University of Nevada, Reno

Ahead of the Storm: Implications of Changing Parameters in U.S. Tropical Cyclone Likelihood and Damage Estimation Models in the Face of Global Climate Change

A thesis submitted in partial fulfillment
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Abstract

The Intergovernmental Panel on Climate Change (IPCC) reports tropical cyclones have been occurring with increasing intensity as a result of global climate change. We examine these projections using stochastic modeling of tropical cyclone frequency and damages over two time periods in the United States. We fit Poisson models to U.S. tropical cyclone frequency data from a pre-climate change era to a post-climate change era and test equality of the Poisson rate parameters from each period to analyze changes in tropical cyclone frequency. We fit lognormal models to damages per storm (adjusted for inflation, population, and wealth) for both time periods. We test the equality of parameters μ and σ over the two time periods to evaluate changes in intensity and volatility of U.S. tropical cyclones. We found significant changes in tropical cyclone behavior between the two time periods with the onset of global climate change.

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I. Introduction

Suzanne Goldenberg reported in a September 2014 article in *The Guardian* that in 2013, natural disasters displaced more people than war (Goldenberg, 2014). Tropical cyclones (TCs) are the most damaging natural disaster, accounting for almost 46% of all deaths due to all natural disasters in the U.S. within the last decade (see Figure 1). We define TCs as the set of tropical storms involving strong winds and heavy rainfall. TC's are also commonly called hurricanes, or typhoons (World Meteorological Organization (WMO), 2015). The names hurricane, typhoon, and tropical cyclone represent the same meteorological phenomena but specify the region where they occur (WMO, 2015). The same storm will be called a "hurricane" if it occurs in the Atlantic, Carribean, and Gulf of Mexico, a "typhoon" if it occurs in the eastern North and central Pacific Ocean, and a "tropical cyclone" if it occurs in the Indian Ocean and South Pacific region (WMO, 2015).

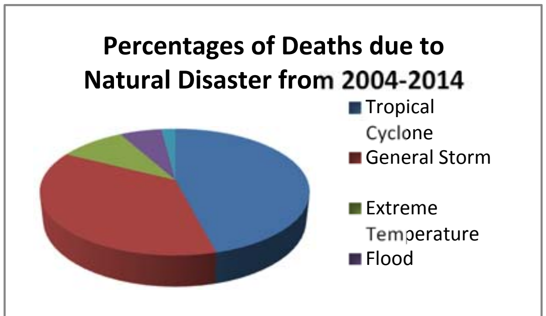


Figure 1.This pie chart shows the percentages of deaths due to natural disaster by disaster type from 2004-2014, highlighting the large proportion of death due to TC. (CRED, 2014)

In the United States alone over 13 million people have been affected by TCs in the last 100 years with over $400 billion in accompanying property damage (Centre for Research on the Epidemiology of Disasters (CRED), 2014). In the past decades, the frequency of these TCs has been rapidly increasing as a result of global climate change, with 63% of TCs in the U.S. over the last century occurring within the last 30 years (CRED, 2014).

Lack of preparation for at-risk communities leads to devastating outcomes in the aftermath of these TCs. Preventative infrastructure and appropriate allocation of responsive aid funding are crucial to the survival and livelihood of affected populations in the event of TCs. The ability to estimate the likelihood of TCs can be used as a political call to action. Estimates of damages due to TCs can be used to prepare a successful response to TCs. There is value in the physical understanding of TCs as well as in predictive statistical modeling of their likelihood and estimated damage. This type of statistical analysis provides critical information to policymakers and responsive aid organizations in understanding the severe threat caused by these TCs.

Stochastic Modeling and Hypothesis Testing

Probabilistic models are valuable tools that can be used to estimate the likelihood of specific events. Models describing occurrence of events in nature are typically stochastic, that is considering the unpredictability and randomness in nature (Taylor and Karlin, 2014). Stochastic models predict likelihoods (chances) of specific outcomes of an event, such as a TC (Everitt, 2002). In the case of TC occurrences, we are often interested in the probability distribution of the number of TCs occurring within a given time frame (Katz, 2002). The probability distribution allows prediction of the number of TCs of a given size to occur in future years. Using stochastic models of future damage produce estimates of the total damage due to TC incurred during a given time period, which is crucial to planning and remediation after TCs.

The most notable changes over time in models for TC data are not in the type of the distribution but in its parameters such as mean or variance. We are interested in how these parameters have changed over time, taking into account recent developments in the study of global climate change. Knowledge of changes in model parameters over time increases potential accuracy of the models and provides useful information about the behavior of TCs in the future.

Natural events vary based on uncontrollable and/or unobservable factors, so we must use statistical methods to determine if changes in the distribution's parameters are due to natural variation in TCs, or if these changes show a significant shift in TC behavior (Larsen and Marx, 2006). We use statistical hypothesis testing to make that decision. We have selected the time frames of 1900-1983 and 1984-2014 to compare TC behavior before climate change concerns had surfaced to TC behavior after the notable onset of global climate change. Because there is no exact year which can be cited as the start of global climate change impacts, we chose 1984 as it provides thirty years of "post-climate change" data for our comparison. Changes in parameters such as mean, give information regarding the changing behavior of TCs in the United States. In particular, we determine the impacts of changing parameters in regards to TC frequency and their associated damages.

The Role of Predictive Modeling

Effective modeling of TC likelihood serves protection of coastal communities because documented increased TC likelihood can motivate policymakers to implement preventative measures within high-risk communities. Quantitative data inspires communities and particularly policymakers to action without psychological factors interfering with perceived risks, a noted obstacle in successful implementation of damage mitigating measures in the *2014 Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report* (IPCC, 2014). Intuitive and cognitive processes significantly hinder the effective implementation of preventative aid, thus there is a need for a quantitative analysis of disaster likelihood, damage response needs, and preventative measures.

David Guston notes the significant effect that “boundary organizations” can have on implementing effective policy (Guston, 2000). Boundary organizations are non-profit organizations that utilize scientific methods to spur political action, thus furthering both research and policy (Guston, 2000). This fusion of scientific research and policy analysis allows the synergy between the two fields and facilitates effective damage mitigation more efficiently (Guston, 2000). The American Meteorological Society notes that in order to prevent deaths due to global climate change, there is a need for a collaboration of social scientists alongside atmospheric scientists (Peterson et al., 2013).

For non-profit organizations, damage estimates provide help to obtain funding because they highlight the need for donations that these organizations rely on. This funding is necessary for effective response in the face of devastating events. Knowing the distributions of TC frequency and damage estimates aids in the implementation of effective damage mitigating infrastructure and education programs for responsive aid organizations.

Damage mitigating measures such as early warning systems, preventative infrastructure, and relocation contribute to decreased damages per TC. Chronological data analysis provides insight into the effectiveness of damage mitigation. The number of deaths due to TC in the United States since 1953 significantly decreased after the implementation of the Severe Local Storms Center (see Figure 2), highlighting the positive impact that TC warning systems can provide (Morris, 2011).

