Volume LXXIII, Part 2 No. 140

PROCEEDINGS

November 9, 10, 11, 1986

A FORMAL APPROACH TO CATASTROPHE RISK ASSESSMENT AND MANAGEMENT

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Abstract

Insurers paid \$1.6 billion on property claims arising from catastrophes in 1984. Researchers have estimated that annual insured catastrophe losses could exceed \$16 billion. Certainly, the financial implications for the insurance industry of losses of this magnitude would be severe; even industry losses much smaller in magnitude could cause financial difficulties for insurers who are heavily exposed to the risk of catastrophe losses.

The quantification of exposures to catastrophes and the estimation of expected and probable maximum losses on these exposures pose problems for actuaries. This paper presents a methodology based on Monte Carlo simulation for estimating the probability distributions of property losses from catastrophes, and discusses the uses of the probability distributions in management decision-making and planning.

INTRODUCTION

There were 28 catastrophes in 1984; they resulted in an estimated \$1.6 billion of insured property damage. Most of these catastrophes were natural disasters such as hurricanes, tornadoes, winter storms, and floods. In 1985, Hurricane Elena caused over \$543 million of insured losses, and a tornado outbreak affecting nine states caused insured damage of \$231 million.

Hurricane Elena barely rated a three on a severity scale ranging from one to five, in which destruction from hurricanes increases exponentially with increasing severity. A hurricane that rated a four hit New York and New England in 1938; 600 people died and wind speeds of 183 mph caused hundreds of millions of dollars of damage.

If this storm were to strike again, dollar losses to the insurance industry could exceed ten billion given the current insured property values on Long Island and along the New England coast. Estimates of the dollar damages that will result if a major earthquake occurs in Northern or Southern California are even larger in magnitude.

A very severe hurricane or earthquake would produce a year of catastrophic loss experience lying in the upper tail of the probability distribution of annual losses from catastrophes. It is the opinion of the author that the 1984 catastrophe loss figure lies in the lower end of this distribution. However, the determination of the shape and the estimation of the parameters that describe this distribution are tasks that are not easily performed using standard actuarial methodologies. Yet since insurers require knowledge of their exposure to catastrophes and the probability distributions of annual catastrophe losses to make pricing, marketing, and reinsurance decisions, actuaries must be able to estimate the parameters of the distributions, including the expected and probable maximum losses.

Standard statistical approaches to loss estimation involve the use of historical data to estimate future losses. However, approaches that employ time series of past catastrophe losses can give poor estimates of potential catastrophe losses. Catastrophes are rare events so that the actual loss data are sparse and their accuracy is questionable; average recurrence intervals are long so that many exogenous variables can change in the time periods between occurrences. In particular, changing population distributions, changing building codes, and changing building repair costs alter the annual catastrophe loss distribution.

Since most catastrophes are caused by natural hazards, and since most natural hazards have geographical frequency and severity patterns associated with them, the population distribution impacts the damage-producing potentials of these hazards. A natural disaster results when a natural hazard occurs in a populated area. Changing population patterns necessarily alter the probability distribution of catastrophic losses. Since the average recurrence intervals of natural hazards in any particular area are long, patterns of insured property values may vary between occurrences to an extent that damage figures of historical occurrences have little predictive power. For example, the 1906 San Francisco earthquake caused losses of $364 million. In 1985 dollars, this equals $4.5 billion. Yet some have estimated that an earthquake of this size could cause damages exceeding $30 billion today.

It is primarily the influence of the geographic population distribution that renders time series models of natural catastrophe losses inadequate, although changing building codes also alter the loss-producing potentials of natural hazards. Over time, building materials and designs change, and new structures become more or less vulnerable to particular natural hazards than the old structures. Of course, changes in building repair costs also affect the dollar damages that could result from catastrophes.

The above issues do not render the estimation problem intractable, but they do indicate a need for an alternative methodology to approaches which employ historical catastrophe losses adjusted for inflation to estimate the probability distribution of losses. Even models which adjust historical losses for population shifts can give only very rough approximations of expected and probable maximum losses.

This paper presents a methodology based on Monte Carlo simulation, and it focuses on property damage arising from natural disasters. The next two sections discuss the simulation approach to catastrophe loss estimation. A windstorm example is then presented. Output analysis, model validation, and model uses are discussed in the following three sections.

THE SIMULATION APPROACH

The simulation approach is, very basically, the development of computer programs which describe or model the particular system under study. All of the system variables and their interrelationships are included. A high speed computer then "simulates" the activity of the system and outputs the measures of interest.

Simulation models may be deterministic or stochastic. Monte Carlo simulation models are stochastic models, and therefore, the variables which they include are random variables. Numbers are generated from the probability distributions of the random variables to assign values to the variables for each model simulation. These probability distributions are either standard statistical distributions (selected on the basis of good fits with empirical data) or actual empirical distributions.

Typically, many simulations or iterations are performed to derive estimates of the measures of interest from Monte Carlo simulation models. This is necessary to ensure that the output distribution has converged to the true distribution and that model derived estimates are "accurate." Obviously, the larger the variances of the model variables, the larger the number of model iterations necessary to reach convergence.

Computer simulation models can provide powerful tools for the analyses of a wide variety of problems, especially problems which involve solutions that are difficult to obtain analytically. Law and Kelton [8] state that "Most complex, real-world systems . . . cannot be accurately described by a mathematical model which can be evaluated analytically. Thus, a simulation is often the only type of investigation possible." The natural hazard loss-producing system is one such system.

THE NATURAL HAZARD SIMULATION MODEL

The natural hazard simulation model is a model of the natural disaster "system." The primary variables are meteorological or geophysical in nature. They may be classified as frequency or severity variables. The frequency variables determine the number of occurrences of the particular events within a given time period. Severity variables account for a hazard's force, size, and duration. These variables are, of course, random variables with stable (time independent[1]) probability distributions.

