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SIMULATION OF THE TORNADO HAZARD IN THE U.S.

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ABSTRACT

On average more than 1000 tornado touchdowns hit the continental U.S. every year causing significant human and economic losses. In order to manage tornado risk, we need to assess tornado hazard, the subsequent damage, and the resulting loss. This paper presents a methodology for tornado hazard assessment, which is an important step in the management of risk. For this purpose, a simulation approach is used to infer the characteristics of future tornadoes from those of past events. This paper first develops the probability distributions of the following tornado parameters needed in the simulation: rate of occurrence, relative frequencies of different Fujita scales, length, width, direction, location, and wind speed at touchdown. Then an approach for generating tornado events using the Latin hypercube method is presented. The method is applied to obtain simulated databases. These databases are first used to check convergence on the underlying parameters. The databases are then used to study the convergence of average annual loss as well as losses that are exceeded with specified probabilities.

1 INTRODUCTION

According to the meteorological definition, a tornado is a violently rotating column of air extending from a thunderstorm cloud, down to the ground. On average more than 1000 tornado touchdowns hit the continental U.S. every year causing significant human and economic losses. There is little literature devoted to modeling tornado hazard. It is generally accepted that the task at hand presents a lot of challenges. In order to evaluate tornado risk, we need to assess tornado hazard, the damage due to the hazard, and the loss resulting from the damage. Thus, the three steps in risk analyses include hazard evaluation, damage estimation, and loss assessment. Such risk analyses are useful for mitigation and for emergency response planning. Risk evaluation involves the assessment of potential losses in future events based on scientific and engineering principles that address important issues such as:

1. Where the events occur
2. How frequently the events occur
3. What the intensity of the events are
4. How the built environment responds and the degree of damage
5. What the subsequent losses are

In this paper, we discuss a methodology for modeling tornado hazard and simulation of the tornado event database for use in risk analyses with Catalyst®, a comprehensive software system for analyzing hurricane, earthquake, and tornado losses. Hazard modeling addresses the first three issues mentioned in the list above in terms of the distribution of the events in time and space as well as their intensity. The hazard component provides estimates of the potential wind speed at a site. The estimated wind speeds are used to assess damage to buildings by means of damage functions. The damage incurred is then translated into monetary loss.

In the development of the probability distributions for the tornado parameters, we use the Storm Prediction Center (SPC) tornado database (Schaefer and Edwards 1999). This database, in particular, contains year, month, day, time, Fujita scale, length, width of the touchdown as well as latitude and longitude of the starting and ending points of the tornado track.

This paper is structured as follows: in Section 2 we briefly describe the methodology for estimating the probability distributions of the different tornado parameters. In Section 3 we present an approach for modeling wind speed distribution. Section 4 is devoted to the simulation methodology. In Section 5 we present the results of convergence tests. Finally, conclusions are presented in Section 6.

2 PROBABILITY DISTRIBUTIONS OF THE TORNADO PARAMETERS

Hazard modeling of tornadoes involves estimation of the following parameters: rate of occurrence in terms of number of tornado days and the number of touchdowns per tornado day, relative frequencies of different Fujita scales, length, width, direction, and location of the starting point of the tornado track. We perform analyses for two large geographical regions of the U.S.: west and east of the Rocky Mountains. This is done because the characteristics of the tornadoes are different in these two regions. For example, the rate of occurrence is much higher in the east than in the west. Details on the estimation of these parameters are given in the subsequent sections.

2.1 Rate of Occurrence

We define rate of tornado occurrences in terms of the rate of occurrence of tornado days and number of touchdowns per tornado day. One of the challenges in estimating parameters of the tornado touchdowns is underreporting. Figure 1 shows the reported number of touchdowns in each year, along with the linear regression line (unless otherwise noted all figures refer to the region east of the Rocky Mountains). Upward trend in the number of reported tornadoes per year is clearly visible. There appear to be no meteorological reasons for the recent increase in the reported number of tornadoes. This increase in reported number of tornadoes is most likely the result of greater population density and public awareness, and improved storm-tracking and reporting networks.