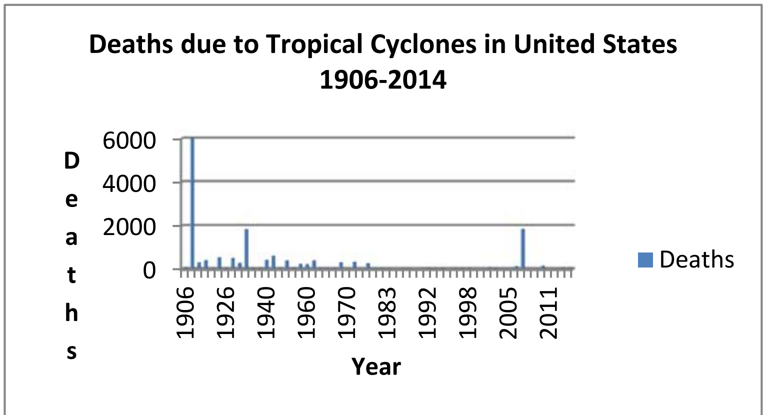


Figure 2: The chart is a histogram of deaths from 1900-2014 due to TC in the United States based on data from the EM-DAT database from the Centre for Research on Epidemiology of Disasters (CRED, 2014)

Additionally, damage estimates are of particular interest to insurance companies which use them in their business operations (Katz, 2002). Quantitative information describing the damages associated with TCs also helps to inspire communities to implement preventative infrastructure.

Goals of the Study

This research evaluates the goodness of fit of existing predictive models for United States TC data. It examines longitudinal changes in parameters for TC frequency and damage models for the United States, comparing data from 1984-2014 to data from 1900-1983, and determines the statistical significance of changes in these parameters.

The change in model parameters provides valuable information to policymakers and climatologists regarding the effects of global climate change on the United States and the effectiveness of damage mitigating measures. The provision of a quantitative predictive model helps to re-focus policymakers' decisions on a larger framework and the need for action in developing policies to combat global climate change and its consequent damages. This research benefits climatologists, policymakers, responsive aid organizations, and the insurance industry which use these predictive models.

This research aims to answer the following question: Are there significant changes in the frequency and average damages of the TCs between two time periods, 1900-1983 and 1984-2014? To answer this question we must answer equivalent questions in statistics:

1. Do existing models fit the recent frequency and damage data?
2. Have the parameters of these models changed in the period from 1984-2014 as compared to 1900-1983 in the U.S.?
3. What do changes in these parameters mean in terms of TC behavior?

Section II will discuss the relevant literature in understanding TC behavior, TC impacts, and statistical methods used to answer the research questions. Section III will discuss data sources and statistical research methods used for quantitative analysis. Section IV will provide the results of the statistical models and hypothesis tests. Conclusions of the research and opportunities for further research are presented in Section V.

II. Literature Review

We review existing literature about TC damages, damage mitigation, application of stochastic models for TC frequency and damages, probability distributions, hypothesis testing, and projections of TC behavior.

Tropical Cyclone Impacts

TCs are responsible for a significant proportion of deaths and damage due to natural disasters, particularly as a result of their increasing size due to global climate change. It is apparent that TCs contribute to a significant proportion of global population affected by, injured, left homeless or dead due to natural disaster (Centre for Research on the Epidemiology of Disasters (CRED) database). In particular, 42% of all property damage in the U.S. from 1900-2014 has been due to TCs (CRED, 2014). These statistics highlight the importance of TC preparation and responsive aid efforts for catastrophic damage due to TCs that claim lives, homes, and cause significant property damage on an annual basis, particularly as the effects of global climate change become more pronounced.

TC damage is not uniform geographically. There are clear regional trends in TC damage over the last century within Asia and the Americas. Asia accounts for 91% of all deaths due to TCs from 1914-2014 (CRED, 2014). It is important to analyze death data and property damage data by continent. For example, the number of developing nations within Asia causes a higher likelihood of death within their populations that experience TCs because there is poor infrastructure in developing countries (CRED, 2014). Conversely, high property values in the developed nations and the strength of their currency cause increased property damage totals (in USD) than in developing nations. There are also regional trends in TC occurrence which suggest that damage mitigation programs should target particular regions in order to be most effective. For example, the costs of cyclone Haiyan in the Philippines were estimated at US $10 billion, showing the extreme damage levels incurred due to large scale catastrophic TCs (Guha-Sapir, 2013). Additionally, the Philippines was the top country in disaster mortality in 2013 (Guha-Sapir, 2013). Again we note the consistency of damages within affected regions. Although the U.S. incurred the most damage in dollar value, when damages are adjusted for GDP, the Philippines, Cambodia, Laos and Vietnam incurred the most damages (Guha-Sapir, 2008). The concentration is notable, with 83.1% of all damage due to natural disasters in 2013 occurring within the United States, Germany, China and the Philippines, (Guha-Sapir, 2008). The concentration of TC occurrences and damages in the U.S. make it a good location to conduct our study on.

Obstacles in Implementation of Preventative Infrastructure

Policy makers' decisions are influenced by the recent past and short-term occurrences rather than the bigger picture. Intuitive and cognitive processes significantly hinder the effective implementation of preventative aid, thus there is need for quantitative analysis of disaster likelihood, damage response needs, and preventative measures. The solution to this obstacle may come in the form of boundary organizations. Boundary organizations are characterized by a fusion of science and political activism in order to achieve effective policy through the application of scientific research (Guston, 2000).

These types of organizations have shown to be most successful in achieving political action, particularly for environmental causes (Peterson, 2013).

Quantitative data we can collect and analyze provides information that will increase an impetus for political action in the changing climate. TC frequency data suggest significant changes in the occurrence of TCs within the United States. Deeper understanding of the changing parameters and predictive models available to anticipate these damages will serve better protection of coastal citizens and property-owners until the mitigation of climate change is achieved.

Predictive Modeling of Tropical Cyclones

Some analytic approaches utilize stochastic modeling in order to predict TC likelihood. Katz developed a stochastic model to estimate the damages incurred due to TCs for the United States (Katz, 2002). Total damages are modeled as a compound Poisson process dependent on two components: 1) occurrence of TC events and 2) damages associated with each individual TC (Katz, 2002). The Poisson distribution is commonly used to model the likelihood of a given number of events occurring within a given time period (Larsen and Marx, 2006). The Poisson distribution is used successfully in climate research, and has previously been fit to TC occurrence data by Bove et al. (1998), Elsner and Bossak (2001), and Katz (2002). Katz fits a Poisson distribution to TC occurrence data in the United States (Katz, 2002).

