Reducing financial impacts on the reinsurance industry: Economic valuation of seasonal hurricane forecasts

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ABSTRACT

Hurricanes can cause significant economic loss in the eastern coastal United States. Forecasts of seasonal hurricane frequency and intensity are available, but the use of these forecasts in the reinsurance industry to mitigate the economic impacts of hurricane landfall is not apparent. If reinsurance utilized forecasts, they could conceivably increase the likelihood of being able to pay insurance companies in the event of a damaging hurricane strike. This would also benefit insurance companies and property owners by stabilizing the insurance industry as a whole.

We first analyzed the dependence of hurricane frequency and damage on El Niño-Southern Oscillation (ENSO). Results indicated that La Niña (El Niño) years experience more (less) frequent, more (less) damaging hurricanes. We then built a simulation model of damage. Assuming knowledge of the ENSO state, the model generated annual total damage based on adjusted Poisson and lognormal distributions of annual hurricane number and storm damage, respectively. We obtained the 5% level of loss exceedance associated with all, La Niña, Neutral, and El Niño years. They showed 20-year period return levels of $33.7, 73.2, 30.1, and 9.9 billion, respectively (constant 1995$).

ENSO state appears to have a considerable effect on the distribution of economic damage. Through the model’s inclusion of specific reinsurance contract options (and associated costs) and a complete hurricane forecast (i.e. not just the ENSO aspect of the forecast), the optimal use and forecast value to the industry could be quantified.

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Section 1: INTRODUCTION

Over the past 50 years, short-term weather forecasts have improved dramatically. Ever-increasing computer power allows powerful forecast models to run many numerical computations. Forecasters then combine their skill and intuition with the output of these models, creating reasonably accurate short-term weather forecasts. Longer-term (i.e. climate) forecasts have also seen improvement from virtually no skill to modest skill. Climate forecasts allow prediction of events that occur well into the future, including seasonal hurricane frequency and intensity and El Niño-Southern Oscillation (ENSO). Currently, hurricane forecasts (and indirectly ENSO forecasts because ENSO is one of several predictors that are involved in hurricane forecasting) are used to predict the upcoming season’s hurricane frequency and intensity. Regarding hurricane forecasts, one should note that it is difficult to issue predictions that have such long lead-times. However, as technology, forecasting techniques, and climate understanding progress, hurricane forecasts will continue to improve.

Now that more-reliable forecasts and information are available, they must be made of maximal benefit to society. Decision makers in many different societal realms utilize weather and climate forecasts in decision models to benefit themselves and others. Some short-term decisions that utilize weather forecasts include the following: issuing community evacuations due to severe weather or biochemical pollutants, advising farmers whether or not to protect their crops from harmful weather, and taking measures to ensure road safety. Long-term decisions that are affected by climate include: determining how much energy a power company should expect to produce and/or purchase for the upcoming season and, the situation of particular interest to us, understanding how hurricane forecasts can be used by reinsurance companies.

1.1 Reinsurance industry

Reinsurance is essentially described as the “insurance of insurance companies,” (RAA, 2004). Reinsurance companies compensate insurance (and other reinsurance companies) according to a contractually agreed upon premium. The purpose of reinsurance is to spread monetary risk so that financial burden is not laid upon a single company during a large insurance payout.

One reason reinsurance is utilized is to protect against catastrophic events, like hurricane landfalls. Depending on the strength of the hurricane and the population and amount of insured property in the region, hurricane damage can cause extreme financial burden for insurance companies. For example, the landfall of Hurricane Andrew in 1992 in southern Florida caused roughly $30 billion in damage (Figure 1). The storm severely strained the insurance industry, as it was the costliest natural disaster in U.S. history. Property owners filed over 700,000 insurance claims, causing some companies to even discontinue hurricane damage-related coverage. In order to minimize risks like this and stabilize financial performance, insurance companies can purchase reinsurance.
The contracts established between reinsurance and insurance companies are usually negotiated annually. Contracts are written on either a proportional basis or an excess of loss basis (RAA, 2004). Proportional basis agreements call for the reinsurance and insurance company to prorate all losses. These contracts are most common for property reinsurance. Excess of loss basis agreements state that the insurer will pay all losses up to an agreed limit; the reinsurer then pays any losses that are greater than that limit.

