PREDICTING THE IMMINENCE OF FIRE DISASTER RISK ON THE ECONOMY OF GHANA: AN EARLY WARNING SYSTEM

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF PHILOSOPHY DEGREE IN RISK MANAGEMENT AND INSURANCE

JUNE, 2015

DECLARATION

I do hereby declare that this work is the result of my own research and has not been presented by anyone for any academic award in this or any other University. All references used in the work have been duly acknowledged.

I bear sole responsibility for any shortcomings.

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CERTIFICATION

I hereby certify that this dissertation is supervised in accordance with the procedures laid down by the University.

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ABSTRACT

This study examines the nature of regional fire risk frequency in Ghana and provides a fire prediction model, fire risk assessment and also contributes to development of disaster risk capacities in Ghana. The study adequately provides with clear messages and consequences of the fire disaster risk and also provide reliable information to institutions on how to respond to the warnings received.

Secondary data obtained from the Ghana Open Data Initiative for this study includes monthly fire frequency count data on Ghana from 2007 to 2011. The data consists of the number of rescues, injury, death, cost of damage and count fire occurrence on all the ten regions including two operational regions in Ghana. An empirical negative binomial probability distribution, normal and Poisson model are fitted to the count fire frequency and fire fatality data in various operational and administrative regions. The likelihood of estimated parameter values of the fitted distribution for fire frequency and fatalities was bootstrapped where standard errors of the bootstrapped parameter helped in computing of the confidence interval of the estimated parameters. The statistical distribution fitted to the fire frequency data helps identify the class of models that is exhibited by the data from each region and provides time leading decisions for Government institutions, academics, risk managers, actuaries and the entire population. Based on the predictions of the statistical models, the study suggest that Government and stakeholders should make available necessary equipment to help fight fire in various vulnerable areas in the regions.

DEDICATION

This work is dedicated to God Almighty for His persistent care and protection, to my late father, Elder Frank Boadi and my dear mum Ernestina Boadi for her constant prayers throughout my study.

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LIST OF ABBREVIATIONS AND ACRONYMS

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CGE	Computable General Equilibrium
EM-DAT	Emergency Events Database
EP	Exceedance Probability
EWS	Early Warning System
GDP	Gross Domestic Product
GLM	Generalised Linear Model
IEWP	International Early Warning Programme
IFRC	International Federation of Red Cross
MLE	Maximum Likelihood Estimation
NADMO	National Disaster Management Organization
NB	Negative Binomial
PMF	Probability Mass Function
SDAP	Sustainable Development Action Plan
STPA	STAMP Based Process Analysis
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UNISDR	United Nations International Strategy for Disaster Reduction
USAID	United States Agency for International Development
P-P	Probability Plot

CHAPTER ONE

INTRODUCTION

1.1 Research Background

As population growth rates increases large number of people and infrastructure within urban centres and disaster prone areas are affected when natural event such as disaster occurs (Grid-Arendal & UNEP, 2002). Globally, Guha-Sapir, Hoyois and Below (2013) annual report indicated that in 2012, 357 natural triggered disasters were registered, this was both less than the average annual disaster frequency observed from 2002 to 2011 (394), and represented a decrease in associated human impacts of disasters in 2012 as compared to previous years. However, natural disasters killed a significant number of the population, e.g. a total of 9,655 people were killed and 124.5 million people became victims worldwide (Guha-Sapir et *al.*, 2013).

Over the past decades, Sub-Saharan Africa has experienced more than one thousand disasters, putting at risk many recent development gains due to the vulnerability of its population and economy and their often-low capacities to cope with natural hazards (Subramanian & Jha, 2010). In Ghana, the periods between 1980 and 2010 data related to human and economic losses from disasters showed that 29 natural disasters occurred where 1,133 people killed with an average of 37 killed per year, and an average of 524,331 affected lives per year (Guha-Sapir et *al.*, 2013). Also the average economic damage per year (thousand US dollars) was 106 resulting in unnecessary losses of social and economic capital (Guha-Sapir et *al.*, 2013).

Considering the recent fire outbreaks, an analysis of disaster impacts in informal settlements shows that fire causes the greatest loss of life and property in Ghana (Sarpong, 2013). Response to fires, especially in informal settlements continues to be a daunting task to the vulnerable population because of low capacities developed to prevent fire risk. Statistically, the forestry sector reveals that the annual loss of revenue from merchantable timber to wildfire is about US$24 million and cumulative effect of wildfires of annual loss of 3% of Gross Domestic Product (GDP) of the country (SDAP, 2010). The country happens to be losing a lot of money and resources due to numerous fire outbreaks. These include losses from domestic, industrial, institutional, vehicular, commercial, electrical fires and bushfires. It can be inferred that the relationship between fire occurrence and it's impact on the socioeconomic status is of a great significance in which Wang, Lu and Li (2005) attest that it requires prediction, fire protection and fire risk assessment.

According to the International Disaster Database over the periods of 1996 to 2012, Ghana has suffered several disaster risks. The summary of natural disaster occurrence indicated that 10 natural disasters occurred over the period 1900 to 2014 (EM-DAT, 2014). This risk resulted from flood, drought, epidemic, wildfire and earthquake (Seismic activity) which killed and affected thousands of the populace of Ghana within the periods. Also, the database informs that 10 technological disasters occurred within the same period (EM-DAT, 2014). Transport Accident, Industrial Accident and Miscellaneous accident (Collapse, Explosion, Fire and Others) were a technological disaster that affected and claimed thousands of life's. Okyere, Yacouba and Gilgenbach (2012) in a study revealed that the cause of natural disasters and hazards in Ghana, mostly in Accra has been mainly from water through flooding or stormy rain or drought, and fire outbreaks. The occurrences of these disasters are not automatic or incidental consequences, mostly felt by the urban centre and therefore requires either forecasting or a forward-looking exploration (Rossel, 2012).

Due to the incessant fire outbreaks over the years, the government has intensified education in the use of fire extinguishers, both at the regional and local level and in all households. The trend of fire risk in Ghana indicates that disaster effect on the economy has become a commercial issue, Rossel (2012) suggested such situations as forecastable. However, although most warnings of environmental hazard are forecastable, Smith and Petley (2008, p.93) asserts that some threats (e.g. Earthquakes and droughts) are insufficiently understood and preparedness has to be based on not just forecasting, but also our ability to predict the magnitude of the impact. Basher (2006) study on early warning systems for natural hazards indicated the need to have not only a sound scientific and technical basis of disaster risk, but with also a strong focus on the people exposed to the risk, and with a systems approach incorporates all relevant factors which will be necessary for identifying the risk. The state of knowledge in response to disaster risk needs an early warning system that will improve firms, policy holder's awareness and understanding, so that it can increase their direct tackling to threats or opportunities (UNDP, 2013). This study developed an early warning system for identifying the likelihood of fire risk on economy, provide empirical systems, afire prediction model that helps identify the risk of fire on the operational and administrative regions under study in order to improve stakeholder's core function of fighting fire outbreaks in the country.

1.2 Research Problem

The stable democracy of Ghana since 1992 which has been attained through political and economic reform, has achieved a strong macroeconomic growth through a sound management of the transaction of government over the periods 1992 to 2013 (USAID, 2012). Thus, the transition has brought a measured level of stability, prosperity, and consolidation putting Ghana on the verge of conducive macroeconomic environment, promoting the profitability of businesses (Pal & Mittal, 2011). This stable economy has led to the reduction in poverty and has shifted the economic status of the country to a middle income status. Globally, Ghana's economic freedom score is 61.8 making it economy 77th in the 2013 index and is ranked 7th out of 46 countries in the sub-Saharan Africa (Miller, Holmes, Feulner, Kim, Riley & Roberts, 2013).

Despite the significant growth and improvements in the quality of life, Ghana faces persistent development challenges which might be due to the disaster risk behaviours posed to the economy (UNDP, 2013). Ghana faces situations where small or manageable hazards impact the population, resulting in unnecessary losses of social and economic capital (UNDP, 2013). The arising disaster risk may be for a short term or a long term process which could be predicted prior to, and adopt ways to prevent it. Ginnetti and Schrepfer (2012) purported that in order to prevent or reduce disaster-related displacement on an economy, emphasis on the need to address some clear gaps in both knowledge and capacity by improving research on the awareness of disaster risks and associated human rights, and the capacity to address them should be a major concern.

Considering the recently probabilistic risk analysis and other catastrophic risk analysis tools which have gained widespread acceptance by the insurance and risk management industries designed for estimating natural hazard damage and estimating the economic and insured losses that result from the occurrence of natural catastrophes (Born & Martin, 2006; Grossi & Kunreuther, 2005) the need to build capacities in the theoretical and empirical lenses within countries to reduce disaster risk is necessary. This study considers historical loss and event information and developed a model which provides early warnings to the risk of fire disaster on the economy of Ghana.

Stochastic dynamics which are best used in handling ecological data is used to identify the variability that existed in count fire data. Due to environmental variations, stochastic process better identify an appropriate model for determining the likelihood of fire occurrence of fatality through fire (Bolker, 2008). The stochastic models will help quantify the likelihood and magnitude of large losses coming from the fire in order to help manage their portfolio of risk and adequacy of loss reserves (Born & Martin, 2006). In this respect, the main contribution of this study is envisaged as follows: empirically fit an appropriate statistical distribution to fire count data, assess the likelihood of a fire risk affecting properties and the economy and determine the fatality that can be expected through fire occurrence.

1.3 Research Purpose

The research is to provide to the government of Ghana, the population, and organization knowledge about a likely occurrence of fire disaster risk. The study provides with clear messages the consequences and subsequently disseminates to stakeholders the risk of fire on various administrative and operational regions, and also provides practiced and knowledgeable responses to risk managers and the public about fire disaster risk (UNDP, 2013).

1.4 Research Questions

1. What distribution best fits the frequency of a disaster risk?
2. What distribution best fits the losses incurred in a disaster?
3. What is the likelihood of fire occurring and how much loss (death) can be expected?

1.5 Research Objectives

The main objective of this study is to empirically model a fire disaster risk and help quantify the likelihood and magnitude of losses.

To achieve this purpose, the study will outline the following related objectives;

1. To fit an appropriate probability distribution(s) to the frequency of a disaster risk.
2. To fit an appropriate probability distribution(s) to the fatality through fire risk.
3. Determine the likelihood of fire occurring and subsequently determine the fatality that can be expected.

1.6 Significance of the study

Potential losses on a community will bring to the vulnerable population losses of their economic and social capital. This however requires that necessary knowledge prior to disaster risks through monitoring, analysing and forecasting of the possible events is required. The study helps communicate or disseminate the imminent situation to local capabilities and risk managers to respond to the warnings received (UNDP, 2013). The study provides reliable information to the appropriate institutions, academicians, risk managers, actuaries and the entire population an empirical model of fire count data and then determines the likelihood of fire risk in order to prepare towards any future uncertainty.

1.7 Chapter Outline

This study is organized in five chapters

Chapter one gives an overview of the background to the study, the problem statement, the purpose of the study, the objectives and research questions, and the significance of the study.

Chapter two examines the relevant literature from both an appreciative inquiry and critical analysis points, establishing a link between previous work and this study. Literatures on fire risk, early warning system, risk assessment, catastrophe modelling and relevant research area are the major focus.

Chapter three draws attention to the methods used in collecting relevant data for achieving the research objective. This chapter further outlines the research design and methodology used. The chapter also covered the study setting, population, data collection method, data processing, analysis techniques and analysis, estimation of model parameters, criteria selection methods, testing of the goodness of fit and ethical considerations.

Chapter four presents the empirical results of the research, interpreting of results and discussing the findings based on the data analyses. This chapter reports the problem investigated, the methods adopted, results found and the conclusions reached, and the study instruments that was also used.

Chapter five presents the summary, conclusions and recommendations of the study followed by references and appendices. This section highlights the core of the study, answers researched questions and provide recommendation on study outcome, and draws from further studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction, Rationale, Scope and Methodology for Review

As identified in the preceding chapter on the need of the an early warning system that will help communicate to the populace of Ghana the risk of fire disaster in the future and identify the likelihood of the disaster. This chapter reviews the concepts of Early Warning System (EWS) focusing on hazards and disaster risk providing the theoretical underpinnings of the study. This chapter provides a summary of relevant literature and states out other methodologies and framework that were used by other studies in assessing disaster risk within which this study will be put into perspective. In this regard, the concepts, methods and principles relevant to the study are reviewed.

Towards this end, this review is being undertaken to

1. Provide an overview of Natural Disaster risk and Early Warning System
2. Provide summaries and analysis of research focused on early warning systems of fire disaster prediction, the issues involved in communicating early warnings to the people at risk.
3. Categories and understand the prevailing issues and research about the strategies during and after implementation of disaster risk early warning system
4. Methods used to provide fire disaster risk EWS
5. Importance of a fire EWS to organizations, risk managers, the populace and Governments.

2.2 An overview of EWS for Natural Disaster Risk

2.2.1 Unraveling Definitions

“A disaster is a sudden, calamitous event that seriously disrupts the functioning of a community or society, causing a widespread human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources” (IFRC, 2013).

United Nations International Strategy for Disaster Reduction- UNISDR (2009) also defines disaster risk as a “potential disaster loss, in lives, health status, livelihoods, assets and services, which could occur to a particular community or a society over some specified future time period”. Disaster risk comprises different types of potential losses which are often difficult to quantify. Nevertheless, with knowledge of the prevailing hazards and the patterns of the risk through EWS to the population and the economy, disaster risks can be assessed and mapped, in broad terms (UNISDR, 2009).

The Early Warning System (EWS) is a set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organisations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss (UNISDR, 2009; IFRC, 2013).

2.2.2 Rationale for EWS of Disaster Risk

Several studies on the occurrence of hazards or disaster around the world focused on providing early warning systems as an integral part in risk communication (Marvin *et al.*, 2013; Souare & Handy, 2013; Mayhorn & McLaughlin, 2012). Study by Marvin *et al.* (2013) indicated the feasibility of early warning systems to warn the development of food safety hazards induced by natural disasters. They showed that the occurrence of new hazards or known hazards in food products in which they previously did not occur could be known using the available information such as an early risk behaviours on plant, animal, human disease focused systems monitoring weather and other environmental conditions (Marvin *et al.*, 2013).

EWS has received attention, globally EWS is used to provide a preparatory ground toward any unforeseen occurrences. From review of studies (e.g. Basher, 2006; Davis & Karim, 2008; Huang & Chou, 2008; Salzano, Agreda, Carluccio & Fabbrocino, 2009; Jin & Lin, 2011; Lautze, Bell, Alinovi & Russo, 2012; He, Zhou, Wang, Xiong & He, 2012; Koyuncugil, Ozgulbas, 2012; Mayhorn & McLaughlin, 2012; Dokas, Feehan, Imran, 2013; Marvin et al., 2013; Souaré & Handy, 2013) it is asserted that most early warning systems focused on providing an early warning sign identification of natural hazards, financial risk, data mining risk detection and also providing societal risk detection using ecological data for example number conflict, the number of voters, the number of fires etc. Interestingly, in providing EWS for natural disaster seems to be reared to many academicians not in the field of disaster risk. However, the Table 2.1 indicates the various studies that provided EWS for various hazards.

These EWS developed by the researcher's seek to provide directives needed to generate and disseminate timely and meaningful warning information to the vulnerable population. Considering the global EWS developed by Basher (2006), it was shown that early warning systems for natural hazards need to have not only a sound scientific and technical basis, but also a strong focus on the people exposed to risk and with a systems approach that incorporates all of the relevant factors in that risk. But since most disaster warning designers are faced with a challenge of risk communication to the people exposed to the risk Mayhorn and McLaughlin (2012) also insisted that more early warning communication tools that will help prevent, reduce the daunting challenge of effectively communicating the seriousness of potentially devastating natural and technological hazards such that people will take action to protect themselves from death, injury, and loss is appropriate.

Table 2. 1: Various Natural disaster EWS

Publication	Natural Disaster Risk	Context of study
Basher (2006)	Global Early Warning Systems for Natural Hazards: Systematic and People-Centred	Global or Country wide Issue
Salzano *et al.* (2009)	Risk assessment and early warning systems for industrial facilities in seismic zones.	Europe
Jin and Lin (2011)	Managing tsunamis through early warning systems: A multidisciplinary approach	South Pacific Region
Mayhorn and McLaughlin (2012)	Warning the world of extreme events: A global perspective on risk communication for natural and technological disaster	Global or Country wide Issue
Huang and Chou (2008)	Risk-based drought early warning system in reservoir operation	Northern Taiwan
Lautze *et al.*, (2012)	Early warning, late response (again): The 2011 famine in Somalia	Somalia
Dokas *et al*. (2013)	EWaSAP: An early warning sign identification approach based on a systemic hazard analysis	Republic of Ireland
Marvin *et al.* (2013)	Proactive systems for early warning of potential impacts of natural disasters on food safety: Climate-change-induced extreme events as case in point	Netherlands

Source: Author’s construct

Also, Lautze *et al*. (2012) purported that problems of late response to early warning, including the need to refocus early warning and support to communities and in-country institutions and systems and to clarify rights, resources, responsibilities and recourse within the international system of assistance providers. From the studies identified, it is assessed that there is a lot of the risk communication problem identified through the early warning systems and therefore people exposed to the risk are not able to prepare towards the risk identified (Basher 2006; Mayhorn & McLaughlin, 2012; Lautze *et al*., 2012). It is therefore necessary that better ways and more appropriate ways of reaching the people at risk through EWS will be provided.