The Poisson distribution is useful when modeling data for combined data sets due to its additive properties. The sum of two Poisson-distributed data sets is still Poisson, allowing us to combine Poisson parameters without affecting the type of the distribution of the data (Larsen and Marx, 2006). This property is utilized in Katz's research to estimate damage from TC events happening in a given time period. Namely, Katz estimates damage during 1925-1995 by multiplying the average number of events during this period by average damage per event during this period (Katz, 2002).

The lognormal distribution is typically a good fit to independently and identically distributed random data describing costs (Larsen and Marx, 2006). For the damage component of Katz's compound Poisson model, a lognormal distribution is utilized to fit damages per event (Katz, 2002). Research by Hogg and Klugman (1984) found that the lognormal distribution demonstrates a good fit to insured TC damage in the United States (Hogg and Klugman, 1984). Katz research weakly supports the use of the lognormal fit to data in the evaluation of damages per TC using normalized data from 1925-1995 by Pielke and Landsea (1998) because cases of extreme values do not fit lognormal damage model (Katz, 2002). However, due to the large variation in damage data, it is to be expected that extreme values are not going to fit a lognormal model very well (Katz, 2002).

When evaluating descriptive statistics associated with monetary values over large time frames, factors such as inflation can skew results toward an increasing monetary trend regardless of actual increased costs. Damages adjusted for inflation are a more objective method of evaluating trends in TC damages as the need for modeling positive skewness is removed by the adjustment (Katz, 2002). Pielke et al. have adjusted TC damage data from 1900-2005 based on inflation, wealth, and population at risk (Pielke et al., 2008). Katz utilizes an earlier release of this data to build the compound Poisson process model estimating damages due to TCs in the United States (Katz, 2002) without such biases.

Testing Equality of Parameters

The parameters of the model describing each time period in the study will provide valuable information regarding the changing behaviors of TCs. Parameters of a distribution describe properties of the distribution such as mean or variance (Larsen and Marx, 2006). To fit a model to a data set these parameters need to be estimated based on the data values (Larsen and Marx, 2006). The Poisson distribution depends on the parameter λ, which is a rate of events per unit time interval for a Poisson process (Larsen and Marx, 2006). Applied to annual TC damage, λ represents the number of TCs occurring per year (Katz, 2002). It is important to note that parameters are *not* variables, but rather descriptive aspects defining a particular distribution (Larsen and Marx, 2006).

To compare two data sets following the same type of distribution, we first test if the parameters of the models fit to these data sets are equal or not. Equality of the parameters coupled with the same previously assumed type of distribution shows that the two data sets came from the same distribution. In the case of comparing two sets of longitudinal data, changes in parameters describe the changes in the behavior of the process over time. For this research, we deal with the Poisson distribution for the number of events and the lognormal distribution for their size measured as damage (Katz, 2002). The lognormal distribution is a transformation of the normal distribution (Larsen and Marx, 2006). If X is lognormally distributed (denoted $X \sim N(\mu,\sigma^2)$), then $Y=\ln X$ is normally distributed (denoted $\ln X \sim N(\mu,\sigma^2)$) and thus can be analyzed with the tests that are used for the normal distribution (Larsen and Marx, 2006).

The parameters of the normal distribution are μ and σ, which describe the mean and standard deviation of the distribution, respectively (Larsen and Marx, 2006). To test equality of averages we use well-known tests for the means of two normally distributed populations. The most common test is the two sample t-test (Larsen and Marx, 2006). The F-test can be used to determine the equality of variances for data coming from normal populations (Larsen and Marx, 2006).

Testing the rate parameter λ of the Poisson distribution is not as well-known, however there are methods that can be used to test the equality of λ for two Poisson distributions. A new test developed by Krishnamoorthy and Thomson allows for the testing of equality of two Poisson rate parameters utilizing unbiased estimators of variance and a newly developed pivot statistic (Krishnamoorthy and Thomson, 2004). This statistic can then be used to find a p-value using the unconditional cumulative distribution function of the data set (Krishnamoorthy and Thomson, 2004). This test has improved upon the test developed by Przyborowski and Wilenski in 1940, and Monte Carlo simulations confirm the improved power of this new test coined the E-test (Krishnamoorthy and Thomson, 2004).

Another test developed to test the equality of Poisson means utilizes Wald statistics. These Wald statistics are used to test the equality two parameters coming from both normally distributed and lognormally transformed data sets (Ng and Tang, 2005). Sample-based methods and constrained maximum likelihood estimation methods are used (Ng and Tang, 2005). For experimental practice, the sample-based methods are more powerful despite existing research endorsing use of the constrained maximum likelihood estimation methods (Ng and Tang, 2005). The Wald statistic named W_3 is found to be one of the most powerful statistics for experimental research, and is given by

$$W_3 = \frac{\ln\left(\frac{X_1}{X_0}\right) - \ln(d)}{\sqrt{\frac{1}{X_0} + \frac{1}{X_1}}},$$

where X_0 and X_1 are the number of observed outcomes in time period t_0 and t_1, respectively, and $d = \frac{t_1}{t_0}$ (Ng and Tang, 2005). W_3 is a Wald statistic and therefore has a normal distribution, so a z-score is utilized to make conclusions about hypotheses (Ng and Tang, 2005). In our case the null hypothesis states the equality of the Poisson rate parameters λ_0 and λ_1 for two data sets (Ng and Tang, 2005).

Expected Changes in Parameters

We test the frequency of Poisson parameters λ_1 and λ_2 to determine if Poisson rate parameters describing TC frequency data have undergone significant changes in recent decades as compared to earlier periods in the United States. The *Intergovernmental Panel on Climate Change Fifth Assessment Report* notes that global climate change produces an increased intensity of TCs, but not necessarily their increased frequency (IPCC, 2014). These climate change expectations would coincide with equality of the Poisson rate parameters for both recent decades and the earlier portion of the 20th century (IPCC, 2014). In the Katz (2002) study of United States TC occurrences from 1925-1995, no evidence of a longitudinal change in the frequency of TC occurrences was found.

We would expect to find increased mean of damages μ in recent decades because mean measures the intensity of TCs, which is expected to increase with global climate change (IPCC, 2014). In developed nations such as the United States, the successful implementation of damage mitigating techniques may help decrease damages per TC despite increasing intensity of TCs over time (IPCC, 2014). The Katz study found that there was weak evidence of a decreasing trend in the mean damages per TC in the United States, which may suggest improvement of damage mitigating measures (Katz, 2002).

The IPCC notes increased volatility of TCs as an effect of global climate change (IPCC, 2014). Therefore we expect to see an increase in the variance of damages σ^2 in the distribution from 1984-2014 as compared to the period from 1900-1983.

III. Methodology

In this section we explain the data sources, probability distributions, methods of hypothesis testing, and testing equality of parameters used in this research.