1.2 Hurricanes, hurricane forecasts, and ENSO

A hurricane is a tropical cyclone with sustained winds exceeding 74 mph. They form when light winds, high, deep-layered humidity, and warm sea surface temperatures (SSTs) are present (HRD, 2004). Hurricane damage is projected with the Saffir-Simpson scale, which categorizes hurricanes based on their maximum sustained wind speed (Table 1). By convention, the hurricane season in the United States begins on June 1 and lasts through November 30. The months of August to October are of particular concern because 95% of intense hurricanes (hurricanes of Saffir-Simpson category 3, 4, or 5) occur during these months (Pielke, Jr. and Landsea, 1999). In the U.S., the Gulf and Atlantic Coasts are particularly susceptible to hurricane landfall (Figure 2).
### Table 1. The Saffir-Simpson hurricane scale. Damage information obtained from the National Hurricane Center.

<table>
<thead>
<tr>
<th>Hurricane scale number</th>
<th>Wind speed (mph)</th>
<th>Damage Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>74-95</td>
<td>Storm surge 4-5 ft above normal. No real damage to building structures. Damage primarily to unanchored mobile homes, shrubbery, and trees. Some damage to poorly constructed signs. Also, some coastal road flooding and minor pier damage.</td>
</tr>
<tr>
<td>2</td>
<td>96-110</td>
<td>Storm surge 6-8 feet above normal. Some roofing material, door, and window damage of buildings. Considerable damage to shrubbery and trees with some trees blown down. Considerable damage to mobile homes, poorly constructed signs, and piers. Coastal and low-lying escape routes flood 2-4 hours before arrival of the hurricane center. Small craft in unprotected anchorages break moorings.</td>
</tr>
<tr>
<td>3</td>
<td>111-130</td>
<td>Storm surge 9-12 ft above normal. Some structural damage to small residences and utility buildings with a minor amount of curtainwall failures. Damage to shrubbery and trees with foliage blown off trees and large trees blown down. Mobile homes and poorly constructed signs are destroyed. Low-lying escape routes are cut by rising water 3-5 hours before arrival of the center of the hurricane. Flooding near the coast destroys smaller structures with larger structures damaged by battering from floating debris. Terrain continuously lower than 5 ft above mean sea level may be flooded inland 8 miles (13 km) or more. Evacuation of low-lying residences with several blocks of the shoreline may be required.</td>
</tr>
<tr>
<td>4</td>
<td>131-155</td>
<td>Storm surge 13-18 ft above normal. More extensive curtainwall failures with some complete roof structure failures on small residences. Shrubs, trees, and all signs are blown down. Complete destruction of mobile homes. Extensive damage to doors and windows. Low-lying escape routes may be cut by rising water 3-5 hours before arrival of the center of the hurricane. Major damage to lower floors of structures near the shore. Terrain lower than 10 ft above sea level may be flooded requiring massive evacuation of residential areas as far inland as 6 miles (10 km).</td>
</tr>
<tr>
<td>5</td>
<td>&gt;155</td>
<td>Storm surge &gt; 18 ft above normal. Complete roof failure on many residences and industrial buildings. Some complete building failures with small utility buildings blown over or away. All shrubs, trees, and signs blown down. Complete destruction of mobile homes. Severe and extensive window and door damage. Low-lying escape routes are cut by rising water 3-5 hours before arrival of the center of the hurricane. Major damage to lower floors of all structures located less than 15 ft above sea level and within 500 yards of the shoreline. Massive evacuation of residential areas on low ground within 5-10 miles (8-16 km) of the shoreline may be required.</td>
</tr>
</tbody>
</table>

*Figure 2. U.S. counties and states most susceptible to hurricane landfall.*

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Over the past couple of decades, hurricane experts have been issuing probabilistic forecasts of hurricane frequency and intensity for the upcoming season, with the hope of minimizing hurricanes’ economic and societal impacts. Although it is difficult to forecast individual hurricane events months (or even more than a few days) in advance, Gray et al. (2004) have shown that the total seasonal probability of hurricane landfall can be predicted with statistical skill. This suggests that hurricane forecasts can be of economic value to the reinsurance industry.

