Hurricane risk pricing, catastrophe models, and data quality:

Why it matters and what should be done about it?

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Introduction:

Over the past 20 years, the colossal increase in computing power has allowed computers to simulate very complex systems that require millions of calculations and operations per second. Simulations virtually reproduce systems and allow the study of their behavior. Using mathematical and physical equations, applications are found in very diverse fields ranging from finance, economics, nuclear physics, climatology, biology, etc…

Simulation software is frequently used to forecast weather, exchange rates fluctuations, stock price movement, or global climate. In most cases, computer simulation is the only available tool generating forecasts from complex models. Assuming that the use of more information into more complex simulators reduces the uncertainty, decision makers often incorporate these forecasts in their decision processes. In some cases, decision makers give simulation tool results a very large weight in their final decision. Some simulation tools such as global climate change or dynamic financial analysis models use the output of very complex models as input to simulate a different system that depends on other systems taking into account hundreds of parameters (for example, global climate change models use the output from solar activity simulation). Similarly, catastrophe models became very sophisticated and complex, using the most recent results from research in tropical meteorology and wind engineering. But just as in global climate models, the sensitivity and uncertainty in catastrophe models should not be overlooked when using model output in decision-making.

Catastrophe models are a good illustration of very complex computer simulations that largely drive business decisions in the insurance and reinsurance industries. This paper proposes a method to assess the sensitivity of insurance pricing methods to data quality[1]

[1] Data quality refers to the level of information about the policy, particularly about the insured building.

and question whether these pricing techniques efficiently use the information in hurricane loss models.

1. The hurricane peril and the associated ratemaking challenges before 1990.

Hurricanes affect societies around the world. Over the past 100 years, the 30 costliest hurricanes[2] landfalling in the US caused over $130 billion[3] in property damage. Mostly due to societal changes such as large increases in exposure, population, and wealth, half of these losses occurred in the past 2 decades. Hurricane Andrew alone caused $30 billion in property damage in South East Florida. Had Andrew followed an equally likely track a further to the North, losses would have exceeded $50 billion.

Until the 1950's, the hurricane peril was covered under various insurance products such as multi-peril policies where rates were combined for the different component coverage (fire, theft, liability, windstorm, etc…) At first actuaries used no more than 5 years of historical experience to price the windstorm component of the policy. Traditional ratemaking techniques faced two main challenges when dealing with the hurricane peril. One is associated to the very low frequency of events, and the other is related to the high range of severities inflicted to property by the very complex windfields of hurricanes. Although major hurricanes[4] represent less than half of the total number of hurricanes, they are responsible for more than 90% of the property losses.

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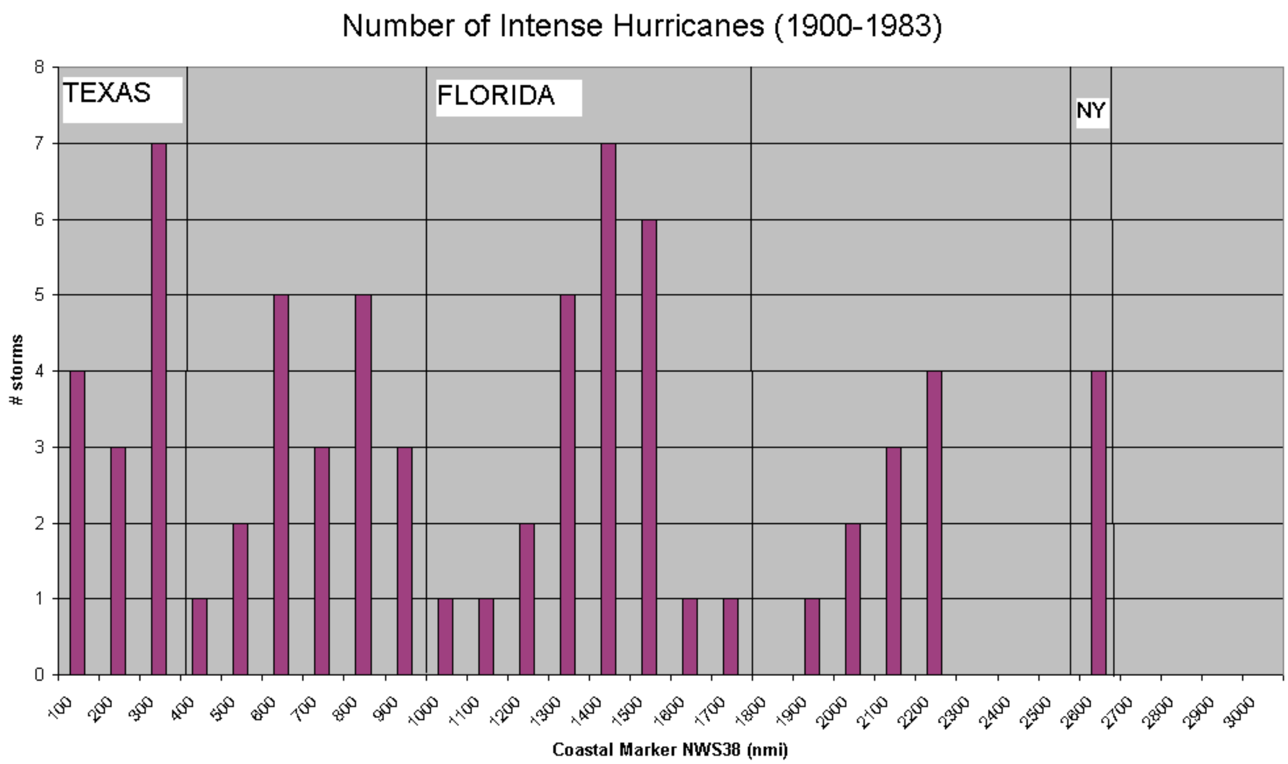
[2] Jerry D. Jarrell, Max Mayfield, and Edward N. Rappaport, NOAA/NWS/Tropical Prediction Center, Christopher W. Landsea, NOAA/AOML/Hurricane Research Division.

[3] All dollars amounts are adjusted to 2000 dollars.

[4] A major or intense hurricane is defined as a one of category 3 or higher on the Saffir/Simpson scale. See Appendix for further info about Simpson Scale.

In 1987, the U.S. Department of Commerce published the list of all hurricanes and their respective meteorological characteristics that made landfall from Texas to Maine[5]. The distribution of major hurricane landfalls from 1900 to 1983 (graph 1) shows how sensitive to location the hurricane peril seems to be.



The coastal segment between mile markers 300 and 400 experienced 7 major hurricanes while the 100-nautic mile gate just to the north was hit by a single similar storm. Is this enough to conclude that the hurricane risk in Houston (TX) is 700% higher than the risk in Beaumont (TX) less than 80 miles away and at a comparable distance from the gulf coast? It raises complex questions regarding intense hurricane storm tracks and more

[5] NOAA Technical Report NWS 38, "Hurricane Climatology for the Atlantic and Gulf Coasts of the United States, Silver Spring, MD, April 1987,U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service.
Map of NWS 38 mile marker in Appendix.

generally their climatology in the Gulf. This illustrates how volatile storm rates seem to be over small distances.