Data

We use the Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED) for our study of TC frequency. We use the advanced search option to obtain TC data for the United States from 1900-1914, shown below:

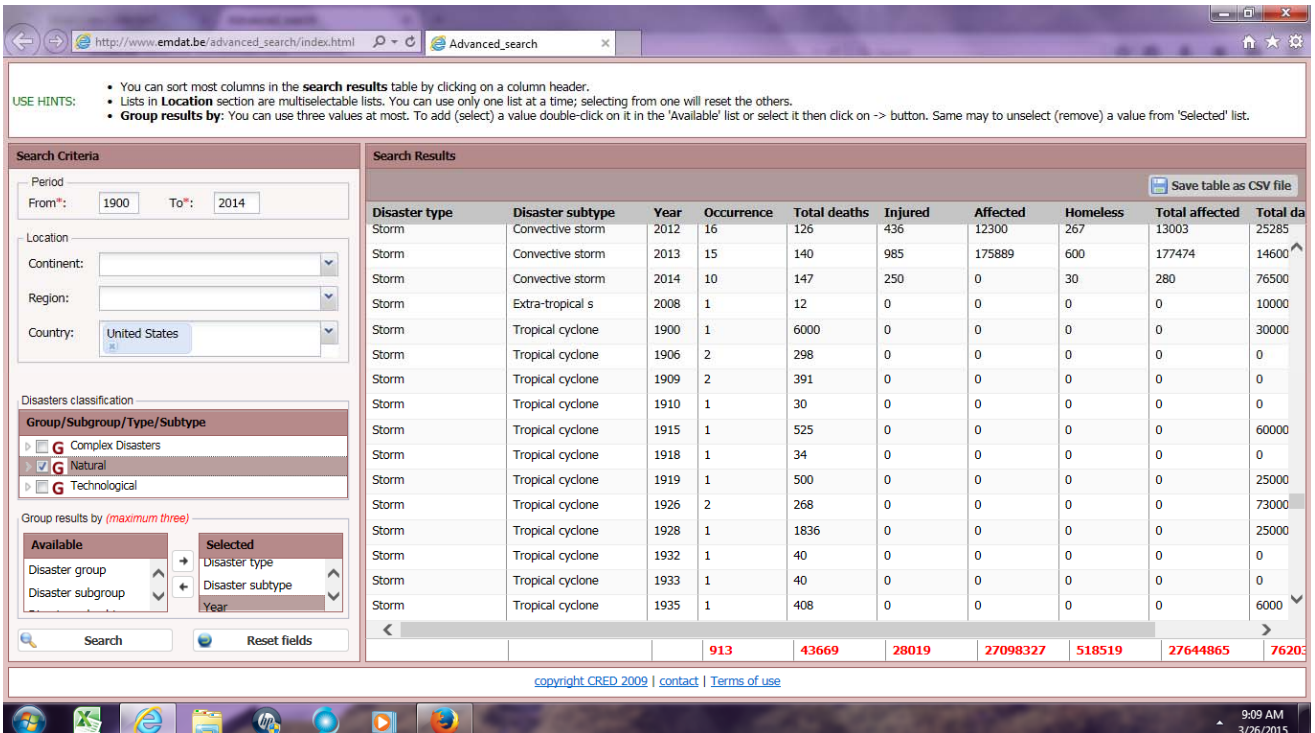


Figure 3: EM-DAT Advanced Search (CRED, 2014)

We refine the time period to 1900-2014 and the region to the United States. We select "Natural Disasters" under Disaster Classification. We sort results by Disaster Type, Disaster Subtype, and then Year. We use the data that is classified as "Tropical Storm." Occurrences are recorded as a separate event for each country that it affects (i.e. a TC that makes landfall in two countries would be recorded as two occurrences in a global data set.) Our data are solely for the United States so TCs are not recorded twice. The TC occurrence data set is available at http://www.emdat.be/advanced_search/index.html.

Damage data per TC for 1900-2005 are taken from Pielke et al. (2008). This data set is adjusted for inflation, wealth, and population by the PL05 method (Pielke et al., 2008). The data set is available at http://sciencepolicy.colorado.edu/publications/special/normalized_hurricane_damages.html.

Damage data per TC for 2006-2014 is gathered using the National Hurricane Center *Tropical Cyclone Reports* (National Hurricane Center, 2014). The reports are available at http://www.nhc.noaa.gov/data/tcr/index.php?season=2014&basin=atl. We review the reports for all TCs in the Atlantic for each year from 2006-2014. If the TC did not make U.S. landfall then damages are not recorded. If the TC makes U.S. landfall then damages are obtained from the "Casualty and Damage Statistics" section of the report. If damages are not reported then we record the damage per TC as zero. Damages from 2006-2014 are not adjusted using the PL05 method. We make the assumption that inflation from 2006-2014 is negligible since the adjustments made for the 2008 Pielke et al. study.

Random Variables

A sample outcome is a possible outcome of an experiment (Larsen and Marx, 2006). The set of all possible sample outcomes of an experiment is called the sample space (Larsen and Marx, 2006). A random variable is a function that associates a number with a certain aspect of a sample outcome in the sample space (Larsen and Marx, 2006). Random variables can be classified into two categories: discrete and continuous. A discrete random variable is defined as a random variable with a finite (or countable) number of possible outcomes (Larsen and Marx, 2006). A continuous random variable is a random variable with an (uncountably) infinite number of possible outcomes (Larsen and Marx, 2006).

For our experiment, we use a discrete random variable X_t to describe the number of TC occurrences occurring within the time interval t. The sample space for X_t is the set of nonnegative integers 0, 1, 2, up to infinity. The damages per TC are denoted by a continuous random variable X. The sample space for X ranges from $[0,\infty)$ because damages must be positive.

A probability mass function (pmf) assigns a probability, or likelihood of occurrence, to each possible outcome of a sample space for a discrete random variable (Larsen and Marx, 2006). A probability density function (pdf) is equivalent to a pmf with the distinction that it is used to compute a probability of events in the sample space for a *continuous* random variable (Larsen and Marx, 2006). A probability distribution describes random variables and is characterized by a certain pmf or pdf (Larsen and Marx, 2006).

The Poisson Distribution

The Poisson distribution is a discrete probability distribution of a discrete random variable X equal to the number of events occurring within a given time period (Larsen and Marx, 2006). If the random variable X has a Poisson distribution (denoted X~Poiss(λ)) then its pmf is given by

$$P(X = k) = \frac{e^{-\lambda t}(\lambda t)^k}{k!}$$

where λ is the average number of events per unit of time, t is the time interval, and k is the number of events occurring during the time interval t (Larsen and Marx, 2006). Thus X is the number of events occurring in time t, where λ is the average number of events in the unit interval.

We fit this distribution to occurrence data for TCs to estimate the probability of a given number of TCs to occur within a given time period. We can find the probability of a given number of TCs, k, to occur within a time period, t, by substituting appropriate values into the probability mass function. For example, the probability of three TCs occurring within one year would correspond to the substitution of k=3 and t=1 into the Poisson pmf.