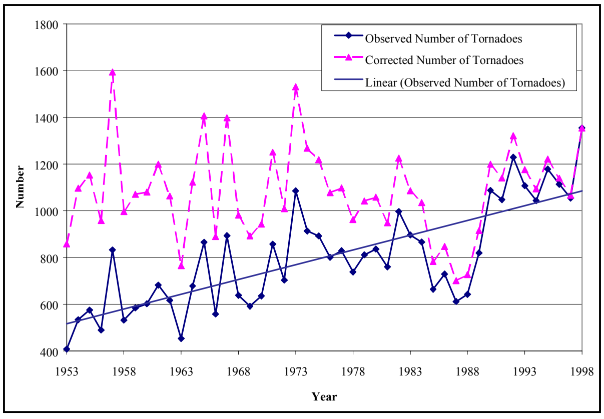

Figure 1: Number of Touchdowns per Year

In order to correct for underreported tornadoes in the pre- 1998 years, we perform linear regression for the number of touchdowns. The regression line shown in Figure 1 is used to "de-trend" the observed number of touchdowns. This way of "de-trending" preserves relative local characteristics of the observed data. Thus, the local maxima and minima are modified proportionally. The dashed line in Figure 1 shows the corrected number of tornadoes per year.

Another difficulty in modeling tornado occurrences stems from the observation that tornadoes are temporally clustered. We can have a large number of consecutive days with at least one tornado followed by the period with no tornadoes at all. Hence, commonly used simulation methods based on the assumption of independence of the events may not produce reliable results. We investigated the number of tornado days as a simulation unit (Brooks 1998). Here, a tornado day is defined as a day with at least one tornado touchdown. It also appears that number of tornado days per year is a more stationary parameter than number of tornadoes per year. Figure 2 shows the observed (solid line) and corrected (dashed line) number of tornado days per year. Corrected number of tornado days is computed using the same methodology as for the number of touchdowns.

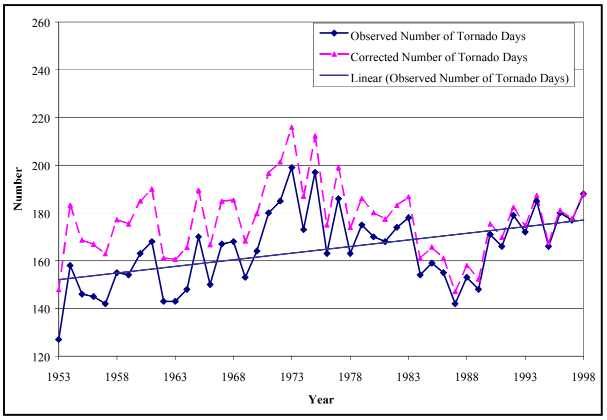

Figure 2: Number of Tornado Days per Year

In order to simulate tornado days, two possible models can be used: the binomial model and the Markov chain model. In the binomial model, each day is simulated independently using marginal probability of having a tornado day for the corresponding month.

To capture temporal clustering of tornado days, we use the two-state Markov chain model. Thus, on any given day, the Markov chain is assumed to be in one of two possible states. We will call these states 0 and 1, where 0 corresponds to a non-tornado day and 1 corresponds to a tornado day. The state for each day depends on the state for the previous day. The Markov chain is characterized by four transition probabilities: p_{01} (transition from state 0 to state 1), p_{00}, p_{11} and p_{10}. Since $p_{01}+p_{00}=1$ and $p_{11}+p_{10}=1$, we need to estimate only two out of four transition probabilities, say p_{01} and p_{11}.

Because of the seasonal nature of tornadoes we estimate transition probabilities for each month separately, assuming they are the same within a month. Estimates are smoothed using linear regression of the empirical transition probabilities on the estimated month specific marginal probabilities of the day being a tornado day. Final estimated transition probabilities p_{01} and p_{11} are shown in Figure 3. Marginal probabilities are also shown in Figure 3. Figure 4 compares empirical distribution of the cluster sizes (number of consecutive tornado days) with the one obtained using Markov chain model and binomial model that assumes independence of tornado days. To produce results for both models we use 100,000 simulation years. For the Markov chain approach, it is first determined whether the first day of each month is a tornado day or not based on marginal probability of having a tornado day for that month. All other days of the month are simulated using transition probabilities. The total number of tornado days simulated using two models are within 0.2% of each other. However, Figure 4 clearly demonstrates that Markov chain model is superior for representing clusters of tornado days. Thus, the Markov chain model is adopted in our simulation scheme.