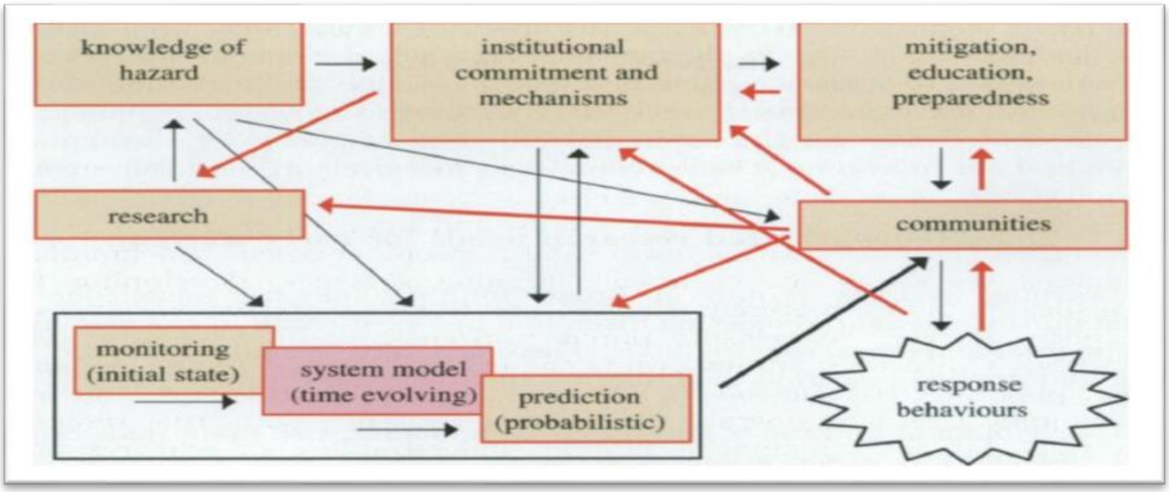
In providing early warning signs based for systemic hazard analysis, Dokas *et al*. (2013) developed the STAMP Based Process Analysis (STPA) that extended to incorporate the identification of early warning sign known as that EWaSAP. After developing the early warning sign that has recently been used, they showed that there was a significant increase in the predefined list of early warning signs. Thus the EWaSAP which used perceivable sets of data was able to indicate in a timely manner the presence of flaws and threats of systemic hazards (Dokas *et al*., 2013). As part of a search of the applicability of early warning systems to warn of the development of food safety hazards induced by natural disasters, with climate-change-induced extreme, Marvin *et al.* (2013) showed the following. They indicated that EWS in the form of better use of the available information such as on plant, animal, human disease focused systems, monitoring weather and other environmental conditions and/or systems collecting publications will help prevent the negative impact of severe natural events on food safety. They informed by using the available information will help risk managers minimize the disaster on food safety (Marvin *et al.*, 2013).

Several researches that looked at developing models to determine risk detection mechanism for the financial sector is also not left out in this study. Since this study is towards a business administration qualification in risk management and finance, it concerns itself with the managerial and operational aspects of the financial EWS. Studies such as early warning systems for banking crises, EWS of risks of energy prices and energy price ratios and Financial early warning system model and data mining application for risk detection are some recent studies identified in this study (e.g. Davis, & Karim, 2008; Koyuncugil, Ozgulbas, 2012; He *et al.*, 2012). From the study of identifying the best EWS for determining banking crisis, Davis and Karim (2008) purported that logit is the most appropriate approach for global EWS and signal extraction for country-specific EWS. In addition, Koyuncugil and Ozgulbas (2012) study on developing financial EWS models and data mining application for risk detection showed that the CHAID algorithm was the EWS which could be used to provide in the decision making process to firms with its automated nature to the ones who have an inadequate financial background. Adding to the EWS identified in the financial risk detection to prevent bank crisis, He *et al.* (2012) also made aware that the CGE model (Computable General Equilibrium) which comprises of the Granger causality test and the cointegration test used to provide an early warning model for risks of energy prices and energy price ratios in China's energy.

Even though most of the EWS system identified above in natural hazards and the financial sector has been in the developed countries, Souaré and Handy (2013) recent study in Africa looked at the historical evolution of conflict early warning systems and early action taken to mitigate it. They identified that in Africa, systems such as Continental Early Warning System (CEWS) of the African Union (AU), the Conflict Early Warning and Response Mechanism (CEWARN) of the Intergovernmental Authority on Development (IGAD), and the Economic Community of West African States' (ECOWAS) Early Warning and Response Network (ECOWARN) and several other systems that target conflicts are in place (Souaré & Handy, 2013). However, considering the statistics from the international disaster database, over the past four decades Sub-Saharan Africa has experienced more than 1000 disasters where over 300 million people were affected through major disaster risk, such as wild fires, droughts, floods, cyclones, earthquakes and volcanoes (EM-DAT, 2010), the occurrences of this disaster in Africa are evolving as in geography, frequency and impact. Although, there various EWS's in place it is, however endowing that more clarity through research will be done to better help provide more direct tackling techniques to threats of disaster in Africa.

Studies have suggested four principles for identifying and responding to messages received from early warning systems. The first is to collect information and opinions from many different, independent sources about possible wild-card scenarios and then use this information to work out the most likely weak signals that would warn of such a scenario. The second principle is to train people in responsible positions to watch out for these signs rather than concentrating solely on the strong signals that permit short term planning. The third is to set up mechanisms to bring these managers together to share their observations and discoveries. The fourth—and perhaps the most important—principle is to build a capacity in the organization in advance for improvisation that will allow sufficient change to deal with the scenario if it arises (Basher, 2006; Rosell, 2011). In as much to provide systems that will include all possible signals that will pinpoint the hazard ahead, Basher (2006) proposed an integrated systems model of early warning system that will encapsulate all these principles. Below in Figure 2.1 is a presentation of the integrated system.

Figure 2. 1: Integrated EWS



Source: Basher (2006)

The integrated EWS proposed by Basher (2006) incorporates research as a main component of getting knowledge of the hazard, and thereby providing monitoring, models and predictions from the knowledge of the hazard to institutions, telling of the mechanisms that can help mitigate the risk, educate and prepare communities on how to respond to the hazard ahead of time.

From the above review of studies on EWS, we can assess that there are no or few studies in Africa, especially in Africa that looks at providing EWS to the natural disaster and the financial sectors of the economies. However, over the decades, the rise of disasters, putting at risk many recent development gains in the Sub-Saharan Africa requires an EWS to provide a forward looking directions to mitigate disaster (Subramanian & Jha, 2010). Several studies that seek to develop capacities that will help mitigate natural disaster are mainly in the developed countries. This study, therefore considered that the issue of EWS on disaster and even in the financial sector is limited and therefore seeks to provide a study that can build capacity and knowledge of fire disaster risk in Ghana through research.

2.3 Fire disaster and Fire prediction

2.3.1 Fire disaster in Ghana and Africa

For some years back Ghana was seen to be far away from major disruptive disaster risk, such as the seismic activities, however it is recorded that Ghana recorded a damaging earthquake far back as 1615 and which major seismic activities have occurred in the years of 1862, 1906 and 1939 (Amponsah, 2004). From these years and beyond, Ghana is reported to have had several disaster risks, according to the International Disaster Risk Database. According to the International Disaster Database over the periods of 1996 to 2012, Ghana has suffered several disaster risks. The summary of natural disaster occurrence indicated that 10 natural disasters occurred over the period 1900 to 2014 (EM-DAT, 2014). According to United Nations Development Programme-UNDP (2010) in Ghana, the most experienced disaster risk are the fire, epidemics, pests and floods, but there are limited capacities within government authorities and among communities to cope effectively with these disaster risks. Due to the increased in the disaster risk identified, UNDP, the government of Ghana, risk managers and many internal and international bodies seek to develop capacities that will seek to identify, assess and monitor disaster risks, enhance early warning systems and strengthen NADMO’s disaster preparedness for effective response at all levels.

2.3.2 Global Issue of Fire Disaster Risk

Globally, the issues of fire disaster risk have received a lot of attention (Mckenzie, Petereson & Agee, 2000; Wang, Lu & Li, 2005; Cheng & Wang, 2008; Syphard, Radeloff, Keuler, Taylor, Hawbaker, Stewart & Clayton, 2008; Zhang, Yao, Liu, Yang & Boken, 2011; Taylor, Woolford, Dean & Martell, 2013; Bistinas, Harrison, Prentice & Pereira, 2014). Most of these studies focused on providing models that will help, statistically quantify the likelihood of the frequency of fire for fire prevention (Mckenzie *et al.*, 2000; Cheng & Wang, 2008; Syphard *et al.*, 2008; Zhang *et al.*, 2011; Bistinas *et al.*, 2014), whereas others provided the understanding of some of the information needed for fire management decision (Wang *et al.*, 2005; Taylor *et al.*, 2013). Table 2.2 and Table 2.3 are publications of various studies identified indicating the focus of their research and the method used to achieve their study.

Table 2. 2: Fire Disaster Risk Publication

Publication	Fire Disaster Risk	Method & Context	Findings
Bistinas *et al.* (2014)	Causal relationships versus emergent patterns in the global controls of fire frequency (2000–2005)	Fitting a Generalised Linear Model (GLM) - Global fractional burnt area data	The model predicts observed geographic and seasonal patterns
Júnior, Oliveira, Pereira, and Turkman (2014)	Modelling Fire frequency and fire return intervals over a12-year time series (1997–2008)	Discrete lognormal model (Brazilian Cerrado)	The estimated parameters were used to calculate fire interval, fire survival and hazard of burning distributions
Jiang, Zhuang and Mandallaz (2012)	Modelling large fire frequency and burned area in Canadian terrestrial ecosystems with Poisson models	Poisson models (Canada)	Calculated the probability of the burned area exceeding a certain size using a compound Poisson process

Source: Author’s construct

From the Table 2.2 and Table 2.3 it is shown that the fire disaster risk publication is enormous, Global study and regional studies have focused on fitting model for fire frequency, fire interval and burnt areas. Most of these studies fitted the discrete distributions such as lognormal, Poisson and negative binomial distribution to the data on fire. It assessed that various models developed for fire data are able to provide timely decisions to mitigate the risk of fire on various regions of study. Most of the stochastic models developed for fire are identified as well and are very important for empirical use. The reviews necessitate study in Ghana to help mitigate fire risk.

Table 2. 3: Fire Disaster Risk Publication

Publication	Fire Disaster Risk	Method & Context	Findings
Wang *et al.* (2005)	Presents an analysis of fire statistical data for China between 1998 and 2002	Method of average analysis, dynamic analysis and factor analysis (China)	Revealed that the government's efforts to fire protection have succeeded to some extent. In addition, fire occurring likelihood (fire frequency) and fatalities in fires have been also analysed
Mckenzie *et al.* (2000)	Estimating past fire frequency where local data are not yet available	Multiple regression models and tree-based (classification and regression tree, or CART) – (Columbia river basin)	The regression models predict fire return intervals from 1 to 375 yr for forested areas, whereas the tree-based models predict a range of 8 to 150 yr
Mandallaz and Ye (1997)	General statistical methodology for the prediction of forest fires	Poisson models (Case studies from France, Italy, Portugal and Switzerland)	Showed that Poisson models incorporating a fire danger index and other explanatory variables are superior to empirical use
Cheng and Wang (2008)	Integrated Spatio-temporal Data Mining for Forest Fire Prediction, based upon historic observations	Dynamic recurrent neural network for spatial forecasting (Canada)	An improved spatio-temporal integrated forecasting framework – ISTFF was proposed

Source: Author's construct

2.3.3 Fire Frequency Prediction

A number of past studies have come out with various types of probability distribution functions that could best be used to model various datasets including fire frequency data. Critically studying publications it is shown that most often, researchers assumes a particular distribution for modelling fire frequency. From the above publications in the Table 2.2 and Table 2.3, it is assessed that various probability risk models that were used to study several fire frequency data are assumed. The Generalized Linear Model, Simulation Models, Poisson Univariate Models, Multiple regression, Neural Networks, Factor analysis and CART are some of the few models that were identified to help mitigate fire risk. These models were used in estimating fire frequencies. According to Wang *et al*. (2005) who used the method of average analysis, dynamic analysis and the factor analysis, they indicated that the government's efforts to fire protection have succeeded to some extent and were able to provide with the model fire occurring likelihood (fire frequency) and fatalities. Similarly, Mckenzie *et al*. (2000) used regression models to predict fire return intervals that showed that fire likelihood from 1 to 375 yr for forested areas, whereas the tree-based models predict a range of 8 to 150 yr across the interior Columbia River basin using georeferenced fire history. Instead of using logistic regression and other identified models by other researchers, Syphard *et al.* (2008) used Poisson univariate and multiple regressions to develop the fire frequency models because they identified that Poisson univariate and multiple regressions were appropriate for count data. Syphard *et al*. (2008) purported that overlaying predictive maps of fire ignitions and fire frequency may be useful for identifying high-risk areas that can be targeted for fire management actions. In as much to determine the relationships between burnt areas and a set of variables related to explicit controls on biomass burning as by Bistinas *et al*. (2014), they showed using the Global Fire Emissions

Database (GFED) data, with 11 predictor variables representing vegetation, climate, land use and potential ignition sources indicated that GLM predicts observed geographic and seasonal patterns, as well as the emergent relationships seen when burnt area is plotted against each variable separately.

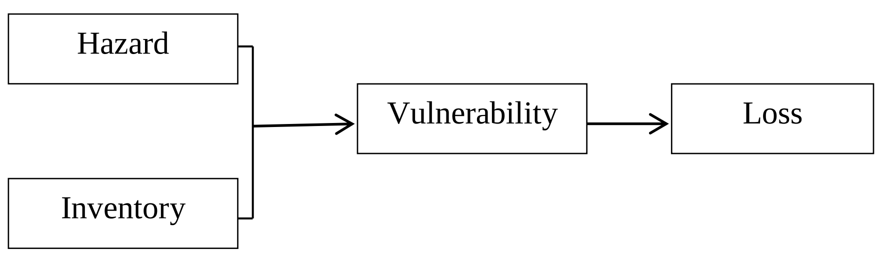
Survival analysis of fire frequency as it is often called in the fire literature as indicated by Moritz, Moody, Miles, Smith, and Valpine (2008) as an increasingly been used fire catastrophe model over a few decades to examine fire interval distributions. Most models that focused on fire frequency have identified fire to follow a Weibull distribution (Agee, 1993; Johnson & Gutsell, 1994; Grissino-Mayer, 1999; Rupp, Olson, Adams, Dale, Joly, Henkelman & Starfield, 2006; Moritz *et al.*, 2008; Morin, 2014; O'Connor, Falk, Lynch, & Swetnam, 2014). For instance, Moritz *et al.* (2008) study seeks to reveal whether the fit of the Weibull model using fire frequency (fire history data) was explicitly communicated considering the sampling decisions and censoring in fire interval data. The study using fire history in 2003 in Southern California showed that Weibull parameter estimates were roughly consistent with previous fire frequency analyses for shrub lands, and they further communicated that inclusion or omission of censored observations can have a substantial effect on parameter estimates. Fire frequency is an estimate of the probability distribution of survival or mortality from fire. According to Johnson and Gutsell (1994), fire frequency studies are generally carried out in order to estimate one of two related distributions: time-since-fire (survivorship) and fire interval (mortality). The time-since-fire or survivorship distribution as indicated by the author, A (t), measures the cumulative proportion of the entire landscape surviving longer than time t, while the fire interval or mortality distribution, f (t), is the probability of fire occurring in the landscape in the interval t to t + Δt per unit time. Another function, the hazard of burning, λ (t), ties together time-since-fire and fire interval distributions. It is the per capita age-specific mortality from fire, sometimes called mortality force or age-specific death rate. The study of Johnson and Gutsell (1994) is consistent with current studies such as Moritz *et al.* (2008) who showed that the models used to characterize time-since-fire and fire interval distributions: are the negative exponential and Weibull models. Although, the various studies shown up for fire frequency censored data is shown to be well modelled with Weibull distribution, it is clear that frequency of fire was collected as a censored but not a count data. Considering count fire frequency data that are used in this study, a distribution fitting procedure which is used to best select a statistical distribution of the data set will be employed. This will be done to avoid choosing any incorrect model that will have serious consequences such that the ability for the system to generate and project in time leading decisions to the study will not be an exemption.