We use a goodness-of-fit test for the Poisson distribution in Minitab to determine the distribution of our data. We use hypothesis testing in order to test the fit of the data. A hypothesis is a statement about a data set. There are two hypotheses that we must define: the null hypothesis, denoted by H_0, and the alternative hypothesis, denoted by H_A. The null hypothesis is a statement denoting “no effect” or “no change”. The alternative hypothesis reflects “expected change” or “research hypothesis”.

The goodness-of-fit test for Poisson tests the following hypotheses:

H_0: Data comes from a Poisson distribution

H_A: Data does not come from a Poisson distribution

We perform all tests on a 5% significance level. The significance level α of a test is the probability of rejecting H_0 when it is true. The testing program computes the p-value for the test given a data set. The p-value is associated with the test statistic. It is the probability of getting a value for the test statistic more extreme than the observed test statistic (Larsen and Marx, 2006). The p-value can be thought of as the "observed significance level." We make a decision of rejecting or not rejecting H_0 based on the p-value and significance level as seen in Table 1:

Table 1: Decision Criteria for Hypothesis Testing based on p-value and α

Relationship between p-value and α	*Decision*
p-value < α	Reject H_0
p-value > α	Fail to reject H_0
p-value = α	Decide using a coin toss

It is important to note that it is nearly impossible for the p-value to be equal to α.

We break our data into two groups which we will call **X** and **Y**. $\boldsymbol{X} = X_1, X_2, \ldots X_N$ is the random variable representing the number of TC occurrences each year for the time period from 1900-1983. $\boldsymbol{Y} = Y_1, Y_2, \ldots Y_M$ is the random variable representing the number of TC occurrences each year for the time period from 1984-2014. We apply the Poisson goodness-of-fit test in Minitab for the data sets **X** and **Y** and make a decision using the decision criteria listed in Table 1 (above).

Testing Equality of Poisson Rates

Parameter λ represents the Poisson rate for TCs. In our study this represents the average number of TCs per year. The expected value of a random variable X, denoted E[X], is the average value of the random variable. The expected value of a Poisson random variable is given by:

$$E[X] = \lambda = \frac{k}{n},$$

where n is the total number of observations in the time period t, and k is the number of TC occurrences observed in t (Katz, 2002). The variance, denoted Var(X), measures the spread of the sample around the mean from a sample of observations from a random variable X. The variance of a Poisson random variable is given by:

$$Var(X) = \lambda = \frac{k}{n}.$$

Note that the expected value and variance for a Poisson random variable are both equal to λ. We estimate λ_X and λ_Y using the sample mean of data in **X** and **Y**, respectively. Then we perform a hypothesis test for the equality of the Poisson rate parameters.

We utilize the test statistic developed by Ng and Tang to perform a hypothesis test for the equality of the Poisson rates (Ng and Tang, 2005). The hypotheses are as follows:

$$H_0: \frac{\lambda_Y}{\lambda_X} = 1$$

$$H_A: \frac{\lambda_Y}{\lambda_X} > 1.$$

These hypotheses test the equality of the Poisson rate parameters for X and Y because if λ_X and λ_Y are equal then $\frac{\lambda_Y}{\lambda_X}$ will be equal to 1. The null hypothesis means that λ_X and λ_Y are equal, and the alternative means that λ_Y is greater than λ_X. The alternative hypothesis corresponds to an increase in the frequency of TCs per year.

We use the W_3 Wald test statistic developed by Ng and Tang (2005) to test the equality of the means. The Wald test statistic is given by

$$W_3 = \frac{\ln\left(\frac{X_Y}{X_X}\right) - \ln(d)}{\sqrt{\frac{1}{X_X} + \frac{1}{X_Y}}},$$

where X_Y is the total number of observed TC occurrences for the period from 1984-2014, X_X is the total number of observed TC occurrences for the period from 1900-1983, t_X and t_Y are the time intervals for **X** and **Y**, respectively, and $d = \frac{t_Y}{t_X}$ (Ng and Tang, 2005). W_3 has a standard normal distribution denoted $W_3 \sim N(0,1)$. See the subsection below for further information regarding the normal distribution. We obtain a p-value for the test using a standard normal table and make a decision using the criteria from Table 1.

The Normal Distribution

The normal distribution is a continuous distribution with probability density function symmetric around its mean (see Figure 4, below). The percentage of observations from any normal distribution within σ, 2σ, and 3σ of the mean are 68%, 95%, and 99.7% respectively. An event corresponds to an interval of values of the normal distribution. The probability of an event is the area under the pdf curve over that interval. The pdf of the normal random variable X with parameters μ and σ, denoted $X \sim N(\mu, \sigma^2)$ is given by:

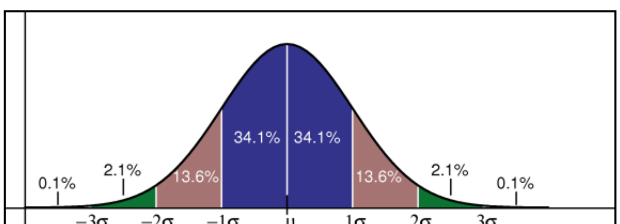


Figure 4. PDF of Normal Distribution with parameters μ and σ. The percentages describe likelihood of events within each range. The tails are shown in green. (Sedgewick and Wayne, 2011)

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}},\ -\infty < x < \infty,$$

where x is the value of the normal random variable, μ is the mean, and σ^2 is the variance (Larsen and Marx, 2006). In the context of this research the mean is the average damage incurred per TC and variance measures the average variation in these damages.

A normal Q-Q plot provides a visual representation of data and helps to determine if it is normally distributed (Salkind, 2006). A Q-Q plot that is a straight line demonstrates an exact fit (Salkind, 2006). We use the command *Probability Plot* with the normal distribution to obtain a Q-Q plot and p-value using Minitab. The command tests the following hypotheses:

H_0: Data comes from a normal distribution

H_A: Data does not come from a normal distribution.

We choose a significance level of 5%, so α=0.05. We use the criteria from Table 1 to make a decision.

The Lognormal Distribution

For data that is continuous and right skewed, or tending toward positive values, the normal distribution is generally not a good fit. The lognormal distribution, which is related to the normal distribution, is often a good choice for these data sets. If X ~ N(μ,σ), then the random variable Y =e^X has the lognormal distribution with parameters μ and σ. If Y comes from the lognormal distribution with parameters μ and σ, then the random variable X = lnY has the N(μ, σ) distribution. The lognormal distribution is a continuous probability distribution describing a random variable defined by the probability density function:

$$f(x) = \frac{1}{\sqrt{2\pi}x\sigma} e^{-\left(\frac{(\ln(x)-\mu)^2}{2\sigma^2}\right)}, \text{ x>0}$$

where x is the value of the random variable and μ and σ are the lognormal parameters (Larsen and Marx, 2006).

