Estimating Extreme Losses for the Florida Public Hurricane Model

Sneh Gulati[1*], Florence George[1], Fan Yang[1], B. M. Golam Kibria[1] and Shahid Hamid[2]

[1]Department of Mathematics and Statistics, and
[2]Department of Finance, Florida International University
Miami, FL 33199, USA.
[*]Corresponding Author: gulati@fiu.edu

Received: 15, August 2013 / Revised: 3, February 2014 / Accepted: 28, February 2014

ABSTRACT

While the world thinks of coastal Florida as a paradise and retirement haven, residents in these areas don't always agree with that depiction. Living under the threat of hurricanes for six months of the year and paying enormous sums of money for wind storm insurance is not exactly paradise. However this has not deterred people from wanting a piece of paradise and migration to Florida has continued unabated. Exposure has increased significantly along coastal regions causing insurance companies to reevaluate their risks. They still focus on estimation of annual insured loss, but increasingly they want to be prepared for extreme losses. This paper attempts to look at various methods of estimating extreme quantiles of the loss distribution in the Public Hurricane Loss Model. Both nonparametric and parametric models are used to estimate the catastrophic quantiles and then compared for accuracy. We found that the Weibull distribution fitted the data very well compare to simple exponential and GDP distributions.

Keywords: Catastrophic Events, Insured Loss, Mathematical Models, Probable Maximum Loss.

1. Introduction

Are residents of Florida living in paradise or insurance hell? It is always sunny, the sky is always blue, there is no winter to speak of, residents can play tennis all year round, swim all year round, so why do residents wonder about the wisdom of living on the coast of Florida? It is the insurance costs and the threat of hurricanes six months of the year! Anyone buying a new home in coastal Florida will attest to the difficulty of getting windstorm insurance for their home and if they are lucky enough to get insurance, it is extremely expensive. A number of residents opt to go without windstorm insurance because they realize that the cost of obtaining insurance is far higher than any payouts they can expect to get.

This was not always the case. Insurance was easy to obtain and not prohibitively expensive until Hurricane Andrew struck Florida in 1992. According to the Insurance Institute of Florida (McChristian, 2012), when it struck; Andrew was the costliest natural disaster in U.S. history in terms of insurance payouts. The insurance claims payout totaled $15.5 billion at the time ($25 billion dollars in 2012). At the time the report was written Hurricane Andrew was the second costliest natural disaster in the US, following damages caused by Hurricane Katrina in 2005.

Prior to Andrew most insurance companies were using past losses to compute premiums. However, there had not been any major hurricanes in the state of Florida for a number of years leading to an underestimate of the insured losses. Several companies had to declare bankruptcy after Andrew. It was Andrew and its catastrophic damage that led to the reevaluation of the calculation of insured losses from catastrophic events and underscored the need for the estimation of losses caused by the ñOne in a hundred year eventò or Probable Maximum Losses.

Hurricane Losses are now evaluated through the use of computer simulation models. These models use historical data to simulate thousands of years of hurricane activity to estimate insured losses. To be used for rate making purposes in Florida, these models have to be certified by an independent body called the Florida Commission for Hurricane Loss Projection Methodology (FCHLPM). In order to be certified by FCHLPM, modelers have to demonstrate compliance with a set of rigorous standards. There are currently five models certified for rate making purposes in Florida. Four of these are owned by private commercial companies and one is publicly funded and has been developed by a team of scientists in the state university system (SUS) in Florida; the Florida Public Hurricane Loss Model (FPHLM). The FPHLM simulates 50,000+ years of hurricane activity. These simulated hurricanes are then tracked till they make landfall in the state of Florida. This allows the model to estimate the wind risk in any region in Florida. This information is then used by the engineers and the actuaries respectively to estimate structural damage and insured losses. The primary output of the model is the annual expected insured loss at any given address. For details on the FPHLM, we refer the reader to Hamid et al. (2008, 2010).

However as said earlier, from an insurerôs perspective, having an estimate of the annual average insured loss will not help them in an event like Hurricane Andrew. They want to be able to hedge against catastrophic events like Andrew which have the potential to bankrupt them. Therefore in the recent years, a lot of attention has focused on the estimation of these extreme events which occur rarely but can have disastrous effects, in other words, attention has shifted from average losses to high quantiles of the loss distribution, also referred to as *Value at Risk* (Var) or Probable Maximum Loss (PML) in the insurance industry. This paper discusses different methods used to estimate the PML for the Florida Public Hurricane Loss Model.
The organization of the paper is as follows. We discuss the theory and the various estimation methods in Section 2. Section 3 discusses the applications of these methods to FPHLM. This paper ends up with some concluding remarks in section 4.

2. Notations and Methodology

2.1 Notations and Preliminaries

As mentioned earlier, the estimation of Probable Maximum Loss (PML) is extremely important in catastrophic event analysis. PML is defined as a loss that is exceeded with a very small probability p (close to 0). In other words, PML concerns itself with the estimation of x^*_p, such that $P(X > x^*_p) = p$, where X is the random variable that represents losses. Simply put, if F represents the c.d.f. of losses, then $F(x^*_p) = 1- p$, where p is such that 1-p is close to one (see Matthys and Bierlant (2003).) A PML is often accompanied by a return period (which is the average number of years that must pass before such a loss is observed); and the return period associated with x^*_p is 1/p. PML can be estimated by nonparametric and parametric methods. Note that while PML is often computed on the basis of annual losses, it can also apply to annual maximum losses.
Perhaps the simplest way to estimate PML is nonparametrically where the extreme quantiles are simply estimated by their empirical counterparts. This is the method that has been used by the Public model to estimate extreme quantiles and is detailed in the next section:

2.2 Non-Parametric Methods

Non-parametric procedures to compute the PML assume that the empirical loss distribution is a close substitute for the population loss distribution, free from any parametric constrains. PML can be produced non-parametrically through order statistics. To estimate PML corresponding to the $100p^{th}$ percentile, the k^{th} order statistic, X_k, is used; where k is determined by sample size N multiplied by p. If the result is not an integer, the smoothed empirical estimate is applied to interpolate two adjacent order statistics through, $PML_p=(1-h)x_j+hx_{j+1}$ where j=[(N+1)p] and h=(N+1)p-j; here [.] indicates the greatest integer function (Wilkinson (1982), Hogg and Klugman (1984)). This method, however, is not applicable for PML_p where p>N/(N+1).