The ENSO phenomenon is an important topic in climate research. ENSO is an alternating of warm (El Niño) and cold (La Niña) SSTs in the central and eastern equatorial Pacific Ocean. The effects of ENSO are far reaching, influencing atmospheric conditions in many parts of the globe (Glantz, 2001). One such affected region is the Atlantic Ocean, in which temperature, pressure, and wind speed conditions change according to the phase of ENSO. La Niña years are conducive to hurricane formation in the Atlantic because diminished upper-level wind speeds and higher SSTs are experienced there. Pielke, Jr. and Landsea (1999) showed that hurricane frequency, intensity, and damage are influenced by ENSO. Based on economic data from past hurricane events, Pielke, Jr. and Landsea found that La Niña years show increased probability of both hurricane frequency and greater hurricane intensity and damage. Therefore, several ENSO-related predictors are used in hurricane forecast models. Some of the predictors include upper level wind components, sea level pressure (SLP), and SSTs of the Atlantic Ocean region.

1.3 Decision modeling

Decision models are tools that allow one to organize information in order to make weather-sensitive decisions in the face of uncertainty. Decision modeling involves listing the “actions” available to the “decision maker”, uncertain “events” along with their associated probability of occurring, and the “outcomes” that result, based on the actions picked and the events that occur. Table 2 further describes these decision-modeling terms. Decision modeling is a prescriptive approach to solving problems in that it “prescribes” the best action that should be taken in the face of event uncertainty (Wilks, 1999). The preferred action is usually one with an optimal outcome that minimizes expected losses or maximizes expected gains (often monetary or societal). Uncertain events can hinder the decision maker’s judgment of which action is best; but, if there is any skill in the forecasting system, it is conceivable that the decision maker can be better off economically by taking forecasts into account. For clarity, actions, events, probabilities, and outcomes are sometimes listed in what is called a decision tree (Figure 3).

Table 2. Elements of decision modeling.

<table>
<thead>
<tr>
<th>Decision modeling terms</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision maker</td>
<td>Chooses action that leads to the optimal outcome</td>
</tr>
<tr>
<td>Action</td>
<td>Strategy employed that leads to the most desirable outcome</td>
</tr>
<tr>
<td>Event</td>
<td>Uncertain occurrence</td>
</tr>
<tr>
<td>Event probability</td>
<td>Measure of the likelihood of the event’s occurrence</td>
</tr>
<tr>
<td>Outcome</td>
<td>Consequence dependent upon action taken and event that occurs</td>
</tr>
</tbody>
</table>
Figure 3. A simple decision tree representing the actions, events, probabilities, and outcomes available to a decision maker. The occurrence probabilities of Events 1 and 2 are \( p_1 \) and \( 1 - p_1 \), respectively.

Probabilistic forecasts are dubbed either “perfect” or “imperfect”. Perfect forecasts describe the occurrence of an event with absolute certainty—the event will either occur (100% chance, probability of occurring = 1) or not occur (0% chance, probability of occurring = 0). The concept of the perfect forecast is sometimes used as an upper bound on the value of imperfect forecasts. The hurricane damage simulation model we employed assumed perfect ENSO forecasts (but still imperfect hurricane forecasts) to make our modeling simpler. Economic value can then be assigned to the hurricane forecasts using this prescriptive, decision-modeling approach.