We test to see if damage data comes from the lognormal distribution. We denote damage data by the lognormal random variable Y. We create a new data set described by the random variable X=lnY. Thus if Y is lognormally distributed with parameters μ and σ, X~N(μ, σ). Thus we test to see if the transformed data set comes from the normal distribution. Our hypotheses are as follows:

H_0: X comes from the normal distribution

H_A: X does not come from the normal distribution.

We break the data into the two time periods 1900-1983 and 1984-2014. We use the *Probability Plot* command in Minitab for the normal distribution to obtain Q-Q plots and p-values for each data set. We choose a significance level of 5%, so α=0.05. We use the criteria from Table 1 to make a decision.

The expected value and variance of the lognormal distribution are given by

$$E[Y] = e^{\mu+\frac{1}{2}\sigma^2}$$

$$Var(Y) = e^{\sigma^2+2\mu}(e^{\sigma^2} - 1),$$

respectively. When μ and σ^2 are unknown, we can compute the sample mean, $\bar{X}$, to approximate μ and sample standard deviation s to estimate σ. We have that

$$\bar{X} = \frac{X_1+X_2+\cdots+X_n}{n},$$

where each X_i for i= 1,2,…,n represents the transformed random variable describing the damage associated with a single TC event and n is the sample size (Katz, 2002). We can approximate the sample standard deviation s using:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2},$$

where n is the sample size, X_i's are the sample observations with i=1,2,…,n, and $\bar{X}$ is the sample mean (Larsen and Marx, 2006). The variance is given by the square of the standard deviation, so we can square s to obtain the sample variance

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

(Larsen and Marx, 2006).

Testing Equality of Parameters μ and σ

We use the two sample t-test to test the equality of means for two normally distributed data sets (Larsen and Marx, 2006). For the test we transform lognormal data to a normal sample using logarithmic transformation. The hypotheses tested are

$$H_0: \mu_X = \mu_Y, \text{ versus}$$

$$H_A: \mu_X \neq \mu_Y,$$

where μ_X and μ_Y are the means of the samples described by the lognormally transformed random variables $X = X_1, X_2, \ldots X_N$ and $Y = Y_1, Y_2, \ldots Y_M$ respectively. Recall that X represents data from the period from 1900-1983 and Y represents data from the period from 984-2014. The test statistic for the two sample t-test test is given by

$$t = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{\sigma_X^2}{n} + \frac{\sigma_Y^2}{m}}},$$

where $\bar{X}$ and $\bar{Y}$ represent the sample means of the data sets X and Y, respectively, σ_X and

σ_Y represent the standard deviation for the data set X and Y, respectively, n represents the number of data observations in the set X and m represents the number of data observations in the set Y (Larsen and Marx, 2006). If H_0 is true, this test statistic has a student t-distribution with n+m-2 degrees of freedom (Larsen and Marx, 2006). We obtain a p-value using the two-sample t-test in Minitab and use the criteria from Table 1 to make a decision.

The F-test can be used to determine the equality of variances for normally distributed data (Larsen and Marx, 2006). We use a logarithmic transformation for the lognormal damage data to obtain a normally distributed data set. The hypotheses tested are

$$H_0\colon \frac{\sigma_X^2}{\sigma_Y^2} = 1$$

$$H_A\colon \frac{\sigma_X^2}{\sigma_Y^2} \neq 1.$$

The test statistic for the F-test is given by

$$\mathrm{F} = \frac{\sigma_X^2}{\sigma_Y^2},$$

where σ_x^2 and σ_y^2 are the variances of the normally distributed data sets X and Y (Larsen and Marx, 2006). The F statistic has n-1, m-1 degrees of freedom, denoted $F_{n-1,m-1}$ where n is the number of observations in X and m is the number of observations in Y. We obtain a p-value using the F-test in Minitab and use the criteria from Table 1 to make a decision.

IV. Results

This section details the results of the study. We provide results of goodness-of-fit for Poisson and lognormal distributions, parameter estimation for each model, and results of equality tests for each parameter when comparing the two time periods of 1900-1983 to 1984-2014.

Tropical Cyclone Occurrences

We test the goodness-of-fit for frequency data to the Poisson distribution for each time period. We obtain p-values of 0.718 and 0.440 for the periods 1900-1983 and 1984-2014, respectively. Thus we have p-values larger than the significance level $\alpha=0.05$ for each period and so we do not reject the null hypothesis. We conclude at 5% significance level that TC occurrence data comes from Poisson populations for both time periods. The results of the goodness-of-fit test for the Poisson distribution are summarized below:

Table 2: Poisson Goodness-of-Fit Results for Occurrence Data

Time Period	*1900-1983*	*1984-2014*
p-value	0.718	0.440
Decision	Do not reject H_0	Do not reject H_0
Conclusion	Data comes from the Poisson distribution	Data comes from the Poisson distribution

We then test the equality of the two Poisson means, λ_X and λ_Y, using the test developed by Ng and Tang (2005). We use the values for λ_X and λ_Y provided by the Poisson goodness-of-fit test in Minitab. We obtained a test statistic of $W_3=7.0395$ for our test. This corresponds to a p-value less than 0.0001, therefore the p-value is less than α and we reject the null hypothesis. Thus we conclude at a 5% significance level that the Poisson mean for TCs occurring in the United States from 1984-2014 is greater than in the period from 1900-1983. For the time period from 1900-1983 in the United States, the rate parameter $\lambda_X = 0.5$. For the time period from 1984-2014 in the United States, the rate parameter is $\lambda_Y = 2.03226$. These parameters show that TCs are *more than four times* as frequent in the period from 1984-2014 as they were in the period from 1900-1983. The conclusions of the test are summarized below:

Table 3: Equality of Poisson Rates

λ for 1900-1983	0.5
λ for 1984-2014	2.03226
Test Statistic	7.0395
p-value	< 0.0001
Decision	Reject H_0
Conclusion	$\frac{\lambda_Y}{\lambda_X} > 1$

Based on these conclusions we obtain the probability mass functions for both periods. For the United States period from 1900-1983, TC likelihood is described by

$$P(X = k) = f(k; 0.5) = \frac{e^{-0.5t}(0.5t)^k}{k!}, k = 0,1,2, \dots$$

For the United States period from 1984-2014, TC likelihood is described by

$$P(Y = k) = f(k; 2.03226) = \frac{e^{-2.03226t}(2.03226t)^k}{k!}, k = 0,1,2, \dots$$

These equations provide the likelihood of k events occurring within t years for each period. Table 4 gives the United States TC likelihoods for k TCs occurring per year for each time period:

Table 4: Probability of k TC Occurrences in One Year

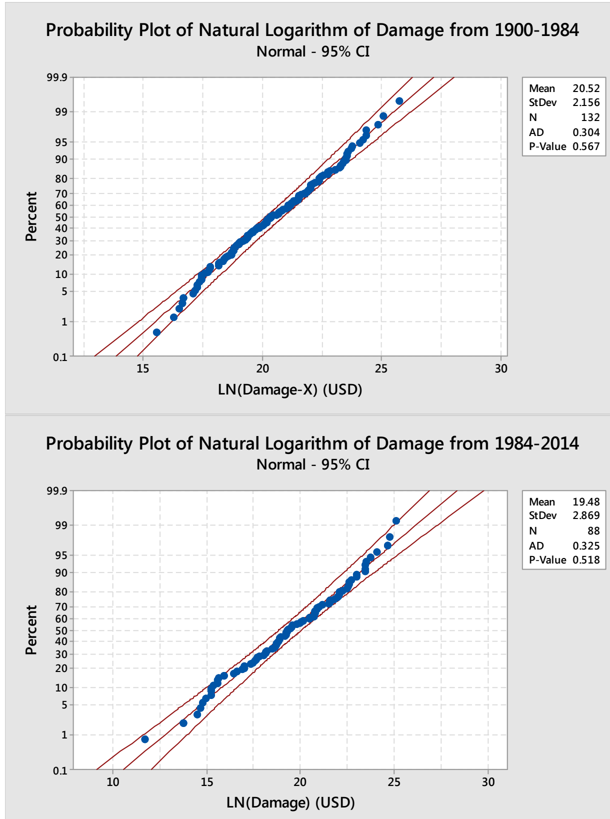
k	*P(X=k) for 1900-1983*	*P(X=k) for 1984-2014*
0	0.6065	0.1310
1	0.3033	0.2663
2	0.07582	0.2706
3	0.01264	0.1833
4 or more	0.00174	0.1488

We note a significant decrease in the likelihood of 0 TCs occurring per year in the period for 1984-2014. This demonstrates increased TC likelihood in the latter period after the onset of global climate change.

Damages

We test the goodness-of-fit of the lognormal distribution to adjusted damage data. We take the natural logarithm of damage data and use a probability plot in Minitab for the normal distribution to test if the damage data is from the lognormal distribution (recall that for the lognormal random variable Y, $X=\ln Y \sim N(\mu,\sigma^2)$). We create a Q-Q plot of the lognormally transformed data to the normal distribution and obtain p-values for the normal goodness-of-fit test. We have the following results from the goodness-of-fit test of the normal distribution to the logarithmically transformed damage data:

Figure 5: Probability Plot of Lognormally Transformed Damages for the Normal Distribution



We see that the probability plots create a straight line, thus the normal distribution fits the transformed damage data.

We obtain p-values of 0.567 and 0.518 for the periods from 1900-1983 and 1984-2014, respectively for the Normal goodness-of fit test for the transformed data. Since we have p-values larger than our significance level α=0.5 we fail to reject the null hypothesis, and conclude that damage data comes from a lognormal distribution. The results of the goodness-of-fit test are summarized in Table 5:

Table 5: Normal Goodness-of-Fit Results for Logarithmically Transformed Occurrence Data

Time Period	*1900-1983*	*1984-2014*

p-value	0.567	0.518
Decision	Do not reject H_0	Do not reject H_0
Conclusion	Data comes from a lognormal distribution	Data comes from a lognormal distribution

To test the equality of the lognormal parameter μ we perform a two-sample t-test on transformed data. We run a two-sample t-test in Minitab and obtain a test statistic of t=2.88. We obtain a p-value of 0.005. The p-value is less than the significance level α=0.05 and we reject the null hypothesis. We conclude that the values for the means in the two time periods are not equal. The results of the two-sample t-test are summarized below:

Table 6: Testing Equality of Logarithmically Transformed Damage Means

μ of Transformed Damages1900-1983	20.52
μ_Y of Transformed Damages1984-2014	19.48
Test Statistic t	2.88
p-value	0.005
Decision	Reject H_0
Conclusion	$\mu_X \neq \mu_Y$

We use an F-test to test the equality of variances for lognormal damage for the two time periods. The test statistic has 216 degrees of freedom. We obtain a test statistic of 0.564 and use an F-table to obtain a p-value equal to 0.002. The p-value is less than our significance level $\alpha=0.05$, therefore we reject the null hypothesis. We conclude that the lognormal parameter σ for the period from 1900-1983 in the United States is significantly different from lognormal parameter σ from 1984-2014. These results are summarized below:

Table 7: Testing Equality of Logarithmically Transformed Damage Variances

σ^2 of Lognormally Transformed Damages 1900-1983	4.648
σ^2 of Lognormally Transformed Damages 1900-1983	8.231
Test Statistic F	0.564
p-value	0.002
Decision	Reject H_0
Conclusion	$\frac{\sigma_X^2}{\sigma_Y^2} \neq 1$

We use the relationship between the normal and lognormal distributions to obtain the parameters for μ and σ. We use the equations for the expected value and variance for lognormal random variables for each period. We obtain the following results for the expected value and variance of adjusted damage data coming from the lognormal distribution (in adjusted USD):

Table 8: Sample Mean and Sample Standard Deviation of Damage Data

Time Period	*1900-1983*	*1984-2014*
Expected Value	\$8.337 billion	\$17.676 billion
Variance	\$7.186 $x10^{21}$	\$1.173$x10^{24}$

We find larger adjusted average damage per TC for the period of 1984-2014. We find significantly larger standard deviation of damage per TC for the period from 1984-2014.

V. Conclusion

We tested the fit of existing statistical models for TCs and found the Poisson and lognormal distributions to provide a good fit to TC frequency and damage, respectively. We have found that TC frequency and damages come from a different distribution in recent decades (because all parameters have changed) when comparing the two time periods of 1900-1983 to 1984-2014.We tested the equality of parameters and the implications of these changing parameters are that global climate change is creating severe consequences for the United States. TCs have become significantly more frequent in recent decades. These TCs are becoming not only more frequent but more damaging. We see the average adjusted damages per storm have significantly increased in recent decades as well. The variation in the damages incurred show that TC behavior is becoming more unpredictable with the onset of global climate change, further emphasizing the need for preventative action and damage mitigation in public policy. It is the intent that this research will provide quantitative evidence that TCs will continue to have devastating consequences on the U.S in the face of global climate change. These TCs are proving to be getting worse with time as global climate change is not being mitigated effectively enough to avoid devastating outcomes.

The testing of equality of Poisson rates developed by Ng and Tang (2005) concludes that the Poisson rate for the period from 1983-2014 is significantly greater than the Poisson rate for the model describing 1900-1983. The Poisson rate λ increased *by a magnitude of four*. This means that the United States has experienced four times as many storms each year as it did in the earlier portion of the century. The model describing TC frequency for the period from 1900-1983 shows a 0.17% likelihood of 4 or more TC occurrences in one year, while for 1984-2014 this likelihood is nearly 15%. We see significantly more TCs in recent decades with the onset of global climate change. We note that our findings contradict the *IPCC Fifth Assessment Report* conjecture that the frequency of TCs will not increase as a result of global climate change (IPCC, 2014). The U.S. is one of the nations most impacted nations by TCs and their frequency is increasing.