The model simulates the physical occurrences of the natural hazards by generating numbers from these probability distributions. Numbers are generated to assign values to each variable for each simulated occurrence. The probability distributions are estimated using historical data combined with the knowledge of authoritative meteorologists and geophysicists.

It is most efficient from a computational standpoint to generate numbers from the well-known statistical distributions. The empirical distributions formed by the raw data may be fit to these theoretical distributions using appropriate goodness-of-fit tests. If the data do fit any of these probability distributions, the moments of the distributions may be estimated and employed by the simulation model.

If the empirical data do not fit any theoretical distributions, the empirical distribution may be used for the generation of values for particular model variables. This procedure, however, has some drawbacks. First, since the sample is a collection of random data, a different sample could yield a very different

[1] There may be a time-space dependence with respect to earthquake severity.

empirical distribution. Second, the generation of random variables from an empirical distribution precludes the possibility of generating values of the variable outside of the observed range, and the observed range may not include all possible values of the variable. If the empirical data are sparse or do not fit theoretical distributions, knowledgeable physical scientists may provide information regarding the ranges of possible values of particular variables, as well as the shapes of the distributions and the most likely values of the variables.

Variables that change with time, e.g., the geographic distribution of exposure units, the insured property values, and the building construction types, are inputs into the model. The probability distribution of losses from natural hazards given these inputs is the model output. Per occurrence as well as annual aggregate distributions are estimated.

The model simulates the physical occurrences of the natural hazards and their effects on exposed properties thousands of times in order to estimate the distributions of losses. Thousands of iterations are performed to ensure that all possibilities have been simulated in accordance with the actual probabilities of occurrence and that the estimated distributions converge to the true distributions.

A WINDSTORM EXAMPLE

A model of the hurricane hazard has been developed and will be used to illustrate the Monte Carlo simulation approach. Exhibit I is a simplified flowchart of the computer model.

Most of the storm data used in the development of the model were obtained from the U.S. Department of Commerce. The data had been collected and analyzed by various agencies of the National Weather Service, and they included 86 years of history spanning the period 1900 to 1985. Complete and accurate meteorological data were available for most of the hurricanes that struck the U.S. in this time period.

A hurricane is a closed atmospheric circulation which develops over tropical waters and in which winds move counterclockwise around a center of pressure lower than the surrounding area. It is a severe tropical storm, with a center of pressure less than or equal to 29 (inches), which causes sustainable wind speeds of 74 mph or more. One hundred and thirteen hurricanes made landfall in the

U.S. during the sample period. One hundred and thirty-eight hurricanes either approached and bypassed (within 150 nautical miles), exited[2], or entered the U.S. during the period.

Annual Frequency

Referring to Exhibit I, the first step of the model (for each iteration) is the generation of the annual number of landfalling hurricanes. Table 1 shows the number of years in which the number of occurrences was 0, 1, 2, and so on. The historical data fit a negative binomial distribution with $s = 5$ and $p = .79$. The chi-square goodness-of-fit test statistic equals 2.923 which is not significant even at the $\alpha = .5$ level.

TABLE 1

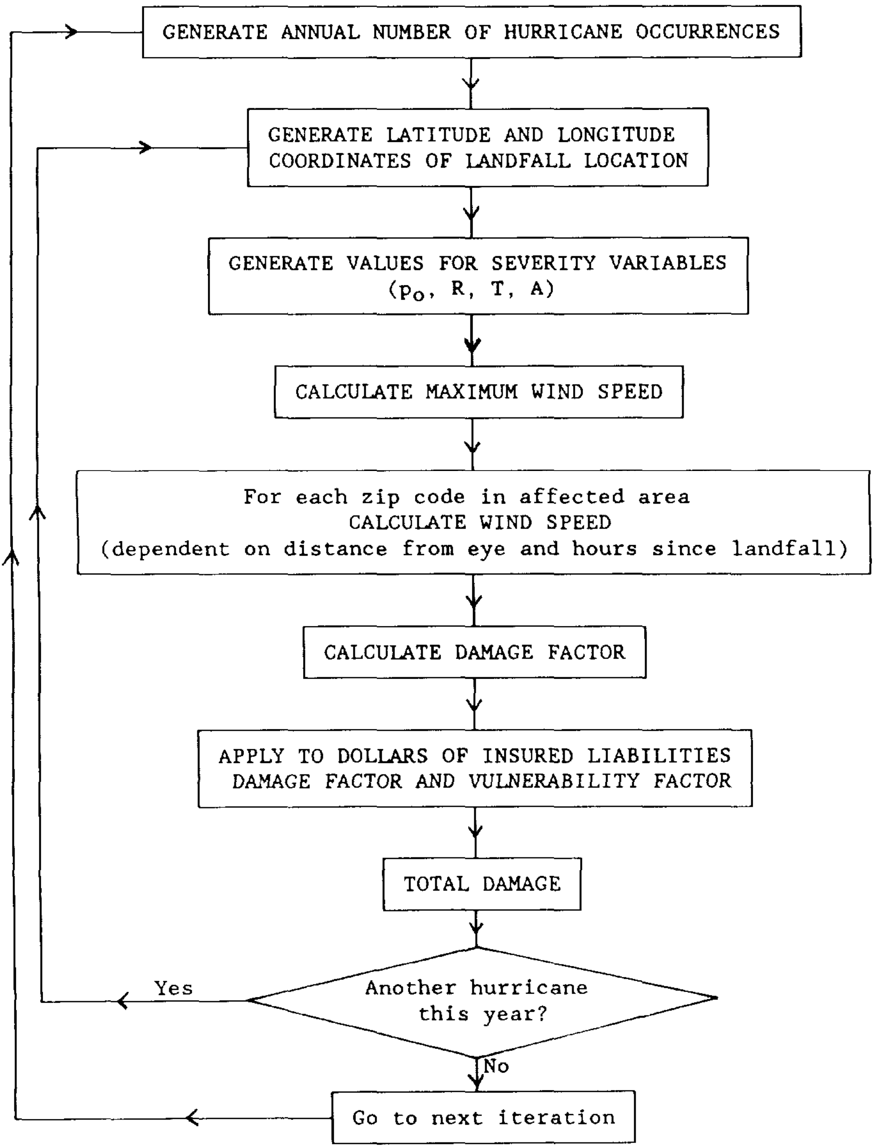
ANNUAL NUMBER OF HURRICANES LANDFALLING IN U.S.
(EXCLUDING EXITING STORMS)
1900–1985

