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Github:
https://github.com/jtmaze/climate-claims-SC

Modeling with Stale Data: Does Disaster Insurance Need an Overhaul in the Face of Climate Change?

Introduction:

Turmoil within insurance markets transform climate attribution from an academic question into an applied problem:

The insurance industry is currently grappling with an emerging crisis characterized by unsustainable risks. Unaffordable policies and bankrupt insurers are garnering national attention. Homeowners increasingly are unable to afford their skyrocketing premiums, placing them in precarious situations, where their home—their most valuable asset—is unprotected. In the riskiest geographies, insurers outright refuse to provide coverage. Due to recent California fire seasons, 19 insurers have revoked their coverage in high-risk locals; a few companies ceased operations in the state entirely. (Flieglem, 2023) At first glance, this crisis might appear to be driven by corporate greed; however, many insurers face their own financial troubles. A recent New York Times article highlights these consistent losses, where property insurers were unprofitable in 18 states during 2023. (Flavelle & Rojanasakul, 2024) Counter intuitively, severe storms, not wildfire and hurricanes have been an increasing share of the losses. (Flavelle & Rojanasakul, 2024) As issuing coverage becomes unprofitable, insurers disappear creating an unhealthy market for consumers. Between 2021 and 2023, nine Florida concentrated property insurers went bankrupt; Florida is a harbinger for a national problem. (Flieglem, 2023)

As private insurers vacate risky markets, more properties are thrust into the arms of the government structured schemes, the "insurers of last resort". In Florida, Citizen's Property Insurance Corporation (CPIC) is emblematic of this process. CPIC was formed in 2002 as a "not-for-profit, tax-exempt, government entity to provide property insurance to eligible Florida property owners unable to find insurance coverage in the private market". (Citizens Property Insurance Corperation, 2024) This means CPIC covers the riskiest properties while simultaneously offering premiums 40% cheaper than the private market. (Reyes, 2023) Unsurprisingly, CPIC's policy count tripled from 400K to 1.2M between 2017 and 2023, given tumult in the private market. (Insurance Information Institute, 2024) This happened despite CPIC's supposed goal to "depopulate" or transition policies into the private market, which properly reflects storm risks. You cannot have your cake (adequate risk management) and eat it too (lower premiums). While CPIC can, in theory, transfer losses to all policy holders by levying assessments, regulators have doubts whether cash-strapped Floridians adequately budgeted for these special assessments. CPIC is now under Federal investigation due to their financial miss-management. Senate Budget Committee Chairman, Sheldon Whitehouse (D-RI) accosted Timothy Cerio (CEO) in an open letter:

“Governor DeSantis’s repeated statements that Citizens is not solvent and the company’s own public comments about their ability to shift their financial losses to Florida policyholders have done nothing to assuage the Committee’s concerns about possible future requests for a federal bailout.” (Whitehouse, 2024)

CPIC is a fiasco of national prominence where poor policy choices exacerbate the escalating climate risks. Florida’s regulatory environment incentivizes frivolous litigation costs on claims negotiations; the state had 76% of claims lawsuits nationally despite having only 6.9% of claims. (The Florida Senate, 2024) Nevertheless, similar examples exist globally throughout developed western nations. The United Kingdom’s public insurance scheme (FloodRe), which levies surcharges on private insures with less risky policies to subsidize the riskiest properties, evolved from a series of amendments, exemptions, and failed efforts to transition risky properties into the private market. (Crick et al., 2018) Due to climate change, schemes like CPIC and FloodRe are increasingly unsustainable. If these “insurers of last resort” fail, the likely outcome is socializing the losses with public funds.

Who should be stuck with escalating bills for disaster insurance —homeowners, taxpayers, financial institutions or carbon emitters—is an ideological question. Regardless, the question will be posed more frequently as losses accumulate. If public ire materializes into restitution, then climate attribution becomes an applied problem, not an academic question. Unfortunately, attaching precise dollar amounts is a troublesome exercise. Attribution requires distinguishing an emitter’s role causing natural disasters from counterfactual scenarios where many natural disasters occur irrespective of emissions. To reproduce this counterfactual world scientists often run general circulation models (GCMs) simulating atmospheric physics with and without anthropogenic carbon emissions. Translating GCM output into weather events is an uncertain process. (Vesely et al., 2019) Nuances of framing such as narrowing the temporal and geographic scales can inflate climate change’s impact relative to natural variability. (Stott et al., 2016) This uncertainty compounds when costs are in economic terms instead of climatological variables, because property values, development patterns and climate-resilient infrastructure are constantly changing (Crick et al., 2018; Jenkins et al., 2018). Attribution science will always contain error bars, and restitution will ultimately be political. Clarence Thomas will choose the model’s lower bound, while Sonia Sotomayor will choose higher values. The promise of climate attribution science is continually narrowing these error bars for the fairest estimates.

Connections between frequentist climate attribution methods

While these insurance debacles have socio-economic factors, such as regulatory capture and moral hazard, a plausible root cause to the industry’s woes is outdated models pricing with stale data. The concept of return intervals, familiar in fields such as hydrology and geosciences, is fundamental to both climate attribution— probabilistic approaches specifically—and actuarial insurance models. A return interval (RI), is the expected occurrence (generally in number of years) for an event with a predetermined magnitude, given patterns in historical data. Unfortunately, non-stationarity, or shifting patterns in historical data complicates RI calculations.