To obtain confidence intervals for PML_p, we use the well known result (see Section 3.2 of Practical Nonparametric Statistics by WJ Conover) that for any 1 Òj ÒN, the probability that

$$P(PML_p < X_{(j)}) = \sum_{i=1}^{j-1} \frac{N!}{i!(N-i)!} p^i (1-p)^{N-i}$$

The above implies that for some r < s ÒN,

$$\begin{aligned} & P(X_{(r)} < PML_p < X_{(s)}) \\ & = P(PML_p < X_{(s)}) - P(PML_p < X_{(r)}) \\ & = \sum_{i=1}^{s-1} \binom{N}{i} p^i (1-p)^{N-i} - \sum_{i=1}^{r-1} \binom{N}{i} p^i (1-p)^{N-i} \\ & = \sum_{i=r}^{s-1} \binom{N}{i} p^i (1-p)^{N-i} \approx 0.95 \end{aligned}$$

Hence to construct a (1- Ŭ)100% confidence interval for PML_p, we need to find r and s with r <s (done through a numerical search) such that

$$\sum_{i=r}^{s-1} \frac{N!}{i!(N-i)!} p^i (1-p)^{N-i} \text{ å } 1- Ŭ$$

If the solution from the computer search is not unique, the pair of r and s that minimizes s-r is selected to give the narrowest interval.

An approximate 95% confidence interval for PML_p is given by (X_r, X_s) using a large sample approximation. The large sample approximation assumes normality to obtain r and s as,

$$r = Np - 1.96\sqrt{Np(1-p)}$$

$$s = Np + 1.96\sqrt{Np(1-p)}$$

In case any value of r and s is not an integer, the smoothed empirical estimate is used.
While extremely simple to use, nonparametric methods to estimate extreme quantiles pose some risk. Data can be scarce in the upper tail of the distribution leading to biased estimates, especially in the case of heavy tailed distribution. The presumption of heavy tails in the case of catastrophic events has given rise to a plethora of different techniques to model extreme quantiles, chief amongst them being ñthe annual maxima methodsò and the ñPeak Over Threshold (POT) methods.

2.3 Annual Maxima Methods (or Block Maxima Methods)

The annual maxima method belongs to a general class of methods called the Block maxima methods. Here, instead of trying to find a distribution that fits the entire data set (or the tail for heavy tailed distributions), the investigator tries to model maximum values in a certain period (called blocks.) The fitted model then is used to estimate extreme quantiles. In this paper, we consider the annual maxima method as proposed by Gumbel (1958) and referenced by An and Pandey (2003). Treating the years as ñblocksò, the maximum values in the ñblockò are fit using the Gumbel distribution. The c.d.f. of the Gumbel distribution is given by $F(y) = \exp(-e^{-(\lambda x-\mu)})$ and it belongs to the general family of extreme value distributions. In the standard Gumbel method, estimators of the parameters are obtained via least squares. The method was later modified by Harris (1996) to consider weighted least squares method for estimating parameters.

2.4 Peaks-Over-Threshold (POT) Method

The peak over threshold method to model extreme events has steadily gained popularity in the recent years and is probably used by the majority of practitioners of extreme value statistics. In this scenario, the modeler is mainly interested in estimating the high percentiles of losses over a threshold u. In other words, the modeler is interested in the distribution of Y = X ï u, provided X exceeds u. Mathematically, we let F_u represent this conditional distribution, which is described as follows:

$$F_u = P(Y \le x \mid X > u) = P(X - u \le y \mid X > u)$$
$$= \frac{F(y+u) - F(u)}{1 - F(u)}$$

where $u>0$ and $x \geq 0$.

It is well known then that under certain conditions and a large enough threshold (Pickands (1975)), F_u is in limit a Generalized Pareto Distribution (GPD) with c.d.f given by:

$$F_{\gamma,\sigma}(x) = \begin{cases} 1-(1+\gamma\frac{x}{\sigma})^{-1/\gamma}, \gamma \neq 0 \\ 1-exp(-x/\sigma), \gamma = 0 \end{cases} \quad (2.1)$$

where $\sigma > 0$ and $x \geq 0$ when $\gamma \geq 0$ and $x \leq -\sigma/\gamma$, when $\gamma < 0$. So for large thresholds u,

$$F_u(x-u) \approx G_{\gamma,\sigma}(x-u) \equiv G_{\gamma,u,\sigma}(x).$$

We use this method as detailed in Matthys and Bierlant (2003). Assume that our original loss data are given by $X_1, X_2, \ldots, X_N$. We select a sufficiently high threshold, u (typically chosen as the order statistic corresponding to a high percentile of the losses; say the 75th percentile or higher) and let N_u be the number of exceedances above u. So if u is the (k+1)st largest observation $X_{(n-k)}$, then N_u is k and the exceedances are given by $Y_1 = X_{(n-k+1)} - u$, $Y_2 = X_{(n-k+2)} - u, \ldots, Y_k = X_{(N)} - u$. We then estimate the parameters of the GPD using the exceedances and let these estimates be given by $\hat{\sigma}$ and $\hat{\gamma}$. Then the conditional tail $\bar{F}_u$ of F is estimated as:

$$\hat{\bar{F}}_u(x) = \begin{cases} 1 - \left(1+\hat{\gamma}\frac{x}{\hat{\sigma}}\right)^{\frac{-1}{\hat{\gamma}}}, \quad 0 < x < x_+ - u \end{cases} \quad (2.2)$$

From (2.1), then the unconditional tail $\bar{F}(x) = \bar{F}_u(x-u)\bar{F}(u)$ and is therefore estimated by:

$$\hat{\bar{F}}(x) = \frac{N_u}{N}\left(1+\hat{\gamma}\frac{x-u}{\hat{\sigma}}\right)^{-1/\hat{\gamma}} \quad u < x < x_+ \quad (2.3)$$