No. Storms Per Year	Observed Occurrence	Relative Frequency	Neg. Bin. Rel. Freq.
0	26	.302	.308
1	29	.337	.323
2	18	.209	.204
3	6	.070	.100
4	6	.070	.042
>4	1	.012	.023

[2] An exiting storm is a hurricane that moves from land to sea and has a central pressure lower than 29 inches.

EXHIBIT I

MODEL FLOWCHART



Locational Frequency

The next step of the model is the determination of the landfall location of each storm. Hurricanes enter the U.S. from the Gulf and East Coasts. The map in Exhibit II shows the U.S. coastline from Texas to Maine divided into 31 smoothed 100 nautical mile segments.[3] The number of hurricanes that entered through each segment or bypassed within 150 nautical miles of the segment during the sample period is also shown.

The numbers indicate that there are variations in locational frequencies. In this case, it would not be correct to generate the landfall location from a distribution which assigns equal probabilities to all values, i.e., a uniform distribution. Neither would one want to use the actual numbers of storms to form the empirical distribution from which the landfall locations will be generated. This is because the selection of length of coastal segment is necessarily arbitrary. If a different length were used, the empirical distribution would be different. Additionally, although several segments are completely free of historical storm occurrences, it is not clear that the probability of hurricane landfall is zero in those areas.

To derive the model locational frequency distribution, the raw data on the numbers of occurrences were smoothed using a procedure selected on the basis of its ability to capture turning points in the data while smoothing slight variations. The coastline was redivided into 50 nautical mile segments, and the number of occurrences for each segment was set equal to the weighted average of 11 successive data points centered on that segment. The smoothed frequency values were obtained as follows:

$$F_i = \frac{\sum_{n=-5}^{5} W_n C_{i+n}}{\sum_{n=-5}^{5} W_n}$$

where C_i = the number of historical hurricane occurrences for the ith segment;

F_i = the smoothed frequency value for the ith segment; and,

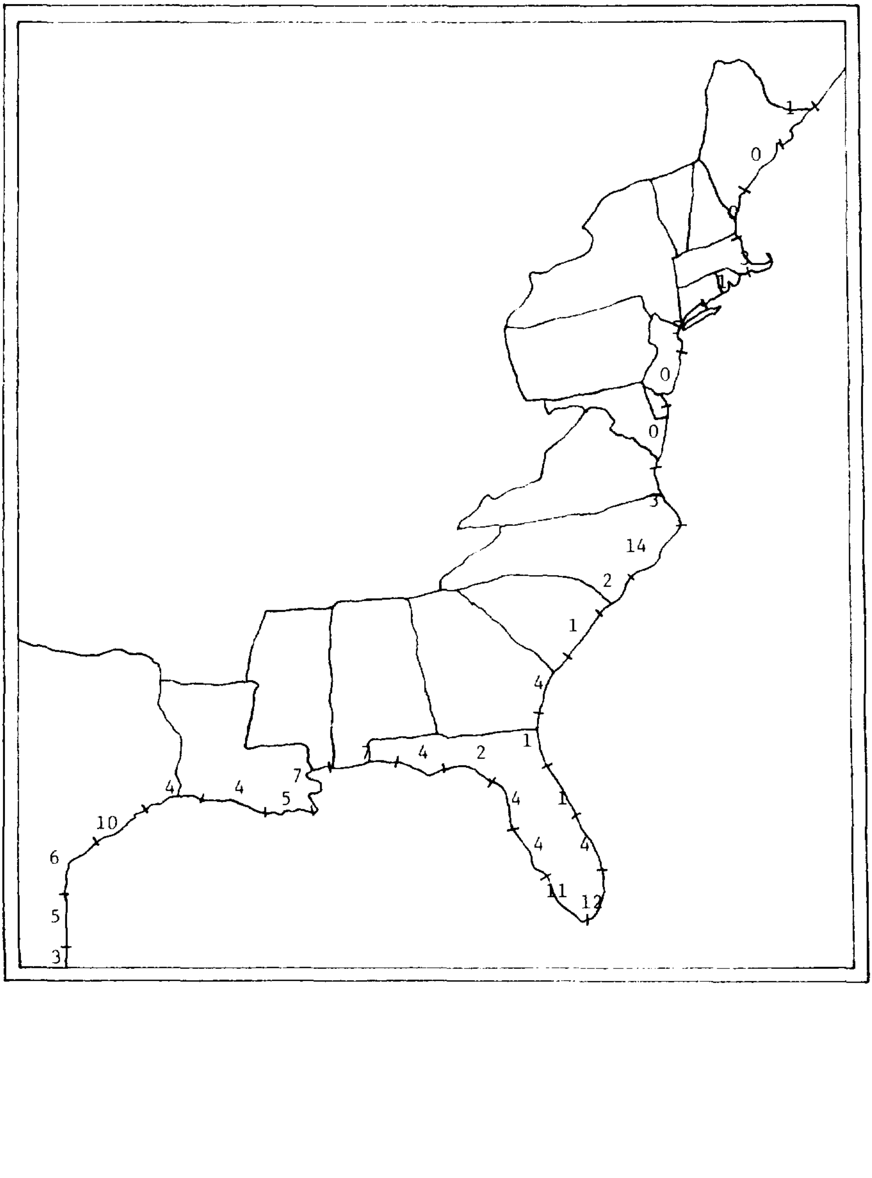
W_n = .30, .252, .14, .028, −.04, −.03

for n = 0, ±1, ±2, ±3, ±4, ±5, respectively.