Although fire frequency analysis is quite new, unique and complicated phenomenon (Born & Martin, 2006; Michel-Kerjan *et al.*, 2013), the above literature has made it challenging to study in Ghana and Sub-Saharan Africa. We can assess that various literature identified in this study is done outside Africa, although disaster events in Africa have affected millions and cause US$ 1.3 billion economic losses that is silently and persistently eroding the capacities of Africans to survive or prosper (EM-DAT, 2010). The review of literature paves way for the study into Africa in particular Ghana on issues of fire disaster risk preparedness.

2.4 Catastrophe Modelling

A random accumulation process nature and binary indicator of the frequency of fire events could be identified using catastrophe models. This phenomenon of occurrence of the event varies to some degree unpredictable as time goes on and therefore requires using probability distributions to scientifically deal with the uncertainties involved and make informed judgments. Catastrophe modelling is identified by Grossi and Kunreuther (2005) as a new way of managing risk that is originated in the fields of property insurance and the science of natural hazards. The author identified the components of a catastrophe model as: hazard, inventory, vulnerability, and loss which as depicted in the figure below

Figure 2. 2: Structure of catastrophe models



Source: Grossi and Kunreuther (2005)

For the above model to be able to provide risk management, Grossi and Kunreuther (2005) make us aware that the output is quantified and presented in a way that is useful to the stakeholders. For instance the EP curve gives an output option that provides a graphical representation of the probability that a certain level of loss will be surpassed in a given time period (Born & Martin, 2006).

2.4.1 Models for Fire occurrence Count Data

Count data typically result from the collapsing repeated binary events on subjects measured over some time period to a single count. The Poisson distribution and the Poisson regression are most popular and fundamental distribution used for the analysis of count data (Gardner, Mulvey & Shaw, 1995). The Poisson distribution gives the probability of the different possible number of occurrences of an event in a given time interval under certain conditions. For count data to be well modelled by the Poisson distribution, it assumes that the;

- events occur independently,
- events occur at random,
- The probability of an event occurring in a given time interval does not vary with time.

The Poisson distribution describes the probability to find exactly r events in a given length of time if the events occur independently at a constant rate μ. An unbiased and efficient estimator of the Poisson parameter μ for a sample with n observations $x_i is\ \hat{\mu} = \bar{x}$ the sample mean, with variance V $(\hat{\mu}) = \mu/n$ (Walck, 2007, pg. 134). In predicting large fire frequency and burned area have received a lot of research using the Poisson distribution (Jiang, Zhuang & Mandallaz, 2012). Using the compound Poisson process, Jiang, *et al*. (2012) was able to calculate the probability of the burnt area exceeding a certain size in the Canadian boreal ecosystems. The authors further in their study identified that the Poisson model simulates the large fire occurrence well during the fire season (May through August) and the compound Poisson threshold probability agrees well with historical records. Extant literature such Dayananda (1977) and Mandallaz and Ye (1997) used stochastic model that encapsulates the Poisson distribution to assess forest fire and predict forest fire occurrence respectively in their study. Mandallaz and Ye (1997) study presented a general statistical methodology for the prediction of forest fires in the context of Poisson models. The authors showed that forest fire that incorporates a fire danger index with other highly important explanatory variables will be best modelled using the Poisson distribution. Although Poisson is identified to be more appropriate in modelling fire count data several studies also used logistic, multiple regression, Markov chain models, Generalised Linear Model (GLM) and many more (Chou, Minnich & Chase, 1993; Martell, 2000; Mckenzie *et al.*, 2000; Bistinas *et al.*, 2014) this could be due to the inappropriateness shown in Poisson modelling ecological data (Linden & Mantyniemi, 2011; Xiao, Ju Zhang & Ji, 2011; Lawless, 1987).

In most of the ecological data which are mostly countable data, stochastic models such as the negative binomial which is seen to encapsulate the overdispersion parameter that is not found in the Poisson distribution is widely identified. Bolker (2008) suggested that due to the unfamiliarity of ecologists to probabilistic models, they turn to use deterministic building block (e.g. linear or Michaelis-Menten functions) rather than the stochastic building blocks (e.g. the negative binomial or gamma distributions). However, in this study, the researcher bridge this gap by using stochastic process to better fit distribution to the fire data. The stochastic model better incorporates noise in some way, it is not often nested and are able to describe skewed the data by converting it to normality in some limit (Bolker, 2008). Considering the various models identified above for assessing fire risk, this study will use a distribution fitting procedure which is best used to select a statistical distribution of a data set.

2.5 Methods used to provide fire disaster risk EWS

Methods used in providing early warning of fire literature is of diverse situation due to the reason that data collected on fire from various macro-economic environment are of different forms. It is asserted that fire data from studies is seen as complex data that include weather history, fire history, fire ignition, fire spread. Also some various studies used data that are censored and also are counted. Due to the nature of data that is collected on fire occurrences in various areas, several methods and models have aroused to help manage fire risk. Critically assessing, it is found out that the two major methods are identified to be used in modelling fire to better provide fire predictions. The deterministic and stochastic methods are the most frequently used methods by ecologist in modelling fire. Most fire prediction models are deterministic, incorporating physical mechanisms for fire spread and fire growth but does not allow for stochastic variability of the output, other than by varying the initial conditions or varying the weather or fuel type to see how a fire will grow or spreads (Boychuk, Braun, Kulperger, Krouglya, & Stanford, 2009). Bolker (2008, p.9) informs that the a purely deterministic model allows only for qualitative comparisons with real systems, however the stochastic models used for modelling fire incorporate noise or randomness in some way describing the stochastic model by specifying a reasonable probability distribution for the variation.

2.6 Importance of an EWS

Early warning signs and systems include procedures, notices and safety management system in place that is of greatest importance or significance to the people at risk. Basher (2006) informs that if an EWS is to be justified on its benefits, there is a need to define and measure not only the benefits but also the contribution made by each part of the system. Leading UN agencies announced at the conference the launch of an International Early Warning Programme (IEWP), that the IEWP is a vehicle to stimulate and coordinate cooperative initiatives to advance early warning methodology and to build early warning capacities (Basher, 2006). EWS provides informing policies that are aimed at preventing crises. EWS gives an advance warning given the lags in effective policy action, producing procedures that are comprehensible for policy makers (Davis & Karim, 2008).

CHAPTER THREE

RESEARCH METHOD

3.1 Introduction

Studies that are aimed at reducing uncertainties and providing strategic choices through forecasting have become much important during and after the world war (II) (Rossel, 2011). This forecasting is based on calculable inputs upon time series and 'what if analysis' and other system-based methodologies involved highly expert opinion. Due to the nature of this method catastrophe modellers have developed alternative methodologies based on stochastic simulation techniques (Grossi & Kunreuther, 2005). The stochastic method provides the most comprehensive depiction of the likelihood of losses from extreme events. In this study, various probabilistic risk analysis tool that uses stochastic process are studied, this will help determine the likelihood of fire occurrence and fatalities. This chapter presents the methodology used in the research. It explains in details the steps in the modelling process which include the data processing methods used in order to achieve the research objective.

Various models have shown up for fire frequency data (Agee, 1993; Johnson & Gutsell, 1994; Grissino-Mayer, 1999; Rupp *et al.*, 2006; Moritz *et al.*, 2008; Morin, 2014), in this study a distribution fitting procedure is used to best select a statistical distribution of the count data set on fire identified in Ghana. In many fire occurrence data sets, frequency distributions do not exhibit a distinct shape, which otherwise would aid the identification of a particular class of models to which the data set belongs. The distribution fitting is used to avoid choosing any incorrect model that will have serious consequences on the ability for the system to generate and project in time leading decisions from the study. The distribution fitting method is preferred, especially in cases which there is a little or no information about the base distribution pattern in data, and there is the desire to find the best distribution type (Mehrannia & Pakgohar, 2014), however, to the best knowledge of the study there is no base distribution of fire data in Ghana which the study seeks to identify. However, for the purposes of benchmarking the candidate models and some models from the review of literature of fire frequencies which are identified are explained.

3.2 Data and Scope

Greener (2008) indicates that secondary data saves a considerable time and gives a useful benchmark or context in which we can set up research design or a way of triangulation results. The source of data used in this study was secondary, the data were obtained from the Ghana Open Data Initiative and bodies that collect, process, archive and disseminate disaster risk information in Ghana and beyond. The study used fire count data from Ghana from 2007 to 2011 which consist of the monthly number of rescue injury, death and count fire frequency on all the regions previewed in the data set in Ghana to provide early warning systems.

3.3 Exploratory Data Analysis

A modelling process helped describe the steps that were followed by fitting a statistical distribution to the past events of fire disaster data. Data analysis included the descriptive statistics and Visualizations of the data set aiding in the prior selection of the possible family of distribution for the data of the research. The exploratory data analysis followed the methods below to achieve the research objectives;

Descriptive Statistics

1. Measures of location (mean, 1st quartile, 2nd quartile)

2. Measures of variation (variance, standard deviation)

3. Measures of symmetry (skewness)

Visualizations

1. Probability plots
2. Line plots

3.4 Modelling Process

The modelling process describes the steps that were followed in fitting a statistical distribution to the fire occurrence data. Most studies that focused on modelling fire frequency have identified fire to follow a Weibull distribution (Agee, 1993; Johnson & Gutsell, 1994; Grissino-Mayer, 1999; Rupp *et al.*, 2006; Moritz *et al.,* 2008; Morin, 2014), where others showed that dataset from fire frequency follows a Poisson univariate distribution (Syphard *et al*., 2008), however Díaz-Delgado, Lloret and Pons (2004) identified that the Poisson model does not allow a complete interpretation, since it does not describe survivorship, mortality or fire risk functions, which are characteristics of fire frequency models. A study by Oliveira, Turkman and Pereira (2013) showed that the discrete lognormal model is more appropriate for fire risk analysis, providing a better estimate of fire interval, survival and hazard of burning distributions. In considering over dispersed count data, Ver Hoef and Boveng (2007) were able to show that the negative binomial model could be used for overdispersed count data. Since this study used discrete count data which may be more prone to more variability than expected, the overdispersion model identified by Ver Hoef and Boveng (2007) was more likely to be identified in this study. It is necessitated this study to consider several overdispersion models as benchmark models of the study. So far, to the best knowledge of this study, studies have identified Weibull, Poisson, Negative Binomial and Discrete lognormal as the distribution of fire data which warrant this study to use them as benchmark distribution. Diverse model are specified for fire because of the differing methodology of fire data obtained from countries of unequal macro indicators, most studies used continuous distribution to represent the variability in wildfire size that can be approximated by a discrete distribution with a suitable size and number of classes. It is therefore relevant that this study used the distribution fitting method since very little or no information about the base distribution pattern of the frequency of fire in Ghana is unknown.

In order to appropriately fit a base distribution to the fire data of Ghana, the steps below were judiciously followed to model the data set;

1. Selection of Certain Family of distributions
2. Estimation of the model parameters
3. Criteria selection to choose the model
4. Testing the Goodness-of-Fit
5. Check the best model that fit the data

3.5 Selection of Certain Family of Distribution

In this step of modelling process considerations were made of a number of probability distributions that has shown up in the review literature as the potential candidate's distribution for fire frequency. Although, the lists of potential probability distributions are enormous, it is worth emphasizing that the choice of distribution is most often to some extended subjective (Achieng, 2010), because priory our data is discrete which means discrete distributions are preferred here. The researchers subjective means of choosing a family of distribution were with regards to the;

1. Output of the exploratory data analysis
2. Type of data considered
3. Prior knowledge and inspection of descriptions of data

Considering there are no known one way that fire data follows, candidate distribution chosen to model monthly number of fatalities and count fire frequency data on all the regions were the Weibull distribution, the Poisson distribution, the Discrete uniform, the Log-normal distribution, and the Negative Binomial distribution. These distributions were chosen because of the skewed nature of the data and from subjective views and in the review of literature.

3.5.1 The Weibull Distribution

The first generalization of the two-parameter Weibull distribution accommodates nonmonotone failure rates were introduced by Mudholkar and Srivastava (1993) and it is known as the exponentiated Weibull (EW) distribution. A random variable, X, has a Weibull distribution with parameter b and c if the probability density function is given by;

Probability Density Function (PDF)

The probability density function equation (3.1) reflecting the frequency of fire occurrence in a given time interval is given as;

$$f(t \mid b,c) = \frac{c}{b}\left(\frac{t}{b}\right)^{c-1} exp\left\{-\left(\frac{t}{b}\right)^{c}\right\} \; ; \; b,c \in \mathbb{R}^{+} \qquad \text{...... eq (3.1)}$$

Cumulative Distribution Function (CDF)

The CDF computes the probability of fire occurrence before or at a time x

$$F(t \mid b,c) = \int_0^t f(u \mid b,c)\, du = 1 - exp\left\{-\left(\frac{t}{b}\right)^{c}\right\} \qquad \text{...... eq (3.2)}$$

Hazard rate (HR)

Gives the probability of a fire to occur within a specific time interval

$$h(t \mid b,c) = \frac{f(t \mid b,c)}{1 - F(t \mid b,c)} = \frac{c}{b}\left(\frac{t}{b}\right)^{c-1} \qquad \text{...... eq (3.3)}$$

where t is the random variable from the distribution

b has the domain $(0, \infty)$; **c** has the domain $(0, \infty)$

b is the scale parameter, indicating the expected interval between fires

c is the shape parameter, shows how the hazard of fire occurrence changes with time since the last fire; thus an indication of the change in fire probability through time

3.5.2 The Poisson distribution

The Poisson model assumes an underlying constant rate of event, it provides the count of events over a fixed amount of time at risk**.** The Poisson model is appropriate for observing Y fires, the probabilities of observing any specific count, y, over a time t for a given area with average frequency μ per unit of time is given as;

$$\Pr(Y = y; \mu t) = \frac{(\mu t)^{y} e^{-\mu t}}{y!} \qquad \text{...... eq (3.4)}$$

Where **μt,** is called the rate of the Poisson process.

The log-likelihood function for Poisson depending on the observed sample data regarded as a function of the parameter is computed with the formula below;

Log-likelihood of Poisson (μ)

$$\ln \mathrm{F}(x) = \sum_i^n X_i \ln \mu - n\mu - \sum \ln(X_i!) \qquad \ldots\ldots \text{ eq (3.5)}$$

3.5.3 The Log Normal Distribution

The lognormal distribution is a probability distribution that has intriguing theoretical and practical properties. Júnior, Oliveira, Pereira and Turkman (2014) used the discrete lognormal model to estimate parameters that were used to calculate fire interval, fire survival and hazard of burning distributions. As the PDF suggests, the lognormal distribution is the distribution of a random variable x in a log space. If the data size is too large it is assumed to be approaching Normal distribution. A random variable x, is said to have a lognormal distribution with parameter μ and σ^2 if $Y = \log x \sim N(\mu, \sigma^2)$

Probability Density Function (PDF) is given as

$$f(x) = \frac{\exp\left(-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right)}{x\sigma\sqrt{2\pi}} \qquad \ldots\ldots \text{ eq (3.6)}$$

Cumulative Distribution Function (CDF) is given as

$$F(x) = \Phi\left(\frac{\ln x - \mu}{\sigma}\right) \qquad \ldots\ldots \text{ eq (3.7)}$$

Where $\Phi(x)$ = The Laplace constants is given by

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_0^x e^{-t^2/2} dt \qquad \ldots\ldots \text{ eq(3.8)}$$

Where μ – Population Mean σ – Population Standard deviation

3.5.4 The Negative Binomial

The negative binomial model is a distribution used for the analysis of count data, identified as a special generalization of the Poison distribution. The negative binomial distribution account for the practices which lead the Poisson model to overdispersion and underdispersion that may be found in a data and therefore provides another parameter that quantifies extra Poisson variation (Lawless, 1987). The nonnegative discrete random variable X has a negative binomial distribution with parameters k and μ, denoted by NB (k,μ). The Probability Mass Function (PMF) of an event x is given by

$$f(X = x) = \frac{\Gamma(x+k)}{\Gamma(x+1)\Gamma(k)} \left(\frac{k}{k+\mu}\right)^k \left(\frac{\mu}{k+\mu}\right)^x \quad \text{for } x = 0, 1\ldots\ldots \qquad \text{eq (3.9)}$$

Where k represents the dispersion parameter. The mean is μ, as in the Poisson model, but the variance is $\mu + \mu k^2$, thus allowing the variance to exceed μ. k is also called size (overdispersion parameter), because it is mathematically equivalent to n in the failure-process parameterization.

