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The purpose of this study is to re-analyze the atmospheric science component of the Florida Public Hurricane Loss Model v. 5.0, in order to investigate if the distributional fits used for the model parameters could be improved upon. We consider alternate fits for annual hurricane occurrence, radius of maximum winds and the pressure profile parameter.

Keywords: Gamma distribution, goodness-of-fit, hurricanes model, normal distribution, Poisson distribution, Weibull

Introduction

Hurricanes are one of the greatest natural hazards; relatively rare in occurrence but capable of causing colossal economic losses. In 1992, "when Hurricane Andrew struck Florida it caused over $30 billion in direct economic losses" (Lokupitiya, Borgman, & Anderson-Sprecher, 2005, p. 4394). Hurricane modeling has become a widely used tool for assessing risks associated with windstorm catastrophes. Since the groundbreaking studies of Russell (1968, 1971) and Tryggvason, Davenport, and Surry (1976), the modeling methods have improved significantly due to increased computing capabilities, new advanced physical and statistical models, and vast growth in quantity and quality of available data. Several private models for simulating hurricane loss have been

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developed in the recent years for use in the State of Florida, but such models typically are commercial and are not available to the research community and public. The Florida Public Hurricane Loss Model (FPHLM) is a notable exception.

The FPHLM is an open public hurricane loss evaluation model, which was developed jointly by specialists in the fields of meteorology, engineering, computer science, finance, and statistics from the Florida State University system (SUS), National Oceanic and Atmospheric Administration (NOAA) Hurricane Research Division, and the University of Miami. This model was created "for the purpose of probabilistic assessment of risk to insured residential property associated with wind damage from hurricanes" (Hamid et al., 2005, p. 552).

FPHLM consists of three main components: first, the atmospheric science component which models the track and intensity of hurricanes that threaten Florida; second, the engineering component which models vulnerability of insured property; and third, the actuarial science component which models the insured loss. In order to be used for rate making purposes in the State of Florida, a model has to the rigorous statistical standards set by the Florida Commission for Hurricane Loss Projection Methodology (FCHLPM.) The purpose of this study it to re-analyze some of the components of the atmospheric component of the FPHLM v 5.0 model certified by the commission in 2011.

The atmospheric science component simulates thousands of storms, their wind speeds, and their decay once on land based on historical hurricane statistics, thus defining probabilistic wind risk for all residential zip codes in Florida. The wind risk information is then passed on to the engineering and actuarial science components to assess damage and annual insured loss. Each component is developed independently and delivered as a one-way input to the next component in line until the end result is achieved. We now look at the atmospheric science component in details.

The first step in modeling annual wind risk for a zip code is the determination of a model for the annual hurricane occurrence (AHO). FPHLM uses a non-parametric method to estimate annual hurricane occurrence, in that we sample from historical records to determine the number of hurricanes in a given year. The research question was if a parametric distribution could be used to estimate AHO instead. The two alternative distributions were the Poisson distribution that assumes homogenous hurricane frequencies (the mean number of hurricanes in any two years is the same) or the Negative Binomial distribution that assumes a non-homogenous annual occurrence rate.

In addition to investigating fits for AHO, it was also decided to reanalyze two other important storm parameters, radius of maximum winds, R_{max}, and the pressure profile parameter, Holland *B*. These two variables are important for estimating loss. Greater values of the radius of maximum winds imply greater losses and, similarly, lower values of central pressure mean a more intense hurricane and therefore higher losses.

The sensitivity and uncertainty analysis shows that loss costs are fairly sensitive to Holland *B* and R_{max} regardless of hurricane category. FPHLM has historically used the Gamma distribution to fit R_{max}. The question arose, however, if there were other distributions that might provide better fits for R_{max}.

Holland *B* is an additional parameter defining the pressure field and maximum wind speeds in a hurricane. It was introduced by Holland (1980) and has been used in many hurricane threat studies since. FHPLM shows that the Holland *B* parameter is inversely correlated with both the size and latitude of the hurricane. Here we investigate alternate models for Holland *B* and see if they explain more of the variability in Holland *B* as compared to the present model.