We use a t-test to test the equality of the lognormal parameter μ for the two time periods and conclude that these parameters are not equal. The F-test of equality of variances for the two lognormally transformed data sets shows that σ is also not equal for the two time periods. From these parameters we found the expected value and variance of TC damage for each period.The expected value of damages per storm was found to be *more than twice as large* in the period from 1984-2014 than the earlier portion of the 20^{th} century. Thus for each storm occurrence we can expect more than twice as much damage to be incurred, a concerning thought when considering events such as Hurricane Katrina and Hurricane Sandy in recent years. Our analysis supports the conclusions found by Katz (2002), who noted an increasing trend in adjusted damages per TC (Katz, 2002). The *IPCC Fifth Assessment Report* projects increased intensity of TCs (IPCC, 2014). Our research supports this projection and we find that TCs are becoming more damaging over time in the U.S. These findings serve as a call to action to enact damage mitigation in at-risk communities. Policy must enact climate change mitigating techniques in order to prevent further devastating damages.

We find a significant increase in the variance of adjusted damages per storm. The variance of storms in the period from 1984-2014 has *increased by a magnitude of* 10^3.

There is greater variation in the damages incurred per storm, meaning that these storms are becoming more unpredictable and thus more difficult to protect ourselves from in the current time period. Our research supports the idea that TC volatility will increase as global temperatures increase (IPCC,2014). There is a need for preventative action in mitigating damage as these TCs are behaving more unpredictably in recent decades than they were in the period from 1900-1983.

We have utilized statistical models to examine the behavior of TCs in the United States across two time periods. From these analyses we have found significant changes in the parameters for each time period and disconcerting implications of these changing parameters. TCs are becoming more frequent, more damaging, and more unpredictable as the effects global climate change have become more pronounced. There is a need for increased funding for responsive aid NGO's, implementation of damage mitigating measures, and changes in policy in order to mitigate the impacts of future TCs. The effects of global climate change will impact the United States in the form of increasingly frequent, damaging, and volatile TCs. Thus with the continuation of global climate change effects, preventative action must be taken.

Further Research

This research was conducted for only United States TC data. Some findings of this research contradict IPCC expectations of TC behavior as global climate change increases. The frequency of TCs demonstrates a significant increase in the United States in the period from 1984-2014 when compared to earlier time periods. A study of another global region may yield different results as reported by the IPCC Report, which focused on the global context, and the United States experiences a large proportion of TC occurrences compared to the global average (CRED, 2014).

The United States is a wealthy nation and experienced increased mean damages per TC when damages are adjusted for inflation, population, and wealth. A comparative study of an impoverished nation against the United States may provide useful information to global aid organizations regarding effective damage mitigation techniques. PL05 normalized damage data would need to be computed in order to maintain the integrity of further global damage studies.

References

Bove, M. C., J. B. Elsner, C. W. Landsea, X. Niu, and J. J. O'Brien. (1998). Effect of El Nino on U.S. landfalling hurricanes, revisited. *Bull. Amer. Meteor. Soc*., 79: 2477–2482.

Centre for Research on the Epidemiology of Disasters. (2014). *EM-DAT: The Emergency Disaster Database, 2014.* Retrieved from http://www.emdat.be/advanced_search/index.html

Elsner, J. B. and Bossak, B. H. (2001). Bayesian analysis of U.S. hurricane climate. *J. Climate*, 14: 4341–4350.

Everitt, B. (2002). *The Cambridge Dictionary of Statistics*. Cambridge University Press, Cambridge.

Goldenberg, S. (2014). "Natural disasters displaced more people than war in 2013, study finds." *The Guardian.*17 September 2014. Web. 23 Sept. 2014.

Guston, D.H., Clark, W., Keating, T., Cash, D., Moser, S., Miller, S., and Powers, C. (2000). Report of the workshop on boundary organizations in environmental policy and science. 9-10 December 1999, Bloustein School of Planning and Public Policy, Rutgers University, New Brunswick, NJ. Belfer Center for Science and International Affairs (BCSIA) Discussion Paper 2000-32. Piscataway, NJ: Environmental and Occupational Health Sciences Institute at Rutgers University and UMDNJ-RWJMS; Cambridge, MA: Global Environmental Assessment Project, Environment and Natural Resources Program, Kennedy School of Government, Harvard University. Retrieved from http://environment.harvard.edu/gea

Hogg, R. V. and Klugman, S. A. (1984). *Loss Distributions* (p. 235). John Wiley and Sons.

Intergovernmental Panel on Climate Change, 2014: Climate Change 2014: Mitigation of Climate Change. *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Katz, R. W. (2002). Stochastic modeling of hurricane damage. *Journal of Applied Meteorology,* 41:754-762. doi: http://0-dx.doi.org.innopac.library.unr.edu/10.1175/1520-0450(2002)041<0754:SMOHD>2.0.CO;2

Krishnamoorthy, K. and Thomson, J. (2004). A more powerful test for comparing two Poisson means. *Journal of Statistical Planning and Inference,*119:23-35.

Larsen, R. J. and Marx, M. L. (2006). *An Introduction to Mathematical Statistics and its Applications* (4th ed.). Pearson Prentice Hall, Upper Saddle River.

National Hurricane Center. (2014). Tropical cyclone reports. [Description of study topic]. Retrieved from http://www.nhc.noaa.gov/data/tcr/index.php?season=2014&basin=atl

Ng, H. K. T. and Tang, M. L. (2005). Testing the equality of two Poisson means using the rate ratio. *Statistics in Medicine,* 24(6): 955–965. doi: 10.1002/sim.1949

Peterson, T. C., Hoerling, M.P., Stott, P. A., and Herring, S. E. (2013). Explaining extreme events of 2012 from a climate perspective. *Bull. Amer. Meteor. Soc.*, 94(9): S1–S74.

Pielke, Jr., R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., and Musulin, R. (2008). Normalized hurricane damages in the United States: 1900-2005. *Natural Hazards Review*, 9(1): 29-42.

Pielke, Jr., R. A., and Landsea, C. W. (1998). Normalized hurricane damages in the United States: 1925–95. *Weather and Forecasting*, 13: 621–631. doi: http://dx.doi.org/10.1175/1520-0434(1998)013<0621:NHDITU>2.0.CO;2

Sedgewick, R. and Wayne, K. (2011). *An introduction to programming in Java*. Retrieved from http://introcs.cs.princeton.edu/java/11gaussian/

Taylor, H. M. and Karlin, S. (2014). *An Introduction to Stochastic Modeling*. Academic Press, San Diego.

World Meteorological Organization. (2015). Natural hazard. [Description of study topic]. Retrieved from http://www.wmo.int/pages/themes/hazards/index_en.html