The log-likelihood function for the Negative binomial depending on the observed sample data regarded as a function of the parameters is computed with the formula below;

Log-likelihood of Negative Binomial (k, μ)

$$\ln F(x) = \sum (x + k - 1)! + nk \ln \mu + \sum x \ln(1 - \mu) - \sum \ln(x!\,(k - 1)!)$$

…… eq (3.10)

3.5.5 The Discrete Uniform Distribution

A non-negative discrete random variable X has a discrete uniform distribution with parameters denoted by DU(a, b)the Probability density function is given by

$$f(x) = \frac{1}{b-a+1} \quad \text{for } x = a, a+1, \ldots\ldots, b \qquad \text{…… eq (3.11)}$$

The discrete uniform distribution is also known as the "equally likely outcomes" distribution.

The survival function of a fire event occurring is

$$s(x) = \frac{b-x+1}{b-a+1} \quad \text{for } x = a, a+1, \ldots\ldots, b \qquad \text{…… eq (3.12)}$$

The hazard function of a fire event occurring is

$$h(x) = \frac{f(x)}{s(x)} = \frac{1}{b-x+1} \quad \text{for } x = a, a+1, \ldots\ldots, b \qquad \text{…… eq (3.13)}$$

The log-likelihood function for the Discrete Uniform distribution also depending on the observed sample data regarded as a function of the parameters is computed with the formula below;

Log-likelihood of Discrete Uniform distribution of parameter (a, b)

$$\ln \mathrm{F}(x) = n \ln\left({}^{1}/_{b - a + 1} \right) \quad \ldots\ldots \text{ eq (3.14)}$$

3.5.6 The Normal Distribution

The negative binomial is a generalization of the Poisson (Xiao, Zhange and Ji, 2015) whiles the normal distribution indicates the possibly convergence of all discrete distributions. Since most discrete distributions converges to the normal, the probability density function of a normal random variable X with mean μ and standard deviation σ is given by

$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right], -\infty < x < \infty, -\infty < \mu < \infty, \qquad \sigma > 0$$

$$\ldots\ldots \text{ eq (3.15)}$$

The normal distribution is commonly denoted by $\mathrm{N}(\mu, \sigma^2)$

3.5 Estimation of Model Parameters

Probability distribution fitting software is used to model the sample data, the fire frequency and fatality data of the study were modelled. The Estimation methods used for a good balance between accuracy and speed of calculations are the Maximum Likelihood Estimation (MLE) for the models under study. Looking at the least square estimate method of modelling parameters, it computes parameters by minimizing the squared discrepancies between observed data, on the one hand, and their expected values on the other hand. It is also used to estimate numerical values for the parameters that minimize the sum of the squared deviations between the observed responses and the functional portion of the model. The method of moments is a type used in estimating model parameters by equating sample moments to parameter estimates. When moment methods are available, they have the advantage of simplicity. However, the method of moments estimation is based solely on the law of large numbers. For instance, if $M_1, M_2, \ldots \ldots$ be independent random variables having a common distribution possessing a mean μ_M. Then the sample means converge to the distribution mean as the number of observations increases.

$$\overline{M_n} = \frac{1}{n}\sum_{i=1}^{n} M_i \quad \rightarrow \mu_M \text{ As n} \rightarrow \infty. \qquad \ldots\ldots \text{ eq (3.16)}$$

The primary use of moment estimates is as starting values for the more precise maximum likelihood and least squares estimates. The maximum likelihood estimates are used in the estimation of the model parameters because they have several desirable properties which include: consistency, efficiency, asymptotic normality and invariance. The advantage of using maximum likelihood estimations is that it fully uses all the information about the parameters contained in the data and it is highly flexible than the others (Denuit *et al.*, 2007).

3.6 Criteria selection and goodness of fit to choose the model

Model selection is an important part of any statistical analysis and, indeed, is central to the pursuit of science in general (Kadane & Lazar, 2004). Most empirical economic research that involves the specification, estimation and evaluation of statistical model base on certain criteria selection to choose an appropriate model for sample data. Model selection is often conducted by ranking models by their out-of-sample forecast error. Such criteria only incorporate information about the expected value, whereas models usually describe the entire probability distribution (Norwood, Ferrier & Lusk, 2001). This Test for goodness of fit usually involves examining a random sample from some unknown distribution in order to test the null hypothesis that the unknown distribution function is in fact a known, specified distribution. Goodness-of-Fit tests can be used to determine whether a certain distribution is fitted properly to the data or not. The statistics of Goodness-of-fit test also helps to rank the fitted distributions according to quality of fit of the raw data.

Model determination is an essential piece of any measurable examination, and to be sure that the model is the well fitted with any of the candidate models. This study used the Log-likelihood statistics, Akaike's Information Criteria (AIC) and the Bayesian Information Criterion (BIC) for the selection of the models identified in this study. Since the criteria selection methods are based on the likelihood statistics of the parameter(s) of each distribution, the likelihood of each distributional parameter is computed and subsequently their AIC values and BIC values are calculated with the formulas below;

$$\text{AIC} = 2k - 2\ln L\,(\theta) \qquad \ldots\ldots \text{ eq (3.17)}$$

$$\text{BIC} = \ln\text{L}(\theta) - \frac{1}{2}k\ln(n) \qquad \ldots\ldots \text{ eq (3.18)}$$

Where K is the number of parameters in the model and lnL(θ) is the maximized log-likelihood

3.7 Check the best model that fit the data (Summary)

In checking the best model that will fit the fire frequency and fire fatality data, the criteria selection methods, the log-likelihood statistics and the also the several goodness of fit test will be based to make a subjective judgment on the appropriate model for the data coming from the various regions under study. At this final stage of the modelling the distributions are now verified graphically using the probability plot to justified the best model for the study. The likelihood plot provides a graphical procedure for evaluating whether a data set follows a given distribution.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter discusses the various distributions of fire frequency count data collected from the Ghana Open Data Initiative from 2007 to 2011. The chapter used exploratory data analysis (histogram, mean, skewness, maximum value, minimum value, standard deviation, and 1st and 3rd quartile), visualization plots and the modelling process to assist in the identification of the family of distribution which the region's fire data followed. The diagnostics test probability plot was used to graphically demonstrate the goodness of fit to the fitted distributions. The Goodness-of-Fit tests were used to statistically test the fitness of the distributions. The log-likelihood statistics and the criteria selection methods such as the Bayesian Information Criterion which are the Akaike Information Criterion (AIC) and Bayesian-Bayes Criterion (BIC) was used to establish the best fit distributions. Statistical predictions through confidence interval assisted in determining the magnitude of fire risk on the various regions in Ghana under study.

4.2 The Exploratory Data Analysis of the Fire Count Data

Fire count data on various regions which were monthly reported statistical descriptive are previewed in this section. The exploratory data analysis is in two parts the descriptive statistics and visualization plots of various fire count data. The section below explains data on fire frequencies of various regions and their subsequent fire fatalities.

4.2.1 Descriptive statistics

In this section, the descriptive statistics of the data under study are previewed among the various regions. It is assessed that data under study consisted of 12 regions of which their fire frequency count data have been collected. The various regions under study are Ashanti, Western, Volta, Upper West, Upper East, Tema, Northern, Head Quarters (Head Qrts), Greater Accra (G. Accra), Eastern, Central and the Brong Ahafo. In as much to provide exploratory analysis of the fire occurrence data means, standard deviations, Variances, skewness, and the 1st and 3rd quartile of the data for each region is presented in the descriptive statistics table. The average of monthly fire received at each region under the study is computed and shown in the table below.

Table 4. 1: Descriptive statistics of fire frequency

Regions	Mean	std. Dev	Variance	Skewness	Q1	Q3
Ashanti	59	26.988	728.37	1.3695	42	69
Western	14.967	7.9602	63.366	1.3101	11	17
Volta	3.4833	5.2424	27.483	2.7244	0	4.5
Upper West	10.233	9.6166	92.479	2.4983	4.5	13.5
Upper East	13.05	8.607	74.081	1.0719	7.5	17.5
Northern	9.2333	7.9254	62.812	1.1771	4	13
Greater Accra*	79.75	21.468	460.869	1.6422	67.75	90.50
HeadQrts	10.6	6.9118	47.773	0.40246	5.5	15.5
G.Accra	48	15.701	246.51	1.4108	37	55
Tema	21.15	7.2292	52.261	0.79891	15.5	24.5
Eastern	16.917	15.112	228.38	3.6849	10	19.5
Central	23.517	13.657	186.53	1.1842	14	28.5
Brong Ahafo	22.183	24.665	608.38	2.3348	9.5	24
Overall	252.33	102.24	10453.0	1.8513	186	291

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

The results in Table 4.1 indicates that the expected monthly fire occurrence in Greater Accra* is seen as the highest among the regions, it indicated that an expected monthly return of fire in Greater Accra is 79.75. This not surprising to see that fire occurrence has the highest monthly frequency in Accra, because it houses most of Ghana's populace. The standard deviation was

21.468, a variance of 728.37 indicating high dispersion of fire occurrence. Also, the lower and upper quartiles of the fire data from the Greater Accra region are 67.75 and 90.5 respectively. Secondly, the next closest region, which has a higher mean monthly fire occurrence is in the Ashanti region, an average of 59 monthly count fire occurrences is expected the region, which has its lower and upper quartiles of the fire occurring at42 and 69 respectively. Subsequently, data show that G.Accra, Central, Brong Ahafo, Tema, Eastern, Western, Upper East, Head Quarters, Upper West, Northern, and Volta region follow in order of frequent occurrence of fire in a particular area. The fatalities that arise as a result of the frequency of fire in a particular region descriptive statistic is also previewed in the below Table 4.2.

Table 4. 2: Descriptive statistics of fire fatalities

Regions	Mean	std. Dev	Variance	Skewness	Q1	Q3
Ashanti	6.6944	6.9435	48.212	1.5173	2	5
Western	0.19444	0.46064	0.21219	2.3529	0	0
Volta	0.11111	0.5152	0.26543	5.0305	0	0
Upper West	ND	ND	ND	ND	ND	ND
Upper East	0.08333	0.49301	0.24306	5.747	0	0
Northern	0.19444	0.61551	0.37886	3.4282	0	0
Greater Accra*	1.389	2.1945	4.8159	2.168	0	2
Head Qrts	0.08333	0.27639	0.07639	3.0151	0	0
G. Accra	0.58333	1.1396	1.2986	2.2157	0	1
Tema	0.72222	1.7258	2.9784	3.3512	0	0.5
Eastern	2.3333	3.44	11.833	1.6532	0	3.5
Central	3.1944	7.6515	58.546	3.878	0	2
Brong Ahafo	3.4722	7.8404	61.471	2.6132	0	0
Overall	17.667	15.171	230.17	1.1194	6.5	28.5

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy, **ND:** No data

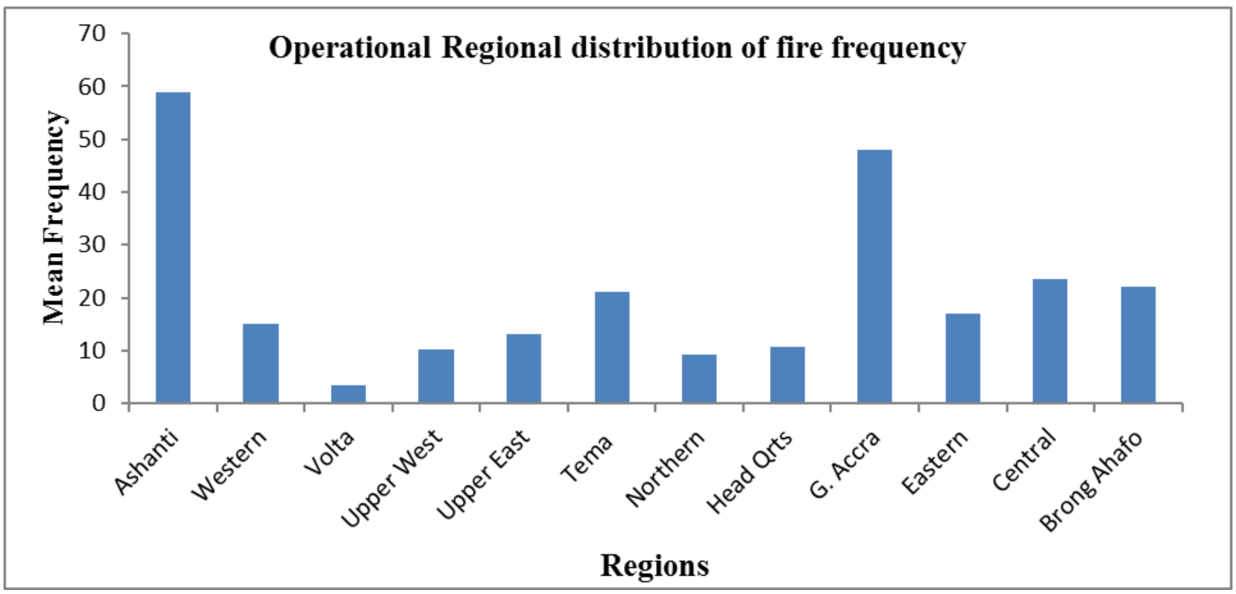
Table 4.2 presents the fire fatalities on the economy, it is designated that the highest expected monthly fire fatality is shown at the Ashanti region with a highest mean of 6.6944. This shows that the higher frequency of fire in the Ashanti region has resulted in a high fatality occurrence through fire. The variance was as high as 48.212 indicating high dispersion from one sample to another. Also, the lower and upper quartiles of the fire fatality data from Ashanti region are 2 and 5 respectively. Secondly, the next closest region, which has a higher expected monthly fatality is the Brong Ahafo region, an average of 3.4722 fatalities occurring with no lower and upper quartiles of the fatalities. It is shown that although Brong Ahafo wasn't shown to have the next highest frequency of fire, fatality from fire in this area is identified the second highest among the regions, an indication that the high frequency of fire does not necessarily indicate higher fatality. Subsequently, data shows that Central, Eastern, Greater Accra*, Tema, G. Accra, Northern, Western, Volta, Head Qrts and Upper East follow in order of magnitude of the fatalities of fire in the country. However, it's shown in the table that over the period of study the Upper West region recorded no fatality (NF) through fire. In overall the fatality data from the study indicates that the expected monthly of fatality through fire in the country is 17.667 where the occurrence is subjected to a low middle number of 6.5 and a high of middle number 28.5 in a month.

In overall, the descriptive statistics of fire frequency indicate that the expected monthly occurrence of fire frequency in the country is 252 and its subsequent fatality (death) is 17.667. Comparing the variances to the mean occurrences of fire and fatality, it is shown that the variances are slightly larger than the means for all regions, indicating that there is a potential overdispersion associated with the fire count data.

4.2.2 Visualization Plot

The figure below is the regional distribution of fire occurrence; the line graph provides a pictorial overview of how fire frequency data behaves by regions. The figure shows trends in data clearly, indicating which of the regions have higher or smaller frequency of fire occurrence. Also for the data of the fire fatality the line chart is also used to display data or information that varies continuously amongst the regions. The line graph is useful for identifying patterns and trends in the data, such as seasonal effects, large changes and turning points. The line chart below is the regional distribution of fire occurrence.

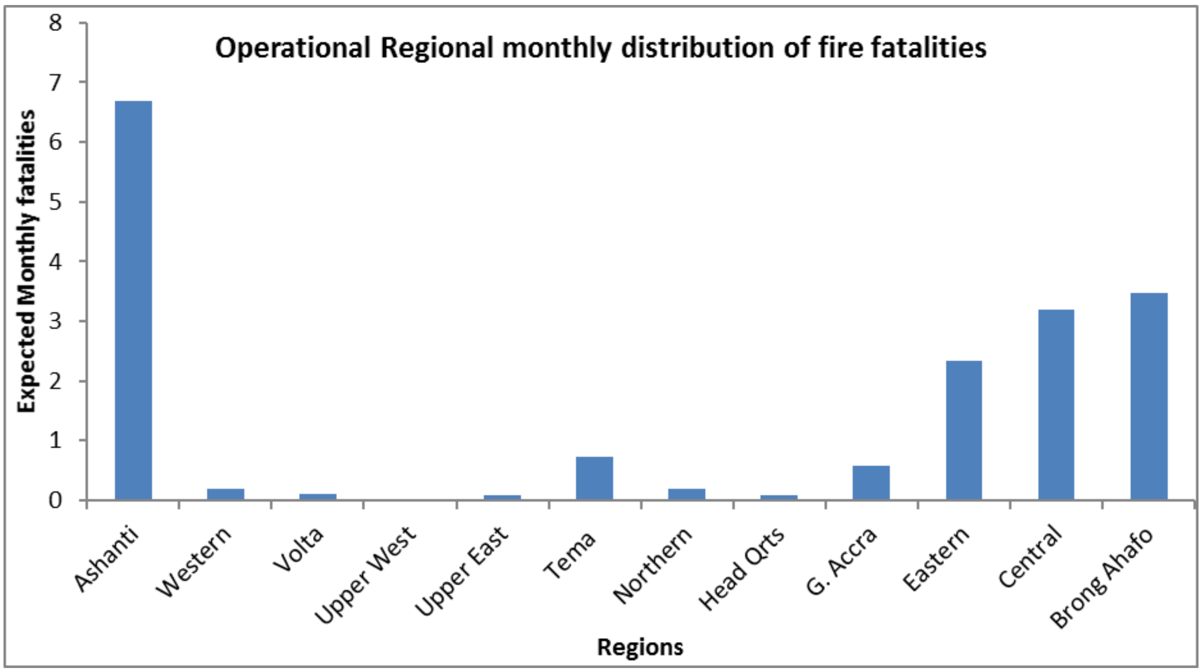
Figure 4. 1:Operational Regional Distribution of fire frequency



The figure above is the regional distribution of fire frequency the figure shows the trends in the fire occurrence data, clearly, there is an indication that Ashanti region has the highest occurrence of fire, whiles Greater Accra follows in the number of fire frequency. It is visualized that the Tema, Central region, Brong Ahafo and Western region have recorded the highest number of fire frequency whiles the other regions are shown in the line graph.