The state of New York (Long Island) also experienced 4 major hurricanes[6] between 1900 and 1983. But New York was the only state hit by major hurricanes from Cape Hatteras (NC) to Maine. Does this mean that New Jersey, Rhode Island or Massachusetts are free from such perils? Again this raises complex questions about the climatology of such windstorms in the North East and their statistical landfalling distributions. It is interesting to note that all 4 storms hit New York State between 1938 and 1960, and none before or since. Does this mean that hurricane climatology in the North East follows cycles? Or was it just "bad luck"? This demonstrates how inadequate hurricane policies ratemaking techniques were when only 5 years of historical experience were used.

From the 1950's to the 1980's, ratemaking techniques tried to solve the frequency problem by looking further back in time. As the amount of available hurricane data increased, actuaries tried to better estimate frequencies for regions or states. But when they started to look at smaller geographic areas such as rating territories, the lack of data surfaced again.

The severity parameter was even more challenging. This was due, in part, to the very wide range of storms intensities. From a weak category 1 to a category 5 (Andrew or Camille), damage to property ranges from minor damage to total devastation. And as opposed to frequency data, insurance losses related to hurricanes were simply not archived before 1949. Actually, it is only in the 1970's and 1980's that loss data started to be recorded. Also, claim data are, most of the time, confidential and well kept by

[6] Hurricanes in the North East tend to be in a transitional state where they become extratropical and lose some of their symmetry, but not their destructive power.

individual insurance companies, and therefore data outside of a specific company's experience is not available for ratemaking actuaries.

To better measure the expected loss associated with the hurricane peril, severity, once it has been assessed, has to be related to the storm intensity, usually a peak gust[7]. But peak gusts could not be measured at each location along the storm path. At best, a very rough estimation of peak gusts was usually available. Hurricanes are extremely complex structures still not well understood. Wind gusts depend on the distance and location from the eye and with respect to the storm direction, on the elevation above the ground, on terrain features (hills, trees, buildings…), on the presence of meso-structures such as tornadoes, downbursts, and other high-speed transients embedded in the main wind field. Also, as we will see later, property damage is highly sensitive to peak gusts for major hurricanes. But these are wind engineering, and tropical meteorology questions, well beyond actuarial knowledge.

Finally, large societal changes over time, such as population, wealth and exposure growth, have to be measured to evaluate expected loss suitably. For example, if the category 4 hurricane that hit Miami in 1926 were to make landfall at the same location today, losses would be greatly higher.

In the early 1980's, computer simulation was thought as a solution to overcome most challenges faced by actuaries. Rate instabilities could be smoothed and severity uncertainty could be precisely measured, as a computer would simulate a large number of events with different respective intensities, and the distributions of severity of losses could be derived. In other words, simulated events would inflict different degrees of damage to property, from which a mean damage, or expected loss, could be calculated.

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[7] Rain and flooding associated to a hurricane are also an important cause of loss but are not currently addressed explicitly in models

2. Catastrophe models.

How did computer modeling become the standard hurricane risk assessment technology? Within 3 years, property losses from 3 events, Hugo (1989) and Andrew and Iniki (1992) reached $45 billion. Due to these unprecedented and unexpected events, as well as other natural disasters, many insurance companies went bankrupt, as they could not pay the claims. This raised important questions about the appropriateness of the methods used for ratemaking and more generally about catastrophe exposure management. Computer modeling had been available for a few years, but these large natural disasters brought to the forefront a more viable approach to catastrophe risk management.

About half a dozen catastrophe modeling companies have developed hurricane models in the past 10 years. These models have a characteristic structure and follow a very similar methodology.

First and most importantly models require information about the exposure. Data describing the risk needs to be collected. When available, physical and engineering characteristics of the risk such as the location (address), construction type (wood or masonry), number of stories, or occupancy (offices or retail), are information that can be used when computing the expected loss. Information about the insurance terms, such as deductible, amount of coverage (limits), and various provisions will allow the model to give the appropriate financial perspective of the risk.

When the exposure data has been formatted in a way that the model can recognize, the modeling process follows three steps.

In the *hazard module*, a full range of possible storms with their respective probability of occurrence, track, and intensity parameters (pressure, wind speed, radius of maximum winds, forward velocity…) are modeled using complex mathematical equations. Different models use different wind field equations. Most hurricane models' catalogs of events are derived from tens of thousands of stochastic storms. These events have been simulated using the statistical characteristics of "smoothed" historical data. In the hazard module, each event is modeled through the exposure data. Depending on the location of the exposure, each storm has either no impact on the exposure (i.e. a storm landfalling in TX does not affect a building in New York) or some impact if the exposure is close to the hurricane path. For each storm and its respective intensity parameters, the wind field equations allow the model to compute the wind speed and a frequency at the exposure location. Local intensities from all simulated events give the probabilistic distribution of wind speeds at the exposure location (figure 2), which is then transferred to the *engineering module* where the corresponding probability distribution of damage will be derived.

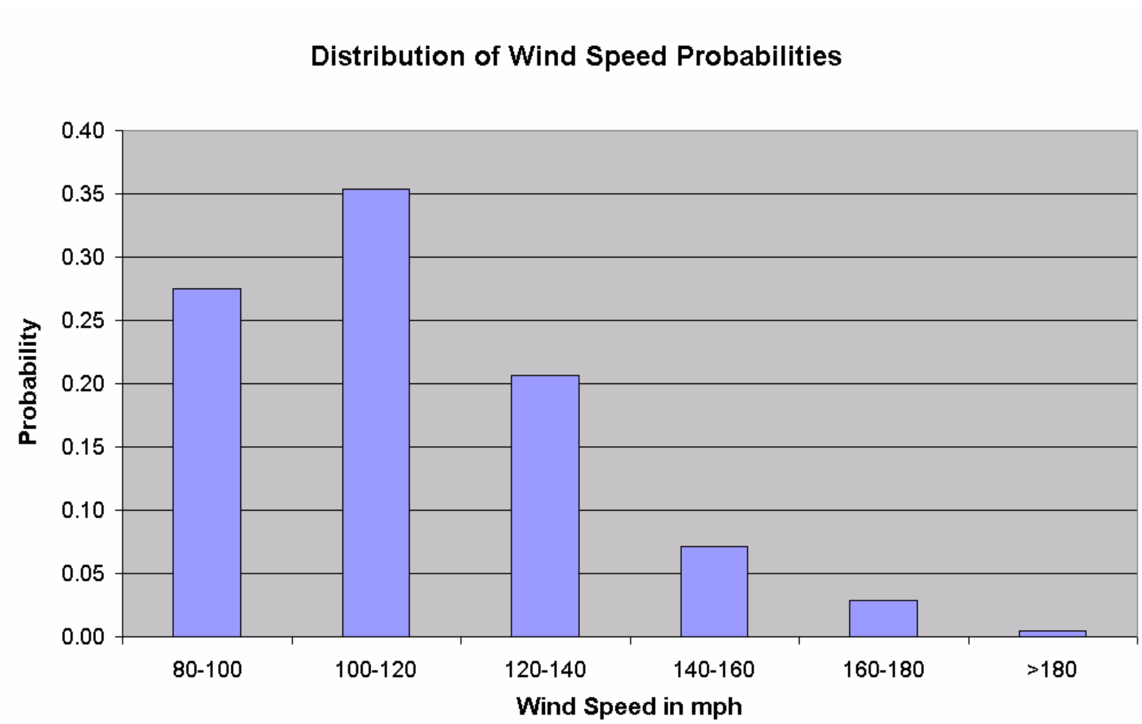


Figure 2. Output sample of *hazard module*

This step uses mathematical relationships (vulnerability functions) that estimate damage levels given a wind speed. These relationships are derived using claims data from previous hurricanes, as well as wind tunnel experiments and theoretical functions derived by wind engineers.