As specified by the FCHLPM, analysis of annual hurricane occurrence and radius of maximum winds (for PHLM v 5.0) is based on the data obtained from historical record for the Atlantic tropical cyclone basin (known as HURDAT) for the period from 1901 till 2010. Earlier data is available but not used due to lack of population centers and uncertainties about meteorological measurements before the start of 20th century. The model for the Holland *B* pressure profile parameter is developed based on a subset of the data published by Willoughby and Rahn (2004) and obtained by NOAA and U.S. Air Force Reserve aircraft between 1977 and 2000.

To find the best fitting distribution, a preliminary analysis of the data was conducted through the use of EasyFit software which allows us to easily fit a large number of distributions to the data. Estimated parameters of the best fitting distributions were then found using the maximum likelihood estimator (MLE) method. In order to determine how well the selected distributions fit the data, they were tested for goodness-of-fit using Kolmogorov-Smirnov, Anderson-Darling, and Chi-Squared tests. Along with the goodness-of-fit tests, the probability density function graphs, Q-Q, and P-P plots were also used to enable visual assessment of the goodness-of-fit and empirically compare several fitted models. In order to determine the model for the estimation of Holland *B*, multiple regression analysis was performed using the PROC REG procedure in SAS.

Annual Hurricane Occurrence

The first step in the study of hurricanes and their impacts is to determine the frequency with which they occur. Annual Hurricane Occurrence (AHO) rate estimates "the frequency of hurricanes occurring in a series of years based on an associated hurricane occurrence probability distribution, which is obtained through statistical analysis and calculation on the basis of historical hurricane records" (Chen et al., 2004, p. 6). In the recent years, substantial research in the area of modeling the occurrence of hurricanes has been done by Chen et al. (2003, 2004), Gray, Landsea, Mielke, and Berry (1992), Elsner and Schmertmann (1993), and Elsner and Jagger (2004). The basic principle of these papers was to develop the statistical models from the available historical data in order to estimate AHO. Based on the obtained probability distributions, the number of hurricanes per year in the future is produced for a desired number of years.

The Poisson and the Negative Binomial distributions are often used by modeling agencies to model AHO. The rate of occurrence of a stochastic process is typically described by the use of the Poisson distribution. However, Poisson distributions assume the mean number of storms in any two non-overlapping time intervals of the same length to be equal. To allow those means to be unequal will lead to the modeling of the annual occurrence by the Negative Binomial distribution. General guiding principles as to the adequacy of the two distributions have been discussed (Thom, 1966), but one cannot accurately determine which model is appropriate until necessary tests are conducted. In this section we determine whether the Poisson or the Negative Binomial is adequate in describing the distribution of the annual hurricane occurrence.

For the assessment of the AHO distribution to be conducted, a suitable data set has to be obtained. Annual counts of tropical storms and hurricanes in the Atlantic Ocean are obtained from the HURDAT (National Oceanic and Atmospheric Administration's Hurricane Research Division, 2012) database, which is maintained by the National Hurricane Center in Miami, Florida and the National Climatic Data Center in Asheville, North Carolina. This historical record for the Atlantic tropical cyclone basin contains positions and intensities of tropical storms and hurricanes recorded every six hours from 1851 onwards. However, as specified by the commission, we use data starting from 1901 for our research due to the unreliability of 19th century data. At the time as this research was conducted, the FPHLM was based on the period 1901-2010, thus all our analysis is conducted on the HURDAT data from 1901-2010. In its analysis of the hurricane counts, FPHLM does not count all hurricanes in the Atlantic. Instead, it counts only the storms in a "threat area" (Figure 1) – within 1000 km of a location (26.0 N, 82.0 W) – in order to focus on storms capable of affecting residential property in Florida.