[3] The coastline is smoothed for irregularities such as inlets and bays.

EXHIBIT II

HURRICANES ENTERING OR BYPASSING THE U.S. 1900–1985



This is the preferred smoothing procedure in climatological analyses because the weighting scheme maintains the frequency and phase angle of the original series of numbers. The endpoints of the series are approximated so that each segment of the coast is assigned a relative frequency. The landfall location of each storm is generated from the thus derived locational frequency distribution.

Severity

Step three of the model is the generation of values for the severity variables. There are four primary variables which account for hurricane severity. These variables are: the minimum central pressure, the radius of maximum winds, the forward speed, and the angle at which the storm enters the coast, i.e., the track direction.

Central pressure (p_0) is defined as the sea-level pressure at the hurricane center or eye. This is the most important variable for computing hurricane wind speeds, and it is a universally accepted index of hurricane intensity. All else being equal, the square of the wind speed varies directly with Δp ($\Delta p = p_w - p_0$ where p_w is the peripheral pressure).

The radius of maximum winds (R) is the radial distance from the hurricane center to the band of strongest winds. Forward speed (T) refers to the rate of translation of the hurricane center from one geographical point to another. Track direction (A) is the path of forward movement along which the hurricane is traveling and is measured clockwise from north.

Hurricane severity varies by location as does frequency. In general, as latitude increases, average hurricane severity decreases. When a hurricane moves over cooler waters, its primary source of energy (latent heat from warm water vapor) is reduced so that the intensity of circulation decreases in the absence of outside forces. As such, the shapes and parameters of the severity variable probability distributions were estimated for each coastal location.

For each severity variable except track direction, samples of data points from 400 nautical mile segments of coastline were used to estimate the parameters of the distribution for each 100 nautical mile segment. Overlapping 400 nautical mile segments were centered on successive 100 nautical mile segments, the data were fit to theoretical statistical distributions, and the parameters were estimated.

The selection of 400 nautical mile lengths of coastline was somewhat arbitrary; 300, 400, and 500 nautical mile segments have all been used in climatological analyses of hurricane data. Obviously, shorter segments capture more of the variation in the historical data while larger segments increase the size and hence the credibility of the data sample used for estimation.

CENTRAL PRESSURE

The distribution of historical hurricane central pressures is a skewed distribution with an upper bound of 29 inches. Tropical storms with higher central pressures will in most cases not produce winds of hurricane force. Since the distribution is truncated at one end, the variable *Pdif* was modeled instead of p_0. *Pdif* was defined as 29 minus the central pressure of the storm. *Pdif* also has a skewed distribution so that the historical data were fit to both lognormal and Weibull distributions using the Kolmogorov-Smirnov goodness-of-fit test.

The Weibull distribution produced the best fit of the empirical data. Table 2 shows the estimated parameters, α and β, for each coastal segment along with the number of data points in each sample, N, and the goodness-of-fit test statistic, KS. No KS statistic was significant at the 99% confidence level.

RADIUS OF MAXIMUM WINDS

The distribution of R for each coastal segment is symmetrical around the average value. The normal distribution provided a good fit of the historical data, and the parameters of this distribution were estimated for each coastal segment. The mean value of R increases with increasing latitude. Exhibit III shows a plot of latitude versus the radius of maximum winds for the historical Gulf and East Coast hurricanes.

The radius of maximum winds seems to be positively correlated with central pressure as well as with latitude. Table 3 shows linear correlation coefficients (Pearson's) between the pairs of variables. Although tests of significance could not be performed on the correlation coefficients since it could not be assumed that pairs of variables form bivariate normal probability distributions, it is assumed that there is a positive correlation between p_0 and R. The meteorological literature on hurricanes supports this assumption.

TABLE 2

CENTRAL PRESSURE—WEIBULL DISTRIBUTION PARAMETER ESTIMATES FOR 100 NAUTICAL MILE SEGMENTS

100 n.mi. Segment	400 n.mi. Segment	α	β	N	KS
1	−150–250	2.020	1.080	9	.223
2	−50–350	1.773	0.974	16	.165
3	50–450	1.882	0.910	22	.147
4	150–550	1.819	0.906	22	.149
5	250–650	1.468	0.748	26	.111
6	350–750	1.350	0.801	23	.094
7	450–850	1.223	0.707	23	.066
8	550–950	1.270	0.690	25	.090
9	650–1050	1.128	0.572	23	.095
10	750–1150	1.161	0.573	20	.107
11	850–1250	1.251	0.426	18	.187
12	950–1350	1.296	0.624	16	.135
13	1050–1450	1.111	0.832	21	.139
14	1150–1550	1.545	0.875	28	.144
15	1250–1650	1.529	0.953	31	.116
16	1350–1750	1.423	0.838	24	.140
17	1450–1850	1.793	0.815	13	.141
18	1550–1950	1.534	0.485	8	.176
19	1650–2050	0.844	0.463	7	.166
20	1750–2150	1.007	0.563	12	.156
21	1850–2250	1.285	0.676	19	.207
22	1950–2350	1.204	0.655	18	.204
23	2050–2450	1.416	0.668	16	.202
24	2150–2550	1.455	0.628	12	.234
25	2250–2650	1.177	0.566	8	.296
26	2350–2750	1.556	0.663	9	.260
27	2450–2850	1.429	0.646	9	.277
28	2550–2950	1.325	0.596	10	.252
29	2550–2950	1.325	0.596	10	.252
30	2550–2950	1.325	0.596	10	.252
31	2550–2950	1.325	0.596	10	.252