Once again from Matthys and Bierlant (2003), we can invert the above equation to get an estimate of high quantiles above the threshold u as follows:

$$\hat{x}_p^* = u + \hat{\sigma}\frac{\left(\frac{N_u}{Np}\right)^{\hat{\xi}}-1}{\hat{\xi}} \quad (2.4)$$

Note that the above method can only be used if p < N_u/N.
Besides using the GPD to fit the conditional tail, we also investigated the use of the exponential and the Weibull distributions as possible fits for the tail. Past research by Yang et. al. (2011) has shown that the losses from PHLM do not tend to be heavy tailed and therefore it seemed prudent to investigate the use of some skewed light tailed distributions as possible fits.
Recall that the CDF of exponential distribution is given by

$$F(x) = 1 - e^{-x/\theta}, \ \theta > 0 \text{ and } x > 0$$

Note that exponential distribution is a special case of GPD. The CDF of Weibull distribution is given by

$$F(x) = 1 - e^{-\left(x/\theta\right)^k}, \ \theta > 0$$

The methodology to estimate the extreme quantile is the same as that for the GPD and so we will not describe it here again.
A big component of the quantile estimation using the POT method is the selection of the threshold value u. As suggested earlier, the threshold value *u* is often unknown but chosen to be one of the order statistics, say the (k+1)st largest observation or $X_{(n-k)}$. For our paper we chose three values of k; that corresponded to the 75th percentile, 80th percentile and 85th of the data distribution. While there are a number of methods available to estimate the parameters, we used the maximum likelihood method to estimate them. For more on POT method, the readers are referred to Leadbetter (1991) and McNeill and Saladin (1997) among others.

3. Data Analysis

Data analysis was conducted on losses generated from the latest certified version of the PHLM; PHLM 5.0. The model generates 56,000 years of hurricane activity in the state of Florida and thus 56,000 years of losses. In keeping with historical hurricane frequencies, where the majority of the times Florida has no land falling hurricanes; 50.9% of the losses were zero. As a result the annual maxima method to estimate high quantiles worked very poorly for our data set. As seen in Figures 3.1 and 3.2, the annual maximum losses are very skewed due to the high proportion of zeros and the Gumbel distribution does not fit the data at all. Hence we decided to use the POT method to estimate PML using both the annual maximum values and the total losses. The estimated PMLõs were compared to the ones obtained via the nonparametric method. To find the PML using the POT method, as in Matthys and Bierlant (2003), we truncate the data at the threshold value and use the conditional tail to compute estimates of the parameters. For example, to model the tail of the annual total loss using the threshold 75th percentile, we considered only the highest 25% of the data that are higher than the 75th percentile. We then subtract the value of the cut-off point from the original data and then use the proposed distributions (GPD, exponential or Weibull), to model these tail data,. The extreme values are then estimated using equations (2.2-2.4). The estimated extreme percentiles or the PML values for maximum annual loss have been estimated for the 80th through 99th percentiles using the proposed distributions and are presented in Table 3.1 and the corresponding goodness of fit tests are presented in Table 3.2. The empirical and fitted CDF of PML for annual maximum loss for GPD, exponential and Weibull distributions over 75th, 80th and 85th percentiles are presented in Figures 3.3, 3.4 and 3.5 respectively. The estimated values of the parameters by maximum likelihood methods are presented under the corresponding figures. We have also estimated the extreme percentiles for total annual loss from 80th through the 99th percentiles using the proposed distributions and presented them in Table 3.3 and the corresponding goodness of fit tests are presented in Table 3.4. The empirical and fitted CDF of PML for total annual loss and for GPD, exponential and Weibull distributions over 75th, 80th and 85th percentiles are presented in Figures 3.6, 3.7 and 3.8 respectively. After carefully reviewing these Tables (3.1 to 3.4) and Figures (3.3 to 3.8), we observed that the 80th and 85th percentiles of Weibull distribution fitted our data very well and performed the best amongst the proposed distributions. Even though studies in literature (see McNeil and Saladin, 1997 for example) suggest that the GPD should be used to model the extreme events, our empirical study suggests that the Weibull is a useful alternate.