What if historical data no longer represents future events? Non-stationarity is a symptom of climate change, probabilistic attribution approaches aim to quantify the degree of non-stationarity caused by climate change. On the other hand, for insurers, miscalculating RIs can significantly impact loss estimates. Increasing natural disasters decreases the RIs for many catastrophic events. If RIs for a given damage threshold shift from 100 years to 70 years due to climate change, insurers could miscalculate their losses by 42%. (Appendix Equation #1)

Given the broader context, I explore the frequency of disaster damages in South Carolina, a state with severe storms and coastal hazards. I apply a probabilistic approach inspired by Dr. Peter Stott, Dr. Daithi Stone, and Dr. Myles Allen's 2004 paper "Human contribution to the European heatwave of 2003." There is a notable exception; I did not incorporate climate modeling forced with emissions and no-emissions scenarios. By assuming that climate change intensified storm impacts over 60 years, this project addresses the following question:

"Is the frequency (RI) of disaster losses from storms in South Carolina increasing over time with climate change?"

Methods:

Primary data source (SHELDUS):

The project's primary data source is the Spatial Hazards Events and Losses Database for the U.S. (SHELDUS). SHELDUS provides event data (i.e. a specific storm) spatially referenced the county FIPS level, covering a wide range of disaster types from 1960 through 2022 for all 50 states. National analysis using SHELDUS is prohibitively expensive, with only South Carolina data available free of charge. Probabilistic modeling of natural disasters performs best with large datasets and less geographic concentration; however, continental U.S. (CONUS) data cost over $100,000, making it unattainable. Nevertheless, I found adequate data to evaluate storm RIs in South Carolina. SHELDUS pre-calculated inflation adjustments, which simplified the workflow for accurate comparisons overtime. With out inflation adjustments, historical economic losses were artificially lower simply due to nominal asset values. All damages values in this report are in inflation adjusted terms. Additionally, SHELDUS computed per-capita adjustments, which were time-specific preventing erroneous values from using 2022 population on 1980 damages. Without per-capita adjustments, damages biased towards populous counties. These time-specific inflation and population adjustments ensured valid temporal comparisons.

SHELDUS also had several key drawbacks including 1) Disorganized hazard classifications 2) Limited spatial granularity 3) Problems with aggregation over multiple counties. The database originally contained 67 unique hazard types with many redundant categories such as "Wind / Lightning", "Wind / Flooding", and "Severe Storm / Flooding." These categories lacked proportioning of event damages to different hazard types (e.g., % wind vs % flooding). To resolve this issue, I reclassified hazards into five broad categories 1) General Storms, 2) Drought/Heat/Wildfire, 3) Hurricanes/Tropical storms, 4) Winter weather, and 5) Unclassified. See Appendix Box #2 for details on hazard reclassification and the proportion of damages. Careful consideration was required contemplating how hazard reclassification might influence results. Another drawback to SHELDUS was limited spatial granularity. To truly characterize spatial risks, the project requires damages data in Census Tract and even Block Group levels. County level data doesn't account for specificity, like a single community concentrated in a floodplain. The final problem with SHELDUS arose with aggregation when catastrophes spanned multiple counties; damages are evenly spread across all affected counties. If 90% of a Storm's damage occurred in one county, all counties were assigned equal damage. This aggregation masks important spatial patterns. Due to a wide diversity of hazards, there are spatiotemporal tradeoffs generalizing unique events that range from thunderstorms to volcanos. How SHELDUS addressed these tradeoffs created drawbacks to accompany the database's advantages.

Challenges with scale in the modeling approach:

Of the five categories, General Storms were best suited for modeling because those damages occurred with regular frequency throughout all of the counties. Other categories, like hurricanes were unfeasible due to geographic concentration in South Carolina. Comprehensive hurricane analysis would require data for the entire Southeastern U.S. For instance, Hurricane Hugo in 1989, accounted for approximately 75% of all damages. Figure #1 illustrates the impact of such monumental events. Hugo's damage also illustrates how population centers have an outsized impact on damage amounts. Because Hugo directly hit Charleston, it was more catastrophic than a similar magnitude storm affecting only rural counties. I removed Hurricane Hugo from all subsequent analyses, because it was massive outlier unsuitable for single state analysis. Less frequent disasters, like Winter Weather, were compelling to explore, but inadequate for modeling RIs.

Spatial context was a critical factor framing the damage RIs. Figure #2 shows the spatial patterns for per-capita damages. Without per-capita adjustments, the total damages map would simply resemble a population map obfuscating information about relative risks. Even on a per-capita basis, damages are generally biased to population centers like Augusta, Charleston, Columbia and Savanah. While the choropleth map contains valuable information, Figure #2: Panel B demonstrates the shortcomings of a frequentist approach to risk analysis. At localized scales risks can be inflated or underestimated depending on arbitrary county borders. Furthermore, a polygon does not reflect heterogeneous risks within a county. (Federal Emergency Management Agency (FEMA), 2023) By restricting this study's analysis to frequently occurring storms at the state-level, I mitigated challenges with scale in probabilistic modeling.