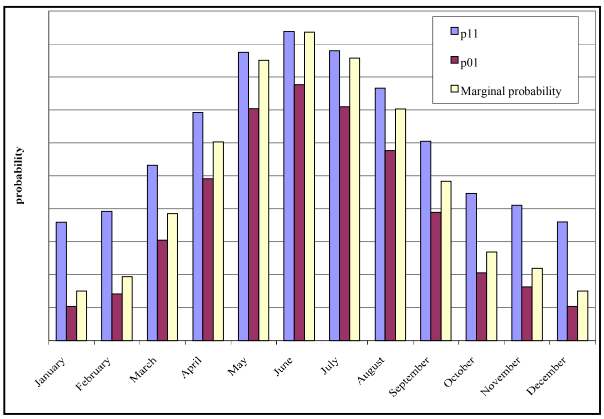

Figure 3: Transition and Marginal Probabilities of a Day being a Tornado Day

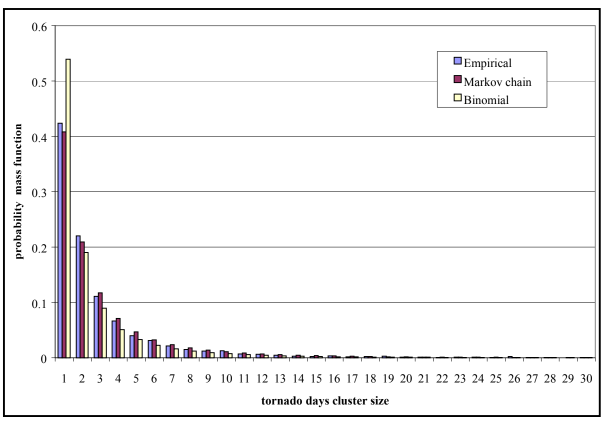

Figure 4: Distribution of the Tornado Days Cluster Size

The number of touchdowns per tornado day is modeled using mixed geometric distribution. The parameters of this distribution are obtained from the SPC tornado data.

2.2 Other Parameters

In this section, we give a brief account of the methodology for estimating the probability distributions of other parameters that characterize tornadoes. One of the parameters that characterizes tornado touchdowns is the Fujita scale. Dr. T. Theodore Fujita developed the Fujita scale (Fujita 1971). This scale relates the degree of damage to the intensity of the wind (see Table 1 in Appendix). The wind speeds have not been directly measured in tornadoes. Engineering analyses of past events indicate that the Fujita wind speeds were over-estimated, especially for the higher categories (Minor et al. 1977). Recognizing the uncertainties in wind speed ranges, Twisdale (1978), used engineering and photogrammetric analyses to update the original Fujita wind speeds in a Bayesian analysis.

As was mentioned earlier in the paper, tornado occurrences were underreported in the earlier years. With respect to the Fujita scale it is very likely that in the earlier years, tornadoes belonging to the lower Fujita scale were underreported. Thus, the relative number of tornadoes belonging to the higher Fujita scales was exaggerated. Presently, we update the relative frequency of Fujita scale by assigning Fujita scale to additional tornadoes calculated according to the procedure described in Section 2.1. The procedure used for assigning Fujita scales to the additional tornadoes is similar in principle to the one that we presented for correcting the number of touchdowns. The corrected relative frequencies of the different Fujita scales are used in the simulation.

According to the historical data for each Fujita scale, there exists moderate positive correlation between length and width of the tornado track. We model length and width jointly by using bivariate lognormal distribution.

For distribution of the touchdown direction, we consider eight octants centered at West, Northwest, North, Northeast, East, Southeast, South and Southwest directions. Relative frequency for each octant is estimated based on historical touchdowns (1953-1998) over entire U.S.. Within each octant directions are assumed to be uniform. Empirical distribution for direction can be seen in Figure 5.