All models now recognize the uncertainty associated with the conversion from wind speeds to damage levels; this is often called secondary uncertainty. In other words, for each wind speed, a distribution of possible losses is derived to better appreciate this uncertainty (figure 3).

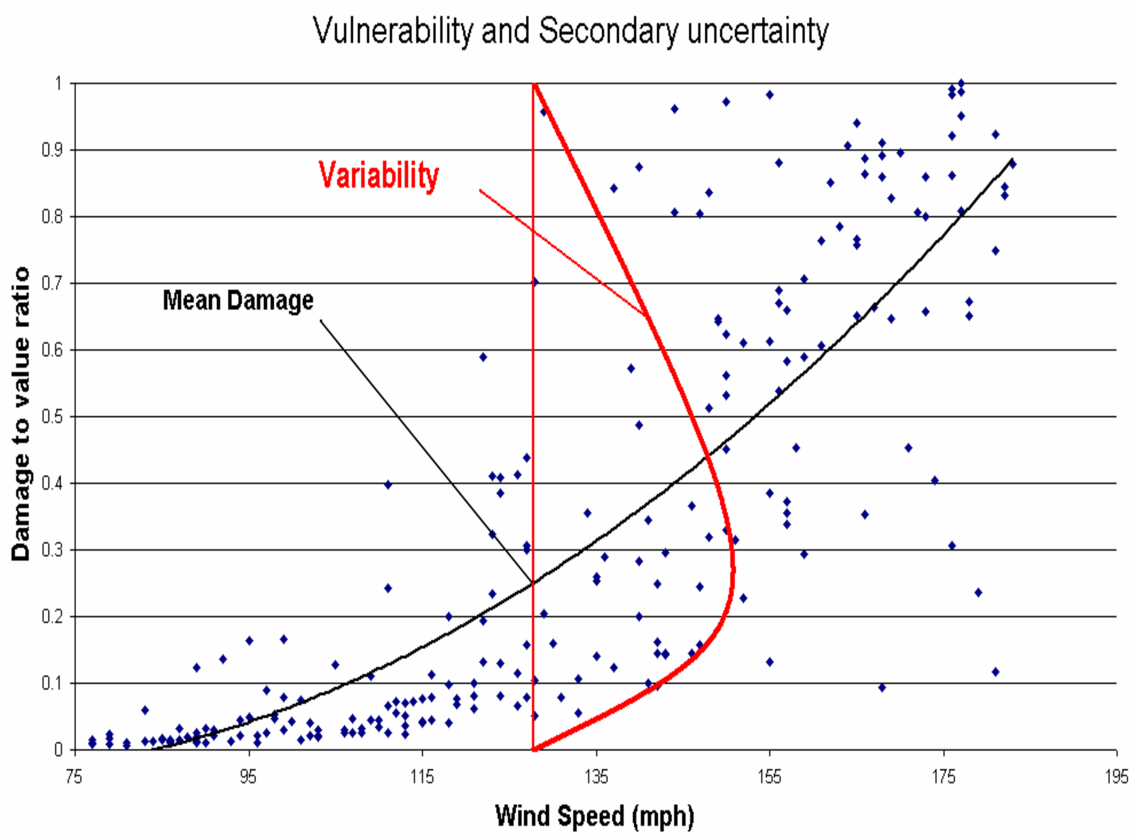


Figure 3. Secondary uncertainty

The distribution of losses for all possible storms is then analyzed in the *financial module*, where deductibles, limits, provisions, co-insurance, and other insurance terms are applied. This allows the model to compute the different perspectives (ground-up, gross, or various reinsurance treaties losses) of the financial risk associated with the hurricane peril for the given exposure. In most models, it is possible to obtain the loss associated with each storm and its probability of occurrence. From this table, an Exceeding Probability (EP) curve can be derived, which displays the annual probability of exceeding any level of loss. The EP curve gives information such as the Probable Maximum Loss (see figure 4). For example, the 100-year PML is the largest loss the insurance company should expect from one event over a 100-year period.