1.4 Economic valuation of forecasts

The economic value of an imperfect forecasting system is measured relative to the situation in which the decision maker does not receive the forecasts (e.g. the decision maker has only climatological information available) (Winkler and Murphy 1985). Climatological data represent long-term averages of the atmospheric state of a particular region. For example, the climatological probability of rain in Miami, Florida, on February 14 may be 30%. A skillful forecast, however, would give a probability that deviates from climatology. A forecast of 45% shows that rain is more likely to occur, while a forecast of 10% shows that rain is less likely to occur—more information is now available, relative to climatology.

The expected expenses of the climatology and forecast probabilities are obtained during the decision modeling process. When action costs (such as a reinsurer renegotiating a contract) and event losses (damage losses due to a hurricane season) are known, the value of information (VOI) such as a forecasting system can be given as the reduction in expected expense (Katz and Murphy, 1987):

\[
VOI = E_C - E_F,
\]
where $E_c$ is the minimized expected loss associated with only climatological information (i.e. no forecast) and $E_r$ represents the minimized expected loss associated with the skillful forecast. This expression is used in economics and decision making to value information and represents the maximum amount that a decision maker would pay to obtain the information.

1.5 Scientific goal and motivation

Hurricanes can cause extensive property damage in the United States along the Gulf of Mexico and Atlantic coastlines, especially during La Niña events. Reinsurance companies offering insurance services in those areas are responsible for providing insurance companies with the money necessary to compensate property owners’ losses. If reinsurance companies utilized long-range probabilistic hurricane forecasts, they could conceivably lessen the probability of being incapable of meeting payment requirements by adjusting annual contracts to more accurately reflect the upcoming hurricane season’s expected impacts. This could serve to stabilize the insurance industry as a whole, causing economic benefits to trickle down to insurance purchasers and property owners by allowing them to insure their property in the event of a hurricane.

In this research we analyzed ENSO’s impact on a hurricane season’s frequency and intensity of tropical cyclones. As a simple simulation of economic hurricane damage, we employed a “perfect” ENSO forecast, yet still an imperfect hurricane forecast. We then ran our hurricane damage simulation in order to project future losses for the reinsurance industry.

In the next section, we present our research methodology. Section 3 provides research results and the discussion of those results. We draw our conclusions and propose future work in Section 4.

Section 2: METHODS

2.1 Understanding the R programming language

R is a statistics-based programming language (R, 2004) that was useful in this research. It provided an object-oriented programming environment, along with access to a variety of probability distributions and methods for fitting these distributions to data. Given a particular ENSO state, the Poisson and lognormal distribution functions were shifted to model past frequency and economic damage of hurricanes, respectively.

2.2 Data

2.2.1 Hurricane damage data

The hurricane damage data extends from 1925 to 1995. Pielke, Jr. and Landsea (1998) adjusted the data not only for inflation, but also changes in population and wealth over time for U.S. Gulf and Atlantic coast regions. All monetary values were listed in 1995 dollars.

2.2.2 ENSO data

We also utilized ENSO state data spanning from 1925–1995. ENSO state was classified based on the work of Trenberth (1997), which utilized SST data (see also Pielke, Jr. and Landsea, 1999). The combination of ENSO and hurricane damage data allowed analysis of ENSO’s affects on the frequency of damaging hurricanes as well as intensity of the damage.
2.3 Analyzing frequency and intensity of economic hurricane damage

We used the R programming language to make plots of the frequency and intensity of damaging hurricanes that made landfall, and their dependence on ENSO state. The damage and ENSO data were input into the program and frequency/intensity information was categorized based on the ENSO state. We plotted histograms and box-and-whisker plots to assess the frequency and intensity of damage, respectively. We took the logarithm of the monetary damage amounts because of the raw data’s positive skewness. This moved the data to a more compressed scale, allowing easier comparison of results.