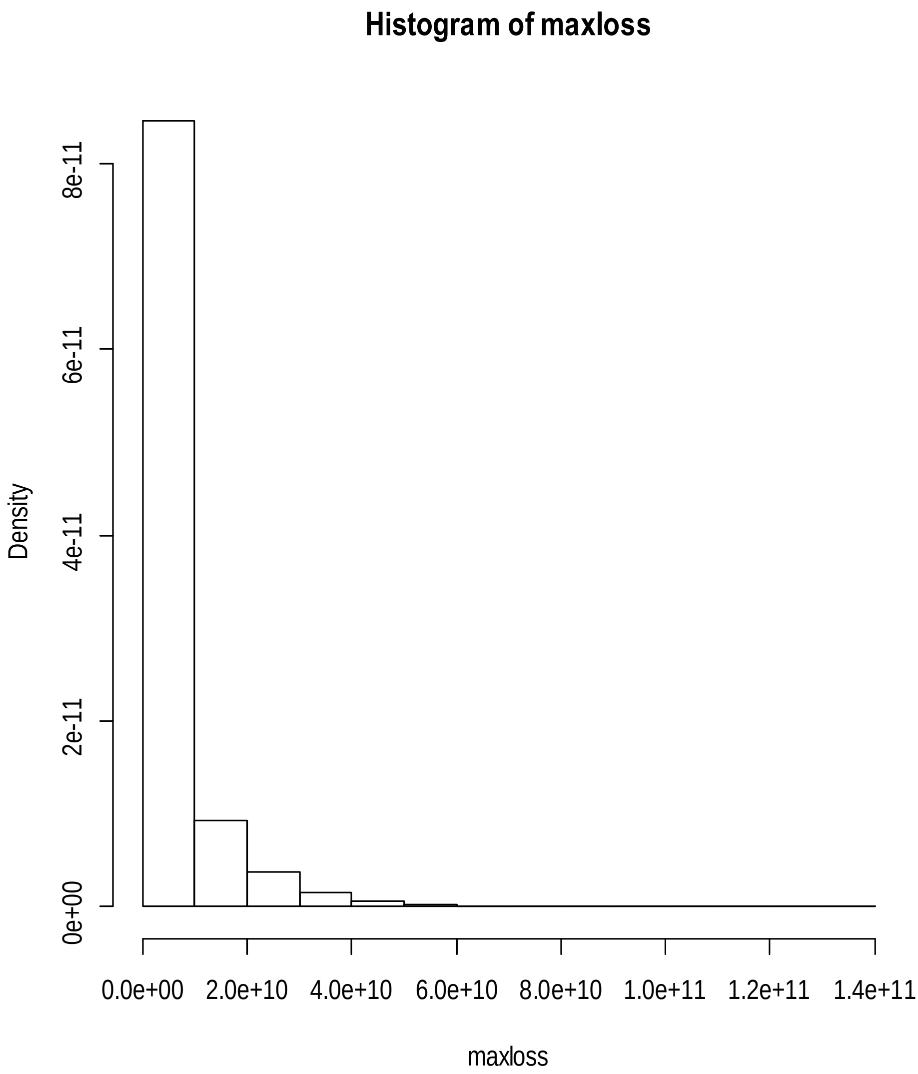


Figure 3.1: Histogram of Annual Maxima

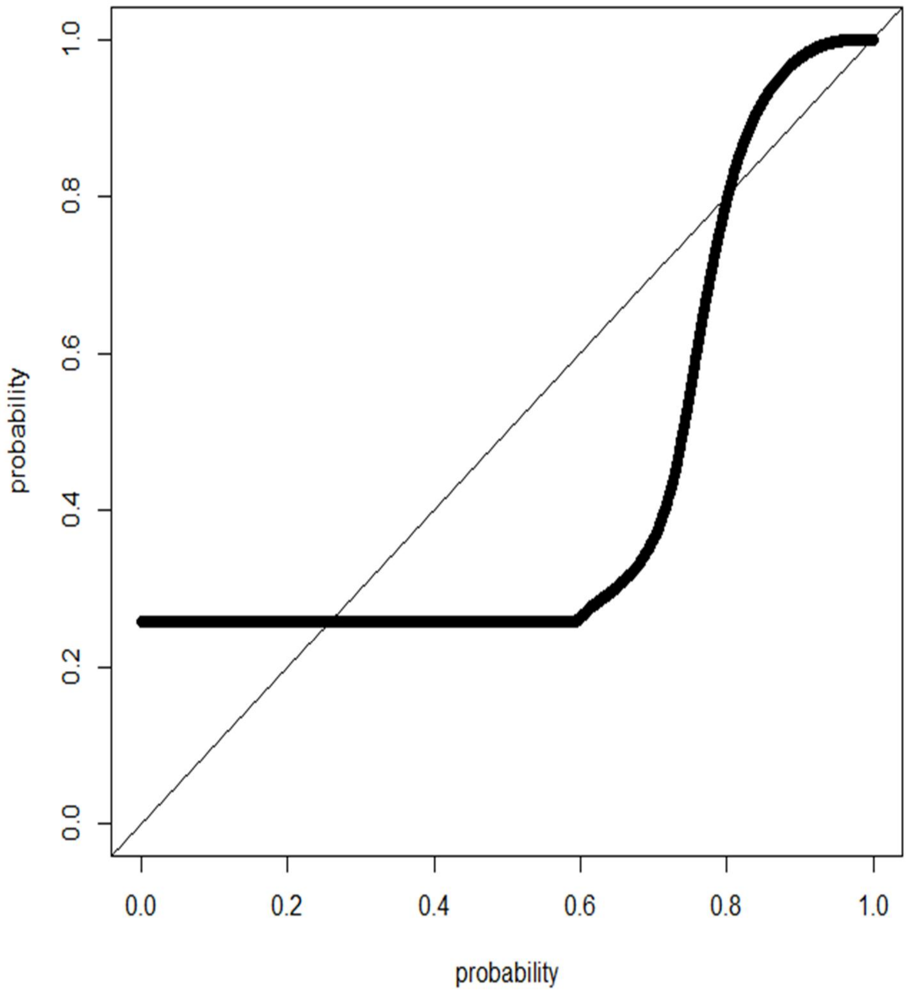


Figure 3.2: PP Plot of Gumbel Fit to the Annual Maximum Losses

Table 3.1: Estimated Percentiles for Maximum Loss

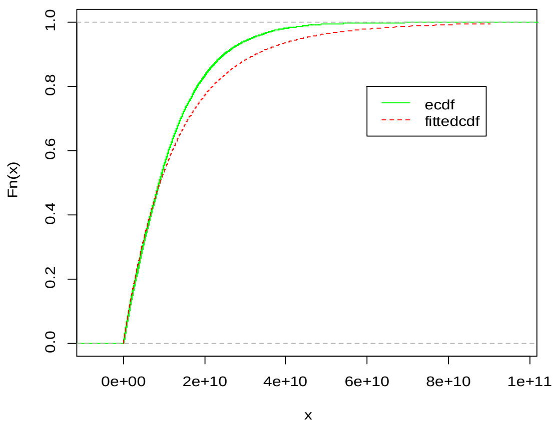
%	GPD75	EXP75	Weibull75	DPD80	EXP80	DATA
99	50469628602	39166813824	36813837546	46659797238	38211426952	36097428119
98	38787245829	31312221585	30022162447	36126514311	30674295302	29568489516
97	32334360677	26717579667	25977573307	30272735246	26265355923	25708380819
96	27918425183	23457629346	23068412163	26251379666	23137163651	22992479523
95	24583115057	20929015430	20785298355	23205493316	20710749218	20792932980
94	21914919502	18862987428	18899945986	20763360705	18728224272	19083752752
93	19698181355	17116185641	17289959409	18730656548	17052023315	17455041054
92	17806510131	15603037107	15881943923	16993270403	15600032000	16142943722
91	16159633226	14268345509	14628349108	15478609693	14319284894	14923310474
90	14703471285	13074423191	13496560241	14137699351	13173617567	13795380518
89	13399905933	11994389081	12463198453	12935975355	12137235406	12790202080
88	12221089095	11008395188	11510900874	11848157854	11191092622	11872872140
87	11146075023	10101368733	10626386538	10855213346	10320725631	11010292341
86	10158724782	9261593402	9799234547	9942462604	9514891664	10174494580
85	9246347697	8479781273	9021077849	9098352849	8764678189	9303213830
84	8398789702	7748444868	8285049163	8313633091	8062900350	8540709736
83	7607803367	7061459914	7585383322	7580783819	7403681401	7776562617
82	6866601445	6413753270	6917115663	6893612519	6782153243	7024887197
81	6169533444	5801075345	6275833169	6246960449	6194238041	6350686382
80	5511846745	5219830952	5657438618	5636485917	5636485917	5636485917