In order to obtain the number of hurricanes in each year from 1901 to 2010, FPHLM looks at each hurricane and its six hourly positions recorded by HURDAT. The first time a hurricane entered the threat area during its track was counted as an occurrence. Subsequent entries by the same storm were not counted, so that any hurricanes could only be counted once. The annual number of hurricanes in any given year range between 0 and 5 with mean 1.1091 and standard deviation 1.1704, as seen in the summary statistics for AHO in Table 1.

Each storm is considered as a point event in time, occurring independently. If λ is a measure of the historically based number of events per year, then $P(X = x \mid \lambda)$ defines the probability of having x events per year, which is given by the Poisson probability distribution function (PDF)

$$P(x) = \frac{\lambda^x}{x!} e^{-\lambda}$$

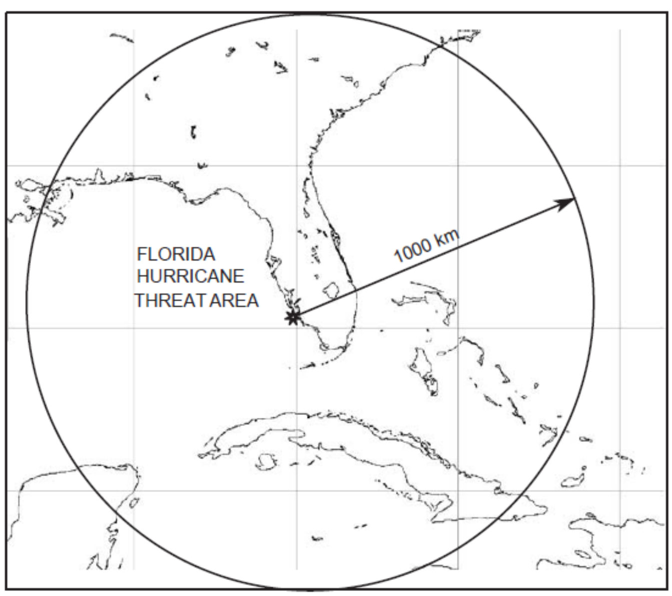

Figure 1. Florida hurricane threat area

Table 1. Descriptive statistics of annual occurrence rate

Sample Size (*N*)	110	Min	0
Mean	1.1091	Median	1
Variance	1.3699	Max	5
Std Deviation	1.1704	Range	5

The parameter λ of the Poisson distribution can be estimated from data by the maximum likelihood estimator

$$\hat{\lambda} = \frac{\sum_{i=1}^{N} x_i}{N}$$

where x_i is the number of events in a given year and N is the total number of years.

However, if it is assumed that the number of events X has a Negative Binomial distribution, then the corresponding pdf for the distribution is given by

$$\mathrm{P}(x) = \frac{\Gamma(x+k)}{\Gamma(x+1)\Gamma(k)} \left(\frac{k}{m+k}\right)^{k} \left(\frac{m}{m+k}\right)^{x}$$

where Γ is the gamma function and m and k are parameters of the distribution. The MLEs of the parameters m and k can be obtained as

$$\hat{m} = \frac{\sum_{i=1}^{N} x_i}{N} \quad \text{and} \quad \hat{k} = \frac{\hat{m}^2}{s^2 - \hat{m}}$$

where s^2 is the sample variance.

The parameters of both the Poisson and Negative Binomial distributions were estimated using annual number of hurricanes dataset and results are presented in Table 2.