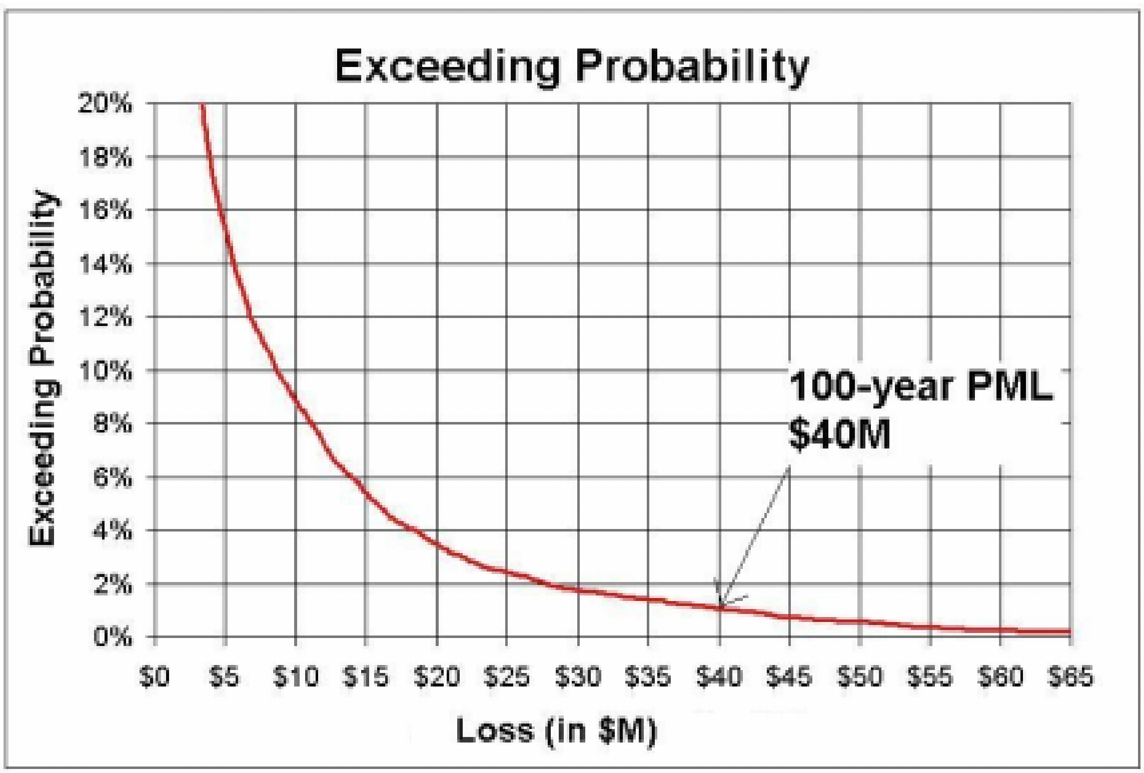
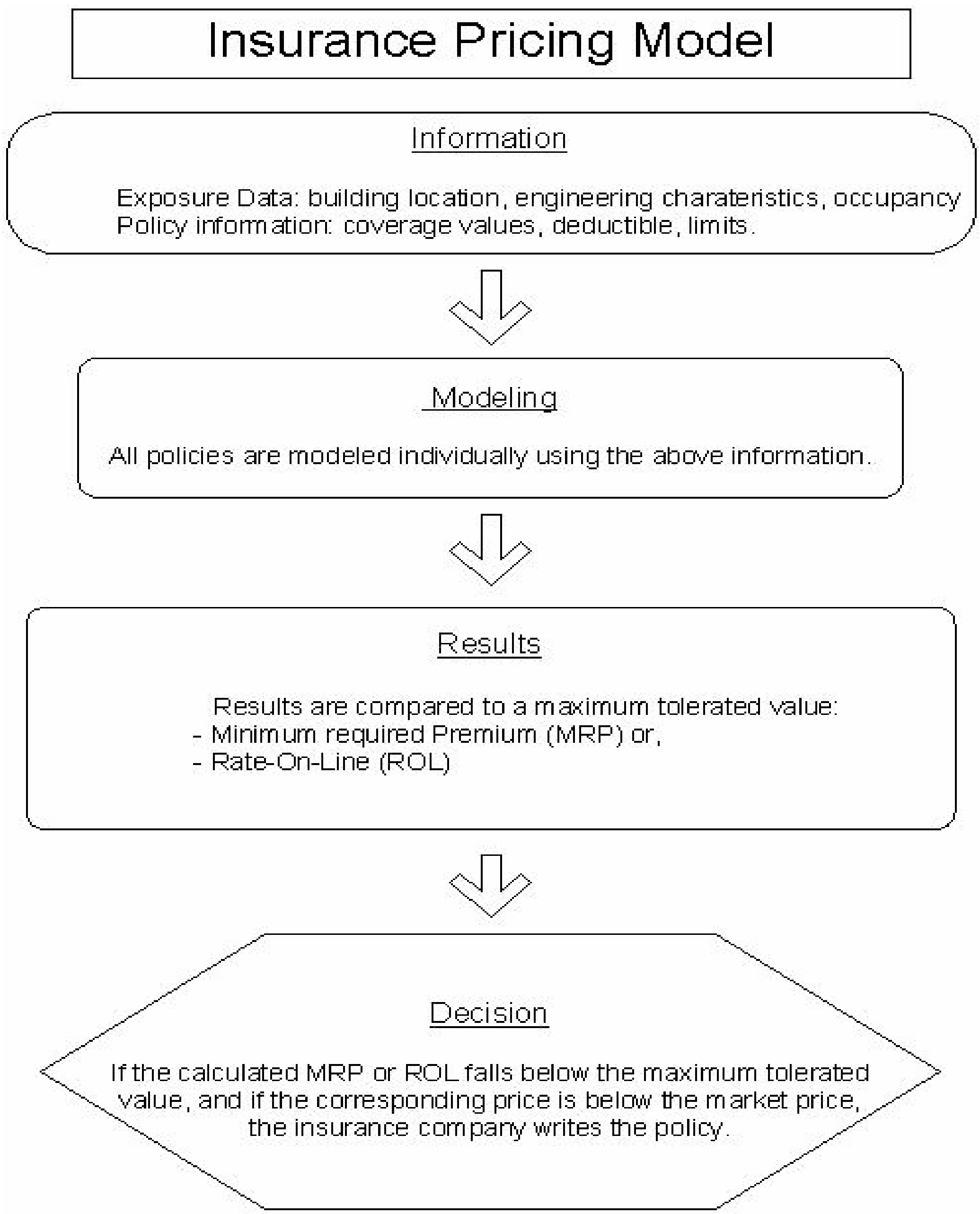


Figure 4. Exceeding Probability Curve

3. Model output and decision processes.

Today, ratemaking, catastrophe exposure management, and more generally insurance decision-making rely heavily on catastrophe modeling technology. The two flowcharts below illustrate how model results drive decisions in these industries. The chart below summarizes the insurance pricing process.



Insurance companies need to gather data about the exposure in order to price the hurricane peril. Most of the time, information about the location of the building, the construction type, the occupancy, the year built, the number of stories, and in some instances, the presence of storm shutters and the shape of the roof are available to the underwriter. Type and amount of coverage (building, content/property, and rent/business income) as well as coverage limits and deductible information are also used in the model. At this point, the modeler needs to enter the data into the model and make assumptions about incomplete information. The modeling takes a few minutes for a policy with 100 buildings. In the model output, the Average Annual Loss (AAL) and the calculated Standard Deviation (SD) are available. The AAL is a measure of the average annual expected loss, and sigma measures the uncertainty associated with the AAL. The model output reflects losses after application of the policy terms (deductible, limits, reinstatements…) also called net loss. From the AAL, two pricing methods are commonly used: The Rate-On-Line (ROL) method, and the Minimum Required Premium (MRP) method.

The ROL method "loads" the AAL with a percentage of the standard deviation also available in the model output, in addition to expenses[8] of the company associated with this policy. This loaded AAL is then measured as a percentage of the Total Insured Value (TIV).

$$ROL\% = 100 * [(AAL + SD * (X \%)) * (1 + \text{Expenses factor})] / TIV$$

ROL is the required premium per 100 dollars of coverage under the given policy for the insurance company to achieve its financial objectives.

[8] Expenses include operating expenses, commissions/fees, future claims processing, reinsurance costs, and profit. Expenses are proportional to the AAL.

The Minimum Required Premium or MRP method fixes an Expected Loss-to-premium Ratio or ELR as a maximum for all the policies to be priced in a given area.

MRP = 100 * [AAL / ELR%]

Given a maximum ELR and a modeled AAL, a premium can be calculated. This is the minimum required premium that the insurance needs to charge to achieve its financial objectives. The ELR implicitly accounts for the expenses detailed in the ROL method. Both methods lead to a minimum price or premium that the insurance has to charge to accept the transfer of risk according to the policy terms. This price is compared to the market price of similar insurance products. If the minimum required premium is below the market price, the underwriter might ask for a higher premium to take advantage of the market conditions. If the market price is lower than the required premium, the future insured will buy insurance from a cheaper provider. This paper provides a methodology to test the sensitivity of the pricing methods, and indirectly, to the decision processes used in the insurance industry to model output.

4. Methodology.

The idea is to model a policy and compute a price for it using one model and a given set of information about the building. The question we want to answer is: how would my price change if I had more information about the building and if I used a different model? The first step is to define the type of policy for which we want to assess the pricing sensitivity. In this paper, four different policies were defined: a typical homeowner policy and three commercial policies in order to see if the pricing sensitivity to model output changes for different policies (table 1). It is important to note that for each of the following tests, the data to be modeled was prepared individually for each model and we resisted to the temptation of using available data converters. These converting tools can add significant uncertainty as they convert data from the format of model A to a different format (model B for example). Each model has its own unique set of vulnerability functions, and in most cases decisions have to be made, since they often do not match one-to-one. For example, one model only has one wood frame function available while another model will have five different wood vulnerability functions. Also building secondary characteristics (such as roof shape, or cladding) are not converted in the process.