2.4 Incorporating a hurricane damage simulation

Our simulation of total hurricane damage was based on the work of Katz (2002). The simulation attributes total economic damage to both the frequency and intensity of hurricane events. The annual frequency of hurricane landfall is modeled with a Poisson distribution, and intensity (i.e. economic damage) per hurricane is modeled with a lognormal distribution.

Assuming knowledge of the ENSO state for each simulated year, the simulation shifted the Poisson and lognormal distributions accordingly, and randomly drew hurricane frequency and damage values from the shifted distributions. In order to calculate a rare event such as 20-year, 5% exceedance losses, the simulation was run for a large number of years. This allowed us to see how costly, lower-probability hurricane events (i.e. events that are of most interest to reinsurance companies because reinsurance is often utilized when these low probability, extreme events occur) varied as a result of ENSO.

Section 3: RESULTS AND DISCUSSION

3.1 ENSO’s affect on hurricane frequency

Upon plotting histograms of the frequency of economically damaging hurricanes occurring per year, we found that La Niña usually experienced more frequent hurricanes than El Niño (Figure 4). During La Niña events, there were no instances of zero damaging hurricanes making landfall. The rest of the distribution was spread out fairly evenly, showing 1 to 5 hurricanes occurring per year. Neutral events showed a distribution similar to that of La Niña events, but there were years when zero hurricanes made landfall. During El Niño events, the frequency distribution shifted toward lower numbers of hurricanes. There were more instances of zero, 1, or 2 hurricanes occurring, and no instances of 4 or 5 hurricanes. Based on these results, it appears that ENSO state influences the annual number of economically damaging hurricanes (consistent with Pielke, Jr. and Landsea, 1999 and Katz, 2002).
3.2 ENSO’s affect on hurricane intensity of economic damage

Box-and-whisker plots displayed a decrease in the median of the damage amounts from individual storms, going from La Niña, to Neutral, to El Niño events (Figure 5). This leads us to believe that the intensity of economic damage resulting from hurricanes has a dependence on ENSO state as well (consistent with Pielke, Jr. and Landsea, 1999 and Katz, 2002).

3.3 Analysis of simulation model output

Depending on which ENSO state was assumed, the simulation output showed a significant change in 20-year return levels for annual total damage (Figure 6). The 5% level of loss exceedance associated with all, La Niña, Neutral, and El Niño years showed 20-year period return levels of $33.7, 73.2, 30.1, and 9.9 billion, respectively (constant 1995$). With respect to
all years in our data set, La Niña years produced return levels with over twice the amount of damage, neutral years showed similar damage amounts, and El Niño years had about one third the damage.

![20-year return period vs. ENSO state](image)

Figure 6. 20-year, 5% level economic losses expected, based on ENSO state.

**Section 4: CONCLUSION AND FUTURE WORK**

Based on our results, it seems that ENSO state has a significant impact on the amount of damage that a reinsurance company can expect (e.g. in terms of 20-year return levels). A company’s utilization of this knowledge could allow it to better plan its financial actions and annual contract negotiations, thereby stabilizing the insurance industry as a whole. This could lead to economic benefits not only for reinsurance, but also insurance and property owners.

At this point, it appears that a hurricane forecast does have value to the reinsurance industry. However, future work is necessary to assess the actual economic value of hurricane forecasts. What we have accomplished is essentially a necessary first step toward the valuation; the loss amounts obtained could be extremely useful in a decision tree constructed by a reinsurance company. However, more information is needed to determine the specific actions (along with their monetary costs) available to a reinsurance company that would be employed given information on the losses expected due to the upcoming hurricane season. Further development would also incorporate a more complete hurricane forecast. We studied the effect of a single hurricane predictor’s (i.e. ENSO’s) influence on hurricane frequency and intensity, when there are in fact several other meteorological predictors used in current hurricane forecasting techniques. Furthermore, when dealing with a specific reinsurance company, one may need to consider the locations where the company insures as well as its attitude toward the risk associated with taking certain actions.

**Section 5: REFERENCES**