For simulating the location of each touchdown, we cover continental U.S. with uniform 1ºx 1º grid (see Figure 8 for the eastern U.S.). Within each geographical region, the number of tornadoes is simulated for each tornado day. These tornadoes are assigned to the different cells based on the relative rates of occurrence of tornadoes for each cell. Because tornadoes are rare events and due to the short time period of historical records, it is possible that the historical rates for two neighboring cells are rather different. These differences cannot be explained by any meteorological or geographical reasons. Hence we apply a smoothing procedure for the number of touchdown occurrences in different cells. Specifically, the number of occurrences per unit area is smoothed using a bivariate isotropic Gaussian kernel centered at the center of the cell being smoothed. Each cell is assigned weight equal to the volume under the Gaussian kernel over that cell. To capture the seasonal geographic trend in tornado occurrences, smoothing is performed by month. Two examples of the results of the smoothing procedure are shown in Figure 6 and Figure 7. Figure 8 shows the map of eastern U.S. with smoothed annual relative rates.

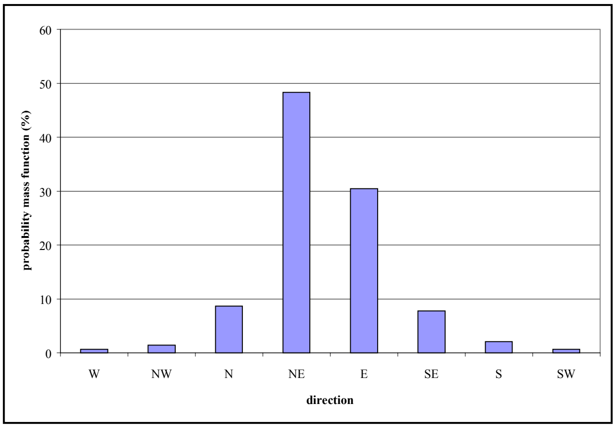

Figure 5: Empirical Distribution of the Tornado Track Direction (entire U.S.)

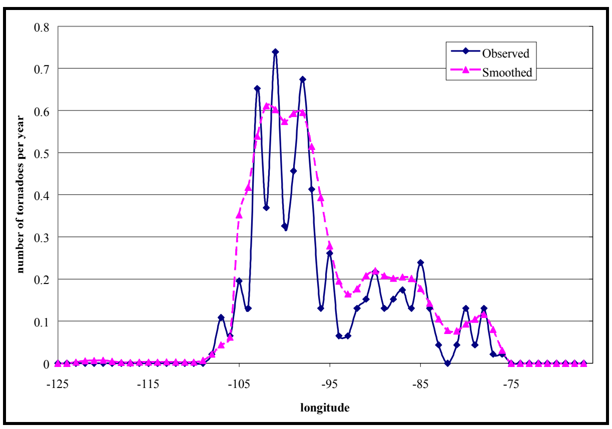

Figure 6: Observed and Smoothed Tornado Occurrence Rates in June at Latitude of 37°N

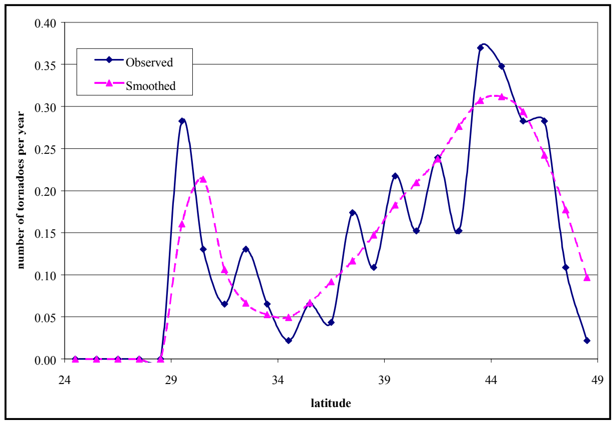

Figure 7: Observed and Smoothed Tornado Occurrence Rates in July at Longitude of 95°W