Policy	Homeowner	Small Commercial	Large commercial
Default Resolution	Street address	Street address	Street address
4 Sites	TX, FL, NC, NY	TX, FL, NC, NY	TX, FL, NC, NY
Default Occupancy	Single-family housing	Offices	Hotel
Default Construction	Wood frame	Steel	Reinforced concrete
Default # of stories	1	2	10
Default Year	1985	1985	1985
Default Modifiers	None	None	None
Structure value	$ 250,000	$ 3,000,000	$ 20,000,000
Contents value	$ 50,000	$ 500,000	$ 4,000,000
ALE/Business income/rent	$ 20,000	$ 300,000	$ 5,000,000
Limit	None	None	$ 5,000,000
Deductible	$ 500	2%	5%

Table1. Policy details

The following two steps give a measurement of that sensitivity.

- Step 1: Model sensitivity

This step consists of modeling the policies individually using different level of information about the buildings. These tests will permit us to measure the sensitivity of the calculated (i.e., modeled) loss to parameters such as geocoding[9], vulnerability and occupancy functions, age, and building secondary characteristics.

[9] Each model has a geocoding engine that maps the building location information. In most cases it translates a street address or a postal code to coordinates of a point (latitude/longitude).

This step will be performed using five models. These models are well accepted pricing and decision-making tools in both insurance and reinsurance industries and have successfully passed the standards set by the Florida Commission on Hurricane Loss Projection Methodology.

- Step 2: Pricing results

The loss results from the first step will be "plugged" in typical pricing methods used in the insurance industry to assess their sensitivity to model output.

Finally, conclusions will be drawn about the use of model output by insurance and reinsurance industries. The objective is to provide answers to questions such as "how to optimize the use of data and models available?" and "can the overall decision process be improved?"

5. Results.

1. <u>Model sensitivity tests</u>

a) *Geocoding sensitivity*

Because loss results are highly dependant on the geographic location, four sites were selected. Each policy was modeled using four different levels of information regarding the location of the building:

- The county only
- The city only
- The postal code only
- The street address

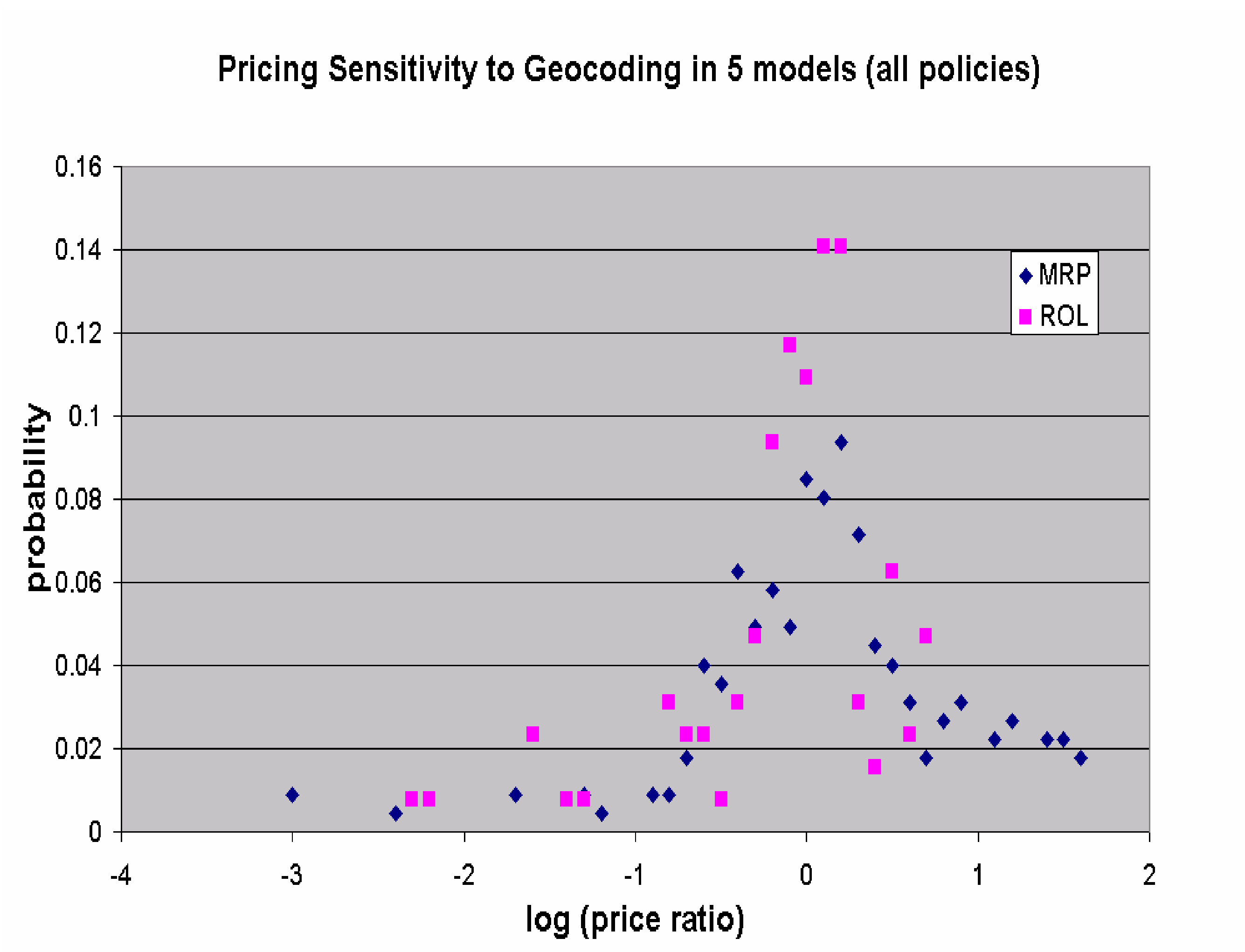
For example, the homeowner policy in Florida was modeled using the information for the homeowner policy detailed in table 1, once using the county (Miami-Dade), once with the city (Miami Beach), once with the postal code (33160), and once with the street address (3628 NE 168th street). This was performed for each of the 4 policies and each of the four sites (TX, FL, NC, NY) resulting in 52 policies. These 52 policies were modeled using the five models. For each of these policies, the Average Annual Loss was calculated, and for three of the five models the Standard Deviation was also determined as it was not easily accessible for two of the five models. Using these loss estimates, a rate-on-line (using the standard deviation) and a minimum required premium (using the average annual loss only) was calculated.

In order to compare the price sensitivities to geocoding for all the policies at all sites and for all models, a base price was fixed for each policy and each site yielding 16 reference-prices. In each case, the reference price was computed using city level geocoding (only the city was provided), "unknown" for all building details (occupancy, construction, age, and stories), and the policy terms defined in table 1. The reference price was calculated using model A and was used across all tests in this paper.

Each policy price was expressed as a percentage of the reference price. For example, the computed price for the homeowner policy with street-level geocoding in Houston was divided by the reference price (city-level geocoding) for the homeowner policy in Houston. The same was done for all policies at all sites where the price corresponding to different levels of geocoding was expressed as a percentage of their respective reference price.