My modeling approach was inspired by extensive climate attribution literature conducting RI analysis for given events under baseline and shifting climate scenarios.(Allen, 2003; Pall et al., 2011; Stott et al., 2016) This study is unique, because it analyzes the economic costs rather than climate variables directly. In lieu or General Circulation Models (GCM) to simulate atmospheric processes underlying climate scenarios, I simply compared historical and modern RIs with the assumption that climate change is happening. I calculated annual storm damage RIs in total dollars to quantify total loss estimates for South Carolina's storms. I also calculated per-capita RIs, because comparisons across historic and modern time periods are more robust on a per-capita basis. Per-capita adjustment ensured increases in damages were not conflated with population increases. I utilized the curve_fit module in scipy.optimize to model the magnitude of storm damage for a given RI. The models were simple logarithmic functions fit to the data. For given damage thresholds in the RI models, a probability mass function (PMF) was used to estimate the number of exceedances for varying thresholds of losses over a 100-year period. See Appendix Box #3 for more background on the PMF.

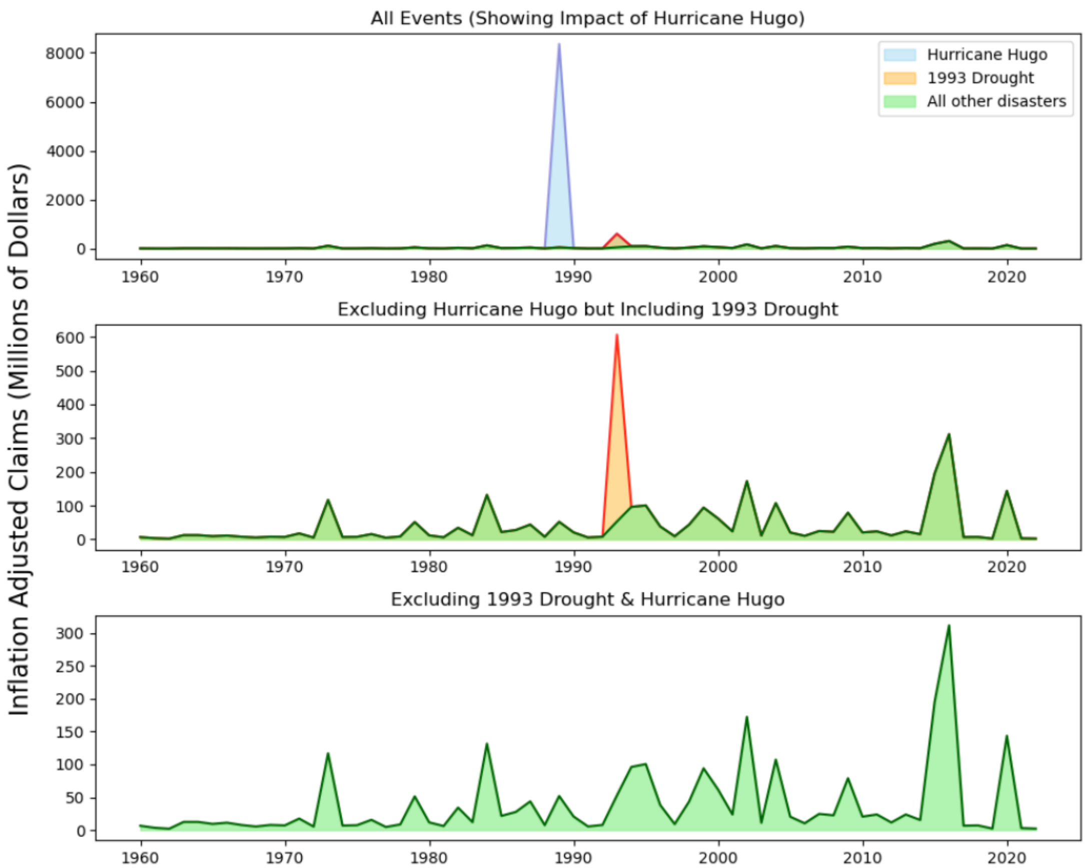

Figure #1: Shows the time series of catastrophe damages for the entire SHELDUS database. The y-scale changes in each panel to illustrate the extent of Hugo's damages.