Table 2. Estimated parameters of the distribution for AHO data

Distribution	Parameter Values
Poisson	$\lambda = 1.1091$
Negative Binomial	$n = 4$, $p = 0.8096$

Note: The parameters of the negative binomial distribution are $n = k + m$ and $p = k/(m + k)$

Table 3. Goodness-of-fit tests for AHO data

	Chi-Squared			Kolmogov-Smrinov		Anderson-Darling	
Distribution	**Statistic**	***p*-value**	**Rank**	**Statistic**	**Rank**	**Statistic**	**Rank**
Poisson	1.71979	0.88640	1	0.32986	1	16.465	1
Neg. Binomial	2.83815	0.58527	2	0.42963	2	28.094	2

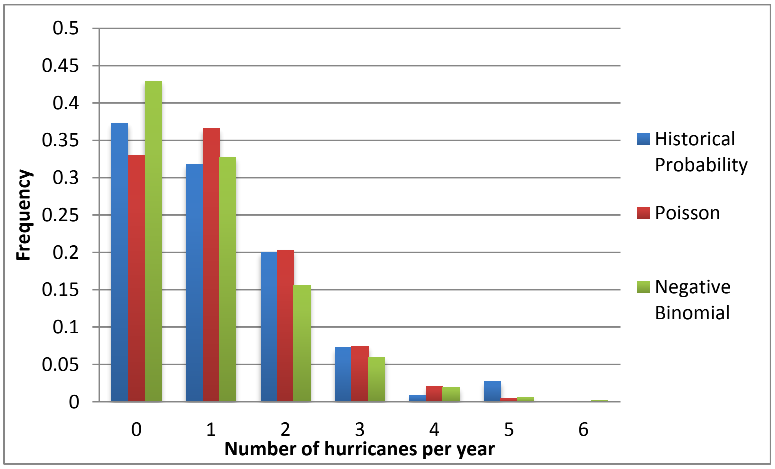

Figure 2. Comparison of simulated vs. historical occurrences

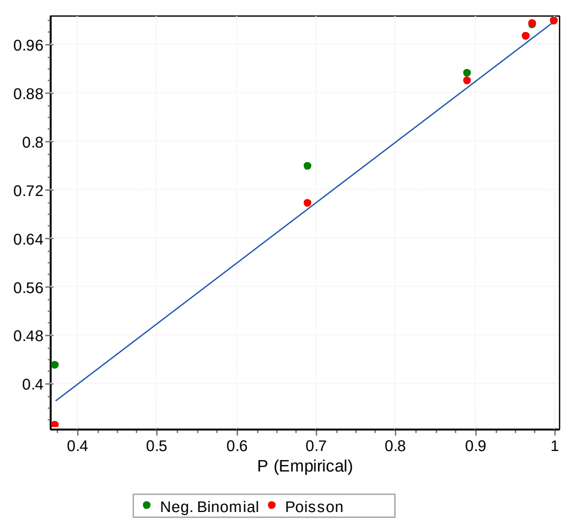

Figure 3. P-P plot

Once distributions were fitted, it was decided to conduct goodness-of-fit tests to see which distribution provided a better fit. The tests considered were the Kolmogorov-Smirnov test, the chi-square test, and the Anderson-Darling test. The results are given in Table 3. It is clear the Poisson distribution provides a better fit for AHO using the threat area.

The distribution graphs were examined to provide a visual assessment and an empirical comparison of the goodness-of-fit. Indicated in Figure 2 are the occurrence rates of historical and modeled hurricane data. A P-P plot of the fitted distributions is presented in Figure 3. It is not clear from Figure 2 which distribution provides a better fit, but Figure 3 does make it clear that the Poisson distribution is a better fit in keeping with the goodness-of-fit tests.

It was concluded the best fitting distribution for the annual hurricane occurrence for the Florida threat area, based on the results of goodness-of-fit tests and the P-P plot, is a Poisson distribution with parameter $\lambda = 1.1091$.

Radius of Maximum Winds

Consider the wind field model for the FPHLM; specifically, consider the radius of maximum winds at landfall, the distance between the center of a cyclone and its band of strongest winds. Meteorologists at FPHLM developed an $R_{\max}$ model using a landfall $R_{\max}$ database from Ho, Su, Hanevich, Smith, and Richards (1987) and supplemented by NOAA HRD research flight data and NOAA-HRD H*Wind analyses (Powell et al., 2005). The current database includes 112 measurements of radius of maximum wind, central pressure, and location at landfall for storms from 1901 till 2010.