This method allows for the comparison of the price sensitivity for all policies and for all models together.

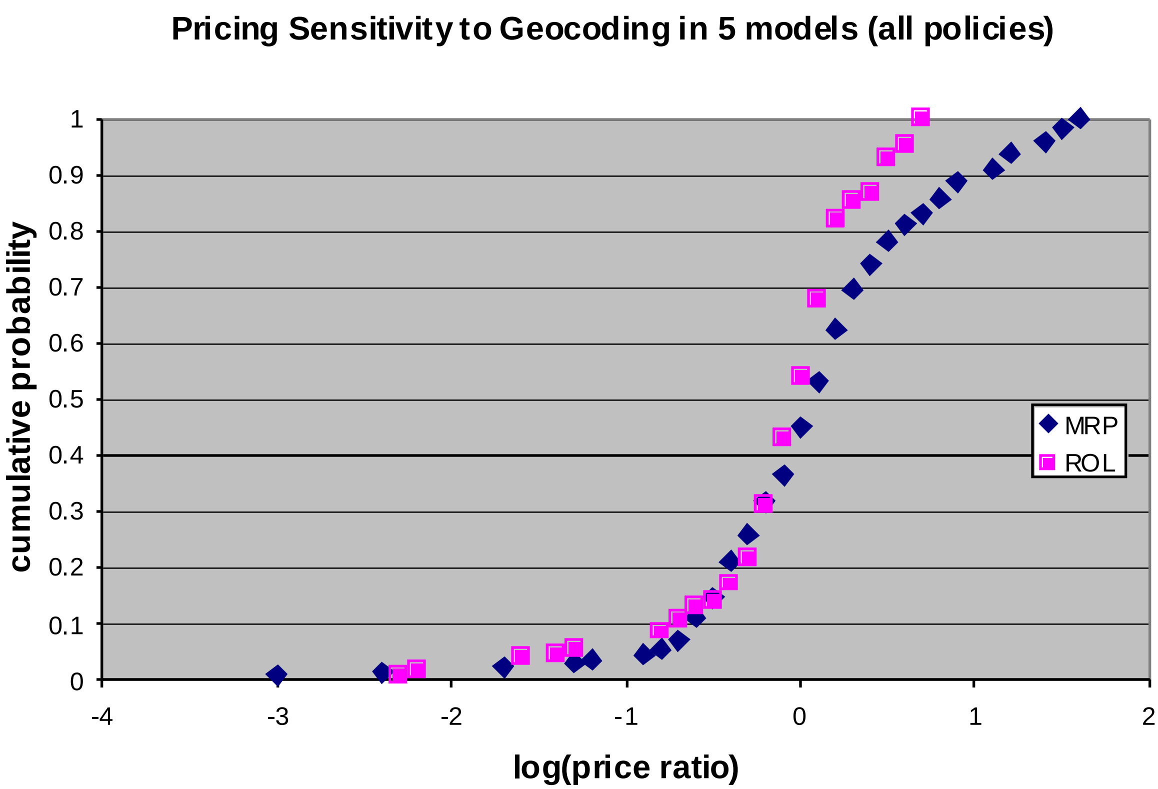
A probability distribution function can be plotted assuming that each policy is equally likely to occur. While this approximation is not a perfect representation of the industry, the policies in this paper have been defined as representative of the policies found in the market. That is, for example, a large commercial policy is likely to be of reinforced concrete or steel frame, and a homeowner policy is more likely to have a wood frame or masonry structural system. Still, it might be more precise to weight the different policies using industry averages when computing the PDF of the overall price sensitivity. The following graph gives the probability distribution of the logarithm of the price ratio, or calculated premium to reference premium for both pricing methods, all policies with different level of information regarding the address of the building, and 5 different catastrophe models (graph 1).



Graph 1: Probability distribution function

On the x-axis, a value of 1/-1 means that the policy calculated premium was 10 times higher/lower than the reference price.

A cumulative distribution can also be derived from the results (graph 2)



Graph 2. Cumulative Distribution Function

From the CDF, it is possible to compute percentiles for each method (MRP and ROL) in order to measure the level of pricing sensitivity to geocoding across the 5 models.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	17%	5%	8%
10%	26%	10%	20%
20%	43%	20%	51%
40%	96%	40%	83%
50%	130%	50%	106%
60%	166%	60%	122%
80%	387%	80%	166%
90%	1159%	90%	298%
95%	2694%	95%	369%

Table 2. Geocoding test percentiles

From table 2, we read that using the ROL method, 10% of the policies have a ROL at least 3 times (298%) higher than the reference price. On the other hand, 20% of the policies will have a ROL less than 50% of the reference price.

b) Occupancy sensitivity

In order to test the pricing sensitivity to the building occupancy, we keep all building details constant as in the geocoding test, but we provide a street address, and let the building occupancy change:

- For the homeowner: Single family housing or unknown.
- For the small commercial: Multi family housing, warehouse, offices, restaurant, general commercial, unknown.
- For large commercial: Hotels, offices, general commercial, unknown.

The following percentiles are calculated:

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	7%	5%	3%
10%	22%	10%	19%
20%	37%	20%	51%
40%	75%	40%	71%
50%	96%	50%	87%
60%	132%	60%	104%
80%	289%	80%	178%
90%	930%	90%	247%
95%	1320%	95%	291%

c) Construction sensitivity

In order to test the pricing sensitivity to the building construction, we keep all building details constant as in the geocoding test, but we provide a street address, and let the building construction change:

- For the homeowner: All construction types available in the models that include wood, masonry, unknown.
- For the small commercial: All construction types available in the models that include wood, masonry, concrete, light metal, steel frame, unknown.
- For the large commercial: All construction types available in the models that include reinforced masonry, steel frame, or other typical high-rise constructions, unknown[10].

The following percentiles are calculated:

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	10%	5%	2%
10%	28%	10%	15%
20%	48%	20%	28%
40%	102%	40%	70%
50%	143%	50%	87%
60%	193%	60%	113%
80%	372%	80%	169%
90%	1074%	90%	247%
95%	1963%	95%	310%

[10] For large commercial, the number of stories was set as a default to 10 stories

d) Age sensitivity

In order to test the pricing sensitivity to the building age, we keep all building details constant as in the geocoding test, but we provide a street address, and let the building age change:

- For all policies: 1970,1985, 2002, unknown

The following percentiles are calculated:

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	23%	5%	17%
10%	35%	10%	43%
20%	53%	20%	56%
40%	92%	40%	82%
50%	125%	50%	104%
60%	160%	60%	128%
80%	276%	80%	176%
90%	1075%	90%	256%
95%	1939%	95%	364%

e) Building secondary characteristics sensitivity

In order to test the pricing sensitivity to the secondary modifiers, we keep all building details constant as in the geocoding test, but we provide a street address, and allow for the presence of storm shutters, wall cladding, as well as different roof shapes:

- Storm shutters: no shutters, engineered shutters, unknown
- Roof shape: Flat, hipped, gable, unknown
- Wall cladding: no cladding, EIFS, reinforced/unreinforced masonry, unknown

The following percentiles are calculated:

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	16%	5%	14%
10%	31%	10%	30%
20%	49%	20%	49%
40%	91%	40%	74%
50%	122%	50%	95%
60%	165%	60%	121%
80%	304%	80%	178%
90%	1075%	90%	271%
95%	1945%	95%	365%

e) Results by policy

1. Homeowner only, all parameters, all models.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	62%	5%	72%
10%	105%	10%	74%
20%	165%	20%	87%
40%	214%	40%	137%
50%	228%	50%	150%
60%	253%	60%	173%
80%	1118%	80%	261%
90%	2917%	90%	428%
95%	3375%	95%	447%

2. Small commercial only, all parameters, all models.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	24%	5%	22%
10%	37%	10%	37%
20%	55%	20%	53%
40%	91%	40%	84%
50%	111%	50%	104%
60%	145%	60%	128%
80%	349%	80%	183%
90%	1079%	90%	286%
95%	1352%	95%	356%

3. Large commercial only, all parameters, all models.

MRP Percentile	Price ratio	ROL Percentile	Price ratio
5%	0%	5%	2%
10%	6%	10%	3%
20%	24%	20%	15%
40%	46%	40%	46%
50%	55%	50%	53%
60%	70%	60%	62%
80%	137%	80%	87%
90%	373%	90%	121%
95%	671%	95%	130%

f) Results by site

1. Texas only, all parameters, all models.

MRP Percentile	Price ratio	ROL Percentile	Price ratio
5%	24%	5%	26%
10%	33%	10%	45%
20%	45%	20%	58%
40%	68%	40%	75%
50%	78%	50%	87%
60%	102%	60%	101%
80%	146%	80%	127%
90%	196%	90%	140%
95%	228%	95%	151%

2. Florida only, all parameters, all models.

MRP Percentile	Price ratio	ROL Percentile	Price ratio
5%	48%	5%	82%
10%	57%	10%	90%
20%	78%	20%	118%
40%	130%	40%	143%
50%	158%	50%	166%
60%	182%	60%	179%
80%	231%	80%	229%
90%	285%	90%	279%
95%	323%	95%	304%

3. New York only, all parameters, all models.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	0%	5%	2%
10%	10%	10%	3%
20%	35%	20%	22%
40%	64%	40%	51%
50%	81%	50%	59%
60%	102%	60%	73%
80%	197%	80%	109%
90%	265%	90%	138%
95%	284%	95%	149%

4. North Carolina only, all parameters, all models.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	7%	5%	10%
10%	22%	10%	16%
20%	42%	20%	34%
40%	579%	40%	53%
50%	835%	50%	74%
60%	1075%	60%	104%
80%	1948%	80%	335%
90%	2917%	90%	428%
95%	3375%	95%	447%

g) Results by model

1. Model A only, all policies, and all parameters.

MRP		ROL	
Percentile	Price ratio	Percentile	Price ratio
5%	8%	5%	18%
10%	20%	10%	37%
20%	41%	20%	53%
40%	61%	40%	74%
50%	77%	50%	84%
60%	111%	60%	105%
80%	170%	80%	143%
90%	224%	90%	192%
95%	278%	95%	231%

2. Model B only, all policies, and all parameters.

MRP Percentile	Price ratio
5%	31%
10%	41%
20%	56%
40%	96%
50%	128%
60%	193%
80%	681%
90%	1867%
95%	2750%

3. Model C only, all policies, and all parameters.

MRP Percentile	Price ratio	ROL Percentile	Price ratio
5%	2%	5%	1%
10%	9%	10%	6%
20%	39%	20%	21%
40%	115%	40%	65%
50%	156%	50%	85%
60%	228%	60%	99%
80%	376%	80%	164%
90%	686%	90%	252%
95%	1552%	95%	298%

4. Model D only, all policies, and all parameters.

MRP Percentile	Price ratio	ROL Percentile	Price ratio
5%	0%	5%	3%
10%	17%	10%	33%
20%	35%	20%	51%
40%	82%	40%	87%
50%	129%	50%	117%
60%	160%	60%	139%
80%	311%	80%	197%
90%	1074%	90%	363%
95%	1293%	95%	442%

5. Model E only, all policies, and all parameters.

MRP Percentile	Price ratio
5%	34%
10%	46%
20%	67%
40%	103%
50%	160%
60%	224%
80%	753%
90%	1810%
95%	2917%

2. Conclusions and remarks

a) Pricing methods.

Each exhibit shows that the MRP method is much more sensitive to model output than the ROL method. This is due to large discrepancies (especially for inland and Northeast locations) in modeled average annual loss between models and within each model for different level of information regarding building details. The ROL method uses the standard deviation, which "smoothes" the final price as the variations in standard deviations are not as large as differences in average annual loss. In other words, the use of standard deviation explicitly in pricing individual policies significantly reduces the range of possible prices.

Also, the loading for standard deviation in the ROL method should reflect the change in coefficient of variation (COV = Standard deviation / Average annual loss) as opposed to the standard deviation only. This comes from the fact that more information regarding the building (construction, occupancy, geocoding…) does not always imply a lower standard deviation. An example would be for the Miami Beach location geocoded at the city-level (AAL: $800, SD: $1,400, COV: 1.75) and at the street-level (AAL: $1,500, SD: $2000, COV: 1.33). The coefficient "%X" in the formula for the ROL should be a percentage of the COV as opposed to a fixed percentage, in order to give credit for additional information and the lower relative uncertainty.

In addition, it should be useful to isolate the policies above the 80-percentile for example and decide whether these are likely to be found in the market or in the current portfolio. If so, additional information should be required to avoid under pricing. The same remark can be made for the 20-percentile and the risk of overpricing policies.

b) Ranking the importance of building information

In order to rank the exposure data by importance with respect to pricing, we first need to know if we are focusing on overpricing or under pricing[11]. To assess the likelihood of overpricing for example, one can look at the 10-precentile[12].

Pricing sensitivity can then be ranked by parameter by deviation from base price:

1. Construction
2. Occupancy
3. Geocoding
4. Secondary modifiers (roof shape, wall cladding, shutters)
5. Age

A similar approach can be used to assess under pricing and rank the importance of parameters. For example one can use the 80 or the 90-percentiles.

c) Pricing sensitivity to policy types (Line of business).

The homeowner policy pricing was less sensitive than the commercial policies because less variability in occupancy and construction is involved (in most cases, homeowner policies are single family housing and wood frame or masonry buildings). The biases in

[11] This assumes that the base prices were calculated using the current information available and used by the insurance company.

[12] The above ranking is almost identical for 5, 10, 20-percentiles, as construction is always the most important parameter, but secondary characteristics are slightly more important than occupancy, and geocoding for the 20-percentile.

the pricing sensitivity distribution toward under pricing (homeowner) or overpricing (large commercial) come from large discrepancies between models in term of absolute prices. For example, in one model, the average annual loss for the large commercial policy in Raleigh (NC) is $52 and in another model it is $1. However, the variability in prices seems to increase with the size of the policy, and is especially important for inland locations. This is probably also related to the absolute value of the deductible (in dollars), and to the fact that large buildings (offices, hotels) are less vulnerable than detached homes. A relatively large deductible will cover small losses for a large policy. However, small discrepancies between models can result in large relative differences in AAL.

d) Pricing sensitivity to location.