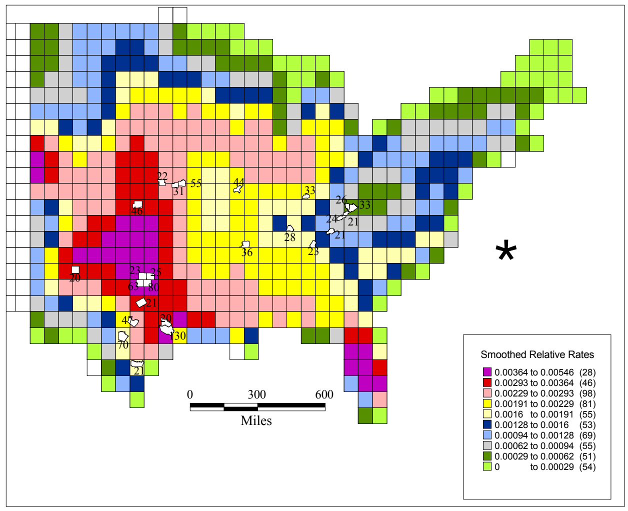

Figure 8: 1° x 1° Cells and Annual Relative Rates of Tornadoes

3 WIND SPEED DISTRIBUTION

A tornado touchdown in our database is defined by its location, length, width, and Fujita scale. All structures within the length and width of the touchdown are susceptible to damage and corresponding losses. In order to estimate losses from each tornado touchdown, the wind speed distribution within the length and width of the touchdown (affected region) needs to be determined.

Along the length of the touchdown, the wind speed usually degrades as the friction with the ground dissipates the energy. A degradation model is used to describe this wind speed variation along the track. Twisdale et al. (1981) studied 150 tornadoes to determine the wind speed variation along the track of tornadoes with different intensities. Figure 9 shows this degradation model.

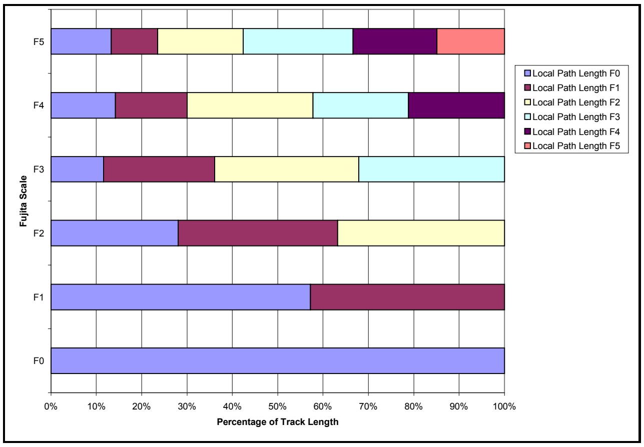

Figure 9: Tornado Degradation Model

The wind speed variation across the tornado vortex is estimated by means of a wind profile model. Garson et. al (1975) proposed a wind velocity profile based on the Hoecker model, which is based on field observations and theoretical model of a Rankine Vortex. This model is adopted because it has both theoretical and empirical background as well as simplicity.

4 SIMULATION

Our methodology for simulating potential losses from tornado events is based on Latin hypercube (Iman and Conover, 1980). Two quantities of interest we concentrate our attention on are: average annual loss (AAL) and probable maximum loss (PML). AAL is defined as the expected annually incurred loss and PML is defined as the loss level that can be exceeded with specified probability in a year. One of the commonly used values is 0.002 that corresponds to 500-year expected return period).

The loss resulting from the tornado events is a complex function of the input model variables. With the Latin hypercube sampling approach, we achieve better convergence than with random sampling for the same number of simulation years. Latin hypercube sampling forces one to sample from the tails of the distributions. The simulation process is summarized as follows:

1) The first day of each month is determined to be a tornado day or not using the marginal probability for that month. The subsequent tornado days of the month are determined using the Markov chain model. All touchdowns within a specified time period are grouped into one event.
2) Latin hypercube sampling is used to obtain the number of tornadoes per tornado day.
3) The total number of touchdowns is used to perform Latin hypercube sampling for the location, by month.
4) Latin hypercube sampling for Fujita scale and tornado track direction is performed using the total number of simulated touchdowns.
5) The total number of touchdowns for each Fujita scale is used to perform Latin hypercube sampling for tornado track length, width and wind speed at touchdown.

The wind speed at each site is computed from all touchdowns within an event. The maximum wind speed from all touchdowns is used to assess damage by means of damage functions that relate wind speed to damage. The damage incurred is then translated into monetary loss.