EXHIBIT III

LATITUDE VS. RADIUS OF MAXIMUM WINDS

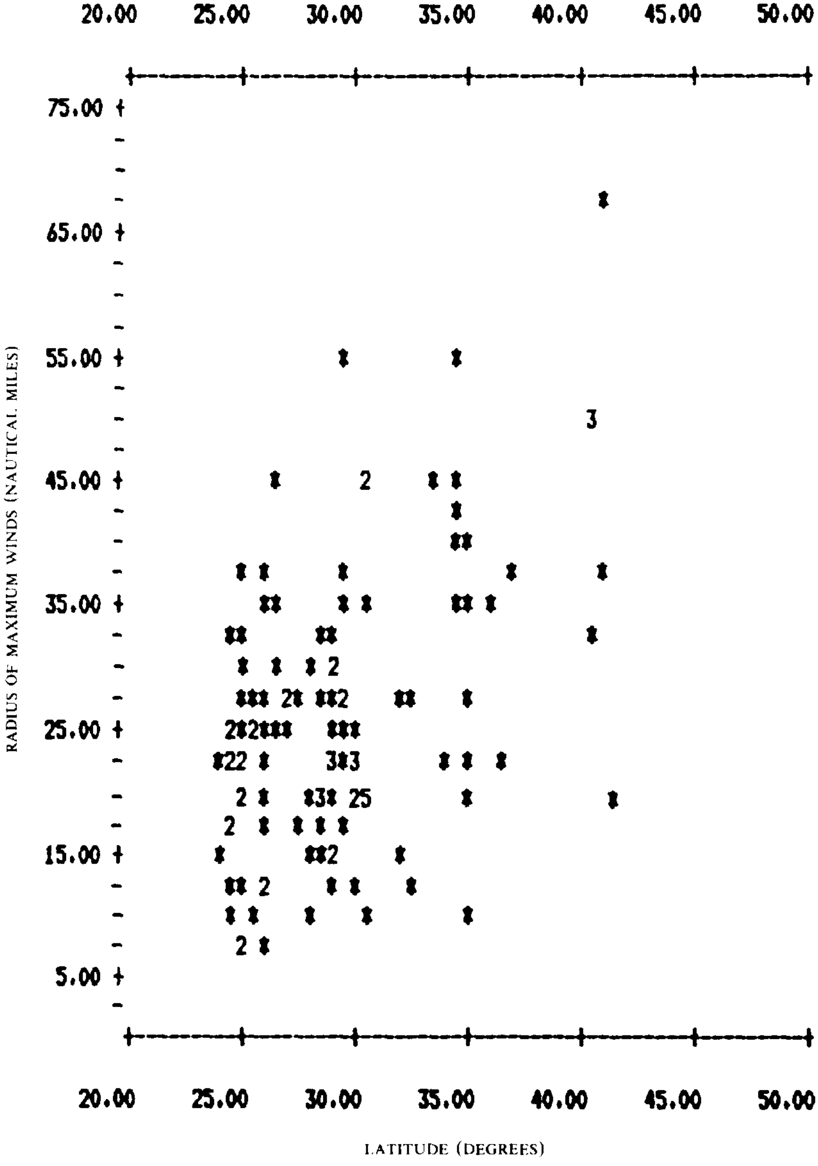


TABLE 3

LINEAR CORRELATION COEFFICIENTS

	East Coast Hurricanes						Gulf Coast Hurricanes				
	p_0	R	T	A	Lat		p_0	R	T	A	Lat
p_0		.27	−.04	−.08	.32	p_0		.31	.04	.17	.17
R			.35	.24	.49	R			.13	.04	.16
T				.42	.73	T				.06	.35
A					.50	A					.11

This correlation is accounted for by the model in two ways. First, since p_0 and R are both correlated with latitude and the distributions of p_0 and R have been estimated at various latitude points, the simulated values of the variables will necessarily be correlated. Also, the lower and upper bounds of simulated R values are determined by the value of p_0 for the simulated storm. As shown in Table 3, p_0 and R are positively correlated so that severe storms typically have smaller R's than weak storms.