Table 3.1 - Continued

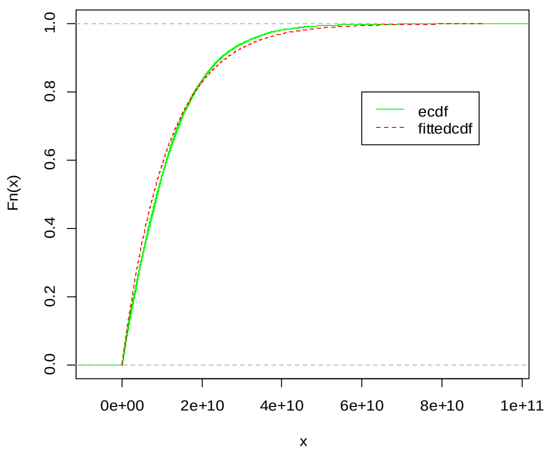
%	Weibull80	GPD85	EXP85	Weibull85	DATA
99	36106240330	41734939243	37012758214	35957269638	36097428119
98	29644298379	32862706321	29920277965	29520167506	29568489516
97	25781131359	27861505018	25771442982	25689675457	25708380819
96	22993301515	24394984502	22827797716	22934193116	22992479523
95	20798611471	21751998820	20544529062	20770105861	20792932980
94	18980691513	19621802624	18678962734	18980703069	19083752752
93	17423380624	17841034654	17101648878	17449686040	17455041054
92	16056904579	16313330938	15735317467	16107121814	16142943722
91	14835949014	14977153333	14530127751	14907417731	14923310474
90	13729317487	13790846719	13452048813	13818885648	13795380518
89	12714515068	12724926830	12476807786	12818170025	12790202080
88	11774672426	11757772412	11586482485	11886842020	11872872140
87	10896674406	10873065791	10767462601	11008677001	11010292341
86	10069939341	10058194872	10009168629	10165438765	10174494580
85	9285545808	9303213830	9303213830	9303213830	9303213830
84	8535500360				8540709736
83	7811918380				7776562617
82	7105611099				7024887197
81	6401913232				6350686382
80	5636485917				5636485917

Table 3.2: Goodness of Fit test for maximum annual Loss

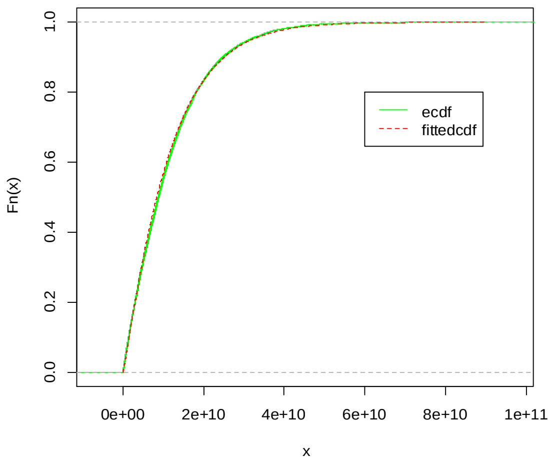
	KS Statistic	**p-value**
GPD75	0.066	2.2e-16
EXP75	0.0458	3.589e-13
Weibull75	0.0201	0.007105
GPD80	0.0592	2.2e-16
EXP80	0.0432	1.65e-09
Weibull80	0.0087	0.7949
GPD85	0.0424	5.605e-07
EXP85	0.0245	0.01279
Weibull85	0.0055	0.9996



a: GPD (shape= 0.1041392 and scale=12494126541)

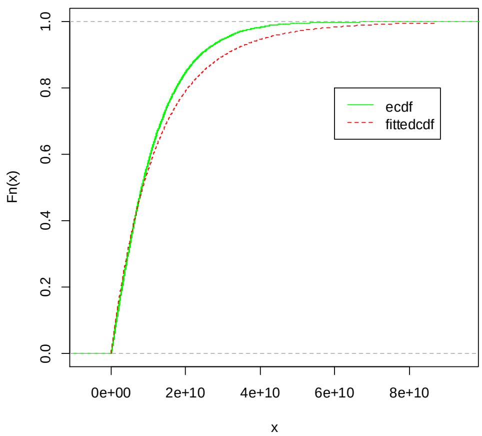


b: Exponential (rate=8.824738e-11)

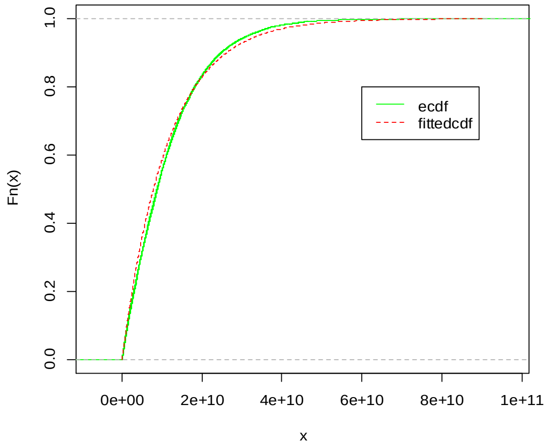


c: Weibull (Shape = 1.092645 and Scale= 11705395635)