5 CONVERGENCE TESTS

To determine the number of simulation years sufficient to reliably estimate losses we performed two types of analyses: check convergence on the model parameters, and check convergence on AAL and PML. We simulated tornado events over different time periods to analyze convergence of the input parameters (see Figure 10 through Figure 12). Figure 10 through Figure 12 show that the parameters converge with less than 1% error after 10,000 simulation years.

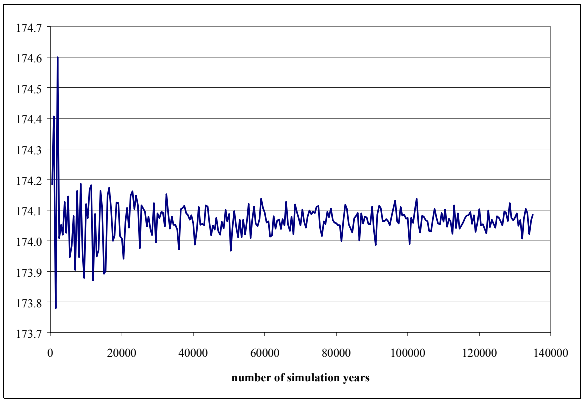

Figure 10: Mean Number of Tornado Days per Year

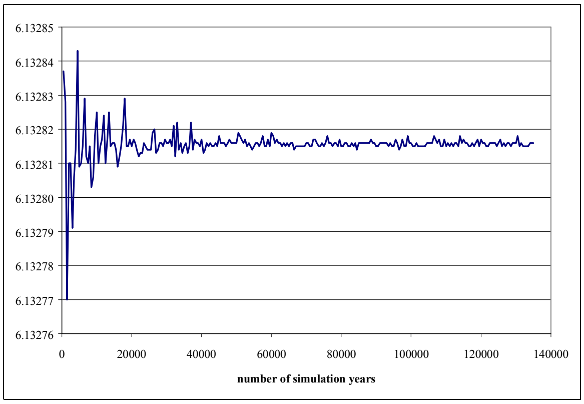

Figure 11: Mean Number of Tornadoes per Tornado Day

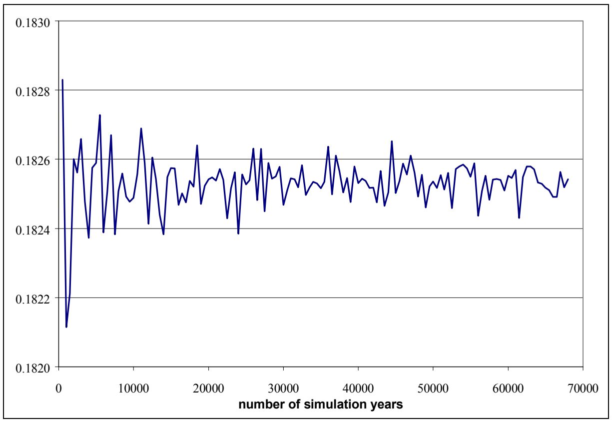

Figure 12: Mean width of the Tornado Path for Fujita Scale 3

We simulated tornado events for significantly large number of simulation years (100,000) in order to study the convergence of PML and AAL for a selected set of portfolios. Each portfolio consists of properties that belong to a county in one of the 6 states: Arkansas, Kansas, Kentucky, Missouri, Tennessee and Texas (see Figure 8). We consider only counties with 20 or more ZIP Codes. Each of the properties is assumed to be located at the center of the ZIP Code. Figures 13 and 14 show the PML curves for two portfolios: all properties shown in Figure 8, and those within St. Louis County. Figure 15 shows the ratios of the mean absolute difference in the AALs to the mean AAL for the sample counties. For counties with more than 30 zip codes, the AALs are within 10% of each other.