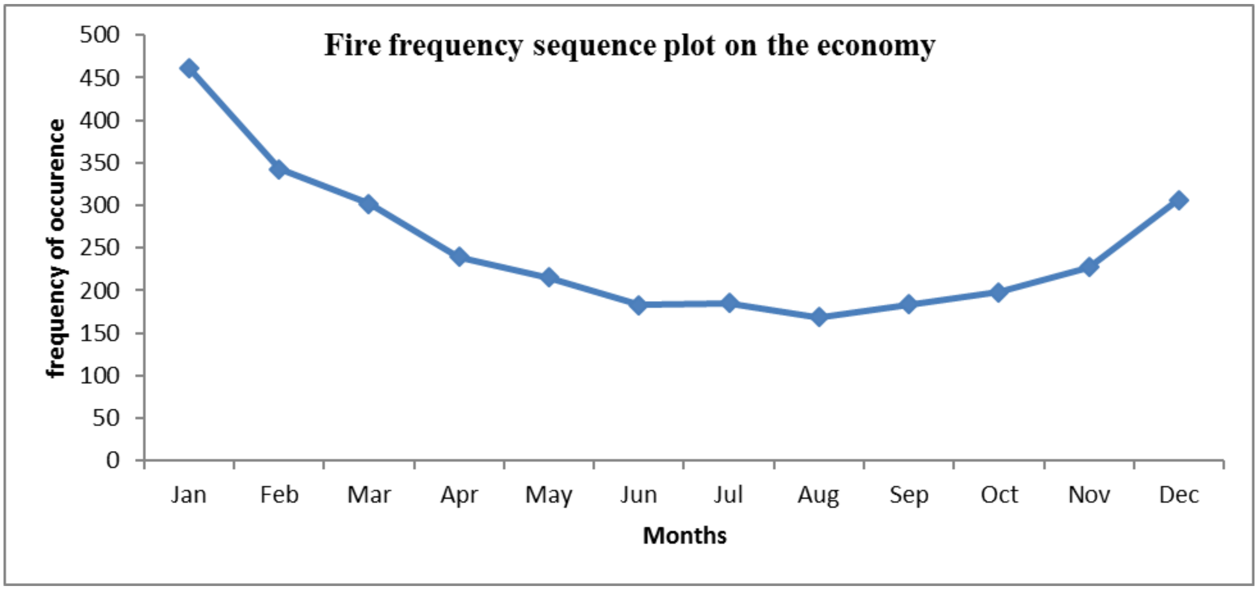
The figure below is the regional distribution of fire fatalities, the figure shows trends in data clearly, indicating which of the regions have higher or smaller fatalities through fire. We can visualize that the Ashanti region, Brong Ahafo region, Central and Eastern region have recorded the highest number of fatalities through fire. Also the other regions have been clearly visualized in the line graph.

Figure 4. 2: Operational Regional Monthly Distribution of fire fatalities



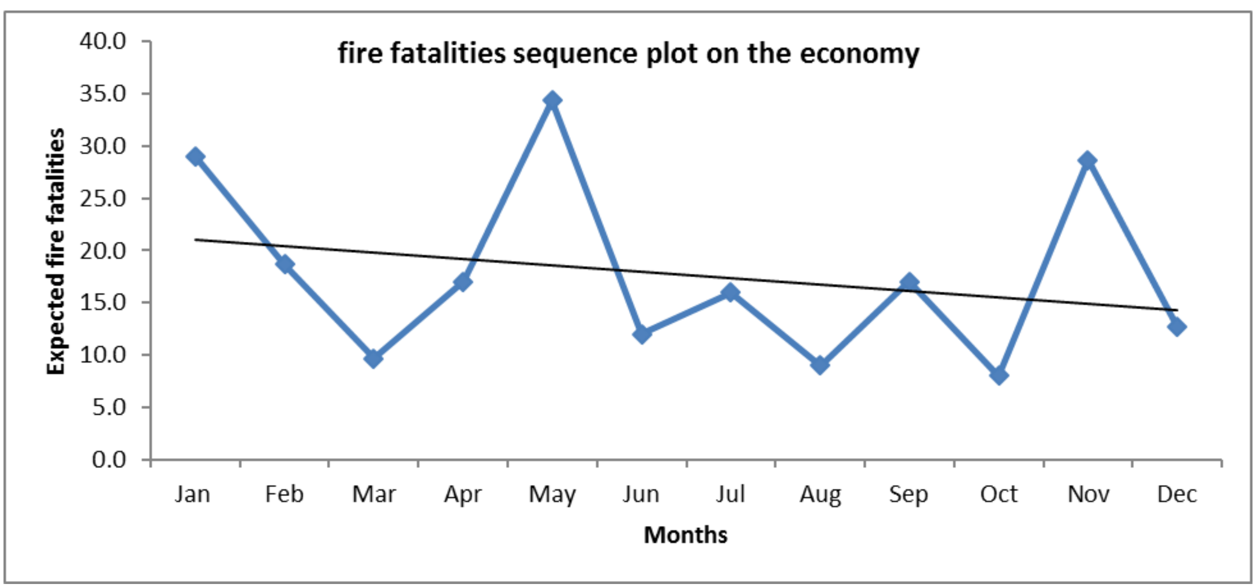
Considering the monthly previewed data, below is a fire frequency sequence plot indicating how fire occurs over the months in the country. It is assessed that highest frequency of fire occurs during the first months of the year where the frequency of fire reduces gradually to the month of August. However, as shown from the graph during the period of September the frequency of fire rises till the end of the year.

Figure 4. 3: Fire frequency sequence plot on the economy



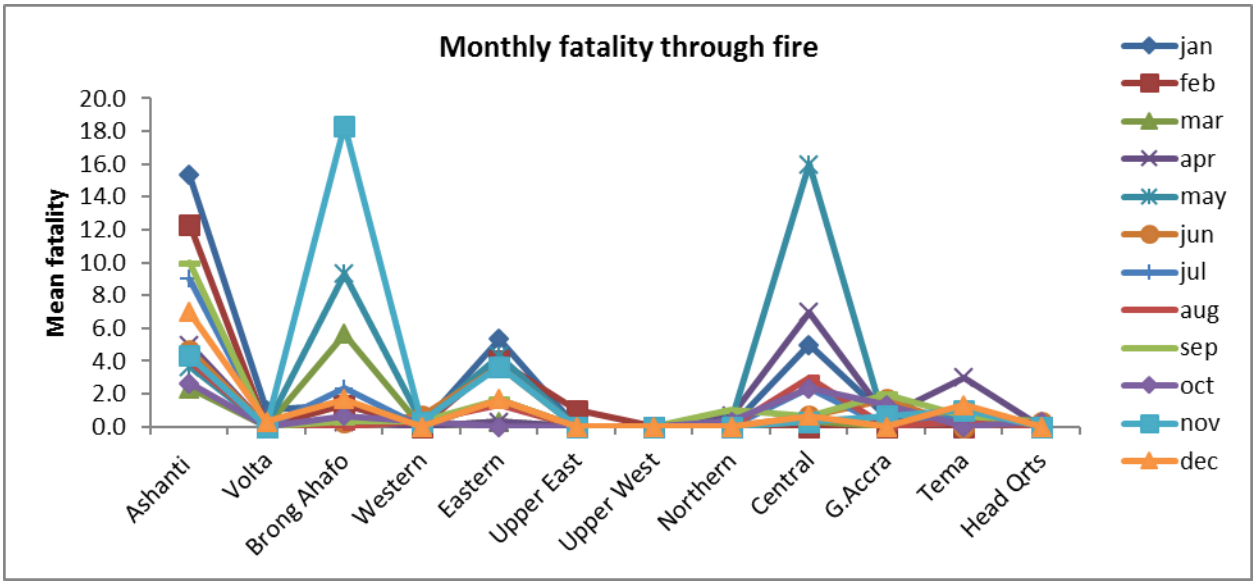
Considering the fatalities that arise as a result of the fire below sequence plot indicates how the monthly fire fatalities increases or decreases in the country. It is assessed that highest fire fatalities recorded during the month may although the frequency plot indicated a reducing trend. January, May and the month November are also seen to have a higher fatality resulting from fire whiles the rest of the months fatalities resulting from fire decreases.

Figure 4. 4: Fire fatalities sequence plot on the economy



The higher fatality that showed up during the month of May is not conforming to the number fire occurrences shown in the fire frequency plot. In order to determine which regions that were contributing to the higher fatality in the month of May, below Figure 4.5 indicates that fatality from Central region contributes more to the fatality that economy incurs. It is also shown that Brong Ahafo region is the next contributing region to the fire fatality that occurs in the month of May. It is also shown in this figure how each of the operational regions risk of fatality through fire occurrence.

Figure 4. 5: Monthly Fire fatalities amongst operational regions



4.3 The Modelling Process

Choosing the best fit distribution for a data set involves several statistical techniques and tools, in estimating the model parameters the Maximum likelihood was used to identify the various models of the count fire data under study. The method of maximum likelihood is intuitively appealing, because it attempts to find the values of the true parameters that would have most likely produced the data that is observed. It is the most versatile method for fitting parametric statistical models to data. The fire frequency data and fire fatalities data from the regions under study (Administrative and Operational regions) were used to help achieve the study objectives.

4.3.1 Selections of Candidate Models and Parameter Estimation

The exploratory data analysis assisted in the selection of the following distribution for the modelling process. Choosing good candidates among a predefined set of distributions, the stochastic process was used to model the variables and its empirical distributions were identified. Due to the nature of the dataset being counted data the researcher based on empirical density cumulative distribution graphs, and the Cullen and Frey graph of theoretical distributions of the Negative Binomial distribution, the Discrete Normal distribution, and the Poisson distribution selected as the candidate models after testing a wide range of distributions. The first step used in fitting a model to the fire frequency data and fire fatalities data was done by finding the parameter estimates of the statistical distribution. Acheing (2010) suggested that in obtaining the parameters of the distribution literally means the statistical distribution has been fitted to the data set.

The table 4.3 below shows the parameter estimates from the three models considered for the fire frequency data based on the exploratory data analysis. The Negative Binomial (r and θ parameters) employs more general specifications which is a standard choice for a basic count data model; the Discrete Normal distribution (μ and δ parameters) used to model experimental outcomes that is characterized by maximum entropy, specified mean and variance; the Poisson distribution (μ) gives probability of observing fire events in a given period of time assuming that events occur independently at a constant rate were fitted to the Ghana fire frequency and fatality data on the entire economy. The parameters obtained for the various statistical distributions are previewed in the Table 4.3 below. The Negative Binomial distribution (Neg. Binomial), the Normal distribution and the Poisson distribution are fitted for the fire frequency data.

Table 4. 3: Parameter estimation of fire frequency by maximum likelihood

	Neg. Binomial		Normal		Poisson
Regions	**k**	[illegible]	**μ**	[illegible]	**μ**
Ashanti	4.029	59.003	59.00	26.9883	59
Volta	0.5206	3.4847	3.4833	5.2424	3.4833
Brong Ahafo	0.6465	22.1834	22.1833	24.6654	22.1833
Western	4.7031	14.9672	14.9667	7.9602	14.9667
Eastern	2.2863	16.9184	16.9167	15.1121	16.9167
Upper East	2.5581	13.0513	13.0500	8.6070	13.05
Upper West	1.7436	10.2343	10.2333	9.6166	10.2333
North	1.3472	9.2339	9.2333	7.9254	9.2333
Central	2.8501	23.5142	23.5167	13.5431	23.5167
Greater Accra*	19.5313	79.7534	79.7500	21.2882	79.75
G.Accra	13.5766	48.0005	48.0000	15.5692	48
Tema	14.8804	21.1502	21.1500	7.2292	21.15
HeadQrts	1.9481	10.6014	10.6000	6.9118	10.6
Overall	8.0865	252.3350	252.3333	101.3842	252.3333

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

Considering the fitted statistical distribution it is assessed that for the negative binomial distribution, Greater Accra* received the highest mean of monthly occurrences of fire with the highest overdispersed parameter of 19.53. This indicates that the region is susceptible to a higher occurrence of fire monthly and the occurrence of fire is riskier than for other regions. Although some regions have higher expected fire occurrences, the overdispersed parameter indicates how risky the occurrences are within months. We can infer that monthly variations of fire occurrence in Tema region are shown to be the next risky region expecting higher changes in the monthly fire occurrence. However, considering variations of fire occurrence from the normal fitted distributions amongst regions, it is shown that Ashanti is a highly risky region, whiles Brong Ahafo, Greater Accra follows subsequently. Comparing the variations amongst the fitted distribution, it is not clear which of the models really gives us the true information. We therefore based on various goodness of fit test to select the best model for fire frequency.

Similarly, considering the fire fatalities through fire occurrence on the economy, fire loss data (death) distributions has been previewed in the Table 4.4 indicating the parameter estimates from the various three models considered for the fire fatality data, based on theoretical and empirical judgments using several probability graphs. The Negative Binomial (r and θ parameters); the Normal distribution (μ, δ) and the Poisson distribution (μ); were fitted to the fire fatality data on the regions and in overall. The parameters obtained from the fire fatality form the various statistical distributions are shown in the Table 4.4 below.

Table 4. 4: Parameter estimation of fire fatalities by maximum likelihood

	Neg. Binomial		**Normal**		**Poisson**
Regions	**k**	μ	μ	σ	μ
Ashanti	1.0315	6.2931	6.6944	6.9435	6.6944
Volta	0.0479	0.1111	0.1111	0.5152	0.1111
Brong Ahafo	0.2090	3.4719	3.4722	7.8404	3.4722
Western	1.7306	0.1944	0.1944	0.4606	0.1944
Eastern	0.4075	2.3333	2.3333	3.4400	2.3333
Upper East	0.0152	0.0834	0.0833	0.4930	0.0833
Upper West	NF	NF	NF	NF	NF
North	0.1311	0.1945	0.1944	0.6155	0.1944
Central	0.2663	3.1943	3.19444	7.6515	3.1944
Greater Accra*	0.4736	1.3886	1.3889	2.1638	1.3888
G.Accra	0.4061	0.5833	0.5833	1.1396	0.5833
Tema	0.1831	0.7221	0.7222	1.7258	0.7222
HeadQrts	3.861e+05	8.332e-02	0.0833	0.2764	0.0833
Overall	1.4792	17.6691	17.667	15.1712	17.6667

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy, **NF:** No Fit

The parameter estimates fitted by the statistical distribution for fire fatality indicates that Ashanti region received the highest mean of monthly occurrences of death through fire with an overdispersed parameter of 1.0315. Considering the overdispersion parameters, it is shown that the Western region, indicates the risky region for which death through fire varies widely within months. Although some regions such as Central, Brong Ahafo and Eastern receives high fatality through fire, the overdispersed parameter indicates less riskiness in the monthly death through fire compared to the Western region. Also, considering variations of fire fatality from the normal fitted distributions amongst regions, it is shown that Brong Ahafo is the highly risky region, whiles Central, Ashanti follows subsequently. Variations amongst the fitted distribution are less communicated and therefore we based on various goodness of fit test to select the best model for fire fatality in order to provide better decisions

4.3.2 Log-Likelihoods Statistics

The natural logarithm (ln) of the likelihood function, called the log-likelihood function is a statistic depending on the observed sample data but regarded as a function of the parameter. The specified likelihood of a parameter indicates a result that usually indicates the possibility that result will take place. However, the log-likelihood is the maximum value of the likelihood function; it is worthwhile to take the decision leading to result if only if the level of likelihood is high enough. The log-likelihood of the fire data were calculated by the maximum likelihood method after the parameters were obtained. The Table 4.5 below is the fire frequency log-likelihood statistics. From the values of the log-likelihood statistics, it is inferred that the Normal distribution and the Negative Binomial distribution have high values enough to identify the likelihood of the parameters of the various fire frequency data from the regions.