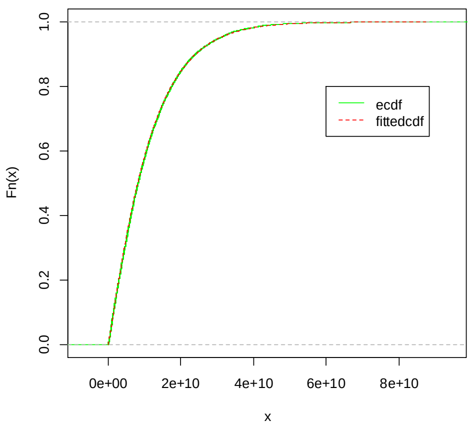
Figure 3.3: Empirical and Fitted CDF of exceedances over 75th percentile



a: GPD (shape= 0.09308283 and scale= 11873254321)

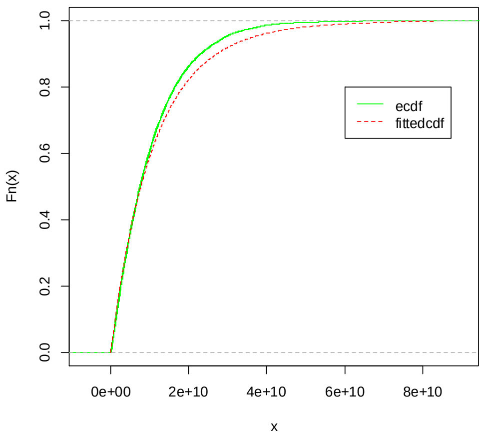


b: Exponential (rate = 9.196432e-11)

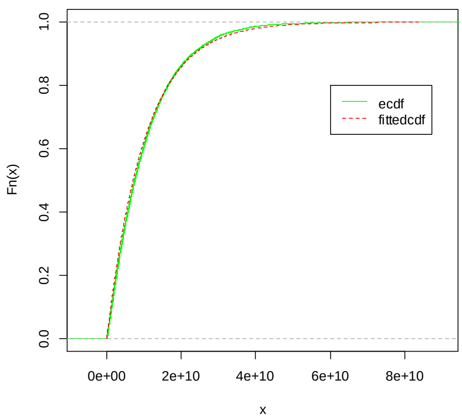


c: Weibull (shape= 1.104051 and scale= 11279081184)

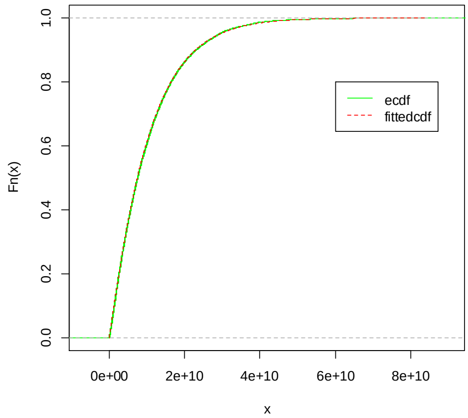
Figure 3.4: Empirical and Fitted CDF of exceedances over 80^{th} percentile



a: GPD (shape= 0.06732337 and scale= 10917490509)



b: Exponential (rate= 9.772987e-11)



c: Weibull (shape= 1.069597 and scale= 10501684398)

Figure 3.5: Empirical and Fitted CDF of exceedances over 85th percentile

Table 3.3: Estimated Percentiles for Total Loss

%	GPD75	EXP75	Weibull75	DPD80	EXP80	Weibull80	DATA
99	59173246304	47275194899	45198538374	56180543024	46497465298	44378754125	43589047610
98	45664275257	37766547866	36634814742	43509600797	37250278227	36216865513	36495804733
97	38151832797	32204345919	31559710375	36446148958	31841020554	31356854031	31411893031
96	32988888032	28257900832	27922884259	31584388025	28003091157	27860550779	27958610320
95	29077135540	25196800208	25077789545	27896703898	25026161840	25115595868	25104171685
94	25940007931	22695698885	22735147425	24936645136	22593833483	22847583744	22965007127
93	23328300913	20581047848	20740075324	22470533693	20537329160	20909371898	21156715045
92	21095647552	18749253799	18999814456	20361015909	18755904086	19212682342	19445834207
91	19148918416	17133496939	17454342749	18520640352	17184575809	17700260757	17869097999
90	17425273443	15688153175	16062544172	16890364946	15778974769	16332756870	16491952922
89	15880357396	14380680702	14794988453	15428494470	14507453962	15081860961	15243311295
88	14481725257	13187051852	13629856151	14104516038	13346646412	13926413362	14125058557
87	13204946087	12089019752	12550493717	12895444305	12278806980	12850046279	13036756746
86	12031176088	11072400815	11543871480	11783543915	11290142089	11839658598	12039662824
85	10945583520	10125951228	10599568948	10754850813	10369717095	10884346025	11000422205
84	9936290712	9240606766	9709080967	9798178662	9508717015	9974541238	10010033707
83	8993642324	8408953480	8865324605	8904431431	8699931760	9101118795	9072036508
82	8109686337	7624849905	8062272278	8066115671	7937388739	8253965681	8176542546
81	7277797759	6883151551	7294660075	7276986818	7216084918	7417956972	7305830090
80	6492400505	6179506142	6557728622	6531787698	6531787698	6531787698	6531787698