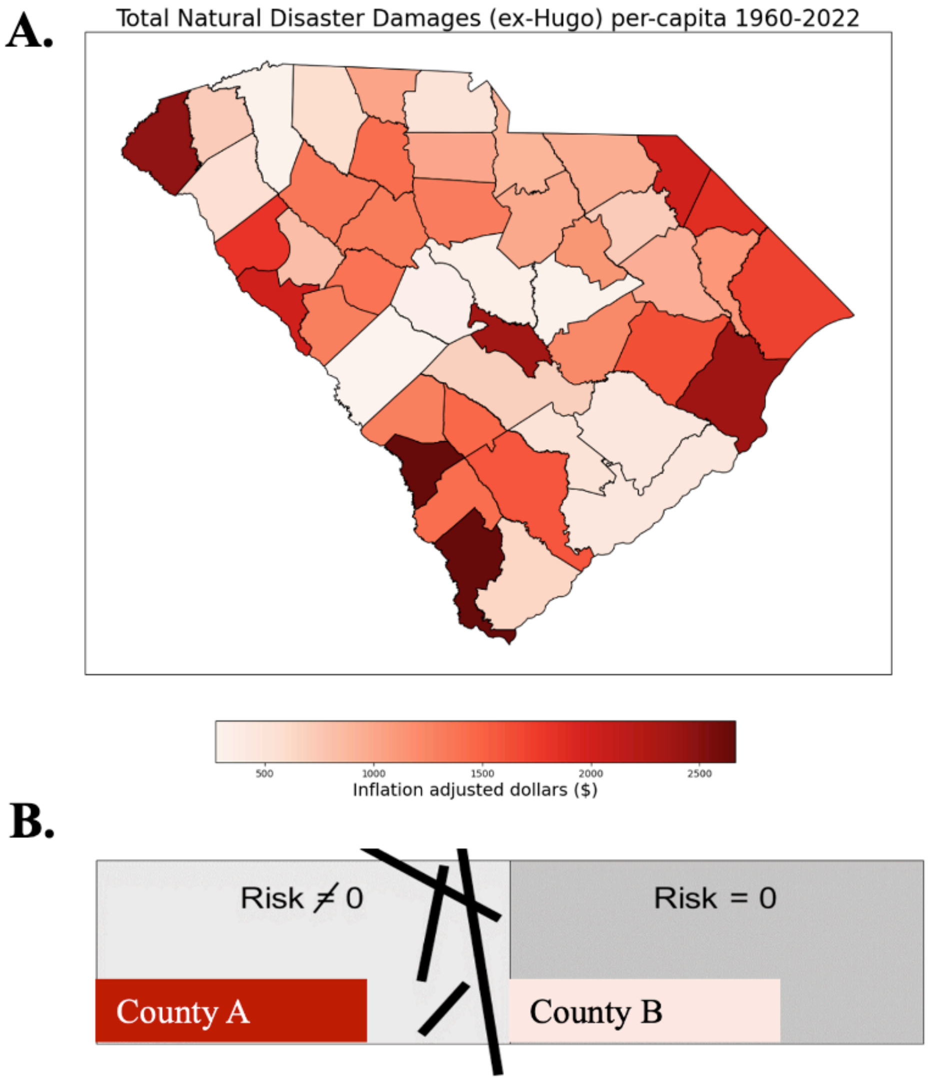

Figure #2: Panel A. is choropleth map showing spatial patterns in total (1960-2022) per-capita damages at the county level. Panel B demonstrates the pitfalls of frequentist analysis, when aggregated to the county level. The black lines are hypothetical storm paths. Panel B is an adaptation from an original figure produced by FEMA in a 2023 report titled "National Risk Index Technical Documentation", which also utilized SHELDUS data.

Results:

Visual representations of damages by hazard type:

The highest impact hazard types displayed considerable variability across counties as demonstrated in Figure #3. While Storms were most common, hurricanes were particularly severe along the coast, and winter weather was destructive in a few northern counties. Winter weather was unexpectedly impactful considering S.C.'s mild climate, but the majority of damage is attributed to a few events, including a massive blizzard in 1993 and several ice storms. In general, multiple hazard types contributed substantial amounts to each county's total damages**.** Figure 4 illustrates the diversity of hazards within counties. Counties had vastly different per-capita damage totals with the highest damage county (Allendale) exceeding five times the losses of the lowest damage county (Alken). Differences between counties' per-capita damages could arise from incongruous asset values, or random chance as discussed in Figure #2, Panel B.

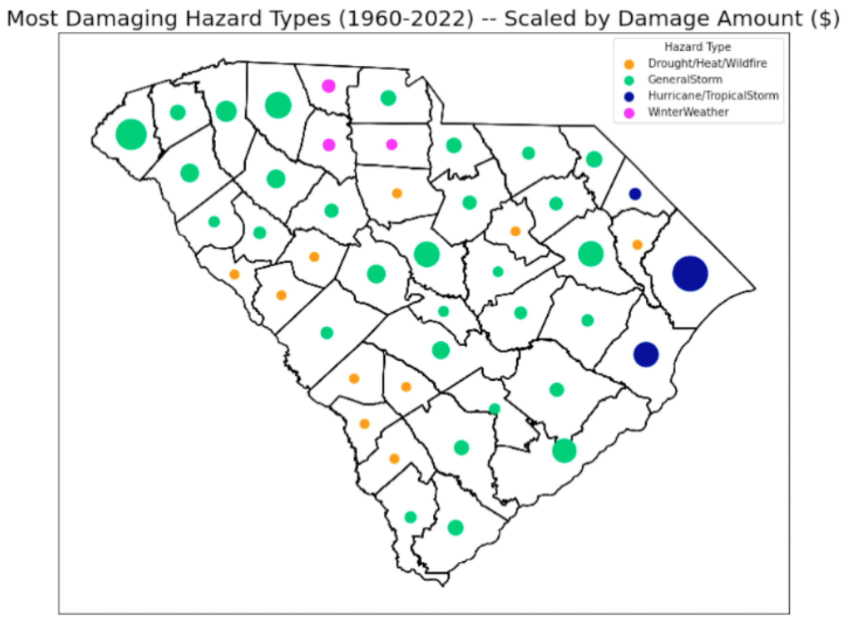

Figure #3: Shows the most damaging hazard type in each county with dots scaled to the total damages (not per-capita adjusted).