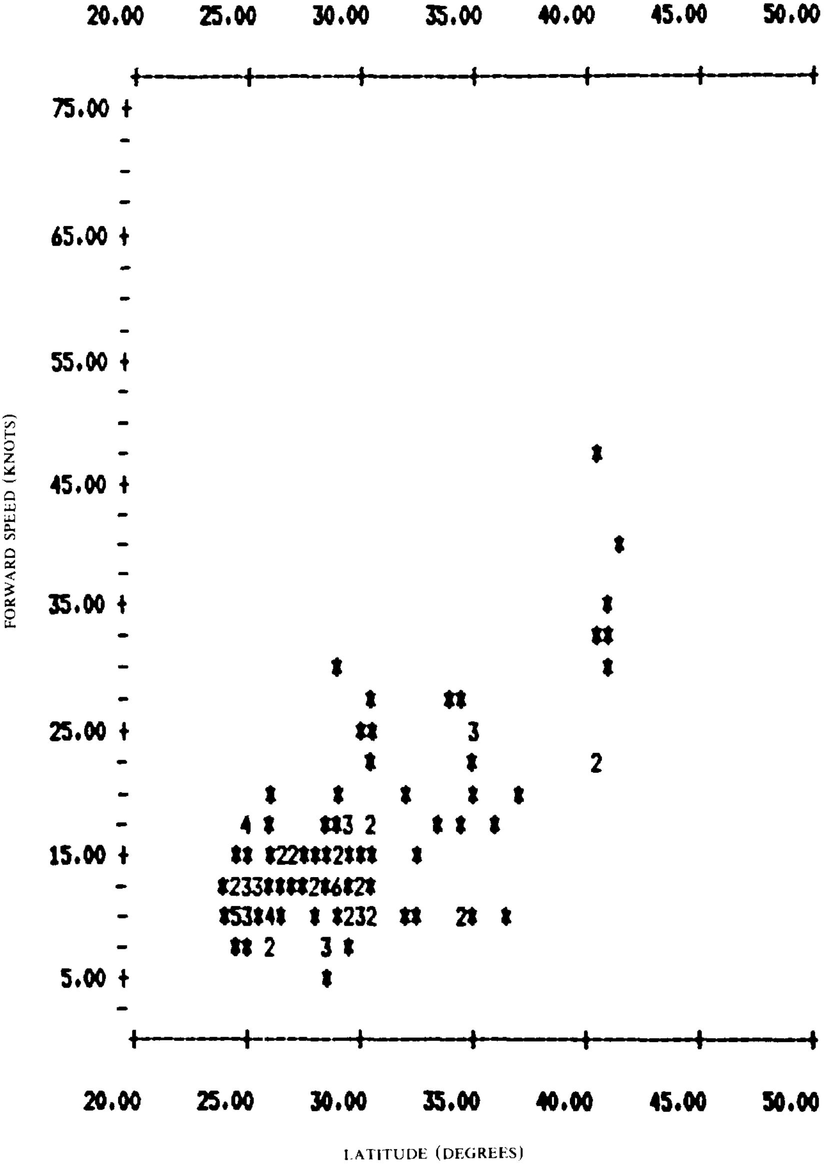
It should be noted at this point that the simulated values of all severity variables are bounded so that only storms with a nonzero probability of occurrence are simulated. The upper and lower bounds of the model variables have been determined somewhat subjectively by meteorologists who are experts on the subject of hurricanes. The model procedure is to regenerate values that are out of range rather than assign a value equal to the lower or upper bound of the range. This ensures that the simulated values will not be clustered at the endpoints of the ranges. Since the estimated distributions fit quite well, the simulated values fall within the acceptable range a high proportion of the time.

FORWARD SPEED

The historical data on forward speed fit lognormal distributions, and these distributions are employed by the model to generate values of T for each simulated storm. The average value of T increases with increasing latitude, and the lower and upper bounds of T are dependent on latitude. Exhibit IV is a plot of latitude versus forward speed for the historical storms.

EXHIBIT IV

LATITUDE VS. FORWARD SPEED



TRACK DIRECTION

Four hundred nautical mile segments were not used to estimate the parameters of the distributions of track direction for each coastal location. Since the orientation of the coastline influences the likely as well as the possible angles of entry at each coastal point, segments of varying length were employed. The length that was selected for each segment was the length of smoothed coastline with the same angle orientation as the segment of interest.

Track direction is distributed symmetrically around its average value, thus values for A are generated from the normal distribution. However, at some coastal locations, the standard deviation is quite wide relative to the range of possible values so that the distributional shape begins to tend to uniform. In these cases, a relatively high proportion of simulated values could need to be regenerated. For example, at three coastal segments, the range of possible values is only $\pm$ one standard deviation wide. Values for A could need to be regenerated 32% of the time for storms landfalling in these segments. Fortunately, the number of such segments is small.

Maximum Wind Speeds

Once values are obtained for all of the severity variables, the maximum sustained wind speed is calculated via straightforward meteorological formulas. The movement of the storm is next simulated by the computer model, and maximum wind speeds are calculated for each zip code area in the affected region.

The wind speed at each zip location is dependent on the distance of the location from R and on the hours since landfall. The wind speeds decrease as the distance from R increases and as the time since landfall increases.

Insured Damages

Dollar damages are estimated by applying damage and vulnerability factors to the insured property values in each zip code area. The damage factors are based on the results of engineering studies of the relationship between wind speed and structural damage. The vulnerability factors account for the variability in inflicted damage due to construction type and age. The dollar damages are accumulated for each storm.

Two thousand years of hurricane experience are simulated by the model. These two thousand iterations provide estimates of the complete probability distributions of annual hurricane losses and per occurrence losses from which expected and probable maximum loss estimates are derived.

OUTPUT ANALYSIS

Exhibit V shows the expected losses as well as the 80%, 90%, 95%, and 99% confidence level losses calculated as the 80th, 90th, 95th, and 99th percentile losses, respectively, for the geographical distribution of property exposures of a hypothetical company. The confidence level losses may be interpreted in two ways. A given confidence level loss shows the loss amount for which the probability of experiencing losses above that amount is 1.0 minus the particular confidence level. For example, for the loss distribution in Exhibit V, the probability of experiencing losses greater than $10 million is .20. The confidence level loss also shows the loss amount for which losses greater than that amount will be experienced, on average, once in every 1.0/(1.0 − confidence level) years. Again, from Exhibit V, losses greater than $10 million will be experienced once in every five years, on average. The loss distribution is highly skewed with a median value which is much below the mean and a high proportion of zero values.