Values of $R_{\max}$, measured in statute miles, range between 5.75 and 52.9 with mean 25.65 and standard deviation 11.2 as seen in Table 4.

The histogram of the data is depicted in Figure 4 and shows that the $R_{\max}$ data is right-skewed. A preliminary analysis of the $R_{\max}$ landfall database was conducted using the Easyfit software. As initial models, we considered right-skewed distributions with a maximum of 2 parameters (extra parameters would have made the use for the wind field model over-complicated and not practical). Moreover, it was desirable to avoid the situations where distributions with more parameters may well fit the data better because of a lot more flexibility in shape, but then the apparent improvement would be spurious due to over-fitting.

Table 4. Descriptive statistics of radius of maximum winds

Sample size	112	Min	5.75
Mean	25.649	Median	24.725
Variance	125.31	Max	52.9
Std. deviation	11.194	Range	47.15

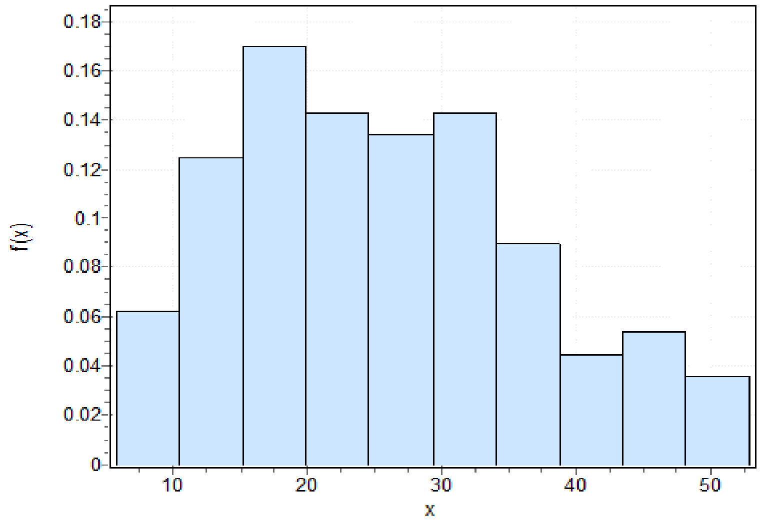

Figure 4. Probability density function radius of maximum winds

Five distributions that were found to be a good fit for modeling R_{max} based on the above criteria were Gamma, Lognormal, Rayleigh, Weibull, and Inverse Gaussian. Gamma and Lognormal are the distributions that were considered in the FPHLM and Gamma was chosen as the best fit. Parameters of selected distributions were obtained using MLEs and results are presented in the Table 5.

Once again, they were tested for goodness-of-fit in order to determine how well the selected distributions fit the $R_{\max}$ data. Due to the continuous nature of the data and the low power of the chi-squared test, the Anderson-Darling and the Kolmogorov-Smirnov tests were employed. They were chosen because they are general, apply to all continuous distributions, and have high power. The results are presented in Table 6.

The distributions are ranked according to the *p*-value of the test, with higher *p*-values indicating a better fit. Regardless of the test being used, both the Lognormal and Inverse Gaussian distributions show a poor fit for $R_{\max}$ data with *p*-values below 0.5 for the K-S test. It was concluded that Lognormal and Inverse Gaussian distributions are not good fits and exclude them from further consideration.

The three distributions for be considered further are Weibull, Rayleigh and Gamma. Gamma distribution is used to fit the radius of maximum winds in the Florida Public Hurricane Loss Evaluation Model, however, notice both the Weibull and Rayleigh perform better than the Gamma distribution according to the tests.

In order to finalize the model, a visual inspection of the data set was conducted starting with the Probability Density Function Graph for the data. The graph displays the theoretical PDFs of the fitted distributions and the histogram of the R_{max} data (Figures 5 and 6). Because the histogram depends on how the data is sorted into bins, two histograms are displayed with the Rmax values binned in 10 and 15 intervals for comparative analysis. All three distributions are plotted on the same graphs. Displaying several distributions at the same time will allow us to visually compare the models and determine how they differ.