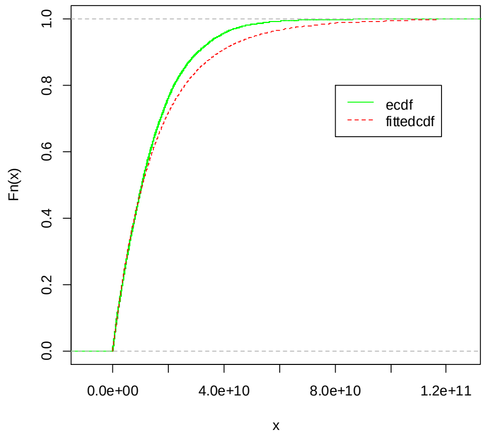
ISBN-1391-4987

Table 3.3: - Continued

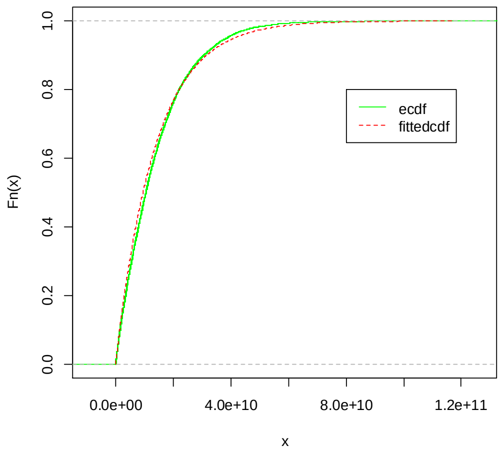
%	GPD85	EXP85	Weibull85	DATA
99	45147553562	45147631750	44046025792	43589047610
98	36407330074	36407379442	35990785095	36495804733
97	31294624274	31294659595	31210082000	31411893031
96	27667100525	27667127134	27778388155	27958610320
95	24853373788	24853394360	25088409657	25104171685
94	22554391183	22554407287	22868270302	22965007127
93	20610628760	20610641413	20972208205	21156715045
92	18926864918	18926874826	19312681045	19445834207
91	17441679768	17441687440	17832720225	17869097999
90	16113136232	16113142052	16492853339	16491952922
89	14911322295	14911326561	15264153186	15243311295
88	13814152032	13814154979	14124050544	14125058557
87	12804853146	12804854963	13053133953	13036756746
86	11870388262	11870389105	12030605126	12039662824
85	11000422205	11000422205	11000422205	11000422205
84				10010033707
83				9072036508
82				8176542546
81				7305830090
80				6531787698

Table 3.4: Goodness of fit for Total Annual Loss

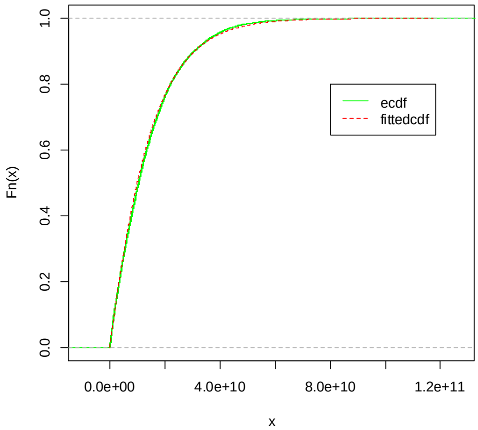
	KS Statistic	p-value
GPD75	0.0563	2.2e-16
EXP75	0.0388	1.427e-09
Weibull75	0.0206	0.00513
GPD80	0.0533	3.031e-14
EXP80	0.0390	7.87e-08
Weibull80	0.0109	0.51970
GPD85	0.0240	0.01554
EXP85	0.0240	0.01554
Weibull85	0.0077	0.96300



a: GPD (shape= 0.09188797and scale= 14965803978)

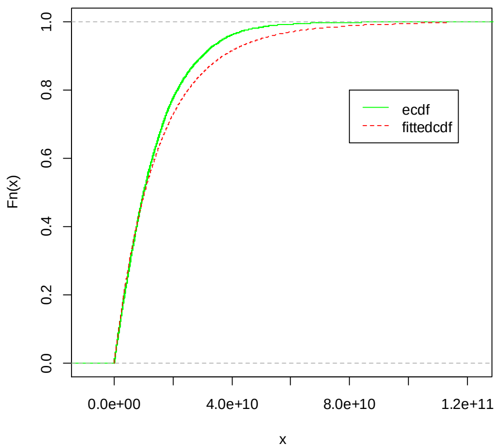


b: Exponential (rate= 7.289651e-11)

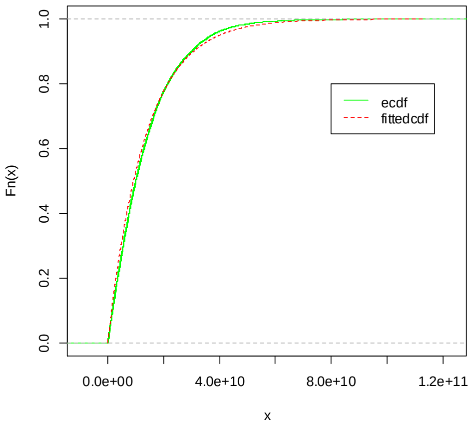


c: Weibull (Shape= 1.065755 and Scale= 14050681208)

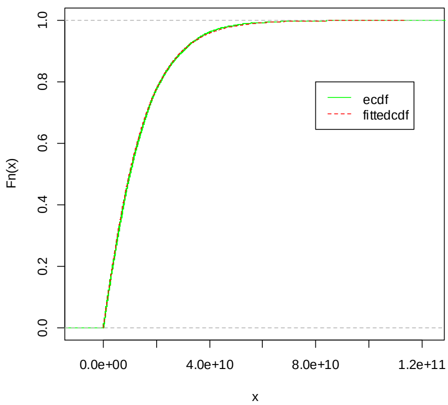
Figure 3.6: Empirical and Fitted CDFs of exceedances over 75th percentile



a: GPD (shape= 0.0875088 and Scale= 14495616327)

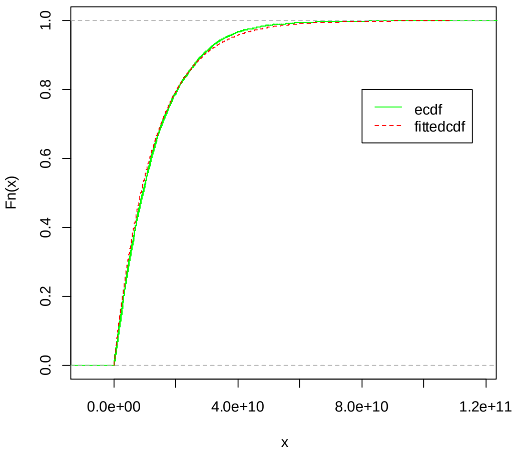


b: Exponential (rate= 7.495762e-11)