EXHIBIT V

MODEL-GENERATED LOSS ESTIMATES (000'S)

Insured Liabilities	Expected Losses	Confidence Level Losses			
		80%	90%	95%	99%
7,170,753	9,011	10,003	24,179	44,827	117,946

Since the estimated loss distribution is so skewed, many model iterations are performed to ensure convergence to the true underlying loss distribution. Unfortunately, there is no straightforward formula for calculating the number of iterations necessary to obtain estimates with specific levels of precision. If computer resources are not a constraint, thousands of iterations should be performed to ensure convergence. If computing power is limited, iterations can be performed in groups of a hundred or so, and the distribution can be tested for significant changes after each group of iterations. When changes become arbitrarily small, the simulation run can be terminated.

MODEL VALIDATION

The validation of simulation models is often problematic. Since simulation models are representations of real world systems, they are usually simplifications of complex systems. As such, statistical tests of differences between actual data and simulated data will typically show statistically significant differences even if the simulation model is a good or at least "acceptable" representation of reality. As mentioned previously, simulation models are often built when no alternative means of analysis are available. The model builder must decide if model performance is acceptable or if more resources should be employed in improving the simulation model. The decision is more of a cost versus benefit decision than an accept versus reject decision.

In cases in which there is little actual data to compare to the simulated data, model validation is even more difficult. The natural hazard simulation model output, i.e., the catastrophe loss distribution, is an estimate of long run average costs given a particular geographical distribution of property exposures. It includes estimates of long run expected losses and probable maximum losses. There are no actual data to compare to the model output.

There are, however, two sets of assumptions to be tested. The first set includes all of the assumptions concerning the physical characteristics of the particular type of natural hazard. Do the physical characteristics of the simulated natural hazards match the characteristics of actual historical occurrences? If the probability distributions of the frequency and severity variables have been selected and estimated properly, simulated occurrences should be very similar to the historical occurrences.

In the hurricane model, the probability distributions of the model variables were fit to theoretical statistical distributions using the chi-square and Kolmogorov-Smirnov goodness-of-fit tests. Since the theoretical distributions were selected on the basis of a good fit with the empirical data, the simulated values of the variables match closely the historical values.

The second set of assumptions to be tested include all of the engineering assumptions which correlate the loss-producing phenomena with actual structural damage. These assumptions are more difficult to test empirically since actual loss data are needed. Testing requires the comparison of losses from particular natural catastrophes with the losses that the model would estimate for occurrences with the same physical characteristics, given the same geographical distributions of exposed properties. Frequently, these data are unavailable. If they are available, they are generally not available in the quantity necessary for statistical testing.

Results of these tests could be used to calibrate the model, however, it is not clear that the model builder would want to calibrate the model to a small number of actual data points. The objective of the model is to project long run average costs, not to predict losses from individual occurrences. There is so much randomness involved in a single occurrence that one cannot expect the model loss estimates to mirror exactly actual losses on each individual occurrence.

The question that arises then is whether or not the model is valid if it cannot be tested statistically. What is the value of the model if one cannot prove that its estimates are "correct"?

The nature of statistics is such that one can never prove that the sample is a true representation of the population. Statistical tests of significance merely provide confidence intervals for parameter estimates which are based on certain assumptions. These tests are used to choose between alternatives or competing hypotheses.

In the case of the catastrophe simulation model, there are no good alternative estimators. Yet there is a real need for the model output, i.e., an estimate of the catastrophe loss distribution. Insurers and reinsurers make decisions every day that affect the catastrophe loss distributions. They need to know how their decisions impact these distributions so that they can make the appropriate risk versus return trade-offs.

The degree of confidence that one has in model-generated estimates is a direct function of the level of confidence in the model assumptions. If each assumption has been tested for reasonability[4], then the model output should provide reasonable estimates. The area of validation of the natural hazard simulation model is an area worthy of further research.

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[4] There are several ways to test for reasonability. One way is to show experts in the field samples of simulated data and samples of actual data. If the experts cannot separate the actual data from the simulated data, the model builder can safely assume that the model is a good representation of reality.

MODEL USES

Knowledge of the probability distributions of property losses due to catastrophes enables management to plan for these events. The natural hazard simulation model helps insurers to manage their exposure to catastrophes; it serves as an aid to decision-making in the areas of pricing, marketing, and reinsurance buying and selling.

Pricing

The model-generated expected loss estimates can be used to calculate catastrophe premium loadings. Theoretically, if an insurer establishes a reserve for catastrophe losses and makes annual contributions equal to the annual expected losses, the insurer will break even with respect to catastrophe losses over the long run.

Of course, competitive factors influence the amount of freedom that an individual insurer has to set prices. If demand is very elastic, small increases in price will lead to large decreases in market share. Pricing can be used as part of marketing strategy to manage the geographical distribution of property exposures and hence the catastrophe loss distributions.

Marketing

The windstorm simulation model output as illustrated in Exhibit V shows the probability distribution of annual countrywide losses from the hurricane hazard. For marketing purposes, however, it may be more useful to divide the country into smaller zones so that the specific areas of high windstorm risk are clearly identifiable.

The computer model can be programmed to accumulate dollar damages by state, by country, or by any other geographical configuration. Exhibit VI shows the state of Louisiana divided into eight zones. The dollars of liability, i.e. exposure, the expected loss, and various confidence level losses[5] are shown for each zone. The figures clearly show that the higher risk areas are the coastal zones. The hurricane is at maximum force just as it crosses over land; as it travels inland, the storm dissipates because of the elimination of its primary energy source (kinetic energy from the sea) and because of surface frictional effects.