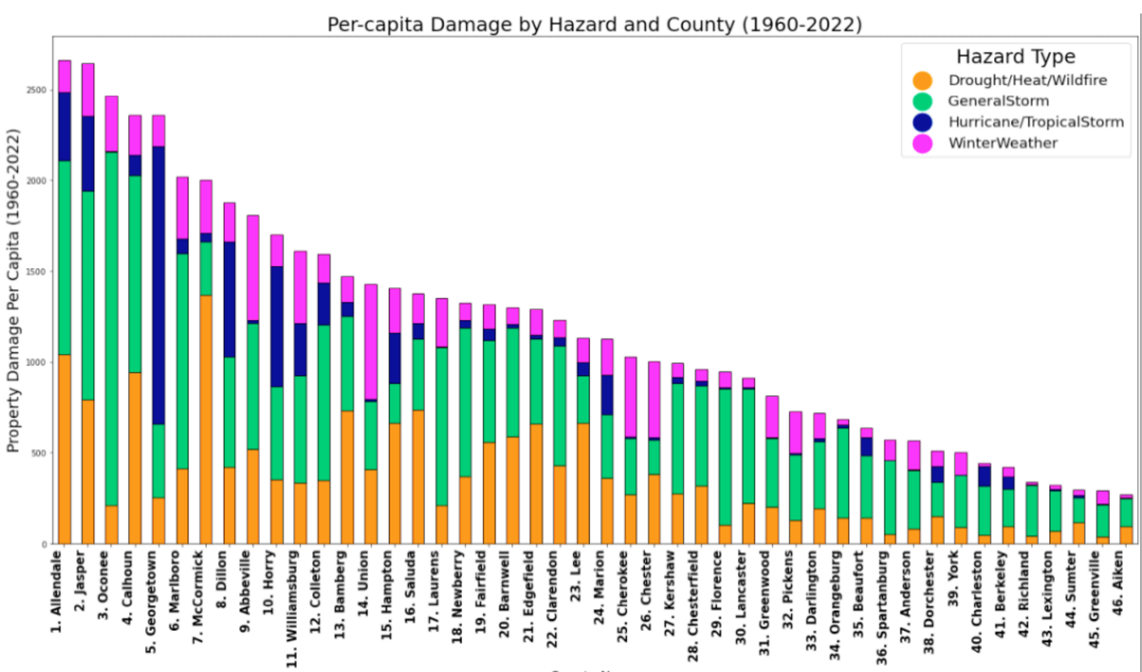

Figure #4: Total per-capita damage grouped by county and ranked descending. Stacked colored bars represent hazard types; Drough/Heat/Wildfire (orange), General Storms (green), Hurricanes/Tropical Storms (navy blue), Winter Weather (pink).

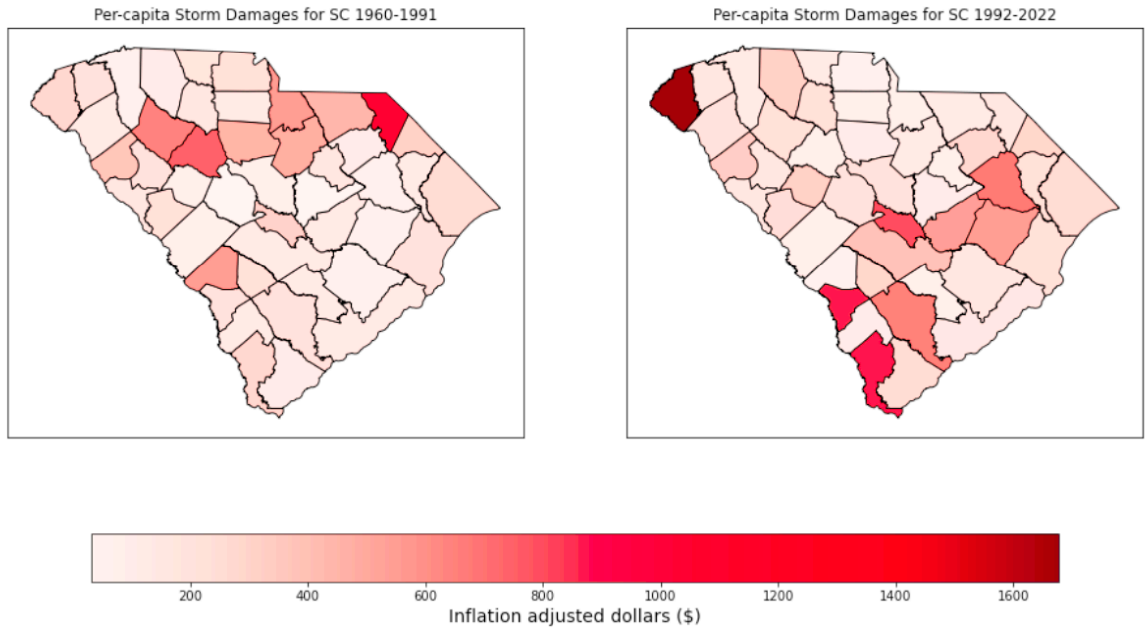

Figure #5: Shows the total inflation adjusted per-capita storm damages comparing the historic (1960-1991) to modern (1992-2022) data. This historical and modern split is the basis for empirical modeling on shifting storm frequencies.