Although it is hard to make a decision about better fit based on these graphs as they require the arbitrary grouping of the data, Weibull and Rayleigh distributions do appear to fit the data better.

Table 5. Estimated distribution parameters for R_{max} data

Distributions	Parameters
Gamma	$\alpha = 5.250$, $\beta = 4.886$
Lognormal	$\delta = 0.492$, $\mu = 3.136$
Weibull	$\alpha = 2.474$, $\beta = 28.666$
Raleigh	$\delta = 17.293$, $\gamma = 3.879$
Inverse Gamma	$\lambda = 134.66$, $\mu = 25.650$

Table 6. Goodness-of-fit tests for R_{max} data

	Kolmogov-Smrinov			Anderson-Darling	
Distributions	**Statistic**	***p*-value**	**Rank**	**Statistic**	**Rank**
Weibull	0.0494	0.9349	1	0.3226	1
Rayleigh	0.0561	0.8530	2	0.3006	2
Gamma	0.0703	0.6124	3	0.5349	3
Lognormal	0.0904	0.3015	4	1.0419	4
Inverse Gaussian	0.0953	0.2450	5	1.8773	5

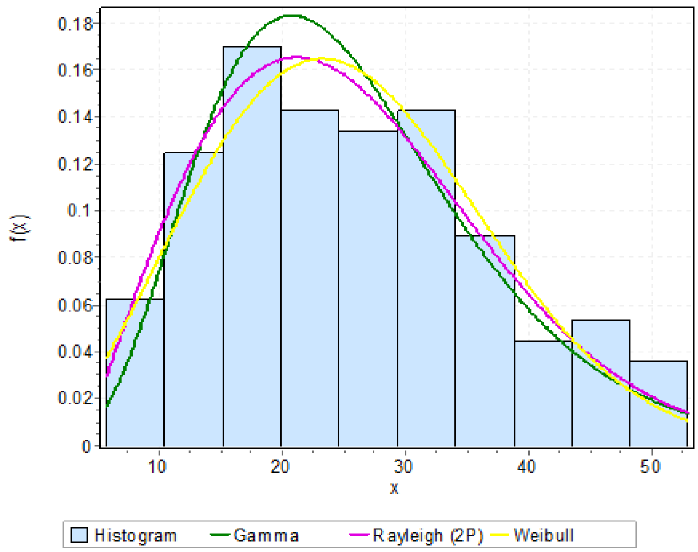

Figure 5. PDF graph with R_{max} values binned in 10 intervals

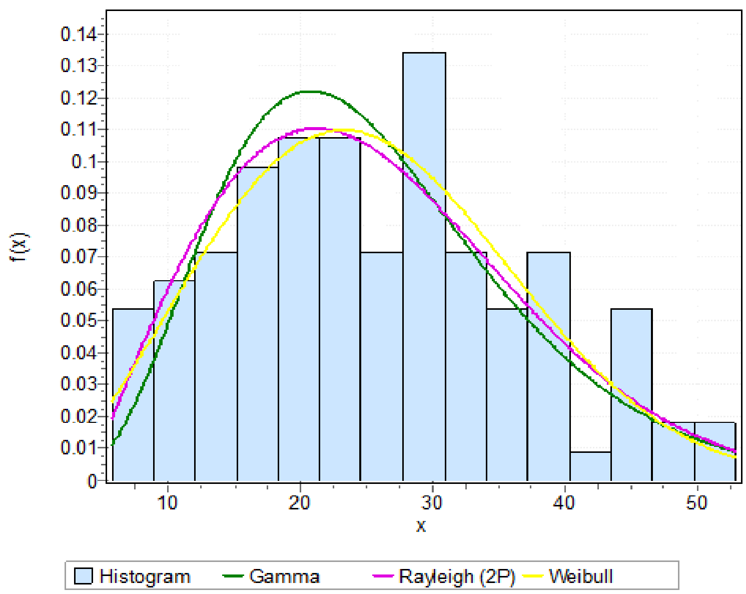

Figure 6. PDF graph with R_{max} values binned in 15 intervals

To avoid grouping of the data, consider the Q-Q plot (Figure 7). Although all three distributions appear to be good fits based on the Q-Q plot, it appears that the Gamma and Rayleigh distributions have points further away from the straight line as values of R_{max} get larger. This is consistent with the results of the Kolmogorov-Smirnov test. Based on the results of the goodness-of-fit test, the PDF graph, and the Q-Q plot, it was concluded the Weibull distribution with parameters $\alpha = 2.4736$ and $\beta = 28.666$ is the best fit for the Radius of maximum winds.