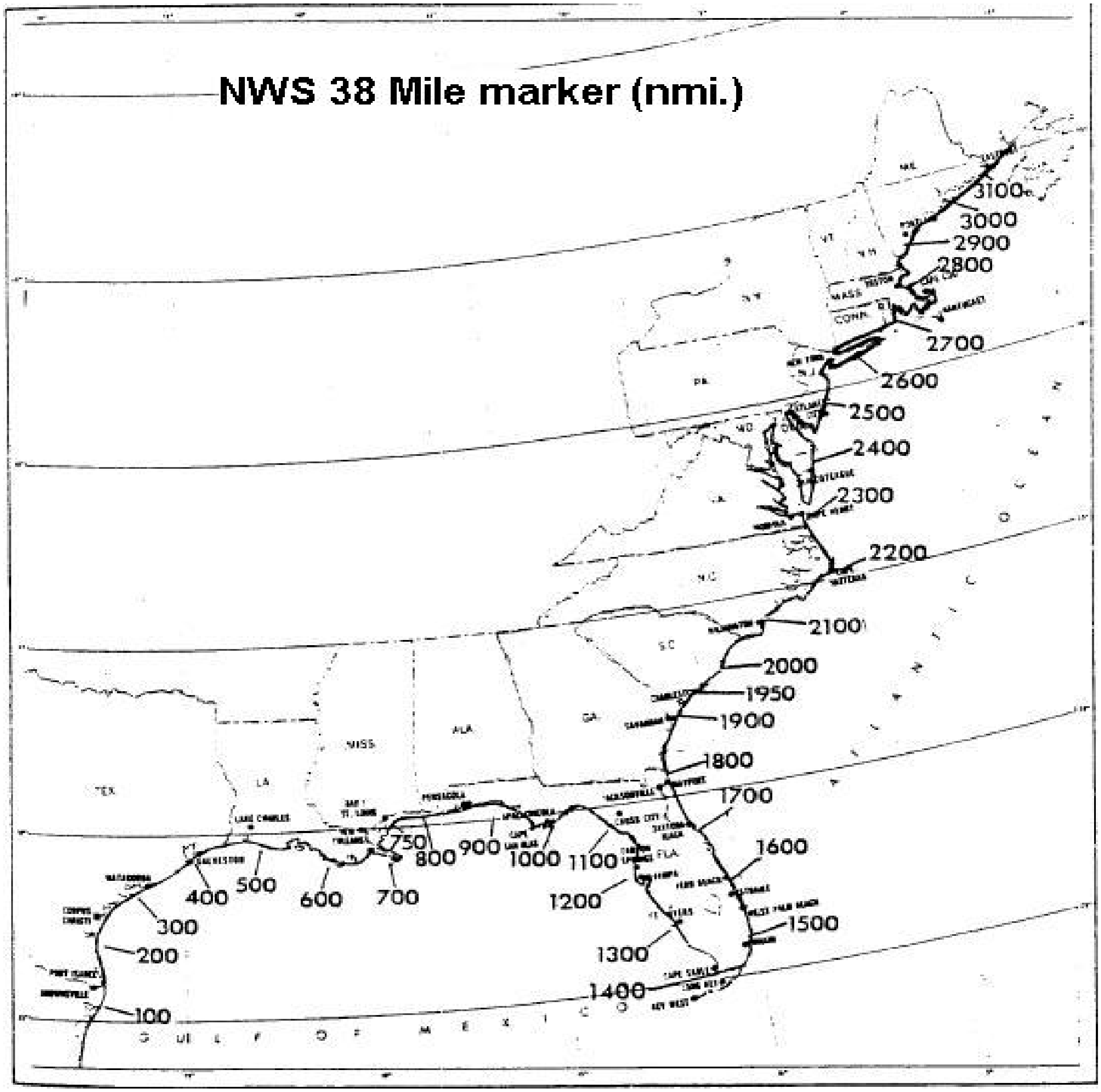
It should not be surprising that pricing is less sensitive in Florida as the availability of historical data with respect to both hazard (storms) and damageability (claim data) is by far the best. Also, the models follow the standards set by the FCHLPM. Texas is more sensitive but in a reasonable range, as opposed to North Carolina and New York where very large differences in pricing are found as shown in the above tables (results section f). The 50-percentile for the MRP method for the North Carolina location underlines the very large discrepancies between models in terms of average annual loss inland.

e) Pricing sensitivity to individual model

Model A has the lowest sensitivity because base prices were computed using this model. In other words, the results for Model A only account for Model A sensitivity as opposed to both “intra and inter-models” sensitivity for the other models. Model C has the highest sensitivity and large discrepancies were found in most cases with the base price. The comparison of the 50-percentile for each model and each method emphasizes these discrepancies in AAL between models and shows that only one perspective (pricing with a single model) of a risk can induce large uncertainty in pricing. On the other hand, when average annual losses are very different between two models (i.e. the above example about the large commercial in North Carolina), it might not be useful (or statistically correct) to simply average different models results.

This paper provides a method for the assessment of the pricing sensitivity to the lack of information or uncertainty related to the quality of data available. It could be applied to any type of policy, anywhere, and to any parameter. For example, a study could focus on a single area (city, state, county…), on homeowner policies only, and on the relevance of using different types of masonry (reinforced masonry, joisted masonry, timber-joisted masonry, unreinforced masonry…). Conclusions would help decide whether it would be worth collecting additional information regarding the type of masonry, as different vulnerability functions are available in models for each of these construction categories. Also, to improve the precision of the distributions detailed in this paper, industry weights could be used, when available, to give a probability for each policy.
Finally, similar tests could be performed for other risks where simulation models are available (earthquake, floods, tornadoes, terrorism…)

6. Appendix:



NWS 38 Mile marker (nmi.)
3100
3000
2900
2800
2700
2600
2500
2400
2300
2200
2100
2000
1950
1900
1800
1700
1600
1500
1400
1300
1200
1100
1000
900
800
750
700
600
500
400
300
200
100

Saffir Simpson scale:

Category	Winds	Effects
One	74-95 mph	No real damage to building structures. Damage primarily to unanchored mobile homes, shrubbery, and trees. Also, some coastal road flooding and minor pier damage
Two	96-110 mph	Some roofing material, door, and window damage to buildings. Considerable damage to vegetation, mobile homes, and piers. Coastal and low-lying escape routes flood 2-4 hours before arrival of center. Small craft in unprotected anchorages break moorings.
Three	111-130 mph	Some structural damage to small residences and utility buildings with a minor amount of curtainwall failures. Mobile homes are destroyed. Flooding near the coast destroys smaller structures with larger structures damaged by floating debris. Terrain continuously lower than 5 feet ASL may be flooded inland 8 miles or more.
Four	131-155 mph	More extensive curtainwall failures with some complete roof strucutre failure on small residences. Major erosion of beach. Major damage to lower floors of structures near the shore. Terrain continuously lower than 10 feet ASL may be flooded requiring massive evacuation of residential areas inland as far as 6 miles.
Five	greater than 155 mph	Complete roof failure on many residences and industrial buildings. Some complete building failures with small utility buildings blown over or away. Major damage to lower floors of all structures located less than 15 feet ASL and within 500 yards of the shoreline. Massive evacuation of residential areas on low ground within 5 to 10 miles of the shoreline may be required.