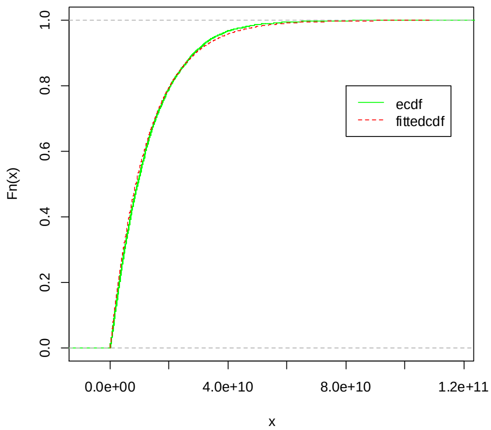


c: Weibull (shape= 1.083365 and scale= 13746592431)

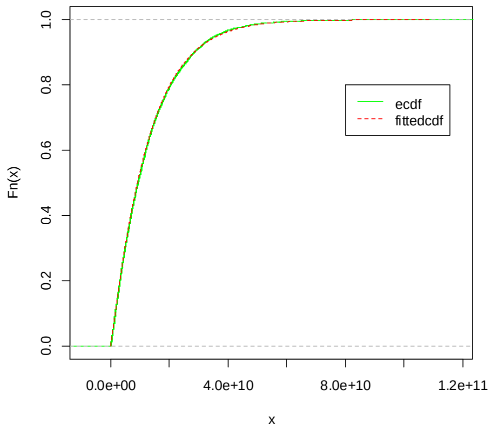
Figure 3.7: Empirical and Fitted CDF of exceedances over 80th percentile



a: GPD (shape= -9.999991e-07 and scale= 12609506862)



b: Exponential (rate= 7.930517e-11)



c: Weibull (Shape= 1.058195 and scale= 12889934915)

Figure 3.8: Empirical and Fitted CDF of exceedances over 85th percentile

4. Summary and Concluding Remarks

This paper considers various distributions namely, GPD, Weibull and Exponential for estimating the extreme quantiles of the loss distribution for the Public Hurricane Loss Model (PHLM). We consider both total annual loss and maximum annual losses. Both nonparametric and parametric models are used to estimate the catastrophic quantiles and then compared for accuracy. For the parametric case, we used the POT method and used the maximum likelihood method to estimate the model parameters. From the empirical analyses, it is evident that the most useful and widely used Weibull distribution fitted our data very well compare to simple exponential and GPD distributions. The conclusion of the paper is limited for the FPHLM data. For any definite conclusion to be drawn from these results, we might need to use some more quantile based methods as well as semiparametric methods. However, this paper might motivate the FPHLM to use parametric methods to estimate the PML as compared to the nonparametric methods we have been using so far.

Acknowledgements

Authors are thankful to FPHLM for providing us with the total annual loss and annual maximum loss. The authors are also grateful to Professors Dan Cooley at Colorado State University and Judy Wang at North Carolina State

University for inspiration for the paper as well as to SAMSI where the first author met had the opportunity to work on research projects related to hurricanes and met Dr. Cooley and Wang.
Finally, the authors would like to express their profound thanks to Dr. Nitis Mukhopadhyay for all his help with the paper and to the editors of the journal for their careful review of this manuscript.

References

1. An Ying and Pandey, M.D. (2005). A comparison of methods of extreme wind speed estimation (Technical Note). *Journal of Wind Engineering and Industrial Aerodynamics*, 93, 535ï 545.
   DOI: 10.1016/j.jweia.2005.05.003
2. Conover, W. J. (1999). *Practical Nonparametric Statistics*, New York: John Wiley.
3. Gumbel, E.J. (1958). *Statistics of Extremes*, New York: Columbia University Press.
4. Hamid, S., Kibria, B. M. G, Gulati, S. et al. (2008). Public hurricane loss evaluation models: predicting losses of residential structures in the State of Florida, *JSM 2008 proceedings* 2008.
5. Hamid, S., Kibria, B. M. G., Gulati, S. et al. (2010). Predicting losses of residential structures in the State of Florida by the public hurricane loss evaluation models with discussion, *Statistical Methodology* 7: 552-573.
   DOI: 10.1016/j.stamet.2010.02.004
6. Harris, R. I. (1996). Gumbel re-visited: A new look at extreme value statistics applied to wind speeds, *Journal of Wind Engineering and Industrial Aerodynamics*, 59: 1ï 22.
   DOI: 10.1016/0167-6105(95)00029-1
7. Hogg, R. and S. A. Klugman (1984). *Loss Distribution*s, New York: Wiley.
8. Leadbetter, M. R. (1991). On a basis for peak over threshold modeling. *Statistics and Probability Letters*, 12: 357-362. DOI: 10.1016/0167-7152(91)90107-3

9. Matthys, G. and Bierlant, J. (2003). Estimating the Extreme Value Index and High Quantiles with Exponential Regression Models, *Statistica Sinica,* 13: 853-880

10. McNeill, A. J. and Saladin, T. (1997). The peaks over threshold method for estimating high quantiles of loss distributions. *Proceedings of XXVIIth International ASTIN Colloquium, Cairns, Australia*, 23-43.

11. McChristian, Lynne (2012). Hurricane Andrew and Insurance: The Enduring Impact of an Historic Storm, White Paper, *Insurance Information Institute,* August 2012.

12. Pickands III, J. (1975). Statistical inference using extreme order statistics. *Annals of Statistics,* 3: 119-131. DOI: 10.1214/aos/1176343003

13. Wilkinson, M. E. (1982). Estimating Probable Maximum Loss with Order Statistics. *Proceedings of the Casualty Actuarial Society*, LXIX: 195-208.

14. Yang, Fan, Kibria, B. M. G, and Gulati, Sneh (2011). Estimation of Extreme Quantiles of Catastrophe Losses through Some Extreme Value Distributions. *JSM 2011 Proceedings*.