Table 4. 5: Log-likelihood Statistics on Fire frequency

Regions	Neg. Binomial	Normal	Poisson
Ashanti	-287.4465	**-282.8604**	-544.5776
Volta	**-139.0218**	-184.5434	-238.5076
Brong Ahafo	**-244.6659**	-277.4605	-797.7536
Western	**-206.0245**	-209.6039	-254.7575
Eastern	**-224.0615**	-248.0662	-407.3627
Upper East	**-208.2541**	-214.291	-292.2417
Upper West	**-198.9483**	-220.9457	-325.3779
North	**-195.6132**	-209.3408	-305.7327
Central	**-240.3668**	-241.4891	-379.8291
Greater Accra*	**-263.9762**	-268.6255	-343.014
G.Accra	**-244.7293**	-249.854	-309.8214
Tema	**-201.7274**	-203.8237	-217.8991
HeadQrts	**-200.3781**	-201.1303	-271.1672
Overall	**-352.5615**	-362.2713	-1278.394

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

Also, the log-likelihood statistics shows that Poisson received the least value of the log-likelihood value for data coming from the Brong Ahafo region, whiles data from the Volta region showed the highest value of log-statistics, which an indication of Negative Binomial distribution best model among the three candidate model of the fire frequency data observed. This analysis suggests that Negative Binomial distribution is enough to capture the severity distribution of fire frequency data from almost all the regions. The Negative Binomial distribution had the highest log-likelihood value across the entire fire frequency data indicating the best model among the three candidate models.

Table 4. 6: Log-likelihood Statistics of fire fatalities

Regions	Neg. Binomial	Normal	Poisson
Ashanti	**-107.0043**	-120.8428	-172.5433
Volta	**-10.6083**	-27.2067	-14.5807
Brong Ahafo	**-70.36418**	-125.2161	-213.0814
Western	**-19.07965**	-23.1770	-19.1564
Eastern	**-70.0520**	-95.5584	-108.881
Upper East	**-6.7878**	-25.6214	-12.2465
Upper West	NF	NF	NF
North	-17.**5092**	-33.6111	-20.9482
Central	**-72.2686**	-124.3383	-192.4193
Greater Accra*	**-56.9940**	-78.8692	-74.1445
G.Accra	**-36.5811**	-55.7851	-42.5462
Tema	**-37.2196**	-70.7267	-55.4107
HeadQrts	-10.4547	**-4.7873**	-10.4547
Overall	**-139.1294**	-148.9803	-295.1953

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

Considering fatality through fire the Table 4.6 is also log-likelihood statistics obtained from the parameter estimates. It is shown that Poisson received the least value of the log-likelihood value for data coming from the Brong Ahafo region, whiles data from the Upper East and Head Qrts region showed the highest value of log-statistics, which an indication of Negative Binomial distribution and Normal distribution best model among the three candidate model of the fire frequency data observed. However, in totality we can infer that the Negative Binomial distribution had the highest log-likelihood values across the entire fire fatality data indicating the best model among the three candidate models.

4.3.3 Criteria Selection Methods

In this section Bayesian Information Criterion which is the Akaike Information Criterion (AIC) and Bayesian-Bayes Criterion (BIC) is used to choose the best out of the candidate model. The criterion selection methods are a sum of two terms, one that characterizes the prediction error of the model, and a second term that characterizes the number of freely estimated parameters in the model. By minimizing both terms, we seek to identify a model that does not over fit the data with too many parameters while also accurately modelling the data.

Table 4. 7: AIC values for the various distributions (Fire Frequency)

Regions	Neg. Binomial	Normal	Poisson
Ashanti	578.8929	569.7209	1091.155
Volta	282.0436	373.0868	479.0153
Brong Ahafo	493.3317	558.9209	1597.507
Western	416.0489	423.2078	511.515
Eastern	452.123	500.1323	816.7254
UE	420.5082	432.582	586.4834
UW	401.8966	445.8914	652.7559
North	395.2264	422.6816	613.4653
Central	484.7335	486.9782	761.6582
Greater Accra*	531.9523	541.251	688.028
G.Accra	493.4585	503.708	621.6427
Tema	407.4548	411.6475	437.7982
HeadQrts	404.7562	406.2607	544.3343
Overall	709.123	728.5427	2558.787

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

In a model selection application, the optimal fitted model is identified by the minimum value of BIC. Also, it becomes interesting when AIC values are compared to the series of models specified a priori, the model with the lowest AIC being the best model among all models specified for the data at hand. So in confirming and fitting appropriate models for fire frequency and fatalities below tables indicates computations of AIC and BIC of the fitted distributions.

In the Table 4.7 above it is shown that the AIC is fitting the Negative Binomial distribution for almost all the fire frequency data whiles fire data from Ashanti is fitted by the Normal distribution. We can therefore emphasize that the fire count data of various regions in Ghana follow a negative Binomial distribution. This means that fire count data on various regions is better modelled by the failure-process parameterization of the negative binomial a good phenomenological description of a patch or clustered distributed with no intrinsic upper limit that has more variance than the Poisson (Bolker, 2008).

Considering the BIC values shown in the Table 4.8 below it is consistent that BIC also has fitted the Negative Binomial distribution to all the fire frequency data with the exception of fire data from Ashanti region which was also confirmed to be better fitted with Normal distribution. It is therefore established that fire count data on various regions in Ghana follow a Negative Binomial and a Normal distribution for data from Ashanti region.

Table 4. 8: BIC values for the various distributions (Fire Frequency)

Regions	Neg. Binomial	Normal	Poisson
Ashanti	583.0816	573.9096	1093.25
Volta	286.2323	377.2755	481.1096
Brong Ahafo	497.5204	563.1096	1599.602
Western	420.2376	427.3965	513.6094
Eastern	456.3116	504.321	818.8197
UE	424.6969	436.7707	588.5777
UW	406.0852	450.0801	654.8502
North	399.4151	426.8703	615.5596
Central	488.9222	491.1668	763.7525
Greater Accra*	536.141	545.4397	690.1224
G.Accra	497.6472	507.8967	623.7371
Tema	411.6435	415.8361	439.8925
HeadQrts	408.9449	410.4494	546.4286
Overall	713.3117	732.7314	2560.882

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

Also, in using the criteria selection method in evaluating the appropriate distribution to the fire fatalities, AIC values and BIC values are also computed accordingly as shown in the respective Table 4.9 and Table 4.10. On previewing the AIC values, it is asserted that the fire fatality in most of the regions is fitted by the Negative Binomial distribution. Meanwhile, data from the Western and Head Quarters is fitted by the Poisson and the Normal distribution respectively. Considering the minimum values of AIC indicated by the distributions, it can be inferred that the negative binomial distribution has the minimum values across the entire fatality distributions an indication of the best model among the three candidate model of fire fatalities data observed. It is imperative from the various goodness of fit statistics that the Negative binomial better fits the data under study whiles the Normal distribution fit few fire data from the study.

Table 4. 9: AIC values for the various distributions (Fire Fatalities)

Regions	Neg. Binomial	Normal	Poisson
Ashanti	**218.0085**	245.6856	347.0866
Volta	**25.2165**	58.4133	31.1613
Brong Ahafo	**144.7284**	254.4322	428.1628
Western	42.1593	50.3540	**40.3128**
Eastern	**144.1039**	195.1167	219.7619
UE	**17.5756**	55.2428	26.4930
UW	NF	NF	NF
North	**39.0184**	71.2222	43.8963
Central	**148.5372**	252.6765	386.8386
Greater Accra*	**117.988**	161.7384	150.2889
G.Accra	**77.1622**	115.5702	87.092
Tema	**78.4392**	145.4534	112.8214
HeadQrts	24.9094	**13.5745**	22.9094
Overall	**282.2588**	301.9605	592.3907

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

On previewing the BIC values, it is asserted that the fire fatality in most of the data is fitted by the negative binomial distribution. Thus a minimum value shown by the BIC values compared to other distributions makes this justification. Meanwhile, data from the Western and Head Quarters is fitted by the Poisson and the Normal distribution respectively. These values are consistent with the log-likelihood values that were selected in the above tables.

Table 4. 10: BIC values for the various distributions (Fire Fatalities)

Regions	Neg. Binomial	Normal	Poisson
Ashanti	**221.1755**	248.8526	348.6701
Volta	**28.3835**	61.5804	32.7448
Brong Ahafo	**147.8954**	257.5992	429.7464
Western	45.3263	53.5210	**41.8963**
Eastern	**147.271**	198.2837	221.3454
UE	**20.7427**	58.4099	28.0765
UW	NF	NF	NF
North	**42.1854**	74.3892	45.4799
Central	**151.7043**	255.8436	388.4222
Greater Accra*	**121.1551**	164.9055	151.8724
G.Accra	**80.3292**	118.7372	88.6760
Tema	**81.6062**	148.6205	114.4049
HeadQrts	28.0765	**16.7416**	24.4930
Overall	**285.4259**	305.1275	593.9742

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

In summary, it can be asserted from the various modelling techniques the various distributions which were fitted by the fire frequency and fire fatalities data are the Negative binomial distribution. Empirically, this study has proven with the log-likelihood statistics, Information Criteria **(**AIC) and the Bayesian criterion (BIC) criteria's the base probability distribution of the fire frequency and losses through fire (fire fatalities). Selection of this model for fire data is consistent with Xiao, Zhang and Ji (2015) study, which used count data models to analyse fire occurrence data that is likely to be dispersed and frequently contain an excess of zero counts (no fire occurrence). They indicated that the that prediction achieved through Negative Binomial model provided a more compelling and credible inferential basis for fitting actual forest fire occurrence (Xiao, Zhang & Ji, 2015).

4.3.4 Parameter Predictions at 95% confidence level

A Confidence Interval is an interval of numbers containing the most plausible values for our population parameter. Simulation was done through bootstrapping sampling parameters fitted by the distribution, including sampling stochastic variates from probability distributions to help make predictions. In determining the likelihood of estimated parameter, parameter values of the fitted distribution of fire frequency and fatalities were simulated through the bootstrapping technique where standard errors of the bootstrapped parameter helped in computing of the confidence interval of the estimated parameters. Simulation is sometimes called forward demonstrating to emphasize that you pick a model and parameters and work forward to predict patterns in the data. The 95% confidence interval produces an interval that contains the actual true parameter value of fire fatality and fire frequency.

Table 4. 11: 95% confidence interval estimates of parameters of fire frequency

	Negative Binomial		Normal	
Regions	k	μ	μ	
Ashanti			59.00±6.83	26.99±4.83
Volta	0.5±0.24	3.48±1.31		
Brong Ahafo	0.65±0.25	22.18±7.08		
Western	4.70±2.31	14.97±2.00		
Eastern	2.29±0.92	16.92±3.02		
Upper East	2.56±1.14	13.05±2.26		
Upper West	1.74±0.71	10.23±2.12		
North	1.35±0.58	9.23±2.16		
Central	2.85±1.21	23.51±3.73		
Greater Accra*	19.53±8.60	79.75±5.10		
G.Accra	13.58±6.14	48.00±3.73		
Tema	14.88±9.12	21.15±1.81		
HeadQrts	1.95±0.89	10.60±2.09		
Overall	8.09±2.92	252.34±22.81		

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

The Negative binomial distribution and the Normal distribution fitted to the fire frequency data set coming from the various operational regions under study; parameters identified above were then simulated and various confidences above are shown the true value where the actual parameter lies. From the various confidence intervals provided we can confidently say that the subsequent fire occurrence can be modelled within the lower and upper limit of the parameter estimated on the various regions.

Also, for fire fatalities estimated parameter was recognized for on the various fatality data from the regions the Negative Binomial distribution, the Normal distribution and the Poisson fit for the fire loss data (fire fatality) from various regions previewed in the table below. The various predictions of the parameters using a 95% confidence interval are shown in the Table 4.12: 95% confidence interval estimates of parameters of fire fatality estimate below.

Table 4. 12: 95% confidence interval estimates of parameters of fire fatality

	Neg. Binomial		**Normal**		**Poisson**
Regions	**k**	μ	μ	σ	μ
Ashanti	1.03±0.57	6.29±2.31			
Volta	0.05±0.11	0.11±0.20			
Brong Ahafo	0.21±0.13	3.47±2.55			
Western					0.19±0.14
Eastern	0.41±0.28	2.33±1.29			
Upper East	0.02±0.04	0.08±0.24			
Upper West	NF	NF	NF	NF	NF
North	0.13±0.23	0.19±0.23			
Central	0.27±0.16	3.19±2.10			
Greater Accra*	0.47±0.39	1.39±0.76			
G.Accra	0.41±0.47	0.58±0.39			
Tema	0.18±0.18	0.72±0.62			
HeadQrts			0.08±0.09	0.28±0.06	
Overall	1.48±0.70	17.67±4.94			

Greater Accra*: Administrative Region, **HeadQrts:** Head Quarters (Operational Region), **G.Accra**: Greater Accra (Operational Region), **Tema:** Operational Region, **Overall:** Fire data on the whole economy

4.3.5 Probability Plots Justifying Best Model

As already shown and proven in the above by the log-likelihood statistics and various criteria selection goodness of fit test that the negative binomial distribution emerged as being a better model for fire data that it is observed. In this section, plot of values for common distributions is displayed, in order to help identify the choice of distributions to fit data. Thus, the plot present theoretical distribution is likely identified by the data under study. Statistics such as the skewness and kurtosis, like all higher moments, have a very high variance, providing a plot that is regarded as indicative only is used to plot and identify the theoretical distributions of the count fire data.

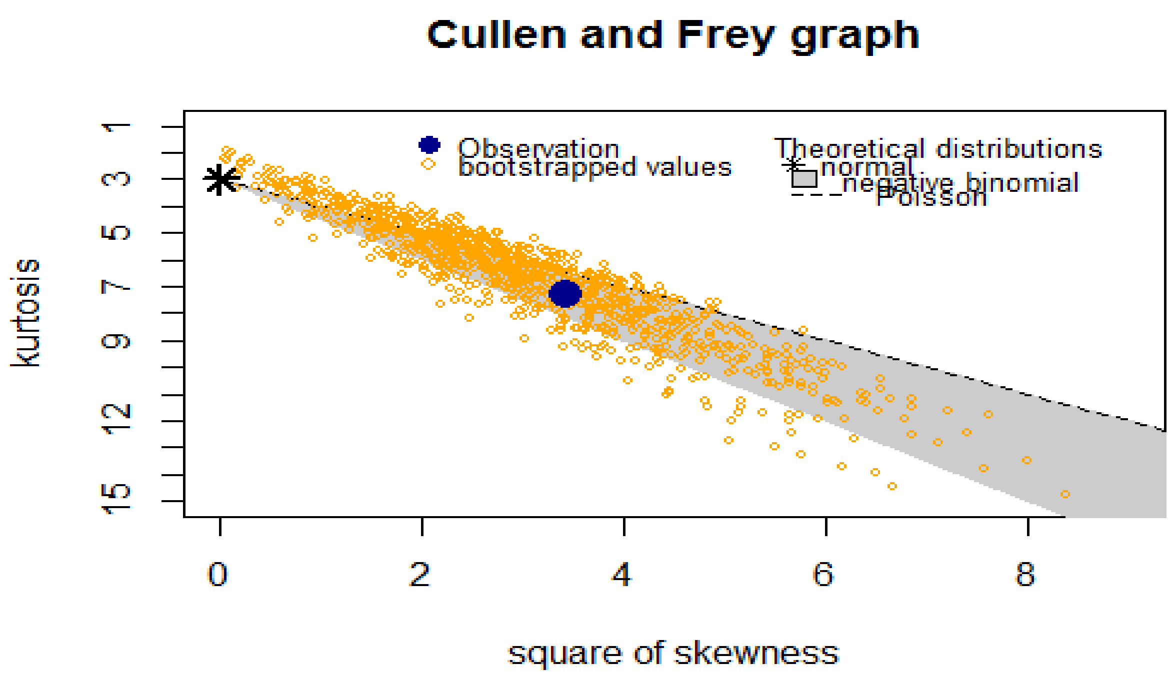
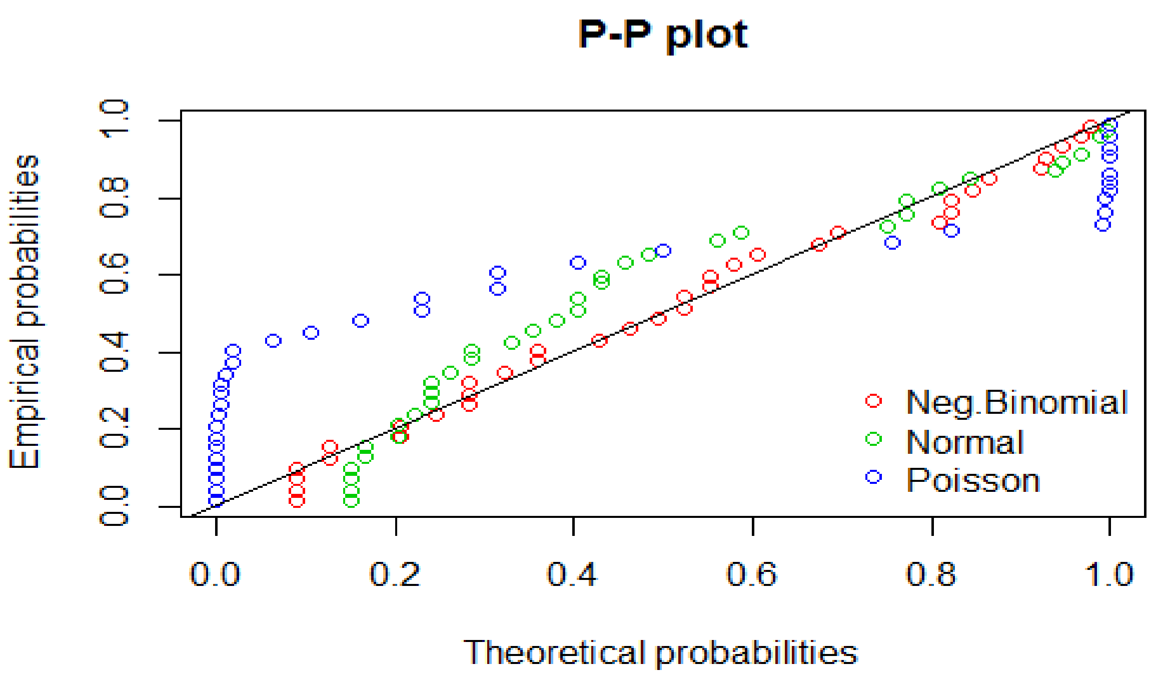


Figure 4. 6: Skewness-kurtosis plot for Overall fire data theoretical distribution

The Cullen and Frey graph for the overall fire frequency data show that theoretically the normal, NB and the Poisson fit for the fire occurrence data. Considering the distribution that better fits the observed data, it asserted that the negative binomial closely fits the observed fire data. Subsequently, the probability plots for overall fire data of the fitted distribution were constructed, because it is necessary to validate goodness of fit test in order to select a statistical distribution that best fits the data.