Modeling the historic and modern RIs for annual storm damages:

While the RI vs. annual damage models performed adequately, residual patterns consistently indicated underprediction for the smallest RIs (< 5 years), overprediction for intermediate RIs (5-20 years), and underprediction for the largest RIs (> 20 years). Figure #6 (Panel B.) shows this residual pattern in the annual damage model (1960-2022). This same pattern in residuals was consistent in total damages and per-capita damages across the total, modern and historic time periods. This consistency in residual patterns indicates opportunity for further model fitting. Using the annual damage to return interval model, I predict the likelihood of breaching certain loss thresholds. Intermediate loss predictions are robust; however, there is substantial uncertainty for the highest damage thresholds. Given historic SHELDUS data, the modal outcome for exceeding \$50 Million and \$100 Million in annualized losses is $k \approx 18$ and $k \approx 6$ occurrences per 100 years respectively (Figure #6, Panel C).

To determine if storm damage amounts are increasing, per-capita damages were analyzed to avoid conflating increasing damages with increasing population. Initial observations from a choropleth map were inconclusive (Figure #5), prompting a more empirical evaluation. Recurrence-damage models fitted to different time periods revealed an outlier problem with a significant tornado outbreak in 1984. Including this outlier produced identical models, but excluding it dramatically changed the results (Figure #7). The diverging models indicated increases in the probability distributions for loss thresholds. For example, the modal outcome for $1000 in per capita losses historically occurred approximately five times per 100 years, but with modern data, the modal outcome shifted to roughly 14 times per 100 years. Additionally, kurtosis increased with wider tails in the PMFs and more uncertainty in modern data. This increase in uncertainty is largely an artifact of the PMF's nature. As λ approaches 0.5, there's more dispersion causing a range of different k-values to have similar probabilities. Regardless, this attribute of PMFs is still transferable to climate events in the real-world. As high RI events become more common, the variability in their number of occurrences also increases.

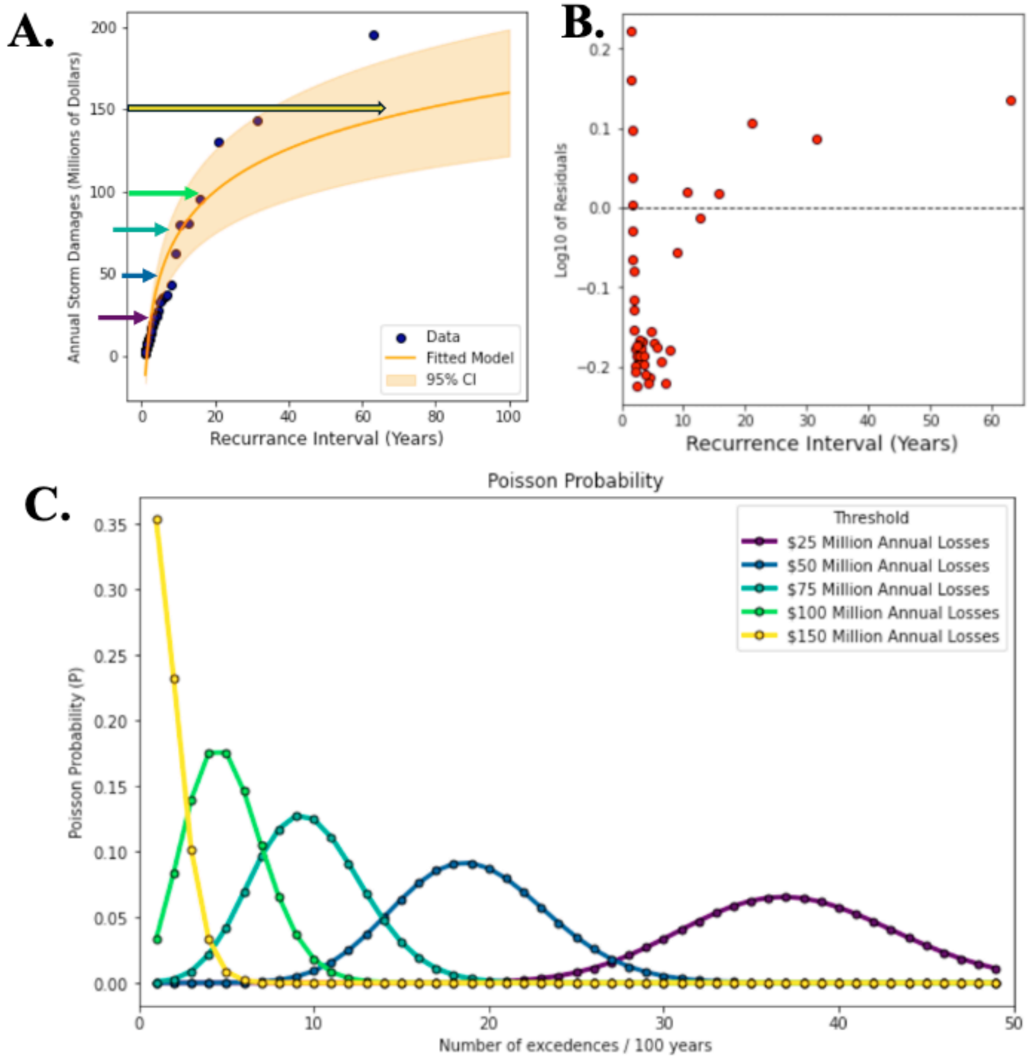

Figure #6: Panel A shows the model for expected annual storm damages for a given return interval fitted over all years (1960-2022). The 95% confidence interval is shaded in orange. Colored arrows correspond to the damage thresholds used in the probability mass function (PMF). Panel B shows the residual plot for annual storm damages RI model. Panel C plots the

PMF for given damage thresholds, showing the expected number of exceedances per 100 years for a given threshold of losses.

