent a fairly exhaustive list of all weather events that occurred each year, so many of the data points were from a general thunderstorm and therefore not anything that you would expect to cause much damage. The histograms here help to visualize these results, as both are heavily skewed to the right.

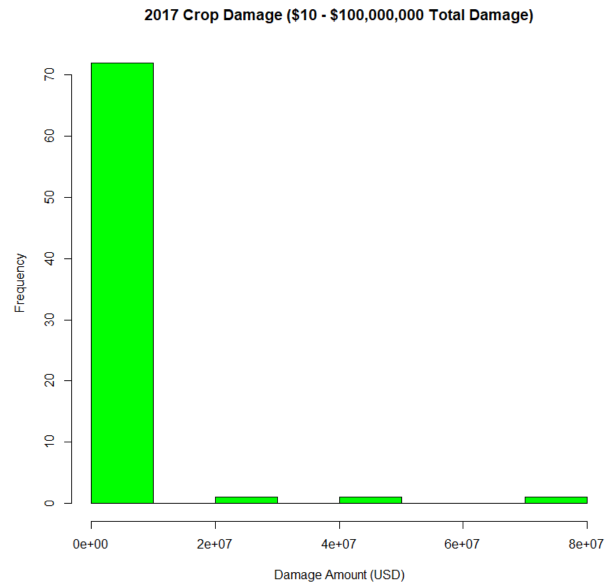




Due to the large percentage of the data being on the left side, I had to limit the minimum and maximum values in the graphs to be able to produce output that would show anything meaningful. The histogram on the left shows the distribution of storms that produced some property damage, but was less than $10,000, while the graph on the right displays the storms in the $1 million to $100 million damage range. Even on such a small range, the histogram on the right has almost all of the observations in the first bin of the histogram. Less than 0.7% of the records for 2017 had property damage amounts that were at least $1 million dollars. To further show how heavily skewed the damage amounts are, I looked at the percentage of storms producing damage of at least $100,000 and found that to be only around 2.7%. I noticed similar trends when looking at other recent years, where I found that the percentage of storms that produced at least $100,000 of damage was 2.1% in 2016, 3.1% in 2014, and 2.6% in 2012. I didn't want to go back too far in the data to make comparisons because, as I discussed earlier, that data is likely not as complete and if it is from too long ago, the damage amounts may not be based off of similar conditions to the data from the 2010's. As an example, for 1950, there are only records of 223 individual events, while most recent years averaged around 10,000 events. Also, looking at 1950, the largest recorded storm produced just $2.5 million of property damage, whereas there were 29 events in 2017 with a damage amount of at least $2.5 million. There are a myriad of potential reasons that I could think of for why this disparity is so great. I think some of it is just the data available wasn't as great for 1950, but also changes in climate, development, and to a lesser extent, inflation, account for the larger damage amounts in more recent years.

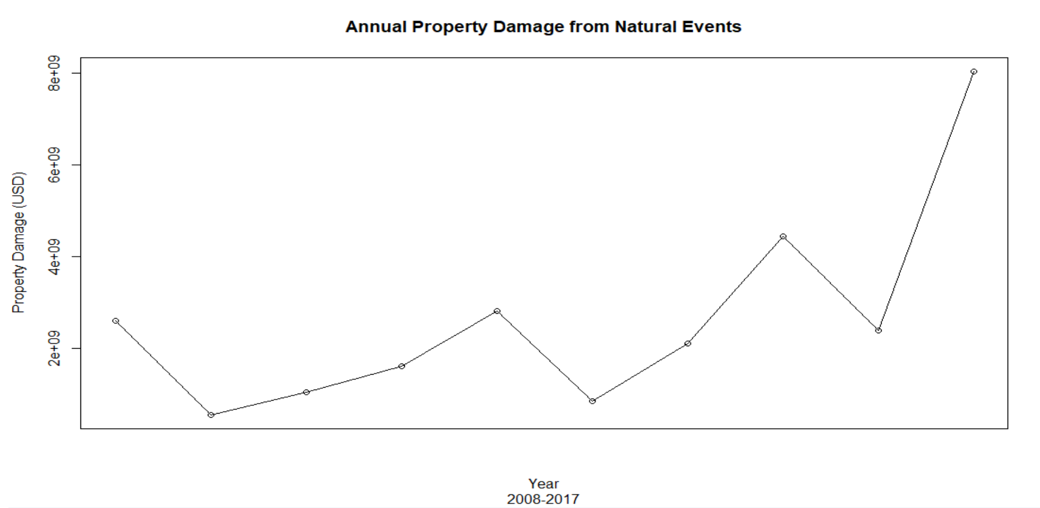
The crop data has the same skewness that the property damage data exhibited, but it is worse in this case. This also seems intuitive, as many events will either be one that isn't severe enough to cause any measurable crop damage, or it simply occurs in an area where crop damage isn't much of a possibility. However, when crop damage was reported, it was often substantial. Looking at the 2017 data, the expected value of crop damage from a storm, given that damage was reported, was just over $2.1 million. It appears that many of these large losses were caused by droughts, floods, and unseasonably cold weather that resulted in crops freezing.





An interesting observation is that the graphs of crop damage look very similar when cut at different points. The first histogram is $100,000 to $100,000,000, while the second shows all storms with non-zero damage. Obviously the units are different as the second histogram includes many observations that were under $100,000, but the distributions appear to be very similar.

I included a plot tracking the reported property damage dollar amounts to structures over the last 10 years. Due to the fairly small sample size, it is hard to say anything definitive, but there appears to be a general upward trend to the data. 2017 was obviously a terrible year for storms, so it will be interesting to see if that represents the continuation of an upward trend for storm damage or if it is just a one year anomaly.



I think there is solid evidence that the damage caused by storms will generally increase for the foreseeable future. Between rising ocean temperatures and a continued influx of people and development moving into coastal areas, it seems that the potential for devastating storms will only rise. Therefore, it will be increasingly more important that insurers are able to accurately model these storms moving forward. Catastrophe models are already very useful for pricing and ratemaking in the insurance industry and, as more data is added to them, they will only get better as time goes on. This should in turn allow insurers a better understanding of their exposures, providing a better experience for both them and the insureds.

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