Figure 4. 7: P-P plot for Overall fire data based on theoretical and Empirical probabilities



The three distributions are separated in space, the P–P plot gives useful comparisons probability distributions that have a nearby or equal location. The Probability plots in Figure above and other at the Appendix 2 for various regional fire depicts a very good fit for negative binomial with almost all the data points falling onto or around the reference line. We can therefore confidently say that the negative binomial distribution does provide the correct statistical model for fire frequency data on the various administrative and operational regions, however, for that Ashanti region was fitted by the normal distribution.

CHAPTER FIVE

CONCLUSION, DISCUSSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the findings from the study, and recommends rational measures for stakeholders, actuaries, insurance managers and Ghana National Disaster risk committee. It again recommends further study in this area for future researchers. The chapter provides the concluding statements of the research based on the findings.

5.2 Summary

This paper illustrates the modelling process that starts with the data collection and preparation phase and results in the estimation of the distribution of the loss through fire (fire fatalities) and the frequency of occurrence of fire are modelled separately. The study upon identifying best fit distributions further predicted the parameters estimated using confidence intervals. The study considered twelve operational regions and the ten administrative regions data that are collected by the Ghana Open data initiative on the economy of Ghana. The result of the study demonstrated that fire frequency data on the economy are best modelled with similar distribution whiles the some of the distribution of loss (fire fatalities) are indeed better modelled with different distributions.

The study revealed that the fire frequency data for most of the regions followed a Negative Binomial distribution while few followed the Normal distribution. Also, it is asserted that the fire fatality data for regions like Ashanti, Volta, Brong Ahafo, Eastern, Upper East, Northern, Central, Greater Accra*, G.Accra, Tema, were fitted by the Negative Binomial distribution. The

Western and Head Quarters fire fatality data were best seen to be modelled by is fitted by the Poisson and the Normal distribution respectively. It indicated by the various statistical test (log-likelihood, AIC, and BIC) that the Negative Binomial distribution, the Poisson distribution and the Normal distribution better model the various fire count data on the operational and administrative regions in Ghana. It is asserted that most of the fire data events have been modelled with Negative Binomial which is identified in the literature to be best for modelling stochastic variability of ecological count data around a theoretical expectation data by taking in the accounts for the overdispersion that arises from the data. Considering the overdispersion nature of the count fire data parameter estimates, bootstrap standard errors provided in the estimates of uncertainty of the parameters that are of interest to the ecological model. Parameters are predicted with the 95% confidence interval provided in the Table 4.11 and Table 4.12 above.

5.3 Conclusion

This study has examined the count fire data of fire occurrence in Ghana data from the Ghana Open Data Initiative and has fitted appropriately theoretical distribution to each regional fire frequency and fatality data. After following the distribution fitting process processes using the R-software with accuracy the study proposes that two parameter probability distribution Negative binomial better models fire occurrence data in Ghana. Although the Poisson model is the simplest count data model, it is highly restrictive, as the variance of the outcome is assumed to equal its expectation. Fire count data sets always exhibit overdispersion where the negative binomial distribution offers a dispersion parameter that well explains the overdispersion of positive count data. Amongst the distribution fitted for the fire fatality and fire frequency data, the negative binomial shown to be best fitted to the fire count data in Ghana.

The two parameter negative binomial model shows that, fire frequency and fire fatality are best being modelled by the overdispersed stochastic process. Fire data which is an ecological count data have been modelled with several distributions such as the Poisson, zero-inflated models, Negative binomial and other hurdle models. Previous research by Xiao *et al.*, (2015) and by Linden and Mantyniemi (2011) show that negative binomial distribution best model ecological count data such as fire. Xiao *et al.*, (2015) showed in their study that the NB model provided a more compelling and credible inferential basis for fitting actual forest fire occurrence. Confirming from previous studies, White and Bennetts (1996) study on the analysis of frequency count data, showed that the negative binomial distribution better gives a goodness of fit of observed count data, the model includes the difference in means as well as the dispersion of the counts. Linden and Mantyniemi (2011) proposed a parameterization of the negative binomial distribution, where two overdispersion parameters are introduced to allow for various quadratic mean–variance relationships, including the ones assumed in the most commonly used approaches.

Fire prediction over decades is modelled as a stochastic process for predicting the occurrence of fires, studies utilized a negative binomial model for related counts to a fire danger rating index (Bruce, 1960). This is study has confirmed from previous studies what fire count data are best modelled, and have empirically fitted the distribution to the fire fatality and fire frequency data on the Ghanaian economy.

The parameters of the NB models of the various administrative regions and operational regions indicate the mean monthly number of fire or fatality through fire that is expected, whiles the second parameter indicates the overdispersion of the data by including unobserved heterogeneity. The parameters of the fitted distribution reflect the fire occurrence and fatality pattern for each region that is expected in a month or on a current fire season. The confidence intervals of various parameters also show the predictions of fire occurrence and fatality that are expected on a season of low returns and of high return of fire in a particular region.

5.4 Recommendations

Efforts need to be supported by researchers, fire officers and risk managers for further improvement and more effective fire management. Data collected on fire should be more robust in order to encapsulate certain activities that lead to fire outbreak. The national disaster risk management and Ghana fire service should deploy resources in various areas that are seen to have a high rate of fatality through fire. Based on the predictions of the statistical models we suggest that Government and stakeholders should make available necessary gadget to help fight fires in various fatality risky areas in amongst the regions.

5.5 Further Research

The need of building fire risk analysis becomes an important tool in providing fire safety. It is therefore necessary that several studies are required to help build fire safety risk analysis, in order to provide information to the potential risk occupants. It is worth realistic in modelling fire risk by considering complex data that may include weather history, fire history, fire ignition and fire spread and other fire details that will help in a more direct tackling of the risk. Studies should focus on fire behaviour modelling, geospatial analysis and remote sensing of fire. Future studies can also consider simulating the fire spread for each weather scenario in the economy and subsequently compute fire spread probabilities from the simulated fire spread data.

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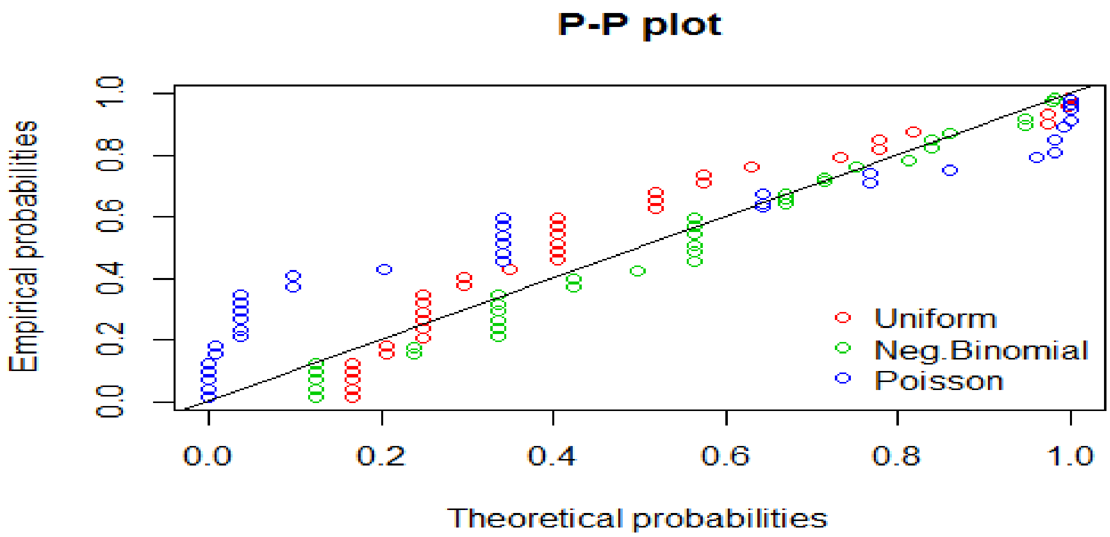
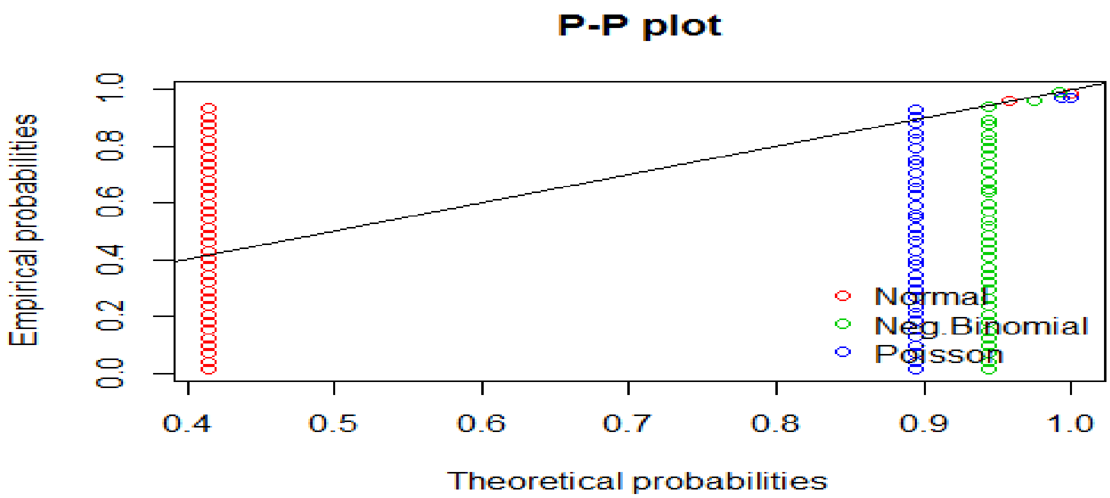
Appendix 1- P-P plot for fire data based on theoretical and Empirical probabilities