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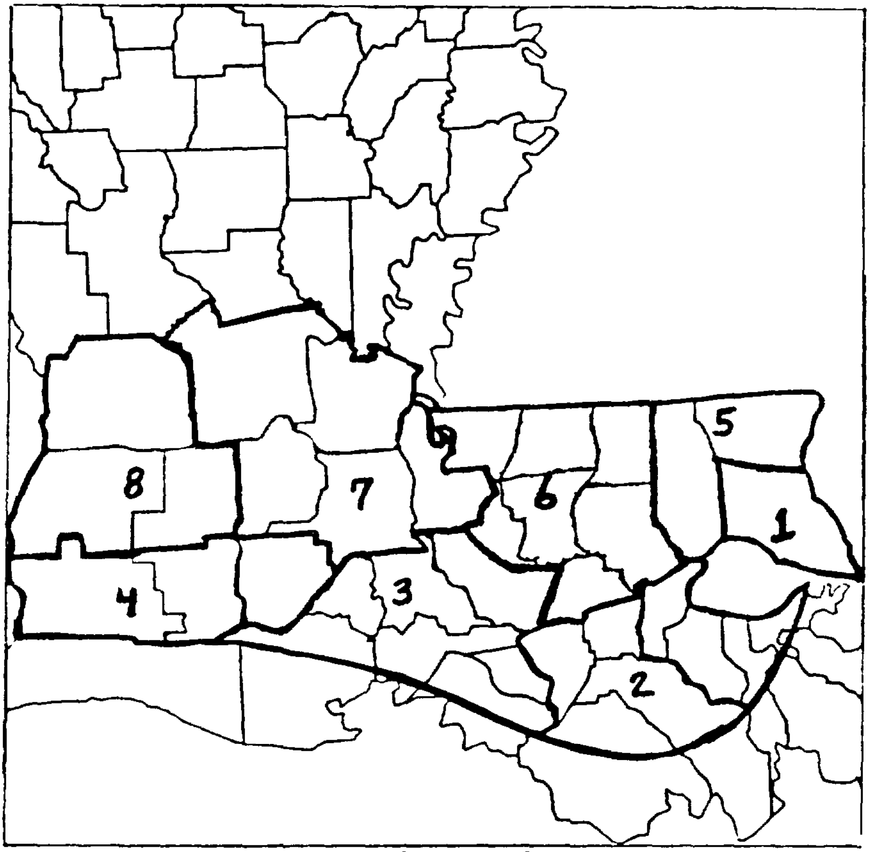
[5] It is interesting to note that for small geographic areas, the confidence level losses may be zero since the frequencies of hurricanes in specific locations are low.

EXHIBIT VI



LOUISIANA WINDSTORM ZONES

Zone	$ Exp	Expected Loss	Confidence Level Losses 80%	90%	95%	99%
LOUIS 1	90,417,112	256,512	0	276,770	1,947,396	4,938,375
LOUIS 2	9,210,113	25,540	0	12,932	213,693	537,371
LOUIS 3	56,674,660	94,866	0	31,306	653,101	2,098,500
LOUIS 4	50,672,900	71,042	0	0	234,088	1,722,377
LOUIS 5	79,796,656	80,965	0	0	547,837	2,021,005
LOUIS 6	176,149,552	231,604	0	0	598,946	6,823,092
LOUIS 7	40,664,716	47,598	0	0	193,227	1,309,985
LOUIS 8	33,114,748	16,552	0	0	5,991	772,278

Because all natural hazards have associated with them geographical frequency and severity patterns, they will produce gradations of damage or pockets of high risk and low risk. Management will want to avoid concentrations of property exposures in high risk areas, and the model output enables the development of marketing plans that are based on the long term profit potentials of various markets.

Property business in high risk areas may be very profitable in years of no natural hazard occurrences. As years pass and no catastrophes occur, insurers may begin to compete for the business in a high risk area. The competition may drive the profits as well as the catastrophe loadings to zero so that there are no resources available to cover the catastrophic losses when they occur. Knowledge of the probability distributions of losses from natural hazards in these areas enables insurers to resist the temptation to write business based on the very recent loss experience in these areas.

The natural hazard simulation model provides an excellent tool for evaluating the exposure to natural hazards resulting from alternative marketing plans. Alternative geographical distributions of property exposures may be input into the model to estimate the resulting catastrophe loss distributions.

Reinsurance

Pricing in accordance with expected losses does not eliminate the risk of large losses since catastrophes can occur when the loss fund is at a level that is not sufficient to cover all of the losses. Nor can marketing plans eliminate this risk since no area of the continental U.S. is free of natural hazards of all types. Insurers can use the probable maximum loss estimates to decide how much reinsurance to purchase for protection against large losses. An estimate of the probable maximum losses enables company management to make the appropriate risk versus return tradeoffs in evaluating reinsurance options.

SUMMARY AND CONCLUSIONS

Catastrophic events can impact significantly the results of property and casualty insurers. Since the losses resulting from the occurrences of catastrophes could affect adversely the financial condition of a company, management must plan for these events. In order to plan for these events, an estimate of the probability distribution of losses is needed.

The Monte Carlo simulation approach to the estimation of the probability distribution of catastrophe losses involves the development of computer models to simulate catastrophes. Each model is developed around the probability distributions of the random variables of the loss-producing "system."

There are several advantages of the simulation approach. First, it is able to capture the effects on the catastrophe loss distribution of changes over time in population patterns, building codes, and repair costs. Second, this estimation procedure provides management with a complete picture of the probability distribution of losses rather than just estimates of expected and probable maximum losses. And finally, the Monte Carlo simulation approach provides a framework for performing sensitivity analyses and "what-if" studies.

Disadvantages of the simulation approach include long model development time and potentially high development costs. Model validation is also problematic. However the benefits provided by the model and the value of the model output would seem to outweigh the costs. The simulation approach, while not perfect in an absolute sense, is far superior to competing approaches to catastrophe risk assessment and management.

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