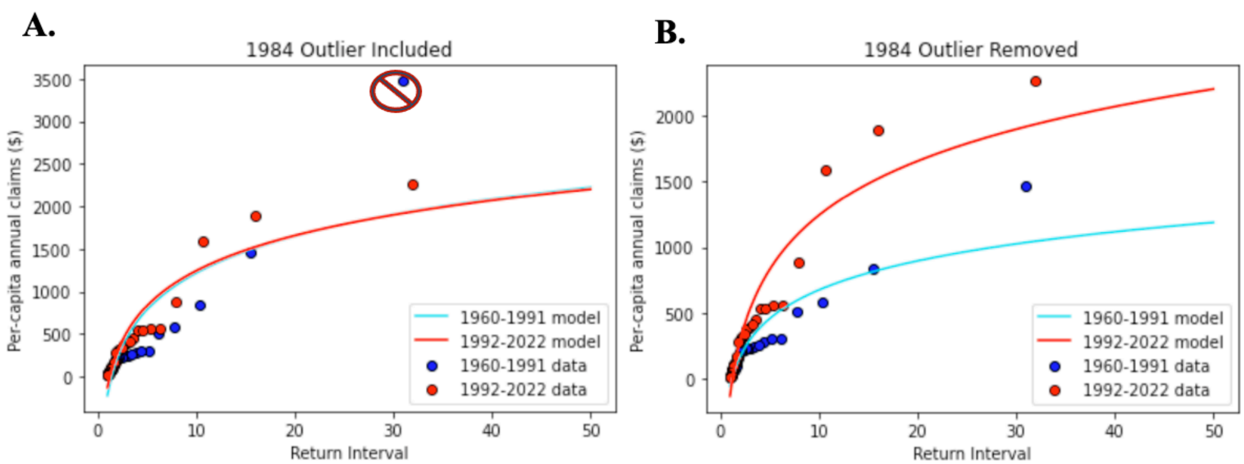

Figure #7: Comparisons between the historic (blue) and modern (red) storm damage datasets and RI vs. damage models. Panel A includes the 1984 tornados and Panel B omits the outlier tornado year.

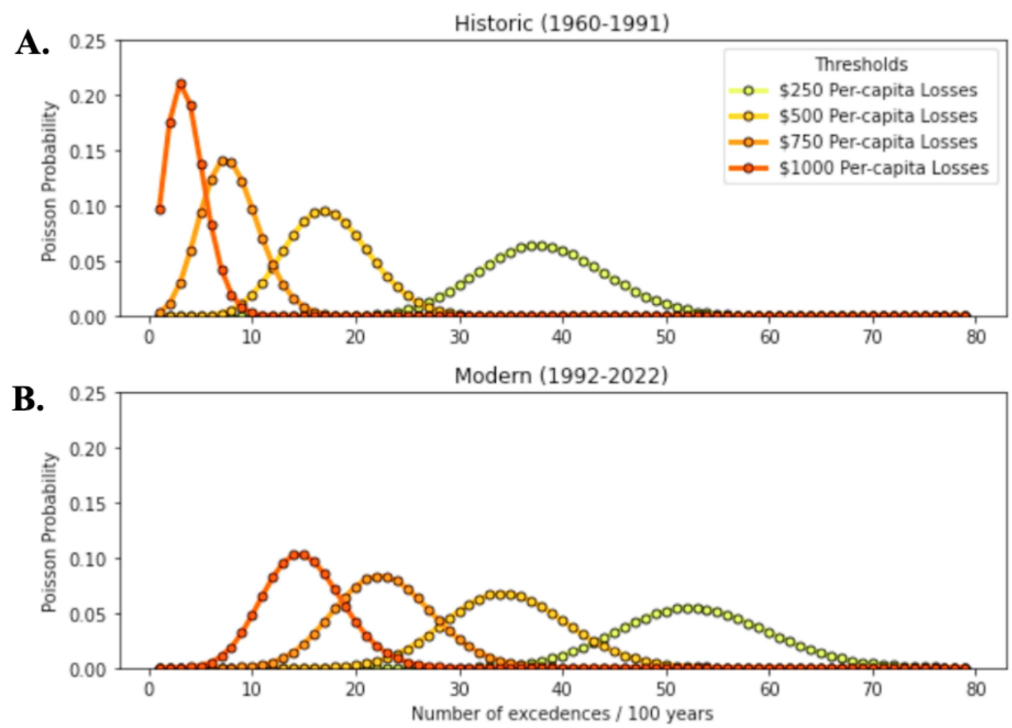

Figure #8: Compares the PMF distributions for the historic (1984 outlier removed) in Panel A and modern in Panel B. The curves are colored according to per-capita damage threshold with $250 (lime green), $500 (yellow), $750 (orange), and $1000 (red).