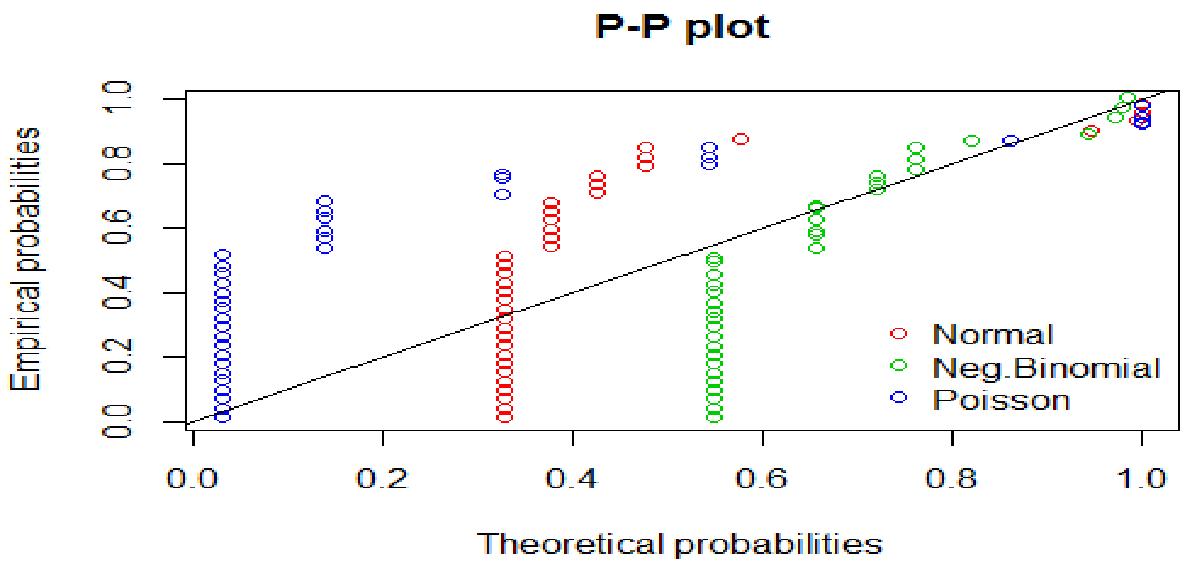
Ashanti Region



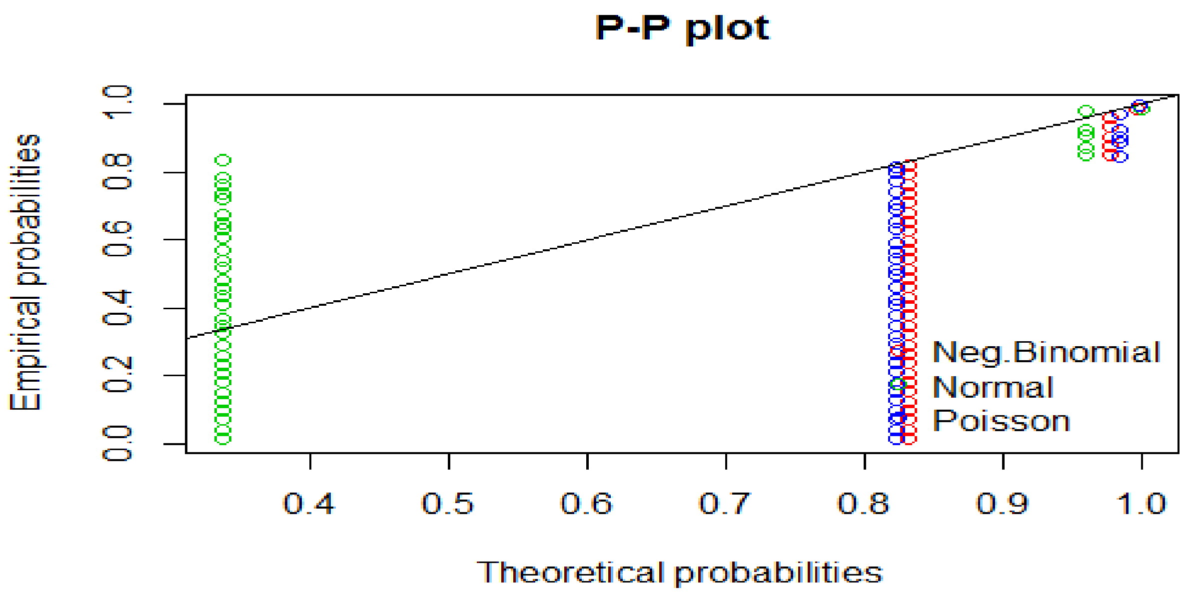
Volta Region



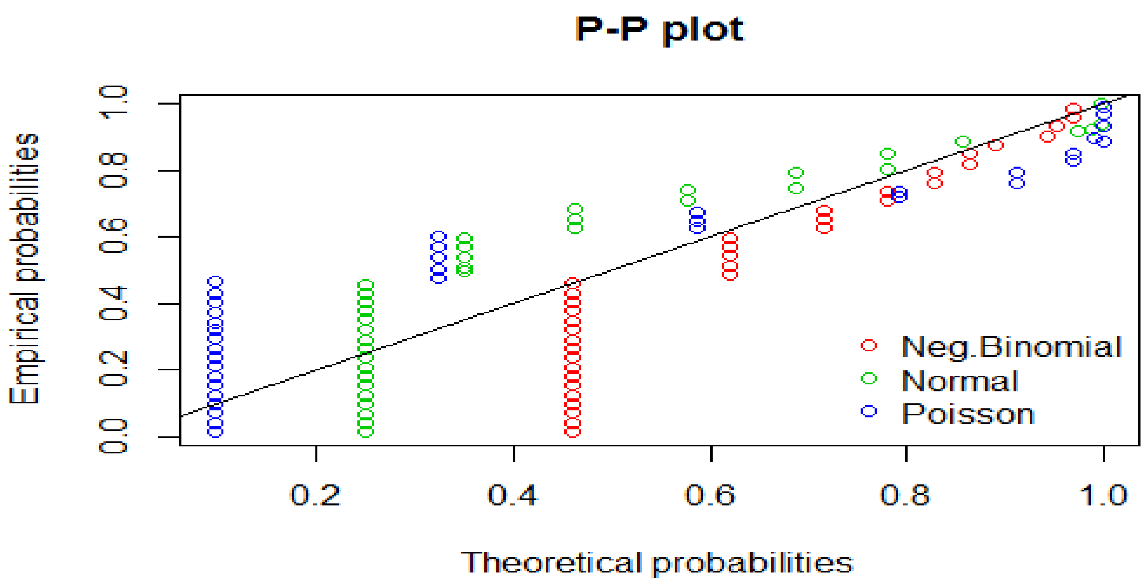
Brong Ahafo Region



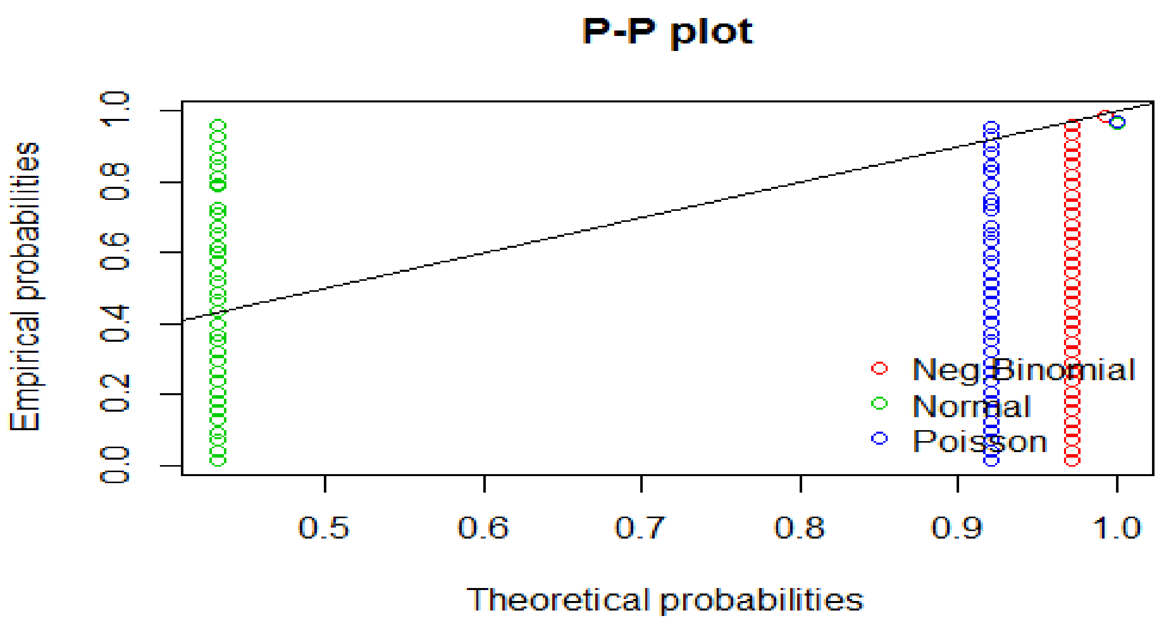
Western Region



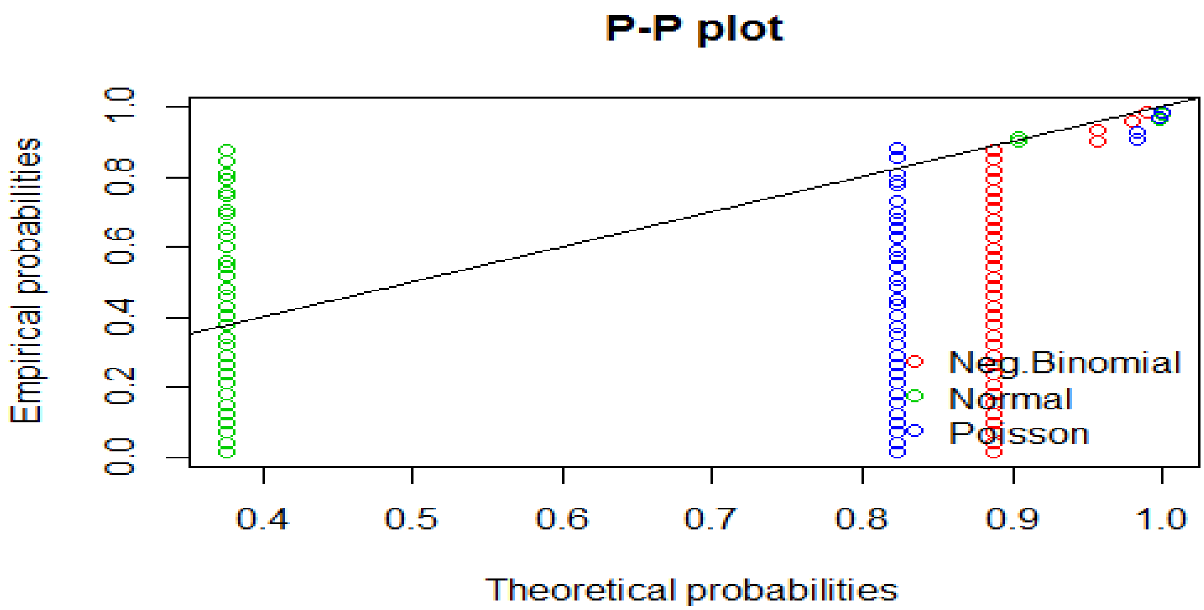
Eastern Region



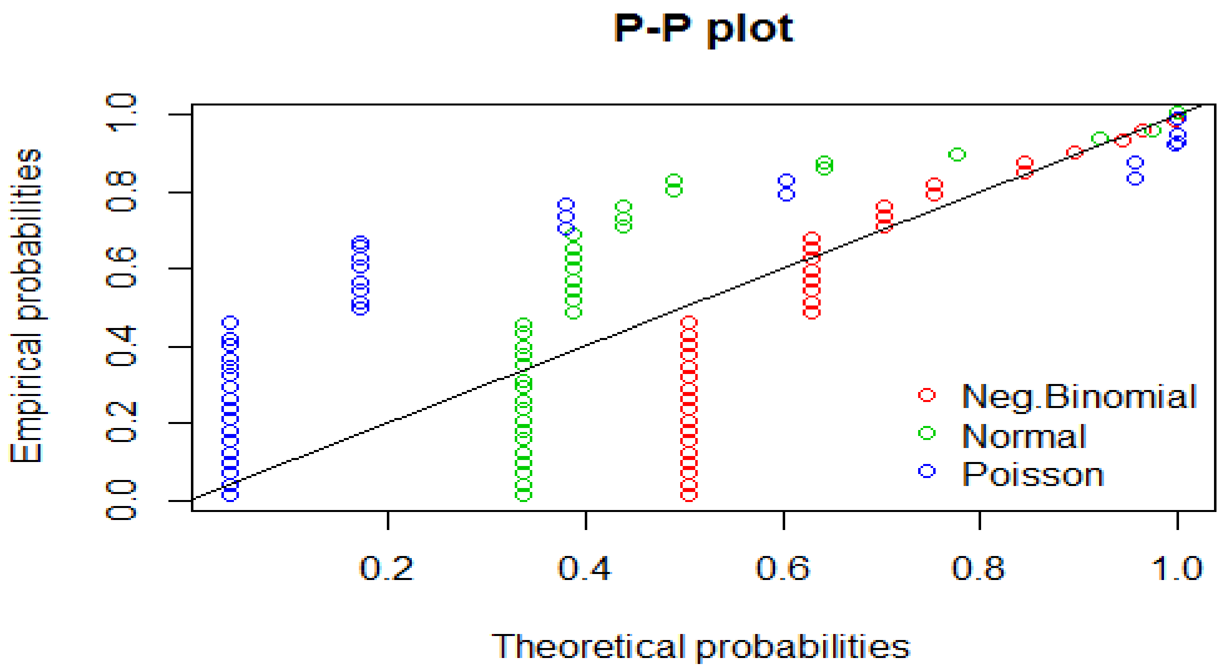
Upper East Region



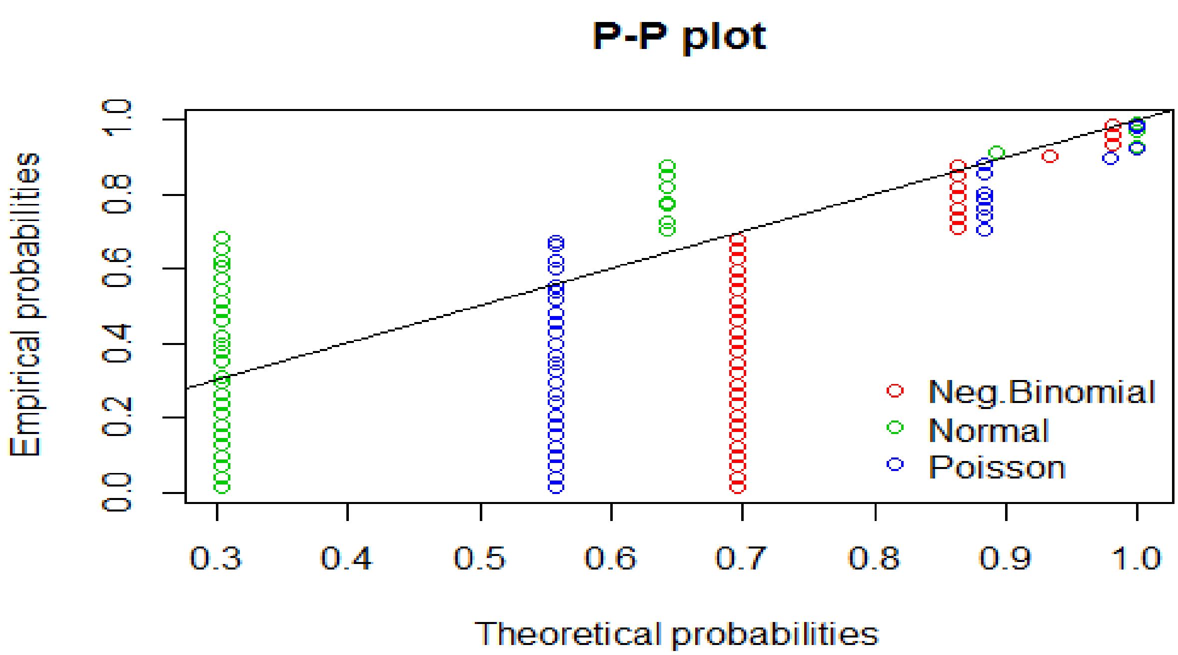
Northern Region



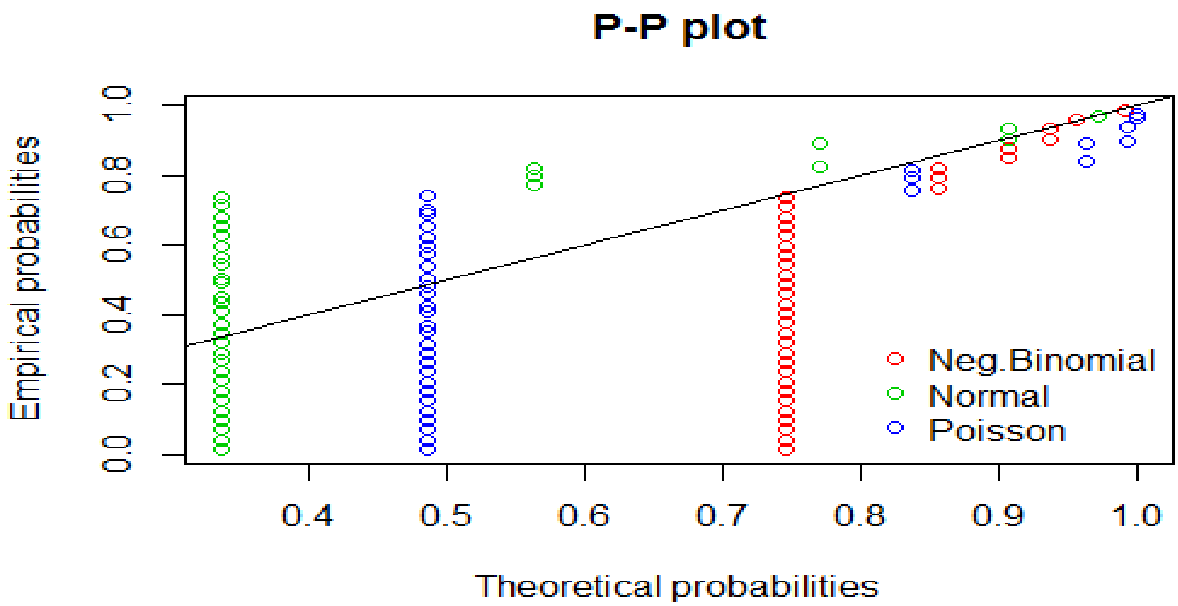
Central Region


P-P plot
Empirical probabilities
0.0
0.2
0.4
0.6
0.8
1.0
0.2
0.4
0.6
0.8
1.0
Theoretical probabilities
Neg.Binomial
Normal
Poisson

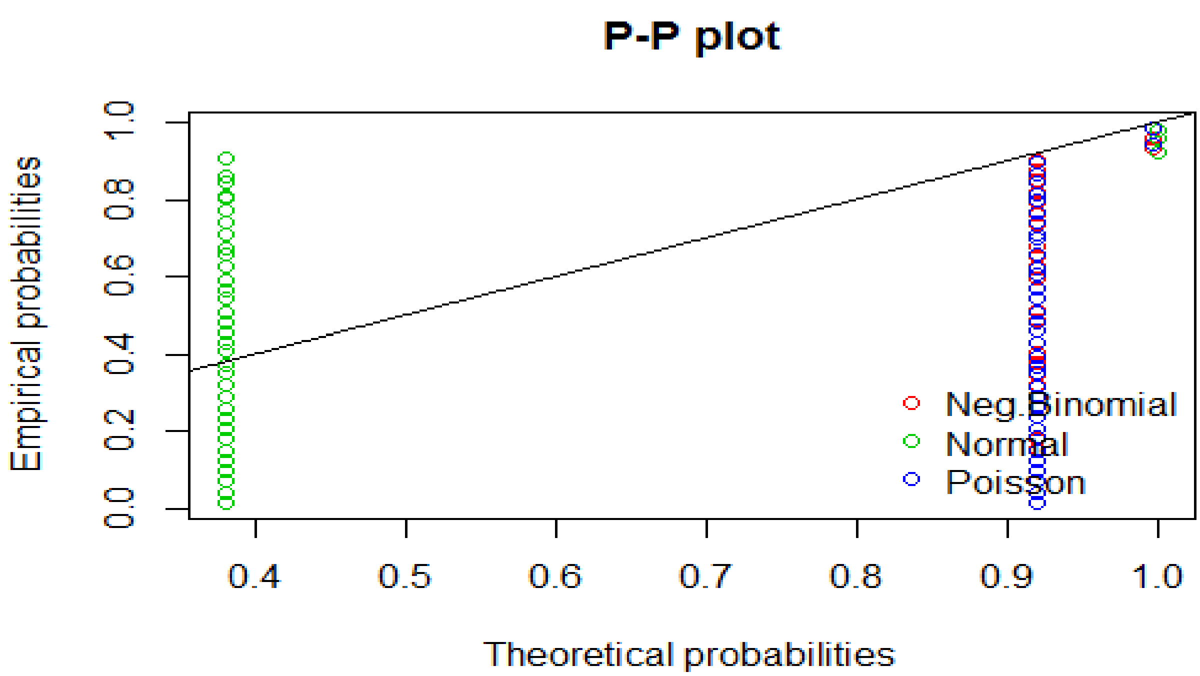
G.Accra


P-P plot
Empirical probabilities
0.0
0.2
0.4
0.6
0.8
1.0
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Theoretical probabilities
Neg.Binomial
Normal
Poisson

Tema Region



HeadQrts



Greater Accra*