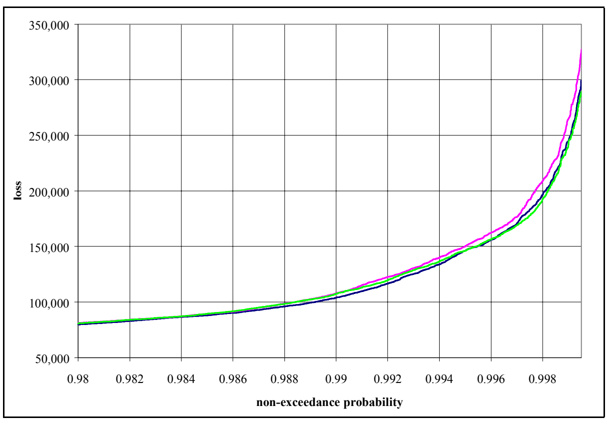

Figure 13: PML Curves for Three Runs of 100,000 Simulation Years for the Portfolio that Consists of All Properties of All Counties

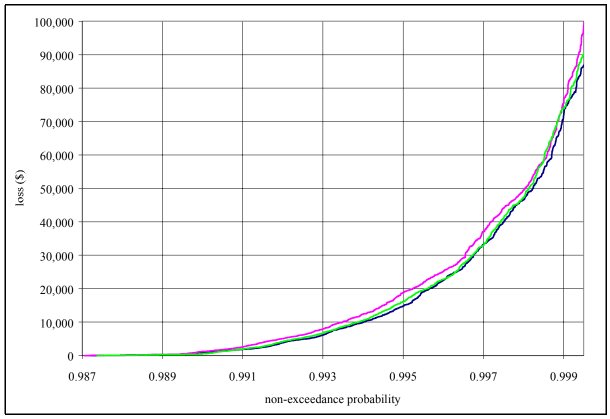

Figure 14: PML Curves for Three Runs of 100,000 Simulation Years for St. Louis County (MO) with 44 ZIP Codes

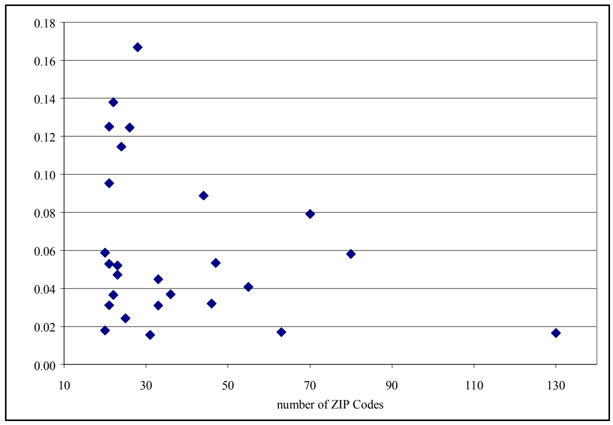

Figure 15: Ratios of Mean Absolute Difference between AALs to the Mean AAL for Three Runs of 100,000 Simulation Years

6 CONCLUSIONS

A methodology for simulating tornado events has been presented in this paper. This methodology has been applied to obtain simulated databases. SPC data are used to develop the parameters of the probability distributions for the model input variables. Several runs for 100,000 simulation years are made and the convergence of average annual loss as well as losses that are exceeded with specified probabilities are examined. Results indicate that even for 100,000 simulation years, the losses still fluctuate. This could be explained by several reasons. These include the dependence of the tornado events on a lot of variables and the usually small area that a tornado affects. Simulation for larger number of years requires a substantial increase in computer storage and memory requirements.

APPENDIX: DESCRIPTION OF FUJITA SCALE

Table A-1: Description of the Fujita Scale

Scale	Wind Speed (mph)	Typical Damage
0	<73	**Light damage.** Some damage to chimneys; branches broken off trees; shallow-rooted trees pushed over; sign boards damaged.
1	73-112	**Moderate damage.** Peels surface off roofs; mobile homes pushed off foundations or overturned; moving autos blown off roads.
2	113-157	**Considerable damage.** Roofs torn off frame houses; mobile homes demolished; boxcars overturned; large trees snapped or uprooted; light-object missiles generated; cars lifted off ground.
3	158-206	**Severe damage.** Roofs and some walls torn off well-constructed houses; trains overturned; most trees in forest uprooted; heavy cars lifted off the ground and thrown.
4	207-260	**Devastating damage.** Well-constructed houses leveled; structures with weak foundations blown away some distance; cars thrown and large missiles generated.
5	261-318	**Incredible damage.** Strong frame houses leveled off foundations and swept away considerable distances; automobile-sized missiles fly through the air in excess of 100 meters (109 yds); trees debarked; incredible phenomena will occur.

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