Discussion:

Material flaws in results:

While initially compelling, my results are materially flawed, because SHELDUS contains temporal inconsistences. The National Center for Environmental Information (NCEI) is the storm data source for SHELDUS. Prior to 1996 NCEI only included damage for tornadoes, thunderstorm wind, and hail. Furthermore, NCEI reports all events prior to 1994/1995 as a range (e.g. $5,000-$50,000). SHELDUS took the lower bound of this range in historic data. These temporal inconsistencies would bias my results to higher climate impacts. While there's potential that I could reconstruct damage ranges for better temporal consistency, this would be an arduous process. After a few hours of effort, I decided reconstructing the NCEI data was beyond the scope of a class project. Resolving the temporal inconsistencies may not even be possible. Connecting with the curators of SHELDUS for solutions is a logical next step.

Identifying areas for improvement:

Besides the glaring data issue, my study could be improved with better RI damage models, analysis at new spatial scales, and comparison with re-analysis climate data. The consistent pattern in residuals speaks to the need for improving model fits. More time could be spent exploring polynomial fitting while being cautious of overfitting given limited observations. I would also like to conduct this modeling approach at different spatial scales. Frequency analysis was only conducted at the state level, but finer-scale analysis could reveal interesting patterns in specific counties or clusters of counties. However, this could risk conflating signal with noise as discussed methods (Figure #2, Panel B). National data would enable exploration of new hazards with lower frequencies (i.e., hurricanes), providing a broader context for understanding storm impacts. Given national data, I could also analyze new hazard types not applicable in South Carolina such as forest fires in the Western U.S. Connecting economic losses in SHELDUS to physical climate variables such as windspeed, precipitation, and even atmospheric pressure anomalies, could add further veracity that losses are due to climate, not socio-economic factors. Initially, I hoped to analyze ERA5 climate data in conjunction with SHELDUS; however, this was too ambitious without additional team members.

Conclusion:

This project contextualized the financial challenges facing the insurance industry with a data-driven approach. Material flaws in SHELDUS's temporal consistency impeded conclusive results; however, broken insurance markets will be a symptom of climate change for decades. The sophisticated insures will require specialists like hydrologists, meteorologists and geophysicists to understand emerging risks. (Khoo & Yong, 2023) Meanwhile, skyrocketing premiums are the primary climate impact experienced by wealthy economically mobile people, who witness minimal physical danger relative to vulnerable poorer groups. In a way, appealing to people's selfish nature is more effective than emotional images of polar bears. As Myles Allen said in 2003, "Even the most impassioned eco-warrior has nothing on a homeowner faced with negative equity" (Allen, 2003)

Appendix:

Box #1: The hypothetical example discussed in Paragraph #3. Simplifying assumptions include 1) A single discrete payout value instead of continuous distribution of payouts 2) A fixed long-term contract in which the asset value is constant (i.e., no inflation), and 3) Zero returns on insurer capital.

$$\boxed{Premium(\$/yr) = \frac{Payout(\$)}{RI(yrs)}}$$

Scenario #1:
- Payout (replacement cost) = $1,000,000
- Historical RI = 100 yrs
- **$10,000 / yr to break-even = $1,000,000 / 100 years**

Scenario #2:
- Payout (replacement cost) = $1,000,000
- Climate Change RI = **70 yrs**
- **$14285 / to yr beak-even = $1,000,000 / 70 years**

Box #2: Provides detail on the hazard reclassification methodology. After the broad reclassification of hazard types, the table shows the percentage of total damages (without Hurricane Hugo) attributed to each hazard type.

```
def hazard_broad_reclass(hazard):
    # 1. Heat, Drought and Wildfire
    if 'Heat' in hazard or 'Drought' in hazard or 'Wildfire' in hazard:
        return "Drought/Heat/Wildfire"
    # 2. Hurricanes and Tropical Storms
    if 'Hurricane' in hazard or 'Tropical Storm' in hazard:
        return "Hurricane/TropicalStorm"
    # 3. General Stormy Weather includes Tornados
    if ('Tornado' in hazard or
        'Severe Storm' in hazard or
        'Thunder Storm' in hazard or
        'Hail' in hazard or
        'Wind' in hazard or
        'Flooding' in hazard or
        'Lightning' in hazard):
        return "GeneralStorm"
    # 4. Winter Weather
    if 'Winter Weather' in hazard:
        return "WinterWeather"
    # 5. Unclassified (e.g. fog)
    else:
        return "Unclassified"
```

```
51.83% GeneralStorm
21.63% Drought/Heat/Wildfire
14.30% Hurricane/TropicalStorm
12.10% WinterWeather
0.14% Unclassified
```

Box #3: Shows the formula for the PMF used to model expected number of exceedances for a given damage threshold over a 100-year period for the RI of a given damage threshold.

$$f(k;\lambda) = \Pr(X{=}k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

λ = The expected number of occurrences for a given time period (The RI).

k = The hypothetical number of occurrences over given time interval.

Pr = The Poisson probability of k occurrences given λ expected occurrences.

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