Although it was shown that the Weibull distribution provided a better fit for R_{max} based on the data set, the Gamma distribution was used for modeling the radius of maximum winds in the FPHLM. The analysis shows the Gamma distribution as a possible fit for the radius of maximum winds, although perhaps not the best fit. Both the Gamma and Weibull distributions are commonly encountered in reliability analysis and it is often difficult to choose between the two. Hence, it should be stressed the Gamma distribution was not rejected as a possible fit for R_{max}. Instead, it was concluded the Weibull might be a better fit.

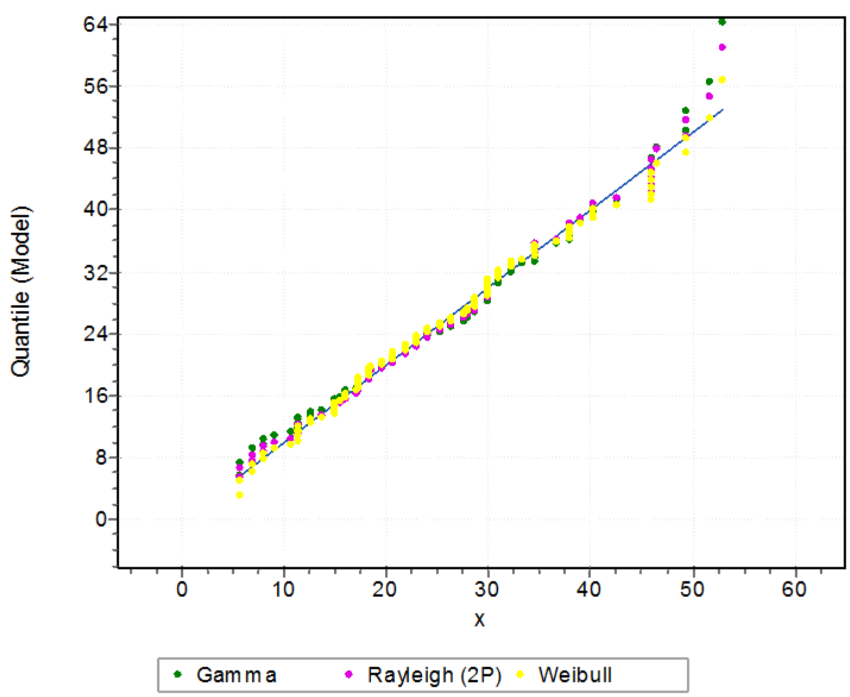

Figure 7. Q-Q plot

Holland *B*

Another important parameter of the wind field model is the Holland *B* parameter. Holland *B* is an additional parameter defining the pressure field and maximum wind speeds in a hurricane. It was introduced by Holland in 1980 and has since been used in hurricane threat studies by many researchers including Powell et al. (2005), James and Mason (2005), Emanuel, Ravela, Vivant, and Risi (2006), Lee and Rosowsky (2007), Hall and Jewson (2008), Vickery and Wadhera (2008), and Vickery, Masters, Powell, and Wadhera (2009), among others. The relation between the pressure of a hurricane, p(r), and the Holland *B* parameter is given as follows:

$$\mathrm{p}(r) = p_c + \Delta p \mathrm{e}^{-\left(\frac{R_{\max}}{r}\right)^B}$$

where r is the distance from the center of the storm, p_c is the pressure at the center of the storm, Δp is the difference between central minimum sea level pressure (p_c) and the outer peripheral pressure (1013 mb), and $R_{\max}$ is the radius of maximum winds. Thus Holland *B* allows for the distinction in the maximum wind speeds observed in hurricanes for a given Δp (all else being equal). With the introduction of the *B* parameter, the maximum wind speeds in the simulated hurricane are proportional to $\sqrt{B\Delta p}$ compared to $\sqrt{\Delta p}$ otherwise.

In meteorological literature, Holland *B* is often modeled as a linear function of the location of the storm, the radius of maximum winds, and the central pressure difference or deficit Δp. FPHLM uses a similar regression fit for Holland *B* based on a filtered subset of the data published by Willoughby and Rahn (2004). The data consist of winds and geo-potential heights obtained by the NOAA and U.S. Air Force Reserve aircraft between 1977-2000, supplemented with Δp, the pressure deficit, and $R_{\max}$ values. FPHLM retains 116 profiles filtered as follows:

1) by Height of flight-level pressure surface ≤ 700,
2) Longitude between 70 and 95 degrees west,
3) Storm relative flight level Vmax > 33 m/s,
4) Latitude between 20 and 34 degrees North.

The final fitted model used by FPHLM is based on statistical analysis as well as validation using storm tracks and is

$$B = 1.74425 - 0.007915\,\text{Lat} + 0.0000084\Delta p^2 + 0.005024 R_{\max} \qquad (1)$$

This model explains about 15% of the variability in the four Holland *B*.

Most Holland *B* models have low R^2 values, and the model used by FPHLM does have higher R^2 values than most available models. It was decided to investigate if equation (1) could be further improved on in terms of a higher R^2 value by examining functions of Holland *B* other than liner functions or by the inclusion of other variables. Using the same data set as the one used by the FPHLM, we considered various fits for Holland *B* using latitude, longitude, Δp, and R_{max} as independent variables.

Matrix scatter plots indicated that using ln(*B*) as an dependent variable rather than *B* might yield better fits. However, a detailed stepwise regression analysis in SPSS did not yield a better fit when using ln(*B*) as a dependent variable. Stepwise regression indicates that the only variable significant in predicting either *B* or ln(*B*) is R_{max}. Using *B* as a dependent variable yields an R^2 of 0.112 while using ln(*B*) as a dependent variable yields an R^2 of 0.122. Although it appears from the analysis there was no statistical need to use Δp or latitude in fitting Holland *B*, it is not recommended to make changes to the present fit for Holland *B* in the FPHLM; the analysis does not yield a better fit and the benefit of validating the fit using actual storms was not available.

Conclusion

The FPHLM is the only open public hurricane loss evaluation model available for the assessment of hazard to insured residential property related to damage from hurricanes in Florida. A numerical analysis of the atmospheric science component of the Florida Public Hurricane Loss Model was conducted to determine if it was possible to develop alternate models for the various hurricane parameters.

Based on the results of goodness-of-fit tests, histograms of historical and modeled occurrences, and P-P plots, it was concluded that the best fitting distribution for the annual hurricane occurrence is the Poisson distribution. The radius of maximum winds has a substantial impact on the area affected by hurricane and modeling of the R_{max} influences the likelihood of the location experiencing strong winds in cases of near misses. The Weibull was chosen as the best fit for the radius of maximum winds. The fit for Holland *B* being used by the FPHLM could not be improved. It was shown the models presented for Annual Hurricane Occurrence and R_{max} are better fits than the ones used by FPHLM, although it was not recommended the FPHLM change its modeling strategies. The models considered by the FPHLM are consistent with models used in meteorological literature. However, this investigation might start a conversation in the meteorological community to search for alternate models for modeling hurricane parameters.

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